RESEARCH ARTICLE

Quality grading and classification of tobacco leaves based on deep learning

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With the rapid development of deep learning technology, its application in the field of agricultural product quality assessment, especially in the quality classification and classification of tobacco leaves, has been widely concerned. As an important cash crop, the accurate evaluation of tobacco leaf quality is very important for the development of the entire tobacco industry. The traditional tobacco leaf quality assessment method relies on manual experience, which is not only inefficient, but also easy to be affected by subjective factors. This study, based on deep learning theory, aimed at the limitations of traditional methods in tobacco quality assessment and investigated in detail the deep learning method for tobacco quality classification and classification based on images. The empirical research on data acquisition, preprocessing, model construction, training, verification, testing, and optimization was carried out systematically. The results showed that the optimized deep learning model performed well in tobacco quality grading and classification tasks, and had higher accuracy, recall rate, and F1 scores than the existing manual methods. At the same time, a series of model optimization strategies were proposed, which laid a foundation for the further development and application of deep learning models in the agricultural field. In addition, this study also exposed issues such as computational resources and interpretability of deep learning models in practical applications, which would become the direction of future research.

Keywords: **d**eep learning; image classification; data processing; model optimization; tobacco leaf.

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Introduction

Tobacco is an important cash crop; the quality of its leaves directly affects the economic value and use value of tobacco. Traditional tobacco quality classification methods mainly rely on manual judgment, which is low efficiency, high cost, and easy to be affected by subjective factors, resulting in unstable and inaccurate classification results. Therefore, the development of an automatic, rapid, and accurate classification of tobacco leaf quality has become an urgent need for industry and scientific research institutions.

With the continuous progress of science and technology, deep learning as an important branch of artificial intelligence has made remarkable achievements in many fields such as image recognition, natural language processing, and recommendation system. In the field of image classification, deep learning, especially convolutional neural networks (CNN), has become the core technology, which can effectively extract image features and achieve accurate classification. The features of CNN such as local perception, weight sharing, and spatial hierarchy show their powerful functions in many applications including medical image analysis, automatic driving, and face recognition. In recent years, deep learning technology has also been gradually applied to the agricultural field to achieve accurate classification and classification of crop quality, thereby improving the efficiency and quality of agricultural production. While it has been used in other crop quality assessments, deep learning is still a relatively new endeavor in tobacco leaf quality classification. In the study of tobacco quality classification, deep learning and image processing technology have been widely used and achieved remarkable results. Numerous scholars have demonstrated the development of this field through different methods and techniques. Chen *et al*. provided a new perspective for quality classification in terms of machine vision and expert knowledge, which had direct implications for tobacco quality classification [1]. Wu *et al*. conducted quality classification through deep learning network combined with X-ray technology, demonstrating the ability of deep learning in accurately identifying complex image data [2]. In addition, Kappacher *et al*. provided a valuable reference for tobacco leaf quality assessment by comparing the application of portable and benchtop NIR sensor technology in black truffle quality assessment [3]. The CMENet model proposed by He *et al*. was especially targeted at tobacco classifying, demonstrating the potential of deep learning technology for customized application in specific fields [4]. Similarly, researchers conducted effective quality classification of tobacco leaves in the fields of computer vision and deep learning, respectively, emphasizing the importance of deep learning techniques in improving classification accuracy and efficiency [5, 6]. Further, scientists provided new insights on image classification and deep learning model optimization, which was of great significance for improving the accuracy and efficiency of tobacco quality classification [7-9]. Other studies demonstrated the application of the improved MASK RCNN algorithm, near infrared spectroscopy technology, and mathematical model in tobacco leaf analysis, further proving the feasibility and effectiveness of these methods in practical applications [10-12].

The existing literatures show that deep learning and image processing technology have great application potential and broad development prospects in tobacco quality classification. These studies not only provide new technical means and theoretical basis for tobacco quality classification, but also provide valuable reference and enlightenment for the research in related fields. [13, 14]. However, the application of deep learning technology in tobacco leaf quality classification still faces challenges such as data collection, model construction, and result evaluation, which needs more in-depth research and exploration. This study aimed to explore the application possibility of deep learning technology in automatic classification of tobacco leaf quality and improve the accuracy and efficiency of tobacco leaf image classification by using deep learning model to automatically extract the features of tobacco leaf images and perform accurate quality classification of tobacco leaf images. The results of this study would significantly improve the efficiency and accuracy of tobacco leaf classification, thereby enhancing the competitiveness and sustainability of the tobacco industry.

Materials and methods

Data source and collection methods

The data source for this study were mainly from tobacco growing bases and processing plants in different regions in the provinces of Yunnan, Henan, and Guangdong, China to ensure the authenticity, diversity, and universality of the data. The collected tobacco data covered different varieties, growth stages, and processing states. Canon EOS 5D Mark IV digital camera (Canon, Tokyo, Japan) and Epson Perfection V600 portable scanner (Seiko Epson Corporation, Nagano, Japan) were used for image acquisition and scanning to ensure high quality and clarity of the images. The images were captured under the natural light during the daytime between 9 am and 4 PM to obtain the best lighting effect. The solid color background cloth was used to control the background noise, ensure the purity of the image background, highlight the characteristics of tobacco. Multiple tobacco varieties including Virginia, Burley, and Oriental were collected, covering all growth stages from germination to maturity and including raw and roasted tobacco leaves. A total of 50,000 images were collected with at least 10% of each variety, growth stage, and processing state. All collected images were graded by tobacco experts for quality and labeled with the variety, growth stage, processing state, and quality grade to ensure accuracy. The diversity of these samples helped the model to understand the characteristics of tobacco leaves more fully in different varieties and states, thus improving the accuracy of classification and grading.

Data range and diversity

Special attention was paid in this study to the range and diversity of data in the data collection stage to ensure the generalization ability and robustness of the model. The data collection covered major tobacco-growing regions in China, including Yunnan, Henan, and Guangdong provinces. The various growth stages of tobacco including germination, growth, flowering, and maturity were included in the data collection. The images of tobacco leaves in different processing states such as ecology and baking were also included. Several different tobacco varieties were selected for data collection to obtain differences in shape, color, texture, *etc*. The images were captured under the same environmental conditions at different points in time to obtain different light and shadow effects. Under each classification, enough images were guaranteed, so that each class of data had a rich internal diversity. Through such data collection methods and strategies, this study ensured the breadth and diversity of the data set and provided a strong support for the construction and training of tobacco leaf quality classification models with superior performance [15-16].

Data preprocessing

After data collection, the raw images went through a quality check and those images that failed this quality check were eliminated from this study. All qualified images were then cropped and resized to ensure consistent size and resolution of the input model by using Adobe Photoshop (Adobe, SAN Jose, California, USA). The median filtering method was applied to process the noise and outlier in the images using MATLAB software (MathWorks, Inc., Natick, Massachusetts, USA). Each tobacco leaf image was manually labeled according to quality standards. The labeling process was done through the assistance of semi-automatic tools to improve the accuracy and efficiency of labeling.

Data enhancement technology

To further enhance the generalization ability of the model, the cleaned data set was enhanced to generate new and different image data through various transformations of the original image, thus expanding the size of the data set. This process would help the model learn more feature information, prevent overfitting, and improve the model's performance on previously unseen data. The main data enhancement techniques used in this study included rotation, flip, zoom, cropping, and color transformation of images. Rotation of the image at different angles could increase the tolerance of the model to angle changes, while randomly cropping a portion of the image could force the model to learn features at different locations. By applying these multiple data enhancement techniques, this study significantly increased the diversity and size of the training dataset to improve the classification performance and stability of the final model.

Model Construction

Based on the characteristics of the experimental data, the Convolutional Neural Network (CNN) was chosen as the basic model. CNN has excellent image feature extraction ability and is a common model applied to image classification tasks in deep learning.

The CNN basic model structure selected by this study was composed as follows: (1) Input layer: it received the pixel value of the tobacco leaf image and set the image size to $H \times W$. Then the input layer dimension was $H \times W \times 3$; (2) Convolutional layer: Multiple convolutional nuclei were used to extract image features. The size of convolutional nuclei was assumed as $F \times F$ and the number of convolutional nuclei was K; (3) Pooling layer: It carried out the undersampling to reduce the size of the feature map; (4) Fully connected layer: It flatten the feature map and classified it. Considering the characteristics of tobacco leaf images and the complexity of classification tasks, the following network structure was designed: (1) Input layer was 256 × 256 × 3; (2) Convolution layers 1 and 2 were convolution kernel size of 3 × 3 with quantity 32, and convolution kernel size of 3 × 3 with quantity 64, respectively, and both activated function of rectified linear unit (ReLU); (3) Pooling Layers 1 and 2 were both maximum pooling with pooling window of 2 × 2; (4) Full connection layer was 128 nodes and the function ReLU was activated. The output layer included the number of nodes that were the number of categories, and the Softmax function was activated. The model structure then could be expressed as:

$$\text{Input} \rightarrow (C_1 \rightarrow P_1) \rightarrow (C_2 \rightarrow P_2) \rightarrow FC \rightarrow \text{Output}$$

where C_1 and C_2 were the convolutional layers. P_1 and P_2 were pooled layers. FC was the fully connected layer. Through this network structure, the local features of tobacco leaf images could be fully extracted and efficiently classified. In subsequent experiments, the research would adjust the network parameters to find a balance between classification accuracy and model complexity.

Model training

Stochastic Gradient Descent (SGD) was applied as the optimizer in this study, and its update rules were as follows:

$$\theta_{t+1} = \theta_t - \eta \nabla J\left(\theta_t\right) \tag{1}$$

where θ_t was the value of the parameter iteration in round t. η was the learning rate, and $\nabla J(\theta_t)$ was the gradient of the loss function J with respect to the parameter θ_t. The Loss function chosen in this study was Cross-Entropy loss, whose expression was shown in the following equation (2):

$$J(\theta) = -\sum_{i=1}^{N}\sum_{j=1}^{C} y_{ij} \log\left(p_{ij}\right) \tag{2}$$

where N was the total number of samples. C was the total number of classes. y_{ij} was the value of the true label of the first i sample on the first j class. p_{ij} was the prediction probability of the model for the first i sample to belong to the first j class.

In the study, hyperparameters such as Batch Size, Learning Rate, and Epochs were set, and overfitting was avoided by Early Stopping, *i.e.* training would be stopped when the performance on the verification set would no longer improve after a certain number of rounds. To obtain better model performance, some key hyperparameters were adjusted in this study. The main hyperparameters to be adjusted included (1) Learning Rate: the step length of updating model parameters was controlled. The study started from 0.1 and gradually decreased to observe the change of model performance; (2) Batch Size: it determined the number of samples used for each parameter update. Different sizes such as 32, 64, and 128 were tried to find a balance between model convergence speed and performance; (3) Training rounds (Epochs): the number of times the entire data set was used for training. A large initial value was set, and the actual number of training rounds was determined by the early stop method. By gradually adjusting these parameters and observing the performance on the verification set, the research gradually found a set of hyperparameter combinations that made the model perform better.

Model verification

In the process of model training and parameter adjustment, the method of cross-validation was adopted to avoid model overfitting and select the model with the best performance. The process of cross-validation could be expressed as follows:

$$CV(k)=\frac{1}{k}\sum_{i=1}^{k}\left(1-\text{ Error }_{i}\right) \tag{3}$$

where k was the selected fold, and Error_i was the verification error rate for the i fold. The study performed a 5 fold cross-validation before this model was put to further verify on the test set and compare the performance with other existing models to ensure that the model in this study was indeed superior.

Model testing and evaluation

The model's performance on a separate data set was tested. The test data set was randomly selected from the data set of this study but was not used for training or validation of the model, thus ensuring the impartiality of the evaluation results. The model was tested by batch forward propagation. Given a batch of tobacco leaf images, the model generated a prediction of the corresponding quality level, which was compared with real labels to calculate the accuracy of the model on the test data set. The model was evaluated not only based on accuracy, but also on several other key metrics, including recall, accuracy, and F1 scores. These metrics provided a more comprehensive assessment of model performance. For accuracy, the ratio of the number of correct predictions to the total number of predictions was calculated using equation (4).

$$\text{Accuracy }=\frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \tag{4}$$

The recall rate, also known as true rate, was calculated using equation (5).

$$\text{Recall }=\frac{\text{True Positives}}{\text{True Positives }+\text{ False Negatives}} \tag{5}$$

The precision rate was calculated using equation (6).

$$\text{Precision }=\frac{\text{True Positives}}{\text{True Positives }+\text{ False Positives}} \tag{6}$$

The F1 score was the harmonic average of accuracy rate and recall rate, which was calculated using equation (7).

$$F1=2\times\frac{\text{Precision }\times\text{ Recall}}{\text{Precision }+\text{ Recall}} \tag{7}$$

Results and discussion

Model performance analysis

The performance changes of the model on the verification set under different values of hyperparameters were shown in Figure 1, where the number of training rounds was set to 50 times. By comparing the performance of the model under different parameter combinations, the results showed that, when the learning rate was 0.01, the batch size was 128, the accuracy of the model on the verification set reached 88.9%, and the loss value was 0.28, which was the best performance. Through the analysis of cross-validation, the validation accuracy and validation loss of the model on different folds were relatively stable. The average validation accuracy of the final model was 87.96%, and the validation loss was 0.304 (Figure 2). The results confirmed that the model selected by parameter adjustment had good generalization ability and was suitable for classification prediction of unknown data. Through in-depth analysis, it was found that the model performed well on some categories of leaf images, while it did not perform well on others. The results demonstrated that the model had a high recognition accuracy for images of category A, but a low recognition accuracy for images of category C (Figure 3). To comprehensively evaluate the performance of the model, this study mainly adopted three evaluation indexes including accuracy rate, recall rate, and F1 score. The results showed that there were differences in the performance of the model in different categories (Figure 4). Category

A had the best performance with an accuracy of 92.5%, and F1 score of 0.917, indicating that the model had a good classification effect for this category. However, for class C, the accuracy of the model dropped to 84.7% and the recall rate was 82%, which could be attributed to the higher complexity of image features or insufficient sample size for the class. Based on these evaluation results, the research could further analyze the performance bottleneck of the model

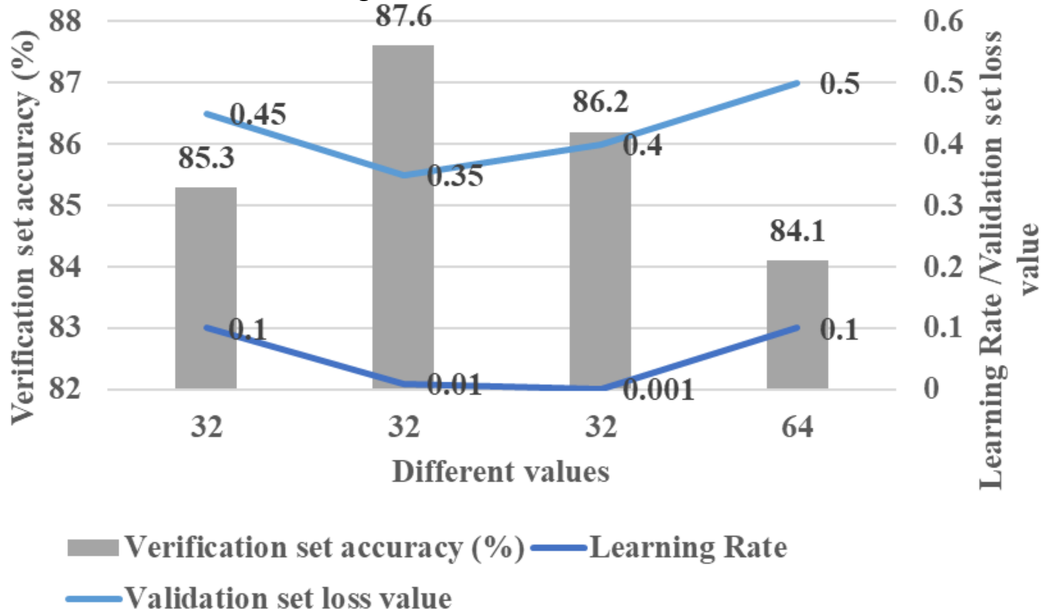

Figure 1. Key hyperparameter adjustment.

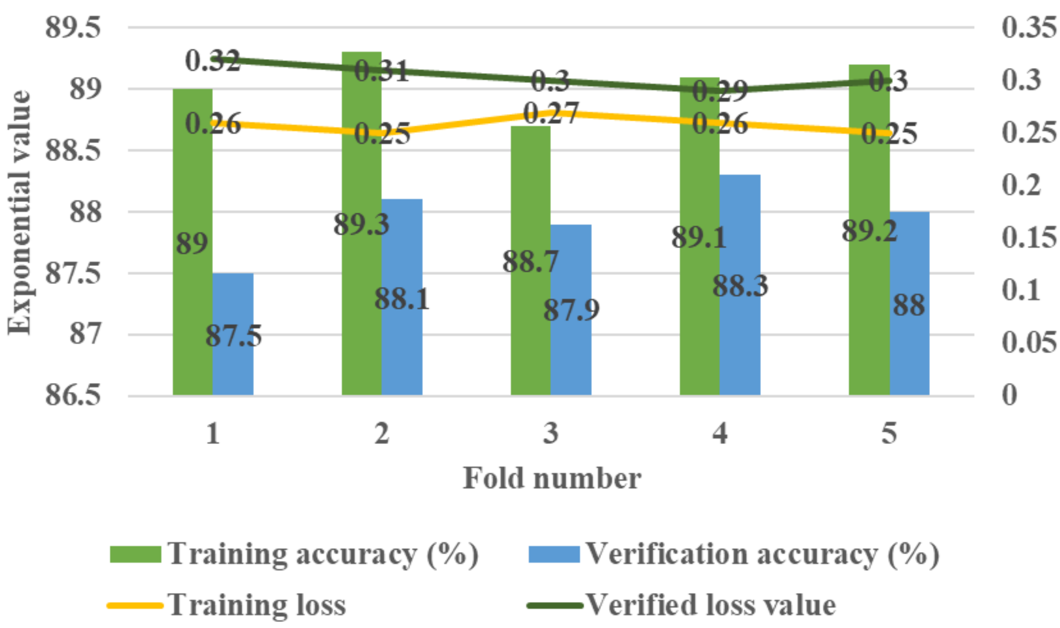

Figure 2. The model verification results of each fold.

and propose targeted improvement strategies to improve the classification performance of the model [17].

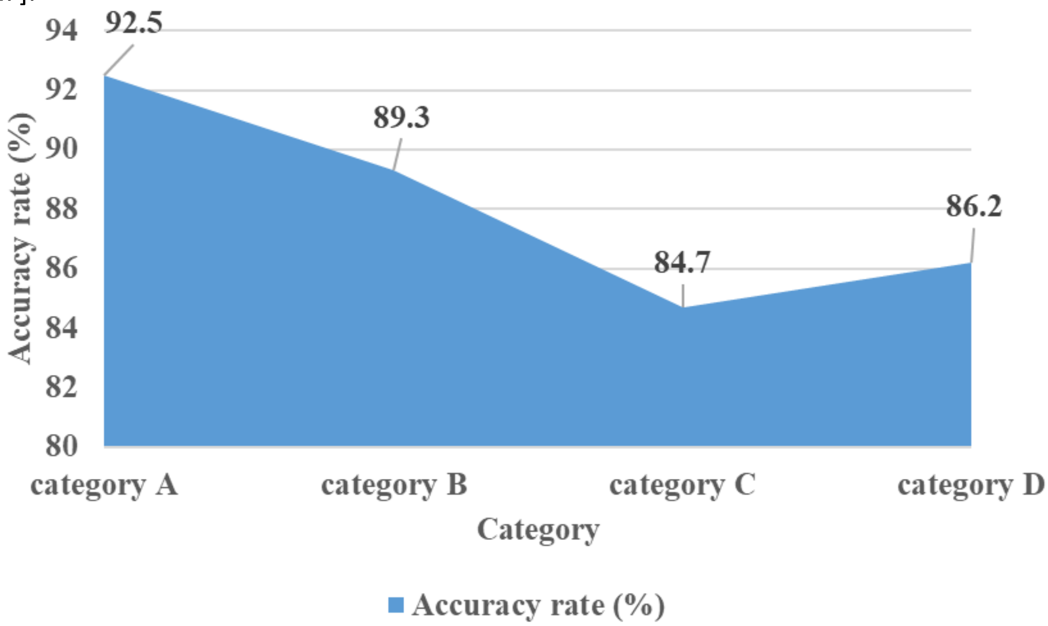

Figure 3. Accuracy of the model in each category.

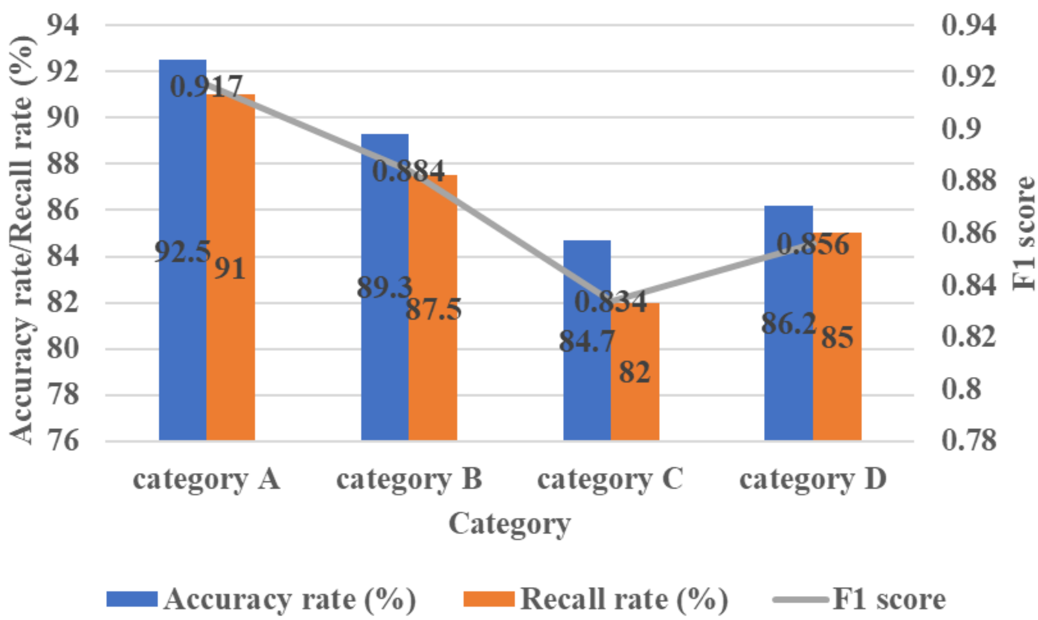

Figure 4. The performance of the model in each category.

Further analysis of the causes of wrong prediction demonstrated that the model mainly showed problems in the following aspects:

(1) Insufficient feature extraction: When the model processes some leaf images with complex textures and shapes, the feature extraction was

insufficient, resulting in a decrease in recognition accuracy.

(2) Class imbalance:

The training data had a small number of samples for some categories, which might lead to poor performance of the model in these categories.

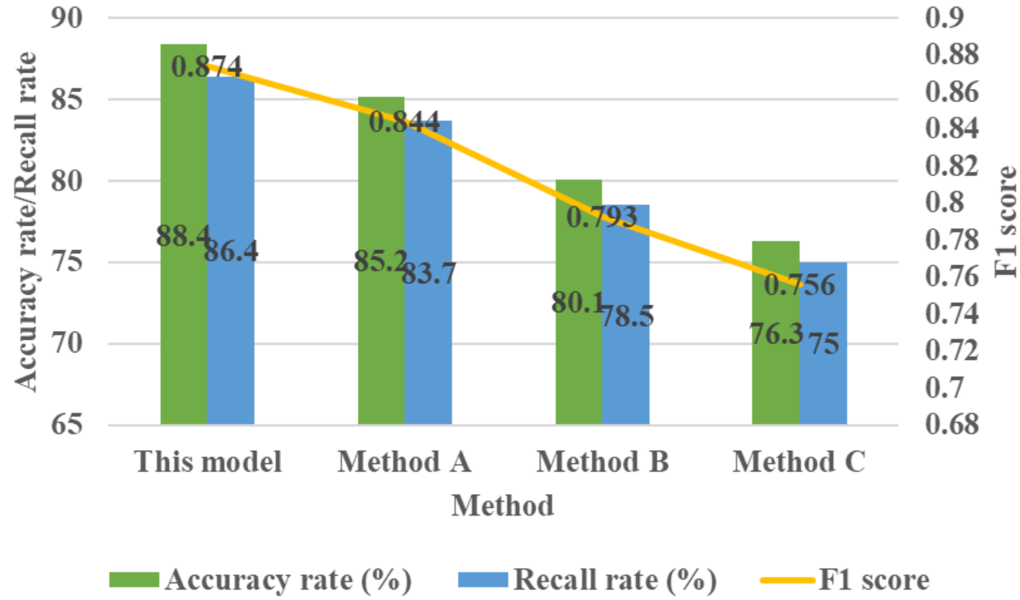

Figure 5. Comparison between this model and the other three existing methods.

(3) Overfitting:
The model performed well on the training set, but degraded on the test set, which might be caused by the phenomenon of overfitting.

Based on the above analysis, this study put forward the following suggestions to improve the model performance:

(1) Enhanced feature extraction capability:
The model could improve the feature extraction capability of complex images by introducing more advanced feature extraction network structure or improving the existing network structure.

(2) Solve the category imbalance problem:
It could be done through data enhancement technology, artificially synthesizing some samples of a few categories, or using resampling method to increase the weight of a few categories of samples in training.

(3) Prevent overfitting:
More stringent model regularization strategies could be adopted such as Dropout, L1/L2 regularization, *etc*. to mitigate the phenomenon of overfitting.

Combined with the evaluation and in-depth analysis of the model performance, the researchers had a more comprehensive understanding of the strengths and weaknesses of the model, which would help the researchers to continuously optimize the model in the subsequent work and improve its performance in image classification tasks.

Comparison with existing methods

The study further compared the performance of designed model with that of other existing methods to show the advantages and rooms for improvement of this developed method in image classification tasks [18, 19]. Three existing methods were employed to compare with the model of this study in terms of accuracy, recall rate, and F1 score (Figure 5). The results showed that this model outperformed other existing methods on all three evaluation indicators. Compared with the nearest method A, the accuracy of this model was improved by 3.2%, and the F1 score was also significantly improved. To better understand these differences, the main characteristics and coping strategies of each approach were analyzed. The results demonstrated that this model achieved excellent performance in image classification tasks by using advanced deep learning theory and combining with effective data preprocessing strategies, which proved that this method was effective and beneficial in some aspects. However, the results also revealed possibilities and directions for further optimization and improvement of model performance such as further exploration of different model architectures, optimization algorithms or loss functions.

Model optimization strategy

Based on the results of this study, the following possible optimization strategies and directions were identified.

(1) Improved data enhancement techniques:
Although a variety of data enhancement techniques had been adopted in this study, further exploration of new image transformation methods such as color dithering, more complex image rotation, and scale transformation can further enrich the diversity of training data, which not only helps to improve the generalization ability of the model, but also hopefully reduces the risk of overfitting, thus achieving better classification results on more previously unseen image samples.

(2) Model architecture adjustment:
Although the current deep learning model performed well in tests, by adjusting the model architecture such as increasing the network depth, the number of convolutional layers or fully connected layers, or introducing advanced modules such as residual blocks and attention mechanisms, more complex features in the image can be captured more effectively. This architectural adjustment is expected to further improve the accuracy of the model when processing complex images.

(3) Hyperparameter tuning:
Using grid search, Bayesian optimization, and other methods, the model's hyperparameters such as learning rate, batch size, and weight attenuation can be further optimized. Finding a combination of parameters that is more suitable for the current task is the key to improving the performance of the model.

(4) Ensemble learning:
Combining the prediction results of different models can obtain more robust classification effects. Applying ensemble learning methods such as Bagging, Boosting, or Stacking can effectively improve the accuracy and robustness of the model, especially in the face of diverse and complex data sets.

(5) Use of semi-supervised learning or self-supervised learning:
Considering that it may be difficult to obtain high-quality labeled data, this study can explore semi-supervised learning or self-supervised learning methods. These methods use a large amount of unlabeled data for model training, which can improve the learning effect and prediction accuracy of the model with limited labeled data.

By implementing the above optimization strategies, this study is expected to further improve the performance of the model in tobacco leaf image classification tasks and meet the application requirements of higher standards. The exploration of these strategies not only has a direct positive impact on current research, but also provides valuable reference and enlightenment for future research in related fields.

Conclusion

This study constructed a model based on deep learning and discussed the model’s application and optimization in image classification, and comprehensively and systematically conducted research on theoretical basis, data processing, model construction, and optimization. In the stage of data collection and pre-processing, the collection method, range, and diversity of data were elaborated, and advanced data cleaning, labeling, and enhancement techniques were adopted to ensure the quality and efficiency of model training. In the process of model construction, after rigorous model design, parameter adjustment, verification and selection, this study successfully constructed a deep learning model with excellent performance. Through comparison and analysis with existing methods, the model demonstrated excellent performance on multiple indicators such as accuracy, recall rate, and F1 score, which verified the effectiveness and feasibility of deep learning in image classification tasks. Based on the results of model performance analysis, a series of model optimization strategies were proposed including improving data enhancement technology, model architecture adjustment, hyperparameter tuning, adopting ensemble learning, and introducing semi-supervised learning or self-supervised learning, *etc*. to further improve the generalization ability and robustness of the model and meet more stringent application requirements. The results of this study not only provided a new and effective method for the field of image classification, but also laid a solid foundation for the further development and application of deep learning. However, the study also recognized that, despite the model's excellent performance, problems such as computational resources, complexity of data acquisition and processing needed to be considered in practical applications, and the interpretability of deep learning models remained a challenge. In future work, we will further explore the optimization direction of the model, improve the practicality and interpretability of the model, and promote the wide application of deep learning in more fields.

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