JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

CATARACT DETECTION USING DEEP LEARNING ALGORITHMS

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Abstract— Cataract refers to the opacification of the ocular lens, resulting in a decline in visual acuity. The current systems have undergone training using a limited dataset, resulting in the issue of overfitting. The suggested approach aims to utilise neural network models for the purpose of classifying between a healthy eye and an eye afflicted with cataract. The detection of cataract is facilitated by the utilisation of the Convolutional Neural Network model. The Convolutional Neural Network (CNN) architecture comprises a total of 34 layers. The picture undergoes a series of convolutional and pooling operations in a hierarchical manner. The output is then acquired at the last layer. The suggested approach employs a deep neural network model to identify the presence of cataract in a picture of the eye.

Keywords — Neural networks, cataract, computer vision, CNN (Convolutional Neural Network), RNN (Recurrent Neural Network).

1. INTRODUCTION

Cataract is a highly widespread ocular condition that impacts a substantial global population of about 65.2 million individuals. The opacification of the lens of the human eye hinders or potentially obstructs the passage of light through the lens, perhaps leading to permanent visual impairment. Consequently, the visual representation formed on the retina exhibits a lack of sharpness, resulting in impaired transmission of the visual stimulus through the optic nerves to the brain, ultimately culminating in a state of visual impairment or blindness.

Based on the findings of the National Blindness and Visual Impairment Survey India 2015-19, it has been determined that cataract is the primary factor contributing to visual impairment and blindness among those aged 50 years and older. Cataract has been identified as the primary cause of blindness in 66.2% of cases, severe visual impairment in 80.7% of cases, and moderate visual impairment in 70.2% of cases within the specified age group.

The National Programme for Control of Blindness was initiated by India in 1976 with the objective of reducing the prevalence of blindness to 0.3 percent by the year 2020. However, based on the survey published on October 10, 2019, the projected prevalence rates for various levels of visual impairment are as follows: 1.99% for blindness, 1.96% for severe visual impairment, 9.81% for moderate visual impairment, and 11.77% for moderate severe visual impairment.

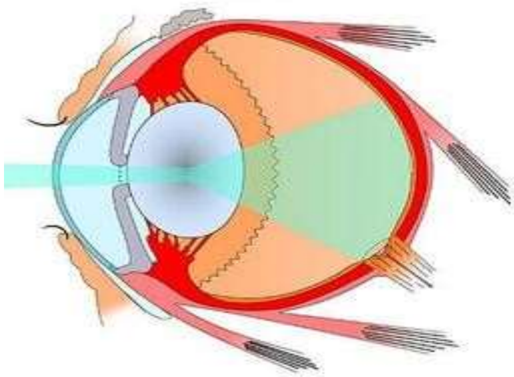

Fig.1: Cataract eye visualization

Source: [10]

Figure 1 depicts an eye affected by cataracts. The obstruction of light transmission through the lens, caused by the clouding of the lens, can lead to varying degrees of visual impairment, ranging from partial to total blindness, contingent upon the extent of cataract development on the lens.

The World Health Organisation (WHO) issued the World Vision Report on October 8, 2019, which highlighted that the significant expenses associated with obtaining eye care services, particularly for individuals residing in rural areas, were a significant contributing factor to the prevalence of visual impairment. The distribution of eye disorders and visual impairment is not equitable in terms of the hardship they impose. Insufficient availability of eye care services is a significant contributing factor to the unequal dispersion [12]. The research recommended the extension of Universal Healthcare Coverage to incorporate eye care services.

The suggested technique has the potential to enhance the ease of categorising cataracts and can be handled by those without specialised expertise. Ophthalmologists possess the ability to perform surgical procedures on various classifications of cataracts in a more expedited manner, hence facilitating the treatment of individuals afflicted with this ocular condition. This research aims to enhance accessibility and efficiency in the identification of cataract disorders.

2. LITERATURE SURVEY

The field of utilising machine learning techniques for the identification of eye disorders has been extensively explored. It was observed that despite the satisfactory accuracy achieved by the models, there was a deficiency in the quantity of training datasets utilised. The previously employed technologies utilised slit lamp pictures or fundus images. Insufficient attention has been devoted to the development of a user-friendly system accessible to a wide range of individuals.

As elucidated in the aforementioned research [3,8], a limited number of fundus pictures were utilised, necessitating the employment of appropriate equipment. The fundus pictures represent the posterior aspect of the image. Consequently, the method possesses a drawback wherein an inexperienced user is unable to get any advantages. The system utilises a Recurrent Neural Network (RNN) technique for the purpose of picture classification. In order to facilitate the detection process, the system makes use of features that have been retrieved from a total of 5378 photos. Several other research (2,9) have employed the Single Perceptron Training Model to categorise eye illnesses into three distinct kinds. The accuracy achieved by the method was 90.82% [3]. The present study has yielded the aforementioned level of accuracy based on the available data. However, it is important to acknowledge the limitations posed by the restricted dataset and the potential risk of overfitting.

Features	Paper [1]	Paper[2,9]	Paper [3]	Paper[7]	Paper[8]	Proposed system
Accuracy	96.1%	94.69%	90.82%	Only feature extraction	95.479%	Depends on data
Dataset size	420 images	Not available	Not available	5378 images	243 images	Dynamic google images
Type of image used	Slit lamp	Slit lamp	Fundus image	Slit lamp	Fundus image	Regular eye images
Classification in	3 types	3 types	4 types	1 types	2 types	4 types
Algorithm used	SVM	Single Perceptron Training Model	CNN	RNN, SVR	Decision Tree, BPNN, SMO	CNN, VGG16 model(16 layers)

Fig. 2: Comparison of existing models and proposedmodel

Figure 2 illustrates that the majority of the prevailing systems employed slit lamp pictures or fundus images for the purpose of detection. Nevertheless, as previously said, it may be impractical to get this in geographically isolated and economically disadvantaged regions. Previous systems have utilised several machine learning methods such as perceptron models, support vector machines (SVM), backpropagation neural networks (BPNN), support vector regression (SVR), recurrent neural networks (RNN), sequential minimal optimisation (SMO), and others. The classification also exhibits variation across preceding systems. A limited number of individuals have categorised the pictures as either two distinct types or three subordinate sub-categories.

3. PROPOSED METHODOLOGY

The proposed system is used to detect the cataract disease using the convolutional neural network model and regular eye images.

3.1 System architecture

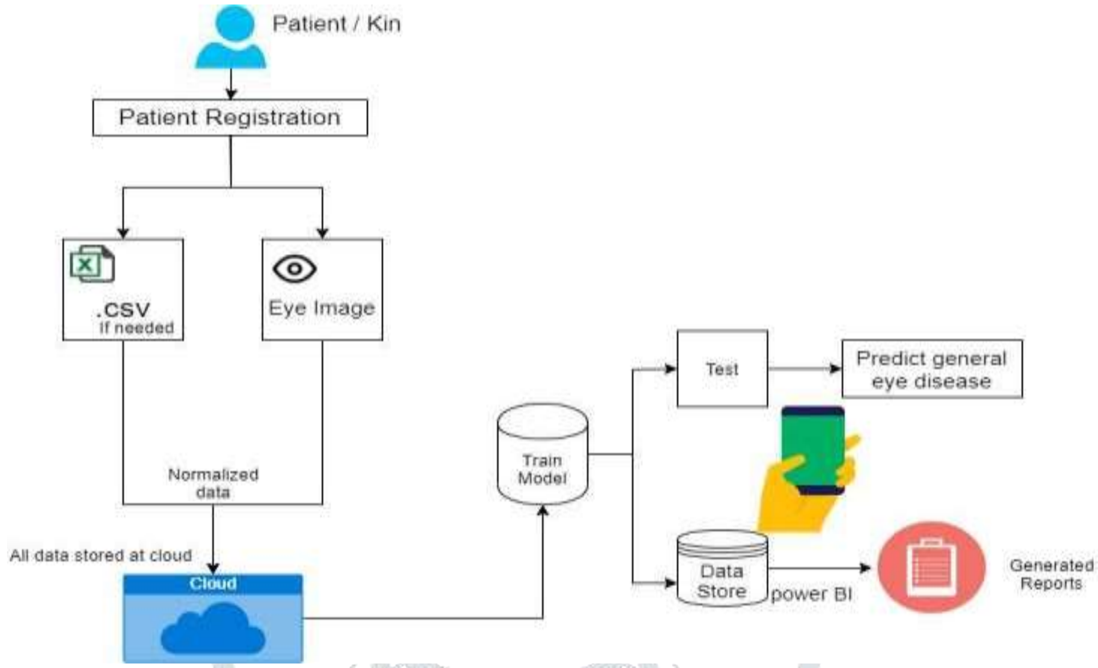

Fig.3: System architecture of the proposed system

The flow of the proposed system is defined by the detection model, as seen in Figure 2.

The patient successfully undergoes the registration procedure, and the relevant data is subsequently stored into the system. The registration procedure involves the collection of several demographic details from patients, including age, lifestyle factors, behaviours such as smoking and alcohol use, family history of cataract, history of eye injury or surgery, current usage of drugs such as steroids, and presence of other coexisting disorders. Upon successful authentication, the user will be sent to the main page, where they will find comprehensive information on different eye disorders, including preventive measures and symptoms associated with each condition.

The ResNet-152 model integrated within the system enables end users to perform cataract detection in their ocular region. The individual is required to select a picture depicting an eye and thereafter upload it onto the server. Subsequently, the picture will undergo processing using the trained model, leading to the computation of the corresponding outcomes. In the event that the likelihood of developing cataracts is determined to be sufficiently elevated, it is recommended that he seek consultation with the nearest ophthalmologist.

The use of cloud databases facilitates the storage of both personal information and the outcomes generated by the Convolutional Neural Network (CNN) model.

3.2. METHODOLOGY

The procedure involves various processes before a result is shown. Sub Processes involved in detecting cataract disease are depicted in modular diagram as shown in fig.6

3.2.1 Load Image

The user uploads the eye image to the server for detection. The image must be taken with JPG extension and will be resized according to requirements of the model.

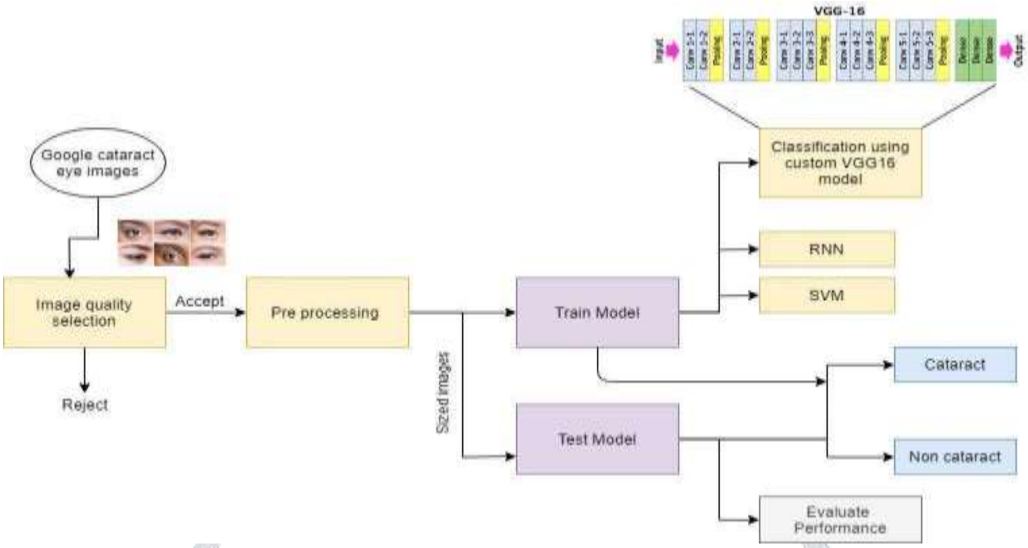

Fig. 4 Modular Diagram

3.2.2 Preprocessing

Preprocessing is employed to manipulate and reconfigure the input data in a manner that enables its utilisation as input for the convolutional neural network (CNN) model. The noise present in the picture is eliminated or diminished to levels that are deemed acceptable. Several aspects are improved. Ultimately, the picture undergoes a process of conversion to a grey-scale representation.

The process of grayscaling involves converting an image from colour to grayscale. In contrast to RGB photographs, grayscale images possess fewer dimensions and encompass a reduced amount of data. In order to enhance the speed and efficiency of image processing, it is advantageous to utilise grayscale photos, since they offer greater benefits to the model. Therefore, the grey scaling approach is utilised. The utilisation of grey scaling is motivated by its ability to preserve the essential characteristics of a picture while simultaneously reducing the computational burden on the central processing unit (CPU). This advantage arises from the fact that black and white (B/W) images occupy less storage space compared to their RGB counterparts.

The initial stage involves the identification and extraction of pupils. The use of the OpenCV module in the Python programming language facilitates the accomplishment of this task. Hough circles are employed within the context of image segmentation. The Hough Circles algorithm is utilised to identify circular shapes inside an image. The detection and extraction of the pupils is followed by their subsequent transfer for further processing.

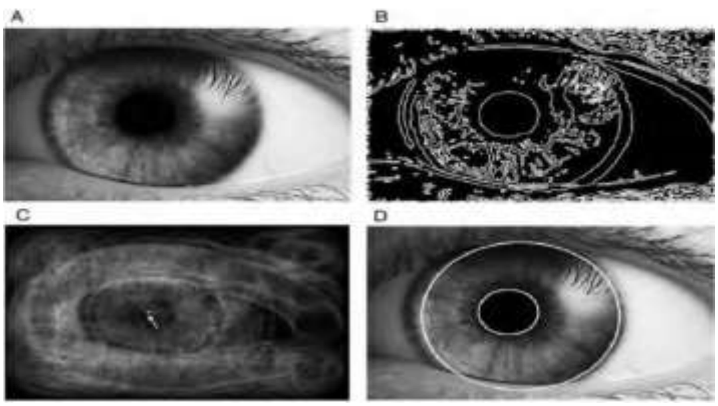

Fig. 5: HoughCircles algorithmSource: [4]

As represented in Fig. 4, shows the stages in detection of pupils from an eye image using Hough Circles.

3.2.3 Processed image into the trainedmodel

Once the system obtains a pre- processed image it is then fed into the model where it passes through several layers of the model.

3.2.4 Classification

Once the presence of cataract is detected in the picture, the suggested method endeavours to categorise it into certain subtypes of cataract.

There exist several classfications of cataracts.

1. The term "nuclear sclerotic" refers to a condition characterised by the hardening or thickening of the nucleus of a cell.
2. The term "cortical" refers to the outer layer of the brain, known as the cerebral cortex.
3. The term "posterior subcapsular" refers to a specific anatomical location.

The ResNet-152 is a convolutional neural network architecture of 34 distinct layers. The aforementioned vision model architecture is widely regarded as one of the most precise to date. Real-time health-care apps have employed this technology in many instances..

3.3 The ResNet Model

Residual networks (ResNets), which have been recently introduced, have demonstrated exceptional performance on the ILSVRC2015 classification test. These networks also enable the training of significantly deep networks, surpassing 1000 layers [11]. The ResNet model is commonly employed for the purpose of picture classification. The architecture comprises a sequence of filters, each with a dimension of 3×3. In contrast to AlexNet, which utilises filters with larger kernel sizes (specifically, 11 and 5 in the first and second convolutional layers, respectively). The use of the ResNet model is motivated by the potential drawbacks of employing the AlexNet and VGG models, namely their extensive layer structures which may lead to issues such as overfitting. The issue is significantly mitigated in the ResNet architecture by minimising the depth of the network layers. A dense layer is a mathematical operation that involves multiplying a matrix of weights with a vector of inputs obtained from the preceding layer. The elements within the matrix represent the transient variables that undergo modification throughout the process of backpropagation.

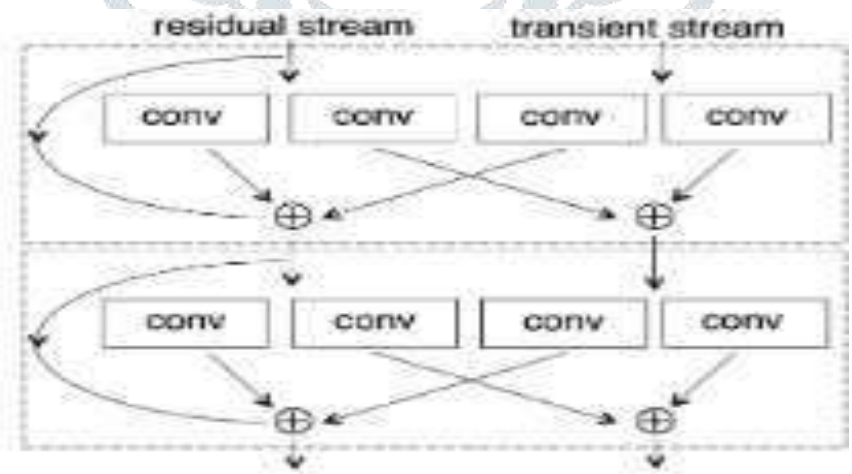

Fig. 6: ResNet layer

Source: [11]

Fig 3 represents different layers present in the ResNet-152 model. This model consists of convolutional layers, Max Pooling layers, Activation layers, Fully connected layers. The convolutional layer is made of 3x3 size whereas the Max Pooling layer is made of 2x2 sized filters.

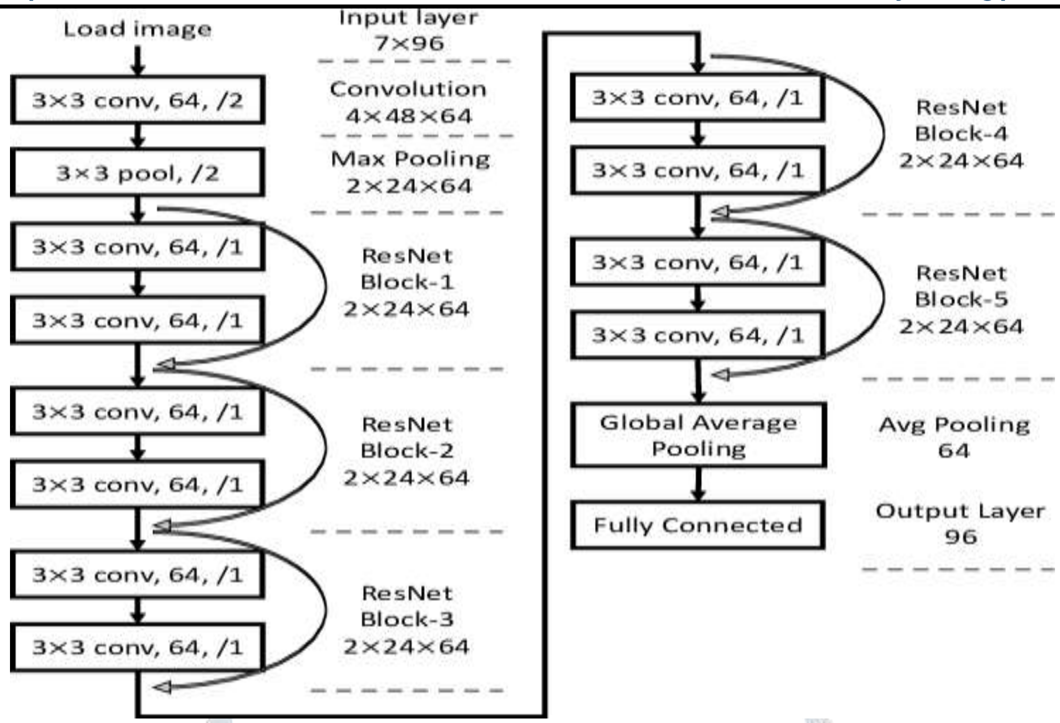

Fig.7: ResNet Architecture [11]

Fig 4 represents the architecture of the ResNet model. The diagram displays the number of filters and size of inputs of each layer. There are 64 filter layers in 1st Convolution layer, 128 filter layers in 2nd Convolution layer, 256 filter layers in 3rd Convolution layer and 512 layers in 4th and 5th Convolution layers.

4. IMPLEMENTATION

The Convolutional Neural Network (CNN) model is developed using the Python programming language, namely Python 3, and executed within the Jupyter Notebook environment. The central processing unit (CPU) was utilised in lieu of the graphics processing unit (GPU) for the purpose of processing. The model was developed using the Tensorflow, Keras, and NumPy libraries. At the outset, the weights were assigned randomly. Throughout the duration of the training, the weights were iteratively adjusted until reaching their ultimate levels. The visual content was acquired from publicly accessible sources specifically designated for scholarly purposes on the website kaggle.com.

5. RESULT AND ANALYSIS

In the first stages, a series of 4-5 convolutional layers followed by pooling layers were employed. The level of accuracy achieved was around 0.99, while the corresponding loss value reached a maximum of 0.30. The ResNet-152 model, which consists of 34 layers of convolution and pooling, was utilised with pre-trained weights. The validation data exhibited an accuracy of around 0.7, with a loss on the order of e-4. Through experimentation with different epochs ranging from 10 to 100, it was shown that the accuracy of the model reached its highest point at 80 epochs.

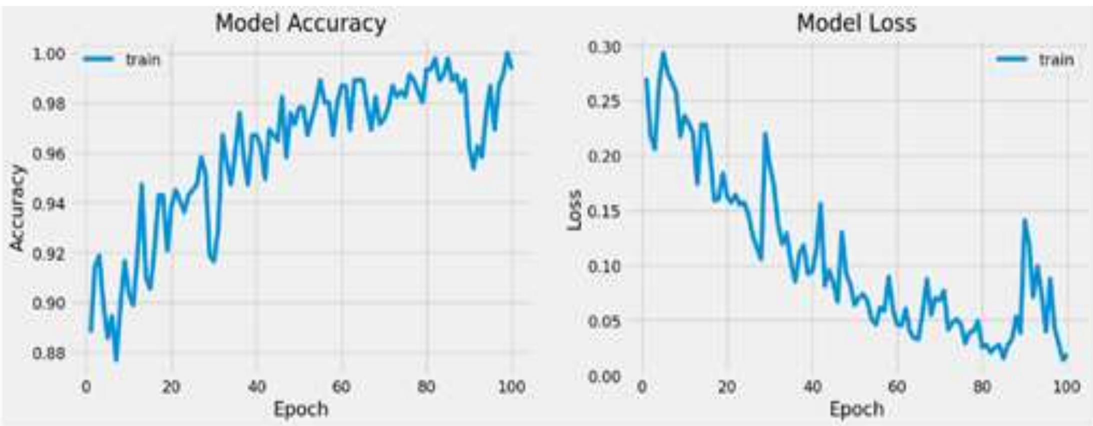

Fig 8: Model Accuracy And Model Loss

Figure 8. represent the model accuracy and model loss graphs, the bifurcation of train and test is represented in the same figure.

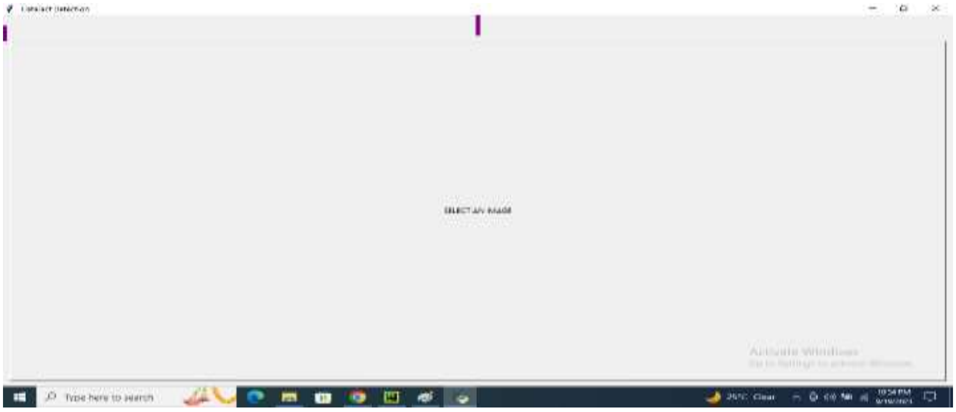

Fig 9 : gui of proposed system

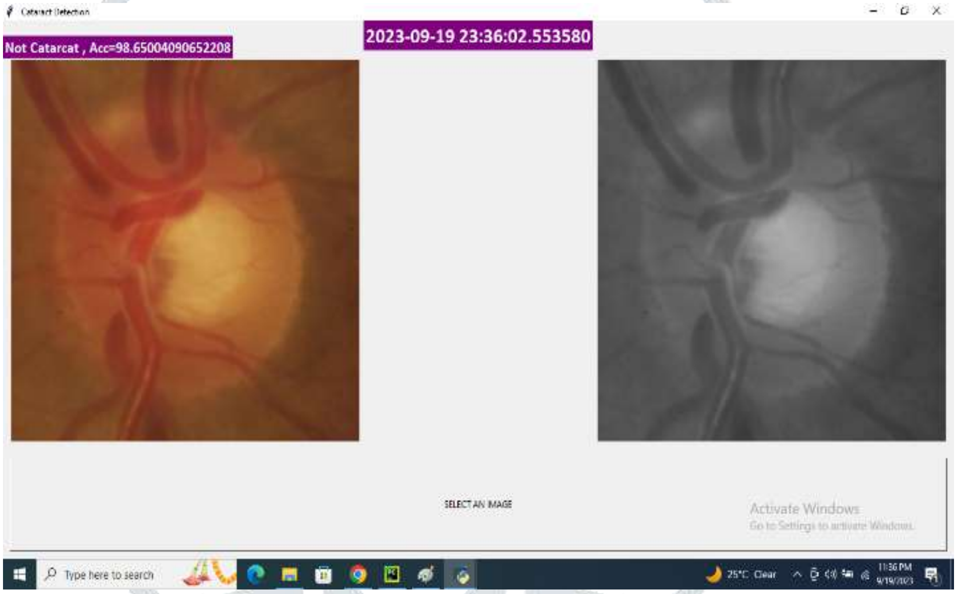

Fig 10 Detection of Non- Cataract eye

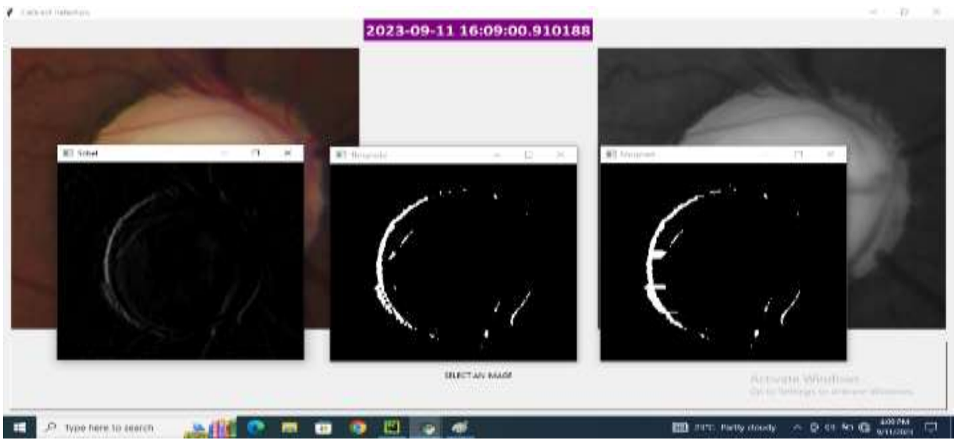

Fig 11 Detection of Cataract Patient

6. CONCLUSION

A convolutional neural network model is constructed by training it on a substantial dataset consisting of both cataract and non-cataract eye pictures, resulting in the acquisition of weights.

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