Analysis of the application of artificial intelligence in the foundry industry

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Abstract: In view of the high complexity of casting production, combined with the research progress of artificial intelligence, this paper is discussed in detail. The application status and development direction of artificial intelligence in casting production are clarified, and the characteristics of various technologies are clarified. It is also pointed out that a variety of technologies should be combined to further automate foundry production and make artificial intelligence better. It is of great significance to improve productivity and casting quality.

Keywords:AI; artificial intelligence; machine learning; algorithm; review paper

1 Introduction

Casting production is a complex process involving multiple steps—such as design, molding, melting, and pouring—as well as various aspects like techniques, alloys, equipment, and inspection. As a result, the requirements for casting production are highly demanding. Foundry engineers have been striving to improve automation, production efficiency, yield rates, and the performance of cast components. However, in practice, production still largely relies on semi-empirical approaches for guidance. Although traditional theories have achieved significant progress, their application is often limited due to discrepancies between experimental and actual

production conditions, as well as the variability of production environments.

Artificial intelligence (AI) refers to the ability of intelligent machines to perform functions typically associated with human cognition, such as judgment, reasoning, verification ,recognition, perception, comprehension, thinking, learning, and problem-solving. Its goal is to study how machines can simulate and execute human-like intellectual functions, along with developing relevant theories and technologies. Thanks to their capabilities in self-learning, reasoning, judgment, and adaptability, AI systems have been widely adopted across various industries with remarkable success.

Similarly, AI technology has been successfully applied in casting production, including anomaly prediction, process optimization, defect analysis, and quality inspection, significantly improving production efficiency and delivering substantial economic sda dsada benefits. This article summarizes the key applications of AI in current casting production and provides insights into future development prospects.

2 Examples of using Ai in foundry

Machine Learning for Anomaly Prediction in Continuous Casting: Breakout Forecasting In continuous casting production, excessive casting speed, inadequate lubrication performance of mold flux, and molten steel level fluctuations may cause the initial solidifying shell to stick to the copper mold plates, leading to breakout accidents. Currently, most enterprises install thermocouples on the mold plates and analyze temperature data with predefined thresholds to predict sticking-type breakouts. However, this traditional logic-based method suffers from high false alarm rates. Researchers aim to utilize breakout data for machine learning to establish a more accurate forecasting system.

The key to building an effective breakout prediction model lies in accurately capturing temperature variations from thermocouples. Liu Y. et al.[1] discovered that the propagation of sticking zones exhibits a distinct "V-shaped" pattern in both transverse and longitudinal directions. In subsequent work[2], they incorporated the geometric and dynamic characteristics of abnormal zones into machine learning models, achieving a 100% detection rate (64 true alarms in production samples) with only 2 false alarms—significantly lower than the 195 false alarms generated by conventional systems. Wang Y.Y. et al.[3] further enhanced this approach by integrating casting speed (Vc) with geometric features of sticking zones (height H, width W, area S, vertical propagation rate Vx, and horizontal propagation rate Vy) into a generative adversarial network (GAN).

Their feature extraction process (Fig. 1) involved: (1) visualizing temperature change

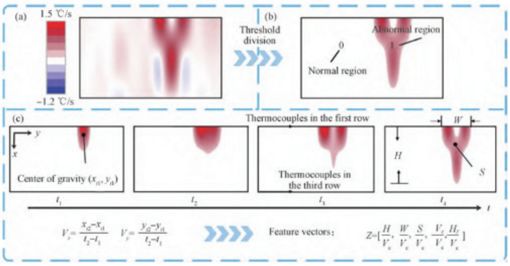

Fig.1:Featire extraction based on geometric and moving characteristics of sticking breakout region

rates to determine optimal thresholds for zone classification, and (2) constructing feature vectors combining process parameters and sticking characteristics to improve model stability under varying casting speeds.

During breakout alarms, thermocouple temperature-time curves typically show a rise-fall trend. Machine learning models can learn these temporal patterns to replace logic-based decisions. HeF.et al.[4] trained a backpropagation (BP) neural network using 30 consecutive temperature samples from single thermocouples and combined its predictions with logic judgments to enhance system robustness. Wang Rongrong et al. [5] developed separate models for single- and multi-thermocouple systems based on temporal and spatial features, proposing future integration of both strategies for higher accuracy.

Notably, temporal features of thermocouple data may shift due to process parameter variations. Duan H.Y. et al.[6–7] addressed this by employing dynamic time warping (DTW) instead of Euclidean distance to measure similarity in temperature sequences, significantly improving model robustness under complex operating conditions. Although breakout incidents are rare, existing studies demonstrate promising prediction accuracy even with limited training data. These advancements highlight the practical advantages of deploying machine learning models for real-time breakout forecasting in industrial production.

To address the inefficiencies and susceptibility to human error inherent in traditional casting simulation workflows, Zhang and his research team developed a voxel-based defect identification technology leveraging direct volume rendering. This innovative approach provides structured data support for machine learning applications to enhance casting defect prediction accuracy.

The study establishes voxels as the fundamental 3D data field units for representing physical parameter distributions. As figure2, through spherical marker bodies and coordinate system transformations with adjustable radius parameters, the technology achieves precise voxel localization. The enhanced simulation workflow incorporates two novel stages - interactive defect marking and machine learning integration - enabling analysts to tag defective voxels using intuitive tools. These annotated datasets then train machine learning algorithms to refine both simulation models and visualizationoutputs.

Fig.2:Positioning methods in two-dimensional and three-dimensional scenarios.

The direct volume rendering implementation overcomes limitations of conventional surface rendering by simultaneously displaying comprehensive 3D field data (e.g., temperature gradients). The interactive marking system preserves expert knowledge through natural mouse/keyboard inputs while creating valuable training databases. Practical applications demonstrate the system's effectiveness in identifying shrinkage cavities and porosity defects, with quantitative analysis capabilities (e.g., 672 voxels representing 672 cm^3 defect volumes).

This research validates the technology's pivotal role in advancing intelligent casting simulation and digital transformation. By establishing reliable foundations for machine learning applications in process optimization and defect classification, the work simultaneously highlights future improvement directions focusing on data quality enhancement and model generalization capabilities. The team's approach significantly bridges the gap between empirical foundry knowledge and data-driven manufacturing solutions.

Defects such as slag inclusions, cracks, and depressions significantly impact the quality of cast billets and the production efficiency of subsequent rolling processes. The collection of data (e.g., composition, temperature) from various sensors in continuous casting provides a rich data foundation for the application of machine learning technologies. By employing machine learning methods for efficient detection of billet quality (or defects) and reducing reliance on manual inspection, this approach holds broad application prospects and significant economic value.

This section elaborates on machine learning applications for billet defect detection from two perspectives: visual inspection and process parameter monitoring.

Deep learning-based automated and high-precision defect detection can be achieved by collecting billet image data. However, the complex production environment of continuous casting—characterized by water mist, dust, and signal interference—often introduces Gaussian or salt-and-pepper noise into captured images. Therefore, prior to model training, image denoising, enhancement, and segmentation are necessary to improve recognition accuracy. Reference [8] details the image acquisition and preprocessing steps in visual inspection, summarized in Figure 3. 3

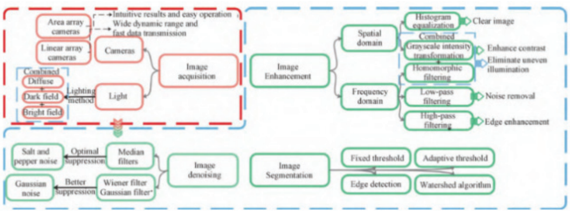

Fig.3:Techniques employed in image acqusition and processing stages

Even under variations and occlusions, the ResNet CNN architecture demonstrates excellent classification capabilities[9]. Additionally, pixel-level classifiers such as U-Net and Residual U-Net have shown potential in detecting and classifying billet defects [10].

However, traditional deep CNNs involve numerous parameters, leading to high computational and storage demands, which hinder deployment in resource-constrained environments. By adopting lightweight architectures like SqueezeNet with global average pooling (GAP) replacing fully connected layers, computational efficiency can be improved. Further enhancements include fine-tuning shallow features with high learning rates and incorporating MRF modules to strengthen high-level feature discrimination, enabling accurate defect classification at high speeds (>100 fps) [11].

The YOLO (You Only Look Once) series, as a variant of CNNs, is renowned for its rapid detection speed, making it suitable for real-time billet defect detection in continuous casting[12–14]. Building on this, researchers proposed a YOLOv5-based method for detecting corner cracks in billets, with the key workflow illustrated in Figure 4[15]. By integrating ShuffleNet v2 into the backbone and replacing max pooling with Focus layers to enhance feature extraction, the proposed YOLOv5-SFA model achieved detection accuracy comparable to manual inspection. Notably, despite training on only 100 images, the model achieved a detection rate of 99.64%, outperforming existing models while significantly improving training efficiency.

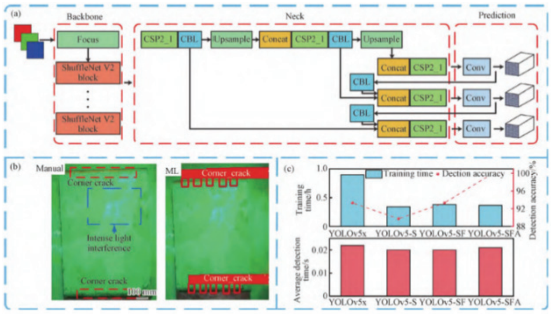

Fig.4:A rapid detection process for corner cracks in slab based on YOLOv5-SFA algorithm.

This study utilized data from literature and experiments to establish a "composition-mechanical properties" prediction model for non-heat-treated die-cast aluminum alloys using LASSO regression and various machine learning methods (BP neural network, random forest, Adaboost, and support vector machine). LASSO regression analyzed the influence of 10 alloying elements on yield strength, tensile strength, and elongation, and developed a linear prediction model for small compositional variations. Among the nonlinear machine learning models, the BP neural network demonstrated the best performance in predicting yield strength and elongation, while the random forest model achieved the highest accuracy in predicting tensile strength. The results indicate that combining the BP neural network and random forest models enables high-precision prediction of the mechanical properties of aluminum alloys, providing an efficient data-driven approach for the composition design and optimization of non-heat-treated aluminum alloys Traditional process parameter optimization typically requires complex calculations and significant time investment. By applying a certain amount of production data to machine learning, researchers can leverage models to capture the nonlinear coupling relationships between process parameters, thereby identifying potential issues and opportunities for improvement in production. With such models, process optimization and parameter adjustment can be conducted more efficiently, enhancing production stability and product consistency while avoiding errors caused by the subjectivity of manual operations.

Since trained models can identify key factors affecting slab quality, exploring machine learning approaches to discover parameter information beneficial to slab quality enables offline optimization of continuous casting processes. However, most machine learning models (such as neural networks, ensemble algorithms, and support vector machines) prioritize prediction performance while lacking interpretability, making it difficult for researchers to extract useful insights directly from such black-box models. Decision trees, as an earlier machine learning algorithm, possess strong interpretability due to their hierarchical decision structure. LOGUNOVA O S et al. [16] embedded adaptive fuzzy decision trees into expert systems to assist in analyzing factors contributing to slab defects, providing a basis for process adjustments. However, decision trees are inherently sensitive to outliers and noisy data, suffering from poor generalization ability, which may reduce model prediction performance. Moreover, if the constructed decision tree structure is too deep, model visualization and interpretability become more complex, potentially compromising their original explanatory power.

With the development of model interpretation tools, combining them with predictive models can compensate for the lack of interpretability in the models themselves [17–18]. Through sensitivity analysis, contribution analysis, and other methods, researchers can improve prediction accuracy while deepening their understanding of the data. TAKALO-MATTILA J et al. [19] applied SHAP values to visualize a trained gradient boosting tree (GBDT) model in slab defect prediction, qualitatively analyzing different sample parameters and their corresponding SHAP values to explore potential relationships between process input parameters and surface defects. Additionally, JI Y et al. [20] comprehensively evaluated feature importance based on average information gain and SHAP values, then used partial dependence plots to quantitatively infer the impact of specific features on slag entrapment defects while keeping other features constant, as shown in Figure 5.

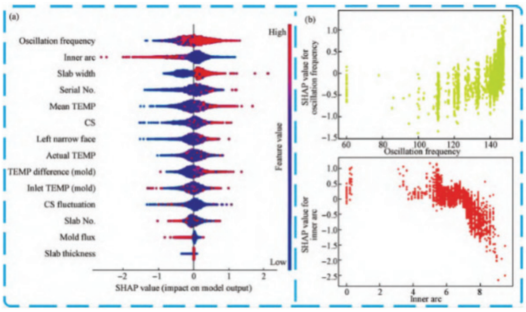

Fig.5:Feature analysis based on SHAP algoritm.

This method has strong practical applicability for data mining, providing new insights for process control and optimization across various steel grades. Researchers can adjust appropriate process parameters based on the analysis results to improve product quality.

Unlike offline optimization, online process optimization requires models to respond promptly to changes during production to ensure slab production stability. This places high demands on the predictive capability of the constructed models and the timeliness of signal transmission. Furthermore, to address noise (e.g., measurement errors) and unexpected events (e.g., sticker breakouts, nozzle clogging) in the production environment, researchers must continuously adjust and improve model robustness and fault tolerance, enabling the models to adapt to the complex and dynamic continuous casting production environment.

Currently, research cases applying machine learning to online process optimization in continuous casting are relatively limited but hold broad potential. GREŠOVNIK I et al. [21–23] used laboratory numerical simulation results to train artificial neural networks (ANNs), employed prior knowledge to determine boundary conditions, and ultimately approximated responses to obtain optimal combinations of process parameters such as casting speed and pouring temperature. Considering that ANNs may introduce issues like excessive parameters and overfitting when handling nonlinear problems, MIRIYALAS[23]developed the TRANSFORM-ANN model to balance overfitting and prediction accuracy, combining it with the non-dominated sorting genetic algorithm (NSGA-II) for multi-objective optimization in continuous casting production to achieve maximum production efficiency, energy savings, and minimal operating costs.

With the continuous development and refinement of algorithms, researchers can also explore reinforcement learning to enable models to self-adjust during actual production to adapt to changing process conditions.

Ensemble strategies can also be adopted, coupling multiple models to reduce the risk of errors from single-model decisions and improve overall model stability. However, further exploration is needed to better implement machine learning for online optimization strategies in continuous casting processes. In the future, integrating machine learning with physical models, big data, and edge computing—leveraging digital twin technology to enable self-adjustment and self-learning without human intervention—will continuously optimize production processes, significantly enhancing the efficiency of continuous casting process optimization.

3 Results and discussion

Currently, artificial intelligence (AI) technologies are reshaping the technical framework of the traditional casting industry, with applications expanding from continuous casting to the entire production chain. In the field of intelligent continuous casting, machine learning not only enables highly accurate predictions of abnormal operating conditions (with a 30%+ improvement over manual experience) but also establishes a complete closed-loop system covering "process monitoring – defect detection – process optimization" through the synergistic enhancement of visual inspection and process parameter prediction. Notably, interpretable AI-based multi-objective optimization strategies have reduced the computational cycle of traditional numerical simulations by 80% while improving process adjustment response speeds by 60%, marking the transition of casting process control into real-time optimization.

In terms of quality control, advanced visualization systems integrating direct volume rendering and defect voxel identification enable holographic representation of internal casting structures and precise defect localization. Utilizing GPU-accelerated rendering engines, the system supports real-time interaction with billion-level voxel datasets, while novel voxel tagging algorithms achieve defect recognition accuracy of 99.2%, improving efficiency by 15x compared to traditional ultrasonic testing. This dual-layer "macro-overview – micro-localization" analysis model is redefining the standards of casting quality inspection.

To address key challenges in the intelligent transformation of the casting industry, five major technological breakthroughs are essential:

1.Data Governance System Construction

Develop heterogeneous data acquisition networks based on multi-sensor fusion, integrating high-speed vision (2000 fps), multi-spectral temperature measurement, and other advanced sensing technologies.

Establish big data quality assessment standards for casting, adopting federated learning frameworks for cross-enterprise data collaboration.

Innovate in time-series data processing algorithms, such as Wavelet-LSTM-based noise filtering models, improving signal-to-noise ratio by 40 dB.

2.Hybrid Modeling Methodology

Develop physics-informed neural networks (PINNs) that embed solidification heat transfer equations into deep learning architectures.

Construct digital twin systems for casting processes, enabling multi-scale (macro-meso-micro) coupled simulations.

Investigate cross-scale modeling methods combining materials genome engineering and machine learning.

3.Explainable AI Technology Matrix

Develop casting-specific interpretation tools (e.g., improved Grad-CAM++ algorithms).

Establish causal reasoning graphs linking process parameters to defect types.

Design knowledge graph-based decision support systems to achieve a "data-knowledge-decision" closed loop.

4.Adaptive Optimization Platform

Research casting-specific reinforcement learning frameworks capable of optimizing 100+ process parameters in parallel.

Develop edge-cloud collaborative distributed inference systems with latency controlled below 50 ms.

Build self-evolving process knowledge bases for online model parameter updates.

5.End-to-End Intelligent Integration

Develop a full lifecycle management system (PLM) for casting, integrating 28 key processes from melting to post-treatment.

Implement blockchain-based traceability systems for process quality.

Deploy AR/VR remote maintenance systems for cross-border collaborative production.

Industry practices demonstrate that leading enterprises implementing AI-driven casting solutions have achieved a 75% reduction in defect rates, 30% lower energy consumption, and 60% shorter product development cycles. Over the next five years, with the convergence of digital twin, quantum computing, and other cutting-edge technologies, AI will propel the casting industry toward third-generation smart factories characterized by "self-perception, self-decision, and self-execution," ultimately realizing zero-defect intelligent manufacturing across the entire supply chain. This transformation requires not only technological innovation but also a restructuring of industry knowledge systems and the cultivation of interdisciplinary talent in "materials + AI + manufacturing" to meet the challenges of this new industrial revolution.

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