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Digital-Twin-Based Monitoring System for Slab Production Process

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Abstract: The growing demand for high-quality steel across various industries has led to an increasing need for superior-grade steel. The quality of slab ingots is a pivotal factor influencing the final quality of steel production. However, the current level of intelligence in the steelmaking industry's processes is relatively insufficient. Consequently, slab ingot quality inspection is characterized by high-temperature risks and imprecision. The positional accuracy of quality detection is inadequate, and the precise quantification of slab ingot production and quality remains challenging. This paper proposes a digital twin (DT)-based monitoring system for the slab ingot production process that integrates DT technology with slab ingot process detection. A neural network is introduced for defect identification to ensure precise defect localization and efficient recognition. Concurrently, environmental production factors are considered, leading to the introduction of a defect prediction module. The effectiveness of this system is validated through experimental verification.

Keywords: digital twin; defect recognition; process monitoring

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1. Introduction

In recent years, the demand for high-quality steel has seen continuous growth across various sectors, as evidenced by a series of recent studies [1]. For instance, in the field of energy, the construction of renewable energy facilities requires a substantial amount of high-strength and corrosion-resistant steel to ensure the long-term reliability of the facilities [2]. Simultaneously, the automotive manufacturing industry is striving to reduce vehicle weight and enhance fuel efficiency, driving the increased demand for high-strength, lightweight steel materials [3]. Furthermore, heightened requirements for high-quality steel have been articulated in infrastructure development, the aerospace industry, and the military sector [4]. The escalation of these demands is partially attributed to the continual elevation of requirements in modern technology and design, where high-quality steel offers superior strength, corrosion resistance, and sustainability characteristics. Consequently, the demand for high-quality steel continues to rise across multiple industries, propelling research in the fields of materials science and engineering to address these challenging requirements.

Currently, with the continuous increase in the application of intelligent industrial technologies, the level of intelligence in steelmaking industry processes remains relatively insufficient. Despite significant progress in the application of intelligent technologies in various industries, including automation control systems, machine learning, and artificial intelligence, application in the steelmaking industry still faces several challenges [5,6]. The intelligent process in this domain is constrained by complex process workflows, extensive equipment and systems, and high requirements for stability and reliability. Therefore, research and practical efforts toward the intelligence of the steelmaking industry remain a focal point for scientists and engineers. In the future, continuous technological innovation and interdisciplinary collaboration hold the promise of ushering in more intelligent and efficient development for the steelmaking industry.

In addressing the quality control challenges in steel production, slab defects emerge as a significant factor influencing the ultimate product quality. Serving as the initial product in the transformation from liquid steel to solid steel, slabs bear a crucial responsibility for ensuring the quality of steel. However, existing methods for slab quality inspection present issues related to high-temperature risks and insufficient precision. Conducting quality inspections in high-temperature working environments not only poses potential hazards to operators but also constrains the accuracy of inspections. Furthermore, current quality inspection methods are unable to effectively pinpoint defects, complicating issue tracking and resolution. Most importantly, existing quality inspection methods fall short in achieving precise quantification of slab production yield and quality. This limitation hampers the transparency and controllability of the production process, impeding the maximization of production efficiency. Consequently, there is an urgent need for the adoption of innovative technologies and methods to enhance the safety, precision, and quantifiability of slab quality inspection while meeting the modern steel industry's demand for high-quality products.

Digital twin (DT) technology has the capability of accurately reflecting the real-time status of physical entities [7]. By digitally modeling the slab production process, detailed information about the slab, including temperature, humidity, and quality, can be obtained. This real-time monitoring aids in the timely detection of potential issues, enhancing the overall responsiveness of the entire production system. DT technology offers a comprehensive visualization model, rendering the production process more transparent. Through digital twins, operators can actively observe the virtual model of the slab in real-time, gaining insights into its status and potential defects. This contributes to improving the controllability of the production process and reducing the occurrence of human errors. Furthermore, conducting simulated experiments on digital twin models allows for the evaluation of the impact of different parameters and strategies on the production process, thereby optimizing production efficiency and product quality. DT technology provides robust support for decision making in production. Through digital modeling of the slab production process, more in-depth analysis and prediction of production trends can be achieved, facilitating the formulation of scientifically sound decisions to enhance the overall efficiency of production.

In summary, the integration of digital twin technology with slab production process detection allows for real-time monitoring and analysis of slab quality during the production process, providing essential production outcomes and associated analytical data. By applying DT technology to quality control and incorporating a defect identification detection network with high stability, this network exhibits outstanding high-precision positioning capabilities. It accurately identifies various defects in slabs, making the production process more controllable and efficient. Additionally, the monitoring system combines various environmental factors in the production environment, including temperature, humidity, and lighting, with quality inspection data. Through the analysis and synthesis of these factors, researchers can more accurately predict the probability of defects in slabs, providing a stronger basis for timely intervention. The application of this integrated analytical approach introduces more intelligence and predictability into the steel production process, with the potential to enhance product quality and improve production efficiency. The monitoring system represents an organic fusion of DT technology with industrial processes, bringing innovative advancements to quality control in the steel industry.

The content of this paper is structured as follows. Section 2 provides an overview of intelligent industrial applications, defect detection technologies, and the current state of intelligent applications in the steelmaking process. Section 3 focuses on the introduced digital twin (DT)-based monitoring system for slab production processes. Section 4 conducts experimental validation of the aforementioned concepts. Finally, the concluding section, Section 5, presents a comprehensive summary of the entire manuscript.

2. Related Work

2.1. Intelligent Industrial Applications

In recent years, significant research progress has been made in the field of intelligent industrial applications, with numerous scholars providing substantial contributions [8–19]. For instance, Aristova et al. [8] have extensively investigated the widespread application of industrial robots and automation systems in the manufacturing sector, resulting in enhanced production efficiency and quality. Concurrently, the work of Arena and colleagues underscores the importance of predictive maintenance technologies based on big data and artificial intelligence in aiming to reduce equipment failures and maintenance downtime [14]. In the energy sector, Wang's research highlights the significance of smart grids, which, through real-time monitoring and optimization of power distribution, contribute to improved energy efficiency [16]. Furthermore, leveraging Internet of Things (IoT) technology, Jin et al. [17] achieved remote monitoring of industrial equipment, thereby enhancing equipment reliability and safety. Finally, Xu et al. [18] propose a blockchain-based intelligent supply chain system to enhance supply chain transparency and traceability.

These studies indicate that the development of intelligent industrial applications has spanned across various domains, including manufacturing, energy, logistics, and others. Additionally, they underscore the crucial role of data analytics, automation technology, and defect detection techniques in this field.

2.2. Defect Detection Techniques

In recent years, defect detection technology has been a popular research direction for many scholars. Significant progress has been made not only in the steel industry but also in various other fields. In the steel industry, X-ray, infrared imaging technology, and ultrasonic technology are commonly used for defect detection [20–24]. Dreher et al. [20] compared the advantages and disadvantages of different non-destructive imaging techniques, including X-ray, in detecting defects in sintered layers. Alzaraa et al. [22] used enhanced ultrasound technology to detect defects in transplanted liver perfusion. Chen et al. [24] constructed a camera ultrasound data fusion (CUfuse) model for detecting surface defects on rails. With the increasing maturity of deep learning technology, many scholars have introduced neural networks into defect detection in the manufacturing industry. Hsu et al. [25] proposed a deep-learning-based method for automatic recognition and tracking of steel products for the intelligent manufacturing of steel. Song et al. [26] developed a new image synthesis method for defect image generation in the steel manufacturing process.

The above-mentioned methods have provided crucial technical support for improving product quality and the reliability of industrial production in the steel industry. Among them, deep learning has the advantage of being more intuitive and faster compared to other defect detection methods. Conventional detection algorithms rely on various sensors and detection devices, which lack stability and are insufficient for meeting the high-precision requirements of defect detection in different smelting plants.

2.3. Intelligent Application of Steelmaking Process

In recent years, intelligent research on the steelmaking process has garnered widespread attention and development. The steelmaking industry is gradually achieving automation control and intelligent optimization [27–29]. Brämming et al. [27] applied multivariate data analysis (MVDA) to develop a dynamic system for vibration and acoustic measurements of converters to predict the tilt of the converter. Antonova et al. [28] validated the proposed method's impact on the steelmaking process. Kaushik et al. [29] evaluated the influence of process conditions on product performance using various techniques, such as full steel and slag chemical measurements, inclusions analysis, process analysis, and thermodynamics. Han et al. [30] introduced big data and Internet of Things (IoT) technologies into the field of steelmaking, enabling early detection of smelting equipment failures. Lu et al. [31] created an instrument for measuring the thickness of thin slab continuous casting and rolling (TSCF) using various devices, such as measuring rods, mechanical devices, and high-definition industrial cameras. Liu et al. [32] proposed a method based on flame image processing and pattern classification for end-point prediction in the basic oxygen furnace (BOF). Zhao et al. [33] suggested a method using region-scanning charge-coupled device (CCD) laser stripe scanning to measure large field-of-view visualizations based on MV in modern steel production lines. Additionally, scholars have discussed the application of intelligent logistics systems to achieve accurate tracking and optimization of raw materials, thereby reducing costs and improving production efficiency [34,35]. Some research has explored novel slag processing technologies and energy efficiency improvements to reduce carbon emissions, aiming to minimize waste and pollution [36,37].

The steelmaking industry has gradually introduced numerous intelligent applications to enhance production efficiency and safety and reduce raw material waste and production costs. The above research emphasizes the practicality of automation, data-driven approaches, visual analysis, and sustainability-related technologies in the smelting process. However, these technologies have not been integrated or applied to the slab production process by combining various aspects, such as vision, data-driven methods, and management. By comprehensively applying these technologies, the steelmaking industry is poised to improve production efficiency and product quality and achieve more environmentally friendly production.

2.4. Research Gaps

From the above analysis, we can identify several existing challenges in the smelting process of the steel manufacturing industry:

1. Lack of a comprehensive slab production process monitoring system:

A comprehensive slab production process monitoring system can visualize relevant production data for comprehensive control and management by staff.

2. Insufficient stability in conventional detection algorithms:

Conventional detection algorithms lack stability, proving inadequate to meet the high precision requirements of varied smelting facilities.

3. Absence of production management and data analysis for slabs:

The production process requires not only defect detection but also the ability to predict the probability of defects based on environmental factors.

These identified challenges play a pivotal role in the intelligent and visualized transformation of the converter steelmaking process under harsh conditions. The subsequent sections of this paper will delve further into a discussion of these issues.

3. The Proposed System

3.1. System Structure

A DT refers to the virtual representation of entities created using digital technologies while maintaining a one-to-one relationship with their corresponding physical objects [38]. DTs offer a comprehensive and visual model, enabling users to gain precise insights into the status of monitored objects. This facilitates better understanding and monitoring of physical entities in the real world. Consequently, this paper proposes a DT-based monitoring system for the slab production process. The system comprises two modules: the defect detection module and the production management module. The defect detection module utilizes a neural network to obtain defect type and positional coordinate information from images. The production management module facilitates data management of slab production output and utilizes objective factors, namely temperature and humidity, to predict the probability of defect occurrence. Figure 1 illustrates the overall structure of the monitoring system.

The digital twin is a virtual replica of a physical object, establishing a bidirectional mapping relationship between the physical entity and its digital model. Following the closed-loop structure of ISO 23247, the system monitors the slab production process through DT-driven implementation [39]. The system encompasses two spaces: the physical space and the virtual space. In this system, the physical layer refers to the collection of entity models present in the production scene during the slab production process, including the slab entity, scanning and imaging devices, and sensing detection devices. Scanning and imaging devices are used to capture images of slabs for subsequent defect identification and classification. Sensors and detection devices primarily collect dynamic environmental data during the production process.

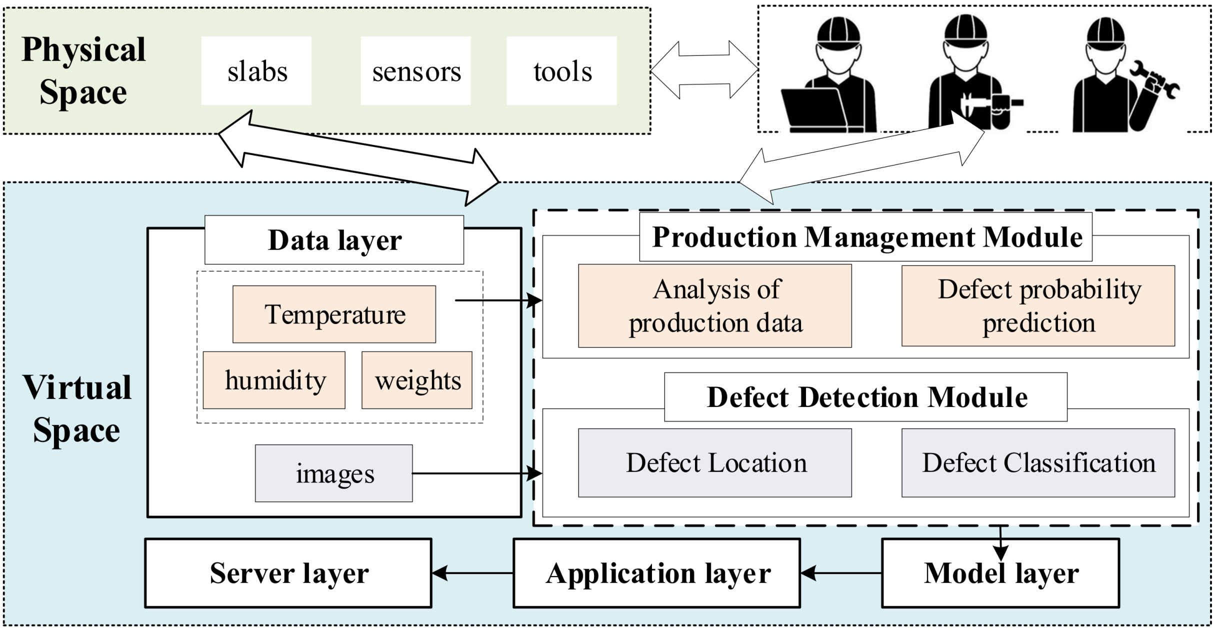

Figure 1. Monitoring system structure.

To facilitate user monitoring and observation, the virtual space must be kept in real-time synchronization with the physical space and reflect its relevant characteristics. The virtual space includes the data layer, model layer, application layer, and service layer, each with distinct functionalities outlined below.

1. Data layer: This layer manages collected temperature, humidity, weight, and image data, forming a historical record for user observation at any time.
2. Processing of data layer: The data obtained from the data layer are processed, with temperature, humidity, and weight data used for calculating production output and predicting the probability of defect occurrence. Image data are employed for identifying the presence of defects and obtaining classification information.
3. Model layer: This layer is responsible for creating a virtual model of the slab and simultaneously displaying the position, size, and classification of defects within the model.
4. Application layer: Acting as a bridge between the server and model layers, this layer facilitates virtual visual monitoring of slabs and production state monitoring. UNITY 3D stands out as a robust and versatile game development engine, offering seamless integration capabilities for a diverse range of data sources [40]. This includes the incorporation of real-time sensor inputs, process parameters, and environmental conditions. Serving as a pivotal layer within the monitoring system, it facilitates the creation of an all-encompassing digital representation of the slab production process.
5. Server layer: The server layer is situated upstream of the application layer, providing an intuitive display of the application layer on various terminal devices. By encapsulating the management system constructed in the application layer into different terminal devices, personnel can actively participate in the direct monitoring and management of the slab production process using PC, phone, pad, Web, and VR clients.

In summary, defect identification and classification in slabs, along with production data management, constitute the pivotal technologies for establishing a slab production process monitoring system based on digital twin technology. Subsequently, this paper focuses on investigating the defect identification model for slabs. Following that, the collected data are employed to construct the production data management module. Finally, the establishment and operation of the digital twin system are accomplished.

3.2. Defect Detection Module

3.2.1. Overall Structure

As illustrated in Figure 2, the defect identification network is composed of two main components: the backbone and the head. The backbone is responsible for feature extraction, while the head is employed for prediction. The input images undergo preprocessing to align them into RGB images of size 640 × 640. These processed images are then fed into the backbone network. Based on the three-layer output from the backbone network, the head layer continues to produce three layers of feature maps with different sizes. Through RepVGG blocks, the network performs predictions for three tasks related to image detection, including classification, foreground–background classification, and bounding box prediction, ultimately generating the final results. Inspired by the YOLOv7 model, model reparameterization is introduced into the network architecture, and a multi-branch network is adopted to enhance feature extraction [41]. An attention unit is incorporated into the model to effectively extract subtle features that are challenging to identify. The introduction of the REPVGG module (as shown in Figure 3) strengthens the network's ability to extract crucial features [42].

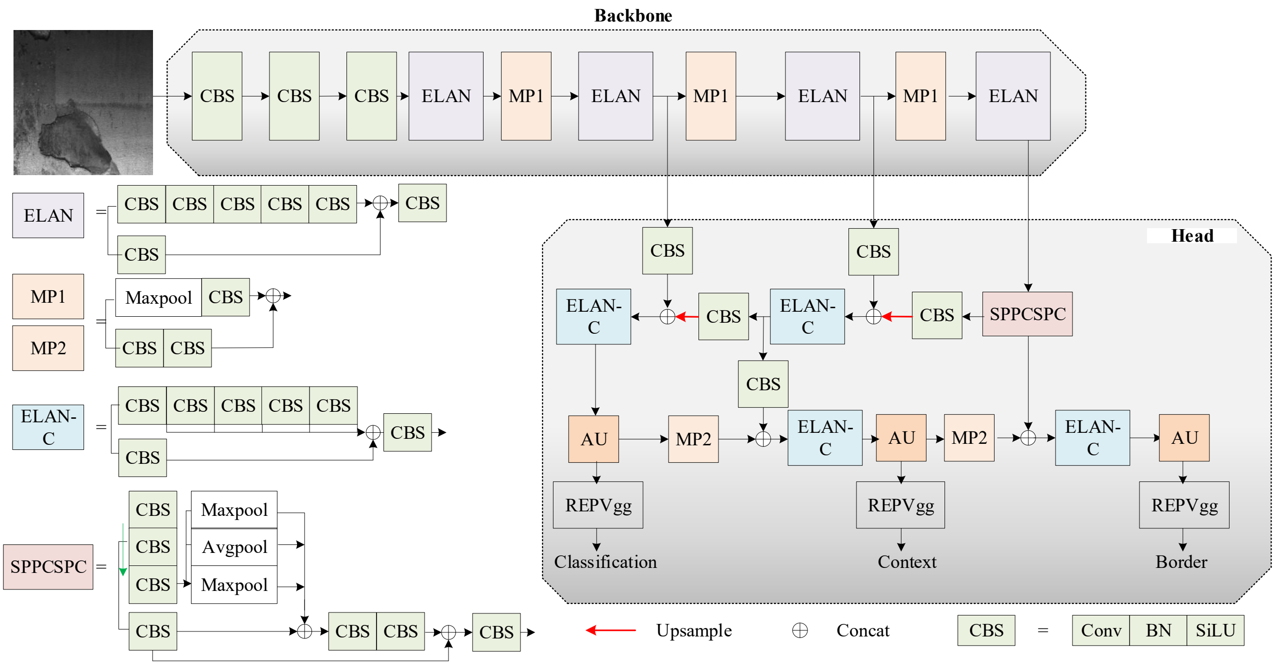

Figure 2. Defect identification module.

The defect recognition network can efficiently perform target detection while reducing computational costs. Among the model's components, CBS combines convolutional layers, Batch Normalization layers, and the SiLU activation function to enhance the model's learning capability. By introducing cross connections between specific layers, CBS effectively alleviates the training difficulty of deep networks. CBS is a crucial component in the recognition network, achieving partial replication of features and enabling better extraction of feature information through the network. This helps to avoid the vanishing gradient problem in deep networks, ultimately enhancing the overall performance of the model.

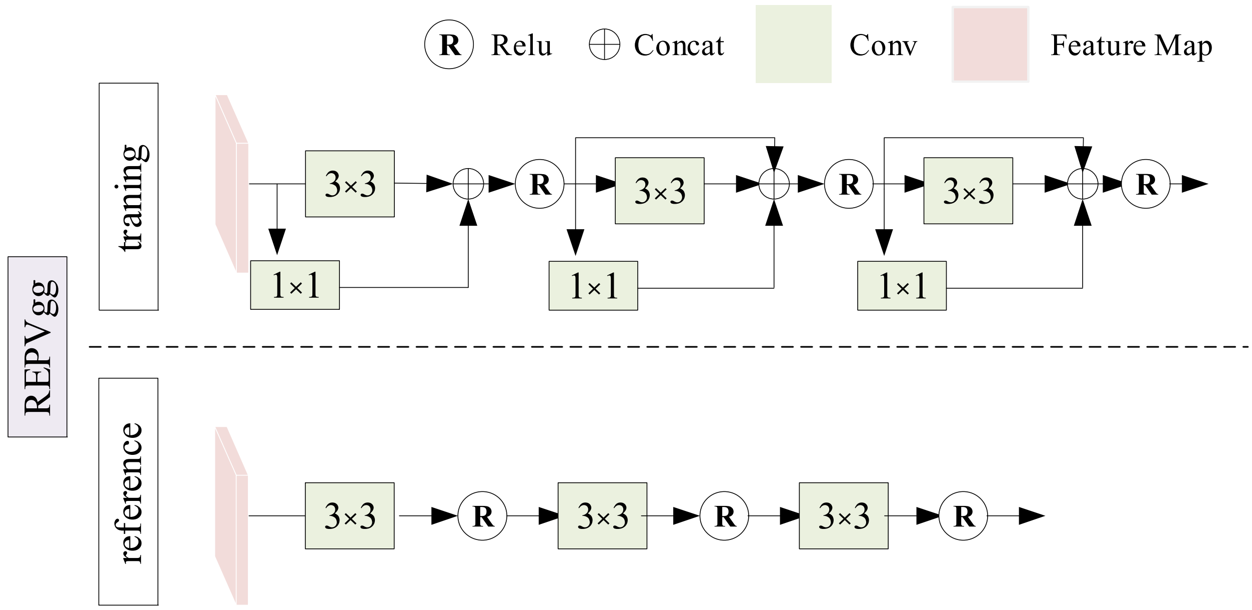

Figure 3. The REPVGG module.

The convolutional layer (Conv) is one of the core components in deep learning. It extracts image features by applying convolutional kernels to the input. In the defect recognition model, convolutional layers are used to progressively extract and combine abstract features of the image, enabling the model to better understand and represent the input image [7].

Batch Normalization (BN) is a regularization method that normalizes each feature within each training batch, accelerating the network's convergence and enhancing model stability. It helps to ensure that the model learns and adapts better to different input data during training.

SiLU, also known as the Sigmoid Linear Unit, is an improved version of the Sigmoid activation function. Compared to traditional activation functions, SiLU exhibits better properties, aiding in mitigating the vanishing gradient problem and speeding up model convergence during training. Its non-linear characteristics help capture complex relationships in input data, thereby enhancing the model's expressive power.

MAXpool, or the max-pooling layer, is used for down sampling by selecting the maximum value within each region of the input image, thereby reducing the size of the feature map. This helps extract critical information from the image while reducing the computational burden. Max-pooling gradually reduces the size of the feature map, allowing the model to speed up computations while retaining essential information.

Average pooling (Avgpool) is a pooling operation used to decrease the dimensions of the feature map. In average pooling, the average value within each pooling window is computed to generate the next layer's feature map. Diminishing dimensions during feature extraction contribute to the model's computational efficiency and robustness to the target, additionally aiding in reducing the risk of overfitting.

ReLU is an activation function employed in each neuron of a neural network. Its mathematical expression is given by $f(x) = \max(0, x)$, where the activation function outputs the input value itself when the input is positive, and it is zero when the input is negative. This effectively addresses the issue of vanishing gradients.

Concatenate (Concat) is an operation in neural networks that involves connecting two or more tensors along a specific dimension. It is utilized to merge features from different parts or layers, offering an efficient means to integrate information from diverse sources. This process provides a more comprehensive feature representation, aiding the model in better understanding and learning the relationships within the input data.

As illustrated in Figure 4, the attention unit (AU) functions in the Head part of the network, utilizing attention mechanisms to weight the predictions of different bounding boxes. It extracts fine-grained features that are difficult to detect and observe in the image, aiming to increase attention to small targets, reduce the occurrence of missed detections in the network model when detecting small targets, and enhance overall detection accuracy. The REPVGG module introduces both a residual branch and a 1×1 convolution branch. This addition is crucial for subsequent reparameterization into a single-path structure, and both the residual branch and the conv 1×1 contribute to increasing the network's performance.

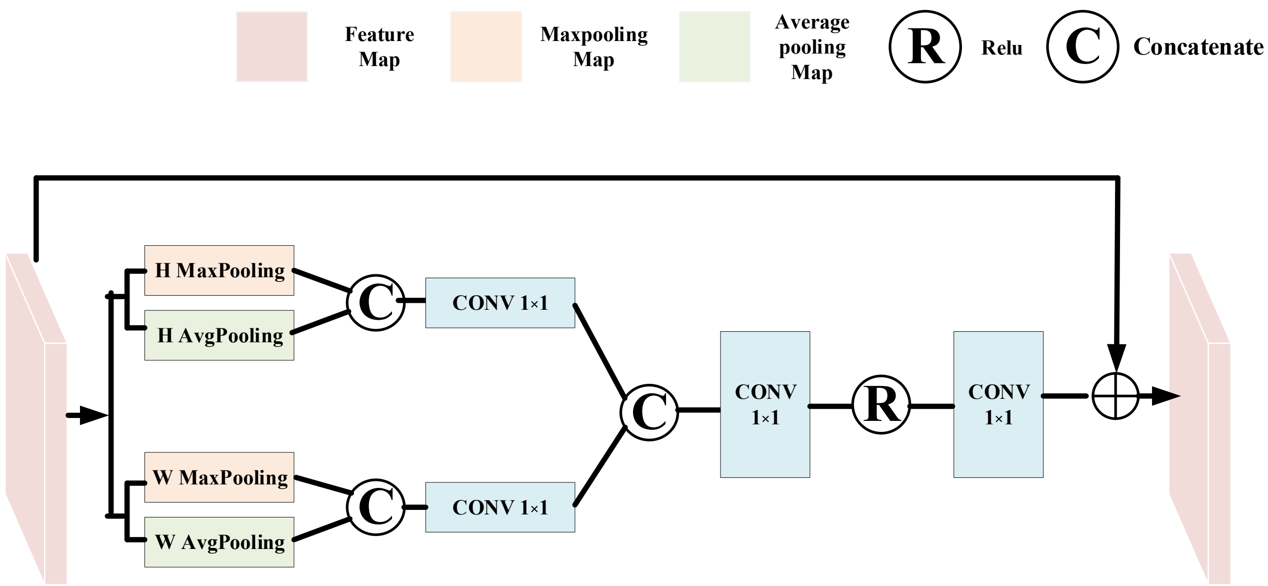

Figure 4. Attention unit (AU).

We integrate different modules into an end-to-end model, which can directly generate object detection outputs from raw image inputs without the need for an additional region proposal step. This simplifies the entire object detection process, enhancing both the training and deployment efficiency of the model. The model can detect multiple targets in a single inference when processing a single image, eliminating the need for multiple inferences. The defect recognition model detects features at different levels of the feature map, allowing it to capture target features at different scales and adapt well to targets of varying sizes. The fully convolutional network structure in the model enables the extraction of global contextual information across the entire image. This contributes to an improved understanding and inference of targets, providing the model with enhanced global perceptual capabilities. Compared to other state-of-the-art models, our model structure is relatively simple, making it easy to comprehend and implement.

3.2.2. Loss Function

The occurrence of defects in slabs is often stochastic, leading to the possibility of encountering low-quality defect samples. Additionally, the presence of various factors may result in inadequate model generalization capabilities. Therefore, this paper introduces a dynamic non-monotonic focal mechanism, denoted as the Weighted Intersection over Union (WIoU), defined as presented in Formula (1) [43].

$$\beta = \frac{L^*_{IoU}}{L_{IoU}} \in [0, = \infty) \tag{1}$$

$$L_{WIoUv3} = rL_{WIoUv1}, r = \frac{\beta}{\delta \alpha^{\beta - \delta}} \tag{2}$$

$$L_{WIoUv1} = R_{WIoU} L_{IoU} \tag{3}$$

$$R_{WIoU} = exp\left(\frac{(x - x_i)^2 + (y - y_i)^2}{(W_i^2 + H_i^2)^2}\right) \tag{4}$$

In this context, L_{IoU}^* represents the monotonic focusing coefficient for L_{WIoU}. L_{IoU} denotes the moving average with a momentum of m. r represents the non-monotonic focusing coefficient composed of β. α and δ are hyperparameters. W_i and H_i indicate the size of the predicted box. R_{WIoU} signifies the amplification of regular-quality anchor boxes for L_{IoU}. L_{IoU} is formulated to reduce R_{WIoU} for high-quality anchor boxes, significantly diminishing attention to the center-point distance when the anchor box and target box overlap well. A smaller β assigns a higher quality to the anchor box, and WIoU allocates to it a small gradient gain, guiding the bounding box regression toward a regular-quality anchor box. A larger β, indicating lower anchor box quality, results in a smaller gradient gain from WIoU, reducing harmful gradients. Simultaneously, it focuses on regular-quality anchor boxes to enhance the model's generalization ability.

3.3. Production Management Module

3.3.1. Yield Management

Production output is often the most crucial metric in manufacturing [44]. Therefore, the system incorporates a production management module, utilizing weight sensors to obtain the weight of each slab, aggregated within the DT monitoring system. Production management of steel slabs plays a vital role in modern steel industries. In the management of steel slab production, weight sensors are widely employed to monitor and control the production process. These sensors are typically installed at critical locations, such as the furnace front, entry, and exit of rolling mills, to measure the weight and weight distribution of slabs. The sensors commonly employ pressure-sensing technology, ensuring reliable operation in high-temperature and high-pressure environments.

Data collection and scale: Weight sensors continuously collect real-time weight data for slabs, often sampling multiple times per second. The scale of the data depends on the speed and demands of the production process, generating a substantial number of data points per hour.

Data transmission rate: Data generated by weight sensors are typically transmitted at a high speed to the data acquisition system. The transmission rate can be adjusted based on the requirements of the production line, usually at a rate of several thousand data points per second.

Integration with the DT production monitoring system: Weight sensor data are integrated into the production process monitoring system, allowing real-time monitoring and analysis of slab quality and weight distribution. Data transmission is achieved through Ethernet, ensuring the timeliness and reliability of the data.

Production output data are not only used for monitoring but also for process optimization. By analyzing the weight distribution of slabs, the production process monitoring system can dynamically adjust certain parameters, such as the furnace temperature and the rolling mill pressure, in real time to ensure the slabs' quality meets specified standards. This feedback control system helps reduce waste, improve production efficiency, and ultimately lower production costs.

Moreover, the weight data of slabs are utilized for optimizing production planning. The production planning system can adjust production sequences and schedules based on the actual weight distribution of slabs, maximizing production efficiency.

In conclusion, production output monitoring plays a crucial role in steel slab production management. Through real-time data collection, analysis, and adjustments to the production process, it aids the steel industry in enhancing production efficiency, quality control, and sustainability.

3.3.2. Defect Prediction

In the realm of steel production, the quality control of slabs is of paramount importance. Various environmental factors, such as temperature, humidity, and illumination, can exert an influence on the quality of slabs. To anticipate the probability of defects in slabs, statistical models can be employed, with logistic regression being a commonly utilized approach [45].

In logistic regression, a predictive model is established using measurements of environmental factors (e.g., temperature, humidity, and illumination) to ascertain the probability of defects in slabs. The formula for the model is as follows:

$$P(D = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 T + \beta_2 H + \beta_3 L)}} \tag{5}$$

In this context, $P(D = 1)$ represents the probability of defects in slabs. The coefficients $\beta_0, \beta_1, \beta_2, \beta_3$ correspond to the regression model. T denotes temperature, H denotes humidity, and L denotes illumination.

In this model, when the values of temperature, humidity, and illumination are specified, the model estimates the probability of defects in slabs. The coefficients of the model, $\beta_0, \beta_1, \beta_2, \beta_3$, can be estimated through statistical methods. Once the coefficients are estimated, the actual measurements of environmental factors can be used to calculate the probability of defects in slabs.

The advantage of the logistic regression model lies in its ability to consider the combined influence of multiple environmental factors on slab quality, providing a mathematical framework to quantify the contribution of different factors to the probability of defects. This facilitates the formulation of adjustment strategies in the production process to reduce defect rates. This approach offers a scientific method for quality control in steel production to minimize defects and waste. Once the parameters are given, the system can estimate the likelihood of defects in real time based on the real-time parameters of the production process. Workers can adjust the relevant slab production environment according to the estimated likelihood of defects during the slab production process.

4. Experiment and Verification

4.1. Experimental Environment and Validation Scheme

To realize the monitoring of the slab production process based on digital twinning in harsh environments, this paper has developed a digital twinning monitoring system for slab production processes.

The on-site standard configuration of the digital twinning monitoring system primarily consists of three components: the Monitoring Control Unit (MCU), the Field Control Unit (FCU), and sensors, including the SA-S6016 dual-color infrared thermometer temperature sensor, the T701E weighing sensor from Right Corporation, the ADAM-3600 humidity sensor from Advantech Corporation, and the GZ-XDS-1 illuminance meter from Jiandanren Technology. The system was implemented on an 11th Gen Intel(R) Core (TM) i7-11700K @ 3.60GHz 3.60 GHz CPU with 32.0 GB memory, using Unity3D 2021.3 and Visual Studio 2013.

Figure 5 illustrates the experimental verification process. Initially, cameras and various functional sensors are employed to gather environmental and slab image data. Subsequently, the defect recognition algorithm is applied to determine the location and category of slab defects. The identified defects with the data acquired from various functional sensors are integrated, enabling the modeling of slabs along with defects and the establishment of a defect database. Additionally, this integration allows for predicting the probability of defect occurrence and monitoring production data.

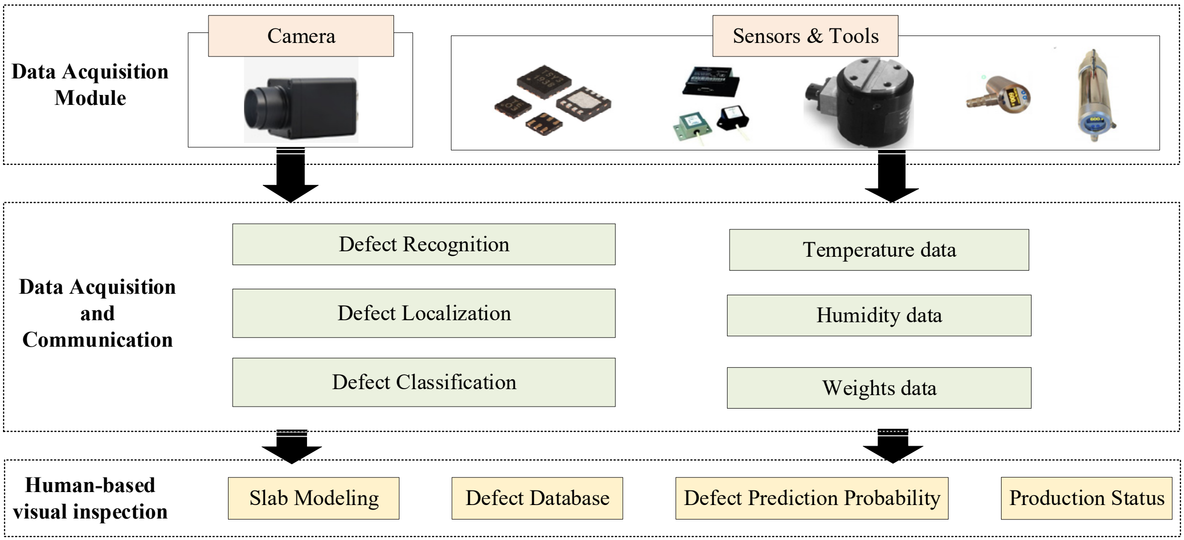

Figure 5. Experimental validation process.

4.2. Verification Process

4.2.1. Target Detection Model Effect Verification

This paper adopts the following parameters as evaluation metrics: Precision (Pre), Recall (Rec), average precision (AP), AP at IoU threshold 0.5 (AP_{50}), AP at IoU threshold 0.75 (AP_{75}), and accuracy. These metrics collectively assess the localization accuracy of the object detection model. The formulas are presented below:

$$recall = \frac{TP}{TP + FN} \tag{6}$$

$$AP = \int_0^1 P(R)dR \tag{7}$$

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{8}$$

Recall represents the proportion of correctly detected targets to the total number of targets. AP (average precision) is the area under the precision–recall curve within the [0, 1] range. AP_{50} denotes the AP value when IoU is fixed at 50%, and AP_{75} represents the AP value when IoU is fixed at 75%. Accuracy indicates the proportion of correctly predicted instances in the given test sample set by the detection model. The evaluation metrics employed in this study are designed to reflect superior model performance, with higher scores indicating better detection capabilities.

The two control sample sets required for validation were utilized to train state-of-the-art (SOTA) object detection models. Following the completion of training, the effectiveness of the proposed model was assessed through a comparative evaluation against the control group. The selected object detection models in this study include CBAM [46], EW-YOLOv7 [47], DS-Cascade RCNN [48], Cascade R-CNN [49], and SSD. The control group was established to validate the superiority of the proposed model.

Upon completion of training of the aforementioned models and the proposed model, a total of 5000 in situ slab images were collected for testing. As shown in Table 1, the evaluation metrics for different SOTA models and the proposed model were computed. The results demonstrate that the preprocessing algorithm proposed in this study significantly improves the recognition accuracy and capability of each object detection model. This suggests that the proposed model, compared to SOTA models, notably enhances the detection accuracy of slab defects. Figure 6 shows the classification, localization, and probability diagram of slab defects identified using recognition algorithms. It can be seen that our algorithm has excellent recognition performance.

Table 1. Test metric scores of the different methods for each test set.

Models	Time (ms)	Rec (%)	AP	AP_{50}	AP_{75}	Accuracy
CBAM	26.3	94.241	41.1	61.7	48.1	76.82
EW-YOLOv7	26.8	93.415	41.4	59.2	45.3	71.61
DS-Cascade RCNN	29.1	97.682	43.2	64.8	47.1	84.67
Cascade R-CNN	26.4	87.132	36.7	54.9	43.5	52.34
SSD	27.4	88.454	38.9	57.3	44.1	70.64
Ours	23.3	98.435	43.9	62.3	47.8	88.42

Gray represents best performance.

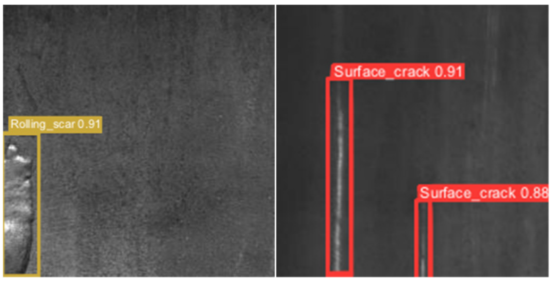

Figure 6. Effective identification of slab defects.

4.2.2. Monitoring System Verification

The smelting plant utilizing a DT-based slab production process monitoring system is a large-scale steel production facility with an annual output of 3.42 million tons of crude steel. The validation process for this monitoring system spanned nearly a year and involved comprehensive testing through actual steel production to ensure its stability and reliability under various environmental conditions. Throughout the validation period, we utilized the monitoring system to record a substantial amount of data, including critical parameters, such as temperature, humidity, and slab quality. Typical production temperatures hover around 300 °C, while humidity is maintained at approximately 60%. The daily volume of generated data amounts to approximately 20 MB. Through the collection and analysis of these data, the system can optimize parameters using a wealth of information, thereby ensuring the production quality of slabs. This provides the smelting plant with a more intelligent and sustainable production solution, effectively enhancing production efficiency and product quality.

Monitoring the slab production process supports users in obtaining a clear understanding of production data and relevant environmental information. Detailed data not only enable a comprehensive grasp of the production status but also allow for improvements in the production environment data through the embedded system, thereby reducing the probability of defects and enhancing production efficiency. The DT-based slab production process monitoring system is divided into real-time monitoring and defect database modules, outlined as follows:

1. Real-time monitoring module: As depicted in Figure 7, the interface displays real-time information related to slab production, including slab models, defect severity, weight, temperature, humidity, working duration, daily output, and the probability of defect occurrence along with adjustment recommendations. The severity of defects and the likelihood of their occurrence are represented by red, orange, and blue colors. Red indicates high severity, orange indicates moderate severity, and blue indicates normal conditions.
2. Defect database module: Illustrated in Figure 8, this module encompasses all historical data on slab defects. Personnel can query defect information, such as the date of occurrence, defect type, temperature, humidity, and weight, through this module.

Figure 7. System interface.

Figure 8. Defect database interface.

Through experiments, the DT-based slab production process monitoring system achieved real-time synchronization and simulation with the actual production process. In the production process monitoring system, users can achieve a full-angle observation of the slab by dragging and rotating, enabling a comprehensive understanding of defect information. When defects are present, the interface marks them in red or orange based on severity. Red indicates a more severe defect, while orange indicates a less severe one. Users can perform subsequent slab processing, such as repair, re-smelting, or discard operations, according to the color indications. In the upper right corner, the system provides a probability prediction of defect existence. If the probability exceeds 70%, it is marked in red; if it exceeds 50%, it is marked in orange. The system suggests measures to reduce the probability of defect occurrence based on environmental information. Staff can choose to modify relevant environmental factors based on prompts or opt to reduce the current production yield to enhance the quality of slabs. Clicking the defect database button redirects the interface to a detailed information page on historical defects, allowing users to navigate through historical defect information using page-up and page-down buttons. The system database is developed using MySQL 5.7 software, storing all defect data generated during the slab production process in MySQL database tables. Corresponding fields are established based on time, defect category, weight, temperature, and humidity. The system also reserves a secondary development interface for future interaction with big data and artificial intelligence models, aiming to achieve a faster, more comprehensive, and convenient system.

5. Conclusions

In addressing the shortcomings in intelligence and production management during the slab production process, this paper establishes a monitoring system tailored for slab production based on digital twin (DT) technology. The defect identification module enables rapid and precise recognition and localization of defects in slabs, including their position and category. The production management module collects, processes, and displays data related to production output and defect predictions. The effectiveness of the system is thoroughly validated. Building upon these foundations, the contributions of this paper are outlined as follows:

1. A comprehensive slab production process monitoring system: Achieves monitoring of the slab production process and encompasses various functionalities, such as defect identification, production output management, and defect prediction.
2. A faster and more accurate defect identification network: Compared to other state-of-the-art models, the precision of the network proposed in this paper is higher.
3. A defect prediction model: Integrates environmental information to predict the probability of defect occurrence in slabs. Users can adjust relevant settings based on this probability to reduce the likelihood of defects, thereby enhancing the production of high-quality steel and minimizing raw material waste.

Through the establishment of the aforementioned monitoring system, the normal operation of the slab production process monitoring system has been realized. Currently, the framework system has been implemented, achieving real-time mapping from physical space to virtual space. However, there are limitations in more advanced applications, such as big data. In the future, improvements and upgrades will be made to the system to achieve a more intelligent and precise system.

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