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Convolutional Neural Network Model for Detection of Diabetic Retinopathy in Clinical Practice

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Abstract—**As per the estimates are done in 2010, diabetic retinopathy accounts for approximately 2.6% of blindness worldwide. The microvascular changes due to prolonged diabetes result in several changes in the retina- such as microaneurysms, haemorrhages, hard exudates and cotton wool spots that characterize different stages of diabetic retinopathy. Visual impairment may get noticed by the patient very late in the disease progression- at a stage when preventive measures might have very limited benefit. Early detection can serve as a warning and can facilitate adopting preventive measures to slow down the progression of the visual impairment due to diabetic retinopathy. Control of blood sugar (glycemic) and blood pressure are major factors that can slow down the progression of diabetic retinopathy.**

Automatic detection of diabetic retinopathy can be very helpful, especially in the field (medical camps) where adequate trained staff might not be available, or when the volumes of people to be screened are so large, that it is physically challenging for a handful of trained medical personnel to detect the condition manually. Automatic detection of diabetic retinopathy may be done by numerous techniques like mathematical morphology, artificial neural networks, pattern recognition, region growing techniques, fuzzy C-means clustering and Gabor filter banks.

We have developed a convolutional neural network model to detect diabetic retinopathy. In this model, we have used Kaggle dataset. The high-quality retinal images from this dataset have been used to train and test the convolutional neural network model to detect diabetic retinopathy by identifying microaneurysms, haemorrhages, hard exudates and cotton wool spots.

Keywords—diabetic retinopathy, Automatic detection, Artificial neural network, Pattern recognition, Convolutional neural network

I. Introduction

Diabetic retinopathy remains a debilitating ailment worldwide, contributing to approximately 2.6% of the blindness worldwide.[1] Longstanding diabetes leads to microvascular changes affecting retina in the form of microaneurysms, haemorrhages, hard exudates and cotton wool spots. If detected early, measures may be taken to halt the progression of the disease and save the patient from blindness. Measures like strict control of blood sugar levels and blood pressure can help, besides laser treatment of eyes to halt the progression of retinopathy.[2-4]

Artificial intelligence enabled image classification models can help detect diabetic retinopathy in a big way by detecting the changes early during the disease progression. These models can be very helpful especially in areas where adequate trained staff might not be available, or when the volumes of people to be screened are so large, that it is physically challenging for a handful of trained medical personnel to detect the condition manually. Automatic detection of diabetic retinopathy may be done by numerous techniques like mathematical morphology, artificial neural networks, pattern recognition, region growing techniques, fuzzy C-means clustering and Gabor filter banks.[2]

We have developed a convolutional neural network model to detect diabetic retinopathy. In this model, we have used Kaggle dataset (link: https://www.kaggle.com/c/diabetic-retinopathy-detection/data). The high-quality retinal images from this dataset have been used to train and test the convolutional neural network model to detect diabetic retinopathy by identifying microaneurysms, haemorrhages, hard exudates and cotton wool spots. The dataset and the code used to develop this model is available on GitHub.

II. Methods

We have used retinal image dataset from Kaggle to develop a convoluted neural network model through python using keras and tensorflow libraries. We have followed the guidelines given on the Kaggle website to make this model.

A. Preprocessing

In the dataset we received from Kaggle, the size of each image is of 3000 x 2000 pixels. Almost every image consists of a black border of significant size. Preprocessing is done to remove this border and retain only the necessary contents of the image. Thereafter all the images are resized to a uniform size of 512 x 512 pixels for each of the R,G,B frames. OpenCV is used for the pre-processing.

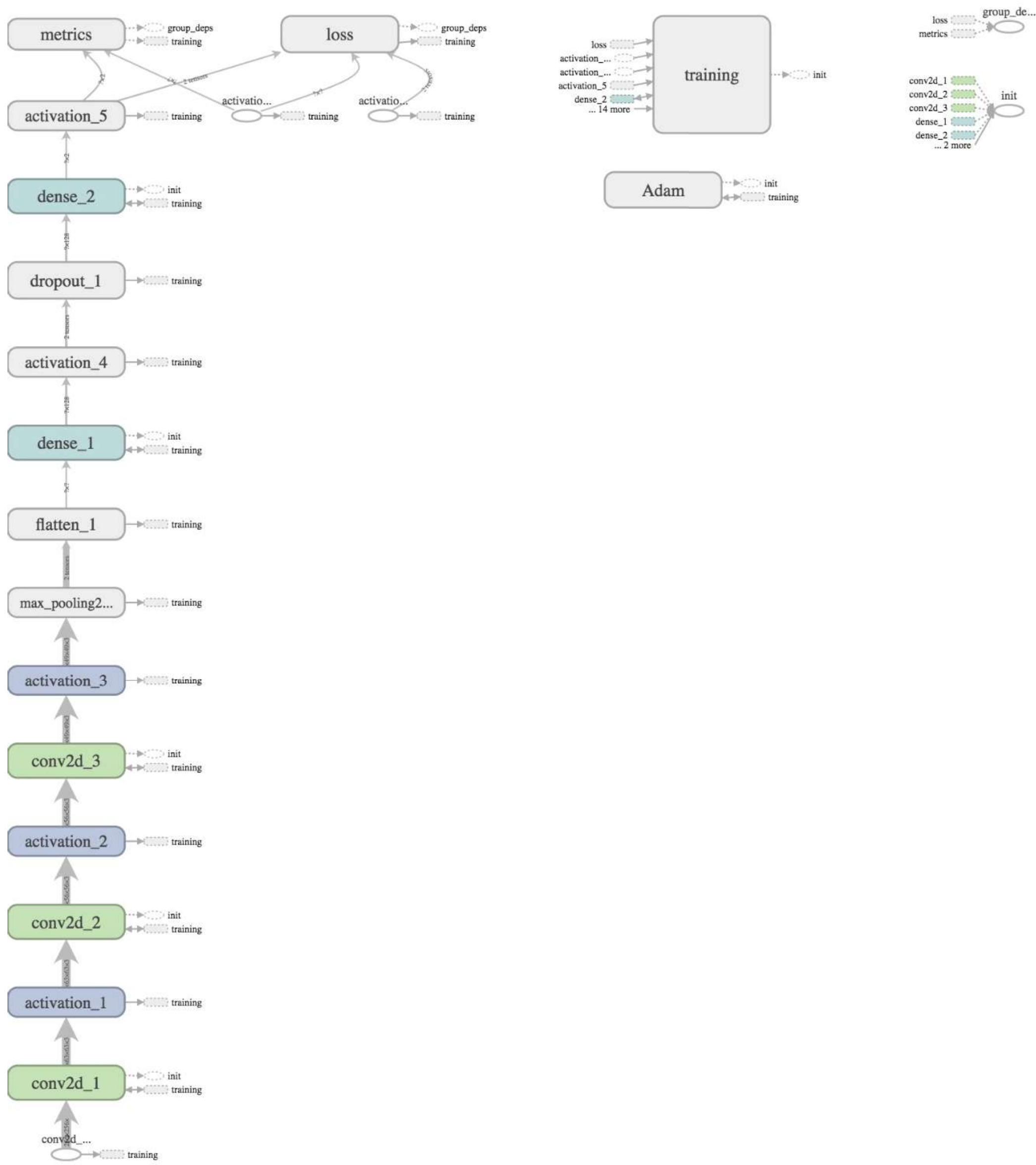
The main steps involved are listed as below:

1. Reading the image from the folder
2. Make a copy of the image and convert the copy to Grey Image.
3. Find the contours in the grey image and calculate the area of each contour
4. Use the dimensions of the maximum area contour in bounding rectangle and crop the original image
5. Resize the crop to 512 x 512 and save it to the folder.

B. Model Architecture

The model is built using Keras, utilizing TensorFlow as the backend. TensorFlow was chosen as the backend due to better performance over Theano, and the ability to visualize the neural network using TensorBoard. For predicting two categories, EyeNet utilizes three convolutional layers, each having a depth of 32. A Max Pooling layer is applied after all three convolutional layers with size (2,2). After pooling, the data is fed through a single dense layer of size 128, and

Figure 1



metrics
loss
training
Adam
activation_5
dense_2
dropout_1
activation_4
dense_1
flatten_1
max_pooling2...
activation_3
conv2d_3
activation_2
conv2d_2
activation_1
conv2d_1
init

finally, to the output layer, consisting of 2 softmax nodes, as shown in figure 1.

Details:

- Adam Optimizer is used in training this mode
- Weights are initialized by the orthogonal initializer
- Cross-Entropy Loss Function is utilized
- Learning Rate of value 0.0001 is used

C. *Training*

Two things can be done for training. Either Transfer Learning or training from scratch can be done here. We found that training from scratch and adding two fully connected layers with dropout gave better results. I used categorical_crossentropy as the loss function and Adam as the model's optimizer.

Hyperparameter tuning is done by using an approach like grid search, Bayesian optimization or the bandit approach. Then we can fit the model. Many more concepts like TTA and differential learning can be used for more accuracy.

For transfer learning, we initially train the newly added layers. We unfreeze all the layers and retrain the whole network.

D. *Testing*

For testing images, we load and pre-process them. They should be of the same size as the training images. We use numpy's expand dimensions method as keras expects another dimension at prediction which is the size of each batch.

We use argmax function to get the predicted class.

III. Result

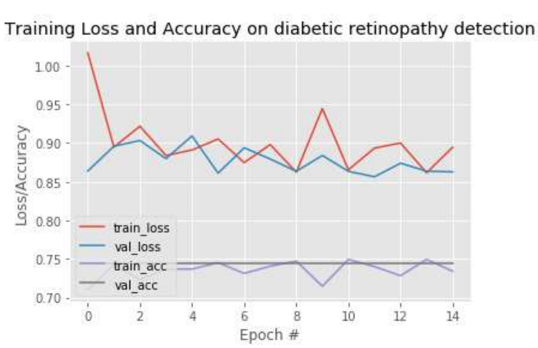
Our model can identify diabetic retinopathy with good credible results. The final accuracy values are:

- Training accuracy = 73.69%
- Testing accuracy = 74.4%

This model can be used in a clinical setting for preliminary analysis.

Figure 2 given below shows training loss and accuracy on detection of diabetic retinopathy.

Figure 2



IV. Discussion

The healthcare industry is a 24-hours a day, seven days a week running industry with the exhaustive involvement of medical personnel. Despite extensive efforts and careful performance of duties, inadvertent mistakes and oversight can happen to lead to painful consequences for patients, families, caretakers and caregivers alike. Medicolegal issues may arise but whatever monetary compensation is given, it neither can satisfy the patient, nor take away the guilt feeling from medical personnel. Hence, applications based on artificial intelligence (AI) are much awaited in the medical community. There should not be any fear of losing jobs (replacing medical personnel with artificial intelligence), as what humans can do in healthcare, machines might not be able to do -like an expression of empathy, reassurance, human touch and placebo effects (some patients start feeling better just after meeting a doctor).

Efforts have been made to develop artificial intelligence models particularly in the field of radiology (AI assisted analysis of X-rays, CT scans and other medical images) and Ophthalmology (AI models assisted analysis of retinal scans). AI models are also available to analyze medical records to suggest the most appropriate treatment. Artificial intelligence models can also help in drug discovery, classification of cancer, better management guidelines for coronary artery disease, and robotic surgeries.[5-8]

We have used python and keras and tensorflow libraries to create a model that analyzes retinal scan images to detect diabetic retinopathy. This model can be a useful tool for nephrology nurses in remote nephrology clinics to begin with. Our model has an accuracy of approximately 74%.

Conclusion

We conclude that we can design a good and reliable convoluted neural network model to detect diabetic retinopathy using python, keras and tensorflow. The model can be very helpful in areas of need where adequate trained staff might not be available, or when the volumes of people to be screened are so large, that it is physically challenging for a handful of trained medical personnel to detect the condition manually. Artificial intelligence enabled image classification models can help detect diabetic retinopathy in a big way by detecting the changes early during the disease progression. Early detection can help medical professionals halt the disease progression by taking adequate measures early, and hence be able to save the patient from blindness.

We can use a similar procedure to develop artificial intelligence enabled image analysis models that help in detecting other diseases and deploy the models for helping healthcare professionals and society. Artificial intelligence has given us promising and exciting results so far. The present is exciting, and the future is going to be something that transcends the imagination. We are really looking at a big change in the way healthcare if done in the present world, and the change looks good and exciting.

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