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Diabetic Retinopathy Detection based on Hybrid Feature Extraction and SVM

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Abstract— **Diabetes is a disease caused by high blood sugar levels in the body. Diabetic retinopathy (DR) is a vision-threatening disease that primarily affects people who have diabetes for many years. It is the major cause of blindness in people with diabetes. Medical work in this domain indicated that blindness could be prevented by providing proper treatment by diagnosing DR at the initial stage. The proper screening requires the training of manual graders to understand the type of DR. However, the overall cost of this screening program increases due to the complexity of this process and workload on pathologists. State of the art methods has focused on simple retinal image analysis to eliminate the patients who are not affected by this disease. Therefore, reducing the overall cost of this process by decreasing the workload of pathologists. The focus of this research work is to automatically detect the severity level of DR instead of just providing information about its presence that can further reduce the DR costs. Therefore, we designed an automated framework to extract the anatomy independent features and trained the SVM classifier to detect different DR stages. We used the Kaggle DR-data set to evaluate the performance of the proposed method. For each stage of DR, which indicates the effectiveness of the proposed technique, an average accuracy of 96.4% was achieved. Experimental results show that the proposed method can efficiently and reliably detect DR in large image data sets. The main contribution of the proposed work is to design efficient, cost-effective and fully automatic DR screening techniques.**

Keywords— Diabetic Retinopathy, DR Stages, CBIR, Proliferative, non-Proliferative.

I. INTRODUCTION

DR is a vision-related disease that affects people who have diabetes. According to the World Health Organization (WHO), about 347 million people worldwide have diabetes and all are at risk of becoming a victim of DR [1]. In the United States of America 29.1 million people are affected by diabetes. The worst effect of DR causes blindness in the affected patient, which can be prevented if proper treatment is provided to the patient at an early stage. However, the detection of DR in the early stages is very tricky, since there are very few symptoms [1].

Diabetic retinopathy is a chronic disease that usually grows from mild non-proliferative diabetic retinopathy (NPDR) to moderate proliferative diabetic retinopathy (PRDR) [2]. NDPR retinal blood vessels develop tiny leaks and damaged due to the higher glucose level in blood. Blood and body fluids from leaks and fatty substances cause swelling in the central part of the retina, blurring vision. In NPDR, various abnormalities exist, i.e. soft exudates, hard exudates, and severe intraretinally microvascular abnormalities. Abnormal blood vessels grow in proliferative diabetic retinopathy (PDR) due to a lack of blood flow in the retina. These vessels cause the bleeding in the retina which blocks the vision and ultimately leads to blindness [3].

There exist different automated methods for the classification of DR severity [4][5]. It can be classified as a classic image analysis based technology. [4] and Deep Neural Networks (DNN) based techniques [5]. The former is trained on whole images whereas; the latter uses separate pathology-specific Convolutional Neural Network (CNN), e.g. hemorrhages, etc. Trained on the patch. Where outputs are combined to predict DR severity [6].

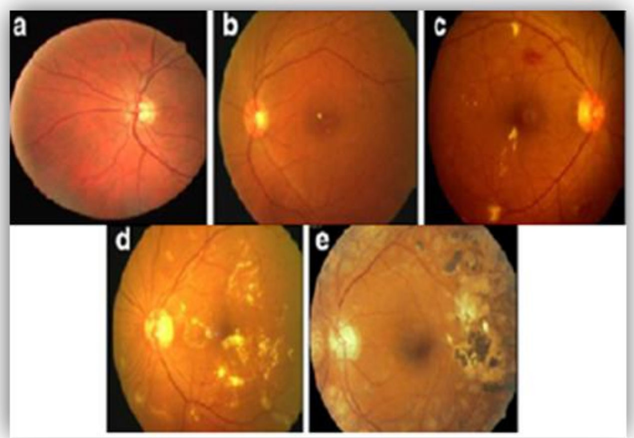

Fig. 1. Phases of DR :(a) Normal, (b) Mild, (c). Moderate, (d). Severe, (e). Prolific.

A hybrid approach based on ImageNet CNN, SVM, and random forest classifiers was proposed in [7] for DR severity detection. In [8], pre-trained CNN was converted into the weakly supervised model (EyeWeS) to detect the DR from low-resolution fundus images and highlighted the regions of the fundus images containing retinal lesions, e.g. exudates, hemorrhages, etc. In [9], the Local Binary Pattern "(LBP)," descriptor was used to analyses the texture information of the retina for fundus images. In [10], the optic disc was detected using the watershed method. Exudates inside the macular portion were then removed through their high dark level variety and morphological reproduction. For Automated recognition of exudates, fuzzy c-means clustering was applied on color retinal images [11]. In [12], blood vessel segmentation was performed by using the ensemble of boosted and bagged decision trees by extracting the morphological features. In [13], deformed deformable model technology was used for the segmentation of the Optic Disc to detect newly created vessels. The data-driven approach finds greens in retinal images using convolutional neural networks for the detection of reference diabetic retinopathy [14]. Subclinical DR detection is significant for retina damage before the vision loss. In [15] provide a rapid analysis of retinal images and present methods used for the detection of subclinical DR.

At present, the existing methods are time-consuming and manual processes, which should be examined and evaluated by an experienced clinician, and by the time, screening results appear, treatment may become delayed. Furthermore, with the growth of diabetes due to the growing population, the infrastructure needed to prevent blindness becomes even more insufficient.

Therefore, to address the needs of DR detection for larger populations, in this paper, the concept of feature extraction and multi-category recognition of content-based image retrieval has been reliably applied. For this purpose, we initially acquire the life structures free element portrayal of images introduced in the fundus image archive. The component extraction process includes the investigation of images in the shape, texture and color areas.

The proposed work's main contributions are saliency feature extraction and a fully automatic system for the detection of DR severity. The proposed DR technique works similarly as human specialists work; thus, it brings down the cost essential for the usage of the screened programs. Our technique can be utilized to make crucial forecasts regarding nearness signs, and seriousness of a few retinal sicknesses in a deterministic way.

The rest of the paper is organized as follows: Section II provides a discussion of the proposed methodology. Section III shows the results of the experiment. Finally, in chapter IV, we will conclude the proposed research work.

II. Proposed Method

With the far-reaching computerized imaging advances, an ever-increasing number of images are accessible to general society. Effective management of a huge repository of images is a difficult task as these vast image libraries don't allow us the textual annotation of images. Thus, the retrieval strategy and handling of the query image from the database has turned out to be very crucial.

To distinguish the DR stages, CBIR is used, and SVM is applied to identify the right phase of desired images. The execution deficiency happens particularly because of one class against all other classes. This strategy provides proficient image retrieval in a multi-class condition where the positive examples are normally lesser than the examples having a place with similar classes. CBIR [16] technique utilizes visual and textual substance to obtain and decide about images from the large repository as per the user's advantage. In CBIR, the user inputs a query image, and the framework is expected to recover comparable images from the database. Besides, CBIR also facilitates searching from extensive and large databases, where the pictures are augmented to be sorted out as per comparative attributes.

Our method segregates important features from the input image and compared them against the features of the desired image. Our proposed framework presents a two-stage process. Firstly, we robustly represent the input images through feature extraction and secondly train the SVM classifier on the extracted features to detect different stages of DR.

A. Pre-processing

In this stage, the input image is transformed from RGB into the YCbCr color space. In YCbCr, chrominance is one of the prevalent shading models for image registration. It contains the luminance (Y) and two shading extraordinary (Cb, Cr) parts [17]. The luminance can be described as a weighted whole of red, green, and blue parts of RGB, and color contrast segments are processed by subtracting luminance from blue (B-Y) and red (R-Y) separately. The transmission of RGB to YCbCr is shown in the following equations:

$$Y = 0.299*r + 0.587*g + 0.114*b \tag{1}$$

$$Cb = 0.866*b - 0.299*r - 0.587g \tag{2}$$

$$Cr = 0.701*r - 0.587g - 0.114*b \tag{3}$$

The benefit of the YCbCr model is the decoupling of the luminance component from the chrome part. Luminance represents the brightness of the image.

B. Feature Extraction

Our feature set consists of color, shape, luminance, texture, and saliency features. Gaussian model is used for saliency calculation as used in [15]. The saliency value E_l^n is computed as follows:

$$E_l^n = \sum \frac{1}{\sigma\sqrt{2\pi}} e^{l_{lm}^2 / (2\sigma^2)} U_{lm}^n \tag{4}$$

Where 'l' is the image patch with 'n' features $m \neq l$, and $n \in (L, C_b, C_r, T, D)$. The spatial distance between image patches

l and m is l_{lm}, whereas, U^{n}_{lm} denotes the difference of feature between patches. So, depth features are the DC coefficients [18].

A color correlogram proclaims the spatial relationship of a couple of hues alteration with distance. The linear vector of Correlogram represented the quantization of an image into 4*4*4 =64 hues. The moments of color are relentlessly utilized for shading pointing configuration, as highlighted in image retrieval systems. The feature set is calculated by using mean, two moments and standard deviation (SD) as in equation 5 and 6:

$$M_i = \sum_{j=1}^{N} \frac{1}{N} X_{ij} \tag{5}$$

$$\sigma_i = \sqrt{\left(\frac{1}{N}\sum_{j=1}^{N} X_{ij} - M_i)^2\right)} \tag{6}$$

Where N is the total number of pixels and X_{ij} is the (i, j) pixel color.

Six measurements in the feature set are calculated by the initial two moments, mean and SD [19]. The Gabor wavelet [20] accepts the image as a piece of information, and converts it into two parameters degree and orientation. Feature sets have been shaped through the mean and SD of Gabor wavelet coefficients. 48 measurements have been acquired by a resultant element. We applied wavelet to change the image with 3 level investigation, SD and mean of the modified parameters are used to shape the feature set with measurement = *40*. Our final feature vector consists of saliency, color, texture and shape features that are combined to form a hybrid feature vector has a dimension of 191.

C. Classification

For the retrieval and classification of images, the SVM classifier is used. We prepared SVM classifier with 70% images to formulate the training dataset and 30% for testing. SVM is the most critical sort of managed order because of its prevalent grouping execution in various applications. SVM is effective in high dimensional spaces. For characterization, “SVMs” isolates the categories through the hyperplane as:

$$(v, \Phi(y)) + b = 0 \tag{7}$$

$$f(y) = sign((v, \Phi(y)) + a) \tag{8}$$

Where y is the located points in the hyperplane v is the weight that determines its orientation and b is the bias of hyperplane in the input space from the origin. In the case of classification, the hyper-plane differentiates between categories and can be built by solving the optimization issue of constrained quadratic whose solution v has an expansion $v = \sum_i \alpha_i \Phi(y_i)$ regarding a subgroup of training patterns lies on edge. SVM uses the support vectors and the kernel function for decision function. In a proper feature space, the RBF kernel provides the dot product of two points. RBF has the examples y and y' used as a feature vector in the input space [21].

$$k_{rbf}(y.y') = \exp\left(-\frac{\| y - y'\|^2}{2a^2}\right) \tag{9}$$

$(\| y - y' \|^2)$ indicates the Euclidean distance, and the parameter α signifies the 'spread' of the kernel and $\gamma = \frac{1}{2\alpha^2}$ then

$$k_{rbf}(y, y') = \exp(-\gamma \| y - y' \|^2) \tag{10}$$

Since the estimation of RBF diminishes with distance and ranges somewhere in the range between 0 and 1. The feature vector of the kernel has a limitless number of measurements for α = 1, its extension is:

$$\exp\left(-\frac{1}{2}\| y - y' \|^2\right) = \sum_{i=0}^{\infty} \frac{(y^t y')^i}{i!} \exp\left(-\frac{1}{2}\| y \|^2\right) \exp\left(-\frac{1}{2}\| y' \|^2\right)$$

$$= \sum_{i=0}^{\infty} \sum_{n_{j=i}} \exp\left(-\frac{1}{2}\| y \|^2\right) \frac{y_1^{n_1} - y_k^{n_k}}{\sqrt{n_1! - n_k!}} \exp\left(-\frac{1}{2}\| y' \|^2\right) \frac{y_1'^{n_1} - y_k'^{n_k}}{\sqrt{n_1'! - n_k'!}} \tag{11}$$

The performance of SVM exceptionally good on the undertaking of discovery from retinal images using the RBF kernel. Figure 2 illustrates the working of the proposed method. Our research has two principle classes, PDR and NPDR. NPDR has advance three levels, which are beginning levels of DR. The proposed method improves accuracy and provides better outcomes when contrasted with different strategies. Multiclass classification is performed by using a one-versus-all SVM classifier. One-versus-all means training a single classifier per class.

III. Experiments and Results

The performance of our proposed technique is evaluated on a standard Kaggle dataset [19], which contains 88705 images. Kaggle dataset comprises a large set of high-resolution images including five levels of diabetic retinopathy. Images were captured through different fundus cameras, and the resolution of images is 3888 x 2592 pixels [22]. We selected the Kaggle dataset for performance evaluation to ensure that our method is tested on a diverse dataset as also adopted by the comparative methods.

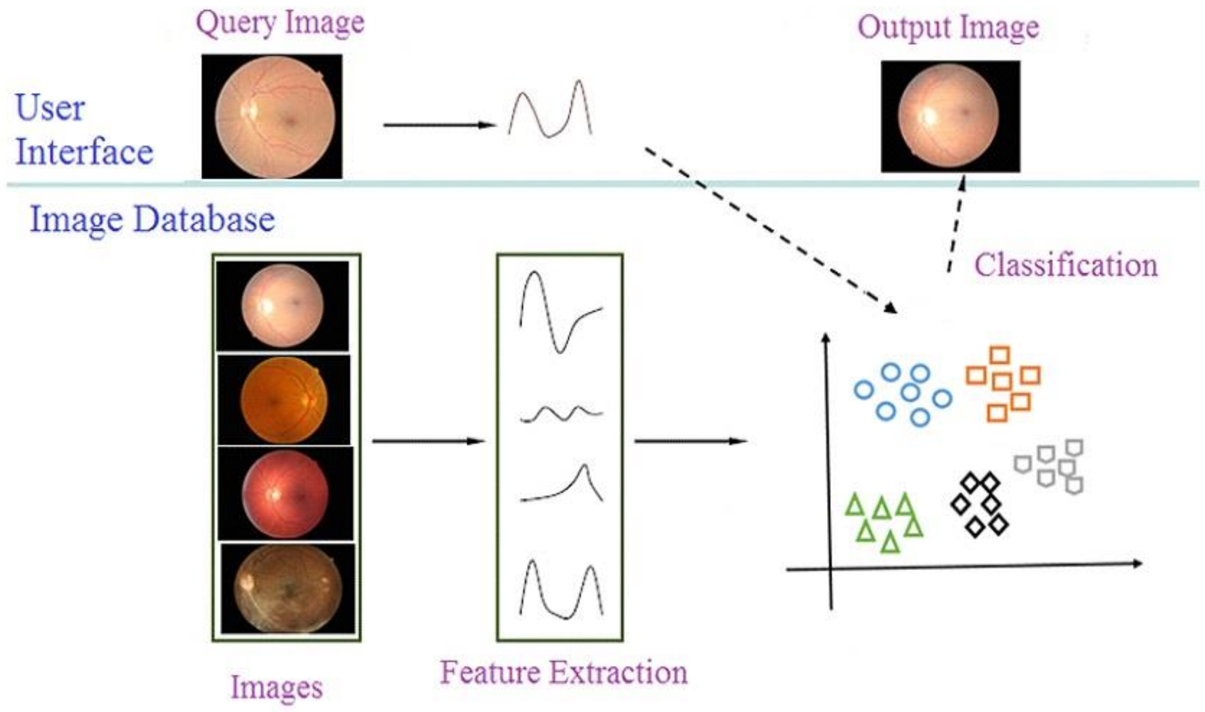

Fig. 2. Proposed System

A. Results

We designed different experiments to measure the performance of our method. The results of these experiments are provided in this section. Besides, we also presented a discussion on the results of these experiments.

To illustrate the significance of the proposed scheme in terms of CBIR, we used a dataset with 1000 images for deep analysis. In pre-processing, we resized the image to reduce the image dimension in terms of pixel space.

Precision, recall, F-1 Score, accuracy, and error rate metrics are used to measure the performance of our framework. The proposed technique takes around approx. 3 minutes for feature extraction and 2 minutes to group 100 images. For all queries, we view the applicable images as those images that have different semantic classes from that of the query image. We computed precision (P_r), recall (R), F1-score ($F1$), accuracy (A_{cc}), and error rate (E_r) as follows:

$$\mathrm{P}_r = TP / TP + FP \tag{13}$$

$$\mathrm{R} = TP / TP + FN \tag{14}$$

$$F1 = 2 * \mathrm{P}_r * \mathrm{R}(\mathrm{P}_r + \mathrm{R}) \tag{15}$$

$$A_{cc} = TP + TN / TS \tag{16}$$

$$E_r = FP + FN / TS \tag{17}$$

Where TP denotes the true positive, FP denotes the false positive, TN as true negative, FN as false negative and TS total samples.

The results obtained from the proposed method are presented in Table 1. More specifically, the proposed method achieves an average precision of 0.961, recall of 0.942, F-1 score of 0.964, an accuracy of 0.965, an error rate of 0.035. From the results, we can observe that our framework provides better detection results in terms of DR severity classification.

We designed an experiment to portray the classification accuracy of different DR stages through confusion matrix analysis. Shown in Table 2 are the results of all 5 DR classes. From the results, we can observe that the severe stage has the maximum performance gain, and mild stage has a low-performance gain because the mild stage is the earliest of DR and difficult to detect.

TABLE I. EVALUATION METRICS

Evaluation Metrics	Results
Accuracy	0.965
Precision	0.961
Recall	0.942
F1-Score	0.964
Error Rate	0.036

TABLE II. CONFUSION MATRIX

DR Stages	No DR	Mild	Moderate	Severe	Prolific
No DR	**96%**	4%	0	0	0
Mild DR	4%	**92%**	2%	0	2%
Moderate DR	0	0	**98%**	1%	1%
Severe DR	0	1%	0	**99%**	0
Proliferative DR	0	3%	0	0	**97%**

In our next experiment, we performed ROC curves analysis to indicate the classification accuracy of the proposed framework, as shown in Figure 3. ROC curves analysis is performed on five different stages of DR as depicted in Figure 3. The proposed method provides the best performance on severe DR and low in case of proliferative DR. The average performance of our method is 96.4% in our case that signifies the effectiveness of our method for classifying the DR severity in the images.

The results in terms of precision, recall, F1-score, and error rate for each DR class are shown in Figure 4. The proposed method achieves better performance with a low error rate. DR F1-score is high with a low error rate for all classes and less than 0.45. The results also indicate that our method achieves the highest average precision and recall rates which are 0.9616 and 0.9428.

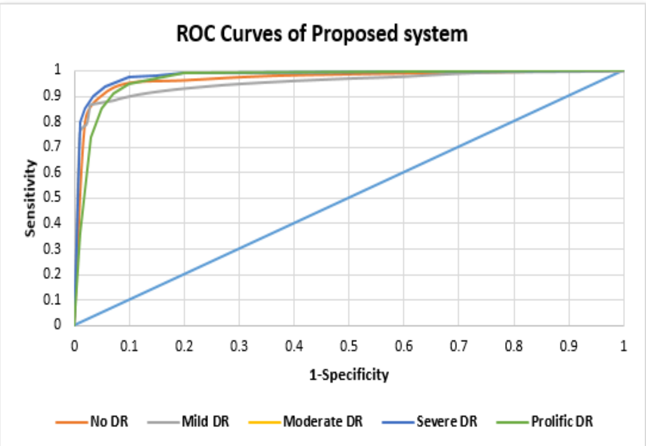

Fig. 3. ROC Curves of Proposed Method

In our last experiment, we compared our method with existing deep learning [23][8] and multiple instance learning [24] based on CBIR methods. In [24], multiple instances of learning-based approaches were presented for CBIR that achieved a classification of DR stages with 96%. In [23][8], deep learning schemes were proposed for CBIR. This method [23] achieves an AUC of 95.8%. In [8], CNN based algorithm was proposed that achieved an AUC of 92.10%. The proposed method achieves an AUC of 96.42%. The AUC values of the proposed and existing methods are presented in Table 3. From the results, we can argue that the proposed method performs better in terms of achieving the best AUC as compared to existing methods [7] [20][21].

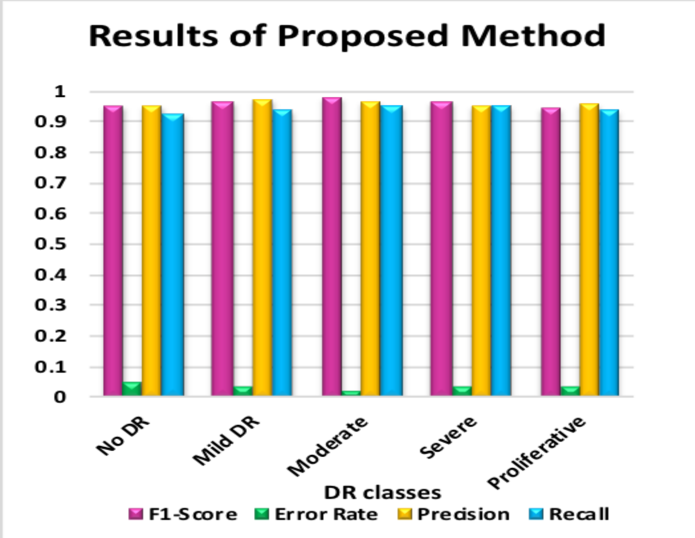

Fig. 4. Results of the proposed method

Our proposed method is evaluated on the Kaggle-DR dataset, which comprises of approx. 88 thousand images are categorized into five stages. Our method only takes 25 minutes to train on the Kaggle dataset with Intel core i7 machine with 16-GB RAM; whereas, the comparative DL-based approaches take approx. 12 hours for training that clearly shows the efficiency of our method.

TABLE III. PERFORMANCE COMPARISON WITH EXISTING METHODS

Technique	AUC
Proposed Method	**96.42%**
Zoom-in-Net [7]	92.10%
Costa et al. [20]	90.00%
EyeWeS inception [21]	95.85%

IV. CONCLUSION

In this paper, we proposed an effective technique for image retrieval of diabetic retinopathy using the saliency, color, texture and shape features. The proposed technique precisely classifies the severity of diabetic retinopathy from a large collection of images. The technique enhances the accuracy of several images and reduces the workload of pathologists. The proposed technique overall average accuracy is 96.4%.

Additionally, our method gives superior detection performance compared to existing state-of-the-art techniques. The proposed research will result in the form of a cost-effective solution that will reduce the reliance over the manual grading process and trained human graders; and hence, can be deployed to cater to the needs of the larger populations suffering from diabetes.

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