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MULTIPLE EYE DISEASE DETECTION USING CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT: Among the most important systems in the body is the eyes. Although their small stature, humans are unable to imagine existence without it. The human optic is safe against dust particles by a narrow layer called the conjunctiva. It prevents friction during the opening and shutting of the eye by acting as a lubricant. A cataract is an opacification of the eye's lens. There are various forms of eye problems. Because the visual system is the most important of the four sensory organs, external eye abnormalities must be detected early. The classification technique can be used in a variety of situations. To examine multiple eye disease detection algorithm based on Optical Coherence Tomography (OCT) scans using Convolution Neural Network (CNN). The proposed work has been deployed with convolution neural networks performed on the OCT image from authenticated data set and accuracy of 91% was achieved using 5-fold cross validation. The highest AUC value for the normal class observed as 1. More than 90% AUC in predicting eye disease for all the classes has been attained using the proposed approach.
Keywords: Cataract, Convolution Neural Network, multiple eye disease, Optic, Optical Coherence Tomography

INTRODUCTION

Diabetic retinopathy (DR) is a condition of the human eye caused due to diabetes. It is caused due to damage of blood vessels in light-sensitive tissues in the retina of the eye, which eventually leads to blindness. Based on studies, it is known that the Western Pacific Region has a higher prevalence of diabetes (152.2 million), and Southeast Asia has a count of 78.3 million. In India, 69.2 million people are affected by diabetes, and almost 36 million people remain undiagnosed. The number of diabetes cases is expected to rise to 109 million in 2035, which could result in an increased risk of eye diseases and blindness soon. Current statistics on Diabetic retinopathy points to the fact that 6 million diabetes patients in India have a sight-threatening form of retinopathy [1].

In recent years, the diagnosis of diseases of the human visual system has advanced greatly to technological innovations and developments in the field of artificial intelligence. Considering the diversity and complexity of eye functions, many diagnostic equipment, tools, methods and algorithms have been developed. Sometimes a doctor can discover a specific disease after a visual analysis of the image. However, in many cases, the diagnosis is not made due to many factors, such as bad experience, fatigue, a variety of shapes, similarities, poor image quality, etc. In these cases, the second opinion is very important and useful, which comes from another expert who uses advanced information technology and algorithms to accurately analyze the image to diagnose eye diseases [1] bagging ensemble is a kind of ensemble learning, it is a set of machine learning models combined to obtain better results. In this study, we focus on bagging ensemble to improve the model's prediction and make it better.

Mo, Weilong, et al. [8] the authors suggest an image recognition algorithm based on the ensemble learning algorithm and the structure of the ELA-CNN to solve a problem that single model cannot correctly predict. They used the bagging ensemble to train their models. the networks' structure was used are combines of ResNet, DenseNet, DenseNet-BC and Inception-Resnet-v2 architecture. in their experiments they used cifar-10 as images dataset, it consists of 60,000 color images. These images were divided into 50,000 in the training set and 10,000 in the test set. The result was the average probability of the prediction vector. Kumar, Ashnil, et al. [9] For classification of medical images based on diagnosis, training, and biomedical research, a set of convolutional neuronal networks of finetuned were used to classify medical images. They used 6,776 training images and 4166 test images. The authors used two different CNN designs, AlexNet and GoogleNet, to images classification. The experiments were performed using individual models and ensemble models. By the result, the ensemble method reached an accuracy corresponding to the best accuracy among other methods of the overall method of 96.59%. Beluch, William H., et al. [10] the authors in this paper explore some of the recently proposed active learning methods that contain big data and CNN classifiers. They compare ensemble-based methods against Monte-Carlo Dropout and geometric approaches. They have found that the ensemble learning better and leads to a more predictable uncertainty, which is the basis of many active training algorithms of convolution Neural Networks, such as S-CNN, K-CNN, DenseNet, InceptionV3 and ResNet -50 to classify Diabetic retinopathy. The dataset was used with MNIST, CIFAR, and ImageNet. They found that ensembles which based on several active learning algorithms were better predicted and achieved a set test accuracy of 90% of the approximately 12,200 images presented. Minetto, Rodrigo, Maurício Pamplona Segundo, and Sudeep Sarkar. [11] Hydra: An Ensemble of Convolutional Neural Networks for Geospatial Land Classification in satellite image. Hydra is an initial CNN that is coarsely optimized, which will serve as the Hydra's body. in this article, authors created ensembles for their experiments using two state-of-the-art CNN architectures, ResNet and DenseNet. they demonstrated their application of Hydra framework in two datasets, FMOW and NWPURESISC45. The result ensemble was achieved accuracy around 84.51%.

Eye diseases have a wide range of shapes, sometimes the textures are difficult to identify and recognize by an ophthalmologist. Therefore, information technology must be used to provide maximum comfort to the patient and ophthalmologist and improve health care system. In this paper, we will use bagging ensemble to evaluate three different CNN structures to identify eye diseases like, Diabetic retinopathy, Glaucoma, Myopia, and so on.

MATERIALS AND METHODS

This paper presents multiple eye disease detection based on chest OCT images using CNN. The first stage involves extracting eye regions from the OCT picture and segmenting each slice in those regions to find respective diseases. The CNN architecture is trained using the segmented regions. The dataset is divided into three sets for the training, validation, and testing phases in the ratio 70%:20%:10% after the images are ready in their binary matrix format. The patient images are then evaluated using CNN. This study's primary goal is to determine eye disease from the extracted features. The suggested system's block diagram is shown in Figure 1. The trained system will be able to recognise the presence of disease in a eye image, as illustrated in the figure. The detection of eye disease is carried out in 2 phases. Phase 1 includes the training phase and the testing phase, and Phase 2 contains the development of GUI for real-time detection. The dataset for all the cases was procured from Kaggle, and the dataset for Glaucoma was procured from Medimrg.

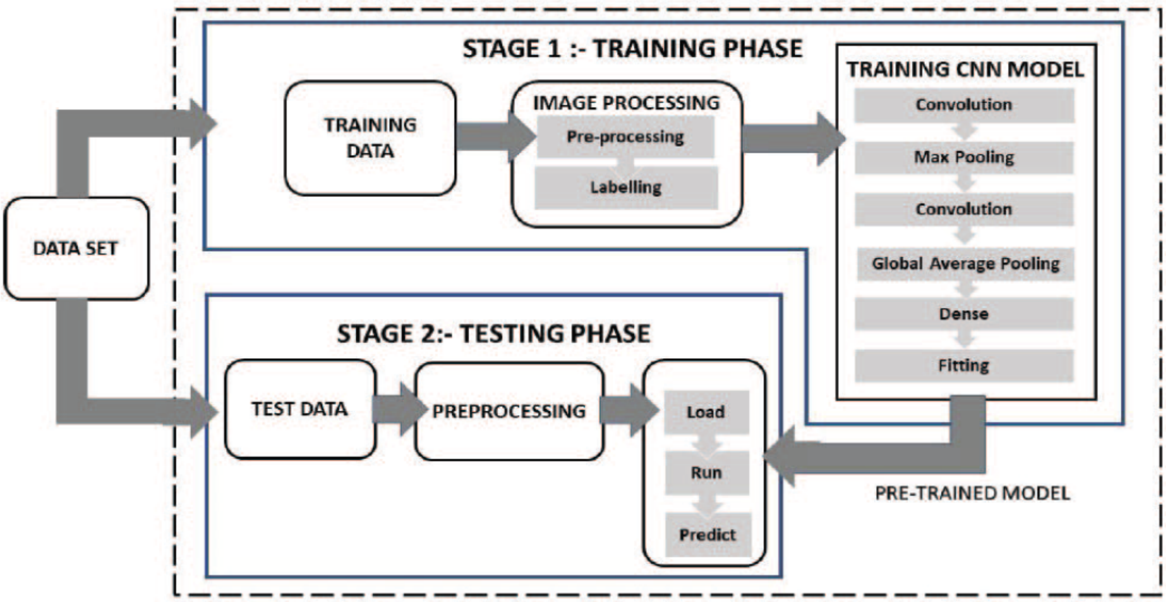

Figure 1: Multiple eye disease detection using Convolutional neural network.

CNN MODEL

The overall architecture structure of the proposed model developed for the classification and prediction is shown in Figure 2. Like the normal conventional CNN model our proposed model has been constructed using several convolution layers (CL), few fully connected layers (FCL). Features are extracted via convolutional layers, and the outputs are simulated by combining these features in fully connected layers. Complete structure of the proposed model for the eye disease detection is as in figure 2.

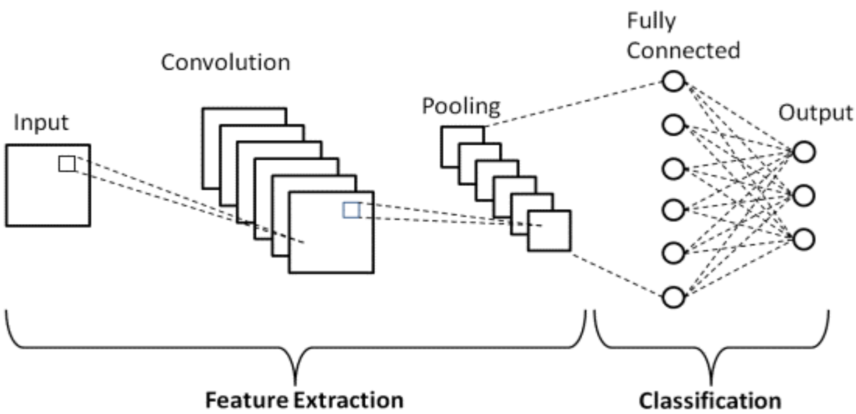

Figure 2: CNN Model

RESULTS AND DISCUSIONS

For the computation processes we have considered the eye Image from Kaggle and Medimrg database and utilised as training and test data set. The size of OCT image will be 512x512x3. At the time of feature extraction this image of both the sets are resized to 224x224x3. Here, 6000 images have been used to conduct the experiment. Among these, images ae classified into Age related Macular Degeneration (1), Hypertension (2), Non-proliferate retinopathy (3), Pathological Myopia (4), Cataract (5), Diabetic Retinopathy (6), Glaucoma (7), Normal (8). Out of the available data, 70% of image data is for training the model and the other 30% for verifying the result and for checking accuracy of the network. The True Positive Rate (TPR), False Positive Rate and Accuracy have been computed and tabulated.

Mean Average Precision(mAP) is a metric used to evaluate machine learningmodels. The mean of average precision (AP) values is calculated over recall values from 0 to 1. Typical, mAP curve for the CNN model for both training and validation is presented in the figure 3.

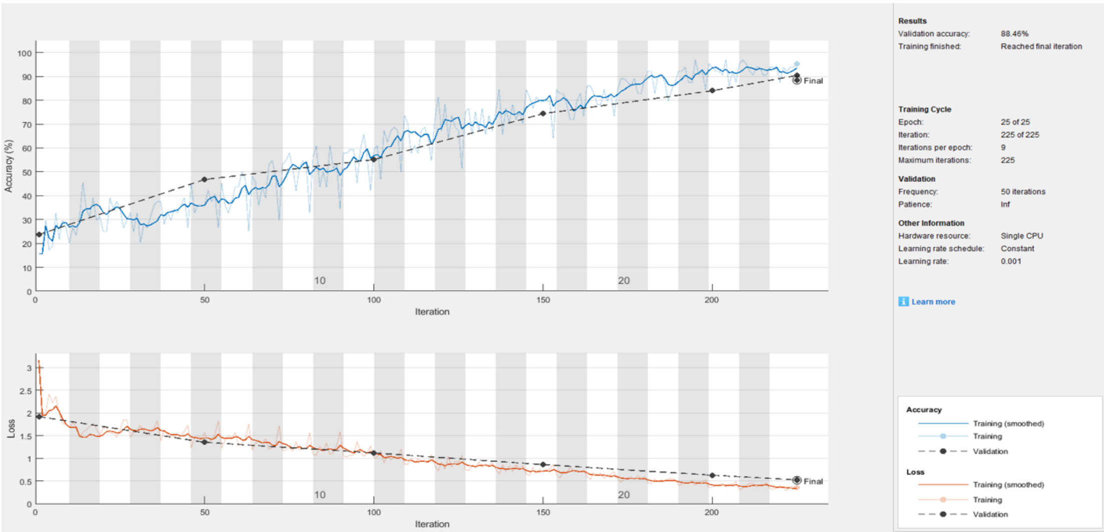

Figure 3: mAP curve

The table 1 shows that the proposed model, for both training and validation, achieves maximum accuracy at the lowest loss. Accuracy for the proposed model, including training and validation, has been discovered in the proposed work. The proposed model overall accuracy has been calculated and tabulated here considering the all the test cases. Here, a 5-fold cross validation has been done, and the outcomes for each fold has been as shown in Table 1. Here, the fourth fold has the highest accuracy, with 91%.

Table 1: Accuracy- 5-Fold Cross validation

Fold	Accuracy%	mAP	
		Training%	Validation%
1	88	88.46	89.36

2	87	87.27	88.85
3	88	87.80	88.50
4	91	87.24	87.84
5	88	89.13	89.21
Average	**88**	**88.46**	**89.36**

Table 2: Performance evaluations for each class

Case	TP	FP	FN	TN	Precision	Recall	F1-Score	Accuracy
1	4098	1161	516	225	0.888	0.947	0.917	88
2	4186	1036	425	353	0.907	0.922	0.914	87
3	4056	1245	412	287	0.907	0.933	0.920	88
4	3784	1687	378	151	0.909	0.961	0.934	91
5	3864	1445	398	293	0.906	0.929	0.917	88

Standard metrics including accuracy, precision, recall, true positive rate, false positive rate, and F1-score are crucial for assessing the suggested model. After machine learning algorithms have been applied to the dataset, Accuracy, Confusion Matrix, Precision, Recall, F1 Score, and AUC have been analysed as performance measures to predict the existence of multiple eye disease using the CNN model. For the current work, eight classes have been selected. The metrics are calculated and tabulated for each class in Table 2.

Figure 4 indicates the classification accuracy for each class. The Confusion Matrix's diagonal points, which are coloured in green, show the correctly categorised samples, whereas the non-diagonal points show the incorrectly identified face samples.

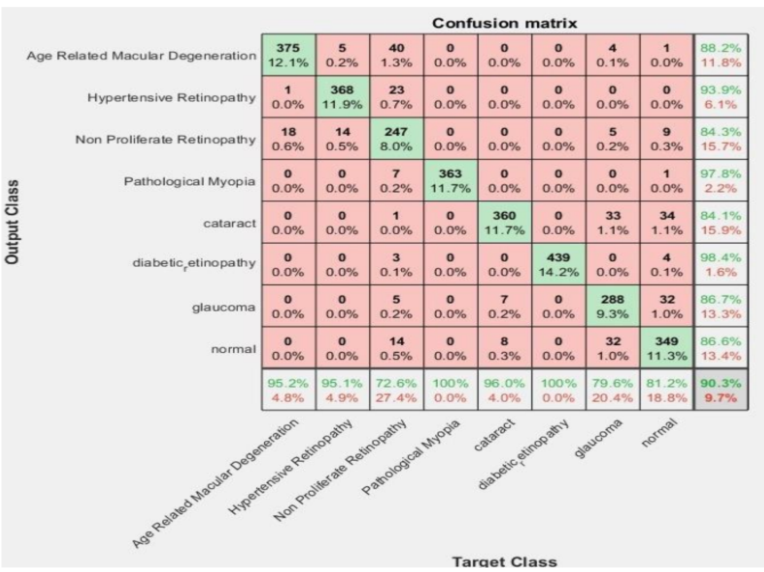

Figure 4: Confusion Matrix

The ROC curve and the corresponding AUC for each class using proposed model is given in Figure 5.

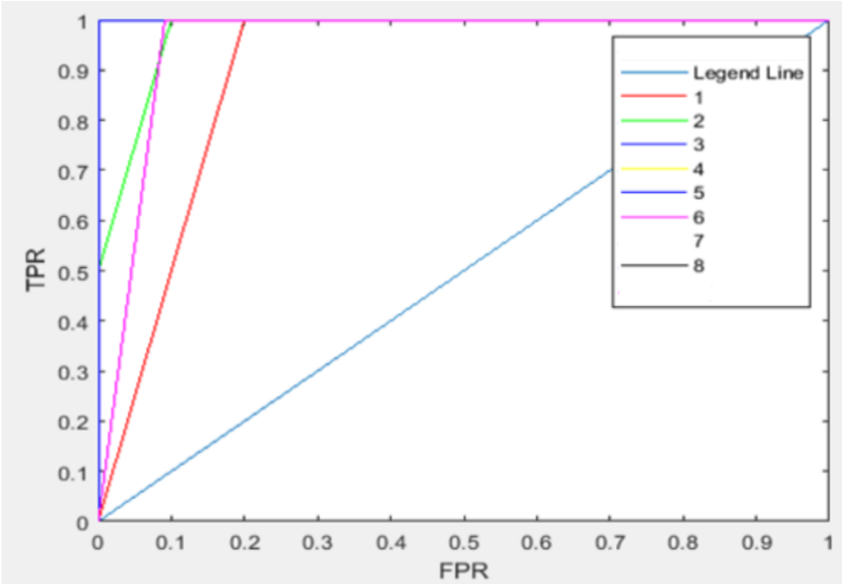

Figure 5: ROC curve

5- Fold cross validation has been performed and results have been recorded in Table 3 to exhibit AUC value for the each of the class. From the table it concludes that maximum AUC value 1 has obtained for class normal (8).

Table 3: AUC for each class

Fold\Class	1	2	3	**4**	**5**	**6**	**7**	**8**
1	0.997	0.981	0.973	0.979	0.987	0.889	0.968	1
2	0.994	0.967	0.945	0.990	0.994	0.965	1	1
3	0.978	0.985	0.961	0.873	0.985	0.899	0.998	1
4	0.969	0.950	1	0.956	0.956	0.993	0.974	1
5	0.994	0.981	0.947	0.897	0.948	1	0.998	1
Average	**0.997**	**0.981**	**0.973**	**0.979**	**0.987**	**0.889**	**0.968**	**1**

CONCLUSION

To predict multiple eye disease, this study suggested an efficient OCT classification system based on the proposed model. experiments to categorise OCT into different classes using the kaggle dataset. The OCT scans tend to vary more considerably amongst patients as the number of patients with disease is found. In conclusion, the application of Convolutional Neural Networks (CNNs) for the detection of multiple eye diseases has yielded promising results. During the 4th fold of our evaluation, the CNN model demonstrated a commendable accuracy rate of 91%, underlining its effectiveness in identifying various eye conditions. Furthermore, the Area Under the Curve (AUC) values, particularly an AUC of 1 for the normal class and AUCs exceeding 0.9 for all other classes, indicate the model's robust ability to distinguish between different eye diseases with high precision. These findings signify the potential of CNNs in revolutionizing the early diagnosis and management of eye disorders, offering a valuable tool for healthcare practitioners, and improving patient outcomes in the realm of ophthalmology.

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