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Restricted Boltzmann Machine Learning Based Detection and Classification of Diabetic Retinopathy

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ABSTRACT

Diabetic retinopathy is a complication of diabetes that targets the eyes by damaging retinal blood vessels. Initially it is asymptomatic or causes fluctuating vision problems. As it becomes severe it affects both the eyes and eventually causes partial or complete vision loss. Primarily occurs when the blood sugar level is unmanageable. The person with diabetes mellitus is always at high risk of acquiring this disease. The early detection can cause the contingency of complete and permanent blindness. The paper proposed Restricted Boltzmann Machine learning algorithm for the early detection of diabetic retinopathy. The densely connected convolutional network densenet-169 is applied for the early detection of diabetic retinopathy and it classifies the images based on its severity levels as no diabetic retinopathy , mild, moderate, severe and proliferative diabetic retinopathy. The datasets with total 410 images were evaluated to train the model and among them are 192 normal images, 46 are in mild stage, 117 are in moderate, 24 are in severe and 31 are in proliferate diabetic retinopathy state. The proposed method is accomplished through various steps data collection, preprocessing, augmentation and modeling with 95% accuracy achieved.

INTRODUCTION

Diabetic Retinopathy (DR) is long-term diabetic micro vascular complication and is major cause of vision loss due to changes in retinal blood vessels. The main visual loss due to DR can be prevented by routine checks and timely intervention at the initial stage. Damage to small blood vessels in the retina is the cause of DR. The retina is light sensitive network that blocks the inside of the eye. It can range from minor to severe. During the initial stages, changes in blood vessels occur but there may be no symptoms. Over time loss of vision can occur if damaged blood vessel such as liquid or bleeding leaks. The diabetic retinopathy ranks 4th as cause of global blindness after cataracts, glaucoma and macular degeneration based on WHO data (2016) survey. It caused 1.9% of severe visual impairments globally and 2.6% of blindness in 2010. The prevalence of retinopathy in patients with DM in the world in 2012 was 35% and 7% among them were the prevalence of proliferative retinopathy.

It is also known as diabetes which causes damage to the retina of the eye and can eventually cause blindness. This is a manifestation of ocular diabetes. Apart from alarming statistics, research shows that at least 90% of new cases can be reduced if there is proper care, alertness and eye monitoring. It can be diagnosed in 5 stages: mild, moderate, severe, proliferative or no disease. The characteristics of this disease include micro aneurysms, leakage of blood vessels, swelling of the retina, abnormal growth of new blood vessels and damaged nerve tissue. Diabetic retinopathy is a micro vascular complication of diabetes mellitus that attacks blood vessels in the retina. To identify this disease is still done manually through the retinal image that is examined by an ophthalmologist and requires a long time. Hence, research is needed to make it easier for ophthalmologists to identify diabetic retinopathy through retinal images so that accurate and fast examination results can be obtained.

Deep Collaborative Network (DCN) has undirected connections between hidden layers composed of stacked Restricted Boltzmann Machines. It uses unsupervised pre-training by contrastive divergence and then fine-tunes the weights by back propagation. The parameters for the stacked RBM are trained by maximum likelihood learning algorithm. In second stage, pre-trained network will be adjusted by supervised learning model such as logistic regression with gradient descent learning process. When compared to other machine learning classifiers the classification time and training time of RBM is maximum. Many researchers have adopted classifiers such as logistic regression, support vector machines and RBM are used in the final layer of DCN. The effects of different parameters such as number of hidden layers, learning rate, momentum value and weight decay values are not much investigated in the paper.

The paper introduces recent literature review in section 2, section 3 discusses the framework of Machine Learning Based Detection and Classification of Diabetic Retinopathy. Restricted Boltzmann Machine learning algorithm for the early detection of diabetic retinopathy is highlighted in section 4. Section 5 discuss the Diabetic Retinopathy predicted mapping result for training data sample and methodology, the experiment design, setup, metrics and results are presented and finally the conclusion.

LITERATURE SURVEY

Convolutional neural networks are more widely used as a deep learning method in medical image analysis and they are highly effective. For this article, the recent state-of-the art methods of DR color fundus images detection and classification using deep learning techniques have been reviewed and analyzed. Furthermore, the DR available datasets for the color fundus retina have been reviewed. Difference challenging issues that require more investigation are also discussed [1].

The author discuss[2] Deep learning techniques like Deep Neural Networks, Convolution NeuralNetworks have been used to Diabetic Retinopathy detection by using retina images. Thisarticle presents the study of Diabetic Retinopathy and the review of deep learning techniques used in medical imaging especially for Diabetic Retinopathy diagnosis and classification by using publically available retina image datasets.

A cross-sectional study of patients with suspected diabetic retinopathy (DR) who had an ophthalmological examination and a retinal scan is the focus of this research. Specialized retinalimages were analyzed and classified using OPF and RBM models. Classification of retinographs was based on the presence or absence of disease-relatedretinopathy. RBM and OPF models extracted 500 and 1000 characteristics from the imagesfor disease classification after the system training phase for the recognition of retinopathy and normality patterns [3].

The author explained [4] how experts are categorized those diabetic retinopathy in to five stages such as normal, mild, moderate, severe Non-Proliferative (NPDR) or Proliferative diabetic patient(PDR). A proposed deep learning approach such as Deep Convolutional Neural Network (DCNN) gives high accuracy in classification of these diseases through spatial analysis. A DCNN is more complex architecture inferred more from human visual prospects. Amongst other supervised algorithms involved, proposed solution is to find a better and optimized way toclassifying the fundus image with little pre-processing techniques. Retinal screening contributes to early detection of diabetic retinopathy and timely treatment. To facilitate the screening process, we develop a deep learning system, named Deep DR that can detect early-to-late stages of diabetic retinopathy. Deep DR is trained for real-time image qualityassessment, lesion detection and grading using 466,247 fundus images from 121,342 patients with diabetes. Evaluation is performed on a local dataset with 200,136 fundus images from 52,004 patients and three external datasets with a total of 209,322 images [5].

3. PROPOSED MACHINE LEARNING BASED DIABETIC RETINOPATHY PREDICTION MODEL

Diabetic retinopathy is a micro-vascular complication of diabetes mellitus that attacks bloodvessels in the retina. To identify this disease is still done manually through the retinal image thatis examined by an ophthalmologist and requires long time. Therefore research proposed to make it easier for ophthalmologists to identify DR through retinal images so that accurate andfast examination results can be obtained. The figure1 represents normal retina and Diabetic Retinopathy.

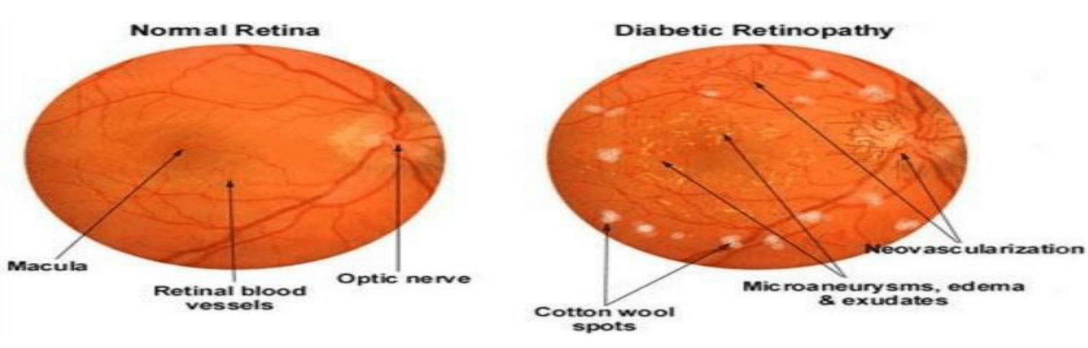


Figure.1 Normal Retina and Diabetic Retinopathy

The data analytics become automated using many techniques, processes and algorithms that work over raw data for better real time application. The information is very useful to optimize processes in increasing the overall efficiency of system. The real time factors for system are inspecting process, cleansing, transforming and modeling data with the goal of discovering useful information, suggesting conclusions and supporting decision-making.

By suggesting informed decisions and biasing for irregular guessing in today's business world data analysis is one among scientific decisions maker in helping businesses operate more effectively. The process of data analysis mainly includes Data requirements, Data collection, Data processing, Data Training, Modeling, algorithms and Data Product. Figure 2 represents proposed framework of Deep Collaborative Network (DCN) based Acute Rheumatic Fever prediction model.

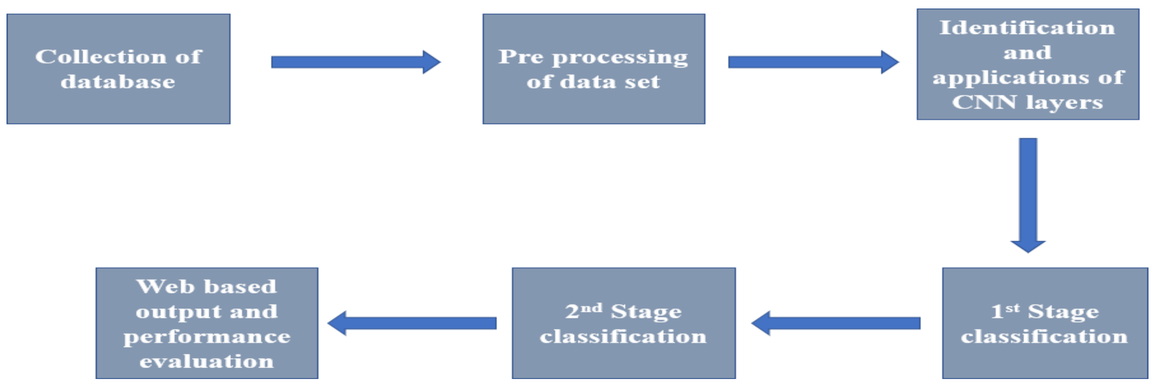


Figure.2 Framework of ML Based Detection and Classification of Diabetic Retinopathy

The process of gathering information of predefined variables pattern in an established systematic fashion will increase the system efficiency. The data collected includes classification of retinopathy data such as mild, moderate, severe and proliferative diabetic retinopathy count. In large data set choosing smaller part of data set and using that subset for viewing or analysis. Training Data is kind of labeled data set used to train deep learning algorithms to make it learn from such data sets and increase accuracy while predating the results. Testing data is quite different from training data as it is a kind of sample of data used for an unbiased evaluation of final model fit on training dataset to check model functioning.

Depending on the prediction target tasks can be classified as regression task or classification tasks. During training the gradient propagates back to convolution through final layer. When building deep learning model three-layer types are specified and layer which passes the features of dataset and there is no computation that occurs in this layer is input layer. It serves to pass features to the hidden layers. The layers between input layer and output layer are hidden layer and there can be more than one. It performs the computations and pass all information to output layer. Output layer represents layer of neural network that will give the results after training the model. It is responsible for producing output variables.

Different training strategies will be used to analyze the performance of model. The accuracies for each training have high variance. In order to solve this problem, K-fold cross-validation can be used. Usually, K is set to 10. In this technique, the model is trained on the first 9 folds and tested on the last fold. The iteration continues until all folds have been used. Each of the iterations gives its own accuracy. The accuracy of model becomes the average of all these accuracies. Predictive models are prone to problem known as over fitting. The scenario whereby the model memorizes the results in training set and isn't able to generalize on data that it hasn't seen.

Deep Neural Network is a feed forward network with more than one hidden layer. Each hidden neuron typically uses the logistic or sigmoid activation function. It requires labeled data in the whole back propagation training process to adjust its weights. It generally needs large amount of balanced labeled data, but the majority of industry data lack such labels. Deep Collaborative Network (DCN) has undirected connections between hidden layers composed of stacked RBM. It uses unsupervised pre-training by contrastive divergence and then fine-tunes the weights by back propagation. The parameters for the stacked RBM are trained by maximum likelihood learning algorithm. In second stage, pre-trained network will be adjusted by supervised learning model such as logistic regression with gradient descent learning process.

RESTRICTED BOLTZMANN MACHINE TRAINING USING MAXIMUM LIKELIHOOD LEARNING ALGORITHM

Restricting the connections between nodes in a Boltzmann machine to only those between hidden and visible node is the

Restricted Boltzmann machine (RBM). Figure 2 shows a simplistic rendering of RBM using maximum likelihood learning algorithm with six visible nodes and four hidden nodes. RBMs can themselves be used as classification, regression, or generative models. A single regression label or class soft max label to the visible units allows for supervised learning and trained model can generate representative samples of the data distribution given clamped visible label unit. The most important use of RBM for the purposes of this study is building block of DCN which trained in an unsupervised manner.

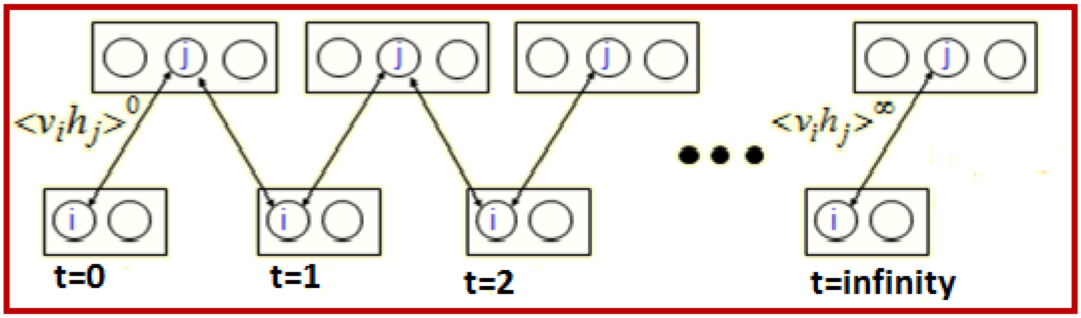


Figure.3 Restricted Boltzmann Machine using Maximum Likelihood Learning Algorithm

Training RBM follows the same principles regardless of its intended use. The energy of a particular state of stochastic binary visible (i) and hidden (j) units is:

$$E(\mathbf{v},\mathbf{h}) = -\sum_i a_i v_i - \sum_j b_j h_j - \sum_{i,j} v_i h_j w_{ij}$$

…….(1)

Energy with configuration v on the visible nodes and h on hidden nodes. A binary state of visible unit I, binary state of hidden unit j, weight between units i and j are the important component of the maximum likelihood learning algorithm for an RBM. The fig.3 describes matching model for visible and hidden nodes. By start with training vector on the visible nodes. Then alternate between updating all the hidden nodes in parallel and updating all the visible nodes in parallel.

$$\frac{\partial \log p(v)}{\partial w_{ij}} = <v_i h_j>^0 - <v_i h_j>^\infty \qquad \text{……………(2)}$$

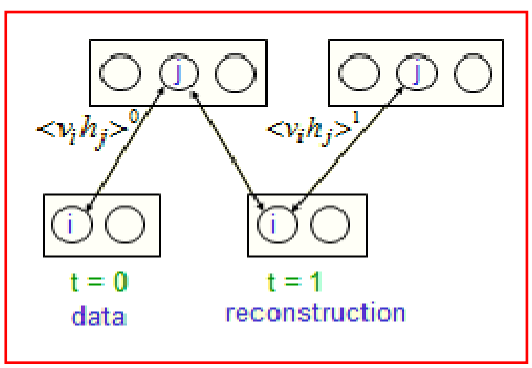


Figure 4 Matching Model for hidden and visible nodes

$$\Delta w_{ij} = \varepsilon\,(<v_i h_j>^0 - <v_i h_j>^1) \qquad \text{……………(3)}$$

Let h is the model parameters where a and b are visible and hidden nodes biases respectively. w is the weight matrix connecting the two layers. The connection restriction inherent in RBM greatly simplifies in learning and model generation. Since the hidden and visible nodes factorize completely, sampling for the entire hidden or visible layers can be done in parallel.

For monitor over fitting a validation set that is roughly 1.5 % the size of training set is selected and resulting 98.5% of the dataset is used for training in batch sizes determined by the user. Each epoch trains the RBM a batch at a time by calculating single step for the entire batch in matrix operations. There are number of hyper parameters that are considered for updating test and train data set are listed in table.1

EVALUATION PERFORMANCE OF TESTING AND TRAINING METHODS

The dataset for research work consists of test data and train data. It has the necessary data for classification and prediction of the rheumatic fever attributes. The collection of raw data is the first step in creating flow for calculations. Splitting of data assures the network is trained and tested for better output. Training data is labeled data set used to train deep learning algorithms to increase the accuracy while predating the results. Testing data is quite different from training data sample used for an unbiased evaluation of final model fit on training dataset to check model functioning. The target is correct output in the dataset for testing accuracy of the trained network. Learning is the method of modifying weights of connections between neurons of a specified network. It is classified into supervised learning, unsupervised learning and reinforcement learning. During training of model under unsupervised learning input vectorsof similar type are combined to form clusters. When new input pattern is applied to neural network model which gives an output response indicating the class to which input pattern belongs. The type of learning where the network itself must discover the patterns and features from input data and relation for input data over the output. The classification is a process of learning to distinguish the data of samples into different classes by finding common features between samples of the same classes. Regression is set of methods for modeling the relationship between one or more independent variables and dependent variable. The purpose of regression is most often to characterize the relationship between inputs and outputs. The predictions made in the hidden layer are collected to produce final layer which is the model's prediction.

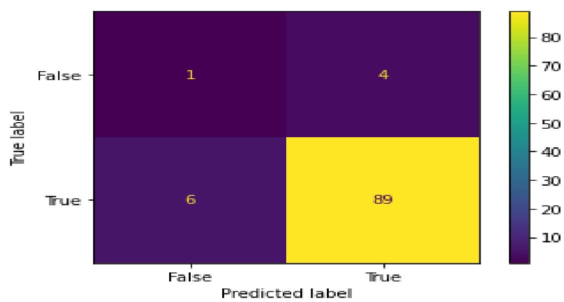


Figure 5 Diabetic Retinopathy predicted mapping result for training data sample

The output graph figure 5 represents outcomes of the train dataset. Diagonal represents true values of dataset and remaining are false values of dataset.

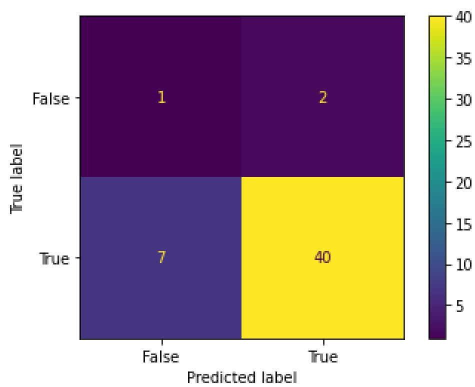


Figure 6 Diabetic Retinopathy predicted mapping result for test data sample

Similarly output graph figure 6 represents the outcomes of test Dataset. Diagonal represents true values of dataset and remaining are false values of dataset. Table.1 shows accuracy comparison chart for two set of training and test data sample. The accuracy results in trail 1 comprise for 91.67± 0.05 for training time of 7.69m with 0.05 model dropout error, 92.45± 0.89 for training time of 10.67m with 0.89 model dropout error, 93.45± 0.50 for training time of 18.96m with 0.50 model dropout error, 94.78± 0.02 for training time of 21.56m with 0.02 model dropout error. It concludes that maximum accuracy 94.78% is obtained at less model dropout error of 0.02. Similarly for trail 2, accuracy 91.23± 1.05 for training time of 19.78m with 1.05 model dropout error, 92.34± 0.08 for training time of 30.10m with 0.08 model dropout error, 93.46± 0.01

for training time of 38.38m with 0.01 model dropout error and 94.67± 0.03 for training time of 19.78m with 0.03 model dropout error respectively.

Table 1. Accuracy Result of Train and Test dataset

No of depths	Training Time1 (m)	Test Case I Accuracy	Training Time 2 (m)	Test Case II Accuracy
1	7.69	91.67±0.05	19.78	94.67±0.03
2	10.25	83.45 ±0.03	42.46	91.23±1.05
3	8.35	87±1.05	27.87	92.67±1.25
4	11.34	90.45 ±0.01	19.09	93.21±0.05
5	16.54	83.45 ±1.79	27.20	90.23±0.08
6	11.23	83.45 ±0.03	38.38	93.46±0.01
7	10.67	92.45 ±0.89	39.70	94.07±1.25
8.	21.56	94.78 ±0.02	26.92	91.67±0.05
9.	23.55	86.45 ±1.34	30.10	92.34±0.08
10	18.96	93.45 ±0.50	52.13	90.12±0.25

DEEP BELIEF NETWORK IMAGE CLASSIFICATION PROCESS

After obtaining the value of 24 features in the feature extraction process using GLCM, the next process is the image classification process using the Deep Belief Network method. The initial stage of the classification process is the process of training data input training or training data. In this study we used 97 input data to be trained. The Restricted Boltzmann Machine (RBM) algorithm is used the number of codes used during the training process, in this method will also use the Contrastive Divergence (CD) algorithm to determine the best value of the weight. The implementation was executed using python language, where a wide variety of libraries were employed for processing of images and to get acquainted with the system for creating convolutional neural network like DenseNet-169. The type of library utilized for image management (like rotation and resizing) and preprocessing was OpenCV. However, the mathematical functions required for the implementation was performed by NumPy. TensorFlowand Scikit-learn were also used for efficient management of deep learning models and for defining the model. The implementation of model makes use of GPU enable device for easier and faster processing. The output obtained is the result of identification of normal retinal images and retinal diabeticretinopathy images. The data obtained from kaggle used in this study are retinal images consisting of normal images and images of diabetic retinopathy.

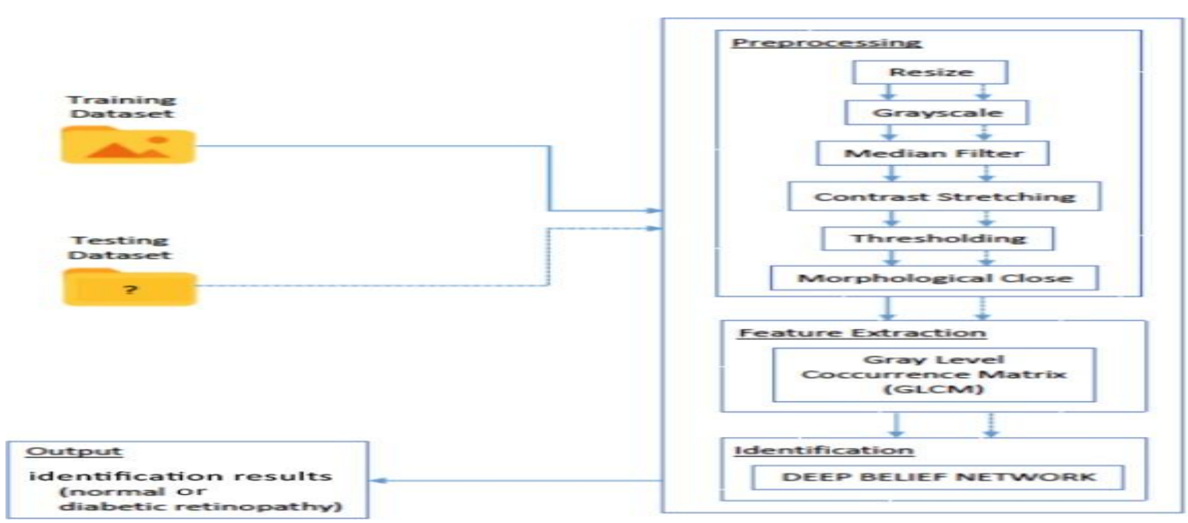
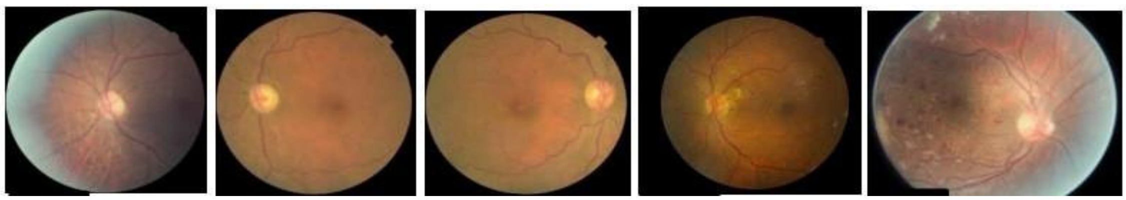


Figure 7 Image classification process using Deep Belief Network

Data used for this study has been taken from Diabetic Retinopathy Detection 2015 and APTOS 2019 blindness detection from kaggle. Both the datasets contains thousands of retinal images under different conditions. For every subject, two images of both the eyes are given asleft and right. The images come from different sources like different cameras, different models, etc. It has an abundance of noise associated with it, which apparently needs to be removed, thus, requiring a number of preprocessing steps. The diabetic retinopathy associatedwith each image has been rated on the scale of 1-5 as:



1. No DR 2. Mild 3. Moderate 4. Severe 5. Proliferative DR

Resizing In the initial stage of the pre-processing process, it is resized to change the imagesize by reducing the size of the image in the horizontal and / or vertical direction to 256x256.This aims to uniform the size of each image used during the training and testing process. The retinal image received is colour image, so the gray scale process needs to be done first to get an image with grey level. This filter is used to eliminate salt & pepper type noise which is often found in retinal images. The median filter works by replacing the value of a pixel with the median value of allpixels in a window.

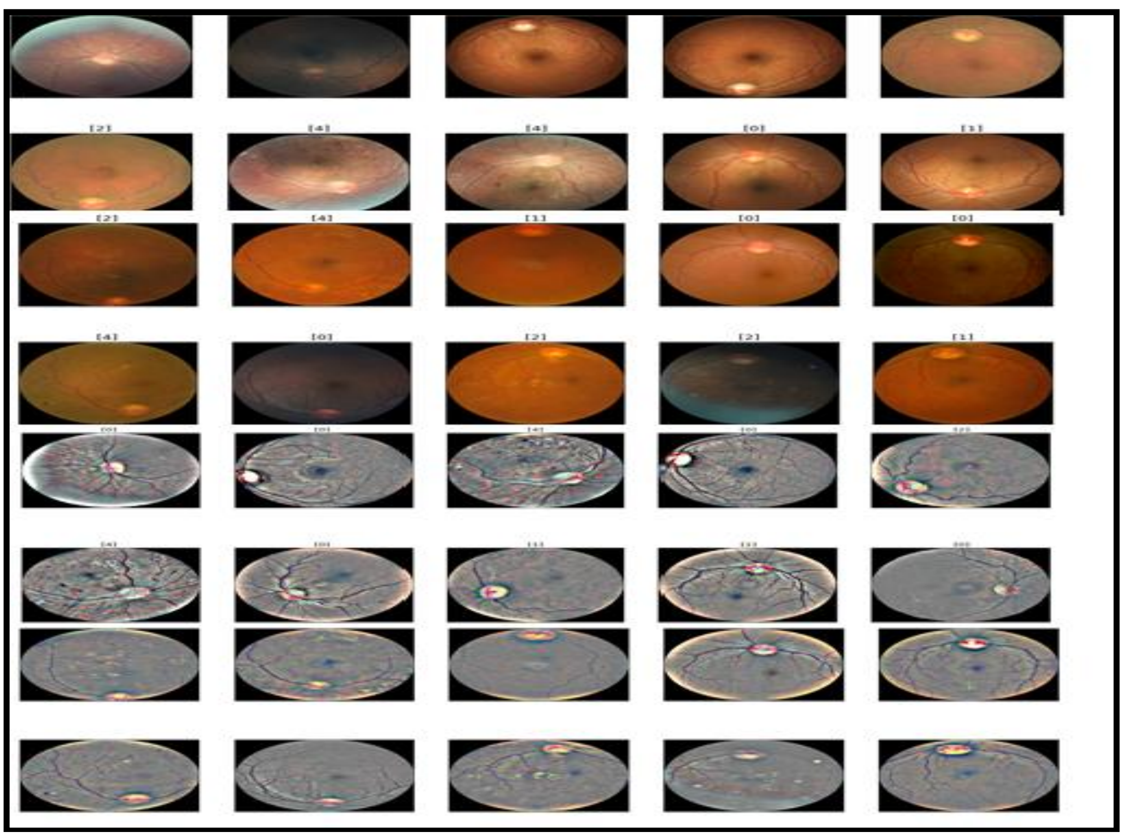


Figure 8 Process of resizing process and identifying Diabetic Retinopathy

The next process is to improve image quality using stretching. Contrast stretching is used toimprove image contrast so that features in the retinal image can be seen more clearly. The next step uses threshold technique to obtain binary images with values 0 and 1 (Blackand White). After the pre-processing stage, the next step is feature extraction. The research proposes feature extraction is Grey Level Co-occurrence Matrix (GLCM) method. Masking is binary image that is used to take certain parts. Masking must have the same dimensions as image as input image. The training set is used to tune the model parameters where the model learns from training data. But in order to produce an independent measure of the model's performance test set is used. The final test is introduced and evaluation results including the characteristics of the classifier

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based on its performance on final to compare to prior work. As shown in figures 9 & 10 we tried to reduce over fitting. A suitable and acceptable accuracy on the test data is obtained substantially. The model with dropout layers performs the best on test data.

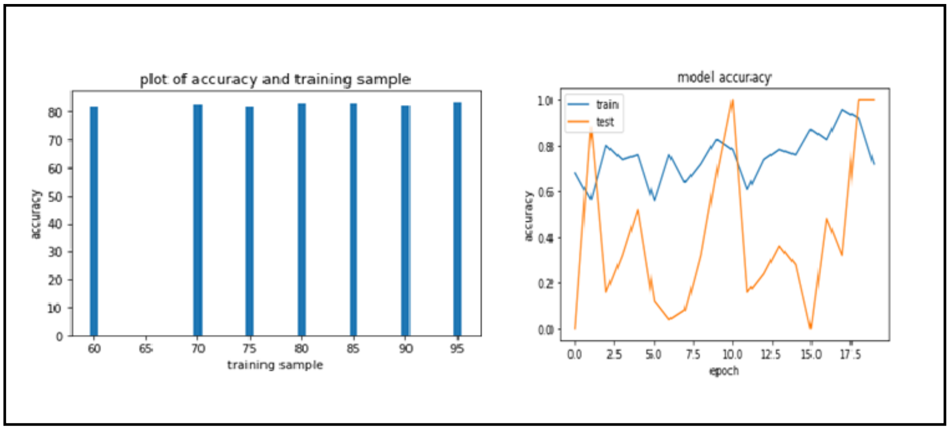

Figure.9 Refinement result for model parameters

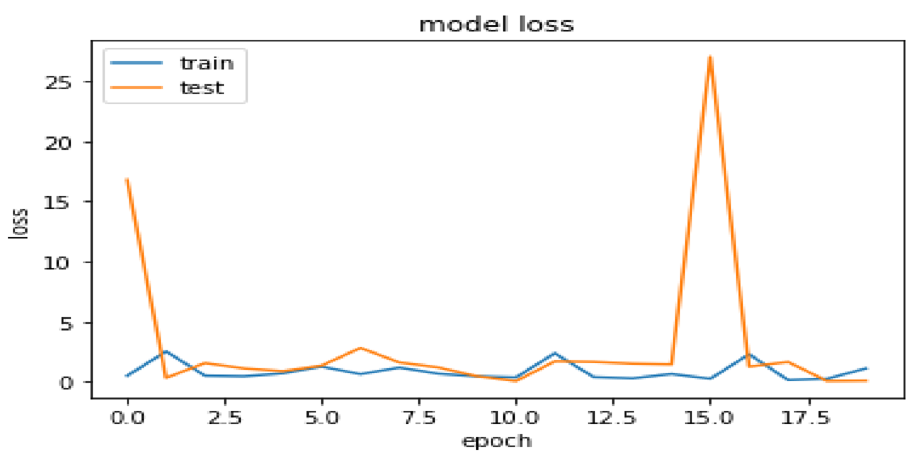

Figure.10 Evaluation result of over fitting

We randomly choose 70 percent of the target trials and 70 percent of the non-target trials as training trials. Since we have 80 trials, we would have 56 training trials for each subject. A total of 410 images were evaluated to train the mode. In these images there are 192 normal images, 46 are in mild stage, 117 are in moderate, 24 are in severe and 31 are in proliferate Diabetic Retinopathy. Figure 11 shows the number of images we used and its types.

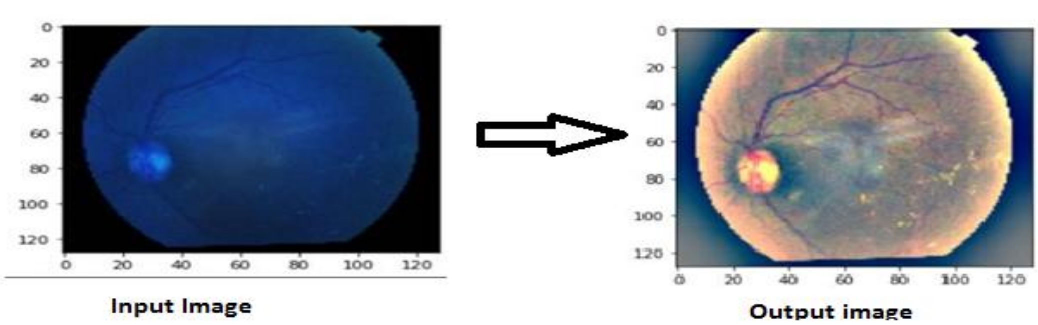

Figure 11 Image data flow from input to output

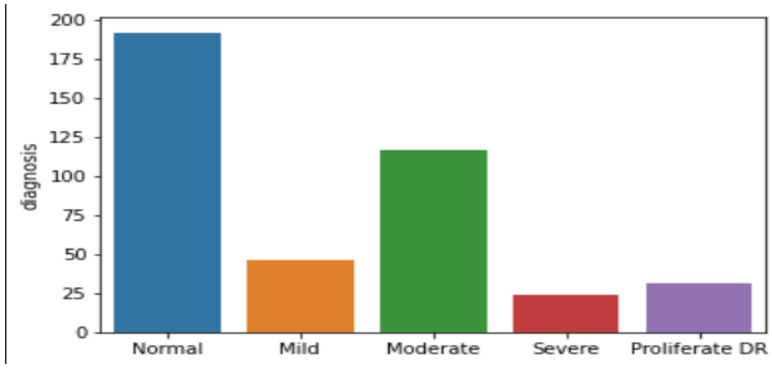

Figure 12. Image ratings

The diabetic retinopathy associatedwith each image has been rated on the scale of 1-5 as:
No DR, Mild, Moderate, Severe and Proliferative DR.Input images is scaled down to 256x256. shows the database input images and itsresized monochrome images.

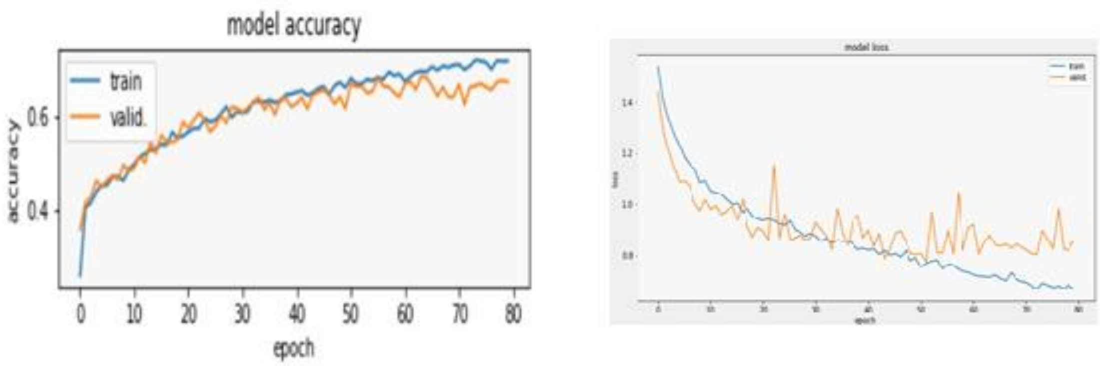

Figure 13. Graph representation of model accuracy

Figure13 shows the graphical representation of Model AccuracyX-axis(epoch), Y-axis(accuracy). An epoch means training the neural network with all the training data for one cycle.

CONCLUSION

Traditional method for detection of DR is prolonged, challenging and costly, thus many researches were brought up to automate the detection process by using machine learning and deep learning approaches. In this work, we presented a comprehensive study of various methodologies for detecting diabetic retinopathy automatically and attempted to propose our own deep learning approach for the early diagnosis of retinopathy by using a DenseNet169 Two datasets: 'Diabetic Retinopathy Detection 2015'and'APTOS 2019 blindness detection' from kaggle were used together for this study. A lot of preprocessing and augmentation was done to standardize the data in a desired format and to remove the unwanted noise. Beside DenseNet-169 classifier, we also used a regression model to draw the comparison between the results. Moreover, machine learning classifiers like SVM, DT and KNN were compared with the proposed system. Where the best accuracy among all was obtained by the proposed model and it also classifies the images into more no of classes. Our proposed model performed better than the regression model by achieving the accuracy of 90% however, 78% accuracy was yielded by the regression model.

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