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An Accurate Assessment of Diabetic Retinopathy using a Deep Learning based Approach

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***Abstract*—Diabetic retinopathy is a disorder that damages the eyes and is an outcome of diabetes. High blood sugar levels damage the blood vessels in the retina, which is the light-sensitive tissue in the posterior of the eye. If not treated, this injury might result in visual issues and perhaps blindness. The datasets used in this investigation is from the IDRiD to investigate the efficacy of Convolutional Neural Networks (CNNs) in diagnosing Diabetic Retinopathy (DR) in fundus pictures. As the accuracy of CNN-based detection relies heavily on the availability of large datasets, leveraging this data becomes crucial owing to high prevalence of diabetes and its associated risk of DR. By employing CNNs, this research aims to optimise the efficiency and accuracy of DR detection compared to manual diagnostics, thereby saving both time and resources. The implementation utilizes Python programming language along with libraries such as Keras, OpenCV, and Numpy, with a focus on image-classification to distinguish between DR and non-DR cases.**

***Index Terms*— Diabetic Retinopathy, Deep Learning, , VGG-16, Image Classification.**

I. INTRODUCTION

The eye is our visual system. Controlling vision and enabling us to see our surroundings, the eye is an amazing organ. Retina is one element among numerous components that make up this intricate sensory organ, which functions as a whole to record and process visual information. An image can travel through the retina's several layers and be precisely focused on it as a consequence of retina's complex architecture. Rods and cones are light-sensitive cells found all over the retina

The human eye's light-sensitive portion enables one to see their surroundings. The image is formed on the retina of the eye rather than a film as in a traditional camera, making it similar to a camera. The iris in the eye performs a similar function to a camera's diaphragm by controlling the pupil diameter to reduce the quantity of light that reaches the retina. A camera lens can be com-pared to the human cornea and crystalline lens. With the cornea, pupil, and lens, light reaches the retina, which is located behind the eye and has light-sensitive photoreceptors. Through the optic nerves, the image formed on the retina is converted into electrical impulses. Because of the serious and widespread health risk that diabetes poses to people worldwide, estimating the outbreak is essential for allocating resources and tracking trends. According to the survey, there was 382 million people with diabetes worldwide in 2013 [1]. This value may go up to 592 million by next 10 years.

Awareness-raising efforts have continued in recent years [16]. Diabetes patients and healthcare practitioners should be aware of the possibilities of diabetic retinopathy as well as the preventive actions that can be taken to lower the risk of blindness.

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Although diabetic retinopathy-related blindness is typically preventable, more individuals should be aware of the need of early detection and treatment. When type 2 diabetes is diagnosed, a diabetic retinal examination is required [22]. Pictures of the retinal fundus can be utilized to identify DR, it is causes different retinal problems. Figure 1 depicts probable apparent symptoms for DR and also normal eye.

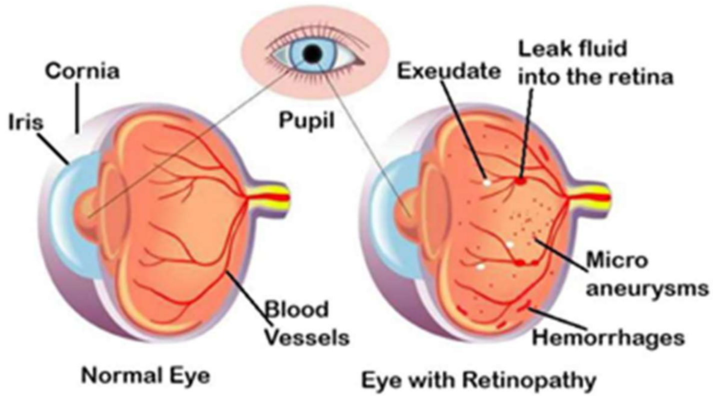

Figure.1. Human eye with normal and diabetic retinopathy

II. Literature Survey

In contemporary research on diabetic retinopathy (DR) detection, there has been a substantial focus on leveraging convolutional neural networks (CNNs) to develop automated and accurate diagnostic tools. Various studies have explored the potential of CNN-based approaches utilizing diverse datasets and methodologies, aiming to improve the precision and efficiency of DR detection while reducing the reliance on manual examination methods. In the most current research, numerous investigations have explored the effectiveness of CNN in detecting DR using various datasets and methodologies. The overview of pertinent literature is provided here.

Firke et al. [1] embarked on their investigation by using a CNN technique to discern diabetic retinopathy within retinal images sourced from the Apatos Blindness Detection database. Their methodology involved an extensive pre-processing stage, including image resizing, pixel rescaling, and label encoding. Through meticulous training on approximately 3789 color retinal images, they achieved commendable results, with their model showcasing sensitivity of 79 percent, precision of 89 percent, and an impressive area under the score of 0.82, thereby demonstrating its robust classification accuracy. Simultaneous to this, Gargeya et al. [2] examined the complexities of DR detection, concentrating on assessing the precision-recall trade-off using the receiver operating graph's area under the curve. Their approach entailed training models on local datasets, which yielded promising outcomes, with an attained AUC of 0.97, coupled with 94% sensitivity and 98% specificity. Furthermore, their models exhibited notable AUC ratings of 0.94 and 0.95 when benchmarked against independent databases, E-Ophtha and MESSIDOR 2, underscoring the efficacy and generalizability of their methodology.

Pratt et al. [3] advanced the field by presenting a CNN-based method tailored towards accurately assessing the severity of diabetic retinopathy utilizing digital fundus images. Their innovative network architecture integrated CNN design principles and data enhancement techniques to discern complex features such as retinal hemorrhages and exudates. Impressively, their CNN achieved a remarkable sensitivity of 95 percent and an accuracy rate of 75 percent on a validation dataset comprising 5,000 images, indicative of its robust performance in challenging classification tasks. Moreover, Liang et al. [4] worked towards the landscape of automated DR classification by addressing pivotal challenges pertaining to classification, segmentation, and detection. Their comprehensive study encompassed the exploration of various CNN architectures, including AlexNet, VggNet, GoogleNet, and ResNet, alongside methods such as transfer learning and hyper-parameter tuning. By leveraging DR images for model evaluation, they underscored the superiority of CNNs and transfer learning in achieving heightened accuracy, with the simplest classification model attaining an impressive accuracy rate of 95.68%.

In the pursuit of computer-aided diagnosis (CAD) solutions for early DR detection, Mansour et al. [5] harnessed the deep neural networks (DNNs) potential by employing the AlexNet architecture. Through meticulous simulation and feature selection processes, their proposed model achieved an accuracy of 97.93% for DR classification, surpassing alternative methodologies. Their findings underscored the pivotal role of feature selection techniques in optimizing classification performance, thus advocating for the adoption of CAD-based solutions in clinical practice. Mateen et al. [6] proposed a symmetrical optimization approach for DR detection, amalgamating PCA (principle component analysis), SVD, (singular value decomposition) and deep neural networks. Their VGG-19 DNN model emerged as a frontrunner, outperforming competing methodologies in terms of classification accuracy and computation time. By leveraging a dataset comprising 35,126 Kaggle photos, they showcased the efficacy of their proposed approach in achieving accurate and efficient DR classification. Furthermore, Ayala et al. [7] pioneered the utilization of CNN models for identifying DR within fundus oculi images, achieving a remarkable accuracy rate of 97.78%. Their methodology entailed the integration of transfer learning techniques to optimize model parameters, thereby enhancing the model's predictive capabilities. Leveraging a dataset encompassing images of medical fundus oculi and corresponding labels from a pathological severity scale, their study underscored the significance of accurate DR prediction in facilitating timely clinical interventions.

Shelar et al. [8] contributed to the discourse on DR detection by proposing a computer-generated model utilizing CNNs with transferred learning. Their model showcased promising results, accurately categorizing diabetic retinopathy cases with an accuracy rate of 84.12%. Their approach expanded the set of automated DR diagnostic tools by offering helpful information for treatment planning by categorizing retinal fundus images into different disease phases. Diabetic retinopathy, a common complication of diabetes, is becoming a global problem. Early detection of this issue is crucial as it can be outcome in blindness. Diabetes affects millions of people globally.and the condition predicted to become more common, new developments in DL and AI have made it is possible for CNN-powered models to identify and categorize diabetic retinopathy in color fundus images. Pranajit Kumar Das et al [9] separates diabetic retinopathy into two stages: diseased and healthy pictures. Three pre-trained CNN models (VGG16, InceptionV3, and MobileNet) were used for transfer learning, training, and testing on the Messidor and Messidor-2 datasets. InceptionV3 achieved the highest classification accuracy of 84%, followed by MobileNet (83%), and VGG16 (78%). VGG16 was the most precise (86% for healthy photos) and sensitive (88% for diseased images).

DL techniques were utilized by Sharia Wasika Ad et al. [10] to accurately detect and classify DR in digitized retinal fundus images. They investigated multiple deep-learning models, such as ResNet50, ResNet152V2, VGG16, and VGG19, to improve classification performance. These models undergo testing and training on diverse benchmark datasets with varying characteristics and complexities. Simulation findings show that the suggested method outperforms alternative methods. ResNet50 emerges with the highest model accuracy of 91.56%, as per architectural performance analysis. Notably, leveraging pre-trained architectures yields impressive results were compared to starting from scratch. Visualization techniques, including accuracy curves, loss curves, ROC curves, and a confusion matrix, are engaged in the showcase classification performance.

DNN possess the ability to be extremely significant in the identification and prognosis of ocular disorders. Retinal data is typically captured using fundus camera, OCT, and OCT Angiography Imaging technologies. Several categories for retinal imaging can be developed based on the severity of diabetic retinopathy. Doctors can receive assistance in detecting a variety of retinal illnesses thanks to this multi-label classification. Anitha T Nair et al [11] compares and evaluates many deep neural networks. On the Kaggle (APTOS) data, pre-trained model ResNet50 has given highest accuracy of 97.2%.

Utilising large number of original retinal pictures labelled for non-DR and DR, the Diabetic retinopathy dataset from Kaggle is utilised in this investigation Md. Sakib Ali Mazumder [12]. Training using labelled data, the procedure uses CNN architectures to differentiate exudates, microaneurysms, and haemorrhages in retinal imaging. ResNet50, VGG16, VGG19, InceptionV3, and MobileNetV2 were the five models that were trained and evaluated during this investigation. With a 96.04% accuracy and a 92.08% Cohen Kappa Score and it is shown that MobileNetV2 performs best in distinguishing between DR and Non-DR data. While MobileNetv2 takes 90 seconds to compile, InceptionV3 takes 85 seconds, and the models Resnet50, VGG16, and VGG19 require the same 62 seconds for each epoch in the research.

In conclusion, these findings show how revolutionary CNN-based methods can be for DR diagnosis and detection. Significant advancements are being made by researchers in developing precise, effective, and scalable solutions to address the global burden of diabetic retinopathy by utilising DL and other approaches.

II. Methodology

This part discusses the techniques used in this work, including the data collection and the pre-processing approach. Using CNN, diabetic retinopathy is recognised. Figure 2 shows simplified block diagram

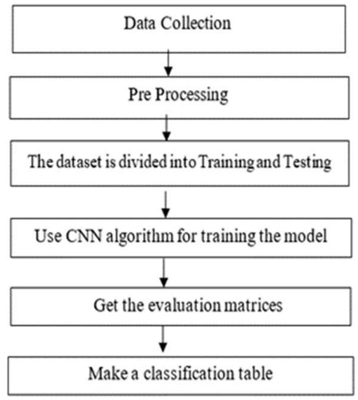

Figure.2. Different steps involved in methodology

A. Data Collection

It is the assemblage of linked, distinct pieces of linked data that could be viewed individually, collectively, or treated as single entity. An information set is arranged using some kind of knowledge structure. This task is carried out using IDRid dataset [21]. This dataset is a collection of retinal pictures acquired from patients with diabetes and is extensively utilised in the creation and evaluation of algorithms to detect diabetic retinopathy and grading. The IDRiD dataset typically includes fundus (retinal) images captured utilising a plenty of imaging techniques, like color fundus photography and fluorescein angiography. There are annotations on these images with information related to DR severity levels, for example, the existence of microaneurysms, hemorrhages, exudates, and other abnormalities associated with the condition. IDRid dataset is employed in a 70:30 ratios with training, testing and validation phases.

B. Pre-processing

The datasets include Images that are pre-processed by using various steps such as resizing, grayscale image conversion and image enhancement. Python, OpenCV, Keras, Tensorflow, and Pillow are a few of the platforms and tools used in pre-processing.

C. Dataset Splitting

30% of the dataset is ustilized for testing, and the remaining 70% for training.

D) CNN algorithm: The term "CNN" stands for Convolutional Neural Network. It is a type of deep neural network, inspired by the biological visual cortex, that's particularly helpful for tasks including images like image recognition, object detection, and segmentation. Below Figure 3 shows the Background of CNN algorithm.

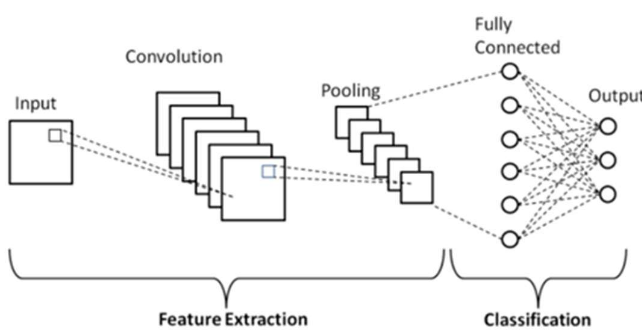

Figure.3. Background of CNN algorithm

Using deep neural network-based approaches like CNN, retinal pictures were categorized as normal and DR. The pre-trained model include VGG16, Model performances were analyzed using IDRid data sets.

Visual Geometric Group (VGG16):

The Visual Geometry Group (VGG) [6] in the University of Oxford developed the VGG-16 CNN architecture. It belongs to the VGG model family, which contains various versions such as VGG-19. Despite being deeper than prior models like AlexNet, VGG-16 is well-known for its simplicity and efficacy. The model of VGG16 is displayed in Figure 4.

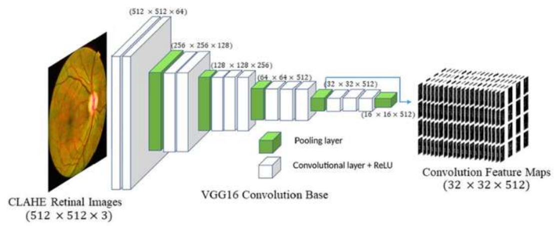

Figure.4. VGG16 Architecture

The CNN has 16 layers and three channels, with an input picture of 224 x 224 pixels [17]. Following the convolution layer, completely connected layers were utilised. The model is more complex, with fewer parameters and increased non-linearity. Three feed-forward neural networks follow a stack of convolutional layers. The soft-max layer is the last output layer. All networks use the same configuration for totally linked levels.

IV. EXPERIMENT AND RESULT

A. Setting Up for Experimentation and Model Training

This experiment is run on a personal computer (Windows 10 operating system), i3 processor having 32 GB RAM, and one TB SSD. Python 3.7 is the coding language used.

B. Result and Observations

A pre-trained CNN models are utilized in binary classification using transfer learning. VGG16 is the used to study the performance of the pre-trained model, to evaluate the model's performance, the performance indicators that are most frequently employed, which are accuracy, precision, loss, validation accuracy and loss in Deep Learning, are calculated using confusion metrics. Accuracy and Loss is compared in Table I & II for Epoch = 100,200 respectively and Steps = 5.

TABLE.1. ACCURACY AND LOSS TABLE FOR EPOCH = 100 AND STEPS = 5

Epochs=100	Loss	Accuracy	Val_loss	Val_accuracy
1/5	0.1440	0.9554	2.6787	0.1300
2/5	0.0808	0.9706	2.8785	0.2473
3/5	0.0594	0.9797	3.2673	0.1075
4/5	0.0524	0.9837	4.0777	0.1400
5/5	0.0470	0.9838	4.1778	0.2151

TABLE.2. ACCURACY AND LOSS TABLE FOR EPOCH = 200 AND STEPS = 5

Epochs=200	Loss	Accuracy	Val_loss	Val_accuracy
1/5	0.1125	0.9610	3.9582	0.1200
2/5	0.0585	0.9756	4.6075	0.1613
3/5	0.0376	0.9858	7.1212	0.1828
4/5	0.0272	0.9924	3.7978	0.1700
5/5	0.0206	0.9970	4.7465	0.1290

Packages for Python offer a great environment for visualizing data. Using the IDRid data sets, VGG16 was trained, and its efficiency was tuned. In step 5, 97.70% accuracy was attained for 200 epochs.
Figure 5 displays the Train and Validation Accuracy and Loss curves.

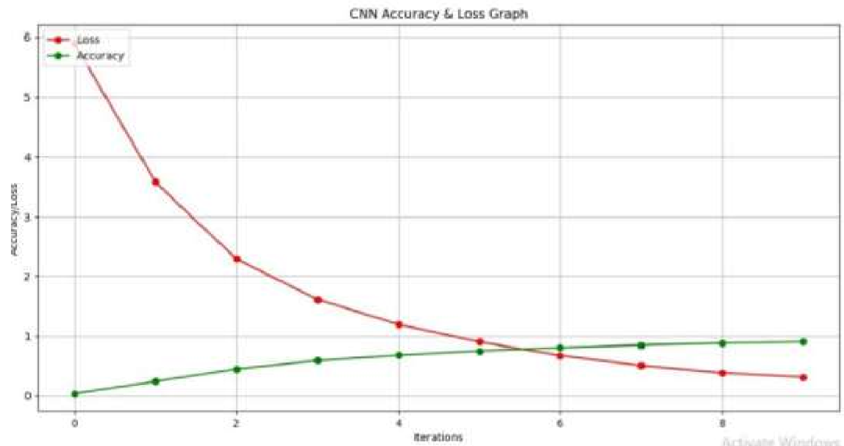

Figure.5. Accuracy and loss graph

The x-axis in this graph represents iterations, and the y-axis represents accuracy/loss. The loss value of a model shows how well or poorly it does following each optimization cycle. The potency of the algorithm is assessed using an understandable accuracy metric
The authors can conclude on the topic discussed and proposed. Future enhancement can also be briefed here.

V. Conclusion

A significant contributing factor to DR is diabetes, which affects the majority of individuals. With the proper care, the symptoms of this primary cause of blindness can be lessened. Consequently, it is essential to develop a model that can recognize DR without the help of a specialist. CNN-based deep-learning algorithms are efficient and accurate at classifying images. In this experiment, we compared an existing model's performance accuracy. To improve efficiency, we implemented the method by changing certain parameters like the quantity of convolution layers and the pooling layer optimizer. In our model, no manual feature removal procedures are necessary. With dropout techniques, our network design has attained a sufficient level of classification accuracy. For 200 epochs in step 5, it was possible to attain a 0.0206 loss and a 97.70% accuracy.
More number of datasets can be utilized in future to boost the model's performance. This model may also be utilized for the evaluation of other type of ocular diseases and this might be beneficial tool to support medical professionals in clinics and hospitals.

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