Categorization of Diabetic Retinopathy using Deep Learning Techniques

N T Renukadevi 1*, K Saraswathi2, S Karunakaran3 and B Anguraj4

1 Assistant Professor (Sr.Gr.), Department of CT-UG, Kongu Engineering College
2 Assistant Professor (Sr.Gr.), Department of CT-UG, Kongu Engineering College
3 Associate Professor, Department of CT-UG, Kongu Engineering College
4 B.Sc. (Information Systems), Kongu Engineering College

Email:renuka.ctug@kongu.edu

Abstract. Diabetic retinopathy is a disease that infects the vision of human eyes suffering from diabetes. It affects the blood vessels of soft tissues at retina, which is located at the backside of the eyes. This disease is evaluated by the physicians based on the retinal images of patients. Detection of the disease initiates human-intensive work for medical practitioners with monetary expenses also. Recent research works have identified that the use of deep learning methods for automatic detection of diabetic retinopathy helps the experts to make quick decision about the patient’s health conditions. In this paper, automated detection of diabetic retinopathy using deep belief networks has been presented which process the retinal images of patients and provides accurate diagnosis of categories of diabetic retinopathy. The proposed method has been trained and tested with Convolutional Neural Networks and Deep Belief Networks. The confidence level of diagnosis is computed and 94.69% with 96.01% are achieved in the detection of Proliferative diabetic retinopathy using CNN and DBN based on the features of data.

Keywords: Diabetic retinopathy, retina, networks, diagnosis

1. Introduction
Diabetes Mellitus (DM) is the disease that cause increase in level of blood glucose for an elongated period of time. This occurs due to variety of reasons like insufficient secretion of insulin by pancreas or the human body is not able to utilize the insulin, etc… DM becomes the dissipated pandemic across the world, especially in India. It leads to the dissemination of syndromes like Diabetic Retinopathy (DR). DR is a complication that creates damages to the blood vessels of soft and thin-skinned tissue called Retina situated at the rear of eyes. Initially, DR shows no or even very mild symptoms of vision problems. The rigorousness and the illness of this disease affect the person suffered from diabetes rapidly. DR is of five categories like No DR, Mild, Moderate, Severe and Proliferate DR.

Research from the recent studies shows that about 90% of patient suffers from diabetes could be keep away from this DR by undergoing diagnose in the early stage itself. [1]. But it depends on the skills of medical experts and both manual labour and time expensive which leads to a challenge in
diagnosis. Hence, manual method of analysis may be not capable to keep rapidly with demand for screening services. [2] And, automated detection of DR classification is needed so that the medical practitioners are able to make decisions quickly. This kind of automatic detection may be done by using Deep Learning methods.

Deep learning (DL) is a subset of machine learning methods works based on artificial neural networks. DL consists of input and output layers with a greater number of hidden layers of nodes. The nodes are interconnected with each other through a tiny structure are called neurons. Each neuron has a weight associated with it. The weight indicates the values of input to the nodes. The neurons are activated with the help of activation functions which acts as a building block of neural networks. Deep learning algorithms includes convolutional neural network (CNN), Deep Belief Network (DBN), Recurrent Neural Network (RNN), etc…

The remaining section of this paper are prepared as follows: Section 2 presents an overview of related work, section 3 explains the working nature of CNN and DBN section 4 shows the experimental results and discussion of those results, section 5 is the conclusion.

2. Literature Review

CNN architecture to recognize the five classes of retinopathy for screening purpose has been proposed using high-end graphics processor unit. The fundus images from public dataset have been taken for training CNN exactly once and real-time dataset to progress throughout the localization capacity of the network. [3] Deep Learning model that computes weights of neuron based on certain features like micro aneurysms, haemorrhages and blood vessels is proposed in[4]. Three models such as CNN, DNN and Feed forward Neural Network (FNN) have been analysed to predict the accuracy in classifying abnormal and normal retinal images and DNN outperforms the other two. [4]

Deep Convolutional Neural Network (DCNN) has been implemented to classify the diabetes as five stages such as ordinary, mild, average, complicated Non-proliferative DR or proliferative DR. Although, DCNN shows good accuracy in public data sets, it has some drawbacks such as more data augmentation is needed and this model requires rigorous graphics processing for high-quality resolution images. [5]

A new framework for screening DR images based on DCNN with fractional max-pooling, Support Vector Machine (SVM). For optimization, Teaching-Learning based Optimization (TLBO) is being used. In addition to this, a mobile application “Deep Retina” has been developed so that the people can be able to test their images using this framework. [6]

A Deep learning system for screening Retinal Haemorrhage (RH) using Ultra-Wide Field (UWF) fundus images has been implemented with the objective to analyse the RH oriented diseases in continuous period of time. [7]

In data set with RGB colour retinal images, the green constituent is chosen to increase the classification accuracy. Entropy is also calculated for grey images and inputs are sent through bichannel CNN. The pre-processing is done by Unsharp Masking feature of the grey scale images and it enhances the accuracy [8]

The entire process of automation based on Artificial Intelligence (AI) has been experimented for diagnosis of DR. Using AI, screening, analytical measures and assistance of treatment are possible nowadays. Prognosis results help to improve the involvement of AI in retina so that the eye specialists and practitioners in health care are able to covenant with the problems of DR in future.[9]
Using wavelet transformation the retinal images were pre-processed and features are extracted to be given as an input to Adaptive Super pixel algorithm for accurate segmentation. [10]

Various texture features for DR images have been extracted such as Local Ternary Pattern (LTP) and energy-based histogram along with Support Vector Machine (SVM) are implemented for the classification of DR. In those feature extraction methods, histogram with SVM gives better accuracy results[11].

A classification model has been developed to identify the occurrence of DR on the pixels of a patient on single and pair of eyes. CNN has been implemented for it and shows good accuracy[12].

3. Proposed Methods
All the five categories of DR require images of good resolution and for that intention pre-processing has to be done. In this work, Gaussian filtered retinal images have been taken and all the images are rescaled to 224 x 224 pixels. Convolutional Neural Networks (CNN) and Deep Belief Network (DBN) are being used for the classification of retina images as normal or DR affected one. The different stages of DR images are depicted in figure 1.

3.1. Convolutional Neural Network (CNN)
This is a type of deep learning method which consists of multilayer perceptrons. It works similar to nerves of our human brain. It is more preferable than other ancestors in the sense that it perceives the features by itself without the direction of human beings. It includes layers such as convolutional layer, activation function, pooling layer and fully connected layer. In convolutional layer, Kernel function or the activation function is used to do the filter operation and to perceive the definite type of feature in the input. In this paper, Rectified Linear Unit (ReLU) is chosen as the kernel function [13]. It is connected to the pooling layer and feature reduction is done since the feature maps from multiple neurons in convolutional layer are connected with single neuron in the next layer. In pooling layer, maximum or average values from cluster of neurons are computed. Finally, fully connected layer connects neurons between layers. It has the entire connectivity among neurons in the preceding layers. The architecture of CNN is depicted in the following figure 2.
3.2. Deep Belief Networks (DBN)

DBN are generative neural networks that are arranged in layers with pile of Restricted Boltzmann Machines (RBMs). [14] RBM consists of hidden and input nodes. There is a strong interconnection among the nodes between the layers instead of intra-connection among the nodes within the own layer. It works based on probability with unsupervised learning algorithm to generate outputs. This unsupervised algorithm produces the best intermediate results in each layer and proceeds towards the next layer by fine-tuning the weights associated with the nodes. Thus, learning works on layer basis with each layer trained at a time.

The input layer includes $I \in \{0, 1\}$ with parameter values $m$ of any real numbers. The hidden layer contains $J \in \{0, 1\}$ with parameter values $n$ of any real numbers. And, $I, J$ represent the count of input and hidden nodes with weight $W_{ab}$. The main point to note here is there is no relationship between nodes in a layer on its own. The energy can be obtained by training the parameters $m, n, W$. The formula for computing energy is given below as equation (1). The architectural diagram of DBN is also depicted in figure 3. [15][16]

$$E(I, J) = -\sum_a^x m_a i_a - \sum_b^x n_b j_b - \sum_i^x \sum_j^x i_a W_{ab} j_b$$

(1)

Figure 3. Design of DBN

At first, the initial weights are identified by unsupervised pre-training process in DBN which shows error detection and good optimization results also. The best possible values of count of layers and nodes are selected based on the data set.

4. Results and Discussion
4.1 Datasets
The diabetic retinopathy dataset has been selected from Kaggle website. The dataset consists of 3662 retina images of 5 categories such as No_DR, Mild, Moderate, Severe and Proliferative. The images are Gaussian filtered scan images which are resized to 224 x 224 pixels. Initially, the dataset is loaded into the local drive and training model is created. About 80% of the images are used for training and 20% for validation. Of 3662 images, 2930 images were taken as training images. Images are normalized with rescaling parameters. The sample training images before pre-processing are depicted as follows in figure 4:

![Figure 4: Images before pre-processing](image)

4.2 Experimental Results
The images were augmented with random rotation, flip and zoom operation and drop out regularization method is implemented. It helps to eradicate the arbitrary selection of constant number of units in layer for single epoch. If the number of units dropped is high, then the regularization is said to be strong enough. Relu activation function is used in order to avoid over fitting of data. The images after augmentation is shown in the following figure 5:

![Figure 5: Images after augmentation process](image)

The following parameters shown in table 1 are used for the implementation of CNN and DBN:

Table 1: Parameter settings of CNN and DBN

| Parameters          | Values |
|---------------------|--------|
| RBM                 | 0.05   |
| Batch size          | 32     |
| Drop out parameter  | 0.2    |
| Activation function | relu   |
| No. of epochs       | 10     |
Hence, the training and validation accuracy are nearer to each other after the augmentation process as shown in figure 6. The training accuracy is to demonstrate how the model is trained and validation accuracy is to calculate the model’s performance.

![Figure 6. Training and Validation accuracy with Loss in CNN](image)

In order to evaluate the performance in classifying the images, confidence measure is computed. Confidence is the likelihood of an input that occurs in different classes. It can be measured for a single input and from that it shows how much the algorithm is confident for that class.

In this research work, the confidence measure is computed using the softmax score for the algorithms CNN and DBN and the results are shown in table 2.

| Classes    | CNN (in %) | DBN (in %) |
|------------|------------|------------|
| No DR      | 84.42      | 87.73      |
| Mild       | 92.45      | 94.76      |
| Moderate   | 93.42      | 95.67      |
| Severe     | 94.18      | 96.59      |
| Proliferative | 94.69     | 96.01      |

5. Conclusion

It is flexible to train DL algorithms for the detection of DR. From the above results, it is concluded that DBN works well when compared to CNN for identification of each of the categories of retinal images. Even though the results are good in confidence measure such as 94.69% and 96.01% using CNN and DBN for the identification of each categories and the best one is Proliferative DR, some optimization process has to be done in order to optimize the accuracy results. In future, DBN along with optimization techniques have to be implemented.

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