Deep Learning Approach for Detection of Diabetic Retinopathy

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***Abstract*—Early Detection of Diabetic Retinopathy is paramount in prevention of vision loss. This study proposes a novel approach to the automatic detection of diabetic retinopathy (DR) using fundus images. This paper compares other techniques and does comparative study of Convolutional Neural Networks (CNNs) and the ResNet architecture to analyze fundus images and classify them based on the severity of DR. The study uses the APTOS 2019 Blindness Detection dataset, a publicly available dataset of over 5,000 high-resolution retinal images collected from patients with varying degrees of DR. The study concludes that the proposed approach provides a promising solution for the automatic detection and classification of DR.**

***Keywords*—Diabetic Retinopathy (DR), Convolutional Neural Networks (CNNs), ResNet, APTOS 2019 Blindness Detection dataset**

I. Introduction

As of 2021, WHO [1] and IDF [2] estimate that there are more than 70 million people with diabetes in India, making it one of the countries with the highest number of people affected by the condition. Diabetes prevalence is rapidly increasing in India and is expected to reach over 100 million by 2030[2]. Diabetes is a chronic medical condition affecting millions of people worldwide, characterized by high levels of glucose in the blood that can cause damage to different organs and systems in the body over time. The onset of the disease is the result of a combination of genetic and environmental factors, and management typically involves lifestyle changes, medication, and regular monitoring [1][2].

The National Eye Institute (NEI) discovered that annually, nearly 1 million people lose their vision due to diabetes [3]. Retinopathy is a medical condition that affects the retina i.e., is the part of the eye tasked with transmitting images to the brain. Diabetic retinopathy is a specific type of retinopathy that is caused by high levels of sugar (glucose) in the blood, as is seen in people Over time, diabetes can lead to damage to the blood vessels due to consistently high levels of sugar in the blood vessels in the retina, leading to various vision problems, including blindness.

Diabetic retinopathy is a common complication of both type 1 and type 2 diabetes and is a major reason of blindness in adults. Early detection and treatment of diabetic retinopathy is essential to prevent vision loss and manage the condition effectively. This can include regular eye exams, laser treatments, and medications, as appropriate. [4]. Diabetic Retinopathy is the major factor of cause of blindness in the age group 20-74 in various countries [5], and it causes 2.6% of blindness worldwide [6]. Early diagnosis of DR can reduce the threat of blindness therefore this is essential for everyone with diabetes who is 12 years or older to have regular retina screening.

In clinical practice, diagnosis of DR is done by analyzing the fundus images, traditionally ophthalmologists and other experts use their domain knowledge to observe the retina lesions to Identify and assess the seriousness of the DR. But this manual detection and grading of DR using fundus images require professional-level expertise and effort. According to a survey made by the International Council of Ophthalmology, it was found out that there are a total of 204,909 ophthalmologists (almost 29 ophthalmologists per 1 million) worldwide and there is a major shortage of experienced ophthalmologists in developing countries [7] [17].

The paper will review the existing literature on the use of fundus images for the detection of diabetic retinopathy, including the accuracy and limitations of different methods. The discussion will highlight the current challenges and opportunities for improvement in this field, including the development of more sophisticated algorithms, the integration of multiple imaging modalities, and the use of deep learning for image analysis. The paper will conclude by summarizing the findings of the literature review and outlining the future directions for research in this area. The purpose of this review is to provide an extensive examination of the latest developments in diagnosing diabetic retinopathy using fundus images and to serve as a resource for researchers, clinicians, and others interested in this important field.

II. Literatre Review

In [8] researchers propose a deep learning approach that uses Convolutional Neural Networks (CNNs) to extract features from retinal images and classify them into different stages of DR. The results of the system showed that the system demonstrated superior performance compared to other advanced methods in both accuracy and speed. It exhibited exceptional precision in detecting diabetic retinopathy and accurately classifying the different stages of the disease. This investigation presents an encouraging approach to address the automatic detection and classification of diabetic retinopathy, which could greatly aid healthcare professionals in the early diagnosis and treatment of the disease [19].

In [9] the model developed is a Deep Neural Network (DNN) model to classify DR in retinal images [21]. Trained and tested on a large retinal image dataset and evaluated on a test set, results showed that the deep neural network model outperformed conventional machine learning methods in terms of DR diagnosis accuracy.

In [10], researchers propose a Deep learning Ensemble method for DR detection. In this paper, they involve training multiple deep neural network models and combining their predictions to improve the accuracy of DR detection. The dataset of many retinal images is used to train and evaluate the approach. Results showed that a deep learning ensemble approach outperforms a single deep neural network model in DR detection accuracy [19][23].

In [11], researchers use a binocular Siamese CNN architecture for DR detection. This involves using two separate CNNs to extract features from both eyes of the patient and compare them to get predictions. A large dataset of retinal images was used to train and evaluate the adopted approach. This method has surpassed other modern methods in terms of accuracy, with an overall accuracy of 94.6%.

In [12], the researchers present a CNN architecture for DR detection and classification that is based on a pre-trained ImageNet model used as a feature extractor and a custom classifier for task of DR prediction. A large dataset of retinal images is used for the model. The outcomes of the study indicate that the CNN architecture achieves accuracy of 93.5% for DR detection and 82.5% for DR classification.

Additional methods for detecting and estimating DR using SVM (Combined with Transfer learning) [13] and use of deep convolutional neural networks (DCNNs)[14] have yielded sensitivity and specificity in the 90% range using different feature extraction methods and preprocessing algorithms [18] [20] [22].

III. Research Methodology

The research methodology adopted for this model including the experimental methods, and set-up are briefed in this section.

The dataset utilized in this study is the "APTOS 2019 Blindness Detection" dataset [15]. This dataset was created by the Asia Pacific Tele-Ophthalmology Society (APTOS) to detect and diagnose diabetic retinopathy (DR) and is publicly available. It was collected through collaboration with multiple ophthalmology departments and clinics across various countries in the Asia Pacific region. With over 5,000 high-quality retinal images of varying degrees of diabetic retinopathy, this dataset is a valuable resource for researchers and practitioners in the fields of ophthalmology and computer vision. Expert ophthalmologists carefully annotated each image, grading them based on the presence and severity of diabetic retinopathy symptoms. This disease is a major cause of blindness worldwide.

The APTOS 2019 dataset is significant for several reasons. Firstly, it provides a large and diverse collection of high-quality retinal images, which is crucial for training and testing machine learning algorithms. Secondly, the annotations provided by expert ophthalmologists are of high quality and offer a reliable and consistent means of evaluating the performance of these algorithms. Finally, the dataset provides an opportunity for researchers to tackle a real-world problem with a significant impact on human health, by developing algorithms that can assist in the early detection of diabetic retinopathy and other retinal diseases.

The APTOS dataset consists of fundus images of eyes, which are high-resolution images of the back of the eye, including the retina, optic nerve, and macula. These images were obtained from patients with a range of DR severity, from no DR to severe cases of the disease rated on a scale of 0 to 4. For our study we have segregated the entire dataset into two categories 0 and 1, 0 describing healthy eyes i.e., images with no DR, and 1 describing defective eyes i.e., images with mild to severe DR, a sample of the dataset can be seen in Fig.1.

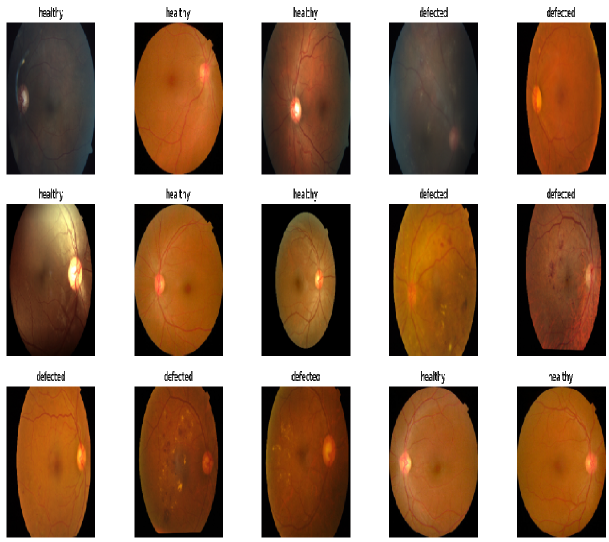

Fig. 1. A sample from APTOS dataset with images categorized as healthy or defected..

The methodology consisted of five distinct stages, namely: Data Collection, Data Preprocessing, Model Selection, Model Building & Training, and Model Testing. Each of these stages is explained in detail below:

A. Data Collection

The Kaggle “APTOS 2019 Blindness Detection” [15] dataset was used for our study; it contains fundus images of eyes diagnosed with DR. These images were rated on a scale of 0 to 4 based on the severity of DR. A total of 2000 images were used for our model.

B. Data Preprocessing

- As it is the case with any real-world dataset, images collected need to be processed before we can work on it. This preprocessing of images is done to ensure uniformity in size and resolution, which further makes it easier for our deep-learning models to process them and extract essential features from them.
- Resizing and Normalization: Since the dataset contains images that vary in size, all images are resized to 256 X 256 X 3, also the intensity values of

pixels are normalized to values ranging between 0 and 1 in order to avoid bias and high training times of the network.

- Class Balancing: Since we are proposing the binary classification of Diabetic Retinopathy, that is whether DR exists in a patient or not, therefore we have divided the entire dataset into two categories 0 and 1, 0 describing healthy eyes i.e., images with no DR and 1 describing defected eyes i.e., images with mild to severe DR.

C. *Model Selection*

CNN is a type of deep learning algorithm that is widely used in image classification, object detection and segmentation. CNN is considered a cutting-edge technique for image classification due to its capability to identify elements in images without complicated preprocessing, as well as its ability to adapt and refine its parameters through transfer learning. Therefore, for our study we are selecting a basic CNN model and the ResNet50 architecture for the binary classification of Diabetic Retinopathy.

- CNN: The primary algorithm utilized in medical diagnosis is Convolutional Neural Networks (CNNs) [16]. CNNs have various key elements, including Convolutional layers (CONV), Pooling layers, Activation layers, and Fully Connected layers (FC). To detect local features, the Convolutional layer utilizes a group of learnable filters to process the input image. A non-linear function such as the ReLU function is introduced through the Activation layer to create non-linearity in the model. Pooling layers decrease the data's spatial dimensions while maintaining crucial information. Finally, the Fully Connected layer uses the extracted features to make predictions.

- ResNet: The Residual Network (ResNet) is a deep learning architecture first introduced in 2015. Its purpose is to mitigate the problem of vanishing gradients in very deep networks, making it possible to train networks with hundreds or thousands of layers and resulting in improved accuracy and performance compared to traditional feedforward networks. The concept of residual learning is central to ResNet, meaning that the network learns the difference between the input and desired output rather than the mapping itself. This is achieved by adding shortcut connections between the input and output layers of each block in the network, facilitating information propagation. The ResNet architecture comprises multiple residual blocks, each of which contains multiple layers of convolution, batch normalization, activation functions, and other necessary layers. The residual connections allow the network to bypass any intermediate layer impacts.

D. *Building And Training*

- For training purposes, the network portioned the dataset into 80:20 for training and testing respectively.

  Firstly, we built a sequential CNN model by stacking four pairs of Convolutional and MaxPooling layers using ReLu activation function, followed by two dropouts, 1 flatten and 2 dense layers (see Fig. 2). For final prediction we are using the sigmoid function as we need to classify between two classes only. Fig. 2 shows the model architecture and summarizes all the layers. The model was then compiled using 'Categorical_Crossentropy' as a loss function and 'Adam' as the optimizer. The model was run for 50 epochs with a batch size of 32.

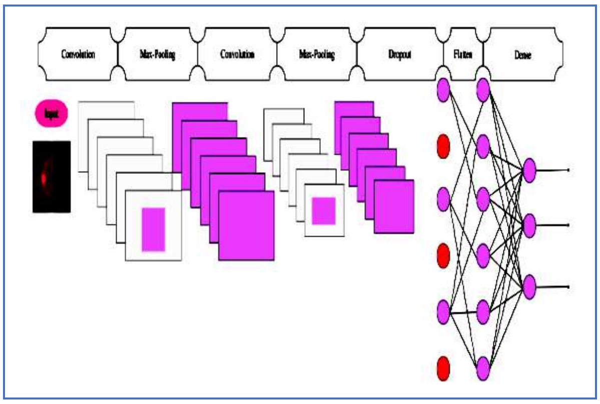

Fig. 1 CNN architecture

- The second model we built was ResNet50, the ResNet50 architecture is with a total of 50 layers, which involves a 7x7 kernel convolution with 64 other kernels and a stride size of 2, followed by a max pooling layer with a stride size of 2. There are 9 additional layers composed of 3x3, 64 kernel convolutions, 1x1, 64 kernel convolutions, and 1x1, 256 kernel convolutions, repeated three times. Fig. 3 shows the model architecture and summarizes all the layers. The model was then compiled using 'Categorical_Crossentropy' as the loss function and

- 'Adam' as the optimizer. The model ran for 100 epochs with batch size of 128.

E. *Model Testing*

For training purposes, the network portioned the dataset into 80:20 for training and testing respectively. The above two trained models are then tested on the test dataset to evaluate their performances on unseen data. The results from these tests are then compared and analyzed so that conclusions can be drawn regarding the performance of the CNN and the ResNet50 models for the binary classification of Diabetic Retinopathy detection.

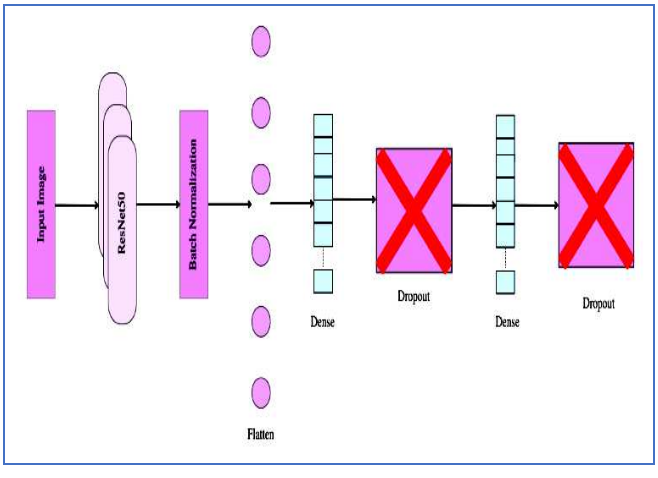

Fig. 2 ResNet50 Architecture

IV. RESULTS

In this research, our goal was to accurately classify whether Diabetic Retinopathy exists or not (0 or 1). For this purpose, we modeled two algorithms: a.) sequential CNN architecture and b.) ResNet50 model. The dataset used for this study [15] had a total of 2000 fundus images which were divided into two classes, healthy (950 images) and diabetic retinopathy (1050 images). The images were re-adjusted to 256X256 pixels and normalized before feeding into the network.

The experimental results (see Table I) show that the proposed technique was able to generalize well to new data and generate High accuracy and yield efficient results.

TABLE I. RESULTS

S.No.	Model		
	Evaluation Criteria	***CNN***	***ResNet50***
1	Training Accuracy	99.88%	84.12%
2	Testing Accuracy	94.02%	94.27%
3	Precision for 0	93%	96%
4	Precision for 1	95%	93%
5	Recall for 0	95%	92%
6	Recall for 1	93%	96%

The CNN model is trained for 50 epochs with a batch size of 32. Throughout the training process, the accuracy and loss of the training set are monitored. The results revealed that the model has a training accuracy of 99.88% and a training loss of 0.17%, indicating that the model was successful in recognizing the features in the eye fundus images and classifying them into healthy and diabetic retinopathy classes. Similarly, we trained the ResNet50 model on the same dataset for 100 epochs with a batch size of 128. Again, the accuracy and loss of the training set was monitored, and it was found that the model was trained with the accuracy of 84.12% and a training loss of 38%. To assess the model's performance, we employed several evaluation metrics such as accuracy, precision, and recall.

V. CONCLUSION

To summarize, early detection and timely treatment of diabetic retinopathy are crucial to prevent vision loss. Fundus imaging is an effective technique for diagnosing this condition as it provides essential information about the retina's health, thereby guiding the course of treatment. The latest advancements in computer vision and machine learning have paved the way for automated methods to diagnose diabetic retinopathy using fundus images. These methods have demonstrated significant potential in enhancing the accuracy and efficiency of the diagnostic process.

In summary, the use of deep learning, particularly CNNs and ResNet, has shown great potential in improving the accuracy of automated diagnosis of diabetic retinopathy using fundus images. The future of this field is likely to see further advances in deep learning techniques and the integration of multiple imaging modalities, which will further improve the accuracy, efficiency, and accessibility of this critical diagnostic tool.

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