ITC 3/54

Information Technology and Control
Vol. 54 / No. 3/ 2025
pp. 1095-1105
DOI 10.5755/j01.itc.54.3.40285

Research on Real Time Prediction Method of Kiln Flame Temperature Based on 5G Communication and CA-ResNet50 Fusion Network

Received 2025/01/23 | Accepted after revision 2025/04/17

HOW TO CITE: Li, J., Li, T., Zhao, Z., Yu, Z., Zhu, M., Liu, N., Wang, D., Deng, P. (2025). Research on Real Time Prediction Method of Kiln Flame Temperature Based on 5G Communication and CA-ResNet50 Fusion Network. *Information Technology and Control,* 54(3), 1095-1105. https://doi.org/10.5755/j01.itc.54.3.40285

Research on Real Time Prediction Method of Kiln Flame Temperature Based on 5G Communication and CA-ResNet50 Fusion Network

Jun Li, Tao Li, Zengyi Zhao, Zhongzhan Yu
Mechanical and Electrical Thermal Research and Development Center, Ceramic Research Institute of Light Industry of China, Jingdezhen 333000, China

Ming Zhu
E Surfing IoT Tech Co., Ltd

Ning Liu
School of Internet of Things, Nanjing University of Posts and Telecommunications

Dahai Wang
Jingdezhen Hongye Ceramics Co., Ltd

Pengfei Deng
China Telecom Co., Ltd. Jingdezhen Branch

Corresponding author: jackson0798@qq.com

As intermittent kilns, shuttle kilns are often used in the production of daily-use ceramics. The temperature has a significant impact on the products inside the kiln, and currently, most shuttle kilns still rely on human observation of the flame to adjust the temperature, which has uncertainties and limitations. This paper proposes a real-time prediction method for kiln flame temperature based on 5G communication and CA-ResNet50 fusion network, which utilizes the low latency and high bandwidth characteristics of 5G networks to collect real-time data and ensure the correspondence between flame images and temperature. And combine the CA (Coordinate attention) mechanism with the ResNet50 network to improve the network's attention to flame image features, thereby enhancing prediction accuracy. The experimental results show that the proposed method can improve the accuracy of temperature prediction based on flame images, providing new ideas for temperature control in shuttle kilns.

KEYWORDS: Shuttle kiln, Attention mechanism, ResNet50, Deep learning

1. Introduction

Shuttle kilns are intermittent firing kilns that can meet the requirements of continuous large-scale production and small-scale intermittent production [24, 22]. They are commonly used thermal equipment in the ceramic production process. The quality of ceramic products ultimately fired is closely related to the kiln firing process, and the firing atmosphere determines the final state of the product. Temperature is the first element in kiln firing, and the firing temperature for different products varies. The firing temperature for blue and white porcelain is generally between 1250 and 1300 °C, while underglaze red needs to be completed at 1200-1270 °C. Therefore, precise control of the temperature inside the kiln is crucial for the quality of the products. At present, the method of determining temperature in shuttle kilns is to insert thermocouples into a certain part of the kiln to reflect the local temperature. In addition, kiln workers often observe flames through their own experience and use temperature measuring cones to determine the temperature inside the furnace. However, the above methods have significant deviations and low efficiency in determining the temperature in the kiln. Subsequently, researchers proposed using PID technology to achieve kiln control for temperature intelligent detection [7, 23], but this method has low accuracy and complex parameter adjustment in the case of constantly changing temperatures.

With the development of deep learning networks, using neural networks to adjust the parameters in the network and learn the relationship between image features and data has become a widely used method, such as [20, 3]. These methods use collected datasets and labels to train neural networks and fit the relationships between data. However, due to the low clarity of the collected images and the delay between data, the trained models have poor performance. Transmission rate and data quality are important indicators in real-time image acquisition. With the development of 5G network technology, transmission rate has far exceeded that of 3G and 4G networks, and the network delay is shortened from 50 ms of 4G to less than 1 ms now, this enables the application of 5G technology in some image acquisition and processing tasks, thereby achieving an improvement in safety and low-latency. For kiln firing, 5G technology can not only obtain high-quality flame images, but also ensure real-time acquisition of flame images and corresponding temperatures. In terms of flame feature learning, ResNet50 network is widely used in tasks such as image classification and recognition. The residual block introduced in this structure can effectively solve the problem of gradient vanishing, thereby enabling the network to learn more complex features. Attention mechanism can allocate more weights to important features, improve the network model's ability to capture key information, and thus enhance the detection and prediction accuracy of the model.

This paper proposes researching flame image temperature prediction based on combining the CA-Resnet50 network and 5G technology. By utilizing the low latency and high bandwidth characteristics of 5G network technology, accurate acquisition of flame images in kilns is carried out, and a high-definition and reliable dataset is established. Secondly, using neural network models and attention mechanisms to assist in training, the corresponding relationship between images and temperature is fitted, fully reflecting the temperature of flame images in different states during firing, accurately grasping the temperature situation inside the furnace, and improving the production quality of products.

2. Related Work

There are many traditional flame image temperature detection methods, such as flame temperature detection based on spectral technique [17], quantitative schlieren technique [14], the light field camera method [12], etc. These methods predict images by manually extracting features, which is complex and has significant errors. The current prediction of flame image temperature generally adopts a neural network-based prediction scheme, which to some extent compensates for the shortcomings of traditional methods and improves prediction accuracy. It learns the features of flame images, corresponds to temperature values in real data, forms a mapping relationship, and uses the powerful fitting ability of neural networks to fit the functional relationship between image features and temperature data, achieving more accurate prediction, such as CNN [11], GAN [1], VGG [15], transformer [19], etc.

CNN networks are commonly used for image classification and prediction. Convolutional layers are used to automatically extract image features, and pooling layers are used to reduce the spatial dimension of features. Finally, fully connected layers are used for classification or regression, solving the problem of insufficient accuracy in traditional image classification methods. ResNet50 is a variant of CNN, which solves the problem of degradation in deep neural network training [4]. As the depth of the network increases, traditional neural networks will encounter the problem of performance degradation. This is because as the number of network layers increases, the gradient gradually disappears during back-propagation, resulting in ineffective training of the weights of shallow networks. ResNet50 solves this problem by introducing residual blocks, each of which contains a "skip connection" that allows information to be directly passed from early layers to later layers, thereby alleviating the problem of gradient vanishing. This structure allows the network to be trained deeper while maintaining performance without degradation. It has been widely used in computer vision tasks such as image classification, object detection, and image segmentation [13, 8, 2]. Attention mechanism is a method that allows neural networks to focus on important parts when processing data. It allows models to selectively allocate attention resources in input information, thereby improving performance for specific tasks. This mechanism mimics the way attention works in the human visual system, where humans selectively focus on a portion of all information. For image tasks, it is a mechanism that focuses on local information of the image, such as a certain texture area in the image. As the task changes, the attention area often changes, and currently widely used attention mechanisms such as SENet [6], CBAM [21], CA [5], etc.

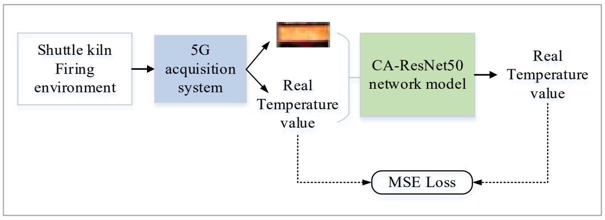
We adopt the CA attention mechanism and the ResNet50 network fusion algorithm. CA attention can be inserted into the network to improve the performance of the network model, which can also better help the ResNet50 network model to more accurately locate and recognize the target of interest in the image. In addition, to ensure low latency and data reliability during data collection, 5G network technology is used as the data collection method to record image status and corresponding temperature values in real time. The collected data is preprocessed and divided into training and testing sets, which are provided to the neural network for training. Based on this, this article proposes a flame image temperature prediction method combining the CA-ResNet50 network and 5G technology. The CA attention mechanism is inserted into the designed ResNet50 network to enhance the network's learning of image feature regions, which can better extract the position and spatial information of features. Combined with the high-speed and low latency characteristics of 5G technology, it can achieve the collection and transmission of high-definition and real-time videos, thereby improving the accuracy of flame image temperature prediction.

3. Proposed Method

The algorithm framework proposed in this paper is shown in Figure 1. A 5G acquisition system is used to collect data from the shuttle kiln firing environment, obtaining high-definition flame images and corresponding temperature values. These data are fed into the CA-ResNet50 network model for training, learning the mapping relationship between the fitted data, and accurately predicting the temperature values of the flame images. Additionally, the loss function is used to adjust the parameters of the model to better approximate the true results. The following text will provide a specific introduction to the 5G acquisition system and CA-ResNet50 model.

Figure 1

Overall network framework.



3.1. 5G Acquisition System

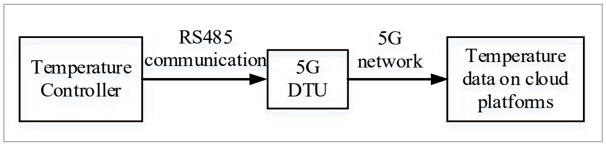
5G technology has faster data transmission speeds, enabling faster information collection, uploading, and sharing, better meeting the network speed requirements of various scenarios in mobile operations. At the same time, the transmission of 5G networks can achieve a delay of less than a few milliseconds, which allows for more real-time acquisition of flame images, synchronized collection of temperature values, and reduction of training set errors in such network environments.

This project adopts 5G IoT Gateway technology as the data terminal device to achieve the collection and wireless transmission of kiln temperature data [18]. We use the Quectel RM500U module for data transmission, with a maximum upstream speed of 900Mbps, the acquisition layer uses Modbus RTU/TCP protocol. At the same time, we choose an industrial camera with a resolution of 2448x2048 (5 million pixels) to capture high-quality flame image.

In terms of data transmission, PTP (Precision Time Protocol) is used to achieve time synchronization between the camera and 5G DTU (Data Transfer Unit), and 5G URLLC (Ultra-reliable and Low Latency Communications) slicing technology is utilized to ensure priority transmission of key data. And then, 5G DTU will transmit the data from the kiln temperature controller to the cloud through a 5G network and obtain temperature data samples. As shown in Figure 2, this project will connect the 5G DTU to the furnace temperature controller and obtain real-time data.

Figure 2

5G data communication.



To optimize the ceramic firing process and improve the quality of ceramic products, industrial camera is used to capture the flame image of the firing atmosphere at the observation hole of the ceramic kiln during the entire firing process. Based on the uRLLC characteristics of the 5G network, real-time remote monitoring of the firing situation inside the kiln can be achieved, and relevant data can be extracted. The flame images and temperature information at each moment correspond one-to-one, establishing a sample of flame images and corresponding temperature data.

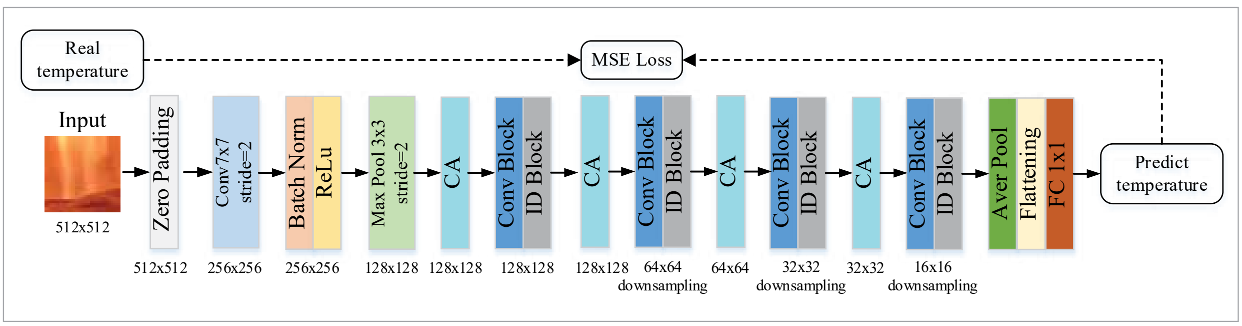
3.2. CA-ResNet50 Prediction Network Model

3.2.1. CA-ResNet50 Model Framework

In order to improve the performance of the model, this paper combines the ResNet50 network with the CA attention mechanism. The CA attention mechanism is added before the convolution block in the ResNet50 network, which automatically learns important information such as flame image color sta-

Figure 3

Proposed CA-ResNet50 model framework.



tus. After the ID block, the attention module is also used to further process and emphasize key features. The CA-ResNet50 network framework is shown in Figure 3, and the network adopts the ResNet50 structure as the main framework, which includes multiple processing stages. Firstly, the input flame image is preliminarily preprocessed by performing convolution, regularization, activation function, and max pooling calculations to extract low-level flame image features. Secondly, the extracted image features are input into the CA attention mechanism, where the network focuses on key image features. The CA module enhances the representation ability of features by using attention weights in both horizontal and vertical directions, guiding the network to focus on key areas. Specifically, the red channel (high temperature) may be strongly correlated with specific spatial locations (flame core), and CA can adaptively enhance the channel characteristics of these areas and transmit them to subsequent structures to strengthen attention to these features. The output results are transmitted to the conv block and ID block, allowing the network to change its dimensions. Their core function is to solve the gradient vanishing problem in deep networks through residual learning, while efficiently extracting multi-scale features, thereby improving the complexity and predictive ability of the model.

After the continuous combination of attention and basic blocks, the feature maps extracted are transformed into prediction probabilities through average pooling and fully connected layers. Specifically, the feature maps are flattened into one-dimensional vector maps. Then map it to the probability space through a series of fully connected operations, and finally output the prediction result.

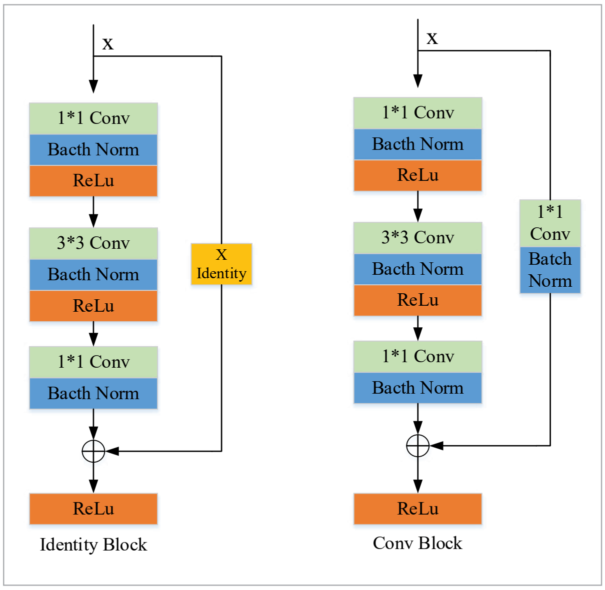
3.2.2. Conv Block and ID Block

The design of the Convolutional Block and the Identity Block enable ResNet50 to be deeper and easier to train, resulting in good performance in tasks such as image prediction. Their structures are shown in the following Figure 4.

The main purpose of Identity Block is to deepen the depth of the network, which consists of three convolutional layers. The first and third convolutional layers are 1x1 convolutional layers, and the middle convolutional layer is 3x3 convolutional layer. They are used to reduce the number of channels, restore the number of channels, and learn features, respectively. The input and output of this structure have the same dimension, and the input is directly added to the output through skip connections, retaining the information of the original input.

Figure 4

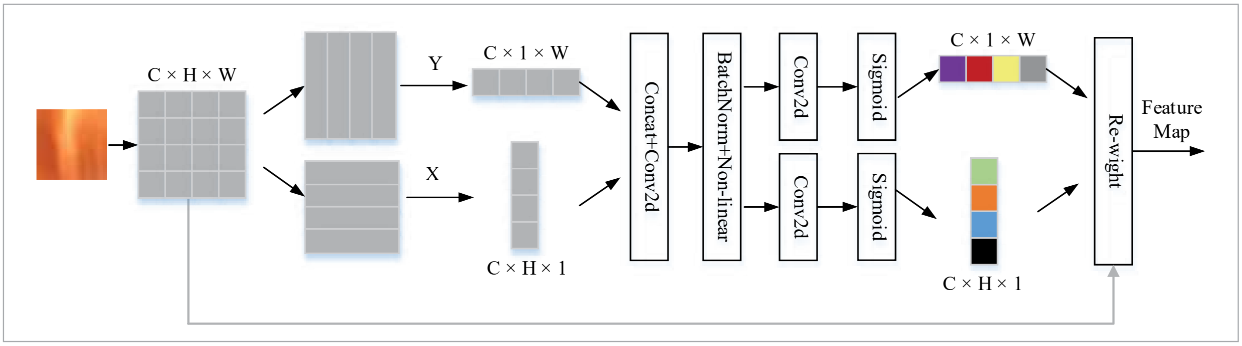
The network structure Identity Block and Conv Block.



The main function of the Convolutional Block structure is to adjust dimensions and achieve downsampling. Similar to the Identity Block structure, it uses two 1x1 convolutional layers and a 3x3 convolutional layer in the middle. The difference is that it adds 1x1 convolution and regularization processing during skip connections, thereby changing the dimensionality of the network. Through the deep network structure and residual learning of the ResNet50 network, complex features in flame images can be effectively captured. Flame images have higher resolution when passing through shallow networks, and can utilize more fine-grained feature information such as edges, textures, etc. Moreover, the receptive field overlap area corresponding to each pixel in the feature map is also very small, which ensures that the network can capture more details in flame images. When performing deep network feature extraction, as the number of downsamplings or convolution increases, the receptive field gradually increases, and the

Figure 5

The network structure of the adopted CA attention.



overlapping area between receptive fields also increases. At this time, the information represented by the pixel points is the information of a region, and the obtained feature information is the feature information of this region or adjacent regions, which is relatively fine-grained and has low resolution, but rich in semantic information. The network improves the performance of the model in image recognition through a layer-by-layer feature extraction process.

3.2.3. CA Module

In addition, to enhance the learning ability of the model, the network can focus on the key areas of the flame image and introduce CA attention. The CA attention mechanism embeds position information into channel attention and calculates attention in two spatial dimensions (height and width), which can more accurately capture the spatial distribution features in the image and comprehensively capture the dependency relationships between features. It not only considers channel information but also direction-related position information, making up for the shortcomings of SE attention and CBAM methods. The network structure of the CA attention mechanism is shown in Figure 5.

In order to alleviate the loss of positional information caused by global pooling in the network, channel attention is decomposed into two parallel feature encoding processes to effectively integrate spatial coordinate information into the generated attention map. Specifically, two global pooling operations were utilized to aggregate input features along both vertical and horizontal directions, generating two feature maps containing direction-specific information. These two feature maps are then encoded into two attention maps, each capable of capturing the long-range dependencies of the input feature map along a spatial direction, enhancing feature representation, and improving network learning of flame image features. This enables more accurate segmentation of flame images and focuses on the color states of the flame parts. The coordinate feature encoding can be represented by Equations (1)-(2), which perform average pooling along the height (H) and width (W) directions, respectively, to obtain horizontal and vertical features, x is the input feature map.

$$z_h(h) = \frac{1}{W} \sum_{0 \le w \le W} x(h, w) \tag{1}$$

$$z_w(w) = \frac{1}{H} \sum_{0 \le h \le H} x(h, w) . \tag{2}$$

After concatenating $z_h(h)$ and $z_w(w)$, attention weights g_h and g_w are generated through convolution and activation function. The final output can be represented as

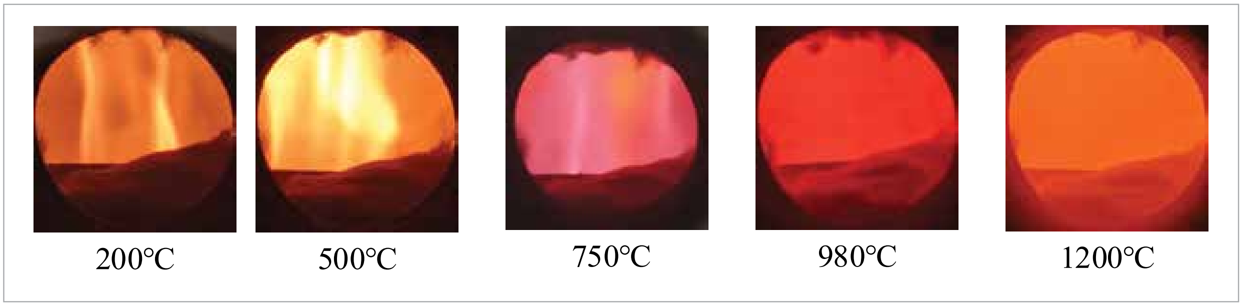
$$y = x \cdot g_w \cdot g_h . \tag{3}$$

3.2.4. Loss Function

After obtaining the prediction results, the loss function is optimized by comparing them with the true temperature corresponding to the flame image. In this paper, the mean square error loss function is used to optimize the network. The mean square er-

Figure 6

Flame images at different stages.



ror calculates the average square of the difference between the predicted temperature value and the actual temperature value, which is used to measure the accuracy of the model prediction. The calculation Equation (4) is as follows:

$$L(t,t') = \frac{1}{n}\sum_{i-1}^{n}(t_i - t_i')^2 . \tag{4}$$

Among them, t is the real temperature value, t' is the temperature value predicted by the model, and n is the number of samples. The network continuously updates training parameters to minimize mean square error and obtain better prediction results.

In the proposed network architecture, incorporating the CA mechanism into the ResNet50 network can enable the model to better capture the interrelationships between different features, improve its performance, and truly extract positive and effective features from flame images.

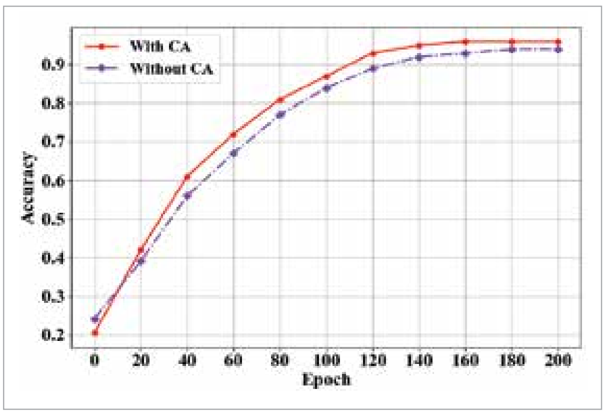
4. Experiment and Analysis

4.1. Experimental Environment

This network framework is implemented by Pytorch and executed on NVIDIA RTX 2080ti. The heating process of ceramic firing in a shuttle kiln can be divided into several stages: generally before 400 °C, it belongs to the low-temperature stage, and the heating rate in this needs to be appropriately controlled to ensure that the billet will not crack due to rapid heating; the oxidation decomposition stage is from 400 °C to 900 °C, mainly to ensure the oxidation atmosphere inside the kiln; 900 °C to 1300 °C is the high-temperature firing stage, and when the temperature rises to around 1050 °C, reduction begins, creating a reducing atmosphere; Around 1300 °C is the insulation stage. The dataset is captured through an observation hole using electronic devices. The dataset consists of flame images and corresponding temperature values recorded during the firing process of a shuttle kiln in Jingdezhen. The flame dataset is collected starting from 50 °C, and a set of flame images is captured for every approximately 10 °C increase in temperature, and saved in JPG format until the shooting ends at 1300 °C. We preprocessed the dataset and obtained 5000 flame images containing corresponding temperatures. The training set and the testing set are divided, with 500 images used as the testing set. Figure 6 shows partial flame image samples at different stages during the heating process of the shuttle kiln. The size of the collected flame images is set to 512x512. The Adam optimizer adaptively adjusts the learning rate of each param-

Figure 7

Prediction accuracy with and without CA.



eter to improve the convergence speed and generalization ability of the model [9], the number of iterations on the entire training dataset is set to 200 epochs. The learning rate is set to 0.0001 to effectively suppress overfitting and accelerate network convergence, which could control the step size of model network parameter updates.

4.2. Evaluation and Comparative Experiment

Send the collected high-definition kiln flame images along with corresponding temperature values to the CA-resNet50 network for training, and obtain a better prediction model after setting the total step size. In the firing process of shuttle kilns, a temperature error of 40°C is usually acceptable, so we predict the test set, with a prediction error range of ± 40 °C being correct. The formula for predicting accuracy is as follows, n_a represents the number of predictions that meet the criteria, and n_s represents the total number of predictions.

$$y_p = \frac{n_a}{n_s} \times 100\% \quad (5)$$

In order to verify that the added attention mechanism can improve the prediction accuracy of the model, this paper conducted comparative experiments to maintain the same experimental environment and variables under the same dataset conditions, with only the difference between adding the CA attention mechanism and not, we test 100 images from the test set respectively, the average prediction accuracy of the test flame image is calculated, and the test results are shown in Figure 7 to demonstrate the role of CA in the network.

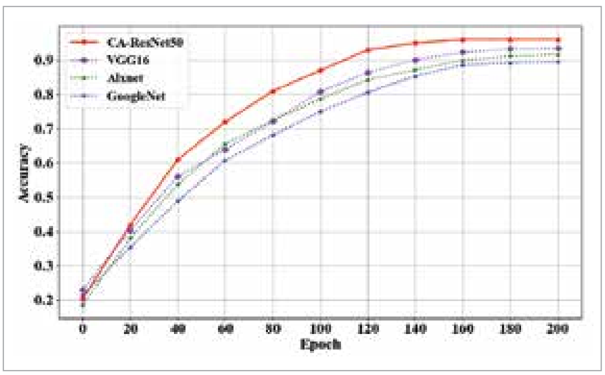
Table 1
Comparison of accuracy between different models.

Model	Accuracy rate
Alexnet	91.%
GoogleNet	90.5%
VGG16	93.8%
CA-ResNet50	**95.2%**

The results from the figure show that after a certain period of training and reaching stability, the prediction accuracy of the network model with added CA is higher than that without added CA. In the early stage of training, due to the higher complexity of the network with added CA, the convergence speed is slower, and the prediction accuracy in the early stage is lower than that of the model without CA. However, as the training gradually increases, the network converges stably. CA can better help the model focus on the input data information to image features, further improving the prediction accuracy.

To further validate the effectiveness of our method, we compared it with several other prediction network models through experiments, including Alexnet [10], VGG16 [15], and GoogleNet [16]. These prediction networks were trained and tested on the same dataset and hyperparameters. The experimental results calculated by Formula (5) are shown in Table 1. The algorithm proposed in this paper has a better prediction rate than other network models, reaching 95%. In addition, we presented the training performance of these models, as shown in Figure 8, which displays the corresponding prediction accuracy of each model at different training periods. In the first 20 epochs, due to the high complexity and unstable convergence stage of the models, the prediction accuracy was low. The proposed model, like other models, showed continuous improvement in prediction accuracy with the iteration of training, and our model has better performance. The above experiments also demonstrate that our algorithm has a stronger network learning ability, can learn flame image features more fully, and is more effective in fitting the relationship between images and data.

Figure 8
Accuracy of different models at the training epoch time.



In order to conduct a more detailed comparative analysis with other models, we chose the Mean Absolute Error (MAE) as the indicator to measure the effectiveness of the model. The calculation formula is as follows, where t_i represents the predicted temperature value and t represents the real temperature value.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|t_i - t\right| . \quad (6)$$

We test the MAE values of 50 flame images for each model and calculate the average. The experimental results are shown in Table 2, the proposed model has a lower MAE value, which indicates that the predicted values are closer to the true values, resulting in better model performance. This further demonstrates that our improved network architecture can enhance model performance.

Table 2

Comparison of the MAE.

Model	MAE
Alexnet	13.7°C
GoogleNet	15.3°C
VGG16	10.6°C
CA-ResNet50	8.5°C

5. Discussion

This paper proposes a method based on CA- ResNet50 network and 5G technology for temperature measurement and control of shuttle kilns, The low latency and high bandwidth performance of the 5G network are used to collect flame images and corresponding temperature data, and the deep residual network ResNet50 is used as the back-bone network, combined with the CA attention mechanism, focusing on the features of flame images, increasing the learning of effective features, reducing the interference of unimportant features, and improving the prediction performance of the network. The method can achieve more efficient intelligent detection in the application of flame temperature in shuttle kilns.

As can be seen from the experimental results, our model significantly outperforms traditional methods and existing deep learning models. Firstly, the accuracy of the prediction reached 95%, indicating a significant improvement in prediction accuracy. This result indicates that the improved model is more effective in predicting flame temperature, resulting in more accurate detection results. Secondly, we conducted comparative experiments on the extracted models, comparing the differences between using attention mechanism and not using it. The experiments showed that the model with added attention could more accurately predict flame temperature. In addition, we compared the changes in prediction accuracy during the training process. In the first 20 epochs, due to the high complexity and unstable convergence stage of the models, the prediction accuracy was low. The proposed model, like other models, showed continuous improvement in prediction accuracy with the iteration of training, and our model has better performance.

In summary, our model has improved the accuracy of flame prediction in shuttle kilns to some extent, but there are also certain limitations, such as requiring different training for different products and weak generalization ability. We hope to further improve the generalization of the model and expand its application in different kilns and products.

6. Conclusions

In order to further improve the temperature judgment and regulation during the firing of ceramics in shuttle kilns, and thus enhance the quality of products, this paper proposes a flame image temperature prediction research technology based on CA-ResNet50 network and 5G technology. The low latency and high bandwidth performance of the 5G network are used to collect flame images and corresponding temperature data, and the deep residual network ResNet50 is used as the backbone network, combined with the CA attention mechanism, focusing on the features of flame images, increasing the learning of effective features, reducing the interference of unimportant features, and improving the prediction performance of the network.

The experimental comparison shows that the method proposed has higher prediction accuracy in this paper, which can achieve more stable flame recognition and more efficient intelligent detection in the application of flame temperature in shuttle kilns. In future research, we will focus on multimodal data collaborative learning and prediction model optimization, which utilize multiple different data modalities for training. We could use flame image data, gas pressure, flow rate, and other data to collaboratively predict flame firing status, further improving the intelligent monitoring and safety production efficiency of kilns.

Data Availability

The datasets are available from the corresponding author on reasonable request.

Funding

This study was supported by Jiangxi Province 03 Special Project and 5G Project (Grant No. 20232AB-C03A33) and Ganpo Juncai Supports Plan (Grant No. 20232BCJ23106).

References

1. Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., Bengio, Y. Generative Adversarial Networks. Communications of the ACM, 2020, 63(11), 139-144. https://doi.org/10.1145/3422622
2. Habbib, A. M., Khidhir, A. S. M. Fire Recognition Using EfficientNet and ResNet50. In Proceedings of the 2023 International Conference on Engineering, Science and Advanced Technology (ICESAT). IEEE, 2023, 18-22. https://doi.org/10.1109/ICESAT58213.2023.10347300
3. Han, Z., Li, J., Zhang, B., Hossain, M. M., Xu, C. Prediction of Combustion State Through a Semi-Supervised Learning Model and Flame Imaging. Fuel, 2021, 289, 119745. https://doi.org/10.1016/j.fuel.2020.119745
4. He, K., Zhang, X., Ren, S., Sun, J. Deep Residual Learning for Image Recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2016, 770-778. https://doi.org/10.1109/CVPR.2016.90
5. Hou, Q., Zhou, D., Feng, J. Coordinate Attention for Efficient Mobile Network Design. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2021, 13713-13722. https://doi.org/10.1109/CVPR46437.2021.01350
6. Hu, J., Shen, L., Albanie, S., Sun, G., Wu, E. Squeeze-and-Excitation Networks. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2020, 42(8), 2011-2023. https://doi.org/10.1109/TPAMI.2019.2913372
7. Huang, W., Zhou, F., Zhong, Z. Energy Saving of Shuttle Kiln Furnace: A Study Based on PLC Control. Journal of Physics: Conference Series, 2021, 2044(1), 012183. https://doi.org/10.1088/1742-6596/2044/1/012183
8. Jabnouni, H., Arfaoui, I., Cherni, M. A., Bouchouicha, M., Sayadi, M. ResNet-50 Based Fire and Smoke Images Classification. In Proceedings of the 2022 6th International Conference on Advanced Technologies for Signal and Image Processing (ATSIP). IEEE, 2022, 1-6. https://doi.org/10.1109/ATSIP55956.2022.9805875
9. Kingma, D. P., Ba, J. Adam: A Method for Stochastic Optimization. arXiv Preprint, 2014, arXiv:1412.6980. https://doi.org/10.48550/arXiv.1412.6980
10. Krizhevsky, A., Sutskever, I., Hinton, G. E. ImageNet Classification with Deep Convolutional Neural Networks. Communications of the ACM, 2017, 60(6), 84-90. https://doi.org/10.1145/3065386
11. LeCun, Y., Bottou, L., Bengio, Y., Haffner, P. Gradient-Based Learning Applied to Document Recognition. Proceedings of the IEEE, 1998, 86(11), 2278-2324. https://doi.org/10.1109/5.726791
12. Liu, Y., Hossain, M. M., Sun, J., Zhang, B., Xu, C. Investigation and Optimization of Sampling Characteristics of Light Field Camera for Flame Temperature Measurement. Chinese Physics B, 2019, 28(3), 034207. https://doi.org/10.1088/1674-1056/28/3/034207
13. Pramanik, S., Dahlan, H. A. B. Age Estimation Using Shortcut Identity Connection of ResNet50 Based on Convolutional Neural Network. In Proceedings of the 2021 International Conference on Electrical Engineering and Informatics (ICEEI). IEEE, 2021, 1-7. https://doi.org/10.1109/ICEEI52609.2021.9611146
14. Sheng, M., Zangjian, Y., Mingxiao, W., Zhongliang, S., Kai, D., Yingjie, Z. Application of Quantitative Schlieren Method in Flame Temperature Measurement. Journal of Experiments in Fluid Mechanics, 2015, (4), 65-69. https://doi.org/10.11729/syltlx20140117
15. Simonyan, K. Very Deep Convolutional Networks for Large-Scale Image Recognition. arXiv Preprint, 2014, arXiv:1409.1556. https://doi.org/10.48550/arXiv.1409.1556

16. Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D. Going Deeper with Convolutions. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2015, 1-9. https://doi.org/10.1109/CVPR.2015.7298594

17. Toro, N. C., Arias, P. L., Torres, S., Sbarbaro, D. Flame Spectra-Temperature Estimation Based on a Color Imaging Camera and a Spectral Reconstruction Technique. Applied Optics, 2014, 53(28), 6351-6361. https://doi.org/10.1364/AO.53.006351

18. Varga, P., Peto, J., Franko, A., Balla, D., Haja, D., Janky, F., Soos, G., Ficzere, D., Maliosz, M., Toka, L. 5G Support for Industrial IoT Applications-Challenges, Solutions, and Research Gaps. Sensors, 2020, 20(3), 828. https://doi.org/10.3390/s20030828

19. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., Polosukhin, I. Attention Is All You Need. Advances in Neural Information Processing Systems, 2017, 30(1), 2.

20. Wang, X., Liang, X., Zhang, C., Liu, Y., Yang, C., Gui, W. TCN-LSTM: A Deep Learning-Based Temperature Prediction Model for Rotary Kilns. In Proceedings of the 2023 China Automation Congress (CAC). IEEE, 2023, 4197-4202. https://doi.org/10.1109/CAC59555.2023.10451546

21. Woo, S., Park, J., Lee, J.-Y., Kweon, I. S. CBAM: Convolutional Block Attention Module. In Proceedings of the European Conference on Computer Vision (ECCV). 2018, 3-19. https://doi.org/10.1007/978-3-030-01234-2_1

22. Zhang, L., Zhang, X., Chen, H., Tang, H. A Robust Temperature Prediction Model of Shuttle Kiln Based on Ensemble Random Vector Functional Link Network. Applied Thermal Engineering, 2019, 150, 99-110. https://doi.org/10.1016/j.applthermaleng.2018.12.092

23. Zhao, J., Wang, W. Application and Study of Kiln Temperature Control System Based on PLC. Journal of Physics: Conference Series, 2022, 2378(1), 012021. https://doi.org/10.1088/1742-6596/2378/1/012021

24. Zhu, Y., Zhao, Y. Hybrid Intelligent Control of Ceramic Shuttle Kiln Firing Temperature. In Proceedings of the 2016 International Conference on Applied Mathematics, Simulation and Modelling. Atlantis Press, 2016, 247-251. https://doi.org/10.2991/amsm-16.2016.55