

Diabetic Retinopathy Detection using Deep Learning

S Deepadharshini¹, S Divya² and S Haritha³

¹⁻³Dept of CSE, Kongu Engineering College, Erode, India

Email: deepadharshinis01@gmail.com, divya.011018@gmail.com, haritha21102000@gmail.com

Abstract—Long-term diabetes is associated with diabetic retinopathy (DR), an eye disorder. DR is the main reason behind blindness in persons of working age globally, affecting an estimated 93 million individuals. If DR is detected early enough, it may be possible to treat or slow the course of vision impairment. However, this can be challenging because the condition usually doesn't manifest until it's too late for effective treatment. To diagnose DR based on the occurrence of lesions connected to the disease's vascular abnormalities, an ophthalmologist or other qualified medical practitioner must view and assess digital colour fundus photographs of the retina. This arduous manual process is being employed today. The automated DR screening technique, which will quicken the detection and decision-making processes, will aid in the management or control of DR advancement. Using machine learning models like CNN (Convolutional Neural Network), VGG-16, and VGG-19, this study provides an automated classification system that evaluates fundus images with various lighting and fields of view and provides a diabetic retinopathy severity score (DR). The dataset contains five criteria, with values ranging from 0 to 4, where 0 denotes an absence of DR and 4 denotes proliferative DR.

Index Terms— Diabetic Retinopathy, CNN- Convolutional Neural Network, VGG-Visual Geometry Group Network.

I. INTRODUCTION

A. Diabetic Retinopathy Disease

Diabetic retinopathy is the name for diabetes problems that harm the eyes (die-uh-BET-ik reti-NOP-uh-thee). The blood vessels in the eye gets damaged and causes poor vision in retinal area. Diabetes retinopathy may not initially cause any symptoms or may just impair a person's eyesight in a minimal way. However, it might cause blindness. Anyone with type 1 or type 2 diabetes has the risk of contracting the disease. The length of diabetes and the level of blood sugar control enhance the risk of acquiring this eye condition.

B. Symptoms

During the early stages of diabetic retinopathy, you might not experience any symptoms. As the situation worsens, you could get:

- You may notice spots or black strings in your vision (floaters)
- distorted vision
- unstable vision
- regions of vision that are dark or vacant
- loss of vision

C. Diagnosis

The best way to identify diabetic retinopathy is through a comprehensive dilated eye exam. Drops are placed in the eyes to enlarge (dilate) your pupils so the examiner can more clearly see inside your eyes. While applying the drops, until they wear off many hours later, the close vision may become blurry. During the examination, the eye doctor will look inside and outside of your eyes. After the eyes have been dilated, a dye injection is delivered into an arm vein. Once the dye has gone through the blood vessels in your eyes, pictures will be taken. On the images, blood vessels that are occluded, harmed, or leaking may be visible.

II. EXISTING SYSTEMS

As demonstrated by Carson Lam, et al [4], convolutional neural networks (CNN) are utilised to stage diabetic retinopathy, utilising fundus photos in colour. Their network models produced test metric performance with validation sensitivity of 95% that was comparable to baseline literature values. They also looked into multinomial classification models and found that errors mainly happen when mild illness is misclassified as normal since CNN cannot detect subtle disease signals. They found that for better recognition of nuanced features, pretreatment using contrast limiting adaptive histogram equalisation and retaining dataset quality utilising expert class label verification are required. Peak test set accuracies on Secondary, tertiary, and quaternary classification models were raised to 74.5%, 68.8%, and 57.2%, respectively, by applying transfer learning to GoogLeNet and AlexNet models from ImageNet that have already been trained.

Filippo Arcadu, et al [3], offer a method that combines deep learning (DL) with colour fundus images (CFPs) acquired during a single visit from a patient with DR in order to estimate how quickly DR may progress. The progression of DR was determined using the Early Treatment Diabetic Retinopathy scale's two-step deterioration, and the proposed DL models were created to forecast this development. Diabetes Retinopathy Severity Scale, and were trained against DR severity scores created by qualified, human reading centre graders working behind a mask six, twelve, and twenty-four months following the baseline assessment. One of these models' estimates of performance for month 12 produced an area under the curve of 0.79. The outcomes show that it is feasible to forecast future DR progression using patient CFPs collected during a single visit. This method might make it possible to identify patients, refer them to a retina specialist for more frequent monitoring, and possibly take early intervention while developing on larger and more varied datasets in the future. Furthermore, it might improve the patient enrolment in DR-focused treatment studies.

Ashish Bora created the deep learning framework [6]. The system was then evaluated using a validation set consisting of 7,976 eyes from an internal validation set and 4,762 eyes from an external validation set. Within two years of screening, 685 (19%) and 346 (15%), respectively, of the 3,678 eyes in the internal validation set and the 2,345 eyes in the external validation set with recorded two-year mild or severe DR outcomes went on to develop the condition that they did not have at the time. The racial and ethnic composition of the two datasets varied as well.

Katrine B. Nielsen, et al. [1] included diagnostic accuracy experiments to assess the performance of their deep learning technique on new patient populations or retrospective datasets. According to 8 investigations, the ranges for specificity and sensitivity were 84.0% to 99.0% and 80.28 to 100.0%, respectively. 78.7 percent and 81.0 percent accuracy rates have been reported by two studies. According to one investigation, the receiver can detect a 0.955 area under the operational curve. One study that looked at diagnostic performance and patient satisfaction discovered that 78.0% of patients preferred an automated DL model over manual human grading.

Ling Dai created DeepDR, a deep learning algorithm that can identify diabetic retinopathy at any stage [9]. 466,247 fundus photos from 121,342 diabetic patients were used to train DeepDR for lesion detection, grading, and real-time image quality evaluation. Three international datasets totaling 209,322 photos are used for evaluation in addition to a local dataset of 200,136 fundus images from 52,004 patients. For the detection of microaneurysms, cotton-wool spots, hard exudates, and haemorrhages, respectively, the relative areas under the receiver operating characteristic curves are 0.901, 0.941, 0.954, and 0.967. For mild, moderate, severe, and proliferative diabetic retinopathy, respectively, the areas under the curves are 0.943, 0.955, 0.960, and 0.972. The external validations' grading area under the curves ranges from 0.916 to 0.970.

Akhilesh Kumar Gangwar and Vadlamani Ravi investigated automatic diagnosis of DR and suggested a unique deep learning hybrid to address the issue. Transfer learning is used to layer a specified block of CNN layers on top of the trained Inception-ResNet-v2 network to create the hybrid model. They used the Messidor-1 dataset for DR and the APTOS 2019 blindness detection to assess the performance of the suggested model (Kaggle dataset). Their model outperformed other published results. They discovered test accuracy to be 72.33% and 82.18%, respectively, using the Messidor-1 and APTOS datasets.

Quang H. Nguyen et al. [5] provide an automated classification approach to assess the severity of DR based on the examination of photos of the fundus with various fields of view and lighting. Their method achieves eighty percent sensitivity, eighty two percent accuracy, eighty two percentage specificity, and 0.904 AUC for categorising images into 5 categories ranging from 0 to 4, where 0 is no disease and 4 is proliferative DR(i.e,no vision).

Deep learning is the foundation of the automatic identification and classification system for fundus DR pictures proposed by K. Shankar et al. Pre-processing, segmentation, and classification are a few of the processes in the suggested approach. During the pre-processing stage of the procedure, extra noise that is present in the edges is eliminated. Then, the valuable areas of the image are removed using histogram-based segmentation. The DR fundus images were then categorised into Using the Synergic Deep Learning (SDL) model, distinct severity levels are identified. The Messidor DR dataset was utilised in the justification of the provided SDL model. The trial's outcomes demonstrated that the provided SDL model provides superior classification compared to the existing models.

Sangheon El [2]. To categorise each of the numerous stages of the DR using the fewest learnable features is the main goal of Pack. The highly nonlinear scale-invariant deep model known as the VGG-NiN model is created by stacking the VGG16, and the network-in-network (NiN). The advantages of the SPP layer allow the proposed VGG-NiN model to process a DR image of any size. The model gains additional nonlinearity from the stacking of NiN, which enhances categorisation in general. The experimental findings show that, in terms of accuracy and effective use of computational resources, the proposed model performs better than cutting-edge approaches.

III. DATASET

The first and most important duty in each application is dataset collection. Here are a few procedures to follow when gathering datasets:

A. Retinal Images

The Kaggle repository is where the project's photos came from. Images taken with a digital camera are contained in it. This dataset is divided into test, train, and validation categories. Five types of images pertaining to the left and right eye picture are contained inside these three files.

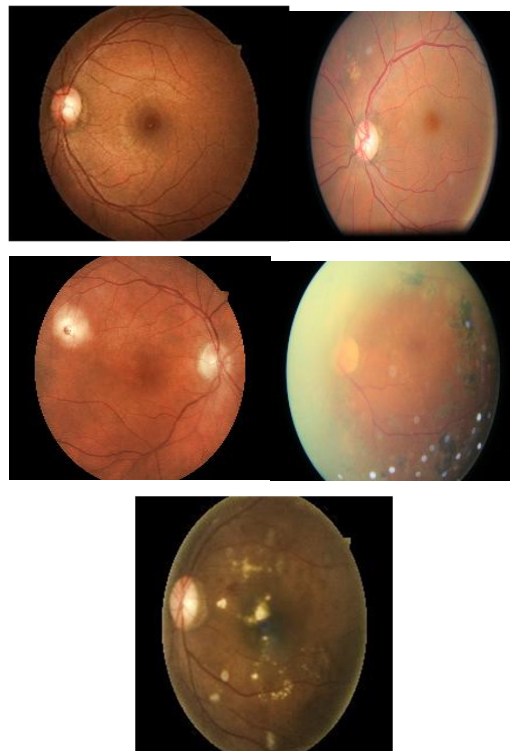


Figure 1. Five classes of eye images

IV. DEEP LEARNING

Deep learning is a form of mimic of the human brain, much like artificial neural networks are. A branch of machine learning called "deep learning" is solely dependent on neural networks. The concept of deep learning is not new. It has been around for some time. Because we have access to more data and computational power than the procedure had in the past, it is more common now. Over the past 20 years, processing power has grown exponentially, which has led to the development of deep learning and machine learning. Deep learning is formally defined as neurons.

A. Deep Learning Techniques

Different deep learning approaches are used to address different challenges. Among them are,

1 Fully Connected Neural Network

2 Convolutional Neural Network

Fully Connected Neural Network

The simplest neural network applications all employ neural networks as their default network architecture. It consists of several flawlessly braided layers. When a layer is fully connected, every neuron in the layer above is linked to every neuron in the layer below.. Additionally, the term "feed forward" describes how neurons in any lower layer are never linked to neurons in a layer above them. Each neuron in a neural network has an activation function that changes its output based on its input. Every aspect of the input has an impact on the outcome. The completely linked layers are typically the last layers of the neural network.

Convolutional Neural Network

A special type of deep learning architecture called convolutional neural networks (CNN) is made to do certain tasks, including identifying images. CNNs were developed using the network of neurons seen in the visual cortex of animal brains. One of a CNN's components is an input layer. However, a two-dimensional array of neurons that represent the image's pixel values commonly serves as the input for basic image processing. It also has an output layer, which is normally made up of a group of output neurons arranged in a single dimension. To process the incoming images, CNN combines convolution layers with sparse connections.

V. VGGNET ARCHITECTURE

Visual Geometry Group, or VGG, is the abbreviation for a deep convolutional neural network (CNN) design that is typical in that it comprises multiple layers. The term "deep" refers to the number of layers, and the VGG-16 or VGG-19, respectively, have 16 or 19 convolutional layers. Innovative item identification models are built using the VGG architecture. The VGGNet, a deep neural network created for a variety of tasks and datasets outside of ImageNet, outperforms benchmarks. It is also one of the most frequently used image recognition architectures available right now.

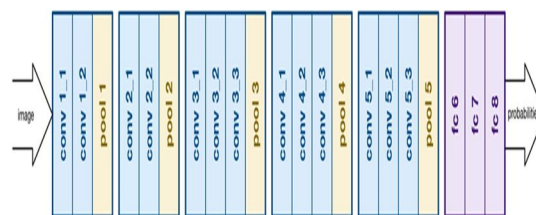


Figure 1. VGGNET Architecture

VGG16 Architecture

VGG16 is a model it is abbreviated as visual geometry group , often it is called VGGNet, which is a 16-layer convolutional neural network model. Two professor named A. Zisserman and K. Simonyan from the University of Oxford created it. This architecture always predicts very high accuracy rate. It can distinguish different objects and it also categorises images in high pixels.It goes 16 layers deep.

VGG19 Architecture

Though theoretically identical to the VGG16 model, the VGG19 model, also known as VGGNet-19, includes 19 layers instead of 16. The model's weight layers are represented by the digits "16" and "19." (convolutional layers). VGG19 has additional layers than VGG16 does. can categorise photographs into 1,000 different object

categories, such as a pencil, mouse, different animals, and a keyboard. The network now includes complete feature representations for a variety of photographs as a result.

Performance Metrics

Various parameters are employed during the evaluation, including

- Accuracy
- Precision
- Recall
- F1 Score

Some basic terms associated with performance evaluation are,

1. True positive: A state where both the expected and actual values are positive.
2. True negative: A state where the expected and actual values are opposite to each other.
3. False Positive: A state in which the value expected is positive but the value actually obtained is negative.
4. False Negative: A state where the actual value is positive and expected value is negative.

A. Accuracy

One of the most crucial factors in assessing the model's performance is accuracy. The ratio of the total sample size to the total of true negatives and true positives is used to calculate accuracy.

$$\text{Accuracy} = \frac{\text{No.of correctly predicted}}{\text{Total number of predictions}}$$

B. Precision

The precision is determined by the quantitative relationship between the variety of positive samples that are correctly or wrongly categorised as favourable and the total samples that are positive. The precision parameter assesses how accurately a model categorises a sample as positive. The formula for calculating precision is shown in the equation below.

$$\text{Precision} = \text{TP}/(\text{TP}+\text{FP})$$

C. Recall

To measure recall, a quantitative relationship between the total number of Positive samples and the proportion of correctly identified Positive samples is used. A statistic called recall assesses a model's ability to recognise positive samples. The more positive samples that were discovered, the higher the recall.

$$\text{Recall} = \text{TP}/(\text{TP}+\text{FN})$$

D. F1 Score

The F1 Score is the harmonic mean of the two precisions. It succeeds in reaching both its minimum value of 0 and its highest value of 1 (perfect precision and recall).

VI. RESULTS AND DISCUSSION

A. Accuracy

Figure 2 displays the accuracy comparison of the DL approaches. Of all the algorithms, it has been demonstrated that the VGG19 is the most accurate. To increase the predictability of the dataset, VGG 19 applies a number of perceptron layers to diverse subsets of the data and chooses the average. The dataset's categorization is determined by the perceptron layers, which combines several layers. As a result, it is shown that VGG19, based on testing accuracy, has the highest accuracy.

B. Precision

The VGG19 algorithm has the highest recall of all the techniques. It employs a number of perceptron on various subsets of the data and averages the outcomes to improve the dataset's accuracy. For the purpose of predicting the dataset's class, the VGG19 combines several perceptron. As a result, it is demonstrated that VGG19 has the highest memory score based on the

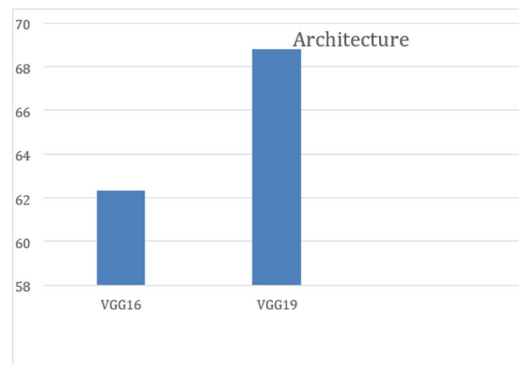


Figure 2 Accuracy Comparison

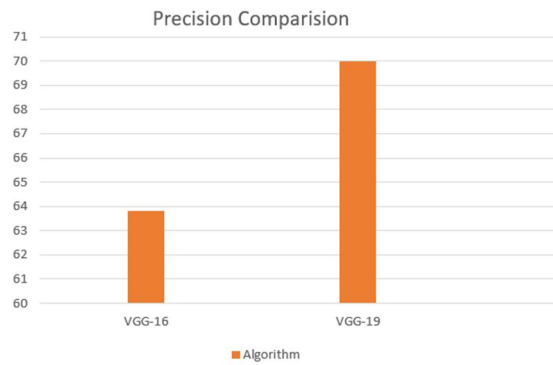


Figure 3. Precision

D. F1 Score

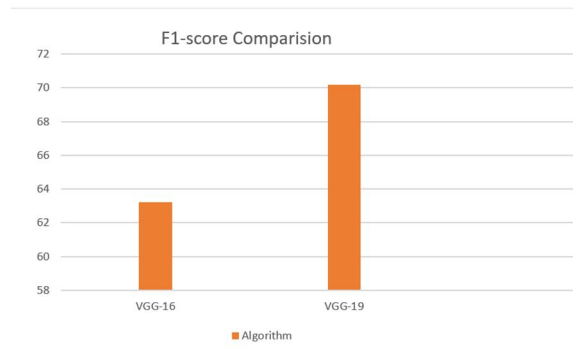


Figure 4 .F1 Score

Figure 3 displays the precision comparison of the DL approaches. It is demonstrated that across all methods, the VGG19 Algorithm has the highest precision score. VGG19 employs a number of perceptron layers on various subsets of the data and averages the outcomes to improve the dataset's accuracy. The VGG19 blends various perceptron layers to forecast the dataset's class. In light of testing precision, it is shown that VGG19 has the highest precision score.

E. Recall

The F1 Score comparison of the DL techniques is shown in Figure 5. Of all algorithms, VGG19 Algorithm has the highest f1 score. It employs a number of perceptrons on various subsets of the data and averages the outcomes to improve the dataset's accuracy. The VGG19 blends various perceptrons in order to forecast the dataset's class. As a result, it is demonstrated by the testing f1 score that VGG19 has the greatest f1 score.

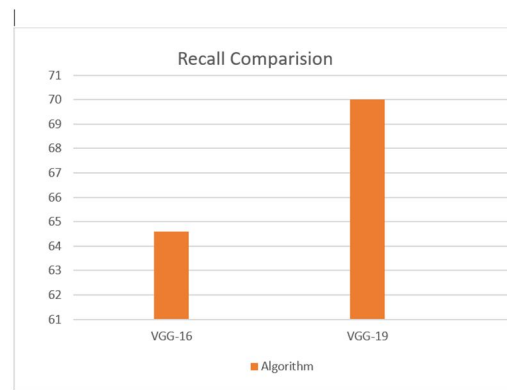


Figure 5. Recall

VII. CONCLUSION AND FUTURE WORK

Identifying and categorising of diabetic retinopathy are developed using the deep learning frameworks VGG16 and VGG19. The model is used to the image dataset of diabetic retinopathy that was obtained from Kaggle. The method focuses on reducing complexity in the deep learning architecture for classifying diabetic retinopathy illness.

With processing times of less than 1 second per photo, the suggested model is noticeably more productive than manual procedures and other approaches employed as a component of operations used in diabetic retinopathy. VGG19 beat the other deep learning methods created among the models used to detect diabetic retinopathy. Across the several classes of the diabetic retinopathy dataset, the VGG19 model achieved an accuracy of 68 percent and a validation accuracy of 65 percent. This strategy advances the state-of-the-art and achieves the goal of treating or detecting diabetic retinopathy early.

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