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ENHANCED LEARNING HYBRID MODELS ON AUTOMATED DIABETIC RETINOPATHY DETECTION IN FUNDUS IMAGES.

[1] P. Aurchana, [2] Kothakonda Manasa, [3] Dr. R. Madonna Arieth, [4] Dr. A. P. Gopu, [5] C. Mahiba,

[1]Professor,Department of Computer Science and Engineering,

Chennai Institute of Technology Chennai, Tamil Nadu

aurchana85@gmail.com

[2]Assistant Professor,

Department of Computer Science and Engineering, School of Engineering

Malla Reddy University, Hyderabad, Telangana.

manasa.kothakonda557@gmail.com

[3]Associate Professor,Department of CSE,Vel Tech Rangarajan

Dr sagunthala R & D Institute of science and Technology,

Avadi Chennai.

drmadonnaariethr@veltech.edu.in

[4]Assistant Professor

Department of Computer Science and Engineering,

Velalar College of Engineering and Technology, Erode, Tamil Nadu, India.

gopumecse@gmail.com

[5]Assistant Professor

Department of Computer Science and Engineering,

Jain University,Bangalore, Karnataka.

mahibaphdcse@gmail.com

Abstract:

Diabetic retinopathy is a direct complication of diabetes mellitus and is commonly characterized by retinal lesion formation leading to impaired vision. If not detected early enough, it leads to total blindness. Diabetic Retinopathy is rarely reversible, and treatment for diabetic retinopathy only delays the onset of blindness. Therefore, the earlier the diagnosis of diabetic retinopathy and the management of the disease, the lower the likelihood of vision loss. Two separate datasets were compared in this study, both of which consist of five different classifications of diabetic retinopathy image types (mild, moderate, no diabetic retinopathy,

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proliferative diabetic retinopathy, and severe). In this study, 80% of the images were used for training, and 20% of the images were used for testing. The performance of an ensemble of Ensemble classification techniques, Random Forest, K-Nearest Neighbor and Logistic regression using Stacking, Voting and Averaging techniques will be evaluated using the accuracy, precision, recall, F1-score and ROC metrics in this study. These metrics are based on the confusion matrix produced by the classification method employed. As a result, it has been shown that the average of the classifiers produces the best results.

Keywords: *Diabetic Retinopathy (DR), Non-Proliferative Diabetic Retinopathy (NPDR), Proliferative Diabetic Retinopathy (PDR)*

I. INTRODUCTION

It is a diabetes-related eye disease which harms the blood vessels of the retina, and it may result in vision loss or complete blindness [1]. It affects as many as 80 percent of diabetics worldwide and is the major cause of blindness in adults in the prime working age, as in the US. The situation occurs due to the high blood sugar rupturing blood capillaries that subsequently permit the blood and fluid to leak into adjacent tissues. Early identification is best achieved with routine eye check-ups since intervention measures can be applied like laser procedures or injections, to stop its progression. Among these, the amount of vision-threatening retinopathy, which is intended to the destructive form, of around 899,000 persons [2][3]. Generally, it consists of NPDR and PDR

1.1 NON-PROLIFERATIVE DIABETIC RETINOPATHY

It is an eye disease associated with diabetes, and it damages blood vessels in the retina, and it can cause blindness or even loss of sight. This is very popular among diabetic people. These ruptured vessels can cause fluid leakage into the retina in its early stages and the swelling rather than the real growth or enlargement of the tissue. NPDR is common in many people with diabetes and it is important to ensure that it is detected early by the regular eye examination to prevent damage to vision. Lifestyle changes, such as managing blood sugar levels and having a healthy routine, may reduce exacerbation of diabetes. [4].

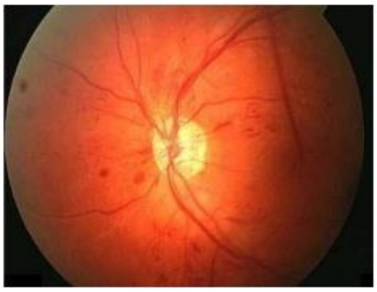

Fig 1: Eye with Non-Proliferative Diabetic Retinopathy

1.2 PROLIFERATIVE DIABETIC RETINOPATHY

It is the most severe and the progressive type of DR which is one of the key factors of vision loss in diabetic patients. It is described as neovascularized, or abnormal growth of new weak blood vessels through retina[5]. Having a little bleeding can lead to development of dark

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floaters in our vision. However, if the bleeding becomes extensive, it could cause significant vision loss. Additionally, the material from these original vessels can evolve into scar tissue, which may harm the macula or even direct to retinal detachment. It is a highly risky condition that can impair both central vision (for detailed sight) and peripheral vision (for broader awareness).

Fig 2: A Proliferative Diabetic Retinopathy affected eye

Stages of Diabetic Retinopathy

Diabetic retinopathy gets sorted into two primary groups by the National Eye Institute (NEI) and similar organizations: NPDR and PDR. NPDR breaks down farther into levels of severity. There are mild, moderate, severe and Proliferative Retinopathy [6]. Fig 3 shows the different stages of DR

- Mild NPDR: The first level, featuring minor issues like microaneurysms (small bulges in blood vessels), often without affecting sight [7].
- Moderate NPDR: More extensive vessel damage appears, including spots of blood or fluid leaks, but no new vessel formation yet [8].
- Severe NPDR: The high spread blockages in blood vessels occur, certainly cutts off oxygen to the retina and elevates the threats of quick progression [9] [10].
- PDR: The last and most particular stage, identified by the current widening, blood vessels that can cause problems [11].

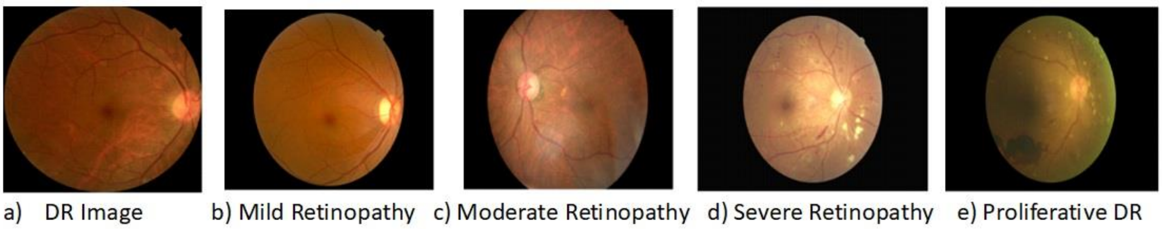

Fig 3: Different Stages of DR

Clarification on Blood and Fluid Leaks (Lesions)

The leakage of blood and fluid out of the retina forming spots known as lesions. More precisely, the source of these leaks is weakened blood vessels not only in the bottom of the retina [12], but also in its own structure. Fig 4. Shows the various forms of DR lesions. They present themselves in different abnormalities, which include: Microaneurysms: Tiny swollen spots on vessels.

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- Hemorrhages: Blood splotches that look like dots.
- Exudates: Fatty deposits forming yellowish patches.

Other spots: Like cotton-wool areas from poor blood flowThese signals may cause other eye issues, and thus it is important to identify them at an intial stage. Fig 4 represents the Blood and Fluid Leak in Lesions

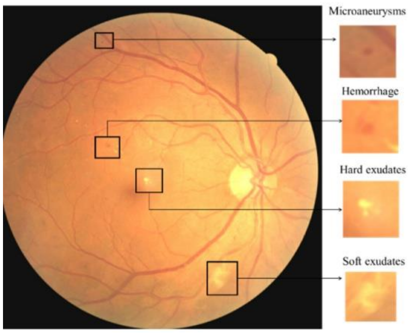

Fig 4: Various forms of DR Lesions

II. LITERATURE SURVEY

In one study [13], the researchers identified four major types of retinal problems: hard exudates, haemorrhages, microaneurysms, and soft exudates. The procedure consisted of a number of phases: image preparation, elimination of optic disks and blood vessels, detection of abnormalities, extraction of the important features, the most successful of them and classification of these features. It was done using the DIARETDB1 dataset. They used open-close watershed method first to remove the optic disc, and then, difference in limited adaptive histogram equalization to enhance the image. They are fed into Gabor filtering to perform segmentation, and into Local Binary Pattern, Texture Energy Measurement, the entropy of Shannon, and entropy of Kapur. Lastly, they employed Deep Belief Network (DBN) with a Modified Gear and Steering-based Rider Optimization Algorithm in classification. This method gave the best accuracy of 93.182.

Two datasets MESSIDOR and IDRiD were used in an additional research study [14] to evaluate the hardness of DR fundus image. The methods employed to grade and classify these images consisted of several stages including segmentation; extraction of feature sets; optimization of the extracted features using cuckoo search; and application of a convolutional neural network to compare results showed that CNN provided gives the satisfactory results of 97.55%.

An alternative study [15] the researchers focused on the automated detection of DR by assessing various characteristics ophthalmoscopy in retinal images. To this end, the researchers used gray level features related to texture of images, i.e., co-occurrence matrices, run-length matrices, and Ridgelet Transform coefficients. SMO was utilized to classify the images. Accuracy levels were 91.05% on the Kaggle database, while 97.05% was attained on the DIARETDB1 database.

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Another study [16] researched to find early stages of DR using a trained deep convolutional network with modified pooling and dropout on DenseNet 121. They trained this algorithm with the APTOS 2019 dataset to develop a model to perform multi-class classifications of DR severity achieving an accuracy of 96.51%. In a hybrid study [17], the authors suggested diagnosing DR using 400 retinal fundus images in the MESSIDOR data set. To do this they employed a bichannel CNN that fused the classification features from gray and green level entropy images utilizing an unsharp mask technique. The resultant accuracy was an amazing 93%. Finally, to help prevent blindness from diabetes, one team [18] developed a combined multi-scale shallow CNN. They sourced images from Kaggle datasets and classified into five categories, which gives satisfactory results 92%.

III. FEATURE EXTRACTION TECHNIQUE

a. Local Binary Pattern

A widely used technique to derive characteristics from images through texture and pattern analysis. The methodology is based on relating each pixel in an image to its neighboring pixels to represent local texture. The steps involved with LBP are as follows:

Firstly, to convert the image into a grayscale, since LBP analyses images in this format. Once transformed to grayscale the methodology uses a very localized, fixed 3 x 3 grid of pixels (8 surrounding neighbor pixels) that includes the center pixel. For the central pixel, its deepness is compared to each of the eight neighbors. The central pixel's intensity is more than or equal to a neighbor's intensity; that comparison results in a value of 1; otherwise, it's 0. It is then computed by arranging these binary results (1s and 0s) in a sequence, either clockwise or counterclockwise. This binary sequence is generated from the eight neighbors in the 3x3 grid and then converted from an 8-bit binary number to its decimal equivalent. An LBP pattern is considered "uniform" if it has no more than two transitions between 0 and 1 (or 1 and 0) in the binary string, which helps in identifying smooth textures. These steps are replicated for everlasting pixel in the image: thresholding neighbors, forming the binary strings, and storing the resulting decimal values in a new LBP array.

Once the LBP array is complete, a histogram is created from it. Since a 3x3 neighborhood can produce 256 possible patterns (ranging from 0 to 255), the histogram will have 256 bins to represent the frequency of each pattern. The final output is this LBP array, which can be used for further analysis, such as classification. In the LBP formula, P represents the number of neighboring pixels considered around a given radius R. Here, gp stands for the intensity of a neighboring pixel, gc refers to the intensity of the central pixel. This setup allows LBP to adapt to different scales and patterns in the image.

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

P is the number of neighboring pixels that are chosen in the radius R, where g_p and g_c are the pixel value of the surrounding and the current pixel respectively.

b. Logistic Regression

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Logistic Regression stands out as a extremely popular algorithm in Machine Learning, particularly in the Supervised Learning area. It concentrates on predicting a categorical dependent variable by leveraging a cluster of independent variables [19]. The outcomes that are categorical rather than numerical, such as yes/no, true/false, or 0/1.

Either than delivering precise numerical predictions like standard linear regression, it produces probability from 0 to 1, which show the chances of a particular outcome happening. In particular, a result of 0.8 might indicate an 80% likelihood of the event. It is achieved by relating an "S"-shaped curve familiar as the logistic function, which models the data to fit into either 0 or 1, either using a straight regression line [20].

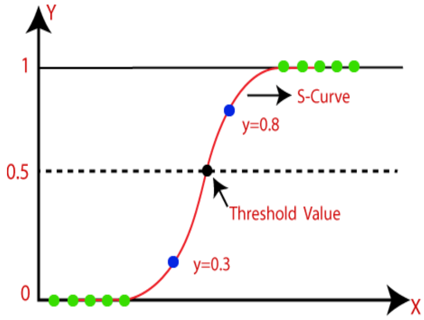

Fig 5: Logistic Regression

c. Logistic Function (Sigmoid Function)

A logistic equation that models a straight line is

$Y=a_{0+}a_1\ x+a_2x_2+a_3x_3+\cdots.a_nx_n$

Logistic regression splits the y-value with (1 – y), because y-values are always between 0 & 1

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

In logistic regression:

The algorithm generates probability estimates (confined to 0 and 1) for binary outcomes, like yes/no or spam/not spam scenarios. It doesn't produce exact 0s or 1s outright, a decision threshold (commonly 0.5) is used to classify: values exceeding the threshold are labeled as 1 (the "positive" category), while those below are labeled as 0 (the "negative" category).

The odds ratio is expressed as $\frac{y}{1-y}$ with y being the predicted probability. This ratio goes from 0 (at y=0) to infinity (at y=1). The logit, or log-odds, is log($\frac{y}{1-y}$ = z), making it a linear function of the features. These places logistic regression in the class of generalized linear models.

d. Random Forest Algorithm

It is an ensemble approach, builds numerous decision trees and merges outputs to enhance accuracy and stability. It includes bagging, each tree learns from a random sample of the data, which curbs overfitting [21]. Decision trees are highly responsive to training data variations, and this method exploits that sensitivity. Additionally, it applies random feature selection:

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During each tree split, only a subset of features is randomly chosen, promoting independence among the trees. For classification, the ultimate prediction comes from the class with the highest vote count across trees [22]. The advantages are effective with missing values, non-linear data, and high-dimensional datasets. It resists overfitting more than individual trees. And the main drawbacks are harder to interpret than basic models.

e. KNN – K Nearest Neighbour

It is a method that mainly addresses classification and regression issues. It categorizes datasets using the distance function's similarity metric. The majority of votes made for the nearest neighbor determines classification data in KNN. KNN classification process is most heavily influenced by the number of neighbors. Additionally, the method not essential specific data points to create the training model because it utilizes all of the training data during testing.

Scanning every possible data point that needs more storage increases the time and cost aspects. It includes choosing the k closest data points, then classifying the points according to k neighbors received the majority of the votes [23]. A prediction is assigned to the class with the highest number of votes for an object in the class. Euclidean, Hammington, and Minkowski distance functions determine a data point's closest neighbors and calculate the distance between them. The K-Nearest Neighbor (KNN) algorithm will perform better when the number of feature(s) is reduced, and the performance of the KNN algorithm improves as the number of feature(s) increase, although it may also be subject to overfitting.

f. Ensemble Techniques

It uses the features extracted earlier to train various machine learning models. It is a technique where multiple machine learning models are trained, their predictions are merged to achieve better results than any single model could on its own. The term "ensemble" describes the group of predictors that are developed to generate these improved forecasts [24]. In this approach, classifiers are trained to differentiate between the various diabetic retinopathy, results from these classifiers, then integrated to produce a more accurate overall output. Fig 6 shows the different ensemble classification of voting, stacking and averaging

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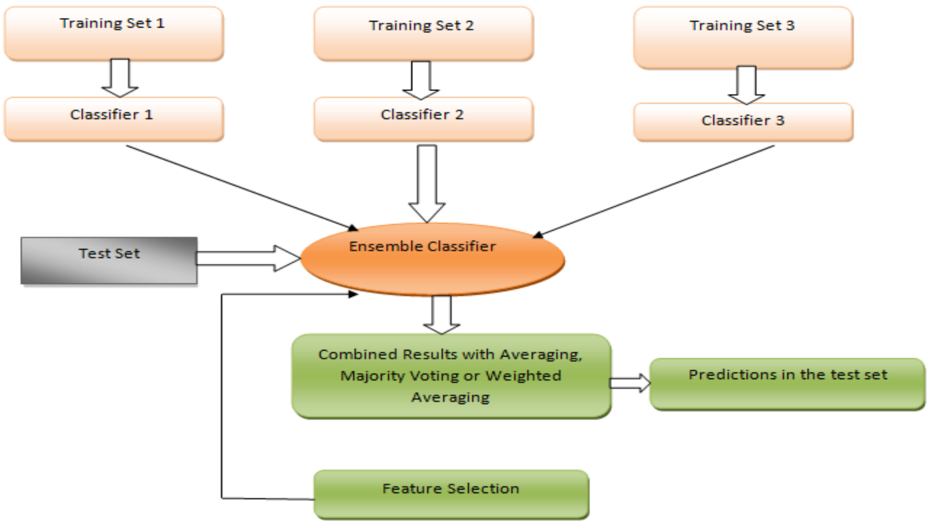

Fig 6: Ensemble classification

Ensemble learning combines multiple models to boost performance, often outperforming individual models by reducing variance, bias, or both. It focuses on using extracted features to train classifiers for diabetic retinopathy stages, then aggregating results. The errors from one model can be offset by others (e.g., via majority voting or averaging). The common methods:

Bagging (e.g., Random Forest): Trains models on bootstrapped data subsets.

Boosting (e.g., AdaBoost, XGBoost): Sequentially trains models, each focusing on the errors of the previous.

Stacking: Trains a meta-model on the outputs of base models [25].

IV. EXPERIMENTAL RESULTS

Two kinds of datasets are used for this work. The datasets are collected from the Kaggle data repository such as dataset1 from https://www.kaggle.com/datasets/sachinkumar413/diabetic-retinopathy-dataset and dataset2 from https://www.kaggle.com/datasets/sovitrath/diabetic-retinopathy-224x224-2019-data .

Dataset1

Total images: 3,563. Class breakdown: Mild (370), Moderate (900), No_DR (1,805), Proliferate_DR (295), Severe (193).

Dataset2

Total images: 2,750 (in grayscale). Class breakdown: Mild (370), Moderate (999), No_DR (1,000), Proliferate_DR (290), Severe (190). Each of the datasets were split into training and test sets; 80% was used for training, and 20% was reserved for testing. This standard approach ensures evaluation reliability. To keep class proportions intact, use stratified splitting.

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Approximate training sizes: around 2,850 for Dataset1 and 2,200 for Dataset2; testing sizes: about 713 for Dataset1 and 550 for Dataset2.

The voting technique involves a group of base classifiers making predictions on a test image, with the final class chosen by majority vote. Ties can be resolved via random picks or weighted rules. It supports both strict (label-based) and flexible (probability-based) voting. In this work base models are trained on the 80% training portion of Dataset1 or Dataset2, focusing on features like retinal abnormalities. Testing aggregates votes to assign stages.

For averaging probabilistic predictions, computes the mean across base models' outputs. In classification, it averages probability scores per class, then picks the one with the top average. It's essentially soft voting and fits probabilistic frameworks. In averaging the base models generate likelihoods for each DR class. The averages determine the class.

In Stacking a layered method where base models' predictions serve as inputs for a "meta-model". The meta-model is trained via cross-validation on training data to optimally blend predictions, reducing overfitting risks. The base models are trained on subsets of the 80% training data. Their results become features for the meta-model, which classifies test images. For instance, combine random forest and KNN outputs via a neural network for DR staging.

Performance Measures

A set of assessment parameters used in this work to assess the effectiveness of different ensemble classification approaches employing stacking, voting, and averaging procedures. The confusion matrix acquired from the classification process's result in the basis for determining these metrics.

V. PERFORMANCE OF VOTING TECHNIQUE USING DATASET1

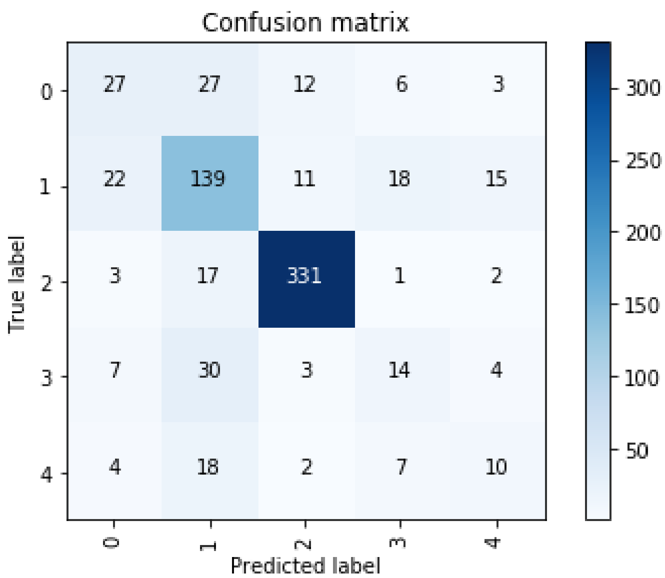

Fig 7: Confusion Matrix Voting Technique Using Dataset 1

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Table 1: Classification Report for Voting Technique for dataset1

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

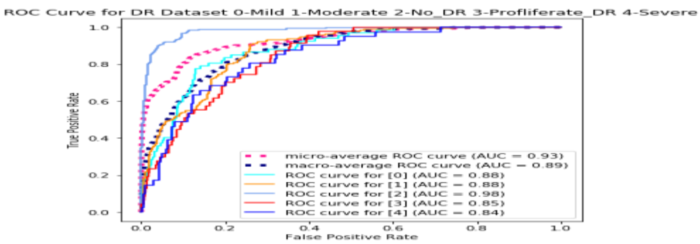

Fig 8: ROC for Voting Technique using Dataset 1

(i) Performance of Stacking using dataset1

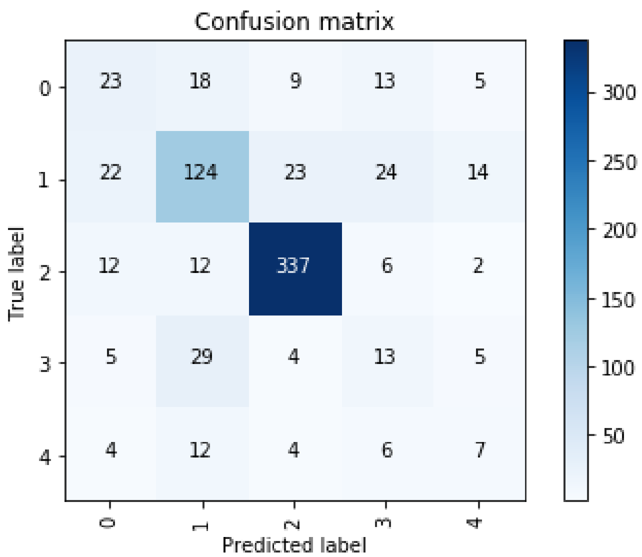

Fig 9: Confusion Matrix for the stacking technique using Dataset1

Table 2: Classification Report for stacking technique using Dataset 1

ts	Precision (in %)	ll %)	F- Score (in %)	Accuracy (in %)

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Mild	35	34	34	
Moderate	64	60	62	
No_DR	89	91	90	69
Proliferate_DR	21	23	22	
Severe	21	21	21	

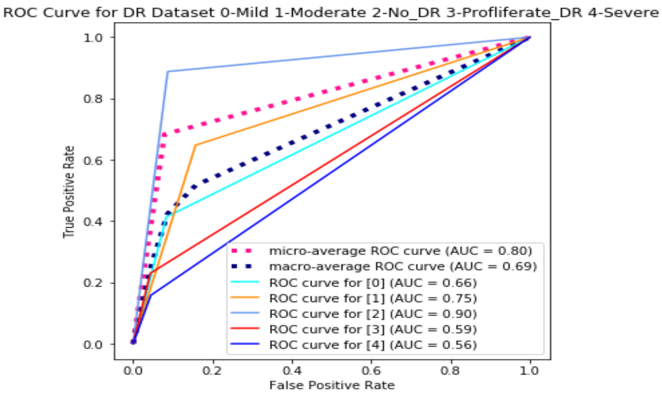

Fig 10: ROC stacking technique using Dataset1

(ii) Performance of the Averaging technique using dataset1

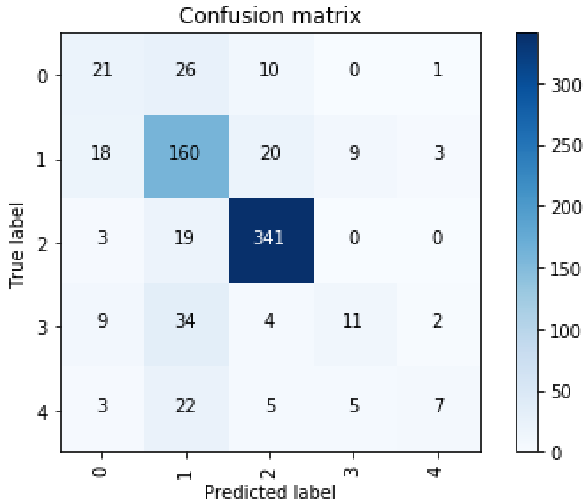

Fig 11: Confusion Matrix Averaging technique using dataset1

Table 3: Classification Report Averaging technique using Dataset1

ts	**Precision (in %)**	**ll %)**	**core %)**	**racy %)**

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Mild	39	36	38	74
Moderate	61	76	68	
No_DR	90	94	92	
proliferate_DR	44	18	26	
Severe	54	17	25	

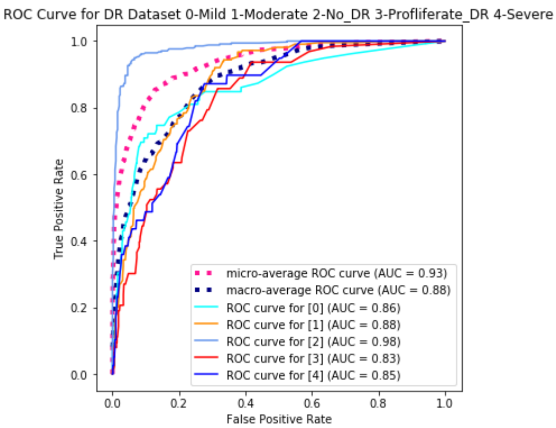

Fig 12: ROC Averaging technique using dataset1

Table 4: Comparison of Performance for dataset1

ts		**Precision (in %)**	**Recall (in %)**	**F- Score (in %)**	**Accuracy (in %)**
Voting Technique	Mild	43	36	39	71
	Moderate	60	68	64	
	No_DR	92	94	93	
	Proliferate_DR	30	24	27	
	Severe	29	24	27	
Stacking Technique	Mild	35	34	34	69
	Moderate	64	60	62	
	No_DR	89	91	90	
	Proliferate_DR	21	23	22	
	Severe	21	21	21	

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Averaging Technique	Mild	39	36	38	74
	Moderate	61	76	68	
	No_DR	90	94	92	
	Proliferate_DR	44	18	26	
	Severe	54	17	25	

Fig 7 and 8 shows the confusion matrix and ROC of Voting Technique for Datadet1.Tabl 1 shows the classification report of different stages of DR for Voting. Fig 9 and 10 shows the confusion matrix and ROC of Stacking Technique for Datadet1. Table 2 shows the classification report of different stages of DR for Stacking. Fig 11 and 12 shows the confusion matrix and ROC of Averaging Technique for Datadet1. Table 3 shows the classification report of different stages of DR for Averaging. Table 4 shows the different comparative analysis of voting stacking and averaging, in which averaging gives the highest accuracy of 74%

(iii) Performance of Voting Technique Using Dataset2

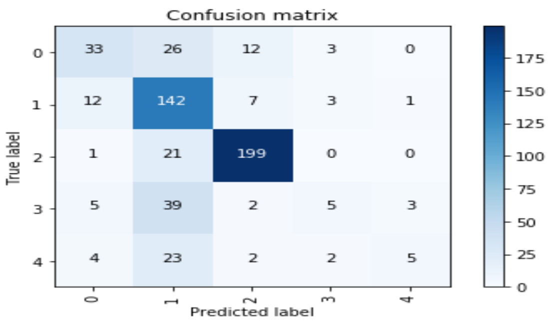

Fig 13: Confusion Matrix Voting Technique Using Dataset2

Table 5: Classification Report for Voting Technique for dataset2

ts	Precision (in %)	ll %)	core %)	racy %)
Mild	60	45	51	70
Moderate	57	86	68	
No_DR	90	90	90	
Proliferate_DR	38	09	15	
Severe	56	14	22	

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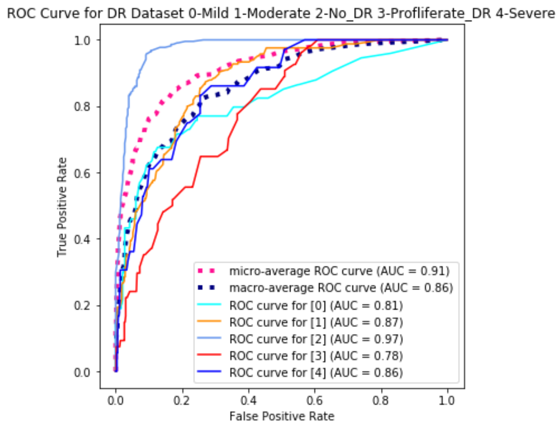

Fig 14: ROC for Voting Technique using Dataset 2

(iv) Performance of Stacking Technique Using Dataset2

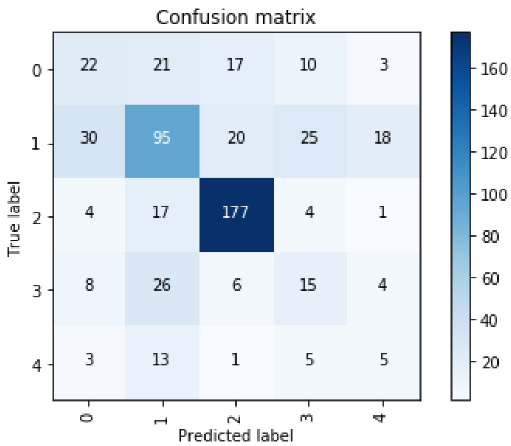

Fig 15: Confusion Matrix Stacking Technique Using Dataset2

Table 6: Classification Report for Stacking Technique for dataset2

ts	Precision (in %)	Recall (in %)	F- Score (in %)	Accuracy (in %)
Mild	33	30	31	57
Moderate	55	51	53	
No_DR	80	87	83	
proliferate_DR	25	25	25	
Severe	16	19	17	

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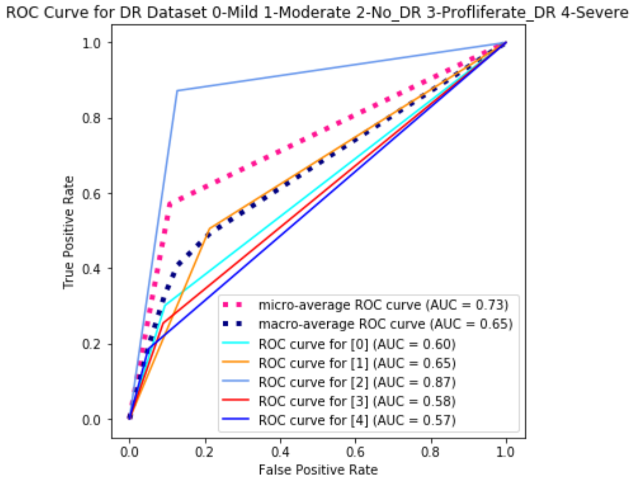

Fig 16: ROC for Stacking Technique using Dataset2\\

(v) Performance of Averaging Technique Using Dataset2

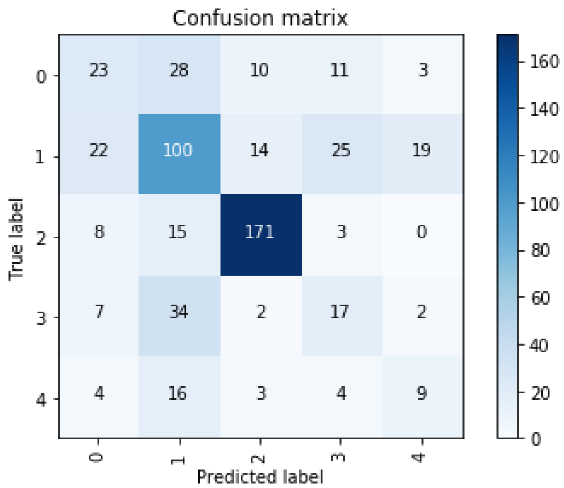

Fig 17: Confusion Matrix Averaging Technique Using Dataset2

Table 7: Classification Report for Averaging Technique for dataset2

ts	Precision	ll	core	racy
Mild	36	31	33	58
Moderate	52	56	54	
No_DR	85	87	86	
proliferate_DR	28	27	28	

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Severe	27	25	26	

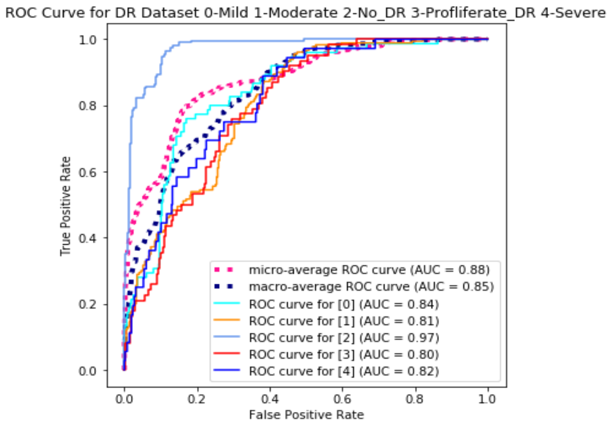

Fig 18: ROC for Averaging Technique using Dataset 2

Table 8: Comparison of the Performance using Dataset 2

ts		Precision (in %)	Recall (in %)	F- Score (in %)	Accuracy (in %)
Voting Technique	Mild	60	45	51	70
	Moderate	57	86	68	
	No_DR	90	90	90	
	Proliferate_DR	38	09	15	
	Severe	56	14	22	
Stacking Technique	Mild	33	30	31	57
	Moderate	55	51	53	
	No_DR	80	87	83	
	Proliferate_DR	25	25	25	
	Severe	16	19	17	
Averaging Technique	Mild	36	31	33	58
	Moderate	52	56	54	
	No_DR	85	87	86	

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	Proliferate_ DR	28	27	28	
	Severe	27	25	26	

Fig 13 and 14 shows the confusion matrix and ROC of Voting Technique for Dataset 2. Table 5 shows the classification report of different stages of DR for Voting. Fig 15 and 16 shows the confusion matrix and ROC of Stacking Technique for Dataset 2. Table 6 shows the classification report of different stages of DR for Stacking. Fig 17 and 18 shows the confusion matrix and ROC of Averaging Technique for Dataset 2. Table 7 shows the classification report of different stages of DR for Averaging. Table 8 shows the different comparative analysis of voting stacking and averaging, in which voting gives the highest accuracy of 70%.

Table 9: Comparison of the Performance using Dataset1 vs Dataset2

ts			**Precision (in %)**	**Recall (in %)**	**F- Score (in %)**	**Accuracy (in %)**
Voting Technique	Dataset1	Mild	43	36	39	71
		Moderate	60	68	64	
		No_DR	92	94	93	
		Proliferate_ DR	30	24	27	
		Severe	29	24	27	
	Dataset2	Mild	60	45	51	70
		Moderate	57	86	68	
		No_DR	90	90	90	
		Proliferate_ DR	38	09	15	
		Severe	56	14	22	
Stacking Technique	Dataset1	Mild	35	34	34	69
		Moderate	64	60	62	
		No_DR	89	91	90	
		Proliferate_ DR	21	23	22	
		Severe	21	21	21	
	Dataset2	Mild	33	30	31	57

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		Moderate	55	51	53	
		No_DR	80	87	83	
		Proliferate_DR	25	25	25	
		Severe	16	19	17	
Averaging Technique	Dataset1	Mild	39	36	38	74
		Moderate	61	76	68	
		No_DR	90	94	92	
		Proliferate_DR	44	18	26	
		Severe	54	17	25	
	Dataset2	Mild	36	31	33	58
		Moderate	52	56	54	
		No_DR	85	87	86	
		Proliferate_DR	28	27	28	
		Severe	27	25	26	

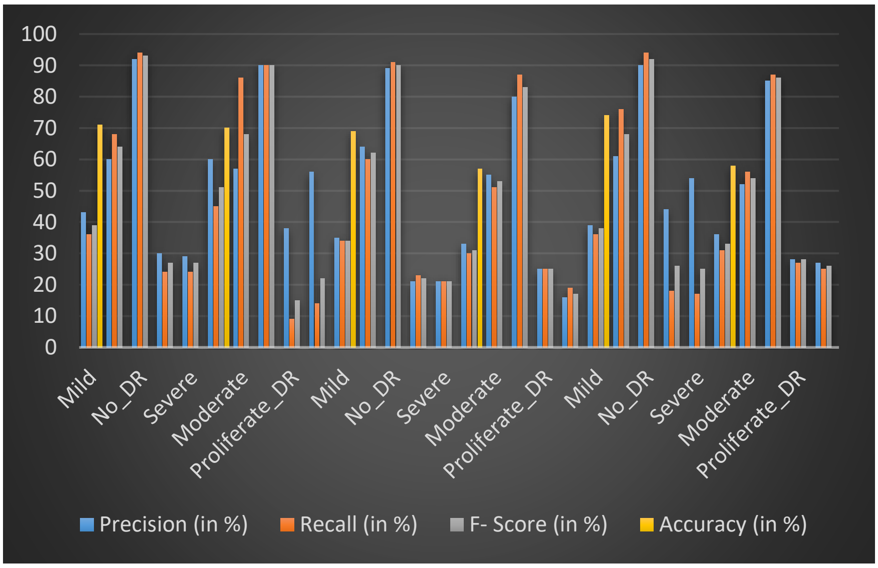

Fig 19: Comparative Result Analysis

Table 9 shows the overall comparison for dataset 1 and dataset 2 for different stages of DR of voting, stacking and averaging. Fig 19 shows the overall result analysis in which dataset 1 for averaging gives the highest accuracy of 74%

VI. CONCLUSION

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Automated screening systems save time and effort needed to decide on diagnoses as well as ophthalmologists and save on costs, and result in timely delivery of patients. DR detection automation systems are significant in the detection of DR at an early stage. The DR stages are dependent on the nature of lesions that occur in the retina. This paper has discussed the latest automated systems of diabetic retinopathy detection and classification who employed Ensemble learning methodologies. The publicly available common fundus DR datasets have been outlined, and Ensemble learning methods have been discussed briefly. In this work different stages of DR where compared with two different datasets with the ensemble technique voting, averaging and stacking, in which averaging for dataset 1 gives the highest accuracy of 74%.

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