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DETECTION OF PROLIFERATIVE DIABETIC RETINOPATHY USING HISTOGRAM OF ORIENTED GRADIENTS

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Abstract—Proliferative Diabetic retinopathy comes under the Opthamolic Disease. The most common cause of blindness among diabetes is diabetic retinopathy. The two primary kinds of diabetic retinopathy are proliferative diabetic retinopathy (PDR) and Non proliferative diabetic retinopathy (NPDR). Proliferative diabetic retinopathy is the term used to describe the rapid development of aberrant blood vessels in fundus images of eye. As a feature extraction, the histogram of oriented gradients is used the magnitude and direction of the fundus images are calculated by this hog feature extraction. Deep learning and machine learning models are currently quite useful for categorising the stage of blindness. Analysis of 3662 Grayscale fundus images. The Proposed method achieved accuracy of 99.9%,98.9%,80.99%,and99% with Support Vector Machine, Random Forest, Voting Algorithm, Gradient Boosting and Decision Tree machine learning Classifiers.

Index terms: Diabetic Retinopathy, Histogram of Oriented Gradients, Support Vector Machine, Random Forest, Gradient Boosting, Voting Algorithm, Decision Tree.

IINTRODUCTION

Diabetic Retinopathy (DR) is more prevalent in patients with long-term diabetes[1]. In general, there are four stages of diabetic retinopathy. The different types of diabetic retinal disease are mild, moderate, severe, and proliferative. The process which undergoes proliferative Diabetic retinopathy has characteristic called Neovascularization [2] and which does not undergoes the abnormal growth in retina blood vessels then Non Neovascularization takes place. The people with high blood sugar levels causes blindness if they are not treated in the initial stage of blindness. The retina of the diabetic people when they are directed by sunlight or other flash light they may not able to see the object. In the beginning stages of Diabetic retinopathy the Ophthalmologists usually suggests to Control the Sugar levels and maintain the proper diet and make a habitat to perform the exercise without skipping. Even though it is not controlled then he used to start the Laser Treatment and will be in the Doctors Observation. In this Paper Proposed a Machine Learning approach for Classification of fundus images and to detect the risk of vision loss in the initial days and to start the Treatment.

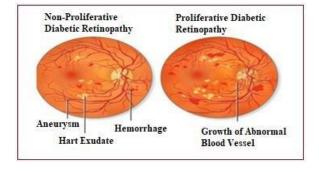


Figure 1: PDR and NPDR[3]

1.1 DATA PREPARATION

In this Paper Gray scale Fundus images dataset having a size of 224 X 224 pixel size [4]which is publicly available in the Kaggle Datasets. This dataset Consists of total of a 3662 images .This dataset is mainly categorized into five Classes. No DR, Mild, Moderate Severe, Proliferative DR are the Classes having 1805,370,999,193,295 number of fundus images in each class. The fundus images are of PNG file format. The Jupyter Notebook is used for performing the Classification of Classes. We need to Observe the the dataset along with CSV file.

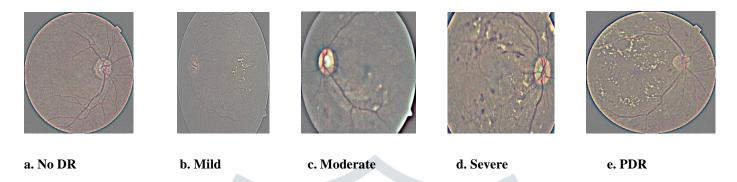


Figure 2: Stages Of Diabetic Retinopathy

These are the five classes we considered as 0,1,2,3,4. Here by figures above we can clearly observe the effect of abnormal blood vessels contained in the hallow part of organ i.e; the fundus image which was examined by the Ophthalmologists.

II LITERATURE SURVEY

M.C.S.Tang et al[5]: Introduced a deep learning approach for neovascularization detection based on transfer learning .A network based on the combination of ResNet18 and GoogleNet is proposed. These two networks are combined using a depth concatenation layer. The performance of the combined network is compared to that of the original pretrained network which include AlexNet,GoogleNet,ResNet18 and ResNet50. Among all ResNet18 and GoogleNet combination outer perform other pretrained networks in detecting neovascularization through transfer learning and Obtained an accuracy of 91.5%.

Gondal et al[6]: Discussed a CNN model for the Diabetic Retinopathy. They are doing a binary classification as normal and mild stages and evaluated a performance using the DiaretDB1 dataset with 93% accuracy.

Prasad et al[7]: Discussed the segmentation techniques and morphological operations to detect the microaneurysms, exudates and blood vessels. According to the reported technique, feature extraction was performed by Haarwaylet transformations.

Srivastavaetal[8]: Describes about diabetic retinopathy including hemorrhages and micro aneurysms using retinal digital photographs. In this approach, Frangi based filtration was performed for blood vessel detection. In the initial stage, Preprocessing was done to decompose the input Image in to smaller sub images and then filtration was implemented one very sub image. Extracted features obtained by filters were fed into SVM for further classification of input images whether images contained lesions or not. The experiments were done on 143 fundus images and achieved an accuracy of 87%.

II EXISTING METHOD

Collected the fundus images from Messidar, Diaretdb0 Datasets available on kaggle websites publicly and performed a Pre-Processing and feature extraction using the Convolutional Neural Networks as shown in figure3 in that to reduce the computational time transfer learning approach is performed[5] i.e.; performed with combination of ResNet18 and GoogleNet Pretrained network and also compared with other pre-trained networks and used for model training and (stored in Test.csv with image ID and its diagnosis label) are used for model testing .The messidar dataset is used for training and some of the images of Diaretdb0 and classified into 80% testing and 20% testing data.To overcome the computational time and better classification the proposed method is implemented in the below subsection.

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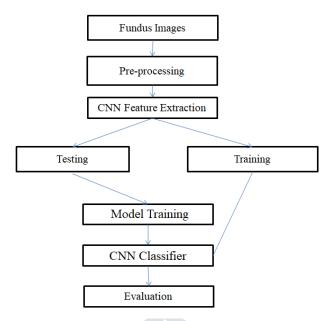


Figure3: Existing Method

III PROPOSED METHOD

The Collected dataset fundus images are given as input to the Pre-Processing at which any noise, missing data are observed manually or by calculating the mean we can identify it. Later the Processed images is given to the feature extraction process. The extracted features are extracted from Hog Feature descriptor and given to the Classifiers like Support Vector Machine, Random Forrest, Gradient Boosting, Voting Algorithm and Decision Tree to detect the stage of a Retinopathy [9] and performance of accuracy is Calculated and Observed the Classification as shown in the figure 4.

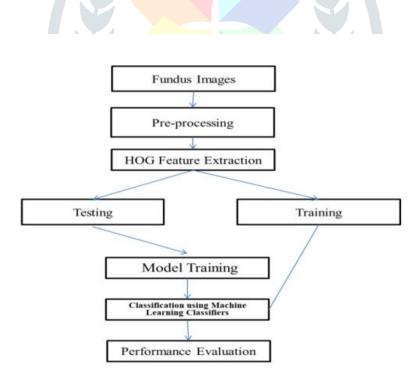


Figure4: Proposed Method

IV METHODOLODY[9]

There are 3 main stages mainly Pre-processing, Feature Extraction, Classification

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A. Pre-Processing

Pre-Processing is the key role for building the Machine Learning Model. Importing the Libraries and Datasets. Splitting the data for training and testing and identifying the missing data. Considered dataset also consists of Comma Separated Values format such that the fundus image dataset information are stored in a tabular form.

B. Feature Extraction

Histogram of Oriented Gradients is used for our feature extraction purpose. HOG is used to extract the information of edges magnitude and Orientation of edge here Orientation means angle Calculated between the direction of the pixel values in a fundus images.

C. Classification

1.Support Vector Machine

The Support Vector Machine (SVM) is a method of supervised machine learning used for classification. The SVM approach seeks a hyperplane in an N-dimensional space that identifies the data points with highly accurate. In the case of two input features, the hyperplane is basically a line. If three input features are present, the hyperplane turns into a 2-D plane. The hyperplane turns into a 2-D plane if there are three input features. Support Vector Machine mainly performs best in binary Classification than the multiple Classification.

2.Decision Tree

One of the machine learning classifiers is the decision tree. A decision tree is a visual representation of a problem's solution based on the conditions provided[10].

3.Random Forest

Random Forest is the one of the Supervised Learning Approach. It comes under the Concept of Ensemble Learning at which it is used to combine the more than two classifiers to solve the complex problems[10]. This Classifier mainly gives better performance for Larger Datasets. Even though Random Forest Classifier is used for Classification and Regression tasks it is more suitable for Regression tasks thus it is a major drawback.

4. Voting Classifier:

A voting classifier is a machine learning model that learns from the training data of a variety of models and predicts an output (class) based on the class that has the highest probability of becoming the output [10].

5.Gradient Boosting Classifier:

Gradient boosting classifiers are a type of machine learning techniques that combine numerous weak learning models to produce a powerful predictive model. Decision Trees plays a key role in the Gradient Boosting Classifier.

V PERFORMACE METRICS[11]

Our Proposed Project is performed in Window 11 with Intel i5 Processor using the Anaconda Software by launching the Jupyter Notebook with Python Programming Language and imported the pandas, numpy, scikit, opency, os, sys Libraries to train and test the considered dataset fundus images to detect the Proliferative Diabetic Retinopathy.

Accuracy: It is the number of correctly classified cases divided by total number of instances

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

Sensitivity: It is the probability of True Positives in the Class.

Sensitivity =
$$\frac{TP}{TP+FN}$$

Specificity: It is the probability of True Negatives in the Class.

Specificity =
$$\frac{TN}{TN+FP}$$

Precision: It is defined as how accurately correctly predicted to the total positive predictions.

Precision =
$$\frac{TP}{TP+FP}$$

Recall: It is defined as corrected predicted to the total number of Classes.

$$Recall = \frac{TP}{TP + FN}$$

F1score:It is defined as total weighted average of precision and Recall.

$$F1 = 2*\frac{\textit{Precision*Recall}}{\textit{Precision+Recall}}$$

Here TP=True Positive, TN=True Negative, FP=False Positive, FN=False Negative

VII EXPERIMENTAL ANALYSIS

A. Confusion Matrix: Confusion Matrix is used to calculate the Performance of the Classifier. In the Confusion Matrix it is represented in the matrix form. It Compares the True Label i.e.; Correctly Predicted to the Actually Predicted Values. Confusion Matrix is of a NXN Matrix here N represents the number of Classes considered for Classification.

1.Random Forest

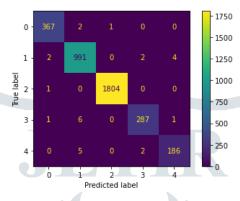


Figure5: Confusion Matrix of Random Forest

2.Decision Tree

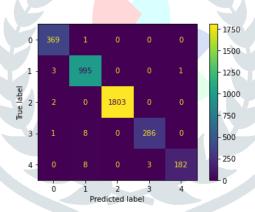


Figure6: Confusion Matrix of Decision Tree

3.Support Vector Machine(SVM)

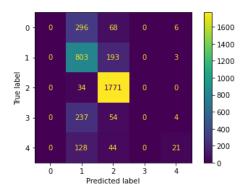


Figure7: Confusion Matrix of SVM

4. Gradient Boosting Classifier

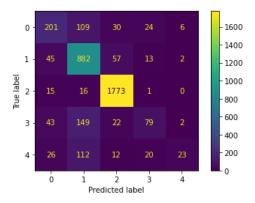


Figure8: Confusion Matrix of Gradient Boosting Classifier

5. Voting Classifier

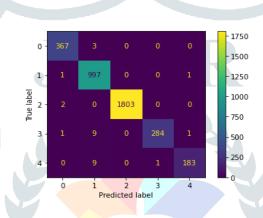


Figure9: Confusion Matrix of Voting Classifier

B.Classification Accuracy

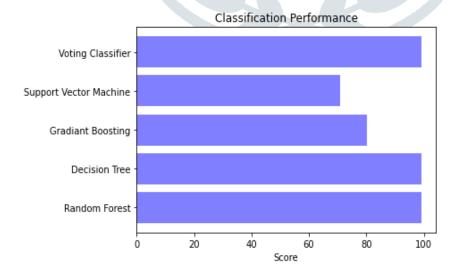


Figure 10: Comparision plot of Classifier Accuracy

TABLE 5.1 COMPARISION OF RESULT VALUES

| Type of Classifier | Accuracy |
|------------------------|----------|
| CNN | 91% |
| Random Forest | 99% |
| Decision Tree | 99% |
| Gradient Boosting | 80% |
| Support Vector Machine | 99% |
| Voting Classifier | 99.9% |

VI CONCLUSION

In this Paper the fundus images with diabetic retinopathy were detected with HOG feature Extraction and machine Learning Algorithm Classifiers like Support Vector Machine, Gradient Boosting, Random Forest, Decision Tree, Voting Algorithm.Out of five Classifiers Voting Classifier gives 99.9% Accuracy which is the best Performance to detect and classify the Proliferative Diabetic Retinopathy.

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