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Design of Surface Quality Monitoring System for CNC Machine Tool Parts based on Edge Computing

Zishuo Wang[1], Tao Ding[1], Hongwei Cui[1], Xingquan Gao[1,2,*]

[1] School of Information and Control Engineering, Jilin Institute of Chemical Technology, Jilin 132022, China

[2] School of Information Engineering, Jilin Industrial Vocational and Technical College, Jilin 132013, China

*xqgao_jl@126.com

Abstract

In response to the problems of surface quality monitoring methods during the process of processing parts in the process of processing parts, there are problems such as low accuracy and poor real -time real -time. This article designs a marginal computing of the surface quality monitoring system of CNC machine tool processing parts. First of all, the system calculates the equipment through the edge computing equipment deployed near the CNC machine tool to collect the vibration signal data during the processing process. Then use the LSTM deep learning algorithm to process and train data. Finally, the training completed high -precision prediction model is introduced into the edge computing device to achieve real -time monitoring of the surface quality of the parts. The experimental results show that the system of the system's surface roughness prediction is 0.04, and the surface quality of the parts during the processing process can be monitored in real time, which significantly improves the intelligent level and quality control capacity of the processing process.

Keywords

Edge Computing; Deep Learning; Quality Monitoring.

1. Introduction

With the rapid development of manufacturing, CNC machine tools have become one of the indispensable equipment in modern industrial production. The surface quality of processing parts is the most important factor affecting product quality. In the process of traditional CNC machine tool processing, the surface quality monitoring method mainly depends on offline measurement in the later period. This method has the limitations of high time delay, high cost, and unable to correct real -time correction. At the same time, with the rapid development of information technologies such as mobile communication, cloud computing, and the Internet of Things, massive data and intelligent applications have caused physical space to be very occupied, and the calculation speed continues to decrease. It is difficult for traditional processing methods to upload data to the cloud in real time in real time. It is of great significance to process the data for processing and feedback, so designing a fast and accurate surface quality monitoring system.

Zarat et al. [1]uses sound transmission signals to characterize the roughness of the surface, and test the surface roughness based on the convolutional neural network. The predicted accuracy is 88%and the square error is 3.35%. Bhandari et al. [2]classified the roughness of the processing surface with sound and force signals, and conducted a benchmark test for the commonly used deep learning algorithm multi -layer MLP, CNN, LSTM, and Transformer model. Classification and evaluation of

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precision processing surface roughness. Wang et al. [3]considered the effects of tool wear, and used the tool wear conditions and sensor signals as input. It designed stack automatic encoders and long - term memory networks as surface roughness prediction models. And apply the TL strategy to SAE-LSTM, so that the surface roughness under the variable cutting parameters can be realized online prediction. Xiao [4]and others introduced an implementation of a unified state monitoring system based on edge computing, which provides a comprehensive service for status monitoring. These services include monitoring algorithm design and generation, monitoring methods and monitoring interfaces. By visual interactive interface, you can design monitoring algorithms online to generate executable procedures, and then realize to the corresponding edge nodes. The edge computing node directly acts on the real -time data of production equipment, which can shorten the response time and achieve efficient state monitoring. LIN et al. [5]uses fast Fourier transformation depth of neural network (FFT-DNN), fast Fourier transform long short-term memory network (FFT-LSTM) and one-dimensional convolutional neural network (1-D CNN) The vibration signal is established with a surface roughness prediction model. Rifai et al. [6]uses CNN to extract representative features directly from digital images of surface texture to achieve surface roughness prediction of typical processing operations under various cutting conditions.

Through the summary and analysis of the above -mentioned research status, most of the methods of traditional relying on neural network monitoring parts are offline monitoring and accuracy. In response to the problem of the accuracy of the surface quality prediction of the parts and the poor monitoring real -time, it proposes a deep learning method based on LSTM, and relying on the vibration signal during the processing process to predict the surface quality of the parts. Based on the edge computing development board, the deep learning model is combined with the edge computing, and the surface quality monitoring system of CNC machine tool processing parts is established to achieve real -time monitoring of the surface quality of the processing parts of CNC machine tools at the end of the machine tool.

2. LSTM Deep Learning Model Establishment

This system adopts the "end-edge" architecture, as shown in Fig 1. The system makes full use of the characteristics of good -time real -time and high safety, and deploy the computing task on the edge of the edge of the machine tool to ensure the real -time nature of the system monitoring processing parts Evaluate.

The "end layer" is located on the CNC machine tool and is mainly used for data collection during the processing of CNC machine tools. The "end layer" uses high -precision signal sensors and corresponding collection cards, which can accurately collect changes in vibration signals during the processing process. These data are transmitted to the edge layer for further processing and subsequent predictions.

The "edge layer" is the middle layer between the "end layer" and "cloud", and is responsible for receiving the processing data collected from the vibration sensor. The edge layer is implemented based on embedded edge computing development boards. It is a series of operations such as saving, reading, extracting features, and input to neural network models for the collected vibration signal data. The edge layer not only provides a low -delayed response speed, but also further reduces the occupation of cloud computing resources, saving bandwidth and computing costs.

This system uses LSTM neural network as a roughness prediction model. The LSTM neural network structure is shown in Fig 2. Compared with circulating neural networks, long -term memory networks have three new door control mechanisms at the implicit layer, namely forget gate, input gate, and output gate. LSTM can effectively control the flow of information through the door control mechanism, which can more effectively handle and memory long -term dependence, making it perform better in long sequence tasks.

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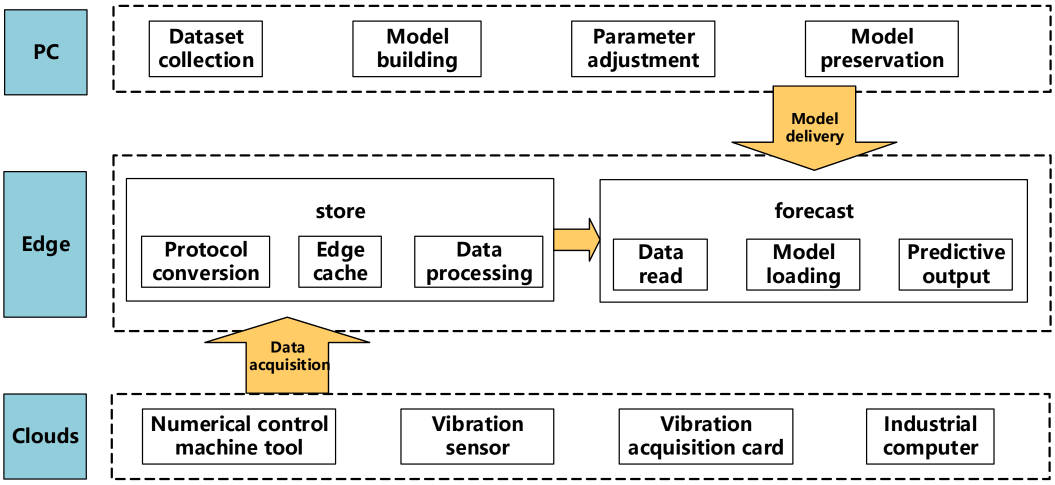

Fig. 1 System overall architecture

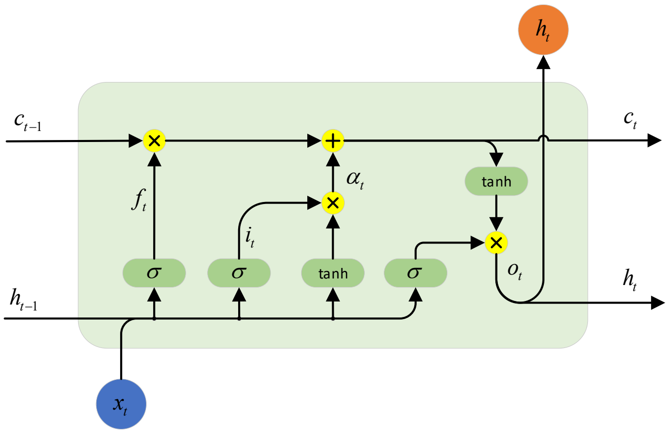

Fig. 2 LSTM neural network structure

The data set used on the PC side using the data set produced by the previous data collection and production of the LSTM neural network model used by this system to adjust the model parameters to ensure that the workpiece surface roughness can be predicted.

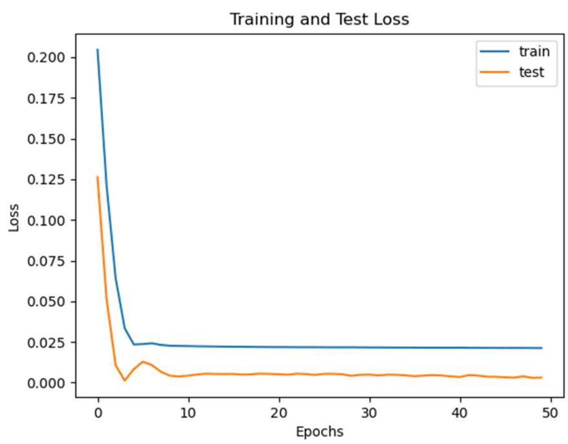

Fig. 3 LSTM model training loss curve

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The loss curve of neural network model training is shown in Fig 3. The steady decline of this curve indicates that the model is effectively fitting training data and gradually optimizing its performance. At the same time, the verification loss curve is consistent with the changing trend of the training loss curve. It can further confirm that the generalization ability of the model is good, and there is no obvious overfitting phenomenon.

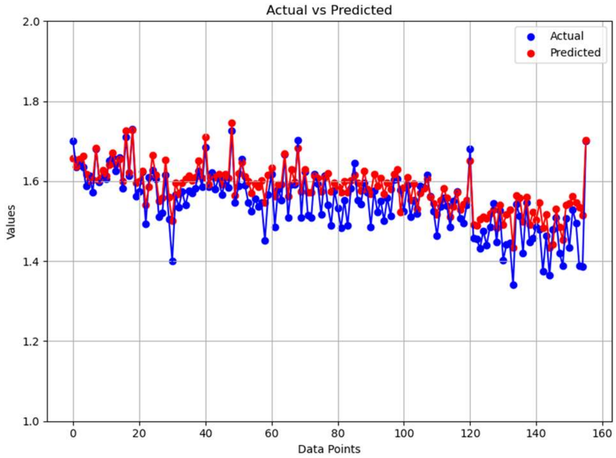

Fig. 4 Model prediction results comparison

The prediction results of this model and test set are shown in Fig 4. For the surface roughness parameter RA (the average deviation of the contours), when the error threshold is 0.1 μm, the model accuracy rate reaches 98.72%. 0.04. It shows that the model predicts the prediction of the surface roughness of the part.

3. Monitoring System System Design based on Edge Computing

3.1 Data Collection Module Design

There are many influencing factors of the surface quality of the parts during the processing of CNC machine tools, including the healthy state of the CNC machine tool, the state of the tool, and the material material. The dynamic information generated by the milling movement between the tool and the workpiece is the most important factor in reflecting the surface quality of the processing parts of the CNC machine tool. During the processing of CNC machine tools, a variety of signals will be generated. During the analysis of various processing signals, it is found that the vibration signal is the most obvious feedback on the surface quality characteristics of the workpiece during the tool processing process. Therefore, this article uses the vibration signal generated during the processing of the machine tool as the main analysis signal, and predicts the surface roughness after the processing of the workpiece. The collection process on the vibration site is shown in Fig 5.

First, install the vibration signal sensor, vibration signal collection card, and industrial computer in the corresponding position of the CNC machine tool. After the CNC machine tool is processed, the vibration collection card is transmitted to the industrial computer. Secondly, the MQTT server and client are built in the edge computing device. The edge calculator and industrial computer use TCP/IP network to communicate, translate data with MQTT protocols and save them into the edge devices. When the MQTT protocol is designed, this article uses the CNC machine tool industrial computer as the publisher, and the edge computing device side as the subscriber. The theme content published is a vibration signal data with time series. The screenshot of the MQTT communication model and the edge subscription data packet is shown in Fig 6 and 7.

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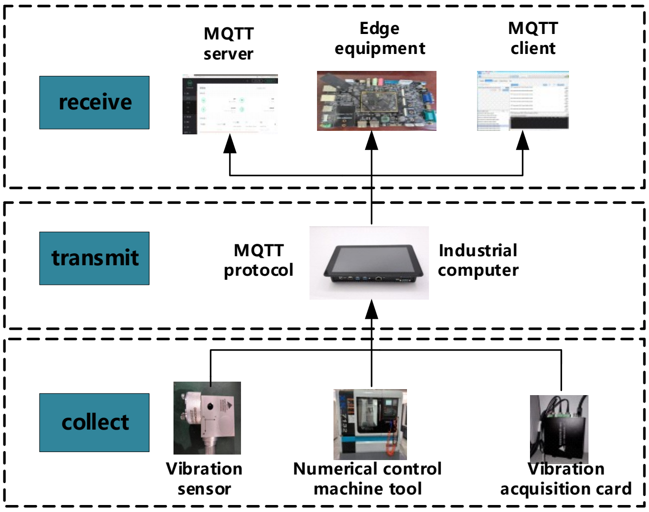

Fig. 5 Vibration signal data collection process

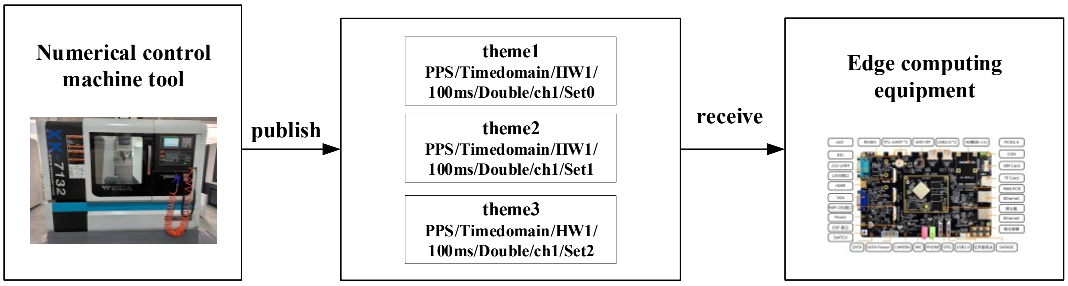

Fig. 6 MQTT communication model

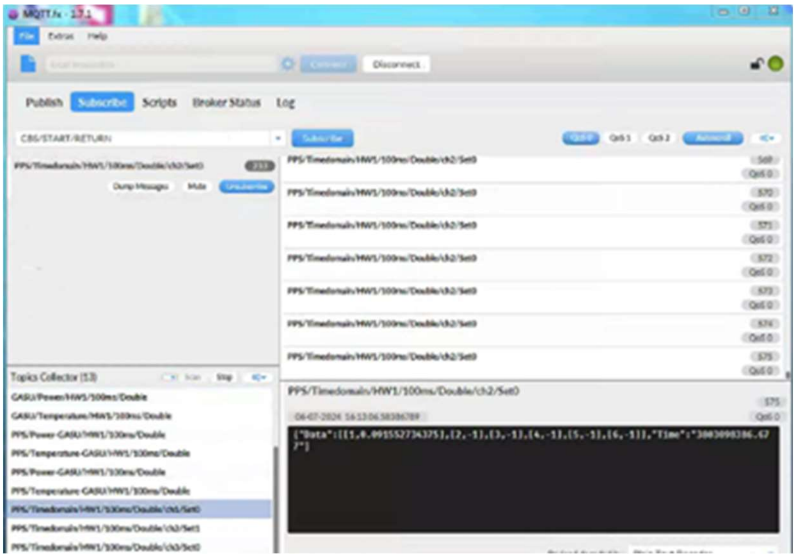

Fig. 7 Screenshot of the edge subscription data

Surface roughness is the most important indicator of the surface quality assessment of parts in industrial processing. During processing, the quality of the surface is closely related to the vibration signal generated during processing. This system uses the vibration signal during processing to be associated with the surface roughness value of the processing parts, and the vibration signal is used to achieve prediction of the surface quality of the parts.

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Fig. 8 Surface roughness collection

As shown in Fig 8, the collection of the surface roughness of the data concentration parts uses a portable surface roughness tester to measure the surface after each processing and correspond to the vibration signal data of each processing. Full data set.

3.2 LSTM Model Deployment

The deployment of neural network model refers to the process of putting the training model in the operating environment for reasoning. The deployment process of this system is shown in Fig 9. Among them, preparations include determining the purpose, preparing data sets, model design, algorithm selection, training models, and reasoning models under the original framework. After the training high -precision model is converted, the format that can be received by the edge device can be obtained, and it is deployed to the edge computing development board for evaluation to ensure the accuracy of the model.

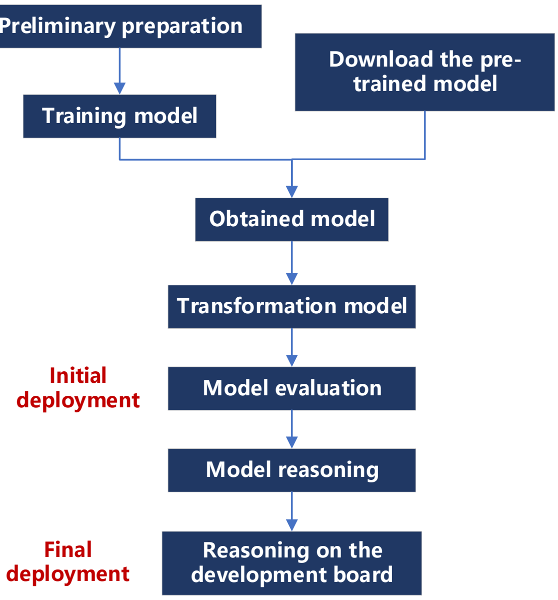

Fig. 9 Model deployment process

This monitoring system uses Rockchip RK3568 edge computing development board. RK3568 is a high-performance multi-core processor with a quad-core ARM Cortex-A55 processor. The main frequency is as high as 2.0GHz. It integrates the ARM Mali-G52 2EE GPU, 1.0 TOPS computing power NPU and other modules, providing rich interfaces such as USB 3.0, USB 2.0, HDMI interface, Gigabit Ethernet port, I2C, SPI, GPIO, UART and other rich interfaces. Can meet the monitoring needs of this system.

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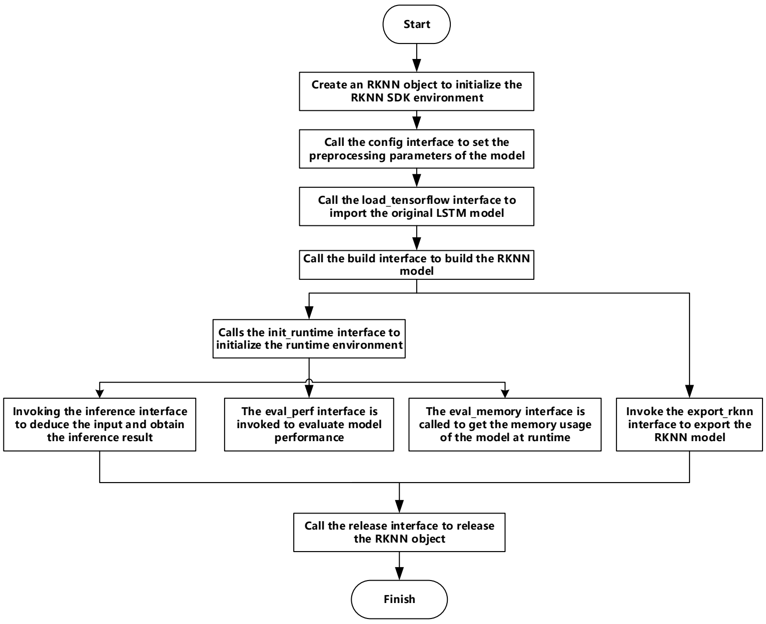

Fig. 10 Model conversion process

Since the LSTM neural network model adopted in this system is based on the TensorFlow framework, and an independent NPU is located in RK3568, which can be used to process the neural network model under the TensorFlow framework. The model conversion process is shown in Fig 10. Use RKNN-Toolkit2 to convert the trained LSTM model to the RKNN model and reasoning on RK3568. First, create an RKNN object and initialize the RKNN SDK environment, and then configure the pre -processing parameters of the model. Then, introduce the trained TensorFlow LSTM model, and use the BUILD interface to build the RKNN model. After initializing the environment, the input data can be reasonably used through the Inference interface to obtain the reasoning result. At the same time, call EVAL_PERF and EVAL_MEMORY interfaces evaluate the performance and memory use of the model respectively. Finally, the RKNN model is exported and the RKNN object is released to end the process.

Load the obtained RKNN model to the RK3568 development board, and write and read and data format conversion procedures on the development board. Then run the programs to read the preserved original vibration signal data for testing. The on -site deployment is shown in Fig 11.

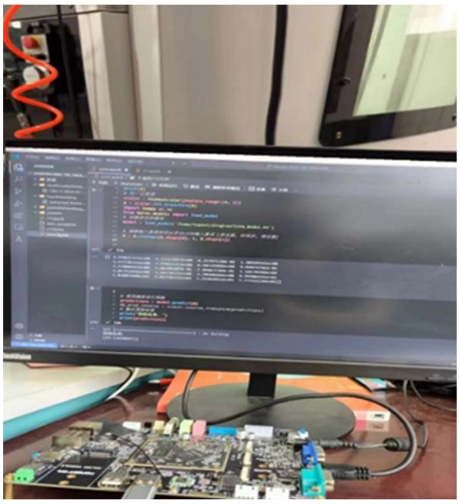

Fig. 11 Model deployment site map

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4. System Implementation

This system uses CNC machine tool as a monitoring object, and the vibration signal in its processing is collected and predicted in real time. In the experiment, the three vibration sensors and the vibration acquisition card were used as the vibration signal acquisition equipment, and the edge computing development board was used as the edge -end computing center.

After importing this model into the RK3568 development board for testing, the model is only 1.1S for the original vibration signal of a processing cycle, which is far lower than the part of the parts processing cycle. Real -time monitoring.

The obtained model is tested in the environment of the RK3568 development board. As shown in Fig 12, the PM-4E-D80 four-blade standing milling cutter surface is used to process the surface of the white steel surface. Four wear state of wear, mid -term wear, later wear, and tool damage. 50 groups of tests are performed in each wear state, and the prediction results in the development board are compared with the PC -side prediction results.

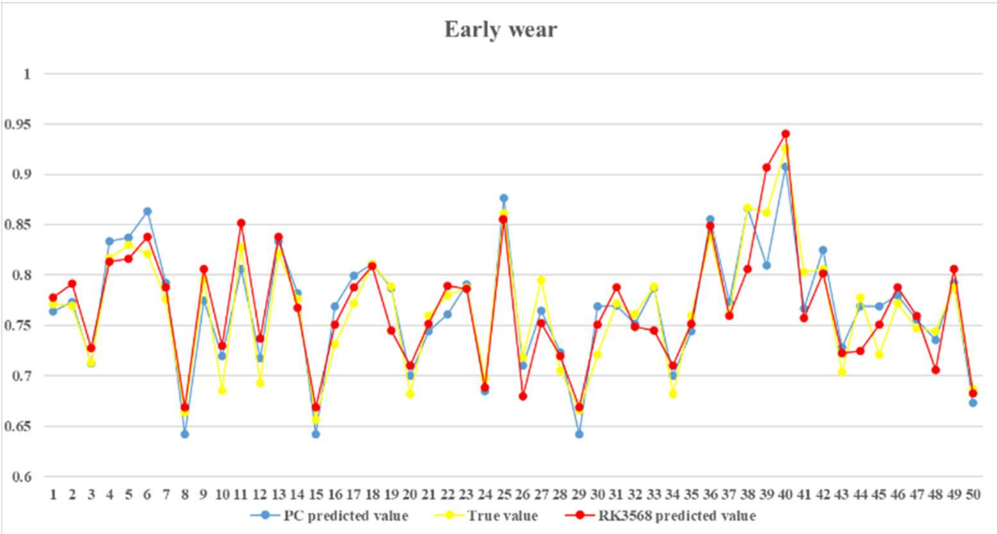

Fig. 12 Comparison of prediction results of knife wear

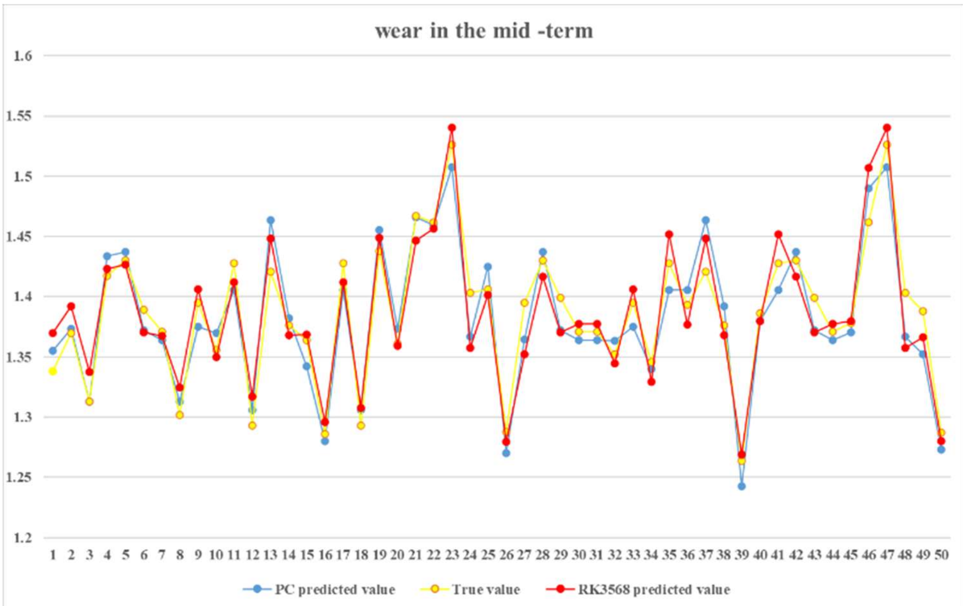

Fig. 13 Comparison of the prediction results of the knife wear in the mid -term

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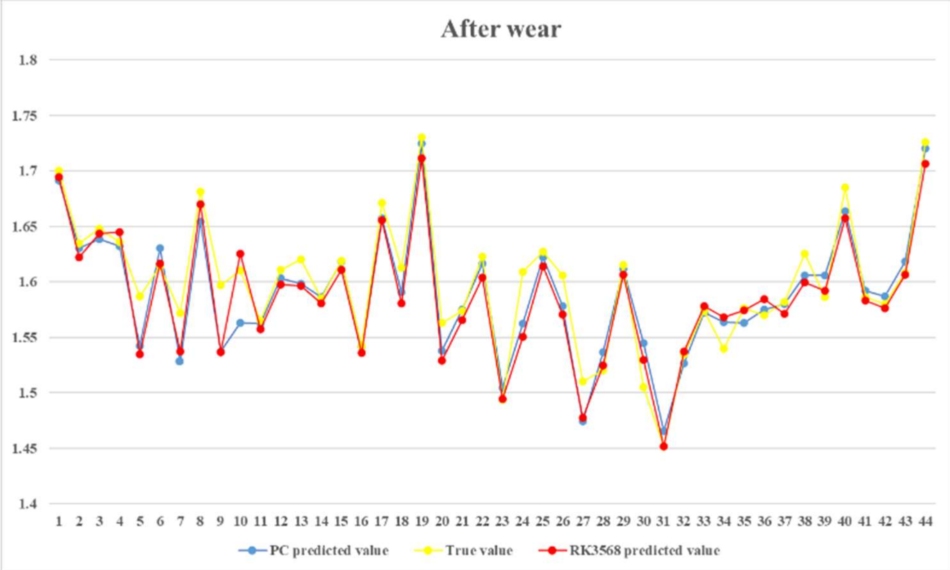

Fig. 14 Comparison of prediction results after wear

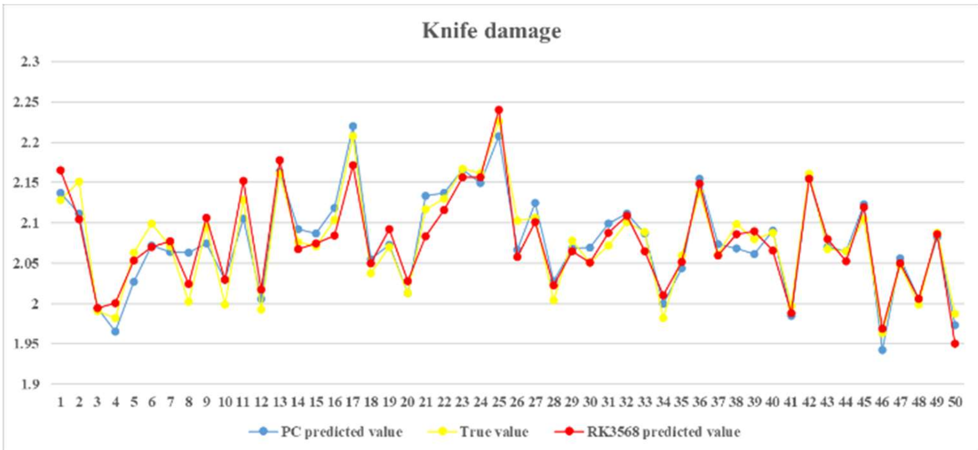

Fig. 15 Comparison of knife damage prediction results

It can be seen from Fig 12 to 15 that during the processing of different knives, the predictive results of the original model of the PC end and the conversion model of the edge end have high accuracy and the predictive accuracy of the PC -end training model. The prediction accuracy is almost the same, and the feasibility of the model conversion is initially verified. The prediction of the surface quality prediction of the edge computing device separately is shown in Table 1. After many testing, the calculation error of the system roughness parameter Ra does not exceed 5%. Further verify the accuracy and feasibility of this system.

Table 1. Monitoring errors on the surface roughness of parts under different wear of tools

The knife is worn	Ra prediction value (μm)	Ra real value (μm)	Error
Early wear (VB <0.1)	0.522	0.548	0.026
Mid -term wear (0.1 <VB <0.2)	1.013	0.998	0.015
Late wear (0.2 <VB <0.3)	1.487	1.469	0.018
Knife damage	2.399	2.421	0.022

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5. Conclusion

This article uses CNC machine tools as the research object, and proposes the design method of the surface quality monitoring system of CNC machine tool processing parts based on deep learning and marginal computing. The system realizes real -time data collection and processing of CNC machine tool processing and real -time monitoring of the surface quality of processing parts. Through experimentalize the accuracy of the system's quality prediction effect on the surface quality of the parts and the real -time monitoring effect of the surface quality of the parts, it improved the intelligence of the machine processing field and provided new ideas for the monitoring of the surface quality monitoring of the processing parts.

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