Identification of Diabetic Retinopathy from fundus images using CNNs

Laxmi Math, Ruksar Fatima

Abstract- *the* ***Diabetic Retinopathy is the diabetes-mellitus to human vision that is the main cause of vision loss. The early stage detection of diabetic retinopathy is can play eminent role in the diabetes treatment. The fundus of retinal image is utilized to recognize the symptoms of diabetic retinopathy. Moreover, the above phenomena led us to propose this paper; here we propose segment based learning approach for identification of diabetic retinopathy. The segment based image level is required to obtain the identification of diabetic retinopathy images, the classifiers and features are equally learned from the data. Then, we adapt pre-trained CNN as the fine tune to achieve the segment level estimation of diabetic retinopathy. For identification of diabetic retinopathy, we achieve accuracy 96.97 and 98.46% at 20 and 30% and also achieve AUC (Area under Curve) 97.51 and 98.50 at 20 and 30% on the Kaggle dataset. Our proposed model outperforms much better than other models.***

Keywords-Diabetic Retinopathy, DL (deep learning), CNN (convolutional neural network).

I. INTRODUCTION

Diabetic retinopathy is main cause of the vision-loss in adults. The diabetic retinopathy consists of background vessels, retina, fundus images, vessels and non-vessels images. Due to diabetic retinopathy, around 4.2 million of adults had the diabetic retinopathy and 655,000 had the vision-loss, which are maximized everyday [1]. It is said to be one of the most common complication of the DM (Diabetes Mellitus). The treatment of diabetic retinopathy is not easy as there is no symptom presented at early phase and patients hardly notice the vision-loss [2]. Most of the people couldn't recognize that they have the diabetic retinopathy until the disease is started to affect their eye that generally occurs in final phase. As an outcome, most of the people might not go via the treatment. Therefore, the scheme of coordinated management is very crucial to address the clinical challenges of the diabetic retinopathy and preventing its development. Early classification and identification of retinal images are being very serious concern to research community. Some works have been accomplished to categorize the malignancy of retinal images using the CSL (conventional shallow learning) method. Anyways, DL methods have achieved the great success in resolving the visual related issues. One of the well-known techniques as CNN have achieved the great momentum after very famous model as "AlexNet" model, which is introduced in the year of 2012. Moreover, several authors have proposed various work of the diabetic retinopathy.

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This works are related to medical field and machine learning that represents several implementation related to the ML. It has been applied by the help of researchers to recognize the diabetic retinopathy. However still there are vacant spaces to do the research in this field to obtain realistic outcome. Below few of the related works has been discussed. In [3], used the computed based method for identification of abnormality in the retinal fundus images. Author has introduced methodology that initially applies the process of noise removal so the quality of image is enhanced. Further works has been consist the removing tracing blood vessels, exudates statistics and picturing optic disc. Then after performing the task of ML methods and FE are utilized to categorize the diabetic retinopathy of the various phases as severe, mild and moderate. In [4], the author introduced the method to enhance the quality of image that contain the operation of morphological on the fundus image with the CLAHE to improve vessels in image. In [5], author demonstrated novel techniques of the imaging transformation for enhancement of the retinal images such as counterlet transform, wavelet transform and curvelet transform. Therefore, this removes various features and transmits the association between three transformations, which is mentioned above. [6], the authors have utilized two types of machines like KNN and SVM for the classification of diabetic retinopathy that provides better comparative outcomes.

In [7], utilized the PNN, the morphological method can be implemented to recognize the EXs in the retinal images to differentiate among abnormal and normal images. The EXs can be recognized in two phases such as fine segmentation and the rough-segmentation. The operation of column wise and morphological are utilized in the rough segmentation, whereas in the fine-segmentation is utilized the morphological restoration. In retinal-images, to discover the presence and absence of the EXs, the several researchers introduce the MLM (Machine learning methods). The mean features, standard deviation (SD) and centroid are removed for each lesion [8]. To recognize the hard EXs of dynamic thresholding and MF (median-filtering) methods are introduced. To categorize the non-lesion and lesion segments, both the wavelet feature and texture can be utilized. The bright lesions can be recognized by utilizing the Sobel edge detector and threshold techniques.

CNN is a tool or algorithm, which recognizes the image through convolving various kernels with the image and discarding the various features types. Moreover, these types of features can be processed in various layers namely FC (fully connected) and the neural layers. Moreover These NL (neural layers) are said to be the reflection of biological NN of diabetic retinopathy.

Here, the key take the weighted contribution of the every single feature and recognizes the detected image using all impact features. This paper proposes the segments based learning approach to achieve identification of diabetic retinopathy. Our approach purposes at enhancing the identification performance by the help of learning features through larger datasets. In comparison with the DB-1 dataset, the image classification achieved by CNNs, out techniques gives clear location of the diabetic retinopathy so the experts can test the identified retinal images. The main aim of our approach is defined as follows. Preprocessing, Scaling, CNN based Segment level Classifier is to evaluate the probabilities of diabetic retinopathy. Whereas, integrating all segment level of diabetic retinopathy map (DRM) is apply to combine all of the segment-level information. And, it performs as the classifier of image – level, creating the DRM and the probability of diabetic retinopathy for every single input image. At training phase, the probability of diabetic retinopathy is utilized to estimate the training loss. Here, the classifiers and features are learned simultaneously. Furthermore, we prolong our segments based learning approach to deal with the improper detections of diabetic retinopathy. This paper is organized such a way that section 1- presents the background and details of diabetic retinopathy, section 2- presents our segment based learning approach in details. Section-4 represents our experimental outcome and section-5 concludes our method.

II. PROPOSED METHODOLOGY

This section defines our segment based learning terminology for the diabetic retinopathy detection . The segment based learning-approach is investigated as the model of classification. This segment based learning approach is to enhance the classification of retinal image in the diabetic retinopathy. Our approach is divided into 4 components such as preprocessing, Scaling, CNN-based segment level Classifier, Combining all segment level of DRM (Diabetic retinopathy map) below, the Figure 1 depicts the detailed outline of proposed approach.

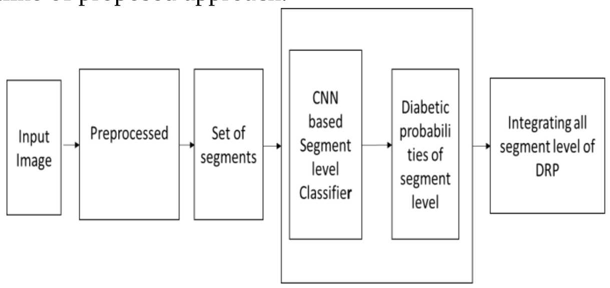

Figure 1: detailed outline of our proposed approach

2.1 Preprocessing

The retinal images are taken from the fundus images and mass screening, which have different types of contrast, image resolution and illumination. By help of DL (deep learning) process these factors are normalizes, DL is the family of computational techniques in the range of computer vision methods and are progressively very popular in the analysis of medical image. Here, we implement the preprocessing as follows:

2.2 Scaling

All retinal images have resized as similar radius-size of FOV (field of view). Then, set the size of radius as pixels to get the size of image nearby to the utilize one. Then, a new technique is utilized for contrast enhancement and illumination equalization.

$$\mathcal{I}_{cx}(a,b,\varsigma) = \alpha\big(\mathcal{I}(a,b) - \mathbb{G}(a,b,\varsigma) * (a,b)\big) + \gamma \quad (1)$$

Where, $\mathbb{G}(a,b,\varsigma)$ is defined as the GS (Gaussian smoothing) kernel with SD ς is applied to resized the images as $\mathcal{I}(a,b)$ to evaluate the background illumination. Then, the factor $\alpha(\alpha \geq 1)$ is utilized to improve constraint; and γ is included to keep the pixel's parameters in range of $[0,255]$. Every single channel of colour image $\mathcal{I}$ can be processed by (1). Lastly, $\mathcal{I}_{ic}$ images are cropped as the rectangular bounding box, masking out segments within 10% outermost of the FOV'S radius, so the bright borders can be eliminated effectively.

Here, the resized images may have the various image height, as most of them do not consist entire retina in the actual image. The resized image have the similar width and height.

2.3 CNN based Segment level Classifier

To recognize the diabetic retinopathy before creating the classification for the entire retinal image. The segments of images are removed from the pre-processing. Then, the images are fed into CNN based segment level classifier to evaluate the probabilities of diabetic retinopathy.

Here, preprocessed image is A with the size of $\mathcal{H} \times \mathcal{W}$ pixels. Let's, stride be d pixels and the size of sliding window $S \times S$. Then, A can be disintegrated into the set of image segments $\{r_{c,d}\}$, where vertical index is $d \in \left\{1,2,\dots,\left\lceil\frac{(\mathcal{W}-S)}{y}\right\rceil+1\right\}$ and horizontal index is $x \in \left\{1,2,\dots,\left\lceil\frac{(\mathcal{H}-S)}{y}\right\rceil+1\right\}$. These two indexes are record as segment of the spatial information. For each segment $x_{c,d}$ is the position of top-left of the corner $(\hbar_x, w_y)$ is defined as:

$$\hbar_c = \begin{cases} 1+(c-1)*y & if (c-1)*y+S \leq \mathcal{H}, \\ \mathcal{H}-(S-1) & otherwise, \end{cases} \quad (2)$$

And

$$w_d = \begin{cases} 1+(d-1)*y & if (d-1)*y+S \leq \mathcal{W}, \\ \mathcal{W}-(S-1) & otherwise, \end{cases} \quad (3)$$

Here, each set have the various number of segments. These segments may be resize to match the input size of CNN.

Then, we adapt pre-trained CNN as the fine tune and the classifier of segment level for the identification of diabetic retinopathy in order to avoid the unnecessary training data.

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In segment based learning approach, we have discovered that CNNs with the random-initial parameters often mis-choose the normal segment of diabetic retinopathy images for the resulting, training in the final breakdown for training process and vibration of the parameter.

The CNN contains many functional layers and all of the layers are organized the image classification and feature learning. The functional layers are classified into 4 categories as pooling layer, auxiliary layer, convolution layer and activation layer. Pooling layer as well as max layer is implemented after convolutional layer, which enhancing translation invariance for the learned features. Whereas, the auxiliary layers are contain the dropout layer and LRN (local-response-normalisation). The convolution layer can be defined as the FC (Fully connected) and convolutional layer. The feature of hierarchical is trained through the convolution layers. The FC layers can be works as the classifier that is capable to estimate any function for the classification. The activation layer consist the soft-max layer and ReLU (rectified linear unit). Specifically, the layers of ReLU are included the convolution layers, and altering learned features as non-linearly into the complex ones, and the soft-max is included to the FC layer, that mapping the output into the PD (probability distribution) for entire classes.

2.4 Integrating all segment level of diabetic retinopathy map (DRM)

After segmenting the estimation level of diabetic retinopathy, we implement the global operation to integrating all segment level of diabetic retinopathy probabilities into the image level of DRM (diabetic-retinopathy-map). Let, $\mathcal{M}$ can be defined as the image map A of diabetic retinopathy, the value of $\mathcal{M}(a,b)$ is defined as:

$$\mathcal{M}(a,b) = \max_{x_{c,d}\, \in \mathbb{G}_{ab}} r_2(x_{c,d}) \quad (4)$$

Where, $\mathbb{G}_{ab}$ is segments group that added the pixel $A\ (a,b)$ in the process of segment extraction.

$$\mathbb{G}_{ab} = \{x_{i,j} \,|\, \hbar_i \le a \le \hbar_i + (S-1), w_j \le b \le w_j + (S-1)\} \quad (5)$$

Here, we generate the identifier map $\mathbb{I}$ to record the segment contributes as the probability of the diabetic retinopathy to M at every single location (a,b):

$$\mathbb{I}(a,b) = arg \max_{x_{c,d}\, \in G_{xy}} r_2(x_{c,d}) \quad (6)$$

After getting the DRM, the threshold can be utilized to segment the segments of diabetic retinopathy. Once, the segment of diabetic retinopathy exists, and then all retinal images are classified as the diabetic retinopathy images. For image A, the image level of DRP (Diabetic retinopathy probability) $\mathbb{P}(A)$ is well defined as max (maximum) value in the DRM.

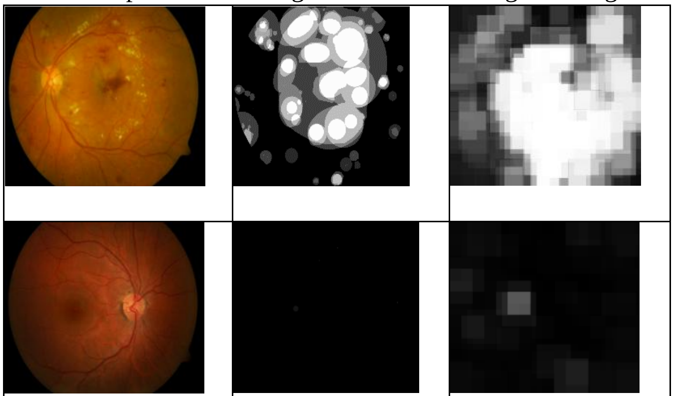
$$\mathbb{P}(A) = \max_{(a,b)} \mathcal{M}(a,b) \quad (7)$$

For our approach, it easily proved the $\mathbb{P}(A)$, which is equivalent to max-pooling over all segment's diabetic retinopathy probabilities.

$$\mathbb{P}(A) = \max_{x_{c,d}} r2(x_{c,d}) \quad (8)$$

III. RESULTS AND ANALYSIS

In this section, we discuss our experimental outcomes performed to show the efficiency of our segments based learning approach. Our proposed model is simulated on 64-bit-windows 10-OS with 16GB RAM that consists the processor of $INTEL\ (R)$ core$(TM)\ i5-4460$. Also, it consists 3.20 GHz-CPU. This is simulated utilizing the MATLAB 2016B. Our segments based learning approach is evaluated on given Kaggle dataset [9] for identification of diabetic retinopathy using CNN. The Kaggle dataset contains training images and higher resolution of the retinal fundus images with transforming the illumination condition taken utilizing various types of cameras and mobile phone. In dataset, the retinal images were marked with 5 various grades which is related to the existence of diabetic retinopathy. There are five types of grades as moderate, negative, mild, proliferative and severe. The dataset contains of the images from both of the left and right eyes. The mild noise is represent in both ground truth and original images.



(a) (b) (c)

Fig.2. classification outcomes by proposed model from Kaggle database (a) original image (b) Ground truth (c) our outcomes of identification of diabetic retinopathy

Comparison with some classification approaches

In this sub section of this research work we provide the comparative analysis of our proposed model with few of the existing classification approaches such as SRC (Sparse Representation Classification), RR (Ridge Regression), ELM (Extreme Learning Machine, LSR (Local Spine Regression), KNN-SSELM (This is Semi-Supervised based ELM (SS-ELM) , CRC (Collaborative Representation Classification) and LRR-SSELM (low-rank representation) for verifying the effectiveness of our approach. The CRC and SRC are for the un-supervised learning, SS-ELM and LSR with KNN are for the semi-supervised learning and ELM and LRC are for the supervised learning. Below table 1 represents few interesting points as the approach of semi-supervised and supervised outperform the un-supervised (CRC and SRC) because of labelled data combination, the combination of labelled data performs poorer than the semi-supervised approaches while un-labeled data can't be explored at training set, our proposed approaches are much better than the other approaches. Because of our approaches can't utilize the both information as unlabeled and labelled to train the classifier, but also assume the relationship among unlabeled and labelled data by generating the graph. Specifically, our proposed approaches outperforms much better than other compared approaches, significantly when the average number of the labeled data is lesser that is valuable for the field of medicine while the process of labeling is not-feasible and time consuming.

Table-1: represents the classification accuracy with various algorithms

	20%	30%
SRC[10]	91.818	92.203
RR [11]	93.76	94.05
LSR[12]	93.76	94.05
KNN-SSELM[13]	94.61	95.21
CRC[14]	94.77	95.43
ELM[15]	93.32	93.84
LRR-SSELM[16]	96.06	97.07
Proposed model	**96.97**	**98.46**

The ROC (Receiver Operating Characteristics) curve is the performance-metric which is utilized to estimate discriminative ability of the binary clasiifier for diabetic retinopathy classifier. This curver is generated by plotting the TPR (true-posive-rate) against the FPR (false-positive-rate) at different types of threshold setting. Below figure 3 and 4 represnts the ROC curve for the classification of diabetic retinopathy.

The AUC (Area Under Curve) of ROC provides the quantitive measure in comparision with various classifiers. Below table 2 represets our model outperfoms over other comparative model on the basis of AUC. Here, we found few combinations of 89 train images our proposed model obtain higher AUC 97.51 and 98.50 with 20 and 30 % than other 5 outcomes.

Table 2: comparision with obatained AUC with various methods

Performance Metrices	AUC	
[17]	0.831	
[18]	0.838	
[19]	0.838	
[20]	0.823	
[21]	0.851	
[22]	0.868	
Proposed model	**97.51 (20%)**	**98.50 (30%)**

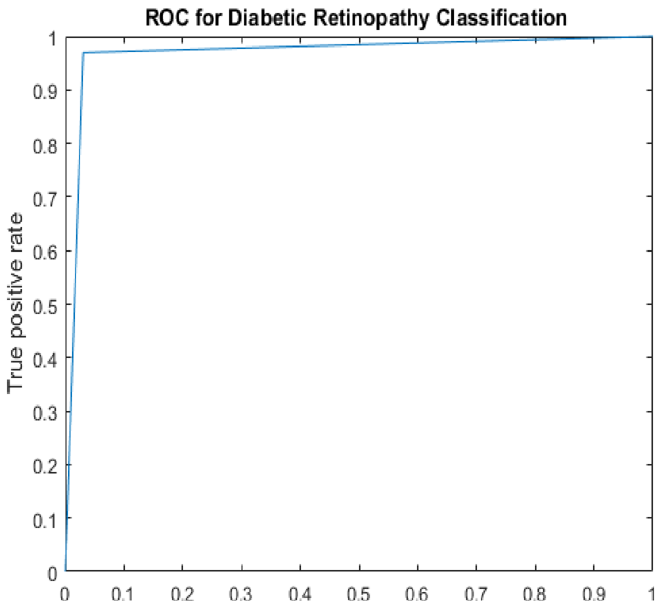


Figure 3: ROC curve at 20% of accuracy.

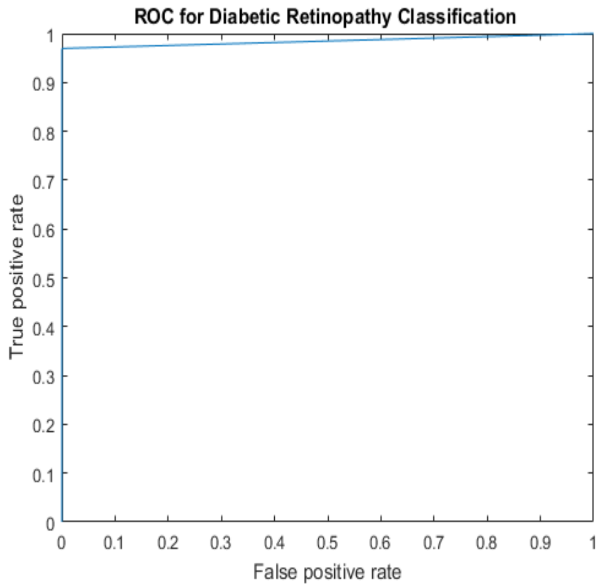


Figure 4: ROC curve at 30% of accuracy.

IV. 4. Conclusion

In this research work, we have proposed novel methodology, which is segment, based learning approach for identification of diabetic retinopathy. The segment based image level is required to obtain the identification of diabetic retinopathy images, the classifiers and features are equally learned from the data. Then, we adapt pre-trained CNN as the fine tune to achieve the segment level estimation of diabetic retinopathy. For identification of diabetic retinopathy, we achieve accuracy 96.97 and 98.46% at 20 and 30% and achieve AUC (Area under Curve) 97.51 and 98.50 at 20 and 30% on the Kaggle dataset. Our proposed model significantly outperforms better than other model. In future work, we are going to combine the methods like active learning and semi-supervised into our segment based learning to achieve the classification of the lesions of diabetic retinopathy.

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