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"GLAUCOMA DETECTION IN RETINAL FUNDUS IMAGES USING DEEP LEARNING ARCHITECTURES"

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ABSTRACT

Diabetic retinopathy (DR) is a common complication of diabetes that can cause retinopathy to affect vision. If not caught early, it can lead to blindness. Unfortunately, DR is not a reversible process and treatment can only maintain vision. Early detection and treatment of DR can significantly reduce the risk of vision loss. Unlike computer-aided diagnostic systems, the manual diagnostic process of DR retinal fundus images by ophthalmologists is time consuming, cumbersome, and expensive, and it is easy to misdiagnose. Recently, deep learning has become one of the most widely used techniques and has achieved better performance in many areas, especially in medical image analysis and classification. In this work Googlenet and Alexnet networks will be used for classification and detection of Diabetic retinopathy are more widely used as a deep learning method in medical image analysis and they are highly effective. The performance will be done in terms of training Accuracy , Learning Rate , training loss, validation loss, validation accuracy ,precision ,recall, sensitivity the execution will be done on MATLAB software.

Key Words: *Eye diseases; glaucoma screening; artificial intelligence; deep learning; image processing; glaucoma classification.*

I. INTRODUCTION

Modern people are in the world of smart and technical. As the days run faster in this technical world, all are interested in inventing new things and all of them are forgetting about their health... "Health" is the primary one for all human being. Diabetic retinopathy is a damage to the retina caused by the complications of diabetes mellitus. The retina is a membrane that covers the back of the eye and it is sensitive to light. It covers any light that hits the eye into the signals that can be interpreted by the brain. This process produces visual images and it is how sight functions in the human eye. Diabetic retinopathy damages the blood vessels within the retinal tissues, causing them to leak fluid and distort visions .Blurred vision, impairment of colour vision, poor night vision are some of the symptoms caused by the diabetic retinopathy[1-3]

Diabetes is a disease in which impaired glucose metabolism leads to much difficulty. Diabetic retinopathy (DR) is one such situation that is distinguished by damage to the blood vessel at back of retina. According to statistics from

International Diabetes Federation (IDF), almost 463 million people worldwide have diabetes, or almost a third of them have symbols of DR Doctors divide DR into 5 diverse phases support on its severity. No DR, mild, sensible, brutal or proliferative DR, exemplify by indication shown in funds photographs or fundus images. Micro aneurysms, exudates, or bleeding are considered signs of DR or are perceived using these retinal fundus scans. In addition, arrangement of irregular blood vessels called revascularization is a hallmark of later phase of DR can be handled efficiently in untimely stages, but recognition of DR in later stages can lead to irreparable vision loss. To diagnose DR early, ophthalmologists regularly recommend that diabetic patients undergo regular fundus medical screening. However, retinopathy caused by diabetes is not usually detected (usually noted in case of deterioration / loss of vision) until significant damage to the fundus in the patient's eye occurs Adequate identification / classification of the DR scene can help physicians determine appropriate intervention measures. Diabetic patients around the world need normal screening for early discovery, which helps with rapid and rapid treatment[4].

Some residential countries have proposed well-structured screening systems to efficiently supervise diseases or provide value and timely conduct. Adequate identification / classification of DR helps physicians determine appropriate interference measures so that prompt treatment can be implemented speedily [5].

II. LITERATURE SURVEY

The cost of organization these program programs is high or lack of adequately qualified healthcare source has required medicinal population to find substitute methods to save time or resources for DR classification. In addition, less residential countries are trying to reduce cost of classifying DR. The use of automatic computer methods connecting artificial intelligence is currently the most advanced method of solving this problem Artificial intelligence (AI) is replication of human aptitude using complex algorithms for software / machines, where the algorithm learns to distinguish patterns in data or then predicts / detects patterns in invisible data.

With increase in number of users of Smartphone-based knowledge, mobile device-based retinal imaging needs an hour to deliver cheap, faster or smarter point-of-care (POCT) expertise for screening. Using mobile technology screening to classify DR phases will help develop treatment plans for patients, thereby reducing global ailment burden or providing budget-friendly, cost-effective tools. Some current revision has appraise presentation of Smartphone-based retinal imaging in related work [6-8]

Syna Sreng et.al. 2020 [9] Glaucoma is a major global cause of blindness. As the symptoms of glaucoma appear, when the disease reaches an advanced stage, proper screening of glaucoma in the early stages is challenging. Therefore, regular glaucoma screening is essential and recommended. However, eye screening is currently subjective, time-consuming and labor-intensive and there are insufficient eye specialists available. We present an automatic two-stage glaucoma screening system to reduce the workload of ophthalmologists. The system first segmented the optic disc region using DeepLabv3+ architecture but substituted the encoder module with multiple deep convolutional neural networks. For the classification stage, we used pretrained deep convolutional neural networks for three proposals (1) transfer learning and (2) learning the feature descriptors using support vector machine and (3) building ensemble of methods in (1) and (2). We evaluated our methods on five available datasets containing 2787 retinal images and found that the best option for optic disc segmentation is a combination of DeepLabv3+ and MobileNet. For glaucoma classification, an ensemble of methods performed better than the conventional methods for RIM-ONE, ORIGA, DRISHTI-GS1 and ACRIMA datasets with the accuracy of 97.37%, 90.00%, 86.84% and 99.53% and Area Under Curve (AUC) of 100%, 92.06%, 91.67% and 99.98%, respectively, and performed comparably with CUHKMED, the top team in REFUGE challenge, using REFUGE dataset with an accuracy of 95.59% and AUC of 95.10%.

Diabetic Retinopathy Stages Classifications-The doctor notes the process of DR by identifying the symptoms. Figure 1 shows a retinal imaging sample with a typical DR lesion with manual markings. The following briefly discusses the typical lesions of DR:

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Hard exudate: Hard exudates is one of retinopathy that defines DR. Hard exudates regularly appears in retinal image as small yellowish-white spots with sharp edges or special sizes [15].

Soft exudates: Soft exudates, also called cotton-like spots, materialize as white spots with fuzzy edges [9]. Exudate, include soft exudate or hard exudate, is one of mainly general early lesions of DR [10].

Microaneurysms: Microaneurysms are original clinically observable symbols of non-proliferative diabetic retinopathy (NPDR) source through dilation of small blood vessels. Microaneurysms typically emerge as clusters of small red dots with jagged edges (20 to 200 microns) [11].

Figure 1. Annotated diabetic retinopathy image showing lesions

Bleeding: When microaneurysms burst in deep deposit of retina, they form bleeding. In United Kingdom, National Health System (NHS) is a overtly support health classification. They have developed Diabetes Eye Screening Program (DESP). According to them, it is used to grade retinal fundus images; frequently up to 3 people it is mandatory to provide class classes. These classifiers must adhere to NHS DESP superiority promise standards one must be able to evaluate imagery to conclude severity of disease. They must then use these levels to generate a "final level" for each eye based on maximum level of difficulty experiential. The stages of DR can be confidential according to company of clinical facial appearance.[12]

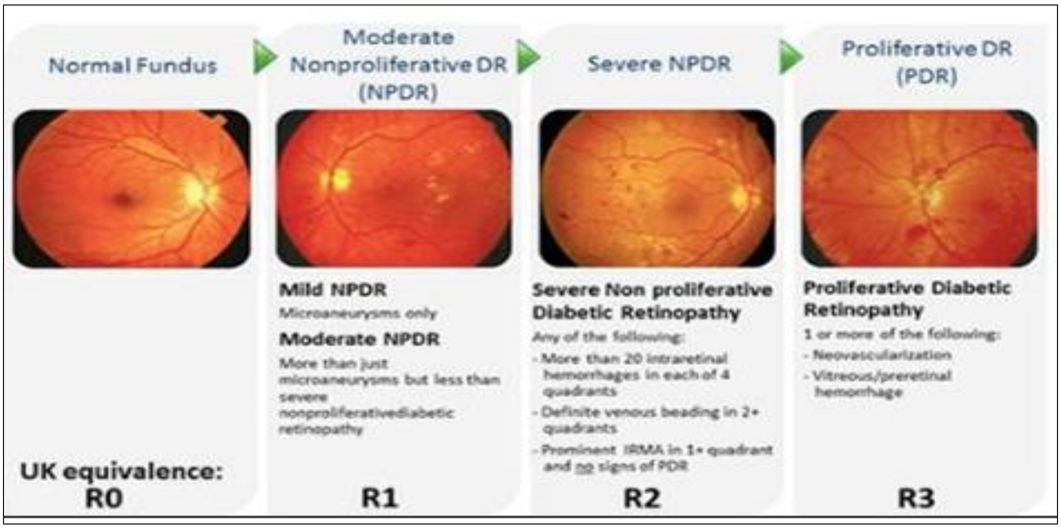

Fig 2. Stages of DR - UK equivalence for Diabetic retinopathy stages

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Figure 1.2 shows different phase of diabetic retinopathy or UK equivalent scale. Normal fundus corresponds to R0. The stages distinguish only by microaneurysms are mild non-proliferative DR stages or next stage in which blood vessels around the retina are rotated, resulting in swelling or decreased blood transport capacity. In the UK equivalent scheme, both mild and moderately non-proliferative DR equals R1. Severe non-proliferative DR is differentiate by more occlusion of blood vessels or manifests as more than 20 intraregional hemorrhages and venous beads in each quadrant. This corresponds to R2 in UK equivalent standard. Proliferative diabetic retinopathy is distinguish by vitreous hemorrhage or formation of new blood vessels (formation of new blood vessels), which are more prone to bleeding or leakage. They correspond to R3 step in British equivalent standard [13-16].

III. PROPOSED APPROACH

Diabetic Retinopathy (DR) is a diabetic complication that affects the eyes and may cause vision impairment or even vision loss. The presence of the disease will result in progressively developing abnormalities such as exudates, hemorrhages and microaneurysms in the retina. As the number of the patient with undiagnosed DR is increasing globally and manually diagnosing DR is cumbersome and time-consuming, performing DR screening automatically has a great significance. Convolutional Neural Network (CNN) has rapidly become a popular tool for medical image processing and analysis. Previous works which applied deep CNN models on the automatic screening of DR needs vast computational resources. In this thesis, we study the use of the computationally efficient deep CNN model for the automatic classification of DR .For this process collected data from the kaggle Website This set is a function taken from an image collection, which is used to predict whether these images are signs of diabetic retinopathy. Then identify the properties and characteristics of the data. After that, the data is divided into two groups, one group is used for training, most of the data is used, and the other group is used for testing. In the set -up training, four different classification algorithms were developed to analyze the model.

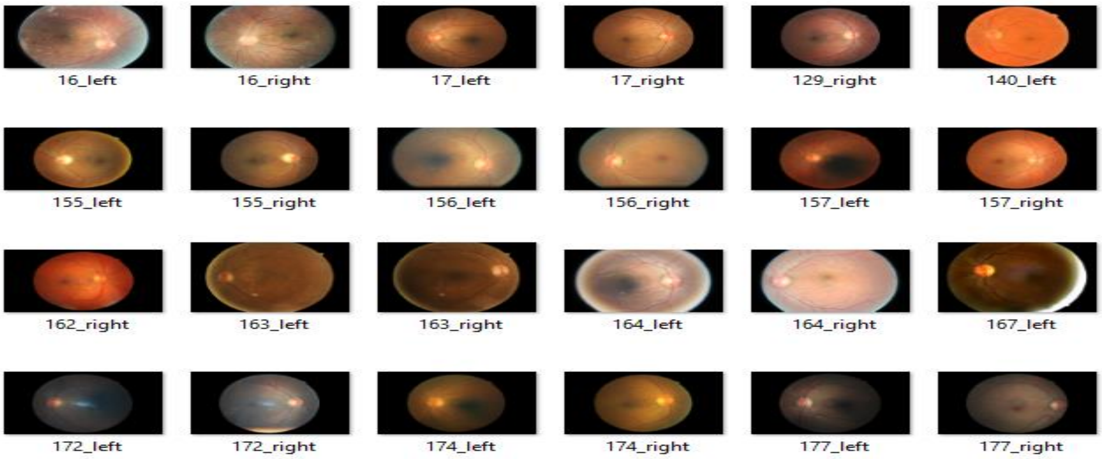

Fig.3 Dataset

The algorithms we use are AlexNet and GoogleNet for classification. After the system has completed the analysis the training data provides new data without leakage. The latest model uses the knowledge gained from the training data to generate results. In the final step, we understand the accuracy of each algorithm and we know which specific algorithm will give us a more accurate diabetic retinopathy diagnosis. Then, the classification is based on the combination of the overactive features associated with the disease taken from the images. The most common features taken from retinal fundus imaging are optic capillaries, blood vessels, hemorrhage, microaneurysms, and exudate. The first task at startup is data collection and advance preparation. It is hoped that changes in color and noise, caused by the race and equipment used to take the images, as well as the details of the machine purchase (such as the experience of the

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operator, will affect the quality of the images. , the type of machine and the mounting drawings). The goal is to address these changes by standardizing the knowledge channel. The rest of the image may be consistent, as it may be related to the desired DR classification pathology.

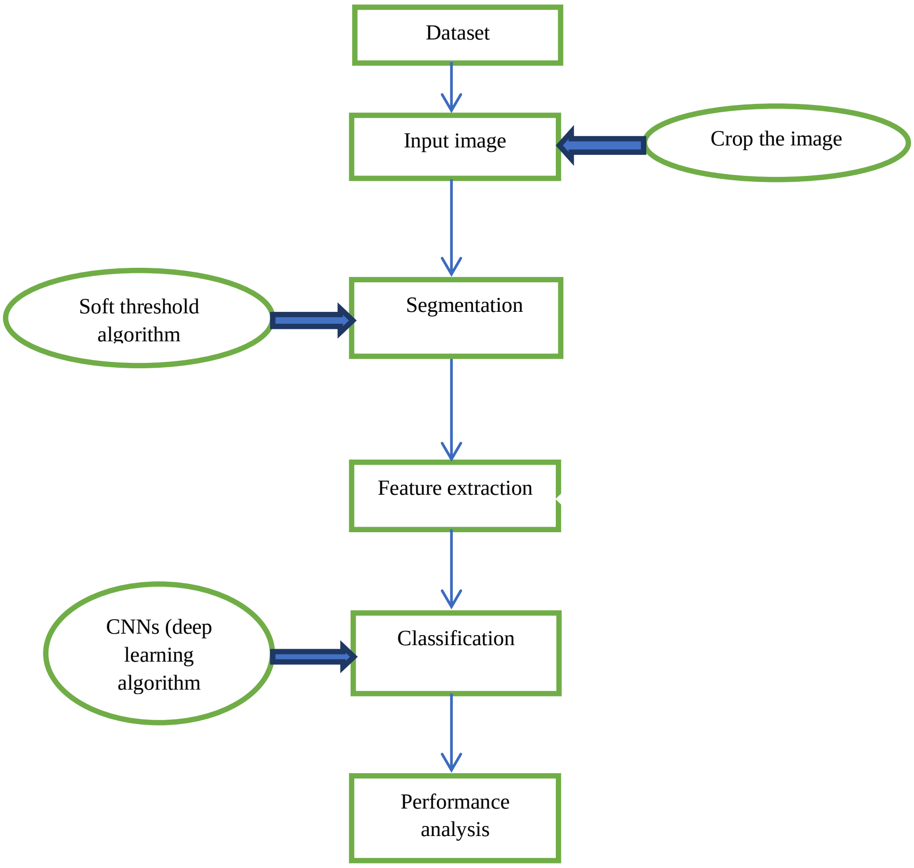

Fig.4.System Architecture

Data Understanding: The data used to conduct this study were taken from 2 and it consisted of conventional fundus retinal images originally collected from kaggel website. The resolution of these images is 1956 * 1934 pixels and these images have also been verified by experts. They determined that the images in the dataset are of good quality, clinically relevant and not duplicated. These images are further divided into five different levels of diabetic retinopathy, namely non-proliferative diabetic retinopathy (designated as "0"), mild non-proliferative diabetic retinopathy (designated as "1") and moderate non-proliferative diabetic retinopathy disease (designated as "2"), severe non-proliferative diabetic retinopathy (designated as "3") and proliferative diabetic retinopathy (designated as "4"). Below are the figures for all categories of diabetic retinopathy, as shown in Figure 4.1

DATA PREPARATION: As mentioned earlier, the dataset consists of 2000 images, which are further divided into five different categories depending on the degree of diabetic retinopathy. Then share the data in training, testing and verification. The training set accounts for 60% of the total data, while validation and test data each account for 20%. The dataset consists of images in JPG format. Both training and validation data are provided with a CSV file containing all relevant image code information. Therefore, we need to map all the images with their respective labels. Another major problem is that each image in the dataset has a different resolution. To avoid this, the image is rescaled and then converted to a fixed scale. Since these are real-world images, the images may be underexposed, overexposed, or even

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out of focus, so we dealt with all situations in the proposed work. Figure 3 shows the distribution of training sets and validation sets

DATA PRE-PROCESSING: The main purpose of this stage is to perform some image enhancement techniques to extract some useful information from the image. Initially, we used different types of pretreatment technologies to improve the performance of the model. After studying many different technologies, we finally chose some technologies for the project that actually helped improve the model's performance. Therefore, the data processing part is divided into two parts, the first part is based on the technology used in the research and test phase, and the second part includes the technology implemented in the final project. All technologies use CV2 library applications.

IV. RESULT DISCUSSION

The search work is performed using the MALAB language Use optimization and advance preparation techniques to increase the size of the data and reduce the noise in the data. The data were then followed by categorizing pre-configured images, AlexNet and GoogleNet -v2 (all of which are well-organized networks),

Performance of AlexNet model

Fig.5 GUI window

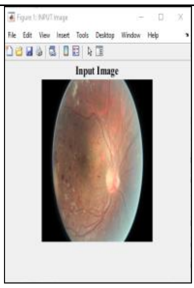	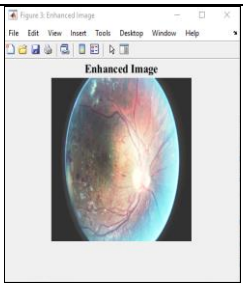	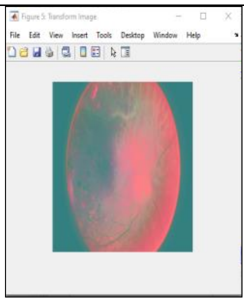	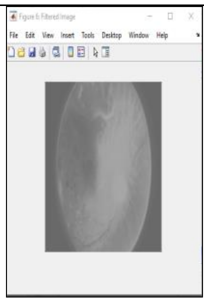	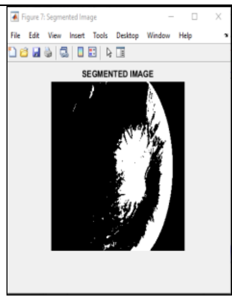
Fig.6 input image	Fig.7 enhanced image	Fig.8 transform image	Fig.9 filtered image	Fig.10 segmented image

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Select the MRI image from files to follow. The image is changed to a grayscale image. The gray level of these images is between 0 and 255, for example, 0 corresponds to black and 255 correspond to white. Grayscale Firstly the images were converted to grayscale in order to enhance the features present within the images, so that the model can learn better.

Segmentation-Image sharing is distribution of image sharing across multiple regions. It is often used to recognize objects in digital images or related information. There are countless dissimilar ways to accomplish image sharing.

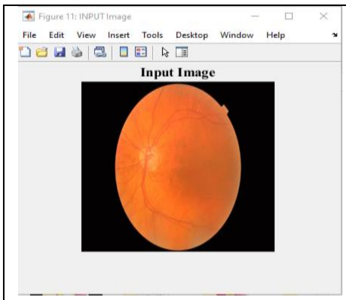	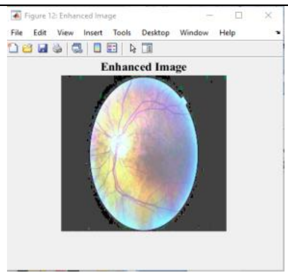	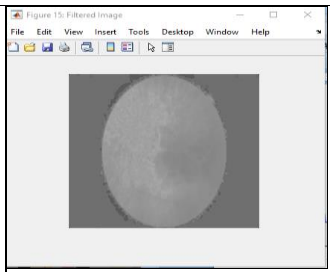	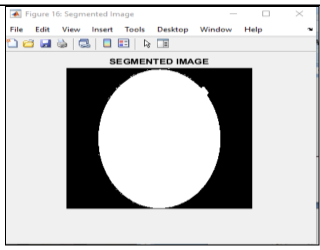
Fig.11 input image	Fig.12 enhanced image	Fig.13 filtered image	Fig.14 segmented image

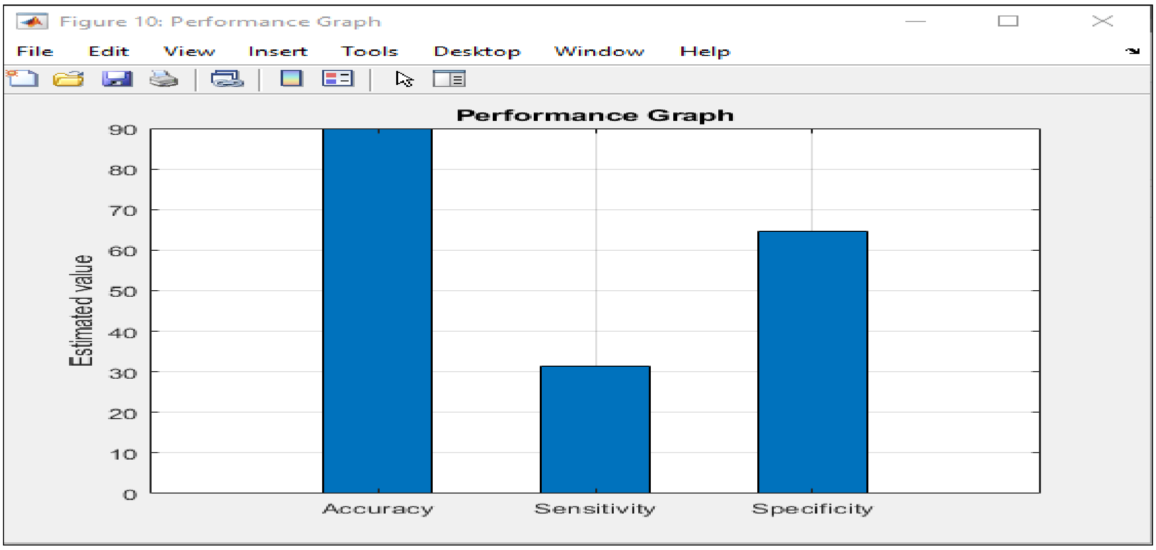

Fig.15 performance graph

Performance of AlexNet model

Classification -The structure of convolutional neural network mainly includes an input layer, convolution layer, pooling layer, fully coupled layer, Activation functions, frequently correct units (ReLUs) layers. The number of layers used their array or opening of other image processing units vary from one architecture to another determining their specificity.

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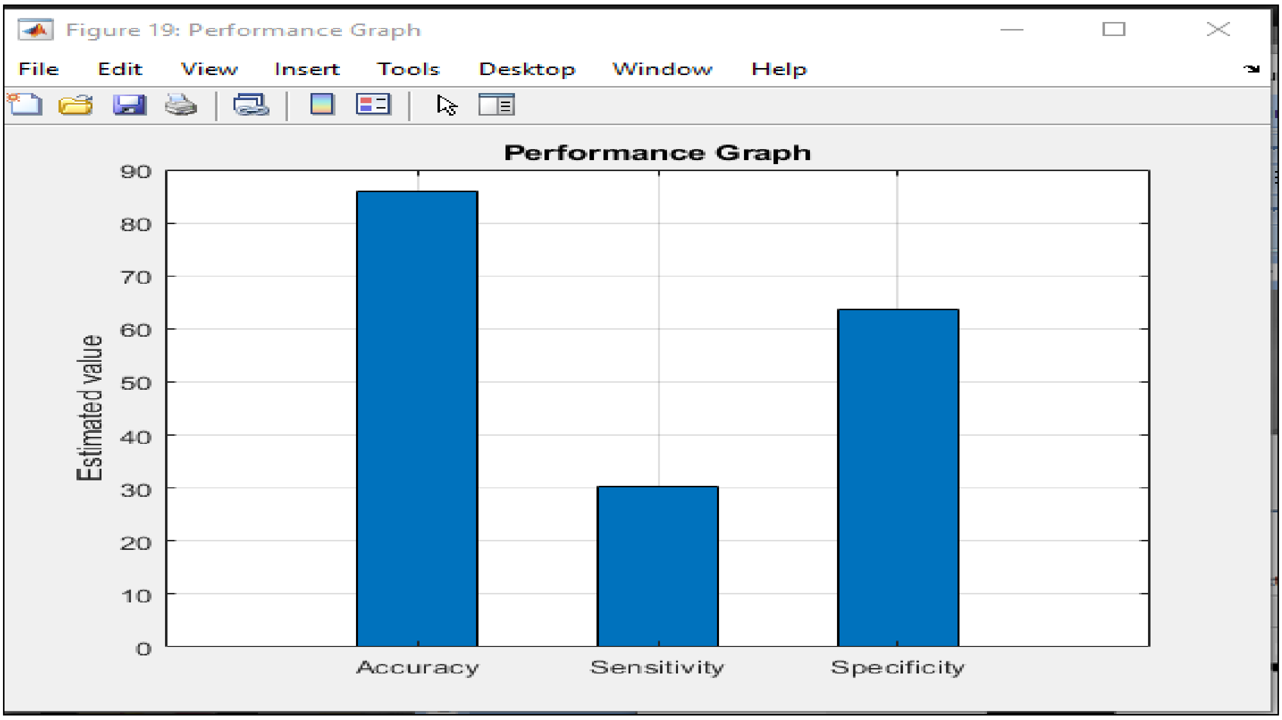
AlexNet: Along with the advances in hardware, the CNN architecture become larger. AlexNet consists of 5 convolutional layers, 3 max-pooling layers, 2 normalization layers, 2 fully related layers, and 1 softmax layer. Each convolutional layer consists of convolutional filters and a nonlinear foundation function ReLU. The pooling layers are used to execute max pooling. Input size is fixed due to presence of fully related layers. AlexNet overall has 60 million parameters.
equally, and the value of each component is 1, and the number of values is 1. For neurons n associated with dissociative dissociation, the sum of 2 ^ n. subset architecture formed. This is often avoided

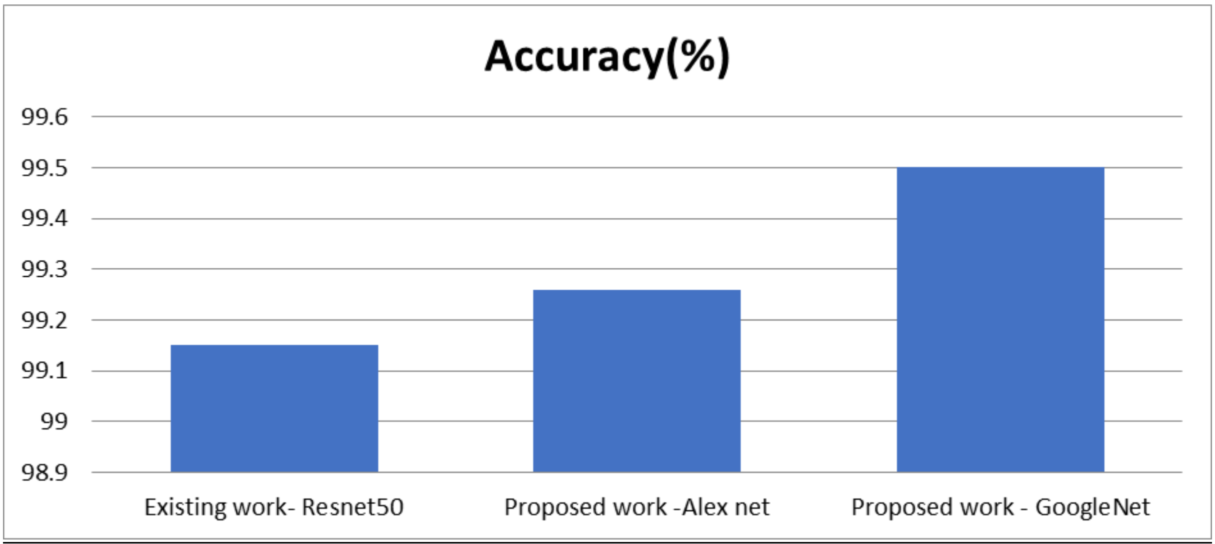
GoogleNet: The GoogleNet architecture is 22 layers deep, including 27 collection layers. 9 original modules are structured line. The end of the Inception model is tied to the global average dining layer. GoogleNet has 4 million standards.



Fi. 16 performance graph

Table 1 comparison table

	Techniques	Accuracy
Existing work	Resnet50	99.15
Proposed work	Alex net	99.26
	GoogleNet	99.50



V. CONCLUSION

In this examine, we were able to accomplish capable outcome in the DR intensity organization system through datasets developed with pre -preparation techniques and image enhancement. Our model uses computationally competent architecture of GoogleNet and AlexNet model which is a popular algorithm that is fast or computationally competent. The model was tested with invisible data to test universality of the model. The results show that model was able to realize good concert due to different method we used in each step of the ML extraction pipeline. In the future, we aim to install and test this model on high -end phones to test its effectiveness as an instantaneous treatment technology for rigorous DR classification.

We examined various trends in the literature on use of artificial intelligence to detect diabetic retinopathy, and examined the behavior of the lightweight architecture and other migration classrooms. We then tested the effectiveness of the category and proved that the lightweight architecture provides comparable results with additional advantages in speed and computational cost efficiency.

In our experiments, we found that we achieved a **91.6%** test with missing data, and the model uses GoogleNet and AlexNet model architecture to demonstrate overall performance.

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