CLASSIFICATION OF EYE DISEASES CAUSED BY DIABETES WITH TRANSFER LEARNING TECHNIQUES

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ABSTRACT

Diabetes is the topmost reason for blindness among adults who are employed or engaged in work-related activities. Diabetic eye disease includes complications such as diabetic retinopathy, cataracts and glaucoma. It is plausible for a person to remain oblivious to the presence of severe diabetic eye disease and suffer from sudden blindness without any prior indications or symptoms. The aim of this paper is to conduct a comparative analysis between developing and training a neural network from scratch and utilizing a pre-trained model via transfer learning in regards to training time, ease of creation, accuracy, and consistency. The proposed method involved using a pre-trained model, EfficientNet, and fine-tuning its top layers on our dataset. This approach achieved a higher test set accuracy of 93% and showed a smooth validation loss curve, suggesting better generalization.

Keywords: Diabetes, Diabetic Retinopathy, Cataracts, Glaucoma, fundus images, Transfer Learning, EfficientNets, Kaggle.

INTRODUCTION

Diabetes is a condition that carries an increased risk of developing eye complications. Diabetic eye disease includes complications such as diabetic retinopathy, cataracts and glaucoma. Among adults aged 45 and over with diagnosed diabetes, 32.2% had cataracts, 8.6% had diabetic retinopathy, and 7.1% had glaucoma. Among adults aged 45 and over with diagnosed diabetes, 9.2% had vision loss due to cataracts, 4.1% had vision loss due to diabetic retinopathy, and 2.1% had vision loss due to glaucoma [1]. Diabetes is the primary factor that contributes to blindness among individuals of working age. It is a potential possibility for an individual to remain uninformed about the existence of severe diabetic eye disease, leading to abrupt and unexpected blindness. Conversely, the task of manually inspecting fundus images of the retina is arduous and time-consuming. The normal eye and damaged eyes with the types of eye diseases caused by diabetes are shown in fig. 1 [2].

In this research, it is aimed to investigate the effectiveness of transfer learning techniques for the classification of eye diseases caused by diabetes. Section 2 analyzes some related works, while the proposed method is explained in section 3. Conclusion is provided by section 4.

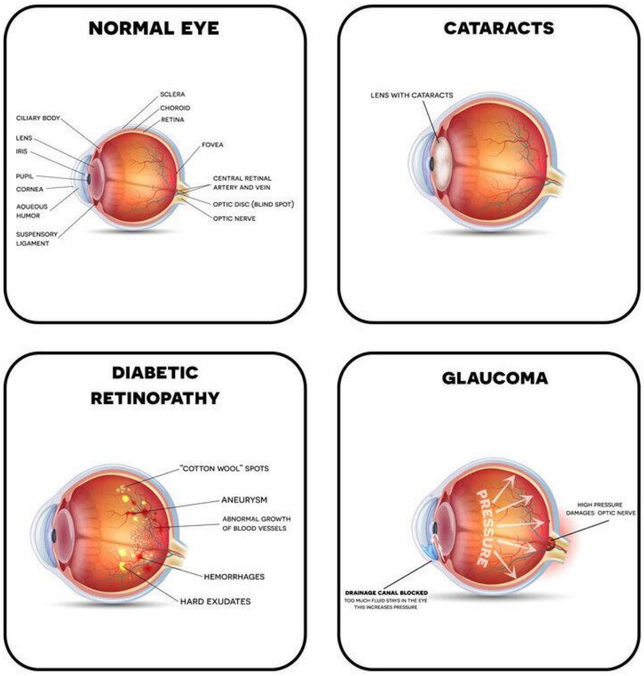


Fig. 1. [2] Chronic complications of Diabetes: Eye diseases

METHODS

Various retinal diseases were accurately classified through machine learning techniques by Naireen et al. [3]. The best performance was achieved using the Gaussian function, but it was observed that after 550 iterations, it had a problem of overfitting. On the other hand, sigmoid activation function was tuned throughout all the iterations and it did not lead to overfitting. However, ReLU and Tan^{-1} activation functions performed less effectively when compared to sigmoid and Gaussian.

Aya Adel et al. [4] introduced a novel transfer learning model utilizing Inception V3 and Xception deep networks for diagnosing three retinal diseases (CNV, DME, DRUSEN) and normal eyes by analyzing Optical Coherence Tomography (OCT) images. The model outperformed state-of-the-art models in retinal eye disease diagnosis with a small dataset of around 6000 images in the training process. The proposed Xception model yielded higher accuracy, precision, recall, and F-score compared to other models. The research highlighted the advantages of using transfer learning in conjunction with SVM hinge loss in addressing the multi-classification problem of retinal eye diseases.

The study which proposed by Junjun He et al. [5] presented a new approach for combining features extracted from color fundus photographs (CFPs) of both eyes to classify ocular diseases. The proposed method learned both unilateral and bilateral attention weights to guide the classifier in utilizing information from both eyes selectively. The experiments showed that the new method is more effective than traditional feature fusion methods. The learned feature weights showed that the network design was reasonable. The study's major contribution was the innovative feature fusion strategy that could be applied to other scenarios requiring the analysis of multi-modal images.

DISCUSSION

The prevalent approaches for classification of eye diseases involve learning-based structures and transfer learning, both of which employ convolutional neural networks (CNNs). The present study focuses on classifying retina images based on types of eye diseases, which is accomplished by enhancing a CNN model through the use of advanced transfer learning techniques.

Data Collection

The dataset used in this study is provided by the Kaggle and comprises of retinal images belonging to four distinct classes, namely Normal, Diabetic Retinopathy, Cataract, and Glaucoma. Each class consists of roughly 1000 images, sourced from a variety of repositories such as IDRiD, Oculur Recognition, and HRF. Figure 2 displays a set of randomly selected retinal images of the human eye, each labeled with its corresponding eye disease class.

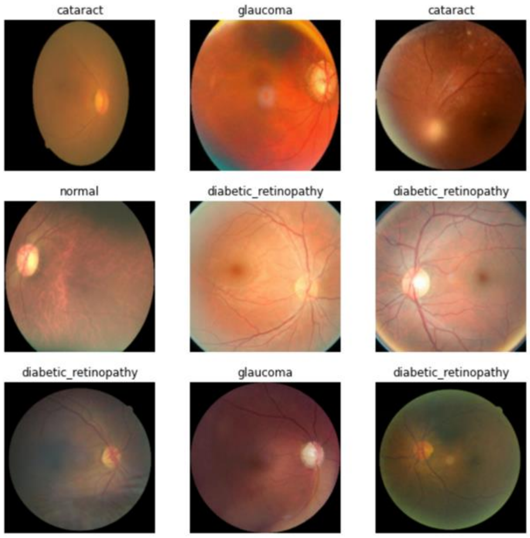


Fig. 2. Random images in the training set

This dataset contains 4227 training images categorized into four classes: normal, diabetic retinopathy, cataract, and glaucoma. The distribution of the number and the percentage of images of each class can be seen in fig. 3.

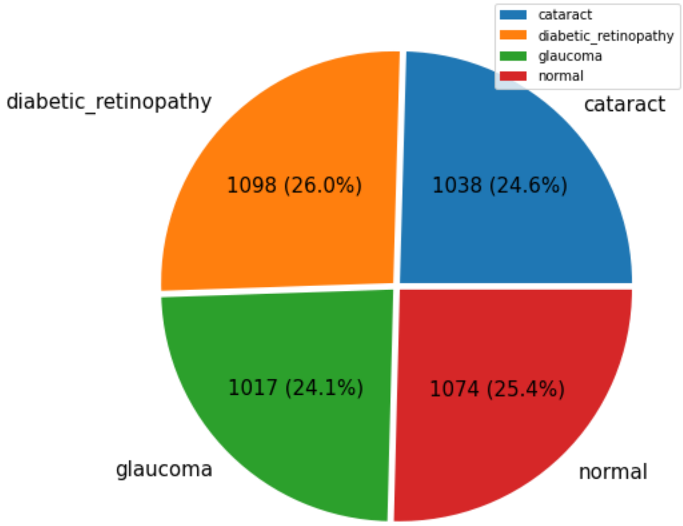


Fig. 3. Distribution of classes

Preprocessing Images

The dataset is divided into batches with size 64 to gains efficient utilization of computational resources and enables the model to be trained on larger datasets without requiring excessive memory. Next step is splitting the dataset into three parts: train (47 batches - 70%) set, validation (13 batches - 20%) set, and test (7 batches - 10%) set. The train set was used to train the model, the validation set was used to tune the hyperparameters and prevent overfitting, and the test set was used to evaluate the final performance of the model. This partitioning allowed to assess the model's ability to generalize to unseen data and provided a more accurate estimate of the model's performance on real-world scenarios.

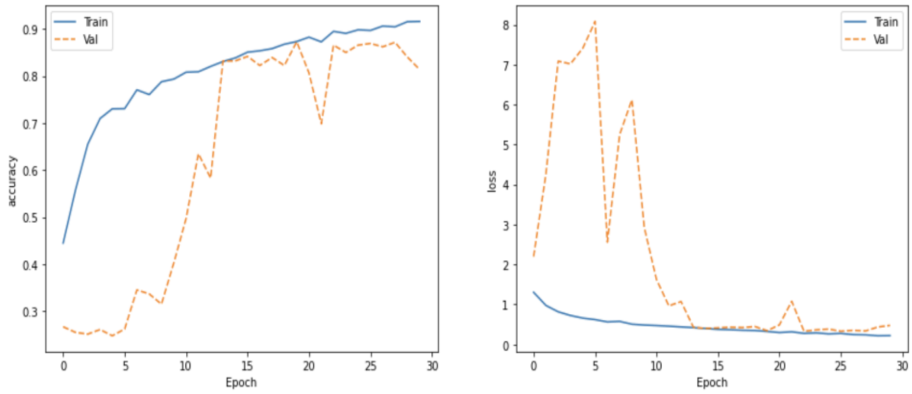
RESULTS

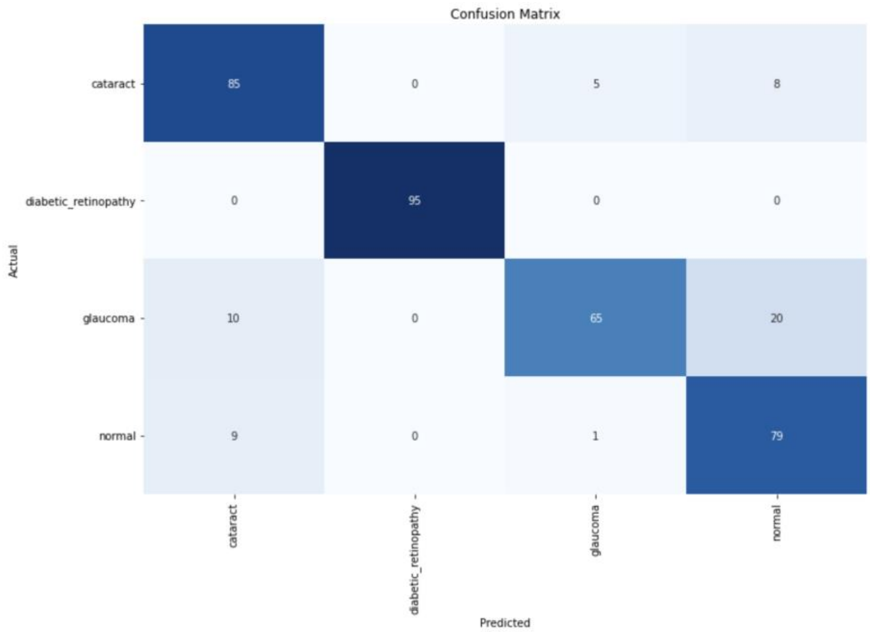
CNN from scratch

In this study, it is aimed to construct a deep neural network with optimal performance while considering the constraints of training time and memory. It is developed the network architecture from scratch and trained it for 60 epochs with a mechanism to terminate the training process early if the model's accuracy did not show significant improvement for 20 consecutive epochs.

The proposed model was evaluated on the test set and achieved an accuracy of 86%, along with a respectable f1-score.

The early stopping mechanism was used during training to prevent overfitting, which resulted in a training duration of 30 epochs. Continuing training beyond this point would likely result in overfitting, as indicated by the validation loss fluctuating and failing to maintain consistency. Each epoch took an average of 63 seconds to complete, making the model relatively efficient. While the model achieved high accuracy, further investigation is needed to improve the consistency of the validation loss and minimize fluctuations.

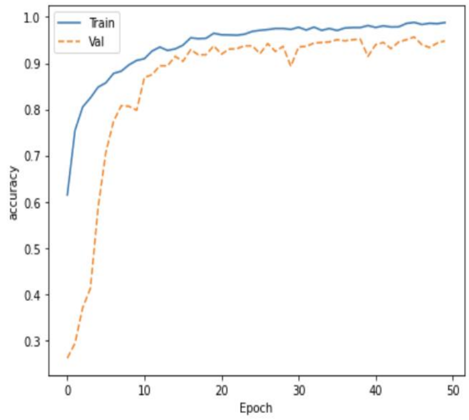


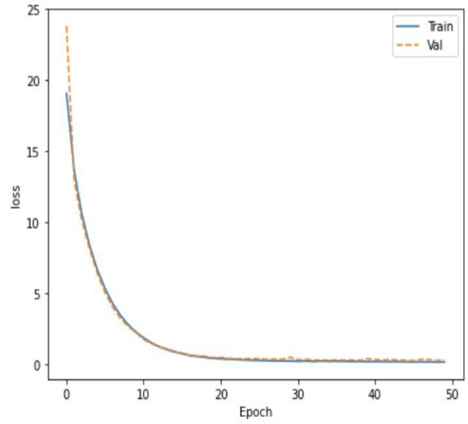


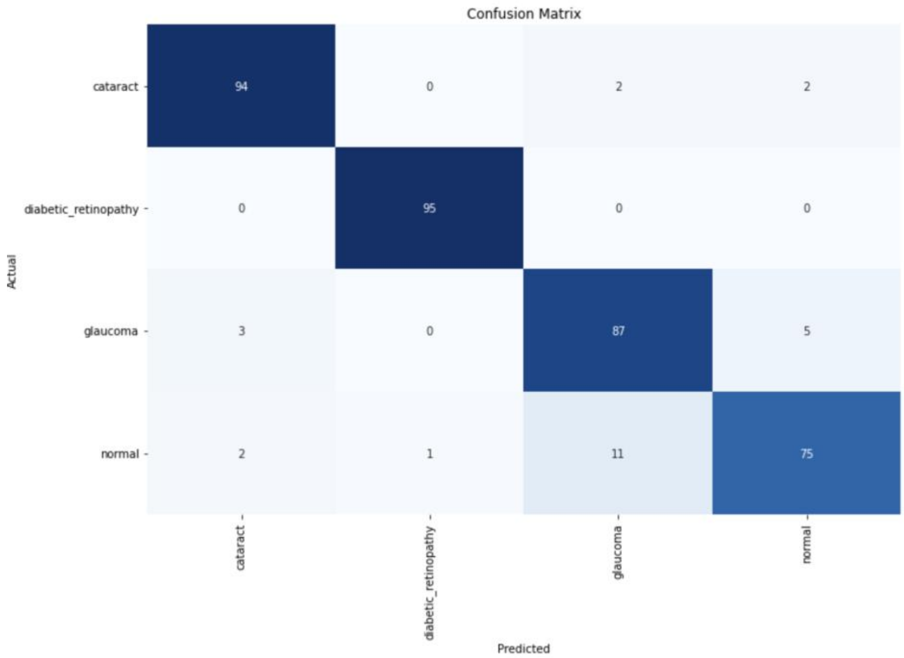
Transfer Learning (Pretrained Model)

In our next approach, we aim to utilize the advantages of transfer learning by employing a pre-trained model and fine-tuning it to adapt to our specific dataset. We have chosen EfficientNet as our pre-trained model because it has demonstrated superior performance on various computer vision tasks, and the pre-training dataset differs significantly from our own data, making it suitable for our purposes. To facilitate adaptation to our dataset, we only made the top-level layers trainable, while keeping the rest of the model's parameters fixed. This approach allows the model to leverage its prior knowledge while also making the necessary adjustments to accurately classify our data.

The pretrained model has performed well, achieving a high accuracy of 93% and f1-score on the test set, after training for 50 epochs without being stopped by the early stopping callback. Each epoch took approximately 50 seconds to execute. Additionally, the validation loss curve demonstrated a consistent and smooth trend, with no noticeable fluctuations, indicating that the model did not suffer from overfitting during the training process.







CONCLUSION

In conclusion, we have explored the effectiveness of using deep learning techniques for the classification of eye diseases. We have experimented with both custom-built and pre-trained neural network models, and have achieved promising results in terms of accuracy and f1-score. Our findings suggest that the use of pre-trained models, such as EfficientNet, can significantly improve the classification performance, especially when fine-tuned to adapt to the specific characteristics of the target dataset. Overall, our study highlights the potential of transfer learning as a powerful method for the classification of eye diseases.

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