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The potential of implementing AI-driven quality control in Ukrainian investment casting facilities

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Потенціал впровадження контролю якості на основі ШІ в українських цехах лиття за витоплюваними моделями

Abstract. *The purpose of this study is to assess how AI can reduce energy consumption, labor intensity, and scrap rates, thereby improving yield and long-term operational efficiency of investment casting foundries. The methodology includes a literature review and feasibility analysis conducted using recent academic studies and industry case reports from 2013 to 2024. Additionally, the study conducted a basic cost-benefit analysis comparing implementation expenses with potential annual savings in scrap reduction, labor optimization, and material efficiency. Findings indicate that key AI applications include process-parameter modeling and machine learning prediction, and automated defect detection through deep learning-based visual and radiographic inspection. Research shows that AI systems can reduce casting defects by 30–50%, with substantial savings in labor and material costs. The study highlights low-cost and open-source options for AI deployment, increasing accessibility for resource-constrained facilities. The originality of the paper is its emphasis on the practical implementation of AI-driven quality control solutions for Ukrainian foundries, investment casting facilities in particular. The practical value of the study lies in a structured, actionable roadmap, including software and hardware requirements, and cost and ROI estimates, that can assist local foundries in beginning their Industry 4.0 transition with a focus on quality optimization.*
Key words: *artificial intelligence, investment casting, quality control, defect detection, Ukrainian foundries, cost-benefit analysis, process optimization.*

Анотація. *Метою цього дослідження є оцінка того, як штучний інтелект (ШІ) може знизити споживання енергії, трудомісткість і рівень браку, тим самим підвищуючи вихід придатної продукції та довгострокову операційну ефективність ливарних підприємств. Методика дослідження включає огляд наукової літератури та аналіз доцільності на основі актуальних академічних досліджень і галузевих кейсів за період з 2013 по 2024 рік. Крім того, проведено базовий аналіз витрат і вигод, що порівнює витрати на впровадження ШІ з потенційними щорічними заощадженнями завдяки зменшенню браку, оптимізації праці та підвищенню ефективності використання матеріалів. Результати показують, що основними напрямами застосування ШІ є моделювання технологічних параметрів та прогнозування за допомогою машинного навчання, а також автоматизоване виявлення дефектів на основі глибокого навчання з використанням візуального та рентгенографічного контролю. Дослідження демонструють, що ШІ-системи можуть знизити кількість дефектів лиття на 30–50% і забезпечити значну економію витрат на оплату праці та матеріали. У дослідженні пропонуються доступні та відкриті програмні рішення, що підвищує можливість впровадження ШІ в умовах обмеженого бюджету. Наукова новизна роботи полягає в акценті на практичному впровадженні рішень контролю якості на основі ШІ саме на українських ливарних підприємствах, зокрема тих, що займаються литтям за витоплюваними моделями. Практична значущість дослідження полягає у створенні структурованої та прикладної дорожньої карти впровадження ШІ, яка включає вимоги до програмного й апаратного забезпечення, орієнтовні витрати та оцінку окупності інвестицій. Це може допомогти українським ливарним підприємствам розпочати перехід до Індустрії 4.0 з акцентом на оптимізацію якості.*
Ключові слова: *штучний інтелект, лиття за витоплюваними моделями, контроль якості, виявлення дефектів, українські ливарні підприємства, аналіз витрат і вигод, оптимізація процесів.*

Introduction. The foundry industry is undergoing a transformation driven by artificial intelligence (AI) and Industry 4.0 technologies. Traditionally considered a complex and heuristic-driven domain, metal casting now benefits from data-driven insights for improved efficiency and quality. Recent surveys highlight an abundance of research applying AI techniques (e.g., neural networks, fuzzy logic, evolutionary algorithms) across various casting processes (sand, die, continuous, and investment casting) [1]. The goals range from optimizing process parameters and product design to predictive quality assurance. This review provides an overview of key AI use case categories in foundries and the most documented use case – quality control and defect detection – focusing on investment casting.

Literature review. Quality control is paramount in investment casting, and AI has made significant inroads in recent years. Traditional quality control in investment casting relies on expert knowledge, simulation tools, and post-process inspections (like X-ray for internal defects or destructive tensile tests for properties). These methods are time-consuming and often catch problems only after a part is made. AI techniques, by contrast, enable predictive and automated quality control – identifying issues earlier or preventing them.

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This review summarizes several key studies (spanning 2013 to 2024) demonstrating AI applications broadly grouped into: (a) process-parameter modeling and optimization for quality outcomes, and (b) automated inspection and defect identification.

On the modeling side, a number of works have used data-driven models to capture the relationship between process parameters and final part quality. For example, Pattnaik et al. [2] optimized the wax pattern production step using a grey–fuzzy logic approach, which significantly improved the wax pattern quality (in terms of dimensional accuracy and surface finish).

Improved wax patterns lead to better final castings, since defects often originate in the pattern or mold. Another pioneering work by Sata & Ravi [3] collected data from 800 heats of steel alloy investment castings and used an ANN to predict mechanical properties (like tensile strength and yield strength) from process parameters and alloy composition. This allowed them to estimate if a casting would meet strength requirements without waiting for lengthy destructive tests; notably, both their ANN and a multivariate regression were fairly accurate, with the ANN being a viable tool for predictive quality control.

Expanding on defect prediction, Sata [4] developed a system to predict the occurrence of common defects in steel investment castings (such as ceramic inclusions, misruns, shrinkage porosity, etc.) using production data. By applying principal component analysis (PCA) to 24 process and composition variables from 500 casting batches, then feeding the reduced data into various ANN models, the study could forecast defect types before casting. The best model (an ANN with a Levenberg–Marquardt learning algorithm) outperformed statistical regression in accuracy. Such a model can warn engineers if a given batch is likely to produce defects, enabling preemptive adjustments.

Similarly, Wang et al. [5] reported using an ensemble of machine learning classifiers to predict final dimensional accuracy of complex cast parts early in the process. Their framework provides an early warning if a casting is predicted to be dimensionally out-of-tolerance, allowing corrections or mold changes to be made in subsequent cycles.

On the inspection side, deep learning has revolutionized how foundries perform quality inspection for investment castings. Yousef & Sata [6] developed an intelligent inspection system for investment cast steel parts using deep CNN models. By training on a large image dataset of cast components (with and without defects), their system could automatically detect surface defects like cracks, cold shuts, and other discontinuities. Among the models evaluated, a residual neural network (ResNet) achieved the highest accuracy in defect recognition and was integrated into a real production line. This reduced the reliance on manual visual inspections and improved the consistency of defect detection.

Another line of research has applied computer vision to X-ray radiographs of investment castings to automatically detect internal porosity or inclusions using deep learning, effectively automating radiographic inspection, which is critical for safety-critical steel components [5].

Collectively, these studies prove that AI is enabling a shift from reactive to proactive quality control in investment casting. Instead of inspecting and scrapping defective steel castings post-production, foundries can now predict and avoid defects, optimize process conditions for quality, and efficiently screen for any anomalies with automated vision systems. This leads to a higher yield of acceptable parts and lower production costs. It also shortens the feedback loop in foundry process development: data-driven models can quickly highlight which process factors most strongly affect quality, guiding engineers to focus on the right levers (for instance, a model might reveal that a slight increase in preheat temperature drastically reduces shell cracking defects).

Finally, an emerging trend is the integration of these AI tools into a digital twin of the investment casting process. In a recent study, researchers built a digital twin for a steel investment casting line that incorporated machine learning models for defect prediction and real-time process optimization. This allowed them not only to predict defects and mechanical properties with high fidelity, but also to prescribe corrective actions during the casting process [5].

Study purpose and objectives. The goal of this study is to explore the potential of implementing AI-driven quality control at a Ukrainian investment casting facility to lower energy, labor, and resource spending, increase productivity, and achieve long-term financial benefits. The core tasks included the research of successful AI-powered quality control cases, the creation of a basic software and hardware requirements list, as well as the calculation of estimated spending and potential economic benefits.

Methodology. This study employs a review and applied feasibility analysis approach to assess the potential implementation of AI-driven quality control systems in a Ukrainian investment casting facility. The research methodology was divided into three primary stages.

First, a comprehensive literature review was conducted, focusing on peer-reviewed academic sources indexed in Scopus and Web of Science, as well as technical whitepapers from leading industrial AI vendors. The literature review covered the years 2013 to 2024.

Second, based on insights from the literature, a baseline implementation framework was developed to assess practical feasibility. This included the identification of data requirements, hardware and software specifications, and potential local or regional vendors for equipment and support. Open-source software solutions and modular, scalable hardware components were prioritized to reflect the constrained budgets typical of small-to-medium Ukrainian foundries.

Third, an economic impact estimation was performed. This involved a basic cost-benefit analysis comparing implementation expenses with potential annual savings in scrap reduction, labor optimization, and material efficiency. The ROI model was constructed using industry benchmarks and case studies cited in the literature, with conservative assumptions for production volumes and defect rates to ensure realistic forecasting.

Findings. A Ukrainian investment casting foundry can improve quality and reduce scrap by introducing affordable AI-driven inspection and process monitoring. The findings below outline data collection, hardware, software, and economic benefits.

Implementing AI-driven quality assessment at a Ukrainian investment foundry facility would necessitate the collection of the following types of data:

Visual inspection data: high-resolution images of wax patterns, cores, wax trees, molds, and cast parts. Multiple images per part (capturing all surfaces and angles) are collected to spot surface defects like cracks, misruns, or roughness.

Sensor data: melt temperature, chemistry parameters, mold preheat temperature, pouring time, shell cooling rate, etc.

Non-destructive testing data: X-ray radiography, dye penetrant inspection with imaging under UV light, etc.

Based on the training data input requirements and AI model development and implementation, the basic hardware requirements were estimated in Table 1 and software requirements in Table 2.

Table 1 — Hardware requirements for implementing AI-powered quality control in an investment casting foundry.

Category	Equpment	Requirements	Vendors
Cameras and lighting	Industrial vision camera	1080p or higher IP-rated casings to shield from dust and heat 2 pcs	Basler, IDS, Visiobit, PromAutomation, Pixlab
	LED light enclosure	Shadow and glare-free	Phillips, OSRAM
Sensors and IoT devices	Thermocouple (with data logger)	Real-time data logging	Siemens, Schneider Electric, Endress+Hauser
	Microcontroller	Heat shielding Wireless transmission	Arduino, Raspberry Pi, ASUS Tinker Board
Computing hardware	Industrial computer	CPU with GPU acceleration Ventilated cabinet UPS backup power Ethernet connection	NVIDIA GTX/RTX series, NVIDIA Jetson Nano or Xavier

Table 2 — Software requirements for implementing AI-powered quality control in an investment casting foundry.

Application	Software solutions	Additional requirements	Examples
Image preprocessing	Open-source libraries	Cropping, contrast enhancement, background removal	OpenCV
Defect recognition	Convolutional neural network (CNN)	Labeled images of quality and defective castings	ResNet Xception YOLOv5 TensorFlow PyTorch
Data analysis and forecasting	Regression or classification algorithms, ANN model	Historical manufacturing process sensor data	Scikit-learn Python library
Integration and user interface	Cloud-based or on-premise dashboard application	Real-time monitoring, data logging, integration with existing software ecosystem	Node-RED dashboard Microsoft Azure IoT Hub Azure Custom Vision

Initially, the models require training on a dataset of defect-free and defective parts (including minor and major defect examples). Some defects may need to be manufactured deliberately in trial castings or use historical scrap parts to build a robust training set. The model will require periodical updates if a new defect type starts appearing or a new product line is introduced. However, the system can continuously learn, as modern AI platforms enable adding new sample images and re-training with little effort, improving accuracy over time.

Alternatively, Ukrainian foundries can rely on commercial solutions from EU vendors. Norican's Monitizer platform is one (used by foundries in Spain, Japan, etc.), focusing on AI for casting processes. Another example is Tvarit AI (Germany), which provides an AI platform for die casting and could potentially be applied to investment casting, emphasizing scrap reduction through data analysis.

Discussion. Considering the significant financial and time investment required to implement AI-driven quality control in Ukrainian foundries, a careful calculation of estimated cost (Table 3) and economic benefits, including a return on investment, is necessary to facilitate decision-making.

Table 3 — Estimated cost of AI-powered quality control setup.

Software and hardware expenses	Estimated cost
Industrial camera(s) and lens	€2000
Lighting and enclosure	€1000
Industrial computer with GPU	€4000
Sensors and DAQ devices	€1000
Software development	€4000–€10000
X-ray unit	€20000–€30000
Other expenses	€2000
Total	€34000-€50000

Additional annual costs can amount to €1000–€3000 in software maintenance and updates, cloud service subscriptions, storage upgrades, light replacement, and camera calibration.

The estimated economic benefits of AI-powered quality control implementation result from:

Yield improvement and scrap reduction. AI-driven process optimization cuts scrap by 40–50% on average. In an investment casting context with higher part cost, even a 10% scrap reduction could translate to significant savings given the expensive alloy and energy per part. Moreover, if wax pattern inspection is automated, defective patterns can be recycled before investing labor and material in making a casting to improve the yield and reduce wasted metal.

Labor cost savings. Implementing AI vision can halve the manual effort needed for inspection. AI can do the first-pass filtering 24/7, minimizing human oversight, including overtime, and reducing wage expenses.

Energy and materials savings. Reducing scrap prevents resource waste on remelting, pouring, and heat treatment. AI-driven optimization improves process efficiency by recommending optimal pouring temperature and other technological parameters and lowers energy usage and emissions in foundries.

The estimated first-year ROI of AI-driven quality control implementation in an investment casting facility depends on its annual production, cost per part, the scrap rate, labor cost, and energy and materials used:

$$ROI = \frac{(S \times C + L + M) - I}{I} \times 100\% \quad (1)$$

Where S – scrap savings, pcs;
C – part cost;
L – labor savings;
M – energy and material savings;
I – initial investment

Conclusion. AI techniques enhance each stage of quality control in investment casting. From optimizing the wax patterns to predicting final part properties and defects, and finally automating the inspection of cast parts, AI provides a toolkit for elevating quality and consistency. These methods are complementary: a foundry could use predictive models to adjust process settings before pouring, and then use deep learning inspection to catch any anomalies on the finished part. Based on successful implementation cases, this study provides a comprehensive roadmap of AI-driven quality control implementation, including hardware and software requirements with potential vendors. The cost-benefit analysis incorporates estimated expenses and savings and a formular for calculating first-year ROI.

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