Electronic component identification system based on FPGA and machine learning

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Abstract. Due to the large number and small size of electronic components, the identification speed is slow and the accuracy is low. This research develops an electronic component identification system based on FPGA and machine learning technology. The core of the system is FPGA, combined with an efficient image processing unit to achieve parallel acceleration of machine learning model calculations. To extract features, we use Hu matrix methods that are robust to position translation, size scaling, and image rotation, which are then used as input data for the convolutional neural network. The network consists of 8 layers and uses ReLU activation function. Experiments show that the system shows a high degree of accuracy and processing speed in different types of part identification, with an average accuracy of 99.15% and an average time of 551.5 milliseconds. The use of FPGA resources and experimental results verify the effectiveness and superior performance of the system. The system has wide application potential in the field of industrial automation, and has certain popularization value in providing efficient and accurate identification of electronic components.

Keywords: FPGA; Machine learning; Image processing; Electronic component identification; Industrial automation.

1. Introduction

In recent years, the rapid progress of artificial intelligence and image recognition technology has played a key role in many fields, such as autonomous driving, big data analysis and product quality inspection. Especially on industrial production lines, it is becoming increasingly important to classify and sort electronic components quickly and accurately. For example, in the electronics manufacturing industry, automation equipment needs to identify different circuit board components to ensure product quality. However, the traditional manual classification method is inefficient and prone to errors. In the complexity and diversity of industrial environments, although robotic sorting systems improve production efficiency, it is often difficult to maintain high accuracy. Traditional recognition algorithms such as template matching, feature extraction and support vector machines have limited effectiveness in these environments.

Based on these considerations, we designed an advanced electronic component identification system that combines FPGA and machine learning technology to improve the identification efficiency and accuracy. FPGA is a programmable logic gate circuit, with the flexibility of external configuration, can call a variety of IP cores according to engineering needs. [1-3] Its unique parallel computing properties make it an excellent choice for neural network acceleration, greatly increasing recognition speed. This system uses 8-layer convolutional neural network to extract high-dimensional features of electronic components through deep learning model, and utilizes the high-speed parallel processing capability of FPGA to significantly improve the speed and robustness of recognition. [4-6] This research not only improves the sorting efficiency on industrial production lines, but also brings a new perspective on electronic component identification technology.

2. System Design

The system consists of a conveyor belt, position sensor, lighting, CCD camera, FPGA-based image processing module, power supply and control computer (Fig. 1). The FPGA core integrates an efficient image processing unit to realize fast parallel computing of machine learning algorithms.

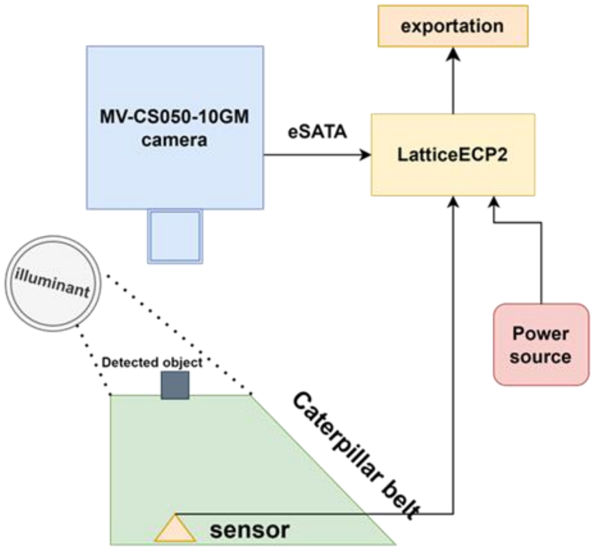

Figure. 1 System design drawing

The model uses a two-part structure (Fig. 2): 1) An ImageNet pre-trained model for transfer learning. 2) The lightweight MobileNetV3 network including convolutional, pooling and attention layers, also used for transfer learning.

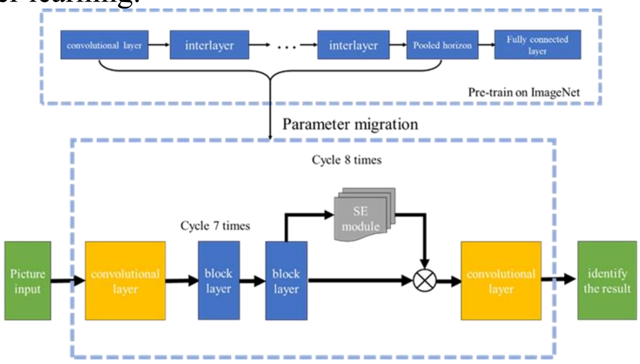

Figure 2. Model structure based on deep learning

The input layer of the network has dimensions of 8×8×1, corresponding to 8 invariant moments. The output layer is 4×1×1 in size and is used for the classification of 4 different electronic components. The network structure consists of 6 convolutional layers and 2 fully connected layers. The activation function uses ReLU, and the classification stage uses Softmax function. The training set and the test set contained 16,896 and 23,481 images, respectively. The weight coefficient is initialized randomly and reaches a stable state after 60 iterations of training. The learning rate is set to 10^-4 for the first 15 iterations, 10^-5 for the next 25, and 10^-6 for the last 20. Batch random gradient descent method was used to optimize the model, and the loss difference threshold was set to 0.001.

After each training, the model outputs a loss value and an accuracy value. Figure 3 shows how the model accuracy improves as the number of iterations increases.

The accuracy of the model stabilizes after about 25 iterations, reaching or exceeding 99%.

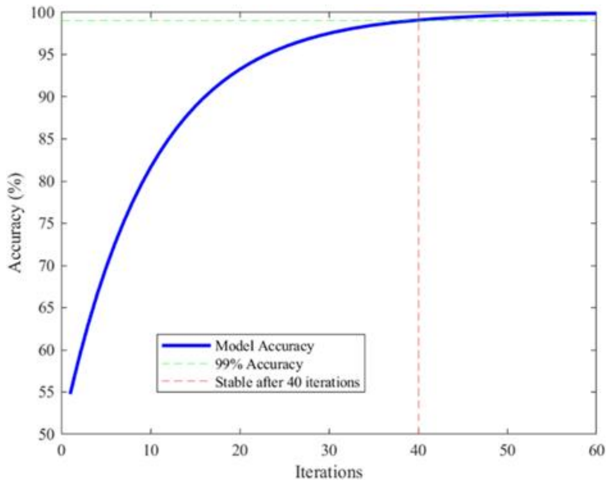

Figure 3. Model accuracy with the number of iterations

With the increase of iterations, the accuracy of the model is gradually improved. It can be observed from the figure that after about 35 iterations, the accuracy of the model stabilizes, reaching about 99%.

3. Experimental results and analysis

3.1 Investigate the effect of transfer learning

Through the in-depth analysis of system hardware and software, this paper successfully developed a set of electronic component identification system based on FPGA and machine learning. In this paper, the system operation test is carried out to evaluate the key performance indicators such as FPGA resource occupancy, identification accuracy and processing time.

Table 1. Transfer learning results of different models

Model	TOP1/%	TOP5/(%)
VGG16	73.01	96.02
VGG16+TF	83.33	98.33
ResNet50	84.22	97.16
ResNet50+TF	84.88	98.78
InceptionV3	85.55	97.45
InceptionV3+TF	87.77	99.02
MobileNetV3	89.25	97.06
Textual algorithm	92.77	99.77

The recognition accuracy of TOP1 and TOP5 was improved after the transfer learning algorithm was adopted in the four models. VGG19 model has the largest improvement, which is 10.29%; MobileNetV3's transfer learning algorithm improved by 3.65%. The transfer learning method can further improve the accuracy of model recognition. During the training, the loss rate of these four models decreased steadily, and the accuracy rate increased steadily, indicating that the model performance was more stable after the transfer learning algorithm was adopted, among which the algorithm proposed in this paper performed best.

3.2 FPGA Resource Usage

Develop a part recognition system based on FPGA and convolutional neural network, conduct online testing, and evaluate the FPGA resource occupancy rate, recognition accuracy rate and time consuming. The total number of parameters of the convolutional neural network model is about 180,000, and all parameters are defined as 16-bit integer types. After completing the hardware structure design of FPGA, this study examined the usage of FPGA resources, as shown in Figure 4.

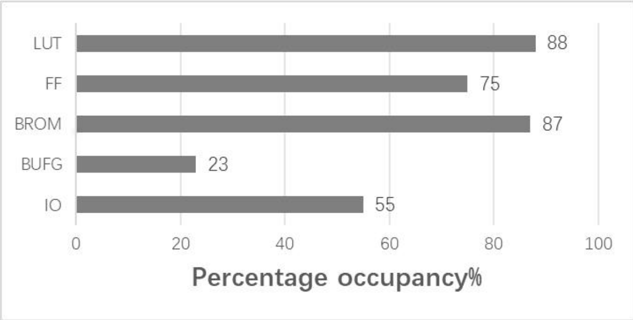

Figure 4. FPGA resource usage

As can be seen from the figure, the remaining resources inside the FPGA are rich, indicating that the system has great potential in terms of expansion, and can be further optimized and expanded according to actual needs.

3.3 Test Result

In this study, the data of random Angle rotation was expanded for samples of 6 parts types, and the expanded samples were tested online. The results are shown in Table 2 below, and Figure 5 is the test legend.

Table 2. Online test results

Mod Type	Sample size / piece	Identify correctly Quantity/sheet	accuracy / %	Average correct Rate /%	Take time /ms	Average cost Time /ms
A	189	187	99.94		554	
B	199	195	98.99		534	
C	197	196	99.49		567	
D	185	183	98.91		551	
E	193	184	99.23	99.15	512	545
F	195	193	98.71		565	

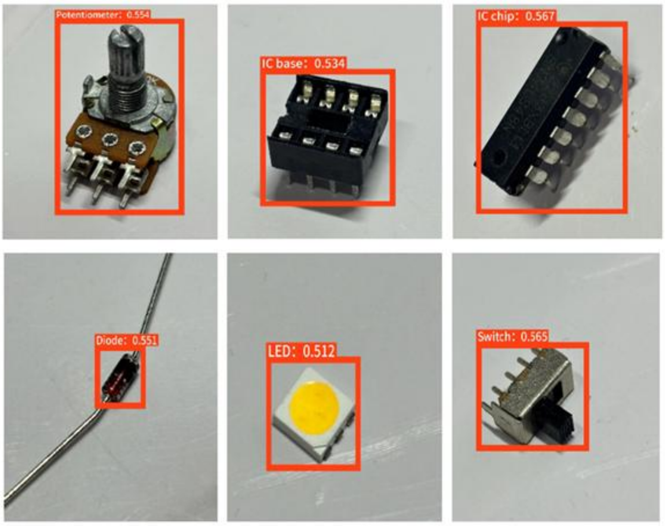

Figure 5. System test legend

As can be seen from the table, the accuracy rate of online identification of 6 kinds of parts is 99.94% of type A, and 98.71% of type F is the highest. The longest time is 567 ms for type C, and the shortest time is 512ms for type E. The average accuracy was 99.15% and the average time was 551.5ms. This shows that our parts identification systems excel in accuracy and speed, providing a reliable solution for the identification and sorting of electronic components on industrial assembly lines.

4. Conclusion

This research successfully designs and implements a set of electronic component identification system based on FPGA and machine learning. Through the in-depth research and development of the system hardware and software, this paper carefully designs the system hardware according to the actual needs, including the image processing unit with FPGA as the core, which effectively improves the image data processing speed, and uses FPGA to carry out high-speed parallel operation of convolutional neural network, speeding up the recognition calculation process. Secondly, a convolutional neural network model is designed and trained, which performs well in the recognition of electronic components. The results show that the electronic component recognition system described in this paper has excellent performance in both accuracy and processing speed, which fully proves the feasibility of using FPGA parallel high-speed characteristics to accelerate the recognition process.

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