COMPUTER VISION BASED CLASSIFICATION OF DIABETIC RETINOPATHY USING IMAGE PROCESSING AND SUPPORT VECTOR MACHINE

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Abstract: The main factor in senior blindness is diabetic retinopathy, a disorder of the retina that affects those with diabetes. It is an asymptomatic condition marked by blood vessel irregularities that could produce in bleeding or fluid leakage and distort vision. Therefore, blood vessel removal is essential in helping ophthalmologists identify this condition early and avoid vision loss. One of the main causes of blindness and vision impairment in diabetics in industrialized countries is diabetes retinopathy (DR), a crippling chronic condition. Studies show that with early detection and treatment, the majority of cases may be averted. During eye screening, doctors use retinal imaging to find lesions related to this disease. The number of photos that need to be carefully reviewed is increasing because there are more and more diabetics. It also takes a while to train new employees in this type of image-based diagnosis because experience is gained via constant practice. In this paper, computer vision-based classification technique developed for identifying diabetic retinopathy from the retina fundus. The feature extraction method is based on a pretrained convolutional neural network which has rich set of feature layers. The classification is performed with a support vector machine algorithm that is based on machine learning. The proposed experimentation is evaluated and analyzed in MATLAB software with 96.66% accuracy and found to be efficient as compared to state of art methods.

Index Terms - **Computer Vision, Diabetic Retinopathy, Deep Learning, Machine Learning, Support Vector Machine.**

I. INTRODUCTION

A condition known as diabetic retinopathy (DR) affects diabetics and damages the retina of the eye, perhaps resulting in blindness. Hyperglycemia, a symptom of diabetes mellitus, is brought on by an inability of the pancreas to produce insulin. The most common cause of blindness in those who are still active is diabetic retinopathy (DR), which can develop microvascular issues that eventually harm the retina. Additionally, according to the World Health Organization (WHO), 347 million individuals worldwide have received a diabetes diagnosis, with an additional 640 million people predicted to be affected by the disease by the year 2040. Diabetes can induce diabetic retinopathy, an asymptomatic retinal condition that results in micro-hemorrhages, exudates, malformations, and vascular tortuosity (Non-Proliferative Diabetic Retinopathy). Blood vessel removal is therefore essential in helping ophthalmologists identify this sickness early on and stop vision loss.

Ophthalmologists advise diabetic patients to have a routine fundus examination to identify DRs early. However, diabetic retinopathies frequently go undetected until the patient has had serious fundus damage (typically manifested as deterioration or loss of vision). Clinicians can choose the best intervention strategies by properly identifying and categorizing DR stages. People with diabetes need to be regularly screened in order to identify the disease early and start treatment right away. Early sickness identification and rigorous screening can identify nearly 90% of diabetic patients, and disease progression can be reduced by averting subsequent complications. The fundamental problem is that distinctive symptoms of DR do not appear until the disease has proceeded to an advanced stage [3]. As a result, regular eye exams and checkups are advised to prevent issues. On the other hand, evaluating the morphological changes and retinal properties in fundus photographs requires difficult and time-consuming labor. Numerous automated computer-aided diagnostic techniques that help ophthalmologists examine retinal abnormalities have been developed in recent years to remedy this problem. The infrastructure needed to prevent DR-related blindness will become even more inadequate as the number of persons with diabetes keeps increasing.

Today, diagnosing DR is a lengthy and difficult process that involves a qualified doctor carefully inspecting and assessing digital color fundus photographs of the retina. By the time human reviewers submit their reviews, which is typically a day or two later, the delayed findings cause missed follow-up, misunderstandings, and delayed treatment. Unfortunately, diabetic retinopathy has no known effective treatment, and the available medicines are at best management strategies. Therefore, it's crucial to identify the condition as soon as possible. Clinicians can identify DR by looking for lesions associated with the vascular abnormalities of the disease. Although this tactic works, it requires a lot of resources. The necessary skills and tools are usually lacking in areas where the local population has a high prevalence of diabetes and where DR detection is most necessary. Prior work using image classification, pattern recognition, and machine learning have made great progress toward the goal of developing a comprehensive and automated DR screening technique. Our objective is to create an automated analytical system that can predict a retinal fundus picture as a consequence. A machine learning based system is developed that can anticipate diabetic retinopathy.

II. RELATED WORK

Researchers have developed or used effective diabetic retinopathy technology, which is detailed below. Using blob detection as the basis for feature extraction, the distinct stages of diabetic retinopathy were then classified using machine learning. Characterizing diabetic retinopathy in retina images using the most effective machine learning classification algorithm was done with an accuracy of 83 percent. Muhammad Messadi and others [5] The method described here is based on the segmentation of blood vessels and the extraction of geometric attributes used in the early diagnosis of diabetic retinopathy. The suggested method was tested using the Messidor and DRIVE databases, and results showed that it had an average sensitivity, specificity, and precision of 89 percent, 99 percent, and 96 percent for retinal vascular segments, respectively, and 91 percent, 100 percent, and 93 percent for classifications of diabetic retinopathy. a convolutional neural network that modifies and, as a result, categorizes the gravity of DR using the VGG-16 as a pre-trained neural network [6]. The class's average accuracy (ACA) was 74 percent, 80 percent at 65 percent species specificity, and 080 at the area under the curve (A UC). Both the challenges and the performance assessment of CAD techniques [7] are looked at. In order to determine whether the input fundus/retinal image from the patient is affected by diabetic retinopathy or not, a graphical user interface that can combine image processing techniques is used. If affected, the graphical user interface will show the severity as well as the action that the user or patient must take [8]. In one investigation, each retinal image was subjected to simultaneous application of the scale invariant feature transform (SIFT) and speeded up robust features (SURF) feature extraction methods in order to capture the Exudates areas [9]. A support vector machine (SVM) classifier uses the exudates in each image to create a feature matrix that is used to predict DR. The model's typical sensitivity for a batch of 100 test images is 94%.

In order to draw a judgement about the presence of sickness, Karan Bhatia et al. [10] used a combination of machine learning classification algorithms on traits gathered from the results of multiple retinal image processing methods. The frequency tuned method (FT) model, spectral residual approach (SR) model, and SDSP model, all of which are based on the DIARETDB1 database and include 89 chosen images for the diagnosis of diabetic retinopathy, were used to test a proposed method [11]. The AUC parameter in the suggested method has the highest value. Retinal images have been used to develop a digital image processing-based DR detection method [12], where the patient's retina is used to obtain the fundus image. They were able to identify PDR and NPDR with 98 percent accuracy in just 39 seconds (half minute). Ali Shojaeipour et al. [13] created the Gaussian filter to enhance images and separate vessels with a high brightness intensity distribution. By using this approach, the task's difficulty and completion time can be reduced. To represent the DR, a semantic analysis was done [14]. This study showed that the unique vascular segmentation framework has increased precision, specificity, sensitivity, F measures, and accuracy. The goal of the suggested study [15] is to categories fundus images with or without signs of DR using a multi-layered perceptron (MLP), an artificial neural network (NN) that was trained using Levenberg-Marquardt (LM) and Bayesian regularization (BR). MLP trained using BR provides better classification performance when compared to LM, with training rates of 72.11% and test rates of 67.37%. (testing).

An improved diabetic retinopathy detection technique was developed using SVM to extract the precise area and number of micro aneurysm from color fundus images [16]. The sensitivity and specificity of the DR detection technique are 96% and 92%, respectively. [17] created a novel method for precisely identifying hard exudates in relation to the severity of the lesion. They

achieved good performance results when compared to current state-of-the-art methods, including sensitivity of 0.87, F-Score of 0.78, and Positive Predict Value (PPV) of 0.76 for hard exudate lesion level identification. The suggested automated software for DR diagnosis and screening [18] was developed using a variety of digital image processing techniques. The recommended method [19] does away with the need for candidate map construction or lesion segmentation prior to classification. Local binary patterns and granulometric profiles are computed in order to extract textural and morphological information from retinal images. The segment-based learning method for identifying diabetic retinopathy [20] makes significant progress in identifying diabetic retinopathy images and their locations inside lesions by simultaneously training classifiers and features from the data. The suggested model performs noticeably better than the old model. J. Jayashree et al. [21] explore diabetic retinopathy using the PSO Feature Selection approach on three different Classifiers. SVM Classifier has a sensitivity of 96.6 percent, a specificity of 96.6 percent, and an accuracy of 98 percent (96.5). SVM Classifier has the greatest metrics percent for PSO Feature Selection. A quick summary of ongoing research employing cutting-edge Deep Learning algorithms to detect Diabetic Retinopathy (DRD) [22]. Early detection for diabetic retinopathy using convolutional neural networks (CNNs) applied to color fundus pictures [23]. Our network models achieved test metric performance that was consistent with baseline literature values with validation sensitivity of 95%. A sophisticated Deep learning system was developed to improve and automate the diagnosis of diabetic retinopathy [24]. A novel deep convolutional neural network-based technique is presented in [25]. (DCNN). The trials' findings show that the proposed method can achieve recognition rates of up to 86.17 percent, which is higher than those previously reported in the literature.

III. PROPOSED WORK

The figure 1 shows the suggested system architecture. Based on retinal images, the Retinal Fundus Image collection classifies patients into categories like normal (N) and diabetes (D) using annotations and quality control management by trained human readers.
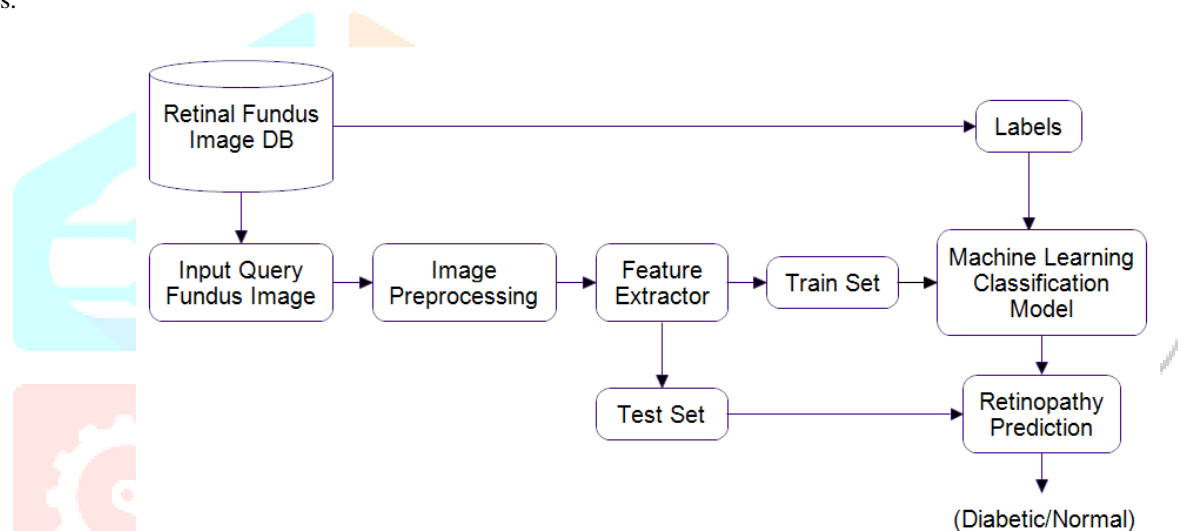

Fig 1: Proposed Block Diagram

3.1 Retinal Fundus Image and Image Preprocessing

Proposed method is being tested on the publicly available dataset Kaggle (APTOS 2019 Blindness Detection), a common benchmark image collection, and is being observed in various ways. The dataset contains images of the retinal fundus that could be used in the design. 100 images in all were used in the experiment. After that, the dataset splitted into training and testing groups of images that made up 70% and 30% of the total. The input images for the model are received and then pre-processed by being resized to match the size of the trained model.

3.2 Feature Extractor

The next phase is retrieving a collection of important attributes from the segmented image using a pre-trained deep learning model. As the pre-trained deep learning model, Inception-v3, which is built on a 48-layer convolutional neural network, used. It was produced by Google and trained for the ImageNet Competition using data from 2012. Reason behind selecting this model because of its excellent categorization performance. To get data from the segmented image, a deep learning model employed that had already been trained. The pre-trained deep learning model that used is Inception-v3. It's as easy as extracting features to use pre-trained deep networks' representational capabilities. Fig 2 shows that inception v3 architecture of pretrained convolutional network.
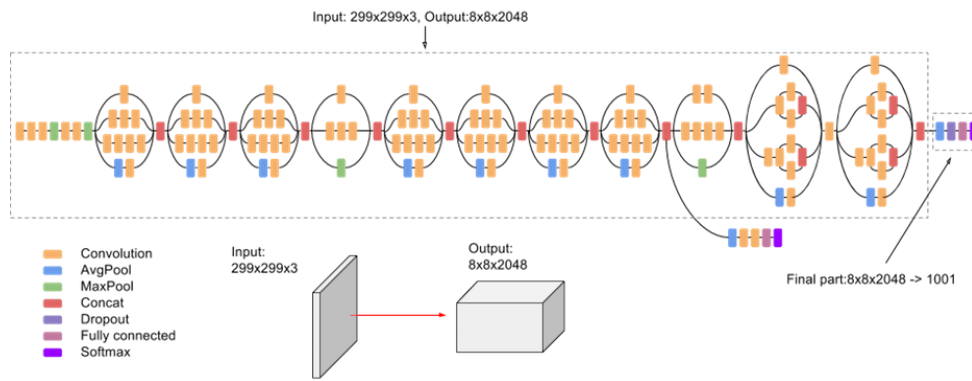
Fig 2: Inception V3 architecture

Inception v3 makes changes to earlier Inception designs with the main goal of using less computational power. It has been demonstrated that Inception Networks (GoogleNet/Inception v1) are more computationally efficient than VGGNet in terms of the volume of parameters the network generates and the expense spent (memory and other resources). When changing an Inception Network, more care must be taken to prevent losing the computational advantages. As a result, it becomes challenging to modify an Inception network for various use cases due to the unpredictable nature of the new network's effectiveness. In an Inception v3 model, a number of ways to strengthen the network have been put out to ease the limitations and facilitate model adaptation. Among the techniques employed are factorized convolutions, regularization, dimension reduction, and parallel calculations. These approaches to learning pre-trained models aim to learn feature hierarchies that contain characteristics from higher levels of the hierarchy that are produced by the composition of lower-level features. By autonomously learning features at various levels of abstraction, a system can learn complex functions mapping the input to the output without just depending on human-made features. Low-level features and high-level features can be used to categoried these features. While objects and events are high-level features, edges and blobs are low-level features.

3.3 Machine Learning Classification and Prediction

The results are then labelled "nondiabetic" or "diabetic" after the images are classified as either "nondiabetic" or "diabetic" using a machine learning classification algorithm. In our case, we used a multi-kernel support vector machine (SVM). The suggested method involves training and testing computer-aided diagnostic models for recognising and detecting diabetic retinopathy. It is simpler and quicker to develop trained prediction techniques from filtered data when features are extracted using image processing and classifier operations are performed using machine learning. The two phases of our proposed methodology are training and testing. The retinal fundus image collection has to be split into two phases, with the train and test picture sets each comprising 70% and 30% of the total dataset, respectively. Prior to feature extraction during the training phase, the original train photo set must be processed, which includes noise reduction, image enhancement, and image scaling. To extract low-level to high-level features, an automated feature extraction method used that made use of a deep convolutional neural network that had already been trained. A feature dataset from the train image set and labels from a related train image set are then collected as input and output data. The support vector machine classifier used in the machine learning model is trained and evaluated using the same data. After the validation was successful, saved the trained model. The test picture set must fulfil the same tasks as the training picture set during the testing phase, up until feature extraction. After obtaining the test feature set, the trained model loaded and forecasted the results as healthy and unhealthy retinal pictures.

SVMs, sometimes referred to as support-vector networks, are supervised learning models that assess data for regression and classification in machine learning. Given a series of training examples, each marked as belonging to one of two categories, an SVM training algorithm develops a model that classifies new examples into one of two groups, resulting in a non-probabilistic binary linear classifier (although methods such as Platt scaling exist to use SVM in a probabilistic classification setting). To make the gap between the two categories as large as feasible, SVM converts training instances to points in space. A popular Supervised Learning technique known as the Support Vector Machine, or SVM, can be used to address classification and regression problems. But it's mainly used in machine learning to solve classification problems. The goal of the SVM method is to determine the best decision boundary or line for classifying n-dimensional space into groups so that subsequent data points can be quickly assigned to the appropriate category. The border of the optimal decision is known as a hyperplane. SVM is used to choose the extreme points and vectors that help build the hyperplane. The technique is referred recognized as a "Support Vector Machine," and support vectors are the extreme examples. Fig 3 shows the how support vector are created based data hyperplane structure. Take a look at the illustration below, which demonstrates the usage of a decision boundary or hyperplane to classify two distinct categories:
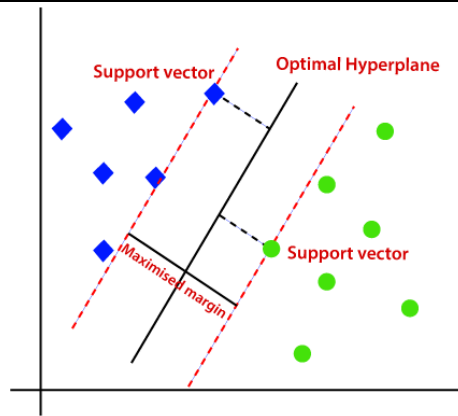
Fig 3: Hyperplane structure of SVM

IV. RESULTS AND DISCUSSION

The proposed system is evaluated on a laptop with an Intel Core i5, 8GB RAM, and Windows 10 as the operating system. The Deep Learning toolbox, together with the Image Processing, Statistics, and Machine Learning toolboxes, were used to create the computer code in MATLAB R2018b. According to the suggested block diagram, this experiment involves three implementation phases: dataset, training and testing.

4.1 Dataset

The Kaggle (APTOS 2019 Blindness Detection) Dataset was used to provide the input images for testing [26]. Sample images from dataset for both labels diabetic and nondiabetic are shown in fig 4.
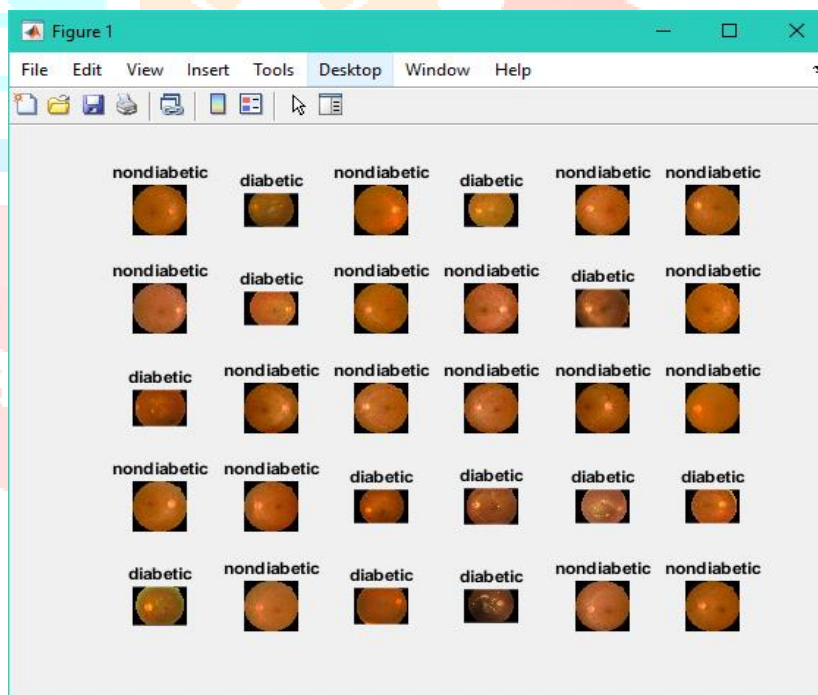

Fig 4: Sample images of retinal image dataset

4.2 Training Phase

According to the size of the deep network used for training, the training set of images must be preprocessed. Then, using an Inception V3 pre-trained deep convolutional neural network with 316 layers, we used an automated feature extraction method to extract features from train photographs (input, feature, classification, and output) as shown in fig 5-6. The "avg pool" feature layer used to extract features from images. The model must then be trained using a multi kernel SVM based on input and output data, with the train image feature dataset serving as the input and labels as the output. Once the training model had been successfully validated, stored it. Validation confusion matrix is shown in fig 7.
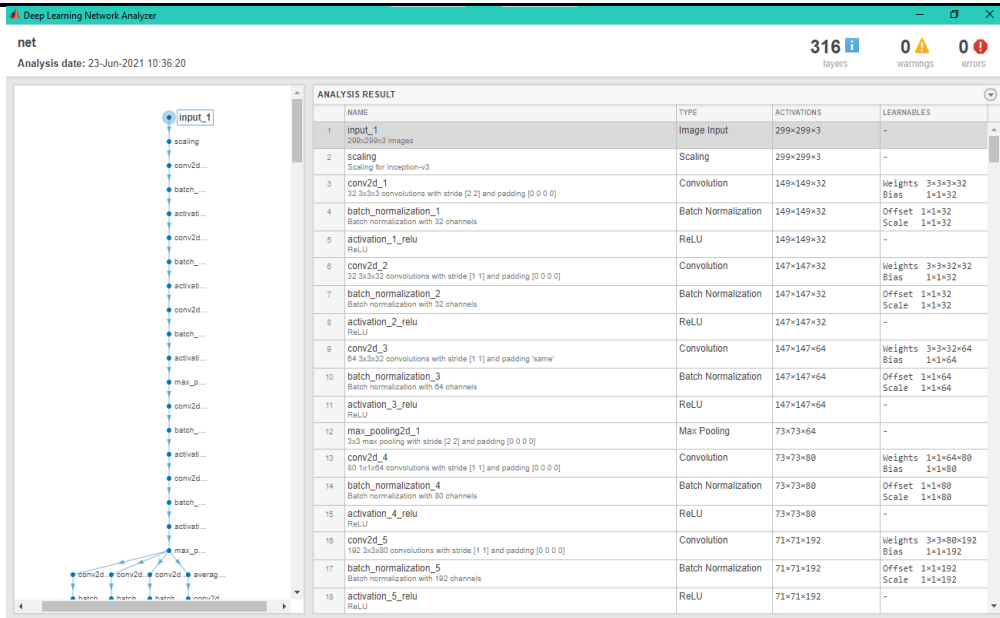
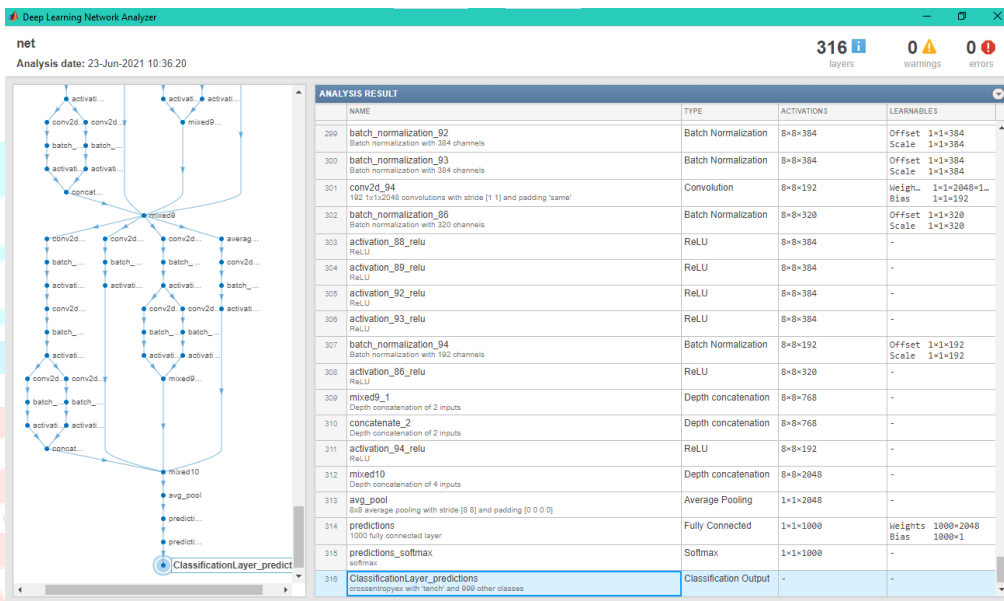Fig 5: Initial layers of Inception V3 architecture
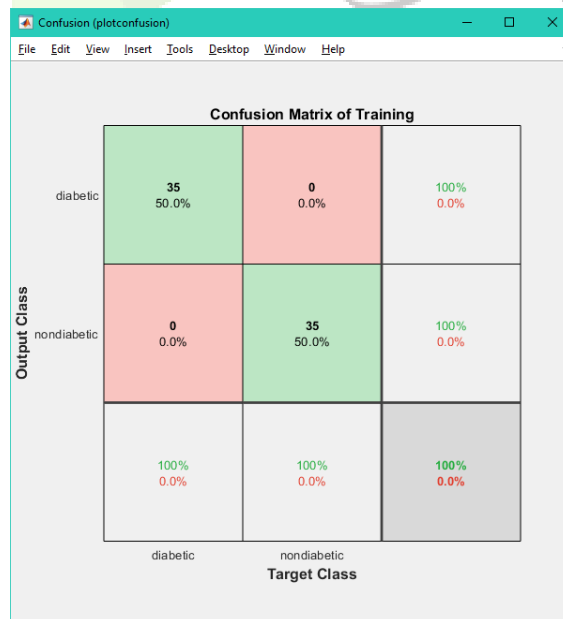

Fig 6: Final layers of Inception V3 architecture

Fig: 7: Confusion matrix of model validation

4.3 Testing Phase

In the testing phase, the same preprocessing and feature extractor is applied for the test images to determine whether the retinal image was diabetic or nondiabetic. Also analyzed all test images from the dataset in this step to get system performance metrics and demonstrate system efficiency as defined in fig 8. Also, ROC graph is shown in fig 9. System performance parameters are evaluated and shown in table 1.
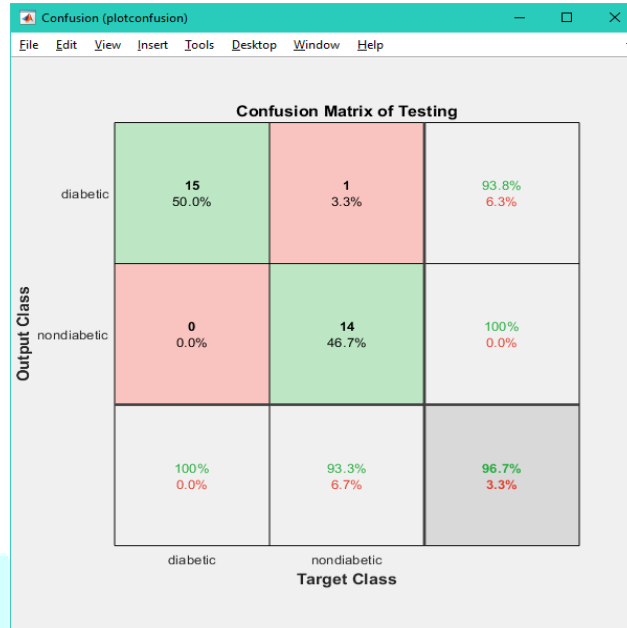

Fig. 8: Confusion matrix of testing phase

Table 1: Result Parameters

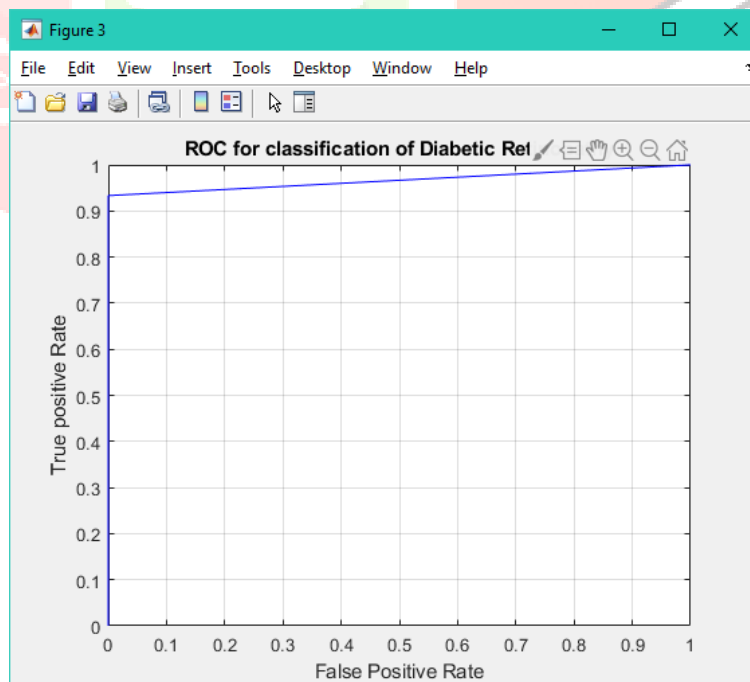| Parameters	Results (%)
Accuracy	96.66
Sensitivity	93.75
Specificity	100
F-score	98.68

Fig 9: ROC plot of testing phase

V. CONCLUSION

Laser analysis is frequently quite helpful in preventing vision loss if done before the retina is seriously damaged, despite the fact that diabetic retinopathy cannot be healed. If the retina is not significantly damaged, surgical removal of the vitreous gel can improve vision. This paper assists in the early detection of retinopathy, which, if left untreated, can result in irreversible vision loss. In order to build a system with increased detection accuracy and efficient feature extraction using a pre-trained deep neural network model, this research proposed a machine learning system that leverages a number of processes ranging from picture pre-processing through classification. Class recognition is 96.66 % accurate overall. The deployment of an effective and profitable computer vision machine in the healthcare system is made possible by the categorization model's simplicity, high recognition rate, and speed. This system could be broadened to include different types of lung infection illnesses. Using GPU reduces the amount of time needed to learn dataset features. The similar method can be applied to any form of dataset for categorization of other illnesses.

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