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VISHAL B. BHAGWAT[1,2*], DHANPAL A. KAMBLE[1], SANDEEP S. KORE[1]

AN OVERVIEW OF MACHINE LEARNING APPLICATIONS IN METAL CASTING INDUSTRIES

This paper presents an overview of different machine learning (ML) techniques and algorithms implemented in metal casting industries. ML has made significant contributions to the field of metal casting by improving various aspects of the casting process. In this work, referred quality research papers are divided into two categories. Firstly, work reviewed for the automation in foundry and quality control. Secondly, the raw material melting, material designs and defect predictions in the metal casting. The literature is extensively studied for types of ML models implemented from 2010 to 2023 for the sand-casting application area especially in the prediction of material melting compositions, desired material properties and occurrence of defects along with involvement of advanced foundry technologies.

Keywords: Metal casting; Machine learning; artificial intelligence; quality control; defects prediction

1. Introduction

It should be highlighted that a completely automated foundry implementing the Smart Factory idea is currently implausible. However, it should be kept in mind that many industrial processes have recently been automated, which has reduced the involvement of operators slightly. A human is still a crucial component in foundry processes, despite having access to more tools that enhance decision-making. The increased demand for metal casting from a variety of industries has contributed significantly to the growth prospects of the worldwide foundry industry. The foundry industry, particularly in India, has experienced explosive expansion in recent years. As a result, India is being considered as a possible hub for multinational corporations looking to establish manufacturing bases abroad for the high-volume, low-cost manufacture of casting components. Models that integrate categorization and prediction techniques enable the acquisition of new production parameters without the need for extensive experimentation.

In summary, machine learning (ML) has significantly enhanced the metal casting industry by improving defect detection, process optimization, predictive maintenance, quality control, and various other aspects, leading to higher efficiency and product quality. The ongoing advancements in ML are likely to further transform the field in the coming years. Here's a review of its applications.

2. Automation in foundry and quality control

ML helps in optimizing energy consumption during the casting process, reducing environmental impact. It can minimize scrap and waste to save resources and costs. It may optimize the supply chain, ensuring timely delivery of raw materials and finished products assisting the foundry automation. Machine learning can predict equipment failures by monitoring sensor data, ensuring timely maintenance, and reducing downtime. It can also predict and control the quality of castings by analyzing historical data, ensuring consistency in product quality. TABLE 1 represents types of algorithms used for foundry automation and quality control.

The steps of data collection and preparation connected to the production process of Austempered Ductile Iron (ADI) cast iron were briefly described in this paper. The processes from the perspective of data mining tools were explained here like data cleaning, merging, reducing, and transforming the data. According to the authors' experience, connecting to CPPS (Cyber-Physical Production Systems) at later stages in relation to different casting production processes may be significantly hampered by the adoption of IoT measurement tools and procedures. The step of production data collection is crucial because it completely depends on data's accuracy and knowledge of the frequency of collection that is essential to create mathematical models and automate the process [1].

1 DEPARTMENT OF MECHANICAL ENGINEERING, VISHWAKARMA INSTITUTE OF INFORMATION TECHNOLOGY, PUNE, INDIA
2 DEPARTMENT OF MECHANICAL ENGINEERING, VIDYA PRATISHTHAN'S KAMALNAYAN BAJAJ INSTITUTE OF ENGINEERING & TECHNOLOGY, BARAMATI, INDIA

* Corresponding author: vishal.bhagwat@vpkbiet.org

Casting is a process that involves a number of transformations and poses a risk of failure. Any process failure causes a flaw in the casting, which ultimately causes the product rejection. Risk was present starting with the right pattern material, sand type, metal type, metal pouring temperature, and so on. The gap between the foundry's current situation and the equipment and techniques available to create castings without defects was highlighted in this study. There is a need to build a support system in the current industrial sector to help people at different stages of production in order to minimize its need for human interaction [2].

An investigation into the potential application of artificial intelligence (AI) in the alteration of the casting production process was conducted. The suggested solution included a model for the data and its illustration of how changing production parameters could affect the cost of metal casting. The cost function was introduced to the prediction model created and reported by Hazela et al. [3]. Computer simulation and a real experiment were used to validate the data that the model produced. It has been demonstrated that even for a smaller number of test results the machine learning techniques and computer simulation can model or reproduce a set of production process parameters. The number of genuine tests may be lowered as a result of this measure, which would lower costs and improve environmental protection [4].

Authors have explained two primary ways. First, a methodology for modifying ML classifiers to predict microshrinkages or ultimate tensile strength was put out, along with a description of the training process. A historical dataset from a genuine foundry process was used to assess the ML classifiers' performance and compare each method's accuracy and applicability. Iron casting foundry operations in detail have been discussed using machine learning methods like Bayesian network, K-nearest Neighbour (KNN) and backpropagation Multilayer Perceptron (MLP) algorithm of ANN. Experiments were conducted, the outcomes described for potential improvements to the casting processes, and finally the future scope was predicted [5].

A centerline segregation is an inherent flaw and can be exceedingly dangerous in steel cast products. The objective of this study was to develop a predictive hybrid model that might detect central segregation severity early on in continuous cast steel slabs by ML techniques. In this, the most crucial physical-chemical variables are tracked and examined. The support vector machines (SVMs) in conjunction with particle swarm optimization (PSO) technique were compared with PSO-MARS (multivariate adaptive regression splines) based models. The hybrid models of PSO-SVM with RBF (Radial Basis Function) kernel function were found superior to MLP and PSO-MARS-based models [6].

Authors have created a method based on data assimilation to predict the heat transfer coefficient (HTC). They conducted unidirectional casting experiments of an alloy with an Al-1 mass%Si content to get the cooling curves during solidification in order to comprehend its utility for calculating the time-dependent heat transfer coefficient. The average error values below 0.8% were found between the measured and simulated cooling curves. The impact of the data assimilation's configuration settings with ML models was assessed. The time-dependent HTC between the mold and the molten alloy can be reasonably estimated using this method without the need for trial and error method of estimation. The cooling curves measured experimentally can be precisely replicated by solidification analysis [7].

The most popular techniques for adjusting the microstructure to improve mechanical properties of aluminum alloys are alloying during melting and applying appropriate heat treatments after solidification. The data-driven ML technique, computational thermodynamics (CT) within the context of the phase diagram calculation method, and also their amalgamations have been best approaches for the design with the rapid development of computer technology. The CT-driven design of casting alloys in the Sc-additional Al-Si-Mg series, and the design of Sr-modified A356 alloys driven by ML was discussed with multiple case studies. Finally, it was discussed how merging CT and ML approaches could improve the computational design approach [8].

A scholarly research of ML methods on the study of continuous casting was presented in this publication in a view of monitoring and controlling complex processes. In order to identify common use cases and methodologies, first the existing work on ML in continuous casting of steel was addressed and later the common concepts into groups were synthesized. The analysis concluded with an explanation of the problems, possible fixes, and future prospects for other research avenues [9]. Fig. 1. shows types of ML models used in foundry automation and quality control.

Here researchers presented artificial intelligence techniques used to real-world quality assurance applications. The issue of production process control calls for the application of techniques such artificial neural networks, fuzzy logic, decision trees, rough set theory, and (CBR) case-based reasoning. Computational intelligence techniques were applied in foundry operations that gave approximated production parameters from experimental data, rules to be formalized as an algorithmic record and inference models to be constructed. However, their drawbacks were also mentioned related to ANN, CaRT (Classification and Regression Tree), fuzzy logic, CBR, etc. The distinct features of each approach enable the conclusion that utilizing multiple algorithms is the only way to provide the user with the full range of benefits [10].

In this research, authors showed how multi-objective optimization of low pressure die casting was achieved by combining ML with three-dimensional numerical simulations. The aim was to create and present a method for determining the beginning and wall temperatures in order to maximize the quality of the final product. The non-dominated sorting genetic algorithm (NSGA-II) was used for the optimization. In order to apply a surrogate model, a feed-forward MLP neural network was first trained using the outcomes of the numerical solution of the fluid flow and energy equations. Simpler representations of the real problem were created as an evaluation tool to confirm the genetic algorithm's findings [11].

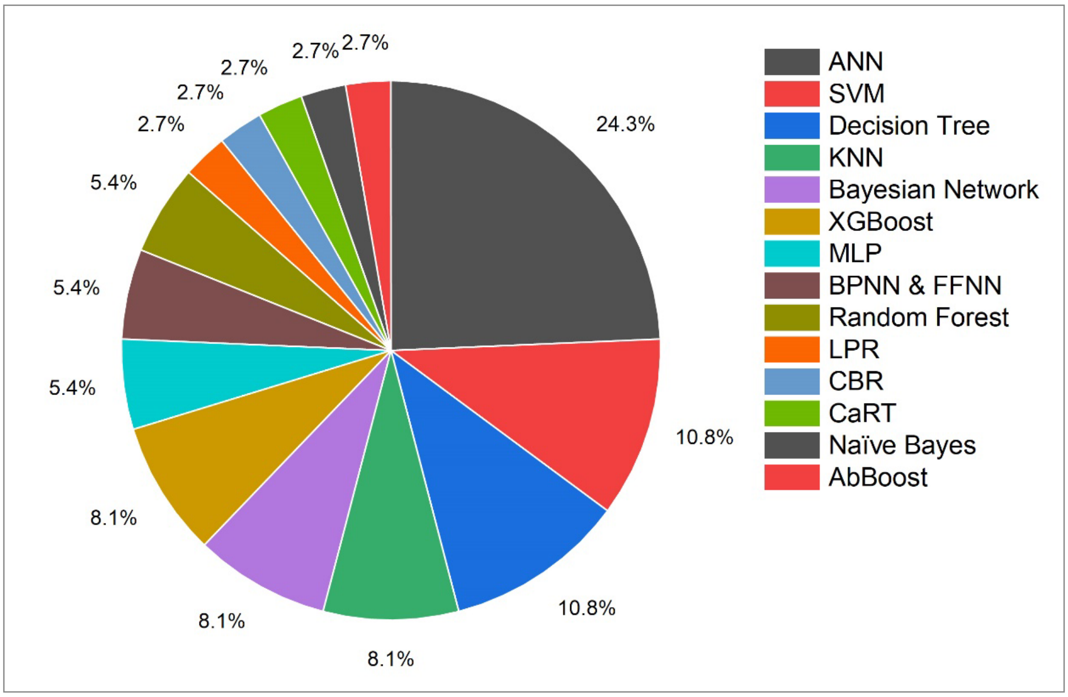

Fig. 1. Types of ML models used foundry automation and quality control

TABLE 1

Machine Learning methods used for automation in foundry and quality control

Authors, Year	Short Description	Machine Learning Methods/Algorithms
Y. Santos et al. (2010)	Applicability of ML models for potential improvement of casting processes	ANN, KNN, Bayesian Network
J. Zhao, X. Liu, A. Yang, and C. Du (2014)	Prediction of material properties for mechanical qualities	SVM, ANN
D. Wilk-Kołodziejczyk et al. (2016)	A method developed for increasing efficiency of computer assisted foundry processes	LPR, Bayesian Network
G. Rojek et al. (2016)	ML models for quality assurance application in foundry	ANN, Fuzzy NN, DT, CBR, CaRT
P.J. García Nieto et al. (2018)	Effect of physio-chemical variables on centerline segregation	SVM with RBF and MLP
S. Shahane et al. (2019)	Multi-objective optimization to maximize quality production	MLP FFNN (NSGA-II)
W. Yi, G. Liu, J. Gao, and L. Zhang (2021)	Calculation of phase diagrams using CT-ML framework	Naïve Bayes, Decision Tree (DT), KNN, ANN
L.L. Zhang et al. (2022)	Use of data mining tools in the CPPS on ADI	ANN
Bramahhazela et al. (2022)	Application of cost function to prediction model	ANN, Bayesian Network
D. Cemernek et al. (2022)	Application of ML models in continuous casting process	BPNN, FFNN, ANN, RF, DT
C.H. Lin, G.H. Hu, C.W. Ho, and C.Y. Hu (2022)	Prediction of quality for pressure castings by restricting defects	XGBoost with Savitzky-Golay filter
D. Wilk-Kołodziejczyk et al. (2023)	Modification of production parameters to lower cost and environmental protection	XGBoost
T. Uyan et al.(2023)	Quality improvement of LPDC products by supervised classification models	SVM, XGBoost with SMOTE
Y. Zhang, Z. Gao, J. Sun, and L. Liu (2023)	Prediction of quality for continuous casting process by controlling slag inclusion	KNN, AdaBoost, DT, RF, Support Vector classifiers, ANN

Here the paper elaborates on the aspects of different technologies and describes the application and development perspective about AI in foundry material design. The authors concentrated on how difficult it is to develop foundry materials and how to combine cutting-edge AI and machine learning research. Detailed discussion was given on statistical regression, ANN and support vector machine (SVM). Specifically, the ways in which artificial intelligence has been applied to the prediction of foundry material qualities are outlined [12].

The suggested method presents an opportunity to improve the efficiency of computer-assisted foundry processes with the adoption of AI-based information and decision-making systems.

Therefore, it may be claimed that the novel approach to handling the problems has given them a new dimension. The fact that the developed solutions form a methodology that is utilized to generate and maintain a knowledge base in the casting industry and other fields of material sciences confirms the scientific qualities of the solutions. The method employed based on decision making was compared with Bayesian Network and found different [13].

An automobile wheel castings of aluminum alloy are widely manufactured by low-pressure die casting (LPDC) but it often suffers with defects like porosity that are unacceptable. Process parameters need to be optimized to improve component quality by eliminating faults. This paper employed cloud-based industry 4.0 platforms for data extraction. Supervised machine learning classification models were suggested using these data to find the conditions that indicate defects in an actual foundry aluminum LPDC process. A model built on the XGBoost classification method was utilized to bridge the connection between the production of damaged wheel rims and process circumstances. This work helped to reduce defects in new product pre-series manufacturing by helping with process parameter adjustment [14].

One of the major aspects that affects quality is therefore the stability of the pressure inside the mold. So, the authors provided a machine learning-based press casting quality prediction technique. The data was smoothed using the Savitzky-Golay Filter, and the time interval was extracted using the first-order difference. Then XGBoost was used to build a classifier after extracting the important data that affects quality. Through the experiment it was seen that the method obtains a number of defectives closely and a good quality prediction accuracy. With this model authors claimed to save significant amounts of time and money, advance warnings of maintenance and defective products and lower the risk of shipment. It ultimately helps in maintaining reputation to increase its competitive advantage [15].

The goal of this case study was to create a machine-learning method that could use process condition sensor data to forecast slag inclusion faults in continuous-casting slabs. The machine-learning methods like K-Nearest Neighbors, AdaBoost, decision trees, random forests, support vector classifiers (linear and nonlinear kernels), and artificial neural networks have been employed. To address unequal data distribution, four oversampling or undersampling algorithms have been implemented. The optimized random forest fared better in the experiment than other machine-learning algorithms, which may offer insightful information for quality control [16].

3. Melting, material design and defect predictions

TABLE 2 represents types of algorithms used for material melting, design and defects prediction in sand casting. Machine learning assists in selecting the right material, designing phases by suggesting improvements in various parameters like strength, castability, heat resistance, and cost. To go through this, ML techniques can optimize casting parameters like pressure, temperature and mold design to enhance product quality and minimize defects. Machine learning models can analyze images of castings to detect defects like porosity, cracks, or inclusions. This helps in early identification and reduces the need for manual inspection. ML-based simulations can predict the behavior of molten metal during casting, aiding in mold design and process improvements.

In this article, a high-volume materials processing exemplar – high-pressure die-casting (HPDC) – was examined. In order to correctly estimate the prediction of good parts and process scrap as decided by the die-casting machine, a complete year production data of HPDC process over 950,000 machine cycles was considered. ML models like random forest and decision tree were used with and without synthetic minority oversampling techniques (SMOTE). Furthermore, the classification ML method employed for tensile specimens was used to forecast the ultimate tensile strength, and the key features found were addressed. Applications involving the processing of materials have been proven to benefit from supervised learning [17].

The work's objective was to determine how well-suited certain classification algorithms and their extensions are for evaluating castings' microstructure. A variety of settings and configurations as well as for a range of input data, including images of the microstructure or type and composition of material were evaluated in experiments. The scientific works on this topic demonstrated application of ML to evaluate the microstructure quality and resulting strength attributes of cast iron. Results from neural networks and traditional machine learning techniques were compared, taking into account factors like learning time, interpretability of results, model implementation ease, and algorithm simplicity [18].

In this work, the elemental composition and temperature were considered when utilizing four ML techniques to forecast the hot ductility of cast steel. Three different steel samples and four ML models were considered in the prediction. RMSE was used to assess the prediction accuracy of the four ML models. The NN model represents complex nonlinearity in a better manner and is found most suitable for prediction of hot ductility. These findings show how useful machine learning algorithms are for forecasting cast steels' hot ductility [19].

When the casting process is modeled as an expert knowledge cloud, ML algorithms that have been appropriately trained can predict the value of UTS. Authors have modified an ANN and the K-nearest-neighbor algorithm for the same goal, building on earlier research that showed excellent results using a Bayesian network-based approach. They compared the data and demonstrated that artificial neural networks were superior to their other counterparts in terms of accuracy in predicting UTS. Nevertheless, it is impossible to discount the potential of Bayesian theory, and more especially, the sensitivity module, as it is a useful technique that gives foundry plant operators a decision support system [20].

Fig. 2 shows types of ML/AI models used in material design, melting and defect prediction work of metal casting. It becomes very challenging to calculate the heat transfer coef-

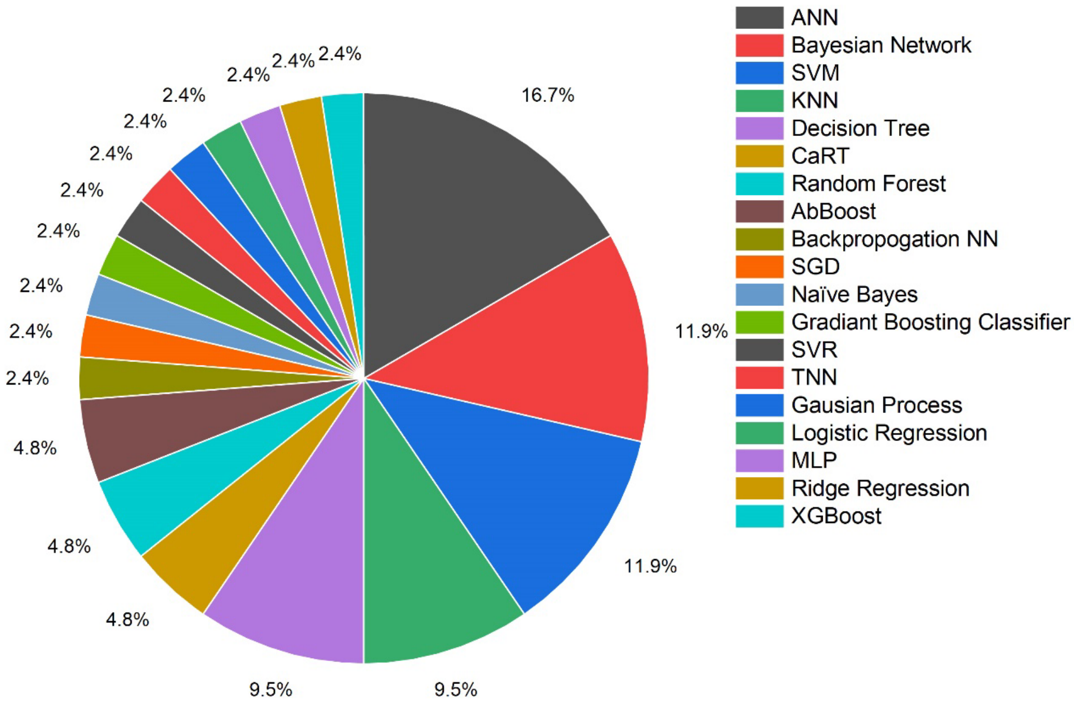

Fig. 2. Types of ML models used in material design, melting and defect prediction

ficient from experiments where the process is influenced by numerous factors like coating material, coating thickness, surface roughness, contacting pressure, oxide layer, gap formation due to casting and mold deformation, etc. This research employed a numerical simulation, back-propagation NN algorithm and inverse analysis based on recorded temperatures to determine the interfacial heat transfer coefficient (IHTC) between the metal mold and the casting. The findings demonstrated a good agreement between the numerically calculated and experimental temperatures. These showed that the inverse analysis method was a practical and useful tool for figuring out the casting-mold IHTC. Additionally, the time-varying IHTC's properties have been discussed [21]. In the steady state studies, a vertical fin standing on a horizontal plate was considered. A Bayesian framework powered by a Markov Chain Monte Carlo approach was employed in conjunction with the measured temperature distribution to estimate fin parameters and HTC and thermal conductivity. The approach described in this paper provides a useful foundation for estimating correlated parameters in inverse heat transfer simultaneously [22].

Experimental research of new materials has been carried out, which enables the production of alloys with cheap production costs and high-performance qualities. The research demonstrated a costly production of austempered ductile iron (ADI) substituting ausferritic ductile iron or bainitic nodular cast iron made with carbides, can be created without the need for casting heat treatment. The suggested methodology identifies material similarities and permits grouping different materials together. All 18 models failed to give good classification results; only clustering analysis allowed a classification group of similar material properties group [23].

The use of ML to regulate the melting of white cast iron metal is discussed in this research. Two supervised machine learning algorithms like SVR and NN were used. The aim was predicting the number of alloying additives to get the appropriate chemical composition. In the training and testing stages, the NN model outperformed the SVR model, making it suitable for use in the control of the production of white cast iron. The utilization of these technologies enhances production accuracy and efficiency, which aligns with the notion of creating intelligent foundries as a component of Industry 4.0 [24].

Authors have expanded use of ML techniques called deep neural networks to alloy solidification modeling in this paper. In light of this, theory-trained deep neural networks (TTNs) for solidification were presented. The fact that TTNs don't require external data for training or prior knowledge of the governing equations' solution is one of their key advantages. Networks with varying widths and depths are trained using TensorFlow's built-in features, and their predictions are carefully analyzed to ensure that they meet the benchmark problem's initial/boundary conditions as well as the model equations. This study demonstrates that TTNs are a practical tool for simulating alloy solidification issues [25].

In this article, ML technique was used for predicting micro-shrinkage defects without loss of UTS in foundry operations. Different machine learning classifiers and regression were compared for determining the ultimate tensile strength and micro shrinkage. Bayesian networks performed best in micro-shrinkage production, while the ANN method performed very well in ultimate tensile production. The optimum strategy of Bayesian theorem was presented in insensitive instances. The Bayesian theorem yields extraordinarily accurate outcomes.

Furthermore, in comparison to all other algorithms, they were around 82% accurate [3]. Accurate casting design is required to eliminate issues that could arise during the shrinkage step and result in the part being rejected. With the numerical outcomes of the finite element simulation casting modeling, a neural network called NNSHRINK was trained. This study described how a hollow cylinder part's casting process' output characteristics were predicted using a neural network both for forecasting and designing the process. The production chain can be shortened by the casting process designers by estimating the precision of the cast pieces with the aid of a trained neural network with numerical and experimental capabilities [26].

In high-precision foundries, micro-shrinkages are regarded as possibly the most challenging faults to prevent. Properly trained ML algorithms may predict the value of a given variable by modeling the foundry process as an expert knowledge cloud. Building on earlier work that showed exceptional outcomes using a Bayesian network-based methodology, authors have modified and examined ANN and the KNN technique for the same goal. A comparative analysis of the acquired results was presented and demonstrated that Bayesian networks outperform their counterparts in terms of suitability for micro-shrinkage prediction [27].

Surface defects are one kind of imperfection that can occur in castings; this work focused specifically on inclusions, cold laps, and misruns. Authors claimed that this approach yields high rates of precision. A new machine vision and machine learning based method was suggested to identify and classify surface defects in iron castings. Retrieving photos from the tested castings was the first step in this method. Subsequently, the segmentation technique pinpointed every potential flaw present in the castings. Ultimately, the potential flaw is categorized as inclusion, cold lap, misrun, or repair using machine learning algorithms. The results of the experiment demonstrated that even though classification accuracy was very good. SVM and KNN was used to trained image data and SVM model found more accurate in predicting results [28-29].

The main non-destructive testing technique for finding flaws in a casting component is now X-ray testing. X-ray images having casting defects were stored in the InteCAST dataset. A comparison of 24 practicable methods for computer-aided X-ray picture defect detection was published in this research. The study assessed eight ML models, including Random Forest, SGD, SVM, Naïve Bayes, AdaBoost, and Gradient Boosting classifiers, together with three feature engineering techniques: Gabor, HOG, and LBP. The results of the experiment showed that an ensemble learning model and LBP feature achieved the best performance, indicating that the suggested approach offers a useful guide for resolving issues with manual detection. Experimental findings

TABLE 2

Machine Learning methods used for melting, material design and defects prediction

Authors, Year	Short Description	Machine Learning Methods/Algorithms
I. Santos, J. Nieves (2009)	Prediction of UTS by unsupervised learning decision support system	ANN, KNN, Bayesian Network
L. Zhang et al. (2010)	Determination of IHTC and comparison of simulation and inverse analysis	Backpropagation NN
N. Gnanasekaran and C. Balaji (2011)	Prediction of HTC and thermal conductivity	Bayesian Network
I. Pastor-López et al. (2012)	Detection of surface defects by machine vision system	Bayesian Network, DT, KNN, SVM
F. Susac et al. (2014)	Prediction of shrinkage by monitoring thermomechanical field	ANN
I. Santos et al. (2014)	Prediction of microshrinkage and modelling high precision casting	ANN, KNN, Bayesian Network
D. Wilk-Kolodziejczyk et al. (2016)	Comparative analysis of material properties and grouping by supervised and unsupervised learning	ANN, KNN, CaRT, SVM
X. Wu et al. (2019)	Detection of X-ray image subsurface defects by supervised classifiers	SVM, SGD, RF, Naïve Bayes, AdBoost, Gradient Boosting Classifiers
N. Dučić et al. (2020)	Controlling of melting and production of white cast iron	SVR, NN
M. Torabi Rad et al. (2020)	Alloy solidification modelling study by deep learning network using Tensorflow	TTNs
D. Hong, S. Kwon, and C. Yim (2021)	Prediction of hot ductility of cast steel using temperature and chemical composition data	RF, Gaussian Process, SVM, NN
A. E. Kopper and D. Apelian (2022)	Prediction of ultimate tensile strength (UTS) and porosity by supervised learning	Decision Tree (DT), Random forest (RF) with SMOTE
K. Jaśkowiec et al. (2022)	Comparison of microstructure images for predicting material property by supervised learning	SVM, RF, DT, Logistic regression, CaRT, MLP AdaBoost
Bramahhazela et al. (2022)	Prediction of UTS and microshrinkage by supervised classifier and regression	ANN, Bayesian Network
S. Chen and T. Kaufmann (2022)	Detection of surface defect due to metal penetration in steel and cast-iron castings	Ridge regression, RF, XGBoost, Gradient Boosting, CatBoost, Extra Randomized Tree Regression

demonstrated the LBP feature-based Gradient Boosting Classifier method, which achieves better accuracy and detects flaws easily. However, it has a tendency to overlook flaws that can be manually detected with ease [30].

The medium-sized steel and cast-iron foundry provided the data needed to create the model. The foundry produces components with weights ranging from 1 to 100 kg using steel and cast iron that are resistant to heat and wear. This contains all production-relevant data from the melting and casting process, mold creation, sand preparation, and data from the quality management department related to component quality. The information about the kind and quantity of components that were scrapped as a result of casting surface defects caused by metal penetrations was added to the dataset, tying the data together. Six distinct machine learning algorithms underwent training, and the SHAP framework was utilized to analyze the model outputs. Random forest models shows better performance in predicting surface roughness and mechanical properties whereas decision tree classifiers are found better in detecting types of defects [31-32].

4. Conclusion

Various machine learning techniques and algorithms are used by researchers for checking quality of production process, melting practices, material design and optimization, simulation and in defect predictions. For training these algorithms huge data is required. From the literature review it is found that ANN, SVM and Decision Tree are the commonly used ML models in the foundry automation and quality control methods whereas ANN, Bayesian Network and SVM are the commonly used models in material melting, design and defect predictions. It's clear that ANN and SVM are most suitable ML techniques for the confirmation of desired material properties and predicting defects in production of sand-casting process.

Applying multiple ML models is not enough. In fact, one need to check fitness of data with applicable kernels e.g. RBF, MLP. Also, in order to balance the not balanced classes, models can be trained with aids like SMOTE. Hence, the more numbers of models can be trained with different possibilities of characteristics or the results. Special casting processes must be studied with ML models as it has less threads in the previous literature.

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