

## Research Article

# Pellet Roasting Management System Based on Deep Learning and Internet of Things

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Pellet is widely used in blast furnace ironmaking. Pellet quality affects the effect of ironmaking, the existing control system of grating-rotary kiln mainly adopts manual control mode, and the quality of pellet production largely depends on the experience, fatigue, and sense of responsibility of the site operators. The use of the Internet of things (IoT) technology in the integration and improvement of enterprise information level, to achieve fine, intelligent production management, at the same time, is conducive to promoting steel enterprises to reduce costs and increase efficiency, energy conservation and emission reduction, transformation and upgrading, and taking a new road to industrialization. According to the working principle and technological characteristics of the grate-rotary kiln at all stages, this paper designs the management system of firing pellets based on convolutional neural network (CNN) and IoT technology, so as to realize automatic recognition of image data obtained by the perceptual layer and make an intelligent analysis of it. The system can classify the working conditions of the current equipment, so as to judge whether the production process parameters of the grate-rotary kiln are up to the standard, thus achieving the goal of controlling the quality of the finished pellet.

## 1. Introduction

At present, steel enterprises are facing difficulties in production and operation and bottlenecks in transformation and upgrading. Therefore, the government vigorously promotes independent innovation in information technology and comprehensively optimizes the information industry structure. The competition among iron and steel enterprises is increasingly fierce. The improvement of the economic index and technological progress of blast furnace iron smelting mainly depends on the improvement of the properties of the raw materials used in the furnace [1]. Pellet ore has the characteristics of high iron grade, uniform particle size, good reduction performance, high mechanical strength, and many micropores. Pellets roasting is an important method of powder ore block of pelletizing process, the material is not only due to rolling into a ball and particle density and physical property change (density, porosity, shape, size, mechanical

strength, etc.), and more importantly, the chemical and physical-chemical properties change (chemical composition, reducibility, expansion, reduction of softening under high temperature, low-temperature reduction softening and melting, etc.), to improve the metallurgical properties of material [2–5]. From the control point of view, the pellet sintering process has the characteristics of nonlinearity, distribution parameters, slow time variation, and large time delay, and it is a typical complex controlled object. A large amount of uncertain information and diverse data make it difficult for traditional control methods to effectively control it.

IoT (Internet of things) is an important part of the new generation of information technology [6]. Through intelligent perception, identification technology, pervasive computing, and other communication perception technologies, it is widely used in the integration of the network, which is also called the third wave of the development of the world

information industry after the computer and the Internet. With the development of RFID (Radio Frequency Identification) technology and the popularization of the sensor network, the interconnectivity between objects is getting deeper. IoT technology has been gradually applied to all aspects of social production and manufacturing, accelerating the development of traditional industrial production and manufacturing. In the process of transformation from traditional industrial production to intelligent production, tangible terminal entity of original data collection and invisible virtual industrial network communication platform should be established to construct industrial network architecture, so as to realize long-term and stable accurate control, reliable perception, trusted service, and real-time transmission integrated service. The IoT technology can intelligently analyze, integrate, and process massive information and realize intelligent control in the decision-making process to effectively deal with randomness, complexity, and uncertainty in the industrial manufacturing process [7–9].

The frameworks of centralized and distributed AI-enabled IoT networks are studied by HAO Song. Key technical challenges, including random access and spectrum sharing, are analyzed for different network architectures. Deep reinforcement learning- (DRL-) based strategies are introduced and neural networks-based approaches are utilized to efficiently realize the DRL strategies for system procedures such as spectrum access and spectrum sensing. Different types of neural networks that could be used in IoT networks to conduct DRL are also discussed [10]. Rachad Atat presents the CPS taxonomy via providing a broad overview of data collection, storage, access, processing, and analysis. This is the first panoramic survey on big data for CPS, where our objective is to provide a panoramic summary of different CPS aspects. Rachad Atat also provides an overview of the different security solutions proposed for CPS big data storage, access, and analytics [11, 12]. Jinsong Wu has focused on investigating the relevance between SDGs and ICT via panoramic reviews and discussions and tried to provide the relevant understandings and visions on relevant issues [13]. In the study by Liao et al. [14], a deep learning- (DL-) based physical (PHY) layer authentication framework is proposed to enhance the security of industrial wireless sensor networks (IWSNs). Three algorithms, the deep neural network- (DNN-) based sensor nodes' authentication method, the convolutional neural network- (CNN-) based sensor nodes' authentication method, and the convolution preprocessing neural network- (CPNN-) based sensor nodes' authentication method, have been adopted to implement the PHY-layer authentication in IWSNs. Among them, the improved CPNN-based algorithm requires few computing resources and has extremely low latency, which enable a lightweight multinode PHY-layer authentication. The adaptive moment estimation (Adam) accelerated gradient algorithm and minibatch skill are used to accelerate the training of the neural networks. Simulations are performed to evaluate the performance of each algorithm and a brief analysis of the application scenarios for each algorithm is discussed.

The metallurgical industry has developed rapidly this year, and enterprises must strengthen their awareness of dealing with risks. Furthermore, integrate existing resources, use IOT technology to strengthen management, reduce management costs, and control risks. The Internet of Things technology can integrate data and resources on the existing industrial control system, production system, logistics system, purchasing system, and sales system of steel enterprises to form a complete information management system, realize full-process management, and reduce management cost and risk [15]. Iron and steel enterprises with IoT technology to intelligent identification, location, tracking, and monitoring and management realize information sharing and connectivity and thus not only can effectively upgrade the traditional iron and steel industry, the integrated ability to improve enterprise management, but also can save the corresponding smelting cost, reduce pollution, protect the environment, and bring good social benefits to the enterprise.

Firstly, this paper introduces the pellet production process and principle. Then, the structure system of IoT technology and key technologies of industrial IoT are analyzed. Finally, based on a deep understanding of the working principle of CNN, a pellet roasting management system based on CNN and IoT technology is established, in order to realize the goal of intelligent control of finished pellet by using this system. The actual operation results of the system show that the control method is effective, and the automatic control of the thickness of the grate kiln is realized. In this paper, CNN and IoT technology are applied to the pellet roasting management system for the first time, achieving the goal of intelligently optimizing the quality of pellets and providing a theoretical and technical basis for achieving intelligent control of pellet production.

## 2. Pellet Production Technology and Principle

The task of pellet sintering is to use high-temperature heating of powdery materials (mineral powders and concentrates) to form blocks without complete melting. As the main raw material of blast furnace ironmaking, the control of the sintering process is a complicated task. The quality control is the key of sintering product quality and production benefit, which directly affects the output and quality of downstream products. Method of pellets that is made of fine grinding concentrate can satisfy the requirement of smelting of block material process: prepare all the raw materials needed for pelletizing, and mix the raw materials evenly according to the predetermined ratio in the experimental plan. Put the uniformly mixed raw materials into the pelletizer for pelletizing experiments. Put the prepared pellets into the furnace for roasting. During the roasting process, a chemical reaction occurs in the pellets to consolidate the pellets, and the resulting product is called pellets. In the process of preparation of pellets, the material is due to not only particle dense physical properties (density, porosity, shape, size, mechanical strength, etc.) on the change but also the chemical and physical properties (chemical composition, reducing softening property, swelling, high-temperature

reduction, drop performance, etc.); the changes in metallurgical performance are improved, so that material from the control point of view and the sintering process can be regarded as a raw material parameters and operating parameters on equipment. The roasting process model diagram is shown in Figure 1.

There are three main pellet production processes: shaft furnace pellet, pellet of belt type roasting machine, and chain grate-kiln pellets. The comparison results of the three industries are shown in Table 1.

This paper mainly studies grate-rotary kiln pellets, whose technological process is shown in Figure 2: the sintering process of pellets consists of several continuous processes, mainly including chain grate, rotary kiln, and ring cooler system. The pellets are first dried and preheated on the chain grate and then sintered in a rotary kiln. The pellet is cooled in the ring cooler, and then the pellet enters the finished product system.

### 3. IoT Technology

*3.1. The Architecture of the IoT.* IoT is a network system of intelligent identification, positioning, tracking, monitoring, and management through RFID devices, infrared sensors, global positioning system (GPS), laser strafing, and other information sensing devices that connect any item to the Internet in accordance with the agreed protocol for information exchange and communication.

IoT is characterized by comprehensive perception, reliable transmission, and intelligent processing. Comprehensive perception refers to the use of RFID, GPS, camera, sensor, sensor network, and other sensing, capture, and measurement technology means, anytime and anywhere on the object information acquisition and acquisition. IoT architecture consists of perception layer, network layer, and application layer; its structure is shown in Figure 3: for the perception layer, the main job is collecting information network layer including mobile communication network, computer network, wireless sensor network, and other private networks; for the application layer, it includes cloud computing, application integration, analytical services, and web services, the same as the IoT application sublayer.

*3.2. Key Technologies of Industrial IoT.* The generic technologies involved in the industrial IoT include five key technical issues: sensor technology, communication technology, network technology, information processing technology, and security technology. Figure 4 is the key technology of industrial IoT. At present, key technologies in the application of the IoT in iron and steel enterprises include steel production information acquisition and integration technology based on the IoT, embedded intelligent detection equipment technology based on the IoT, multi-pollution, and large-scale network networking technology under strong shielding environment [16, 17].

Compared with the traditional Internet, the IoT has its distinctive characteristics. First, it is a wide range of perceptual technologies. There are a large number of different

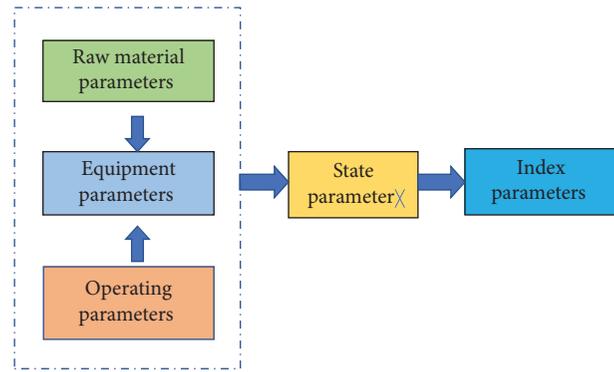


FIGURE 1: Model diagram of pelletizing process.

types of sensors deployed on the IoT. Each sensor is an information source, and the information content and format captured by different types of sensors are different. The data obtained by the sensor are real-time, and the environmental information is collected periodically at a certain frequency to constantly update the data. Second, it is a ubiquitous network built on the Internet. The important foundation and core of IoT technology is still the Internet, which integrates with the Internet through various wired and wireless networks to transmit the information of objects in real time and accurately. The information collected by sensors on the IoT needs to be transmitted through the network at regular intervals. Due to the huge amount of information, it forms a huge amount of information. In the transmission process, in order to ensure the accuracy and timeliness of data, various heterogeneous networks and protocols must be adapted. In addition, the IoT not only provides the connection of sensors but also has the ability of intelligent processing and intelligent control over objects. The IoT combines sensors with intelligent processing to expand its application field by using various intelligent technologies such as cloud computing and pattern recognition. IoT can analyze, process, and process meaningful data from the vast amount of information obtained by sensors, and then adapt it to the different needs of different users and discover new application fields and patterns.

### 4. CNN Model Structure

CNN is a feed-forward neural network, whose artificial neurons can respond to the surrounding units in a part of the coverage area and have excellent performance for large image processing. It includes the convolutional layer and the pooling layer and is a pattern recognition method that combines artificial neural network and deep learning theory, which has become one of the research hotspots in the field of image classification [18]. Different from the traditional image classification method, CNN does not need to extract specific manual features from images for specific tasks. Instead, it simulates human visual system and performs hierarchical abstract processing on the original images to produce classification results. CNN is one of the most popular algorithms for image and video deep learning. Like other neural networks, CNN is composed of an input layer,

TABLE 1: Comparison of three pelletizing methods.

Roasting process	Belt roasting machine method	Grate-rotary kiln method	The whole furnace
Main characteristics	(1) Easy to operate, manage, and maintain	(1) Simple equipment structure	(1) Simple equipment structure
	(2) Can handle all kinds of ore	(2) Even roasting, high yield, and good quality	(2) No special requirements for the whole furnace equipment material
	(3) The calcining cycle is shorter than the shaft furnace method, and the length of each section is easy to control	(3) It can handle all kinds of ore and produce self-fusible pellets	(3) Good use of heat inside the furnace
	(4) Can handle the raw material which is easy to loop	(4) High-temperature resistant alloy steel is not used in rotary kiln and low alloy steel is used in grate	(4) uneven roasting
	(5) Uneven mass of upper and lower pellets	(5) Rotary kiln easy to produce “ring”	(5) Single capacity is small
	(6) High-temperature resistant alloy steel is needed for trolley and grate	(6) If the cooling effect of ring cooling machine is not good, it is not suitable for “ring” materials	(6) Poor adaptability of raw materials, mainly used for magnetite
Quality of products	Good	Well	Poor
Infrastructure investment	Medium	Good	Poor
Operating expenses	Slightly high	Low	Ordinary
Power consumption	Slightly high	Low	High

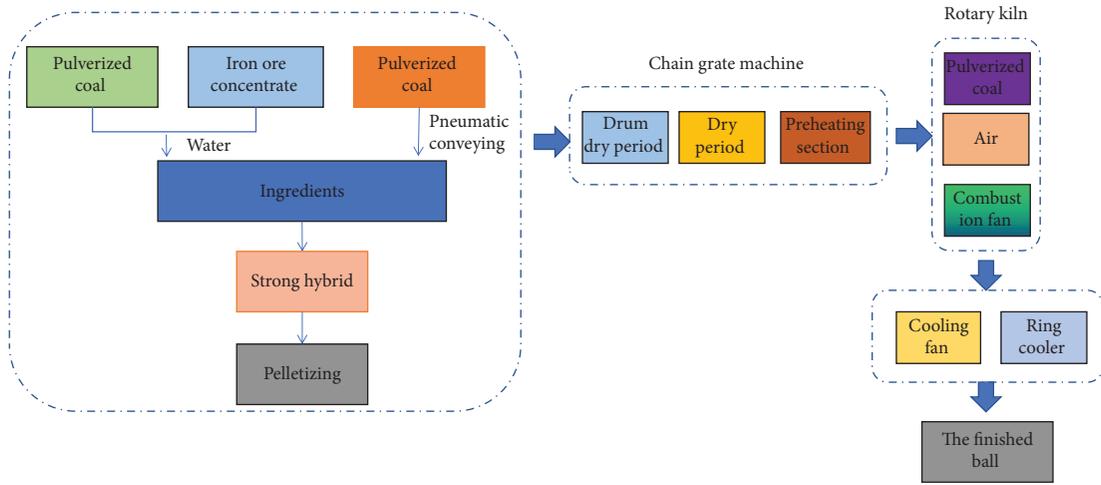


FIGURE 2: Pellet production process flowchart.

an output layer, and multiple hidden layers in the middle; its structure is shown in Figure 5 [19, 20].

**Feature detection layers:** these layers perform one of three types of operations on data, namely, convolution, pooling, or modified linear unit (ReLU). Convolution puts the input image into a set of convolution filters, each of which activates certain features in the image. Pooling simplifies the output by reducing the number of parameters to be learned by performing nonlinear downsampling. Modified linear unit (ReLU) enables faster and more efficient training by mapping negative values to zero and positive values. These three operations are repeated on dozens or hundreds of layers, each learning to detect different features.

The calculation expression of the feature image size of the convolutional layer is

$$L_{l+1} = \frac{L_l + 2p - f_1}{s_1} + 1. \quad (1)$$

In this formula,  $L_{l+1}$  is the convolutional layer output feature image size,  $L_l$  is the convolutional layer input feature image size,  $p$  is the feature map filling layer,  $f_1$  is the convolutional layer convolution kernel size, and  $s_1$  is the convolution step size.

The convolutional layer contains an activation function to help express complex features, which can achieve the purpose of better fitting the objective function. This study

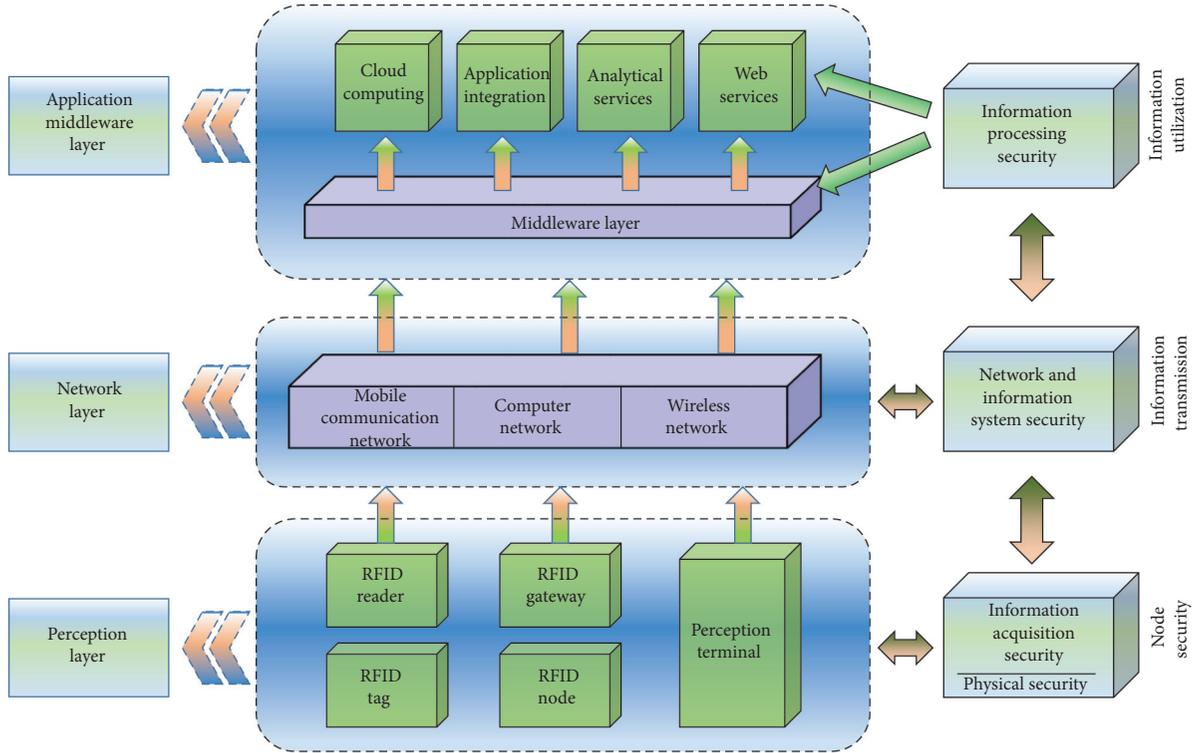


FIGURE 3: System structure diagram of Internet of things (IoT).

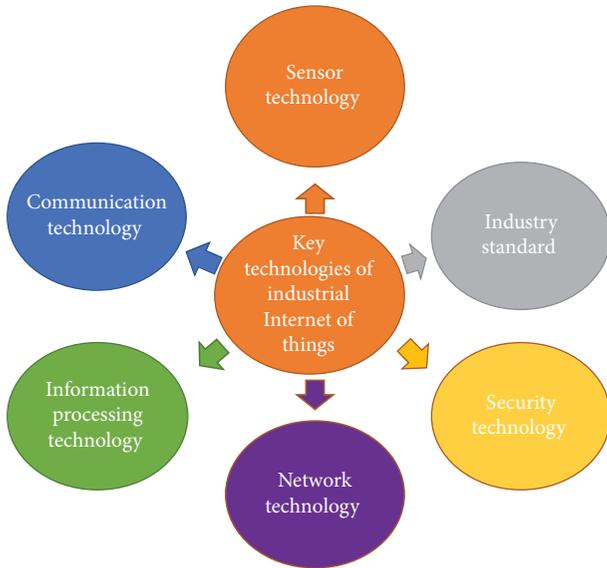


FIGURE 4: Key technologies of industrial IoT.

uses the ReLU function as the activation function, and the expression is as follows:

$$f(x) = \begin{cases} x & (x \geq 0), \\ 0 & (x < 0). \end{cases} \quad (2)$$

After feature extraction in the convolutional layer, the output feature map is passed to the pooling layer for feature

selection and information filtering. The calculation expression of the feature image after pooling is as follows:

$$L_o = \frac{L_i - f_2}{s_2} + 1. \quad (3)$$

In this formula,  $L_o$  is the output feature image size of the pooling layer,  $L_i$  is the pooling layer input feature image size,  $f_2$  is the pooling layer convolution kernel size, and  $s_2$  is the pooling step.

Classification layer: after feature detection, CNN architecture is transferred to classification. The next-to-last layer is the full connection layer, and the output is the vector of  $K$  dimension, where  $K$  is the number of classes that the network can predict. This vector contains the probability of each class of any image to be classified. The last layer of the CNN architecture uses the softmax function to provide classification output; the expression is as follows:

$$y_{kn} = \frac{\exp(a_{kn})}{\sum_{j=1}^q \exp(a_{kj})}. \quad (4)$$

In this formula,  $y_{kn}$  is the predicted probability that the  $k$ -th sample belongs to the  $n$ -th class,  $q$  is the number of classification categories,  $a_{kn}$  is the component of the  $k$ -th sample output and the  $n$ -th type product in the vector, and  $a_{kj}$  is the component of the  $k$ -th sample output and the  $j$ -th type product in the vector.

The training stage of the CNN mainly includes two stages, and its process flowchart is shown in Figure 6.

In the forward propagation process, the square error cost function is used, and the expression is as follows:

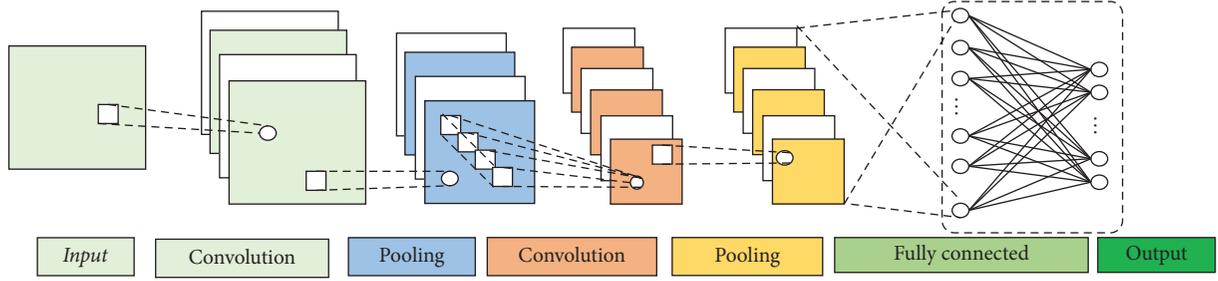


FIGURE 5: Convolutional neural network (CNN) structure diagram.

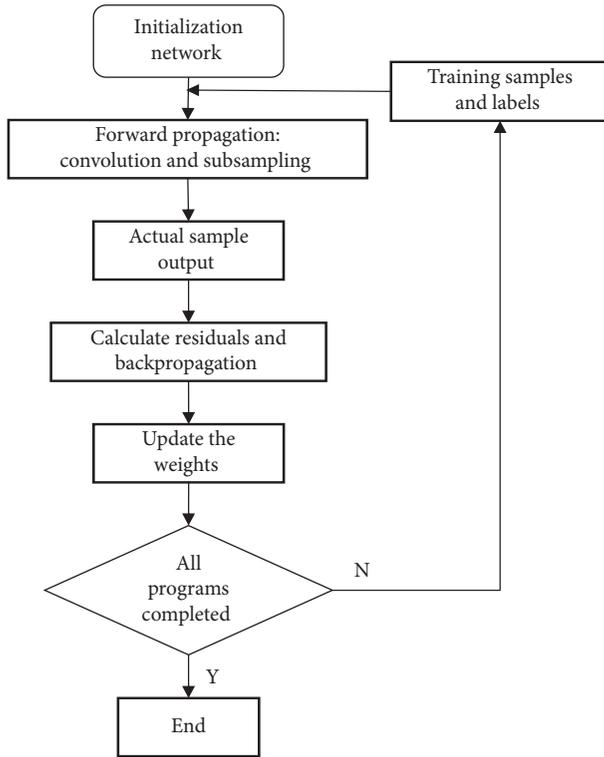


FIGURE 6: CNN training process flowchart.

$$E^N = \frac{1}{2} \sum_{n=1}^N \sum_{k=1}^c (t_k^n - y_k^n)^2, \quad (5)$$

where  $c$  is the number of categories,  $N$  is the number of training samples,  $t_k^n$  represents the  $k$ -th dimension of the label corresponding to the  $n$ -th sample, and  $y_k^n$  represents the  $k$ -th output of the network output corresponding to the  $n$ -th sample.

Use  $l$  to represent the current layer, and the output of the current layer is

$$x^l = f(u^l), u^l = W^l x^{l-1} + b^l. \quad (6)$$

$f(x)$  is an activation function, generally a sigmoid function or a hyperbolic tangent function.

The error backpropagated can be regarded as the sensitivity of the basis of each neuron, defined as

$$\frac{\partial E}{\partial b} = \frac{\partial E}{\partial u} \frac{\partial u}{\partial b} = \delta. \quad (7)$$

Sensitivity calculation formula for layer  $l$  is as follows:

$$\delta^l = (W^{l+1})^T \delta^{l+1} \circ f'(u^l). \quad (8)$$

“ $\circ$ ” in the formula means that each element is multiplied. Neuron sensitivity of the output layer is as follows:

$$\delta^L = f'(u^L) \circ (y^n - t^n). \quad (9)$$

For the first layer, the derivative of the error for each weight of the layer is the cross product of the input of the layer and the sensitivity of the layer. Then, the obtained partial derivative multiplied by a negative learning rate is the updated weight of the neuron in this layer:

$$\frac{\partial E}{\partial W^l} = x^{l-1} (\delta^l)^T, \quad (10)$$

$$\Delta W^l = -\eta \frac{\partial E}{\partial W^l},$$

where  $\eta$  is the learning rate of the weight.

## 5. A Pelletizing Management System Based on CNN and IoT Technology

*5.1. Pelletizing Management System Was Established.* Chinese iron and steel enterprises have many years of experience and achievements in industrialization and informatization construction and have a good foundation for the application of IoT. Through the IoT technology, steel enterprises can carry out intelligent identification, positioning, tracking, monitoring, and management and realize information sharing and interconnection, so as to effectively transform and upgrade the traditional steel industry and integrate and improve enterprise management capacity. As blast furnace smelting gradually tends to be large and intelligent, the requirements of blast furnace smelting on burden structure become increasingly strict, and the rationality of burden structure becomes the key to ensure smelting quality.

The grate-rotary kiln is formed by the junction of a set of equipment of pellet production system, contains the chain grate machine, rotary kiln, ring cold machine, and relevant subordinate unit, pellets roasting process is divided into

three stages, drying and preheating, roasting, cooling, these three stages are completed in three equipment; as a result, many links will directly or indirectly affect the yield and quality of pellet production. At the present stage, most of the grate-kiln system is still under manual control; that is to say, the workers rely on experience to control, so the production and quality of pellet completely depend on the state of the workers. In addition, the composition of each raw material is not stable, so the quality of the raw material ball and the thickness of the layer change greatly, which brings many problems for the automatic control of the grate-kiln system.

According to the working principle and process characteristics of each stage of the grate-rotary kiln production process, this paper designs a set of pelletizing management system based on CNN and IoT technology. Its system workflow is shown in the following figure. The system is helpful to reduce environmental pollution in the industrial production process, to save energy and reduce energy consumption and promote sustainable development, to improve the production and quality of sinter pellets, and to improve the control ability of the process, which is expected to promote the technical progress of the industry.

The pelletizing management system based on the IoT adopts three-layer architecture, as shown in Figure 7. The bottom layer is the sensing layer, which is based on the sensor network nodes to sense the values of relevant parameters in the pelletizing field in real time, and these nodes form a network by themselves, forming the information transmission and preprocessing mechanism between nodes. The second layer is the network access and transmission layer, which is mainly used to transmit the on-site sensing and preprocessed data to the monitoring center through the network. In this layer, existing industrial Ethernet or wireless LAN in the metallurgical industry can be adopted. The third layer is the application layer, namely, the pelletizing process management, control, and service layer. The main tasks of this layer include data analysis and storage, process engineering response and control, and abnormal alarm and control that is to make real-time response, control, and decision on metallurgical process based on field data.

In this paper, the author studies on the system the introduction of the IoT in the process of pellet production technology, using historical data training network CNN model, realizes the perception layer for automatic recognition of image data, and carries on the intelligent analysis, categorizing the working conditions in the current equipment good or bad. According to the working conditions of the current pellets roasting equipment, it is classified, and the process parameters of the grate machine and rotary kiln are accurately adjusted and set to achieve the purpose of accurately controlling the quality of pellets.

*5.2. Instance Analysis of Emulation.* The control difficulties of grate-rotary kiln system mainly include grate layer thickness control, grate-kiln temperature control, and raw material moisture control. Taking grate thickness control as an example, it is necessary to ensure the stability of the thickness of grate and the change of the thickness of grate in order to maintain the gas permeability and the stability of pellets temperature control. The grate machine must ensure that the thickness of pellets on it is uniform. If the thickness is not uniform, a large amount of high-temperature gas will pass through the place where the thickness of the pellets is thin, and the gas resistance is small. This will seriously damage the thermal efficiency of the grate machine, resulting in greater changes in the strength of the pellets after roasting, unstable strength, which will affect the quality of pellets.

Use historical data training network CNN model, and apply it to the roasting management system based on IoT technology in gas machine material thickness detection and intelligent control; the results show that, compared with the traditional control method, in this paper, the designed algorithm can improve the chain of gas machine material layer thickness control precision, at the same time ensure that the chain gas machine material layer permeability under the premise of effectively improves the production of pellets, and effectively improve the pellet production. The production data curve of automatic thickness adjustment of chain grate is shown in Figure 8.

It can be seen from Figure 8 that the fluctuation of the thickness of the layer treated by the automatic recognition and control system designed in this paper is significantly reduced, which effectively overcomes the fluctuation of the amount of raw materials and ensures the smooth change of the thickness of the layer. At the same time, the control precision of the grate layer is improved, which lays a foundation for optimizing the temperature field of the chain grate.

The operating curve of its air permeability is shown in Figure 9. The time interval of sample points is 10 minutes.

The gas permeability fluctuation of the pellet sintering chain grate is 3.7%, while that of manual control is 9.5%. It can be seen that the thickness and velocity of chain grate automatically controlled by CNN and IoT technology can effectively reduce the fluctuation of gas permeability, as shown in Figures 10 and 11, which will play an important role in improving the output and quality of finished pellets.

By using this system, the fluctuation of physical properties of finished pellets, such as rolling drum and screening index, is greatly reduced, so as to improve the first-grade product rate of finished pellets and improve the continuity and stability of the pellet production process.

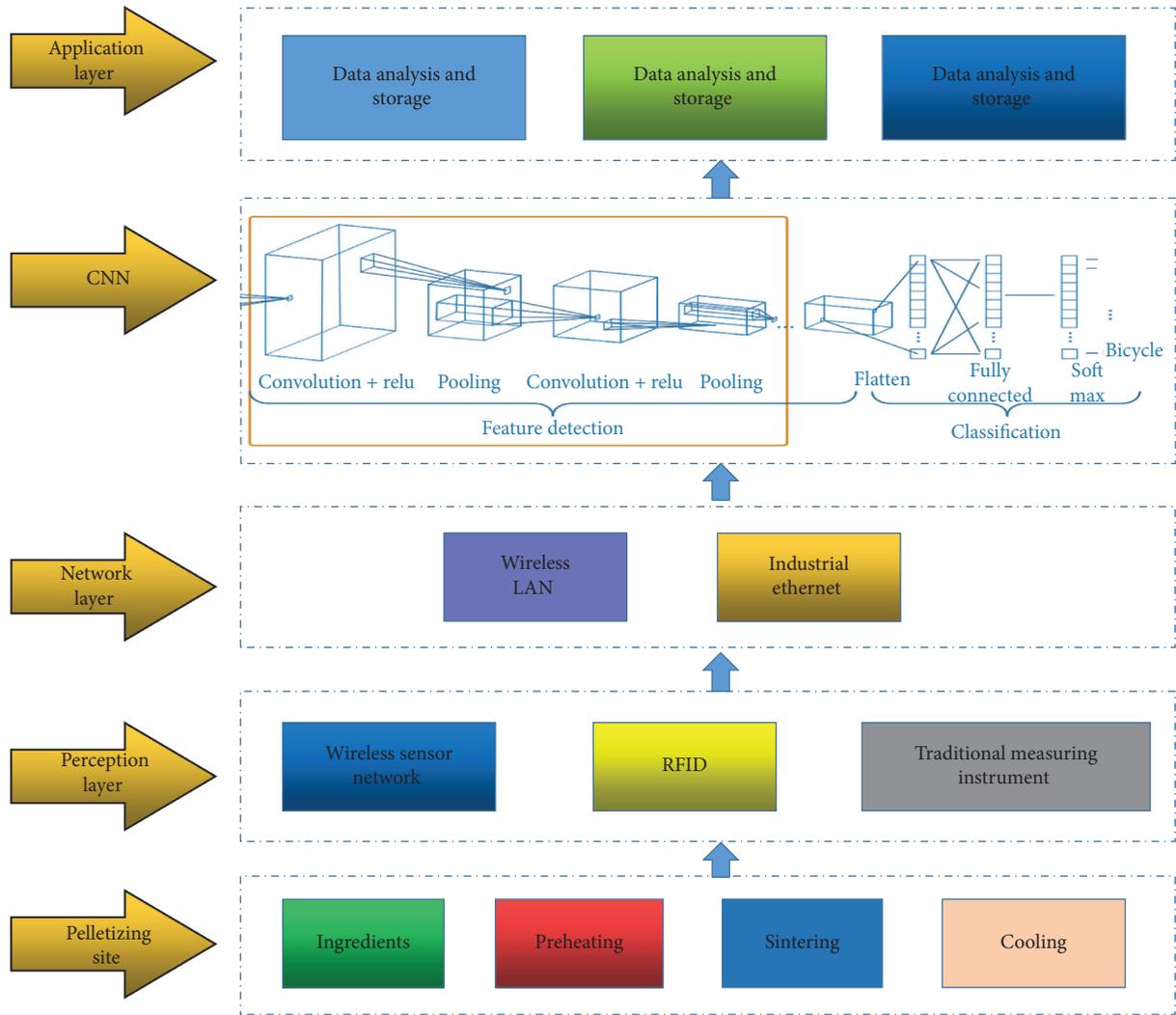


FIGURE 7: A pelletizing management system based on CNN and IoT technology.

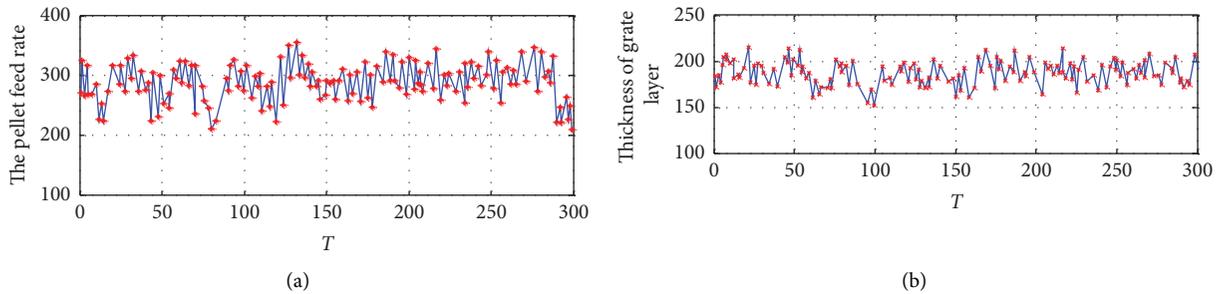


FIGURE 8: Production data curve of automatic thickness adjustment of chain grate.

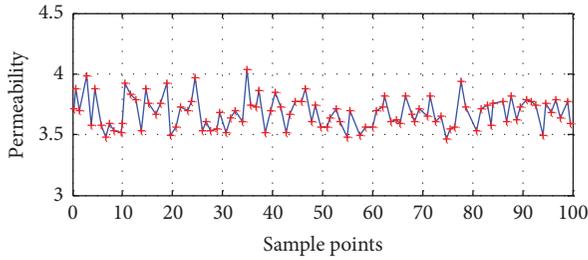


FIGURE 9: Comprehensive gas permeability operation curve.

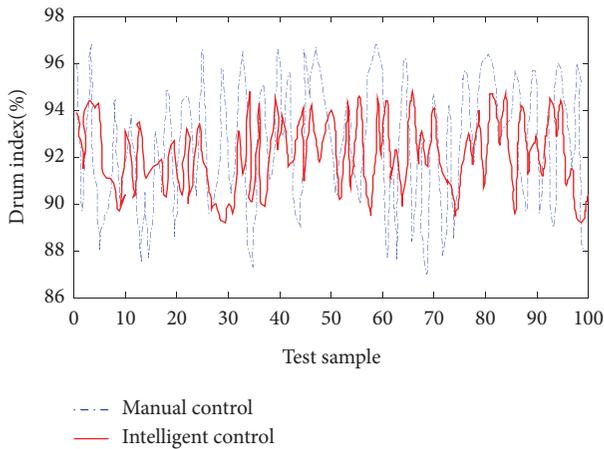


FIGURE 10: Comparison of rational energy drum index of finished pellets.

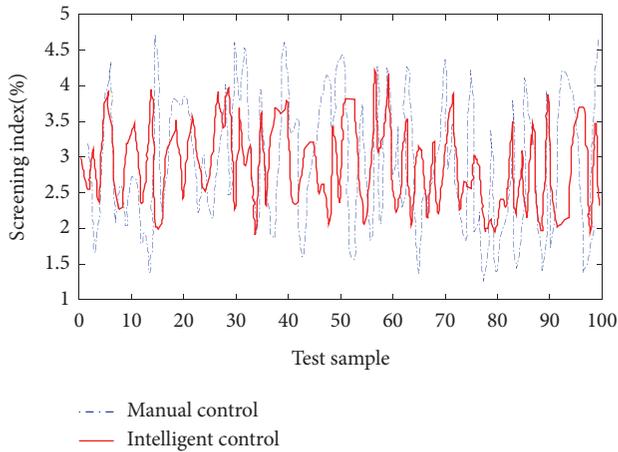


FIGURE 11: Comparison of mineral rational energy screening index of finished pellets.

## 6. Conclusion

The grate-rotary kiln oxide pellet production technology advantages are as follows: production technology is advanced, production stability is relatively taller, pellets are made of high quality, hardness is strong, pellets are reasonable in structure, the existing grate-rotary kiln control system control mode mostly uses the manual control mode,

and pellet production quality depends largely on the site operator experience, fatigue, and the sense of responsibility. The pellet roasting management system based on CNN and IOT technology can automatically identify image data through the perception layer and can perform intelligent analysis at the same time. On this basis, it is classified according to the working conditions of the equipment, and the technological process in the rotary kiln is judged. Ensure that the parameter settings in the production process are accurate, and achieve the purpose of controlling the quality of pellets. The effect of the system shows that the control method is effective, and the thickness of the grate is automatically controlled. Finally, it lays a solid foundation for the automatic control of the temperature field of chain grate, rotary kiln, and ring cooler.

## Data Availability

All the data in the paper are true and reliable, and the data used in the chart of the paper can be obtained from the author.

## Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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