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Adaptive machine learning classification for diabetic retinopathy

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Abstract
Diabetic retinopathy is the main cause of the blindness worldwide. However, the diabetic retinopathy is hard to be detected in the initial stages, and the procedure of diagnostic can be time-consuming even for experienced-experts. The segment based learning approach has shown the benefits over learning technique for detection of diabetic retinopathy: only the annotation of image level is required get the lesions and detection of diabetic retinopathy. Anyways, the performance of existing methods are limited by the utilization of handcrafted features. This paper proposes the segment based learning approach for detection of diabetic retinopathy, which mutually learns classifiers and features from the data and gets significant development on recognizing the images of diabetic retinopathy and their inside the lesions. Specifically, the pre-trained CNN is adapted to get the segment level DRE (Diabetic retinopathy Estimation) and then Integrating all segment level of (DRM) is utilized to make the classification of diabetic retinopathy images. Lastly, an end-to-end segment based learning approach to deal with the irregular lesions of diabetic retinopathy. For detection of the diabetic retinopathy images obtain area under of ROC curve is 0.963 on the Kaggle dataset and also obtains sensitivity and specificity 96.37% and 96.37% on the higher specificity and sensitivity that outperforms much better than existing model.

Keywords Diabetic retinopathy · CNN (convolution neural networks) · DL (deep learning) · Fundus images

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1 Introduction

Diabetic Retinopathy is one of the main cause of preventable vision loss among the working aged adults in world [20]. It is expected 35% of patients with DM (diabetic mellitus) suffer from the diabetic retinopathy. The risk of diabetic retinopathy maximizes as longer a person has the DM. According to WHO, diabetic retinopathy is expected to harm more than 77% of patients who had diabetes 20 yrs. and more [15]. Fundus photography is commonly utilized the imaging method for identification of diabetic retinopathy in retina. It has been utilized for the diabetic retinopathy screening due to its low cost, transmission, high-resolution and easy storage. To simplify the identification of diabetic retinopathy, many classification methods have been improved to categorize the severity of diabetic retinopathy in mass screening in that the severity levels of diabetic retinopathy are well defined by various diabetic retinopathy related to the features. The diabetic retinopathy treatment is not easy as there is no symptom, which is shown at initial phases of the diabetic retinopathy, and rarely patients notice the vision-loss. Most of the patients couldn't realize that they have diabetic retinopathy until disease started to harm their eye that usually occurs in final phase.

The severity and diagnosis of diabetic retinopathy are basically based on the retinal examination. Clinically, the classification of diabetic retinopathy can be parted into two parts such as PDR and NPDR. The PDR (proliferative diabetic retinopathy) is categorized by the help of neovascularization without and with the complications of retinal detachment and early appearance of the vitreous hemorrhage and NPDR (non-proliferative diabetic retinopathy) with the ischemia in various severity but without the retinal neovascularization. The disease of NPDR microvascular consist the lipid exudates, IRMA (intraretinal microvascular abnormalities), microaneurysms, venous beading change, blot hemorrhages and retinal dot. Based on extent and degree of these lesions, the NPDR can be separated into 3 levels: moderate NPSR represents the severe microaneursyms, mild NPDR represents with few retinal hemorrhages and microaneurysms, the soft exude or hemorrhage is not reaching the severe level of NPDR that is associated with the marked retinal hemorrhage in four quadrants, the IRMA in at least 1 quadrant and venous beading in at least 2 quadrants. Below Table 1 represents the diabetic retinopathy classification.

Therefore, the retinal vessels can be recognized by utilizing several methods like a method of multiconcavity modeling is introduced to manage both of the unhealthy and healthy retinas simultaneously [16]. These measure of concavity are integrated together according to statistical

Table 1 The classification of diabetic retinopathy

Category	Level	Manifestation
No Diabetic Retinopathy	0	There is no abnormalities
Mild	1	Only Micro-aneurysms
Moderate	2	Micro-aneurysms Retinal dot and blot hemorrhages Hard exudates or cotton wool spots No signs of severe non-PDR
Severe	3	More than 20 intra-retinal hemorrhages in each of the 4 quadrants definite venous beading in 2 or more quadrants prominent intra-retinal microvascular abnormality (IRMA) in 1 or more quadrants No signs of proliferative retinopathy
PDR	4	Vitreous/pre-retinal hemorrhage Neovascularization

distributions to recognize the vessel in retinal images. The WELR (Wavelets and Edge Location Refinement) methods are utilized to get the retinal vessels [1] that obtains TP (true positive) and FP (False positive) rate and the accuracy score. AMT (Adaptive Median Thresholding) can be the finest methods for identification of the retinal vessels [18]. The structure of RBVN (Retinal Blood Vessel Network) extraction in Premature Infants is recognized in [26], which is consider few challenges like low quality of image, low contract and high noise. In [7], the author introduces the Centre line and Bit plane identification method, which proved to be successful in the identification of the retinal vessel while the technique of multidirectional-morphological-bit plane has been exploited to obtain the extracted vessel [11]. The presence of exudate can be executed by different methods like MCT (morphological compact tree). In [10], discussed the efficient utilization of the histogram analysis for exudates identification in the retinal images. The optical disc is hindrance in identification process of exudates and that's why optical disc requires to be separated and recognized from exudates.

Early classification and detection of retinal disorder always being very serious concern to research community. Some of the works have been performed to categorize the retinal image using conventional learning methods. Anyways, DL (Deep Learning) methods have gained the tremendous success in solving the eye related issues [19]. One of the well-known method CNN has gained tremendous momentum after very famous method "AlexNet" which is introduced in the year of 2012 [14]. Firstly, this technique utilized to categorize the natural images. In later, many variants methods are utilized to solve several real lives of eye related issues such as the detection of retinal images [6]. The classification of image rate might be degraded because of various problems as illumination and contrast that can be developed by different types of image pre-processing methods. In [3], utilizes the linear unsharp-masking filter to improve the detailed data and edge then the improved imaged feed to the CNN technique as SI2DRNet-v1 for the classification of retinal images. Whereas in [25], categorized the set of retinal images where the CLAHE (Contrast-Limited Adaptive Histogram Equalization) and pre-processing method is used to enhance the image visibility. In [22], classify the set of retinal images for recognizing the initial status of the diabetic retinopathy and those images can ne preprocessed by the method of adaptive histogram equalization to enhance the contrast of image.

In this paper, we take complementary benefits from segment based learning approach and deep learning and introduce segment based learning approach to obtain both detection of diabetic retinopathy and lesions of diabetic retinopathy. In comparison with existing techniques, our approach intents at maximizing the identification performance by the learning approach from larger datasets. Compared with all image classification obtained by CNNs [4], our approach gives explicit locations of the lesions of diabetic retinopathy so the recognized retinal images can be tested by the experts. Our segment based learning approach is described as follows. Preprocessing is applied to all of normalizing factors and retinal images like contrast, image scale and illumination. Then the image segments are removed from preprocessed image and fed into the CNN-based-segment-level classifier to evaluate their probabilities of diabetic retinopathy. Afterwards, integration operation is applied to integrate all segment level of Diabetic retinopathy map. It acts as the classifier of image level, creating DRM and the image level of DRP for every single input image. At the time of training, the image level of DRP is utilized to compute training loss. Thus, classifiers and features are learned simultaneously. Further, we extend our segment based learning approach to deal with the irregular lesions of diabetic retinopathy. This paper is organized in such a way that section

1 represents the introduction, section 2 represents related work, and section represents our segment based learning approach and section 4 represents result analysis and finally concludes our work.

2 Literature survey

Many works has been done in this field and there are different way for recognizing the diabetic retinopathy. For its identification authors have worked on different methods as recognizing the blood vessels and various lesions like hemorrhage, microaneurysms and exudates etc. a change in size and shape of the blood vessels is better way to recognizing the diabetic retinopathy. In same way different types of lesion helps in recognizing the diabetic retinopathy. In paper [8], focuses on MLPNN (Multi-Layer-Perception-Neural-Network) to recognize the diabetic retinopathy in the retinal images. The classifier of MLPNN is represented to categorize the retinal images as abnormal and normal. The feature vector can be formed with 64-point DCT (Discrete Cosine Transform) with 9 statistical parameters like average, energy, entropy, Euler number, correlation, homogeneity, standard deviation, contrast and mean. The Train-N-Times technique has been utilized to train MLPNN to discover the feature subset. The cross validation rates and training by MLP-NN are 100% for identification of abnormal and normal retinal images. Whereas in [4], the author introduces the utilization of various texture features for diabetic retinopathy as LESH (Local-Energy based-Shape-Histogram) and LTP (Local Ternary Pattern) [30]. SVM (Support Vector Machine) are utilized for classification of the removed histogram. They introduced histogram-binning method for the feature representation.

This paper [21], introduces an algorithm, which contains the identification of diabetic retinopathy with aim to develop the accuracy of existing work. The technique utilized to recognize the features of diabetic retinopathy namely blood vessels, exudates and hemorrhages that can be classified into many phases that are optic disc removal, image pre-processing, hemorrhages detection, exudate detection and vessel detection. Anyways, the identification for hemorrhages and blood vessel was performed because of same intensity characteristics. The introduced algorithm tested and trained utilizing 89 and 49 fundus images. The images are utilized in training which is obtained from Hospital Serdang, Malaysia while images are utilized in testing were gained from DIRETDB1 dataset. All of the images were classified into 4 diabetic retinopathy phases such as PDR, NPDR, severe NPDR and moderate NPDR. All of the images were taken under various illumination conditions. Whereas in [17], introduced CNN-model for RDR (referable diabetic retinopathy). They utilized 2 publicly datasets such as Diaret-DB1 and Kaggle, where Kaggle dataset is utilized for the training purpose and Diaret-DB1 is utilized for testing. They have used binary classification as mild and normal stages, which are considered as the non-referable diabetic retinopathy where other 3 stages are utilized as RDR.

In [27], introduces novel architecture that categorizes images as abnormal/normal, non-referable/referable of the diabetic retinopathy and obtains higher AUC on the referable and normal diabetic retinopathy. In [24], introduced 3-CNN models for the binary classification and recognize the lesion of diabetic retinopathy. They have utilized DiaretDb1 and Kaggle dataset for testing and training respectively. The classification of state-wise is discussed by [2] and proposed CNN model with dropout regularization method that trained on the kaggle dataset and tested on the STARE and DRIVE dataset. They performed preprocessing and augmentation steps by utilizing the image-editing tool. Moreover, in [9] the architecture of CNN is applied to Kaggle dataset. Preprocessing is done on dataset, utilized non-local mean denoising, and included the delta value to obtain equal level of the image brightness.

In [23], introduced the architecture of CNN and utilized for categorizing 5 stages but couldn't categorize the mild phase correctly because of architecture nature. Another limitation is utilized skewed dataset, which led to the higher specificity with tradeoff in less sensitivity. Whereas in [28], represented the D-CNN (Deep-CNN) for 2-stages of diabetic retinopathy as NPDR and normal. The preprocessed data is specified as an input to two types of given networks as global and local. For grading, the lesions are underlined and sent to global network. They also have utilized kappa scores and class weight for model evaluation. Anyways, in their work PDR stage wasn't considered.

We also attempt to utilize CNN to enhance the detection performance of diabetic retinopathy. Our works differs into 2 aspects first adapting pre-trained CNN to solve the various task in similar image domain from classification of image to the recognition of object. We adapt CNN to obtain the detection of diabetic retinopathy in the domain of retinal images. Second, we introduce end-to-end segment based approach, which could have the estimation for the regions of diabetic retinopathy and further enhances the performance of detection.

3 Proposed methodology

In this section, we describe about our segment-based learning approach e for the identification of Diabetic retinopathy. Our segment-based learning approach is considered as the classification model. This approach is to improve classification of the retinal images in diabetic-retinopathy. Our approach is classified into four components like Preprocessing, CNN-based segment level classifier, Integrating all segment level of Diabetic Retinopathy below Fig. 1 depicts the outline of proposed approach.

3.1 Preprocessing

All retinal images are taken form the fundus images and mass screening that have different types of contrast, image resolution and illumination. With the help of Deep Learning (DL) process, these factors are normalized for Diabetic retinopathy diagnostics.

3.2 Scaling

The retinal images have rescaled as same as radius size of the FOV (field of view). Afterwards, set the radius size as pixel to acquire the image size that close to the utilize one. Then, a novel method is used for the contrast improvement and the illumination equalization.

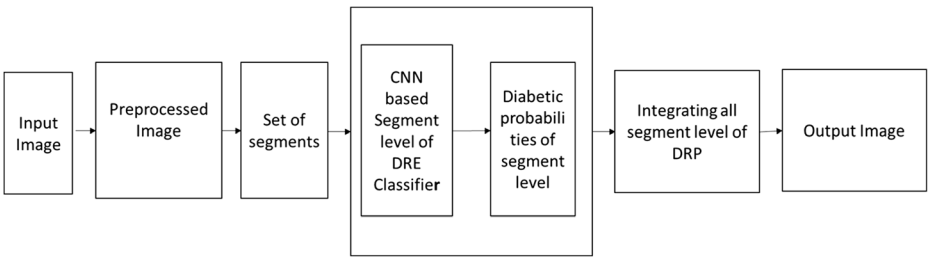


Fig. 1 the outline of proposed work

$$\mathbb{I}_{ik}(m,n,\varsigma) = \alpha(\mathbb{I}(m,n) - \mathbb{G}(m,n,\varsigma) * \mathbb{I}(m,n)) + \gamma \quad (1)$$

Where, the Gaussian smoothing (GS) kernel is $\mathbb{G}(m,n,\varsigma)$ with ς standard deviation (SD) is applied to rescale the images $\mathbb{I}(m,n)$to estimate its background-illumination. Then, factor $\alpha(\alpha \geq 1)$ is basically used to improve the contrast and γ intensity is added to keep the pixel's parameter in [0,255] range. Every channel of the color image $\mathbb{I}$ is processed by the help of (1). Finally, images $\mathbb{I}_{ik}$ are cropped as the bounding box of rectangular and masking out the segments within 10% of outermost FOV's, so the highlighted borders can be effectively removed.

Here, the cropped images may have various image-height, as few of them do not consist all of the retina in original image. Then, they will not resized to have similar height and weight. Or else, it may cause undesirable geometric-distortion because of not equal scaling with horizontal and vertical directions.

3.3 CNN based segment level of DRE (diabetic-retinopathy-estimation) classifier

To identify Diabetic retinopathy before making the classification for all retinal image. The image segments are concatenated from Preprocessing. Then they are fed into the CNN-based segment-level DRE-classifier to estimate the probabilities of the Diabetic retinopathy.

Let, M be the preprocessed image with $\mathbb{H} \times \mathbb{W}$ pixel's size, $P \times P$ be the sliding window and stride be s pixels. Then, M is decomposed into the set of image-segments $\{k_{c,d}\}$, where horizontal index is $d \in \left\{1, 2, \ldots, \left\lceil \frac{(\mathbb{H}-P)}{s} \right\rceil + 1 \right\}$ and vertical index is $c \in \left\{1, 2, \ldots, \left\lceil \frac{(\mathbb{W}-P)}{s} \right\rceil + 1 \right\}$. These indexes are record the segment's spatial data. For each $k_{c,d}$ segment, the position of $(\langle_x, \sqsupseteq_d)$ top-left-corner is defined as:

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

And

$$\wp_d = \begin{cases} 1 + (d-1) * s & if (d-1) * s + P \leq \mathbb{W}, \\ \mathbb{W} - (P-1) & otherwise, \end{cases} \quad (3)$$

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

Then, we adapt pre-trained CNN as fine-tune and segment level classifier it for the detection of the Diabetic retinopathy to avoid inefficient training form the scratch, which is entirely based on the data of medical imagining. In our segment based learning approach, we have found the CNNs with random-initial-parameters often mis-select segments of the Diabetic retinopathy images for resulting and training in vibration of the parameters and final breakdown for the training process.

The CNN consists more than one functional layers and all layers are well-organized to obtain the image classification and feature learning. These layers can be roughly classified into four different layers such as activation layer, pooling layer, convolution layer and auxiliary layer. The activation layer contains ReLU and soft max (rectified linear unit). Specifically, the ReLU layers are included to convolution layers and changing learned features as non-linearly into the more-complex ones. The soft max is included to FC layer, which mapping its output to the probability distribution (PD) for all of the classes. The pooling layers are as the max

pooling, which is applied after the convolutional layer that enhancing translation invariance for the learned features. The convolution layer is also known to be fully connected (FC) or convolutional layer. The hierarchical features are learned through convolution layers. The stack of the FC layers works as the classifier that is capable to approximate any function for the classification. Whereas, the auxiliary layers consist LRN and Diabetic retinopathy layers. All layers are utilized to manage the responses across feature-channels and improvising the generalization model for the classification of image.

To accommodate our segment level of DRE, the pre-trained CNN is altered by replacing thousand way of FC layer with 2-way of the FC layer, and its weight of filter are initialized from GD (Gaussian distribution) with SD (standard deviation). For each image segment $k_{c,d}$, the layer of terminal soft-max will be the output as probability distribution (PD) $p(k_{c,d}) = [p_1(k_{c,d})p_2(k_{c,d})]'$, where, probability of Diabetic retinopathy is $p_1(k_{c,d})$ and normal probability is $p_2(k_{c,d})$.

3.4 Integrating all segment level of DRE

After the segment level of DRE, we apply the operation of global aggregation to integrate all segment level of Diabetic retinopathy probabilities into image level of the DRM (Diabetic Retinopathy Map). Let DRM be the X of the image M, the value $X(m, n)$ is defined as:

$$X(m,n) = \max_{k_{c,d} \in \mathbb{G}_{mn}} p_2(k_{c,d}) \tag{4}$$

Where, segments group is $\mathbb{G}_{mn}$ which add the pixel $X(m, n)$ in segment extraction process:

$$\mathbb{G}_{mn} = \{c_{c,d} | h_c \leq m \leq h_c + (P-1), w_d \leq b \leq w_d + (P-1)\} \tag{5}$$

We also create the map of identifier $\mathbb{I}$ to record the segment, which contributes its probability of the Diabetic retinopathy to X at each location (m, n):

$$\mathbb{I}(m,n) = arg \max_{k_{c,d} \in \mathbb{G}_{mn}} p_2(k_{c,d}) \tag{6}$$

After achieving the DRM, threshold can be used to segment out the regions of Diabetic retinopathy. Once the region of Diabetic retinopathy exists, all of the retinal image will be classified as the images of Diabetic retinopathy. Therefore, for M image, its image-level of $\mathcal{P}(M)$ DRP (Diabetic retinopathy probability) is defined as the max value in its DRM.

$$\mathcal{P}(M) = \max_{(m,n)} X(m,n) \tag{7}$$

For our segment based learning approach, it can be proved easily that $\mathcal{P}(M)$ can be equivalent to max-pooling over all of the segment's Diabetic retinopathy.

$$\mathcal{P}(M) = \max_{k_{c,d}} p_2(k_{c,d}) \tag{8}$$

At training time, the level of image $N \in \{1, 2\}$, where 2 is for Diabetic retinopathy class and 1 is for normal class that will be given for each X image. Then, the loss function of cross-entropy is formulated as:

$$\mathcal{L} = -(1(N=1)log(1-\mathcal{P}(M)) + 1(N=2)\log\mathcal{P}(M)) \tag{9}$$

Where, indicator function be 1(.) that equals to 1 if input is 0 and true otherwise. The SGD (Stochastic gradient descent) is utilized to reduce the loss-function, and the backpropagation of gradients to CNN that can be calculated as:

$$\frac{\partial\mathcal{L}}{\partial\mathcal{P}(M)} = \begin{cases} \frac{1}{1-\mathcal{P}(M)} & if\ N=1 \\ -\frac{1}{\mathcal{P}(M)} & if\ N=2 \end{cases} \tag{10}$$

And

$$\frac{\partial\mathcal{P}(M)}{\partial\mathcal{p}\left(k_{c,d}\right)} = \begin{pmatrix} -\frac{\partial\mathcal{P}(M)}{\mathcal{p}_2\left(k_{c,d}\right)} \\ \frac{\partial\mathcal{P}(M)}{\mathcal{p}_2\left(k_{c,d}\right)} \end{pmatrix} \tag{11}$$

Let location be $(\widehat{m},\widehat{n})$ that has max value $\mathcal{P}(M)$ of X, then we have:

$$\frac{\partial\mathcal{P}(M)}{\partial\mathcal{p}_2\left(k_{c,d}\right)} = \begin{cases} 1 & if k_{c,d} = F(\widehat{m},\widehat{n}) \\ 0 & otherwise \end{cases} \tag{12}$$

In backward pass, the segment $F(\widehat{m},\widehat{n})$ that contributes the max DRP to training image, which is convoluted to update the parameter of CNN, while other segments can dropped out for the computational efficiency.

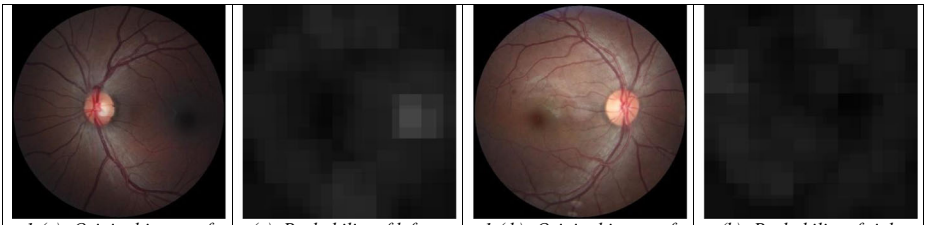
3.4.1 Extension for segment based learning approach

The Diabetic retinopathy lesions have the improper size and shape and normally the segment based learning approach is better to managing the variance. Here, we introduce segment based learning approach to improve the robust estimation of the segments of Diabetic retinopathy and further enhance the performance identification.

To estimate the diabetic retinopathy at input scale, we resize input image with more than one scales and simultaneously evaluate the DRM. For input image M, let $M^{\mathbb{s}}$ Is defined as the resized image with the help of precise scale $\mathbb{s}$, and *so* can be the set of scales, which is utilized in more than one scale. Let $\mathbb{s} \in \delta$ Is the set of segments, which is removed from $X^{\mathbb{s}}$. Hence, the image M can be disintegrated into the set of multi-scale segments: $\bigcup_{\mathbb{s}}\left\{k_{c,d}^{\mathbb{s}}\right\}$. Based on (4) and (6), here we get single scale MLL as the outputs of Multi-scale MLL as $F^{\mathbb{s}}$ DRM and $\mathbb{I}^{\mathbb{s}}$ Is the identifier map for every single $M^{\mathbb{s}}$. The final Diabetic retinopathy X for image M turns to the averaged one across the all scales.

$$X(m,n) = \frac{1}{|\delta|}\sum_{\mathbb{s}}\tilde{X}^{\mathbb{s}}(m,n) \tag{13}$$

Where, resized DRM is $\tilde{X}^{\mathbb{s}}$ of $X^{\mathbb{s}}$, which have similar image size as well as X. Here, NN (Nearest Neighbour) interpolation is utilized, so the corresponding resized of identifier map $\tilde{\mathbb{I}}^{\mathbb{s}}$



1 (a): Original image of left eye | (a). Probability of left eye | 1 (b): Original image of right eye | (b): Probability of right eye

Fig. 2 Label-0 (No Diabetic Retinopathy)

for $\mathbb{I}^{\mathbb{s}}$ that can be created very easily, and keep track the segment, which contributes the DRP at each new place. In comparison to the single-scale of Diabetic retinopathy map, the regions of Diabetic retinopathy can be gained by the help of thresholding around map from the multi-scales.

For our multi-scale-MLL approach, the DRP $\mathcal{P}(M)$ of the image M is described as (7). Anyways, it is not equal to max pooling anymore. Consider the location $(\widehat{m},\widehat{n})$ in the M that has maximum value of (M), the (7) is reformulated as:

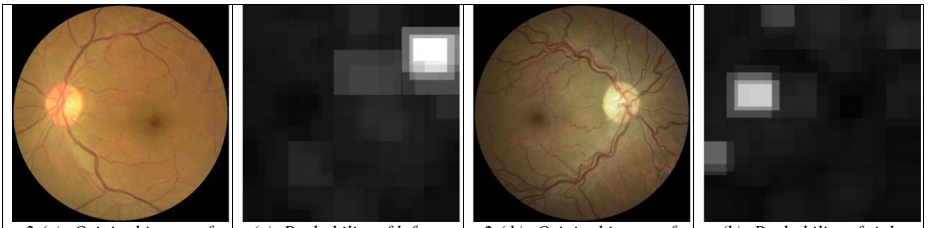
$$\mathcal{P}(M) = \frac{1}{|\delta|}\sum_{\mathbb{s}} \mathcal{p}_2, \left(\tilde{\mathbb{I}}^{\mathbb{s}}(\widehat{m},\widehat{n})\right) \tag{14}$$

Let, $k_{c,\ d}$ Can be the image segment that is from the set of multi-scale segments: $k_{c,d} \in \bigcup_{\mathbb{s}}\left\{k_{c,d}^{\mathbb{s}}\right\}$..

Then, at the time of training our segment based learning approach, the backpropagation of gradients to CNN are still formulated as (9) and (10). Anyways, according to the relationship among $\mathcal{P}(M)$ and $p2(k_{c,\ d})jn$ in 11 and 13, after differentiating equ (13) we get:

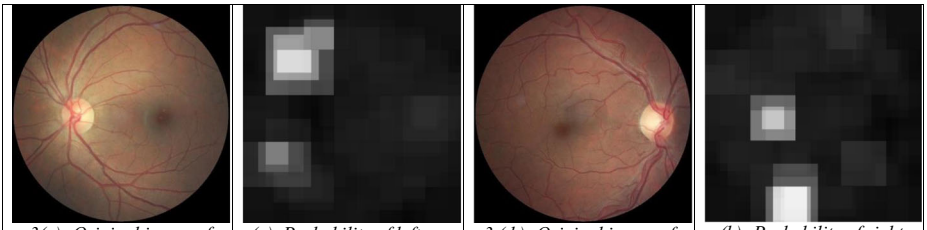
$$\frac{\partial \mathcal{P}(M)}{\partial p_2\left(k_{c,d}\right)} = \begin{cases} \dfrac{1}{|\delta|} & if\ k_{c,d} \in \bigcup\limits_{\mathbb{s}}\{\tilde{F}^{\mathbb{s}}(\widehat{m},\widehat{n})\} \\ 0 & otherwise \end{cases} \tag{15}$$

Therefore, for every single scale, that overlaps most-likely region of the Diabetic retinopathy of average DRM and that has local maximum of the Diabetic retinopathy probability will elaborated in backpropagation. To CNN, the gradients BP (Back propagated) will be equally disseminated to such segments from all of the scales. Furthermore, in backward pass, we dropout at most $|\delta|-1$ elements of $\bigcup_{\mathbb{s}}\{\tilde{F}^{\mathbb{s}}(\widehat{m},\widehat{n})\}$ for the training image, minimizing



2 (a): Original image of left eye | (a). Probability of left eye | 2 (b): Original image of right eye | (b): Probability of right eye

Fig. 3 Label-1 (Mild)



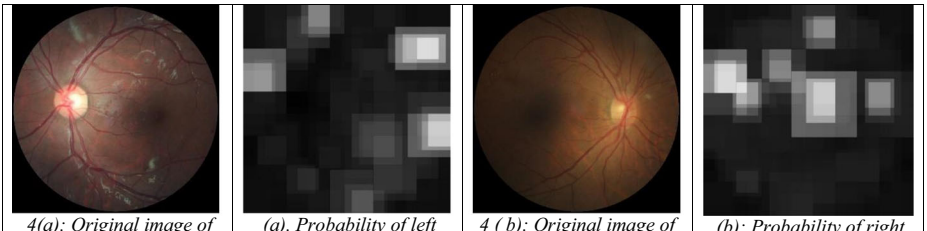
3(a): Original image of left eye | (a). Probability of left eye | 3 (b): Original image of right eye | (b): Probability of right eye

Fig. 4 Label-2 (Moderate)

correlation among the scales and enhancing the generalisation model for the identification of Diabetic retinopathy.

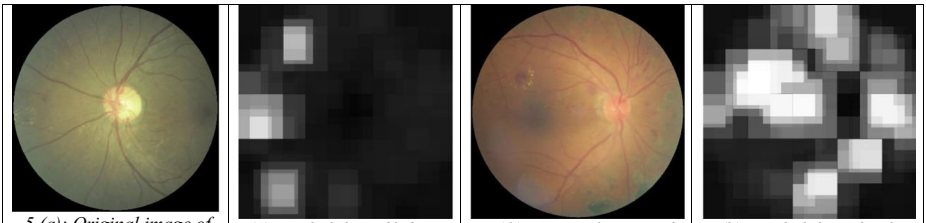
4 Experimental results

Our proposed model is evaluated on Kaggle dataset [5] and DIARET-DB1 [13] for detection of diabetic retinopathy. Kaggle dataset consists the training images and test images. These images are acquired under different types of imaging conditions. Each of them has been graded by the help of experts into five stages such as 0-No-Diabetic-Retinopathy, 1-Mild, 2-Moderate, 3-Severe and 4-Proliferative-Diabetic Retinopathy. Here, we utilize all training images to evaluate and train our segment based learning approach, we refer to No-Diabetic-Retinopathy as normal class and other stages as the class of diabetic retinopathy. Below Figure represents the Label of diabetic retinopathy at Label 0, Label 1, Label 2, Label 3 and Label 4. The Kaggle dataset contains the images from both of the right and left eyes. Figure 2, 3, 4, 5 and 6 shows the original image of left and right eye and Probability of Diabetic Retinopathy. DIARET-DB-1 dataset is the public database for benchmarking the detection of diabetic retinopathy from the digital images. This database consists the digital images of the eye fundus and professional annotated GT (ground truth) for many lesions of diabetic retinopathy such as soft-exudates, hemorrhages, hard-exudates and micro-aneurysms. The original images and probability are represented in Fig. 7. The experimental outcomes are simulated on 64bit-windows 10-OS with 16GB RAM that consists the processor of $INTEL\ (R)$ core(



4(a): Original image of left eye | (a). Probability of left eye | 4 (b): Original image of right eye | (b): Probability of right eye

Fig. 5 Label-3 (Severe)



5 (a): Original image of left eye | (a). Probability of left eye | 5 (b): Original image of right eye | (b): Probability of right eye

Fig. 6 Label-4 (Proliferative-Diabetic-Retinopathy)

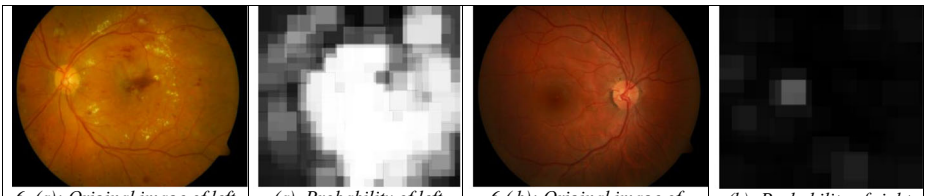
(TM) $i5$–4460. Also, it consists 3.20 GHz-CPU. This is simulated utilizing the MATLAB 2016B.

For higher-sensitivity, the specificity of proposed model is 96.37% while specificity of Binocular and Monocular is 82.2% and 77.4%. The outcome of our proposed model is represented in Table 2. It states that our proposed model obtains higher performance than other two model as Monocular and Binocular model, which means our proposed model, has much greater potential in the clinical application. The ROC curve is very popular performance metric, which is utilized to estimate the binary classifier's discriminative ability. The specificity and sensitivity are metrics, which is widely utilized to estimate the binary-classifier performance as the outcome of clinical examination. The sensitivity signifies the sample rate of classifying TP (true positive) as positive. The specificity signifies the sample rate of classifying the TN (True Negative) as negative.

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{FP + TN}$$

Where TP signifies the number of TP samples in prediction outcome. Similarly, FP signifies the number of FP samples, FN signifies the number of FN samples and TN signifies the TN samples. The ROC is generated by plotting the sensitivity as TP rate vs specificity FP rate since each threshold is matches to the pair of specificity and sensitivity. The ROC of proposed model and existing model is shown in Fig. 8 respectively, the AUC of our proposed model is 0.96 while AUC of Monocular and



6 (a): Original image of left eye | (a). Probability of left eye | 6 (b): Original image of right eye | (b): Probability of right eye

Fig. 7 Original image and probability of DIARET-DB-1 dataset

Table 2 Evaluation outcome of proposed model

	Monocular Model [12]	Binocular Model [29]	Proposed Model
AUC	0.940	0.951	0.963
Sensitivity	77.4%	82.2%	96.37%
Specificity	63.5%	70.7%	96.37%

Binocular is 0.94 and 0.95. The first point is the higher sensitivity point of which the sensitivity is fixed and second point is the higher specificity point of which the specificity is fixed. Below Fig. 8 represents the higher sensitivity and specificity of the proposed model.

5 Conclusions

In this paper, we introduce segment based learning approach for detection of diabetic retinopathy by taking the benefits from segment based learning approach: only the annotation of image level is required to obtain the lesions and detection of diabetic retinopathy, meanwhile the classifiers and features are mutually learned from the data. The pre-trained CNN is altered and fine tuned into the framework to obtain segment level of DRE (Diabetic Retinopathy Estimation). An end-to-end segment based learning approach is applied to get better lesion of irregular diabetic retinopathy. Compared to existing model for detection of diabetic retinopathy, our proposed approach

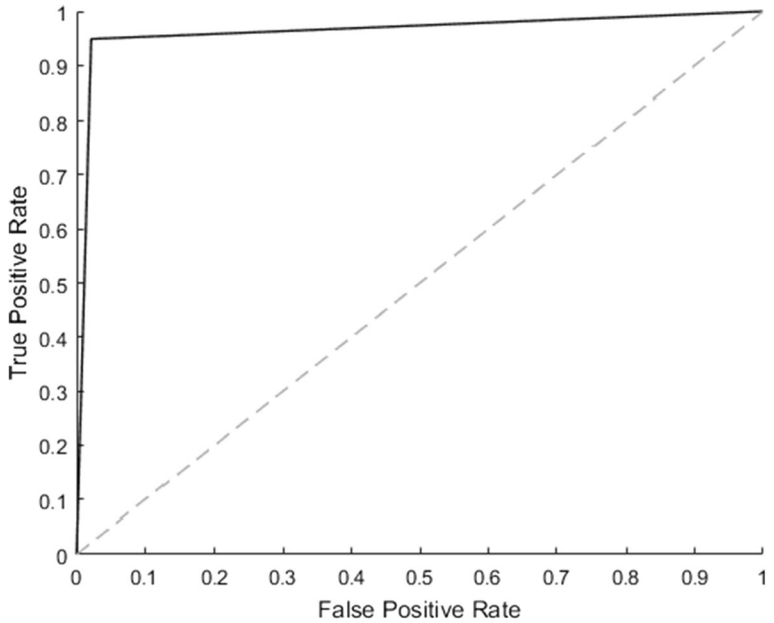


Fig. 8 ROC of proposed model and existing model

significantly develops the detection performance. The evaluation outcomes shows that our proposed model obtains higher performance with an AUC of 0.963 and sensitivity and specificity 96.37% and 96.37% on the higher specificity and sensitivity operating point that outperforms much better than existing model.

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