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Multiple Eye Disease Detection using HOG and LBP on Convolution Neural Network

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Abstract: The eyes are among the most crucial systems in the human body. Despite their small size, life without vision is unimaginable for humans. The eyes are protected from dust particles by a thin layer known as the conjunctiva, which acts as a lubricant and reduces friction during the opening and closing of the eyes. A cataract refers to the clouding of the eye's lens. Multiple eye disease exists, and since the visual system is the most vital of the four sensory organs, it is essential to detect external eye abnormalities early. In the proposed method HOG and LBP approach are used for feature extraction. Further, the research involves using Convolution Neural Networks (CNN) to analyze Optical Coherence Tomography (OCT) scans for detecting multiple eye diseases. In this study, a CNN was applied to OCT images from a validated dataset, achieving an accuracy of 91% through 5-fold cross-validation. The highest Area Under the Curve (AUC) value observed for the normal class was 1. The proposed method achieved over 90% AUC in predicting eye diseases across all classes.

Keywords: *Cataract, Convolution Neural Network, multiple eye disease, Optic, Optical Coherence Tomography*.

1. Introduction

Diabetic retinopathy (DR) is an eye condition caused by diabetes, resulting from damage to the blood vessels in the retina's light-sensitive tissues, which can ultimately lead to blindness [1]. Studies indicate that the Western Pacific Region has a high prevalence of diabetes, with 152.2 million cases, while Southeast Asia has 78.3 million cases. In India, 69.2 million people suffer from diabetes, and nearly 36 million remain undiagnosed [2]. Projections suggest that diabetes cases in India will rise to 109 million by 2035, significantly increasing the risk of eye diseases and blindness. Current statistics reveal that 6 million diabetes patients in India have a sight-threatening form of retinopathy [3]. In recent years, advancements in technology and artificial intelligence have greatly improved the diagnosis of diseases affecting the human visual system. Given the diversity and complexity of eye functions, numerous diagnostic tools, equipment, methods, and algorithms have been developed. Sometimes, a doctor can diagnose a specific disease through visual image analysis [4-5]. However, many factors, such as inexperience, fatigue, varied shapes, similarities, and poor image quality, can hinder accurate diagnosis. In such cases, a second opinion from another expert using advanced information technology and algorithms is crucial for accurately diagnosing eye diseases [6]. Claiming ensemble is a type of ensemble learning that combines multiple machine learning models to achieve better results. This study focuses on using bagging ensemble to enhance the model's prediction accuracy. Authors [7] propose an image recognition algorithm based on ensemble learning and the ELA-CNN structure to address the limitations of single models. They employed the bagging ensemble to train their models, incorporating networks like ResNet, DenseNet, DenseNet-BC, and Inception-ResNet-v2. Their experiments used the CIFAR-10 dataset, which includes 60,000 color images, divided into 50,000 for training and 10,000 for testing. The average probability of the prediction vector was the result. In this [8] work authors used fine-tuned convolutional neural networks (CNNs) to classify medical images for diagnosis, training, and biomedical research. They worked with 6,776 training images and 4,166 test images, employing two different CNN architectures, AlexNet and GoogleNet. The experiments [9] involved both individual and ensemble models, with the ensemble method achieving a top accuracy of 96.59%. Here, [10] authors explored recent active learning methods incorporating large datasets and CNN classifiers. They compared ensemble-based methods against Monte-Carlo Dropout and geometric approaches, finding that ensemble learning provided more predictable uncertainty, a key aspect of many active training algorithms for CNNs, such as S-CNN, K-CNN, DenseNet, InceptionV3, and ResNet-50. Their dataset included MNIST, CIFAR, and ImageNet, with ensembles based on several active learning algorithms achieving a test accuracy of 90% on approximately 12,200 images. Here, [11] authors introduced Hydra, an ensemble of CNNs for geospatial land classification in satellite images. Hydra begins with a coarsely optimized initial CNN, which

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serves as its body. The authors created ensembles using ResNet and DenseNet architectures and applied the Hydra framework to the FMOW and NWPURESISC45 datasets, achieving an accuracy of 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.

2. 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.

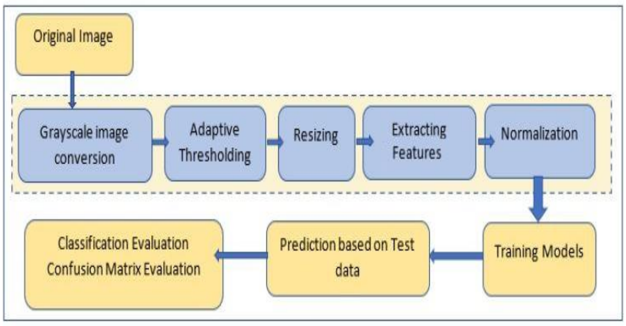


Fig 1: Multiple eye disease detection using Convolutional neural network.

2.1 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 [12]. Complete structure of the proposed model for the eye disease detection is as in figure 2.

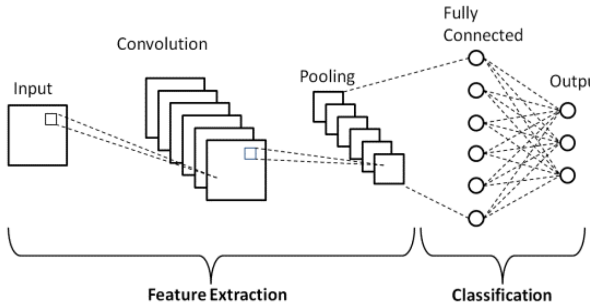
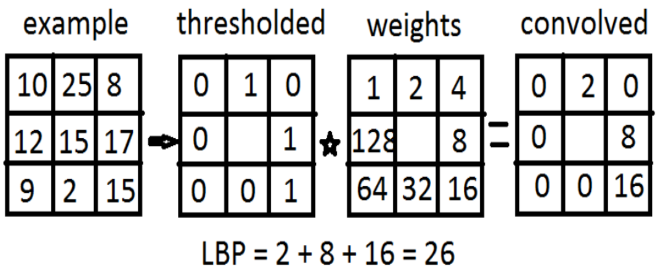


Fig 2: CNN Model

2.2 Local Binary Patterns (LBP)

The initial Local Binary Patterns (LBP) operator operates on the eight neighboring pixels surrounding a central pixel within a segmented unit called a cell [13]. Each pixel in the cell is compared to its eight neighbors, and a binary code of one or zero is assigned to each neighbor based on whether its value is greater than or equal to the value of the central pixel. These binary codes are then combined to form a decimal number with 256 possible values, which serves as the texture descriptor for the central pixel [14]. Figure 3 illustrates the original LBP operator.



$$LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)2^p \quad (1)$$

$$s(x) = \begin{cases} 1, x \geq 0; \\ 0, otherwise \end{cases} \quad (2)$$

2.2 HOG

The Histogram of Oriented Gradients (HOG) feature extraction method is widely used in image processing to record the frequency of gradient orientations in specific regions of an image [15]. The image is divided into small, connected areas called cells, and a HOG descriptor is computed for the pixels within each cell. This process involves calculating the gradient magnitude and angle to quantify the texture and structure of the image [16-17].

2.3 Support Vector Machine

SVM is a kind of machine learning algorithm that recognises patterns and performs regression using the concepts of statistical learning and structural risk minimization [18]. Finding the ideal hyperplane to maximally maximize the margin between positive and negative examples while successfully separating the former from the latter is the primary objective of support vector machines (SVM) [19]. SVM's benefit is its capacity to handle non-linear data and challenging classification issues. Additionally, because it maximizes the margin between classes, it is resistant to overfitting [20].

3 Results and Discussions

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 learning models. 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.

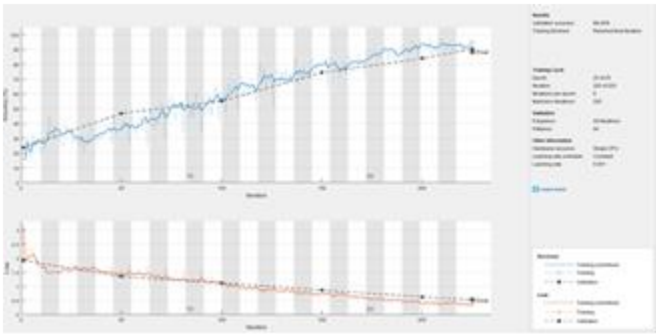


Fig 3: mAP curve

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 of 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
Avg:	**88**	**88.46**	**89.36**

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.

Table 2- Performance evaluations for each class

Fold	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	0.92	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

Figure 4 indicates the classification accuracy for each class. The Confusion Matrix's diagonal points, which are coloured green, show the correctly categorized samples, whereas the non-diagonal points show the incorrectly identified face samples. The ROC curves in figure 5 and confusion matrix in figure 4 for LBP and SVM showcase their performance across various threshold values and provide insights into their ability to correctly classify instances.

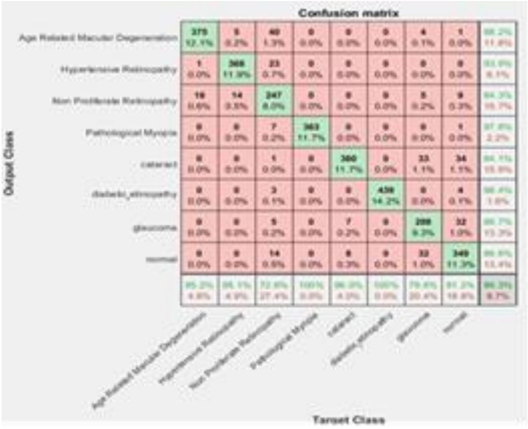


Fig 4: Confusion Matrix

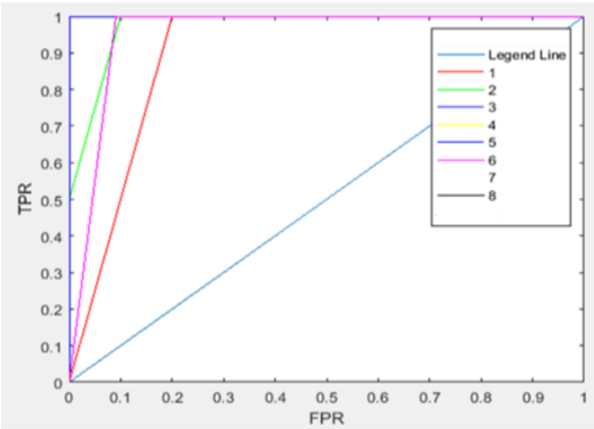


Figure 5: **ROC plot**

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

Table 4: Accuracy of each class for HOG

Fold	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	0.99	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	0.95	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
Avg	**0.997**	**0.981**	**0.973**	**0.979**	**0.987**	**0.889**	**0.968**	**1**

In a similar approach, multiple eye disease detection can be effectively performed using HOG with CNN. Among these approaches, LBP has been found to offer the best accuracy and performance across various parameters as listed in Table 4. This combination leverages the strengths of traditional feature extraction methods and modern deep learning techniques.

Table 4: Accuracy of each class for HOG and LBP classifier

Fold	TP	FP	FN	TN	Precision	Recall	F1-Score	Accuracy
1	4022	1037	523	418	0.905	0.795	0.846	0.757
2	3983	1086	512	419	0.904	0.785	0.841	0.749
3	4097	1205	389	309	0.929	0.772	0.844	0.747
4	3875	1723	235	167	0.958	0.692	0.803	0.685
5	3689	1685	346	280	0.929	0.686	0.789	0.672

Table 5 provides comparison between HOG and LBP feature extraction using CNN model. When comparing accuracy and precision, HOG demonstrates a higher precision of 0.925, while LBP has a precision of 0.88. However, LBP significantly surpasses HOG in terms of accuracy, achieving 0.88 compared to HOG's 0.722. Thus, while HOG is more precise, LBP offers much greater overall accuracy.

Table 5: Compare each class for HOG

Parameter	HOG	LBP
Precision	0.925	0.88
Recall	0.746	0.87
F1-Score	0.824	0.88
AUC	0.895	0.91
Accuracy	0.722	0.88

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. When comparing HOG and LBP, HOG shows a higher precision of 0.925 compared to LBP 0.88, but LBP significantly outperforms HOG in accuracy 0.88. 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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