Załącznik nr 2 do Regulaminu
postępowania w sprawie nadania stopnia doktora na Uniwersytecie Zielonogórskim

UNIWERSYTET
ZIELONOGÓRSKI

Dziedzina nauk inżynieryjno-technicznych
Dyscyplina: inżynieria mechaniczna

Dineshkumar Musalekar

New approach to dynamic management of technical knowledge to construct a smart and flexible Die Casting Mould Manufacturing towards intelligent manufacturing

Nowe podejście do dynamicznego zarządzania wiedzą techniczną umożliwiające rozwój inteligentnego i elastycznego procesu produkcji form odlewniczych zgodnie z koncepcją inteligentnej produkcji

.

Promotor: prof. dr hab. inż. Justyna Patalas-Maliszewska

Rozprawę akceptuję: …………..………..……….

Zielona Góra 2026

Contents

List of abbreviations:

AI	Artificial Intelligence
AIMS	Artificial Intelligent driven IoT Monitoring System
AR	Augmented Reality
VR	Virtual Reality
NLP	Natural Language Processing
GUI	Graphic User Interface
ERP	Enterprise Resource Planning
MES	Manufacturing Execution System
PLM	Product lifecycle management
CAD	Computer Aided Design
CAM	Computer Aided Manufacturing
EMD	Electronic Measuring Device
CNC	Computer Numeric Control
3D	3 Dimensional
2D	2 Dimensional
NOK	Not OK
ANN	Artificial Neuron Network
TKB	Technical Knowledge Base
i4.0	Industry 4.0
i5.0	Industry 5.0
HVAC	Heating, Ventilation Air Conditioning
DFM	Design For Manufacturability
HITL	Human In The Loop
PLC	Programmable Logic Control
NLP	Natural Language Processing
SOP	Standard Operating Procedure
CNN	Convolutional Neuron Network
RNN	Recurrent Neuron Network
LSMT	Long Short-Term Memory
RUL	Remaining Useful Life
DOE	Design Of Experiments
KPI	Key Performance Index
MAE	Mean Absolute Error
RSME	Root Mean Square Error
SMEs	Small and Medium Enterprises
BOM	Bill Of Material
EDM	Electrical Discharge Machining
CNC	Computer Numeric Control
CPSs	Cyber-Physical systems
DM	Dynamic Management
IIoT	Industrial Internet of Things

IM	Intelligent Manufacturing
IoT	Internet of Things
ML	Machine Learning
OEE	Overall Equipment Efficiency
PPM	Parts Per Million
T2	Trials 2
PPAA	Production Part Approval Process
FDPR	Full Day Production Run
NG	Not Good
CH	Cylinder Head
FH	Front Head
PVD	Physical Vapor Deposition
HPDC	High Pressure Die Casting
mm	milii meters
ms	milli seconds
m/s	meters per second
AL	Aluminum
Mn	Magnesium
Cu	Copper
Si	Silicon
Fe	Iron
DMC	Diecasting Machine Cell
MLP	Multilayer Preceptor
MSE	Mean Squared Error
RMSE	Root Mean Squared Error
AC	Air Condition
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
PC	Persona Computer
HMI	Human Machine Interface
RELU	Rectified Linear Unit
kN	Kilo Newton
SP	Sustainable Production
SDG	Sustainable Development Goals
HRC	Human Robot Collaboration
TEEP	Total Effective Equipment Performance
TK	Technical Knowledge

Summary

Modern manufacturing enterprises must become increasingly flexible in order to maintain competitiveness in a rapidly changing market environment. One of the key solutions is the implementation of tools and methods aligned with the concepts of Industry 4.0 and even Industry 5.0, aimed at building autonomous and highly efficient production environments. This doctoral dissertation proposes a new approach to dynamic technical knowledge (TK) management in the die casting mould manufacturing process within the automotive and metal industries. The research particularly focuses on high-precision die casting mould manufacturing, where product quality significantly determines process efficiency. Technical knowledge often remains dispersed among experienced engineers or hidden within machine records, making process execution highly dependent on individual expertise and susceptible to inconsistencies and disruptions.

The main objective of the dissertation is to develop a framework for dynamic technical knowledge management in order to build an intelligent and flexible die casting mould manufacturing and die casting process. The research problem was formulated through the following questions:
(1) How can technical knowledge related to the die casting mould manufacturing process be acquired, stored, and transferred in order to increase process efficiency? (2) How can decisions aimed at increasing the efficiency of the die casting process be supported based on stored technical knowledge?

In the die casting environment, fluctuations in parameters such as molten metal temperature, injection speed, cooling rates, and mould wear patterns significantly affect product quality and mould durability. To manage this complexity in data, information, and knowledge acquisition, a research workstation was developed, including a Bühler 840T die casting machine and IoT-enabled sensors distributed throughout the die casting line. These sensors collect real-time operational parameters such as cavity pressure, thermocouple readings, machine vibrations, mould temperature, and lubricant flow. ERP and MES systems are integrated to collect contextual data, including production orders, part numbers, material batches, and operator shifts. This integration ensures that technical knowledge is not isolated but closely connected with the production environment.
The research work was carried out in the following stages:

1. Characterization of the die casting mould manufacturing process

The manufacturing process was modelled and its detailed workflow was presented, divided into the following stages: (a) Understanding part design and customer requirements: detailed 2D and 3D documentation is obtained from the customer and analysed to understand tolerances and the limitations of die casting and CNC machines planned for production. (b) Die casting mould design: the mould is designed and virtually manufactured before physical production. Prior to actual manufacturing, the entire design is tested and

validated through 3D simulations to analyse solidification, thermal behaviour during die casting, mould filling velocity, air evacuation, etc.

(c) Mould manufacturing: based on the mould design, a BOM (Bill of Materials) is prepared and components are ordered from approved suppliers. Each mould component undergoes a sequence of manufacturing operations. (d) Mould trials and correction process: mould design teams, manufacturing engineers, process engineers, and quality engineers prepare measurement and validation reports.

2. Development of a technical knowledge base for the die casting mould manufacturing process.

Two key areas of expert technical knowledge were identified. The first is design-related technical knowledge acquired by mould design engineers through experience, continuous learning, and improvement of similar moulds or subsequent revisions of the same mould. Key factors include the number of cavities, location of parting lines, position and dimensions of inlets and venting channels to ensure appropriate aluminium alloy flow and solidification time, enabling both high quality and optimal cycle time. The location and quantity of cooling channels ensuring optimal thermal management are also critical. Casting tolerance design must consider tolerances required for subsequent manufacturing processes such as CNC machining.

The second area of expert knowledge concerns process engineers' technical expertise regarding process parameters and trade-offs between them. This includes process duration, hydraulic pressure in different phases, mould temperature cycle management, molten aluminium temperature, and production cycle time. As a result, a technical knowledge base was developed consisting of specialist expertise from mould design engineers, knowledge derived from IoT-enabled sensor data installed on die casting machines, knowledge acquired from integrated ERP systems, and data continuously updated by process engineers and production operators.

3. Development of a technical knowledge sharing method to build an intelligent and flexible die casting mould manufacturing process and formulation of a predictive model for disturbance detection using IoT and artificial intelligence technologies

The knowledge-sharing model based on deep learning techniques was trained using a dataset of 9,919 instances from the "Valeo_Renault CH" project, containing 39 input parameters such as alloy temperature, clamping force, and cycle time. After testing various configurations, a single-layer MLP system with 20 hidden neurons achieved a prediction accuracy of 98.94%. Raw categorical, textual, and numerical data are preprocessed into machine-readable formats using techniques such as one-hot encoding for multiclass classification (prediction classes: BAD, LOK, LOT, OK, and OUT).

The AI-based technical knowledge sharing model provides real-time alerts to production managers, enabling preventive actions by detecting negative trends in cavity pressure or injection speed before defects or machine failures occur. Furthermore, it enables prediction of component fatigue to support preventive tool maintenance and significantly minimize downtime.

4. Development and implementation of an IT system supporting dynamic technical knowledge management in the service department of the die casting mould manufacturing process

As a result, a decision support system for dynamic and flexible process management was developed and verified through practical implementation on a Bühler 840T die casting machine within the “Mahle_PSA FH” project. The system functions as a real-time decision support platform dividing production status into three visual zones:

• GREEN (Continue): Predicted good parts > 98%.

• YELLOW (Correction): Predicted good parts between 95% and 98%; the system sends alerts (SMS/e-mail) requesting expert intervention to prevent downtime.

• RED (Stop): Predicted good parts < 95%; the system automatically stops production and notifies management about the need for process correction.

The effectiveness of the proposed method was verified and confirmed under real industrial conditions through a case study of the die casting mould manufacturing process and die casting process.

The developed dynamic technical knowledge management approach, implemented within the IT system, enables the formulation of recommendations regarding necessary corrective actions in the analysed process or prediction of potential defects before they occur. The system records operator feedback and measured process parameters during mould manufacturing in order to continuously improve AI models.

The scientific contribution to the discipline of mechanical engineering is a new method for dynamic technical knowledge management, enabling the development of an intelligent and flexible die casting mould manufacturing process. The research problem was solved by developing a technical knowledge base involved in the die casting mould manufacturing process in order to improve process efficiency. It was empirically demonstrated that the proposed approach effectively improves the efficiency of the die casting mould manufacturing process, including:

- Overall Equipment Effectiveness (OEE): Increase by 8%, from a 6-month average of 71% to 78%.
- Scrap reduction: Internal scrap rate (NOK parts) reduced by 22%, significantly decreasing energy, material, and labour losses.
- Mould life: A 13% increase in the number of good parts produced throughout the tool lifecycle was observed.
- Sustainability: By optimizing parameters and reducing waste, the system directly supports Sustainable Development Goals (SDGs) and the environmental objectives of Industry 5.0.

Moreover, the developed method constitutes an original and universal solution applicable to die casting mould manufacturing processes in automotive and metal industry enterprises.

Summary in Polish

Nowoczesne przedsiębiorstwa produkcyjne muszą stawać się coraz bardziej elastyczne, aby utrzymać konkurencyjność na zmiennym rynku. Rozwiązaniem jest wdrażanie narzędzi i metod zgodnych z koncepcją Przemysłu 4.0 lub nawet Przemysłu 5.0 w celu budowania autonomicznych i wysoce wydajnych środowisk produkcyjnych. W pracy doktorskiej zbudowano nowe podejście do dynamicznego zarządzania wiedzą techniczną (TK) w procesie procesu produkcji form odlewniczych w przedsiębiorstwie branży motoryzacyjnej i metalowej. Badania koncentrują się w szczególności na produkcji form odlewniczych w sektorze o wysokiej precyzji, w którym jakość produktu w znaczącym zakresie determinuje efektywność realizacji procesu. Wiedza techniczna często pozostaje rozproszona wśród doświadczonych inżynierów lub ukryta w rejestrach maszyn, co sprawia, że realizacja procesu jest w dużym stopniu zależna od indywidualnej wiedzy i podatna na niespójności czy zakłócenia.

Głównym celem pracy doktorskiej jest opracowanie podejścia do dynamicznego zarządzania wiedzą techniczną w celu zbudowania inteligentnego i elastycznego produkcji form odlewniczych i produkcji odlewów. W rozprawie został sformułowany problem badawczy, gdzie poszukiwania jest odpowiedź na pytania: (1) w jaki sposób można pozyskiwać, przechowywać i przekazywać wiedzę techniczną związaną z procesem produkcji form do odlewania ciśnieniowego w celu zwiększenia efektywności tego procesu? (2) w jaki sposób można wspierać decyzje dotyczące zwiększania efektywności procesu odlewania ciśnieniowego na podstawie zgromadzonej wiedzy technicznej?

W środowisku odlewania ciśnieniowego wahania parametrów, takich jak temperatura ciekłego metalu, prędkość wtrysku, szybkość chłodzenia czy wzorce zużycia formy, mają istotny wpływ na jakość produktu oraz trwałość formy. Aby zarządzać tą złożonością pozyskiwania danych, informacji i wiedzy zbudowano stanowisko badawcze, które obejmuje maszynę odlewniczą Bühler 840T oraz czujniki wyposażone w technologię IoT, które zostały rozmieszczone w całej linii odlewania ciśnieniowego w celu rejestrowania parametrów operacyjnych w czasie rzeczywistym, takich jak ciśnienie w gnieździe formy, odczyty z termopar, drgania maszyny, temperatura formy oraz przepływ środka smarującego. Systemy informatyczne klasy ERP i MES są integrowane w celu gromadzenia danych kontekstowych, w tym zleceń produkcyjnych, numerów części, partii materiałowych oraz zmian operatorów. Integracja ta zapewnia, że wiedza techniczna nie jest odizolowana, lecz ściśle powiązana ze środowiskiem produkcyjnym.

Prace badawcze przeprowadzono w następujących etapach:

1. Dokonano charakterystyki przebiegu procesu produkcji form odlewniczych.

Zamodelowano przebieg procesu i zaprezentowano szczegółowy jego przebieg w podziale na następujące etapy: (a) zrozumienie projektu części i potrzeb klienta: od klienta

pozyskiwana jest szczegółowa dokumentacja 2D i 3D. Dokumentacja ta jest analizowana w celu zrozumienia tolerancji oraz ograniczeń maszyn do odlewania ciśnieniowego i obrabiarek CNC, na których planowana jest produkcja tych części. (b) projektowanie formy do odlewania ciśnieniowego: forma jest projektowana i wytwarzana wirtualnie, zanim zostanie fizycznie wykonana. Przed rozpoczęciem rzeczywistej produkcji formy cały projekt jest testowany i walidowany w symulacji 3D w celu sprawdzenia procesów krzepnięcia, zjawisk cieplnych podczas odlewania ciśnieniowego, prędkości wypełniania formy, odprowadzania powietrza itp. (c) produkcja formy: na podstawie projektu formy przygotowywany jest BOM (zestawienie materiałowe), a następnie zamawiane są komponenty od zatwierdzonych dostawców. Każdy element formy przechodzi kolejne procesy technologiczne. (d) próby formy i proces korekcji: zespoły projektowania i produkcji form, inżynierowie procesu produkcyjnego oraz inżynierowie jakości opracowują raporty pomiarowe.

2. Zbudowano bazę wiedzy technicznej dla procesu produkcji form odlewniczych.

Wyróżniono dwa kluczowe obszary wiedzy eksperckiej technicznej. Pierwszy to wiedza techniczna projektowa, która jest zdobywana przez inżynierów konstruktorów dzięki ich doświadczeniu, ciągłemu uczeniu się oraz udoskonalaniu podobnych form lub kolejnych wersji tej samej formy. Do najważniejszych czynników należą: liczba gniazd, lokalizacja linii podziału formy, położenie i wielkość wlewów oraz położenie, wielkość i liczba kanałów odpowietrzających, tak aby zapewnić odpowiedni czas przepływu stopu aluminium i jego krzepnięcia, umożliwiając uzyskanie zarówno wysokiej jakości, jak i najlepszego czasu cyklu. Istotne są również lokalizacja i liczba kanałów chłodzących zapewniających optymalne zarządzanie temperaturą. Projektowanie tolerancji odlewów musi uwzględniać tolerancje wymagane w kolejnych procesach produkcyjnych, takich jak obróbka CNC. Drugi obszar wiedzy eksperckiej to wiedza techniczna inżynierów procesu dotycząca parametrów procesowych oraz kompromisów pomiędzy nimi. Obejmuje ona między innymi czas trwania i ciśnienie hydrauliczne stosowane w różnych fazach procesu, zarządzanie cyklem temperatury formy, temperaturę ciekłego aluminium oraz czas cyklu produkcyjnego części. W rezultacie zbudowano bazę wiedzy technicznej w postaci wiedzy technicznej specjalistów, takich jak inżynierowie projektujący formy, wiedzy na podstawie danych i informacji gromadzonych za pomocą czujników wyposażonych w technologię IoT, zainstalowanych na maszynach do odlewania ciśnieniowego, wiedzy pozyskanej z systemu informatycznego klasy ERP, który jest zintegrowany z maszynami do odlewania ciśnieniowego, oraz danych aktualizowanych przez inżynierów procesu i operatorów produkcji.

3. Opracowano metodę dzielenia się wiedzą techniczną w celu zbudowania inteligentnego i elastycznego procesu produkcji form odlewniczych i następnie sfomułowano model predykcyjny do wykrywania zakłóceń w procesie przy zastosowaniu technologii IoT i sztucznej inteligencji.

Model dzielenia się wiedzą z wykorzystaniem podejścia głębokiego uczenia został wytrenowany z wykorzystaniem zestawu danych 9919 instancji z projektu „Valeo_Renault CH”, zawierającego 39 parametrów wejściowych, takich jak temperatura stopu, siła zacisku i czas cyklu. Po przetestowaniu różnych konfiguracji, jednowarstwowy system MLP z 20 ukrytymi neuronami osiągnął dokładność predykcyjną na poziomie 98,94%. Surowe dane (kategoryczne, tekstowe i numeryczne) są wstępnie przetwarzane do formatu czytelnego dla maszyn przy użyciu technik takich jak kodowanie jednokrotne (one-hot encoding) w celu klasyfikacji wieloklasowej (predykcja klas: BAD, LOK, LOT, OK i OUT). Model udostępniania wiedzy technicznej z wykorzystaniem sztucznej inteligencji dostarcza kierownikowi produkcji alerty w czasie rzeczywistym, umożliwiające podjęcie działań, śledząc negatywne trendy ciśnienia w gnieździe lub prędkości wtrysku, zanim wystąpią wady lub uszkodzenia maszyny. Ponadto umożliwia prognozowanie zmęczenia podzespołów, aby zaplanować prewencyjną konserwację narzędzi, radykalnie minimalizując przestoje.

4. Opracowano i wykonano system informatyczny wspomagający dynamiczne zarządzanie wiedzą techniczną w dziale serwisowym w procesie produkcji form odlewniczych.

W rezultacie zbudowano system wspomagania decyzji do dynamicznego i elastycznego zarządzania procesem, który zweryfikowano poprzez praktyczne wdrożenie na maszynie odlewniczej Bühler 840T w ramach projektu „Mahle_PSA FH”. System ten pełni funkcję systemu wspomagania decyzji, dzieląc produkcję w czasie rzeczywistym na trzy strefy wizualne:

- ZIELONY (Kontynuuj): Przewidywana liczba dobrych części > 98%.
- ŻÓŁTY (Korekta): Przewidywana liczba dobrych części pomiędzy 95% a 98%; system wysyła alerty (SMS/e-mail) z prośbą o interwencję eksperta w celu zapobiegania przestojom.
- CZERWONY (Zatrzymaj): Przewidywana liczba dobrych części < 95%; system automatycznie wstrzymuje produkcję i powiadamia kierownictwo o konieczności skorygowania procesu.

Zweryfikowano i potwierdzono skuteczność zastosowania proponowanej metody w warunkach rzeczywistych na przykładzie studium przypadku procesu produkcji form odlewniczych
i produkcji odlewów.

Zbudowane podejście do dynamicznego zarządzania wiedzą techniczną, zaimplementowane w systemie informatycznym, pozwala na formułowanie rekomendacji dotyczących koniecznych korekt w działaniach w analizowanym procesie lub na predykcję potencjalnych defektów przed ich wystąpieniem. System rejestruje informacje zwrotne od operatorów i wartości mierzonych parametrów w trakcie realizacji procesu produkcji form odlewniczych w celu udoskonalania modeli AI.

Wkładem naukowym do dyscypliny inżynieria mechaniczna jest nowa metoda do dynamicznego zarządzania wiedzą techniczną, której zastosowanie umożliwia rozwój inteligentnego i elastycznego procesu produkcji form odlewniczych. Rozwiązano problem badawczy, tj. zbudowano bazę wiedzy technicznej zaangażowanej w realizację procesu produkcji form odlewniczych w celu zwiększenia efektywności tego procesu. Udowodniono empirycznie, że zastosowanie zbudowanego podejścia skutecznie poprawia efektywność procesu produkcji form odlewniczych, tj.:

- Całkowita wydajność maszyn (OEE): Wzrost o 8%, ze średniej 6-miesięcznej wynoszącej 71% do 78%.
- Redukcja braków: Wskaźnik braków wewnętrznych (części NOK) spadł o 22%, co znacznie zmniejszyło koszty związane ze stratami energii, materiałów i robocizny.
- Żywotność formy: Zaobserwowano 13% wzrost liczby dobrych części wyprodukowanych w całym cyklu życia narzędzia.
- Zrównoważony rozwój: Poprzez optymalizację parametrów i redukcję odpadów, system bezpośrednio wspiera Cele Zrównoważonego Rozwoju (SDG) i cele środowiskowe Przemysłu 5.0.

Ponadto opracowana metoda stanowi oryginalne i uniwersalne rozwiązanie możliwe do zastosowania w badanym procesie produkcji form odlewniczych w przedsiębiorstwach branży motoryzacyjnej i metalowej.

1. Introduction

Nowadays the manufacturing enterprises to be competitive in the market, should be more adaptable to rapidly changing needs (Carayannis et al. 2022). **Intelligent Manufacturing (IM)** is an advanced manufacturing paradigm that integrates Industry 4.0 (I4.0) technologies, e.g. artificial intelligence (AI), machine learning (ML), cyber-physical systems (CPSs), industrial Internet of Things (IIoT), robotics, and big data analytics to create smart autonomous, and highly efficient production. Literature defines IM as a data-driven and knowledge-based approach that enables real-time monitoring, prediction, decision-making, and optimization throughout the manufacturing lifecycle (Zhong et al., 2017; Lee et al., 2015). By connecting machines, sensors, and digital platforms, intelligent manufacturing systems can achieve self-awareness, self-diagnosis, and self-optimization, supporting applications such as predictive maintenance, automated quality inspection, intelligent scheduling, digital twins, and adaptive control. These technologies enhance productivity, reduce downtime, improve flexibility, and enable mass customization. However, studies also highlight challenges including data security, interoperability of heterogeneous systems, scalability of analytics, and the need for explainable and trustworthy AI.

Dynamic management (DM) refers to an adaptive, real-time decision-making approach in which manufacturing continuously respond to changing internal and external conditions. Literature describes DM as a strategic and operational capability that enables continuous adjustment of plans, resources, and workflows to maintain performance in uncertain, volatile, and rapidly evolving environments (Teece, 2007; Eisenhardt & Martin, 2000). It involves integrating data analytics, monitoring systems, and feedback loops to detect variations, predict future states, and implement corrective actions. In manufacturing and engineering domains, DM is supported by Industry 4.0 technologies, which allow real-time scheduling, resource allocation, risk mitigation, and performance control. Studies emphasize that DM improves responsiveness, resilience, and decision accuracy by replacing static, rule-based processes with flexible, context-aware strategies. However, literature also notes challenges such as data complexity, coordination across distributed systems, and the need for strong digital infrastructure.

Technical knowledge (TK) refers to the specialized skills, domain expertise, and practical understanding required to perform tasks, operate technologies, and solve complex problems in engineering, manufacturing, and scientific environments. Literature defines TK as a combination of theoretical principles, procedural skills, and experiential insights that enable individuals and organizations to design, analyze, implement, and optimize systems (Nonaka & Takeuchi, 1995; Polanyi, 1966). It includes explicit knowledge—such as formulas based on the acquired data and information, standards, manuals, and documented methods—and tacit knowledge, which involves intuition, hands-on experience, and context-dependent problem-solving ability. In modern industrial settings, technical knowledge is increasingly shaped by digital competencies, including data analytics, automation, programming, AI tools, and simulation technologies. Researchers emphasize that strong technical knowledge enhances innovation capability, operational efficiency, decision-making accuracy, and technology adoption. However, literature also highlights challenges such as rapid technological change, knowledge obsolescence, and the need for continuous learning and knowledge-sharing systems. Overall, technical knowledge forms the foundation for skilled work, technological development, and sustainable competitiveness in the knowledge-driven economy.

The activities that initiate the management of TK is acquiring, processing and formalizing of knowledge available within a given manufacturing organization. The tools that support this process are Industry 4.0/Industry 5.0 (I4.0/I5.0) technologies: CPSs, IoT, cloud computing, big data analysis, AI augmented reality (AR) and virtual reality (VR), cybersecurity (Trakadas et al. 2020). The big volume of data acquired by the sensors and using IoT during the machining process results the need of applying AI to effectively elaborate the big data (Marti-Puig et al., 2024). IoT is now a platform that offers a useful planning approach (Lee et al., 2022). AI-driven IoT is transforming manufacturing enterprises into smart factories (Nitin and Gupta 2024). IoT sensors located on the machines, devices are used to collect data, and next AI-based algorithms are applied to develop the predictive models to monitor and improve the resource, quality and cost efficiency (Ullrich et al., 2024). AI-based solutions applied to the systems supporting machining process managing and providing facilitate e.g. real-time monitoring, improve quality, transparency and flexibility of the process (Psarommatis, May, and Azamfirei 2023). According to the definition of the concept, I5.0 provided by the European Commission manufacturing processes should shift from smart manufacturing to human-centric technology development and adoption (Park et al. 2018). Solutions are being sought enabling collaboration between humans and smart machines to improve the capability of humans. An example of a channel of communication between the human and machine are sensors and computer vision to natural language processing (NLP) and GUI commands (Akhter et al. 2021). Applying AI into manufacturing process in the context of I5.0 indicate, that effective exploration of the variable space in manufacturing systems guarantees the improvement of production planning and scheduling (Psarommatis et al. 2023). Next, precise modelling of process dynamics and optimization of production parameters with the AI-based models provide to improve the quality of manufactured parts (Deepak et al., 2024). It solves also many challenges in sustainable production, such as optimizing energy resources, logistics, supply chain management and waste management (Li, Chen, and Shang 2022). This trend provides a vision for the future of work in modelling AI-based solutions applied to the machining process in the light of I5.0. Early detection of faults and prediction of future machine operation ensure their reliability and effective maintenance (Kim et al. 2018). Moreover, automation of repetitive, time-consuming tasks by robots, as well as study of harmonious cooperation between humans and machines can enhance the production quality (Nasir and Sassani 2021). To summarize, the analysis of the scientific literature highlights, that the big challenges associated with AI adoption in manufacturing are issues related to data acquisition and management, human resources, infrastructure, security risks, trust, and implementation difficulties (Leberruyer et al. 2023).

Research by (Akundi et al. 2022) reviewed I5.0 trends but noted poor domain-specific classification. (Kasinathan et al. 2022) studied smart cities and villages under the Industry 5.0 lens, finding a gap in rural deployment models. (Breque, Nul, and Petridis 2021) emphasized human-centric values but lacked industrial validation. (Mourtzis et al. 2022) reviewed transition challenges from Industry 4.0 to Society 5.0, citing missing hybrid frameworks. (Fraga-Lamas, Lopes, and Fernández-Caramés 2021) introduced Green IoT and Edge AI for sustainability but faced concerns over scalability and data security. (Dwivedi et al. 2023) explored circular supply chains, noting the absence of predictive circularity monitoring models (Balogun, Edem, and Mativenga 2016) proposed E-smart toolpath strategies, yet real-time feedback integration remains limited. Nasir and Sassani (2021) examined deep learning in machining, identifying the lack of deployment in SMEs. (Sudianto et al. 2021) developed low-cost temperature monitoring with Arduino, but sensor accuracy was inadequate for complex setups. Liu (2023) introduced digital twin-based evaluations, requiring validation across varied environments. (Rüstem et al. 2022) made multiple contributions—from monitoring hole machining and tool condition imaging to hybrid lubrication—but common gaps included limited real-time integration and adaptive control (Ntemi et al. 2022) emphasized quality diagnosis in CNC infrastructure, noting the absence of AI-based fault prediction. Zoumpekas et al. (2024) presented 3D point cloud-based tool identification but required lighter algorithms. (Park et al. 2018) optimized machining feedrates, but multi-objective optimization was missing. (Cheng et al. 2017)and (Celent et al. 2022) both advanced smart tooling and sustainable decision-making, respectively, but required broader validation and analytics integration. (Kim et al. 2018) focused on ML for smart machining with limited generalizability. (Sorrenti et al. 2022) reviewed tool wear monitoring and noted poor ERP/MES system integration. (Pimenov et al. 2024) investigated advanced sensor fusion and image processing for tool condition monitoring, both suffering from high implementation costs or real-time constraints. (Bartsch et al. 2021) , (Yao et al. 2024) and (Nahavandi 2019) developed ML-based digital twins for parameter optimization, but lacked cross-industry case studies. Ji, (Breque et al. 2021) and (Zhang et al. 2018) proposed hybrid predictive digital twins but needed stronger integration of data-driven and physics-based models.

This first review reveals that while progress in intelligent and human-centric manufacturing is notable, there remains a clear demand for real-world validation, real-time system integration, dynamic AI adaptability, and measurable impact frameworks—especially as manufacturing moves toward the intelligent manufacturing.

Therefore, the main objective of this work is developing a new approach to DM of TK to construct a smart and flexible Die Casting Mould Manufacturing and die casting process.

Die Casting Mould Manufacturing involves the design and production of high-precision steel moulds used to form complex metal components through high-pressure injection of molten alloys such as aluminium, zinc, or magnesium. The process includes CAD/CAM-based mould design, material selection (typically H13 or premium hot-work tool steels), precision machining using CNC milling, EDM, and grinding, followed by heat treatment to enhance hardness and thermal resistance. Accurate cavity design, gating systems, ejector mechanisms, and cooling channels are critical to ensure dimensional accuracy, surface finish, and long mould life. Die casting mould manufacturing requires advanced technical knowledge, strict quality control, and close tolerance machining, as mould performance directly affects production efficiency, cycle time, and overall product quality.

This may sound as a simple process on a prima fascia. However, as the die casting mould goes through thermal shocks (from about 600 to 200 degree centigrade) in every cycle, the life of the mould which is generally measured as the number of good parts produced will depend on thousands of factors such as quantity of the defective parts produced, which in turn depends on many more factors such as process parameters of the diecasting machine, design of the mould which include the type of alloy, design of cooling system, parting lines, vacuum system, inlets, squeeze pins etc.

This makes the whole process of manufacturing of die casting mould and subsequently the parts dependent on very large number of variants and technical knowledge and experience of the engineers involved in both Mould design and manufacturing and the manufacturing process engineers of die casting production.

In the evolving context of intelligent manufacturing, the proposed research model introduces a holistic framework for dynamically managing TK to enable a smart and flexible die casting mould manufacturing process. This model blends AI and IoT and human expertise to address practical challenges faced in real-world die casting operations and facilitates intelligent decision-making throughout the lifecycle of mould manufacturing.

1.1 Objectives and Scope of Work

The here main scientific objectives are formulated:

Objective 1:

Development the new approach to DM of TK in the complex area of die casting mould design manufacturing as well as die casting parts manufacturing and die casting process, involving hundreds of variants and large amount of technical knowledge base.

Objective 2:

Construction of the smart and flexible model for increasing the efficiency of the Die casting Mould Process and die casting process.

Implementation objective:

Development and implementation of the system for the real time online technical knowledge acquisition through IoT sensors, and ERP systems to monitor and predict the efficiency of Die Casting Mould process and die casting process.

1.2 Research problem and research questions

Manufacturing enterprises today face the dual challenge of meeting highly individualized customer demands while maintaining efficiency, quality, and responsiveness. This shift necessitates moving from traditional, rigid automation systems toward intelligent, adaptive, and data-driven production paradigms. In this context, the evolution from I4.0 to I5.0 further emphasizes the need for intelligent manufacturing practices that integrate digital technologies with human knowledge and values.

In the mould manufacturing sector—particularly in die-casting applications—maintaining the high quality of technically complex components is critical. However, current practices often lack comprehensive systems that integrate real-time data acquisition, predictive analytics, and human-machine collaboration to support proactive quality management.

Therefore, the main research questions in this work are:

1. **How to obtain, store and transfer technical knowledge involved in the Die Casting Mould Manufacturing process in order to increase the effectiveness of this process?**

2. **How can decisions about increasing the efficiency of the Die Casting process be supported based on stored technical knowledge?**

Research Thesis is:

The integration of technical knowledge and AI-based models into a unified monitoring framework can significantly improve the dynamic management of mould quality towards intelligent manufacturing.

Therefore, the research model can be as follow (Figure 1).

Figure 1: Research model.

The technical knowledge is critical and the most important part of the mould manufacturing and die casting parts production process which often is gained through years of experience, trial and errors and many failures of the engineers involved. It also often remains with the engineers while part of that being tranfered to the next generation of engineers and part of that being effectively recorded in the company's data base for meaningful use for future. There are several types of technical knowledges involved in this process. The most important ones are described below.

Mould Designing Knowledge is a critical and the most important knowledge in which the part design is studied by mould design engineers in conjunction with the part design engineers, the mould design engineers proceed with the mould design forming elements considering important parameters like parting lines, casting allowances, drafts etc. The casting allowances considered are also checked for feasibility of the CNC machine allowances by CNC machine technologists to ensure that they fall within the CNC machine tolerances on which the parts are excepted to machined after casting. After the main part cavity designs are done, the filling and overflow with vacuum designs are finished. The other systems like cooling channels, the mould body, squeeze pins, ejectors etc are designed and integrated to complete the mould design.

Before the mould is taken for actual manufacturing the entire design is tested and validated on a 3D simulation to check for solidification, thermal die casting, filling velocity, air evacuation etc. Many corrections are done to the mould design to make sure that heat signatures, solidification, the velocity of filling and extraction of fumes are within the acceptable range and theoretically (and with the simulation) the mould design is good to go for production.

The knowledge about the die casting parts to be manufactured from the perspective of the mould designing & manufacturing is very important for mould design engineers and they gain this knowledge through studying the 2D and 3D drawings of the parts to understand the tolerances, limitations of the diecasting and CNC machines on which these parts are planned to be produced. The key parameters like the weight of the part, the wall thickness of the parts, the curvature and radius for the flow, surface flatness tolerances etc are studied and clarified with the customer's design team. At times, some of the design parameters of the parts are modified if they are not critical to end the functionality of the parts. This may help to reduce the scrap in the production or increase the tool life or reduce the cycle time. Such exchange of information and modification is based on the knowledge and experience of mould design engineers.

Knowledge about the process parameters of Process Engineers can be defined via the selected parameters. There are several process parameters involved in ensuring a defect free continuous manufacturing of the die castings and are set and optimized by the manufacturing process engineers. Many times, these parameters around pressure, temperature plunger movements, squeeze pin, micro spraying etc can be trading off with some of the final efficiencies such as cycle time (OEE) mould life, porosity levels ib the castings (quality) etc.

Knowledge about Mould Maintenance and Repairs - the moulds are designed to live their expected life which is measured in terms of number of good parts produced out of them. Based on the few factors the moulds are expected to last for 80,000 to 150,000 good shots (good parts produced from these shots. In case of single cavity the numbers are same as shots and in multiple cavity they are multiplied by the number of cavity).

In order to ensure that they last and exceed these numbers, the mould need pre-check and post check of the mould conditions with checklists and knowledge base. They are serviced after every batch of manufacturing which can be several thousands of parts or few shifts of production. They are checked for micro cracks on the insert bodies to do micro welding, nitride coating of the surface, cleaning of the cooling channels, servicing of the plungers, pneumatics, checking of sensors etc.

Improving the efficiency of die casting mould process can be monitored and measured using appropriate indicators. There are several direct and indirect ways of measuring the process efficiencies which are interconnected as they influence one another. The easier and direct ways in which these process efficiencies are measured at the end may ultimately result in the OEE (Overall Equipment Efficiency) and TEEP (Total Effective Equipment Performance) of the diecasting machine or the cell. Therefore, and based on expert knowledge, the following parameters were adopted to assess the improvement in the effectiveness of the analyzed process. According to the OEE (Overall Equipment Efficiency) the availability is affected by the losses arising from mould breakdowns, machine breakdown, set up time etc. The performance is affected by the Cycle time against the standard, the micro stoppages et. While the Quality is affected by the good parts produced of the total parts produced. The major inputs that go in to lowering the OEE which we refer as blocker to a better OEE are the quantities of NOK (defective parts produced which are measured in ppm (parts per million), the breakdown of the mould which results in lowering the OEE again.

The cycle time which is dependent on how good the design and quality of the mould is and is also influenced by the optimization of the process parameters. Most often it's a trade off between producing good parts vs lower cycle time of production of the parts. TEEP gives even better measure than OEE as it not only covers all the factors in OEE, but also the Utilization. This helps for overall capacity planning, investment planning and benchmarking etc.

The diecasting mould life, which is measured as the number of good shots (shots in which the good parts are produced). Based on the complexity of the parts, the number of cavities, size and shape of the parts and the die casting machine on which they are going to be loaded, it may vary from 80,000 to 150,000 good shots. Often the bench mark is based on the historic experience of execution of the similar mould or parts. However, production of bad parts (bad shots) will substantially reduce the tool life due to the fact that the wear and tear of the mould still takes place for producing bad parts which also consumes machine time reducing OEE. It's the % of time that the diecasting cell is effectively used to produce

OK (good parts). The blockers to this from the operations point of view are NOK (defective parts produced), Mould breakdown, Machine breakdown, the machine set up time, increases in cycle time than planned. All the above, mentioned deficiencies ultimately show up in this efficiency parameter.

Cost of Mould Mentainance is a result of the quality of mould (design and manufacturing) and how good the process parameters are set. The cost of mould maintenance involves planned cost such as the regular maintenance before the mould is loaded like welding and polishing of micro cracks on the surface, nitride coatings, cooling channels and other hydraulics servicing, cleaning etc. However, the unplanned mould breakdown are the real cost drivers resulting from the loss in OEE of the diecasting machine, hours and at time shifts of time to unload the mould repair and upload them. In some circumstances these may also attract huge indirect cost like additional transport costs to ship the parts to cover up the loss in production time, line stoppages up the supply line which may be in millions of euros!

Scrap Ratios at the production are standard parameter monitored and measured in ppm. These internal scrap ratios are again dependent on many parameters such as allowed porosity in the casted parts, allowed tolerances in mechanical dimensions, complexity of the parts etc. They also are dependent on the age of the mould. The general observation is that as the mould gets older the scrap ratio also starts to increase. This may vary from 5000 ppm to 30000 ppm based on all the above factors.

1.3 Research method

Below, the characteristics of the sought-after elements of the new method are presented (Figure 2).

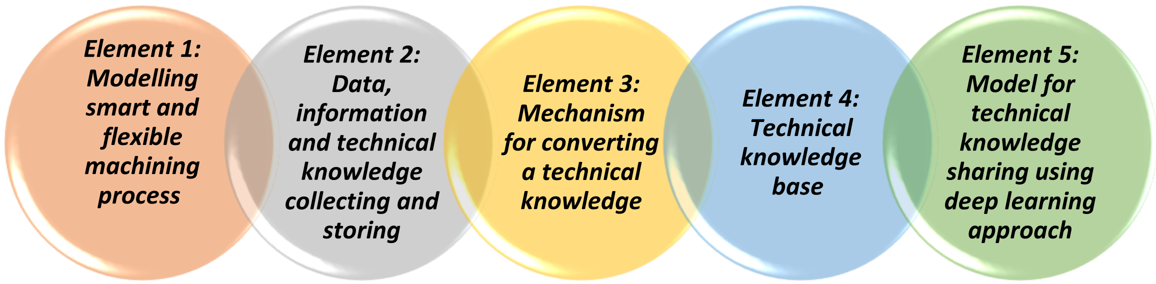


Figure 2: A novel method for DM of TK

Element 1: Modelling smart and flexible machining process

Element 1 focuses on developing a smart, adaptive, and flexible machining framework that can dynamically respond to design complexity, material properties, tooling conditions, and operational constraints in die casting mould manufacturing. Unlike conventional machining—which relies on fixed parameters and manual decision-making—smart machining systems incorporate real-time monitoring, AI-supported decision rules, and digital models to optimize machining processes across different mould geometries and production scenarios.

At the core of this element is the ability to model machining processes as intelligent, feedback-driven systems. The model evaluates multiple inputs such as contour complexity, tool path strategy, cutter engagement, cutting forces, spindle load, and thermal effects. It integrates these
factors with historical machining knowledge to automatically adjust parameters such as feed rate, spindle speed, step-down depth, coolant flow rate, and tool selection. This adaptiveness ensures precise surface finishing, improved tool life, and reduced machining time, especially when dealing with complex mould cavities, thin sections, deep ribs, or high-precision features.

A crucial capability of this system is flexibility—the ability to reconfigure machining strategies without manual reprogramming. For instance, when machining inserts or die blocks with varying hardness levels (e.g., hardened H13 steel segments), the model adjusts tool paths and cutting parameters to prevent tool wear or thermal cracks. Similarly, when geometric changes occur during mould design revisions, the system automatically recalculates optimal machining steps based on updated CAD models, eliminating delays caused by manual NC reprogramming.

Element 2: Data, information and technical knowledge collecting and storing

The foundation of this method lies in continuous and context-aware data acquisition. In a typical die casting environment, fluctuations in parameters like melt temperature, injection speed, cooling rates, and die wear patterns significantly affect product quality and mould life. To manage this complexity:

- **IoT-enabled sensors** are embedded across the die casting line to capture real-time operational parameters such as cavity pressure, thermocouple readings, machine vibration, die temperature, and lubricant flow.
- **ERP and MES systems** are integrated to gather contextual data, including work orders, part numbers, material batches, and operator shifts. This integration ensures that technical knowledge is not isolated but deeply linked with the production environment.
- **Expert technical knowledge** There are two sets of expert knowledge relevant in the context of this project. One is the design expertise which is critical in designing of the mould in the first place. This is gained over a period of time by virtue of

experience by the design engineers by continuously learning and improvising similar moulds or the next revisions of the same mould. The various factors involved here are – number of cavities, locations of the parting lines in the mould, position and size of inlet and position, size and number of outlets in order to have optimal time for flow of aluminium alloy and solidification to achieve both good quality and best cycle time. The location and quantity of cooling channels for best thermal management. Design of the casting tolerances so that they are sufficient to take in to consideration of the tolerances for the next manufacturing process of CNC machining.

The second set of expert knowledge comes from the process engineers. This is gained over a period of time by virtue of experience by producing similar parts over a period of time. The various process parameter knowledge and their trade off with each other's is very critical knowledge gained. They include, duration and hydraulic pressure applied in different phases, mould temperature cycle management, molten aluminium temperature, cycle time of the part etc.

Element 3: Mechanism for converting a technical knowledge

Once data is collected, it must be meaningfully analyzed to uncover patterns, correlations, and root causes of inefficiencies. This is achieved through:

- **Feature extraction** techniques are used to determine critical process indicators (CPIs) and key control parameters that significantly influence outcomes like porosity levels, dimensional accuracy, and surface finish.
- **Artificial Neural Networks (ANNs)** trained on historical and real-time data to recognize complex interdependencies between parameters such as molten metal temperature, shot pressure, and cooling time, which affect mould integrity and casting defects.

Element 4: Technical Knowledge Base

Element 4 focuses on developing a centralized Technical Knowledge Base (TKB) that systematically stores, organizes, and retrieves all technical knowledge generated throughout the die casting mould manufacturing process. In traditional environments, knowledge remains fragmented across operator experience, machine logs, design documents, and maintenance records, making it difficult to achieve consistent decision-making. The proposed Knowledge Base overcomes this limitation by integrating design rules, machining strategies, process parameters, sensor data, defect histories, maintenance logs, and operator feedback into a unified digital repository. This structured knowledge environment supports real-time decision-making, enables accurate root-cause analysis, and allows best practices to be reused across future mould projects. For example, if porosity defects occur in a new mould, the Knowledge Base can retrieve similar past cases, highlight correlated parameters such as low die temperature or shot pressure fluctuations, and provide evidence-based corrective actions. By continuously updating itself through IoT data, AI-generated insights, and human expertise, the Knowledge Base becomes the core intelligence layer of the research model, ensuring improved process stability, faster problem resolution, and sustainable knowledge retention within the die casting ecosystem.

Element 5: Model for technical knowledge sharing using AI

At this stage, the system provides actionable insights in real-time:

- The AI monitors trends such as increasing cavity pressure or fluctuating shot velocity and alerts operators to impending deviations that could result in defects or mould damage.
- Predictive analytics assist in **proactive interventions**, such as pre-emptively scheduling die maintenance based on fatigue indicators, thereby reducing downtime and improving efficiency of the process.

The proposed research method is a base for creating a robust system where:

- **Smart sensors and systems collect critical manufacturing data and information.**
- **Advanced AI models convert this data and information into technical knowledge.**
- **Real-time insights improve die casting efficiency, mould longevity, and defect control.**
- **Human judgment enhances AI intelligence, forming a feedback-rich decision support system.**

Ultimately, this proposed dynamic technical knowledge management approach (Figure 1), which includes the novel method (Figure 2) not only transforms the **die casting mould manufacturing process** into a smart and flexible system but also exemplifies the core vision of **Industry 5.0**—harmonizing advanced technology with human insight to drive innovation, sustainability, and productivity in manufacturing. The proposed research model demonstrates how technical knowledge—historically fragmented across roles, machines, and documents—can be dynamically centralized, digitized, and optimized using AI and IoT. The flexible structure of research model supports plug-and-play integration with other intelligent systems (e.g., predictive maintenance, energy monitoring), thereby constructing the foundation of an intelligent, human-centric, and sustainable die casting mould manufacturing process.

2. Dynamic management of technical knowledge within an intelligent manufacturing

2.1 Intelligent manufacturing in Industry 5.0

The industrial landscape has witnessed a dramatic transformation over the past decade, driven by the technological advancements introduced under the banner of Industry 4.0 (I4.0) (Mourtzis et al. 2022). This phase, often described as the "Fourth Industrial Revolution," emphasized the digitization and automation of manufacturing processes through technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), robotics, cloud computing, cyber-physical systems (CPSs), and big data analytics (Yao et al. 2024). These technologies enabled factories to become “smart,” where machines could communicate, make decisions, and optimize operations with minimal human intervention. However, as digitalization matured, new questions emerged about the role of human workers, the sustainability of processes, and the resilience of supply chains (Vazquez, Torres, and Perez 2021). This gave rise to Industry 5.0 (I5.0)—a concept introduced and promoted by the European Commission—which builds upon the technological foundation of I4.0 but shifts the focus toward human-centricity, sustainability, and resilience (Khan et al. 2023). While Industry 4.0 sought efficiency through automation and connectivity, Industry 5.0 rebalances the equation by placing humans back at the center of the manufacturing ecosystem (Kasinathan et al. 2022). It promotes the idea of collaboration rather than replacement—where advanced digital technologies support and enhance human capabilities, rather than fully automate or eliminate them (Kaasinen et al. 2022).
Industry 5.0 marks a transformative evolution from automation-centric Industry 4.0 to a human-centric, resilient, and sustainable production environment. While Industry 4.0 emphasized cyber-physical systems, IoT, and real-time data analytics for smart manufacturing, Industry 5.0 brings humans back to the core by integrating advanced AI, collaborative robots (cobots), and decision intelligence with human creativity, adaptability, and domain expertise(Srivastava et al. 2021).

The intelligent manufacturing paradigm in Industry 5.0 revolves around dynamic, real-time decision-making, personalization, and continuous learning, especially relevant in die casting, forging, aerospace, automotive, and medical device manufacturing. It enables manufacturers to respond to high-mix, low-volume demands, optimize resource use, reduce defects, and meet evolving sustainability goals (Li et al. 2022).

A good example for Die Casting Industry – Smart Mould Manufacturing is a Case automotive Compressor Parts. It is stated, that in high-precision die casting industries, such as Heating, Ventilation, Air Conditioning (HVAC) compressor component production**,** intelligent manufacturing systems enable:

- AI-powered mould health monitoring systems (e.g., using thermal imaging, pressure sensors, and IoT-enabled strain gauges) to detect early signs of wear or defects.

- A digital twin of the mould and injection process simulates performance and predicts lifespan.
- ANN-based quality classifiers integrated with ERP and MES systems enable real-time alerts for casting inconsistencies.
- Operators interact with cobots that assist in die changeover, guided by AI recommendations to reduce cycle time. (Jutidharabongse et al., 2020)

A next good example is a leading Japanese automotive parts manufacturer implemented an Artificial Intelligent driven IoT Monitoring System (AIMS - based system) in its Indian die casting facility. The system detected cooling channel clogging in moulds earlier than traditional inspection, allowing proactive maintenance and extending mould life by 15% (Shahane et al. 2020).

For Forging Industry – Human-in-the-Loop Quality Adjustment**,** based on a Case: Crankshaft Production, in large-scale forging operations for crankshafts or connecting rods:

- Smart hammers and presses are integrated with real-time load sensors**,** temperature probes, and vibration analysis tools.
- AI systems predict grain flow defects and suggest optimized forging temperatures and pressures.
- Workers are equipped with augmented reality (AR) headsets to receive AI-generated instructions during die alignment or post-forging inspections.
- Human supervisors validate AI decisions, refining the training data to improve model adaptability to new materials.

A good example can be a German forging company collaborated with Siemens to implement a self-learning forging line**.** Defect rate decreased by 30%, and operator workload was reduced through predictive forging parameter tuning supported by real-time AI feedback (Dong, Taylor, and Cootes 2022), (Rožanec et al. 2022).

Next, as is stated in Additive Manufacturing and Hybrid Mould Production**,** in high-performance tool and die manufacturing:

- AI models predict the optimal parameters for hybrid manufacturing (CNC + 3D printing) of complex die inserts.
- Layer-by-layer defect prediction enables immediate process correction.
- Human engineers collaborate with AI in design for manufacturability (DFM) stages, enhancing product quality and reducing lead times (Alafaghani et al. 2020).

Across these industries, intelligent manufacturing in the I5.0 era leads to:

- Hyper-customization of die designs based on customer feedback (Mourtzis et al. 2022).
- Resilient supply chains through AI-enabled production planning and risk forecasting.

- Enhanced operator safety and training using simulation and digital twin environments.
- Sustainable production by optimizing energy and material usage through AI feedback loops.

In the context of the mould manufacturing industry, especially in the production of high-precision die-casting moulds used for air conditioning components in luxury automobiles, the transition from I4.0 to I5.0 becomes highly relevant. The manufacturing of moulds demands both technical precision and human craftsmanship, especially when dealing with complex geometries and tight tolerances (Bartsch et al. 2021).

For example, Industry 4.0 technologies like IoT sensors can monitor temperature, vibration, and wear conditions on CNC machines used in mould making. These sensors generate vast streams of data, which are analyzed using AI algorithms to detect anomalies or predict potential quality issues. This level of automation undoubtedly increases productivity and reduces scrap rates (Hoffmann and Reich 2023).

However, Industry 5.0 enhances this system by incorporating the knowledge and experience of human operators into the decision-making loop. For instance, if a machine learning model detects a deviation in surface finish quality, it may flag it as a potential defect. A human technician, equipped with years of hands-on experience, can then review the flagged issue using augmented reality (AR) tools and provide feedback that helps refine the AI model further. This human-AI collaboration ensures both precision and contextual understanding—something pure automation often lacks (Anjul and Ganguly 2018).

A good real-Life example is Siemens' “Human-Centric Digital Twin”. An illustrative real-life example is Siemens’ implementation of a “Human-Centric Digital Twin” in its manufacturing facilities. In one of their plants, digital twins were used to simulate the entire production process of precision parts. IoT devices collected live machine data, and AI models predicted deviations from ideal performance. Instead of allowing the system to auto-correct blindly, skilled engineers interacted with the digital twin via a graphical interface, provided contextual insights, and helped tune the system parameters. This collaborative loop greatly improved quality outcomes while preserving human intuition and expertise. In a similar vein, this thesis proposes an AI-driven IoT Monitoring System (AIMS) for the mould manufacturing industry that not only predicts and monitors quality using data from sensors and ERP systems but also leverages expert human knowledge. By integrating Artificial Neural Networks (ANN) with real-time sensor data and human-in-the-loop mechanisms, the system aligns perfectly with the principles of Industry 5.0 (Sundaram and Zeid 2023).

I4.0 is technology-driven, focusing on automation, system integration, and data utilization. I5.0 is value-driven, emphasizing ethical AI, human empowerment, and environmental sustainability. For mould manufacturing, this evolution signifies a shift from robotic automation toward smart collaboration between machines and humans to deliver high-quality, custom-tailored products efficiently. This transformation is not just a technological upgrade but a strategic realignment of values and priorities in manufacturing, where human creativity, experience, and intuition are seen as vital resources, rather than bottlenecks (Sundaram and Zeid 2023).

2.2 Technical Knowledge Management Process

In the realm of intelligent manufacturing under Industry 5.0, technical knowledge management (DM OF TK) plays a pivotal role in enabling real-time decision-making, process optimization, and human-machine collaboration. As manufacturing environments become more complex, dynamic, and data-driven, managing technical knowledge effectively becomes both a strategic necessity and a competitive advantage (Allahyari et al., 2017a)

DM of TK refers to the systematic process of capturing, organizing, sharing, and applying domain-specific technical knowledge to support decision-making, innovation, and operational efficiency in industrial environments. Literature defines DM of TK as a framework that integrates explicit knowledge—such as design specifications, process parameters, machining rules, material properties, and maintenance procedures—with tacit knowledge gained from expert experience, intuition, and problem-solving skills on the shop floor In manufacturing contexts, DM of TK plays a critical role in ensuring that essential technical information is not lost, siloed, or dependent solely on individuals but is transformed into institutional knowledge accessible across teams (Allahyari et al., 2017b). Modern DM OF TK incorporates digital tools such as databases, knowledge bases, IoT platforms, and AI-driven analytics to convert raw data into actionable insights, enabling continuous improvement and faster troubleshooting. By facilitating knowledge reuse, reducing variability in decision-making, and supporting advanced technologies like predictive maintenance and smart machining, TKM enhances productivity, accuracy, and sustainability. Overall, literature emphasizes that effective TKM is foundational for Industry 4.0 and Industry 5.0 systems, where human expertise and digital intelligence must work together to maintain high-performance manufacturing operations (Oliva et al., 2019).

Traditional technical knowledge management involves the storage of static information in manuals, databases, or expert systems. However, Industry 4.0/5.0 demands dynamic and real-time knowledge management, where knowledge updates contextualized and distributed across systems and human operators. In this setting, the focus shifts from documentation to actionable knowledge flows**,** enabling faster response to variations in process conditions, product design changes, and customer demands. **Next, for die casting Industry** dynamic DM OF TK enables automatic adjustment of shot pressure or die temperature based on defect trends like porosity or flash. Knowledge from seasoned toolmakers is codified and applied in AI models for predictive maintenance of dies, extending tool life and ensuring consistent part quality.

2.3 Good Practices in Technical Knowledge Management within a Manufacturing Environment

Effective **DM of TK** in manufacturing involves the identification, capture, storage, dissemination, and continuous improvement of process, product, and operational knowledge. In an Industry 5.0 setting—where human expertise collaborates with smart machines and digital systems—these practices are evolving to become more data-driven, collaborative, and dynamic. Table 1 shows the selected practices in Technical Knowledge Management within a Manufacturing Environment (Nielsen, 2006).

Table 1 Practices in Technical Knowledge Management within a Manufacturing Environment

Practice	Description	Example in Die Casting	Example in Forging
1. Knowledge Capture from Experts	Systematically documenting tacit knowledge from skilled technicians, engineers, and operators.	Recording expert toolmaker inputs on gate design and thermal control strategies.	Capturing die-correction methods used by experienced blacksmiths for complex shapes.
2. Real-Time Data Collection and Analytics	Using sensors, IoT devices, and AI to collect and analyse production data for decision-making.	Monitoring molten metal temperature, cavity fill time, and cooling rate using embedded thermocouples and sensors.	Collecting forging force, strain rate, and billet temperature via load cells and thermal cameras.
3. Visual Knowledge Representation	Utilizing visual tools like flowcharts, digital twins, CAD/CAM simulations, and augmented reality.	3D mould filling simulation models integrated with process control dashboards.	Forging simulation software (e.g., DEFORM) showing material flow and die stress zones.
4. Digital Documentation and Knowledge Repositories	Storing SOPs, troubleshooting guides, process histories, and maintenance logs in digital databases.	Cloud-based process logs with defect maps linked to specific batches or operators.	Centralized database storing parameters of successful and failed forging attempts with root cause analysis.
5. Collaborative Platforms and Knowledge Sharing	Promoting team-based learning, peer-to-peer discussions, and digital communication tools.	Operators share real-time process adjustments via tablets or factory-floor apps.	Cross-functional teams of metallurgists and machinists collaborate via Microsoft Teams or internal wikis.

6. Training and Skill Transfer Using Technology	Use of VR, AR, and simulation-based training to upskill employees.	VR-based training module on die temperature control and defect mitigation.	AR-guided forging tool changeover procedures for new operators.
7. Continuous Feedback Loops	Establishing mechanisms for continuous feedback and knowledge evolution.	Process engineers update AI rulesets based on casting defect trends.	Forge masters review and refine lubrication schedules based on die wear feedback.
8. Integration with MES/ERP Systems	Linking knowledge systems with enterprise-level planning and execution platforms.	Casting process deviations trigger alerts in the MES and initiate review workflows.	ERP integration helps track raw material properties, linking them to forged component outcomes.

The following benefits of Practicing DM of TK in Intelligent Manufacturing can be distinguished:

- **Reduces dependency on individual experts** by systematizing and preserving institutional knowledge.
- **Improves product quality** by using historical data and predictive analytics to guide process adjustments.
- **Accelerates training** through simulation, VR, and AI-guided learning paths.
- **Enables adaptive manufacturing** where process settings adjust in real-time based on contextual knowledge.
- **Fosters innovation** through collaborative problem-solving and cross-domain knowledge application.

Therefore, it is assumed, that in the context of achieving the objective 1 the new approach to DM of TK involves five key stages (Figure 3), which integrates the method (Figure 2):

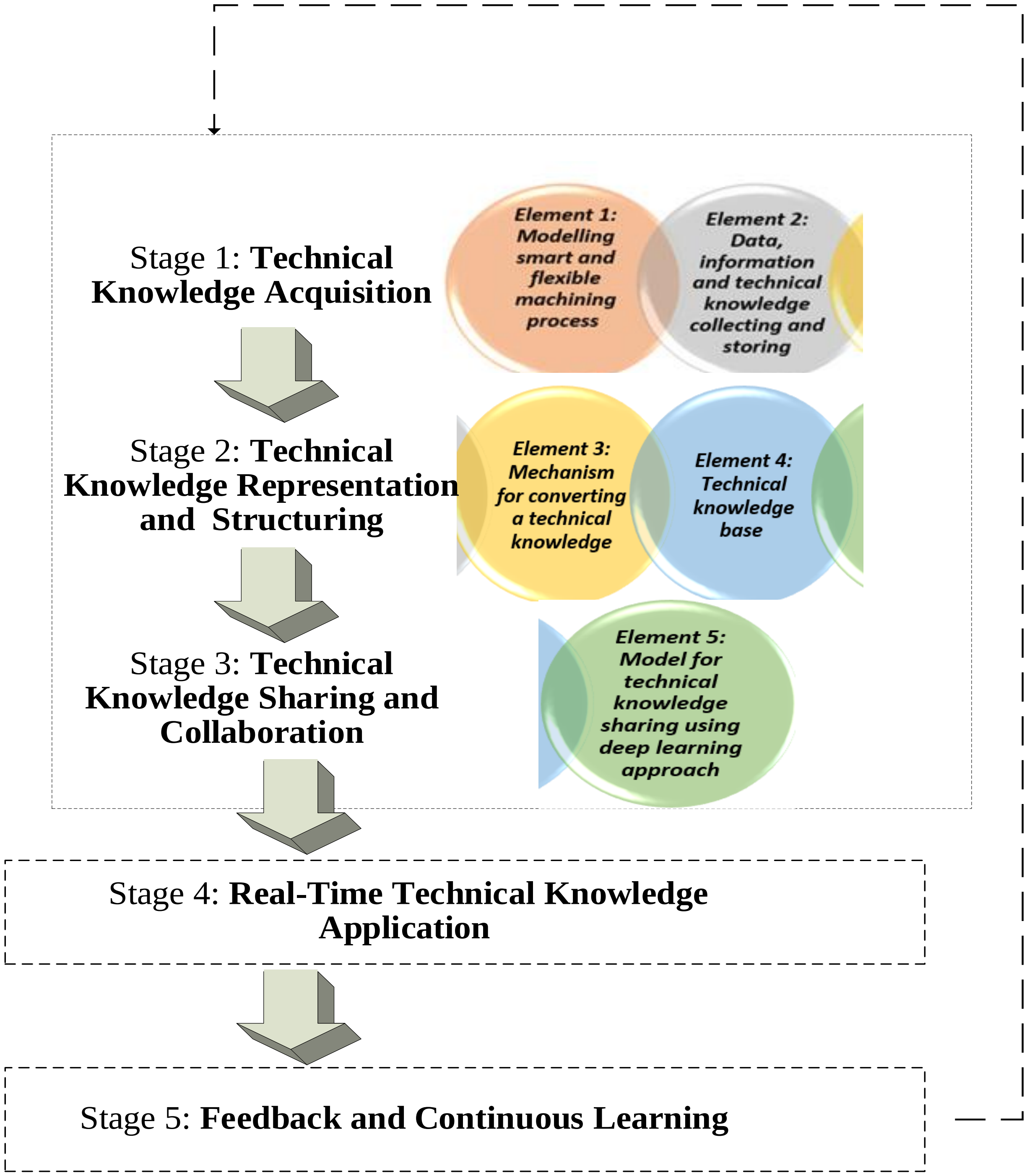


Figure 3: A new approach to DM of TK

Element 1: Modelling smart and flexible machining process

1. **Stage 1: Technical Knowledge Acquisition**: IoT sensors and machine controllers in die-casting and forging machines collect real-time data on parameters such as temperature, pressure, cycle time, and material flow. This data is interpreted using AI algorithms to extract tacit knowledge from expert operators and implicit trends from historical production runs. (Y. Y. Cheng et al., 2019a).

2. **Stage 2: Technical Knowledge Representation and Structuring**: Technical knowledge is structured using ontologies or digital twins, representing physical assets, machine conditions, and manufacturing rules. In die casting, for example, a digital twin can represent the thermal cycle of the mould, enabling better thermal management strategies.
3. **Stage 3: Technical Knowledge Sharing and Collaboration**: Knowledge is shared across departments using cloud platforms and integrated ERP/MES systems. In forging industries, experienced operators' techniques for handling alloy behaviour during hot forging are digitized and shared with new operators through AR/VR-based training modules.
4. **Stage 4: Real-Time Technical Knowledge Application**: During production, AI-powered systems recommend process adjustments based on previously validated knowledge. For example, if a die casting mould exhibits early thermal fatigue, the system suggests process parameters to extend tool life based on prior cases and predictive analytics.
5. **Stage 5: Feedback and Continuous Learning**: The system captures operator feedback and machine responses, which are reintegrated into the knowledge base to improve future decision-making. Reinforcement learning and continual model retraining ensure that the AI evolves with process variations and new materials.

2.4 Conclusions

The integration of intelligent manufacturing principles and dynamic management of TK management strategies forms the foundation for a robust Industry 4.0/5.0-ready manufacturing system. From Section 2.1, it is evident that intelligent manufacturing in Industry 4.0/5.0 is no longer limited to automation and efficiency but extends to human-machine collaboration, resilience, and customization. Real-life examples from industries such as die casting and automotive part manufacturing demonstrate how embedding IoT, AI, and digital twins improves process adaptability and enhances decision-making precision. These technologies facilitate predictive maintenance, defect prevention, and improved tooling life cycles.

Section 2.2 emphasized the necessity of new strategies for dynamic management of TK. Unlike static documentation-based systems, dynamic management leverages real-time data, collaborative tools, and AI-driven analytics to keep knowledge relevant and actionable. These strategies ensure that technical know-how evolves with process changes, new material innovations, and shifting market demands. They also support cross-functional learning and innovation through better accessibility and contextualization of knowledge.

Section 2.3 focused on practical practices in knowledge management within a manufacturing environment. Successful practices include embedding knowledge capture at the point of operation, enabling operator feedback loops, and integrating historical data with real-time insights. Examples include ERP-integrated dashboards for defect traceability, AI models learning from human corrections, and digital standard operating procedures (SOPs) that adapt based on process performance.

So, the new **approach to DM of TK was formulated, which includes the main stages: (1) TK Acquisition**, **(2) TK Representation and Structuring**, **(3) TK Sharing and Collaboration**, **(4) Real-Time TK Application**, **(5) Feedback and Continuous Learning.** Manufacturing organizations aiming for Industry 4.0/5.0 must adopt a holistic approach that tightly integrates intelligent technologies with dynamic and practical technical knowledge management. This not only ensures production efficiency and quality but also supports human-centric innovation, flexibility, and long-term competitiveness in complex manufacturing environments like die casting and forging.

3. Methods for dynamic management of technical knowledge according to the concept industry 5.0

In the era of Industry 5.0, where human-machine collaboration and hyper-personalization are at the forefront, DM of TK evolves beyond traditional databases and documentation. The focus shifts to intelligent, adaptive, and human-centric systems that support lifelong learning, knowledge sharing, and real-time decision-making. DM of TK in Industry 5.0 is not only about preserving expertise but also about transforming tacit knowledge into actionable insights through smart technologies, ensuring sustainability, resilience, and agility in manufacturing and engineering processes.

3.1 Methods and tools for collecting, storing and converting technical knowledge

In Industry 5.0, knowledge is not only an asset but a dynamic resource that needs to be constantly enriched, contextualized, and distributed. The methods and tools used for DM this technical knowledge are outlined below according to the proposed **approach to DM of TK**.

Methods and tools for TK collecting

Technical knowledge collection begins with IoT-enabled sensors, cyber-physical systems, and smart machines that continuously capture real-time operational data such as temperatures, pressures, cycle times, machine loads, and quality metrics. This data is enriched with contextual information gathered from Manufacturing Execution System (MES), PLM (Product Lifecycle Management): and Enterprise Resource Planning (ERP), ensuring that process events, material batches, design revisions, and operator actions are fully traceable (Jelavic, 2011). For knowledge storage, Industry 5.0 leverages integrated Knowledge Bases, cloud platforms, ontologies, and semantic knowledge graphs that structure machine data, design rules, and maintenance histories into accessible formats. These platforms support both explicit knowledge and tacit knowledge. The explicit knowledge is the one which is easily recorded, articulated and shared. Examples of such knowledge are - documents, CNC programs, standard operating procedures (SOP). Where as the tacit knowledge that is gained through human experience involving human intuition, culture, skills etc. These can be captured from human experts through digital forms, annotations, voice-assisted logging, and interactive AI interfaces. The conversion of raw data into meaningful technical knowledge is achieved using AI and machine learning models—such as neural networks, decision trees, and pattern-recognition algorithms—which analyze complex relationships, identify root causes, and generate predictive insights. Importantly, Industry 5.0 embeds a Human-in-the-Loop (HITL) approach, where operators validate AI recommendations, correct misinterpretations, and contribute intuitive insights that machines cannot infer. This continuous feedback refines the knowledge models, ensuring that both digital intelligence and human expertise evolve together. Overall, Industry 5.0 promotes a hybrid knowledge management ecosystem where machines collect and process data autonomously, while humans guide and enrich the system, resulting in more resilient, adaptive, and intelligent manufacturing operations (Alves et al., 2023b).

1. **Sensor-based Data Acquisition (IoT):**
   - Real-time collection of machine, environmental, and operator data.
   - Tools: Smart sensors, PLCs, wearable devices.
   - Example: Monitoring tool wear or process parameters to capture implicit expert knowledge.
2. **Human-Machine Interaction Logs:**
   - Data collected from user interactions with machines, interfaces, or collaborative robots (cobots).
   - Techniques: Eye-tracking, gesture recognition, voice commands.
   - Example: Process parameter settings with engineers id and time stamp, machine failure logs with time stapms etc.
3. **Crowdsourced Knowledge Capture:**
   - Platforms that gather inputs from operators and engineers to identify common issues, tips, and best practices.
   - Tools: Wikis, forums, mobile apps with feedback features.
   - Example : Downloads from the ERP system / Smart sheets for pareto analysis
4. **AR/VR-assisted Knowledge Capture:**
   - Workers perform tasks while wearing AR glasses or working in VR environments, allowing implicit knowledge to be recorded (e.g., sequences, gestures).
   - Tools: Microsoft HoloLens, PTC Vuforia.
   - Example : Virtual training, Virtual maintenance

S**toring knowledge in an Industry 5.0–driven manufacturing environment involves organizing and preserving technical, operational, and experiential information in a structured and accessible digital repository** (Nascimento et al., 2021)**.** Modern systems use integrated Knowledge Bases, cloud platforms, semantic databases, and digital twins to store explicit knowledge such as design files, process parameters, maintenance records, tooling strategies, and quality inspection reports. At the same time, Industry 5.0 emphasizes capturing tacit knowledge—operator experience, troubleshooting insights, and expert decision patterns—through digital forms, annotation tools, voice interfaces, and AI-assisted documentation. Knowledge is categorized using ontologies and metadata standards, ensuring that data from IoT sensors, ERP/MES systems, and AI analytics can be seamlessly linked, indexed, and retrieved. Real-time updates from machines and human inputs ensure that the stored knowledge remains current, accurate, and context-rich (Grabowska et al., 2022). By centralizing and structuring information, knowledge storage supports traceability, efficient problem-solving, decision consistency, and continuous improvement across the die casting mould manufacturing process, forming a core foundation for intelligent and human-centric production systems (Y. Y. Cheng et al., 2019b).

1. **Digital Twins and Cyber-Physical Systems:**
   - Store live models of machines/processes enriched with expert insights.
   - Serve as living knowledge bases that evolve with operational data.
   - Example : Digital twin of the machine to keep the status and history of the machine performance, maintenance records.
2. **Knowledge Graphs and Ontologies:**
   - Structured representations of domain knowledge to support semantic understanding and interoperability.
   - Tools: Protégé, Neo4j.
   - Example: Different process parameters and their relations and interactions to the specific quality outputs.
3. **Cloud-based Knowledge Repositories:**
   - Centralized, scalable storage with role-based access.
   - Tools: SharePoint, Confluence, Git-based systems for version control.
   - Example: The whole organisations data on the ERP system accessible from everywhere.
4. **AI-integrated Knowledge Bases:**
   - Knowledge stored in structured and unstructured formats is made searchable and usable via NLP.
   - Tools: IBM Watson Discovery, Azure Cognitive Search.
   - Example: An intelligent layer reading multiple files (set of data) to narrow the key words to provide synthesised answers and citations.

Methods and tools for TK Representation and Structuring

Converting Knowledge in an Industry 5.0–enabled technical knowledge management framework involves transforming raw data and fragmented information into meaningful, actionable, and context-aware insights that support intelligent decision-making. This conversion process relies heavily on advanced analytical tools such as machine learning models, neural networks, statistical methods, and pattern-recognition algorithms that analyze real-time and historical data from sensors, machines, and production systems. Through these techniques, implicit relationships—such as the influence of shot pressure on porosity, or the effect of cooling rate on mould fatigue—are extracted and converted into explicit technical guidelines or predictive rules. At the same time, the human-in-the-loop (HITL) mechanism allows expert operators to validate, correct, or refine these AI-derived insights, ensuring that tacit knowledge becomes part of the formal knowledge system. Decision-support tools, digital twins, and visualization dashboards further translate complex technical findings into understandable formats, enabling engineers and operators to quickly interpret patterns, identify root causes, and apply corrective actions (Lai et al., 2020). Ultimately, converting knowledge bridges the gap between raw manufacturing data and operational intelligence, ensuring continuous learning, improved process stability, and more human-centric decision-making within smart die casting mould manufacturing environments (Pattanasing et al., 2022).

1. **AI/ML for Knowledge Extraction and Transformation:**
    - Natural Language Processing (NLP) to convert documents, maintenance logs, or conversation transcripts into structured knowledge.
    - Machine Learning to detect patterns, classify knowledge types, and predict outcomes.
    - Example: Based on the various process parameters and their relations, predicting the probable outcome quality of the parts produced by the die casting machine cell.
2. **Tacit to Explicit Knowledge Conversion:**
    - Using cognitive systems to interpret operator actions and transform them into SOPs or training modules.
    - Example: Recording expert adjustments on CNC machines and converting them into best-practice guides.
3. **AR/VR-enabled Knowledge Transfer:**
    - Knowledge delivered through immersive simulations for training, reducing cognitive load.
    - Tools: Unity, Unreal Engine, EON Reality.
    - Example: Using the machine maintenance and machine operations knowledge to train the new employees using AR / VR tools to reduce cost and risk before they are put on the real job.
4. **Conversational Agents and Chatbots:**
    - Assist in real-time knowledge dissemination using human-like interfaces.
    - Tools: ChatGPT (for contextual support), custom LLMs trained on internal documentation.
    - Example: AI assist tools for quick data and knowledge gathering
5. **Expert knowledge:**
    - Collecting and storing the expert knowledge gained by experts through experience.
    - Example: expert knowledge of design elements from design engineers and process parameter knowledge of the manufacturing process engineers.

TK Structuring is related to the knowledge base of the organisation. Knowledge Base is the structured respiratory of the organisations intellectual capital. It is structured in a way to have right access to the right people of the organisation for maximum utilisation and also at the same time should be secured too. It is also a continuously dynamic process where the knowledge is continuously captured, refined, stored, accessed to right people and audited.
Next, according to the stage 3 "Knowledge Sharing and Collaboration" of the new approach DM of TK knowledge is shared across departments using cloud platforms and integrated

ERP/MES systems. Therefore, it is needed to describe the techniques for visualization TK for sharing it.

3.2 Visualization of technical knowledge

In the context of Industry 5.0, where the focus is on human-centric, resilient, and sustainable manufacturing, the visualization of technical knowledge plays a crucial role in bridging the gap between human expertise and digital intelligence. Visualization techniques transform complex technical data into intuitive, easily understandable formats, allowing both engineers and decision-makers to derive actionable insights quickly and accurately.

Modern visualization tools include interactive dashboards (which are dynamic control centres where the knowledge base, knowledge graphs and HMI logs interact), Augmented Reality systems (AR acts as a visual bridge that overlays Knowledge Base and Knowledge Graphs directly on to the physical world)), digital twins (which is a virtual real time replica of a physical object, process or a system), and 3D simulations that offer real-time representations of production systems, process flows, and quality trends. These tools enable workers and engineers to see data trends, performance metrics, machine health status, and production anomalies in a more digestible form, making it easier to understand the implications of data without deep statistical or technical knowledge.

For example, in a die casting mould manufacturing facility, visual dashboards may display real-time process parameters such as temperature, pressure, cooling time, and defect detection rates—directly correlated with AI predictions and ERP records. These insights help in proactive decision-making, immediate intervention, and continuous process improvements.

Moreover, visual knowledge representation supports training and knowledge transfer by preserving expert insights in visual forms such as process videos, annotated CAD drawings, and simulation models. This ensures that tacit knowledge becomes explicit and shareable, which is vital in retaining critical skills within an organization and aligning with the human-centric goals of Industry 5.0.

3.3 Deep learning approach used for technical knowledge management

Finally, to realise real-Time Knowledge Application and to have feedback and Continuous Learning (stages 4 and 5 of the approach to DM of TK) deep learning offers a transformative approach to managing technical knowledge. Deep learning, a subset of machine learning based on artificial neural networks with multiple layers, enables systems to learn complex patterns, relationships, and rules from vast amounts of industrial data without the need for manual programming.

Deep models (feed-forward DNNs, ensemble learners, and increasingly transformers / graph neural networks) learn complex, non-linear relationships among process control variables (temperature, feed-rate, pressure, speed, composition) and quality outcomes (dimensional accuracy, tensile strength, surface finish). Once learned, these models can be used for real-time process tuning, virtual sensors, or as surrogate models inside optimization loops (e.g., Bayesian optimization, reinforcement learning)(Abualigah et al., 2021).

Deep learning models, particularly Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks, are widely used to extract and manage technical knowledge from diverse sources such as:

- Sensor data from IoT-enabled manufacturing machines**.**
- Historical maintenance records and ERP data**.**
- Images and videos of manufacturing processes (e.g., for defect detection in die casting or forging).
- Operator logs and process descriptions**.**
- Predictive Maintenance (LSTM for time-series sensor data):

Convolutional neural networks (CNNs)

In CNN, the network does not look at the whole image, but a kernel (filter) of a small matrix of say 3X3 or 2X2 that sliders across the whole image and sums it up. This process is called Convolution. After several rounds of convolution and pooling, the data is flattered in to a long vector and is fed in to traditional neural network.

CNN automatically learn hierarchical visual features to detect and localize surface defects (scratches, cracks, pores, inclusions) and to classify part quality. They replace manual rule-based image processing pipelines and hand-crafted features. In the case of the object recognition CNNs include (1) image-level classifiers (ResNet, EfficientNet, DenseNet) that classify entire patches or whole images as defective/non-defective and dense prediction / segmentation networks (U-Net, Mask R-CNN, DeepLab) used when defect localization is required. For small/rare defects, patch-based training, multi-scale feature extraction, and attention modules are common. Data preprocessing often includes illumination normalization, defect augmentation (cutmix, synthetic defect generation), and use of high-resolution imaging (multi-spectral, thermal, or X-ray depending on the modality) (Chen et al., 2023).

CNNs have produced large gains in accuracy and robustness for steel/semiconductor/printed-circuit-board surface inspection and in additive-manufacturing defect detection. Methods that combine CNN backbones with anomaly-detection heads or one-class learning (train on only "good" examples) are particularly useful where defect labels are sparse. Transfer learning from large vision datasets plus domain-specific fine-tuning is a standard practice (Aguerchi et al., 2024).

Recurrent Neural Networks (RNNs) are a class of neural networks designed to handle sequential data. RNNs have a "memory" that allows information from previous steps to influence the current output. Therefore, they are very useful tools to use where the order matters.

The defining feature of an RNN is the hidden state (h_t) At each time step t, the network takes the current input (x_t) and the hidden state from the previous step (h_{t-1}) to calculate the new state

The basic mathematical representation is:

$$h_t \ = \emptyset \ (\ W_t h_{(t-1)} + \ W_x \, x_t + b \ )$$

Where:
h_t:New hidden state
h_{t-1} : Previous hidden state (the "memory")
x_t: Current input
W_t, W_x:Weight matrices
$\emptyset$: Activation function (usually tan h or ReLU)

RNNs have two challenges when the sequencing becomes too long.

Vanishing Gradient Problem: As the sequence grows, the gradients used to update weights become extremely small during backpropagation. This means the network "forgets" information from the beginning of long sequences.

Exploding Gradients: Conversely, gradients can become too large, causing the model's weights to oscillate wildly or crash.

To overcome these two memory issues, researchers developed more sophisticated Long Short-Term Memory (LSTM) networks that use "gates" to control what information is kept or discarded:

Long Short-Term Memory (LSTM) networks While a standard RNN has a simple "short-term" memory, an LSTM can decide which information is worth keeping for the long haul and what can be deleted. The core of the LSTM is the cell state $C_t$the LSTM uses three "gates" to add or remove information.

The Forget Gate
This gate decides what information from the previous cell state should be thrown away.
Input: h_{t-1} and x_t
Output: A number between 0 (completely forget) and 1 (completely keep).
The Input Gate

This gate decides which new information will be stored in the cell state. It has two parts: a sigmoid layer decides which values to update, and a *tanh* layer creates a vector of new candidate values C_t

The Output Gate

Finally, the output gate decides what the next hidden state h_t should be. This is a filtered version of the cell state, used for the actual prediction at that time step.

Mathematical Representation

The update of the cell state is calculated as:

$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$

Where:

f_t: Forget gate activation

i_t: Input gate activation

$\tilde{C}_t$: New candidate values

Predictive maintenance (PdM) uses continuous sensor streams (vibration, temperature, acoustic, current, pressure, etc.) to forecast failures or Remaining Useful Life (RUL), allowing planned service instead of costly unplanned downtime. Recurrent architectures — especially LSTM and encoder–decoder LSTM (and hybrid CNN–LSTM variants) — are widely used because they model temporal dependencies, handle variable-length sequences, and can be trained to produce either classification (anomaly vs. normal) or regression (RUL) outputs (Abdelhamid et al., 2022).

Typical architectures & inputs — vanilla LSTM, stacked LSTM, LSTM autoencoders for anomaly detection, and hybrid CNN–LSTM (CNN for feature extraction from short-time spectrograms + LSTM for temporal modeling). Multivariate time-series are common (multiple sensors), so multivariate LSTM and multivariate encoder–decoder designs are typical. LSTM-autoencoder frameworks are popular for unsupervised feature learning and anomaly scoring; supervised LSTM regression models are used for RUL prediction (Mathew et al., 2024).

Representative studies & empirical findings — a number of applied studies show that LSTM-based methods outperform classical statistical approaches (ARIMA, simple thresholding) and many traditional ML models on real industrial datasets when temporal patterns govern degradation. Hybrid models that combine CNNs (for local feature extraction) with LSTMs (for sequence modeling) are frequently reported to improve accuracy for rotating machinery and motor vibration data. A growing body of literature also integrates attention or transformer encoders with LSTM encoders/decoders to improve long-range dependency modeling and interpretability (X. Zhang et al., 2024).

Typical approaches — supervised regression models that predict product quality from process parameters; surrogate models used within multi-objective optimization; reinforcement-learning agents for closed-loop control; and digital-twin frameworks where a deep-learning model acts as the fast surrogate of a slower physics simulator. Feature-importance/SHAP analyses are often used to interpret which parameters most affect quality(L. Cheng et al., 2024).

Representative literature — systematic reviews and applied studies show machine learning (including deep learning) improving parameter selection in machining, additive manufacturing, and continuous process industries. Researchers combine physics-informed constraints with data-driven learners to ensure feasible/physically meaningful suggestions.

Datasets & metrics — experimental DOE (Design of Experiments) datasets are common for training and validation. Metrics include R^2, MAE/RMSE for predictive accuracy, and downstream KPIs such as yield improvement, scrap reduction, or throughput increase when models are used for optimization.

By incorporating deep learning into technical knowledge management, manufacturing firms can evolve beyond reactive workflows and establish adaptive and intelligent systems that continuously learn and improve — aligning seamlessly with the goals of Industry 5.0.

Challenges & gaps — dataset shift when new materials or tools are introduced, expensive labeling (quality tests can be destructive), and multi-objective tradeoffs (e.g., speed vs. surface finish). Also, closed-loop implementation needs safety guards and human-in-the-loop checks.

Open directions — integrating online learning for adaptive optimization, combining reinforcement learning with domain knowledge for safe control, and using uncertainty-aware surrogates so optimization can account for model confidence.

3.4 Conclusions

DM of TK in Industry 5.0 is marked by the convergence of human intuition and machine intelligence, enabling knowledge to be collected intuitively, stored systematically, and converted dynamically. These processes ensure that technical know-how becomes a shared, scalable, and continuously improving resource, enhancing productivity and innovation while aligning with sustainability and human-centric goals.
The integration of effective knowledge management methods and advanced technologies is crucial to realizing the vision of Industry 5.0, which emphasizes human-centric, sustainable, and resilient manufacturing systems.
In Section 3.1, the methods and tools for collecting, storing, and converting knowledge, where the use of IoT sensors, cloud platforms, and intelligent data acquisition systems enables seamless knowledge capture and real-time updates are explored. These tools transform raw industrial data into usable knowledge, fostering informed decision-making and continuous improvement.

In Section 3.2, we highlighted the visualization of technical knowledge as a powerful means to bridge the gap between human operators and complex data. Dashboards, heatmaps, digital twins, and AR/VR interfaces empower engineers and decision-makers to interact with data intuitively, facilitating rapid comprehension, troubleshooting, and collaboration.

In Section 3.3, the deep learning approach was shown to play a pivotal role in extracting, managing, and interpreting complex technical knowledge. Through neural networks, manufacturers can harness large-scale data for predictive maintenance, defect detection, and process optimization — enhancing adaptability, operational efficiency, and human-machine synergy.

Together, these approaches lay the foundation for realising the novel approach to intelligent, responsive, and inclusive manufacturing systems — the cornerstone of Industry 5.0.

4. Method for technical knowledge sharing to construct a smart and flexible Die Casting Mould Manufacturing process towards intelligent manufacturing

The die casting mould industry is a core enabler for automotive, aerospace, electronics, and consumer goods manufacturing. High-precision moulds determine product quality, dimensional accuracy, and cycle time. With global markets demanding lighter, more complex, and customized products, die casting manufacturers face the challenge of producing flexible, high-quality moulds under shorter lead times and stricter tolerances. Mould design and manufacturing depend heavily on tacit expert knowledge—decisions on alloy selection, gating system design, cooling layout, and process parameters are traditionally based on engineer experience rather than standardized digital methods. This results in inconsistencies, inefficiencies, and limited knowledge reuse when expert personnel retire or shift roles.

Many die-casting SMEs (Small and Medium Enterprises) operate with disconnected CAD/CAM, simulation, and production management systems. The absence of an integrated digital thread means process knowledge generated during design, machining, and maintenance phases remains siloed. Without systematic knowledge sharing, intelligent automation and process optimization become difficult. The global transition toward *Industry 4.0 and 5.0* emphasizes cyber–physical systems, real-time monitoring, and adaptive manufacturing. For die casting, where tooling cost and process stability are critical, *flexibility and adaptability* can only be achieved when technical knowledge flows seamlessly between design, simulation, production, and maintenance stages.

4.1 Modelling smart and flexible machining process

In traditional mould manufacturing setups—particularly in die-casting moulds for high-end automotive components—the process faces several practical challenges:

High-precision die casting mould manufacturing faces several persistent challenges that hinder process stability and quality assurance. A major limitation lies in the lack of real-time feedback from machining centers during intricate cavity milling operations. Without continuous monitoring, tool wear, thermal deformation, and micro-vibrations often go unnoticed, leading to subtle geometric deviations that compromise mould accuracy. Moreover, inefficient resource utilization, such as prolonged machine idle time and unexpected breakdowns, further increases production costs. Quality deviations are frequently detected only during post-production inspection**s**, when defects are costly or impossible to correct—resulting in significant rework, scrap, or rejection of mould components. These issues primarily arise due to data invisibility on the shop floor. In traditional setups, operators depend on scheduled manual inspections or personal experience, which cannot capture transient process anomalies that occur in milliseconds yet critically affect mould surface finish and dimensional accuracy(Javaid et al., 2022).

To overcome these limitations, consider a **high-precision mould shop manufacturing AC compressor housing moulds** for luxury automotive applications—components that demand micron-level precision and are machined from hardened tool steel. To ensure superior quality and operational efficiency, a **smart IoT-based monitoring system** is deployed on CNC milling machines. **Vibration sensors** mounted near the tool head continuously detect chatter or instability that may compromise fine cavity details. **Temperature sensors** embedded in both the spindle and the workpiece provide early warnings of thermal expansion, ensuring dimensional control during deep-pocket milling operations. In parallel, **current sensors** integrated into the machine's motor circuitry monitor cutting loads and identify abnormal power fluctuations associated with tool wear, material adhesion, or chip accumulation. All these sensor streams are transmitted in **real-time to an edge computing unit**, which performs on-site data analysis to detect anomalies instantly and alert operators or control systems. Simultaneously, data are synchronized with a **cloud-based analytics platform**, where AI models—trained on historical machining data—analyze patterns, predict tool degradation, and recommend **optimized tool-change schedules** before any visible deterioration occurs (Magalhães et al., 2022). The manufacturing of high-precision automotive compressor components demands a tightly controlled process where even the smallest deviation in tooling, casting, or machining can lead to functional failure or customer rejection. Mould manufacturing in a die-casting environment typically begins with the design and fabrication of complex mould assemblies using advanced tool steels such as Dievar, chosen for their resistance to thermal fatigue and deformation under high pressure and temperature. These moulds are intricately engineered to include multi-cavity layouts, conformal cooling channels, and vacuum venting systems to ensure optimal casting conditions. Once moulds are installed on high-tonnage casting machines (like the 840T Bühler die casting unit), they undergo continuous cycles involving metal injection, solidification, ejection, and die spraying. At each stage, a variety of parameters—such as melt temperature, plunger velocity, injection pressure, spray duration, and cycle time—influence the final casting quality. Any deviation in these parameters may lead to internal porosity, dimensional inaccuracy, or surface defects. After casting, components proceed through CNC machining operations (on platforms such as Okuma and Fanuc), followed by leak testing to ensure functional integrity. These machining and post-processing steps are just as critical as the casting stage in achieving the desired tolerance and surface finish, particularly when working with tight specifications like ±3 microns.

Figure 4 below shows the entire process of mould manufacturing process until its launched for a full-scale production. This process has four distinct stages as elaborated in the flow chart below.

Understanding the part design and customer needs: In this stage the detailed 2D and 3D drawings are obtained from the customer. These drawings are studied to understand the tolerances, limitations of the diecasting and CNC machines on which these parts are planned to be produced. The key parameters like the weight of the part, the wall thickness of the parts, the curvature and radius for the flow, surface flatness tolerances etc are studied and clarified with the customer's design team. At times, some of the design parameters of the parts are modified if they are not critical to end the functionality of the parts. This may help to reduce the scrap in the production or increase the tool life or reduce the cycle time. Such exchange of information and modification is based on the knowledge and experience of mould design engineers.

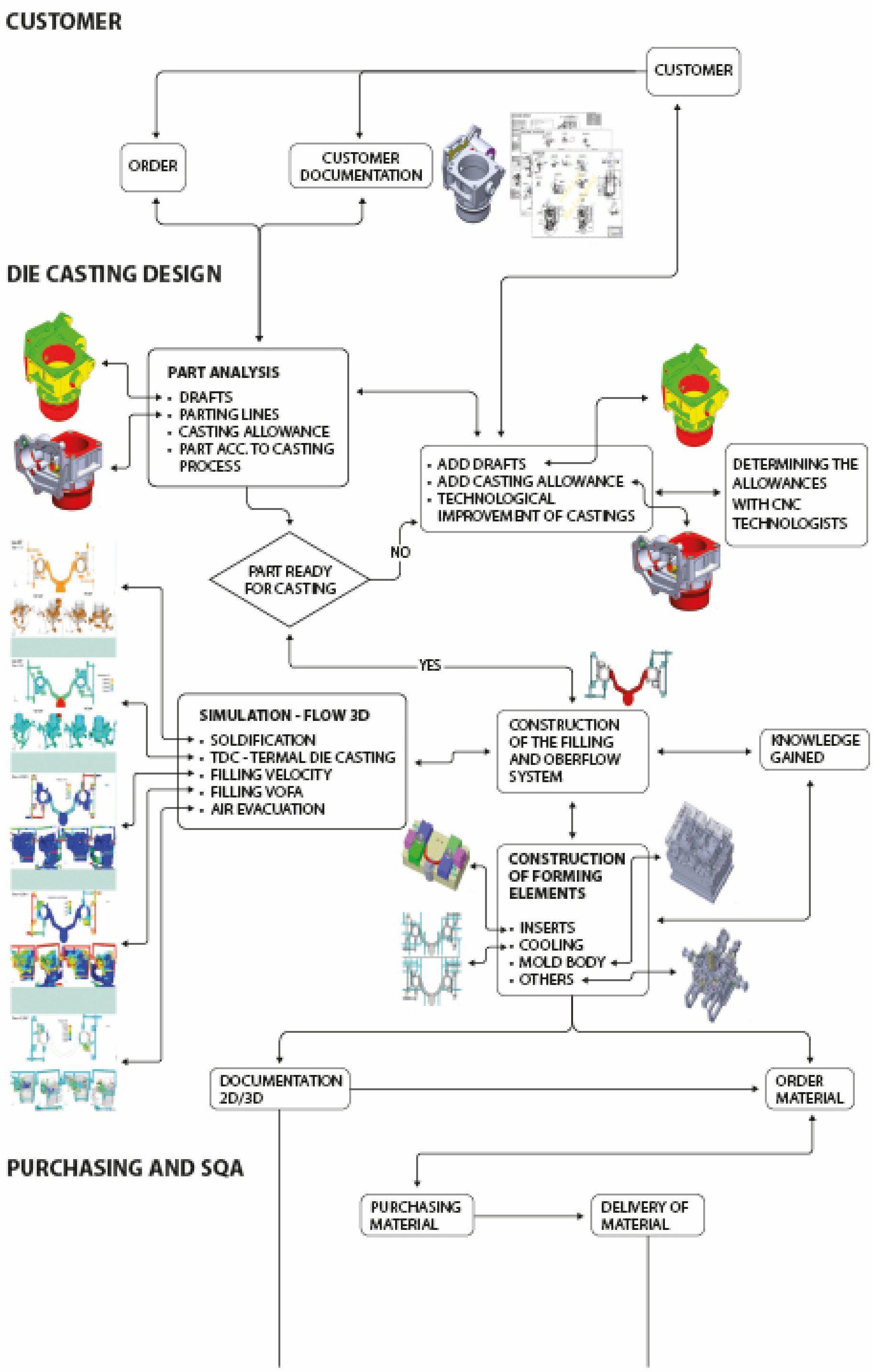
Die Casting Mould Design: This is a critical and the most important process in which mould is designed and manufactured (virtually) before its really manufactured physically. After the part design is studied by mould design engineers in conjunction with the part design engineers, the mould design engineers proceed with the mould design forming elements considering important parameters like parting lines, casting allowances, drafts etc. The casting allowances considered are also checked for feasibility of the CNC machine allowances by CNC machine technologists to ensure that they fall within the CNC machine tolerances on which the parts are excepted to machined after casting.

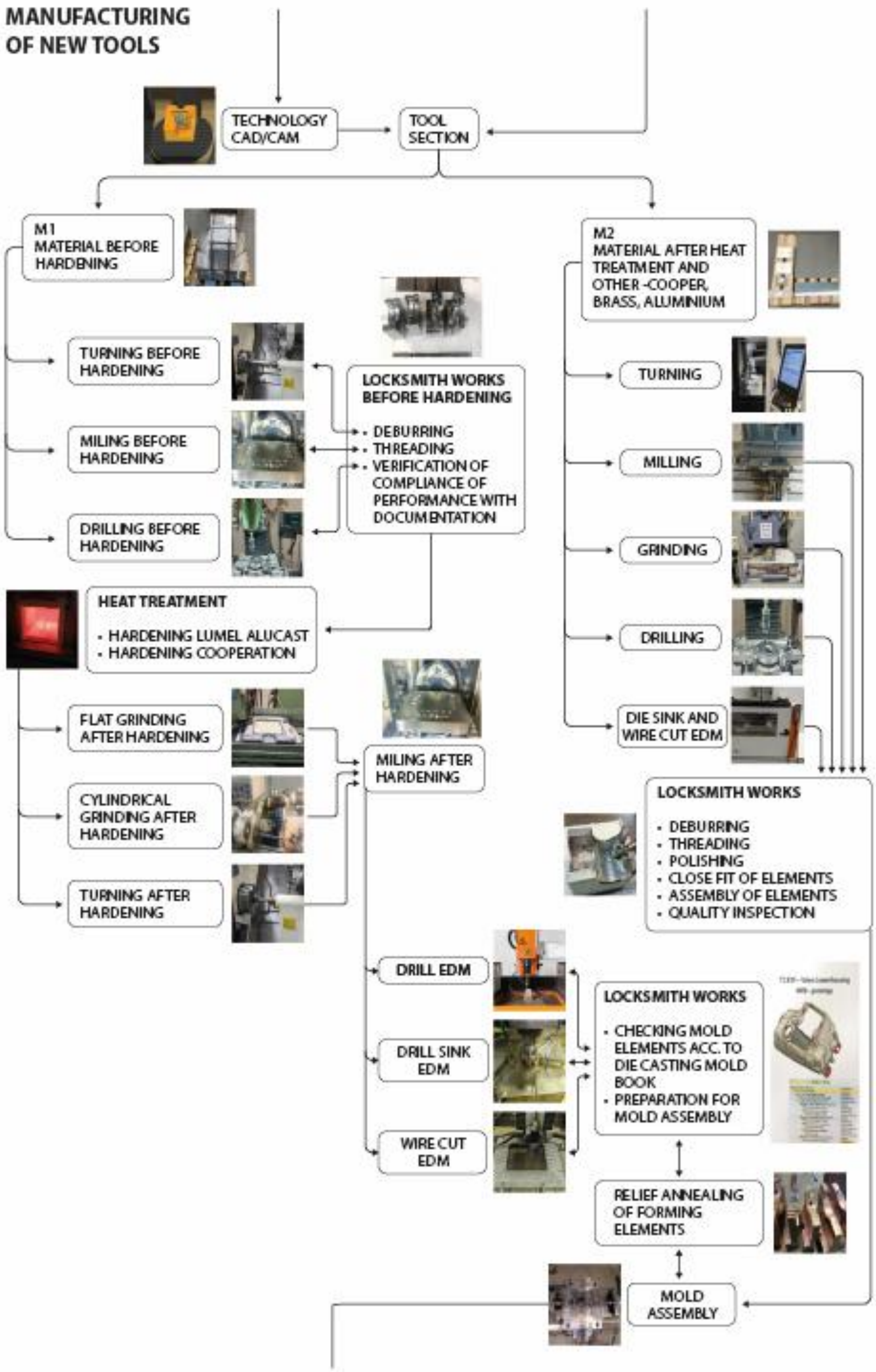
After the main part cavity designs are done, the filling and overflow with vacuum designs are finished. The other systems like cooling channels, the mould body, squeeze pins, ejectors etc are designed and integrated to complete the mould design.

Before the mould is taken for actual manufacturing the entire design is tested and validated on a 3D simulation to check for solidification, thermal die casting, filling velocity, air evacuation etc. Many corrections are done to the mould design to make sure that heat signatures, solidification, the velocity of filling and extraction of fumes are within the acceptable range and theoretically (and with the simulation) the mould design is good to go for production.

Mould Manufacturing: Based on the mould design, the BOM (bill of materials) are prepared and procured from the approved suppliers. Each of the mould elements undergo different processes as illustrated below turning, milling, grinding and drilling operations on various machines. Some of the elements go for heat treatment after these processes. Post heat treatment, some elements undergo further processes like flat grinding, Cylindrical grinding, turning, milling, die sink EDM, wire cut EDM, drill EDM etc. While some elements go through manual processes by skilled locksmiths like deburring, treading and polishing. Finally all the elements are checked by the lock smiths and tool shop engineers with the drawings and the assembly of the mould takes place. The flatness of the male and female side of the mould is checked on the bluing press and the final polishing is done to ensure flat contact between the two sides on the mould.

Mould Trial and Correction Process: This is a joint process involving the mould design and manufacturing team, production process engineers, quality engineers. The mould is used to produce the first set of parts with optimizing the process parameters. The parts are sent to in house measurement laboratory for the measurement reports. The variances are studied debated and assigned to process parameter changes or the mould element modification or adjustments. The mould is dis assembled and the corrections to the elements / inserts of the mould are carried out. The moulds are assembles and T2 trials are done to ensure that the parts produced are as per the design and within the tolerances. These parts are sent to the customer with the PPAP (Production Part Approval Process) documents for approval. Subsequent to such approval, if the parts are critical the customer may carry out a FDPR (Full Day Production Report) by witnessing the production to ensure the sustainability and reliability of the manufacturing process.


CUSTOMER
CUSTOMER
ORDER
CUSTOMER DOCUMENTATION
DIE CASTING DESIGN
PART ANALYSIS
• DRAFTS
• PARTING LINES
• CASTING ALLOWANCE
• PART ACC. TO CASTING PROCESS
• ADD DRAFTS
• ADD CASTING ALLOWANCE
• TECHNOLOGICAL IMPROVEMENT OF CASTINGS
DETERMINING THE ALLOWANCES WITH CNC TECHNOLOGISTS
PART READY FOR CASTING
NO
YES
SIMULATION - FLOW 3D
• SOLDIFICATION
• TDC - TERMAL DIE CASTING
• FILLING VELOCITY
• FILLING VOFA
• AIR EVACUATION
CONSTRUCTION OF THE FILLING AND OBERFLOW SYSTEM
KNOWLEDGE GAINED
CONSTRUCTION OF FORMING ELEMENTS
• INSERTS
• COOLING
• MOLD BODY
• OTHERS
DOCUMENTATION 2D/3D
ORDER MATERIAL
PURCHASING AND SQA
PURCHASING MATERIAL
DELIVERY OF MATERIAL



MANUFACTURING OF NEW TOOLS
TECHNOLOGY CAD/CAM
TOOL SECTION
M1 MATERIAL BEFORE HARDENING
M2 MATERIAL AFTER HEAT TREATMENT AND OTHER -COOPER, BRASS, ALUMINIUM
TURNING BEFORE HARDENING
MILING BEFORE HARDENING
DRILLING BEFORE HARDENING
LOCKSMITH WORKS BEFORE HARDENING
• DEBURRING
• THREADING
• VERIFICATION OF COMPLIANCE OF PERFORMANCE WITH DOCUMENTATION
TURNING
MILLING
GRINDING
DRILLING
DIE SINK AND WIRE CUT EDM
HEAT TREATMENT
• HARDENING LUMEL ALUCAST
• HARDENING COOPERATION
FLAT GRINDING AFTER HARDENING
CYLINDRICAL GRINDING AFTER HARDENING
TURNING AFTER HARDENING
MILING AFTER HARDENING
LOCKSMITH WORKS
• DEBURRING
• THREADING
• POLISHING
• CLOSE FIT OF ELEMENTS
• ASSEMBLY OF ELEMENTS
• QUALITY INSPECTION
DRILL EDM
DRILL SINK EDM
WIRE CUT EDM
LOCKSMITH WORKS
• CHECKING MOLD ELEMENTS ACC. TO DIE CASTING MOLD BOOK
• PREPARATION FOR MOLD ASSEMBLY
RELIEF ANNEALING OF FORMING ELEMENTS
MOLD ASSEMBLY

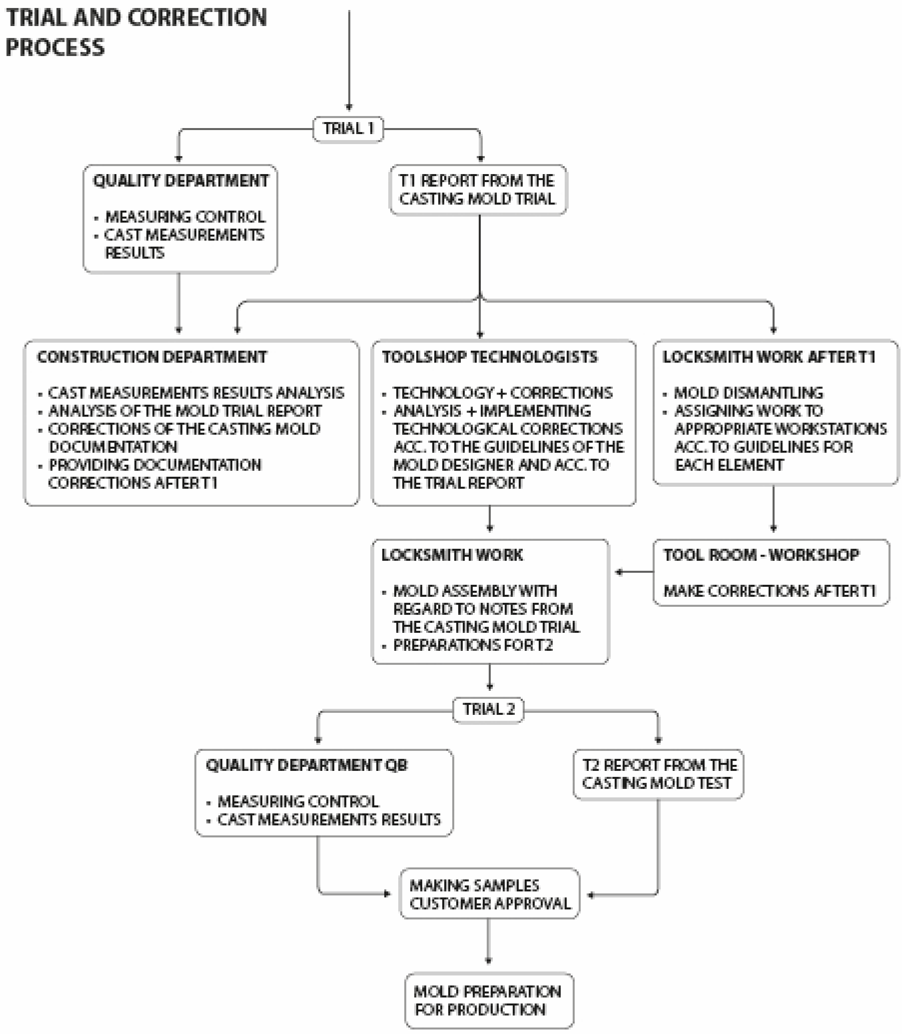


Figure 4: The flow of the die castings process

To summarise, the manufacturing process (Figure 4) was modelled and its detailed workflow was presented, divided into the following stages: (a) Understanding part design and customer requirements: detailed 2D and 3D documentation is obtained from the customer and analysed to understand tolerances and the limitations of die casting and CNC machines planned for production. (b) Die casting mould design: the mould is designed and virtually manufactured before physical production. Prior to actual manufacturing, the entire design is tested and validated through 3D simulations to analyse solidification, thermal behaviour during die casting, mould filling velocity, air evacuation, etc. (c) Mould manufacturing: based on the mould design, a BOM (Bill of Materials) is prepared and components are ordered from approved suppliers. Each mould component undergoes a sequence of manufacturing operations. (d) Mould trials and correction process: mould design teams, manufacturing engineers, process engineers, and quality engineers prepare measurement and validation reports.

4.2 Data, information and technical knowledge collecting and storing

So, for the analyzed process (section 4.1) further elements of the novelty method (Figure 2) were presented process of data and information acquiring.

In die-casting production relies heavily on the seamless integration of IoT sensors across the shop floor. At the core of this implementation is the 840T fully automated Bühler die-casting machine cell (Figure 5), a high-tonnage precision casting unit central to producing compressor housing parts for automotive applications. This machine is equipped with strategically positioned sensors that are specifically designed to acquire real-time process data critical for quality control and predictive analytics.

Figure 5 Buhler Diecasting Machine - real photos within the factory.

As shown in Figure 5, the die-casting machine features several key sensor placements:

- Plunger Reset Sensor (green arrow): This sensor resets the plunger to its home position before each shot cycle. Accurate resetting ensures consistency in stroke length and timing, which is vital for maintaining repeatability across casting cycles.
- Plunger Position Sensor (red arrow): This sensor continuously tracks the plunger's movement across the three casting phases—slow shot, fast shot, and intensification. By accurately determining the plunger position in real-time, the system can monitor

transition points between phases and detect anomalies like premature phase switching or velocity dips.

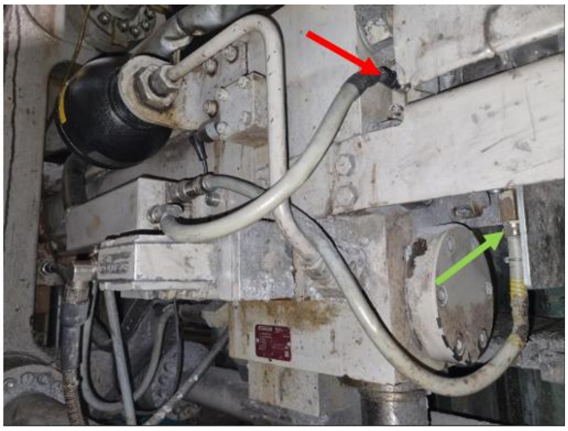
- Pressure Sensors (blue arrows): Mounted near the casting chamber and on compressed gas tanks (Figure 4b), these sensors are responsible for capturing:
    - The hydraulic pressure applied during the shot.
    - The actual pressure exerted on the molten alloy inside the mould.
    - The pressure profile across the three casting phases.

The switching points of speed and pressure are dynamically computed using the feedback from piston position sensors (Figure 6). These sensors provide high-resolution data, enabling the system to map out the casting phases and correlate the pressure-velocity curve with potential defect occurrences like cold shuts or gas porosity.

This robust IoT sensor network feeds continuous data into the AIMS (AI-based Intelligent Monitoring System) platform. By digitizing traditionally manual checkpoints, the shop floor now enables:

- Edge-level monitoring: Real-time, low-latency data capture and processing directly at the machine level.
- Data integrity and traceability: Every cycle's operational metrics are recorded, timestamped, and indexed for retrospective analysis and audit.
- Predictive maintenance and defect forecasting: Through pressure and motion trends, the system can pre-emptively alert operators to tool wear, poor lubricant application, or metal turbulence conditions.

Thus, integrating these smart IoT sensors bridges the gap between physical processes and digital intelligence. It ensures that data collected during each casting cycle is both context-aware and machine-actionable, laying the foundation for advanced AI models to analyze, learn, and optimize performance over time.



a)

Sensor for resetting the plunger position (green arrow).
Sensor for calculating the plunger position (red arrow).
There is a scale (ruler) on the piston, on the basis of which the piston position is calculated using the above sensors.
The switching points of speed and pressure and the three casting phases are read from the piston position sensor.

Pressure Sensors (blue arrows): Mounted near the casting chamber and on compressed gas tanks

b)

Figure 6 Plunger position measuring sensors a) Pressure measuring sensors b) located on the Diecasting machine

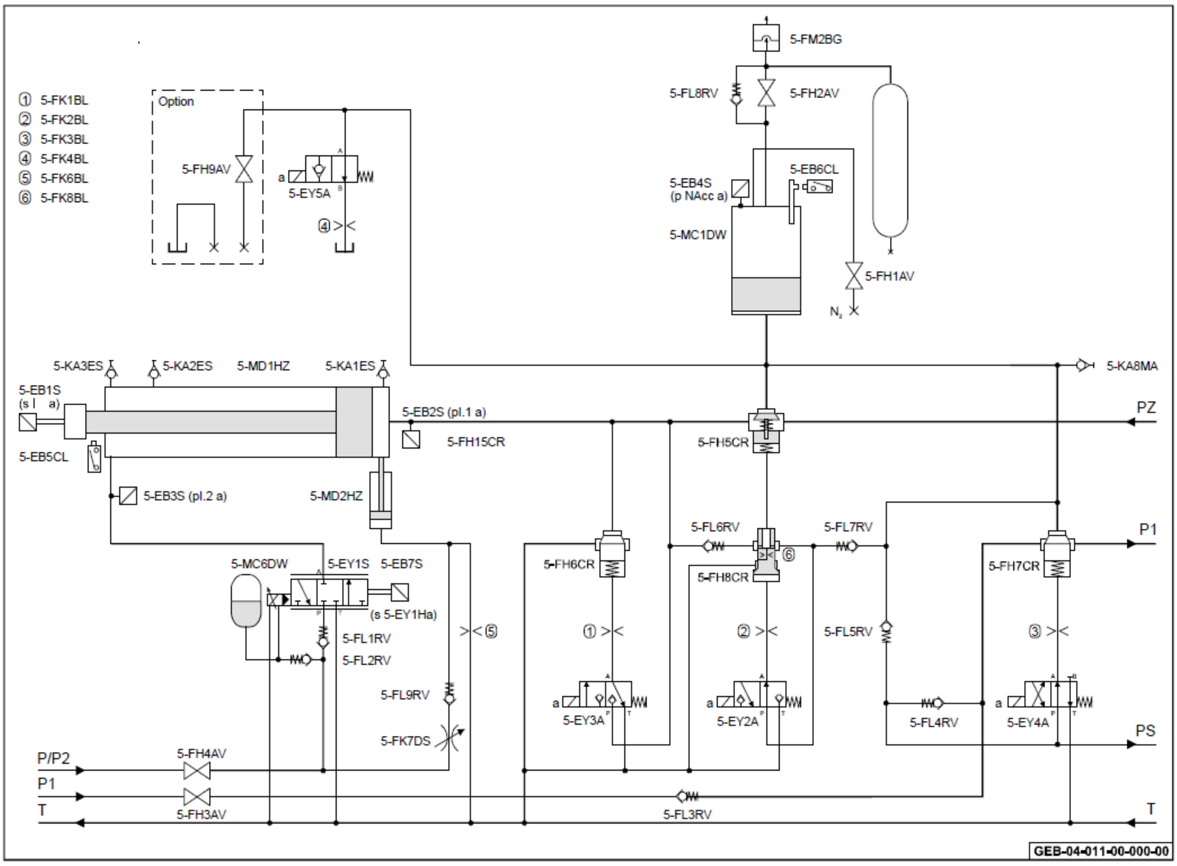


Figure 7 Plunger Position Measuring and Pressure Sensors Installed on the Diecasting Machine

(a) Pressure Measuring Sensors – These sensors are mounted on the compressed gas tanks and near the hydraulic units of the diecasting machine. They are responsible for measuring real-time chamber pressure, hydraulic system pressure, and pressure exerted on the molten metal during various phases of the casting cycle. This data helps identify inconsistencies that could lead to blowholes, shrinkage defects, or incomplete filling of the mould cavity.

(b) Plunger Position Sensors – Installed along the plunger cylinder and linear motion path, these sensors track the exact position of the plunger throughout the diecasting process. They enable the identification of switching points between the three critical casting phases:

1. Slow shot phase – initial plunger movement before metal reaches the mould cavity.
2. Fast shot phase – rapid acceleration to fill the mould cavity quickly.
3. Intensification phase – pressure is maintained to compensate for metal shrinkage.

The precise feedback from these sensors provides the velocity and displacement profiles of each shot. The AI model then analyzes this information to detect any deviations from the standard profile, helping to flag issues such as misaligned dies, improper venting, or plunger wear.

Together, the sensors shown in Figure 4a and Figure 4b act as the digital eyes and ears of the AI-driven monitoring system, ensuring that every casting cycle is measurable, analyzable, and optimizable in real-time. Their deployment transforms the traditional diecasting shop floor into a smart, cyber-physical environment aligned with Industry 5.0 goals of human-machine collaboration and self-learning systems.

Data collecting and storing

A sudden spike in spindle temperature and tool load is detected while finishing a narrow cooling channel in the mould. The AI model, trained on historical defect data, predicts a potential dimensional inaccuracy and suggests immediate tool inspection. This real-time alert allows the operator to pause the process, check the tool, and avoid producing a defective part—saving both time and material. The analysed real life machining process, namely die castings is realized in the foundry and the machine park includes Bulher 840 Tonnes closing force horizontal cold chamber die-casting machines and DMG Moriseki 3 axis and 5 axis milling machines which are used for manufacturing of the die casting forming elements of the moulds. This area is supported by an Enterprises Resource Planning (ERP) system SAP HANA, and additionally the IOT sensors for measuring, real time actual pressure on they alloy, pressure on the hydraulic cylinder, actual switching points of the speed and pressure of the plunger of the three phases of casting, are installed on the die casting machines. On the CNC machines, the IOT sensors to collect the power consumption on real time basis. In addition to this the temperature of the moulds are collected manually using thermal cameras periodically during the diecasting process (the same can be extended to be done by IOT enabled thermal camera to take images after each shot of the mould). It is assumed that the analysis of the life of the die casting mould is based on defined parameters that influence the formation of defects during the die castings process.

In the context of Industry 5.0, which emphasizes the synergy between human expertise and intelligent systems, the deployment of data collection infrastructure forms the foundation for any AI-driven monitoring and optimization system. Our approach integrates real-time data acquisition, manual inputs, and edge computing, tailored specifically to the highly demanding mould manufacturing process used in producing compressor components for premium automotive air-conditioning systems.

On the CNC machines, selected IoT sensors are strategically installed to collect real-time power consumption data. These readings not only indicate energy usage but can also reflect indirect signs of tool wear, machining anomalies, or unexpected loading conditions. By continuously monitoring electrical parameters, the system gains the ability to detect deviations early in the process, allowing for predictive maintenance and energy optimization.
In parallel, the temperature of the die moulds is currently measured manually using infrared thermal cameras at periodic intervals. These measurements help identify uneven heating, cooling rates, or hotspots that might indicate thermal fatigue, warping, or improper cycle timing. Although manual, this process is envisaged to be upgraded by implementing IoT-enabled thermal imaging systems mounted near the mould to automatically capture and store thermal profiles after every casting cycle. This enhancement would eliminate human error and facilitate comprehensive temperature mapping, especially during continuous production cycles.

Data is further enriched by manual entries and real-time captures from the ERP system (SAP HANA). This includes:

- Gross and net weights of each casting part.
- Alloy type and associated material properties.
- Standard cycle times, as predefined by process technologists.
- Production batch sizes and raw material traceability data.
- Shift-wise records of manpower deployment and production scheduling.

While many of these inputs are currently updated manually by shop-floor employees and planners, critical indicators such as total number of components produced and NG (Not Good) parts are captured automatically from the machine and relayed directly into the ERP. This real-time feedback loop enables instant yield calculations, rejection analysis, and trend monitoring without relying on retrospective manual compilation.
This diverse and multi-source dataset forms the input for the next phase of our framework—AI-driven analysis and optimization.

These are very useful set of data when the new part is taken up for design and their subsequent production. They act as a starting point or benchmarks for the design and process engineers.

4.3 Technical Knowledge base

This research was conducted using a real-life industrial case study centered on the mould manufacturing process of high-precision compressor parts, specifically two production orders from the Valeo_Renault CH family. These components, critical to automotive air-conditioning systems, require extremely tight dimensional tolerances—such as ±3 microns on a 100 mm diameter—and must be entirely free from porosity, as any defects may result in gas leakage and pose fire hazards. As a result, every part undergoes 100% leak testing after machining. Parts that do not meet the tolerance or quality requirements are scrapped, making the process highly sensitive to variations in manufacturing parameters.

This very demanding high-precision compressor part is not only complex but can have significant influence due to various parameters in different stages such as its mould design, the part design itself, preparation of its alloy and the process of diecasting manufacturing itself through its various process parameters. These parameters are not only critical but also are largely interlinked with some trade-off between each other's.

The sources of the data being collected can be broadly classified as

- data being collected based on the technical knowledge of the specialists such as mould design engineers
- data being collected through the IoT enabled sensors placed on the diecasting machines
- data being collected from the ERP system which in turn is connected from the die casting machines and data being updated by the process engineers and production operators

Additionally, to create the TK base the expert technical knowledge was defined and acquired.

Expert knowledge data base is continuously evolving data updated and saved largely in two buckets. One is the design expertise which is critical in designing of the mould in the first place. This is gained over a period of time by virtue of experience by the design engineers by continuously learning and improvising similar moulds or the next revisions of the same mould. The various factors involved here are – number of cavities, locations of the parting lines in the mould, position and size of inlet and position, size and number of outlets in order to have optimal time for flow of aluminium alloy and solidification to achieve both good quality and best cycle time. The location and quantity of cooling channels for best thermal management. Design of the casting tolerances so that they are sufficient to take in to consideration of the tolerances for the next manufacturing process of CNC machining.

The second set of expert knowledge comes from the process engineers. This is gained over a period of time by virtue of experience by producing similar parts. The various process parameter knowledge and their trade off with each other's is very critical knowledge gained. They include, duration and hydraulic pressure applied in different phases, mould temperature cycle management, molten aluminium temperature, optimal cycle time for the part etc.

As the objective of this research is to objectively collect all such technical knowledge from this real time project Valeo_Renoult CH project to establish the correlations and predictability if any.

The real time production data of this project is collected for 3 days of production from 19/01/2024 06:00:23 until 21/01/2024 22:35:27 covering the production of 3609 parts without any production break. Such data acquired falls mainly under the group process parameters of the table 1 listed below.

The data regarding the mould design, part design and the alloy preparation are gathered through detailed technical interviews with design and production engineers, which forms the knowledge base for this project. Even though most of such data remains unchanged during the process of the subject batch of production, the very selection of these parameters can also be subject of further study based on the data collected over the years for various different types of projects.

Mould Designing Parameters:

Design of the mold												
Date of castin	Time of casti	Type of steel - main forming element	Hardness - main forming elements [Hr	Coating of forming elements [type] No/PVD/N	Stress relieving after mold test [y/n]	Stress relieving continuation (no of cycle	No of Cavities [pcs]	Cooling system (oil, water) [O/W]	Gate inlet area [mm2]	Overflows inlets area [mm2]	Ventings chanels area [mm2]	Vacumm system included [y/
19/01/2024	06:00:23	Dievar	46	No	Y	0	2	W	390	224	87,6	Y

Dievar steel is chosen for the inserts manufacturing over the traditional H 13 steel as the expected volumes of production for this project is more than half a million parts per year. This makes the project high runner project with the frequent change of the inserts. Dievar steel is known for its exceptional toughness against heat cracks, gross cracks and long tool life.

Hardness (Hrc) of the forming elements is 46 which is well within the range of 44 to 42 Hrc for such applications which is achieved through heat treatment processes. This is critical to ensure that the forming element surface remains intact during the high velocity flow of the aluminium alloy and also the parts produced are dimensionally intact over the life of the mould.

NO *Coating on the Forming elements* was chosen for this project as the design Engineers felt that with Dievar materials its not needed and probably after more than 50% of the usage of the mould PVD (Physical Vapour Deposition) coating using Chromium Nitride can be considered

Stress Relieving Test after mould trials are carried out to neutralise the high stress created in the mould due to initial thermal shocks on the inserts. If these stresses are nor released they may lead to dimensional instability, reduced toughness and premature cracking.

Number of Cavities is one of the most important decision for the mould designers to make based on various factors such as the closing force of the HPDC machine intended to produce the parts, the volumes of the parts (high runner project or the low runner), Complexity of the part, previous quality experience of the similar parts, flow simulation results etc. Based on all these parameters, two cavities were decided for this mould which uses 840 T closing force Bulher machine bearing asset number Ph 156 to produce these parts.

Water Cooling for the mould is used as its cost effective as it absorbs significant amount of heat very quickly and helps in bringing down the cycle time between two consecutive shots.

The *Gate inlet Area* is designed as 390 sq mm for this two cavity mould based on the flow simulation results while designing the mould. This is an optimisation between speed at which the molten alloy flows through at a velocity between 20 m /s to 60 m/s. The size of this gate should be to ensure high filling speed avoiding die erosion. Larger gate inlet will lead to sluggish filling and solidification of some parts of the mould before the mould cavity is 100% filled in.

The *Venting Channel Areas* are designed as 2 X 73 X 0,6 sq mm for both cavities together totalling 87,6 sq mm and these are assisted by vacuum system which assists to such the impurities, fumes etc to reduce the porosity in the moulds.

Design of the Part / Castings Parameters:

Design of the part / casting								
Average part wall thickness [mm]	projected of the casting area onto the parting surface [mm2]	share of part weight in the entire injection (%	Maximum speed of alloy during cav. Filling [m/	Filling time [ms]	Leak test preasure requirements [Pa] if no	Plunger Diammeter [mm]	Whole cast weight [g	Part complexity (according assumption from 1-5
3,7	61946	47,4	45	44	N	80	3165	3

As these parts are designs of customers projects which form the parts of the bigger systems with their own limitations and requirements, the diecasting moulds designers have limited influence on these parameters and often gave to be consulted and approved by the customers who are the designers of the parts.

Based on the design of the part and the experience of the design team of Lumel Alucast the complexity of this part was rated as 3 on a scale of 1-5 with 5 being the most complex part.

Some of the part design parameters such as the *average thickness of the part* is 3,7 mm and the weight of each part is 743,77 grams making the two parts in the cavity equalling 743,77 X 2 = 1487,55 grams. With the *whole cast weight* of 3165 grams based on the mould design consideration such as the inlet gate area, out let gate areas, vacuum channel, *the ration of the part weight to the entire casting* is 47,4%

The plunger diameter(mm) , max speed of the alloy during cavity filling (m/s) and filling time (sec) are all interlinked to each other's and are decided based on the design formulas to optimise and testing the same on the flow simulation to find the best balance between cycle time of production and expected quality of parts and mould life.

The total casting area on the parting surface is one of the most critical parameter to chose the right clamping force required for the machine. The clamping force has to be good enough to ensure that the flashes do not appear from the parting area as they form the high pressure points from within while the cavity is filled.

Alloy Prepetition Parameters:

Parameters alloy preparation					
Alloy type [name]	Alloy temparature (melting C d	Type of melting furnace (shaft, crucible S/H)	Density index of alloy [numb	Number of shots per batch [pcs]	% of scrap ratio in the alloy composition [%]
ADC12	730	S	1	7218	60

Each of these alloy preparation parameters can have a very significant influence as all the parameters are significantly interlinked. The brief description and significance of each one of them is as follows.

Alloy type: Even though the main chemical composition of the alloy used in high pressure aluminium diecasting is Alluminium (Al) itself, but the other elements such as silicon (Si), copper (Cu) , Iron (Fe), Mangenesium (Mn) and their percentages determine optimal type of alloy suitable for the product being manufactured for its mechanical strength, corrosion resistance, fluidity etc.

Alloy Temperature: The pouring temperature of the Aluminium alloys ranges from 600 to 750 degree Celsius. However, based on the internal logistics, ambient temperature of the production hall this may adjusted for compensating for the heat losses in pouring from the melting & holding furnace, the transport distance to the holding furnace on the diecasting cell.

Type of Melting Furnace: There are mainly two types of melting furnaces, the crucible furnaces, which are more suitable for small batch productions with frequent change in type of alloys and the other type is Shaft furnace which is more suitable for high volume melting with much higher energy efficiency as they have temperature zones for melting and holding the alloy making it more energy efficient when they are used in full capacity.

Density Index of the Alloy: This is a very critical parameter of the alloy to ensure that the porosity in the parts produced is at the minimum ensuring that the parts achieve the expected mechanical strength and leakage resistance. The expected index can be up to 2% max based on the application of the part.

% of scrap ratio in the alloy composition: This is the percentage of internal scrap generated from the overflow of the same type of alloy to the new alloy ingots used to melt. This percentage is set based on how critical some of the parameters like corrosion resistance of explosive proof the final parts are expected to be.

Process Parameters:

Process parameters													
Alloy temparature (casting C deg	First phase speed [m/s	Second phase speed [m/s]	Third phase pressure in the alloy [b	Tablet hight (mm	Closing force [k	Cycle time [s]	Shot sleeve filling factor [%]	Automatic process [y/n]	Casting machine number [No	solidification time	Vacuum level [mba	Type of spraying (Micro/emulsion) [M/E	Quality atribute OK/BAD/L(
690	0,15	4,32	875	20	8444	47,1	61	Y	ph156	8	250	M	OK
690	0,15	4,34	889	17	8446	51,8	61	Y	ph156	8	250	M	OK
690	0,15	4,34	876	19	8446	48,5	61	Y	ph156	8	250	M	OK
690	0,15	4,36	879	20	8456	50,7	61	Y	ph156	8	250	M	OK
690	0,15	4,33	887	19	8450	47,5	61	Y	ph156	8	250	M	OK
690	0,15	4,31	877	21	8449	48,4	61	Y	ph156	8	250	M	OK
690	0,15	4,34	876	21	8449	47,6	61	Y	ph156	8	250	M	OK
690	0,15	4,34	890	18	8448	47,9	61	Y	ph156	8	250	M	OK
690	0,15	4,35	881	21	8446	49,8	61	Y	ph156	8	250	M	OK
690	0,15	4,33	878	21	8455	47,3	61	Y	ph156	8	250	M	OK
690	0,15	4,34	875	20	8452	47,6	61	Y	ph156	8	250	M	OK
690	0,15	4,32	879	18	8460	48,5	61	Y	ph156	8	250	M	OK
690	0,15	4,32	877	21	8450	50,1	61	Y	ph156	8	250	M	OK
690	0,15	1,15	258	14	8211	1347,8	61	Y	ph156	8	250	M	BAD
690	0,15	1,15	201	20	8314	69,4	61	Y	ph156	8	250	M	BAD
690	0,15	1,15	201	19	8339	46,3	61	Y	ph156	8	250	M	BAD
690	0,15	1,15	232	23	8353	46,4	61	Y	ph156	8	250	M	BAD
690	0,15	1,15	269	33	8377	46,3	61	Y	ph156	8	250	M	BAD
690	0,15	1,15	250	22	8400	46,4	61	Y	ph156	8	250	M	BAD
690	0,15	1,15	252	30	8423	46,8	61	Y	ph156	8	250	M	BAD
690	0,15	3,96	838	21	8434	47,4	61	Y	ph156	8	250	M	LOK
690	0,15	4,2	855	24	8456	46,7	61	Y	ph156	8	250	M	LOK
690	0,15	4,32	869	23	8480	46,6	61	Y	ph156	8	250	M	OK

For the current research we will analyse all the process parameters collected during the production process from various IoT enabled sensors from the machines, data entered through operators and ERP system integrated with the machine.

While data from 13 different parameters are being collected for 3609 parts produced over 3 days as enclosed in the Excel file named “DM 19.12.2024-21.12.2024 CH Renault data “ who’s small sample database is presented above as the appendix 1.

Some of these parameters remained or kept constant throughout the process due to the obvious choice. These primarily include – *Casting machine*, 840 T Buhler with machine asset number – Ph 156, the *type of spraying system* implemented for this fully *automated die casting machine cell* (DMC) is micro- spraying which reduces the possibilities of porosity as it uses very tiny amount of water and emulsions compared to traditional water spraying system to clean the mould surface after every cycle.

The other process parameters remained constant throughout the manufacturing process. They are - alloy temperature at 690 degree centigrade, vacuum level of 250 mbar, first phase speed of 0,15 m/sec, short sleeve filling factor of 61% and the solidification time of 8 secs.

The other variable factors which included second and third phase speed, table height, closing force and cycle time had a direct influence on the quality attribute of the final part.

The technical knowledge base was built based on the data described above and the knowledge from experts, which is described in Table 2.

Table 2 Technical knowledge base: the parameters alloy preparation in the real-life die castings process.

Parameters alloy preparation			
Parameters	Meausre	Value	Photo
Alloy type	Numerical alloy designation	ADC12	
	Chemical designation of the alloy	(AlSi9Cu3(Fe))	
Alloy temperature (melting C deg)	Actual material temperature	815 ºC	

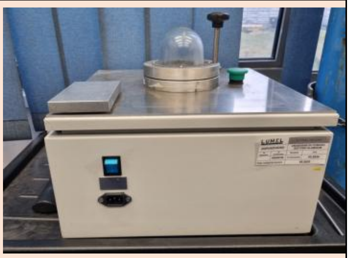
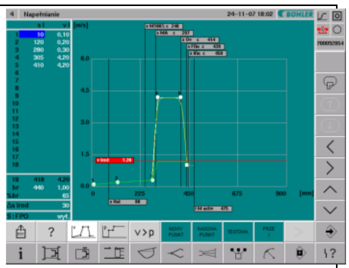
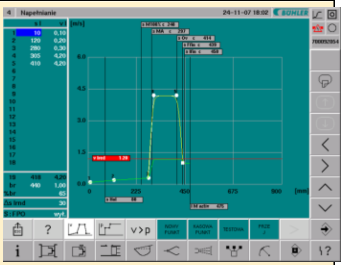
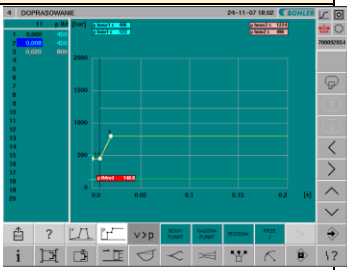
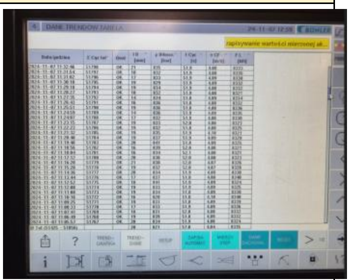
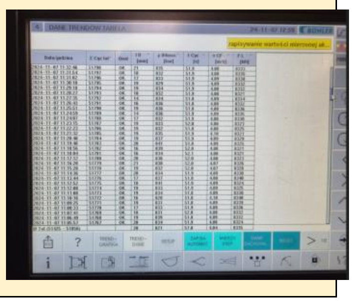
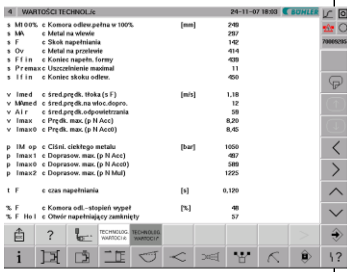
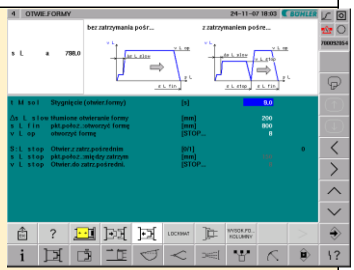
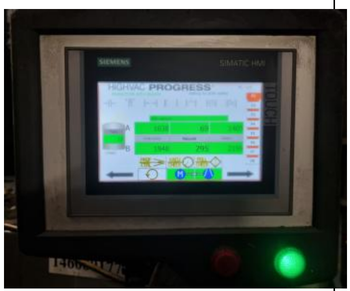
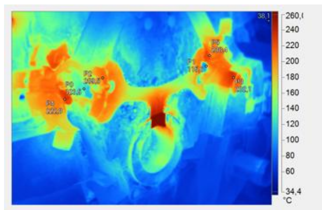
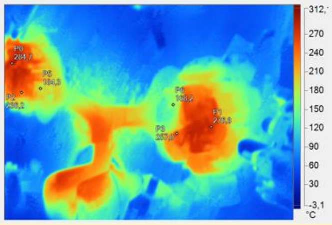
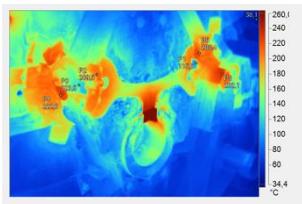
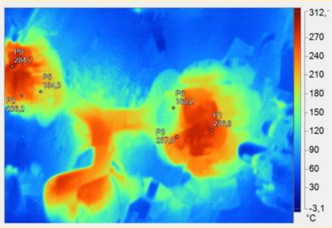
	Set material temperature	800 ºC	
Type of melting furnace	Shaft Furnace	STRIKOMELTER MH II – T 2000 / 1500 G-eg	
Density index of alloy	Percentage	0,89%	
Number of shots per batch (pcs)	Per shift	500	
% of scrap ratio in the alloy composition	Percentage	max 40%	

Table 3 The parameters of the real-life die castings process.

Process Parameters			
Parameters	Meausre	Value	Photo
Alloy temperature (casting C deg)	Actual material temperature	694 ºC	
	Temperature range	680 ÷ 700 ºC	

First phase speed [m/s]	From the sensors as explained before (m/s)	0,30	
Second phase speed [m/s]	From the sensors as explained before (m/s)	4,20	
Third phase pressure in the alloy [bar]	From the sensors as explained before (bar)	730	
Tablet high [mm]	mm	15	
Closing force [kN]	Kn	8330	
Cycle time [s]	Sec	51,8	

Shot sleeve filling factory [%]	Percentage	48%	
Automatic process [y/n]		YES	
Casting machine number [No]	Description	PH156 - Buhler 84D Compact	
Solidification time [s]	Sec	9,0	
Vacumm level [mbar]	A	69	
	B	295	
mould temperature fixed side [C deg]	°Centigrade	Max 222,8°C-232,1°C Min 115,6°C - 123,5°C	

mould temperature moving side [C deg]	°Centigrade	Max 276,8°C – 284,7°C Min 168,2°C 184,3°C	
delta of temperature fixed side [C deg]	°Cetigrade	101 ÷ 117 °C	
delta of temperature moving side [C deg]	°Cetigrade	100 ÷ 108 °C	

To summarise, a technical knowledge base was developed consisting of specialist expertise from mould design engineers, knowledge derived from IoT-enabled sensor data installed on die casting machines, knowledge acquired from integrated ERP systems, and data continuously updated by process engineers and production operators.

To evaluate the proposed methodology and test the hypothesis, real-time production data was collected from the manufacturing process of Valeo_Renault CH compressor parts over a span of three consecutive production days. The dataset represents over 3,000 individual parts, captured across a comprehensive set of 39 process and material parameters as defined in Table 1. In total, the dataset comprises 9,919 entries, each corresponding to a unique observation recorded during the diecasting process. These entries reflect a wide range of variables influencing the final quality of the components, including mould design, casting parameters, alloy preparation variables, and real-time machine sensor data.

This mould is designed and benchmarked based on the expert knowledge gained by the design engineers to have the following expected life and the same is considered for the economic consideration with the customer.

120,000 shots X 2 cavity = 240,000 good parts to be supplied with the first set of mould body and the first set of inserts and next set of 240,000 good parts with same mould body but with the new set of inserts and the next set of 240,000 good parts with the same mould body and next set of inserts. In short the mould body is expected to last for 3 sets of inserts.

However the expected NOK parts as per the experience and the nest bench marking for the parts with this level of complexity is about 20,000 to 30,000 ppm of NOK to the total parts produced, which mean indirectly that these moulds should produce 2-3 % more parts to deliver the expected number of the good parts.

In order to deliver these number of parts, the TEEP and OEE are calculated in order to utilise the investment and capacity to work 22 shifts in a week at an OEE of 70%

Therefore the most important parameter to monitor boils down to OEE and the critical contributors to this OEE are mould breakdowns (direct result of mould design) and number of NOK parts produced to the total parts produced (direct result of process parameters and the mould design)

4.4 Mechanism for converting a technical knowledge

Both the data for analysis and the classification information contained columns of text, so they had to be appropriately transformed to be used by machine learning algorithms. Each column of data can have different data types, and the goal is to unify this data into a numerical form that is needed to train the model. This was converted into a format that can be used by the neural network.

Before the dataset could be effectively utilized for training a neural network model, it underwent an extensive data preprocessing phase to standardize all variables into a machine-readable numerical format. Given that the original dataset comprised a combination of numerical, logical, categorical, textual, and temporal data, preprocessing was crucial to ensure uniformity and compatibility with machine learning algorithms.

Each of the 40 columns in the dataset was assessed for its data type and appropriately transformed. If a column contained numeric values (e.g., integers or doubles), it was retained in its original form. Logical values (i.e., true/false) were converted into binary values, with false mapped to 0 and true mapped to 1. For columns already labeled as categorical, the individual categories were encoded using integer values to represent distinct classes. If the column consisted of textual strings or cell arrays of strings, it was first converted into a categorical format and then encoded into integers. In cases where date or time data was included, it was transformed into a numerical representation—typically the number of days elapsed from a defined origin date (the MATLAB epoch, i.e., January 0, 0000). When columns had mixed values, such as alloy codes or material specifications like “ADC12”, “46000”, or “ADC13”, each unique entry was mapped to a unique integer (e.g., 1, 2, 3, etc.) to maintain their distinction while enabling computational processing. Columns with unsupported data types were flagged for manual review.

Additionally, the output labels—which indicated the part quality (e.g., BAD, LOK, LOT, OK, OUT)—were prepared using one-hot encoding. This method converts each class label into a binary vector, where only the index corresponding to the actual class is marked as ‘1’ and all others as ‘0’. This transformation was essential for enabling the neural network to perform multi-class classification, allowing the model to learn patterns for accurately predicting the quality class of each component. For instance, if a part belonged to class “OK”, the encoded output would be [0 0 0 1 0], corresponding to the five defined quality categories (1–5).

An illustrative sample of the preprocessed and encoded dataset is presented in Table 5, showing how raw process data and categorical labels were numerically encoded to serve as effective inputs for the AI model. This structured preprocessing ensured that all features, regardless of their original data type, were fully optimized for training, validation, and testing within the MATLAB-based neural network framework. Table 4 shows the Sample input data after encoding.

Table 4 Sample input data after encoding

Type of steel - main forming	Hardness - main forming	Coating of forming elements	Stress relieving after mold	Stress relieving continuation	No of Cavities [pcs]	Cooling system (oil, water)	Gate inlet area [mm2]	Overflows inlets area [mm2]	Ventings chanels area [mm2]	Vacumm system included	Average part wall thickness	projected of the casting area	share of part weight in the	Maximum speed of alloy	Filling time [ms]	Leak test preasure	Plunger Diammeter [mm]	Whole cast weight [g]	Part complexity (according
1	46	1	1	0	2	1	390	224	87,6	1	3,7	61946	47,4	45	44	1	80	3165	3

Alloy type [name]	Alloy temparature (melting C	Type of melting furnace	Density index of alloy	Number of shots per batch	% of scrap ratio in the alloy	Alloy temparature (casting C	First phase speed [m/s]	Second phase speed [m/s]	Third phase pressure in the	Tablet hight (mm)	Closing force [kN]	Cycle time [s]	Shot sleeve filling factor [%]	Automatic process [y/n]	Casting machine number	solidification time [s]	Vacuum level [mbar]	Type of spraying	[illegible]
1	730	1	1	7218	60	690	0,15	4,32	875	20	8444	47,1	61	1	3	8	250	2	1

For the analysed case study:

The raw dataset was imported directly into MATLAB for further analysis and pre-processing. Upon import, a data matrix of size 9919 × 40 was constructed, where each row corresponds to a unique part instance, and each column represents a specific parameter or attribute. The last column (the 40th) in the matrix contained the target classification labels, denoting the quality classification of each part. Therefore, the dataset was separated into two subsets: an input matrix of size 9919 × 39 (representing the features used for prediction), and an output matrix of size 9919 × 1, representing the classified quality outcomes.

The classification labels in the output matrix were represented by numeric codes, which are defined as follows:

- 1 – BAD: Indicates the part is rejected due to critical quality issues.
- 2 – LOK: Denotes a locally acceptable part with borderline quality.
- 3 – LOT: Represents a lot-based conditionally accepted part.

- 4 – OK: A fully acceptable part with no quality issues.
- 5 – OUT: Parts identified as outside of control parameters or process range.

These labels were used as ground truth for training, validating, and testing the artificial intelligence models developed in this study. A sample of the input data used for quality analysis is illustrated in Table 5, showcasing the structure of the input matrix as well as the diversity of the parameters included. This well-structured and labelled dataset formed the foundation for building and validating the AI-based classification model, detailed in the forthcoming sections.

Table 5 Sample Dataset

Type of steel - main	Dievar	Dievar	Dievar	Dievar	Dievar	…	Dievar	Dievar
Hardness - main forming	46	46	46	46	46	…	46	46
Coating of forming	No	No	No	No	No	…	No	No
Stress relieving after mold	Y	Y	Y	Y	Y	…	Y	Y
Stress relieving	0	0	0	0	0	…	0	0
No of Cavities [pcs]	2	2	2	2	2	…	2	2
Cooling system (oil,	W	W	W	W	W	…	W	W
Gate inlet area [mm2]	390	390	390	390	390	…	390	390
Overflows inlets area	224	224	224	224	224	…	224	224
Ventings chanels area	87,6	87,6	87,6	87,6	87,6	…	87,6	87,6
Vacumm system included	Y	Y	Y	Y	Y	…	Y	Y
Average part wall	3,7	3,7	3,7	3,7	3,7	…	3,7	3,7
projected of the casting	61946	61946	61946	61946	61946	…	61946	61946
share of part weight in the	47,4	47,4	47,4	47,4	47,4	…	47,4	47,4
Maximum speed of alloy	45	45	45	45	45	…	45	45
Filling time [ms]	44	44	44	44	44	…	44	44
Leak test preasure	N	N	N	N	N	…	N	N
Plunger Diammeter [mm]	80	80	80	80	80	…	80	80
Whole cast weight [g]	3165	3165	3165	3165	3165	…	3165	3165
Part complexity	3	3	3	3	3	…	3	3
Alloy type [name]	ADC12	ADC12	ADC12	ADC12	ADC12	…	ADC12	ADC12
Alloy temparature	730	730	730	730	730	…	730	730
Type of melting furnace	S	S	S	S	S	…	S	S
Density index of alloy	1	1	1	1	1	…	1	1
Number of shots per batch	7218	7218	7218	7218	7218	…	7218	7218
% of scrap ratio in the	60	60	60	60	60	…	60	60
Alloy temparature (casting	690	690	690	690	690	…	690	690
First phase speed [m/s]	0,15	0,15	0,15	0,15	0,15	…	0,15	0,15
Second phase speed [m/s]	4,32	4,34	4,34	4,36	4,33	…	4,34	4,34
Third phase pressure in	875	889	876	879	887	…	876	890
Tablet hight (mm)	20	17	19	20	19	…	21	18
Closing force [kN]	8444	8446	8446	8456	8450	…	8449	8448
Cycle time [s]	47,1	51,8	48,5	50,7	47,5	…	47,6	47,9
Shot sleeve filling factor	61	61	61	61	61	…	61	61
Automatic process [y/n]	Y	Y	Y	Y	Y	…	Y	Y
Casting machine number	ph156	ph156	ph156	ph156	ph156	…	ph156	ph156
solidification time [s]	8	8	8	8	8	…	8	8
Vacuum level [mbar]	250	250	250	250	250	…	250	250
Type of spraying	M	M	M	M	M	…	M	M
Quality atribute	OK	OK	OK	OK	OK	…	OK	OK

The application of Artificial Intelligence (AI) in industrial manufacturing has significantly transformed traditional quality control and process optimization practices. In the context of this study, AI techniques were employed to monitor, analyze, and optimize the die casting process used in the production of Valeo_Renault CH compressor parts. Given the critical nature of these components, where dimensional accuracy and absence of porosity are vital for safety and performance, AI integration becomes essential to ensure consistent product quality and reduce defects.

For this purpose, a Multi-Layer Perceptron (MLP) neural network was adopted as the primary AI model. A **neural network** is a machine learning model inspired by the structure and functioning of the human brain. It is composed of interconnected units called **neurons**, organized in layers:

Network Structure

- **Input Layer**: Receives input features (e.g., process parameters, alloy conditions).
- **Hidden Layers**: Perform transformations on inputs through weighted connections.
- **Output Layer**: Produces predictions or classifications (e.g., part quality: BAD, LOK, LOT, OK, OUT).

Function of a Neuron

Each neuron performs the following operation:

$$\mathbf{z} = \mathbf{i} = \sum_{1}^{n} \boldsymbol{w_i x_i} + \mathbf{b} \qquad \textbf{(1)}$$

$$\mathbf{a} = \mathbf{f}(\mathbf{z}) \qquad (2)$$

Where:

- x_i: Input features
- w_i : Weights
- b: Bias
- f: Activation function (e.g., ReLU, Sigmoid)
- a: Output of the neuron

Forward Propagation

In **forward propagation**, input data passes through layers, and each neuron applies a weighted sum and an activation function to determine its output. This continues until the final output layer is reached.

Activation Functions

- **Sigmoid**: $\sigma(z)=\frac{1}{1+e^{-z}}$
- **ReLU (Rectified Linear Unit)**: f(z)=max(0,z)
- **Softmax**: Converts outputs to probability distribution in classification.

Loss Function

To evaluate the error, a loss function such as **Mean Squared Error (MSE)** or **Cross Entropy** is used:

$$\text{MSE}=\frac{1}{n}\sum_{i=1}^{n}(yi-\hat{yi})^2$$

Where:

- y_i: True output
- $\hat{y_i}$: Predicted output

Backpropagation and Weight Update

- **Backpropagation** computes the gradient of the loss with respect to each weight using the chain rule.
- **Gradient Descent** updates weights to minimize loss:

$$w - \eta \cdot \partial w / \partial L$$

Where:

- η: Learning rate
- L: Loss function

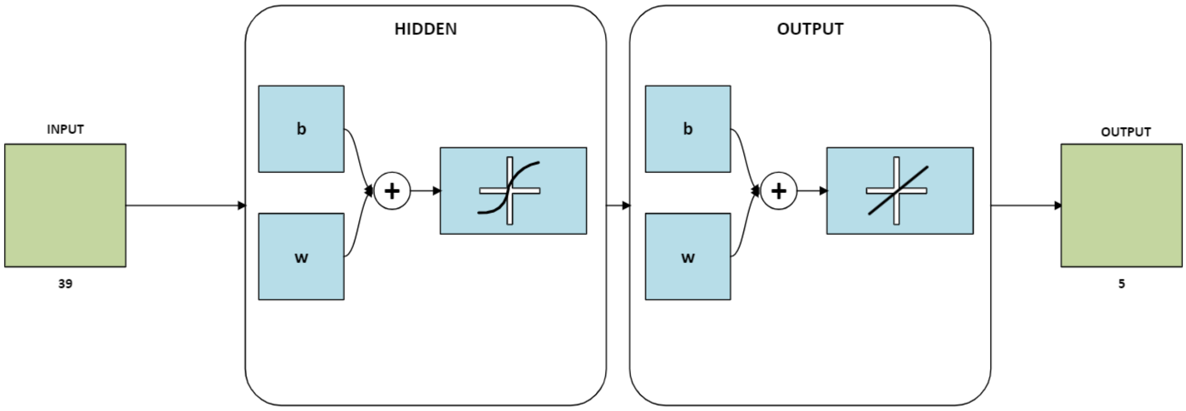


Figure 8 ANN Structure

The dataset, comprising 9,919 records over 39 input parameters, was sourced through real-time data acquisition from IoT-based sensors and the SAP HANA ERP system. The full dataset consisted of **9919 samples**, each with **39 input features**. The data was divided as follows:

- **Training Set (70%)**: 6943 samples
- **Validation Set (10%)**: 992 samples
- **Test Set (20%)**: 1984 samples

This division ensured a robust evaluation, where the model was trained on one subset, validated for tuning on another, and tested on completely unseen data.These parameters encompassed a wide spectrum—from alloy preparation and mould material properties to detailed die casting machine settings and environmental conditions. The dynamic and multivariate nature of this data necessitated the use of robust AI methods for classification and prediction tasks. So, the MLP Algorithm for Mould Manufacturing Quality Classification is developed.

Step 1: Input and Initialization

Input:

- *Dataset from the enclosed Excel file named "DM 19.12.2024-21.12.2024 CH Renault data.xlsx" (appendix 1) D with N = 9919 samples and M = 40 features (39 input features + 1 target class).*
- *Class labels Y ∈{1 = BAD, 2 = LOK, 3 = LOT, 4 = OK, 5 = OUT}.*

Model Parameters:

- *Hidden Neurons: Variable (5, 10, 20, 25, 30) for 1/2-layer experiments.*
- *Learning Rate (η): 0.01*
- *Maximum Epochs: 1000*
- *Min Gradient: 1e-7*
- *Goal (performance target): 1e-9*
- *Early Stopping: If validation performance doesn't improve for 6 epochs (max_fail = 6)*

Step 2: Data Preprocessing

1. ***Load Dataset*** *into MATLAB:*
   D = readmatrix('mould_dataset.xlsx') or readtable() depending on format.
2. ***Split Dataset:***
   - *Input Matrix X = D(:,1:39)*
   - *Output Vector Y = D(:,40)*
3. ***Categorical to Numeric Conversion:***
   - *Apply grp2idx() or categorical() to convert string/text columns.*
4. ***Normalization:***
   - *Normalize each input feature using Z-score normalization:*
     X_norm(i) = (X(i) - mean(X)) / std(X)
5. ***One-Hot Encode Output Labels:***
   - *Create a 5-class binary matrix:*
     Y_encoded(i,j) = 1 if Y(i) == j, else 0
6. ***Data Splitting:***
   - *Training: 70% → 6943 * 39*
   - *Validation: 10% → 992 * 39*
   - *Testing: 20% → 1984 * 39*

Step 3: MLP Network Architecture and Initialization

1. ***Layer Definitions:***
   - ***Input Layer:*** *39 neurons (one for each feature).*
   - ***Hidden Layer(s):***
     - *Single-layer or two-layer depending on experiment.*
     - *Neuron counts: 5, 10, 20, 25, 30 (chosen based on performance).*

- *Output Layer:* *5 neurons (for 5-class output).*

2. ***Activation Functions:***
   - ***Hidden Layer:*** *tansig (Hyperbolic tangent sigmoid function)*
     f(x) = (2 / (1 + exp(-2x))) - 1
   - ***Output Layer Options:***
     - *purelin:*
       f(x) = x
     - *softmax: (for multiclass classification)*
       f(x_i) = exp(x_i) / sum(exp(x_j)) for j = 1 to 5
     - *logsig: (logistic sigmoid)*
       f(x) = 1 / (1 + exp(-x))
3. ***Weight Initialization:***
   - *Randomized using MATLAB functions:*
     W1 = randn(H, I)   // Hidden weights
     b1 = randn(H, 1)
     W2 = randn(O, H)   // Output weights
     b2 = randn(O, 1)
     Where:
     - *I = 39 (input neurons)*
     - *H = number of hidden neurons*
     - *O = 5 (output neurons)*

Step 4: Training via Forward and Backward Propagation

For each epoch (1 to E = 1000):

For each sample (x_i, y_i):

1. ***Forward Propagation:***
   *Z1 = W1 * x_i + b1*
   A1 = tansig(Z1)
   *Z2 = W2 * A1 + b2*
   A2 = activation(Z2)   // softmax, logsig, or purelin
2. ***Loss Calculation (Cross Entropy):***
   For softmax:
   L = -sum(y_i . log(A2))*
3. ***Backward Propagation:***
   - ***Output Layer Error:***
     dZ2 = A2 - y_i
     *dW2 = dZ2 * A1'*
     db2 = dZ2
   - ***Hidden Layer Error:***
     *dA1 = W2' * dZ2*
     dZ1 = dA1 . (1 - A1.^2)   // derivative of tansig*
     *dW1 = dZ1 * x_i'*
     db1 = dZ1
4. ***Parameter Updates:***
   *W1 = W1 - η * dW1*

*b1 = b1 - η * db1*
*W2 = W2 - η * dW2*
*b2 = b2 - η * db2*

5. ***Validation Check:***
   - *After each epoch, compute validation loss and accuracy.*
   - *If validation loss does not improve for 6 epochs,* ***stop training (early stopping).***

Step 5: Evaluation on Test Set

1. ***Forward Propagation on Test Data:***
   *A1_test = tansig(W1 * X_test' + b1)*
   *A2_test = softmax(W2 * A1_test + b2)*
2. ***Convert Predictions:***
   predictedLabels = argmax(A2_test)
3. ***Accuracy Calculation:***
   Efficiency (%) = (sum(predictedLabels == testLabels) / N_test) × 100
4. ***Mean Squared Error (MSE):***
   MSE = sum((A2_test - Y_test).^2) / N_test
5. ***Root Mean Squared Error (RMSE):***
   RMSE = sqrt(MSE)
6. ***Other Metrics (if required):***
   - ***Precision, Recall, F1-Score***
   - *Use confusionmat() in MATLAB for detailed matrix.*

Step 6: Save and Deploy Model

1. ***Save Trained Model:***
   save('MLP_trained_model.mat', 'W1', 'W2', 'b1', 'b2')
2. ***Model Integration:***
   - *Export model to be used in ERP or IoT platforms via MATLAB Compiler or Simulink models.*

The MLP (Figure 8) , with a single hidden layer of 20 neurons, effectively mapped the complex, nonlinear relationships between the process parameters and the resulting part quality. Unlike conventional statistical or rule-based approaches, the MLP learned from historical data patterns to predict quality outcomes such as BAD, LOK, LOT, OK, and OUT. This predictive insight allowed the system to proactively identify sub-optimal process conditions and enable real-time corrective actions.

Model Architecture Summary**:**

- **Input Layer**: 39 neurons (1 per feature)
- **Hidden Layer**: 20 neurons (tansig activation)
- **Output Layer**: 5 neurons (purelin activation)
- **Weights (W)**: Learned connection strengths between layers

Bias (b): Learned adjustments for each neuron before activation

Our real-life case study focuses on die moulds used in manufacturing compressor components for high-end car AC systems. These parts require extreme dimensional precision and surface integrity. Any defect—be it porosity, misruns, cold shuts, or thermal cracks—can render the part unusable. Thus, understanding and predicting defect formation is paramount.
The MLP neural network is trained using the following input parameters:

- Real-time power consumption from CNCs.
- Thermal data from moulds (temperature readings).
- Plunger position and pressure switching points from IoT sensors.
- Cycle time deviations from ERP.
- NG vs OK part classification from machine data.

The output of the model is a quality classification—whether the part is likely to be Good or Not Good, or more precisely, a probability score indicating the likelihood of defect occurrence.

To ensure robust training and to prevent overfitting, the dataset is partitioned into:

- Training Set – used to train the neural network on the relationships between process inputs and product quality.
- Validation Set – used to tune hyperparameters and prevent overfitting by monitoring performance during training.
- Test Set – used to evaluate final model performance on unseen data.

Performance metrics such as accuracy, precision, and Mean Squared Error (MSE) are computed to assess the model. Through iterative training and tuning, the neural network learns optimal combinations of process parameters that influence defect formation. The finalized model is capable of real-time inference, flagging high-risk casting cycles before the actual part is rejected, thus reducing scrap rates and enhancing first-pass yield.

Additionally, MLPs can be trained efficiently on standard computing hardware without requiring specialized GPUs. This makes the architecture ideal for industrial applications like the one in this study, where quick deployment, interpretability, and lower energy consumption are important practical concerns. Moreover, the chosen MLP structure strikes a balance between learning complexity and generalization. It is capable of recognizing patterns in the manufacturing process that lead to quality deviations while avoiding overfitting to specific production batches.
The training dataset was divided into training (70%), validation (15%), and test (15%) subsets. The model's learning process involved adjusting the network weights to minimize the mean square error (MSE) between predicted and actual quality labels. The validation set played a crucial role in monitoring the model's generalization ability, and performance metrics such as accuracy, precision, and recall were computed to evaluate the classification quality. Once optimal performance was achieved, the test dataset—unseen during training—was used for final evaluation, ensuring unbiased assessment of the model's predictive capability.

The finalized MLP (Multi-Layer Perceptron) network was implemented and executed using the MATLAB R2023b environment, leveraging the capabilities of the Deep Learning Toolbox. After importing and pre-processing, the dataset comprised a total of 9919 instances, each with 39 input features, resulting in a structured 9919×39 matrix. To ensure proper model training, generalization, and evaluation, the dataset was randomly partitioned into three distinct subsets using a 70:10:20 split ratio:

- Training Set (70%) – 6943 samples
- Validation Set (10%) – 992 samples
- Test Set (20%) – 1984 samples

The training set was used to adjust the network weights through backpropagation. The validation set was employed to monitor the model's generalization performance during training and to prevent overfitting. The test set remained unseen during the training process and was used exclusively for final performance evaluation.

Training of the MLP model was carried out until the validation loss (mean square error) ceased to improve for six consecutive epochs, as defined by the net.trainParam.max_fail = 6 stopping criterion. This early stopping mechanism prevents overfitting by halting the training process once the model begins to lose generalization ability. The optimal model was obtained at the 139th epoch, achieving a minimum validation MSE of 0.003702, indicating that the model's predicted outputs closely approximated the actual class labels with minimal squared deviation.

The confusion matrix is a tabular representation of actual versus predicted classifications. In the case of a 5-class problem, it is a 5×5 matrix, where the diagonal elements represent the correctly classified instances for each class. The off-diagonal elements indicate misclassifications. This matrix serves as the foundation for computing other key evaluation metrics.

True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN)

To understand performance metrics, it is important to define four foundational terms:

- **True Positive (TP):** When the model correctly predicts a sample as belonging to a particular class.
  Example: The model correctly classifies a "BAD" part as "BAD".
- **True Negative (TN):** When the model correctly predicts that a sample does **not** belong to a particular class.
  Example: The model correctly classifies a "LOK" part as not being "BAD".
- **False Positive (FP):** When the model incorrectly predicts a sample as belonging to a class when it does not.
  Example: The model predicts a "LOK" part as "BAD", which is incorrect.
- **False Negative (FN):** When the model fails to predict a class that it should have.
  Example: The model predicts a "BAD" part as "OK" — it missed identifying the true class.

The accuracy (termed as **efficiency**) of the network was computed using the formula:

$$Efficiency = \frac{\sum_{i=1}^{N} predictedLabels_i == testLabels_i}{N} * 100 \quad (3)$$

Where:
$\sum_{i=1}^{N} predictedLabels_i == testLabels_i$ - is the sum of cases where the predicted labels are equal to the test labels.
N- is the total number of samples. Table 6 shows the ANN layer wise accuracy.

Table 6 Layer wise accuracy

Configuration	Accuracy (%)
1 Layer – 5 Neurons	97.98%
1 Layer – 10 Neurons	96.30%
1 Layer – 20 Neurons	**98.94%**
1 Layer – 25 Neurons	98.45%
1 Layer – 30 Neurons	97.89%
2 Layers – 5 Neurons	98.75%
2 Layers – 10 Neurons	98.52%
2 Layers – 20 Neurons	98.37%
2 Layers – 25 Neurons	98.69%
2 Layers – 30 Neurons	98.79%

The best performance on **test data (98.94%)** was achieved with **1 hidden layer and 20 neurons**, which was selected as the final modelThese concepts apply **individually to each class**, treating each class in a one-vs-all manner during evaluation. In a multiclass classification task like the mould dataset (with 5 output classes: BAD, LOK, LOT, OK, OUT), the terms True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) are defined per class. These metrics are derived from the confusion matrix and are used to assess the model's classification behavior class by class.

Let us define these terms with an example based on the classification of moulds.
Suppose the model predicts one of five mould classes for each sample:

- BAD = Class 1
- LOK = Class 2
- LOT = Class 3
- OK = Class 4
- OUT = Class 5

The confusion matrix summarizes the classification performance of the model on test data. For example, consider a portion of a hypothetical confusion matrix (Table 7):

Table 7 Confusion Matrix example 1 (5 Classes)

Actual \ Predicted	BAD	LOK	LOT	OK	OUT
BAD	100	5	3	1	1
LOK	6	95	4	3	2
LOT	2	4	90	5	4
OK	1	2	3	98	4
OUT	0	1	2	3	94

Let's take Class: BAD (Class 1) and explain the four terms

1. True Positive (TP)

Definition: The number of instances that are actually BAD and are also predicted as BAD.

Example for BAD:

TP = 100

This means the model correctly predicted 100 samples as BAD when they truly were BAD.

2. False Positive (FP)

Definition: The number of instances that are not BAD but the model incorrectly predicted them as BAD.

Example for BAD:

Look at the BAD column (excluding the BAD row):

- LOK → BAD: 6
- LOT → BAD: 2
- OK → BAD: 1
- OUT → BAD: 0

  FP = 6 + 2 + 1 + 0 = 9

  This means 9 samples were wrongly predicted as BAD.

3. False Negative (FN)

Definition: The number of instances that are actually BAD but predicted as some other class.

Example for BAD:

Look at the BAD row (excluding the diagonal):

- BAD → LOK: 5
- BAD → LOT: 3
- BAD → OK: 1
- BAD → OUT: 1

  FN = 5 + 3 + 1 + 1 = 10

  This means 10 BAD samples were misclassified.

4. True Negative (TN)

Definition: The number of instances that are not BAD and were not predicted as BAD.
How to calculate TN for BAD:
Take all entries in the matrix excluding the BAD row and BAD column.

Table 8 Confusion Matrix Example 2 (BAD Class)

Predicted \ Actual	LOK	LOT	OK	OUT
LOK	95	4	3	2
LOT	4	90	5	4
OK	2	3	98	4
OUT	1	2	3	94

Add all these:

$$\text{TN} = 95 + 4 + 3 + 2 + 4 + 90 + 5 + 4 + 3 + 98 + 4 + 2 + 3 + 94 = 417$$

Table 9 Summary Table for Class: BAD

Term	Meaning	Value
TP	Correctly predicted BAD	100
FP	Other classes misclassified as BAD	9
FN	BAD samples predicted as something else	10
TN	All correctly predicted non-BAD samples	417

Table 9 and 10 shows the confusion matrix and summary table class BAD

Accuracy

Accuracy is the ratio of total correct predictions to the total number of samples. It is a basic and widely used metric but may not be sufficient when the class distribution is imbalanced.

Interpretation in mould dataset:

If the model classifies most moulds correctly across all five classes (BAD, LOK, LOT, OK, OUT), the accuracy will be high.

Limitation:

If one class (e.g., “OK”) has a large number of samples, a model may get high accuracy by predicting “OK” most of the time — even if it performs poorly on the minority classes like “BAD” or “OUT”.

Precision

Precision measures the model’s ability to correctly identify only the relevant instances of a class. It is the ratio of correctly predicted positives to all predicted positives.

Interpretation in mould dataset:

If the model predicts a sample as “BAD”, precision tells us how often that prediction is actually correct.
High precision means the model has few false positives, i.e., it does not wrongly label other classes as “BAD”.

Recall (Sensitivity or True Positive Rate)

Recall measures the ability of the model to find all the relevant cases belonging to a specific class. It is the ratio of correctly predicted positives to all actual positives.
Interpretation in mould dataset:
For class “LOT”, recall tells us how many of the actual “LOT” moulds were correctly identified by the model.
High recall means the model has few false negatives, i.e., it is good at catching all instances of that class.

F1 Score

The F1 Score is the harmonic mean of Precision and Recall. It provides a balanced measure of the two and is especially useful when classes are imbalanced.
Interpretation in mould dataset:
If the model predicts class “OUT” well in terms of both precision and recall, the F1 Score for “OUT” will be high.
Advantage: It punishes extreme values in either precision or recall and gives a more reliable view of performance in complex datasets.

Macro and Weighted Averages

In multiclass problems like mould classification, we compute average scores across all classes:

- Macro Average:

Treats all classes equally by computing the average of precision, recall, and F1 score for each class without considering their frequency.

- Weighted Average:

Takes into account the number of samples in each class (support), giving more weight to frequent classes.
Interpretation in mould dataset:
If class “OK” has more samples, the weighted average will reflect its impact more than the macro average, which treats all classes the same.

Mean Squared Error (MSE) and Root Mean Squared Error (RMSE)

Although traditionally used for regression tasks, MSE and RMSE can be applied to neural network output layers where the outputs are continuous (e.g., after a softmax layer).

- MSE measures the average squared difference between the predicted output and the actual output.
- RMSE is the square root of MSE and brings the scale back to the original unit.

Interpretation in mould dataset:
If the network assigns probabilities to each class (e.g., 0.9 for “BAD”, 0.05 for “LOK”), these metrics measure how far the network’s predicted probability distribution is from the ideal one-hot encoded label.
Lower values of MSE and RMSE indicate better model performance.

Confusion Matrix Visualization

A confusion matrix is a table that shows how often the model predicts each class compared to the actual class. It gives detailed insight into which classes are being confused with others.

In the mould classification problem:

- The diagonal elements show correct predictions for each class (e.g., actual "LOT" predicted as "LOT").
- The off-diagonal elements show misclassifications (e.g., "BAD" predicted as "LOK").

This matrix helps identify patterns such as:

- "LOT" often being misclassified as "OK".
- "OUT" rarely being confused, indicating it is a more separable class.

To evaluate the predictive performance of the developed Multi-Layer Perceptron (MLP) model in classifying the die casting mould condition, a series of structured experiments were conducted using MATLAB R2023b with the Deep Learning Toolbox. The model architecture and training strategy were systematically tuned to optimize classification performance while maintaining generalization capabilities.

4.5 Conclusions

Die Casting mould manufacturing and parts manufacturing is one of the very complex manufacturing processes with several dozens of complex parameters having a complex influence on each other's and at many times trading off with one another. At the same time, this is also one of the most important industry for automotive, process automation, aviation and many industries where aluminum parts play a very crucial role which has been analysed in detail in section 4.1

In section 4,2 the detailed design and manufacturing of the diecasting mould and the entire manufacturing process of the diecasting parts is described to appreciate its complexity, knowledge base of experts, inputs from the IoT based sensors, data from ERP system and their interdependencies in section 4.3 and 4.4

In section 4.5 the 39 inputs variables and the expected 5 variable outputs of 3 days of production with the dataset comprised a total of 9919 instances, each with 39 input features, resulting in a structured 9919×39 matrix is pre-processed MLP (Multi-Layer Perceptron) network was implemented and executed using the MATLAB R2023b environment, leveraging the capabilities of the Deep Learning Toolbox. To ensure proper model training, generalization, and evaluation, the dataset was randomly partitioned into three distinct subsets using a 7split ratio: Training Set (70%) – 6943 samples, Validation Set (10%) – 992 samples, Test Set (20%) – 1984 samples. The best results obtained was with layer , hidden neurons 20 with the predicted accuracy of 98.94%

The AI-based technical knowledge sharing model provides real-time alerts to production managers, enabling preventive actions by detecting negative trends in cavity pressure or injection speed before defects or machine failures occur. Furthermore, it enables prediction of component fatigue to support preventive tool maintenance and significantly minimize downtime.

The **contribution to the field of the mechanical engineering discipline** lies in the **development and validation of the new method**, specifically tailored for the mould manufacturing industry**,** integrating IoT-based real-time data and expert knowledge acquisition from critical process points, technical knowledge base, Artificial Neural Network (ANN)-based predictive analytics for quality assessment.

5. A decision support system for dynamic and flexible machining process management

The model for technical knowledge sharing using AI is developed and next implemented in the form of decision support system for dynamic and flexible machining process management

5.1 Assumption and dataset

In conducting this research, several assumptions were made to ensure a structured and valid experimentation process within the mould manufacturing environment. Firstly, it was assumed that the IoT-based sensors deployed on the shop floor are calibrated accurately and consistently collect real-time data related to process parameters such as temperature, pressure, cycle time, and material flow. Secondly, the ERP system data, which includes historical production records, quality inspection reports, and machine maintenance logs, is assumed to be accurate, complete, and representative of normal production operations. It is also assumed that the selected features influencing mould quality are comprehensive and validated through domain expert consultation, which contributes to effective feature engineering.

The real time data from the various IoT enabled sensors along with the production related data from the ERP system is acquired with every production cycle and flows to the prediction program housed on the serve. The predictor programmer output is used with visualisation and pushed on to the cloud. The email and SMS are sent to the assigned experts on the predicted quality of the product for any expert intervention, if needed. The system also helps in keeping the full traceability of the input and output variables for every cycle of production on the data base.

There are total 39 input variables which are referred as features. Some of these features do not vary for the given part production. Examples of them are, number of cavities is going to be two always, the alloy type , casting machine are other examples. On the other hand the features like, Cycle time, first phase speed, second phase speed, third phase speed etc have direct influence on the output quality of the part.

The analysis of the sample features raised the question of whether it is possible to change the values of the sample features in such a way that the sample is correctly classified, i.e., assigned to class 4. Such an approach would enable the analysis of the impact of features on the classification process by iteratively changing feature values until the sample is correctly assigned to the appropriate category. The proposed approach is based on creating a set of unique feature values (uniqueValues) for the test samples, which includes all values actually occurring in the data for each feature. Instead of using aggregated measures such as averages or extreme values, which may not reflect actual characteristics (e.g., sensor readings), this set relies exclusively on actual data, ensuring a more accurate representation of the real behavior of the analyzed parameters. For each feature in the dataset, all unique values present in the test data are collected. This makes it possible to reference actual readings and parameters that have been measured, eliminating the risk of errors associated with improper data aggregation.

In the next stage of the process, samples misclassified by the model are analyzed. In misclassified samples the values of individual features are iteratively changed to all available options from the created unique Values set. After each change, a new class prediction is made for the sample. The process is repeated until the desired classification is achieved (e.g., assignment to class 4). However, if, after testing all values for a given feature, the correct classification is not obtained, the checking process continues with other features in the sample. The process ends when the correct classification for a given sample is achieved or after all features have been tested.

In this way, each feature in the sample is analyzed for its impact on the classification result, and by changing its value to all possible options, the modification that leads to correct classification can be identified.

This approach allows for a more detailed identification of key features influencing the model's decisions, as it is based on actual data rather than theoretical average values. Testing all options for a given feature ensures a more accurate fit to real-world conditions, which in turn can lead to a better understanding of which feature values are important in the classification process and how they can be modified to achieve the desired outcome.

As a result of the conducted experiments, the classification of samples to class 4 was successively modified for 128 out of 130 samples.

In this experiment, the following features were modified to achieve assignment to the correct class:

- Feature 10 – 8 times
- Feature 17 – 7 times
- Feature 29 – 19 times
- Feature 3 – 13 times
- Feature 30 – 11 times
- Feature 31 – 8 times
- Feature 32 – 39 times
- Feature 8 – 23 times
- 132 out of 167 samples:

In this experiment, the following features were modified to achieve assignment to the correct class:

- Feature 29: 40 times
- Feature 30: 36 times
- Feature 3: 23 times
- Feature 8: 16 times
- Feature 12: 9 times

- Feature 10: 2 times
- Feature 16: 2 times
- Feature 31: 2 times
- Feature 15: 1 time
- Feature 9: 1 time

The varying number of samples analyzed results from the different splitting of the dataset into training, validation, and test sets. Figure 10 illustrates the possibility of the simulation of process parameter value changes in order to improve the quality level of manufactured parts.

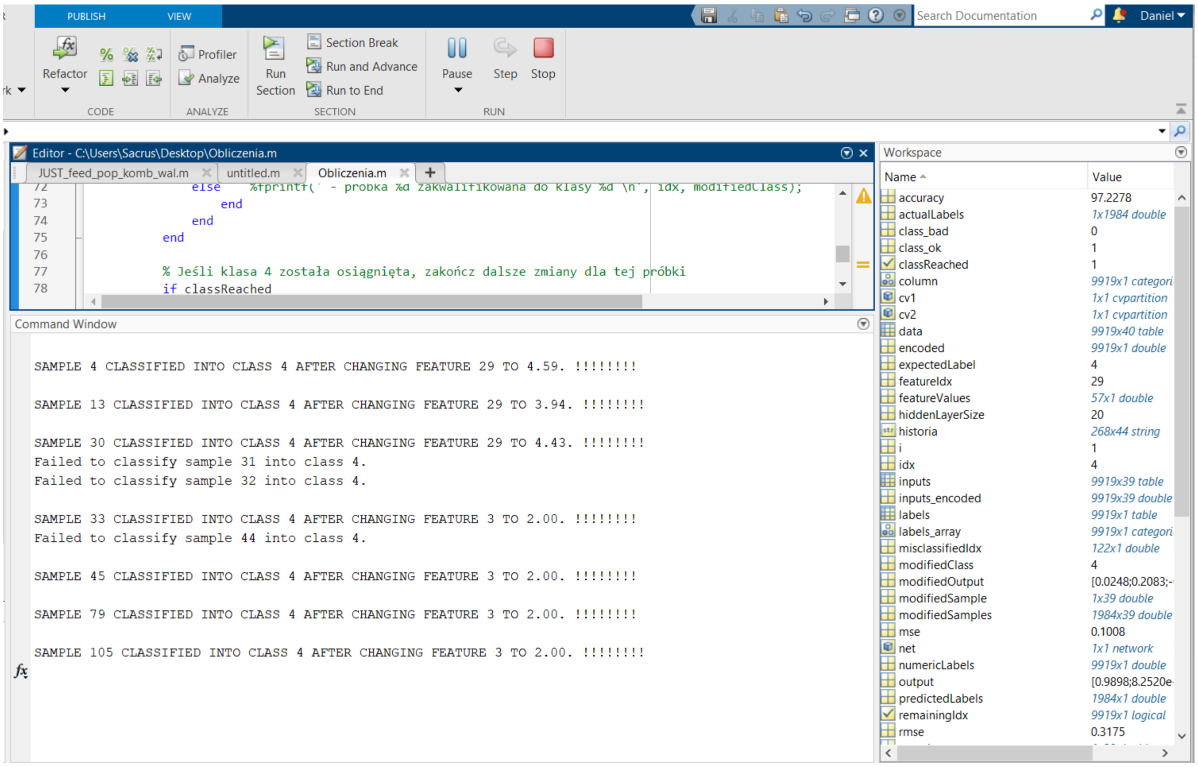


Figure 9 The operation of the script that modifies the features of a sample

Therefore, the developed model enables simulation of process parameter value changes in order to obtain the belonging of the output parameter to the best class. In the practice, this means that it is possible to predict the quality of the manufactured product by changing the input parameters. Knowing that the data is obtained during the implementation of the process, it is possible to use the developed model as a tool supporting proactive product quality management.

By analyzing these parameters, the system can accurately classify new production orders into predefined quality categories ranging from Class 1 to Class 4, with Class 4 indicating acceptable quality, and Class 5 signifying products that are outside acceptable limits ("OUT").

Mould Industry (Source/Physical System)

This section represents the **physical environment** or **industrial setting** where the monitoring takes place and data originates.

Casting Machine: This is the core piece of industrial equipment, likely a large press or molding unit in a **mould industry** setting. It's the source of the physical process being monitored.

Human Operators/Users: These figures represent the **personnel** involved in operating and monitoring the casting machine. They interact with the physical system and potentially the monitoring system interfaces.

TK Acquisition (Data Processing)

This stage focuses on **collecting and storing** the data generated by the physical system is collected for production of Mahle FH PSA project for the production from 12.12.2025 to 17.12.2025 of 3718 shots of production are listed in the enclosed exel file “Mahle_FH_PSA_Class 5” The selected part is quite similar to the part Valeo_ Renault part on which the model was trained data collected in “DM 19.12.2024-21.12.2024 CH Renault data” Exel file. Both are compressor parts with similar weight size, shape, cavity, alloy, machine etc.

- **Data Acquisition (Process):** This is the **process** of collecting relevant operational data (e.g., temperature, pressure, cycle time) from the casting machine, typically via embedded sensors and IoT devices (though not explicitly drawn, this is implied by "IoT Monitoring System").
- **Dataset** or collected **raw data** that has been acquired. This data is the input for the subsequent prediction stage.
- **Server:** This element represents the **centralized storage, processing, and management unit** for the acquired data. It could be an on-premise server or a cloud service responsible for storing the large volumes of IoT data and hosting the AI model.
- **PC/Laptop:** This element likely represents a **local monitoring station, data analyst, or engineer's interface** used for configuring the system, preliminary analysis, or running local applications related to the monitoring system.

Prediction the Quality of Manufactured Product (AI & Output)
This final stage involves using the collected data to perform the core task of the AIMS, which is predictive quality assurance, and delivering the results.

PC (with Prediction Output): This PC, connected to the server, runs the **Artificial Intelligence (AI) model** or algorithm (represented by the boxes underneath) that analyzes the acquired data to **predict the quality** of the manufactured product.

AI/Model Components (Boxes with lines): These interconnected boxes symbolically represent the **AI and Machine Learning algorithms** (the "AI-driven" part of AIMS). They take the processed data and output a prediction (e.g., "Pass," "Fail," or a probability of defect).

Mobile Device (Smartphone): This represents the **end-user interface** for consuming the final result. It shows that the prediction and monitoring alerts are delivered to operators or managers in a real-time, accessible format, enabling timely intervention or process adjustments.

5.2 Implementation of the System in the Company

The concept of integrating **AI-driven IoT monitoring** for mould manufacturing was implemented on a fully automated **840T Buhler die-casting machine** used for compressor mould production. The system aimed to correlate process parameters with product quality using a combination of **IoT-based real-time data acquisition** and **AI-based predictive analytics**.

Implementation Steps according to developed approach (Figure 3):

Stage 1: Technical Knowledge Acquisition

IoT-enabled sensors were strategically installed at critical machine points — pressure sensors in hydraulic circuits, piston position sensors on plunger assemblies, and thermal sensors on mould surfaces. Next, real-time data such as plunger position, alloy pressure, mould temperature, and cycle time were streamed continuously into the **ERP system (SAP HANA)**.

Stage 2: Knowledge Representation and Structuring

The raw sensor data were automatically cleaned and logged through a central data acquisition unit and stored in ERP databases for easy retrieval and analysis. Expert technical knowledge allowed determining critical values for the quality of parts (OK, BAD, LOK, LOT, OUT).

Stage 3: Knowledge Sharing and Collaboration

A **Multilayer Perceptron (MLP)** neural network was trained using **9,919 real data samples** collected over a one-month production cycle. The model predicted part quality categories (OK, BAD, LOK, LOT, OUT) based on 39 critical parameters.

Stage 4: Real-Time Knowledge Application

The deployed AI model was integrated with the production dashboard to provide predictive feedback. Operators received alerts when input parameters deviated from optimal ranges, enabling proactive adjustments.

Stage 5: Feedback and Continuous Learning

Continuous learning was incorporated. As more data accumulated, the model retrained automatically to improve prediction accuracy beyond **98.9%**, ensuring process optimization and early fault detection.

Next, the procedure for the Usage of the Concept is elaborated.

Initialization Stage:

- Start with the machine calibration and sensor validation routine.
- Ensure all IoT sensors are synchronized with the central gateway and ERP interface.

Production Monitoring Stage:

- During each die-casting cycle, the sensors record real-time data of casting phases, pressure levels, and temperature differentials.
- The AI algorithm classifies ongoing production quality and suggests corrective measures if deviations occur.

Decision Support Stage:

- The operator receives digital feedback on the HMI (Human Machine Interface) regarding predicted mould quality.
- If the system forecasts quality degradation, the operator either manually adjusts key parameters (pressure, alloy temperature, shot speed) or allows the automated control loop to make the correction.

Post-Production Analysis:

- The data are evaluated to identify the most influential process parameters affecting part quality.
- Insights are used to refine the next production batch, enhancing yield and minimizing rework.

As the research finding has proven quick learning model and highly reliable predictability of the quality of parts judged by this model to the accuracy of about 98%, The same is implemented in the manufacturing environment effectively to predict send alarm for continuing or stopping the production by categorising them in three distinct zones namely Green, Yellow and Red.

When the model output of predicted percentage of good parts (OK + LOK + LOT) is more than 98% this is termed as “GREEN” and the production can continue which is displayed by the illumination of the “GREEN” light.

When the model output of predicted percentage of good parts (OK + LOK + LOT) is between 95% to 98% this is termed as “YELLOW” and the production can continue with close monitoring and is displayed by the illumination of the “YELLOW” light and an email and SMS sent to the production supervisor.

When the AIMS model output of predicted percentage of good parts (OK + LOK + LOT) is less than 95% this is termed as “RED” and the production is stopped automatically by AIMS and is displayed by the illumination of the “RED” light and an email / SMS sent to the production supervisor and the production manager.

5.3 Experimental work

The practical implementation of the concept described in the section 5.4 is implemented with a similar project “Mahle _ PSA_ FH” which is also a compressor diecasting with two cavities, same alloy, similar weight and manufactured on the similar machine. The details of its practical implementations are described in the following section

Implementation of the Model and Its Visualization

The implementation of the proposed **method** was executed according to the stages in the developed approach (Figure 3). The model’s integration within the die-casting production line provided both predictive insights and proactive control capabilities aligned with Industry 5.0 principles.

Table 10: Statistical description of the dataset

Index	Time Stamp	Machine ID	Clamping Force [kN]	Heel Thickness [mm]	Max presuure during ND [bar]	Cycle Time [s]	Casting Piston Velocity [m/s]
count	3718	3718	3718	3718	3718	3718	3718
mean	05:54.7	10516359	8380.472	24.98924	780.4868	65.8674	3.945266
min	12-12-2025 13:23	10516359	7918	9	202	47.2	1.78
25%	19:04.7	10516359	8359	24	803	47.4	4.09

50%	15-12-2025 18:13	10516359	8389	25	819	47.4	4.11
75%	16-12-2025 11:13	10516359	8414	26	828	47.5	4.12
Max	17-12-2025 09:52	10516359	8486	37	866	9190.8	4.37
Std	NaN	0	60.3538	2.290543	144.5643	264.7719	0.569619

The dataset used in this study consists of **3718 observations**, where each row represents a single production cycle recorded from the casting machine. The data contains several operational parameters related to the casting process. These parameters were collected from the machine monitoring system and used as input variables for the Artificial Intelligence–based classification model**.** The dataset includes seven variables: index, Timestamp, Machine ID), Clamping force, Heel thickness, Maximum metal pressure during ND phase, Cycle time, and Casting piston velocity**.**

The index column represents the sequential numbering of the observations in the dataset and is mainly used for reference purposes. The Time Stamp variable records the date and time at which each production cycle was registered. The dataset spans a time period from 12 December 2025 at 13:23 to 17 December 2025 at 09:52**,** indicating that the data was collected over several consecutive days of machine operation.

The Machine ID variable identifies the machine used during the production process. In this dataset, the machine ID remains constant at **10516359**, indicating that all observations were recorded from the same machine. As a result, this variable does not contribute significant variability to the dataset.

The **Clamping Force** represents the force applied by the machine to keep the mold closed during the casting process and is measured in **kilonewtons (kN)**. The average clamping force recorded in the dataset is approximately **8380.47 kN**, with values ranging from **7918 kN to 8486 kN**. The standard deviation of **60.35 kN** indicates relatively small variation, suggesting stable machine operation in terms of clamping force.

The **Heel thickness** is measured in **millimetres (mm)** and represents the thickness of the casting heel. The average heel thickness in the dataset is approximately **24.99 mm**, with values varying from **9 mm to 37 mm**. The standard deviation of **2.29 mm** indicates moderate variation in this parameter.

The **Maximum pressure of molten metal during the ND phase of the casting process**, is measured in **bar**. The mean pressure recorded is **780.49 bar**, while the minimum and maximum values are **202 bar** and **866 bar**, respectively. The relatively high standard deviation of **144.56 bar** indicates significant variability in metal pressure conditions during production.

The **Cycle time** represents the total time required to complete one casting cycle and is measured in **seconds**. The average cycle time is approximately **65.87 seconds**, with the majority of cycles occurring around **47.4 seconds**, as indicated by the median and quartile values. However, the maximum value of **9190.8 seconds** suggests the presence of extreme outliers, which may correspond to machine stoppages or operational interruptions.

The **Casting piston velocity** represents the velocity of the piston during the casting process and is measured in **meters per second (m/s)**. The average piston velocity recorded in the dataset is **3.95 m/s**, with values ranging from **1.78 m/s to 4.37 m/s**. The standard deviation of **0.57 m/s** indicates moderate variation in piston speed during operation.

Overall, the dataset provides detailed information about the operational parameters of the casting machine. These variables were used as **input features for the Artificial Neural Network model**, enabling the model to analyze process conditions and classify the production data accordingly.

Stage 1: Technical Knowledge Acquisition

The dataset used in this study was obtained from an **industrial die casting machine monitoring system**. The machine continuously records operational parameters during each production cycle. These parameters are stored automatically in a digital database and exported in **Excel format** for further analysis.

The collected dataset contains **3718 observations**, where each observation corresponds to a **single casting cycle** of the machine. The data was recorded over a period from **12 December 2025 to 17 December 2025**, representing continuous machine operation over multiple production shifts.

Each record contains several key process parameters that describe the operational state of the machine during casting. The main variables included in the dataset are:

Time Stamp – timestamp indicating the date and time of the recorded production cycle

Machine ID – machine identification number used to identify the casting machine

Clamping Force [kN] – clamping force applied to keep the mold closed during casting

Heel Thickness [mm] – thickness of the casting heel

Max metal pressure during ND Phase [bar] – maximum metal pressure during the ND phase of the casting process

Cycle time [s] – total cycle time required to complete one casting operation

Casting piston velocity [m/s] – velocity of the casting piston

These parameters represent critical process variables that influence casting quality and production efficiency. The dataset was used as input for developing an Artificial Intelligence-based classification model to identify the quality status of the casting process.

Stage 2: Knowledge Representation and Structuring

Data Processing and cleaning

Before applying machine learning techniques, several **data pre-processing steps** were performed to prepare the dataset for model training and evaluation. Initially, the dataset was inspected for missing values, duplicate entries, and inconsistent data formats. Since all columns contained **3718 valid entries**, no missing values were detected in the dataset. Duplicate rows were also checked and removed if necessary to ensure data consistency.

Feature Selection

The dataset included both operational parameters and identification variables. The **machine ID column** remained constant for all observations and therefore did not contribute useful information for classification. As a result, this column was excluded from the model training process.

The **timestamp variable** was used only to identify the data collection period and was not used as a predictive feature in the machine learning model.

The remaining variables representing machine process parameters were selected as **input features** for the classification model.

Outlier Detection

Exploratory analysis revealed that most **cycle time values were around 47.4 seconds**, while a maximum value of **9190.8 seconds** was observed. This extremely large value likely corresponds to machine downtime or operational interruption. Such extreme values were carefully examined during preprocessing to ensure they did not adversely affect the model performance.

Feature Scaling

Since the dataset contains variables with different units and ranges (e.g., pressure in bar, force in kN, velocity in m/s), **feature normalization** was applied. Standardization techniques were used to scale the features so that each variable contributes equally during model training.

Dataset Preparation

After pre-processing, the dataset was divided into **training and testing subsets**. The training dataset was used to train the Artificial Neural Network model, while the testing dataset was used to evaluate the classification performance.

The prepared dataset was then used as input for the **machine learning model to classify casting process conditions into different quality categories**, such as *bad, lok, lot, ok,* and *out*.

Stage 3: Knowledge Sharing and Collaboration

In this study, a **Feedforward Artificial Neural Network (ANN)** was developed to classify the casting process data into five quality categories: **bad, lok, lot, ok, and out**. The model was implemented using **Python with the TensorFlow and Keras deep learning libraries**. The ANN model was designed to learn complex relationships between machine process parameters and the corresponding casting quality class.

The neural network architecture consists of **two layers**. The first layer is a **hidden layer containing 20 neurons**, which uses the **Rectified Linear Unit (ReLU)** activation function. This activation function introduces nonlinearity into the model and allows the network to learn complex patterns from the input data. The second layer is the **output layer**, which contains **five neurons corresponding to the five output classes**. The **Softmax activation function** is applied in this layer to produce probability distributions for each class.

Table 11: ANN Architecture

ANN Component	Configuration	Description	Inference	Justification
Network Type	Feedforward Artificial Neural Network	Data flows from input layer → hidden layer → output layer without feedback loops	Suitable for supervised classification tasks	Simple architecture with efficient learning capability
Input Layer	n neurons (equal to number of input features)	Receives normalized feature vectors from the dataset	Each neuron corresponds to one input variable	Ensures all input parameters contribute to model learning
Hidden Layers	1 hidden layer	Intermediate layer that learns internal representations of data	Enables extraction of nonlinear relationships between variables	Single hidden layer reduces model complexity and training time
Hidden Neurons	20 neurons	Processes weighted input signals and passes them through activation function	Provides sufficient capacity to learn patterns in the dataset	Balance between underfitting and overfitting
Hidden Layer Activation Function	ReLU (Rectified Linear Unit) LOGSIG TANSIG	Applies nonlinear transformation $f(x)=\max(0,x)$, LOGSIG outputs values between 0 and 1, while TANSIG outputs values between −1 and 1.	Helps the network learn complex relationships	Prevents vanishing gradient problem and speeds up training

Output Layer	k neurons (equal to number of classes)	Produces classification results for each class	Each neuron represents probability of a class	Enables multi-class prediction
Output Activation Function	Softmax	Converts output values into probability distribution	Ensures predicted probabilities sum to 1	Standard activation for multi-class classification
Loss Function	Categorical Crossentropy	Measures difference between predicted probabilities and true labels	Lower loss indicates better prediction	Most suitable loss function for multi-class classification
Optimization Algorithm	Adam Optimizer	Adaptive gradient descent method that updates weights during training	Improves training convergence speed	Combines advantages of momentum and adaptive learning rate
Weight Adjustment	Backpropagation	Updates network weights based on error gradients	Reduces prediction error iteratively	Core learning mechanism in neural networks
Training Epochs	100	Maximum number of iterations over the training dataset	Allows model to sufficiently learn patterns	Ensures convergence while preventing premature stopping
Batch Size	32	Number of samples processed before weight update	Improves computational efficiency	Provides balance between training stability and speed
Regularization	Early Stopping	Stops training when validation loss stops improving	Prevents overfitting	Ensures model generalization on unseen data

The model was trained using the **Adam optimization algorithm**, which is widely used for deep learning applications due to its adaptive learning rate capability. The **categorical cross-entropy loss function** was used because the problem involves **multi-class classification**.

Training Procedure

Before training the neural network, the dataset was divided into **training, validation, and testing subsets**. The splitting strategy was designed to ensure reliable model evaluation.

The dataset was divided as follows:
70% Training Data – used to train the neural network
10% Validation Data – used to monitor the model performance during training
20% Testing Data – used for final model evaluation
During training, the model processed the dataset in **mini-batches of 32 samples**, and the maximum number of training iterations was set to **100 epochs**.
To prevent overfitting and improve model generalization, an **Early Stopping technique** was implemented. Early stopping monitors the validation loss and stops the training process when the validation performance no longer improves for a specified number of epochs. This ensures that the model retains the best-performing weights.

Confusion Matrix Analysis
To further evaluate the classification performance of the model, a **confusion matrix** was generated. The confusion matrix compares the **true class labels** with the **predicted class labels** produced by the neural network.

The confusion matrix obtained from the test dataset is shown below:

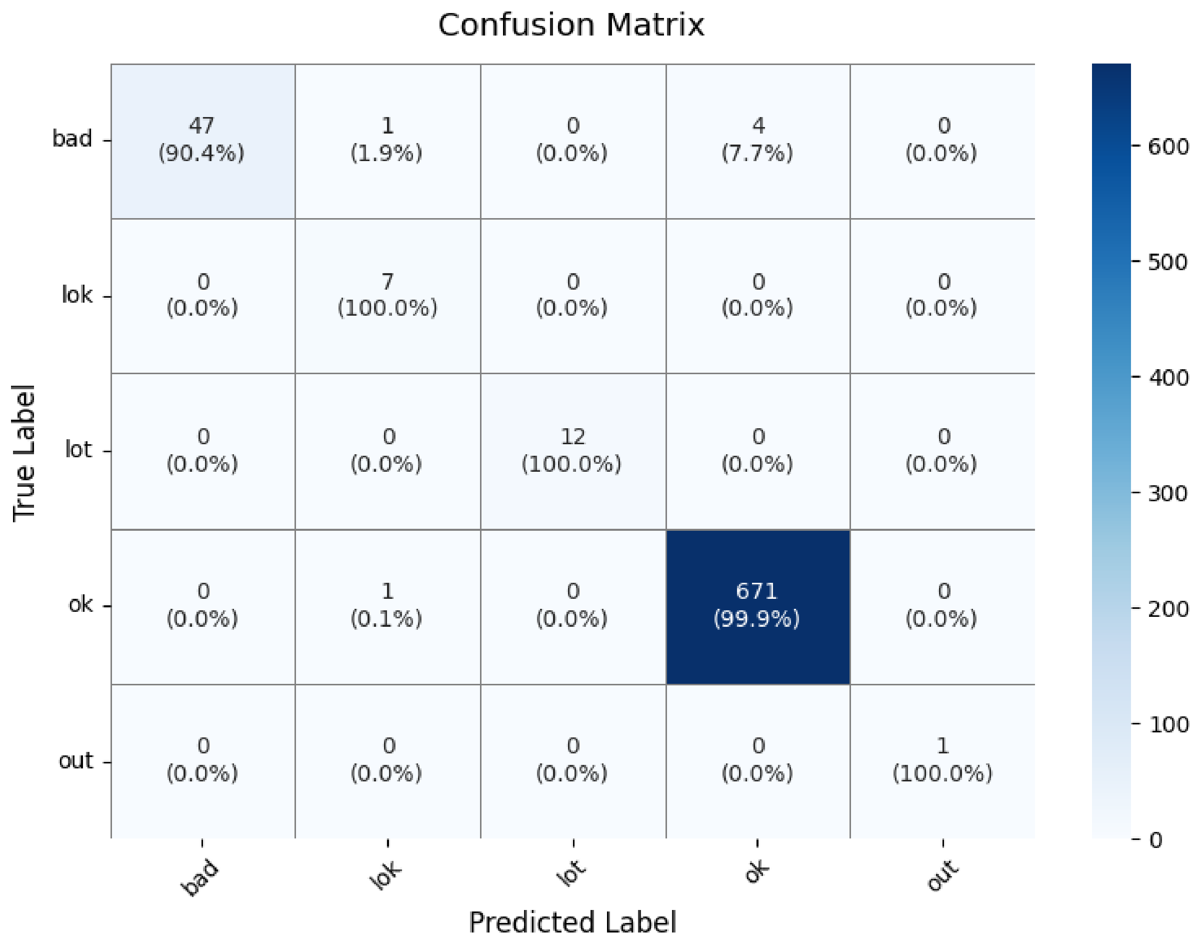


Figure 10 Confusion Matrix

Model Training Performance

The training process showed a **rapid improvement in accuracy during the initial epochs**, indicating that the model quickly learned the patterns present in the dataset. As training progressed, the **training loss and validation loss gradually decreased**, demonstrating stable learning behaviour.

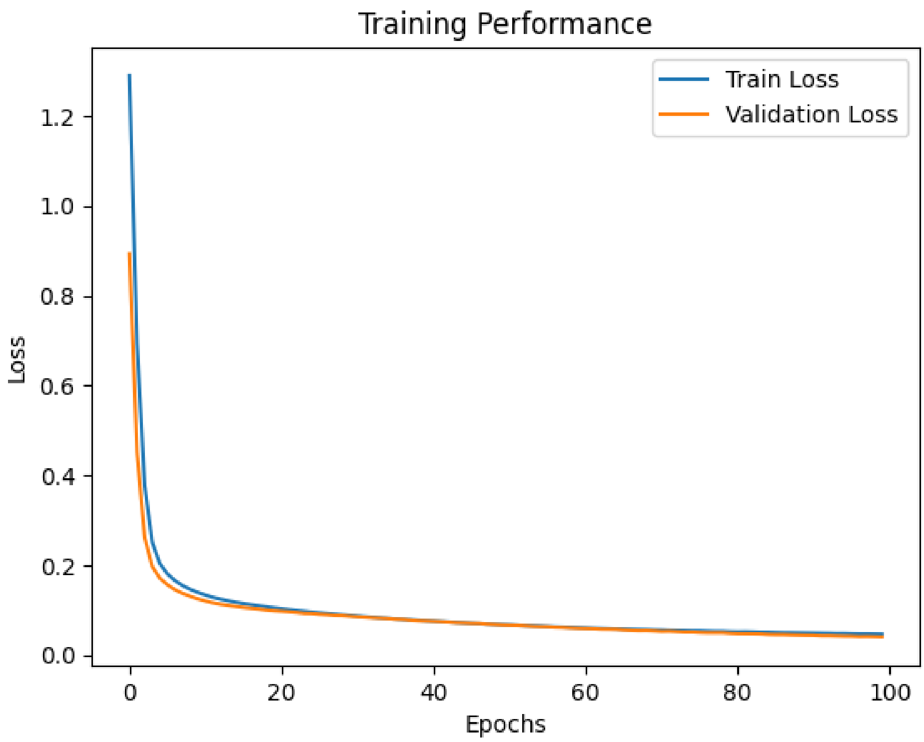


Figure 11: Epochs wise loss

By the final epoch, the model achieved the following performance metrics:

Training Accuracy: 98.65 %

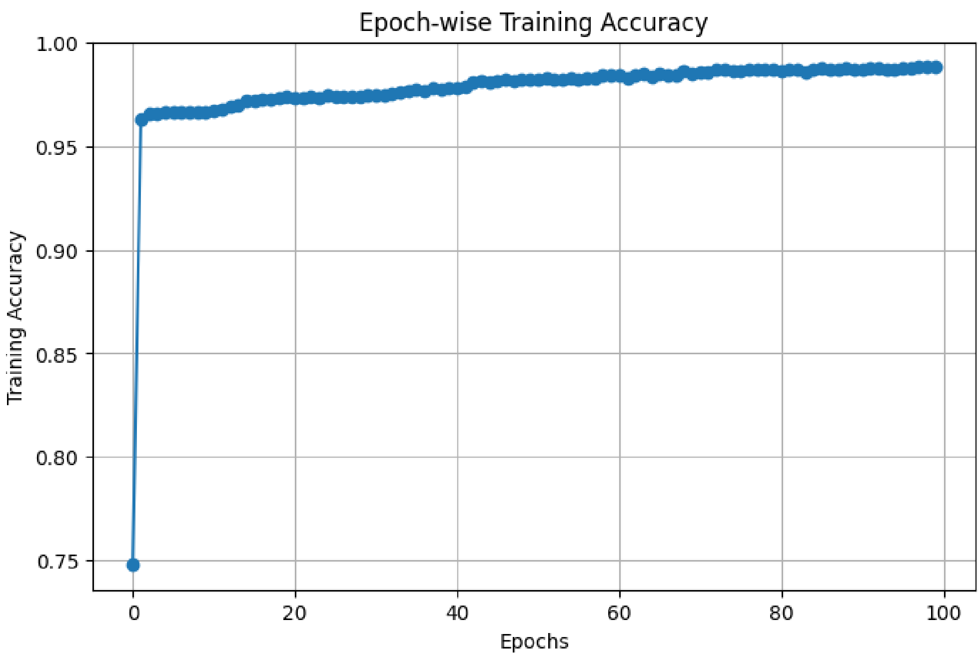


Figure 12: Epochs wise training accuracy

Validation Accuracy: 98.39 %

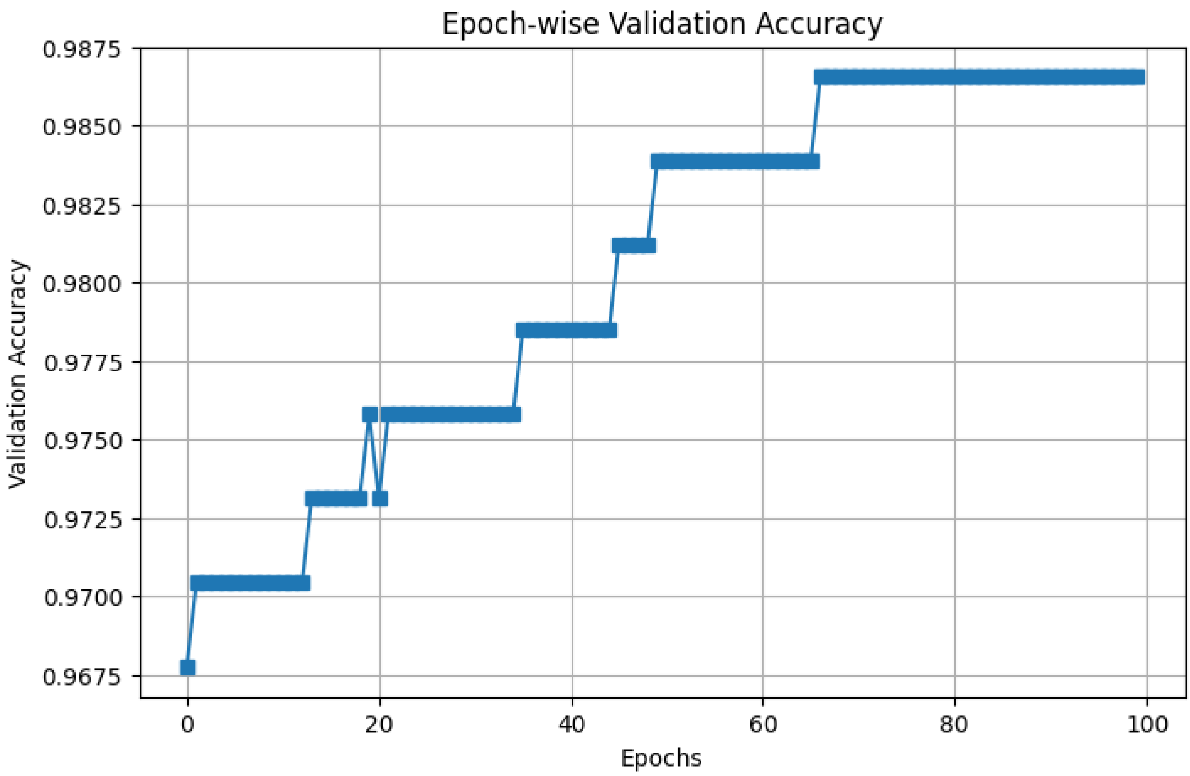


Figure 13: Epochs wise validation accuracy

Testing Accuracy: 98.92 %

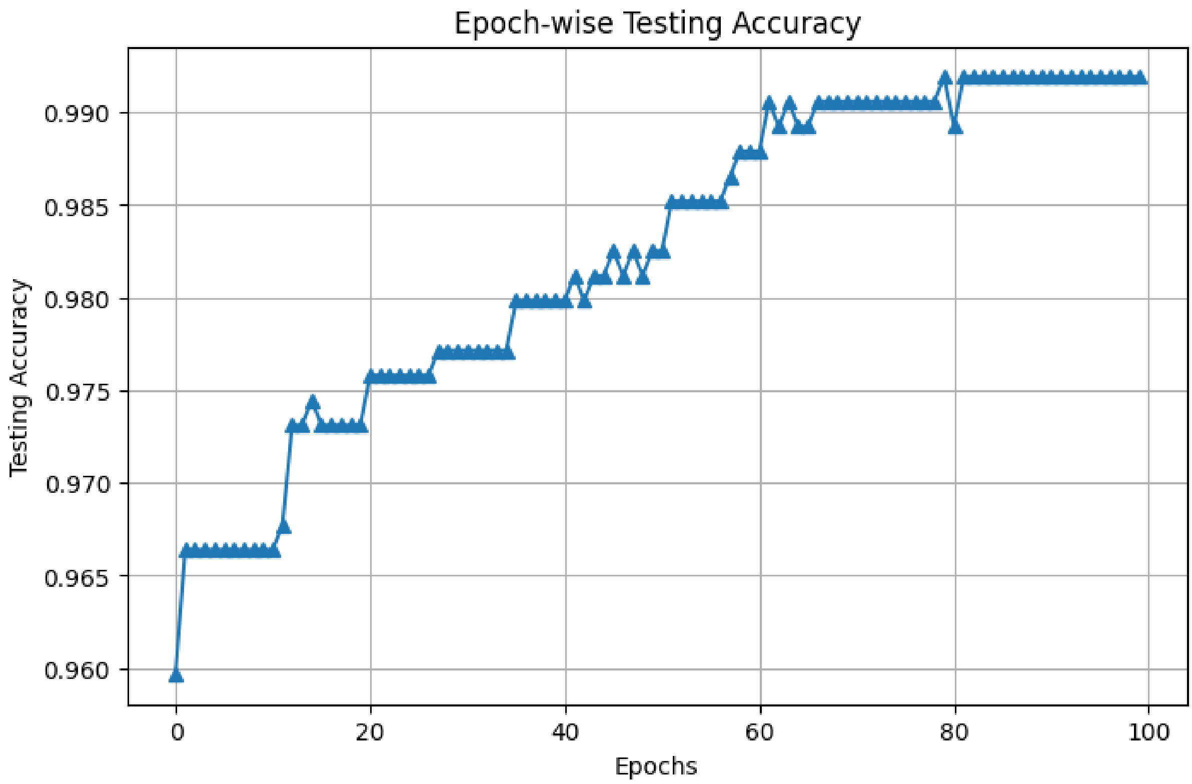


Figure 14: Epochs wise testing accuracy

The small difference between training and validation accuracy indicates that the model **generalizes well and does not suffer from significant overfitting**.

Index	Function	Test Accuracy [%]	Train Accuracy [%]	Validation Accuracy [%]
0	PURELIN	97.17741935	97.1944658	97.58064516
1	LOGSIG	97.84946237	97.5019216	97.58064516
2	TANSIG	99.05913978	98.65488086	98.65591398
3	RELU	98.92473118	98.73174481	98.38709677

Table 12 Performance of a Network with Different Activation Functions in the Last Layer of an MLP

The performance of the Artificial Neural Network (ANN) was evaluated using four different activation functions: **PURELIN, LOGSIG, TANSIG, and RELU**. The comparison was performed based on **training accuracy, validation accuracy, and testing accuracy**. The results obtained from the experiments are summarized in the table and discussed below.

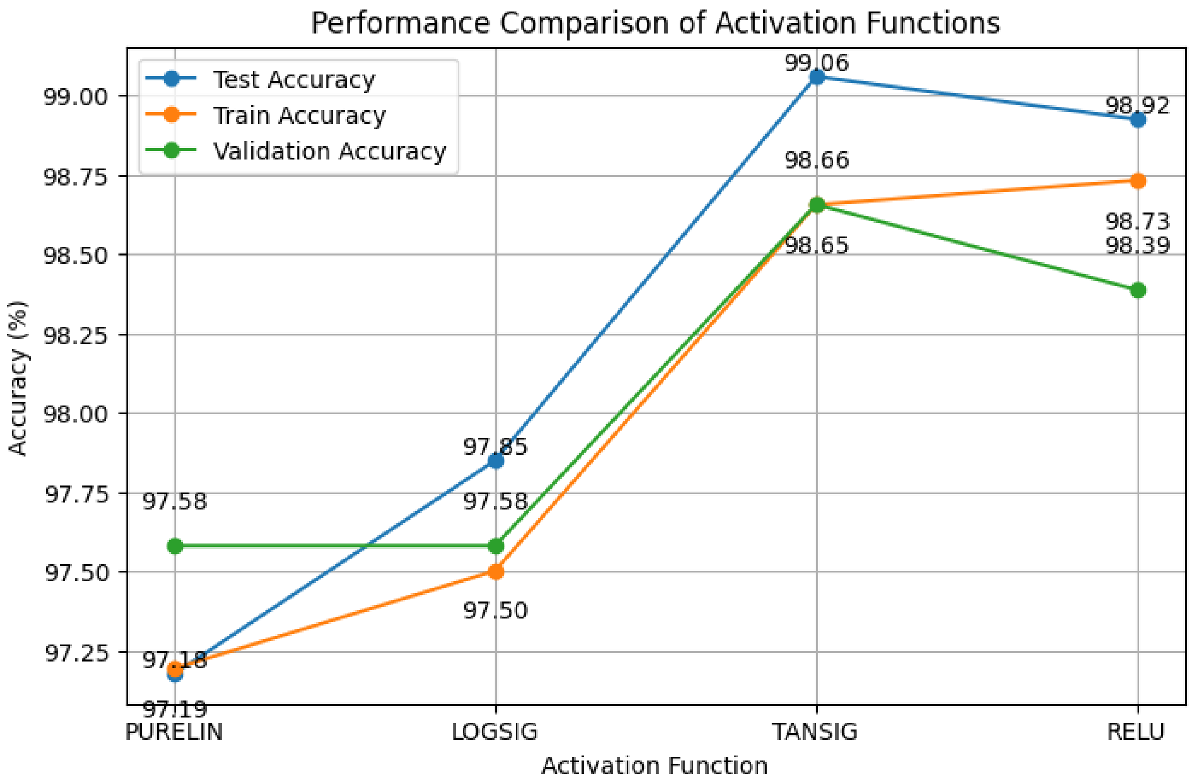


Figure 15: Performance Comparison of Activation Functions

The **PURELIN (linear) activation function** produced a testing accuracy of **97.18%**, with training and validation accuracies of **97.19%** and **97.58%**, respectively. Although the results are relatively high, the linear activation function is limited in its ability to model complex nonlinear relationships within the dataset. Consequently, the classification performance is slightly lower compared to other nonlinear activation functions.

The **LOGSIG (sigmoid) activation function** achieved a testing accuracy of **97.85%**, with training and validation accuracies of **97.50%** and **97.58%**, respectively. The sigmoid function introduces nonlinearity into the network, allowing the model to capture more complex patterns in the data compared to the linear function. This results in a noticeable improvement in classification performance.

The **TANSIG (hyperbolic tangent) activation function** provided the **best performance among all tested functions**, achieving a testing accuracy of **99.06%**, a training accuracy of **98.65%**, and a validation accuracy of **98.66%**. The tanh function maps inputs into a range of **−1 to 1**, which often improves gradient propagation and learning efficiency. As a result, the network can better represent nonlinear relationships present in the dataset, leading to superior classification accuracy.

The **RELU (Rectified Linear Unit) activation function** also demonstrated strong performance, with a testing accuracy of **98.92%**, training accuracy of **98.73%**, and validation accuracy of **98.39%**. RELU is widely used in modern neural networks due to its computational efficiency and ability to mitigate the vanishing gradient problem. Although its performance is slightly lower than TANSIG in this study, it still provides highly competitive classification results.

Overall, the experimental results indicate that **nonlinear activation functions significantly improve the classification performance of the ANN model** compared to the linear activation function. Among the tested functions, **TANSIG achieved the highest overall accuracy**, followed closely by **RELU**, demonstrating their effectiveness for modeling nonlinear patterns in the dataset. These findings suggest that selecting an appropriate activation function plays a critical role in improving the predictive performance of neural network models.

stage 4: Real-Time Knowledge Application

The proposed model represents a comprehensive framework for proactive quality control and intelligent decision-making in the mould manufacturing industry.

As the research finding has proven quick learning model and highly reliable predictability of the quality of parts judged by this model to the accuracy of about 98%, The same is implemented in the manufacturing environment effectively to predict send alarm for continuing or stopping the production by categorising them in three distinct zones namely Green, Yellow and Red.

A similar new project "**Mahle FH_PSA**" is chosen for the practical implementation of the project on a Buhler 840 T machine, as shown in the picture X below in order to test and run the assumptions and conclusions made from the earlier project "**CH Renault**" using the MATLAB. The algorithm is written in the Python to run the "prediction run" program to read the data real time from the machine and predict the output. In order to ensure that the output is simple and practical, the five possible outputs from the previous experiments are now grouped as only two. The outputs OK, LOK and LOT are grouped as **OK** so that they are all treated as desirable output to continue production. The outputs BAD and OUT are grouped as **BAD** as they are treated as the undesirable outputs to continue the production. The two XL files named "mahle_FH_PSA_class5" and "mahle_FH_PSA_class2" contain the production data from 12/12/2025 to 17/12/2025 covering 3718 production shots grouped in these two categories. Both these files are enclosed. When these data sets are run through the program for training the models the resultant outputs are as under.

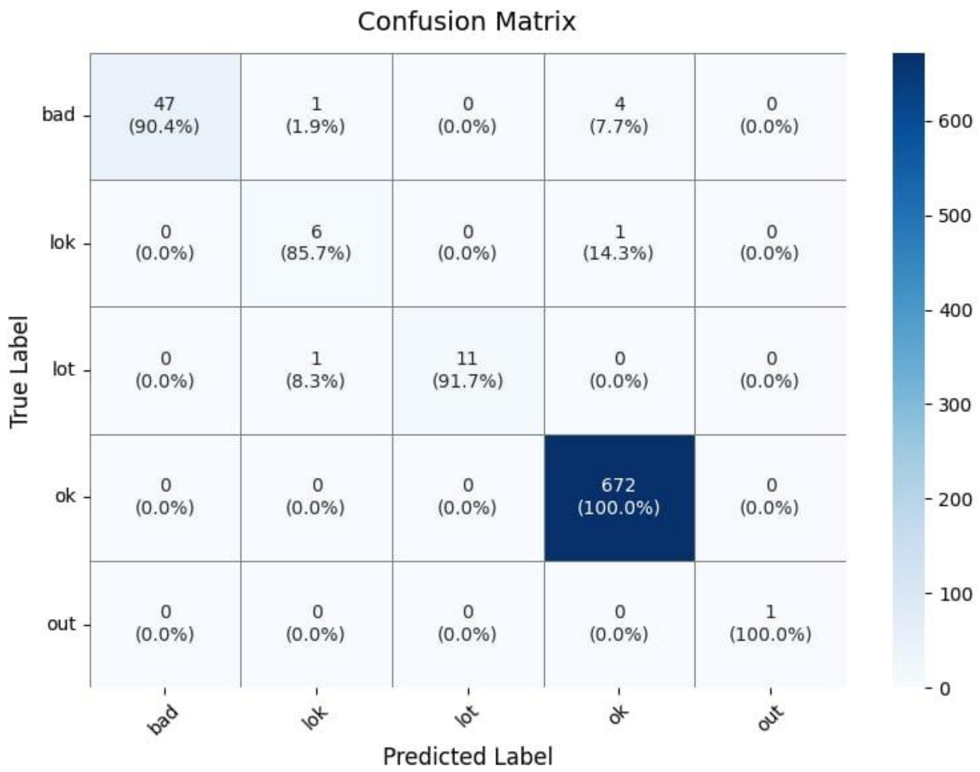


Figure 16 : Confusion matrix with 5 outputs of *bad*, *out*, *lok*, *lot*, *ok*

In order to make a more practical decision for the production process Engineers to intervein with their knowledge base, the outputs are reduced to two as *bad (bad + out) and OK (OK + lot +lok) and the confusion matrix looks as under*

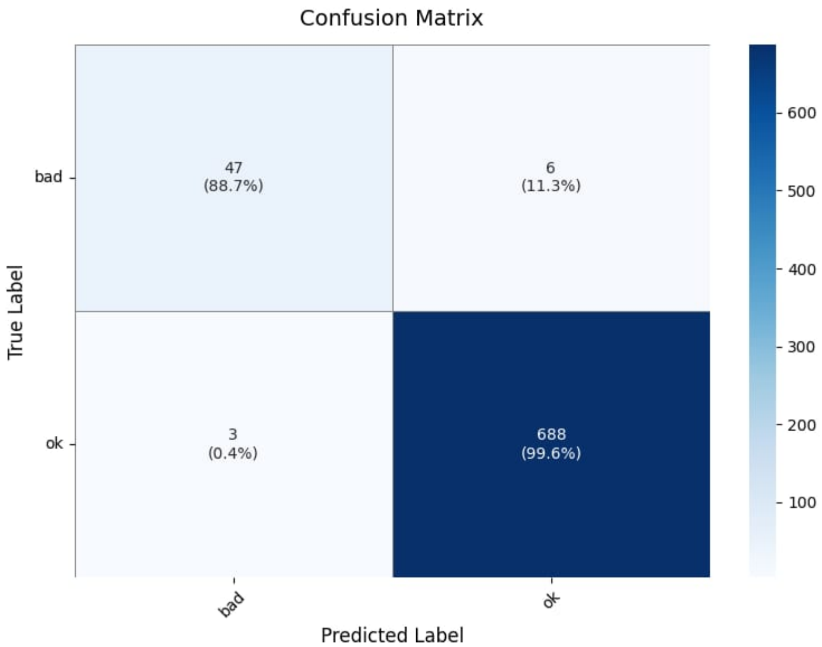


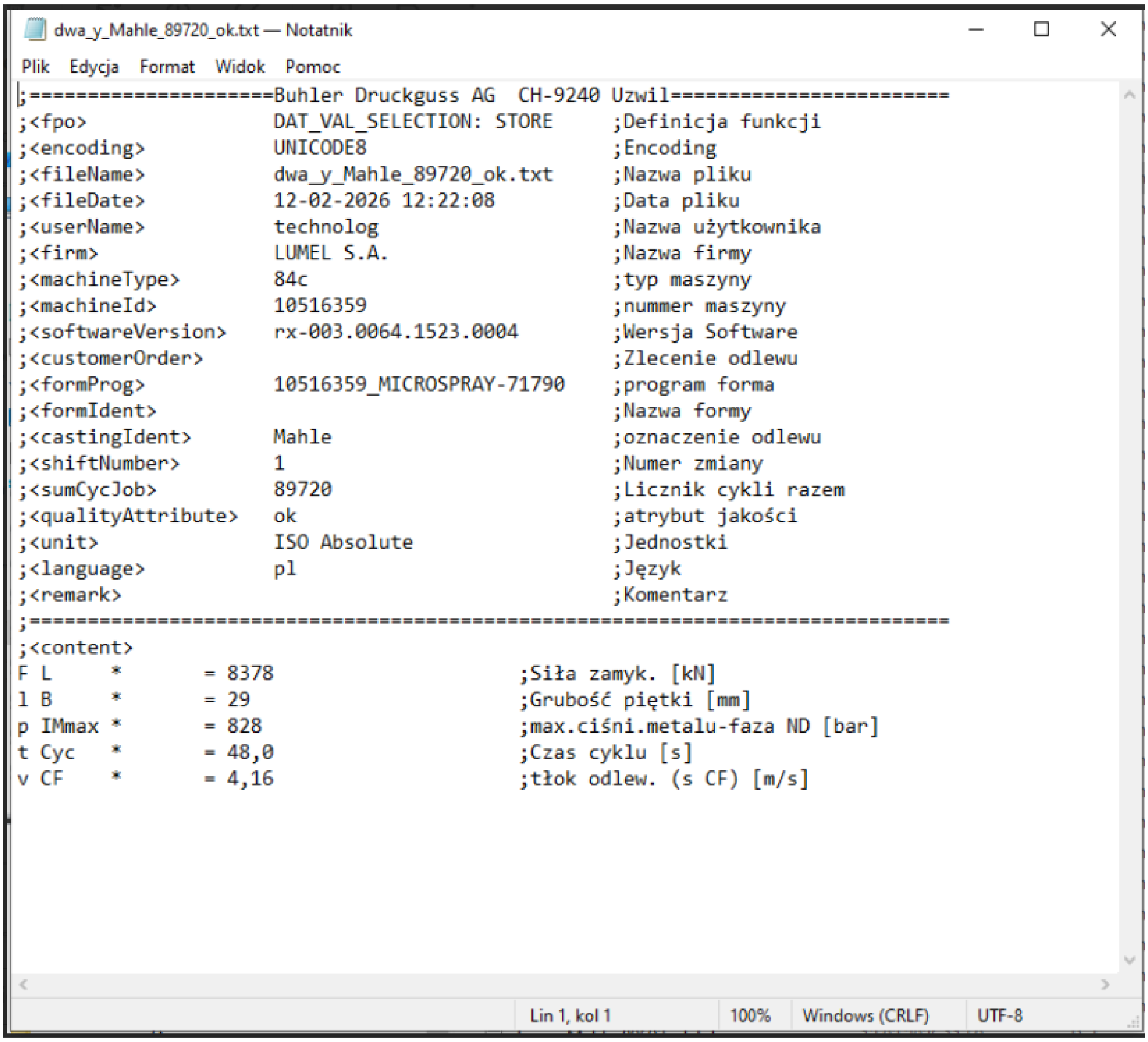
Figure 17 : Confusion matrix with 2 outputs of *BAD* (*bad, out), OK (ok+ lok +lot)*

Data Acquisition and Pre-processing

The implementation of this project is done on the Buhler 840 T machine as shown in the figure 10.

Figure 18 Bulher Die casting machine cell

The Buhler machine sends the data in the text file with the desired input parameters for every production shot in the format below.



```
dwa_y_Mahle_89720_ok.txt — Notatnik
Plik  Edycja  Format  Widok  Pomoc
;====================Buhler Druckguss AG  CH-9240 Uzwil=======================
;<fpo>                 DAT_VAL_SELECTION: STORE      ;Definicja funkcji
;<encoding>            UNICODE8                      ;Encoding
;<fileName>            dwa_y_Mahle_89720_ok.txt      ;Nazwa pliku
;<fileDate>            12-02-2026 12:22:08           ;Data pliku
;<userName>            technolog                     ;Nazwa użytkownika
;<firm>                LUMEL S.A.                    ;Nazwa firmy
;<machineType>         84c                           ;typ maszyny
;<machineId>           10516359                      ;nummer maszyny
;<softwareVersion>     rx-003.0064.1523.0004         ;Wersja Software
;<customerOrder>                                     ;Zlecenie odlewu
;<formProg>            10516359_MICROSPRAY-71790     ;program forma
;<formIdent>                                         ;Nazwa formy
;<castingIdent>        Mahle                         ;oznaczenie odlewu
;<shiftNumber>         1                             ;Numer zmiany
;<sumCycJob>           89720                         ;Licznik cykli razem
;<qualityAttribute>    ok                            ;atrybut jakości
;<unit>                ISO Absolute                  ;Jednostki
;<language>            pl                            ;Język
;<remark>                                            ;Komentarz
;============================================================================
;<content>
F L     *      = 8378                    ;Siła zamyk. [kN]
l B     *      = 29                      ;Grubość piętki [mm]
p IMmax *      = 828                     ;max.ciśni.metalu-faza ND [bar]
t Cyc   *      = 48,0                    ;Czas cyklu [s]
v CF    *      = 4,16                    ;tłok odlew. (s CF) [m/s]

Lin 1, kol 1    100%    Windows (CRLF)    UTF-8
```

Figure 19: Text file with IoT data of one production cycle

Even though 39 input features exist, there are these five features which have the direct influence on the out feature. Therefore the machine is programmed to pick up these 5 features with every shot of production and transmit them real times to the AIMS model. These five features are as follows for this shot of production.

Closing Force in kN - 8378
Heel Thickness in mm – 29
Max pressure metal phase in bar – 828
Cycle time in sec – 48,0
Piston speed in m/sec 4.16

For every part production cycle one such text file is received from the Buhler machine to the AIMS. The series of such files are received real time as shown below

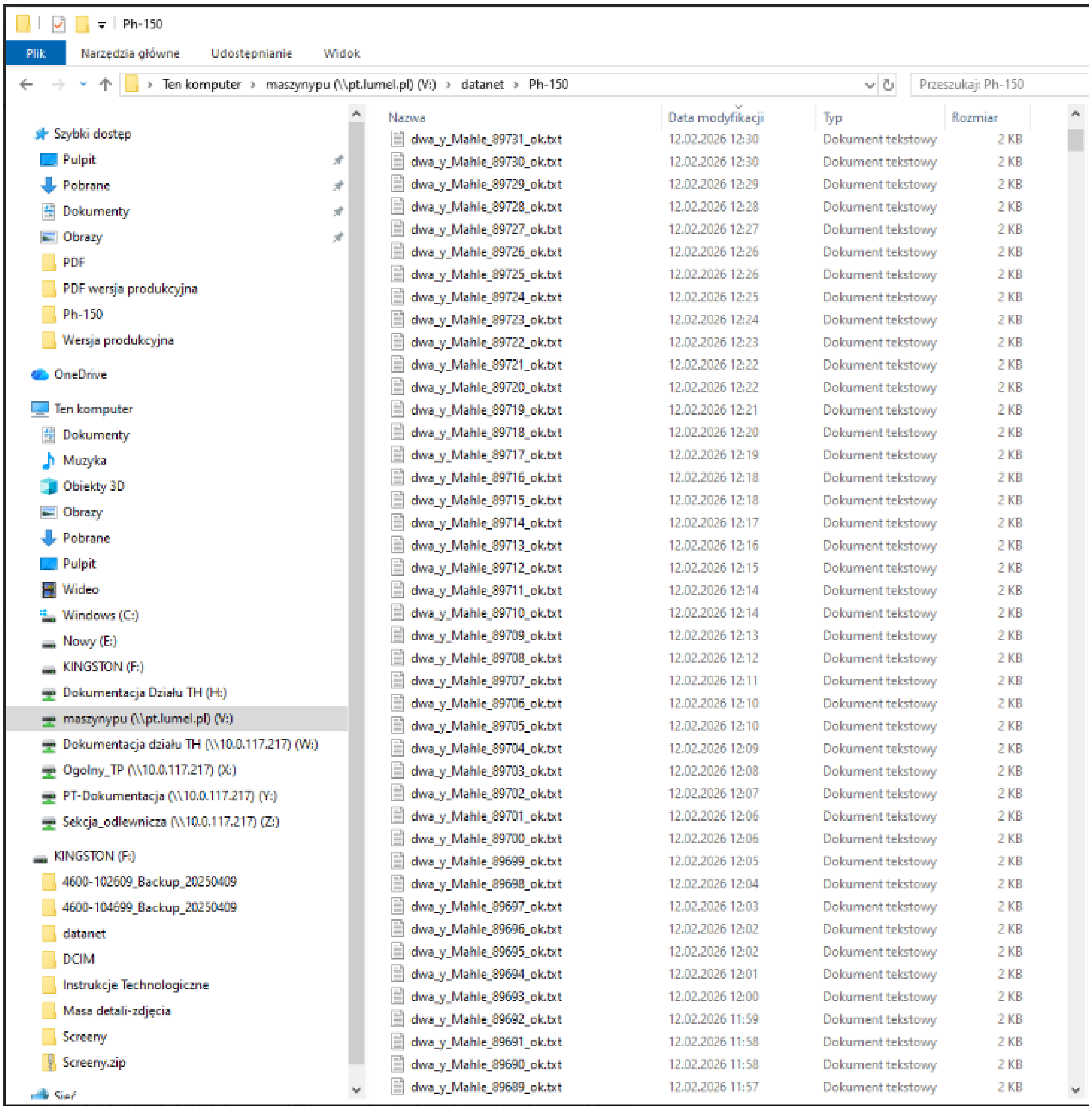


Figure 20: Series of text files with IoT data of for every production cycle

Model Training and Testing

The Python based "prediction_run" executable program situated in the AIMS which is already trained and tested with the data on this project from its production from 12/12/ 2025 till 17/12/2025 as described before is reading each set of production process parameters to predict the output.

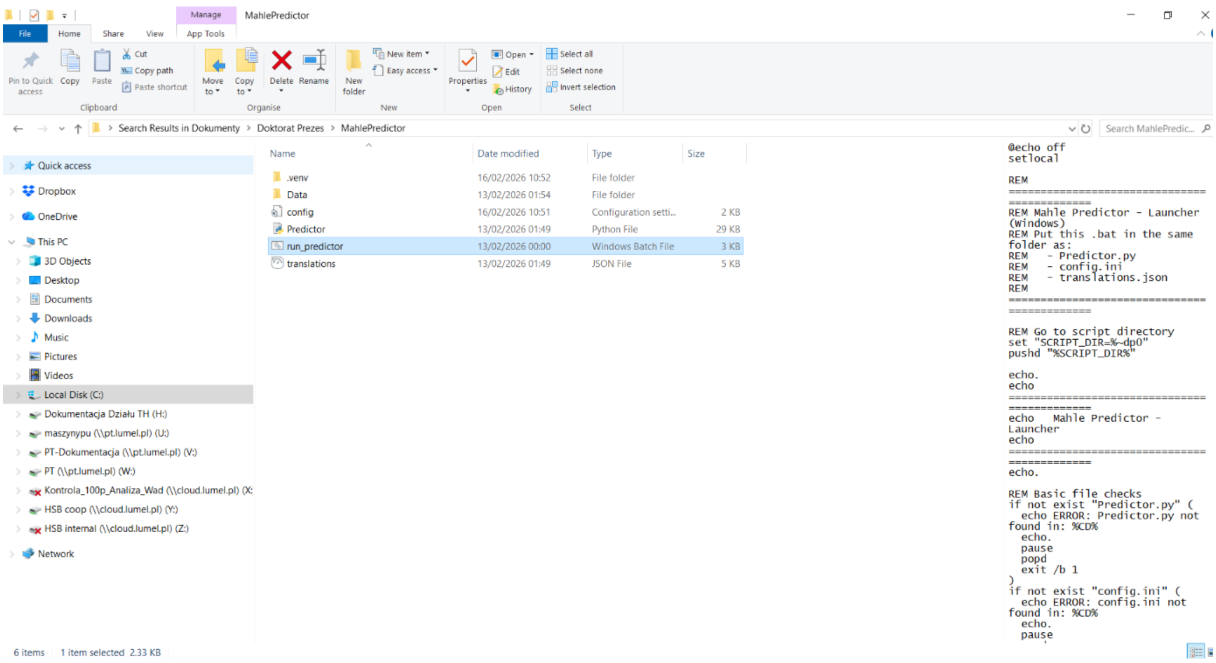


Figure 21: Prediction Run Program files on the computer

The program is enclosed for ready reference and the executable program is enclosed in "predictor.py" as annexture 3 to this thesis.

en

title	"HPDC casting quality prediction"
cycle	"Cycle"
initializing	"Initializing {pct}%"
data_directory	"Data directory"
files_per_cycle	"Files per cycle"
refresh	"Refresh"
decision_2	"Decision (2-class)"
probabilities_2	"2-class probabilities"
test_accuracy_2	"2-class test accuracy"
na_not_enough_labeled	"N/A (not enough labeled data)"
prediction_5	"5-class prediction"
probabilities_5	"5-class probabilities"
test_accuracy_5	"5-class test accuracy"

class_distribution	"Class distribution (label5)"
source_oldest	"Source range (oldest)"
source_newest	"Source range (newest)"
waiting_no_files	"No files found. Waiting..."
warn_not_enough_labeled	"Not enough labeled data to train (need >= 10 labeled files)."
warn_training_failed_2	"2-class training failed: {err}"
warn_training_failed_5	"5-class training failed: {err}"
press_ctrlc	"Press Ctrl+C to exit"
decision_continue	"CONTINUE"
decision_adjust	"ADJUST"
decision_stop	"STOP"
pred	"pred"
conf	"conf"
decision_threshold	"Decision thresholds"
app_time	"Start time"

The cycle time of production is 50 seconds which means theres one part produced at each 50 seconds and one packet of text information containing all the set input process parameters is transmited from the IOT based sensors from the Buhler 840T machine. The process and prediction time based on the trained model is 0,97 second (less than 1 sec)

Based on the predictor output of the Good parts (OK + LOT +LOK) of the class 2 confusion matrix and Bad parts (BAD + OUT), the points of GREEN (OK to continue), YELLOW (Adjust) and RED (to stop) can all be set dynamically based on the complexity, novelty and quality expectations of the project which makes the tool very practical and meaningful.

For example, if a complex new project is implemented for the first time the YELLOW (Adjust) band can be between 85% to 95% compared to an established project where these limits can be set to 95% to 98%

This approach will ensure appropriate advance alarm to the process engineers about the future quality output without creating a neusance particularly for the newly implemented complex projects. Once these projects mature the quality expectations can be pushed up.

The outputs of the predictor program of the AIMS RED (stop), YELLOW (Observe) and GREEN (Continue) are sent by email and SMS to the production Engineers and the production Supervisor / Manager

The deployed AI model was integrated with the production dashboard to provide predictive feedback. Operators received alerts when input parameters deviated from optimal ranges, enabling proactive adjustments.

Stage 5: Feedback and Continuous Learning

The trained model is situated in the AIMS as shown in the diagram below.

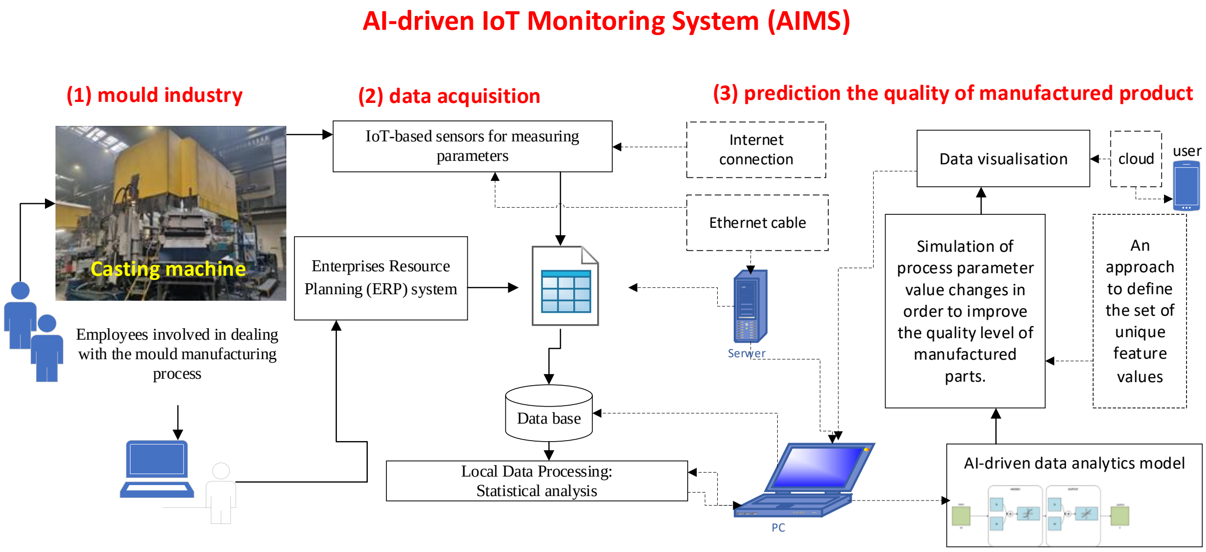


Figure 22: AI-driven IoT Monitoring System (AIMS) for mould industry supporting proactive management *(Patalas-Maliszewska, J., Musalekar, D. & Halikowski, D. (2025)*

Based on the output of this trained model, the decision to continue the production (GREEN) is made when the predicted OK parts in class 2 (OK + LOK +LOT from the class 5 out puts) is the more than 98% to continue the production

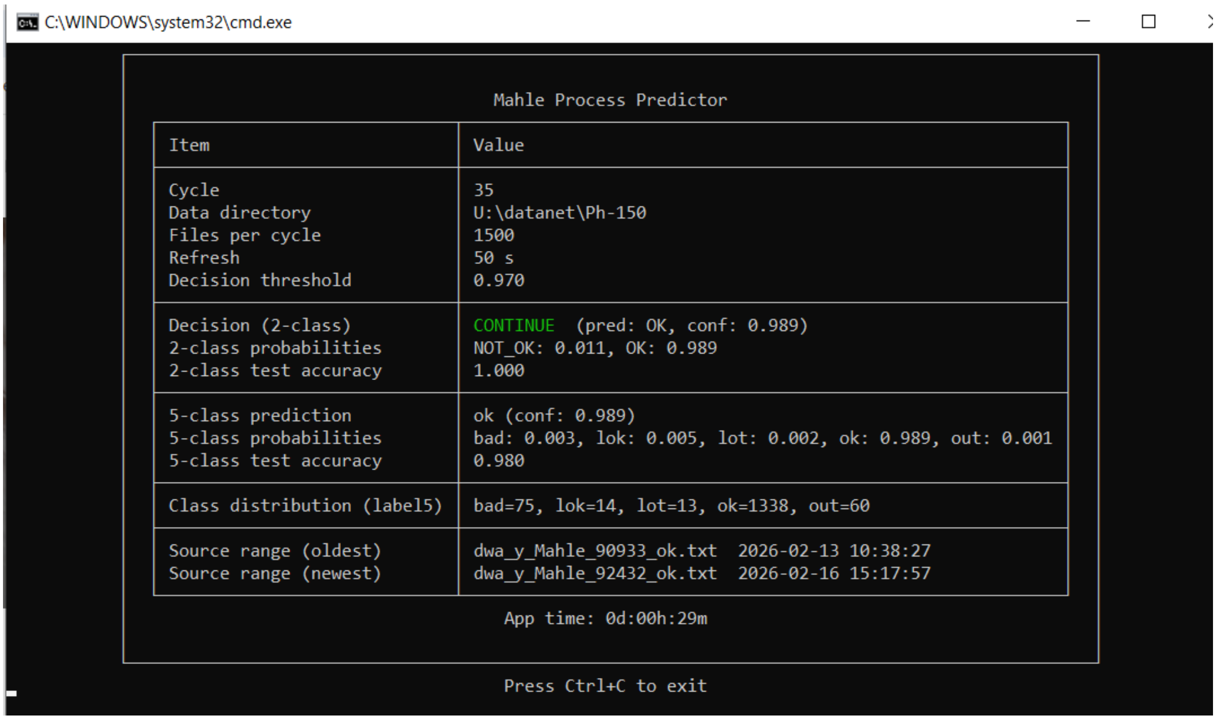


Figure 23: The screen shot of such an output of prediction program indicating to keep the production to continue.

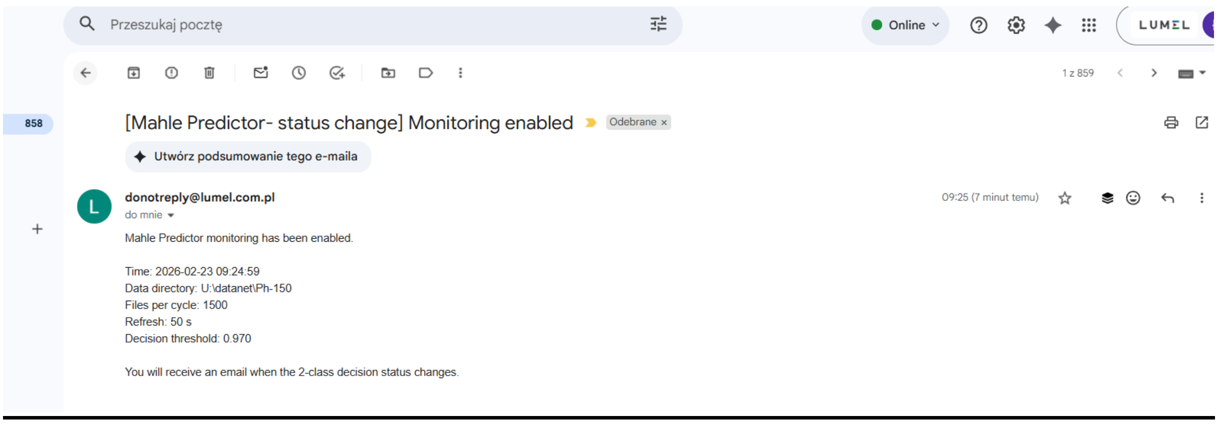


Figure 24: The screen shot of email triggered from AIMS indicating to keep the production to continue.

Based on the trained model the output is to Adjust (YELLOW) when the predicted OK parts in class 2 (OK + LOK +LOT from the class 5 out puts) is between 95% and 98% This enables the production engineers to use their knowledge base to check and prevent a possible STOP save the related costs with the production stoppage.

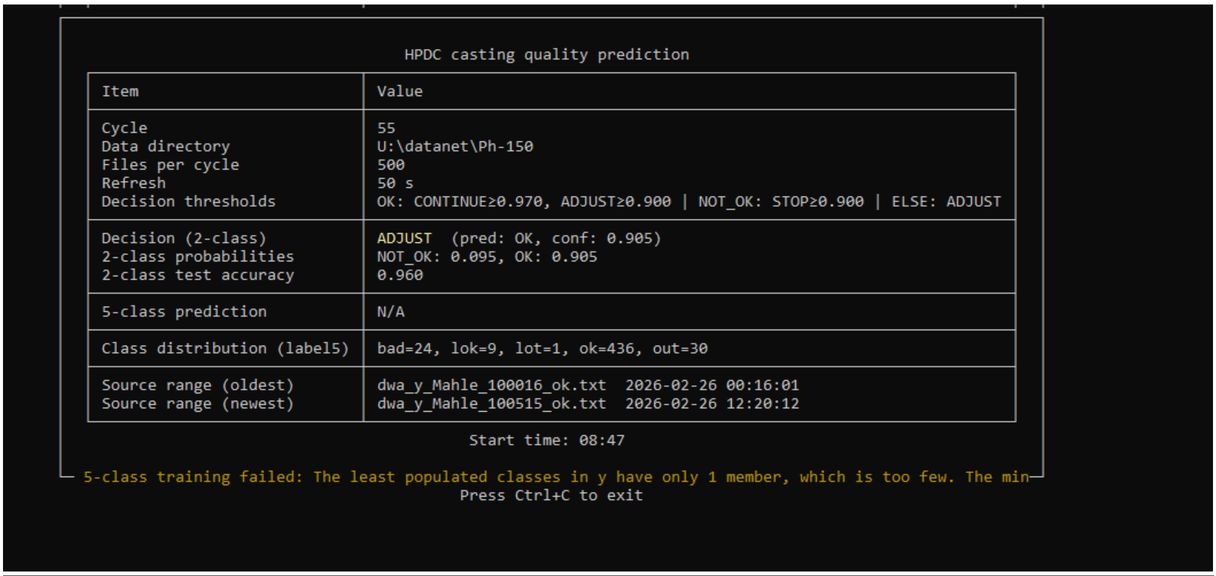


Figure 25: The screen shot of such a prediction program output indicating to ADJUST the production and use the knowledge base to check, course correct production

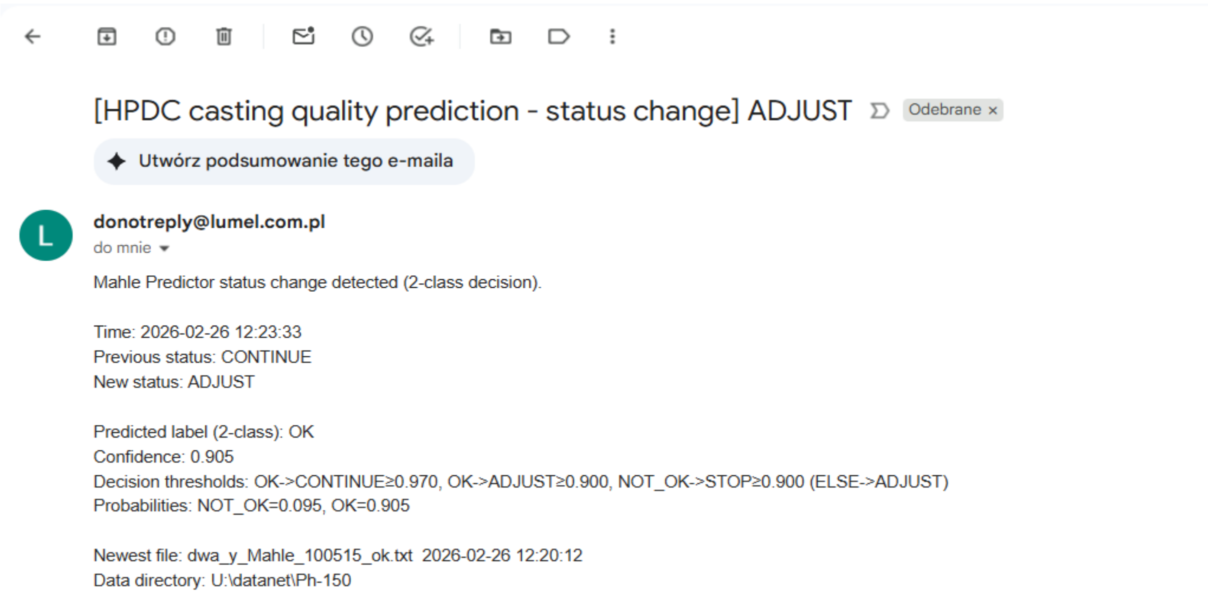
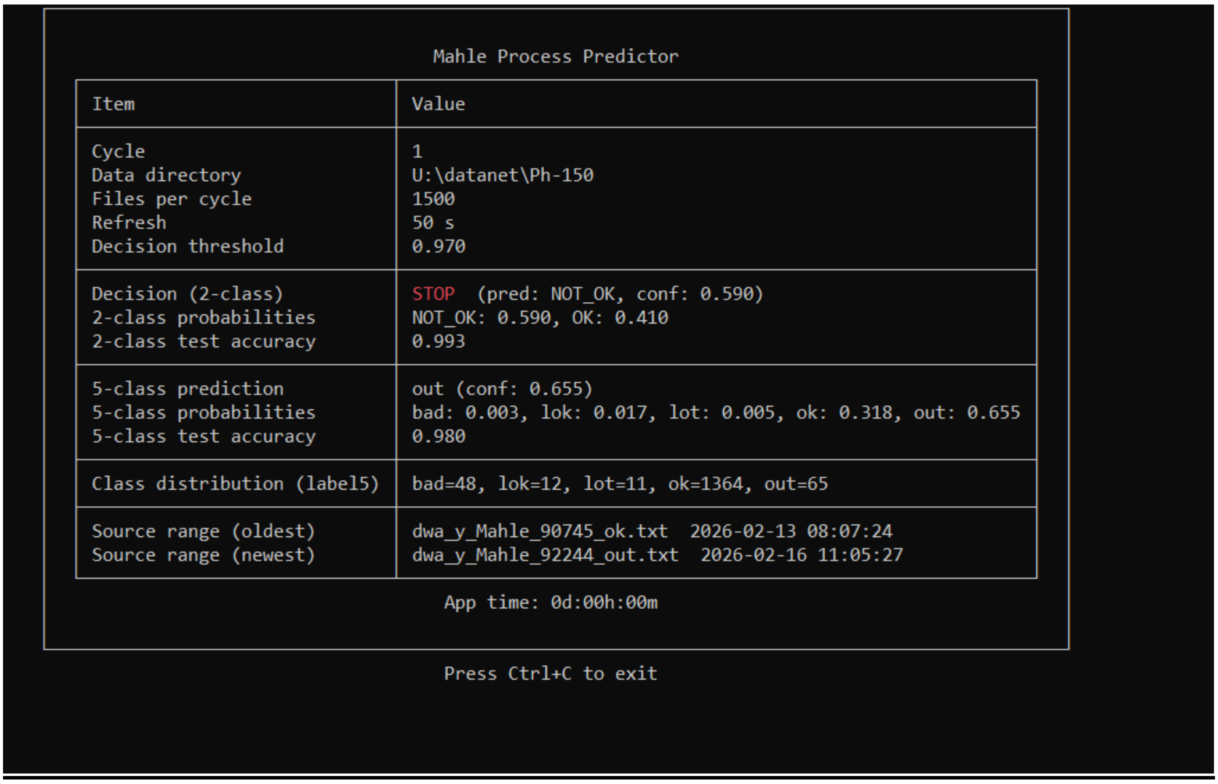


Figure 26 The screen shot of email triggered from AIMS indicating to keep to Observe and Adjust the production.

Based on the trained model the output is to STOP the production (RED) when the predicted OK parts in class 2 (OK + LOK +LOT from the class 5 out puts) is with the less than 95% to stop the production.



Mahle Process Predictor

Item	Value
Cycle Data directory Files per cycle Refresh Decision threshold	1 U:\datanet\Ph-150 1500 50 s 0.970
Decision (2-class) 2-class probabilities 2-class test accuracy	STOP (pred: NOT_OK, conf: 0.590) NOT_OK: 0.590, OK: 0.410 0.993
5-class prediction 5-class probabilities 5-class test accuracy	out (conf: 0.655) bad: 0.003, lok: 0.017, lot: 0.005, ok: 0.318, out: 0.655 0.980
Class distribution (label5)	bad=48, lok=12, lot=11, ok=1364, out=65
Source range (oldest) Source range (newest)	dwa_y_Mahle_90745_ok.txt 2026-02-13 08:07:24 dwa_y_Mahle_92244_out.txt 2026-02-16 11:05:27

App time: 0d:00h:00m

Press Ctrl+C to exit

Figure 27: Prediction Stop (RED) AIMS output

The screen shot of such a predictor program output indicating to stop the production and use the knowledge base to check, correct and start production

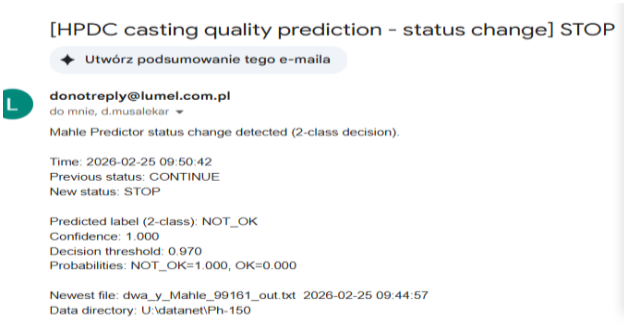


Figure 28: The screen shot of email triggered from AIMS indicating to the production to STOP.

For the practical purpose, the informations from the AIMS is sent as SMS to the designated phones of the production process Engineer and the production supervisor in real time to use their knowledge base to make a course correction so that the bad parts are not produced.

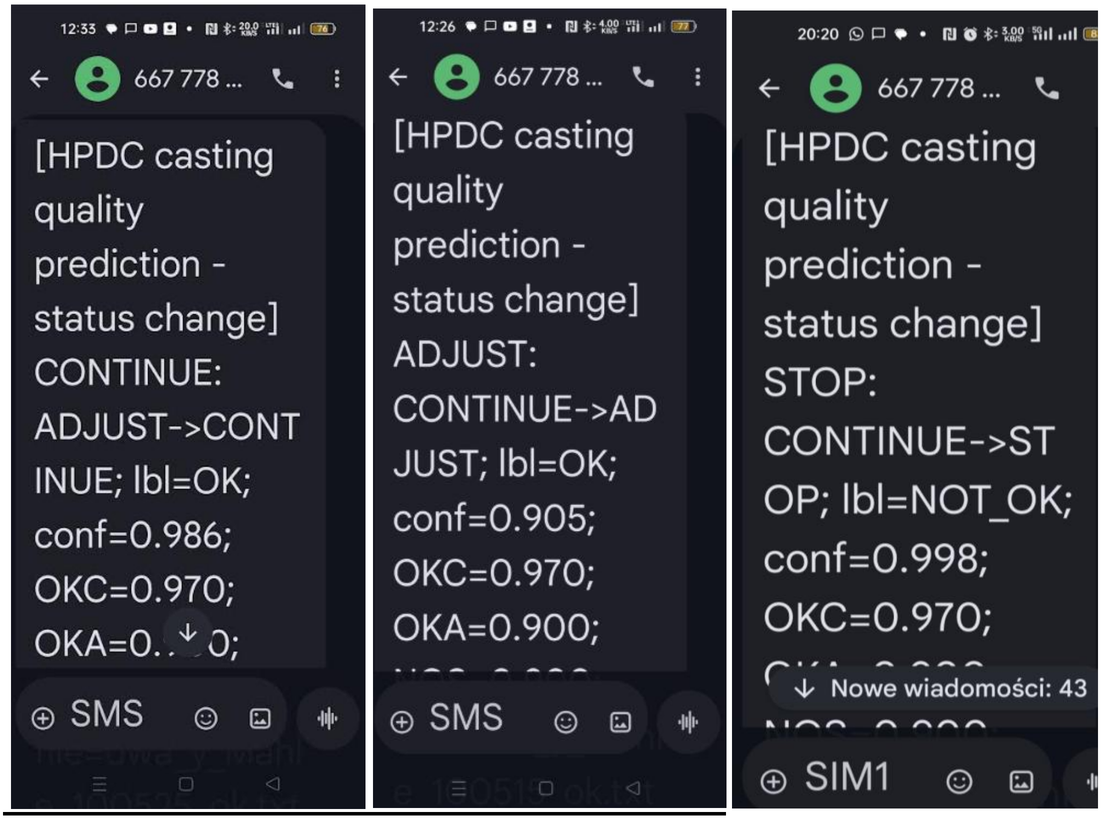


Figure 29: Mobile SMS screen shots to a) CONT b) ADJUST c)STOP

The screen shot of SMS triggered from AIMS indicating to keep the production to CONTINUE, ADJUST or STOP

5.4 Increasing the efficiency of the Die Casting process be supported based on stored technical knowledge

In order to verify the research model, how the proposed method contributes to increasing the efficiency of die casting mould process the following factors are verified and described below: Life of the Die casting mould, Maintenance cost of the Die casting mould, Down time of the Die casting machine cell due to un predictable mould break down (Improve OEE- Overall Equipment Efficiency), Reduction of the cycle time of the diecasting process (Improve OEE), Reduction in the scrap ratios of the parts produced, Improving Total Effective Equipment Performance (TEEP).

- The life of the die casting mould which is measured in terms of number of good parts produced before the renewal of the diecasting mould. This can range from 80.000 shots to 150.000 shots based on the number of cavity, complexity of the parts etc. In the case of subject part and similar parts the bench mark has been to produce 120.000 shots X 2 cavity for the first set of moulds and add 25.000 ppm of

NOK parts which effectively makes 120.000 X 1,025 = 123.000 shots and the same for the second and third set of inserts in the same mould body. With the implementation of AIMS model the improvement observed is about 13% after the implementation from the historic data which can be extrapolated from 123.000 shots to make it about 139.000 shots

- The mould breakdown which is up planned and also results in several hours of machine breakdown reduced by 16% in the one month of implementation to the last 6 months average on this project.

- Maintenance cost of the Die casting mould which is directly connected to the breakdown is improved by 16%. However the impact of this is beyond 16% as it also means cost saving involved in mould unloading and loading on the machine which takes about 1 shift (8 hours) of die casting machine time. Extra skilled maintenance crew of 2-3 workers. Also the Die casting machine cell down time. There are also other indirect costs such as extra transport cost to catch up the delay / backlog to supply to costumers. Risk of production line stoppages at the customers factories which at times run in to 100's of thousands to millions of euros.

- The OEE and hence the TEEP improved by 8% for the four weeks of implementation of AIMS on the Mahle_PSA project. The OEE improved from the last 6months average of 71% to 78% since implementation.

- Scrap ratio of the manufacturing which is measured in ppm (parts per million) and can range from 10.000 to 50.000 ppm NOK to total parts produced. The production of more number on NOK parts leads to reduction of mould life, lost production capacity and machine amortisation cost, lost energy and manpower cost as direct costs and other indirect huge costs like delayed supply to the customer leading to extra transport, line stoppage costs. For the mould and the part under consideration and similar group, the NOK ppm is 25.000 and with the predictive AIMS, this can be expected to improve by about 22% i.e. to drop the NOK ppm from 25.000 to 19.500

- The ration of planned to unplanned machine maintenance changed form 62:38 to 79:21 during the one month of implementation of this project to the last 6 months average.

- The cycle time which is the time interval between two consecutive sets of parts (shots) of the die casting process. Based on the number of cavities and size of the part can vary between 20 sec to 60 sec. For the mould and the part under consideration and similar group, the cycle time for production of two parts (one shot with two cavities) is 50 sec. The improvement in cycle time could not be achieved much during this period of 4 weeks. Only about 2 sec reduction could be achieved to keep the high level of OK parts.

- Improving Total Effective Equipment Performance (TEEP) improved by 8% for the four weeks of implementation of AIMS on the Mahle_PSA project. The OEE improved from the last 6months average of 71% to 78% since implementation.

6. Contribution to the mechanical engineering discipline and future research

Sustainability in Industry 5.0 is not a peripheral benefit but a core objective, driven by environmental, economic, and regulatory pressures. Sustainable Production (SP) entails:

- Reducing energy and resource consumption through efficient process control
- Minimizing environmental impact, such as emissions, material waste, and energy loss
- Ensuring safety, compliance, and long-term ecological balance

The strong interlinkage between human-centric technological development and SP is evident. For instance, when operators are empowered with intelligent tools (e.g., AI-based dashboards or decision support systems), they can make greener, data-informed choices, aligning manufacturing actions with broader Sustainable Development Goals (SDGs). Citing Van Erp et al. (2024), there is a pressing need for industries to operate within sustainable boundaries while still delivering competitive performance.

A key differentiator of Industry 5.0 is its people-first approach. Unlike the purely automation-driven paradigm of I4.0, Industry 5.0 promotes collaboration between humans and intelligent machines, respecting worker roles, enhancing well-being, and supporting inclusion. This includes:

- Human-Robot Collaboration (HRC) systems that distribute tasks based on cognitive and physical strengths
- Ergonomic workplace designs aided by sensor feedback and digital twins
- Worker-centric interfaces, such as voice or gesture-controlled machines
- Real-time feedback loops, where workers receive intuitive alerts from AI systems for adaptive decision-making

The contribution to the mechanical engineering is a novel method for DM of TK. The research problem was solved by answering RQ1, which was to build a database of technical knowledge involved in the die casting mold manufacturing process in order to increase the effectiveness of this process. Next, it was empirically proven that the use of the developed approach to DM of TK effectively improves the efficiency of the die casting process, including:

- Overall Equipment Effectiveness (OEE): Increase by 8%, from a 6-month average of 71% to 78%.
- Scrap reduction: Internal scrap rate (NOK parts) reduced by 22%, significantly decreasing energy, material, and labour losses.
- Mould life: A 13% increase in the number of good parts produced throughout the tool lifecycle was observed.

- Sustainability: By optimizing parameters and reducing waste, the system directly supports Sustainable Development Goals (SDGs) and the environmental objectives of Industry 5.0.

Moreover, the developed method constitutes an original and universal solution applicable to die casting mould manufacturing processes in automotive and metal industry enterprises.

Furthermore, the developed method provides an original and universal solution applicable to the studied die casting mold manufacturing process in automotive companies.

In the mould manufacturing context, the proposed model can be extended to HRC workstations, enabling real-time monitoring of both process quality and human interactions. This creates a feedback-rich environment where machines support, rather than replace, human expertise.

As recent global disruptions have shown (e.g., COVID-19, supply chain breakdowns), resilience is essential for survival. Agility, adaptability, and reconfigurability are vital traits for modern manufacturing systems. According to Leng et al. (2023), resilient industries are characterized by their ability to:

- Rapidly adjust production based on demand or disruption
- Reallocate resources using AI-based predictive analytics
- Maintain operational continuity through redundant digital infrastructure and self-healing systems

The developed system contributes to resilience by enabling real-time decision-making, process reconfiguration, and predictive failure diagnostics. However, there is a clear need to tailor such systems using industry-specific data models, making them simultaneously universal in structure yet customizable in execution—as emphasized by Marti-Puig et al. (2024).

A crucial challenge lies in bridging the digital skills gap. As smart manufacturing technologies become more integrated into shop-floor operations, workers must be upskilled to:

- Operate intelligent systems (e.g., digital twins, AI dashboards)
- Interpret AI-generated insights
- Collaborate with autonomous agents or cobots

Future research should focus on developing training frameworks and adaptive learning platforms tailored to the needs of blue- and white-collar workers. Such initiatives would directly improve not only productivity and process safety but also employee satisfaction and retention.

The emergence of Generative Artificial Intelligence (GAI), such as ChatGPT, Diffusion Models, and generative design tools, has transformative implications for the manufacturing sector. As discussed by Gupta (2024), GAI enables:

- Automated generation of optimized designs based on constraints and past performance
- Intelligent recommendation systems for process parameter tuning
- Context-aware predictive maintenance strategies
- Human-in-the-loop decision support, where operators receive dynamically generated process suggestions

In the mould industry, applying GAI to historical defect datasets, sensor data, and mould wear analysis could enable precise process planning, early detection of failure trends, and even automatic documentation generation for audits and compliance.

Despite the progress demonstrated in the system architecture, several open challenges and research gaps remain:

1. Cross-domain integration: How can technologies from smart cities, healthcare, or agriculture be adapted for resilient manufacturing ecosystems?
2. Real-time sustainability monitoring: Can AIMS be expanded to track real-time carbon footprint, water usage, or circularity metrics?
3. GAI explainability: As AI becomes more autonomous, how can manufacturers ensure the transparency and accountability of decisions made by AI systems?
4. Digital ethics and inclusion: How can we ensure AI applications respect data privacy, prevent bias, and ensure accessibility to marginalized workforce groups?

The transition from Industry 4.0 to Industry 5.0 demands a multi-dimensional transformation. It requires not only technological readiness but also cultural, environmental, and ethical shifts. The AIMS model presented in this study addresses critical challenges across sustainability, human-centricity, and resilience. It forms a foundational pillar for proactive, intelligent, and responsible manufacturing that aligns with the values and goals of Industry 5.0. Future research must prioritize cross-functional integration, generative AI applications, and worker empowerment to fully realize the vision of a smarter, safer, and more sustainable industrial future.

References

1. Abdelhamid, A. A., El-Kenawy, E. S. M., Alotaibi, B., Amer, G. M., Abdelkader, M. Y., Ibrahim, A., & Eid, M. M. (2022). Robust Speech Emotion Recognition Using CNN+LSTM Based on Stochastic Fractal Search Optimization Algorithm. *IEEE Access*, *10*. https://doi.org/10.1109/ACCESS.2022.3172954

2. Abualigah, L., Diabat, A., Mirjalili, S., Elaziz, M. A., & Gandomi, A. H. (2021). The Arithmetic Optimization Algorithm. *Computer Methods in Applied Mechanics and Engineering*, *376*. https://doi.org/10.1016/j.cma.2020.113609

3. Aguerchi, K., Jabrane, Y., Habba, M., & Hassani, A. H. E. (2024). A CNN Hyperparameters Optimization Based on Particle Swarm Optimization for Mammography Breast Cancer Classification. *Journal of Imaging*, *10*(2). https://doi.org/10.3390/jimaging10020030

4. Aker, E., Othman, M. L., Veerasamy, V., Aris, I. B., Wahab, N. I. A., & Hizam, H. (2020). Fault detection and classification of shunt compensated transmission line using discrete wavelet transform and naive bayes classifier. *Energies*, *13*(1). https://doi.org/10.3390/en13010243

5. Akhter, F., Siddiquei, H. R., Alahi, M. E. E., & Mukhopadhyay, S. C. (2021). An IoT-enabled portable sensing system with MWCNTs/PDMS sensor for nitrate detection in water. *Measurement: Journal of the International Measurement Confederation*, *178*. https://doi.org/10.1016/j.measurement.2021.109424

6. Akundi, A., Euresti, D., Luna, S., Ankobiah, W., Lopes, A., & Edinbarough, I. (2022). State of Industry 5.0—Analysis and Identification of Current Research Trends. *Applied System Innovation*, *5*(1). https://doi.org/10.3390/asi5010027

7. Alafaghani, A., Qattawi, A., Truong, J., Jaman, M. S., & Sun, J. Q. (2020). Optimizing fused deposition modeling processing parameters using response surface method for strong parts. *ASME 2020 15th International Manufacturing Science and Engineering Conference, MSEC 2020*, *1*. https://doi.org/10.1115/MSEC2020-8528

8. Allahyari, M. S., Damalas, C. A., & Ebadattalab, M. (2017a). Farmers' technical knowledge about integrated pest management (IPM) in olive production. *Agriculture (Switzerland)*, *7*(12). https://doi.org/10.3390/agriculture7120101

9. Allahyari, M. S., Damalas, C. A., & Ebadattalab, M. (2017b). Farmers' technical knowledge about integrated pest management (IPM) in olive production. *Agriculture (Switzerland)*, *7*(12). https://doi.org/10.3390/agriculture7120101

10. Alves, J., Lima, T. M., & Gaspar, P. D. (2023a). Is Industry 5.0 a Human-Centred Approach? A Systematic Review. In *Processes* (Vol. 11, Issue 1). https://doi.org/10.3390/pr11010193

11. Alves, J., Lima, T. M., & Gaspar, P. D. (2023b). Is Industry 5.0 a Human-Centred Approach? A Systematic Review. In *Processes* (Vol. 11, Issue 1). https://doi.org/10.3390/pr11010193

12. Anjul, R., & Ganguly, S. K. (2018). Artificial Intelligence in Metal Casting Industries: A Review. *International Journal of Advanced in Management, Technology and Engineering Sciences*, *8*(Iii).

13. Balogun, V. A., Edem, I. F., & Mativenga, P. T. (2016). E-smart toolpath machining strategy for process planning. *International Journal of Advanced Manufacturing Technology*, *86*(5–8). https://doi.org/10.1007/s00170-015-8286-5

14. Bartsch, K., Pettke, A., Höbert, A., Lakämper, J., & Lange, F. (2021). On the digital twin application and the role of artificial intelligence in additive manufacturing: A systematic review. In *JPhys Materials* (Vol. 4, Issue 3). https://doi.org/10.1088/2515-7639/abf3cf

15. Breque, M., Nul, L. D., & Petridis, A. (2021). Industry 5.0—Towards a sustainable, human- centric and resilient European industry. In *European Commission*.

16. Celent, L., Mladineo, M., Gjeldum, N., & Zizic, M. C. (2022). Multi-Criteria Decision Support System for Smart and Sustainable Machining Process. *Energies*, *15*(3). https://doi.org/10.3390/en15030772

17. Chen, Y. C., Chen, M. Y., Chen, T. Y., Chan, M. L., Huang, Y. Y., Liu, Y. L., Lee, P. T., Lin, G. J., Li, T. F., Chen, C. A., Chen, S. L., Li, K. C., & Abu, P. A. R. (2023). Improving Dental Implant Outcomes: CNN-Based System Accurately Measures Degree of Peri-Implantitis Damage on Periapical Film. *Bioengineering*, *10*(6). https://doi.org/10.3390/bioengineering10060640

18. Cheng, K., Niu, Z. C., Wang, R. C., Rakowski, R., & Bateman, R. (2017). Smart Cutting Tools and Smart Machining: Development Approaches, and Their Implementation and Application Perspectives. *Chinese Journal of Mechanical Engineering (English Edition)*, *30*(5). https://doi.org/10.1007/s10033-017-0183-4

19. Cheng, L., Zhao, Y. G., Li, P. P., & Yan, L. (2024). Sizing and Shape Optimization of Discrete Truss Employing a Target-Oriented Krill Herd Algorithm. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering*, *10*(2). https://doi.org/10.1115/1.4064644

20. Cheng, Y. Y., Zhang, B. L., Fang, T. H., Liu, L., Zhao, X. P., Ye, Z. L., Fan, X. H., Zhang, Y. J., & Li, Z. (2019a). Intelligent and lean manufacturing for Chinese

medicine: Theory and its applications. *Zhongguo Zhongyao Zazhi*, *44*(23). https://doi.org/10.19540/j.cnki.cjcmm.20191203.301

21. Cheng, Y. Y., Zhang, B. L., Fang, T. H., Liu, L., Zhao, X. P., Ye, Z. L., Fan, X. H., Zhang, Y. J., & Li, Z. (2019b). Intelligent and lean manufacturing for Chinese medicine: Theory and its applications. *Zhongguo Zhongyao Zazhi*, *44*(23). https://doi.org/10.19540/j.cnki.cjcmm.20191203.301

22. Dong, X., Taylor, C. J., & Cootes, T. F. (2022). Defect Classification and Detection Using a Multitask Deep One-Class CNN. *IEEE Transactions on Automation Science and Engineering*, *19*(3). https://doi.org/10.1109/TASE.2021.3109353

23. Dwivedi, A., Agrawal, D., Jha, A., & Mathiyazhagan, K. (2023). Studying the interactions among Industry 5.0 and circular supply chain: Towards attaining sustainable development. *Computers and Industrial Engineering*, *176*. https://doi.org/10.1016/j.cie.2022.108927

24. Esenogho, E., Mienye, I. D., Swart, T. G., Aruleba, K., & Obaido, G. (2022). A Neural Network Ensemble with Feature Engineering for Improved Credit Card Fraud Detection. *IEEE Access*, *10*. https://doi.org/10.1109/ACCESS.2022.3148298

25. Fraga-Lamas, P., Lopes, S. I., & Fernández-Caramés, T. M. (2021). Green iot and edge AI as key technological enablers for a sustainable digital transition towards a smart circular economy: An industry 5.0 use case. *Sensors*, *21*(17). https://doi.org/10.3390/s21175745

26. Grabowska, S., Saniuk, S., & Gajdzik, B. (2022). Industry 5.0: Improving humanization and sustainability of Industry 4.0. *Scientometrics*, *127*(6). https://doi.org/10.1007/s11192-022-04370-1

27. Handzic, M. (2011). Integrated socio-technical knowledge management model: An empirical evaluation. *Journal of Knowledge Management*, *15*(2). https://doi.org/10.1108/13673271111119655

28. Hoffmann, R., & Reich, C. (2023). A Systematic Literature Review on Artificial Intelligence and Explainable Artificial Intelligence for Visual Quality Assurance in Manufacturing. In *Electronics (Switzerland)* (Vol. 12, Issue 22). https://doi.org/10.3390/electronics12224572

29. Javaid, M., Haleem, A., Singh, R. P., & Suman, R. (2022). Enabling flexible manufacturing system (FMS) through the applications of industry 4.0 technologies. *Internet of Things and Cyber-Physical Systems*, *2*. https://doi.org/10.1016/j.iotcps.2022.05.005

30. Jelavic, M. (2011). Socio-technical knowledge management and epistemological paradigms: Theoretical connections at the individual and organisational level.

Interdisciplinary Journal of Information, Knowledge, and Management, *6*. https://doi.org/10.28945/1337

31. Jutidharabongse, J., Aujirapongpan, S., & Ritkaew, S. (2020). Dynamic knowledge management capability and strategic intuition of thai entrepreneurs. *Entrepreneurship and Sustainability Issues*, *7*(4). https://doi.org/10.9770/jesi.2020.7.4(25)

32. Kaasinen, E., Anttila, A. H., Heikkilä, P., Laarni, J., Koskinen, H., & Väätänen, A. (2022). Smooth and Resilient Human–Machine Teamwork as an Industry 5.0 Design Challenge. *Sustainability (Switzerland)*, *14*(5). https://doi.org/10.3390/su14052773

33. Kannadasan, K., Edla, D. R., & Kuppili, V. (2019). Type 2 diabetes data classification using stacked autoencoders in deep neural networks. *Clinical Epidemiology and Global Health*, *7*(4). https://doi.org/10.1016/j.cegh.2018.12.004

34. Kasinathan, P., Pugazhendhi, R., Elavarasan, R. M., Ramachandaramurthy, V. K., Ramanathan, V., Subramanian, S., Kumar, S., Nandhagopal, K., Raghavan, R. R. V., Rangasamy, S., Devendiran, R., & Alsharif, M. H. (2022). Realization of Sustainable Development Goals with Disruptive Technologies by Integrating Industry 5.0, Society 5.0, Smart Cities and Villages. In *Sustainability (Switzerland)* (Vol. 14, Issue 22). https://doi.org/10.3390/su142215258

35. Khan, M., Haleem, A., & Javaid, M. (2023). Changes and improvements in Industry 5.0: A strategic approach to overcome the challenges of Industry 4.0. *Green Technologies and Sustainability*, *1*(2). https://doi.org/10.1016/j.grets.2023.100020

36. Kim, D. H., Kim, T. J. Y., Wang, X., Kim, M., Quan, Y. J., Oh, J. W., Min, S. H., Kim, H., Bhandari, B., Yang, I., & Ahn, S. H. (2018). Smart Machining Process Using Machine Learning: A Review and Perspective on Machining Industry. In *International Journal of Precision Engineering and Manufacturing—Green Technology* (Vol. 5, Issue 4). https://doi.org/10.1007/s40684-018-0057-y

37. Lai, Z. H., Tao, W., Leu, M. C., & Yin, Z. (2020). Smart augmented reality instructional system for mechanical assembly towards worker-centered intelligent manufacturing. *Journal of Manufacturing Systems*, *55*. https://doi.org/10.1016/j.jmsy.2020.02.010

38. Leberruyer, N., Bruch, J., Ahlskog, M., & Afshar, S. (2023). Toward Zero Defect Manufacturing with the support of Artificial Intelligence—Insights from an industrial application. *Computers in Industry*, *147*. https://doi.org/10.1016/j.compind.2023.103877

39. Li, C., Chen, Y., & Shang, Y. (2022). A review of industrial big data for decision making in intelligent manufacturing. In *Engineering Science and Technology, an International Journal* (Vol. 29). https://doi.org/10.1016/j.jestch.2021.06.001

40. Liu, P. (2023). An Entrepreneurship Incubation Process Model and Gamified Educational Software Designed for Sustainable Education. *Sustainability (Switzerland), 15*(19). https://doi.org/10.3390/su151914646

41. Magalhães, L. C., Magalhães, L. C., Ramos, J. B., Moura, L. R., Moraes, R. E. N. de, Gonçalves, J. B., Hisatugu, W. H., Souza, M. T., Lacalle, L. N. L. de, & Ferreira, J. C. E. (2022). Conceiving a Digital Twin for a Flexible Manufacturing System. *Applied Sciences (Switzerland), 12*(19). https://doi.org/10.3390/app12199864

42. Mathew, J. K., Nair, K. R., Kalpana, B., Arumugasamy, M., & Sharanyaa, S. (2024). AN INTRUSION DETECTION APPROACH IN WIRELESS SENSOR NETWORK SECURITY THROUGH CNN-BI-LSTM MODEL. *Journal of Theoretical and Applied Information Technology, 102*(2).

43. Mourtzis, D., Angelopoulos, J., & Panopoulos, N. (2022). A Literature Review of the Challenges and Opportunities of the Transition from Industry 4.0 to Society 5.0. In *Energies* (Vol. 15, Issue 17). https://doi.org/10.3390/en15176276

44. Nahavandi, S. (2019). Industry 5.0-a human-centric solution. *Sustainability (Switzerland), 11*(16). https://doi.org/10.3390/su11164371

45. Nascimento, L. da S., Reichert, F. M., Janissek-Muniz, R., & Zawislak, P. A. (2021). Dynamic interactions among knowledge management, strategic foresight and emerging technologies. *Journal of Knowledge Management, 25*(2). https://doi.org/10.1108/JKM-01-2020-0044

46. Nasir, V., & Sassani, F. (2021). A review on deep learning in machining and tool monitoring: Methods, opportunities, and challenges. In *International Journal of Advanced Manufacturing Technology* (Vol. 115, Issues 9–10). https://doi.org/10.1007/s00170-021-07325-7

47. Nielsen, A. P. (2006). Understanding dynamic capabilities through knowledge management. In *Journal of Knowledge Management* (Vol. 10, Issue 4). https://doi.org/10.1108/13673270610679363

48. Nitin, & Gupta, S. B. (2024). Artificial Intelligence in Smart Agriculture: Applications and Challenges. In *Current Applied Science and Technology* (Vol. 24, Issue 2). https://doi.org/10.55003/cast.2023.254427

49. Ntemi, M., Paraschos, S., Karakostas, A., Gialampoukidis, I., Vrochidis, S., & Kompatsiaris, I. (2022). Infrastructure monitoring and quality diagnosis in CNC

machining: A review. In *CIRP Journal of Manufacturing Science and Technology* (Vol. 38). https://doi.org/10.1016/j.cirpj.2022.06.001

50. Oliva, F. L., Couto, M. H. G., Santos, R. F., & Bresciani, S. (2019). The integration between knowledge management and dynamic capabilities in agile organizations. *Management Decision*, *57*(8). https://doi.org/10.1108/MD-06-2018-0670

51. Park, H. seok, Qi, B., Dang, D. V., & Park, D. Y. (2018). Development of smart machining system for optimizing feedrates to minimize machining time. *Journal of Computational Design and Engineering*, *5*(3). https://doi.org/10.1016/j.jcde.2017.12.004

52. Patalas-Maliszewska, J., Musalekar, D. & Halikowski, D. (2025). Artificial intelligence-driven internet of things monitoring system towards industry 5.0 – A case study of mold manufacturing process. Advances in Science and Technology Research Journal, 19(8), 479–494. https://doi.org/10.12913/22998624/205494

53. Patalas-Maliszewska, J., Musalekar, D. & Halikowski, D. (2025). Artificial intelligence-driven internet of things monitoring system towards industry 5.0 – A case study of mold manufacturing process. Advances in Science and Technology Research Journal, 19(8), 479–494. https://doi.org/10.12913/22998624/205494

54. Pattanasing, K., Aujirapongpan, S., Dowpiset, K., Chanthawong, A., Jiraphanumes, K., & Hareebin, Y. (2022). Dynamic Knowledge Management Capabilities: An Approach to High-Performance Organization. *HighTech and Innovation Journal*, *3*(3). https://doi.org/10.28991/HIJ-2022-03-03-01

55. Pereira, A. M. H., Silva, M. R., Domingues, M. A. G., & Sá, J. C. (2019). Lean six sigma approach to improve the production process in the mould industry: A case study. *Quality Innovation Prosperity*, *23*(3). https://doi.org/10.12776/QIP.V23I3.1334

56. Pimenov, D. Y., Silva, L. R. R. da, Ercetin, A., Der, O., Mikolajczyk, T., & Giasin, K. (2024). State-of-the-art review of applications of image processing techniques for tool condition monitoring on conventional machining processes. In *International Journal of Advanced Manufacturing Technology* (Vol. 130, Issues 1–2). https://doi.org/10.1007/s00170-023-12679-1

57. Piorkowski, B. A., Gao, J. X., Evans, R. D., & Martin, N. (2013). A dynamic knowledge management framework for the high value manufacturing industry. *International Journal of Production Research*, *51*(7). https://doi.org/10.1080/00207543.2012.709650

58. Psarommatis, F., May, G., & Azamfirei, V. (2023). Envisioning maintenance 5.0: Insights from a systematic literature review of Industry 4.0 and a proposed

framework. In *Journal of Manufacturing Systems* (Vol. 68). https://doi.org/10.1016/j.jmsy.2023.04.009

59. Rožanec, J. M., Novalija, I., Zajec, P., Kenda, K., Ghinani, H. T., Suh, S., Veliou, E., Papamartzivanos, D., Giannetsos, T., Menesidou, S. A., Alonso, R., Cauli, N., Meloni, A., Recupero, D. R., Kyriazis, D., Sofianidis, G., Theodoropoulos, S., Fortuna, B., Mladenić, D., & Soldatos, J. (2022). Human-centric artificial intelligence architecture for industry 5.0 applications. *International Journal of Production Research*. https://doi.org/10.1080/00207543.2022.2138611

60. Rüstem, B., Mustafa, K., Yu, P. D., Üsame, A. U., Kumar, G. M., & Erdi, K. M. (2022). Advance monitoring of hole machining operations via intelligent measurement systems: A critical review and future trends. In *Measurement: Journal of the International Measurement Confederation* (Vol. 201). https://doi.org/10.1016/j.measurement.2022.111757

61. Shahane, S., Aluru, N., Ferreira, P., Kapoor, S. G., & Vanka, S. P. (2020). Optimization of solidification in die casting using numerical simulations and machine learning. *Journal of Manufacturing Processes*, *51*. https://doi.org/10.1016/j.jmapro.2020.01.016

62. Sorrenti, S., Dolcetti, V., Radzina, M., Bellini, M. I., Frezza, F., Munir, K., Grani, G., Durante, C., D'Andrea, V., David, E., Calò, P. G., Lori, E., & Cantisani, V. (2022). Artificial Intelligence for Thyroid Nodule Characterization: Where Are We Standing? In *Cancers* (Vol. 14, Issue 14). https://doi.org/10.3390/cancers14143357

63. Sudianto, A., Jamaludin, Z., Rahman, A. A. A., Novianto, S., & Muharrom, F. (2021). Automatic Temperature Measurement and Monitoring System for Milling Process of AA6041 Aluminum Aloy using MLX90614 Infrared Thermometer Sensor with Arduino. *Journal of Advanced Research in Fluid Mechanics and Thermal Sciences*, *82*(2). https://doi.org/10.37934/arfmts.82.2.114

64. Sundaram, S., & Zeid, A. (2023). Artificial Intelligence-Based Smart Quality Inspection for Manufacturing. *Micromachines*, *14*(3). https://doi.org/10.3390/mi14030570

65. Trakadas, P., Simoens, P., Gkonis, P., Sarakis, L., Angelopoulos, A., Ramallo-González, A. P., Skarmeta, A., Trochoutsos, C., Calvo, D., Pariente, T., Chintamani, K., Fernandez, I., Irigaray, A. A., Parreira, J. X., Petrali, P., Leligou, N., & Karkazis, P. (2020). An artificial intelligence-based collaboration approach in industrial iot manufacturing: Key concepts, architectural extensions and potential applications. *Sensors (Switzerland)*, *20*(19). https://doi.org/10.3390/s20195480

66. Vazquez, J. P. G., Torres, R. S., & Perez, D. B. P. (2021). Scientometric analysis of the application of artificial intelligence in agriculture. *Journal of Scientometric Research*, *10*(1). https://doi.org/10.5530/JSCIRES.10.1.7

67. Yao, X., Ma, N., Zhang, J., Wang, K., Yang, E., & Faccio, M. (2024). Enhancing wisdom manufacturing as industrial metaverse for industry and society 5.0. *Journal of Intelligent Manufacturing*, *35*(1). https://doi.org/10.1007/s10845-022-02027-7

68. Zhang, C., Pan, X., Li, H., Gardiner, A., Sargent, I., Hare, J., & Atkinson, P. M. (2018). A hybrid MLP-CNN classifier for very fine resolution remotely sensed image classification. *ISPRS Journal of Photogrammetry and Remote Sensing*, *140*. https://doi.org/10.1016/j.isprsjprs.2017.07.014

69. Zhang, X., Ma, Y., & Wang, M. (2024). An attention-based Logistic-CNN-BiLSTM hybrid neural network for credit risk prediction of listed real estate enterprises. *Expert Systems*, *41*(2). https://doi.org/10.1111/exsy.13299

70. Zoumpekas, T., Leutgeb, A., Puig, A., & Salamó, M. (2024). Machining tool identification utilizing temporal 3D point clouds. *Journal of Intelligent Manufacturing*, *35*(3). https://doi.org/10.1007/s10845-023-02093-5

List of Figures

List of Tables

List of Appendixes

Appendix 1 - Production data of Project Renault Exel file “DM 19.12.2024-21.12.2024 CH Renault data .xlsx”

Appendix 2 - Production data of Project Mahle _PSA Exel file “mahle_FH_PSA _5 class.xlsx”

Appendix 3 - Production data of Project Mahle _PSA Exel file “mahle_FH_PSA _2 class.xlsx”

Appendix 4 – Predictor program “predictor.py”

Appendixes

Appendix 1 - Production data of Project Renault Exel file “DM 19.12.2024-21.12.2024 CH Renault data .xlsx”

	shortText	dt Cyc *		qualAttr	l B *	p lMmax *	t Cyc *	v CF *	v CF *	F L *								
Casting machine	Shot number	Date/hour	Automatic process	Quality attribute	Tablet hight	Third phase pressure	Cycle time	First phase speed	Second phase speed	Closing force	Shot sleeve filling	Solidification time	Vacuum level	Mold temperature moving side	Mold temperature fix side	Delta temperature moving side	Delta temperature fix side	Type of spraying
			Y/N		[mm]	[bar]	[s]	[m/s]	[m/s]	[kN]	[%]	[s]	[mbar]	[°C]	[°C]	[°C]	[°C]	[M / E]
ph156	1	19/01/2024 06:00	Y	OK	20	875	47,1	0,15	4,32	8444		8	250			45	50	M
ph156	2	19/01/2024 06:01	Y	OK	17	889	51,8	0,15	4,34	8446		8						M
ph156	3	19/01/2024 06:02	Y	OK	19	876	48,5	0,15	4,34	8446		8						M
ph156	4	19/01/2024 06:02	Y	OK	20	879	50,7	0,15	4,36	8456		8						M
ph156	5	19/01/2024 06:03	Y	OK	19	887	47,5	0,15	4,33	8450		8						M
ph156	6	19/01/2024 06:04	Y	OK	21	877	48,4	0,15	4,31	8449		8						M
ph156	7	19/01/2024 06:05	Y	OK	21	876	47,6	0,15	4,34	8449		8						M
ph156	8	19/01/2024 06:06	Y	OK	18	890	47,9	0,15	4,34	8448		8						M
ph156	9	19/01/2024 06:06	Y	OK	21	881	49,8	0,15	4,35	8446		8						M
ph156	10	19/01/2024 06:07	Y	OK	21	878	47,3	0,15	4,33	8455		8						M
ph156	11	19/01/2024 06:08	Y	OK	20	875	47,6	0,15	4,34	8452		8						M
ph156	12	19/01/2024 06:09	Y	OK	18	879	48,5	0,15	4,32	8460		8						M
ph156	13	19/01/2024 06:10	Y	OK	21	877	50,1	0,15	4,32	8450		8						M
ph156	14	19/01/2024 06:32	Y	BAD	14	258	1347,8	0,15	1,15	8211		8						M
ph156	15	19/01/2024 06:33	Y	BAD	20	201	69,4	0,15	1,15	8314		8						M
ph156	16	19/01/2024 06:34	Y	BAD	19	201	46,3	0,15	1,15	8339		8						M
ph156	17	19/01/2024 06:35	Y	BAD	23	232	46,4	0,15	1,15	8353		8						M
ph156	18	19/01/2024 06:36	Y	BAD	33	269	46,3	0,15	1,15	8377		8						M
ph156	19	19/01/2024 06:36	Y	BAD	22	250	46,4	0,15	1,15	8400		8						M
ph156	20	19/01/2024 06:37	Y	BAD	30	252	46,8	0,15	1,15	8423		8						M
ph156	21	19/01/2024 06:38	Y	LOK	21	838	47,4	0,15	3,96	8434		8						M
ph156	22	19/01/2024 06:39	Y	LOK	24	855	46,7	0,15	4,2	8456		8						M
ph156	23	19/01/2024 06:39	Y	OK	23	869	46,6	0,15	4,32	8480		8						M
ph156	24	19/01/2024 06:40	Y	OK	21	876	46,6	0,15	4,33	8490		8						M
ph156	25	19/01/2024 06:41	Y	OK	25	865	46,6	0,15	4,34	8500		8						M

.

.

.

.

.

.

3582	ph156	3578	21/01/2024 22:11	Y	OK	18	879	47	0,15	4,29	8401		8						M
3583	ph156	3579	21/01/2024 22:11	Y	OK	19	878	46,8	0,15	4,32	8398		8						M
3584	ph156	3580	21/01/2024 22:12	Y	OK	19	873	46,9	0,15	4,31	8401		8						M
3585	ph156	3581	21/01/2024 22:13	Y	OK	17	881	47	0,15	4,32	8411		8						M
3586	ph156	3582	21/01/2024 22:14	Y	OK	16	877	47	0,15	4,3	8411		8						M
3587	ph156	3583	21/01/2024 22:14	Y	OK	18	879	47,5	0,15	4,3	8410		8						M
3588	ph156	3584	21/01/2024 22:15	Y	OK	18	881	47,8	0,15	4,28	8400		8						M
3589	ph156	3585	21/01/2024 22:16	Y	OK	18	878	46,9	0,15	4,34	8401		8						M
3590	ph156	3586	21/01/2024 22:17	Y	OK	20	868	47,2	0,15	4,32	8418		8						M
3591	ph156	3587	21/01/2024 22:18	Y	OK	18	872	47,5	0,15	4,3	8418		8						M
3592	ph156	3588	21/01/2024 22:18	Y	OK	19	887	47,2	0,15	4,29	8417		8						M
3593	ph156	3589	21/01/2024 22:19	Y	OK	19	876	47,9	0,15	4,32	8409		8						M
3594	ph156	3590	21/01/2024 22:20	Y	OK	17	872	47,1	0,15	4,34	8393		8						M
3595	ph156	3591	21/01/2024 22:21	Y	OK	19	879	46,9	0,15	4,31	8400		8						M
3596	ph156	3592	21/01/2024 22:22	Y	OK	18	877	47,1	0,15	4,31	8386		8						M
3597	ph156	3593	21/01/2024 22:22	Y	OK	19	870	47	0,15	4,31	8390		8						M
3598	ph156	3594	21/01/2024 22:23	Y	OK	20	868	47,9	0,15	4,32	8395		8						M
3599	ph156	3595	21/01/2024 22:24	Y	OK	19	873	47,3	0,15	4,29	8400		8						M
3600	ph156	3596	21/01/2024 22:25	Y	OK	20	885	47	0,15	4,31	8390		8						M
3601	ph156	3597	21/01/2024 22:26	Y	OK	19	882	47,4	0,15	4,32	8405		8						M
3602	ph156	3598	21/01/2024 22:26	Y	OK	19	881	47,5	0,15	4,31	8409		8						M
3603	ph156	3599	21/01/2024 22:27	Y	OK	18	871	47,2	0,15	4,31	8392		8						M
3604	ph156	3600	21/01/2024 22:28	Y	OK	17	879	47	0,15	4,31	8399		8						M
3605	ph156	3601	21/01/2024 22:29	Y	OK	18	877	47,7	0,15	4,31	8388		8						M
3606	ph156	3602	21/01/2024 22:29	Y	OK	19	893	47,1	0,15	4,33	8388		8						M
3607	ph156	3603	21/01/2024 22:30	Y	OK	20	892	47,1	0,15	4,32	8397		8						M
3608	ph156	3604	21/01/2024 22:31	Y	OK	20	880	47,1	0,15	4,3	8388		8						M
3609	ph156	3605	21/01/2024 22:32	Y	OK	19	873	48,1	0,15	4,33	8397		8						M
3610	ph156	3606	21/01/2024 22:33	Y	OK	18	881	47,1	0,15	4,3	8401		8						M
3611	ph156	3607	21/01/2024 22:33	Y	OK	20	880	47,3	0,15	4,31	8405		8						M
3612	ph156	3608	21/01/2024 22:34	Y	OK	19	884	47,1	0,15	4,3	8406		8						M
3613	ph156	3609	21/01/2024 22:35	Y	OK	17	876	47,2	0,15	4,31	8405		8						M

Note : The full file is available in XL soft version

Appendix 2 - Production data of Project Mahle _PSA Exel file “mahle_FH_PSA _5 class.xlsx”

1	Data pliku (Time Stamp)	Nazwa zbioru (File name)	ID maszyny (Machine ID)	Siła zamyk. (Closing Force) [kN	Grubość piętki (Heel Thickness)[mm	max.ciśni.metalu-faza ND (Max metal pressure in ND phase) [bar	Czas cyklu (Cycle Time) [s]	tłok odlew. (s CF) (Piston Velocity)[m/s]	class (Out Put)
2	12/12/2025 13:23	dwa_y_Mahle_53436_ok.txt	10516359	8384	27	827	47,4	4,11	ok
3	12/12/2025 13:24	dwa_y_Mahle_53437_ok.txt	10516359	8389	22	841	47,4	4,08	ok
4	12/12/2025 13:24	dwa_y_Mahle_53438_ok.txt	10516359	8390	27	826	47,5	4,08	ok
5	12/12/2025 13:25	dwa_y_Mahle_53439_ok.txt	10516359	8392	25	825	47,4	4,08	ok
6	12/12/2025 13:26	dwa_y_Mahle_53440_ok.txt	10516359	8390	27	826	47,3	4,07	ok
7	12/12/2025 13:27	dwa_y_Mahle_53441_ok.txt	10516359	8386	26	824	47,4	4,1	ok
8	12/12/2025 13:28	dwa_y_Mahle_53442_ok.txt	10516359	8386	25	828	47,4	4,09	ok
9	12/12/2025 13:28	dwa_y_Mahle_53443_ok.txt	10516359	8385	27	823	47,4	4,09	ok
10	12/12/2025 13:29	dwa_y_Mahle_53444_ok.txt	10516359	8392	26	828	47,4	4,09	ok
11	12/12/2025 13:30	dwa_y_Mahle_53445_ok.txt	10516359	8386	26	813	47,4	4,09	ok
12	12/12/2025 13:31	dwa_y_Mahle_53446_ok.txt	10516359	8385	24	829	47,4	4,11	ok
13	12/12/2025 13:32	dwa_y_Mahle_53447_ok.txt	10516359	8389	24	834	47,4	4,11	ok
14	12/12/2025 13:32	dwa_y_Mahle_53448_ok.txt	10516359	8395	27	829	47,4	4,11	ok
15	12/12/2025 13:33	dwa_y_Mahle_53449_ok.txt	10516359	8395	28	826	47,4	4,09	ok
16	12/12/2025 13:44	dwa_y_Mahle_53450_bad.txt	10516359	8111	31	210	664	1,82	bad
17	12/12/2025 13:45	dwa_y_Mahle_53451_bad.txt	10516359	8253	31	263	48	1,82	bad
18	12/12/2025 13:46	dwa_y_Mahle_53452_bad.txt	10516359	8279	34	225	48	1,79	bad
19	12/12/2025 13:47	dwa_y_Mahle_53453_bad.txt	10516359	8289	33	214	48,1	1,81	bad
20	12/12/2025 13:47	dwa_y_Mahle_53454_bad.txt	10516359	8318	32	230	48	1,82	bad
21	12/12/2025 13:48	dwa_y_Mahle_53455_bad.txt	10516359	8344	33	209	48,1	1,81	bad
22	12/12/2025 13:49	dwa_y_Mahle_53456_lot.txt	10516359	8363	26	855	47,6	3,7	lot
23	12/12/2025 13:50	dwa_y_Mahle_53457_lok.txt	10516359	8383	24	843	47,5	3,93	lok

mahle_zbiorcze +

1	Data pliku (Time Stamp)	Nazwa zbioru (File name)	ID maszyny (Machine ID)	Siła zamyk. (Closing Force) [kN	Grubość piętki (Heel Thickness)[mm	max.ciśni.metalu-faza ND (Max metal pressure in ND phase) [bar	Czas cyklu (Cycle Time) [s]	tłok odlew. (s CF) (Piston Velocity)[m/s]	class (Out Pu
3699	17/12/2025 09:36	dwa_y_Mahle_57133_ok.txt	10516359	8403	26	805	47,5	1,99	ok
3700	17/12/2025 09:37	dwa_y_Mahle_57134_ok.txt	10516359	8425	24	801	47,4	2	ok
3701	17/12/2025 09:38	dwa_y_Mahle_57135_ok.txt	10516359	8429	24	802	47,5	1,99	ok
3702	17/12/2025 09:38	dwa_y_Mahle_57136_ok.txt	10516359	8433	25	801	47,4	2	ok
3703	17/12/2025 09:39	dwa_y_Mahle_57137_ok.txt	10516359	8446	24	795	47,4	2	ok
3704	17/12/2025 09:40	dwa_y_Mahle_57138_ok.txt	10516359	8455	25	798	47,5	1,99	ok
3705	17/12/2025 09:41	dwa_y_Mahle_57139_ok.txt	10516359	8456	22	797	47,5	2	ok
3706	17/12/2025 09:42	dwa_y_Mahle_57140_ok.txt	10516359	8461	22	787	47,5	1,99	ok
3707	17/12/2025 09:42	dwa_y_Mahle_57141_ok.txt	10516359	8470	27	804	47,5	1,99	ok
3708	17/12/2025 09:43	dwa_y_Mahle_57142_ok.txt	10516359	8352	28	799	47,6	1,99	ok
3709	17/12/2025 09:44	dwa_y_Mahle_57143_lok.txt	10516359	8361	27	799	47,6	2,42	lok
3710	17/12/2025 09:45	dwa_y_Mahle_57144_lok.txt	10516359	8363	24	801	47,5	2,49	lok
3711	17/12/2025 09:46	dwa_y_Mahle_57145_ok.txt	10516359	8366	28	806	47,4	2,52	ok
3712	17/12/2025 09:46	dwa_y_Mahle_57146_ok.txt	10516359	8374	24	805	47,4	2,53	ok
3713	17/12/2025 09:47	dwa_y_Mahle_57147_ok.txt	10516359	8372	25	801	47,4	2,53	ok
3714	17/12/2025 09:48	dwa_y_Mahle_57148_lot.txt	10516359	8376	27	806	47,6	3,72	lot
3715	17/12/2025 09:49	dwa_y_Mahle_57149_lok.txt	10516359	8370	23	780	47,5	3,92	lok
3716	17/12/2025 09:50	dwa_y_Mahle_57150_ok.txt	10516359	8385	25	783	47,4	4,11	ok
3717	17/12/2025 09:50	dwa_y_Mahle_57151_ok.txt	10516359	8394	24	796	47,5	4,08	ok
3718	17/12/2025 09:51	dwa_y_Mahle_57152_ok.txt	10516359	8435	19	765	47,5	4,09	ok
3719	17/12/2025 09:52	dwa_y_Mahle_57153_bad.txt	10516359	8428	26	824	47,6	4,11	bad
3720									

mahle_zbiorcze +

Note : The full file is available in XL soft version

Appendix 3 - Production data of Project Mahle _PSA Exel file “mahle_FH_PSA _2 class.xlsx”

	A	B	C	D	E	F	G	H	I
1	Data pliku (Time Stamp)	Nazwa zbioru (File name)	ID maszyny (Machine ID)	Siła zamyk. (Closing Force) [kN]	Grubość piętki (Heel Thickness)[mm]	max.ciśni.metalu-faza ND (Max metal pressure in ND phase) [bar]	Czas cyklu (Cycle Time) [s]	tłok odlew. (s CF) (Piston Velocity)[m/s]	class (Out Put)
2	12/12/2025 13:23	dwa_y_Mahle_53436_ok.txt	10516359	8384	27	827	47,4	4,11	ok
3	12/12/2025 13:24	dwa_y_Mahle_53437_ok.txt	10516359	8389	22	841	47,4	4,08	ok
4	12/12/2025 13:24	dwa_y_Mahle_53438_ok.txt	10516359	8390	27	826	47,5	4,08	ok
5	12/12/2025 13:25	dwa_y_Mahle_53439_ok.txt	10516359	8392	25	825	47,4	4,08	ok
6	12/12/2025 13:26	dwa_y_Mahle_53440_ok.txt	10516359	8390	27	826	47,3	4,07	ok
7	12/12/2025 13:27	dwa_y_Mahle_53441_ok.txt	10516359	8386	26	824	47,4	4,1	ok
8	12/12/2025 13:28	dwa_y_Mahle_53442_ok.txt	10516359	8386	25	828	47,4	4,09	ok
9	12/12/2025 13:28	dwa_y_Mahle_53443_ok.txt	10516359	8385	27	823	47,4	4,09	ok
10	12/12/2025 13:29	dwa_y_Mahle_53444_ok.txt	10516359	8392	26	828	47,4	4,09	ok
11	12/12/2025 13:30	dwa_y_Mahle_53445_ok.txt	10516359	8386	26	813	47,4	4,09	ok
12	12/12/2025 13:31	dwa_y_Mahle_53446_ok.txt	10516359	8385	24	829	47,4	4,11	ok
13	12/12/2025 13:32	dwa_y_Mahle_53447_ok.txt	10516359	8389	24	834	47,4	4,11	ok
14	12/12/2025 13:32	dwa_y_Mahle_53448_ok.txt	10516359	8395	27	829	47,4	4,11	ok
15	12/12/2025 13:33	dwa_y_Mahle_53449_ok.txt	10516359	8395	28	826	47,4	4,09	ok
16	12/12/2025 13:44	dwa_y_Mahle_53450_bad.txt	10516359	8111	31	210	664	1,82	bad
17	12/12/2025 13:45	dwa_y_Mahle_53451_bad.txt	10516359	8253	31	263	48	1,82	bad
18	12/12/2025 13:46	dwa_y_Mahle_53452_bad.txt	10516359	8279	34	225	48	1,79	bad
19	12/12/2025 13:47	dwa_y_Mahle_53453_bad.txt	10516359	8289	33	214	48,1	1,81	bad
20	12/12/2025 13:47	dwa_y_Mahle_53454_bad.txt	10516359	8318	32	230	48	1,82	bad
21	12/12/2025 13:48	dwa_y_Mahle_53455_bad.txt	10516359	8344	33	209	48,1	1,81	bad
22	12/12/2025 13:49	dwa_y_Mahle_53456_ok.txt	10516359	8363	26	855	47,6	3,7	ok
23	12/12/2025 13:50	dwa_y_Mahle_53457_ok.txt	10516359	8383	24	843	47,5	3,93	ok
24	12/12/2025 13:51	dwa_y_Mahle_53458_ok.txt	10516359	8389	25	842	47,4	4,09	ok
25	12/12/2025 13:51	dwa_y_Mahle_53459_ok.txt	10516359	8410	26	846	47,4	4,1	ok
26	12/12/2025 13:52	dwa_y_Mahle_53460_ok.txt	10516359	8421	25	840	47,5	4,05	ok
27	12/12/2025 13:53	dwa_y_Mahle_53461_ok.txt	10516359	8425	27	832	47,5	4,07	ok
28	12/12/2025 13:54	dwa_y_Mahle_53462_ok.txt	10516359	8429	28	825	47,5	4,09	ok
29	12/12/2025 13:55	dwa_y_Mahle_53463_ok.txt	10516359	8435	28	823	47,5	4,1	ok
30	12/12/2025 13:55	dwa_y_Mahle_53464_ok.txt	10516359	8439	26	828	47,5	4,1	ok
31	12/12/2025 13:56	dwa_y_Mahle_53465_ok.txt	10516359	8430	27	819	47,5	4,11	ok
32	12/12/2025 13:57	dwa_y_Mahle_53466_ok.txt	10516359	8439	27	828	47,5	4,09	ok
33	12/12/2025 13:58	dwa_y_Mahle_53467_ok.txt	10516359	8431	27	827	47,4	4,07	ok
34	12/12/2025 13:58	dwa_y_Mahle_53468_ok.txt	10516359	8436	26	828	47,5	4,1	ok
35	12/12/2025 13:59	dwa_y_Mahle_53469_ok.txt	10516359	8444	23	796	47,5	4,11	ok

mahle_zbiorcze

•

•

•

•

•

•

•

•

•

	A	B	C	D	E	F	G	H	I
1	Data pliku (Time Stamp)	Nazwa zbioru (File name)	ID maszyny (Machine ID)	Siła zamyk. (Closing Force) [kN]	Grubość piętki (Heel Thickness)[mm]	max.ciśni.metalu-faza ND (Max metal pressure in ND phase) [bar]	Czas cyklu (Cycle Time) [s]	tłok odlew. (s CF) (Piston Velocity)[m/s]	class (Out Put)
3689	17/12/2025 08:57	dwa_y_Mahle_57123_ok.txt	10516359	8243	17	761	47,6	3,71	ok
3690	17/12/2025 09:29	dwa_y_Mahle_57124_bad.txt	10516359	7999	26	229	1923	1,84	bad
3691	17/12/2025 09:30	dwa_y_Mahle_57125_bad.txt	10516359	8114	33	226	48,1	1,82	bad
3692	17/12/2025 09:31	dwa_y_Mahle_57126_bad.txt	10516359	8261	31	222	48,1	1,83	bad
3693	17/12/2025 09:31	dwa_y_Mahle_57127_bad.txt	10516359	8284	31	220	48	1,82	bad
3694	17/12/2025 09:32	dwa_y_Mahle_57128_bad.txt	10516359	8302	28	242	48,1	1,83	bad
3695	17/12/2025 09:33	dwa_y_Mahle_57129_bad.txt	10516359	8333	30	219	48	1,82	bad
3696	17/12/2025 09:34	dwa_y_Mahle_57130_bad.txt	10516359	8350	30	226	48	1,82	bad
3697	17/12/2025 09:35	dwa_y_Mahle_57131_ok.txt	10516359	8377	26	808	47,7	1,91	ok
3698	17/12/2025 09:35	dwa_y_Mahle_57132_ok.txt	10516359	8388	25	803	47,5	1,98	ok
3699	17/12/2025 09:36	dwa_y_Mahle_57133_ok.txt	10516359	8403	26	805	47,5	1,99	ok
3700	17/12/2025 09:37	dwa_y_Mahle_57134_ok.txt	10516359	8425	24	801	47,4	2	ok
3701	17/12/2025 09:38	dwa_y_Mahle_57135_ok.txt	10516359	8429	24	802	47,5	1,99	ok
3702	17/12/2025 09:38	dwa_y_Mahle_57136_ok.txt	10516359	8433	25	801	47,4	2	ok
3703	17/12/2025 09:39	dwa_y_Mahle_57137_ok.txt	10516359	8446	24	795	47,4	2	ok
3704	17/12/2025 09:40	dwa_y_Mahle_57138_ok.txt	10516359	8455	25	798	47,5	1,99	ok
3705	17/12/2025 09:41	dwa_y_Mahle_57139_ok.txt	10516359	8456	22	797	47,5	2	ok
3706	17/12/2025 09:42	dwa_y_Mahle_57140_ok.txt	10516359	8461	22	787	47,5	1,99	ok
3707	17/12/2025 09:42	dwa_y_Mahle_57141_ok.txt	10516359	8470	27	804	47,5	1,99	ok
3708	17/12/2025 09:43	dwa_y_Mahle_57142_ok.txt	10516359	8352	28	799	47,6	1,99	ok
3709	17/12/2025 09:44	dwa_y_Mahle_57143_ok.txt	10516359	8361	27	799	47,6	2,42	ok
3710	17/12/2025 09:45	dwa_y_Mahle_57144_ok.txt	10516359	8363	24	801	47,5	2,49	ok
3711	17/12/2025 09:46	dwa_y_Mahle_57145_ok.txt	10516359	8366	28	806	47,4	2,52	ok
3712	17/12/2025 09:46	dwa_y_Mahle_57146_ok.txt	10516359	8374	24	805	47,4	2,53	ok
3713	17/12/2025 09:47	dwa_y_Mahle_57147_ok.txt	10516359	8372	25	801	47,4	2,53	ok
3714	17/12/2025 09:48	dwa_y_Mahle_57148_ok.txt	10516359	8376	27	806	47,6	3,72	ok
3715	17/12/2025 09:49	dwa_y_Mahle_57149_ok.txt	10516359	8370	23	780	47,5	3,92	ok
3716	17/12/2025 09:50	dwa_y_Mahle_57150_ok.txt	10516359	8385	25	783	47,4	4,11	ok
3717	17/12/2025 09:50	dwa_y_Mahle_57151_ok.txt	10516359	8394	24	796	47,5	4,08	ok
3718	17/12/2025 09:51	dwa_y_Mahle_57152_ok.txt	10516359	8435	19	765	47,5	4,09	ok
3719	17/12/2025 09:52	dwa_y_Mahle_57153_bad.txt	10516359	8428	26	824	47,6	4,11	bad
3720									
3721									

mahle_zbiorcze

Note : The full file is available in XL soft version

Appendix 4 – Predictor program "predictor.py"

```
clear;
clc;

load data.mat

if istable(data)
    inputs = data(:, 1:end-1);
    labels = data(:, end);
else
    error('Unsupported data format.');
end

inputs_encoded = [];

for i = 1:width(inputs)
    column = inputs{:, i};

    if iscellstr(column) || isstring(column)
        encoded = grp2idx(categorical(column));
        encoded = encoded(:);
    elseif isnumeric(column)
        encoded = column(:);
    elseif islogical(column)
        encoded = double(column(:));
    elseif isdatetime(column)
        encoded = datenum(column(:));
    elseif iscategorical(column)
        encoded = double(column(:));
    else
        error('Unsupported column type: %s', class(column));
    end

    inputs_encoded = [inputs_encoded, encoded];
end

labels_array = table2array(labels);

if iscategorical(labels_array)
    numericLabels = double(labels_array);
elseif iscellstr(labels_array) || isstring(labels_array)
    uniqueLabels = unique(labels_array);
    labelMap = containers.Map(uniqueLabels, 1:numel(uniqueLabels));
    numericLabels = cellfun(@(x) labelMap(x), labels_array);
elseif isnumeric(labels_array)
    numericLabels = labels_array;
else
    error('Unsupported label type: %s', class(labels_array));
end

target = full(ind2vec(numericLabels'));

cv1 = cvpartition(size(inputs_encoded, 1), 'HoldOut', 0.3);
trainIdx = training(cv1);
remainingIdx = test(cv1);

cv2 = cvpartition(sum(remainingIdx), 'HoldOut', 1/3);
valIdx = remainingIdx;
valIdx(remainingIdx) = test(cv2);
testIdx = remainingIdx;
testIdx(remainingIdx) = training(cv2);
```

```
trainInputs = inputs_encoded(trainIdx, :);
valInputs = inputs_encoded(valIdx, :);
testInputs = inputs_encoded(testIdx, :);
trainLabels = target(:, trainIdx);
valLabels = target(:, valIdx);
testLabels = target(:, testIdx);

hiddenLayerSize = [20];
net = feedforwardnet(hiddenLayerSize);

net.divideFcn = 'divideind';
net.divideParam.trainInd = find(trainIdx);
net.divideParam.valInd = find(valIdx);
net.divideParam.testInd = find(testIdx);

net.trainParam.goal = 1e-9;
net.trainParam.epochs = 100;
net.trainParam.min_grad = 1e-7;
net.trainParam.max_fail = 30;
net.layers{end}.transferFcn = 'softmax';

[net, tr] = train(net, trainInputs', trainLabels);

testOutputs = net(testInputs');
predictedLabels = vec2ind(testOutputs);
actualLabels = vec2ind(testLabels);
accuracy = sum(predictedLabels == actualLabels) / numel(actualLabels) * 100;
disp(['Test Accuracy: ' num2str(accuracy) '%']);

trainOutputs = net(trainInputs');
trainpredictedLabels = vec2ind(trainOutputs);
trainactualLabels = vec2ind(trainLabels);
trainaccuracy = sum(trainpredictedLabels == trainactualLabels) / numel(trainactualLabels) * 100;
disp(['Train Accuracy: ' num2str(trainaccuracy) '%']);

valOutputs = net(valInputs');
valPredictedLabels = vec2ind(valOutputs);
valActualLabels = vec2ind(valLabels);
valAccuracy = sum(valPredictedLabels == valActualLabels) / numel(valActualLabels) * 100;
disp(['Validation Accuracy: ' num2str(valAccuracy) '%']);

figure;
plotconfusion(testLabels, testOutputs);

figure;
plotperform(tr);

mse_val = mean((predictedLabels - actualLabels).^2);
disp(['Test MSE: ' num2str(mse_val)]);

rmse = sqrt(mse_val);
disp(['Test RMSE: ' num2str(rmse)]);
```