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DEEP LEARNING BASED RUSSIAN HANDWRITEN RECOGNITION

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Annotation. This paper presents a Russian handwriting recognition algorithm based on deep learning. The algorithm combines improved VGG network feature extraction capabilities with LSTM time modeling capabilities and introduces data enhancement and optimizer tuning strategies. Experimental results show that the proposed algorithm is significantly superior to the existing methods in recognition accuracy and training efficiency.

Keywords: Russian Handwriting recognition, Deep learning, VGG network, LSTM network, Data enhancement.

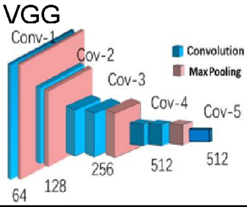
Introduction. Russian handwriting recognition is of great value in the field of information processing. With the increase in communication between China and Russia, the demand for automated Russian handwriting recognition systems is growing. However, due to the complexity of the Russian Cyrillic alphabet and the diversity of writing styles, the existing recognition systems are still lacking in accuracy and speed. In recent years, deep learning techniques have made significant progress in the field of text recognition, but there has been relatively little specialized research on Russian handwriting.

The main part. The model used in this paper is based on EasyOCR framework, which combines LSTM, VGG convolutional neural network and CTC loss function. EasyOCR is an open source OCR framework that supports multiple languages. The EasyOCR framework is shown in Table Through data enhancement, optimizer adjustment and parameter filtering, the original model is improved, and the recognition accuracy is increased. In this paper, VGG is used to extract feqatures from handwritten images to provide high-quality input for recognition. LSTM is a recursive neural network, which can effectively deal with long-term dependency in sequence data and capture the context information of character sequences, so as to improve the recognition accuracy. The CTC loss function is suitable for the character sequence annotation in handwriting recognition, allowing the model to predict the character sequence directly without pre-segmentation of the input image.

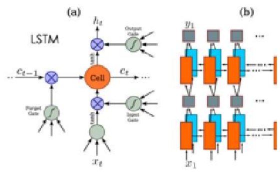
Table 1- The EasyOCR Framework Table

CRNN

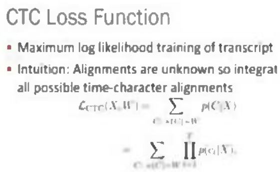
VGG



LSTM



CTC



Model Structure and Parameter Tuning. In order to optimize the performance of the model, we adjusted the parameters, including: data enhancement, optimizer Settings, parameter filtering. Through the experiment, we got the following improvement. The experimental results show that the improved algorithm shows significant improvement in both training and validation loss. The training loss of the original algorithm decreases rapidly in the initial stage, but the verification loss fluctuates after reaching a certain degree, which indicates that there may be overfitting phenomenon. However, the training and verification losses of the new algorithm show a steady decline trend, and the final loss value is lower than that of the original algorithm, showing better generalization ability. In terms of accuracy, the performance of the improved algorithm continued to improve, eventually reaching an accuracy of about 42%. In contrast, the accuracy of the original algorithm increased rapidly in the early stage of training and then stabilized at about 30%. This result shows that the improved algorithm has obvious advantages in learning ability and adaptability. In the comparison of training time, the total training time of the improved algorithm is about 5000 seconds, which is reduced from 6000 seconds of the original algorithm. This result shows that the improved algorithm has a significant improvement in training efficiency, especially when dealing with large-scale data sets, and can save more computing resources and time. Overall, the improved algorithm is superior to the original algorithm in terms of loss, accuracy and training time, demonstrating better model optimization and training efficiency. These results provide strong support for the practical application of Russian handwriting recognition.

Performance Comparison and Experimental Analysis. Comparison of training and validation losses is shown in Table . Training accuracy comparison is shown in Table Comparison of total training time is shown in Table .

The original algorithm drops rapidly in training loss, but the validation loss stabilizes or even rises slightly after an initial drop, indicating possible overfitting.

The new algorithm shows a steadier decline in both training and validation losses, and the final loss values are lower than those of the original algorithm, showing better generalization. The comparison of training and validation losses is shown in Table .

Table 2- Comparison of training and validation losses Table

Iterations	Original Method		Proposed Method	
	Train Loss	Valid Loss	Train Loss	Valid Loss
10000	0,1	1,5	0,25	0,9
20000	0,05	1,8	0,1	1
30000	0,05	2,1	0,05	1,2
40000	0,05	2,2	0,05	1,3
50000	0,05	2,2	0,05	1,4

The accuracy of the original algorithm rose rapidly in the early stages but then grew slowly and eventually stabilized at about 30 %.

The accuracy of the new algorithm continues to rise throughout the training process, eventually reaching about 42 %, showing better learning ability and higher accuracy. A comparison of the training accuracies is shown in **Error! Reference source not found.**

Table 3- Training accuracy comparison

Iterations	Accuracy	
	Original Method	Proposed Method
10000	25%	32%
20000	25%	35%
30000	27%	36%
40000	27%	36%
50000	30%	42%

The total training time of the original algorithm grows linearly with the number of iterations, eventually reaching about 6000 seconds.

The total training time of the new algorithm grows at a slower rate, eventually totaling about 5000 seconds, showing greater time efficiency throughout the training process. Comparison of total training time is shown in **Error! Reference source not found.**

Table 4- Comparison of total training time

Iterations number	Time Comsuption for trainning	
	Original method	Proposed method
50000	6000	5000

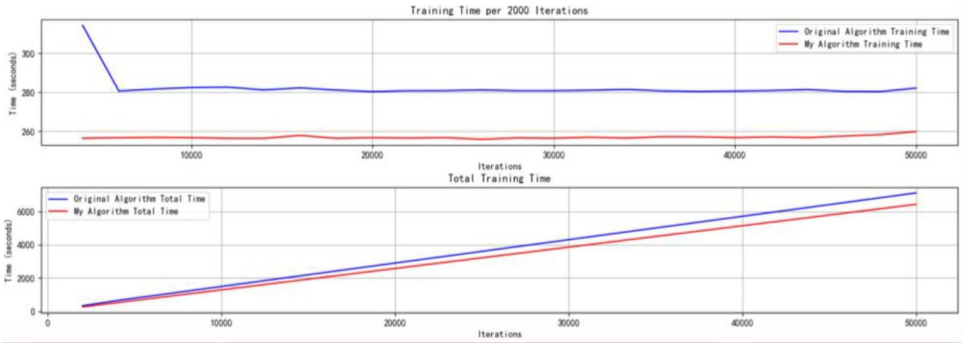


Figure 1. Comparison of total training time

Conclusion. By optimizing the model structure and adjusting the parameters, the accuracy and speed of Russian handwriting recognition are significantly improved. The experimental results show that the improved model is superior to the original algorithm in terms of training time and total training time, showing higher efficiency and better performance. Future research will explore deeper network structures to further improve performance and investigate more efficient feature extraction methods for handwriting recognition in other languages and for deployment and optimization on mobile devices.

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