Cataract Detection Using Deep Learning

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Abstract

In a human life a very common disorder that occurs is, eye disorder named CATARACT, this eye disorder is mostly common in humans within the age group of 40–50 years. If neglected can lead to eye blindness. One can avoid this type of eye disorder from getting worse by detecting it on-time.

So we are proposing our model that uses Deep Learning to detect this disorder, using Fundus Images.

The model contains fully connected hidden layers with cost function and activation functions to properly train the model and optimize it and to significantly reduce the computational cost compared to other models. Total 1130 affected and 1130 non affected images are feeded to model in order to train model properly so that model doesn't get overfitted.

I. INTRODUCTION

A cataract refers to the condition where the eye's lens becomes cloudy, resulting in symptoms such as blurry vision, sensitivity to glare, and reduced night vision. It is a significant global cause of visual impairment and blindness. At his early stage it does not affect much but as time passes it can lead to eye blindness. At its starting stage if it is detected it can avoid surgery and prevent blindness. According to WHO there are 285 million persons with vision impairments worldwide. About 39 million have poor and very limited vision and the rest are visually impaired. In word due to Cataract 33% of vision impairity and 51% of blind disorders are getting generated. According to data in the word, blindness will cross 40mn by 2025. In addition, the number of cataract surgeries of all kinds has surged recently. According to studies, there are more female patients than male patients. This

covers cataract surgery and nuclear and cortical cataracts (p = 0:02 – 0:05). Additionally, the non-white community has a higher prevalence of it (p = 0:001). The majority of the cases are cataract-related. It is regarded as one of the major contributors of blindness.Based on where and how it develops, cataract can be divided into three major groups: Posterior Sub Capsular (PSC) Cataract, Nuclear Cataract, and Cortical Cataract. The risk of blindness can be considerably decreased with early detection and treatment of cataracts.The complexity is that every human has different eye size, shape, and cataract occurs differently in them, and it also depends on age, gender, and eye type make it difficult to provide an automatic system for cataract detection. In recent years, researchers have looked into automatic cataract detection using several imaging modalities.Mostly cataract detection model uses i) Slit lamp ii) retro-illumination iii) ultrasonography iv) fundus pictures are typically the four types of images used by automatic cataract detection and categorization systems. Fundus pictures have drawn a lot of attention in this sector among these imaging modalities because fundus-cameras can be used by anyone with ease. The Slit-Lamp method needs a professional Ophthalmologist. Therefore, an automated cataract diagnosis method based on fundus pictures is crucial to streamlining the early cataract screening procedure While numerous automatic cataract detection systems based on deep learning have been documented in research works, they still exhibit limitations like suboptimal detection accuracy, an excessive number of model-parameters, and substantial computational expenses.The drawbacks noted above are addressed by our work, that divides patients into two categories: either a cataract or other ailments .The proposed method introduces several innovative elements: firstly, reducing the model's parameters, including layers and weights, to enhance computational efficiency and minimize costs. Secondly, enhancing detection accuracy through the implementation of a novel “deep-neural-network” architecture. Consequently, the suggested technique allows for effective screening of a large population and accurate grading of cataracts.

The following are the article's primary contributions:

- The datasets used in this study include the HRF[14](high resolution fundus) dataset, the fundus image registration (FIRE)[15] dataset, the ACHIKO-I fundus image dataset, the Indian diabetic retinopathy image (IDRiD) dataset, a colour fundus image database, and the digital retinal images for vessel extraction (DRIVE) [11]database.are all combined, reorganised, and preprocessed to create a cataract dataset. Then, using a data augmentation method, it is expanded to a sizable number of photos.
- In this study, a novel 16-layer deep learning neural network architecture is introduced for cataract detection. The proposed network aims to accurately identify the presence of cataracts
- 5 C-NN model including VGG16, VGG19 and Res Net-50 have been used to compare and show the effectiveness of our suggested model.
- Further section of this paper are divided as:

The relevant recent works are briefly covered in Section II. The proposed Model for cataract detection is described in Section III. Section IV presents the experimental setup. Section V of the report discusses the experimental findings. In part VI, we wrap up this study by providing future work directions.

II. RELATED WORKS

Modern automatic cataract detection methods comprise of three steps: feature extraction, pre-processing, and classification. Based on the algorithms employed in the feature extraction or classification stages, these techniques are divided into two groups: machine learning (ML)-based and deep learning (DL)-based methods. These techniques have been covered in recent studies [9] -[12]. We quickly review a few of the most important works from both groups in this section.

A. Past Works Based On Machine Learning

There are many [13] Proposed techniques for cataract identification, designed for widespread screening or as a step before classifying cataracts.The study focused on training the linear discriminant analysis (LDA) algorithm.

using an improved texture feature.A clinical database experiment's results showed an accuracy of 84.8%. A three-step automated cataract detection approach was proposed by Yang et al. A top to bottom hat transition was used to increase the foreground/background contrast. Features were thought to be the luminance and texture. To divide the cataract

Based on their severity, a backpropagation neural network (BBNN) classifier was built.An automated classification of cataracts based on fundus pictures was published by Guo et al

[27].Wavelet transform and sketch-based techniques were used for the feature extraction process. Subsequently, a multiclass discriminant analysis approach was employed for cataract diagnosis and classification,for wavelet transform-based feature extraction being 90.901% and 77.10%, and for sketch-based feature extraction being 86.0% and 74.0%, respectively. Fuadah et al[26]. “used the K-Nearest Neighbour (KNN) in conjunction with the dissimilarity”, contrast, and uniformity aspects of textures. With a high accuracy of 97.5%, this technology was developed for cellphones.The Hough circle detection transform was used by[8]Jagadale. to identify the lens's centre and radius.The statistical features were then retrieved and applied to an SVM classifier for accurately identification.of 90.25%. An Android smartphone-based technique was presented by Sigit et al[25]. A single-layer perceptron approach was used to classify the data, and its accuracy was 85.0%. Recently, a hierarchical feature extraction-based technique for cataract grading was proposed in[24]. The cataract severity grading problem's four-class classification was split into three neighboring two-class classes.These were first integrated using 3 separate neural networks. For cataract identification and grading, this technique attained accuracy levels of 94.83% and 85.98%, respectively.

B. Different Models Using DeepLearning

To address the limitations of manually designed attributes and their applicability across various medical imaging modalities, deep learning methods can be employed to learn essential characteristics and incorporate them into the model development process. Using slit-lamp pictures, Gao et al[5]. investigated a deep learning-based method for determining the seriousness of Nuclear Cataracts. They utilized a convolutional neural network (CNN) to extract local filters by analyzing patches of the input images.Furthermore, a set of recursive neural networks (RNNs) was employed to extract higher-order features. Finally, support vector regression was employed for cataract grading, leveraging the learned features. This integrated approach aimed to enhance the accuracy and effectiveness of cataract assessment.For cataract identification and grading, Zhang [20]. developed the Deep CNN that made use of the feature maps from the architecture's pooling layers. This approach was quick and had accuracy rates for cataract identification and grading of 93.52% and 86.69%, respectively. An approach for a 6 level cataract classifier using a mixture of Deep-CNN and Random Forests was proposed by Ran et al[23].The suggested DCNN for extracting features at various levels from fundus pictures was made up of three modules. On the other hand, RF implemented a more complex six-level cataract grading using a feature dataset that DCNN developed and utilised. This technique has an average accuracy of 90.69%. The professionals may be better able to comprehend the patients' conditions with the use of this six-level grading system. Based on fundus pictures, Pratap-Kokil [22] provided a computer-assisted approach for classifying from mild to severe cataract severity. This technique used transfer learning to automatically classify cataracts using a pre-trained CNN.Utilising feature extraction and a SupportVectorMachine classifier with a 4-stage CCR of 92.91%, the final classification was completed. A tournament-based ranking CNN system made up of binary CNN models and tournament structure was suggested by Jun et al. [40] to grade cataracts.An automated cataract diagnosis method with a 95.77% accuracy rate was proposed by Hossain [21]. DCNNs and an optimised Residual NN classification model are used. Recent studies by Zhang [12]. According to an attention-based MultiModel Ensemble method for automatically detecting cataracts on ultrasound pictures had "the greatest accuracy (97.5%)" among the various deep learning-based methods in the research works published. An object detection network, three grading networks, and a model ensemble module made up the system as a whole in this method. Despite the limitations posed by subpar training data, the performance of this method was still commendable. One notable drawback, however, was its reliance on assessing the level of blur in retinal images, which could potentially indicate the presence of various eye disorders, including cataracts, corneal edema, and diabetes mellitus. Consequently, this approach may face challenges in distinguishing between different types of eye conditions. [Khan et al] recently attained accuracy that is nearly identical (97.47%).

Different models have been put out by different authors, and they differ in terms of accuracy. The novelty of this study lies in the suggested approach yields superior outcomes to earlier studies.

III. PROPOSED ARCHITECTURE

A particular kind of ANN called as convolutional neural network(CNN) is made for processing data with a grid-like structure, like photographs. CNNs are frequently employed in computer vision applications like as image recognition.CNNs operate by subjecting the input data to a number of convolution procedures. Convolution describes how the shapes of two images are changed. The input data and a filter are the two functions in the context of CNNs. In order to extract features from the input data, the filter uses a tiny number matrix.CNNs have the capacity to learn features from images in a structured way. The ability to learn low-level features like edges and corners and then utilise those features to learn higher-level features like objects and faces suggests that they are capable of doing so. CNNs are able to perform image recognition tasks with such high accuracy due to hierarchical learning.In deep learning-based methods, the characteristics of the images are extracted and integrated with classification phases, whereas they are divided in manual feature extraction techniques.To overcome the drawbacks of manual feature extraction and lower the computational cost, our model using deep learning is presented. Figure 1 represents the architecture of our proposed model, which contains SIXTEEN layers, of which 50% of layers are in 1st 4 blocks and the rest of these are for grading. The first block inputs are RGB images(224×224) and 32 filters with Ks(3×3).Max pooling layers with stride of 2 is applied.In order to conserve space. With blocks having ReLu activation functions. As the third block, an identical block is utilised, but with 64 filters and there are 128 filters in the fourth block.

The output from all these are forwarded to the remaining layers(flatten dense and drop out layers) which are fully connected to each others.As this is a binary classification model so here we are using a Sigmoid Function. The formula is :

$\sigma(x) = 1 / 1 + e^{(-x)}$

To investigate how the block numbers affect classification accuracy ,so cataract detection with three alternative models built on 3, 4, and 5 blocks with three distinct sets of parameters were utilised.

are created and assessed on the dataset, namely (16, 32, 64), (32, 32, 64, 128), and (32, 32, 64, 96, 128), respectively. The level of accuracy attained using these models is shown in Table 2. The efficiency of the model is enhanced by using four blocks instead of three. However, at 5-blocks, this efficiency was diminished. The four block(32,32,64,128) filters model did better than the rest.

No.Of Blocks	Info about Filters	Accuracy%
3	**16,32,64**	**97.80%**
4	**32,32,64,128**	**99.13%**
5	**32,32,64,96,128**	**97.12%**

Figure 2 : Shows the Efficiency achieved from these models

To know more and better about the model we should look into deeper aspects and specifically the total no. of blocks and cnn layer. We go deeper and look in to the effects of layers n the model as shown by Fig. 2 which clearly shows that at layers 4 the models accuracy goes higher and at 5 it again start falling down. The first layers extracts patterns such as corners, dots, edges...etc then these patterns are combined together and more expensive extraction of patterns takes places like circles and squares..etc. So adding more layers can increase the accuracy but not every time, this is shown in table above. Most used loss function in binary classification is log **loss function** = **-(y(log(py)) + (1-y) log(1-py)**, where y is real value (0 or 1) as per dataset and py is the predicted value and the log used here is normal log.

IV Setup

A Pre Processing

Datasets are collected from various sites and repositories. So here arises the problem, they are not same in sizes and many other characteristics are not identical, like their feature columns..etc. So Images are scaled to a single size (224 × 224 px). An important step here is to normalize the dataset, in order to have proper distribution, this helps in better and faster convergence rate. The formula we used for this is :

$X_n = (X - X_{min}) / (X_{max} - X_{min})$

Here, X max and X min :- max and min values of datasets, and Xn and X are of the same range.

Table 2
Dataset Classes

Category	Number of Images.(Training)	Number of Images(Testing)	Total
Non-Cataract	1960	107	2067
Cataract	2560	119	2679

B. Data Augmentation

One difficult problem that prevents further advancement in deep learning is the absence of a sizable training medical imaging collection. Consequently, four geometric changes are performed to training samples to enrich the dataset in order to address the dataset's inadequacy namely rescaling, rotating images(at random angles, zooming and horizontal flip. This gives as many data as 4 times of the original dataset this not only gives us abandoned data, but also prevents the model from getting overfitted. The ratio for training : test is 80 : 20

C Implementation

All process and experiments are done in our personal computer (properties: processor -Ryzen 5, GPU – 4GB NVIDIA GTX GEFORCE 1650 Ti, models are implemented using Python Keras and Tensorflow, with learning rate of 0.0001 and optimized using ADAM. Which gives the effective and optimized output.

D Evaluation

To check the efficiency of a model, accuracy is not enough. We also need to check various other

Parameters like F1 score Recall, precision.. and many other

Table 3
Performance Comparison

Train : Test	Model	Accuracy(%)	Precision(%)	Recall(%)	F1 Score(%)
90 : 10	VGG-16	91.35	86.19	91.92	89.94
	VGG-19	91.88	**86.68**	91.76	89.97
	ResNet	91.11	85.69	90.43	86.52
	OurModel	**92.92**	86.37	**95.43**	**89.59**
80 : 20	VGG-16	91.35	86.19	91.93	90.54
	VGG-19	92.88	86.68	91.92	89.97
	ResNet	97.41	96.75	97.39	97.04
	OurModel	**99.13**	**99.08**	**99.17**	**99.07**
70 : 30	VGG-16	94.45	86.19	96.49	94.34
	VGG-19	95.63	86.68	93..68	96.13
	ResNet	96.21	95.62	97.43	96.78
	OurModel	**98.96**	**98.24**	**99.08**	**98.15**

From Table 3 we can see the performance of each model and can check the f1 score and precision which are one of the important criteria for a model to be successful.

We can check how many false positive and false negative are predicted by our model which is one of the key features. We can visualize this using Confusion Matrix.

Table 4
Running Time Comparison

Model	Total Layers	Avg Running Time
VGG-16	16	3148s
VGG-19	19	3278s
ResNet	177	2765s
OurModel	16	1035s

V Conclusion and Future Scope

Our Proposed system successfully recognizes cataract from the given fundus images, at a very high accuracy rate. Which is also lightweight, hence it is computationally low cost and faster to implement. We had augmented datasets to make it more to improve the model's training, we tried the trial and error method for various layers, activation function, loss function and used many optimization algorithms to make our model fast and lightweight. We compared our model performance to different models, *ref Tables 3 and 4.* However our model cant differentiate between different age groups and where the cataract is exactly located.So this needs further development.

Declarations

Competing Interests:

The authors declare that they have no competing interests.

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Figures

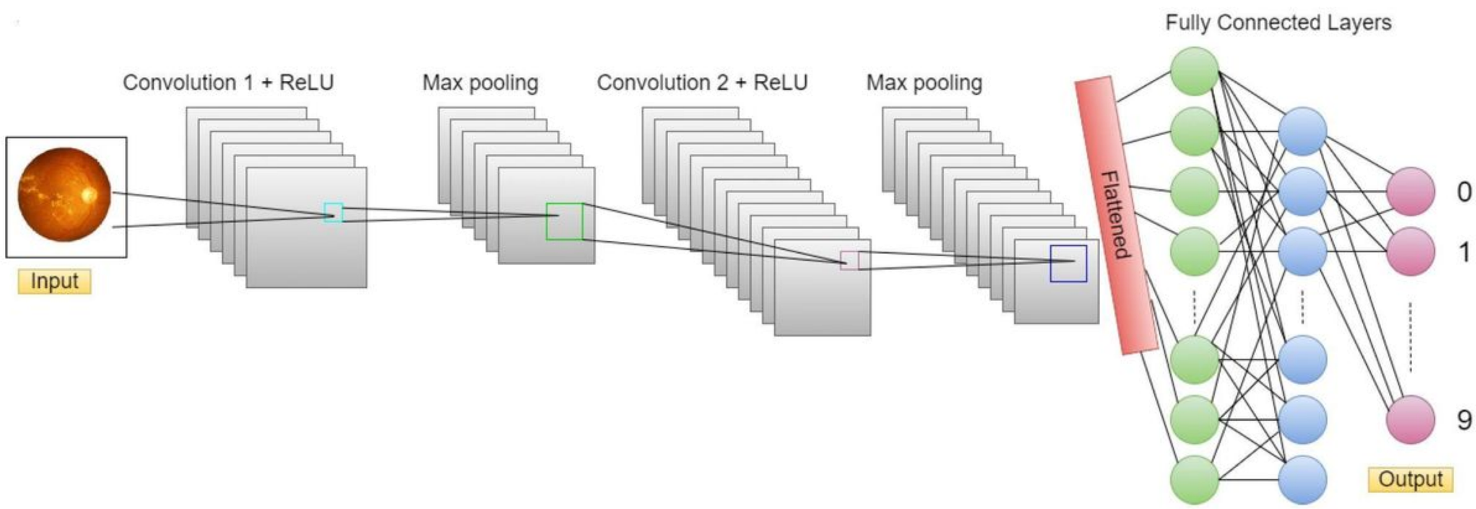

Figure 1

This is a architectural view of proposed model

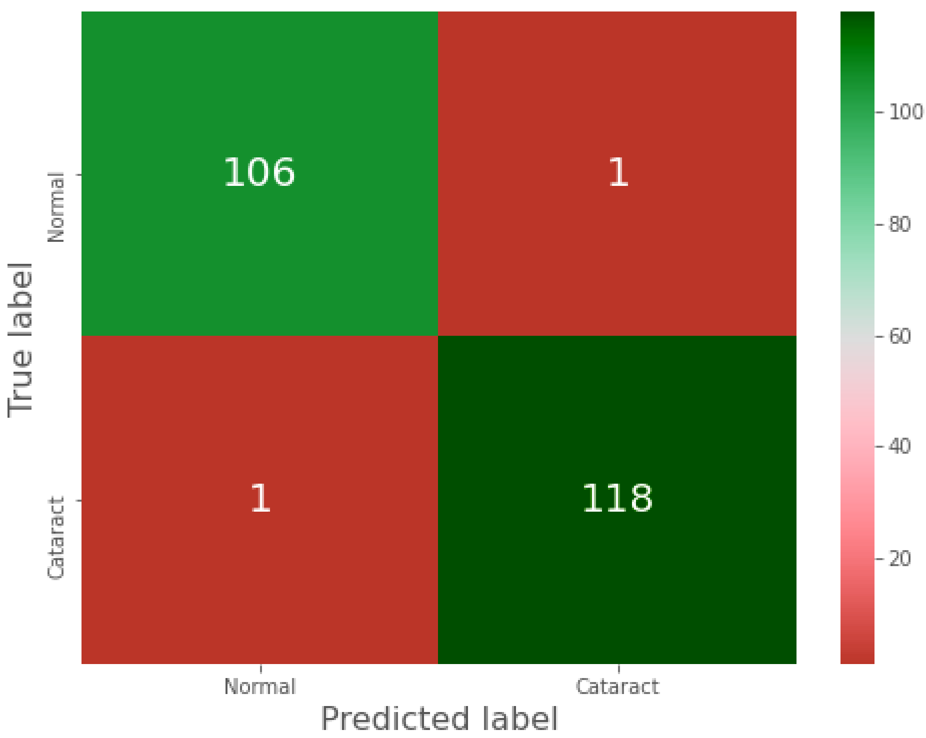

Figure 2

Confusion matrix

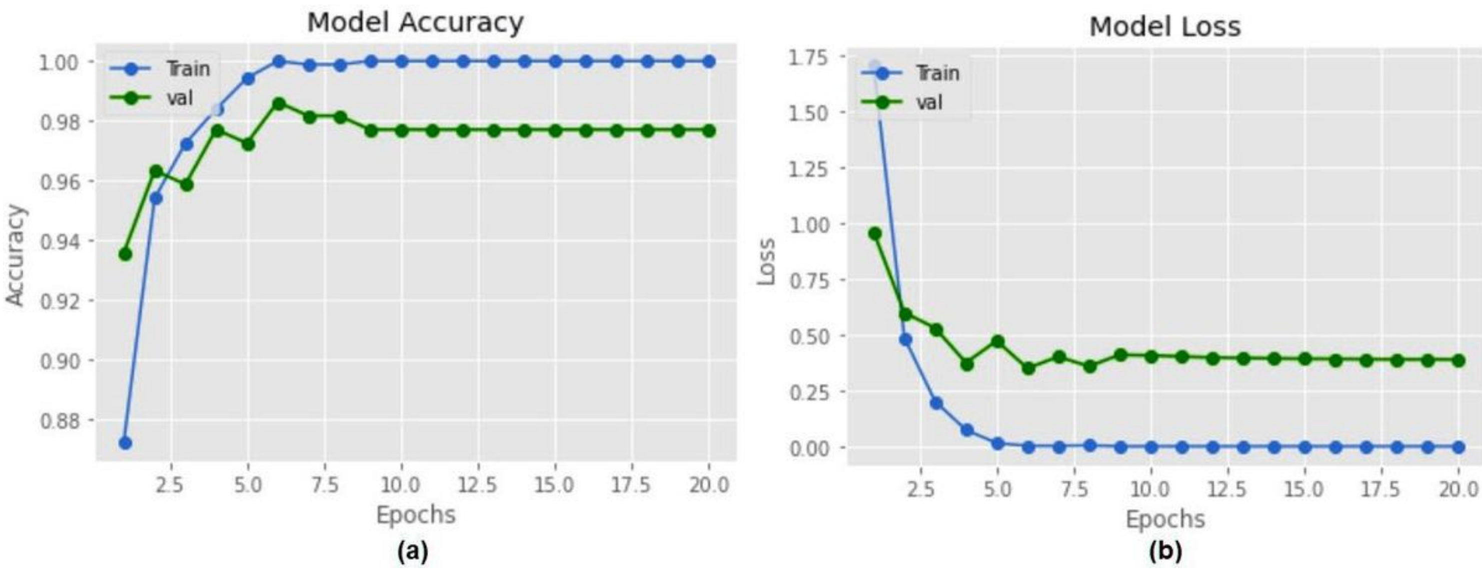

Figure 3

Accuracy and Loss Graph