Comparative Evaluation of Machine Learning Techniques for the Detection of Diabetic Retinopathy

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***Abstract*—Diabetic Retinopathy (DR) is a common diabetes disorder that attacks blood vessels in the light-sensitive tissue known as the retina. It is among the most common causes of loss of vision among patients with diabetes, and it is the leading cause of reduced vision and blindness even among aged adults. Naturally, this occurrence begins with no apparent change in vision. For the identification of DR, ophthalmologists use the retinal image of a patient known as the fundus image, and the blood vessels may also be captured explicitly from the retina. This paper presents a comparative study of five commonly used machine learning techniques: K-Nearest Neighbor, Support Vector Machine and Discriminant Analysis, Naïve Bayes, and Ensembles. The texture characteristics of the fundus image were extracted using the Local Binary Pattern (LBP) descriptor. And this feature extracted using LBP was used to train the classifiers. The proposed method classifies the retina's fundus pictures as "no DR" or "current DR." The Ensemble Classifier (EC) technique generated a better DR detection accuracy of 98.31% than the other four classifiers and existing works based on the classifiers' comparative analysis.**

Keywords— Diabetic Retinopathy, Classification, Feature Extraction, Ensemble Classifier, Machine Learning

I. INTRODUCTION

Diabetes is the most common condition in the human body that causes many complications worldwide [1]. According to estimates from 2014, this disease's incidence rose from one hundred million patients in 1980 to four hundred and twenty-two million patients, with a global prevalence of 4.7% to 8.5% [2]. Patients with a history of diabetes are more prone to diabetic retinopathy [1]. Diabetic retinopathy (DR) is a disease that tends to worsen and is one of the critical causes of blindness and vision loss [3]. DR is a diabetes-related eye condition that arises when the retina's blood vessels swell and leak fluid, leading gradually to vision impairment [4]. Diabetes causes high blood sugar levels that accumulate in the blood vessels, causing damage that impedes or inhibits blood flow to the body's organs, including the eyes, affecting up to 80% of all patients with diabetes for ten years or longer [5]. This assumption facilitates the application of automated diagnostic screening methods to larger populations. DR symptoms include blurred vision, eyespots, and night vision difficulties [6].

The minor disparity between different grades and the existence of many small essential characteristics renders the task of identification very difficult [7]. However, the current approach to detecting DR is a very laborious and time-consuming task that relies heavily on a doctor's capacity [8]. DR automatic detection is necessary to solve these problems. Early-stage identification of DR, which can prevent blindness with appropriate care, is also crucial for diagnosis [9]. The creation of intelligent systems to assist ophthalmologists' decision-making has attracted the scientific community's attention in various works concerning incorrect diagnosis [10][11].

This paper aims to conduct a comparative evaluation of five machine learning methods, namely: Discriminant Analysis Classifier (DAC), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Ensemble Classifier (EC), and Naïve Bayes (NB) classifier utilized for Diabetic Retinopathy (DR) detection and classification. Hence, the significant contributions of this paper include:

1. Classification of retinal fundus images into No DR or Present DR
2. Comparative experimentation of five different classifiers on the features obtained using the LBP feature descriptor.

The rest of this research is structured as follows: a description of related works is given in Section II. Section III explains the methods used for conducting the research. Section IV describes the findings obtained during the experiment and addresses the results presented. In Section V, conclusions have been drawn, and possible studies are presented in Section VI.

II. RELATED WORKS

In the field of computer vision, the task of detecting DR early is a challenging issue. Diagnostic clarity criteria aim to identify clinical characteristics of Diabetic Retinopathy such as haemorrhages, microaneurysms, soft exudates, and hard exudates. It is an essential issue for a proper diagnosis to extract these signs as they help to determine the actual condition of DR.

Kirange et al. [2] proposed a new method for early-stage identification of DR by recognizing all microaneurysms, the first symptoms of DR, and correctly assigning labels to retinal fundus images grouped into five classes according to the seriousness of lesions. The five grading groups are: No DR, Mild DR, Medium DR, Severe DR, and Proliferative DR. Five standard classifiers were used in this proposed system to perform the classification task. These classifiers are SVM, KNN, Neural Networks (NN), NB, and Decision Tree (DT). The NB classifier was proposed to have surpassed the other four classifiers with an accuracy of 77.86%. Both the Gabor and the LBP descriptor were used for the extraction of features. However, the components extracted using the Gabor descriptor performed much better with an accuracy of 77.86% as compared to the LBP features that provided 41.84% accuracy. A drawback of this analysis is that it focused more on early-stage DR identification without considering the DR proliferation stage.

A graph-based approach to classifying retinal images was suggested by Mangrulkar[12]. The retinal images were pre-processed to eliminate noise and remove irrelevant information. The Canny edge detector was then utilized to identify the edges of the items in the image. Using the kirsch template that defines the presence of an edge, the segmentation process was then performed. The Kirsch model is used for the retrieval of blood vessels from the retinal image. Together with the graph nodes extracted from the image, the Speed-Up Robust Features (SURF) features were extracted by finding the intersection points (that is, pixels with more than two neighbours) and the terminal ends. Using the graph-based method, classification was carried out, and the Artery Vein Ratio (AVR) was measured. The AVR ratio is a realistic measure to classify a diabetes-free or diabetes patient. The proposed process achieved an accuracy of 88%. Without considering a more advanced DR stage, this research only focused on the early phase identification of DR.

A new approach to the diagnosis of Age-related Macular Degeneration (AMD) and DR, as proposed by Morales et al. [13]. The presentation of a new technique for the diagnosis of AMD and DR was the objective of this method. Five experiments were developed and tested using the suggested procedure: separating DR from normal, AMD from normal, pathological from normal, DR from AMD, and the three different classes (AMD, DR, and Normal): The LBP was used as the feature descriptor technique. The most important finding of this study is that the new method can differentiate groups based on an analysis of the retina's spatial texture, thereby removing the retinal lesion's previous segmentation. The results show that using LBP as a texture descriptor for fundus images offers useful retinal disease screening features. This work, however, only investigated the LBP without further searching for more texture descriptors.

A multi-stage transfer learning system and an automated method for detecting the DR stages from a single human fundus image were proposed by Tymchenko et al. [14]. Three Convolutional Neural Network (CNN) architectures (EfficientNet-B4, EfficientNet-B5, and SE-ResNeXt50) were ensemble. CNN was used as a function extractor and as a classifier. The CNNs pre-trained by Imagenet were used for encoder activation. The proposed technique was used for the early detection of DR and achieved a sensitivity and specificity of 0.99.

The Shapley Addictive exPlanations (SHAP) were used to explain characteristics that lead to the disease process evaluation—using SHAP guarantees that the model learns beneficial features during preparation and uses correct characteristics at an inferential time. This approach's main advantage is that it increases generalization and eliminates uncertainty using a network ensemble, pre-maintained on a large dataset and precisely tuned to the target dataset. This analysis can be extended with SHAP calculation for the entire ensemble, not just for a particular network, which can provide a more precise optimization of hyper-parameters.

Li et al. [5] introduced a novel algorithm based on a Deep Convolution Neural Network (DCNN). In this paper, the regular DCNN max-pooling layers were replaced by a fractional max-pooling layer. Two DCNNs with differing numbers of layers were prepared for classification to achieve more discriminatory features. After integrating features from image metadata and DCNNs, the SVM classifier was trained to learn the inherent limits of distributions of each class. The proposed DR method classifies DR phases into five categories, labelled with an integer ranging from 0 to 4. The test results indicate that the proposed technique can reach a recognition rate of up to 86.17%. The dataset used for training in this study had an insufficient number of images of lesions 3 and 4, limiting the proposed method.

Arade and Patil [3] conducted a comparative study of DR using the K-NN and Bayesian classifier. An automated image processing system that detects DR gradation is presented in this paper. Blood vessel segmentation was done using the kirsch process, as it was found that retinal photos effectively differentiated the blood vessels. Differentiated vessels were extracted using moment invariants, grey level features. The DR severity was identified along with K-NN and Bayesian classifier using a feed-forward neural network. To validate the results obtained with an ophthalmologist, it was indicated that the Bayesian classifier generates results comparable to the expert opinion than the K-NN classifier. The accuracy of the Bayesian classifier obtained is 74%, while the precision for K-NN is 66%. It is possible to expand this work by training more classifiers.

III. METHODOLOGY

This section presents the techniques used to achieve the aim of this study. Fig. 1 illustrates the methods used.

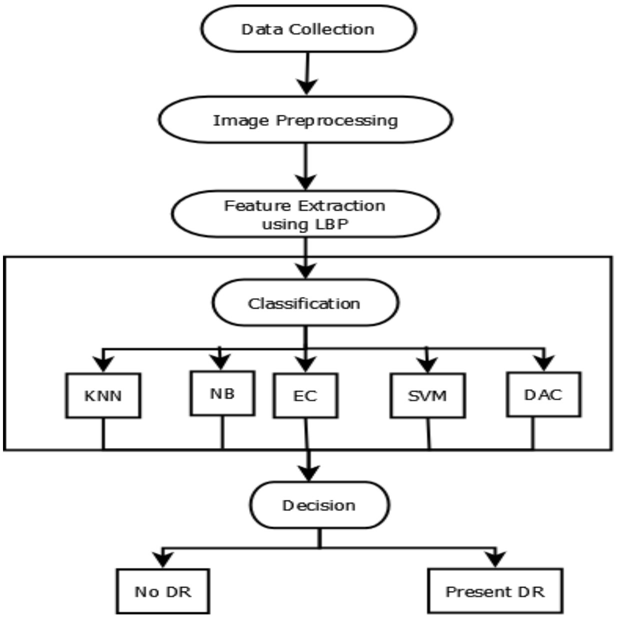

Fig. 1.Proposed System

A. Dataset

The database consists of 130 colour fundus images, 20 of which are regular and 110 showed signs of DR (hard exudates, microaneurysms, haemorrhages, soft exudates, and neovascularization). The photos were collected from the Imageret project [15], and this set of data is referred to as "calibration level 0 fundus images. To train the classification models, 80% of the data set was used, and the remaining 20% was used to test the model."

B. Image Preprocessing

The retinal fundus images were pre-processed to remove noise and correct the uneven illumination. In this proposed process, the input colour image was converted to a grey level image, and the grey-level image was improved using histogram equalization.

C. Feature Extraction

Feature Extraction is a dimensionality reduction method by which the initial raw data collection is reduced to more controllable classes. It also deals with creating variables to get around issues while describing the data with adequate accuracy. In this study, the LBP descriptor was used to extract DR features.

1) Local Binary Pattern (LBP)

Local binary patterns (LBP) is a powerful grey-scale texture operator used in many computer vision tasks due to its computational simplicity[16][17]. In LBP, the first stage is to create a label centred on the local neighbourhood of the pixel defined by the radius, R, and several points, P [13], for each pixel of the image in which the label is placed. The neighbouring pixels are the threshold for the neighbourhood's central pixel's grey value, creating a binary string. The LBP label value is derived for each pixel by summing the weighted binary string with powers of 2 [17].

LBP is an adaptive image texture descriptor that sets the neighbouring pixel thresholds to the current pixel value[18]. Given the neighbourhood of the C sample points on the R radius circle and given a pixel at (xp, yp). It is possible to express LBP, as shown in Equation (1) :

$$\mathrm{LBP}_{C,R(x_p,y_p)} = \sum_{C=0}^{C-1} s(i_C - i_P)2^C \qquad (1)$$

where i_c and i_p are, respectively, grey-level values of the central pixel and P surrounding pixels in the circle neighbourhood with a radius D, and function f(x) is defined in Equation (2) as:

$$f(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases} \qquad (2)$$

D. Diabetic Retinopathy Classification

Machine learning's capacity lies in its ability to generalize by correctly classifying unknown data based on models built using the training dataset. The collected retinal fundus images have been categorized into two classes: No DR and Present DR. No DR category implies that the fundus image is a normal image whereas the present DR category means that DR is present in the fundus image. In this research, experimentation was carried out using five classification techniques, and these techniques are discussed in the subsections below.

1) Discriminant Analysis Classifier (DAC)

DAC is a multivariate statistical technique that is used to create a model for group membership prediction. The model comprises discriminating functions that emerge to provide the best group discrimination based on a linear combination of predictive variables. Such functions are derived from a sample of established group memberships [19]. They could then be applied to new individuals with measures related to the same variables and unknown memberships. While in behavioural sciences, discriminatory analysis is not widely used as the assumptions are not always easy to satisfy. DAC is a multivariate statistical and mathematically robust approach used in cases where groups are defined a priori. Each instance must be scored on one or more quantitative indicator measures and scored on a group test. Discriminant analysis is a method of classification. DAC operates when continuous quantities are calculated on independent variables for each measurement[20].

2) Support Vector Machine (SVM)

SVM is an algorithm used in supervised learning. The algorithm is based on statistical learning theory [21]. The algorithm is founded on the structural risk minimization principle; it can compact the array of raw data to a support vector set and learn how to obtain a function for classification decision [22]. The SVM model iterates over a collection of labelled training samples to discover a hyper-plane that, by finding data points, generates an optimal limit for the decision. Support vectors optimize class separation [23]. In the input space, the decision function of a binary SVM is represented in equation (3) below:

$$\gamma = h(x) = sign\left(\sum_{j=1}^{n} u_j y_j K(x, x_j) + v\right) \qquad (3)$$

where x is the feature vector to be categorized, j indexes the training instances, n is the number of training instances, y_j is the label (1 or –1) of training example j, K(,) is the kernel function, and u_j and v are fit to the data to maximize the margin. Training vectors for which $u_j \neq 0$ are called support vectors [24].

3) Naïve Bayes (NB)

The NB Classification illustrates both a supervised learning approach and a statistical classification system. It presumes an intrinsic probabilistic model and helps measure the probabilities of the results, to acquire principled uncertainty about the model [24]. The NB classifier is a probabilistic approach of machine learning focused on using the Bayes theorem with elevated assumptions of feature independence. NB classifiers are highly scalable and need many linear parameters in the number of problem functions for learning [25]. In NB Bayes theorem offers a way of computing the posterior probability $P(x|y)$from$P(x)$, $P(y)$ and$P(y|x)$. Equation (4) and (5) presented the equation for posterior probability$P(x|y)$.

$$P(x|y) = \frac{P(y|x) \times P(x)}{P(y)} \quad (3)$$

$$P(x|y) = \frac{P(y_1|x) \times P(y_2|x) \times \ldots \times P(y_n|x) \times P(x)}{P(y_1, \ldots, y_n)} \quad (4)$$

4) Ensemble Classifier (EC)

Ensemble learning generates various base classifiers from which a new classifier is obtained that performs better than any of the components classifiers. These base classifiers may differ according to the algorithm, hyper-parameters, representation, or training set used [26]. The principal objective of the ensemble approach is to decrease bias and variance. Ensembles combine multiple hypotheses to establish a more robust inference [27]. An ensemble is a supervised learning technique itself, as it can be trained and then used to make predictions [27]. Therefore, the ensemble classifier reflects a single hypothesis. However, within the model's hypothesis space from which it is built, this hypothesis is not inherently included. Thus it has been shown that ensembles have more versatility in the functions they can represent. Experimentally, where there is a substantial variance between models, ensembles tend to produce better performance [28]. Many ensemble methods, therefore, aim to encourage diversity among the models that they combine.

5) K-Nearest Neighbor (KNN)

K-NN is among the most straightforward algorithms for machine learning tasks. An item is classified by the "distance" from its neighbours, and the item is assigned to the class of its nearest k-distance neighbours that is most prevalent [29]. The algorithm becomes the nearest neighbour algorithm if k = 1, and the object is assigned to the class of its nearest neighbour. This number K specifies the number of neighbours an item has [30].

The Euclidean distance, which is a linear distance between 2 points in Euclidean space, is generally used to measure the distance between 2 vector positions in multi-dimensional space [30]. If two vectors y_i and y_j are given where yi =(y_{i1}, y_{i2}, y_{i3}, …, y_{in}) And y_j =(y_{j1}, y_{j2}, y_{j3}, …, y_{jn}) Then the Euclidean distance between y_i and y_j is given in equation (6) as:

$$D(y_i, y_j = \sqrt{\sum_{k=1}^{n} (y_{ik} - y_{jk})^2} \quad (6)$$

K-NN algorithm can be summarized as follows:

- Step 1: Along with a new sample, specifies a positive integer k.
- Step 2: Pick k entries that are closet to the new instance in the database.
- Step 3: For those entries, the most common classification is found.
- Step 4: This is the classification we give to the new sample.

E. Performance Metric

- **Accuracy:** Accuracy is specified as the rate of correct classifications. This is the number of predictions, divided by the total number of predictions made, that is correct. In equation (7), the exact formula is given:

  Accuracy=(TP + TN)/(TP + TN + FP + FN) (7)

  TP stands for True Positives, TN stands for True Negative, FP stands for False Positives, and FN stands for False Negative.

- **Recall:** Recall: it is also known as sensitivity. Recall is a statistic that calculates the amount of accurate positive predictions that could have been made from all positive predictions. The recall is determined on the basis of the formula in equation (8).

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \quad (8)$$

- **Precision**: Precision: is a metric calculating how many positive predictions are accurately made. The amount of true positive elements is calculated as divided by the sum of true positives and false positives [31]. Precision is defined according to the formula in equation (9).

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \quad (9)$$

- **Specificity:** This is the percentage of true negatives that during testing are correctly detected by the classifier. Specificity is computed using the formula in equation (10).

$$Specificity = \frac{True\ Negatives}{True\ Negatives + False\ Positives} \quad (10)$$

IV. Result and Discussion

In this work, experiments were conducted on five different machine learning algorithms: DAC, KNN, SVM, EC and NB classifier with respect to DR identification and classification. The LBP feature which was extracted from the pre-processed fundus images was feed to the five classifiers. The results of the different classification techniques are shown in Table 1.

TABLE 1. DIABETIC RETINOPATHY CLASSIFICATION RESULT

Techniques	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)
Discriminant Analysis Classifier (DAC)	86.76	84	80	91.7
Support Vector Machine (SVM)	94.46	91	89	96.9
Naïve Bayes (NB)	79.08	76	73.6	93
K-Nearest Neighbor (K-NN)	90.62	89.8	88.67	95.5
Ensembles Classifier (EC)	**98.31**	**95**	**100**	**97.3**

Table 1 shows that Ensembles classifier (EC) produced the highest classification accuracy with a value of 98.31% compared to K-NN, SVM, NB, and DAC with classification accuracy 90.62%, 94.46%, 79.08%, and 86.76%, respectively. Based on the precision metric, it can be seen that EC produced a higher precision value of 95% as compared to DAC, NB, K-NN, and SVM with 84%, 76% 89.8%, and 91% respectively. Table 1 shows that EC has a high recall value of 100% inferring that number of correct positive predictions made out of all the positive predictions is better than the positive prediction made by DAC, SVM, NB and K-NN with a recall of 80%, 89%, 73.6 % and 88.67% respectively. Evaluating from the specificity perspective, EC produces the highest specificity of 97.3%, followed by SVM with a specificity of 96.9%. EC classifier is more appropriate for a reliable DR identification compared to the other four classifiers from the results of accuracy, recall, precision, and specificity obtained.

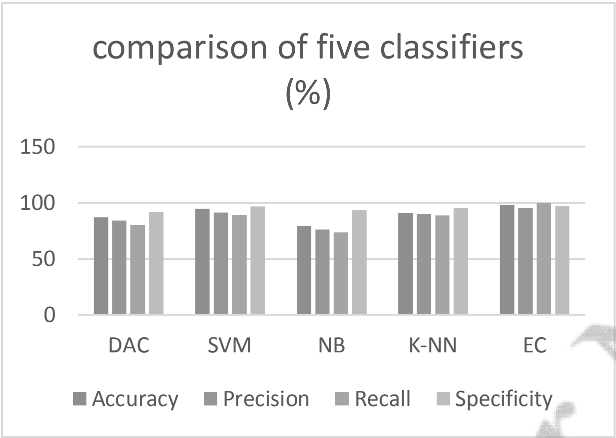

Fig. 2. Comparison of Five Classifiers

Fig. 2 presents a graphical representation of the values of precision, accuracy, recall and specificity depicted in table 1.

TABLE 2. COMPARISON OF ENSEMBLE CLASSIFIER WITH RELATED WORKS

Algorithm	Accuracy (%)
Ensemble (proposed method)	**98.31**
Deep Neural Network-PCA-Firefly[31]	97
Artificial Neural Network (ANN)[32]	96

Table 2 shows a comparison of the Ensemble classifier's accuracy (EC) and the DNN-PCA-Firefly and ANN. The proposed method achieved a higher accuracy of 98.31% compared to DNN-PCA-Firefly and ANN, which reached an accuracy of 97% and 96% respectively.

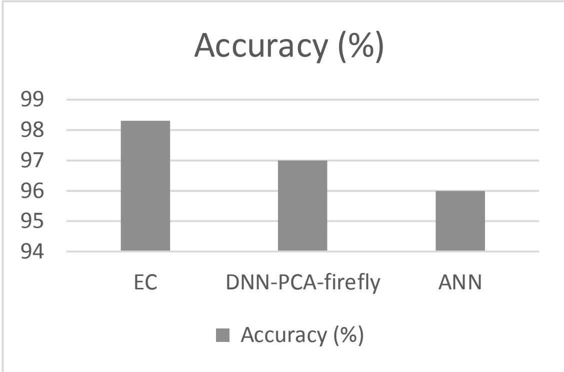

Fig. 3. Comparison with related works

Fig. 3 presents a graphical representation of the values of precision, accuracy, recall and specificity depicted in table 2.

V. Conclusion

This paper produced a comparative result for five classifiers, namely: K-NN, SVM, DAC, NB and EC in respect to DR detection and classification using LBP extracted features. The obtained results demonstrate that using LBP texture descriptors for fundus images provides useful DR disease screening features. From the presented comparative analysis, the investigation of K–NN, SVM, DAC, EC and NB has been executed. The performance metric shows that EC performs better when contrasted with the other four methods. The accuracy estimation of the EC technique was observed to be 98.31% which shows the high effectiveness of EC for DR identification. It can be inferred from the results obtained that the application of the EC technique for the classification of the fundus image produces better results than those provided in current works. In conclusion, a comparative evaluation of five machine learning techniques for diabetic retinopathy identification has been presented.

VI. Future Works

In this study only the LBP feature descriptor was used, hence for future work more feature descriptors such as Histogram of Oriented Gradient, SURF, Scale Invariant Feature Transform etc. can be used or combined to improve the system robustness. In this work, the comparative analysis was focused on five machine learning techniques. The number of machine learning techniques used can be increased to improve the study's flexibility and robustness for future work.

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