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A Deep Learning Algorithm for English Handwriting Evaluation Using CNN

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Abstract : Automatic analysis rule for English handwriting quality is planned during this paper. English handwriting analysis is an important half in elemental English teaching. Generally, typical document image process approaches admit overseen options for capturing applied math or structural information. In distinction, we tend to profit of Convolutional Neural Networks (CNNs) for extracting options from raw image pixels. The performance of this rule is more practical than ancient machine learning strategies and also the accuracy is larger than 94% in our experiment. Supported this rule, an intelligent English handwriting marking system is intended and it's already on-line.

Index Terms - **English handwriting quality, automatic evaluation, Convolutional Neural Networks, marking system**

I. Introduction

English handwriting quality analysis has been a hot topic in elemental English teaching. One in all the vital technique for assessment is English handwriting competition. Current analysis ways virtually rely on pure manual work, that have some important disadvantages, like totally different analysis standards from person to person, comparatively low potency, and high labor prices. Therefore, the event of automatic analysis ways has recently attracted abundant attention thanks to the high accuracy and potency.

Document image process has been wide employed in the sector of character recognition, text detection, and document image classification, however seldom seen in handwriting-quality evaluations. Within the current literature, Chongbiao Tai [1] and Loloish Peng [2] have studied the standard analysis algorithmic rule of written Chinese characters. The variations between the 2 higher than algorithms chiefly lie the feature extraction ways. Within the paper [1], the feature extraction algorithmic rule is predicated on Gabor rework combining with the rule-based feature extraction technique. In distinction, the algorithmic rule in [2] is predicated on direction rules and connected element detections.

Feature extraction

Feature extraction is a vital a part of written document image process. Previous approaches for feature extraction most trust handmade options for capturing applied mathematics or structural data. The strategies supported applied mathematics options, like example matching, zoning [3], moments [4, 5], n-tuples [4, 6] etc., have an occasional quality and a straightforward coaching. However, their skills to resist deformation are poor, also because the conformity for similar characters. The strategies supported structural options, like skeleton, outline, form options, etc., are sturdy to deformation, however have a really high quality. So, a additional general approach that mechanically learns effective visual representations for written document pictures is desired.

Convolutional Neural Networks (CNNs)

Recent advances in deep learning have made it possible to extract high-level features from raw sensory data, leading to breakthroughs in computer vision. Yann LeCun et al. [4] first proposed to use Convolutional Neural Networks for handwritten digit recognition. Le Kang et al. [5] presents a general approach for document classification using Convolutional Neural Networks. Xu-Yao Zhang et al. [6] set new benchmarks for both online and offline handwritten Chinese character recognition applying deep learning. Aiquan Yuan et al. [7] proposed a method for offline handwritten English character recognition based on Convolutional Neural Networks. In this paper, an automatic evaluation algorithm is presented for English handwriting quality using Convolutional Neural Networks (CNNs). Experiments on real-world data set show that our approach is more effective than conventional machine learning methods. Moreover, an intelligent English handwriting marking system based on our algorithm is designed and put into use.

II. REASEARCH METHODOLOGY

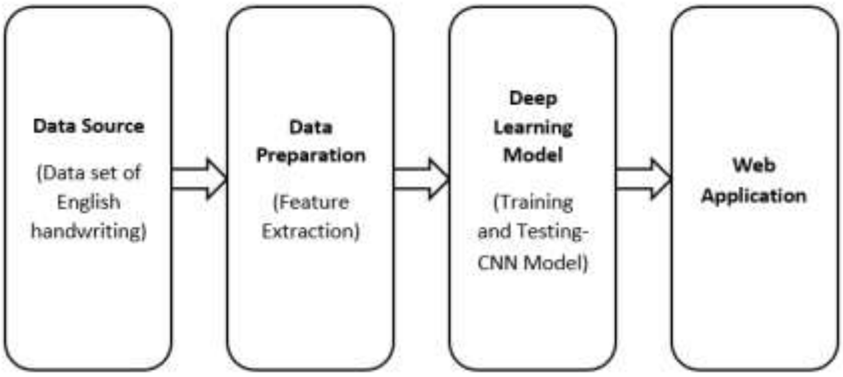

Fig.1 Workflow of system model

2.1 Data Source

In this Data set is given to model. Data set consist of various types of English handwriting samples. The data set has a total about 24000 images of different kind of English handwriting samples.

2.2 Data Preparation

English handwriting region extraction: Fig. 2 shows the flow of English handwriting region extraction. Firstly, convert original RGB image to grayscale image and blur the grayscale image. Secondly, use Canny operator [8] to detect edges and extract contours from image edges. Then, find the minimum enclosing rectangle for each contour. Finally, find the largest enclosing rectangle and ensure that it is the correct English handwriting region.

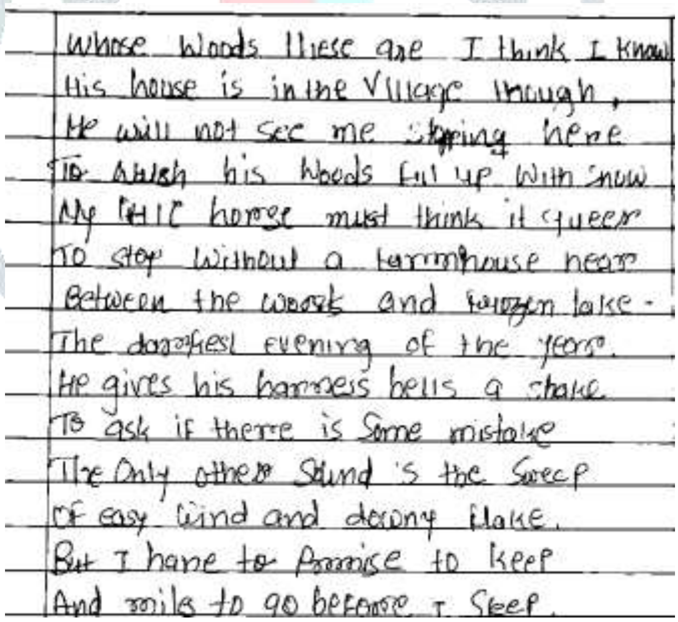

Fig.2 Preprocessed image of resolution 224 × 224.

In this first we need to convert original RGB image to grayscale image. That will be blur the grayscale image. Then detect edges and extract contours. After that find the minimum enclosing rectangle for each contour. Lastly, the largest enclosing rectangle is the English calligraphy region.

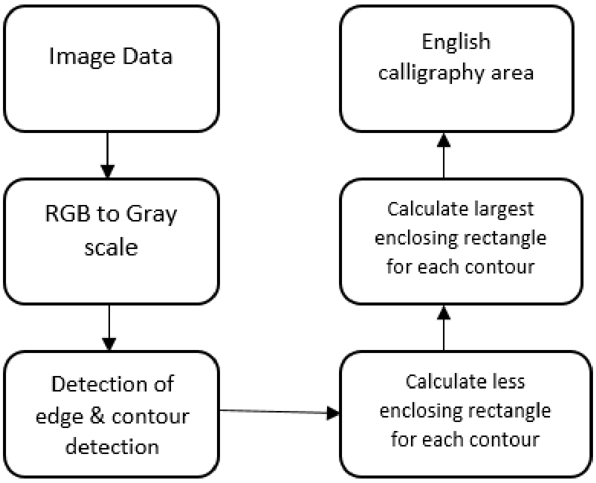

Fig.3 Work flow of English handwriting Feature extraction.

2.3 Deep Learning Model

Fig. 4 shows the architecture of the system model. The model is the classical ResNet-18 [13. The CNN model can be summarized as 224 × 224 - 112 × 112 × 64 - 56 × 56 × 64 - 28 × 28 × 128 - 14 × 14 × 256 - 7 × 7 × 512 - 1 × 1 × 512 - 2.
In this Convolution Neural Network, First we need to design the network architecture of the our system model. After that train the model using the given dataset. Lastly using CNN model can evaluate the English handwriting.

In training phase we first adopt softmax with loss as the loss function and perform Stochastic Gradient Descent(SGD). However, the risk of misclassification of different categories is sometimes different and our positive and negative samples are unbalanced, so we also try to use weighted softmax with loss as loss function and compare two loss functions.

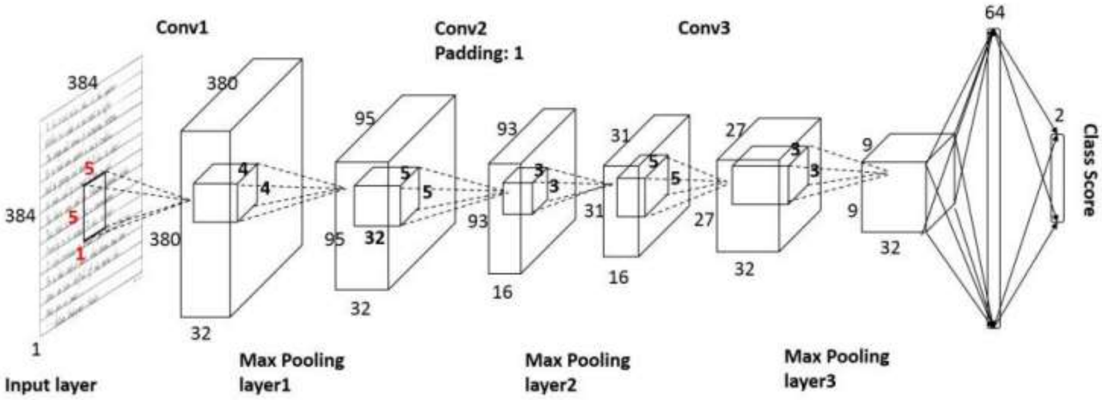

Fig. 4 Architecture of system network CNN model

III. Experiment

We conduct experiments on English handwriting data set from junior high school and high school students' homework. We compare the traditional machine learning methods with CNN on the same data set.

3.1 Data set

The data set has a total about 24000 images. we divided the samples into award-wining and non-award-winning two categories. The two categories have about 4800 images and 19200 images respectively. Then we divide the data set into training sets, validation sets, and test sets in a ratio of about 4: 1: 1.

3.2 Evaluation

We mainly compare CNN methods with conventional machine learning methods. For traditional machine learning methods, we extract fourteen statistical features about the number of rows, the number of words, word space, word width, word height, word slope (the average slope of all the nearest vertical lines in the word), and the number of words deviating from the baseline. Then we apply the tree-based feature selection method. By comparing the importance of the features, two of the less important features are removed. Finally, we adopt Logistic Regression (LR), Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), and Gradient Boosting Decision Tree (GBDT) five classifiers to evaluate the classification results. The results of machine learning methods and CNN method are showed as Fig. 5.

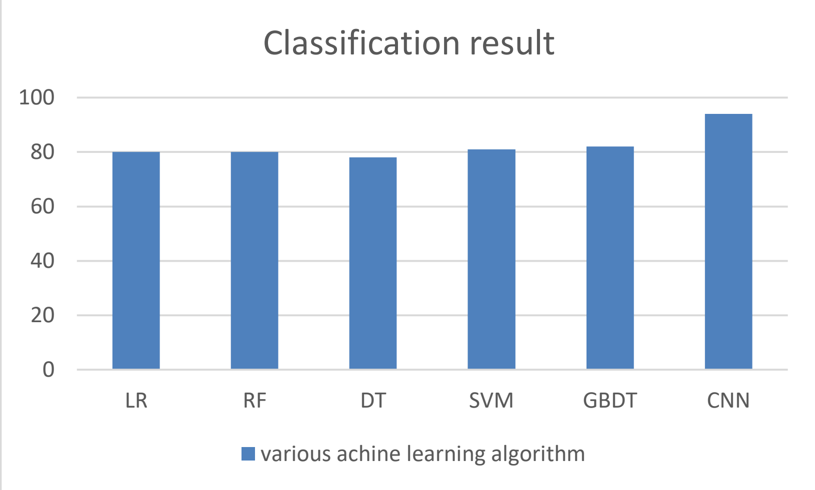

Fig.5 Image classification result

As is shown in Fig. 5, the Gradient Boosting Decision Tree classifier has best classification performance among the five traditional classifiers. However, CNN has the higher accuracy than GBDT. Therefore, CNN has the better performance than traditional machine learning methods.

Compared to the original model, recall for most models using weighted softmax with loss increases, which met our expectations. Among all the models, the model with loss weight of 1.5 performs best, which achieves the highest accuracy of 96.0% and F1 value of 95.6%. Therefore, we set the loss weight to 1.5 for positive samples while 1.0 for negative samples. The specific results are shown in TABEL I.

Table 1. Output of different weight loss functions

	Result		
	Recall	Precision	Accuracy
Softmax function with Loss	90.8%	95.0%	94.4%
Weighted Softmax function with Loss	93.0%	97.1%	96.0%

IV. Conclusion

To meet the requirement of automatic evaluation of English handwriting quality in English teaching, this paper has proposed an automatic evaluation algorithm for offline English handwriting quality based on CNNs. Experiments on real-world data set show that our approach is more effective than conventional machine learning methods. Of course, the features extracted by CNNs are difficult to understand. We hope that in the future, understandable features can be extracted as evaluation criteria and corresponding suggestions can be given to students and teachers.

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