Annals of R.S.C.B., ISSN: 1583-6258, Vol. 25, Issue 2, 2021, Pages. 268 - 277
Received 20 January 2021; Accepted 08 February 2021.

Automated Diabetic Retinopathy Detection Based on Convolutional Neural Network

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ABSTRACT

Diabetic Retinopathy is a serious eye disease that originates from diabetes mellitus and it is the most common cause of blindness in the developed countries. Exudates, the most prevalent clinical signs of diabetic retinopathy and the detection of exudates in the diagnosis of diabetic retinopathy has vital clinical significance in monitoring the progress of the desease. The convolutional neural network is adopted to diagnose the diabetic retinopathy from the fundus images. Convolutional Neural Network architecture is developed with data augmentation to identify the pixel-wise exudate identification for a better result and accuracy.
Kewowrds: Diabetic Retinopathy, Exudates, Convolutional Neural Network,Image Classification

INTRODUCTION

Diabetes complication that affects eyes, named Diabetic Retinopathy (DR) is caused by the damage to blood vessels of the light-sensitive tissue at the back of the eye. Exudates can be seen as the most common symptoms during the early period of DR and the major cause of vision loss in non-proliferative. DR exudates are formed due to the leakage of blood and are characterized by bright spots with sharp margins. The challenge in the automatic detection of exudates from the retinal fundus images is the uneven illumination and poor contrast. Under these complex conditions, several related exudate detection methods have been proposed, which can be divided into Thresholding-based, Region growing-based, Morphological-based and Pixel-based classification categories. In this paper, both global, local luminosity and contrast enhancement approaches are applied to the preprocessing step to overcome these problems. The automatic detection of exudate has been extensively investigated with different techniques proposed. Typically, the detection of exudates can be broadly divided into three steps getting exudate candidates, extracting features and machine learning. Various algorithms had been developed for extracting the exudate candidates, including morphological operation based approaches, clustering based approaches and pixel-level feature based machine learning. Since the number of diabetes affected people is increasing worldwide, the need for automated detection methods of DR is increasing as well. The ophthalmologist uses fundus images for diagnosis and monitoring of various eye diseases including related DR cases. Fundus photography will capture the whole retina, fovea, macula and optic disc and creates images for it. The fundus camera captures the retina fundus images which are often imperfect with low contrast and blurry. In order to improve the reliability of diagnosis and reduce the dependence on human experts, several previous studies

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have been developed automatic and semi-automatic diagnosis of medical images using artificial neural networks.

A key tool to detect various eye diseases is color retinal photography. Principal Component Analysis was used where as to detect the shape of the optic disk, modified active shape model is developed. This technique achieved 100% sensitivity and 71% specificity in detecting exudates [1]. The diagnosis of DR based on the detection of retinal lesions such as microaneurysms, exudates and drusen in retinal images acquired by a fundus camera using sparse coding techniques was proposed. Strong structures of retinal images can be captured with the help of dictionary learning techniques and make descriptors for image classification.The propsed method uses linear Support Vector Machines with sparse codes providing better performance for iamge classification. It achieved a sensitivity and a specificity of 96.50% and 97.70% for the normal class 99.10% and 100% for the drusen class and 97.40% and 98.20% for the exudates. An automatic classification of retinal images that discriminates between images containing different bright lesions namely drusen and exudates is proposed [2]. The detection and diagnosis of retinal lesions with appropriate binary classifiers for three different types of lesions was proposed. Based on the properties of each lesion, features had been derived. The features had been validated with large volumes of datasets using various performance parameters. The individual performance, per frame, of the MA detector is 93% sensitivity and 89% specificity, of the HEM detector is 86% sensitivity and 90% specificity, and of the BL detector is 90% sensitivity and 97% specificity. The proposed system achieved an average 95–100% sensitivity and 70% specificity at a per patient basis [3]. The detection of diabetic retinopathy from digital retinal photographs had been developed from the existing algorithms and the performance parameters are evaluated from a large screening population. 60% were true negatives, 0.8% were false negatives, true positives were only 4% and false positives were 33%. Automated detection of diabetic retinopathy using published algorithms cannot yet be recommended for clinical practice [4].

Gardner et al [5] implemented DR detection using neural networks and pixel intensity values for yes or no classification of DR16. Among the 200 images dataset, each image were split into patches and each is classified by a clinician before implemented using SVM. The area of exudates and blood vessels along with the texture parameter features are used by Nayak et al [6]. Features were entered into the neural network to classify images into normal, nonproliferative retinopathy and proliferative retinopathy. They demonstrated a classification accuracy of 93%, sensitivity of 90% and specificity of 100%. Acharya et al [7] have created an automated method for identifying the five-classes. Features, which are extracted from the raw data using a higher order spectra method, are fed into the SVM classifier and capture the SVM method reported an average accuracy of 82%, sensitivity for medonrelatively small datasets and the drop insensitivity and specificity was likely due to the complex nature of the five class problem. The accuracies of 96% and 94.6% were achieved on the DIARETDB0 and DIARETDB1 image databases respectively. Each of the previous five class methods required feature extraction from the images before being input to an SVM classifier and have only been validated on small test sets of approximately 100 images.

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METHODOLOGY

The propoped system is represented as a block diagram, shown in figure 1. Each blocks in the propose system is explained below.

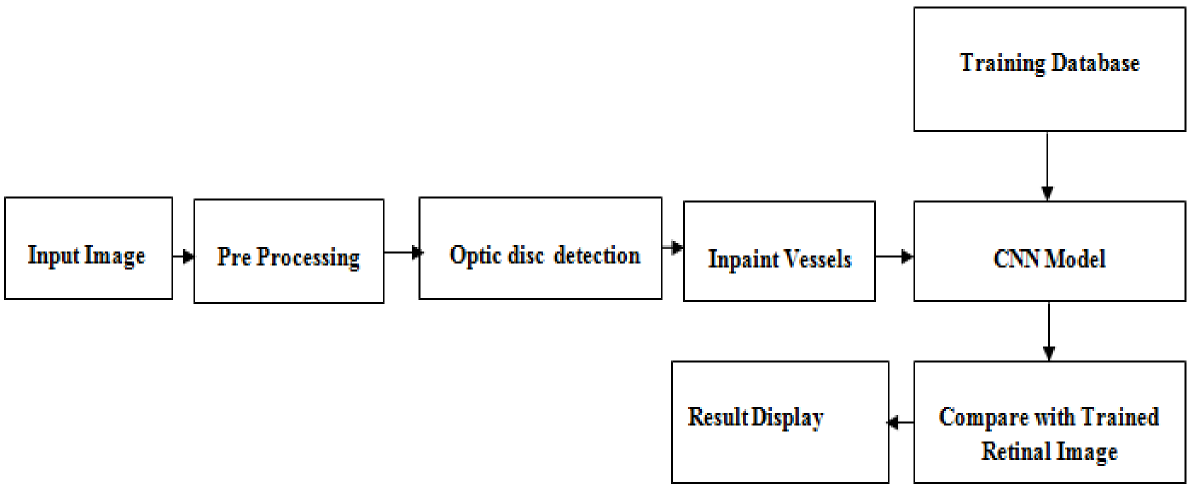

Figure 1. Block diagram representation of the proposed system

Preprocessing

Preprocessing is a step in which the digital color retinal images were transformed in to a hierarchical data format. Preprocessing involves cropping of images to isolate the circular colored image of the retina. Images is normalized to represent pixels in the range 0 to 1. Contrast adjustment was performed using CLAHE filtering algorithm. The dataset was resized to 512 x 512 pixels.

Optic Disc Detection

The change in the optic disc (OD) is an indicative measure of come specific disease. A two-stage approach was developed to localize and segment the border of the OD. First, vessel orientation and brightness were used to determine the center of the OD and score function was modified from whose maximum indicates the pixel that possesses the best OD-border like structure around it.

Augmentation

To improve network localization capability and reduce over fitting, the number of images were augmented. Images were augmented with zeros padded randomly, zoomed, rolled and rotated. The network was trained with the preprocessed images. The localization ability of the modeled network was improved throughout training with the real-time data augmentation. Each image was randomly augmented with random rotation 0-90 degrees during every epoch.

Training

10290 images were given as input to train the Convolutional Neural Network (CNN) to realize image classification quickly. Neural networks suffer from severe over-fitting, especially in a dataset such as ours in which the majority of the images in the dataset are classified in one

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class, that showing no signs of retinopathy. To solve this issue, for every batch loaded for back-propagation, the class-weights were updated with a ratio respective to how many images in the training batch were classified as having no signs of DR. The overfitting risk is reduced using stochastic gradient descent with Nestrov momentum. A low learning rate of 0.0001 was used for 5 epochs to stabilize the weights. The accuracy of the network reached to 70% within a couple of large epochs and lowering the learning rate every time, training loss and accuracy got saturated.

Hemorrhages Detection

Microaneurysms is small red dots in the superficial layer of the retina which is the earliest sign of retinopathy and depending upon the depth of the dots in retina, its termed as hemorrhages. The following steps are involved in detecting hemorrhages including preprocessing. The image was resized to 512 x 512 pixels and converted to grey scale image. First the green channel is extracted from the image since at this channel the disease is seen clearly and easily detectable. Median filter is applied with a radius of 8 pixels to create a background and remove the background from original image. The resulting image contains blood vessels and hemorrhages. The blood vessel is removed using a vessel mask and the image has hemorrhages indications alone.

Exudates Detection

The exudates are mostly visible in gray-scale images. Median filtering is applied to reduce the noise and Histogram Equalization is applied to enhance contrast and brightness. Gray Scale Closing is applied to remove blood vessels in the retina mostly in the optic disc area. A flat disc shaped structure element is considered the radius is eight. The image is thresholded to binaries and the resulting image is used as a mask. Reconstruction by dilation was applied on the overlaid image. The output of this step is the detection of high intensity optic disc with the elimination of all other artifacts.

Convolutional Neural Networks

In neural networks, Convolutional neural network (ConvNets or CNNs) is one among the most categories to try to to images recognition, images classifications. CNN based image classifications has an input image, processes and classifies the image under certain categories. An image to computers is an array of pixels and depends on the resolution of the image. To train and test in deep learning CNN models, each input image will undergo a series of convolution layers with filters (Kernels), Pooling, fully connected layers and apply Sigmoid function to classify an object with probabilistic values between 0 and 1. The figure represents the complete flow of CNN to process an input image and classifies the objects based on values.

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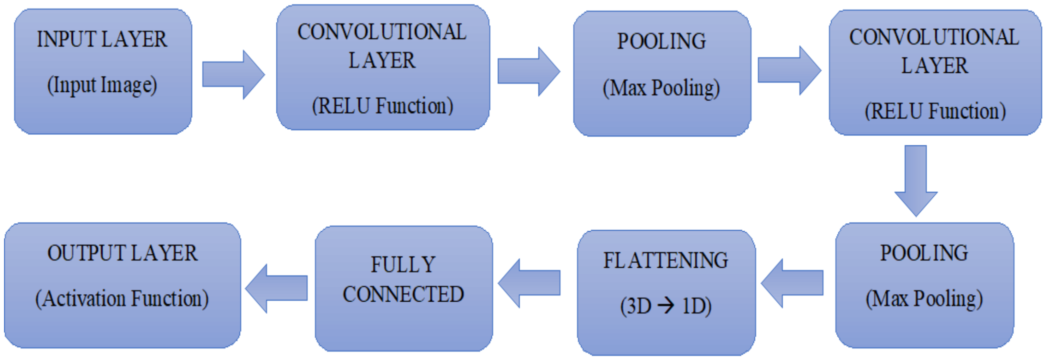

Figure 2 Block Diagram of CNN Algorithm

Convolution is that the first layer to extract features from an input image. Convolution preserves the connection between pixels by learning image features using small squares of input file. It is a mathematical process that takes two inputs like image matrix and a filter or kernel. Padding can be performed using two different ways as follows,

1. Pad the picture with zeros (zero-padding) in order that it fits
2. Drop the part of the image where the filter did not match.

This is called valid padding which keeps only valid part of the image. Stride is that the number of pixels shifts over the input matrix. When the stride is 1, then move the filter 1 pixel at a time. When the stride is 2, then move the filters to 2 pixels at a time then on. ReLU stands for Rectified Linear measure for a non-linear operation. The output is $f(x) = \max(0,x)$. The purpose of ReLU is to introduce non-linearity in ConvNet. Since, the important world data would want our ConvNet to find out would be non-negative linear values. There are other non-linear functions like tanh or sigmoid which will even be used rather than ReLU. Most of the scientists use ReLU since performance wise ReLU is best than the opposite two. Pooling layers section would scale back the amount of parameters when the pictures are overlarge . Spatial pooling also called subsampling or down-sampling which reduces the dimensionality of every map but retains important information. Spatial pooling can be of different types: Max Pooling, Average Pooling and Sum Pooling. Max pooling takes the most important element from the rectified feature map. Taking the most important element could also take the typical pooling. Sum of all elements within the feature map call as sum pooling. Fully Connected Layer flattens our matrix into vector and feed it into a fully connected layer like a neural network. The feature map matrix are going to be converted as vector

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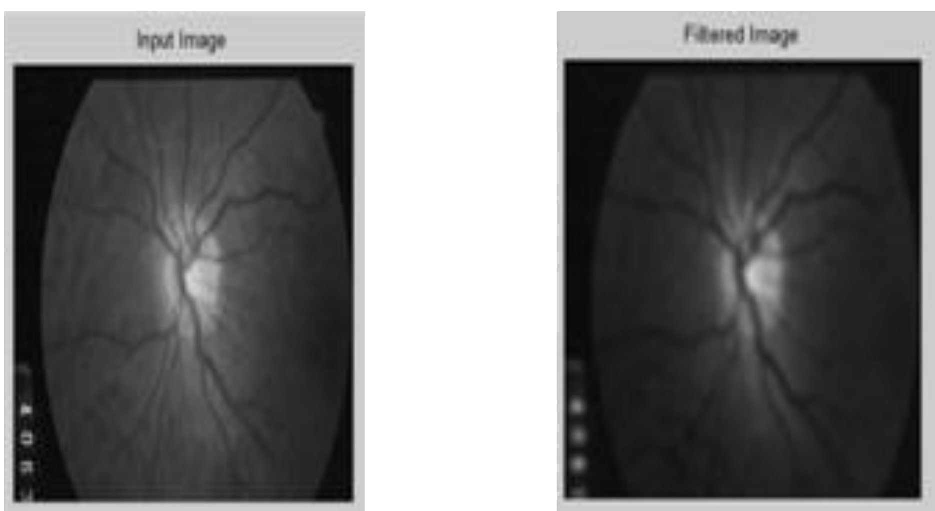
(x1, x2, x3 …). With the fully connected layers, we combined these features together to make a model. Finally, we have an activation function called sigmoid to classify the outputs as Antharasis Bacterial Blight or Black Rot.

Results And Discussion

CNN reveal that the Moderate and severe diabetic retinal images contain macroscopic features at a scale that current CNN architectures, such as those available from the ImageNet visual database, are optimized to classify. Conversely, the features that distinguish mild vs normal disease reside in less than 1% of the total pixel volume, a level of subtleness that is often difficult for human interpreters to detect. Medical images with subtle features that can be crucial for diagnosis. The most often deployed architectures are optimized to acknowledge macroscopic features like those present within the ImageNet dataset. We may therefore require a replacement paradigm for diagnosing diseases via CNN models. This could be a two stage lesion detection pipeline that involves feature localization followed by classification and further preprocessing steps to segment out pathologies difficult to discern by manual inspection, and eventually rebalancing network weights to account for sophistication imbalances seen in medical datasets. Overall, our future goals involve improving detection of mild disease and transitioning to tougher and beneficial multi-grade disease detection. The experimental results are shown in figure 3.



a) Figure Input Image b) Filtered Image

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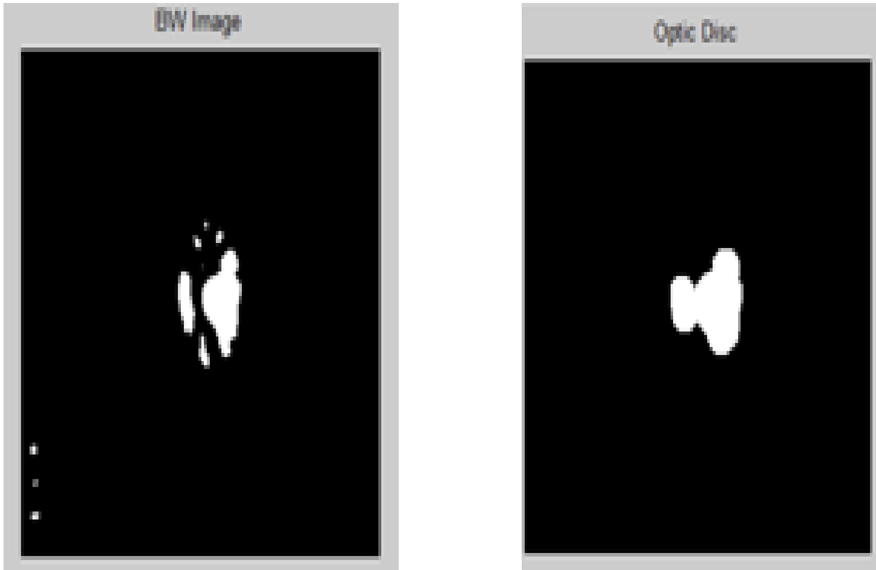
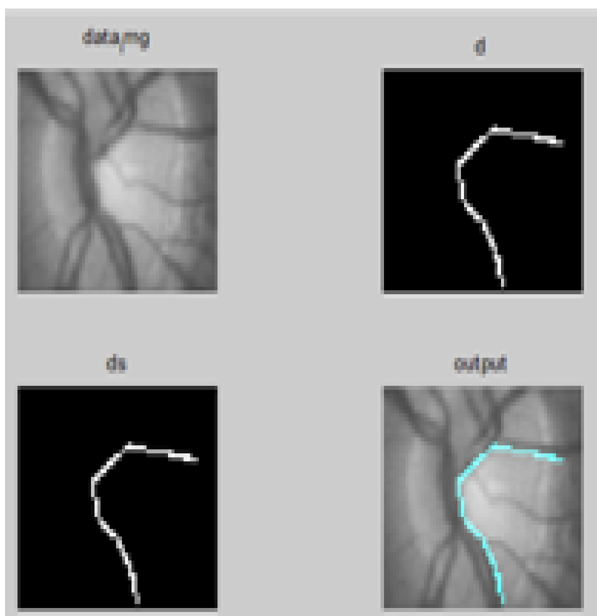


c) Disc Identification



d) Segmentation

Figure 3. Preprocessing, Disc Identification and Segmentation Results

Figure 4 and 5 shows the CNN approach for skeleton extract and the region extraction with respect to the original image.

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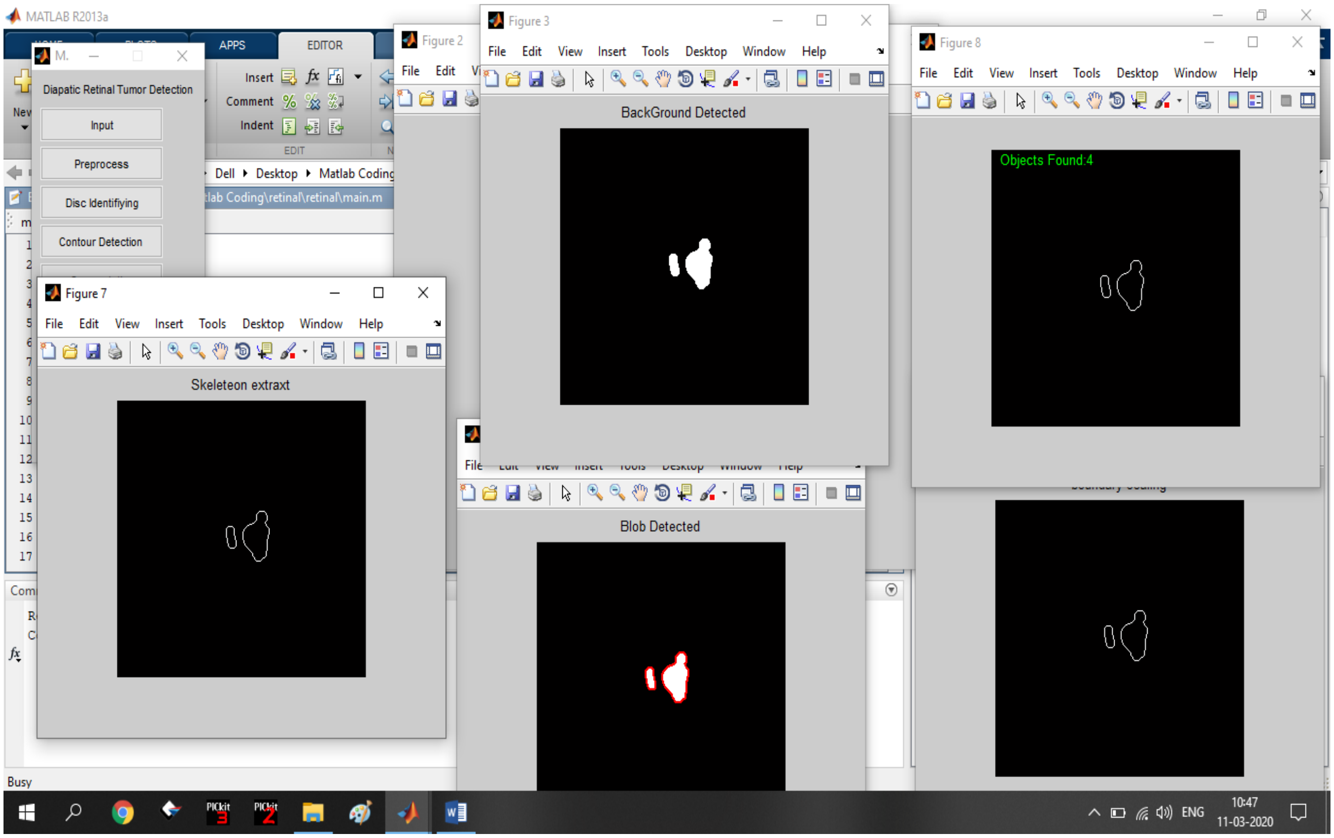

Figure 4. Skeleton Pattern

Figure 5. Region Extraction

Conclusion

Large proportion of vision loss problem can be prevented by automated detection of diabetic retinopathy using CNN method. The proposed network shows the ability to learn the features from the digital fundus images, classifying the DR cases accurately. The advantage of the proposed CNN trained model classifies more than thousands of images every minute resulting this model applied in real-time applications. The comparable results produced by this model with the earlier proposed methods without specific feature detection using general dataset. This network also learns to detect a good eye and the issue with this model is to distinguish between the conditions range of DR. The CNN models having high variance and low bias may allow these models to be used for wider range of non-diabetic diseases also.

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