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Prediction Of Cardio Vascular Disease From Retinal Fundus Images Using Neural Networks

Prof. Dr. E. Malar[1], Raghu Prasath V[2], Rahavi S[3]
[1, 2, 3] PSG Institute of Technology and Applied Research, Neelambur,Coimbatore
emr@psgitech.ac.in, raghuvishwaa@gmail.com, rahaviselvarajan3098@gmail.com

Abstract

Cardio Vascular Disease (CVD) has become the largest single cause of death among humans nowadays. Retinal fundus images play a significant role in the identification and stratification of CVD. CVD can be foreseen by the presence of hemorrhage, exudates, micro aneurysms, and corkscrew arteries in the retinal fundus. In this work, a deep learning model developed using Convolutional Neural Networks (CNN) is proposed for the prediction of CVD. The proposed model is trained with the anomalies in fundus images using image processing tools. Nearly 249 images from publicly available datasets like HRF, DIARETDB1 and MESSIDOR are used for training and testing the model. The trained model is able to predict CVD with an accuracy of 88.5%.

Keywords: *Cardio Vascular Disease (CVD), hemorrhages, micro aneurysm, exudate, corkscrew artery, Convolutional Neural Network (CNN).*

1. Introduction

CVD is a major cause of disability and premature death throughout the world and contributes substantially to the heightening expenses of human services [1]. CVD is not a single disease. It is a collection of diseases affecting the vascular, cardiac and sensory systems. These include Coronary Heart Disease (CHD); hypertension; angina; stroke; Diabetic Retinopathy (DR). The major risk factors of CVD are demographic characteristics, family history of CVD, smoking, physical inactivity, abnormal lipids and lipoproteins, obesity, hypertension and diabetes [2].

Diabetic retinopathy is an eye disease, caused due to diabetes mellitus [3]. Diabetes mellitus is classified into juvenile diabetes (T1D) and adult-onset diabetes (T2D). Type 1 is caused due to the inadequate levels of insulin in blood and Type 2 diabetes is a chronic disease characterized by a high level of sugar in the blood. People with diabetes mellitus are more prone to CVD. They develop morphological changes in the eye like corkscrew arteries, hemorrhages, micro aneurysms, and exudates. In order to determine the acuteness of DR, an automated grading system was proposed by F. Ari Mukti1 et al. [4]. CVD accounts for 44 percent of people with Diabetes mellitus type 1 and 52 percent of people with Diabetes mellitus type 2 [5]. The existing non- invasive techniques like Echocardiography, Cardiac Magnetic Resonance (CMR), Nuclear Imaging, and Computed Tomography (CT) play a major role in CVD detection [6][7]. These techniques have their own drawbacks like a high level of radiation exposure and are costly [8].

Retinal fundus image aids in the detection of abnormalities in the retina of the eye. By studying these fundus images, abnormalities can be characterized non- invasively [9]. The significant portions of the fundus image are the retina and optic nerve. The weakening of blood vessels in the retina (inner membrane of the eye) indicates DR. It can also be identified by the presence of hemorrhages (blood leakage from arteries and veins), micro aneurysms (tiny bulges in the retinal blood vessels), and exudates [10][11]. These features are depicted in Figure 1. Michael D. Abramoff et al. analyzed the fundus images for evaluation of the above-mentioned abnormalities [9]. In the retinal hemorrhage, blood leaks into the retina whereas in the vitreous hemorrhage blood escapes into the vitreous humor of the eye. Ventricular and atrial septal aneurysms cause myocardial infarction [12]. The size of these aneurysms varies from 14 µm to 136 µm. These structures can be saccular, fusiform and focal bulges [3]. Exudates are fluids oozing out from the infected areas which are composed of serum, pus, white blood cells, and dead cells.

These exudates can be classified into two types: hard and soft exudates. Hard exudate occurs during the initial levels of the CVD [13][4].

These anomalies can be extracted from the retinal fundus images via image processing techniques. The blood vessels are segmented from the retinal fundus image by morphological filtering. Clustering, a machine learning tool is used to separate the exudates from the fundus image. Canny Edge detection technique is used in the segmentation of micro aneurysms. Ryan Poplin et al. utilized a deep learning network for feature extraction from the retinal fundus images [15]. A class of deep, feed- forward artificial neural networks (CNN) has been applied to analyze visual imagery.

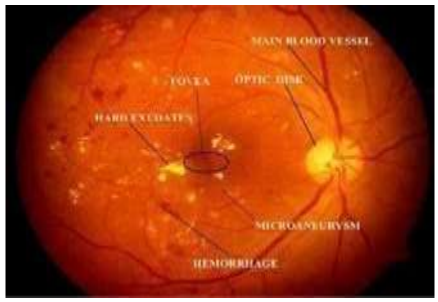

Figure 1:Labelled Fundus Image depicting features of the retina

2. Literature Survey

CVD is a major cause of disability and premature death throughout the world and contributes substantially to the escalating costs of health care [1]. The major cause of mortality in diabetes is CVD, which is exacerbated with hypertension [2]. CVD risk factors include demographic characteristics, family history of CVD, smoking, physical inactivity, abnormal lipids and lipoproteins, obesity, hypertension and diabetes [2]. V Krishna Sree and P Sudhakar Rao concentrated mainly on age-related macular degeneration, diabetic retinopathy, and glaucoma which cause blindness in industrial world. Their algorithm captures the affected pixels and reports their location so that it can be treated [3]. Fanji Ari Mukti1 et al. proposed an automated grading system using FDCT features and SVM classifier, to know the severity level of DR based on the retinal fundus images. This system will be very useful for automatic screening for DR disease [4]. Michael D. Abràmoff et al. analyzed the fundus images for clinical evaluation of retinal vasculature, identification of retinal lesions, assessment of Optic Nerve Head (ONH) shape, building retinal atlases, and to automate methods for population screening for retinal diseases [9]. R Manjula Sri and V Rajesh proposed a method for detection of micro- aneurysm via Eigen value analysis by means of hessian matrix [10]. Bithi Barua and Md. Mehedi Hasan proposed a new approach for retinal image analysis. The features extracted from High Resolution Fundus (HRF) dataset are given for training of Artificial Neural Network (ANN) classifier by backpropagation algorithm [12]. Bahadar et al. presented a comprehensive review on the techniques, strategies and algorithms used for the extraction of the retinal blood vessels from the fundus images. These techniques are classified into logical groups based on the underlying methodologies employed in the retinal vessel extraction [13]. Ryan Poplin et al. utilized deep learning for feature extraction from retinal fundus image. They developed deep learning models using features like optic disc and blood vessel for each prediction [14]. Toufique A. Soomro et al. proposed a method for segmenting the blood vessels which uses morphological filtering and anisotropic diffusion filtering to reduce the background noise [15]. Amir Abdul Khaliq et al. developed a model for the automatic segmentation of the retinal blood vessels through a series of simple preprocessing steps. These steps include Contrast (CLAHE) and Gaussian filter [16].

3. Database Collection

Images from the different publicly available datasets are used in the proposed system. These datasets are used by many researchers for the detection of diabetic retinopathy [16]. The Datasets used to classify blood vessels, micro aneurysms, and exudates and also for the training and testing of the CNN model are mentioned below.

A. MESSIDOR database:

MESSIDOR is a research program funded by the French Ministry of Research and Defense. The database contains 1200 fundus images, captured by the 3 CCD cameras mounted on a Topcon TRC NW6 Non- Mydriatic retinography with a 45-degree field of view.

B. DIARETDB1 database:

DIARETDB1 is a public database used in DR detection. This database consists of 89 color fundus images of which 84 contain at least mild signs of the DR and 5 are considered as normal who do not have any signs of DR.

C. High-Resolution Fundus (HRF) database:

HRF Image Database is a public database that was established by a collaborative research group to support comparative studies on segmentation algorithms on retinal fundus images. This public database contains 15 images of healthy patients, 15 images of patients with diabetic retinopathy and 15 images of glaucomatous patients.

Table 1: Dataset Summary

Dataset Name	Number of Images	Resolution	Number of images used		
			Healthy eyes	DR affected eyes	
				For feature extraction	CNN prediction
MESSIDOR	1200	10 MB	30	50	30
DIARETDB1	89	1.6 MB	20	54	15
HRF Image database	45	Several	15	0	20

Table 2: Dataset Links

MESSIDOR	http://www.adcis.net/en/Download ThirdParty/Me ssidor.html
DIARETDB1	https://www.it.lut.fi/project/imager et/diaretdb1/di aretdb1_v_1_1.zip
HRF	http://www5.cs.fau.de/fileadmin/r esearch/datasets /fundus-images/all.zip

4. Methodology

The retinal fundus image is resized, masks are applied; RBG is split; images are converted to grayscale and re-shaped according to need of algorithm. Figure 2 shows the flow of the process used in the methodology.

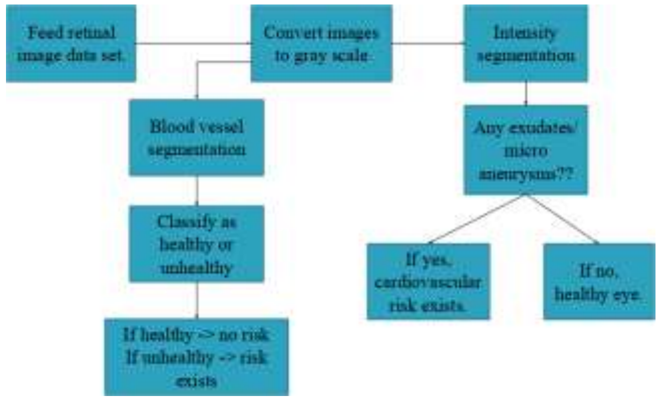

Figure 2: Block Diagram

A. Blood Vessel Segmentation:

In blood vessel segmentation, after morphological filtration, CLAHE algorithm is applied, to improve the contrast of the fundus images since the background and the vessels have the same color. To eliminate noise and blobs from the image, green channel images are separated from RGB image and thresholding is done. Similarly, CLAHE based segmentation is done automatically to separate retinal blood vessels from fundus image [16]. Figure 3 shows the images obtained during various steps of blood vessel segmentation.

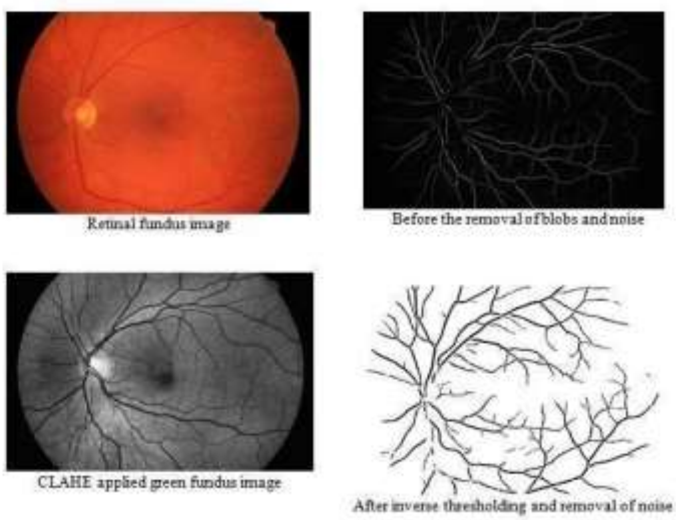

Figure 3: Blood Vessel Segmentation

B. Micro aneurysms Segmentation:

A multi-step Canny Edge Detection algorithm is used in micro aneurysm segmentation. In this algorithm, a 5x5 Gaussian filter is applied. This filter uses a Sobel edge detection operator to detect horizontal (Gx), vertical (Gy), and diagonal edges. Edge thinning Non- Maximum suppression technique is used to remove unwanted pixels. If these edges lie in between minimum and maximum threshold values, then the edges are classified as edges and non- edges based on their connectivity. This step is called Hysteresis Thresholding. After thresholding is done, different sized (small and big) micro-aneurysms are detected and marked in white color and is depicted in image 4. These extracted micro- aneurysms are overlapped on fundus image to locate their position. Figure 5 depicts the position of the micro aneurysms on the fundus image. The Canny Edge Detection algorithm also helps in counting the number of micro aneurysms present in the affected eye. Table 2 shows the micro aneurysm count of various fundus images. Micro aneurysm can also be detected via Eigen value analysis [10].

Table 3: Micro aneurysms

Image	Micro aneurysms count
Image 1	693
Image 2	0
Image 3	4093
Image 4	36
Image 5	1655

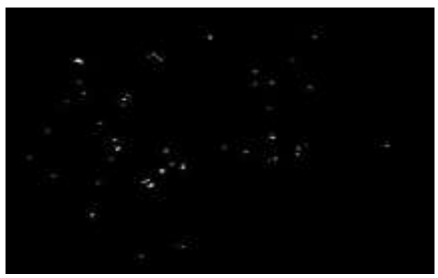

Figure 5: Micro aneurysms overlaid on fundus image

C. Exudates Segmentation:

Exudates are separated by using clustering, which is a machine learning tool. The optic disk regions are selected and cropped. A circle is drawn around the region of interest i.e., the regions were exudates are present. Then on applying the clustering algorithm, a set of data points are grouped and each one of these data points is classified into a specific group. K-means clustering, an unsupervised learning method is used, in case of unlabeled data i.e., data without defined categories or groups. The 'means' in K- means refers to averaging the nearest cluster while keeping the centroids at its minimum size. Figure 6 shows the appearance of blood vessels and exudates after segmentation.

Figure 4: Micro aneurysms

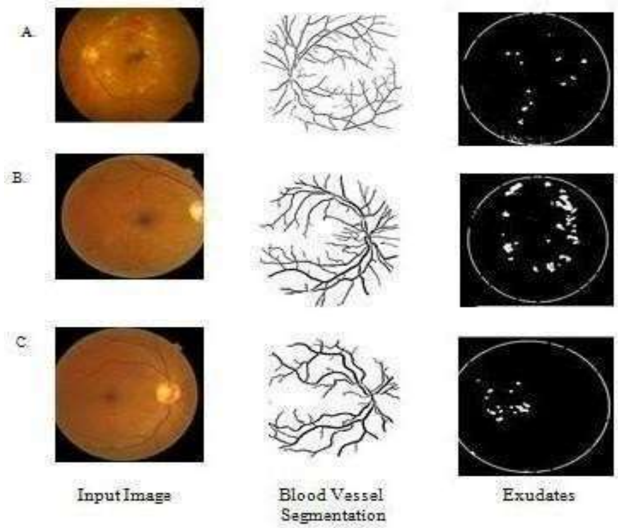

Figure 6: Output Images of three fundus images after Segmentation

D. Implementation with CNN:

A Convolutional Neural Network (CNN) is a class of deep feed-forward artificial neural network which uses a variation of multilayer perceptron. Each neuron in this network processes the data based on the activation function. Convolutional layers apply convolution to emulate the response of an individual neuron to visual stimuli and pass the result to the next layer. Keras is an open-source Neural Network library, designed to be modular and it runs on top of TensorFlow. Keras contains numerous implementations of neural-network building blocks such as layers, objectives, activation functions, optimizers which makes image and data analysis easier.

Table 4: Network Description

Language	Python
Library	Keras, TensorFlow
Tool	Convolution Neural Network

TensorFlow is extremely flexible, which allows deploying network computation to multiple CPUs, GPUs, and servers. This makes TensorFlow an excellent choice for training distributed deep learning networks.

The proposed model uses CNN to classify the retinal images as healthy and unhealthy. An unhealthy retinal fundus image is detected by the presence of abnormalities like microaneurysm, exudate or hemorrhage. Each neuron in the network receives the input and a dot product is performed. These images are then processed by sending them into different layers. In the Input Layer, the image is given as the input to the whole CNN for processing. The image is represented as an array of pixel elements. The value of each pixel in this matrix will range from (0 – 255). The Convolution layer extracts features from the input image obtained from the input layer. This layer maintains the interconnectivity between two or more pixels in the network. The Pooling layer reduces the computations and minimizes the effects caused by variations and deformities in the input image. In the flattening layer, the pooled feature map is flattened to insert this data into an artificial neural network. The dense layer uses a sigmoid activation function and serves as a platform

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between the previous and next neuron. Figure 7 shows the various layers involved in the CNN model and Table 5 shows the number of hidden layers and activation function used.

Sigmoid(x) = 1 + e^(-x)

Table 5: Description of Layers

Name of the layer	Activation Function	Number of Hidden Layers
Conv2D _1	relu	60
MaxPooling2D _1	relu	30
Conv2D _2	relu	27
MaxPooling2D _2	relu	13
Conv2D _3	relu	11
MaxPooling2D _3	relu	5
Dense _1	sigmoid	1

II. RESULTS AND DISCUSSION

The efficiency of the neural network is heavily reliant on the training data (more the training data, better is the accuracy). A total of 234 images were used, out of which 130 images were used to train the model. These images contained about 65 healthy eyes and 65 DR affected eyes. The training and testing ratio used in the network is 7:3. The model is trained by the neural network by altering the weights of the layers. After training is completed, testing data is used to calculate the accuracy of the model. The images from the publicly available datasets like HRF Image database, DIARETDB1, and MESSIDOR are given as input to

the CNN model and its efficiency are evaluated. The accuracy of model is displayed in Figure 8. It can be seen that an average accuracy of 88.5% is obtained. An average loss of 11.5% for validation is calculated and depicted in the graph.

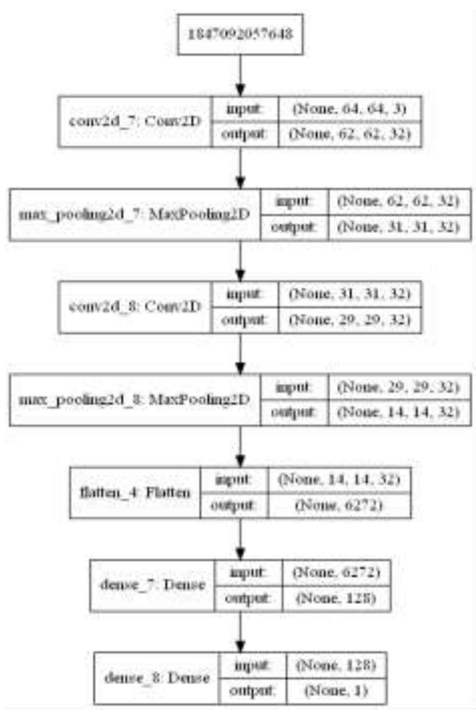

Figure 7: CNN Layers

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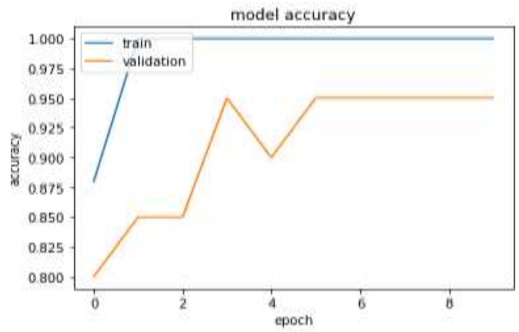

Figure 8: Model Accuracy

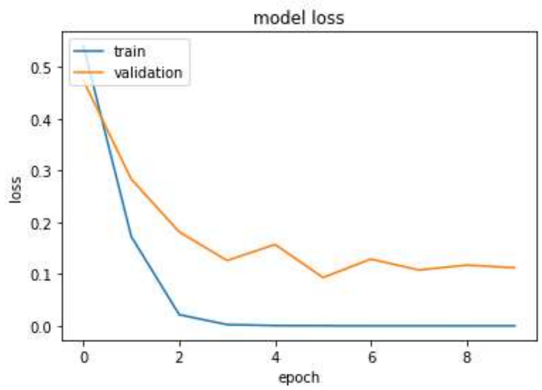

Figure 9: Model Loss

5. Conclusion

To diagnose and predict the chances of occurrence of CVD, the retinal images present in the publicly available datasets like HRF Image database, DIARETDB1, and MESSIDOR were subjected to a set of standard preprocessing techniques and the grey-scale images are obtained. After these preprocessing steps, various algorithms are applied to the images for feature extraction. The morphological operations like opening and closing are performed to separate the blood vessels from the fundus images. The Canny Edge detection algorithm is used to extract the small and big micro aneurysms. The clustering algorithm is applied to obtain the hard and soft exudates. The accurate detection, segmentation, and identification of exudates, microaneurysms from fundus image form a base for automated computing systems that are designed for the prediction of CVD. In the real world, the implemented methodologies would enhance precision and dwindle the workload of an ophthalmologist by diagnosing a large volume of data with high accuracy in a small amount of time. In the future, this project could be extended to identify the different stages of CVD from the retinal fundus images.

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