Fundus Image Recognition Based on Deep Learning: Methodology and Experimental Analysis

Qizhi Yang[1], Wegayehu Enbeyle Sheferaw[2, *]

[1] Northern Jiangsu People's Hospital Affiliated to Yangzhou University, Yangzhou, Jiangsu, China
[2]Department of Statistics, Mizan-Tepi University, Tepi, Ethiopia
Institute of Health Research, Faculty of Health Science, University of Canberra, Bruce, Australia
*Email: wegayehu@mtu.edu.et

Abstract

Fundus is an important research object in ophthalmology. Ophthalmologists often diagnose human eye diseases through fundus images. To improve the diagnosis rate of eye diseases by ophthalmologists, the feasibility of using image processing and artificial intelligence technology to intelligently identify fundus images is studied. The fundus image data is effectively processed using a variety of image technologies included in OpenCV and MATLAB. Convolutional neural networks with different structures and parameters are established using TensorFlow to extract features and train the processed fundus images. The recognition rate is improved by changing the hierarchy and adding the center loss function to optimize the network. The fundus images are input into the network to achieve rapid classification of fundus diseases and display the corresponding recognition probability. 500 250*166-pixel fundus images of eight categories including diabetes and glaucoma are selected for classification training and test experiments. The results show that the recognition rate of the network model reaches 44.81% when the number of iterations is 20,000. This method realizes the recognition of fundus images and can help ophthalmologists assist in the judgment of eye diseases.

Keywords: Artificial Intelligence; Image Processing; Convolutional Neural Network; Image Recognition; Fundus Image

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1. Introduction

Fundus screening is a common and cost-effective method for eye disease examination. The morphology and characteristics of fundus images vary for different eye diseases, and they change with the patient's environment and conditions [Bernardes, et al., 2011; Bernabé, et al., 2021]. They also vary among different populations and age groups. ophthalmologists often judge eye diseases by observing fundus images and their own experience.

The rapid development of digital image processing technology has played a positive role in the field of medical imaging [Doi, 2006; Scholl, et al., 2011]. Modern ophthalmologists have abandoned the traditional human eye observation mode and use contemporary computer technology to make better judgments. However, with the increasing number of patients with eye diseases, the pressure on ophthalmologists is also increasing day by day [Resnikoff, et al., 2020; Lim, et al., 2020]. Long-term reliance on image processing technology will inevitably cause physical and mental fatigue, and it is difficult to detect eye diseases early because ophthalmologists usually rarely see corresponding symptoms in the early stages of eye diseases.

The rise of artificial intelligence has penetrated almost every field [Bohr & Memarzadeh, 2020; Hamet & Tremblay, 2017]. AI medicine has become one of the hottest fields in the field of artificial intelligence. There are many precedents abroad for applying artificial intelligence technology to the medical field. Image recognition technology, which has a very wide range of applications, has always played an important role in the field of medical imaging as an important branch of artificial intelligence and has been used both at home and abroad [Ker, et al., 2017; Razzak, et al., 2017].

Based on digital image processing technology and big data technology, combined with artificial intelligence technology, doctors can use the models established by AI to further improve the diagnostic accuracy of disease types, thereby greatly improving diagnostic efficiency and reducing diagnostic pressure [Dilsizian & Siegel, 2014; Ghaffar Nia, et al., 2023].

After consulting the data, it was found that in the field of ophthalmology, there are currently a few precedents for using fundus images as identification objects. The team of Naval Medical University built an artificial intelligence deep learning algorithm model for auxiliary diagnosis of diabetic retinopathy based on more than 180,000 fundus color photos from EyePACS. Under laboratory conditions, the sensitivity and specificity of the model were 95.3% and 79.5% respectively. The team of Nantong University School of Medicine developed a remote intelligent fundus screening cloud platform project.

In actual ophthalmic diseases, in addition to eye diseases caused by diabetes, there is also blindness caused by glaucoma, cataracts, age-related macular degeneration and many other reasons [Zetterberg, 2016; Klein & Klein, 2013]. Since some image sources may be blurred, a lot of image preprocessing is also required in advance.

In recent years, with the continuous innovation of artificial intelligence algorithms, in addition to deep learning models such as Convolutional Neural Networks (CNNs), researchers have also explored the integration of attention mechanisms, transfer learning, and Generative Adversarial Networks (GANs) into fundus image recognition tasks

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[Showrov, et al., 2024; Saeed, et al., 2021]. Attention mechanisms help models focus more effectively on key pathological areas, thereby improving interpretability and diagnostic accuracy. Transfer learning enables the reuse of knowledge from large-scale datasets, allowing good performance even with relatively limited ophthalmic data. GANs have been utilized to generate high-quality synthetic fundus images, effectively expanding datasets. These new technologies have significantly strengthened the robustness and clinical applicability of fundus image recognition systems [Mamo, et al., 2024; Kumar & Paul, 2023].

As AI is increasingly applied in the medical field, challenges such as model transparency, clinical interpretability, and patient data privacy have also attracted much attention [Albahri, et al., 2023; Band, et al., 2023]. When designing an autonomous fundus image recognition system, it is essential to ensure compliance with relevant medical data regulations such as HIPAA in the United States or China's Personal Information Protection Law. Enhancing the explainability of model outputs is crucial to gain the trust of doctors and patients and to promote the practical application of intelligent diagnostic systems [Nasarian, et al., 2024; Dhar, et al., 2023].

Based on the processing of fundus images, an autonomous fundus image recognition system adapted to the artificial intelligence framework was proposed, which can simultaneously identify eye diseases caused by other reasons including diabetes, glaucoma, cataracts, hypertension, etc. to a certain extent, and give the corresponding probability.

2. Image Processing

In actual judgment, some image sources may be blurred. To allow the computer to better recognize them, the fundus image recognition method proposed in this paper is divided into two steps. The first step is image processing, and the second step is image recognition.

For fundus images, the image processing algorithm in this paper is mainly based on Python and MATLAB and is combined with the image open-source library OpenCV. The execution process is to obtain the image source from a third party and go through a series of image processing processes such as system preprocessing and image segmentation and use it for image recognition. The processing flow is shown in Figure 1, and each step is briefly described below:

(1) Image acquisition: Obtain standard fundus image sources output by clinical medical instruments from a third-party database.

(2) Image enhancement: Since the acquired image sources may have uneven quality and blur, the image sources need to be preprocessed to eliminate noise. Enhancement is done through the CLAHE algorithm.

(3) Image denoising: After enhancing the source image, the noise needs to be removed due to possible errors in image acquisition and preprocessing, which is achieved through Gaussian smoothing.

(4) Image segmentation: Segment the pre-processed cell images. Image segmentation is a very important step, and reasonable segmentation is an important guarantee for subsequent processing.

(5) Morphological processing: Corrosion and expansion of segmented cells.

(6) Invert: Swap black and white to more intuitively highlight the cell morphology and edges.

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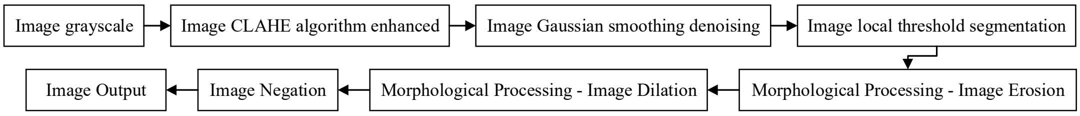

Figure 1 Fundus image processing flow

In addition to the basic image processing steps, the fundus images were further subjected to adaptive histogram equalization to enhance the contrast in local regions, especially around blood vessels and lesions. This method ensures that subtle pathological features, which are critical for accurate diagnosis, are not lost during preprocessing. To improve robustness, the images were also resized to a uniform scale and normalized, which allows the recognition model to better adapt to variations in input data [Pei, et al., 2023; Chen, et al., 2005].

Consider that fundus images often suffer from illumination inconsistencies and artifacts, a color normalization step was introduced to standardize the color tone across different samples [Narasimha-Iyer, et al., 2006; Besenczi, et al., 2016]. This reduces the impact of variations caused by different imaging devices and environmental conditions, thereby improving the reliability of feature extraction in the subsequent recognition phase. Advanced noise filtering techniques such as bilateral filtering were tested during preprocessing, but due to computational efficiency concerns, Gaussian smoothing was ultimately selected for this study.

The datasets for fundus image processing and image recognition come from the Peking University "Smart Eye" International Fundus Image Intelligent Recognition Competition (odir2019). The official provides 5,000 sets of structured desensitized ophthalmology datasets containing the patient's gender, age, binocular color fundus photos, and doctor's diagnostic keywords. The dataset is divided into 8 labels, including normal (N), diabetes (D), glaucoma (G), cataract (C), AMD (A), hypertension (H), myopia (M) and other diseases/abnormalities (O).

Due to functional limitations, a total of 500 image data including 8 labels were selected as the original data. To ensure balanced distribution across different disease categories, stratified sampling was employed during dataset selection, which maintain a reasonable proportion of each label in the training and testing sets. This helps prevent model bias toward categories with larger sample sizes and ensures more objective evaluation results in the subsequent recognition process.

While preprocessing, data augmentation techniques were also applied to further enrich the training set and improve model generalization [Maharana, et al., 2022; Shorten & Khoshgoftaar, 2019]. Common augmentation operations include random rotation, horizontal and vertical flipping, brightness adjustment, and slight random cropping [Takahashi, et al., 2019; Alomar, et al., 2023]. These operations simulate different shooting angles and lighting conditions that might be encountered in actual clinical environments, thereby enhancing the model's adaptability to unseen data.

A preliminary quality control module was introduced before the formal preprocessing pipeline to filter out severely defocused, overexposed, or underexposed images [Gaiani, et al., 2016; Qiu, et al., 2020]. Only images meeting basic clarity and exposure standards were included in the subsequent processing stages, to ensure the reliability of the training data source. For images with mild quality issues, a targeted enhancement and correction strategy was adopted, rather than simple exclusion, to maximize data utilization.

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The image preprocessing strategy adopted in this study comprehensively considers the quality diversity of fundus images and the technical requirements of downstream recognition models. Through a combination of enhancement, normalization, decision, segmentation, augmentation, and quality control, a high-quality input dataset was prepared for subsequent model training and evaluation, lay a solid foundation for achieving accurate and robust fundus image recognition.

3. Building Deep Models

3.1 Learning method and neural network selection

In machine learning, in addition to the two common forms of supervised learning and unsupervised learning, there is also semi-supervised learning, that is, in the dataset, only a small part has corresponding matching labels, and most of the data are unknown labels. The basic rules hidden in semi-supervised learning need to be mined through the corresponding labels of known data. The mining process can be regarded as the process of machine learning.

Because the official dataset already provides many corresponding labels, training can be done first after the required dataset is classified. This article adopts semi-supervised learning. Compared with fully supervised learning, semi-supervised learning can better adapt to the complex reality of medical data, where high-quality, accurately labeled samples are often scarce, and labeling costs are high. Semi-supervised learning also leverages abundant unlabeled data, which enhances model generalization and robustness.

Convolutional neural network, abbreviated as CNN, is often used for image classification. Convolutional neural networks mainly extracts feature values from images through self-set convolution kernels and classifies them according to the feature values. The establishment and recognition process of the neural network in this paper is shown in Figure 2:

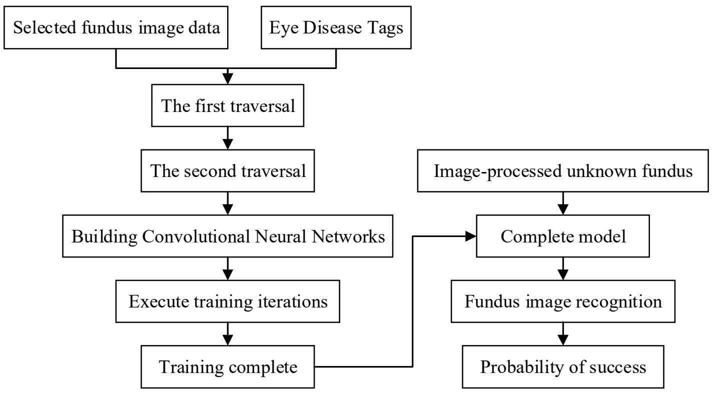

Figure 2 Network training process

450 fundus source images with 250×166 pixels and corresponding labels were selected as training sets for training. The image set was traversed for the first time, and the labels of the image set were traversed for the second time. The convolutional neural network was established. The convolution layer designed in this paper has two layers, with 1024 neurons. The optimization algorithm uses the gradient descent algorithm. After the CNN is built, training begins. After the training is completed, the complete model is obtained. The fundus image source with unknown labels is loaded into the model for recognition. Image recognition is built in conjunction with the SOFTMAX classifier.

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To further improve model performance, Rectified Linear Unit was selected as the activation function in the convolutional layers, which can effectively avoid gradient vanishing problems and accelerate convergence speed during training [Wang, et al., 2017]. Batch normalization layers were inserted after each convolutional layer to stabilize the learning process and reduce sensitivity to parameter initialization [Wu, et al., 2018].

During training, a mini-batch gradient descent method was adopted, the batch size is 32 to ensure a balance between training speed and model convergence. The learning rate was initially set to 0.001 and gradually decayed during training according to the validation set performance, which prevents overfitting and ensures that the model converges to a better local minimum.

Considering the relatively small size of the dataset, data augmentation strategies such as random rotation, scaling, and brightness adjustment were incorporated into the training pipeline to artificially expand the dataset size and enhance the model's ability to generalize to new images. Early stopping strategies were also applied during training: if the validation loss did not improve over the present number of epochs, train would be terminated early to avoid model overfitting.

The SOFTMAX classifier mapped the output of the last fully connected layer to a probability distribution across eight disease categories. The category with the highest probability was selected as the final prediction result. In the evaluation phase, performance indicators such as accuracy, precision, recall, and F1 score were used to comprehensively evaluate the recognition ability of the model. Through multiple rounds of experiments, the final model achieved relatively good recognition results on fundus images from different disease types and varying qualities, which verifies the feasibility and practicality of the method proposed in this paper.

3.2 Model testing

After actual testing, it was found that the fundus image in the dataset is 2400×2400. To train the neural network model normally, the network structure needs to be modified. Otherwise, excessive capacity will lead to insufficient video memory and cause training failure.

There are two ways to improve this. The first is to reduce the image size, and the second is to reduce the amount of data input to the model. The features contained in a complex image set need to be supported by enough pixels. If the image pixels are greatly reduced to meet the needs of model operation, the essence of classification will be lost [Wu, et al., 2019].

A certain amount of training must be ensured at the same time. After many attempts, the image input was finally set to 250×166 pixels. This ensures that important features in the fundus images, such as optic disc edges, blood vessel distributions, and lesion areas, are preserved as much as possible, while keeping the computational load within acceptable limits for hardware resources.

This paper uses 32 7×7 convolution kernels, that is, extracts 7×7-pixel sub-areas, takes the input image source as a 4D vector, uses a grayscale image as the input form, and sets it as a function to automatically calculate the one-dimensional size. The width of the image source is 250 and the height is 166. Compared to using RGB three-channel input, grayscale processing simplifies the model complexity, reduces parameters, and shortens training time without significantly affecting the recognition accuracy for fundus features, as most

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pathological features mainly manifest through brightness and texture variations rather than color information.

In the process of building the model, special attention should be paid to the parameters of the fully connected layer of the neural network. The fully connected layer is classified according to the features of the convolutional layer and the pooling layer. The SOFTMAX model can be used for the final output. The fully connected layer is set to 63×24×64 because of the size of the input image, with a total of 1,024 neurons.

The choice of 1024 neurons strike a balance between learning sufficient abstract feature representations and preventing overfitting. Moreover, a dropout layer with a probability of 0.5 was added after the fully connected layer during training. Dropout randomly deactivates some neurons during each iteration, which helps improve the model's generalization ability and reduces the risk of overfitting caused by small sample sizes.

After adjusting the network structure, the model was able to successfully complete multiple rounds of training. During the testing phase, the trained model was applied to a new set of fundus images with unknown labels. By evaluating performance metrics such as overall accuracy, per-class recall rate, confusion matrix, and Area Under the Curve score, it was verified that the adjusted neural network could still effectively recognize and classify fundus images of different disease types even under limited resolution conditions.

Through appropriate image resizing, grayscale preprocessing, network architecture optimization, and regularization strategies, this paper successfully solved the problem of large image input leading to video memory overflow, which provides a reliable foundation for subsequent fundus image intelligent recognition.

4. Experimental Results

4.1 Experimental conditions

This paper uses a workstation with a single GPU of GTX1080, a CPU of I7-8700K, and a memory of 12G. 500 250×166 data sets containing 8 labels are extracted as training sets, and an additional 50 data sources are used as test sets to evaluate the performance of the model. Considering the time cost, the model converges after 500 iterations of training.

The hardware selection in this experiment ensures a good balance between performance and accessibility. Although GTX1080 is not the latest GPU, it has sufficient computing power to complete medium-scale neural network training and inference tasks. Meanwhile, the I7-8700K CPU ensures that data preprocessing and augmentation tasks can be executed efficiently without becoming a bottleneck.

To simulate a more realistic clinical application scenario, the 500 images selected for training covered fundus images of different diseases under various shooting conditions, including differences in lighting, clarity, and image equipment, which effectively improved the generalization ability of the model. Before formal training, the training set and test set were randomly shuffled to ensure that the data distribution was balanced and to avoid model bias caused by the order of data input.

In terms of training strategy, this paper adopts a small batch Stochastic Gradient Descent (SGD) method. The batch size is set to 32, the initial learning rate is 0.001, and the learning rate decay strategy is applied during the training process to ensure that the model can converge stably. An early stopping mechanism is introduced to monitor the loss value on the validation set during training. If the validation loss does not improve for 20 consecutive epochs, training is automatically terminated to avoid overfitting.

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4.2 Experimental results

With the help of a third-party database, the project extracted 550 fundus images and guided their classification into 8 groups, namely normal (N), diabetes (D), glaucoma (G), cataract (C), AMD (A), hypertension (H), myopia (M) and other diseases/abnormalities (O).

The training samples are 500, and the remaining 50 are used as test samples. The 8 categories are used as output nodes to train the network. Considering the time cost, after 500 iterations, the recognition rate reaches nearly 45%.

After the classifier is trained, it is used to predict and classify 50 test samples to test its classification accuracy. The evaluation results show that eye diseases caused by myopia and cataracts have significant image features and obvious differences, they are easier to distinguish and achieve good recognition results. However, symptoms such as AMD, diabetic retinopathy, glaucoma and hypertension do not have a good recognition effect and there is obvious classification interference.

Further analysis of the confusion matrix shows that most of the classification errors occur between diabetic retinopathy (D) and hypertensive retinopathy (H), and between glaucoma (G) and AMD (A). These diseases all cause changes in retinal blood vessels and optic disc morphology, and the early features are very similar, which makes it difficult for the network to distinguish effectively with limited data.

The error is that the algorithm cannot extract the characteristic points of each disease very well, and it is still difficult to distinguish even after the initial image processing. It is necessary to find new feature parameters to find their significant features. Potential feature points that can be considered in future work include the degree of optic disc cupping, macular degeneration patterns, microaneurysms, and neovascularization features [Fraser, et al., 2013].

The image processing in this article uniformly binarized the data set before importing it into the training model, and color can be used as a classification feature, we will gradually improve these aspects in the future. In fundus images, hemorrhage areas usually appear dark red, while exudates show bright yellow features. If the color information is preserved and effectively used, the network may better distinguish between different lesion types. Future research can also explore the use of multi-channel input and integrate attention mechanisms into the convolutional neural network to enhance the model's focus on critical regions, thereby improving classification performance.

Although the current model achieves preliminary classification results under limited conditions, there is still considerable room for improvement in recognition, accuracy and robustness. Future optimization directions include expanding the dataset scale, fine-tuning model hyperparameters, and introducing advanced network structures such as ResNet, DenseNet, or Vision Transformer (ViT) to further enhance fundus disease recognition capabilities.

5. Conclusion

The method of fundus image recognition combines image processing and artificial intelligence technologies. The fundus images are processed, analyzed and characterized, and input into the convolutional neural network model for recognition and classification.

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The experimental language is mainly Python, and image processing and image recognition are supplemented by OpenCV and TensorFlow respectively.

The experimental results show that by combining the gradient descent algorithm and convolutional neural network, the system can effectively establish a learning model and give a classification probability. It can recognize fundus images to a certain extent, but considering the limitations of function and time cost, there is still much room for improvement.

Through the experimental process, it was found that different preprocessing methods have a significant impact on the recognition results. Fine-tuning these preprocessing techniques can further improve clarity and feature extraction accuracy of fundus images, thereby enhancing the performance of the deep learning model. The choice of model hyperparameters also has a direct impact on the final classification accuracy.

In the future, data augmentation techniques such as image rotation, and brightness adjustment will be introduced to expand the training dataset, and help the model learn more robust features and reduce the risk of overfitting. Ensemble learning methods will be considered to integrate multiple models to further improve recognition performance.

Considering the practical application environment, lightweight neural network models suitable for mobile devices will be explored, which enable real-time analysis and auxiliary diagnosis in primary medical institutions. These improvements will lay a solid foundation for the large-scale promotion and application of intelligent fundus screening systems.

The next step is to continue to perfect and improve the recognition rate, build a better hardware platform and improve the image processing algorithm. The neural network model will be further deepened, and finally the research results of the fundus will be put into practical application by combining embedded and intelligent Internet of Things technologies.

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