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Ocular Disease Recognition and Detection using VGG Algorithm

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Abstract: *The detection of ocular diseases is the most interesting point for the Optometrist. Due to the cost of the devices that discover and classify the different types of ocular disease. Artificial Intelligence (AI) based image processing and Machine Learning are currently utilized to classify and detect ocular disease. In this chapter, we present an improved classification model based on an improved VGG to classify the ocular disease of the stored eye image datasets. The dataset was collected and prepared to generate the image list and then the data are divided into 80% training and the remaining 20% for testing. We highlighted to classify the cataract and diabetes disease from the eye ocular images. The proposed pre-trained model is tested based on deep neural networks based on VGGNet. We utilized VGGNet-16 and VGGNet-19 and applied the Adam optimizer to improve the results of VGGNet and tackle the overfitting problem.*

Keywords: Image processing, Ocular disease, Deep learning, VGG, Machine Learning

I. INTRODUCTION

Iris cataract tumours are the most dangerous tumours in the eye, commonly known as ‘eye tumours’.Most cataracts develop when aging or injury changes the tissue that makes up eye’s lens. Protiens and fibres in the lens begin to break down, causing vision to become hazy or cloudy. Some inherited genetic disorders that cause health problems can increase your risk of cataracts. The term ocular is used with tumour to represent that it is accompanied with eye. It can be intraocular, which means inside the eye or extra-ocular which means that it affects the outside part of the eye. The most common types of diseases are detected are cataract, diabetic retinopathy, redness level. Some other tumours related to the eye are Lacrimal Gland Tumour, lid tumour, etc. The exact cause of this disorder is not known, but certain risk factors have been noticed. The disorder is seen more often in people who have light eye colour. Age, certain inherited skin disorders, exposure to ultraviolet (UV) light, certain genetic mutations etc are also considered as the reasons for eye tumours. The eye tumour can be spread and shall affect thevision.

Routine checkups are the best methods for diagnosing the tumour. Ophthalmoscope is commonly used to diagnose. Ultrasound, Fluorescein angiography test OCT, Semiconductor Detectors are the other common methods to diagnose. Needle biopsy is rarely used for diagnosis. CT and MRI are best in diagnosing extraoccular and intracranial extension. Diagnosis of eye tumours is considered according to age, health state, suspected disease, symptoms and past examination records. Cytogenetics and gene expression profiling are used to collect more information about prognosis. Iris tumours are most common eye tumours and it is classified into different types. For earlier detection of these tumours, generalised procedure is needed to diagnose the abnormality.

The two most commonly used therapeutic procedures are surgery or radiation therapy. In Radiation therapy damage produced in the tumour cells causes them to die and slowly shrink. The most common radiation therapies are endocrine therapy, brachytherapy, or sealed source radiotherapy [5]. Shrinking of the tumour region can be completely cured with local therapy. The local therapy consists of laser photocoagulation, cryotherapy, thermotherapy, Plaque radiotherapy etc. Laser photocoagulation is the primary therapy with xenon or argon arc. This coagulates all blood supply to the tumour and it can control 70% of the abnormality. Cryotherapy commonly treated for small tumours. The procedures for chemotherapy start with cryotherapy as a preparation step. Thermotherapy is the method of applying heat to the affected area using ultrasound, microwaves, or infrared radiation.

Ophthalmology is a branch of medical science that investigates the disorders of the eye. Bio medical imaging software is the efficient tool for ophthalmologists in diagnosing eye diseases. These imaging techniques also help them in surgical treatment. Most of the image diagnosing machines are working with the principle of machine learning. Fundus and OCT image records can reveal the symptoms of diabetes. Many cameras are available now for capturing iris regions of the eye. These images are used both for biomedical and biometric applications. Theeye tumour examinations can be undertaken with the pictures. More research works should come across in the field of ocular disease detection detection

II. LITERATURE SURVEY

In this paper , the author proposes an image processing technique to identify the ocular disease. This experiment was conducted with 10 normal and 10 diseased images. The median filtered image segmented into two parts. A cataract disease was detected in the affected area.In this paper ,the author investigates the symptoms of diseassimilar to diabetic retinopathy with biomedical imaging. The author analysed this case with 9 patients and identified as diabetic retinopathy. They might be mistaken for glaucoma becauseof similar symptoms such as pain, severe headache, red eye, etc

In this study, they insisted on the importance of diagnosing diseases correctly by comparing nine cases misdiagnosed as glaucomainitially.

Here the author presented automated methods to segment iris images for early detection of eye tumour. Vander Lugt corelator based active contour method is used to segment the iris portion. K-means clustering model is used to label the timorous tissue.

III. DATASET

Ocular Disease Intelligent Recognition (ODIR) is a structured ophthalmic database of 5,000 patients with age, color fundus photographs from left and right eyes, and doctors' diagnostic keywords from doctors. This dataset is meant to represent the ''real- life'' set of patient information collected by Shanggong Medical Technology Co., Ltd. from different hospitals/medical centers in China. In these institutions, fundus images are captured by various cameras in the market, such as Canon, Zeiss, and Kowa, resulting in varied image resolutions. Annotations were labeled by trained human readers with quality control management2. They classify patients into eight labels including normal (N), diabetes (D), glaucoma (G), cataract (C), AMD (A), hypertension (H), myopia (M), and other diseases/abnormalities (O).

After preliminary data exploration I found the following main challenges of the ODIR dataset:

1. Highly unbalanced data. Most images are classified as normal (1140 examples), while specific diseases like for example hypertension have only 100 occurrences in the dataset.
2. The dataset contains multi-label diseases because each eye can have not only one single disease but also a combination of many.
3. Images labeled as "other diseases/abnormalities" (O) contain images associated to more than 10 different diseases stretching the variability to a greater extent.
4. Very big and different image resolutions. Most images have sizes of around 2976x2976 or 2592x1728 pixels.

All these issues take a significant toll on accuracy and other metrics. In recent times, the discovery of clinical signs and the grading of optical conditions have been considered engineering grueling tasks. In addition, worldwide experimenters have published their styles and a set of EFIs and OCTs databases with different optical conditions, population, accession bias and image resolution. The available optical datasets for each optical complaint, the type of optical image and the study population are presented in Table 1.

IV. PERFORMANCE METHODS

Deep learning approaches have shown astonishing results in problem domains like recognition system, natural language processing, medical sciences, and in many other fields. Google, Facebook, Twitter, Instagram, and other big companies use deep learning in order to provide better pplications and services to their customers. Deep learning approaches have active applicatio s using Deep Convolutional Neural Networks (DCNN) in object recognition, speech recognition, natural language processing, theoretical science, medical science, etc.

In the medical field, some researchers apply deep learning to solve different medical problems like diabetic retinopathy, detection of cancer cells in the human body, spine imaging and many others. Although unsupervised learning is applicable in the field of medical science where sufficient labeled datasets for a particular type of the disease are not available. In particular, the state-of-the-art methods in ocular images are based on supervised learning techniques.

4.1 Performance Metrics in Deep Learning Models

The performance comparison of deep learning methods in classification tasks is performed by the calculation of statistical metrics. These metrics assess the agreement and disagreement between the expert and the proposed method to grade an ocular disease 35,62,74. The performance metrics used in state-of-the-art works are presented in Equations (1 - 7) as follows:

$$\text{Area under the curve } (AUC) = \frac{\sum \quad Rank(+) - |+| * \frac{(|+|+1)}{2}}{|+| + |-|} \quad (1)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (3)$$

$$Specificity = \frac{TN}{TN + FP} \quad (4)$$

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

$$f - score = \frac{2 * Precision * Recall}{Precision + Recall} \quad (6)$$

$$Kappa\ coefficient = \frac{p_o - p_e}{1 - p_e} \quad (7)$$

V. DEEP LEARNING METHODS FOR DIAGNOSIS SUPPORT

5.1 Dl Methods using Eye Fundus Images

The state-of-the-art DL methods to classify ocular diseases using EFIs are focused on conventional or vanilla CNN and multi-stage CNN. The most common vanilla CNN used with EFIs are the pre-trained inception-V1 and V3 models on the ImageNet database (http://www.image-net.org/). The inception-V1 is a CNN that contains different sizes of convolutions for the same input to be stacked as a unique output. Another difference with normal CNN is that the inclusion of convolutional layers with kernel size of 1x1 at the middle and global average pooling at the final of its architecture 79. On the other hand, inception-V3 is an improved version batch normalization and label smoothing strategies to prevent overfitting 91. 94 used the U-Net model proposed by 92 to segment the retinal vessel from EFIs. Then, two new datasets were created with and without the vessels to be used as inputs in the inception-V1. This method obtained an AUC of 0.9772 in the detection of DR in the DRIU dataset. 96 and 98 proposed a patch-based model composed of pre-trained inception-V3 to detect DR in the EyePAC dataset. 98 used a private dataset with segmentations of clinical signs to classify an EFI into normal or referable DR with a sensitivity of 93.4 % and specificity of 93.9 %. The ensembled of four inception-V3 CNN by 96 reached an accuracy of 88.72 %, a precision of 95.77 % and a recall of 94.84 %.

The multistage CNN is centered first on the detection of clinical signs to sequentially grade the ocular disease. 95 located different types of lesions to integrate an imbalanced weighting map to focus the model attention in the local signs to classify DR obtaining an AUC of 0.9590. 97 used a similar approach to generate heat maps with the detected lesion as an attention model to grade in an image-level the DR with an AUC of 0.954. 99 uses a four-layers CNN as a patches-based model to segment exudates and the generated exudate mask was used to diagnose DME reporting an accuracy of 82.5 % and a Kappa coefficient of 0.6. Then, 104 proposes a three-stage DL model: optic and cup segmentation, morphometric features estimation and glaucoma grading, with an accuracy of 89.4 %, a sensitivity of 89.5 % and a specificity of 88.9 %. Finally, 101 proposed a model to segment optic disc and cup and calculate a normalized cup-discratio to discriminate healthy and glaucomatous optic nerve of EFIs. Table 2 presents a brief summary of DL methods in eye fundus images used to support an ocular diagnosis.

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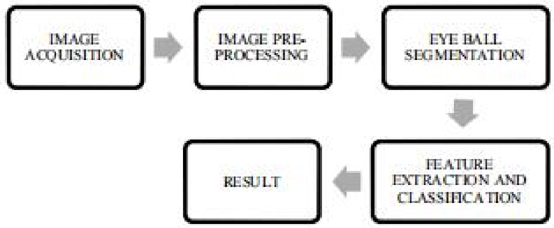
VI. PROPOSED SYSTEM

Deep learning techniques are mainly employed in the detection of ocular disease.The below figure shows the pipeline of the proposed method.



6.1 Image Acquisition

Image acquisition is the advent of a digitally encoded illustration of the visible traits of an object, consisting of a bodily scene or the interior shape of an object. The term is frequently assumed to mean or encompass the processing, compression, storage, printing, and display of such images. As eye tumours have different types, many open dataset are available for research purposes. Only a limited number of image data are available for study. The images were collected from Miles Research, Eye cancer and uveal melanoma image databases.. We have prepared 10 abnormal and 10 normal images after analysing the disease conditions. More data is needed for deep learning techniques. So image augmentation technique is applied to increase the number. Augmentation step contains a rotation of each image, width shift range of 0.1, height shift range of 0.1, brightness range of (0.3,1.0), horizontal and vertical flip. A new dataset has been created with 2000 images.

6.2 Image pre-processing

Image pre-processing step aims to prepare the input data for further analysis. It may use automated algorithms. Filtering is a vital procedure in signal processing, for outlining the capabilities of image, filtering suppresses completely or partially some elements of image. Image pre-processing mainly depends with the source. Two parameters influence the picture quality. Intrinsic parameters are related with materials made and extrinsic parameters are related with the environment where the image captured. Most of the images are in RGB format. Gray scale conversion is needed for converting the image into two dimensional arrays. Gray scale conversion methods are based on average, lightness and luminosity.

Let R, G, B are the colour planes of an image.

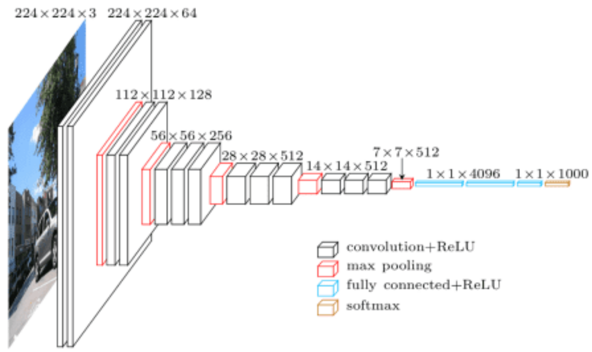
$$\text{Average} = \frac{(R+G+B)}{3} \quad (1)$$

$$Lightness = \frac{(\max(R,G,B) + \min(R,G,B))}{2} \quad (2)$$

$$luminosity = 0.21\,R + 0.72\,G + 0.07\,B \quad (3)$$

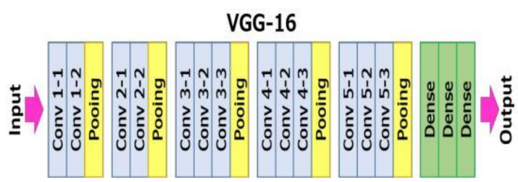
6.3 Eyeball Segmentation

Segmentation is the process of splitting the entire image into different parts. Here eyeball is the region of interest (ROI) where the features of tumours exist. As the iris region is in circle shape, Hough circle detection is employed to separate the ROI . The Hough transform is a technique of feature extraction which is used in many processes like digital image processing, image analysis, and computer vision. Two circle regions are inside the eyeball. The outer region can be easily separated and the inner region may not clear in diseased image. So outer circle detection is prioritised. Canny based edge detection algorithm prepares the boundary of these regions. Gradient of the images extracted by applying different threshold values.



6.4 Architecture Used: VGG-16

VGG16 is a convolutional neural network model. The input to cov1 layer is of fixed size 224 x 224 RGB image. The image is passed through a stack of convolutional (conv.) layers, where the filters were used with a very small receptive field. Three Fully-Connected (FC) layers follow a stack of convolutional layers. The first two have 4096 channels each, the third performs 1000-way ILSVRC classification and thus contains 1000 channels (one for each class). The final layer is the soft-max layer. The configuration of the fully connected layers is the same in all networks.All hidden layers are equipped with the rectification (ReLU) non-linearity.



VII. DISCUSSION

This review reports the deep learning state-off-the-art works applied to EFIs and OCT for ocular diagnosis as presented in Tables 2 and 3. The main DL methods in the detection of ocular diseases using EFIs are focused on the fine-tuning of pre-trained CNNs such as Inception V1 [94] and Inception V3 [96]. In addition, the pre-trained CNNs applied to OCT obtained an outstanding performanceas reported with pre-trained ResNet [35],[105], VGG-16 [111] and Inception V3 [74]. Thus, the feature extraction stage performed by CNNs using a non-medical domain dataset from ImageNet is enough to discriminate healthy and unhealthy patterns from ocular images. On the other hand, the best CNN models using OCT volumes as input are customized models with two or three stages. In particular, these DL models used two or more ocular medical datasets reported in Table 1 to perform the feature extraction of local signs, added to a classification stage for grading the ocular diseases as reported for EFIs in [95],[97],[99]-[103] and for OCTs in [106]-[109].

The number of free public available datasets contributes to the design of new DL methodologies to classify ocular conditions as reported in Table 1. However, the use of a private dataset limits the comparison among performance metrics reached by DL methods [74],[98],[110]-[111]. The replication of studies reported by [98] and [110] have been criticized for the lack of information related to the description of the method and the hyperparameters used [113]. The use of public repositories as GitHub (https://github.com/) to share datasets and codes is still a need. Nowadays, the growing interest of big technology companies and medical centers to create open challenges has increased the number of ocular datasets such as the DR detection by Kaggle [53],[84], the blindness detection by the Asia Pacific Tele-Ophthalmology Society (APTOS) [54] and iChallenge for AMD detection by Baidu [34]. These new datasets contain diverse information related to acquisition devices, image resolution, and worldwide population. Moreover, DL techniques are leveraging the new data to the design of new robust approaches with outstanding performances as reported in Tables 2 and 3.

The lack of validation of DCNN models with real-world scans or fundus images is still a problem. We found a couple of methods validated with ocular images from medical centers [96], [108]-[111]. However, the number of free public real-world ocular images is limitedto five sets of images [31],[46],[53]-[54],[74]. The clinical acceptance of the proposed DCNN models depends critically on the validation in clinical and nonclinical datasets.

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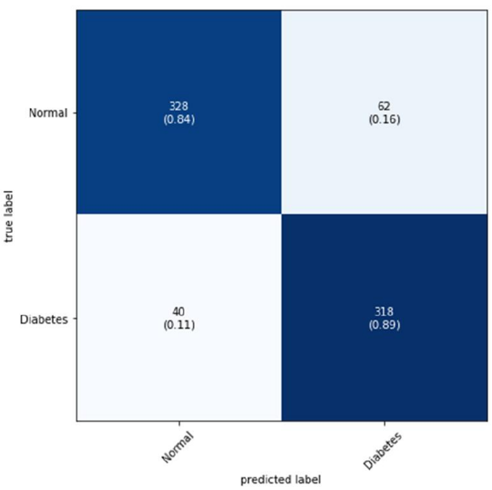
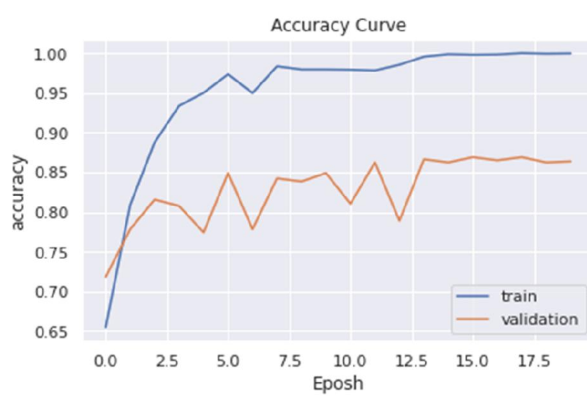
VIII. RESULTS

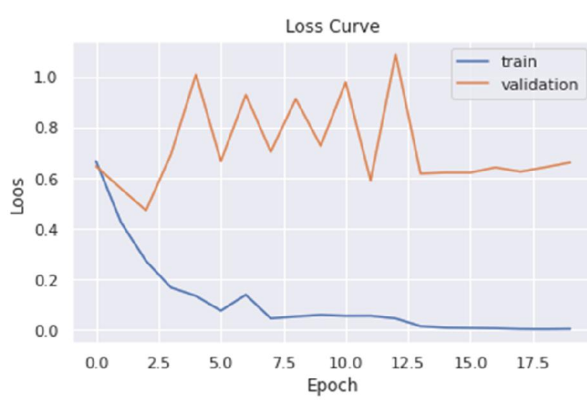
Ocular Disease Recognition, Diabetic Prediction using VGG19 and VGG16, Accuracy and Loss curves

7.1 Prediction Graphs

	precision	recall	f1-score	support
0	0.89	0.84	0.87	390
1	0.84	0.89	0.86	358
accuracy			0.86	748
macro avg	0.86	0.86	0.86	748
weighted avg	0.87	0.86	0.86	748







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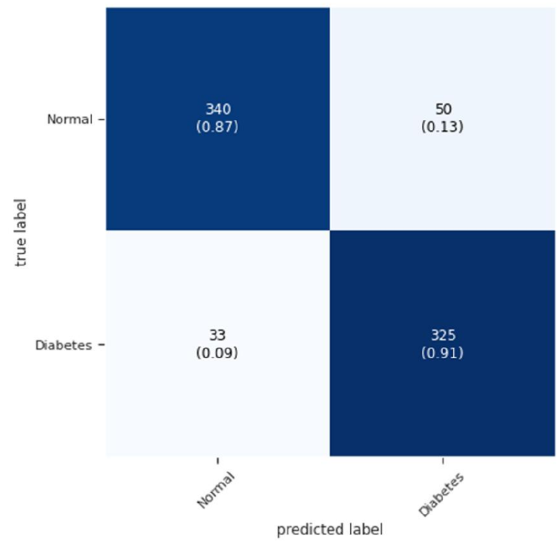

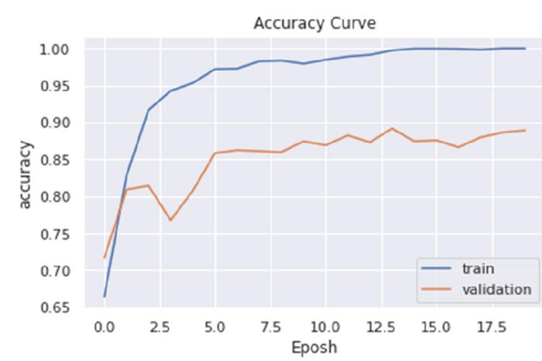

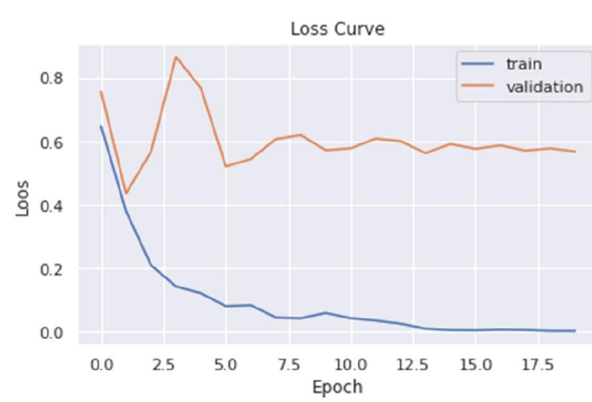

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1	0.86	0.90	0.88	358
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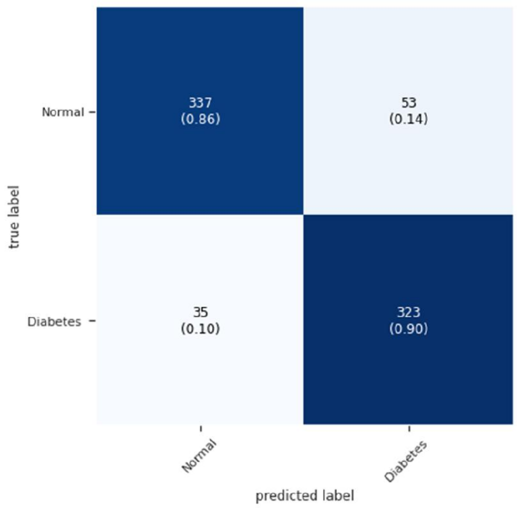
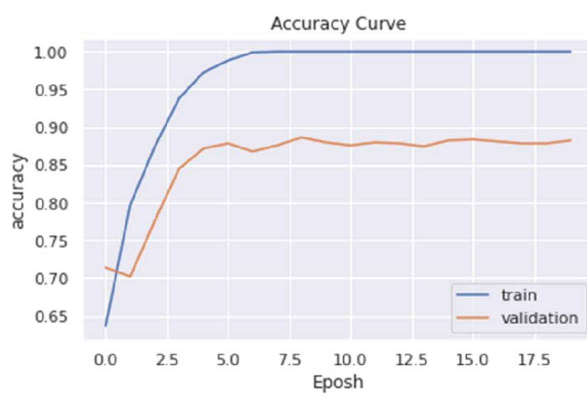
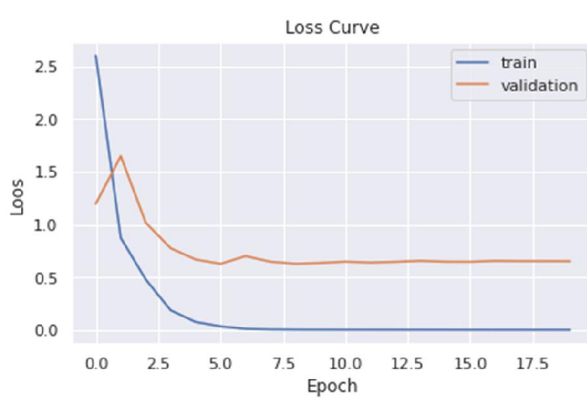
macro avg	0.88	0.88	0.88	748
weighted avg	0.88	0.88	0.88	748

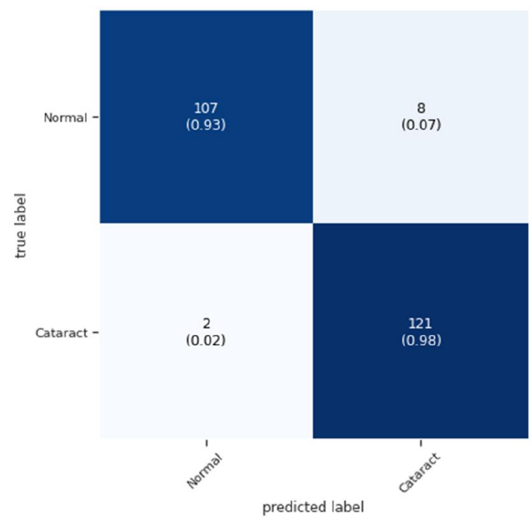


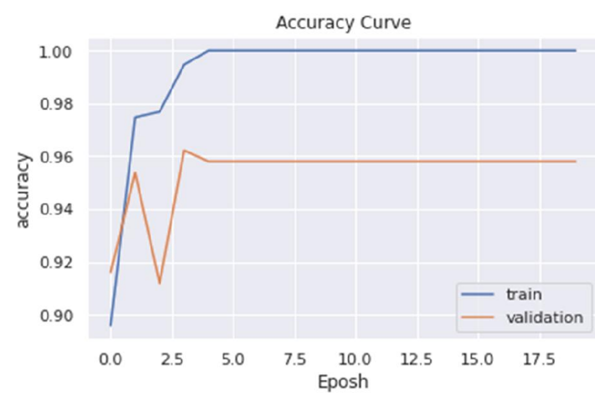


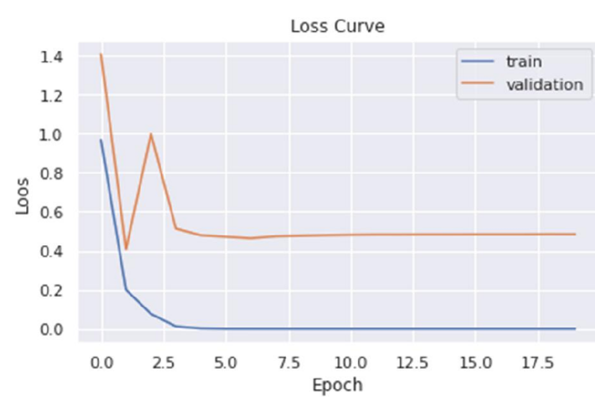


7.4 Prediction Graphs

	precision	recall	f1-score	support
0	0.98	0.93	0.96	115
1	0.94	0.98	0.96	123
accuracy			0.96	238
macro avg	0.96	0.96	0.96	238
weighted avg	0.96	0.96	0.96	238







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We also wish to express our sincere thanks to Visvesvaraya Technological University for accepting ours into the graduate program. In addition, We are deeply indebted to all the staffs of our college.

X.CONCLUSION

Research work in ocular tumour or tumour needs more attention in the present world. Many open sources are available for this research work. We selected eye diseased images from different databases for study purposes. We have developed VGG algorithm which is a novel work in the field of ocular diseased detection. Our method classifies the normal images with 98% accuracy and abnormal images with an accuracy of 95%. Both of these results show that our model is able to distinguish the images.

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