Diabetic Retinopathy Image Classification Using Machine Learning and Local Binary Patterns Features

2023 8th International Symposium on Electrical and Electronics Engineering (ISEEE) | 979-8-3503-0167-0/23/$31.00 ©2023 IEEE | DOI: 10.1109/ISEEE58596.2023.10310398

1st Mihaela Miron
Department of Computer Science and Information Technology
Faculty of Automation, Computers, Electrical Engineering and Electronics,
Dunarea de Jos University of Galati
Galati, Romania
mihaela.miron@ugal.ro.

2nd Anisia Culea-Florescu
Department of Electronics and Telecommunications,
Faculty of Automation, Computers, Electrical Engineering and Electronics,
Dunarea de Jos University of Galati
Galati, Romania
anisia.culea@ugal.ro.

3rd Simona Moldovanu
Department of Computer Science and Information Technology
Faculty of Automation, Computers, Electrical Engineering and Electronics,
Dunarea de Jos University of Galati
Galati, Romania
simona.moldovanu@ugal.ro.

***Abstract*— Diabetic Retinopathy (DR) is a condition caused by diabetes that affects the blood vessels in the retina. Detecting the disease early and providing appropriate treatment are crucial in slowing its progression. Therefore, there is great potential in utilizing Machine Learning (ML) to improve the identification and monitoring of DR development in patients. Our study aims to explore the performance of six ML algorithms, namely Random Forest (RF), Adaptive Boosting (AB), K-Nearest Neighbor (K-NN), Gaussian Naive Bayes (GNB), Support Vector Machine (SVM), and Quadratic Discriminant Analysis (QDA), in two binary classifications involving three classes: non-diabetic retinopathy (NoDR), moderate retinopathy (MR), and severe retinopathy (SV). These ML algorithms were applied to ten features extracted using local binary patterns (LBP). The first classification task involved distinguishing between NoDR and MR, while the second task involved differentiating between NoDR and SV. The RF technique achieved the highest classification accuracy, with 0.912 for the first task and 0.94 for the second task.**

Keywords*— *diabetic retinopathy, machine learning, accuracy

I. INTRODUCTION

Diabetic retinopathy (DR) is one of the most common microvascular conditions affecting the eyes caused by diabetes and can lead to vision loss if left untreated. Studies show that people in Europe are affected by this complication in percentages between 3%-4%, while the increased risk is for patients with type 1 diabetes compared to type 2 [1-3].

Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR) are the two main phases of the DR [4]. The initial stage exhibits micro-aneurysms (MA), which are small circular red dots at the end of blood vessels, and the intermediate stage shows flame-shaped hemorrhages in the retina when MAs get ruptured. The DR in the initial phases is known as NPDR and can be classified into Mild, Moderate, and Severe. Due to the lack of healing, the severe stage displays the development of new scar tissue.

Retinal images, typically obtained from fundus photography or optical coherence tomography (OCT), are used to diagnose DR. Because medical images are complex, the manual analysis is time- and money-consuming because it can only be completed by highly qualified experts in the field. Consequently, the number of methods used in assisting clinical decision-making has been steadily growing in recent years.

The classification of medical images in recent papers is based on the extraction and analysis of textural information from the images, along with machine learning algorithms. Machine learning algorithms often require a set of representative features to learn from. In the case of diabetic retinopathy, features can be extracted from the retinal images using various methods such as edge detection, texture analysis, and vessel segmentation. R. Priya et al. [5] analyzed the efficiency of three ML architectures: support vector machine (SVM), probabilistic neural network (PNN), and Bayesian Classification. A small dataset of images was used because they manually extracted features in these architectures to categorize the images into binary classes. Their accuracy results are 97.6%, 94.4%, and 89.6% for SVM, PNN, and Bayesian Classification, respectively.

While comparing the performance of the common classifiers KNN, SVM, and PNN—Yadav et al. [6] and Amin et al. [7] discovered that SVM has the highest accuracy among them.

Instead of using an ophthalmoscope, N. Kashyap et al. [8] proposed that the retina eye image be captured using a phone camera with an external lens. Once the image is captured, they carry out their feature extraction and predictions using the method of Discrete Wavelet Transform and ML Euclidean distance calculation. And for binary classification, their result was Precision 63% and Recall 57%.

In this study for diabetic retinopathy image classification the performances of six classifiers: Random Forest (RF), Adaptive Boosting (AB), K-Nearest Neighbor (K-NN), Gaussian Naive Bayes (GNB), Support Vector Machine (SVM), and Quadratic Discriminant Analysis (QDA) are analyzed. The methodology was applied to ten features extracted with local binary patterns.

As a result of our study, a high accuracy classification between noDR vs. MR and between noDR vs. SV could be very useful for detecting diabetic retinopathy in the early stage.

The next sections of this paper are structured as follows: Section II presents an overview of the image database, hardware, and software used in the study. Section III provides a detailed explanation of the local binary pattern. Section IV elaborates on the various machine-learning techniques employed in this research. In Section V, experimental results are summarized. Finally, the conclusion of the article is presented.

II. Image Database, Hardware and Software

The image dataset APTOS 2019 Blindness Detection (https://www.kaggle.com/c/aptos2019-blindness-detection) contains 2804 Non-Diabetic Retinopathy, 999 Severe Retinopathy, and 295 Moderate Retinopathy photos captured utilizing fundus photography under a variety of imaging settings.

Because the dataset images may be a different size, and may vary in many other ways, in our paper all images are preprocessed with Gaussian filters and resized to 224 x 224. An example for each category is shown in Fig. 1.

The local binary patterns features were extracted with Matlab R2018a and the classifiers from Scikit-learn Python 3.9 – based library were used.

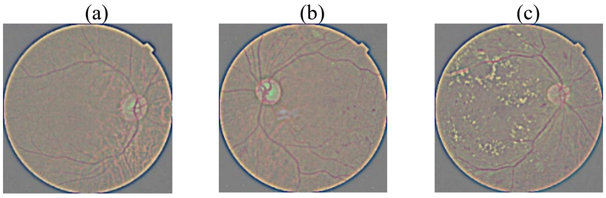

Fig. 1. (a) Non-Diabetic Retinopathy; (b) Moderate Retinopathy; (c) Severe Retinopathy

The hardware used in this work has the following specifications: Inter (R) Core (TM) i7-8550U CPU @ 1.80 GHz; Memory (RAM) 8 GB DDR4; GeForce MX150 4 GB video; hard disk 500 GB SSD.

III. Local Binary Pattern Features

In fields such as facial recognition and target identification, the local binary pattern is distinctive due to its powerful textural operator. The local binary pattern operator, introduced by Ojala et al. [9], creates a binary code by comparing a nearby pixel with its center patch gray unit. If a neighboring pixel's value is less than the center value, this operator assigns a value of 0. Otherwise, a unit value is assigned.

For a given pixel with (x_i, y_i) coordinates, the resulting LBP can be expressed in decimal form as:

$$LBP_{k,R}(x_i, y_i) = \sum_{k=0}^{k-1} s(t_k - t_i)2^k \quad (1)$$

where t_k and t_i are gray-level values of the central pixel and k surrounding pixels in the circle neighborhood with a radius R, and function $s(x)$ being defined as:

$$s(x) = \begin{cases} 1 & if \quad x \geq 0 \\ 0 & if \quad x < 0 \end{cases} \quad (2)$$

The operator $LBP_{k,R}$ provides 2^k output values, corresponding to 2^k different binary patterns generated by P pixels in the neighborhood.

In our case, the output array represents the completed LBP histogram features. Each binary value in the histogram corresponds to a feature. Specifically, the histogram is calculated for the first ten features.

IV. Machine Learning Classifier

DR is asymptomatic at the early stages and could lead to vision loss if it is left untreated. So, the potential of using MLs becomes very promising to enhance the detection and monitoring of disease evolution in patients [10] and is considered an option that aim to reduce the physician's workload by providing a practical and cost-effective method [11]. Therefore, our study is focused on investigating the effectiveness of using features extracted with local binary patterns to feed six MLs which perform two binary classifications with three classes: Non-Diabetic Retinopathy (NoDR), Moderate Retinopathy (MR) and Severe Retinopathy (SV). From the supervised techniques, mentioned by the scientifical literature for solving classification problems, are investigated: Random Forest (RF), Adaptive Boosting (AB), K-Nearest Neighbor (K-NN), Gaussian Naive Bayes (GNB), Support Vector Machine (SVM) and Quadratic Discriminant Analysis (QDA).

A. A. Random forest (RF)

Random Forest is an extensively used machine learning technique for both classification and regression tasks [12 -13]. This classifier works with several uncorrelated decision trees, each with different prediction outputs obtained on various subsets of a given dataset. The decision is taken by a majority voting mechanism that combines these outputs and finds the most frequently appeared prediction to obtain the overall prediction of the entire dataset. It is popular due to less training time, high accuracy, and efficiency when applied to large datasets.

B. B. Adaptive Boosting (AB)

Adaptive Boosting is an ensemble method, highly valuable for high speed, low complexity, and good compatibility [14]. This classifier is first fitting on the original dataset and then on additional data. Thus, the weights of incorrectly classified instances are adjusted, and subsequent classifiers can perform better in difficult cases [15].

C. C. K-Nearest Neighbor (K-NN)

K-Nearest Neighbor classifier is a supervised learning technique, intensively applied for solving classification, regression and data mining tasks. Since it is a non-parametric method, no assumption related to data distribution is performed. In K-NN classification, the data is grouped into clusters or subsets to classify new data based on its similarity with previously trained data [16]. The parameters are K – the number of nearest neighbors and d - the distance between neighbors (Euclidean distance, Hamming distance, Manhattan distance, and Minkowski distance).

D. D. Gaussian Naive Bayes (GNB)

The Gaussian Naive Bayes classifier performs a probabilistic classification based on the Bayes theorem and it is very effective on an extensive range of complex problems [17]. This classifier assumes that all features are independently and equally contributing to the probability of a sample belonging to a specific class. It uses the maximum likelihood method to estimate the values for mean and standard deviation for each class.

E. E. Support Vector Machine (SVM)

The support Vector Machine technique works similarly to linear discriminant analysis. This method separates feature vectors into several classes by finding the hyperplane with the maximal margin. Some of the advantages of using the SVM are [18]: effective in high dimensional spaces, when the dimensions are greater than the number of samples, memory efficient, and versatile. Determining the optimum kernel for the decision function is the key point for achieving good accuracy.

F. F. Quadratic Discriminant Analysis (QDA)

Quadratic Discriminant Analysis is a statistical classifier that uses a quadratic decision surface as a boundary between two or more classes [19]. Each class has its own covariance matrix.

The hyperparameters of the ML classifiers used in the learning process are presented in Table 1.

TABLE I. TABLE 1. HYPERPARAMETERS OF THE MACHINE LEARNING MODELS

Technique	Hyperparameters
RF	n_estimators=100, random_state=43
AB	n_estimators=100, algorithm='SAMME.R', random_state=43
KNN	n_neighbors=1, weights='uniform', algorithm= 'auto', metric='minkowski'
SVM	kernel='rbf', degree=3, gamma='scale', decision_function_shape='ovr'
QDA	priors='None'
GNB	priors='None', var_smoothing=1e-9

The hyperparameters not mentioned are applied with the default values. To determine the optimum values of hyperparameters we documented other similar studies and consulted the official page of the Keras Library.

V. RESULTS OF THE EXPERIMENTS

The validation of the proposed study was carried out using six ML algorithms. The process involved two steps: first, the extraction of LBP features, and second, their classification using ML techniques.

Before classifying the data, the mean ± standard deviation of each LBP feature $F_i, i = \overline{1,10}$, as shown in Table 2, were analyzed. The features were then sorted according to the classes NoDR, MR, and SV.

TABLE II. TABLE 2. THE MEAN AND STANDARD DEVIATION FOR EACH STUDIED LBP FEATURES

Features	NoDR	MR	SV
F1	2741.68±37.2	2701.55±44.1	2705.23±36.3
F2	42.55±17.95	48.47±37.96	44.13±31.90
F3	33.26±22.85	12.65±15.45	12.84±15.16
F4	20.88±16.35	21.15±16.79	24.03±18.85
F5	17.28±14.38	27.19±12.56	27.79±11.34
F6	12.98±14.80	29.15±13.07	29.75±13.61
F7	6.68±8.78	19.10±10.34	17.97±9.19
F8	4.18±6.03	11.84±7.12	10.72±7.39
F9	4.64±5.26	9.47±7.32	9.06±7.80
F10	6.86±6.70	10.45±8.89	9.48±8.78

The classification performance is evaluated in terms of accuracy, where the true positives (TP), the false positives (FP), the true negatives (TN) and the false negatives (FN) are extracted from the confusion matrix.

$$accuracy = (TN + TP)/(TN + TP + FN + FP) \quad (3)$$

Table 3 provides a summary of the confusion matrix for each ML classifier.

TABLE III. TABLE 3. THE CONFUSION MATRIX OF EACH ML

MLs	Matrices Confusion [[TP FN] [FP TN]] noDR vs. MR	noDR vs. SV
RF	[[217 22] [39 423]]	[[234 19] [24 424]]
K-NN	[[197 54] [43 407]]	[[435 11] [26 28]]
AB	[[201 50] [25 425]]	[[435 11] [30 24]]
GNB	[[186 65] [98 352]]	[[372 74] [28 26]]
QDA	[[209 42] [72 378]]	[[406 40] [21 33]]
SVM	[[209 42] [72 378]]	[[406 40] [21 33]]

In Fig. 2, a comparison of the accuracy for each ML classifier is presented. The RF classifier stands out with the highest accuracy of 0.94. Specifically, when classifying between noDR and SV, the RF classifier demonstrates the highest accuracy overall.

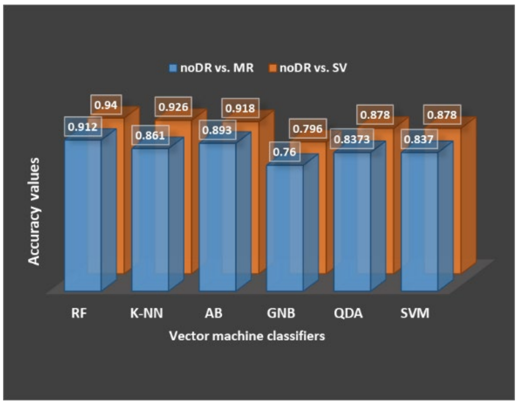

Fig. 2. The accuracy values for each ML classifier

This study's results indicate that the RF, K-NN, and AB classifiers achieve an accuracy of over 0.9 for the noDR and SV classes. However, the GNB classifier yields different results due to the presence of a high number of false negative (FN) and false positive (FP) samples, which ultimately reduces the accuracy.

The experiments show that MLs require quality input data to classify accurately. The research performed by Gayathri et al. [20] with deep learning and machine learning classifiers fed with global and local features extracted from the IDRiD dataset, obtained an accuracy of 99.62%. The proposed system by Punithavathi *et al.* [21] in the context of using color and shape features together with MLs achieved a precision of 82%.

Compared with other studies, the results within this study, (shown in Fig. 2) are obtained with different classification techniques. Furthermore, accuracy can be improved with LBP features if the ML classifier is chosen taking into consideration the quality of the data.

CONCLUSION

In summary, this research has highlighted the efficiency of LBP features for differentiating diabetic retinopathy levels.

The results from the study demonstrate that the suggested approach leads to improved accuracy when RF is used with specific hyperparameters mentioned in this study.

The proposed features show great potential for non-diabetic retinopathy and severe retinopathy classification. RF classifies diabetic retinopathy with an accuracy of almost 94%, while K-NN obtains an accuracy value of approximately 92%. AB consistently shows better results for the same classes. Therefore, we can conclude that LBP features extracted from retinal images have the potential to make a significant impact on the classification process of diabetic retinopathy.

The results are promising so future research will integrate the presented MLs and convolutional neural networks to enhance diabetic retinopathy detection.

REFERENCES

[1] Prokofyeva E, Zrenner E. Epidemiology of major eye diseases leading to blindness in Europe: a literature review. Ophthalmic Res. 2012;47:171–188.

[2] Hammes HP. Optimal treatment of diabetic retinopathy. Ther Adv Endocrinol Metab. 2013;4:61–71.

[3] Deutsche DG. Nationale VersorgungsLeitlinie Typ-2-Diabetes Prävention und Therapie von Netzhautkomplikationen. Berlin: Bundesärztekammer (BÄK); 2010. pp. 1–42.

[4] Memon W. R., Lal B. and Sahto A. A., "Diabetic retinopathy", The Prof. Med. J., 2017, vol. 24, pp. 234-238.

[5] Priya, R., and P. Aruna. "Diagnosis of diabetic retinopathy using machine learning techniques." ICTACT Journal on soft computing 3.4. 2013.

[6] Yadav, D.; Karn, A.K.; Giddalur, A.; Dhiman, A.; Sharma, S.; Yadav, A.K. Microaneurysm detection using color locus detection method. Measurement 2021, 176, 109084.

[7] Amin, J.; Sharif, M.; Yasmin, M.; Ali, H.; Fernandes, S.L. A method for the detection and classification of diabetic retinopathy using structural predictors of bright lesions. J. Comput. Sci. 2017, 19, 153–164.

[8] Kashyap N., Singh D. K. and Singh G. K., "Mobile phone based diabetic retinopathy detection system using ANN-DWT," 2017 4th IEEE Uttar Pradesh.

[9] Ojala, T., Pietik¨ainen, M., Harwood, D.: A comparative study of texture measures with classification based on feature distributions. Pattern Recognition 29 (1996) 51–59

[10] Oh, K., Kang, H.M., Leem, D. et al. Early detection of diabetic retinopathy based on deep learning and ultra-wide-field fundus images. Sci Rep 11, 1897 (2021). https://doi.org/10.1038/s41598-021-81539-3

[11] Alazzam, Malik & Alassery, Fawaz & Almulihi, Ahmed. (2021). Identification of Diabetic Retinopathy through Machine Learning. Mobile Information Systems. 2021. 1-8. 10.1155/2021/1155116.

[12] Breiman L. Random forests. Mach Learn 2001;45(1):5–32.

[13] https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html

[14] Hui Liu, Chapter 5 - Data mining and processing for train unmanned driving systems, Editor(s): Hui Liu, Unmanned Driving Systems for Smart Trains, Elsevier, 2021, Pages 211-252, ISBN 9780128228302.

[15] https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.AdaBoostClassifier.html

[16] K. Taunk, S. De, S. Verma and A. Swetapadma, "A Brief Review of Nearest Neighbor Algorithm for Learning and Classification," 2019 International Conference on Intelligent Computing and Control Systems (ICCS), Madurai, India, 2019, pp. 1255-1260.

[17] Gangadhar Shobha, Shanta Rangaswamy, Chapter 8 - Machine Learning, Editor(s): Venkat N. Gudivada, C.R. Rao, Handbook of Statistics, Elsevier, Volume 38, 2018, pp. 197-228, ISSN 0169-7161, ISBN 9780444640420.

[18] https://scikit-learn.org/stable/modules/svm.html

[19] https://scikit-learn.org/stable/modules/lda_qda.html

[20] Gayathri, S.; Gopi, V.P.; Palanisamy, P. Diabetic retinopathy classification based on multipath CNN and machine learning classifiers. Phys. Eng. Sci. Med. 2021, 44, 639–653.

[21] Punithavathi, I. H., GaneshKumar, P. Annotation and Retrieval of Retinal Images using Support Vector Machine with Active Learning. IEEE International Conference on Intelligent Techniques in Control, Optimization and Signal Processing (INCOS), 201