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Automated Diabetic Retinopathy Detection using Convolutional Neural Network

Nitin Shivsharan
E&TC Dept. Sinhgad College of Engineering Pune, India shivsharan.nitin@gmail.com
Sanjay Ganorkar
E&TC Dept. Sinhgad College of Engineering Pune, India srganorkar.scoe@sinhgad.edu

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Abstract

Diabetic retinopathy (DR) is normally encountered in individuals who are affected by diabetes for longer time. The vision of patient will be regular and his retinal blood vessels get affected mildly. Protein and fluid might seep out from the blood vessels due to diabetes. Several factors are related with the development of DR like genetic parameters and metabolism control density. This work aims to establish a new automated DR recognition scheme, which involves phases such as "(i) Segmentation (ii) Feature Selection and (iii) Classification". At first, the input fundus image is processed under segmentation phase, and once after this, the feature selection takes place, where 30 features are chosen over the 70 features by exploiting the adaboost algorithm. These selected features are then subjected to Convolutional Neural Network (CNN), from which the presence of disease is classified. Finally, the betterment of adopted scheme is compared and validated over other classifiers.

Keywords – *Diabetic Retinopathy Detection; Segmentation; Feature selection; CNN classifier; Sensitivity..*

Nomenclature

Abbreviation	**Description**
DR	Diabetic Retinopathy
CNN	Convolutional Neural Network
DM	Diabetic Mellitus
MA	Microaneurysms
CAD	Computer-Aided Diagnosis
OD	Optic Disc
GMM	Gaussian Mixture Model
DGF	Discrete Gaussian Filter
KNN	K-Nearest Neighbours
SVM	Support Vector Machine
FPR	False Positive Rate
FNR	False Negative Rate
FDR	False Discovery Rate
NPV	Negative Present Value
MCC	Matthews Correlation Coefficient

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I. Introduction

In these days, DR is regarded as an important issue experienced by diabetic patients. Further, DR is the widespread and rigorous eye disease that often paves the way for vision loss for the present population. The detection of DR at prior stage avoids the failure of vision in individuals. DR can be detected earlier by observing certain aspects such as blood vessels irregularities, leak and so on [1] [2]. Usually, DR occurs when the blood vessels are affected by diabetes. At initial stage, the arteries in tissue layer of the retina begin to flow out and small haemorrhages are formed [3]. The vessels, that leaks from the lipoproteins result in blurred vision.

An additional hassle is that the growth of weaker blood vessels that split and leaks blood into the eye, and so the image cannot be projected to the brain by the retina, that paves the approach for blindnes [4]. Actually, DR is said to be a much risky disease tempted by DM [5], [6] and [7]. The DR may be a most vital cause of vision failure among individuals affected by diabetes and it's necessary to monitor them at certain intermissions for distinguishing the symptoms of DR at previous stage. During the screening process, ophthalmologists examine the eyes for indications of exudates or MA [8].

Diagnosis of DR in the earlier stage [9] is considered as the most important dilemma that requires monitoring and screening as quick as feasible. Furthermore, enhanced screening leads to premature diagnosis that reduces the risk of blindness. Nowadays, CAD systems are introduced that offers automated diagnosis in a precise way [10] [11]. It diagnoses DR by mining the optic disc by concerning the above-said issues in the existing systems [12] [13]. Also, it aids [14] [15] the experts in taking appropriate decisions, thus leading to quicker and more accurate diagnostic decisions with high reliability.

- This paper establishes a novel automated DR detection model that includes steps like segmentation, feature Selection and classification.
- Adaboost algorithm is used to select the appropriate features and CNN model is used for classification purpose.

Section II describes the reviews on DR. Section III portrays the adopted methods for DR detection. Section IV portrays the results and the paper is concluded by section V.

II. Literature review

In 2019, Liu *et al.* [1] have implemented a novel technique called WP-CNN that deployed numerous weighted paths into CNN. The adopted scheme was simulated by the technique of ensemble learning. Here in this model, numerous path weight coefficients were optimally chosen using back propagation, and accordingly, the mean of output features were considered for speedy convergence and redundancy minimization. Finally, the effectiveness of the adopted scheme was proved from the simulation outcomes in terms of accuracy, F-measure and so on.

In 2020, Zago *et al.* [2] have established a novel approach for recognizing DR by means of deep patch based model. The implemented identification model has minimized the complexities and it also improved the system performance using CNN architecture. Furthermore, the analysis connected with the enforced theme was administrated and the superior outcomes were earned for sensitivity and accuracy.

In 2020, Kumar *et al.* [3] have developed a better approach for detecting haemorrhages and MA that contributed on the overall enhancement in the earlier identification of DR. Moreover, an improved segmentation technique was presented in this work for segmenting the blood vessels and optic disc. In addition, classification was performed by means of NN model that was trained using the MA features. Finally, the outcomes have demonstrated the enhancement of the adopted scheme in terms of accuracy and so on.

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In 2019, Shanthi and Sabeenian [4] have presented a scheme that concerned on the classification of fundus images using CNN framework. The CNN scheme has classified the images depending on the severity of the disease, by which high accuracy was attained. In the end, the classification accuracy of the adopted model was established from the performed analysis.

In 2018, Wan *et al.* [5] have implemented an automated technique for classifying a specified set of fundus images. Accordingly, in the presented work, CNN approach was adopted for detecting DR that incorporated segmentation, classification and detection phases. At last, the betterment of the adopted model was validated in terms of optimal accuracy when compared over the conventional techniques.

III. Adopted Methods for DR Detection

Fig. 1 shows the pictorial demonstration of the adopted scheme. This research work aims to establish a novel DR detection model that includes steps namely, "segmentation, feature selection and classification". At first, the input fundus image is applied to the segmentation process. After segmentation, feature selection takes place, where 30 features are chosen over the 70 features, for which the adaboost algorithm is exploited. These selected features are then classified by means of the CNN that detects the presence or absence of the disease.

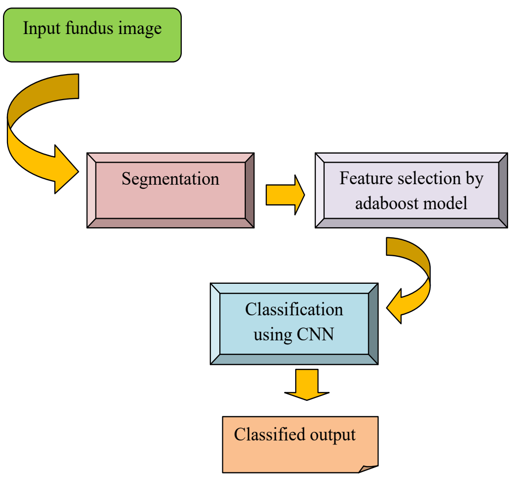

Fig. 1. Pictorial view of the proposed model

A. *Segmentation*

Initially, it is very important to identify the key regions of the blood vasculature areas along with the areas related to the OD [17]. This is because the vasculature can be mistaken in following automated phases if not masked out in the earlier stages. Therefore, a region oriented "MinIMaS algorithm" [18] is introduced that identifies the areas, which rely on the meeting point of the bright regions and largest red region in the image. If the entire intersecting bright portions are recognized as (C) then the portion with $OD(C_{OD} \subset C)$ is said to be the brightest region with reduced pixel intensity sum, and highest compactness (so),, which is given in Eq. (1). If the portion with lowest pixel intensity sum is dissimilar to the portion with the highest solidity $(i_1 \neq i_2)$, then the portion with lowest "pixel intensity sum" is ignored $\left(C = C \setminus C_{i_1}\right)$. Thus, Eq. (1) is re-computed for the left over areas.

$$C = \{C_1, C_2, \ldots. C_r\},\ i \in \{1,2.....r\},$$

$$\text{If, } \Lambda(C) = \begin{bmatrix} i_1,\ i_2 : i_1 = \arg\min\limits_{i}\ Intensity(C_i), \\ i_2 = \arg\min\limits_{i} so(C_i) \end{bmatrix} \quad (1)$$

$$C_{OD}(\Lambda(C)) = \begin{cases} C_{i_1} = C_{i_2} & : i_1 = i_2 \\ C_{OD}\left(\Lambda\left(C = C \setminus C_{i_1}\right)\right) & : i_1 \neq i_2 \end{cases} \quad (2)$$

Following the recognition of C_{OD}, every image is gradient smoothened by median filtering $\left(I_{bg}\right)$ for detecting the main areas of the blood vasculature (C_{vasc}). Further, it is subtracted from image Im for attaining the shade rectified image $\left(Isc = \mathrm{Im} - I_{bg}\right)$, followed by region growing and thresholding. The extraction of biggest red region is denoted by C_{vasc}. When the blood vessels and OD are identified and hidden as background portions, foreground candidate portions $\left(C_{fore}\right)$, which might signify DR lesions are identified, thus producing a segmented image, denoted by Im_{se}.

B. *Feature Selection*

For the feature selection process, adaboost model is deployed by which the top 30 features were chosen from 78 features. These features were

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arranged in descending order of feature's weights. "The adaboost algorithm [19], is a machine learning model that attempts to create a more power classifier through combining a set of weak classifiers". Throughout the training process, update of weights is based on the errors in prior iterations. Thus, the erroneously classified samples can be correctly categorized in subsequent iterations. For carrying out the learning process, labelled training samples $(a_1,b_1)....,(a_n,b_n)$ are given as learners input, in which b_i denotes a label connected by instance a_i. For every epoch $ti = 1,2....,Ti$, the learner portrays a distribution probability dis_t for various examples. Accordingly, an error weight dis_t is determined for every weak learner, based on dis_t. Therefore, the related significance of every example is addressed by the distribution dis_t in all epochs. Following the completion of Ti epoch time, the weaker learners were united into a single classifier. Subsequently, the class density is approximated by "Bayes rules" under the "normal distribution probability function". In the end, feeble classifiers are united by adaboost.

The final selected features such as "area, Minimum distance from centre of, Major Axis length, Minor Axis length, Variance of pixels for the object region in I_{green}, Mean of pixels for the object region in I_{green}, Variance of pixels for the object region in I_{bb}, Variance of pixels for the object region in I_{ab}, Diameter of a circle that with same area as the object, Variance of pixel intensities for the object region in I_{red}, Variance of pixel intensities for the object region in I_{sat}, Length of smallest rectangle (bounding box) around the object, Mean pixel intensity for the object region in I_{red}, Eccentricity of an ellipse, Variance of pixel intensities for the object region, Filled Area, Width of smallest rectangle (bounding box) around the object, Minimum distance from C_{vasc}, Minimum pixel intensity for the object region in I_{sat}, Mean pixel intensity for the object region in $I_{\text{int}e}$, Orientation, Perimeter, Minimum pixel intensity for the object region in I_{red}, Maximum pixel intensity for the object region in $I_{\text{int}e}$, Minimum pixel intensity for the object region in $I_{\text{int}e}$, Solidity, Euler number of the object, Maximum pixel intensity for the object region in I_{red}, Maximum pixel intensity for the object region in I_{sat} and Mean pixel intensity for the object region in I_{sat} " are selected using adaboost model and is termed as fe.

C. *CNN Classifier*

In CNN [16], the image features fe is described by a function as per Eq. (3), such that fe is assigned with a size of $m_1 \times m_2$.

$$\mathrm{Im}_{Se} : \{1,...m_1\} \times \{1,...m_2\} \to A \subseteq \Re, (i,j) \mapsto fe_{i,j} \tag{3}$$

Consider filter $L \in \Re^{2g_1+1 \times 2g_2+1}$ and for optimal image features fe, the "discrete convolution" with filter L is specified by Eq. (4), here filter L is computed as per Eq. (5).

$$(fe_i * L)_{p,r} := \sum_{v=-g_1}^{g_1} \sum_{u=-g_2}^{g_2} L_{v,u} fe_{p+v,r+u} \tag{4}$$

$$L = \begin{pmatrix} L_{-g_1,-g_2} & \dots & L_{-g_1,-g_2} \\ \vdots & L_{0,0} & \vdots \\ L_{g_1,-g_2} & \dots. & L_{g_1,g_2} \end{pmatrix} \tag{5}$$

A normally exploited filter is the DGF $L_{H(\sigma)}$, given in Eq. (6), where σ indicates the "standard deviation of Gaussian distribution".

$$\left(L_{H(\sigma)}\right)_{p,r} = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(\frac{p^2+r^2}{2\sigma^2}\right) \tag{6}$$

Consider layer s as a convolution layer and assume that the input has $n_1^{(s-1)}$ feature maps from the previous layer, with the dimension of $n_2^{(s-1)} \times n_3^{(s-1)}$. Thus, CNN considers unprocessed images as input.

The s layer includes $n_1^{(s)}$ feature maps with $n_2^{(s)} \times n_3^{(s)}$ dimension at its output. Eq. (7) shows the i^{th} feature map in s layer and here $F_i^{(s)}$ points out

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the bias matrix and $L_{i,j}^{(s)}$ indicates filter dimension of $2g_1^{(s)}+1\times 2g_2^{(s)}+1$ that connects the i^{th} feature map in s layer with j^{th} feature map in layer $(s-1)$.

$$X_i^{(s)} = F_i^{(s)} + \sum_{j=1}^{n_1^{s-1}} L_{i,j}^{(s)} * X_j^{(s-1)} \quad (7)$$

By exploiting the discrete convolution at certain areas of input feature maps, the output feature map holds a dimension as per Eq. (8).

$$n_2^{(s-1)} - 2g_1^{(s)} = n_2^{(s)} \text{ and } n_3^{(s-1)} - 2g_2^{(s)} = n_3^{(s)} \quad (8)$$

The convolution layer and its functions are given in Eq. (9) and for relating it with multilayer perceptron, it can be remodelled as per Eq. (10). All $X_i^{(s)}$ in s layer involves $n_2^{(s)}.n_3^{(s)}$ units ordered in 2D array. Here, Eq. (10) shows the output obtained as a result of evaluation by the unit at position (p,r).

$$\left(X_i^{(s)}\right)_{p,r} = \left(F_i^{(s)}\right)_{p,r} + \sum_{j=1}^{n_1^{(s-1)}} \left(L_{i,j}^{(s)} * X_j^{(s-1)}\right)_{p,r} \quad (9)$$

$$\left(F_i^{(s)}\right)_{p,r} + \sum_{j=1}^{n_1^{(s-1)}} \sum_{v=-g_1^s}^{g_1^s} \sum_{u=-g_2^s}^{g_2^s} \left(L_{i,j}^{(s)}\right)_{v,u} \left(L_{i,j}^{(s)}\right)_{p,r} \left(X_j^{(s-1)}\right)_{p+v,r+u} \quad (10)$$

The trainable weights available in the network is given by filters $L_{i,j}^{(s)}$ and bias matrices $F_i^{(s)}$.

IV. RESULTS AND DISCUSSION

A. *Simulation Procedure*

The implemented DR approach was executed in “MATLAB” and the corresponding outcomes were achieved using “DIARETDBI dataset”. Here, the performance of the presented CNN technique was compared over the other conventional classifiers like GMM [33], KNN [34], SVM [28] and NN [29]. Moreover, the analysis was carried out in terms of “accuracy, sensitivity, specificity, and precision, FPR, FNR, FDR, NPV, F1-score and MCC” by varying the learning percentages from 50,60,70,80 and 90.

B. *Performance Analysis*

The performance analysis of the adopted CNN model for DR detection is given in Table I for various measures. From the analysis, better performance is attained by the presented approach when evaluated over the conventional schemes. Particularly, the accuracy of the presented CNN scheme is 22.11%, 20.57%, 86.08% and 19.74% better than GMM, KNN, SVM and NN approaches. The F-score of the suggested CNN model is 42.27%, 50.09%, 36.32% and 22.16% better than GMM, KNN, SVM and NN models. Therefore, the betterment of the presented CNN scheme is validated successfully.

TABLE I. PERFORMANCE ANALYSIS OF IMPLEMENTED AND EXISTING SCHEMES

	GMM [20]	KNN [21]	SVM [22]	NN [23]	CNN
Sensitivity	0.8167	0.5254	0.49	0.75648	1
Accuracy	0.76	0.7697	0.4987	0.775	0.928
Precision	0.7665	0.7935	0.6468	0.89	0.9254
Specificity	0.644	0.8576	0.6456	0.85686	0.9171
FNR	0.07333	0.46333	0.498	0.2015	0
FPR	0.557	0.07863	0.5189	0.07958	0.00212
FDR	0.2165	0.25867	0.5761	0.1025	0.05687
NPV	0.53433	0.81867	0.6631	0.9256	0.92012
MCC	0.6593	0.5699	0.07869	0.80142	0.94575
F1-score	0.68571	0.4869	0.6213	0.7986	0.9756

C. *Impact on Varying Learning Percentages*

The performance analysis of the implemented approach is given by Fig. 2 by varying the learning percentage from 50, 60,70, 80 and 90. From the analysis, at 50th learning percentage, the adopted scheme is 9.81%, 8.33%, 7.66% and 0.49% better than GMM, KNN, SVM and NN approaches. Likewise, at 80th learning percentage, the adopted CNN scheme is 6.58%, 5.32%, 2.82% and 0.89% better than GMM, KNN, SVM and NN approaches. On considering the 90th learning percentage, the adopted CNN scheme is 3.45%, 3.35%, 1.01% and 0.69% better than GMM, KNN, SVM and NN

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approaches. Thus, the improvement of the adopted CNN scheme is proved from the simulated outcomes.

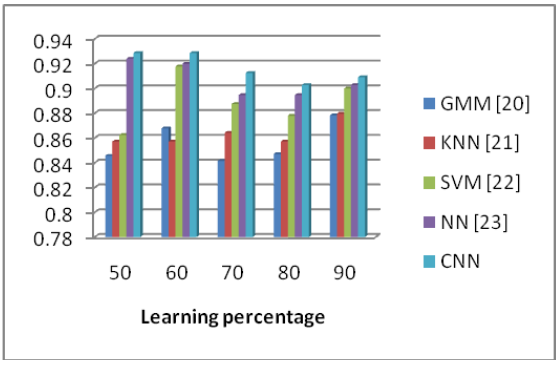

Fig. 2. Analysis on Proposed over Conventional Classifier Models for varying learning percentage

V. Conclusion

This work has established a novel DR detection model, which includes steps like "segmentation, feature selection and classification". At first, the input fundus image was subjected to segmentation process. Following the segmentation, feature selection takes place and thus 30 features were chosen over the 70 features by exploiting the adaboost algorithm. These selected features were then classified using the CNN framework, from which the presence or absence of the disease was observed. In the end, analysis was done to validate the betterment of the suggested CNN model. From the analysis, at 50^{th} learning percentage, the adopted CNN scheme was 9.81%, 8.33%, 7.66% and 0.49% better than GMM, KNN, SVM and NN approaches. Likewise, at 80^{th} learning percentage, the adopted scheme was 6.58%, 5.32%, 2.82% and 0.89% better than GMM, KNN, SVM and NN approaches. On considering the 90^{th} learning percentage, the adopted CNN scheme was 3.45%, 3.35%, 1.01% and 0.69% better than GMM, KNN, SVM and NN approaches. The presented CNN is used for diabetic retinopathy identification, which can automatically identify the deep features from the image. So that it is easy to distinguish the normal and abnormal cases. Thus, the enhancement of the adopted CNN model was proved from the results.

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