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DIABETIC RETINOPATHY DETECTION USING STACKED SPARSE AUTOENCODER

S.SARANYA RUBINI. M.E

ASSISTANT PROFESSOR

V.ASVITHA, E.BRINDHA, G.JAYASHREE, S.JEGAN

Department of Computer Science and Engineering,

Coimbatore Institute of Technology

ABSTRACT

Diabetic retinopathy is one of the most common forms of diabetic eye diseases which is caused to the people who have diabetes for significant number of years. It occurs when changes in blood glucose levels cause changes in retinal blood vessels. In some cases, these vessels will swell up and leak fluid into the rear of the eye. So a network is developed which can identify the intricate features involved in the classification task such as micro-aneurysms, exudate and haemorrhages on the retina and consequently provide a diagnosis automatically. The proposed model includes a Sparse autoencoder integrated with Convolutional Neural Network and Support Vector Machine. The Sparse autoencoder uses back propagation technique to generate the output value from the given input. It extracts the features from the images and the selected features are fed into CNN for dimensionality reduction. CNN eliminates the need for manual feature extraction, as it extract features directly from the images. Then the extracted features are classified using SVM to detect whether it is a healthy or a defected retina.

Keywords: Sparse autoencoder, CNN, SVM, Backpropagation, DR detection, Image processing.

1. INTRODUCTION

Diabetes has become one of the biggest health problems in the world. The prevalence of diabetic retinopathy (DR) among patients with diabetes varies from 28.5% to 39.6% in different parts of the world. It is a chronic metabolic disorder characterized by raised blood glucose level either due to insulin deficiency or insulin resistance. Insulin, a hormone secreted by the pancreas, helps glucose from food get into the cells of our body to be used for energy. Sometimes our body doesn‟t make enough. Glucose then stays in our blood and doesn‟t reach our cells thus results in diabetes[1]. Sometimes, the retinal blood vessels swell up which leak fluid into the rear of the eye. In some cases, abnormal blood vessels will grow on the surface of the retina[2]. The images of the retina in the case of normal and diabetic retinopathy is shown in Figure 1.

Early-stage detection of diabetes could be beneficial for increasing the life expectancy of suffering patients and reducing the treatment cost. Various techniques related to conventional machine learning models have been used by researchers in the past time with the involvement of manual feature extraction based learning. The four stages of diabetic retinopathy which includes mild nonproliferative, moderate nonproliferative, severe nonproliferative and proliferative retinopathy.

In mild Nonproliferative retinopathy, the small areas of ballon-like swelling in the retina‟s tiny blood vessels called microaneurysms occur. In moderate Nonproliferative retinopathy, blood vessels that nourish retina are blocked. In severe Nonproliferative retinopathy, many more blood vessels of retina are blocked. In advanced stage called Proliferative retinopathy, the new blood vessels will grow due to the signals sent by the retina for nourishment. The new blood vessels are abnormal and fragile. If they leak blood, it results in severe vision loss or even blindness.

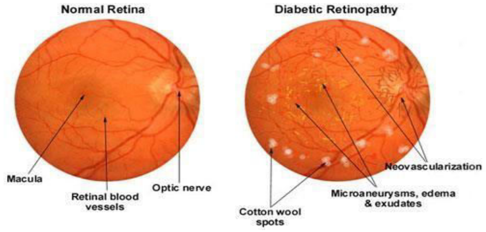


Fig1. Normal retina and affected retina

2. RELATED WORKS

Many researches have been done on the field of Diabetic retinopathy by various researchers. Harry Pratta et al [8] proposed a new approach for five-class classification of Diabetic retinopathy. Majority of the works for the classification of five-class diabetic retinopathy had been done using SVM classifier. Using image processing techniques, the features were extracted and the extracted features were fed into SVM for further classification. In this paper, they had also tried CNN for five-class classification. The datasets were collected from the Kaggle coding website which contains 80,000 images of approximately 6M pixels per image. The deep learning package with the Theano machine learning back end was used. In preprocessing, the color normalization was done using OpenCV and the image was resized to 512*512 pixels. After that 10 convolutional layers and 3 fully-connected layers were used. In convolutional layers RELU and maxpooling activation functions were used. All the maxpooling layers were set with 3*3 kernel size and 2*2 strides. The dropout functions on the dense layers were set with dropout function inorder to reduce overfitting. Since the dataset contains more images of the patients who contain no DR, the network was well trained on the images of no DR. This causes overfitting.

Alexander Rakhlin et al [9] proposed a new approach using deep learning classification framework. In this paper, two datasets were used namely kaggle dataset and Messidor-2. Forpreprocessing the images, the normalization was done. The method used was convolutional neuralnetwork with deep layered structure that combines the near pixels into local features. In this paper,binary classification was used. The result was either 0 or 1. The architecture used in this projectwas nearly originated from VGGNet. The number of layers used was 19 deep layers with 8013393 parameters. The pixels of the image was reduced to 512*512. The scores obtained from the previous stage was fused into final diagnosis inorder to produce good results. They also combined the other eye scores inorder to get more accuracy. The main disadvantage is that since the images were collected from different hardware, it results in decreased accuracy. The two datasets were used only for testing not for training.

Shaohua Wana et al [10] proposed a new method using deep convolutional neural network. In this paper, kaggle dataset were used which contains 35136 images with the resolution of about 3500*3000 . Since the dataset contains noisy data, normalization and data augmentation were used along with non-local means denoising(NLMD). They had used Alexnet, Vggnet, Googlenet and Resnet inorder to discuss how these models worked for this dataset. In Alexnet, 5 convolutional layers followed by 3 fully connected layers were used. The input image was passed of size 227*227. Vgg net contained 5 sections of convolution, each section contained 2-3 convolutional layers. In Googlenet, inorder to reduce over-fitting the full connected layers were converted into sparse layers. Using Resnet, more features were extracted.

Carson Lam [11] demonstrated the use of convolutional neural networks (CNNs) on color fundus images for the recognition task of diabetic retinopathy staging. The network models achieved test metric performance comparable to baseline literature results, with validation sensitivity of 95%. However, improving detection of mild disease and transitioning to more challenging and beneficial multi-grade disease detection. It focuses on automatic detection of diabetic retinopathy through detecting exudates in colour fundus retinal images and also classifies the rigorousness of the lesions. Decision making of the severity level of the disease was performed by SVM classifier.

Baisheng Dai [12] proposed a new approach for Retinal Microaneurysms Detection Using Gradient Vector Analysis and Class Imbalance Classification. In this paper, the microaneurysms (MA) extraction consisted of two steps i.e., candidate MA"s extraction and classification. In the first step, inorder to remove the noise and to preserve the boundary of MA"s, an edge-preserving smoothing method was applied. The green channel of the color fundus image was used as an input image. In order to remove the vessels, morphological grayscale reconstruction algorithm with the K map was used. From the resulted candidate MA"s, inorder to remove dark background noise, localization and augmentation was done. To perform localization , second order derivative wasused.After these two steps, segmentation and feature extraction were done. ROC database and DiaRetDBI V2.1 database was used. Rusboost classifier was used to classify the true MA"s from non MA"s. For classification, KNN classifier was used. Random forest classifier was used to recognize true MA"s from class imbalanced data.

Syed Ayaz Ali Shah et al [13] proposed a new approach for Automated microaneurysm(MA) detection in diabetic retinopathy using curvelet transform. The dataset used in this project was Retinopathy Online Challenge(ROC) dataset which consisted nearly 50 images. Automated MA detection involved three steps namely candidate selection, features extraction and classification. The images given as input was resized to 800-pixel and divided into red, green and gray band. The shade correction was done to green band and the blood vessels were extracted using two-dimensional Gabor wavelet. The candidates were obtained using local thresholding and stastical feature based technique. In feature extraction, three features namely color-based, Hessian-matrix based and curvelet coefficient based features were selected. In classification, the features extracted was used in each step inorder to classify the images with MA"s and no MA"s.

Majority of the works for the classification of five-class diabetic retinopathy had been done using SVM classifier. Using image processing techniques, the features were extracted by Convolutional Neural Network and the extracted features were fed into SVM for further classification. The proposed model uses Sparse Autoencoders for dimensionality reduction to increase the accuracy and further integrating it with CNN for feature extraction and SVM for classification.

3. MATERIAL AND METHODS

3.1. PROPOSED MODEL

The proposed model integrates Stacked Sparse autoencoder with Convolutional Neural network for feature extraction and SVM for classification. The Sparse autoencoder uses back propagation technique to generate the output value from the given input. It extracts the features from the images and the selected features are fed into CNN for dimensionality reduction. CNN eliminates the neccesity for manual feature extraction and its done by extracting features directly from images. In initial stage, the first autoencoder layer is trained with the original input vector which is same as the target vector.

That layer tries to reconstruct the input vector by extracting the specified features with the structure of autoencoder. The second sparse autoencoder layer is trained by taking the output vector as the input vector from first layer and it produces the output vector of the second autoencoder layer.

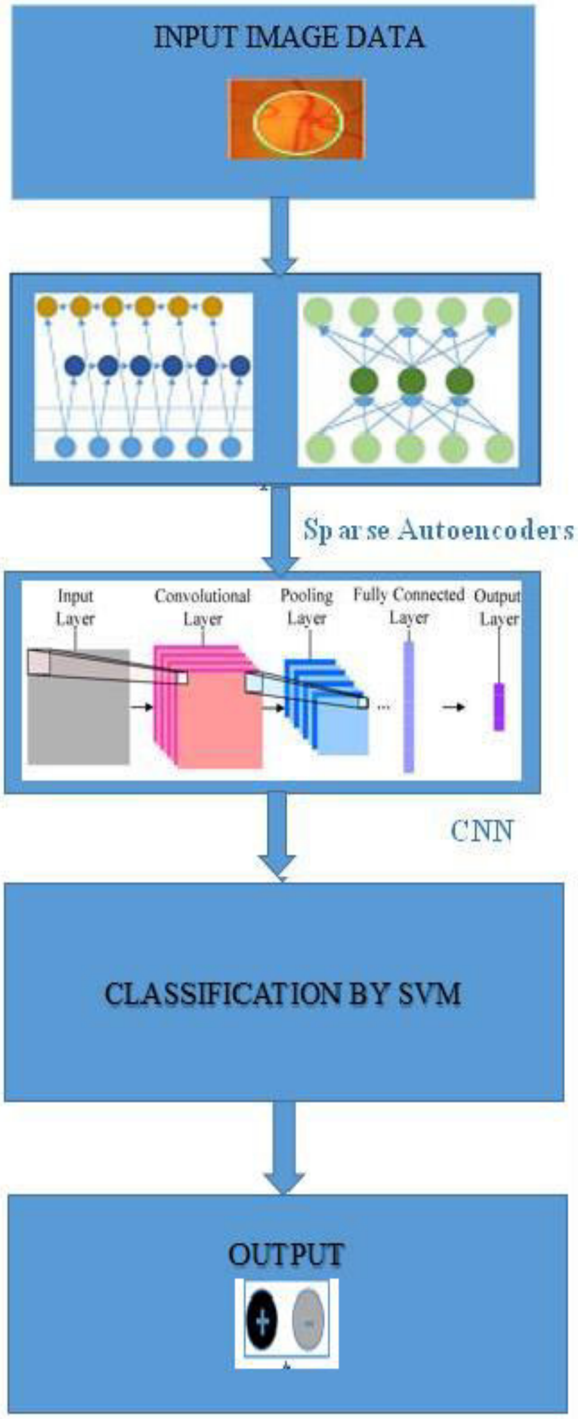


Fig2. System Architecture

Now the second autoencoder layer automatically tries to rebuild the input. The stacked sparse autoencoder is concatenated with the convolutional neural networks for further dimension reduction. At the end, to improve the performance of classification, SVM is employed, which is referred to as supervised classification technique.

3.2. PREPROCESSING

The dataset contained images from patients of varying ethnicity, age groups and extremely varied levels of lighting in the fundus photography. This affects the pixel intensity values within the images and creates unnecessary variation unrelated to classification levels. The Color normalization which is implemented on the images using the package of OpenCV. The images were also high resolution and therefore leads to significant memory size. The image dataset was resized to 64x64 pixels which retained the intricate features but reduced the memory size of the dataset.

The proposed model is tested on Messidor dataset used for training with 120 images and 30 images for testing. Messidor – venture database, comprises of 150 retinal images caught utilizing a shading video 3CCD camera. Before setting up for the training and testing process on the language of Python, the image dataset has to be arranged properly to ease the process of deep learning. Therefore, initially, the images that has been numbered are merged into one single folder. The RGB image what we get is called input signal. But as per the algorithm it requires grey images, as more number of features are extracted from grey scale image rather than coloured image. After this, all the images have been compressed that compressed images have been fit into one file which is .mat(Microsoft Access Table) file type. The base condition for any kind of image processing algorithm is that the size of the images must be of the same size for image processing. Therefore, during the compression of the image processing, the image size has been resized. Basically, this .mat file contains all the fundus images for DRD which is stored as a number of array and it is used in deep learning process. On the training session, 80% of data on the folder which containing the numbered images have been used to train the neural network. After that, remaining 20% data on the folder are used to testing the neural network.

3.3. SPARSE AUTOENCODERS(SAE)

An **autoencoder** is a neural network model which seeks to learn a compressed representation of an input. It is an **unsupervised** learning method, although technically say, it is trained using **supervised** learning methods, which is also referred to as a self-**supervised** which uses back propagation technique to generate the output value from the given input values to the model. It uses two principal components called encoder which compresses the input image and decoder which again decompresses the image. A supervised learning problem have access to labeled training examples named as (x (i) , y(i)). Neural networks have an own way of defining a complex and non-linear form of hypotheses which is h(W,b(x)), with parameters named as W, b that fit into our data. The loss function of auto encoder is formed by two different parts. They are the loss function and regularization. The loss function which helps to calculate the difference between the input and output data and regularization term which prevents the autoencoders from overfitting. In sparse autoencoders, it consists of a single hidden layer which is connected to the input layer which forming the encoding step. The hidden layer is connected to the output layer which representing the decoder. The sparsity penalty is included during the training of sparse auto encoders. The sparsity penalty is constructed using L1-regularization and KL- divergence. The loss function involves activations of hidden layers of hidden layers such that only few nodes are activated when sample input is feed into the network. In this model, “neuron” is one of the computational unit that takes as input x1, x2, x3 and outputs

$$h_{W,b}(x) = f(W^T x) = f(\textstyle\sum_{i=1}^{3} W_i x_i + b),$$

where f : R 7→ R is called the activation function. In these notes, we will choose f(·) to be the sigmoid function:

$$f(z) = \frac{1}{1+\exp(-z)}.$$

In this case of training an autoencoder on 64×64 pixels images, so that n = 4096. Each hidden unit which is ‘i’ computes the function of the input using the activation function. The Sparse autoencoder is mainly used for feature selection and feature extraction. In preparation of selecting the features from the input, it uses the technique called backpropagation to change the weighted inputs that is it scales down the input for achieving the dimensionality reduction.

FEATURE DIMENSION REDUCTION USING L-BFGS

Limited-memory BFGS is an optimization algorithm in the family of quasi-Newton methods that approximates the Broyden-Fletcher-Goldfarb-Shanno using a limited amount of computer memory. Gradient is a class that computes the gradient of the objective function being optimized, i.e., with respect to a single training sample of MESSIDOR image set, at the current parameter value of DNN. The library includes gradient classes for common loss function. The gradient class takes as input a training example, its label, and the current parameter value. Updater is a class that computes the gradient and loss of objective function of the regularization part for L-BFGS. Compared with the predominant stochastic gradient descent methods used in neural network training, the L- BFGS algorithm can provide great simplification in parameter tuning and parallel computation. For example, the dimensionality of the parameter is the sum of the dimensionalities of $W_1 \in R^{m\times d}$, $W_2 \in R^{d\times m}$, $b_1 \in R^m$, and $b_2 \in R^d$, which is $2md + d + m$. Where W is a weight matrix and is the bias vector. Then compared with conventional BFGS algorithm, which requires the computing and storing of $(2md + d + m) \times (2md + d + m)$ Hessian matrices, the L-BFGS algorithm saves a few vectors that represent the approximations implicitly. Therefore, the computational complexity of L- BFGS algorithm are nearly linear in $2md + d + m$, which makes it suitable for feature optimization problems with large diabetic retinopathy data. To be more specific, L-BFGS algorithm save the past updates of Θ and corresponding gradients. Finally sort these scores and return the indices of the optimal features with largest score values. The return is a tuple containing two elements. The first element is a column matrix containing weights for every feature, and the second element is an array containing the loss computed for every iteration.

3.4. CONVOLUTIONAL NEURAL NETWORK(CNN)

A subset of machine learning called deep learning is popular nowadays because of its high performance across many types of data. A great way to use deep learning to classify images is to build a convolutional neural network (CNN). Computers see images using pixels. Pixels in images are usually related. For example, a certain group of pixels may signify an edge in an image or some other pattern. Convolutions use this to help identify images. A convolution multiplies a matrix of pixels with a filter matrix or „kernel" and sums up the multiplication values. Then the convolution slides over to the next pixel and repeats the same process until all the image pixels have been covered.

A Convolutional Neural Network (CNN) is constructed using one or more convolutional layers followed by one or more fully connected layers as multilayer neural network. The architecture of a CNN takes the 2D structure of an image as an input (or other 2D input such as a speech signal). In order to achieve this, the local connections are made to each layers and weights are assigned to each node followed by some form of pooling which results in translation invariant features. One of the benefits of CNNs is that they are easier to train and have fewer parameters than fully connected networks with the same number of hidden units. The CNN contains many functional layers and all of the layers are organized for image classification and feature learning. The functional layers are classified into 3 categories as pooling 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. 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 consists of ReLU (rectified linear unit). Specifically, the layers of ReLU includes the convolution layers, and altering learned features as non-linearly into the complex ones.

3.5. SUPPORT VECTOR MACHINE(SVM)

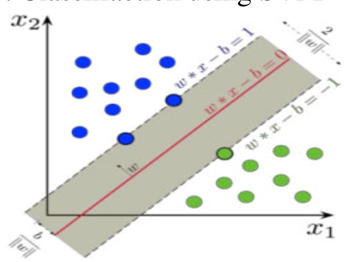
Support vector machines are supervised learning models with associated learning algorithms that analyze the data used for classification and regression analysis. SVMs are based on the idea of finding a hyper-plane that best divides a dataset into two classes, One of the major advantage of SVM is that once a boundary is established, most of the training data is redundant so that classification will be done efficiently. These data points are called support vectors because they support boundaries.

H0=w.x+b=0

H1=w.x+b=+1

H2=w.x+b=+2

Fig3. Classifiaction using SVM



4. EXPERIMENT

Since the input image size is 64x64, there will be 4096 neurons in the input layer of Sparse autoencoder. After passing the input through the input layer, the number of neurons are optimized using LBFGS optimization algorithm and the weight will be adjusted accordingly. Then the optimized features are passed through feedforward network where number of neurons are reduced to 400. These neurons are again passed as input to the second sparse autoencoder. Again by applying optimization algorithm features will be optimized and then it will be forwarded to feedforward network where the neurons are reduced to 225. 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 class, that showing no signs of retinopathy. To solve this issue, real-time class is implemented. Then the extracted features from the second sparse autoencoder are fed to convolutional neural network consisting of 30 layers for feature extraction. The extracted features are given to Support Vector Machine to classify whether it is a defected or a healthy retinal image.

5. CONCLUSION AND FUTURE WORK

The increasing prevalence of diabetic retinopathy and the subsequent rise in the number of diabetes related complications are of considerable challenge for health care. The lack of specialists for classification of diabetic retinopathy has stimulated the scientific community to improve and develop more efficient solutions for the screening of retina.The network has shown promising signs of being able to learn the features required to classify the fundus images, accurately classifying the majority of proliferative cases and cases with no DR. Based on the experiments and observations, it is evident that the proposed model outperforms other model with an accuracy of 99%. The only issue incurred is time complexity. The network takes about 2 hours for training. So in future work will be based on reducing time complexity by using various analogous algorithms and to collect a much cleaner dataset for better observations. It is concluded that the proposed **SSAE-CNN-SVM** framework for diabetic retinopathy classification can be used as powerful tool for the disease diagnosis process.

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