Comparative analysis of deep learning models for the detection and classification of Diabetes Retinopathy

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***Abstract*— In recent years, diabetic retinopathy (DR), particularly in the elderly, has gained widespread recognition as a cause of blindness. The DR, which comes in a variety of forms and also has a variety of causes, is easily curable with early detection. Early detection of DR is challenging when manual medical approaches are used, and results are frequently inaccurate despite how long they take to complete. Therefore, a better approach to DR detection and prediction is required. Therefore, the purpose of this paper is to detect and classify diabetic retinopathy in patients using deep learning and compare different machine learning models to determine the one that performs best. The models employed are Convolutional Neural Network (CNN) that uses a four-layer VGG net plus an additional neural network to make it a custom five-layer network, K Nearest Neighbour (KNN) and Support Vector Machine (SVM). The IDRID which is the Indian Diabetic Retinopathy Image Dataset is where the dataset was acquired. When compared to other deep learning systems like KNN and SVM, which had an accuracy of 86% and 66% respectively, CNN attained an accuracy of 92%.**

Keywords*— *Diabetic Retinopathy, Deep CNN, KNN, SVM, Deep Learning

I. INTRODUCTION

Diabetes is a chronic disease that occurs when blood sugar is excessively high [1]. It is a condition that typically develops when the pancreas cannot effectively handle insulin or does not secrete enough of it [2]. The chronic hyperglycemia of diabetes primarily leads to a serious breakdown of the body, and because these damages are typically long-lasting, it also causes dysfunction and failure of several body parts, which includes the blood vessels, the heart, nerves, eyes, and kidneys. According to the World Health Organization (WHO), diabetes is the sixth most fatal condition [3]. As at the year 2011, 61.3 million Americans between the ages of 20 and 79 were reported to have diabetes and, it is predicted that by the year 2030, the number may increase to approximately 102 million [4].

Diabetic retinopathy (DR) is a vascular condition of the retina [2]. Chandrakumar and Kathirvel [5] defined diabetic retinopathy as damage to the retina brought on by diabetes. It's a primary illness that affects up to 80% of all victims for a considerable amount of time—at least 20 years [5]. Nearly everyone with type 1 diabetes and 60 to 80 percent of people with type 2 diabetes often have retinopathy over time [2,6]. According to The Foundation of the American Society of Retina Specialists [1], diabetic retinopathy (DR) is among the foremost causes of permanent blindness in the American working class, affecting around 5.4% of Americans over the age of 40 [7].

Proliferative diabetic retinopathy (PDR) and non-proliferative diabetic retinopathy (NPDR) are the two different categories of diabetic retinopathy [2]. When fluids delivered by the retina for hydration stimulate the growth of new blood vessels to bypass blood, then the PDR occurs[2]. In doing so, they develop along the retina and on the vitreous gel's surface before filling the eyes. Hence, as the eye ages, the eye vitreous decreases, causing the delicate vessels to also shrink and damages the eye. Real vision problems and a lack of eyesight manifest once they expel blood [8]. An illustration of retinal pictures with NPDR and PDR is shown in Fig 1.

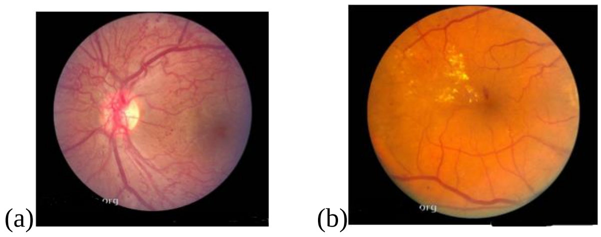

Fig. 1. Diabetic retinopathy comes in two different forms: (a) Proliferative diabetic retinopathy (PDR), and (b) Non-proliferative diabetic retinopathy (NPDR). [2]

It is germane to begin the treatment of diabetes, as well as diabetic retinopathy, as quickly as possible before they get worse. While research is still in its early stages, the defects in the retina can be corrected. Globally, the incidence of diabetes and diabetic retinopathy is rising, and current conditions make manual procedures potentially unable to meet the requirement for early detection, thereby necessitating the use of automated approaches as soon as possible. The World Health Organization (WHO) and the International Diabetes Federation (IDF) met in Geneva through their advisory group

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and emphasized the importance of being open to computerized scanning technologies that scan based on images of the color fundus. However, there were still some fundamental problems with the computerized system, and requests were made to create substitute systems that are smarter and have faster prediction and detection. Since this is an open issue, there is enough information accessible for as many individuals or organizations to contribute solutions to the DR pandemic. Artificial intelligence, machine learning, and most recently, deep learning are mathematically oriented systems that can easily adapt to various difficulties in a variety of sectors which is why they are being considered the best solution for early prediction and detection of DR. As the number of patients with diabetes continues to rise, this will provide a plethora of data that will be used to train existing models to be able to better detect DR, which will decrease stress on the part of the medical staff and also aid in the curing the problem more quickly. When determining whether a patient has diabetes or DR, medical professionals look for certain characteristics or symptoms. The machine will learn to recognize these specific characteristics that doctors use to identify people as diabetic or having DR, as well as the type of DR each patient has [9].

II. LITERATURE REVIEW

An Automated Detection and Classification of Fundus Diabetic Retinopathy Images with the use of a Synergic Deep Learning Model was developed by Shankar et al. [10]. They put forward a model for detecting and classifying fundus diabetic retinopathy according to severity using a deep learning model. The methods started with the preprocessing stage, where extra noise in the edges was eliminated. A histogram-based segmentation was also used to bring out the useful regions. A Synergic deep learning (SDL) model was used to classify the DR fundus images into different severity models, and it was justified with a thorough simulation on the Messidor DR dataset. The review of their study showed that the proposed SDL model performed better in terms of classification than the ones already in use. Although the accuracy, sensitivity, and specificity of the work were all 99.28, 98.54, and 99.38, there was still potential for improvement, because such system that was trained with few data (1200 images) are prone to overfitting. The system could use more data in training as the dataset was less than 10,000 images.

Akhila, Ambarish, and Unnikrishnan [11] developed a deep neural network to detect diabetic retinopathy. A desktop application was created as a result of this research to assist in the diagnosis of diabetic retinopathy. It was a real-time system that required little to no internet utilization. A deep neural network design paradigm using tensor flow was used to construct the framework. Thousands of images were used to train and test the model. The deep neural network was built with five layers: one Fully Connected (FC) layer, two pooling layers and two convolution layers. For detecting certain global configurations of the traits that the lower layers of the network identified, the FC layer was used. The methodology allowed for two different screening options: immediate screening and picture screening. However, the study was constrained by the fact that it could only operate in binary form, which meant that it could only warn whether or not an eye was infected with DR; it could not classify the DR. Additionally, it was only operating on desktop computers.

Deep learning models were used in the study of Dutta, Manideep, Basha, Caytiles, and Iyengar [12] on the classification of images of diabetic retinopathy. Their study's objective was to develop an automated knowledge model to recognize the main causes of DR. They used three alternative strategies to train their model: back propagation neural networks, Convolutional neural network, and deep neural networks. After testing the models, it was discovered that the CNN and DNN were the most successful due to the CPU training time and their ability to effectively remove background noise from the images. These models also produced results with a high degree of accuracy. They also employed the weighted Fuzzy C-means algorithm to determine the required target class threshold. Integrating the model with current NPDR screening algorithms for greater prioritizing and resourcefulness of the delivery of eye care would be a better method to create the system.

A Deep Learning-based automated system for the detection of diabetic retinopathy was developed by Naithani, Bharadwaj, and Kumar [13]. In this study, a pre-programmed DR evaluation framework was used to classify the images according to the four severity levels of the disease pathology. They were able to recognize that a convolutional neural network (CNN) would successfully extract specific visual highlights from an input image with a characteristic weight matrix without sacrificing spatial arrangement information. They used CNN to make use of the numerous images they obtained from unprocessed pixels, and a doctor performed the screening. The model's high probabilities and low inclination made it possible for CNNs to diagnose a wider spectrum of non-diabetic disorders as well. The system was tested and trained using AlexNet and GoogleLeNet, which were then divided into three models, namely 2-ary, 3-ary, and 4-ary classification models. With a number of techniques, including batch normalization, L2 regularization, dropout, learning rate policies, and gradient descent update rules, they were calibrated to perform best on a training dataset. A Kaggle dataset of 35,000 retinal images with 5-class labels (normal, mild, moderate, severe, end stage) and a physician-approved Messidor-1 dataset of 1,200 color fundus images with 5-class labels served as their main data sources for the investigations. However, when there were more classes, the work's performance suffered.

An improved method for detecting and classifying diabetic retinopathy using deep convolutional neural networks was proposed by Hemanth, Deperlioglu, and Kose [9]. The study suggested a strategy that combined the use of contrast-limited adaptive histogram equalization techniques with image processing using histogram equalization. Convolutional neural networks were used to classify data as the next step in this technique. By comparing the method to 400 retinal fundus images from the MESSIDOR database, the procedure was shown to be effective. The average values for several performance evaluation metrics obtained were accuracy 97%, sensitivity (recall) 94%, specificity 98%, precision 94%, F1 Score 94%, and GMean 95%. Their method proved effective and fruitful enough in identifying diabetic retinopathy from retinal fundus images, in contrast to other relevant studies. By including the usage of alternate solution strategies, this work could perform better. The system might also use a significant number of additional fundus images by accessing various databases, such as Kaggle, which has thousands more images.

Khalifa, Loey, Taha, and Mohamed [14] published an analysis of Deep Transfer Learning Models for Detecting Medical Diabetic Retinopathy. This study aims to boost the detection of DR at the early stages for increased recovery possibilities and the potential to reduce patient vision loss. Advanced computer science techniques, such as artificial intelligence (AI) and deep learning (DL), were used. They looked at deep transfer learning models for medical DR detection in this research. The dataset from the 2019 Asia Pacific Tele-Ophthalmology Society (APTOS) conference was used to train and test the deep learning models. The study helped create the APTOS 2019 dataset. The study was an early adopter of the APTOS 2019 dataset. In this study, AlexNet, Res-Net18, SqueezeNet, GoogleNet, VGG16, and VGG19 were utilized as models. In contrast to larger models like DenseNet and InceptionResNet, these models were chosen because they have less layers. The overfitting issue was solved by using data augmentation approaches to strengthen the models. At 97.9%, the AlexNet model's accuracy was at its highest. As a result of the fewer layers in the model utilized in this study, training time and computational complexity were reduced. However, the system was not able to classify different types of DR.

III. METHODOLOGY AND DATA ANALYSIS

Several stages must be examined in order to automate the classification and detection of DR. Care must be taken when removing the retinal lesions. Exudates, micro-aneurysms, and hemorrhages are among these retinal abnormalities. To ensure the correct identification of DR in a patient, these traits must be properly classified. If the classification is not carried out as accurately as possible, it could result in problems such as varying lighting and contrast throughout the images and the retinal lesions being too similar to recognize in comparison to the blood vessels, the optical disc, and the fovea [15].

Models considered in this study were CNN, SVM, and KNN. The models were picked because, most of the previous works focused more on DL models, and we sought to investigate the performance of ML models against a DL model in classifying different categories of DR.

The system's classification procedure consists of five main steps: data collecting, pre-processing, data splitting and label binarization, augmentation and data modeling, and training.

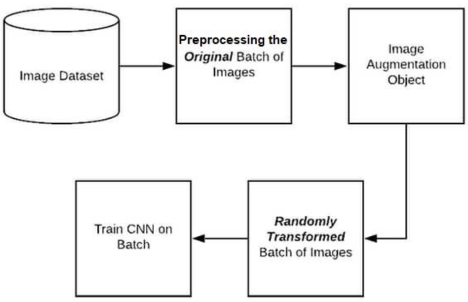


Fig. 2. Procedures for system classification

A. Dataset collection

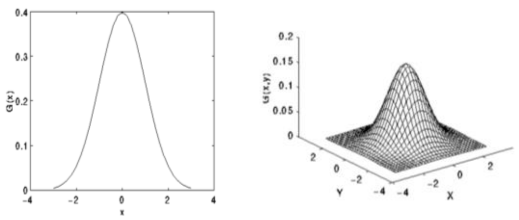
The Indian Diabetic Retinopathy Image Dataset (IDRID), [16] is an open source data collecting platform. It has 413 images of DR Data with annotations and images. 413 original color fundus images were used in this study, according to the documentation. These datasets included color images with varying heights, widths, pixels, and matrices. The acquired IDRID pictures were divided into three categories: normal, non-proliferate, and proliferate.

B. Data Preprocessing

To allow for its intended usage, the data must first be transformed into a hierarchical data format. The primary goal of preprocessing data is to eliminate noise and filter images from the gathered data to organize the images during neural network training [10].

Li, Yeh, Chen, and Chung [17] in their research employed three techniques which were also adopted in this research work, the techniques involved scaling the data into the same size so the models do not learn the images according to their sizes, color divergence was also removed thus the local mean color value was set at 50% grayscale to avoid learning the images by color, and finally, the outer edges were trimmed 10% from the image borders.

It was necessary to resize the images in order to make them uniform and usable by our model because the images included in the dataset for this study were of different sizes. First, the data images were filtered using a Gaussian blur to reduce noise and provide images that could enhance our model's capacity for learning. A 5 by 5 kernel is employed for the Gaussian blur. The Gaussian blur, also known as Gaussian smoothing, is a 2D convolution operator that blurs images by excluding noise and other ostensibly superfluous features. It utilizes a bell-shaped kernel to mimic the appearance of a Gaussian hump. Fig. 3 compares a 1D image (before employing Gaussian blur) and the outcome following the use of Gaussian blur.



(a) (b)

Fig. 3. A 1-D Gaussian distribution with mean 0 and =1 is shown in the graph, while a 2-D Gaussian distribution with mean (0,0) and =1 is shown in (b). Source: [17]

Figure 3a's Gaussian distribution takes the shape of

$$G(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{x^2}{2\sigma^2}} \quad (1)$$

Where σ is the standard deviation of the distribution. Assuming that the distribution has a mean of zero (i.e. it is centered on the line x=0).

The Gaussian distribution in Figure 3b has the form of

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (2)$$

The 2D distribution is anticipated to be used via convolution as a "point spread" function in gaussian smoothing. According to Fisher, Perkins, Walker, and Wolfart [18] before convolution can be applied to the photos, these images are constructed as discrete pixels required to provide a discrete approximation to the Gaussian function. Examples of photos before and after pre-processing are shown in Fig. 4.

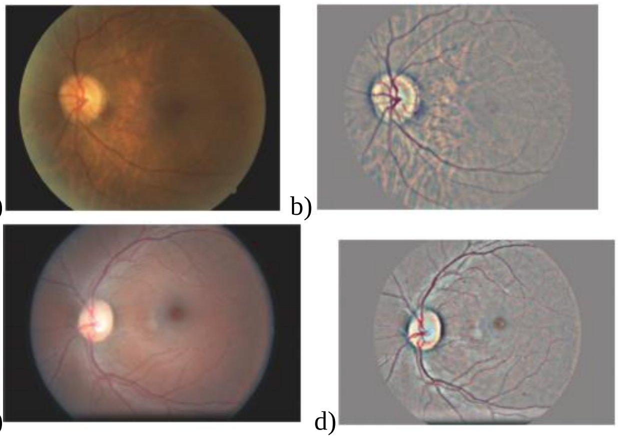

a) b) c) d)

Fig. 4. While b and d display the photos following preprocessing, a and c display the images beforehand

The photos were converted to an array after using the Gaussian blur to remove the noises. Images, texts, and videos are the most frequently obtained types of data, Machine Learning (ML) and Deep Learning (DL) algorithms however accept numeric data. The images to be used will be converted into a group of numerical values. Each image to be used was thus converted into its array equivalent so that it can be fed into the neural network to be used. The images were then scaled to fit within the [0, 1] range since these images are made up of pixels that fall between [0, 255]. The formula (3) is used to normalize the image into the range [0, 1] from [0, 255]:

$$x_{i_{new}} = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{3}$$

Where $x_{i_{new}}$ is the new range the image was normalized into, x_{max}(255) is the maximum range it was normalized from while x_{min} (0) is the minimum range it was normalized from.

C. Data Splitting and Label Binarization

The data must be divided into training and testing after preprocessing and ensuring that it is suitable for modeling (Test). Eighty percent of the data used in this study were for training, while twenty percent were for testing. Additionally, the categorical labels (those that are divided into various categories) are changed into numbers so they can have five distinct values that are further divided into binarized integer values that reflect the category they are fall into using a process called One Hot Encoding.

D. Data Augmentation

The model tends to learn through varied sizes of the images of the dataset as opposed to the original photographs recorded as provided, so data augmentation helps to make the model more resilient and versatile by increasing the amount of images through the aforementioned procedures.

Our dataset only contains 413 images, which is regarded insufficient for this research. To improve the system's detection and classification, the number of images was increased to 10,119, which will be enough for the training process. Additionally, data augmentation makes the model more resilient to noise and transformations of all kinds and prevent overfitting. Our augmentation technique uses four different methods. The first method is rotation, wherein the images in the data are rotated to an angle 30°; the second is shearing the images within a range of 0 and 15%; also, the images are augmented via zooming by scaling the z axis either up or down. The flipping method is the last augmentation technique wherein the images are vertically or horizontally flipped. After applying these four techniques, the images were thereafter augmented to 10,119 images which were used in training and testing the model.

Additionally, by using this strategy, the system was protected from the requirement to memorize data and the data was made more reliable and accountable for training and testing.

E. Training and Data Modeling

There are various characteristics in the data that the system will need to watch out for during training and modeling in order to correctly group them into their respective categories. A KNN and SVM model was used in training the model while for the CNN model, A custom 5-layer convolutional network, named RNet, was modeled as the architecture of the system for efficacy. The 5-layer network is referred to as RNet for simplicity and straightforward network comparison. This RNet consists of a proprietary one-layer network and a tiny VGG network, giving the architecture a total of five layers. The goal of the CNN model's optimizer is to close the gap between a label's actual value and its predicted value. The SGD (Stochastic Gradient Descent) optimizer was used in this system.

IV. Experimental Setup and Discussion

At various phases, experiments were carried out to check the effectiveness of the system and assess how precise and helpful the recommendations were. The IDRID dataset [16] was used for the studies.

This system experienced some training losses, just like other machine learning algorithms. The classifier performed admirably because the training loss while training this network was fairly small. Typically, the loss' purpose is to assess how well the model worked.

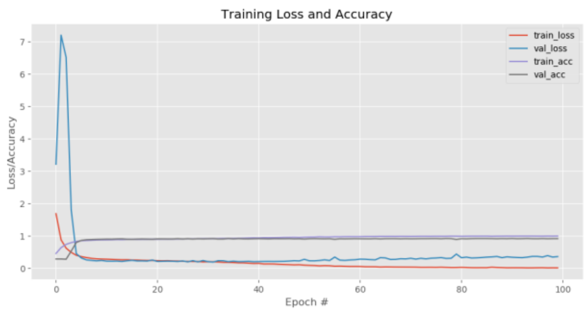


Fig. 5. Plot of the Training loss and accuracy graph

A. Perrformance Evaluation of the System

In determining how accurate the system was able to make predictions, images with pre-existing knowledge of what category they belong were fed into the system. These were compared with the responses of the system and used in getting its accuracy. To determine which model performed best after training and testing them, the steps followed involves the models getting the dataset images, learning about the features of the data and making predictions from the knowledge the model had acquired from the data fed into it. For the different classifications of DR, the metrics used in analyzing its performance were precision, F1 score and recall while the accuracy of the entire model was equally gotten. The tables I and II compare the outcomes of each of the models and also the result of the system with existing systems from other researchers.

TABLE I. COMPARISON OF RESULTS OF THE DL MODEL WITH OTHER ML MODELS

S/N	MODELS	CLASS	PRECISION	RECALL	F-1 SCORE	ACCURACY
1	CNN	NO DR	0.99	0.98	0.99	0.92
		PROLIFERATE	0.94	0.9	0.92	
		NON-PROLIFERATE	0.9	0.9	0.9	
2	KNN	NO DR	0.95	0.93	0.94	0.86
		PROLIFERATE	0.87	0.87	0.87	
		NON-PROLIFERATE	0.8	0.82	0.85	
3	SVM	NO DR	0.75	0.91	0.82	0.66
		PROLIFERATE	0.73	0.36	0.48	
		NON-PROLIFERATE	0.62	0.73	0.66	

B. *Comparative Analysis of the proposed system with existing works*

TABLE II. COMPARATIVE ANALYSIS OF THE ACCURACY OF THE SYSTEM WITH EXISTING WORKS

Authors	**Approach/Technique**	**Accuracy**
Lam, Yi, Guo, and Lindsay, [19]	Deep Convolution Neural Network	66.8%
Revathy , Nithya , Reshma, Ragendhu, and Sumithra [20]	Machine Learning	82.0%
Shankar et al., [10]	Synergic deep learning	99.3%
Nikhil and Angel [21]	Artificial Neural Network	80.1%
Current Research	Deep Convolution Neural Network	92.5%

V. CONCLUSION

Modern data and image evaluation techniques like convolutional neural networks (CNN), K-nearest neighbors (KNN), support vector machines (SVM), and others are widely used, particularly in the field of health where they are used to detect and classify diseases, and they have shown to be efficient and effective over time. In order to effectively predict and classify DR the CNN, SVM, and KNN techniques were employed. The CNN model used the RNet which is a custom 5-layer convolutional network. The models were tested on 10,119 augmented images from 413 images. For CNN, KNN, and SVM, the average results for accuracy, precision, recall, and F1-score for normal, proliferate, and non-proliferate DR were 92, 86, and 66 percent, respectively. Future research may take into account assessing the system using a larger dataset and investigating more models.

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