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Research Article

Automated Detection and Classification of Diabetic Retinopathy using Machine Learning and Ensemble Techniques

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ABSTRACT

Diabetic retinopathy is an eye condition caused by chronic diabetes. Diabetes is a serious consequence because it can harm blood vessel tissue that is sensitive to light. People of working age are predominantly affected by this ailment. At first, diabetic retinopathy may show no symptoms. On the other hand, it can eventually result in blindness. The suggested approach makes use of the Local Binary Pattern feature extraction technique. The K Nearest Neighbour, Random Forest, and Logistic Regression algorithms are given the features that were extracted. Stacking, voting, and averaging are ensemble strategies that combine them during training and testing. Images of diabetic retinopathy, which are categorized as mild, moderate, no diabetic retinopathy, proliferating diabetic retinopathy, and severe, are gathered for this project from the Kaggle dataset. The experimental results show that averaging produces good results of 74%.

Keywords: Local Binary Pattern (LBP), Diabetic Retinopathy (DR), K Nearest Neighbour (KNN), Random Forest (RF), Diabetes, Voting classifier.

1.INTRODUCTION

Diabetic Retinopathy is the most frequent eye disease among diabetics and the leading cause of blindness in the population. The human eye is the vision-sensing organ. Diabetic retinopathy (DR) refers to the impact of diabetes on the eye, particularly on the retina, which is the specialized nerve tissue of the eye.It damages the blood vessels within the retina, by leakage of blood and fluids into the surrounding tissue [1]. Diabetic retinopathy impacts a significant proportion of diabetic individuals globally, affecting as much as 80% of them, and it stands as one of the primary causes of blindness within the United States. In the western world, it is the second primary reason for vision loss, and specifically among individuals of working age, it is the predominant cause of blindness. In the United States, the rate of retinopathy among adults aged 40 years and above is 3.4% or approximately 4.1 million individuals. Among these, the rate of vision-threatening retinopathy, which is considered the most damaging type, is 0.75% or around 899,000 people [2]. Diabetic eye disease consists of two forms of diabetic retinopathy. They are Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR).

The earliest stage of diabetic retinopathy is called non-proliferative diabetic retinopathy. There are many people with diabetes. Small blood vessels leak in NPDR, causing retinal enlargement. Macular edema is the medical term for macular enlargement [3]. The most important typical cause of diabetes-related vision loss Retinal blood vessels can also close as a result of NPDR. This is known as macular ischemia. When this happens, the spot cannot receive blood. Exudates, small particles, can sometimes form on the retina. They can also damage our vision. Everyone with NPDR has blurred vision [4]. The most severe stage of diabetic eye disease is called PDR. When the retina begins to sprout new blood vessels, this happens and so, it is called as neo vascularization. The vitreous often bleeds into these delicate new blood vessels [5]. Some dark floaters can be seen if they bleed a little. If the bleeding is severe, they may lose their vision. The tissue created by these new blood vessels can scar. Scar tissue can damage the macula or cause retinal detachment. PDR is quite dangerous and can damage both central and peripheral vision.

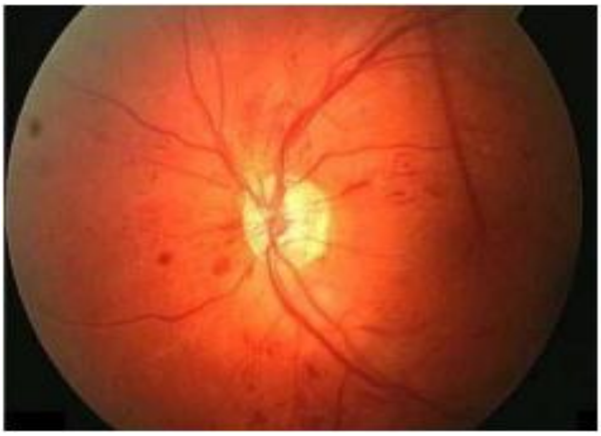


Fig. 1a Non-Proliferative Diabetic Retinopathy

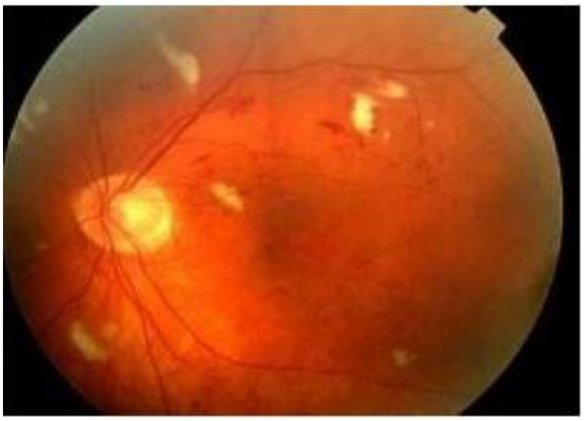


Fig. 1b Proliferative Diabetic Retinopathy

The diabetic Retinopathy is classified into four stages namely mild, moderate, severe and Proliferative Retinopathy according to National Eye Institute (NEI). From the bottom of the retina there is a leakage of blood and fluid which appear as spots is called as lesions [6]. The lesions are identified as red lesion or shiny lesions, whereas red lesions are associated with microaneurysms (MA) and hemorrhage (HM), while the bright lesions involve soft and hard exudate (EX).

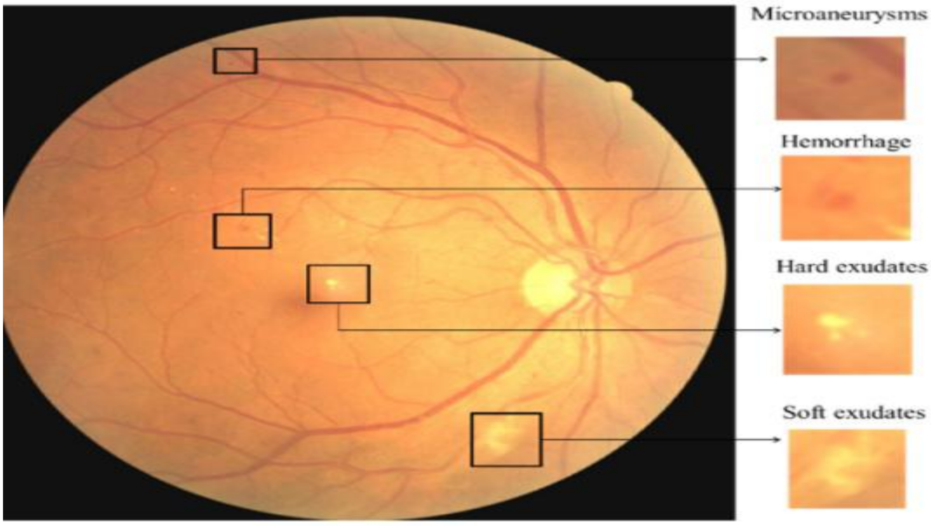


Fig 2 Different types of DR Lesions

Hard exudates seems as bright yellow spots, while soft exudate, also known as cotton, resembles as fine, yellowish white spots caused by nerve fibre damage. Minute swellings or bulges distinguish the early stage of diabetic Retinopathy in the retina's blood vessels [7]. These swollen spots are referred to as microaneurysms. Small amounts of fluid may seep into the retina due to these microaneurysms, causing the macula, or the rear of the retina, to expand. Despite this, there are frequently no obvious signs pointing to a problem.

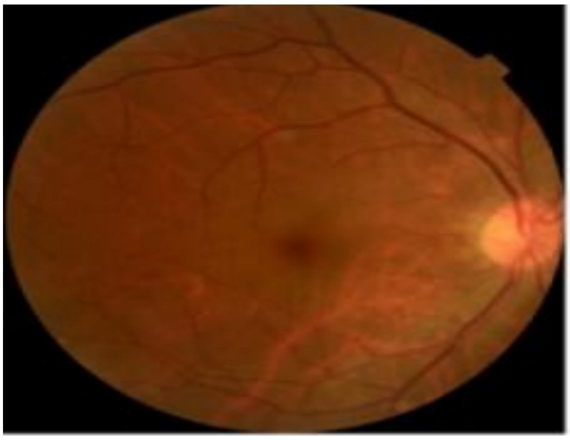


Fig 3a DR Image

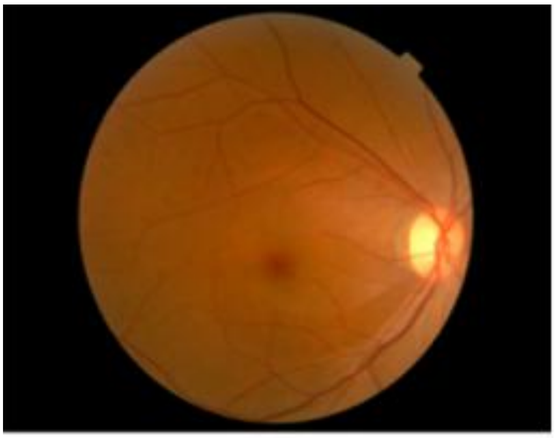


Fig 3b Mild Retinopathy

At this point, the small blood vessels enlarge even more, obstructing blood supply to the retina and inhibiting adequate nutrient uptake [8]. If blood or other fluids accumulate in the macula, blurring of vision is the only observable symptom in this stage. It is also called proliferative retinopathy. At this point, the blood vessels become even more clogged. This means that even less blood goes to the retina. Because of this, scar tissue is formed [9]. The lack of blood signals your retina to create new blood vessels. When the blood vessels become completely blocked, it is called macular ischemia. This can cause blurred vision and dark spots, which some call "floaters.". In this stage there is a high chance of loss of vision [10]. Once the vision is lost in this stage, probably there is no chance to get back vision again.

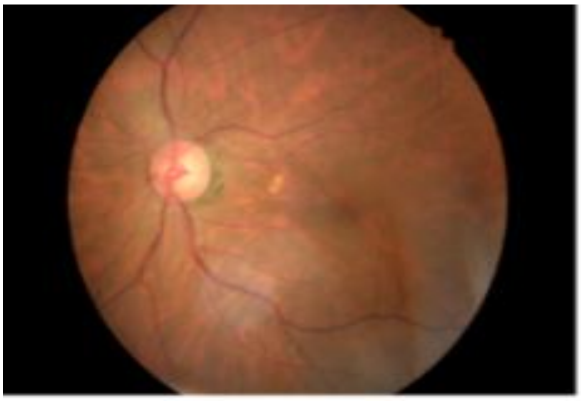


Fig.4a Moderate Retinopathy

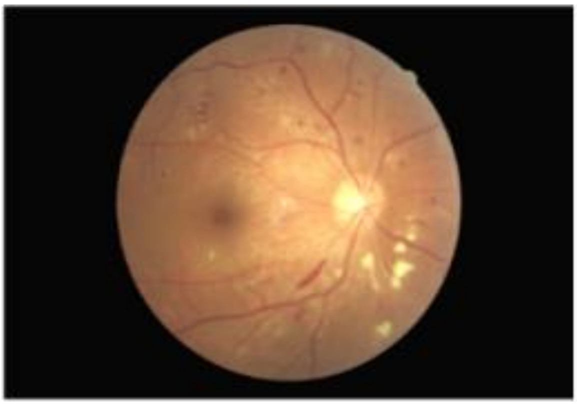


Fig.4b Severe Retinopathy

In the last stage of the disease, new blood vessels continue to grow in the retina. These thin, weak blood vessels bleed easily, causing scar tissue to form in the eye [11]. This scar tissue can pull the retina away from the back of the eye, causing a retinal detachment. Retinal detachment usually results in blurred vision, decreased vision, and even permanent blindness.

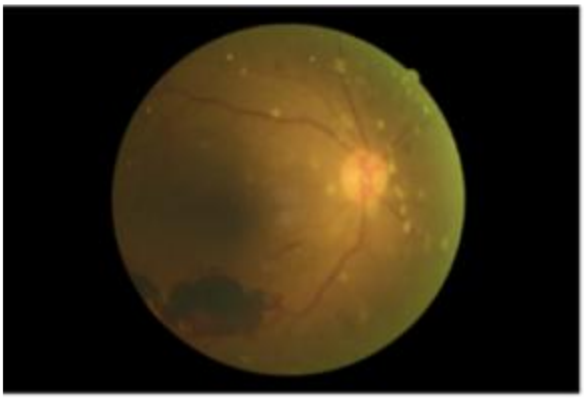


Fig.5 Proliferative DR

Literature Survey

In the proposed work a four class classification namely hard exudates, haemorrhages, Microaneurysm, and soft exudates is used to identify the retinal abnormalities [12]. The work consists of pre-processing, Optic Disk removal, Blood vessel removal, Segmentation of abnormalities, Feature extraction, Optimal feature selection, and Classification. For this DIARETDB1 datasets have been used. For preprocessing Contrast Limited Adaptive Histogram Equalization and then optic disc removal is done by open-close watershed transformation. After the segmentation is done top hat transformation and Gabor filtering is used. The features are extracted using Local Binary Pattern, Texture Energy Measurement, Shanon's and Kapur's entropy. The extracted features are fed into Deep Belief Network (DBN)-based classification algorithm and Modified Gear and Steering-based Rider Optimization Algorithm (MGS-ROA) by comparing with Neural Networks, KNN, SVM, DBN and the conventional Heuristic-Based DBNs, such as PSO-DBN, GWO-DBN, WOA-DBN, and ROA-DBN with the evaluation metrics. It was found that it gives the highest accuracy of Accuracy of 0.93182.

In this research [13] work two datasets were used namely MESSIDOR and IDRiD were used to find out the severity of DR using the fundus images. In order into find out the severity of DR it is graded and classified. The steps involve segmentation, feature set extraction, feature optimization using cuckoo search and convolutional neural network (CNN) is used. When comparing it was found that CNN givesthe maximum accuracy of 97.55%. In this work [14] automatic and early detection of DR is diagnosed. To extract the ophthalmoscopic features from the retina images based on textural gray-level features like co-occurrence, run-length matrix, coefficients of the Ridgelet Transform are used. And also, Sequential Minimal Optimization (SMO) classification is used to classify the retina images. When compared with Kaggle & DIARETDB1 datasets, Kaggle got the 91.05% and DIARETDB1 datasets have received the highest accuracy of 97.05%

In order to detect the early stage of DR [15] using deep convolutional neural network namely pooling, dropout and softmax layers, pre-trained denseNet 121 was used many modifications and trained APTOS 2019 dataset on multi-class classification to detect the severity of DR with accuracy of 96.51%. A hybrid method [16] was proposed to detect the DR, for this 400 retinal fundal images was used MESSIDOR database for which bichannel CNN combining the features of entropy images of the gray level and the green component was preprocessed by unsharp masking which achieves the highest accuracy of 93%. To reduce the blindness due to diabetics a combined multi scale shallow CNN was proposed [17]. For this images was collected from was collected from Kaggle datasets which was classified into five class classification, which attained the highest accuracy of 92%.

3. METHODS

3.1 Feature Extraction

The **Local Binary Pattern (**LBP) model is another feature extraction method frequently used to filter the textures and patterns in an image. By comparing each pixel's value to those of the neighboring pixels, it establishes the local representation of the texture. The LBP approach involves these steps. Building an LBP texture description to convert the image to grayscale is the first stage. The LBP descriptor only works with pixels in a fixed 3 × 3 neighbourhood.

• The central pixel is taken into account, and its threshold is set against its surrounding eight pixels.

• If the center pixel's intensity is greater than or equal to that of its neighbour, we keep the value at 1 or set it to 1.

• Either in a clockwise or counter clockwise direction, the LBP value for the central pixel is calculated.

• The binary test is run on the 8 neighbours in the 3 x 3 neighbourhood.

• After storing the binary test results in an 8-bit array, we transform them to decimal values.

LBP is regarded as uniform if it has no more than 0-1 or 1-0 transitions.

• For each pixel in the input image, the thresholding, collection of binary strings, and storage of the output decimal value in the LBP array processes are repeated.

• The output LBP array's histogram is then computed.

• Because there are 256 different patterns in 3 x 3 neighborhoods, a minimum value is 0 and a maximum value is 255.

Consequently, we create a 256-bin histogram of LBP.

Finally, the output array contains the calculated value.

$$LBP(P,R) = \sum_{p=0}^{p-1} f\left(g_p - g_c\right)2^p$$

P is the number of neighboring pixels selected at the radius R, where gp and gc denote the pixel intensities of the current and nearby pixels, respectively. As a result, each pixel's LBP descriptor is shown as follows:

3.2 Contextual of the Proposed system

i) Logistic Regression

One of the most often used Machine Learning algorithms, within the category of Supervised Learning, is logistic regression. Using a predetermined set of independent factors, it is used to predict the categorical dependent variable [21]. In a categorical dependent variable, the output is predicted via logistic regression. As a result, the result must be a discrete or categorical value. Rather of providing the exact values of 0 and 1, it provides the probabilistic values that fall between 0 and 1. It can be either yes or no, 0 or 1, true or false. Instead of constructing a regression line, we fit a "S" shaped logistic function, which predicts one of two maximum values (0 or 1). Logistic Regression is a major machine learning approach because it can generate probabilities and classify new data using both continuous and discrete datasets. Logistic Regression can be used to categorise observations using many forms of data and can quickly discover the most efficient factors for classification.[22] The logistic function is depicted in the following image:

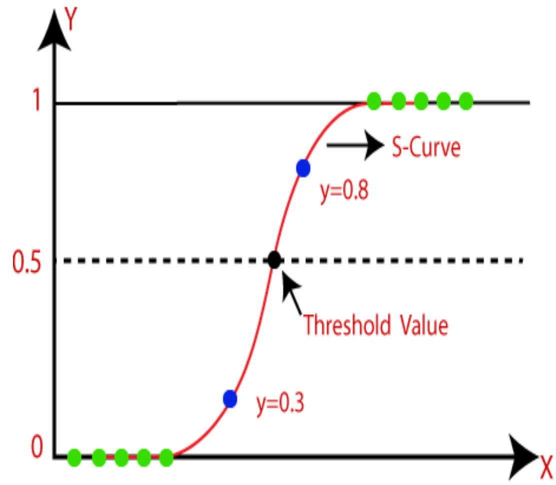


Fig. 6 Logistic Regression

Logistic Function (Sigmoid Function)

- The sigmoid function is a mathematical function that maps predicted values to probabilities. Map each real value to another value in the range 0 to 1. Logistic regression values must be between 0 and 1 and must not exceed this limit, resulting in an 'S' shaped curve.
- The sigmoidal curve is called the sigmoid function or logistic function. Logistic regression uses the concept of a threshold that defines the probability of 0 or 1.
- For example, values above the threshold tend to be 1, and values below the threshold tend to be 0.

The logictic equation of a straight line is

$$Y=a_0+a_1 x + a_2x_2 + a_3x_3 + ...a_nx_n$$

In the logistic regression y value is divided by (1-y) since y value lies between 0 to 1

$$\frac{y}{1-y}; \text{ 0 for } y=0, \text{ and infinity for } y=1$$

There are three types of logistic regression. They are Binomial, Multinomial and Ordinal where Binomial works on only two class classification of dependent variables, multinomial logistic regression works on three class classification of unordered types of dependent variables, ordinal works on more than 3 possible ordered types of dependent variables.

ii) Random Forest Algorithm

Random forest [23] is made up of individual decision trees that work together as an ensemble. In random forest, individual trees divide class prediction, and the class with the most votes becomes the model's prediction. The main idea behind random forest is the integration of several uncorrelated trees that work together to predict. Random forest employs two strategies to ensure that the behaviour of any individual tree is not overly associated with that of the other trees in the model [24]. The first method is known as bagging, and it takes use of the fact that decision trees are very sensitive to the data they are trained on, and even minor modifications to the training set can result in huge improvements.

iii) KNN – K Nearest Neighbour

KNN is a traditional machine learning technique that is mostly used to handle classification and regression problems[25]. KNN classifies datasets based on the similarity measurement of the distance function. It is a non-parametric supervised learning technique with multiple applications in data mining, image processing, intrusion detection, pattern recognition, and other fields. The classification of data in KNN is determined by the majority of votes cast for the nearest neighbour. In KNN, the number of neighbours is the most crucial deciding factor in the classification process. In addition, the method uses all of the training data in the testing phase, removing the need for distinct data points for training model creation.

The time and expense factors increase in order to scan all available data points that demand additional storage. The KNN technique involves selecting the k nearest data points, followed by classification of the points based on the majority of votes for the k neighbours. The class with the most votes from their objects is chosen for prediction. The Euclidean, Hammington, and Minkowski distance functions calculate the distance between data points and find their nearest neighbours. KNN's performance improves when the number of features is reduced. Overfitting occurs as the number of characteristics increases.

iv) Ensemble Techniques

This section focuses on developing a highly reliable computer-aided medical system. The features extracted in the first portion are used to train several models in this section. Ensemble learning is a method in which several machine learning models are trained and improved predictions are generated, hence improving the performance of single machine learning models. The term "ensemble" refers to the predictors that are trained to make predictions [26]. Classifiers to distinguish between stages of diabetic retinopathy and the outputs of all classifiers are combined**.**

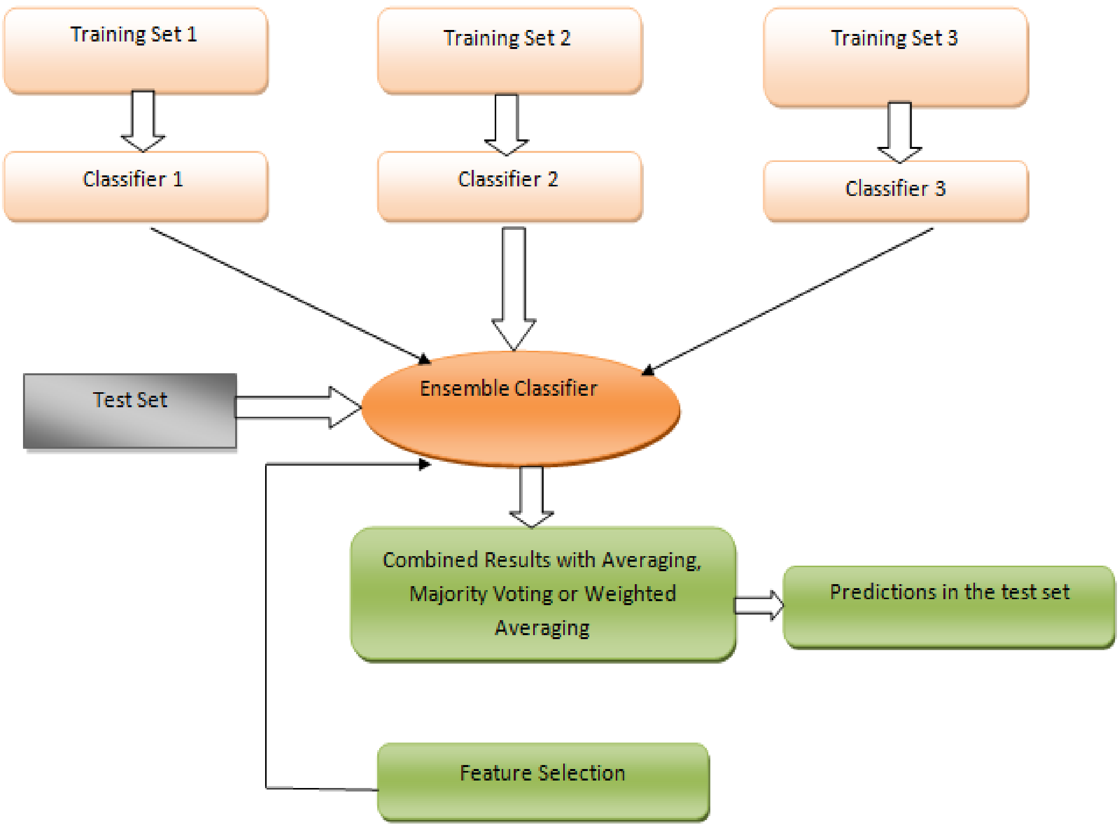


Fig.7: Ensemble classification

In this paper, various ensemble algorithms are used to improve the accuracy of Diabetic Retinopathy. The main objective is to merge the multiple classifiers to attain better performance when compared to the individual classifier. In the proposed work three different machine learning models, namely logistic regression, random forest, and KNN classifiers, are merged finally training and testing is done which produces the results. Stacking is an ensemble technique in which a meta-classifier is used to integrate various classification models. Each model passes its predictions to the model in the layer above, and the model in the topmost layer takes decisions depending on the models below. Several layers are stacked one on top of the other [27]. The initial dataset's input features are fed into the bottom layer models. The prediction is made by the top layer model using the bottom layer's output. The original data is fed into various separate models during stacking. The weights of each model are then computed, and the meta classifier is then used to estimate the input and output of each model. The models that perform the best are chosen, while the rest are eliminated. A meta classifier called the majority voting classifier is used to integrate any classifier through majority vote. The majority of the classifiers' projected class label would be the final class label. The final class label d_j is defined as

$$d_j = mode\{c_1, c_2, \ldots. c_n\}$$

where $\{c_1, c_2, \ldots. c_n\}$ represents the individual classifiers that participate in the voting.

4. EXPERIMENTAL RESULTS

4.1 Dataset

The dataset collected from the Kaggle data repository. The dataset contains five classes diabetic retinopathy images such as mild, moderate, no_dr (no diabetic retinopathy),proliferate_dr and severe. The mild contains 370 images, moderate contains 999 images, no_DR contains 1805 images, proliferate_DR contains 295 images and the severe contains 193 images. In this work 80% data taken for training and 20% taken for testing. There are three kinds ensemble technique used to classify the diabetic retinopathy disease. They are voting classifier method, averaging method and stacking method.

4.2 Performance Measures

To evaluate the performance of Ensemble classification techniques of Random Forest, K Nearest Neighbour and Logistic Regression using Stacking, Voting and Averaging techniques, a set of evaluation parameters namely Accuracy, Precision, Recall, F-score and ROC are used in this work. These measures are determined based on the confusion matrix derived from the outcome of the classification process. The confusion matrix is 5*5 matrix containing a set of four elements, namely True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) where TP identified as prediction is correct, TN as prediction is wrong, FP as correct value is predicted wrong, and FN as wrong value is predicted right. They are defined as follows:

Accuracy

A measuring system's accuracy is the amount of measurement that produces genuine (no systemic mistakes) and consistent (no random errors) results.

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

Precision

The number of true positives (TP), or the number of items correctly labeled as belonging to the positive class, divided by the total number of elements labeled as belonging to the positive class (i.e., the sum of true positives and false positives, or items incorrectly labeled as belonging to the class), is used in classification work to determine the precision for the class.

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

Recall

Recall is defined as the number of TP divided by the total number of items in the positive category

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

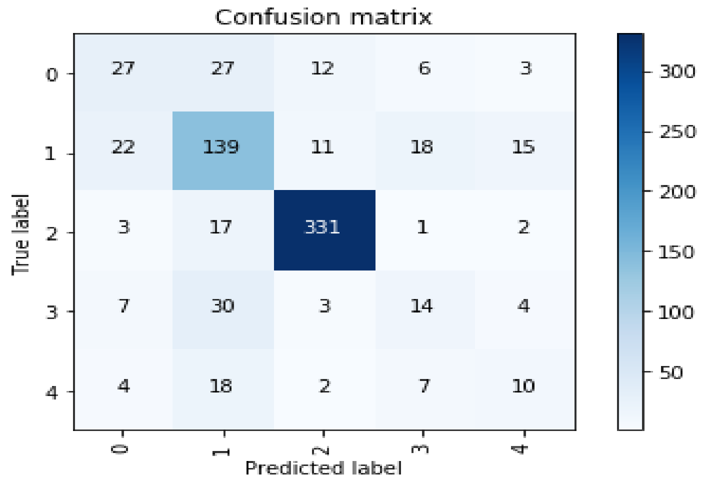
F-Measure

F-Measure is a measure of test precision and takes into account both test precision and recall when calculating the score

$$F - Measure = 2\frac{Precision * Recall}{Precision + Recall}$$

4.3 Performance of voting Classifier

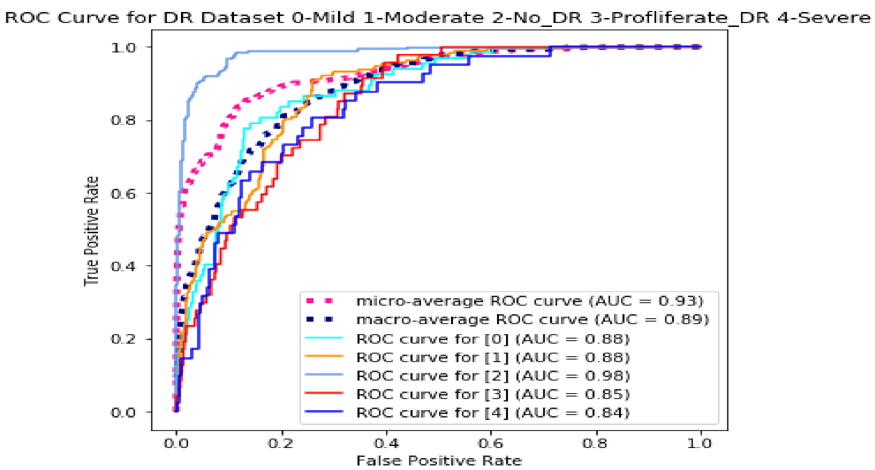
1) Confusion Matix



2)Classification Report

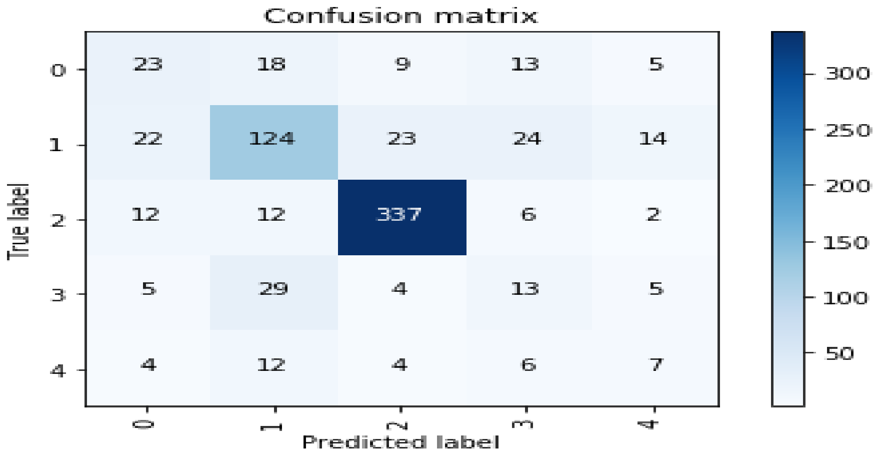
Inputs	Precision (in %)	Recall (in %)	F- Score (in %)	Accuracy (in %)
Mild	43	36	39	
Moderate	60	68	64	
No_DR	92	94	93	
Proliferate_DR	30	24	27	71
Severe	29	24	27	

3)ROC



4.4 Performance of Stacking

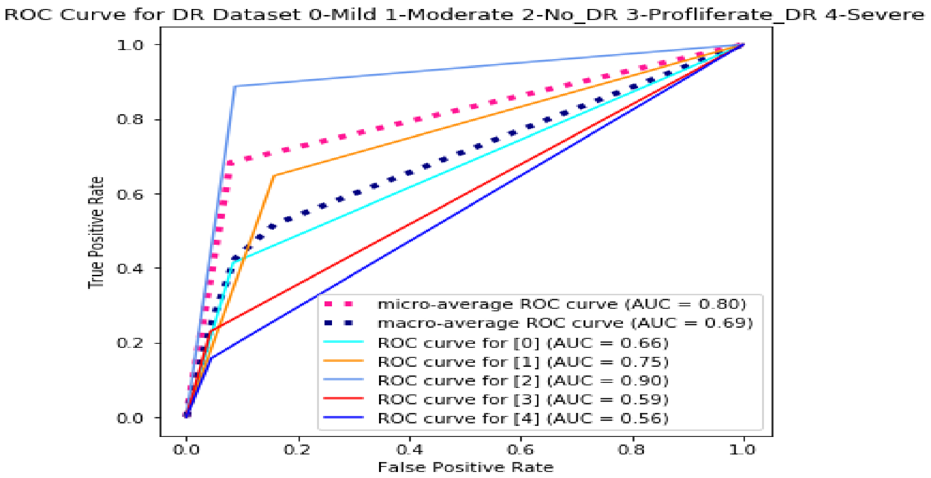
a) Confusion Matix



b) Classification Report

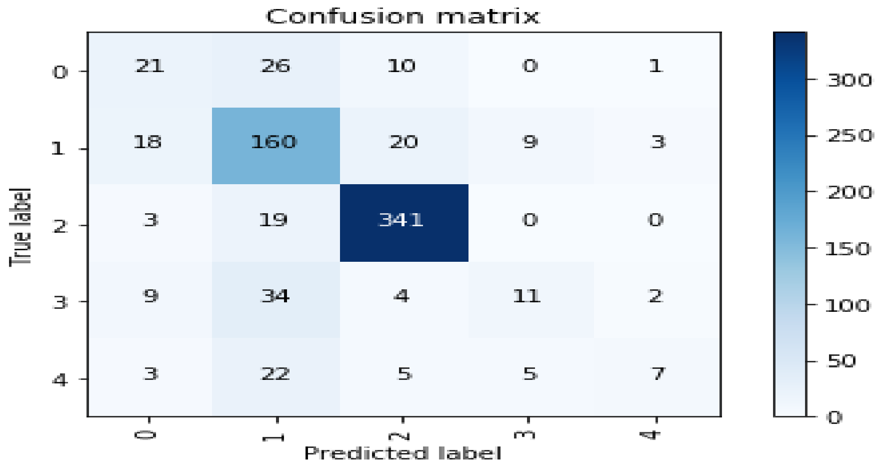
Inputs	Precision (in %)	Recall (in %)	F- Score (in %)	Accuracy (in %)
Mild	35	34	34	69
Moderate	64	60	62	
No_DR	89	91	90	
Proliferate_DR	21	23	22	
Severe	21	21	21	

c)ROC



4.5 Performance of Averaging

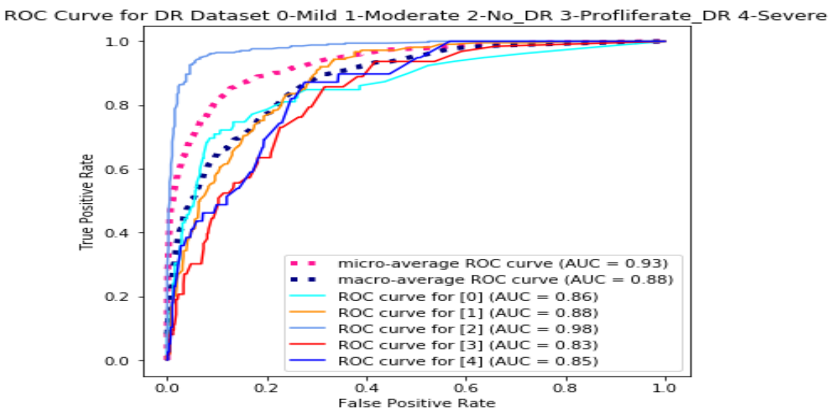
a)Confusion Matix



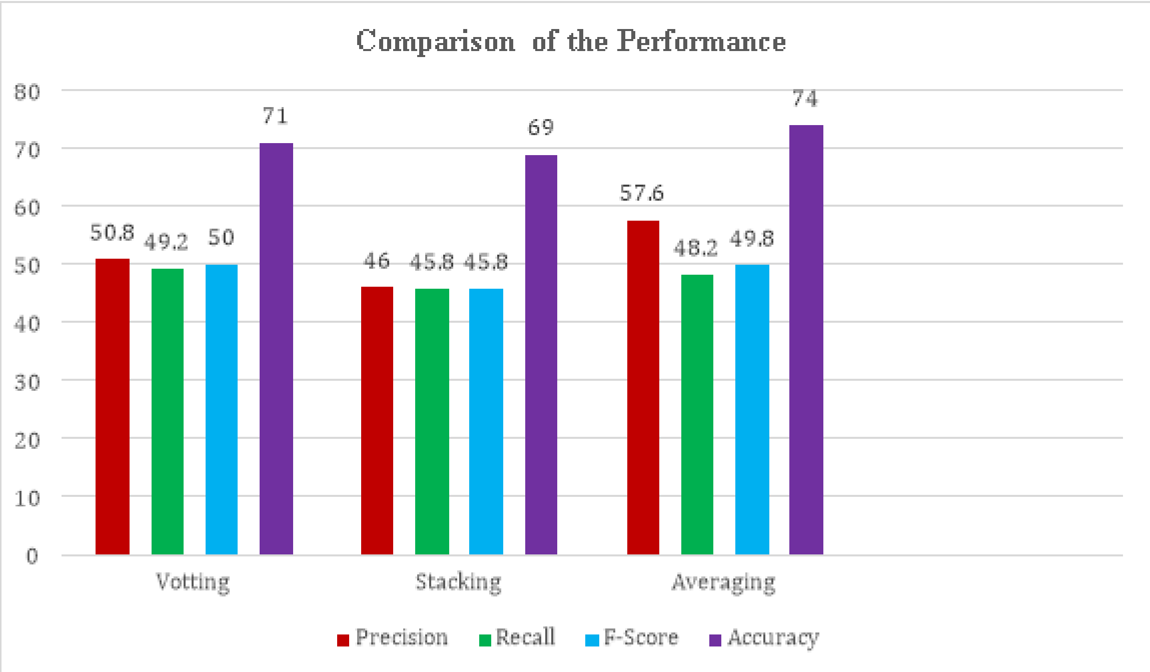
b)Classification Report

Inputs	Precision (in %)	Recall (in %)	F- Score (in %)	Accuracy (in %)
Mild	39	36	38	74
Moderate	61	76	68	
No_DR	90	94	92	
proliferate_DR	44	18	26	
Severe	54	17	25	

c) ROC



4.6 Performance Comparison



5. CONCLUSION

In conclusion, this project demonstrates a promising approach to detecting and classifying diabetic retinopathy using machine learning techniques. By employing the Local Binary Pattern (LBP) feature extraction method and leveraging classifiers such as K-Nearest Neighbour, Random Forest, and Logistic Regression, the study effectively identifies different stages of diabetic retinopathy. The integration of ensemble techniques, particularly averaging, achieved an accuracy of 74%, highlighting the potential of combining multiple models to enhance performance. While the results are encouraging, there remains scope for improvement in accuracy and robustness, which could be addressed through advanced deep learning models, better handling of class imbalances, and larger datasets. This work contributes to the development of automated, reliable diagnostic tools for early detection and management of diabetic retinopathy.

6. FUTURE ENHANCEMENT

Implement Convolutional Neural Networks (CNNs) for automated feature extraction and classification, as they are highly effective in medical image analysis. Explore advanced architectures like ResNet, EfficientNet, or DenseNet to improve classification accuracy and handle complex features. Use data augmentation techniques (e.g., rotation, flipping, scaling) to artificially increase the dataset size and improve model generalization. Incorporate additional datasets from diverse sources to enhance model robustness and address class imbalance issues. Apply techniques like SMOTE (Synthetic Minority Oversampling Technique) or class-weight adjustments to balance the dataset and improve detection of underrepresented categories like severe or proliferative diabetic retinopathy.

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