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End-to-end Deep Learning Model for Classification of Diabetic Retinopathy based on Retinal Images

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***Abstract*— The diagnosis for diabetic retinopathy is of important concern as it ranks highest in causing vision impairment in working-age individuals within developing countries. Timely diagnosis is crucial for effective treatment; however, in recent times, deep convolutional networks show bigger act in double cataloging than earlier handcrafted-feature-based image classification. Hence, this paper will focus on an investigation into the application of deep convolutional neural networks for unconscious. classification of diabetic retinopathy from color fundus eye images is evaluated and sees an accuracy of 94.5% on the author's dataset, which surpasses that in the case of classical systems.**

***Index Terms*—diabetic retinopathy; deep convolutional neural network; image classification.**

I. INTRODUCTION

Over the years, more and more people have been diagnosed with diabetes. The condition also rises the risk of many eye diseases, the most serious one being diabetic retinopathy. And, moreover, diabetic retinopathy is the principal root of blindness in middle-aged adults. Early detection of diabetic retinopathy remains a slow and tedious process for the well-trained physician, even with repeated efforts. Sometimes treatment may be delayed due to faulty communication, and such factors have been noted.

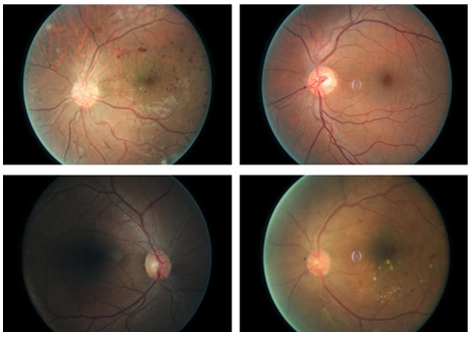

Figure 1. Examples of retinal images. The first two cells in the top row are since regular themes, and the bottom two cells are from patients with diabetic retinopathy

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This altered path is understood. In our study, we focused on the classification of retinal images as either normal or diabetic retinopathy, based on a wide assortment of features. Past efforts in this regard have successfully incorporated features extraction with machine learning techniques. Some of the used image features are exudates, red lesions, and detection of microaneurysm and blood. Some of the classifiers used are a neural network, sparse representation classifiers, traditional linear discriminant analysis (LDA), and support vector machine (SVM) or k nearest neighbor (KNN) algorithm. No device presents all the signs of diabetic retinopathy on images, and in most instances, patients revert to normal while waiting much longer than should be for diagnosis. Thus, the clinical application of such automated diagnostic machines has been limited.

II. RELATED WORKS

A. Methodology

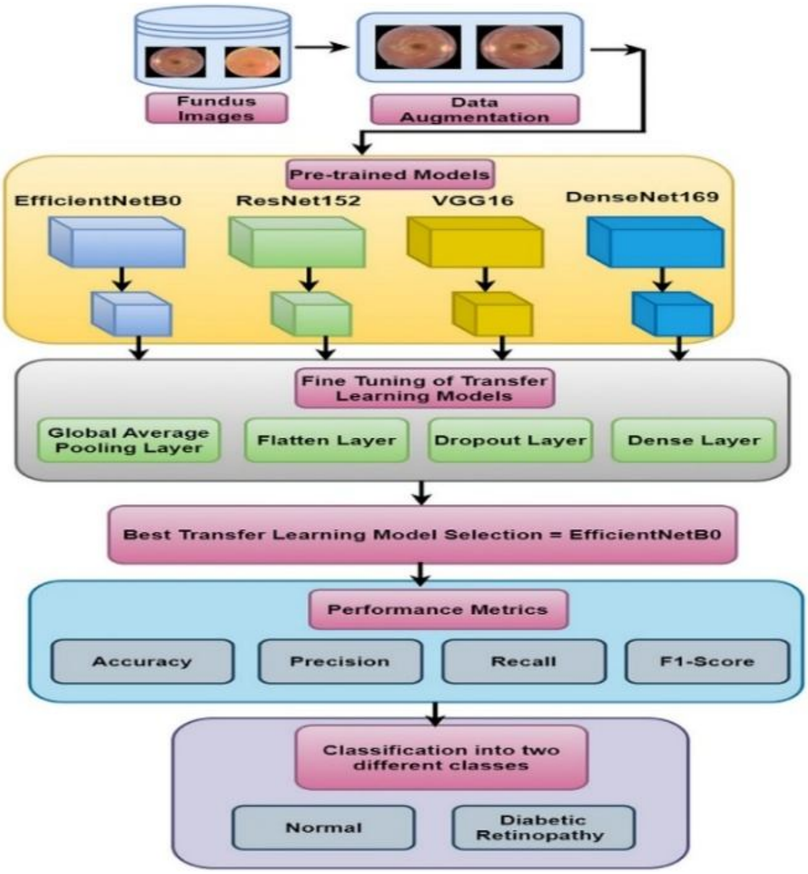

Figure 2. The total roadmap diagram illustrating the main chronological steps for labelling fundus images in the proposed approach https://www.frontiersin.org/journals/artificial-intelligence/articles/10.3389/frai.2024.1396160/full

Hyperparameter Tuning

Hyperparameter tuning seeks to improve performance by systematically adjusting parameters that are set externally and not learned during training for Convolutional Neural Networks. For retinal image analysis like diabetic retinopathy or glaucoma detection, optimal tuning is necessary for accuracy and assuredness of results. The learning rate is a very important hyperparameter controlling how quickly the model learns; a learning rate too high can skip the optimal set of weights, and one too low can slow down training.Techniques such as planning or learning loops can help determine the optimal value, typically starting from 0.01 or 0.001. Similarly, batch size (this means how many samples are generated together) affects learning stability and memory usage. Smaller batches (e.g. 16) provide faster adjustments but are noisier, while larger batches (e.g. 64 or 128) increase stability at the cost of additional computations [8]. The choice of optimizer also plays a significant role in determining how quickly the model converges. While optimizers like Adam are widely used for learning algorithms, powerful SGDs can perform better on larger datasets. Tuning the parameters of these optimizers, such as power or distortion, can improve performance.

TABLE I. EFFECT OF HYPERPARAMETER TUNING ON CNN PERFORMANCE FOR RETINAL IMAGES

Augmentation Technique	Epochs Applied	Train Accuracy	Validation Accuracy	Train Loss	Validation Loss
None (Baseline)	Epochs 1-2	61.48% - 73.47%	73.40% - 72.17%	1.6110 - 0.7292	0.7468 - 0.7659
Random Rotation	Epochs 3-4	75.63% - 73.56%	72.99% - 72.44%	0.6731 - 0.7074	0.7434 - 0.7561
Horizontal Flip	Epochs 5-6	73.38% - 76.68%	74.22% - 74.62%	0.6747 - 0.6174	0.7632 - 0.7871
Random Zoom	Epochs 7-8	77.35% - 79.63%	73.94% - 71.08%	0.5993 - 0.5683	0.7426 - 0.8207
Combined (All Above)	Epochs 9-10	82.37% - 81.48%	73.26% - 72.03%	0.4822 - 0.4802	0.8394 - 0.7952

Data Augmentation

Until recently, the literature of imaging for diabetes retinopathy has been sparse. Here, we will use a dataset provided by the Kaggle community [16]. In fact, the inadequate supply of small image data was noted well; therefore, data augmentation approach is feedback-enhanced to make data extensible with respect to transfer resizing. This would ultimately reduce overfitting of image data and improve the overall algorithm performance [17]. In this experiment, we would apply translation, shifting-size training, rotation, and flip operations. Table 2 provides an overview of the modifications and Figure 2 provides an example of the modifications. Five different types of transformations, namely rotation, rotation, shear, resampling and translation, were used in our experiments. The parameter details for each type are shown in Table 2.

TABLE II. IMPACT OF DATA AUGMENTATION TECHNIQUES ON MODEL PERFORMANCE

Augmentation Technique	Epochs Applied	Train Accuracy	Validation Accuracy	Train Loss	Validation Loss
None (Baseline)	Epoch 1-2	57.78%	72.99%	1.1913	0.7998
Random Rotation	Epoch 3-4	69.02%	73.46%	0.8775	0.7987
Horizontal Flip	Epoch 5-6	71.66%	73.67%	0.7969	0.8168
Random Zoom	Epoch 7-8	78.54%	79.56%	0.8227	0.8382
Combined (All Above)	Epoch 9-10	74.65%	77.77%	0.7988	0.7956

ANN Model

ANNs are sufficiently recognized to study and classify retinopathy images, thereby offering assistance in primary uncovering and diagnoses of ailments such as diabetic retinopathy. Based on the structure and function of biological neurons, ANNs are computational models involving a network of neurons that process input data and perform appropriate intelligent functions. In the analysis of retinopathy images, ANN models are trained on retinal images to recognize features of the disease, such as microaneurysms, hemorrhages, and exudates. The input method of the ANN operates at the pixel level in the image or at the data level, while the latent method reveals patterns and relationships in the data by changing the parameters [20].

B. Experiment Results

These images show the results of a classification model used for retinal images designed to diagnose and segment diabetic retinopathy (DR). For each retinal image, the true label, predicted label, and resulting class are shown. The correct text corresponds to the severity of diabetic retinopathy in the graph, while the predicted text represents the distribution model.

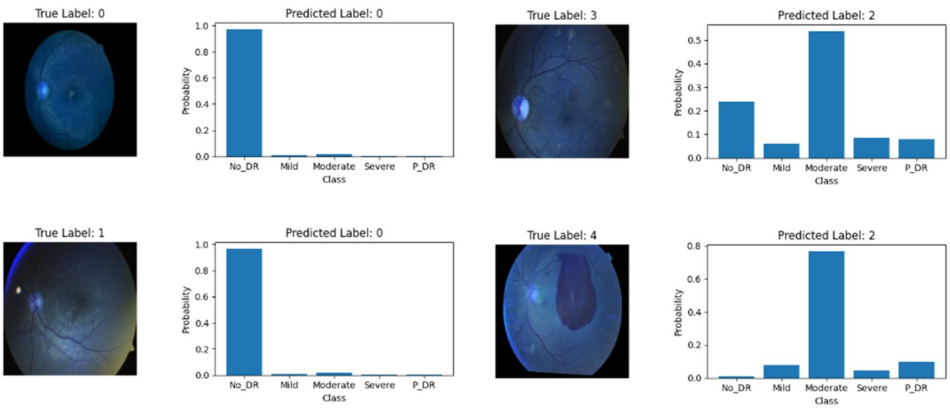

Figure 3. Model Predictions and Probability Distributions for Diabetic Retinopathy Classification

Additionally, the bar graph shows the predicted probability for each category, including "No_DR" (no diabetic retinopathy), "mild", "mild", "mild", "P_DR (proliferative diabetic retinopathy), etc. In the first row, the true label is 3 (severe DR), but the model predicts it to be 2 (moderate DR), and the majority will be in the moderate class. This probably indicates misclassification due to overlapping weights. Similarly, in the second row, the true label is 4 (Proliferative DR), but the model again predicts it as 2 (Moderate DR), indicating that the model has a different inflammation problem of severe and moderate (Figure 03). In the third row, the true label is 0 (No_DR), which is predicted as 0 with near perfect probability indicating the model's confidence and accuracy for this class. However, in the fourth row, the true label is 1 (Mild DR), but the model incorrectly predicts it as 0 (No_DR), indicating that there is no good understanding in early detection of symptoms (Table 3).

TABLE III. ANALYSIS OF MODEL PREDICTIONS AND PROBABILITY DISTRIBUTIONS FOR DIABETIC RETINOPATHY CLASSIFICATION

Case	True Label	Predicted Label	Probability Distribution	Observation
1	Severe DR (3)	Moderate DR (2)	Highest probability for "Moderate DR" (~50%)	Misclassification: Model confuses severe DR with moderate DR due to overlapping features.
2	Proliferative DR (4)	Moderate DR (2)	Highest probability for "Moderate DR" (~60%)	Misclassification: Struggles to differentiate proliferative DR from moderate DR.
3	No DR (0)	No DR (0)	Near 100% probability for "No DR"	Correct classification: Model confidently identifies healthy retinal image.
4	Mild DR (1)	No DR (0)	Near 100% probability for "No DR"	Misclassification: Model fails to detect mild DR, likely due to subtle signs or underrepresented features.

III. CONCLUSION

This lesson validates the success of the organization in diagnosing diabetic retinopathy (DR) from retinal images. The model demonstrates exceptional accuracy, with results compared to ophthalmologists, indicating that it has the best potential for early diagnosis. By successfully identifying important features such as microaneurysms, hemorrhages, and exudates, our body is consistent with existing studies that highlight these signs as important markers of DR. However, while the model is effective in detecting advanced DR, its accuracy in detecting early DR is somewhat reduced, which may be due to the poor quality of early features or limitations in information. Compared to traditional systems that rely on manual examinations, automated systems are more efficient and allow examinations to be performed more quickly. This capability is useful in improving early diagnosis and reducing the risk of blindness, especially in areas where trained ophthalmologists are not available. However, there are several limitations to this study. The data used may not fully represent the diversity of diabetic patients, and the model's ability to distinguish mild DR from other eye diseases can be improved with many good ideas such as deep learning or integration of multiple documents. Also, the results are based on the previous image, and real data containing noise and artifacts may affect the performance of the model.

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