EAI Endorsed Transactions
on Pervasive Health and Technology

Research Article **EAI.EU**

Effective Cataract Identification System using Deep Convolution Neural Network

P. N. Senthil Prakash[1*], S. Sudharson[2] , Venkat Amith Woonna[3] and Sai Venkat Teja Bacham[4]

[1,2,3,4]School of Computer Science and Engineering, Vellore Institute of Technology, Chennai, India

Abstract

INTRODUCTION: The paper introduces a novel approach for the early detection of cataracts using images captured using smartphones. Cataracts are a significant global eye disease that can lead to vision impairment in individuals aged 40 and above. In this article, we proposed a deep convolution neural network (CataractsNET) trained using an open dataset available in Github which includes images collected through google searches and images generated using standard augmentation mechanism.
OBJECTIVES: The main objective of this paper is to design and implement a lightweight network model for cataract identification that outperforms other state-of-the-art network models in terms of accuracy, precision, recall, and F1 Score.
METHODS: The proposed neural network model comprises nine layers, guaranteeing the extraction of significant details from the input images and achieving precise classification. The dataset primarily comprises cataract images sourced from a standardized dataset that is publicly available on GitHub, with 8000 training images and 1600 testing images.
RESULTS: The proposed CataractsNET model achieved an accuracy of 96.20%, precision of 96.1%, recall of 97.6%, and F1 score of 96.1%. These results demonstrate that the proposed method outperforms other deep learning models like ResNet50 and VGG19.
CONCLUSION: The paper concludes that identifying cataracts in the earlier stages is crucial for effective treatment and reducing the likelihood of experiencing blindness. The widespread use of smartphones makes this approach accessible to a broad audience, allowing individuals to check for cataracts and seek timely consultation with ophthalmologists for further diagnosis.

Keywords: CataractsNET, Cataract Detection, CNN, Deep Learning, Pre-trained networks

Received on 23 December 2023, accepted on 16 March 2024, published on 22 March 2024

doi: 10.4108/eetpht.10.5525

*Corresponding author. Email: pn.senthilprakash@gmail.com

1. Introduction

Cataracts, a prominent global eye disease, manifests slowly and initially has no impact on vision. Nevertheless, over time, it may affect sight and potentially lead to vision impairment in individuals aged 40 and above [1]. The breakdown of proteins results in their accumulation around the eye, causing cloudiness in the lens and heightened sensitivity to light, leading to discomfort [2]. The various factors, including smoking, diabetes, steroid use, eye injuries, surgeries, and unprotected exposure to sunlight, can accelerate the development of cataracts [3].

According to the World Health Organization (WHO) report [4], approximately 285 million individuals worldwide experience visual impairment. Out of this group, 39 million have restricted vision, while the rest suffer from impaired vision. Cataracts are attributed to 33\% of visual impairment and 51\% of blindness [5]. Among the leading causes of blindness which includes glaucoma [6], corneal opacity, trachoma and diabetic retinopathy [7], cataract accounts for the majority of cases. As one of the foremost factors contributing to blindness, cataract plays a significant role in visual impairment [8].

Eye diseases can be detected through the extraction and identification of significant image features, such as clouding in the pupil region, by utilizing various image parameters. In modern times, diverse image processing techniques, coupled with the application of different Convolutional Neural Network (CNN) architectures, facilitate the classification of normal and cataract-affected eyes. The diagnosis of cataract can be carried out using either fundus images [9-11] or anterior segment images [12-14] that can be captured by using medical equipment like a fundus camera or a simple DSLR camera. Additionally, slit lamp images have also been employed for cataract detection.

Identification of cataracts in the early stage is crucial for effective treatment and substantially diminish the likelihood of experiencing blindness. In this present study, a novel effective cataract identification system has been proposed using CataractsNET from the anterior eye images. The eye images used in this study are collected from the standard dataset [15].

a. A novel cataractNET is designed with 9-layered network model.
b. Designed network is a lightweight network model when compared to existing state-of-the-art models.
c. The proposed network outperforms other state-of-the-art network models in terms of accuracy, precision, recall and F1 Score.

Figure 1. Sample images from the dataset

2. Related Works

CNNs are widely used in computer vision tasks, such as natural image classification, medical image classification and for segmentation problems. Here, some of the works related with deep learning-based cataract diagnosis system have been outlined. Qian et al., have focused on slit lamp images and primarily utilized the Hough detection algorithm to isolate the circular part of the eye [16]. By incorporating a novel neural network layer on top of SqueezeNet, the dataset was utilized for image classification, effectively categorizing the images into three distinct classes. In [17], a comprehensive evaluation of various image processing techniques and deep learning models for cataract diagnosis were presented, providing an effective comparison among them.

In [18], they introduced a computer-aided cataract detection system, suitable for mass screening of cataract grading. They presented an improved texture feature that was utilized to train the linear discriminant analysis (LDA). The experimental outcomes on a clinical database highlighted 84.8% accuracy. A three-step automatic cataract detection method has been proposed in [19]. They employed a top-bottom hat transformation to enhance the contrast between the foreground and background. The severity of cataracts was classified into mild, medium, or severe stages using a backpropagation neural network (BBNN) based classifier. Gao et al., have explored a deep learning approach to grade the severity of Nuclear Cataracts from slit-lamp images. Additionally, Higher-order features were extracted using a collection of recursive neural networks (RNNs). Support vector regression [20] was used in the grading of cataracts.

In [21], a Deep CNN (DCNN) for cataract detection and grading has been introduced by utilizing the activation maps produced by pooling layers of the deep learning model. This approach demonstrated higher time efficiency and yielded 93.52% accuracy in diagnosing cataract. The authors employed a modified version of the Inception V3 algorithm with significant features to classify anterior segment eye images into three categories: normal eye, immature cataract, and mature cataract [22]. A classification approach utilizing a radial basis function [RBF] classifier was introduced to distinguish between normal eyes and abnormal eyes, comprising five different categories [23].

To create a concise cataract screening system that automatically analyzes images by extracting information within a pupil. The presented hybrid feature extraction technique combines Discrete Wavelet Transform with Log Gabor Transform to categorize images into normal, early, and advanced-stage cataracts [24]. In [25], the authors presented an algorithm for detecting eyes in facial images, which utilized the circular hough transform. To address illumination variations, they incorporated a median filter to enhance the image contrast and brightness.

In [26], systematic segmentation algorithm was introduced for pupil. Initial stage initiates with the application of an image filter in MATLAB, followed by illumination removal. Next, a Power Log Function is applied, and then the binary removal process takes place, where the Bwareaopen function in MATLAB is used to eliminate unwanted pixels. In [27], Junayad et al., provided a detailed description of a novel CNN architecture that demonstrates significantly higher accuracy compared to existing architectures when applied to fundus image datasets.

Upon examining the aforementioned studies, a clear conclusion can be drawn that the majority of the existing research relies on CNNs applied to fundus images. However, ophthalmologists assert that visible wavelength eye images, focusing on the anterior segment of the eye, provide undeniable results compared to fundus images.

3. Experimental Design, Materials, and Methods

A. Data Overview

The dataset consists of cataract images collected from google searches and also images generated using standard augmentation approaches like rotation, zooming etc. Dataset includes 8000 images used to train the model and 1600 images were used to test the model. Both the training set and test set of the dataset have equal number of the images representing cataract class and normal class.

B. CataractNET Architecture

In our proposed model, we have used three convolution layers, three max pooling layers and three dense layers. The first convolution layer has 32 kernals each of size 64 X 64. Convolution operation is performed over the input image by adding padding to ensure the important information present in the border regions are not missed. This layer is used to extract the significant features from the given image.

$$G[i,j] = \sum\sum h[u,v]\, f[i+u, j+v] \qquad (1)$$

The equation (i) represents the mathematical operation involved in the convolution operation. In the equation, h refers to the input image and f refers to the filter. Resultant activation map is then passed to max pool layer with size 2 X 2. The architectural diagram of the proposed CatatractNET is shown in Fig. 2.

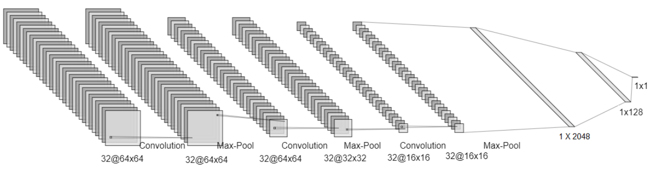

Fig. 2: CataractsNET Architecture

The second convolution layer has 32 filters each of size 64 X 64 and with same stride. Applying stride operation ensures that extracted information from first level of layers is not been missed. Then the resultant activation map is passed to the third convolution layer with the same configuration as the earlier convolution layers. The resultant activation map is then given to max pool layer with size 2 X 2. The activation map from the final max pool layer i.e. 8 X 8 X 32 is then flattened and then passed to first fully connected dense layer with 2048 nodes. The weighted results from the first dense layer are passed to second fully connected dense layer which has 256 nodes. The final output layers give the result whether the input image belongs to cataract class or normal class.

4. Results and Discussion

A. Model Performance and Evaluation

We have used the images collected from google searches and also images that were generated using standard data augmentation techniques like zooming, rotation etc. For the training the model 8068 eye images were used which includes 3714 cataract eye images and 4354 normal eye images. Similarly, 1600 images were used for testing the model in 50% of the images belongs to cataract class and remaining 50% belongs to normal class.

The proposed method's performance is compared with bench marking ResNet50 and VCG19 deep learning models with respect to the four performance metrics including accuracy, precision, recall and F1 score. The proportion of occurrences that were correctly classified to all of the instances is known as accuracy. Evaluation with respect to evaluation metrics ensures the models performance even if the dataset is not balanced.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1Score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

B. Accuracy

The proposed method has given accuracy of 96.20% whereas the benchmarking model ResNet50 has given 95% accuracy VGG19 model has given 92.50% accuracy. The results clearly highlight the fact that the proposed method has given better classification accuracy for the images captured during smartphones.

C. Precision

To analyse the performance of the proposed method further, precision evaluation metrics is used. Precision highlights the capability of the model in rightly identifying the positive occurrence of cataract disease. Proposed CataractsNet has given the precision of 96.1% while ResNet50 has obtained 94% precision and VGG19 has received 91.9% precision for the given dataset.

D. Recall

The evaluation metric recall also referred as sensitivity expresses the capability of the model to rightly identify the cataract cases among all the classified cataract cases. The CataractsNet method obtained 97.6% sensitivity whereas ResNet50 has obtained 95.4% and VGG19 acquired 93.1% sensitivity.

E. F1 Score

F1 score is a balanced sum of precision and recall. It exhibits the capability of the model's accuracy over the entire dataset. The proposed method acquired 96.1% of F1 score whereas the other methods i.e. ResNet50 obtained 95.8% and VGG19 obtained 92.5% F1 score.

The above results clearly highlight the fact that the proposed CataractsNet outperforms other similar methods like RestNet50 and VGG19. Thus, CataractsNet model can be embedded with mobile application and can be used to classify the cataracts using the images captured using mobile device.

TABLE I: Comparison of Different Performance Metrics

Methods	Accuracy	Precision	Recall	F1 Score
ResNet-50	0.95	0.94	0.954	0.958
VGG19	0.920	0.919	0.931	0.925
Proposed CataractNET	**0.962**	**0.961**	**0.976**	**0.961**

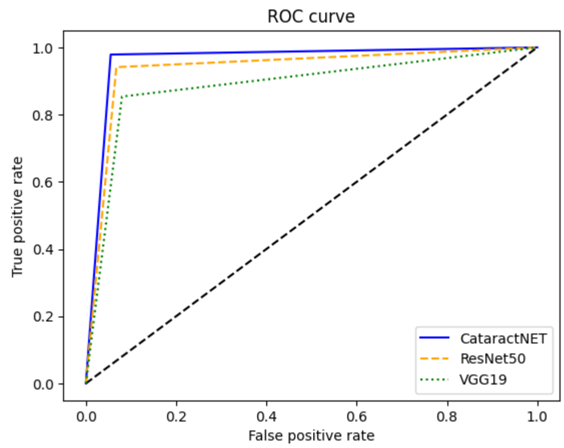

Fig. 3: ROC Curve of different Deep Learning Models

5. Conclusion:

Identifying cataracts in the earlier stages will help to treat better else it will lead to even vision loss. Recent studies reveals that even children are getting cataracts in the recent days due to various factors including pediatric diabetes, usage of steroids, side effects of other eye diseases like glaucoma. Much research work has been carried out to identify the cataract using computer vision algorithms and machine learning models. Most of the approaches uses the eye images that were captured using slit lamps or ophthalmoscope. However, it will be challenging to ensure the availability of such resources in remote rural areas.

Hence, we proposed a deep learning model which uses the images captured using smartphones. The proposed CataractsNet model was trained using the cataract images and normal images collected from google images along with augmented images. Further, the model can be used to classify the given images captured using smart phones. The proposed method has given remarkable performances when compared with other deep learning methods

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