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DEEP LEARNING MODEL FOR OPTICAL DIAGNOSIS OF AN RETINA

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Abstract-Ophthalmologists often consider the health of the eye's vascular system when making diagnoses. In order to analyse disorders of the retinal vasculature, this project suggests analysing retinal images with an emphasis on the accurate identification of arteries and exudates. Retinal blood vessel comparisons play a crucial role in the early diagnosis of various illnesses. Retinal disorders such as diabetic macular edoema, drusen, and choroidal neovascularization may be detected with the use of a Deep learning model trained using the Convolution Neural Network (CNN) method. Retinal tissue may be imaged quickly and precisely using optical coherence tomography (OCT), a sort of image processing. To detect the retinal disorder, we employ the Keras deep learning framework. The most important result of this work is a method for diagnosing optical disorders from a photograph of the retina. Furthermore, the model may be represented in a web application by integrating it with the python flask framework.

Keywords: Deep Learnin,CNN,OCT,RNN.

1. INTRODUCTION

The days of limited access to health records are long behind. This is both a challenge and an opportunity for image analysis because of the exponential growth in data size (the transition to big data) brought on by

improvements in picture capture technology. In order to keep up with the ever-increasing volume of medical pictures and modalities, doctors need to put in long hours of labour that are subjective, prone to human error, and may show significant difference from one expert to the next. Alternative solutions exist, such as the use of machine learning techniques to automate the diagnostic process; nevertheless, standard machine learning approaches are insufficient when faced with complex problems. The ability to efficiently and accurately diagnose large medical imaging datasets is a goal that might be realised via the union of high performance computing with machine learning. In addition to facilitating the selection and extraction of characteristics and the creation of new ones, deep learning may also aid in the diagnosis of illness, the measurement of predictive targets, and the provision of actionable prediction models to aid physicians in their work.

Both ML and AI have made tremendous strides in recent years. Medical image processing, computer-aided diagnosis, interpretation, fusion, registration, segmentation, image-guided treatment, retrieval, and analysis, all rely heavily on ML and AI techniques. Information in photos may be extracted and represented more efficiently and effectively using ML techniques. With the help of ML and AI, medical professionals can make more precise diagnoses, estimate the likelihood of illness, and take preventative measures in a shorter amount of time. To better grasp how to examine the general deviations that will contribute to illness, these methods aid physicians and researchers. These methods combine traditional, non-learning algorithms like Support

Vector Machine (SVM), Neural Network (NN), KNN, etc., with deep learning algorithms like Convolutional Neural Network (CNN), Recur-rent Neural Network (RNN), Long Short Term Memory (LSTM), Extreme Learning Model (ELM), Generative Adversarial Networks (GANs), etc. For-mer algorithms have difficulty processing natural pictures in their raw form, are time-consuming, take a lot of work for adjusting the features, and rely on expert knowledge. Newer algorithms can learn quickly and automatically from raw data. These algorithms make an effort to automatically learn several layers of abstraction, representation, and information from a huge number of pictures displaying the desired behaviour. Traditional approaches to automated illness detection in medical imaging have a proven track record of success, but recent breakthroughs in machine learning have sparked a deep learning boom. A wide variety of applications, including voice and text recognition, lip reading, computer assisted diagnosis, face identification, and drug discovery, have shown promise performance and speed from deep learning based algorithms.

1.1 Aim of the Project

To Develop a deep learning model for the optical diagnosis of an retina and to develop further it with python flask for web application to get end user interface.

2. PROPOSED SYSTEM

The goal of this project is to create a deep learning model for detecting retinal disorders such diabetic macular edoema, drusen, and choroidal neovascularization using the most trustworthy algorithm and the required frameworks.As neural networks are similar to the human brain, they are used in deep learning to train the model.This model employs a technique for image processing called optical coherence tomography (OCT). To achieve micrometre resolution, this method employs low coherence light.The goal is to put the model for the web app into production in the cloud.

Data Collection

Since we're utilising deep learning to identify illnesses in OCT pictures here, we needed access to patient images. As a result, we amassed 5.4 GB worth of CNV,DME,DRUSEN,NORMAL images captured in real time throughout the month of October. In this data collection, we find four distinct types (NORMAL,CNV,DME,DRUSEN). Each kind of picture has its own subdirectory within one of three main directories (train, test, val) (NORMAL, CNV, DME, DRUSEN). There are hardly any pictures in the "test" or "val" directories. There are 83484 pictures in the "train" folder. Retinal oct pictures show that three is a class. This is a list of them

Choroidal neovascularization (CNV)

A condition known as choroidal neovascularization (CNV) occurs when new blood vessels form in the choroid layer of the eye. Neovascular degenerative maculopathy (i.e. 'wet' macular degeneration) is often brought on by choroidal neovascularization[1] and is often aggravated by high myopia, malignant myopic degeneration, or age-related changes.

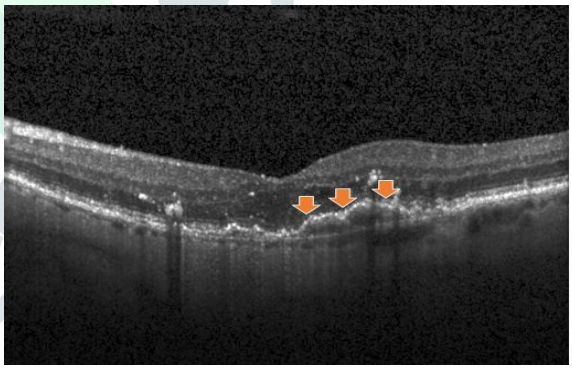


Fig1: Oct image of CNV diseased retina

Diabetic Macular Edema (DME)

Diabetic macular edoema (DME) occurs when fluid builds up in the macula and damages central vision. Macula refers to the central macula region of the retina, which is located in the rear of the eye and provides the clearest vision. Damage to the optic nerve from DME may cause gradual vision loss over the course of months, eventually making it unable to concentrate effectively.

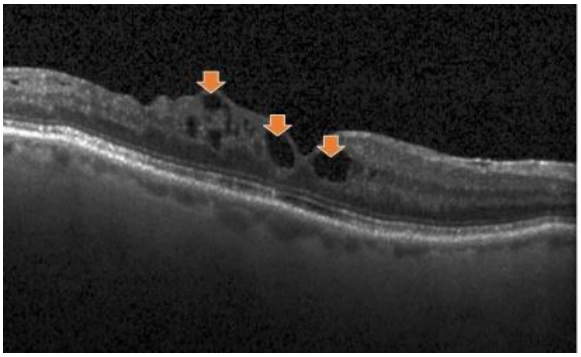


Fig2: Oct image of DME diseased retina

Drusen

Drusen are deposits of yellow pigmentation beneath the retina. Drusen are composed of lipids, a kind of fatty protein. The drusen probably do not contribute to AMD (AMD). However, drusen raises the odds of getting age-related macular degeneration. Drusen may come in a variety of forms. The drusen that make up this kind of rock are minute, isolated, and widely spaced. Drusen of this sort may not impair eyesight for a very long period, if at all. Hard drusen are small and widely spaced, whereas "soft" drusen are huge and closely clustered. The edges of soft drusen are not as sharp as those of hard drusen. The risk of age-related macular degeneration is higher in those with this soft drusen.

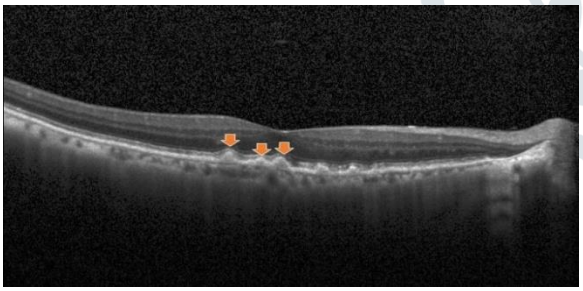


Fig3: Oct image of drusen diseased retina

NORMAL or Normal Eye Retina

The human eye sees normally when light hits the retina from the front rather than the back. Persons with normal eyesight are able to discern details in both close and vast distances.

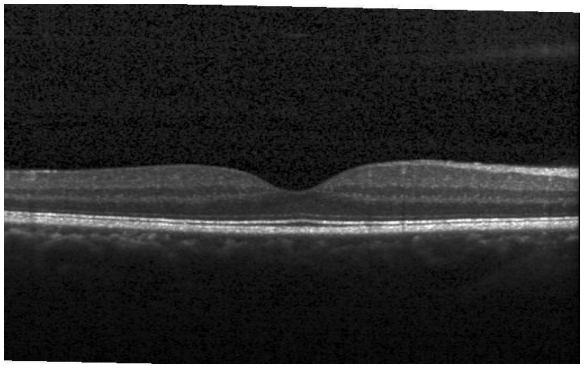


Fig4: Oct image of Normal retina

Organizing the data into Train, Test,Validation set

The data is gathered and then separated into two sets, the train set and the test set, with each set including four additional subfolders labelled CNV, DME, DRUSEN, and Normal. In this case, a visual depiction is shown below.

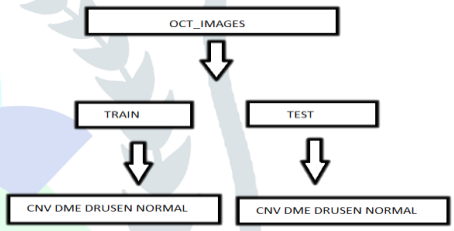


Fig5: Organizing the data into Train, Test,Validation set

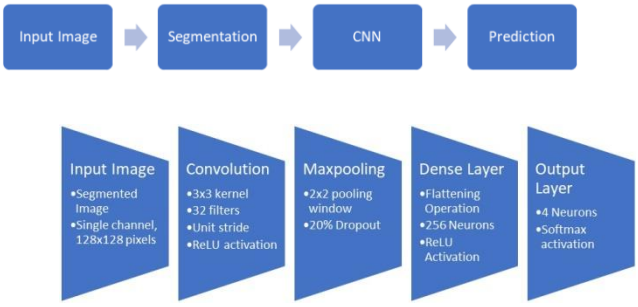
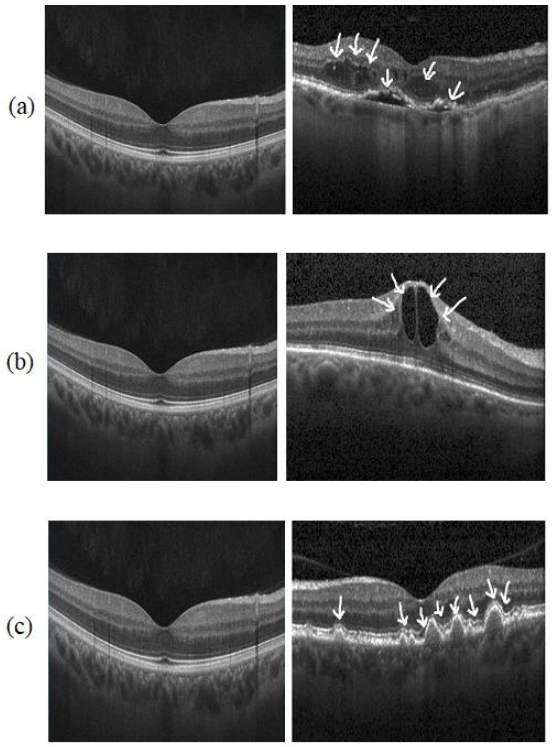


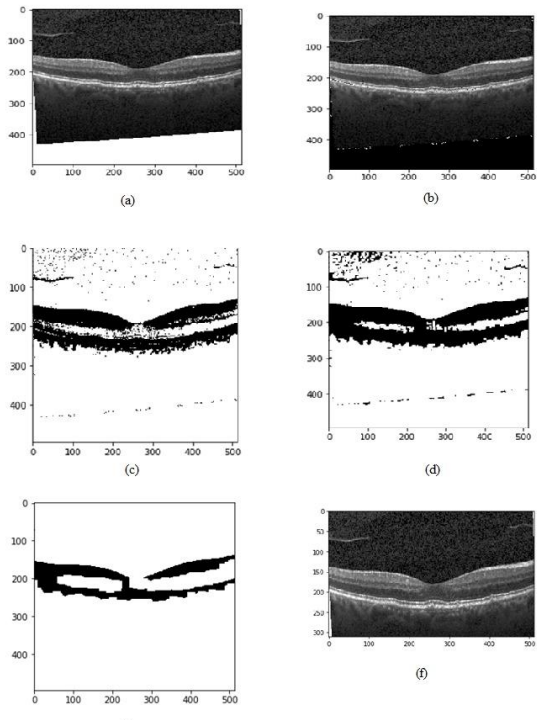
Fig6: System Architecture

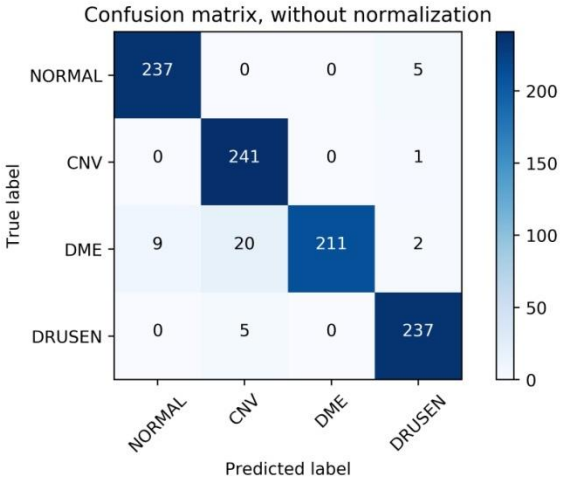
3. RESULTS

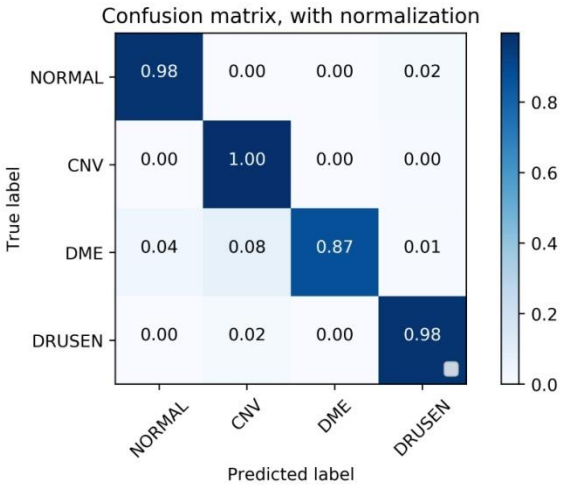
Table1:Accuracy Metrics

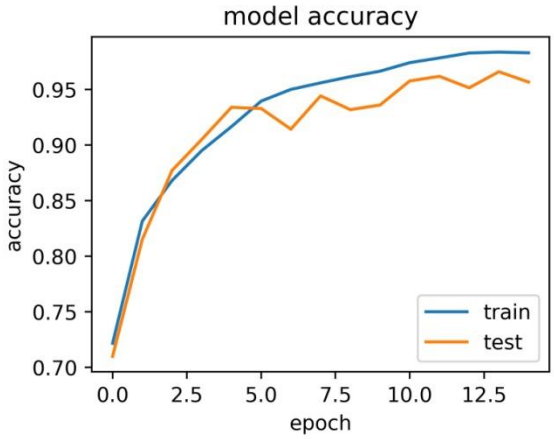
	Precision	Recall	F1-Score
Normal	0.96	0.98	0.97
CNV	0.91	1.00	0.95
DME	1.00	0.87	0.93
Drusen	0.97	0.98	0.98
Average	0.9519	0.9566	0.9562

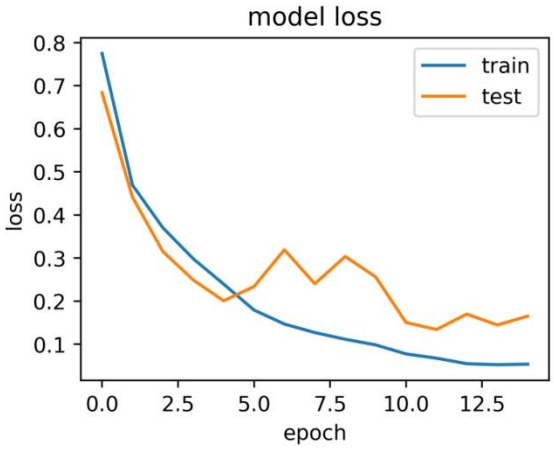












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In [46]: model.summary()
```

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 126, 126, 32)	320
max_pooling2d_4 (MaxPooling2	(None, 63, 63, 32)	0
dropout_4 (Dropout)	(None, 63, 63, 32)	0
flatten_4 (Flatten)	(None, 127008)	0
dense_7 (Dense)	(None, 128)	16257152
dense_8 (Dense)	(None, 4)	516

Total params: 16,257,988
Trainable params: 16,257,988
Non-trainable params: 0

4. CONCLUSION

Accuracy is improved by transfer learning compared to a manually constructed network.The recall matrix comparison reveals that labels 1 and 3 are somewhat misclassified. We find that the recall matrix generated by InceptionNet outperforms all others. The Inception Net model seeks to strike a balance between all of these groups. It's perfect for us to use as a benchmark.

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