Diabetic Alert System Using Retinal Images

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Abstract

Diabetic Eye Disease(DED) is a diabetic condition characterized by divergence in the retina's blood vessels,it plays a vital role in many underdeveloped countries causing the loss of vision among people. Ophthalmologists normally test Diabetic Retinopathy manually, which is a time-consuming process; therefore, this method aims to automate disease diagnosis. This project's purpose is to develop an automated approach for detecting this disease in people. It is also in its infancy. Supervised learning algorithms are utilized to categorize a collection of images in this project. For this task, a variety of image processing techniques and filters are used to improve a number of key features before classifying them using a sequential model. A trained convolutional neural network model extracts features from fundus images and sends an email to the appropriate ophthalmologist if diabetes is detected.

Keywords — Convolutional Neural Network, Diabetes, Image Processing, Retinopathy.

Introduction

Diabetic Retinopathy, which is caused by diabetes, is a highly spreaded disease caused in the eyes; nearly 93 million people are affected by this disease all over the world. It occurs when the person's blood sugar level in the blood is increased, by which the blood vessels in a person's eye get affected. These blood vessels have the potential to swell and leak. They also cause the flow of blood to stop and the formation of new unwanted blood vessels in the retina. All of these modifications have the potential to distort your perception. Diabetes eye disease develops in two stages.

NPDR refers to the early stage of diabetic eye disease (non-proliferative diabetic retinopathy). It affects a large number of diabetics. Tiny blood vessels leak in NPDR, causing the retina to swell. Macular edema occurs when the macula swells. This is the fact that most diabetes patients lose their eyesight which indeed results in the closure of retinal blood vessels. This is known as macular ischemia. When this happens, the macula does not receive sufficient blood. Exudates, which are tiny particles, can form in the retina at times. When someone is said to have an NPDR, he most likely has blurry vision.

There is a more complicated stage in this diabetic retinal disease that is said to be Proliferative Diabetic Retinopathy which takes place when new blood vessels are developed at the retina. This is referred to as neovascularization. It is observed that at the vitreous the newly formed blood vessels frequently bleeds. If they only bleed slightly, you may notice a few dark floaters. If they bleed a lot, their vision may be obstructed. In some cases scar tissue is formed by these new blood vessels. Scar tissue can wreak havoc on the macula or lead to a detached retina. When a person is said to have PDR then there is a high chance that the person's central and peripheral vision might get damaged.

The goal of this project is to use image processing to implement a deep learning method, such as convolutional neural networks, in order to detect whether the retina is affected by high sugar levels. So that, in the event of a retinal detachment, people's vision can be saved as soon as possible.

Most DR patients are aware of this disease only when they move to the critical stage which results in losing the entire vision, once when they reach this phase the medical treatment can't do any good to these patients. Identification screening techniques that are automated have a significant impact on cost, time, and labor savings. Diabetic patients who are screened for the presence of diabetic retinopathy have a 50% lower risk of going blind.

With the continuous growth in the people getting affected by the disease, automated systems are becoming increasingly important, as the number of ophthalmologists is insufficient to handle all patients and also people in rural areas are so far away that they do not have any local ophthalmologists to go and have a consultation. In scenarios like this, the retinal detection system could play a significant role in the early detection of diabetes while also allowing ophthalmologists to treat the disease more effectively.

I. Literature Review

Several studies have been conducted to detect diabetic retinopathy. In their diabetes diagnosis method, soft computing was used. Their system is built with fuzzy if-then rules and neural network parameter tuning. In order to reduce output error, they used a Neuro fuzzy system in the framework to facilitate learning and adaptation. A client-server knowledge-based system was developed in this study for disease analysis and storing the corresponding solution in a database. Their proposed work and simulated results are effective, and the client server sends a message for first aid treatment after analyzing the diagnosis results of the patients[1].Their pre-processing is based on raw retinal fundus images and involves techniques such as green channel extraction, histogram equalization, image enhancement, and resizing. Based on GDA and Least square SVM a entirely unique cascade learning system is formed. This system is divided into two stages. (i)They used the GDA technique as a pre-processing step to classify the data with the symptoms of diabetes and without diabetes. (ii)They used LS-SVM to classify a diabetes dataset in the second stage. By utilizing the ten fold cross validation, the model achieved 78.21 percent classification accuracy, but their proposed system, Generalized Discriminant Analysis–Least-square Support Vector Machine, achieved 82.05% of accuracy during the classification. They utilized classification accuracy and confusion matrix to assess the system's performance, they also used the k-fold cross-validation method during the evaluation of the model[3]. They used background subtraction to detect hard exudates in relation to lesion level with high accuracy. The decorrelation stretch-based method was used in the final stage of the algorithm to remove false exudate lesion detections. They ran their algorithm through its paces on the DiaretDB database, which has the information about which images are labeled diabetic and normal. The performance of the algorithm was much greater than the state of art methods present in the time of the research for finding the levels of hard exudate[4]. The proposed framework constructs a graphical user interface (GUI) that incorporates various techniques that are capable of retrieving features from retinal images.

Their detection of Diabetic Retinopathy is done correctly at the start to avoid major impact on patients eyes such as losing vision. To predict the disease, they did segmentation first and then classified the segmented image using SVM classifier. Their framework not only aids in the early detection of the disease, but also serves as support for eye specialists refuting the patient's report. They conclude by saying that development of more sophisticated techniques is required for the detection of retinopathy[5]. The haralickmetrices from grayscale converted images are extracted for training, and these features are then utilized to classify new data by comparing them. Because it was deployed in a GUI, the model was specifically developed to take up minimal processing time[6]. The extraction of the features in the retinal images are completely automated using deep learning techniques. When machine learning is utilized for Diabetic Retino Detection, the number of exudates, hemorrhages, and micro aneurysms is extracted using manually developed pre-processing techniques[7]. Automated screening methods drastically shorten the time it takes to determine diagnoses, saving ophthalmologists time and money while also allowing patients to receive treatment earlier[8]. DenseNet121 was trained with 3662 high resolution fundus images to achieve a quadratic weighted kappa score of 0.8981[9]. DenseNet-169 has been trained with a specific retinal dataset and this trained model is considered for the diabetes detection purposes, along with this model, augmentation and modeling techniques are used. The dataset used is APTOS data[10-20].

II. Deep Learning Algorithm

Deep Learning is a type of machine learning technique which is designed to work like brain. By continuously evaluating data with a particular neural network, deep learning algorithms aim to make similar conclusions as humans. The machine learning algorithm requires the data to be preprocessed in ways by which it can process but this step is partially avoided by the Deep learning methodology. By going through the deep learning approach the human power is avoided especially in the places where manual feature extraction process is required which in this case it is automated while considering the deep learning approach. These algorithms are highly capable of interpreting data in image formats including PNG,JPG,JPEG etc. and also textual formats.

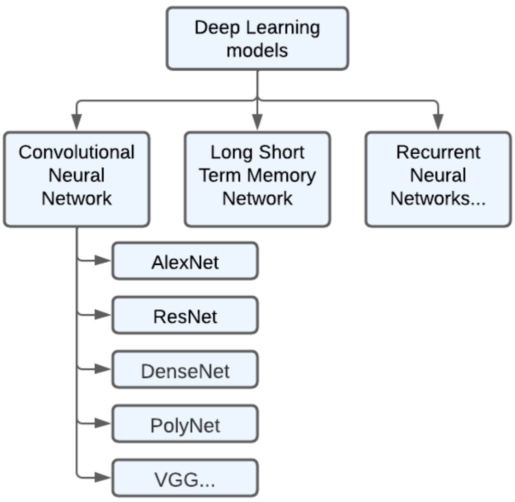

Fig. 1. Types of Deep Learning Models

Figure 1 lists the different types of Deep Learning models as well as the types of commonly used CNN models. When processing with images is considered, CNN plays a vital role for this purpose. It is widely used for its capabilities of learning different features automatically from a given picture and implementing the pattern learned to detect other images similar to it. It is highly used for image classification tasks.

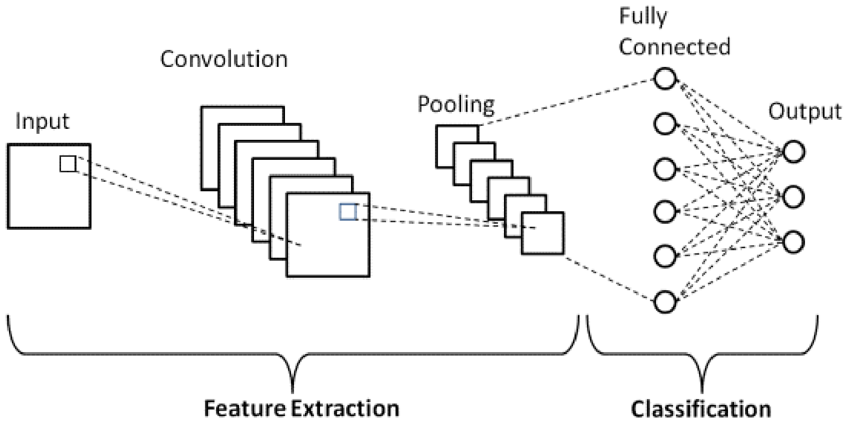

Fig. 2. Common CNN Architecture

Convolutional Neural Network will be used for this use case that we considered. Figure 2 depicts the various layers that have been embedded to form the CNN model. CNN's basic architecture consists of 5 layers which are mostly common among different CNN models. The very first layer that is seen in CNN is the Convolutional layer, which is in charge of extracting the features from the input image. To extract the features, it slides a specific size filter across the input image. Pooling layer is the one which stands next to the convolutional layer, which connects the Convolutional layer to the Fully Connected layer. It's ultimate goal is to minimize the number of connections between the layers. Finally, there is a Fully Connected layer that is closer to the outer layer. It contains the weights, biases, and neurons. The classification part of the model comes into picture at this stage. Following that is the Dropout layer, which is critical for preventing the model from becoming overfitted. Overfitting causes a model to perform better on the training dataset, but when new data is used to test the model, the accuracy is relatively low. For example, if we set the dropout value to 0.2, 20% of the nodes are dropped at random. Finally, the activation functions are one of the most important layers because it has the ability to learn about the relationship between variables in the best way possible. Activation functions that are commonly used include ReLU, Softmax, tanH, and Sigmoid.

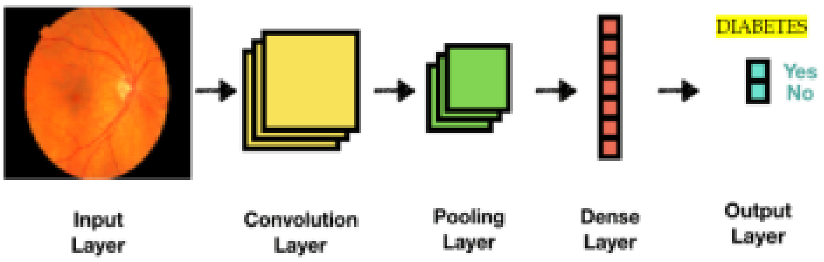

Fig. 3 Overview of CNN Architecture for Diabetes Detection

Figure 3 depicts CNN architecture which is utilized in this project for detecting dilated retinal images. The input image that is the retinal image is first passed to the convolutional layer, after the features are initially extracted in this layer it passes to the next layer called pooling layer, the output from the pooling layer is fed to the dense layer which is followed by the output layer. Finally, at the output layer, it classifies the image and returns a binary value of '0' if the retina is dilated or '1' if it is not dilated.

III. MODULES

A. Data collection

The dataset named MESSIDOR which is an open source dataset has been utilized in this retinopathy detection. The retinal dataset is employed. Three ophthalmologic departments combined to capture the color numerical images of the Messidor database's posterior pole. It was captured by keeping the camera on a Topcon TRC NW6 non-mydriatic retinography. The Camera is a color video 3CCD camera which is configured to capture only a narrow 45-degree field view. 1440X960, 2240X1488, or 2304X1536 are the pixel intensities of the images. These are captured with 8 bits per color plane. There were 800 images dilated in retina (0.5 percent Tropicamide) and 400 without retinal dilation. The 1200 images are divided into three sets, one for each of the ophthalmologic departments. zipped subsets of 4 are formed with each single set. There are 100 TIFF images in a single set; among these each and every single image has a medical diagnosis which is recorded in an excel file.

Medical diagnoses

There are 2 different diagnoses that have been done for each image with the venture of medical experts, the first one is Retinopathy grade and the second one is Risk of macular edema.

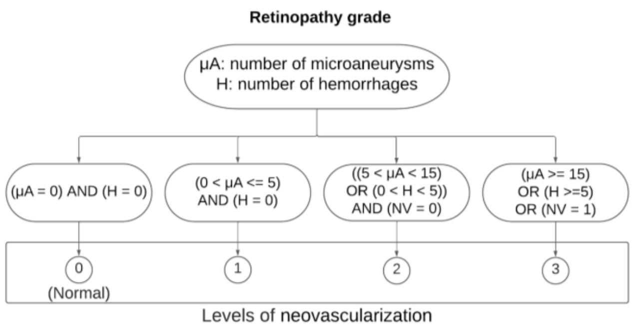

Fig. 4. Retinopathy grade

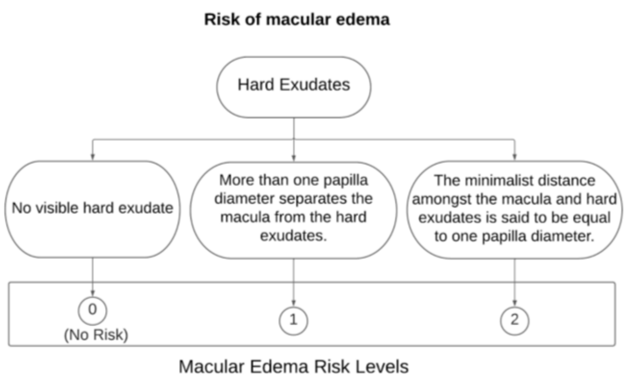

Fig. 5 Risk of macular edema

In the first method the number of microaneurysms and hemorrhages are considered in to account to find the level of the disease but in the second method the hard exudates are taken in to account to calculate the risk levels of Macular Edema.

B. Dataset Preprocessing

The image data has been labeled as diabetes and no diabetes, and the noisy image data has been manually removed. The data is split in a ratio of 80:20 in which 20% of the data is considered for testing and the rest 80% of the data is considered for training purposes. So, the training set contains 960 images that include both dilated and non-dilated images, while the test set contains 240 images that include both types of images.

Fig. 6. Dilated Retinal Image

Fig. 7. Non-Dilated Retinal Image

C. Model Development

The image of the patient's fundus is fed into the Convolutional Neural Network (CNN) model. This model predicts whether the Retinal image contains diabetes-related signs or not. If the person's retina shows no signs of diabetic infection, the model moves on to the next patient's retinal image for identification. If the retina detects diabetes, it sends an email to the appropriate ophthalmologist. As a result, the patient is given medical treatment to help him keep his vision. It has the potential to reduce the overall incidence of matured diabetes-related blindness.

Our model consists of 3 convolution layers. To extract features from images, available filters are used. This is done at the convolutional layer. In these layers, the convolution is carried out by converting the values from the image to smaller dimensions using a filter. An active function (Relu) and a Max pooling operation follow each convolution layer. Activation function is a very crucial aspect to a CNN model's architecture as only this function can allow or block information from the previous nodes to the next layer. In the Max Pooling function, the largest value is taken from the feature map. It has been the most used activation function in image classification as it does not activate all of the layer's neurons simultaneously. If the output from the previous nodes is greater than zero,the neurons are activated and when the value is less, they are deactivated. After the convolution layers, a drop out function with the value of o.5 (50% of drop out) is added. Overfitting happens when a model learns from the training data more than required as the may cause a negative scenario in which the model's performance for new data drops significantly compared to training accuracy. To solve this problem a dropout layer is established in the network. When a dropout layer is established in a model it deactivates a certain number of neurons based on the value declared in the dropout layer which makes the model size smaller. To avoid the chances of overfitting, half of the nodes in the network are deactivated randomly by establishing a dropout layer with 0.5 dropout value. Later the returned values are passed into a dense layer where the classification of diabetes or not will be done. A dense layer is a fully connected neural network layer. Using the SoftMax function, each data point's probability belonging to a class (In this case, Diabetes or No Diabetes) is calculated. It is mostly preferred for a binary classification CNN model as it returns probability of the classes. The model's summary is shown in Figure 9.

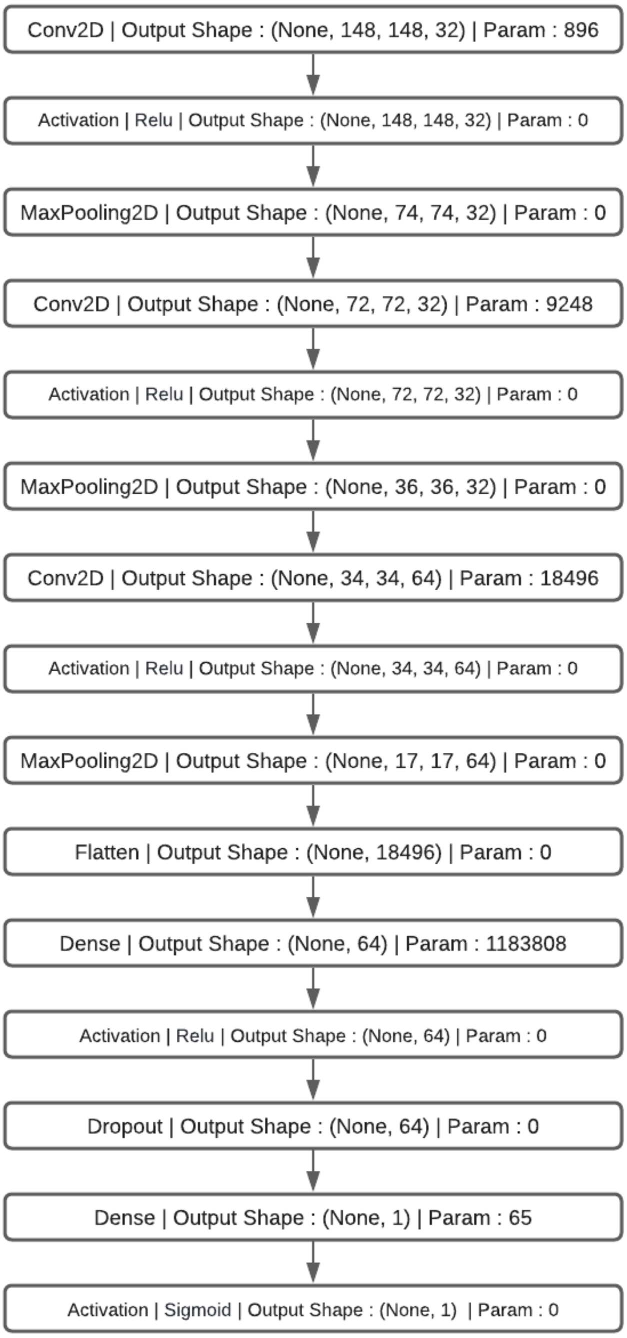

Fig. 8. CNN Architecture for Diabetes

There are nearly 1200 images of retina used to train the Convolutional model. In which 800 (Diabetes-affected retinal images) and 400 (Retinal images which are not affected by diabetes). The model was trained using the following parameters. The train samples are 120, validation samples are 30, epochs are 80,and batch size is 30.

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 148, 148, 32)      896

 activation (Activation)     (None, 148, 148, 32)      0

 max_pooling2d (MaxPooling2D  (None, 74, 74, 32)       0
 )

 conv2d_1 (Conv2D)           (None, 72, 72, 32)        9248

 activation_1 (Activation)   (None, 72, 72, 32)        0

 max_pooling2d_1 (MaxPooling  (None, 36, 36, 32)       0
 2D)

 conv2d_2 (Conv2D)           (None, 34, 34, 64)        18496

 activation_2 (Activation)   (None, 34, 34, 64)        0

 max_pooling2d_2 (MaxPooling  (None, 17, 17, 64)       0
 2D)

 flatten (Flatten)           (None, 18496)             0

 dense (Dense)               (None, 64)                1183808

 activation_3 (Activation)   (None, 64)                0

 dropout (Dropout)           (None, 64)                0

 dense_1 (Dense)             (None, 1)                 65

 activation_4 (Activation)   (None, 1)                 0

=================================================================
Total params: 1,212,513
Trainable params: 1,212,513
Non-trainable params: 0
```

Fig. 9. Model Summary

Initially, the preprocessed and split fundus images are given to the Dense CNN model for training, and it is also fine tuned using the parameters listed above. The trained model is saved, and when a fundus image is fed into it, it classifies it as diabetic or non-diabetic, labeling it with 0 or 1. If the model predicts that the image contains signs of retinal dilation, an email is sent to the doctor.

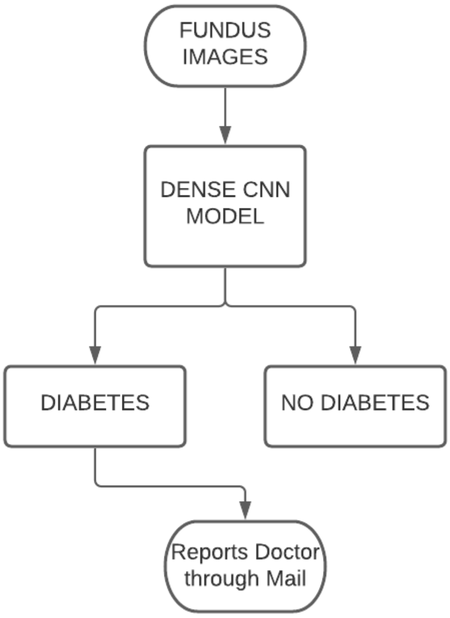

Fig.10. Flow Chart

D. Implementation

Our model is a binary classification model. It is well known that a CNN based binary classification algorithm is best suited for implementing classification between only two different types of classes. In this case, we're implementing the same scenario in which we'll determine whether a fundus image is dilated or not. The fundus image with dilation is labeled as "0" and the image which has no-dilation is labeled as "1". Figure 8 depicts a dilated image labeled "0," while Figure 9 depicts a non-dilated image labeled "1."

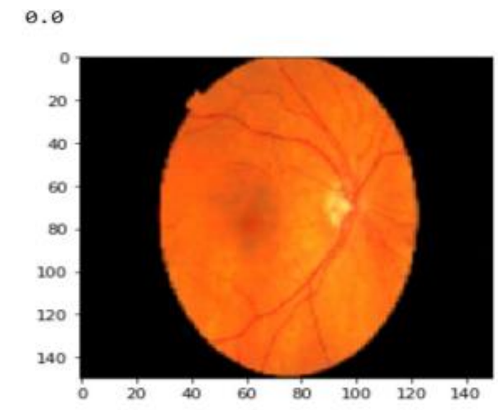

Fig. 11. Predicted Dilated Image with label ‘0’

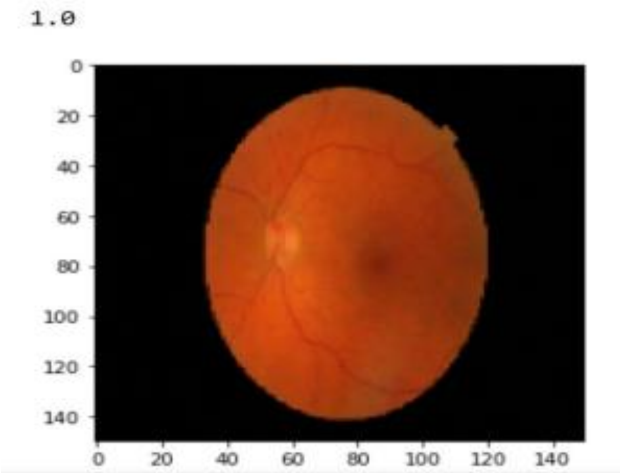

Fig. 12. Predicted Non-Dilated Image with label ‘1’

IV. EXPERIMENTAL RESULT AND DISCUSSION

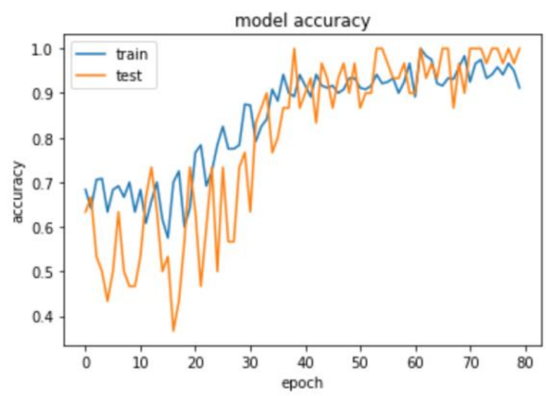

Fig. 13. Model Accuracy Graph

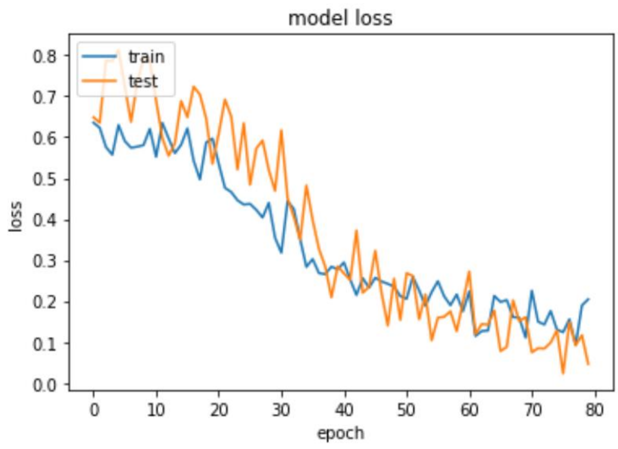

Fig. 14. Model Loss Graph

When it comes to training, as seen in Figure 13, the training accuracy at the initial epochs was around 70%, but as the number of epochs increased, so did the accuracy, and when it comes to training loss, we can see from Figure 14 that it started with a loss of 60%, but then it decreased drastically at each epoch and was nearly 10% at the end.

When it comes to testing, Figure 13 shows a step fall as well as a step rise between consecutive epochs, but at the end, the testing accuracy reached a whopping percentage of 99.7, while the testing loss eventually decreased and reached around 5%.

If the model detects diabetes in the person's retina image, an email is sent to the appropriate Ophthalmology doctor. SMTP is used for sending mail. It is a module used to deliver mail from any application. Below is an image which shows the message received by the doctor post the prediction of dilation.

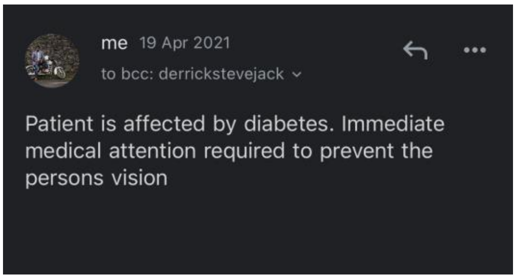

Fig. 15. Alert Mail sent to the Doctor

V. CONCLUSION

This research work is entirely focused on CNN image processing methodology. With this approach the trained CNN model is utilized for the high-level detection of any diabetic symptoms in person's retinal image. With this project work, we will be able to detect Diabetic Retinopathy with high accuracy using our qualified neural network, and Early detection of this condition will be aided by our technology. The system is also configured for the automatic notification for the doctor through EMail if the model has detected the retinal image to have diabetic prodromes in it.

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