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Automated Diabetic Retinopathy Detection Using Pretrained Deep Neural Network

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Abstract: : *Diabetic retinopathy damages the retina of then patient. It is most frequent in the patients who have had diabetes for longer than 10 years. This problem is occurring in millions of people worldwide but medical practitioners and the tools required for detection of diabetic retinopathy is scare for serving the mass population. The work already was to serve this problem using the application of machine learning but the efficiency of machine learning algorithm depends on the quality of feature extraction which requires domain knowledge. The work presented in this paper overcome the problem by using deep learning algorithm which automatically identifies the pattern and classifies the retina images into one of the five class based.*

Index Terms - Deep Learning, Diabetic, Diabetic Retinopathy, Convolutional Neural Network

I. INTRODUCTION

According to International Diabetes Federation (IDF)
Diabetes Atlas 2017 [HYPERLINK \l "IDF17" 1], more than 425 million people are affected from diabetes. The statistics shows increase of 10 million cases in past two years. As in 2015 it was reported 415 million. The people lived in low and middle income countries are more prone to effect by this disease. The report shows that there will be 629 million people with diabetes in the World in 20452]. The Diabetic Retinopathy (DR) is a medical condition that damage the retina of eye which cause the blindness. With the proper treatment and monitoring of the eyes the new cases of diabetic retinopathy can be reduced up to 90%. The longer a person has diabetic , higher are chances of developing the diabetic retinopathy. The people with diabetic of 20 years or more at 80% of risk of diabetic retinopathy[2]. As of now, recognizing DR is a tiresome and manual process which requires a clinician to inspect and assess fundus photos of the retina [HYPERLINK \l "RJW09" 3]. These images are then analyzed by clinicians and reported in day or two, which cause the deferred outcomes prompt lost development, miss communication, and postponed treatment4].. While this methodology is viable, its resources requirement are high. The expertise and tools required to examine the mass population are lacking.

A.DIABETIC RETINOPATHY TEXONOMY

Diabetes causes from the high sugar present in the blood.The diabetic can cause diabetic retinopathy if not treated earlier. The diabetic patients with 10 years or more diabetes are at greater risk of diabetic retinopathy. The high blood sugar damages the tiny blood vessels that supplies blood to retina which cause diabetic retinopathy. The light detected by retina converted to signal which passes to brain through the optic nerve. In later stages it leads to
scarring and cell loss due to abnormal increase in blood vessels. Diabetic retinopathy clinically validated into four stages [HYPERLINK \l "Eli17" 5] that includes mild nonproliferative retinopathy, moderate nonproliferative retinopathy , severe nonproliferative retinopathy, and proliferative diabetic retinopathy (PDR). The details cause and effects of these four stages are explained in the table I.

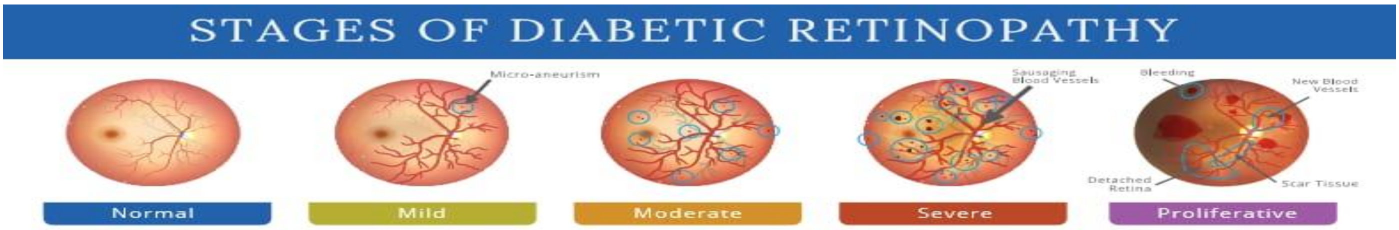


Figure 1:Stages of Diabetic Retinopathy.

Table 1:- Stages of Diabetic Retinopathy.

Mild nonproliferative retinopathy	This is the initial stage of DR. It causes micro aneurysms in the blood vessels that may cause leak of fluid into the retina. Very small swelling in the retina's blood vessels, called micro aneurysms
Moderate nonproliferative retinopathy	This is progressive stage that causing the swell and distortion of the blood vessels that are connected to retina for transporting blood for retina's nourishment. This may sometimes loss their ability to transport
Severe nonproliferative retinopathy	This is severe condition where many blood vessels blocked thus causing less supply of blood to retina compared to the minimum requirement. These areas exude growth factors that signal retina for growing new blood vessels.
Proliferative diabetic retinopathy (PDR)	This is the advanced stage of diabetic retinopathy .Due to blockage of tiny blood vessels retina form new vessels which grow inside.

The sample images of eye with no diabetic retinopathy are shown in figure 2(a) and sample images of eye with proliferative retinopathy are shown figure 2(b). These sample images are taken from Kaggle6].

Figure 2(a): No Diabetic Retinopathy.

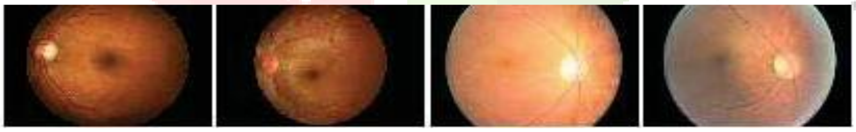


Figure 2(b):Proliferative Retinopathy.

When these blood vessels thicken, they can develop leaks, which can then lead to vision loss. The **four stages of diabetiretinopathy** are classified as mild, moderate, and severe nonproliferative and proliferative.

II. LITURETURE SURVEY

Multiple automated diagnosis systems have been developed over the last decade. Since human experts usually focus on some typical lesions associated with DR such as microaneurysms, hemorrhages and hard exudates (see Fig.1) when evaluating fundus photographs, many works paid attention to automatedly detect and segment these lesions or calculate some numerical indexes [3]. Shahin *et al.* [4] developed a system to automatedly classify retinal fundus images into those with or without proliferate diabetes retinopathy. They adopted morphological processing to extract pathological features such as blood vessels area and exudates area as well as two indexes including entropy and homogeneity. These features are fed into a shallow neural network and a sensitivity of 88% and a speci_city of 100% are obtained.

Jaafar *et al.* [5] proposed an automated algorithm, which mainly consist of two part: the top-down segmentation to segment the exudates legion and a polar coordinate system centered at the fovea to grade the severity of hard exudates. Based on a small dataset of 236 fundus images, it reaches a sensitivity of 93.2%. Casanova *et al.* [6] introduce an algorithm of random forest to discriminate people with or without DR with the accuracy of more than 90% and assess the DR risk based on graded fundus photographs and systemic dataThus, the deep learning method with the ability to learn signi_cant features directly from the fundus photography has aroused the attention of researchers in recent years. Quellec *et al.* [7] proposed a system to detect referable DR by employing a deep convolutional neural network (CNN) and automatedly segment DR lesions by creating heatmaps of the convolutional layer which shows the potential to discover new biomarkers in images. They adopted the CNN structure with an ensemble learning method from the solution ranked second in the Kaggle Diabetic Retinopathy competition [8] and obtained a good detection result with the area Az under the Freeresponse receiver operating curve (FROC) of 0.954 in the Kaggle dataset. Gulshan *et al.* [9] adopted a deep CNN model named Inception V3 to detect referable diabetic retinopathy (RDR) based on a development dataset which contains more than 128 thousand fundus images. Bene_ted from the large training data and well sifted expert grading to the fundus images, the work achieved an impressing performance with the area under the receiver operating curve (AUC) of 0.991/0.990 and sensitivity of 97.5%/96.1% on two different test sets respectively. Gargeya and Leng [10] proposed a method that combines deep CNN with traditional machine learning algorithm. In their work, fundus images are fed into a residual network after pre-processing, and then the characterization of images obtained from the last pooling layer of network, appended with several metadata variables, is sent into an decision tree classifier to differentiate between healthy fundi and fundi with DR. As a result, the method achieves an AUC of 0.94 with sensitivity of 0.93 and specficity of 0.87 on a test set obtained from public.

In this paper, a deep learning based method which is inspired by the diagnostic process of human ophthalmologists is proposed to automatically classify the fundus photographs into 2 types _ with or without RDR.

Diabetic retinopathy damages the retina of the patient. It is most frequent in the patients who have had diabetes for longer than 10 years. This problem is occurring in millions of people worldwide but medical practitioners and the tools required for detection of diabetic retinopathy is scare for serving the mass population. The work already was done to serve this problem using the application of machine learning but the efficiency of machine learning algorithm depends on the quality of feature extraction which requires domain knowledge. The work presented in this paper overcome the problem by using deep learning algorithm which automatically identifies the pattern and classifies the retina images into one of the five class based. "Automated Diabetic Retinopathy Detection Using Pretrained Deep Neural Network For Classification & Texture & Color Features For Feature Extraction**"** is the working strategy of our system.

III. PROPOSED SYSTEM

This section describes the workflow of the research and the Pretrained Deep learning algorithms used in this study. This section also explains how the dataset was generated, pre-processed, and trained and tested. "Fig. 1" shows the entire process used to build the machine learning models in this research. The workflow divided into two phase training and testing phase to build machine learning model. The data are split into training and testing phase, testing phase accounting for 80% of the total data. The remaining 20% are used as the test set. In training phase step by step procedure follows for overall system performance to predict accurate output. Same as like in testing phase, feature extracted from test data to given for the prediction. Feature construction transformed the raw input into meaningful forms, adding the nonlinearity and introducing the physics of the flow into the machine learning model.

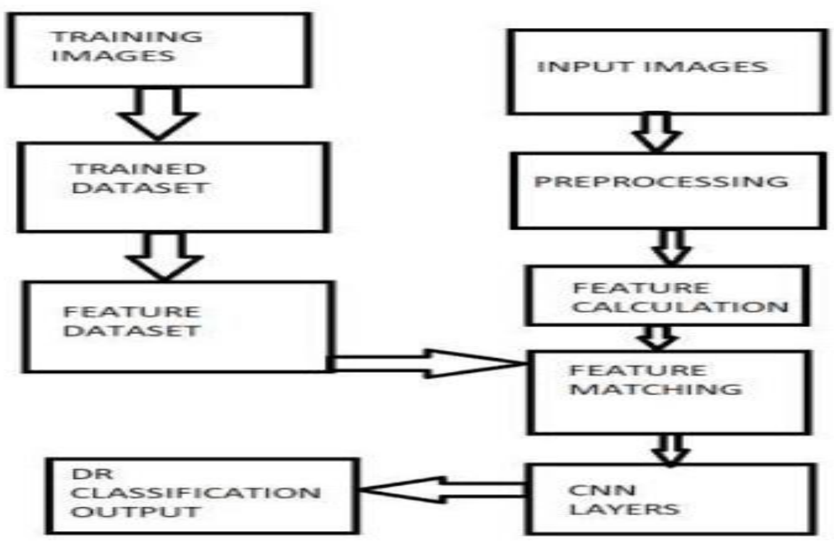


Figure3.Proposed Computerized Model.

- **Database**:- The database present in the study is microscopic image in the Jpeg or Png format. The dataset collected from the KAGGLE Data set. Kaggle allows users to find and publish data sets, explore and build models in a web-based data-science environment, work with other data scientists and machine learning engineers, and enter competitions to solve data science challenges. The image is first acquired through camera connected to the microscope. Despite the differences between Kaggle and typical data science, Kaggle can still be a great learning tool for beginners. Each competition is self-contained. You don't need to scope your own project and collect data, which frees you up to focus on other skills. The image is cap- tured in the jpg and png form. Another source to collect dataset related RBC images from internet source. ErythrocytesIDB is a standard database [2], which is available at //erythro- cytesidb.uib.es/. In Open-CV, the captured or imported RGB image is three dimensional and each pixel is represented by an element of a matrix whose size corresponds to the size of the image.

- **Pre-processing**:- To prepare the input images according to the standard input of the proposed system, pre-processing is applied on the dataset. The aim of pre-processing is an improvement of the microscopic image data that suppresses unwanted distortions or enhances some image features important for further processing. In pre-processing certain operation performed resize image, remove noise and destroyed unwanted spot or holes to gives wrong meaning. This is beneficial for accurate detection and classification of red blood cells. The acquired image in RGB form and converted into grey. Median filter used to remove noise, find all connected component and clear the border.

- **Feature Calculation**:-A feature is a piece of information which is relevant for solving the computational task related to a certain application. Features may be specific structures in the image such as points, edges or objects. Features may also be the result of a general neighborhood operation or feature detection applied to the image. The features can be classified into two main categories:
- **Feature extraction**:- is a process of dimensionality reduction by which an initial set of raw data is reduced to more manageable groups for processing. A characteristic of these large data sets is a large number of variables that require a lot of computing resources to process. Feature extraction is the name for methods that select and /or combine variables into features, effectively reducing the amount of data that must be processed, while still accurately and completely describing the original data set.

- **Feature Matching**:-Feature matching means finding corresponding features from two similar datasets based on a search distance. One of the datasets is named source and the other target, especially when the feature matching is used to derive rubbersheet links or to transfer attributes from source to target data. a process by which the nervous system sorts or Feature detection is filters complex natural stimuli in order to extract behaviorally relevant cues that have a high probability of being associated with important objects or organisms in their environment, as opposed to irrelevant background or noise.

- **Feature Dataset**:- A feature dataset is a collection of related feature classes that share a common coordinate system. Feature datasets are used to spatially or thematically integrate related feature classes.

- **Deep Neural Network**:-Deep Neural Networks (DNNs), also called convolutional networks, are composed of multiple levels of nonlinear operations, such as neural nets with many hidden layers (Bengio et al., 2007; Krizhevsky et al., 2012). Deep learning methods aim at learning feature hierarchies, where features at higher levels of the hierarchy are formed using the features at lower levels (Dean et al., 2012). In 2006, Hinton et al. (2006) proved that much better results could be achieved in deeper architectures when each layer is pretrained with an unsupervised learning algorithm. Then the network is trained in a supervised mode using back-propagation algorithm to adjust weights. Current studies show that DNNs outperforms GMM and HMM on a variety of speech processing tasks by a large margin (Hinton et al., 200).

1.1 NETWORK ARCHITECTURE AND IMPLEMENTATION.

The deep learning model proposed in this paper is a novel convolutional neural network with Siamese-like architecture of which block diagram is shown in Fig.2. Basically, the model accepts two fundus images corresponding to the left eye and right eye as inputs and then transmits them into the Siamese-like blocks. The information from two eyes is gathered into the fully-connected layer and finally the model will output the diagnosis result of each eye respectively, i.e., with or without referable DR. To a large extent, the pipeline of our model is inspired by the clinical diagnosis process of DR in real life. The detail of the model block, as well as the explanation of the network architecture is laid out in subsections below.

1.2 INCEPTION V3

Inception V3 [12] is a well known deep CNN model. The basic architecture of Inception V3 is shown in Fig.3. The outstanding performance of Inception V3 is benefited by several network connection techniques, such as adopting batch normalization, using MLPconv layers to replace linear convolutional layers and factorizing convolutions with large kennel size [12] [13]–[15]. With these techniques, the num- ber of the network parameters as well as the computational complexity are reduced significantly, and thus the network can be built much deeper and get stronger non-linear expres- sive ability than that of the conventional CNN models.By adopting the transfer learning method, Inception V3 can be customized to perform different image classification tasks. For example, it was modified to make several binarypredictions by replacing the final layer with customized layers to classify different stages of DR [9]. In this work, Inception V3 is embedded into the Siamese-like blocks of the network after removing the final layer in order to extract high-dimensional features of fundus images. Besides, the original rectified linear unit (ReLU) activation function used in Inception V3 is replaced by Leaky ReLU, since the latter one has a better characteristic of gradient propagation for large CNN models. The leaky rate is set to be 0.1.

1.3 SIAMESE-LIKE NETWORK STRUCTURE

In most cases, when patients take fundus examinations in the hospital, both of their eyes will be photographed. And rather than just watching the photograph of a single eye, ophthalmologists will put fundus photographs of both eyes together and make a diagnosis to retinal disease by referring to these two photographs and comparing them with each other since the physiological and pathological conditions of one eye has important guiding significance for the diagnosis .

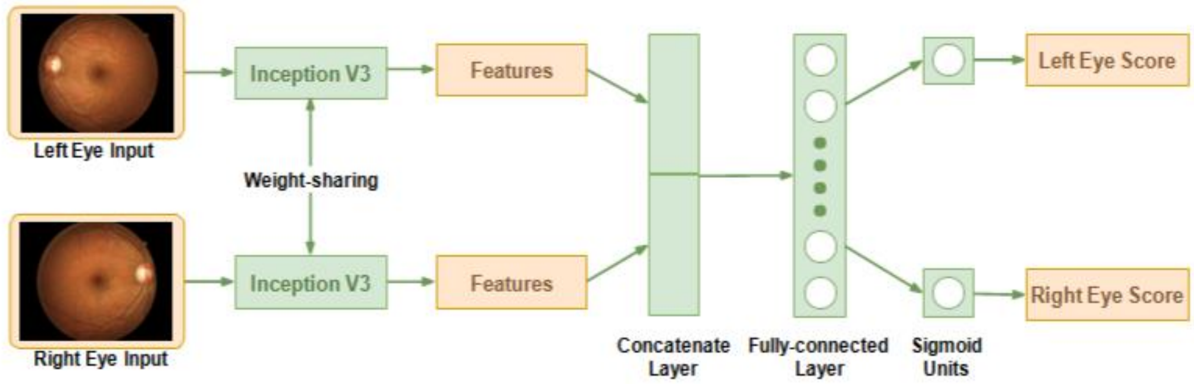
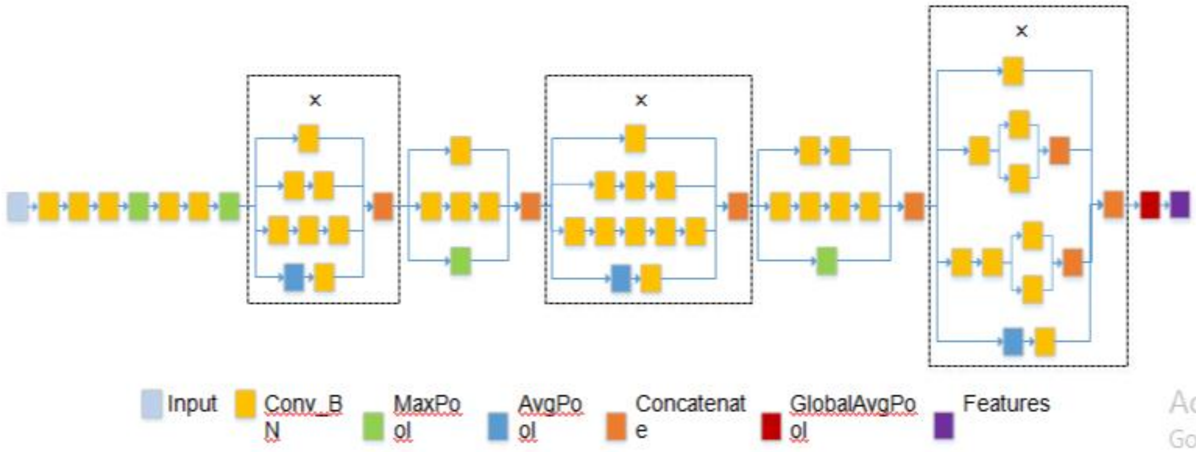


FIGURE 2. Block Diagram of the proposed Siamese-like binary classification convolutional neural network.



Block Diagram of Inception V3 architecture without the last layer. Conv_BN represents convolutional layer with batch normalization, MaxPool represents max pooling layer and AvgPool represents average pooling layer. "× t" represents that the structures in dashed blocks are repeated.(FIGURE;-4)

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

"Fig. 2" shows Analysis of normal cells ROI extracted from the microscopic image taken as input in "Fig. 2(a)".Resize input image are converted into gray scale and enhance quality of image in "fig.2 (d)". Morphological operation and threshold based segmentation is applied shown in "fig. 2(e)".obtain gray scale image to extract texture feature are HU-moment and haralick. "Fig. 2(g)" it can be concluded that cells detected as normal cells category. Same result it is concluded for "fig.3 (g)" Sickle cells.

4.1 PERFORMANCE EVALUATION

The measurement of an accuracy for the network architecture is estimated by correctly classified DR suffered images from the pool of images in the different dataset. Also evaluate the algorithm which will be suffered by over-fitting or under-fitting could be visualized by plotting the training and validation loss. A whole objective is to minimizing the cost function of the deep convolutional neural network results significantly reflected in the testing datasets. In terms of diabetic retinopathy performance measurements, Specificity(SP), Sensitivity(SE) and Accuracy(Acc) are the crucial parameters for deciding the algorithms. Four parameters which take part in measuring those performances are : True Positive(TP) - Correctly detected DR images True Negative(TN) - Correctly detected Non-DR images False Positive(FP) - Number of Non-DR images are detected wrongly as DR images False Negative(FN) - Number of DR images are detected wrongly as Non-DR images At last, the Sensitivity, Specificity and Accuracy are measured for each fundus images available in the database

Sensitivity(true positive rate or recall) measures how likely the test is positive who someone have a diabetic retinopathy. Specificity(true negative rate) measures how likely the test is someone don't have the diabetic retinopathy. Positive predictive value is also called as Precision.Accuracy measures the diabetic and non-diabetic patients from the database.

4.2 Hardware and Software requirements :

For augmentation, Image editor tool is used for contrast adjustment, color balance adjustment, rotate or cropping. At preprocessing stage, monochrome conversion and resizing is done with the numpy package. Convolutional Neural Network(CNN), multi-layer deep architecture are implemented using Theano and Lasagne libraries. Simple datasets are are handled with the hardware Intel i5 @2.30GHz, 4GB RAM Ubuntu 14.04 Theano API python libraries are used. For handling large kaggle dataset, Graphics Processing Unit is needed. Amazon EC2 web service instance is used.

4.3 CALCULATIONS

In the field of machine learning and specifically the problem of statistical classification, a confusion matrix, also known as an error matrix, is a specific table layout that allows visualization of the performance of an algorithm, typically a supervised learning one (in unsupervised learning it is usually called a matching matrix). Each column of the matrix represents the instances in a predicted class while each row represents the instances in an actual class (or vice versa). The name stems from the fact that it makes it easy to see if the system is confusing two classes (i.e. commonly mislabelling one as another). It is a special kind of contingency table, with two dimensions (”actual” and ”predicted”), and identical sets of ”classes” in both dimensions (each combination of dimension and class is a variable in the contingency table).

- Terminology and Derivation from confusion Matrix

Condition Positive(P)= the number of real positive cases in data.

Condition Negatives(N)= the number of real negative cases in the data.

true positive (TP) true negative (TN) false positive (FP) false negative (FN).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$TPR(TruePositiveRate)/Recall/Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity \ or \ True \ Negative \ Rate(TNR) = \frac{TN}{TN + FP}$$

$$Precision \ or \ positive \ predictive \ value(PPV) = \frac{TP}{TP + FP}$$

$$FScore = \frac{(2 * Precision * Recall)}{(Precision + Recall)}$$

4.4 RESULT ANALYSIS

Sensitivity is defined as the ability of a test to detect correctly people with disease. Sensitivity = TP / (TP + FN) Specificity is defined as the ability of a test to exclude properly people without disease condition. Specificity = TN / (TN + FP) True positive (TP) is the condition when a test result is positive and individual can detect the disease. True negative (TN) is the condition when the result is negative and individual is not diagnosed with the disease. False positive (FP) is the condition when a test result is positive and individual cannot express it. False negative (FN) is the case when the result is negative and individual can have it. SVM results in 68% accuracy. NPRTOOL classifier results in 61.6% and random forest results in 90% accuracy. After voting of three classifiers, the testing set results in 62.37% accuracy. Convolutional Neural Network approach produced accuracy of77.7%o,sensitivity score of 77.4% .This Proposed system results in Accuracy of 94%,Sensitivity of 93% and specificity of 94.71%.and this results are much better than the previous models with higher accuracy and high gain. Table Below shows the camparison between all reference model and Proposed System model.

TABLE 2:- Camparison between all Reference model and Proposed System model.

REF. NO.	METHODOLOGY	RESULT
1	Exudate Detection DR with Convolutional Neural Networks	An accuracy of 91.92%
2	Automated DR detection & Classification System	from 63.97% to 72.54% for sensitivity, 97.32% to 99.88% for specificity, 80.65% to 86.21% for accuracy.
3	Red Lesion Affected By Diabetic Retinopathy In Digital Fundus Image	Sensitivity = 88 % Specificity = 92 %
4	Automatic Diabetic Retinopathy Detection Using Digital Image Processing	Sensitivity = 87 %
5	Symptom Analysis of Diabetic Retinopathy by Micro-Aneurysm Detection Using NPRTOOL	61.6% sensitivity 41.4% specificity.
6	Implementation of Diabetic Retinopathy Prediction System using Data Mining	The accuracy of NN algorithm which is more than Naïve bayes algorithm and time required for classification for NN is less than naïve bayes also memory required for naïve bayes is greater than the NN. Hence NN is better than naïve bayes in terms of accuracy and time.
7	Diabetic Retinopathy Grade Classification based on Fractal Analysis and Random Forest	An accuracy of 62.37%
8	Automated Diabetic Retinopathy Detection Based on Binocular Siamese-Like Convolutional Neural Network	Sensitivity = 77.4 % Specificity=63.5%
	(PROPOSED METHOD.) AutomatedDiabetic Retinopathy Detection Using Pretrained Deep Neural Network.	Accuracy=94% Sensitivity=93% Specificity=94.71%

V. CONCLUSION AND FUTURE WORKS

Among other existing supervising algorithms, most of them are requiring more pre-processing or post-processing stages for identifying the different stages of the diabetic retinopathy. Also, other algorithms mandatorily requiring manual feature extraction stages to classify the fundus images. In our proposed solution, Pretrained Deep Neural Network,is a wholesome approach to all level of diabetic retinopathy stages. No manual feature extraction stages are needed. Our network architecture with dropout techniques yielded significant classification accuracy . True positive rate(or recall) are also improved. This architecture has some setbacks are: An additional stage augmentation are needed for the images taken from different camera with different field of view. Also, our network architecture is complex and computation-intensive requiring high-level graphics processing unit to process the high resolution images when the level of layers stacked more.

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