Department of Electrical and Computer Engineering
North South University

Senior Design Project

Developing a Mobile Application using Deep Learning for Cataract Classification

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ECE Department

SUMMER, 2023

LETTER OF TRANSMITTAL

June, 2023

To

Dr. Rajesh Palit
Chairman,
Department of Electrical and Computer Engineering
North South University, Dhaka

Subject: **Submission of Capstone Project Report on "Developing a Mobile Application using Deep Learning for Cataract Classification "**

Dear Sir,

With due respect, we would like to submit our **Capstone Project Report** on **"Developing a Mobile Application using Deep Learning for Cataract Classification"** as a part of our BSc program. The report deals with Cataract Detection using Smartphone Cameras. This project was very much valuable to us as it helped us gain experience from practical fields and apply in real life. We tried to the maximum competence to meet all the dimensions required from this report.

We will be highly obliged if you kindly receive this report and provide your valuable judgment. It would be our immense pleasure if you find this report useful and informative to have an apparent perspective on the issue.

Sincerely Yours,

Tasnia Ishrat Khan

....

ECE Department
North South University, Bangladesh

Fatima Ibrahim

....

ECE Department
North South University, Bangladesh

APPROVAL

Tasnia Ishrat Khan (ID # 1911539642), Fatima Ibrahim (ID # 2121340642) from Electrical and Computer Engineering Department of North South University, have worked on the Senior Design Project titled "**Developing a Mobile Application using Deep Learning for Cataract Classification"** under the supervision of Dr Mohammad Monirujjaman Khan partial fulfillment of the requirement for the degree of Bachelors of Science in Engineering and has been accepted as satisfactory.

Supervisor's Signature

……………………………………….

Dr Mohammad Monirujjaman Khan

Associate Professor

Department of Electrical and Computer Engineering

North South University

Dhaka, Bangladesh.

Chairman's Signature

……………………………………….

Dr. Rajesh Palit

Professor

Department of Electrical and Computer Engineering

North South University

Dhaka, Bangladesh.

DECLARATION

This is to declare that this project is our original work. No part of this work has been submitted elsewhere partially or fully for the award of any other degree or diploma. All project related information will remain confidential and shall not be disclosed without the formal consent of the project supervisor. Relevant previous works presented in this report have been properly acknowledged and cited. The plagiarism policy, as stated by the supervisor, has been maintained.

Students’ names & Signatures

1. Tasnia Ishrat Khan

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2. Fatima Ibrahim

ACKNOWLEDGEMENTS

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Furthermore, the authors would like to thank the Department of Electrical and Computer Engineering, North South University, Bangladesh for facilitating the research. The authors would also like to thank their loved ones for their countless sacrifices and continual support.

ABSTRACT

Developed a Mobile Application using Deep Learning for Cataract Classification

One of the leading global causes of vision loss and blindness is the cataract. The percentage of blind people is around 50%. As a result, early cataract detection and prevention may limit vision loss and blindness. Contrary to cataract, artificial intelligence (AI) has made significant progress in the treatment of glaucoma, macular degeneration, diabetic retinopathy, corneal abnormalities, and age-related eye diseases. However, the vast majority of cataract detection algorithms in use are built using common machine learning techniques. On the other hand, manual extraction of retinal features is a laborious method that needs a skilled ophthalmologist. In order to detect cataracts, we have built the framework of an Android application. We then used algorithms to extract accuracy, graphs, trainable and untrainable parameters, and differentiation of cataract and non-cataract eye images from a gathered dataset. In order to identify the cataract using color fundus images, we presented the VGG19 (Visual Geometry Group), and digital image we presented Inception V3, which is a CNN (convolutional neural network) model. This will be incorporated into an Android application. The results of fundus image, the training procedure demonstrate that the model attained a flawless accuracy of 1.0000 on the training data for epochs 10 to 15. It scored an accuracy of 0.963 on the validation set, which is still quite high. With values ranging from 0.25 to 0.27, the validation loss was similarly largely consistent.The model is doing well and has mastered correctly classifying the photos. On the test data, the model produced a loss of 0.25735 and an accuracy of 0.9241. The result of the digital image, accuracy is 0.973 on the validation set, which is quite high and on the test data, the model produced a loss of 0.26753 and accuracy of 0.93491. The significance of these results is that the model performs effectively, can reliably categorize test photos with high accuracy, and will be trustworthy for patients to utilize.

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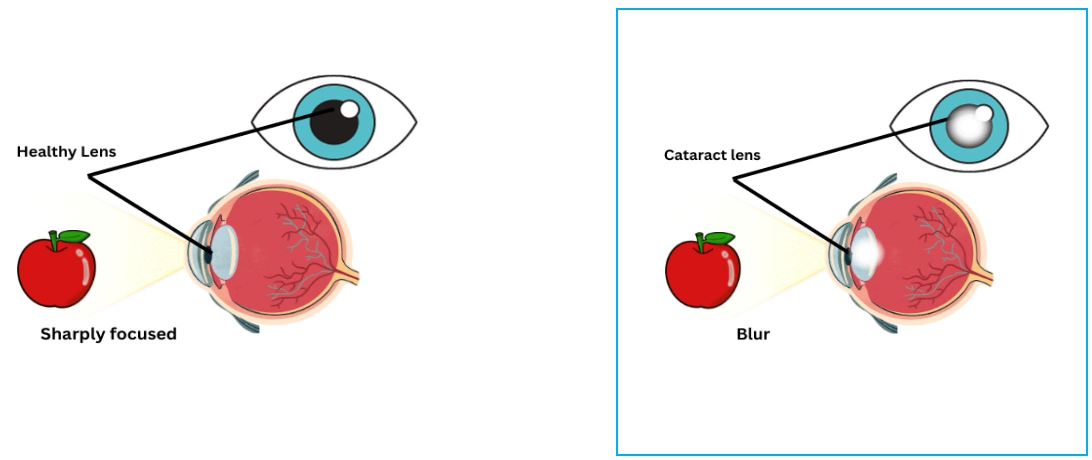
1.1 Background and Motivation

1.1.1 Background

Cataract is a condition that affects the eye's lens, causing it to become cloudy or opaque, which can impair vision. The lens is normally clear and helps to focus light on the retina at the back of the eye allowing us to see images clearly [1].

However, as we age, proteins in the lens may start to clump together and cause cloudiness, resulting in a cataract. Other factors that may contribute to the development of cataracts include genetics, eye injury, exposure to ultraviolet radiation, and certain medications [1].

Symptoms of cataracts may include blurry or hazy vision, sensitivity to light, seeing halos around lights, difficulty seeing at night, and a gradual loss of color vision. Treatment for cataracts typically involves surgery to remove the cloudy lens and replace it with an artificial lens, which can improve vision and quality of life for many people [1].



(a) (b)

Figure 1 : Normal Eye and Cataract Eye

In the above Figure 1 (a) we can see a normal eye, where light is being refracted easily. In Figure 1 (b), however, we can see a cataract affected eye that cannot refract the light properly.

There are several different types of cataracts, which are categorized based on their location within the lens and the cause of their formation. The most common type of cataracts are discussed as follows. Firstly, there are age-related cataracts. These are the most common type of cataracts and are caused by the natural aging process. They usually develop gradually over time and are often found in people over the age of 60. Then there are Congenital cataracts. These are present at birth or develop during childhood and can be caused by genetic or developmental factors. Also, Traumatic cataracts are also prevalent in society. These are caused by injury or trauma to the eye and can develop immediately or years after the injury. Moreover, there are Secondary cataracts. These can develop as a complication of other conditions, such as diabetes, or as a result of certain medications or eye surgeries .

The various signs and symptoms of cataract areas are as follows a) Blurry Vision b) Difficulty seeing things at night c) Eyes get sensitive to light. d) Brighter light needed for reading e) Halo or circular formation is seen around light sources f) The colors may appear to be more yellowish g) Double vision.

A cataract is a type of eye illness in which the eyes seem hazy. Cataracts cause frosty or foggy eyesight. A person with cataract eyes has difficulty reading, driving, and even recognizing other people's faces [1]. According to the World Health Organization (WHO), there are roughly 285 million visually impaired persons worldwide, including 39 million blind people and 246 million who suffer from moderate to severe blindness [2]. According to the 1998 World Health Report, 19.34 million persons are blind bilaterally (less than 3/60 in the better eye) due to age-related cataracts. This represented 43% of all blindness cases [3]. The cataract gets worse by the day. Recent cataract cases climbed by 43.6%, with nuclear cataracts accounting for 23.1%, posterior subcapsular cataracts (PSC) for 13.1%, and cortical cataracts for 22%, but only 26.8% underwent cataract surgery. Aside from that, the number of cataract surgeries has climbed in recent years. Studies reveal that there are more female patients than males. This encompasses both nuclear and cortical cataracts, as well as cataract surgery ($p = 0.02$-0.05). Furthermore, it is more common in the non white community ($p = 0.001$) [4].

Cataracts develop as a result of aging and the use of crystalline lenses. Many interdependent elements, including the lens' microscopic structure and chemical content, preserve the lens' transparency and optical homogeneity. A progressive deposit occurs in the lens where a yellow-brown pigment is seen which increases with aging. This also reduces the transmission of light into the eyes. The symptoms of cataract basically depend on the types of cataracts, the lifestyle of a person, and also his visual requirements. Intracapsular and extracapsular cataract extractions are the two terms used interchangeably. Intracapsular extraction entails removing the entire lens while keeping the capsule intact. In the developed world, this approach is hardly used for treatment. It is still popular in underdeveloped countries since it requires fewer expensive and sophisticated instruments. It does not need a highly stable electricity supply. Besides that, it can be performed within a short training period. Another method is extracapsular extraction. The nucleus of the lens is removed in one piece; a relatively large incision is required. Cataract disease can be detected using transfer learning-based intelligent methods and ocular image datasets. Preliminary cataract detection and prevention may help to minimize the rate of blindness.

1.1.2 Motivation

This project's primary goals are to aid in early cataract detection and lessen reliance on heavy medical equipment which could otherwise produce unreliable results. We want to do our part to keep communities safe and to preserve their vision. We intend to introduce a more affordable and effective way of cataract detection that would not only lower the cost but also assist poor populations in gaining access to improved facilities.

Better cataract surgery has been developed recently than it did 20 years ago. Refractive lenses often work well on patients who have cataracts that are still in the early stages. If outpatient treatment with corrective lenses and pupillary dilation fails to improve the patient's vision, surgery for the removal of the cataract and intraocular lens implantation should be performed in the hospital. The cataract detection software would improve many people's lives.

1.2 Purpose and Goal of the Project

1.2.1 Purpose

Our goal is higher accuracy and less cost. If we bring this prediction system to mobile phones, people won't have to go to the hospital for unnecessary tests. People can receive treatment from their homes, which will reduce the cost of tests, traveling and make the process more convenient for patients. Using machine learning for cataract prediction will generate results with higher accuracy and reliability. Early detection of cataracts can lead to earlier treatment and better outcomes, including the prevention of severe vision loss. If everyone uses our system they will easily find out their cataract without any cost, stress and accurate accuracy.

1.2.2 Contribution

Our goal is a mobile application that works on the detection of cataracts and type of classification on the basis of namely; normal and cataract in an attempt to reduce errors of manual detection of cataracts in the early ages.

1.2.3 Novelty

The final output of the project could be a web or mobile application that healthcare providers and individuals can use to input the necessary data, receive a risk assessment for cataracts, and receive recommendations for preventative measures and treatment options. The goal of the project is to help people with less costly treatment and those people who have no money for expensive tests. This system also improves patient outcomes and reduces the burden of cataract-related vision loss on individuals and society as a whole.

1.3 Organization of the Report

The report was organized as follows. In Chapter 1, we described the primary objective of this chapter is to introduce problem definition, Background Study,Goal of the project. In Chapter 2, we described the Research literature Review about Existing systems and Limitation. In Chapter we have Describe Methodology with system model, diagram and design and explain software\hardware components and implementation. In Chapter 4, we have Experiment Result, Investigation, how much work is done about a project explained with result, tables, figure.Chapter 5: Impact of the project on social, health, environment, technology and sustainability. In Chapter 6, we have Project planning and budget. In Chapter 7 we have Complex Engineering Problems and Activities In Chapter 8: Project summary, limitation and future improvement.

Chapter 2 Research Literature Review

2.1 Existing Research and Limitations

We looked at current journals and publications to better understand the problem and discussed viable solutions for improving the accuracy of our Vgg19 model and Inception V3 model. To compare our efforts, we used an existing dataset and looked at their model. Preprocessing, feature extraction, feature selection, and classifier or mode are the four key elements of the cataract classification method. A study says that image processing techniques can be used for detecting cataract in eyes through analyzing fundus images.

Md Kamrul Hasan, Tanjum Tanha, Md Ruhul Amin, Omar Faruk, Mohammad Monirujjaman Khan, Sultan Aljahdali, and Mehedi Masudan proposed an image classification model to differentiate a healthy eye and an eye with cataract. To classify types of images, it uses the VGG16 model. The accuracy of cataract detection (accuracy class) using this model was 97,23%[7] precision= 99,11%, sensitivity= 97,12%. And this system is similar to ours but their dataset was a small amount but we are using a large amount of data.

Another existing system is cataract detection using deep learning. This system used fundus images for classification. The proposed approach achieved 92.7% accuracy[8]. The author of this system was Neha Varma(Ajay Kumar Garg Engineering College), Sunita Yadav(Ajay Kumar Garg Engineering College), Jay Kant Pratap Singh Yadav(Ajay Kumar Garg Engineering College)

Indian Institutions of Information Technology of Pune, author Yatharth Vijaykumar Kale and other authors Ashish Shetty, Rajeshwar Patil, Yogshwar Patil proposed an automatic Cataract Detection Using Ensemble Model. This system provides three models consisting of pretrained Xception, DenseNet201, and InceptionV3. The final model is capable of detecting the classes with an accuracy of 91.18%[9].

Another system is a smart cataract detection system which is proposed by B. J. D. Kalyani, U.Hemavathi, K. Meena, JB. S. Deepapriya. The proposed system uses an efficient deep learning model with CNN and LSTM for detecting and classifying healthy eyes from cataract eyes. The proposed system produced an accuracy of 98.5 [10] for the custom dataset.

Another existing system is Ocular fundus using machine learning which is similar to ours and the author of this system was Masum Shah Junayed, Md Baharul Islam, Arezoo Sadeghzadeh, Saimunur Rahman. They implemented techniques such as support vector machines, random forest, decision tree, logistic regression, naïve Bayes, k-nearest neighbors, XGBoost, light gradient boosting, and voting classifier. Improved results were obtained through light gradient boosting. They also used KNN, CNN, logistic regression, Random forest algorithm. The average accuracy is 99.13%[11].

Another existing system is cataract detection using Ensemble Neural Networks and Transfer Learning which is proposed by Renato Racelis Maaliw III (Southern Luzon State University), Alvin Sarraga Alon (National Research Council of the Philippines), Ace Lagmanb FEU (Institute of Technology), Manuel B. Garcia (Far Eastern University). This system builds models combined with Alex Net, InceptionV3, Xception, and InceptionResNetV2 using a weighted average algorithm produces 99.20% (normal vs. cataract) and 97.76% (normal to severe)[12] accuracies compared to standalone models. But they didn't use the fundus image.

The Vivekanand Education Society Institution Of Technology, author Saroj Kailash Panda and Nikhil Panjwani proposed an Automated Detection of Cataracts Using a Deep Learning Technique. In this system, the input image is taken as a front viewed eye image captured with smartphone camera application instead of using the existing fundus images such that it makes the model user friendly and less expensive, leading to early detection of cataract which is similar to ours. In this model, the VGG16, a pretrained model, is applied on convolutional neural network (CNN) architecture which is deployed over the data set obtained. On modeling the system with collected samples, the neural network algorithm has resulted with an accuracy rate of 92.1% [13]for cataract detection. But their accuracy is less and they also used small data sets.

A cataract is clouding of the eye lens which results in decrease of vision. The existing systems are limited to use of small size image datasets resulting in lesser accuracy, and user-friendly application is not available. The proposed model is designed to use image classification models to differentiate a healthy eye and an eye with cataract. To classify types of images, it uses the VGG16 model. The accuracy of cataract detection (accuracy class) using this model was

97,23%, precision= 99,11%, sensitivity= 97,12%. And this system is similar to ours but their dataset was a small amount but we are using a large amount of data.[14]

Different authors have proposed various models, and they have achieved different accuracy levels. The major contribution of this paper is to detect cataract disease using Vgg19 Model and Inception V3 model or transfer learning-based intelligent methods.

Chapter 3 Methodology

3.1 System Design

3.1.1 System Theory

This section describes specific processes and system design that are followed and maintained in order to conduct tests on the project for cataract disease detection. We used a Deep Learning model for our project system.

Deep learning is the method of machine learning and artificial intelligence that is intended to intimidate humans and their actions based on certain human brain functions to make effective decisions. Deep learning is used for large data sets. We used two data sets: one is a fundus image and another is a digital image. Deep learning has three layers- 1) Input layer – The input layer has input features and a dataset that is known to us. 2) Hidden Layer – Hidden layer, just like we need to train the brain through hidden neurons and 3) Output layer – value that we want to classify.

Now, we will talk about the types of Deep Learning algorithms**.** Mainly we can categorize Deep learning into two types and then we further drill down each type into various deep learning algorithms.

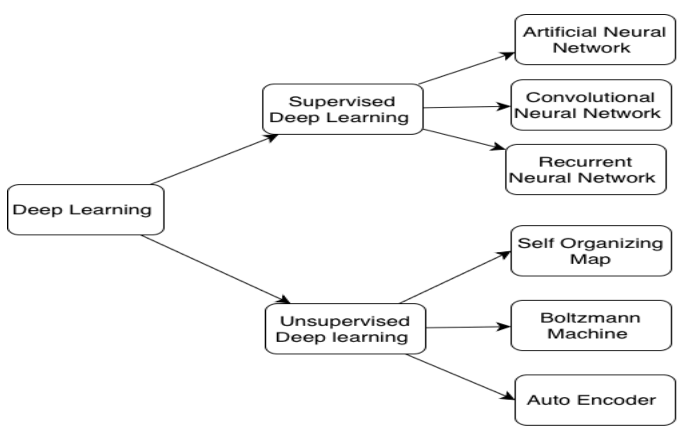


Figure 2: Deep Learning Algorithm

In Figure 2, we can see the classes of deep learning, and the respective examples of each particular class.

CNNs (Convolutional Neural Network) are designed to automatically and adaptively learn spatial hierarchies of features from images, making them highly effective in tasks such as object detection and pattern recognition. Their ability to capture intricate patterns in data has led to significant advancements in computer vision applications. A deep learning CNN consists of three layers: a convolutional layer, a pooling layer and a fully connected (FC) layer.

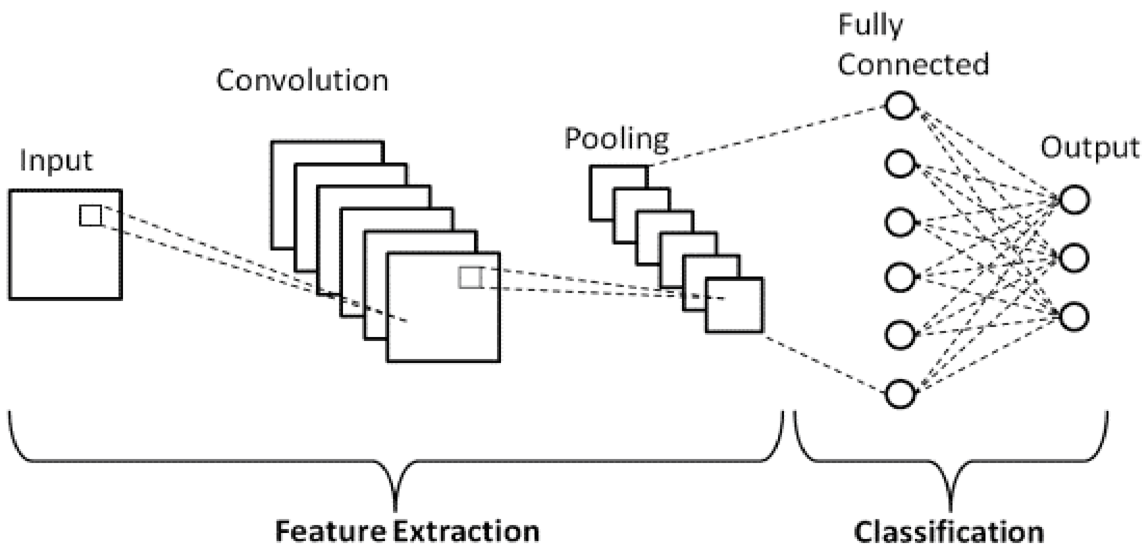


Figure 3: CNN Layer Architecture

In Figure 4, we can see the CNN Layer Architecture. The architecture is divided into two main sections: Feature Extraction and Classification.

VGG is known for its simplicity and effectiveness in image classification tasks, particularly in computer vision and deep learning research. The VGG architecture is characterized by its deep network structure with small 3x3 convolutional filters and max-pooling layers. It consists of several convolutional layers followed by fully connected layers. The original VGG network comes in several variants, with VGG16 and VGG19 being the most commonly used configurations.

Inception-v3 is a convolutional neural network architecture from the Inception family that improves on previous versions by using Label Smoothing, Factorized 7 x 7 convolutions, and an auxiliary classifier to propagate label information lower down the network.

The F1 score, crucial in assessing binary classification models, considers true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). Using the components of the confusion matrix, we can define the various metrics used for evaluating classifiers—accuracy, precision, recall, and F1 score.
The Formula of F1 Score defined as

$$\text{F1 Score} = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad \dots\dots\dots\dots \quad (1)$$

incorporates these values, where TP represents correct positive predictions, TN reflects correct negative predictions, FP indicates incorrect positive predictions, and FN denotes incorrect negative predictions. The F1 score ranges from 0 to 1, with 1 signifying a model achieving perfect precision and recall balance.

Accuracy is one of the criteria used to evaluate classification models. Essentially, validity refers to our model's percentage of true projections. The formula below is used to calculate binary classification accuracy in terms of pros and cons.

$$\textbf{Accuracy}= \frac{TN + TP}{TN + FP + TP + FN} \quad \dots\dots\dots\dots \quad \textbf{(2)}$$

To calculate the recall, divide the number of True Positives (TP) by the total number of True Positives and False Negatives. In contrast, the number of positive predictions divided by the number of positive class values in the test data is equal to the number of positive forecasts divided by the number of positive class values in the test data. It's also called the "True Positive Rate" or "Sensitivity."

Recall= $\frac{TP}{TP + FN}$ • • • • • • • • • • **(3)**

Precision is determined by dividing the total number of True Positives and False Positives (FP) by the number of True Positives. To put it another way, it is the sum of positive predictions divided by the expected number of positive class values. Positive Predictive Value is another term for it.

Precision= $\frac{TP}{TP + FP}$ • • • • • • • • • • **(4)**

Specificity refers to the fraction of real negatives projected to be negative. As a result, a small proportion of actual negatives will be interpreted as positives, resulting in false positives. This fraction is sometimes called the "false positive rate." The sum of specificity and false positive rate always equals one.

Specificity= $\frac{TN}{FP + TN}$ • • • • • • • • • • **(5)**

A confusion matrix, essential in machine learning performance evaluation, depicts a classification model's accuracy by detailing true positives, true negatives, false positives, and false negatives. This N x N matrix, tailored to the number of target classes (N), facilitates a comprehensive analysis of model performance, pinpointing misclassifications, and guiding enhancements. In binary classification, represented by a 2 x 2 matrix, the confusion matrix encapsulates four values—true positives, true negatives, false positives, and false negatives—providing a detailed snapshot of the model's predictive capabilities. In Figure 8 we can see an example of the confusion matrix.

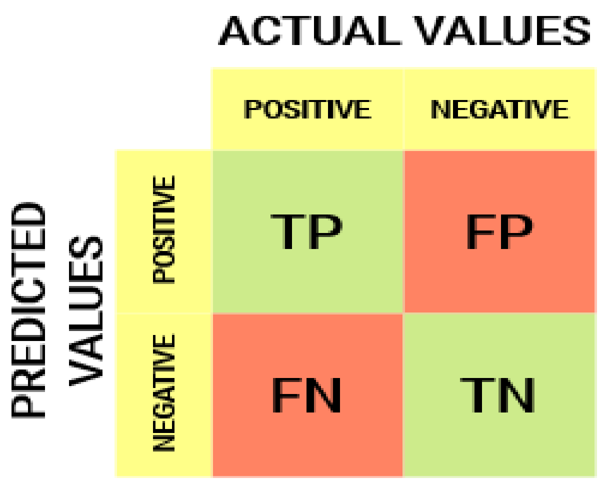


Figure 4: 2X2 Matrix Table

After converting the model into a tensor flow lite model, it was implemented in an Android application using Android Studio. Android Studio is the official integrated development environment for Google's Android operating system, built on JetBrains IntelliJ IDEA software and designed specifically for Android development. For our application cataract detection we used android studio software and implemented it as an android application. In Figure 9 we can see the workflow of Android Studio.

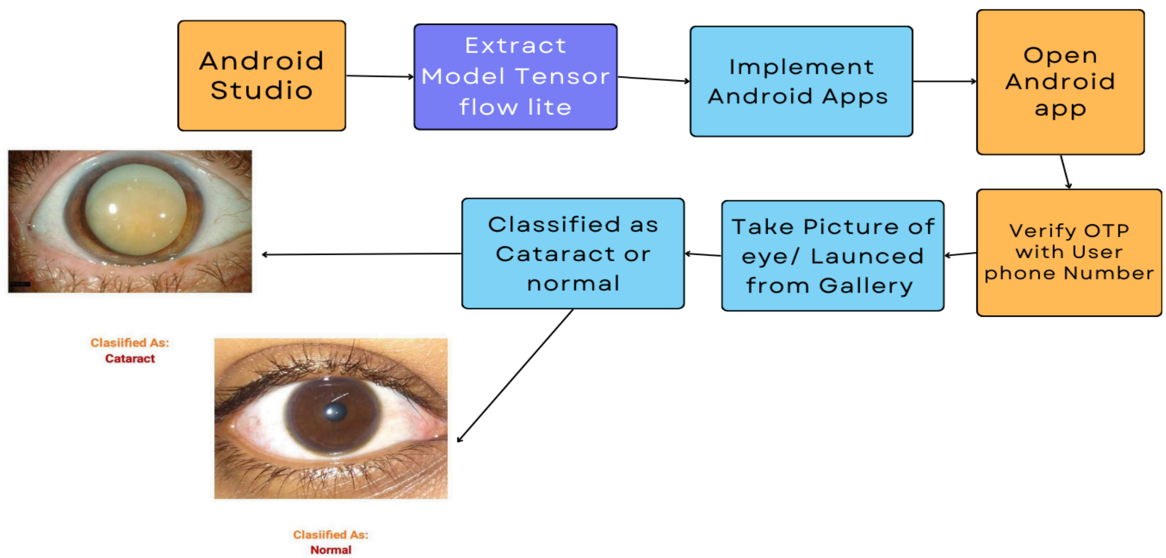


Figure 5: Workflow of Android Studio

TensorFlow Lite works with TensorFlow models that have been translated into a smaller, more portable, and efficient machine learning model format. TensorFlow Lite on Android supports pre-built models as well as the ability to create and convert your own TensorFlow models.When a model processes data, also known as running an inference, it generates prediction results as new tensors and sends them to the Android app, allowing it to take action, such as displaying the result to a user or doing further business logic.

3.1.2 System Methodology

The system used was Deep Learning Convolution Neural Network (CNN) algorithm with Visual Geometry Group (VGG19) architecture for fundus image and Inception V3 for digital images.

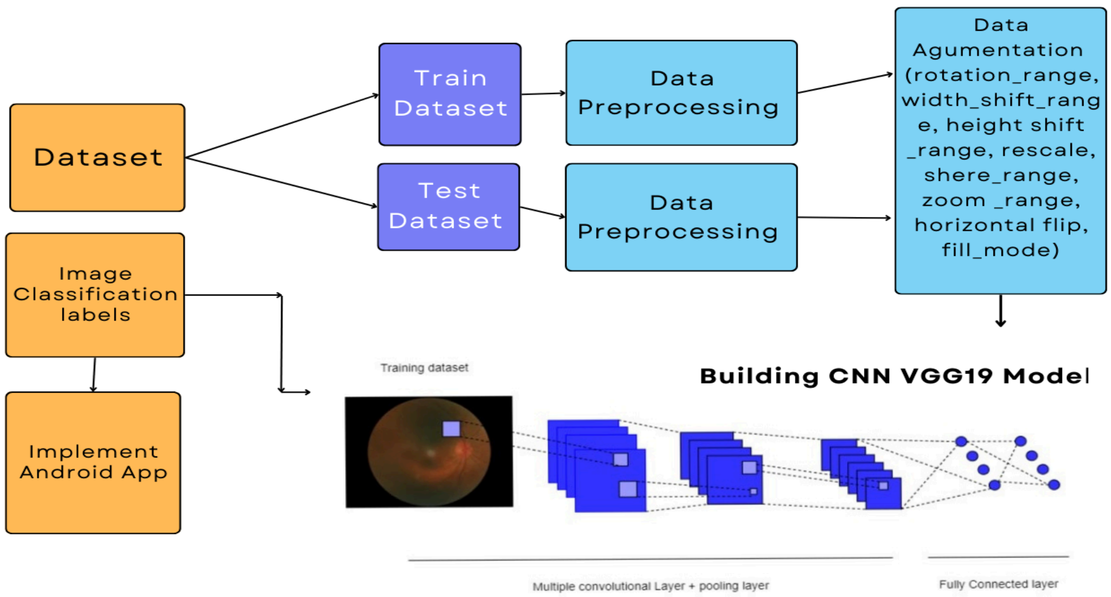


Figure 6: Deep Learning Workflow

The dataset employed in this suggested system consists of 1088 fundus pictures. The Ocular Disease Intelligent Recognition (ODIR) database is a structured ophthalmic database including 5000 patients' ages, color fundus images of their right and left eyes, and diagnostic keywords given by doctors [15]. The dataset is made up of actual patient data. From the previously mentioned datasets, we solely utilized cataracts and ordinary fundus pictures for our purposes.

The proposed system dataset combines photographs of normal, diabetes, glaucoma, cataract, pathological myopia, hypertension, age-related macular degeneration, and other diseases/abnormalities. As a result, we have separated all fundus photographs except cataract and ordinary fundus photographs in the first phase. Labels were used to filter the data. Because they were obtained with different cameras, experimental fundus pictures had varying image sizes. As a result, we used OpenCV to resize the picture to 24X24 pixels. The dataset is next loaded and converted into an array format for training purposes using the NumPy library.

VGG Nets are based on the most essential features of convolutional neural networks (CNN). In Figure 5 we can see the basic concept of how a CNN, an example used is VGG, works.

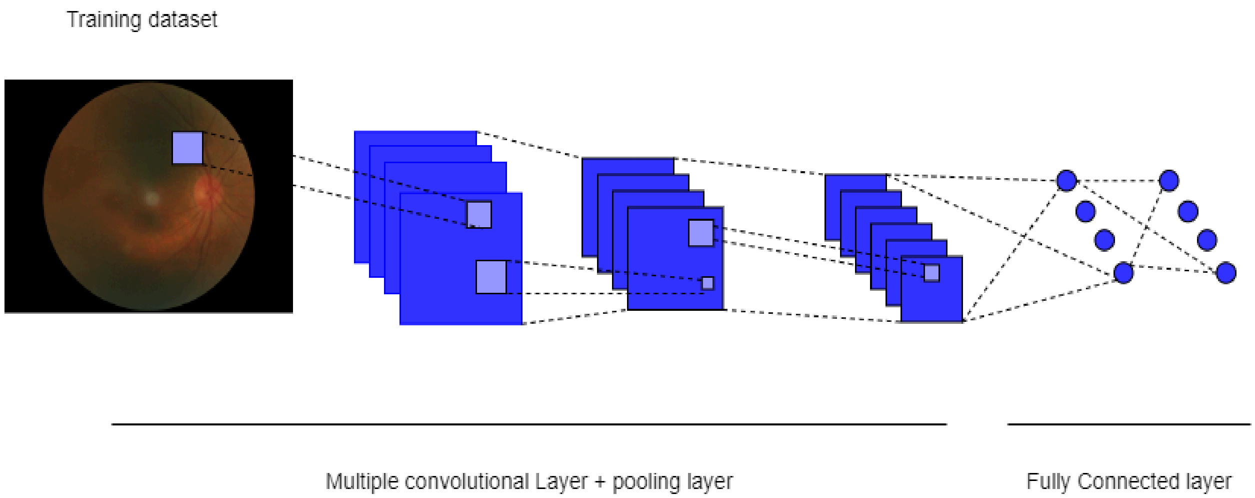


Figure 7: VGG Architecture

The VGG-16 consists of 13 convolutional layers and three fully connected layers. VGG-19 consists of 16 convolutional layers and three fully connected layers.

The VGGNet takes in an image input size of 224×224. For the ImageNet competition, the creators of the model cropped out the center 224×224 patch in each image to keep the input size of the image consistent.

VGG's convolutional layers utilize a 3×3 receptive field, optimizing spatial feature learning. The inclusion of 1×1 convolution filters with ReLU activation accelerates training, and a fixed stride of 1 pixel maintains spatial resolution during convolution, enhancing the network's effectiveness in image recognition tasks.

All the hidden layers in the VGG network use ReLU. VGG does not usually leverage Local Response Normalization (LRN) as it increases memory consumption and training time. Moreover, it makes no improvements to overall accuracy.

The VGGNet has three fully connected layers. Out of the three layers, the first two have 4096 channels each, and the third has 1000 channels, 1 for each class. In Figure 6 we can see the Fully Connected Layers.

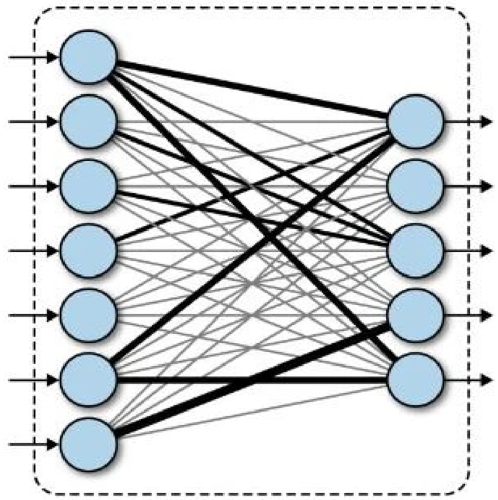


Figure 8 : Fully Connected Layer Architecture

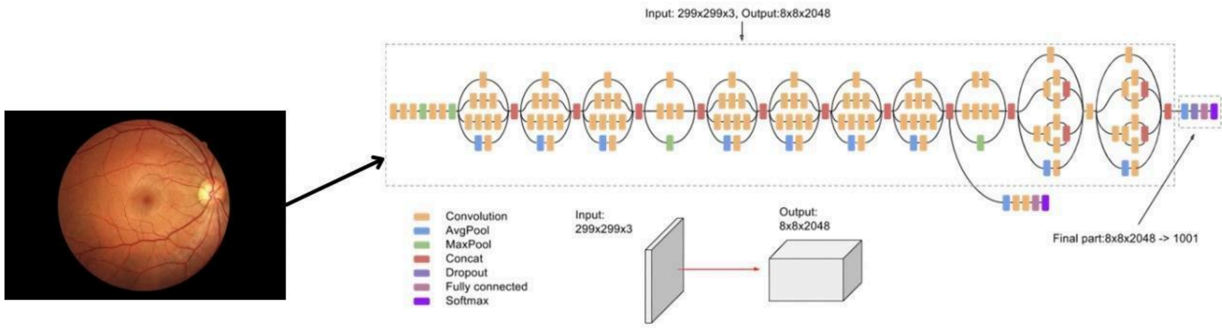


Figure 9: Inception V3 Architecture

In Figure 7 we can see the Inception V3 Architecture. Initial Convolutional Layers: These layers perform the initial processing of the input image, extracting basic features.

Inception Modules: The distinctive feature of Inception v3. Each module uses multiple filters of different sizes (1x1, 3x3, 5x5) and pooling operations simultaneously. This allows the network to capture features at various scales and improves its ability to recognize complex patterns.

Auxiliary Classifiers: Intermediate classifiers are added to the network to provide auxiliary gradients during training. This helps with the vanishing gradient problem and can lead to more stable training.

Reduction Blocks: Interspersed between Inception modules, these blocks include convolutions and pooling to reduce the spatial dimensions of the feature maps.

Fully Connected Layers: These layers process the extracted features and make the final predictions.

3.1.2.1 ER Diagram

In Figure 10 we can see the ER Diagram for android application. Users can verify by phone number, classifying, checking medical history, and taking pictures. Admin will update medical history and classification type.

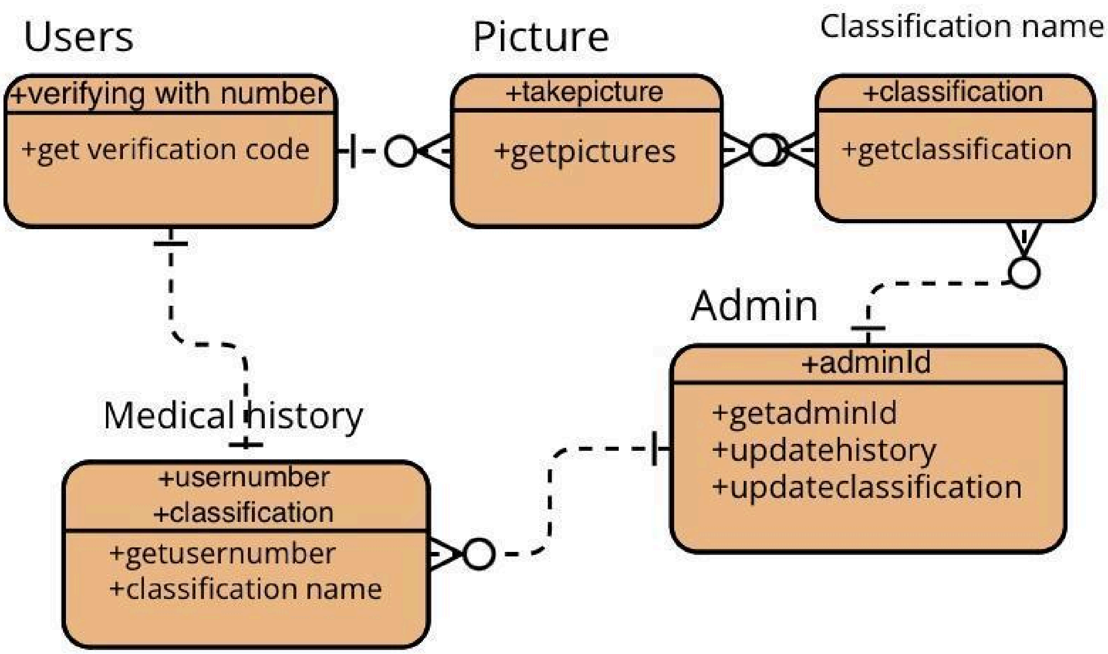


Figure 10 : ER Diagram

3.1.2.2 Use Case Diagram

There are two users: admin and user. Users can add their Image for cataract classifications, also see their medical history and admin update user medical history, classification type. In Figure 11 we can see the Use Case Diagram.

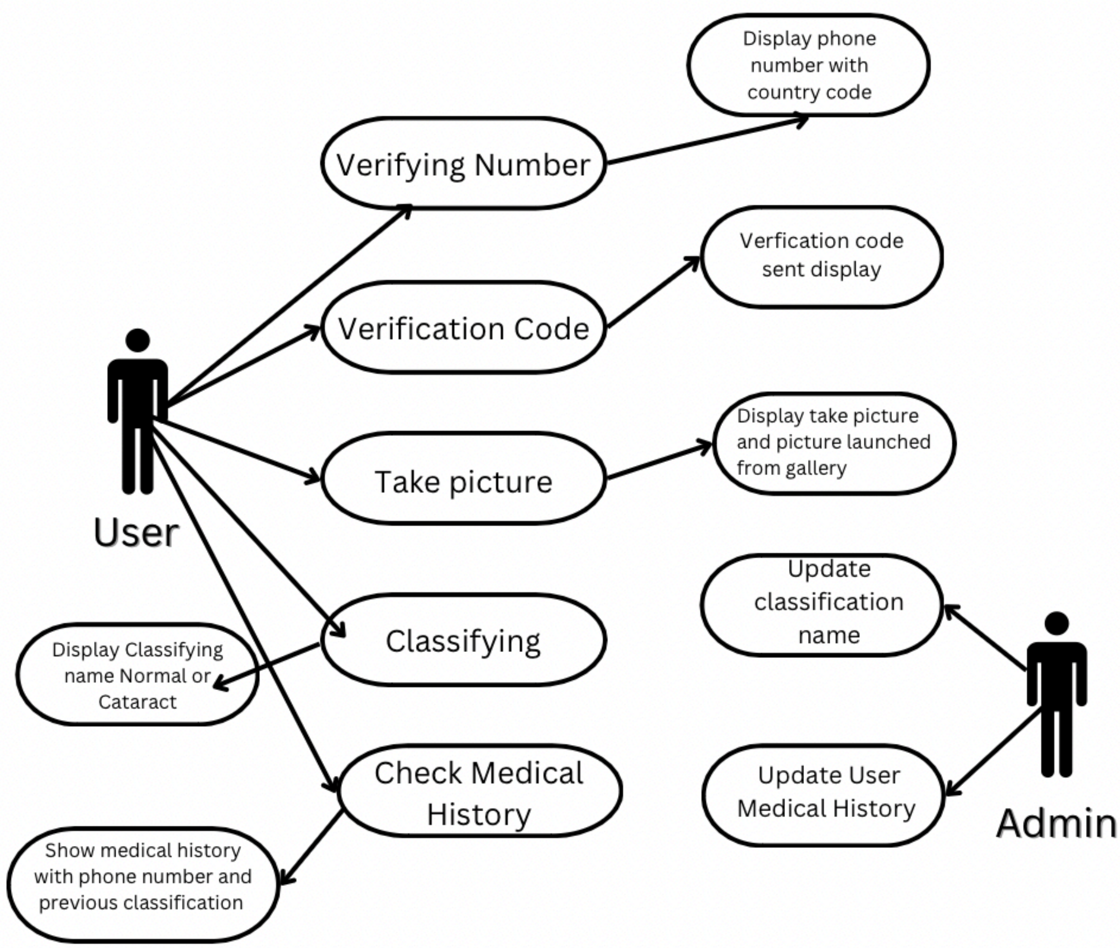


Figure 11: Use Case Diagram

3.2 Hardware and/or Software Components

Our project is an AI related project. We applied Deep learning models. For Deep learning models software components are- Dataset, preprocessing technique, model evaluation, features selection etc. For the dataset we collected data from kaggle. After collecting data we preprocessed data by removing null values then testing the data using CNN algorithm. After preprocessing data we used the VGG19 and Inception V3 for accuracy. And we used the Python language for these techniques. And For mobile applications we used java language and for data store we used firebase cloud store. For the back end we used Java language and for the front end we used an xml file.

Table I: List of Software/Hardware Tools

Tool	**Functions**	**Why selected this tool**
Google Colab	**For Python Code we used Google Colab**	**This software is easy to run and it shows the figures instantly.if there is any error it shows clearly on the console pane. libraries can be installed on the console.**
Tensor Flow	**Library Function**	**It helps implement best practices for data automation, model tracking and performance.**
Scikit Learn	**Library Function**	**For classification, regression clustering, dimensionality.**

Numpy	**Library Function**	**numpy arrays are faster and more compact than python lists. numpy uses much less memory to store data.**
OpenCv	**Library Function**	**allows to perform image processing and computer vision**
Pandas	**library Function**	**allow us to analyze big data and make conclusion based on statistical theory**
Android studio	**For Android Application**	**best tools for app development. We design our apps pages easily. Store data in firebase. application should be able to run on different devices.**

3.3 Hardware and/or Software Implementation

For data pre-processed, testing and training and for accuracy we used Google Colab with Python language. For the library we used tensor flow, Numpy, Scikit learn, CV2 , Pandas etc .

For android development we used android studio IDE. For data-store we used Firebase cloud store.

Chapter 4 Investigation/Experiment, Result, Analysis and Discussion

In this section, we discuss the performance of the proposed Cataract Net. We basically used the VGG19 model for fundus images and Inception V3 for digital images. We split the dataset into a training and testing set as 20%-80%.

4.1 CNN model using VGG19

We preprocess the dataset and remove null values. We process a Data frame containing information about fundus scans. We find the collected data lengths and labels. We process Left and Right eye fundus. This is an image displaying randomly selected from dataset. The dataset seems to contain pairs of images and corresponding categories, where 0 represents "Normal" and 1 represents "Cataract." In Figure 12, we can see the data visualization of the fundus images.

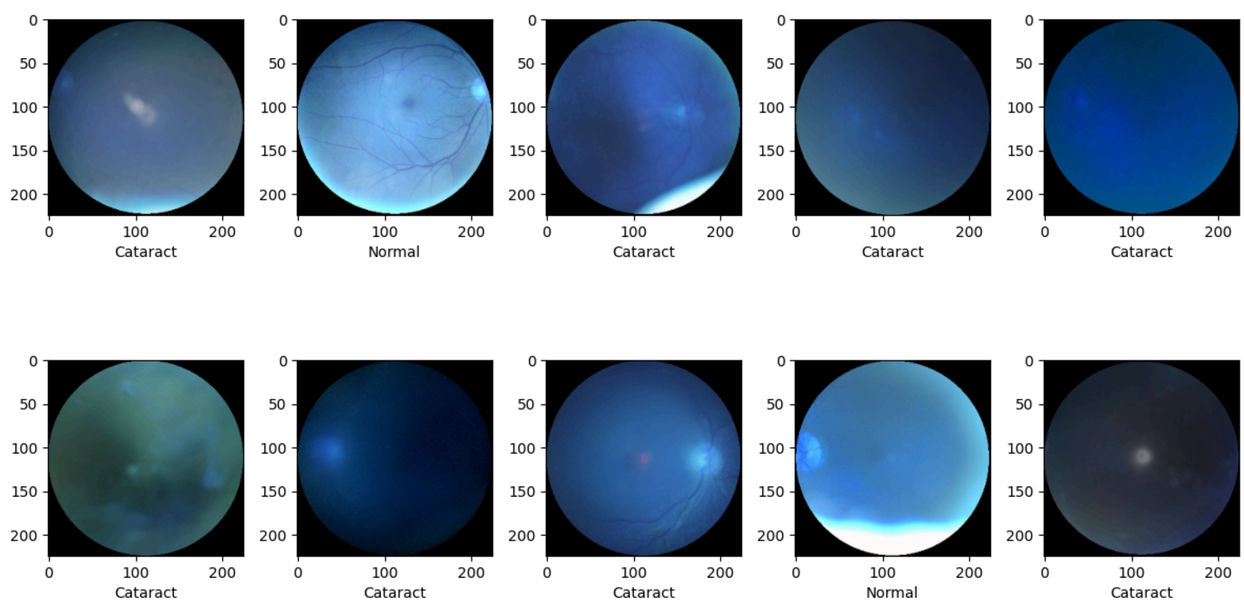
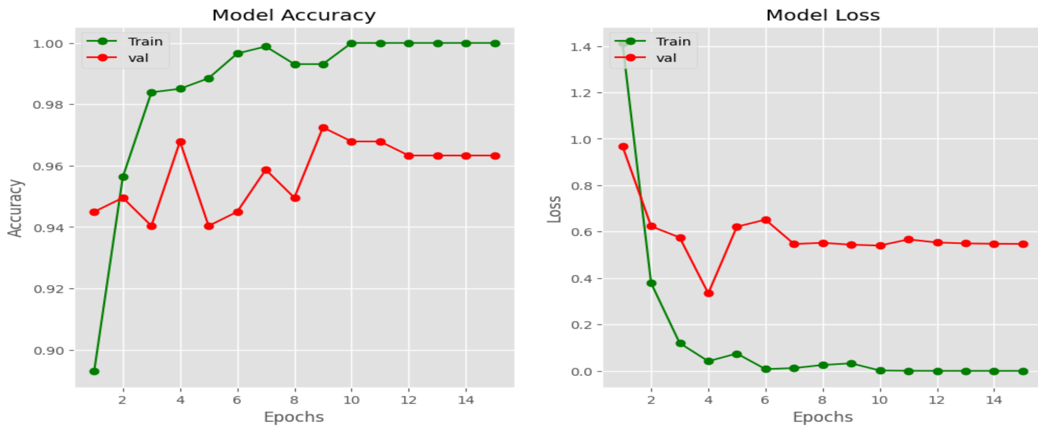


Figure 12: Data Visualisation for fundus images

The table below shows a fundus image classification report. For classification, 106 normal images are used and 112 cataract images are used. For cataract images, the f1 score is 0.96, and for normal images, the f1 score is 0.96.Total of 218 images, where the accuracy is 0.96. The model is compiled using Adam optimizer, binary cross-entropy loss, and accuracy as the metric. It utilizes Model Checkpoint and Early Stopping callbacks, saving best weights and stopping early if no improvement in validation accuracy after 5 epochs. Training runs for specified epochs, saving best weights based on validation accuracy. Epochs 10-15 show perfect training accuracy (1.0) and high validation accuracy (0.963).

Table II: Classification Report (VGG19)

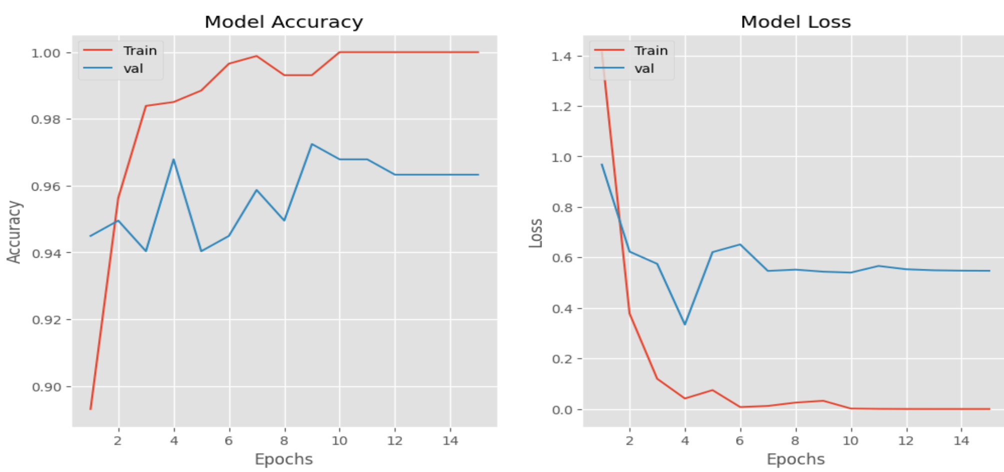
	Precision	Recall	f1 score	Support
0 (normal)	0.95	0.97	0.96	106
1 (cataract)	0.97	0.96	0.96	112
accuracy			0.96	218
macro avg	0.96	0.96	0.96	218
weighted avg	0.96	0.96	0.96	218



(a) (b)

Figure 13: Model of Loss and Accuracy

The left subplot figure 13(a) represents the model's accuracy over epochs, while the right subplot figure 13(b) represents the model's loss over epochs. The "Train" line corresponds to the training set, and the "val" line corresponds to the validation set.The red line is validation set and green line train set. Train accuracy is higher than validation accuracy which does not occur any type of overfitting.



(a) (b)

Figure 14: Model of Accuracy and Loss without dots

The left subplot figure 14(a) represents the model's accuracy over epochs, while the right subplot figure 14(b) represents the model's loss over epochs. The "Train" line corresponds to the training set, and the "val" line corresponds to the validation set.The red line is validation set and blue line train set. Train accuracy is higher than validation accuracy which does not occur any type of overfitting..

Figure 15 below shows a digital image classification report. For classification, 106 normal images are used and 112 cataract images are used. For the cataract image, between 112 and 107 images are true positives. For normal images, between 106 and 103 images are true negative.

From this graph we can see the number of eye images correctly classified as cataract or normal. Right bar shows the colour variation of different numbers of images present. Deeper colour represent higher numbers and lighter colour represent lower numbers. True positive and True negative shows deeper colour which classified images correctly. And false negative and false positive shows lighter colour which classified images incorrectly.

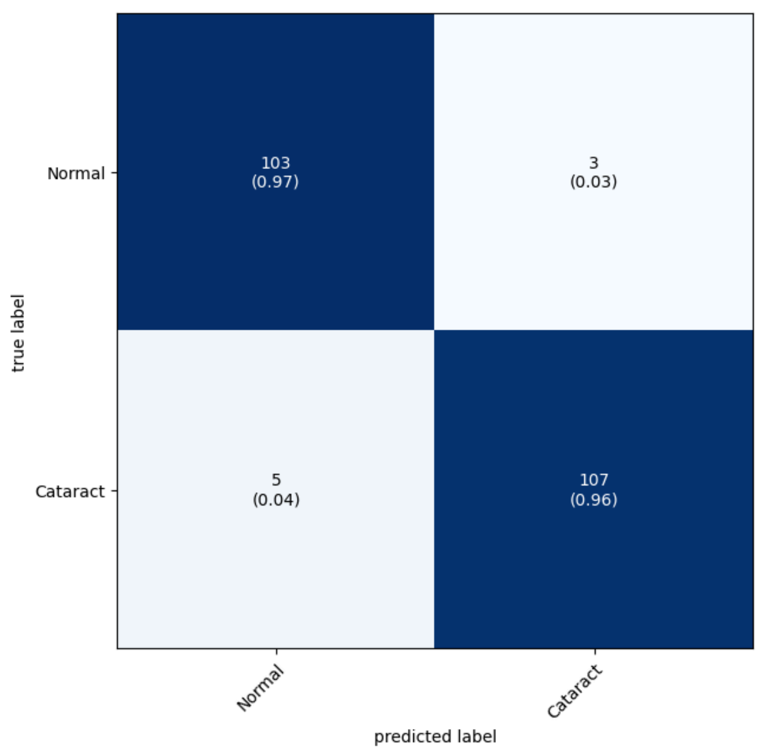
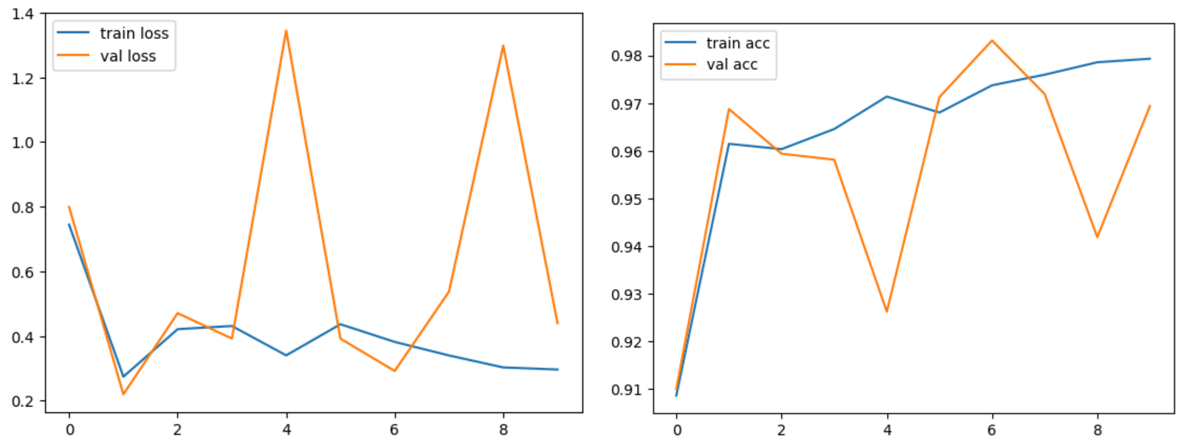


Figure 15: Confusion Matrix (VGG 19)

4.2 CNN model Using Inception V3

The below graph shows the digital image accuracy, which is used by the Inception V3 model.



(a) **(b)**

Figure 16: Model loss and Accuracy

The left subplot figure 16(a) represents the model's loss over epochs, while the right subplot figure 16(b) represents the model's accuracy over epochs. The "Train" line corresponds to the training set, and the "val" line corresponds to the validation set.The orange line is validation set and blue line train set. Train accuracy is higher than validation accuracy which does not occur any type of overfitting..

The table below shows a digital image classification report. For classification, 800 normal images are used and 800 cataract images are used. For cataract images, the f1 score is 0.97, and for normal images, the f1 score is 0.97. Total of 1600 images, where the accuracy is 0.97.

Table III: Classification Report (Inception V3)

	precision	recall	f1 score	Support
Cataract	0.95	0.99	0.97	800
Normal	0.99	0.94	0.97	800
accuracy			0.97	1600
macro accuracy	0.97	0.97	0.97	1600
weighted accuracy	0.97	0.97	0.97	1600

The graph below shows a digital image classification report. For classification, 800 normal images are used and 800 cataract images are used. For the cataract image, between 800 and 795 images are true positives. For normal images, between 800 and 756 images are true negative.

From Figure 17 graph we can see the number of eye images correctly classified as cataract or normal. Right bar shows the colour variation of different numbers of images present. Deeper colour represent higher numbers and lighter colour represent lower numbers. True positive and True negative shows deeper colour which classified images correctly. And false negative and false positive shows lighter colour which classified images incorrectly.

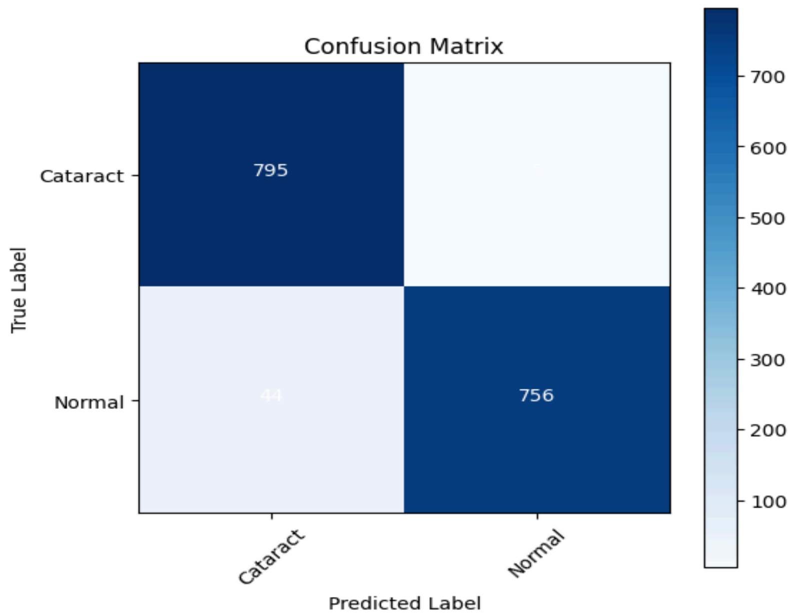
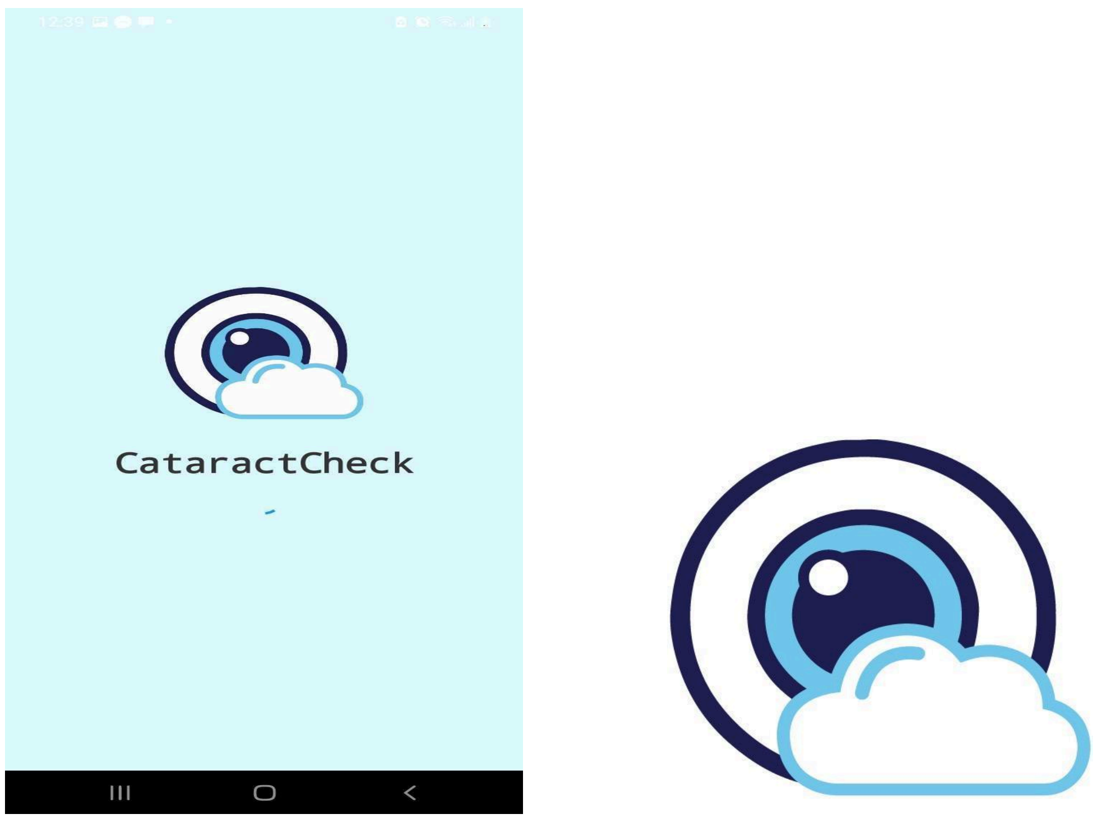


Figure 17: Confusion Matrix (Inception V3)

4.3 Experimental Result of Android Application

We designed three pages of apps. Splash screen, OTP verification, and classification of eye images. New users will be verified by their phone number. After verifying the phone number, the user can easily test or classify eyes by taking pictures from the camera and pictures launched from the gallery.

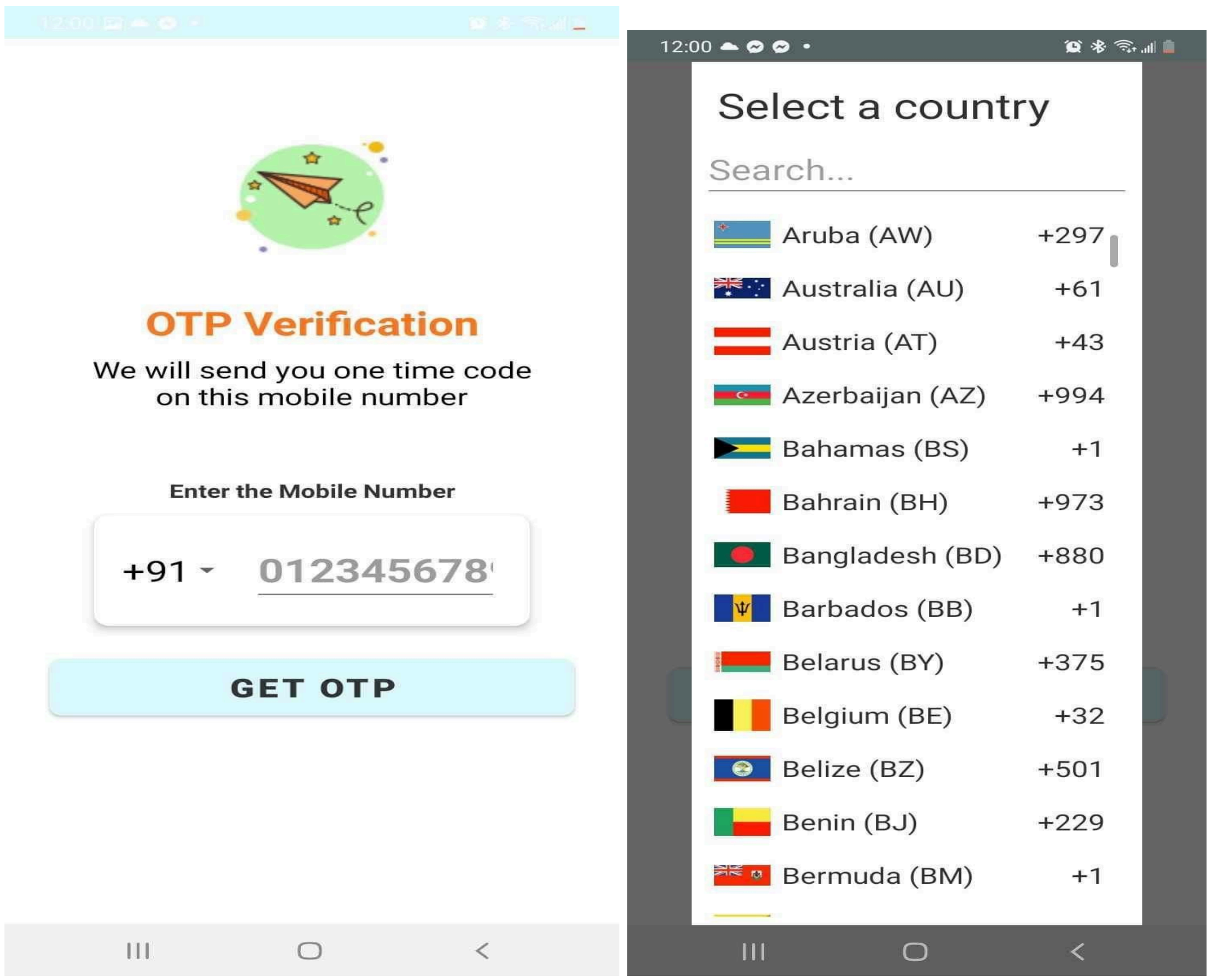


(a) (b)

Figure 18: Splash Screen Panel and Logo Of our Mobile Application

In figure 18(a) we are showing the Opening Screen of our mobile application. After rotating for 3 seconds it automatically enters the OTP Verification panel. In Figure 18(b) we are showing the logo of our mobile application which represents the cloudy eye. We designed this logo to keep it in mind that cloudy lenses occur due to cataract.

The following is the OTP Verification panel. The user will enter a phone number with the country code. Then it will redirect to the Firebase cloud store, whether the user is human or not. After a few seconds, the user will get the verification code on their phone number.

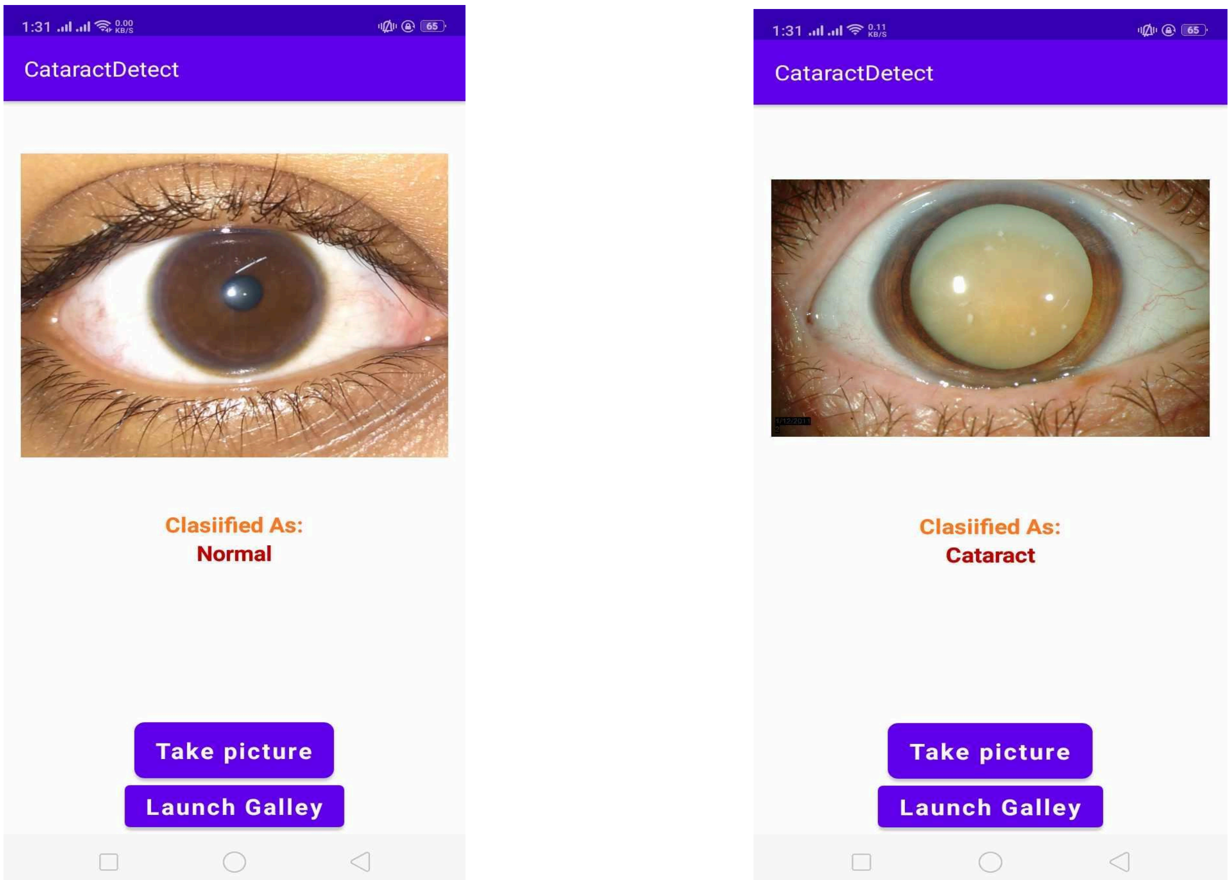


(a) (b)

Figure 19: OTP Verification panel and Country Code for Input Number

In Figure 19(a) we are showing an OTP Verification panel where users will enter their number with their country. For our country the code +880********** with a 10 digit number. For India the code +91******** with an 8 digit number. In Figure 19(b) we are showing the country code panel. This panel has approximately 200 country codes. After pressing the flag the respective country codes automatically are inserted into the input box.

The following is the classifying panel. After the user gets verified with their phone number, they will see the classifying page, where they can take pictures from the camera for classifying eye images and also launch pictures from the gallery. It will be classified into two classes: normal or cataract. If the user inputs a Cataract image, it will show Cataract, and if the user inputs a Normal image, it will show Normal. It can also classify fundus images.

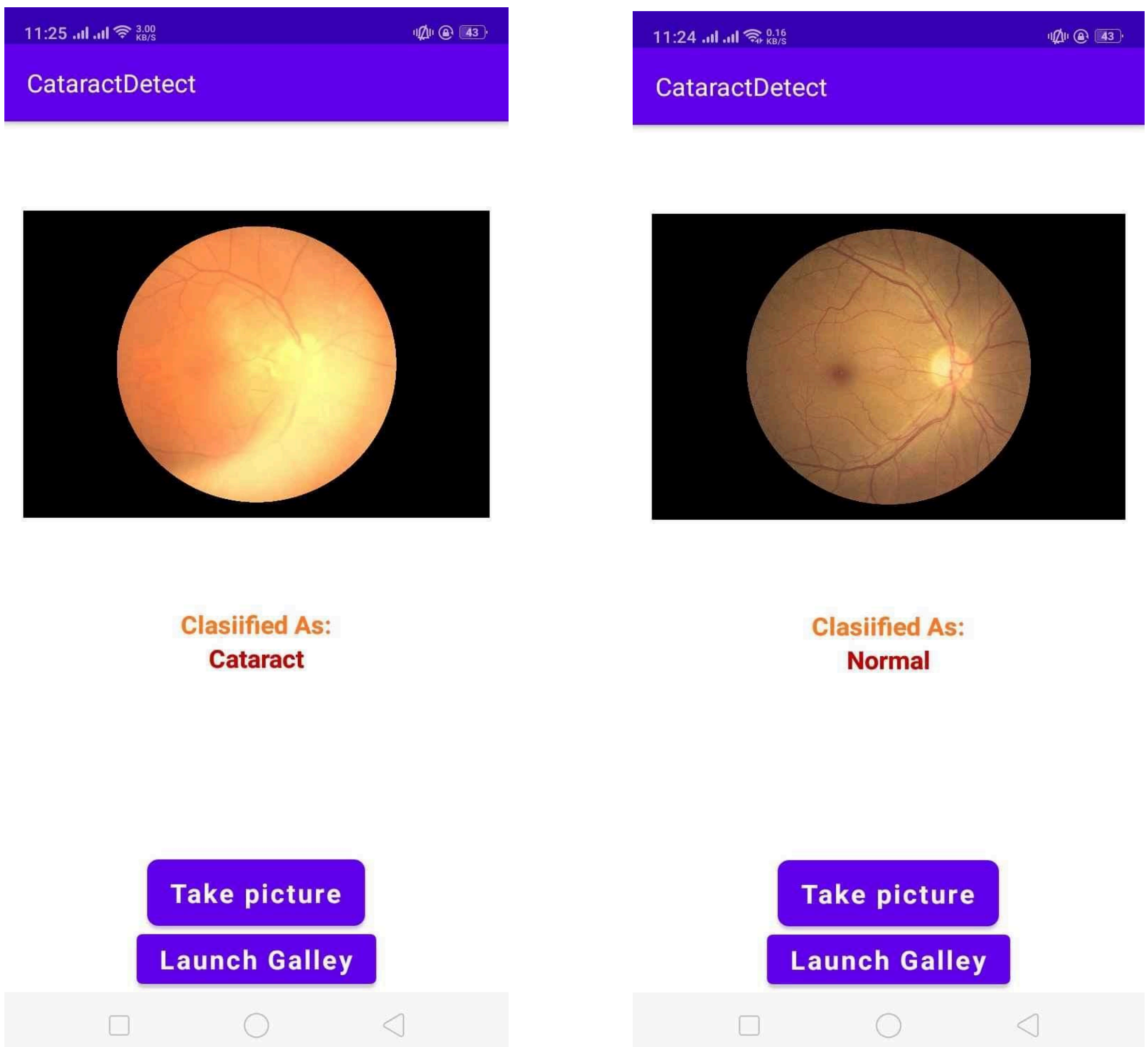


(a) (b)

Figure 20: Digital Image Normal Classify and Digital Image Cataract Classify

In Figure 20(a) we are showing the digital images output which is classified as Normal. This is an image which shows the mobile application being tested by one of our team mates. In Figure 20(b)we are showing the digital images output which is classified as Cataract. This is an image which shows the mobile application being tested by one of our digital image databases.

In figure 21(a) we are showing the fundus image output which is classified as Cataract.This is an image which shows the mobile application being tested by one of our fundus image databases. We launched this picture from the gallery. In figure 21(b) we are showing the fundus image output which is classified as Normal .This is an image which shows the mobile application being tested by one of our fundus image databases. We launched this picture from the gallery.



(a) (b)

Figure 21: Fundus Image Cataract Classify and Fundus Image Normal Classify

Chapter 5 Impacts of the Project

5.1 Impact of this project on societal, health, safety, legal and cultural issues

5.1.1 Societal impact

This project will reduce travel and healthcare visits. People can devote more time to their jobs, families, and friends. Furthermore, this effort will assist people in becoming more self-sufficient and independent. They won't have to worry about frequently requesting a caretaker to take them to the doctor. People can do jobs in many sectors of this project. Also, if we can attend many social healthcare programs we can encourage people to use these applications for saving both money and time.

5.1.2 Health impact

The app will help people identify signs of cataracts at an early stage. Early detection allows for timely intervention and treatment, potentially preventing further deterioration of vision and improving the overall eye health. By reaching a larger population, the app helps ensure that more people can benefit from early cataract detection and timely treatment. People will be able to monitor their eye health over time and also be warned if there are risks of cataracts happening in the future.

5.1.3 Safety

The app would have a leading role in keeping the patient safe. It would constantly prompt the user for checking current eye health and produce medical reports based on the current date so that the patients can be monitored whether they are at risk of developing cataracts or not. There will be timely intervention if the patient is at risk. As cataract patients are at risk of being hurt or tripping due to poor vision, the cataract detection app would help. The app is safe to use as the model is generating a 94.9% accuracy.

5.1.4 Legal

In many countries, medical devices, including healthcare apps, are subject to specific regulations and must meet certain safety and performance standards. Cataract detection apps that provide diagnostic or treatment recommendations may fall under these regulations. Developers and operators of the app may need to ensure compliance with relevant laws, obtain necessary certifications, and follow regulatory procedures to legally market and distribute the app. Cataract detection apps often collect and process personal health information from users. It is important for app developers and operators to comply with data protection laws and regulations to ensure the privacy and security of user data. This includes obtaining informed consent from users, implementing appropriate security measures to protect data from unauthorized access or breaches, and complying with data storage and retention requirements. If the cataract detection app is promoted or advertised, there may be regulations governing the advertising and marketing of healthcare products or services. App developers and operators should be aware of restrictions on claims, testimonials, and promotional activities to ensure compliance with applicable laws. The project may need to comply with various regulations related to data privacy, medical device regulations, and ethical guidelines for healthcare research. Compliance with these regulations can ensure that the project operates legally and ethically, protecting the rights and safety of patients and stakeholders.

5.1.5 Culture

A cataract detection app that is available in multiple languages and considers cultural sensitivities can improve access to eye care for diverse populations. By offering language options and culturally relevant information, the app can bridge language and cultural barriers, ensuring that individuals from various cultural backgrounds can understand the app's instructions, educational content, and diagnostic results. Cultural factors can contribute to health disparities, including disparities in access to healthcare services and utilization. A cataract detection app can help address these disparities by reaching underserved communities or regions where access to specialized eye care may be limited. By incorporating cultural considerations and providing targeted outreach, the app can increase awareness, early detection, and access to appropriate care within culturally diverse populations. A cataract detection app can serve as an educational tool to raise awareness about cataracts, dispel cultural myths or misconceptions, and provide accurate information about treatment options. By promoting culturally sensitive educational content, the app can contribute to a better understanding of cataracts within diverse cultural communities and empower individuals to make informed decisions about their eye health.

5.2 Impact of this project on environment and sustainability

5.2.1 Environmental impact

This project helps to reduce the need for paper by providing digital alternatives such as an online medical prescription and report. Also it helps to promote energy conservation by reducing the need for physical transportation. Additionally, the use of mobile devices, such as smartphones or tablets, for diagnostics is generally more energy-efficient compared to traditional diagnostic equipment, resulting in lower energy consumption and greenhouse gas emissions. By using less energy, the app helps reduce greenhouse gas emissions and contributes to mitigating climate change. For example, apps that provide good online service can reduce the number of vehicles on the road. As a result, there would be lower fuel consumption and greenhouse gas emissions associated with transportation. Furthermore, it will reduce the need for cumbersome medical equipment that will take more energy to produce as well as release toxic waste to the environment.

5.2.2 Sustainability

A cataract detection app can help conserve valuable healthcare resources. The app utilizes advanced algorithms and artificial intelligence to analyze images and detect cataracts, leading to quicker and more accurate diagnoses. This efficiency reduces the need for repeat tests or unnecessary procedures, thereby conserving medical supplies, energy, and personnel time. The app's ability to reach individuals in remote or underserved areas can improve accessibility to eye care services. By providing early detection and timely intervention, the app can help prevent vision deterioration, reducing the need for more complex and resource-intensive treatments in the future. This efficiency in detecting and treating cataracts can contribute to more sustainable use of healthcare resources. Early detection of cataracts through the app facilitates timely treatment, which can help individuals preserve their vision in the long term. This can have positive social and economic impacts by enabling individuals to remain active, independent, and productive members of society, reducing the need for additional support or assistance.

Chapter 6 Project Planning and Budget

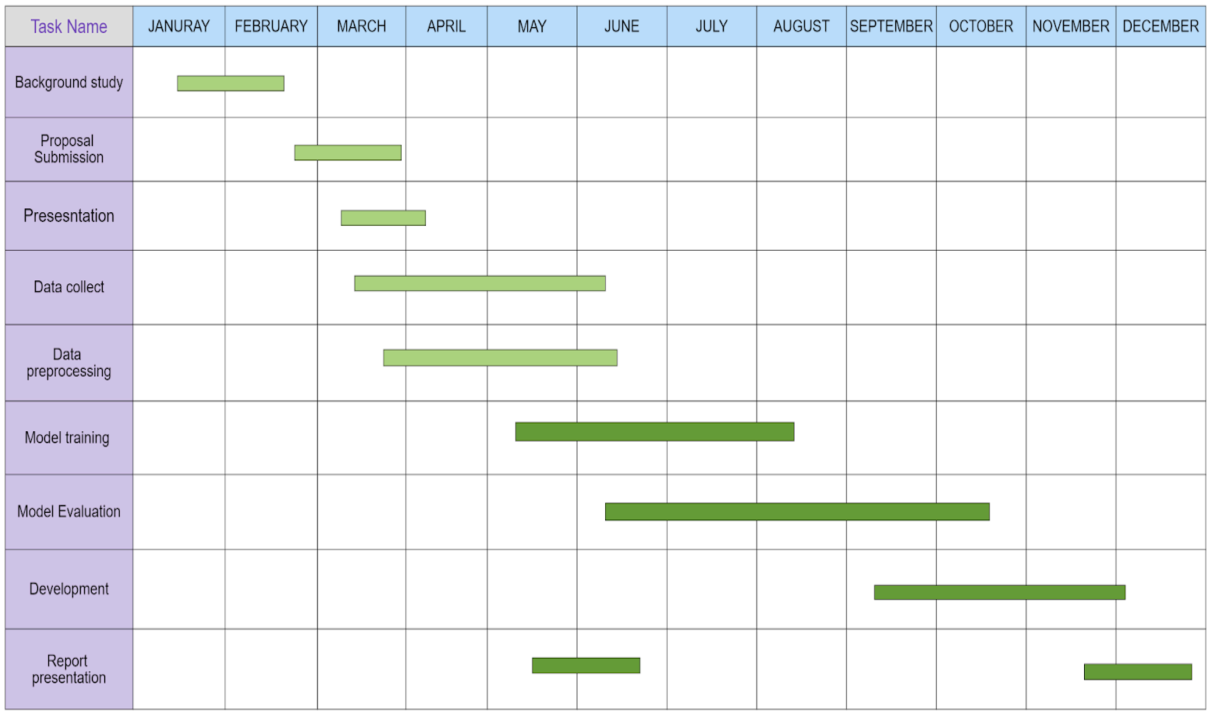


Figure 22: Gantt chart for Cataract Application Development

In Figure 22, we can see the table for Gantt Chart. It shows the different parts and planning of our project divided between the 12 months. We had 9 different components and tried to finish our relevant work within that time frame.

In order to build this application, we utilized open source libraries and free software, such as Google Colab and Android Studio and resources available on the internet. However, if the project were to be implemented in real-life with enhanced quality the following budgeting needs to be considered.

Chapter 7 Complex Engineering Problems and Activities

7.1 Complex Engineering Problems (CEP)

Table IV: Demonstrates the complex engineering problem attributes of Cataract Application development

Attributes		**Addressing the complex engineering problems (P) in the project**
P1	Depth of knowledge required	The project requires knowledge of Java and Android Development, Python for Machine Learning, Data pre-processing, training and testing with VGG19 model using Python libraries (TensorFlow, Scikit Learn, Numpy, OpenCv and Pandas)
P2	Range of conflicting requirements	Sensitivity vs Specificity: Sensitivity refers to the ability of the app to correctly identify cataracts when they are present, while specificity refers to its ability to correctly identify the absence of cataracts. Increasing sensitivity may lead to a higher number of false positives, incorrectly identifying cataracts in healthy eyes. Conversely, increasing specificity may result in false negatives, failing to detect cataracts in some cases. Finding an optimal threshold that balances sensitivity and specificity is crucial.
P3	Depth of analysis required	There is no unique way to design. Understanding the disease and the attributes that contribute to it must be researched. Extensive data collection and

		analysis. Algorithms with high accuracy must be used. Regulatory requirements, data privacy laws, and medical device regulations must be researched for each country for practical implementations.
P4	Familiarity of issues	Basic function implementations using Java and Python were known. Android development using Android Studio was known. However, for this project we had to learn about implementing the libraires, data pre-processing, testing and training.
P5	Extent of applicable codes	Libraries are pre-written code, functions, routines, or other resources that can be utilized to build complex systems by saving time. Here libraries such as (TensorFlow, Scikit Learn, Numpy, OpenCv and Pandas) were used.
P6	Extent of stakeholder involvement	There are several stakeholders that need to be involved including the owner of the device, installing places, Ministry of Information, healthcare professionals, patients, App Developers, health institutions etc.
P7	Interdependence	Project involves a number of interdependent sub-systems such as Android Studio is used for development of the app, Firebase to connect to the online database and Spyder to deal with the data pre-processing, testing and training.

7.2 Complex Engineering Activities (CEA)

Table V: Table of Complex Engineering Problem Activities

Attributes		**Addressing the complex engineering activities (A) in the project**
A1	Range of resources	This project involves human resource, money, modern tools (simulation software/mobile APP), etc.
A2	Level of interactions	Involves interactions between different stakeholders including group members to design the device, doctors to verify the accuracy of the data, health organizations to collect data, etc.
A3	Innovation	Brings eye care to the doorsteps of patients. Uses the back camera of smartphones to make cataract detection quick and easy. No medical equipment is required.
A4	Consequences to society / Environment	Impacts our society since it monitors the eye health of people and helps them get early treatment and prevent vision loss.
A5	Familiarity	Needs to be familiar with implementing image processing algorithms such as VGG19 to be able to pre-process, test and train data. Also, needs to know how to work with android development environments to incorporate the detection results in the app.

Chapter 8 Conclusions

8.1 Summary

Cataracts are the major cause of blindness among adults aged 40 and older. Multiple studies have also indicated that cataracts increase the likelihood of car accidents and accidental injury among the elderly. This study describes a proof-of-concept self-screening cataract smartphone application. It enables the general population to do early detection utilizing a smartphone equipped with a camera and flash. This not only allows practically anyone to undertake self-screening at any time and from any location, but it also serves as a portable screening solution in areas with limited medical facilities or professionals. Research has revealed that such a method is feasible. Cataract prediction technology can improve accessibility to healthcare. It has the potential to reduce healthcare costs and improve productivity. Careful consideration is needed for potential social, economic, and environmental impacts.

8.2 Limitations

The following work was done 1) We collected our dataset 2) Preprocessing dataset 3) Training and testing dataset 4) Found accuracy with graph 5) Also we designed our android application and Implement it an android application. However, our project had a few limitations as well. Some of the limitations of the work that we did are insufficient data set (more data more efficiency), new features to be added and continuous improvement could be done.

8.3 Future Improvement

These are some of the future work that we have in mind: 1) We will try to increase the accuracy of our project. 2) We will try to add more features in our android application and 3) We will try to progress our classification system, which will detect more diseases related to the eyes.

The project could include detection of various other prominent eye diseases in Bangladesh such as Trachoma, Diabetic Retinopathy, Glaucoma, etc. For cataract detection itself, the system can be tested with new algorithms and technologies to increase the accuracy. It can also include grading and classification of the cataract, i.e whether it is mild, medium or severe. The application can be integrated with telemedicine so that people living in remote places can consult with a doctor and receive medicine deliveries at their doorsteps. Future improvements may also involve integrating multiple imaging modalities, such as optical coherence tomography (OCT), slit-lamp biomicroscopy, or ultrasound, with the cataract detection app. Combining information from different imaging techniques can provide a more comprehensive assessment of cataracts, aiding in accurate diagnosis and treatment planning. Incorporating augmented reality technology into the app could enhance the visualization of cataracts. Users could visualize their eyes with cataracts in real-time or overlay cataract simulations on their vision, improving their understanding of the condition and potential treatment outcomes. Collecting and analyzing anonymized data from a large number of app users can contribute to population-level studies, identifying trends, risk factors, and potential correlations related to cataracts. This data-driven approach could help in advancing research, improving treatment outcomes, and contributing to the understanding of cataract studies.

8.4 Appendix

The following codes are snippets from Google Colab for processing images with Inception V3.

```
plt.plot(r.history['loss'], label='train loss')
plt.plot(r.history['val_loss'], label='val loss')
plt.legend()
plt.show()
plt.savefig('LossVal_loss')

# plot the accuracy
plt.plot(r.history['accuracy'], label='train acc')
plt.plot(r.history['val_accuracy'], label='val acc')
plt.legend()
plt.show()
plt.savefig('AccVal_acc')
```

Figure 23: Code snippet of plotting training accuracy and validation accuracy, and training loss and validation loss

```
def plot_confusion_matrix(cm, classes, title='Confusion Matrix', cmap=plt.cm.Blues):
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    for i in range(len(classes)):
        for j in range(len(classes)):
            plt.text(j, i, str(cm[i, j]), horizontalalignment="center", color="white")

    plt.xlabel('Predicted Label')
    plt.ylabel('True Label')

class_names = list(test_generator.class_indices.keys())
plt.figure(figsize=(6, 6))
plot_confusion_matrix(confusion, classes=class_names)
plt.show()
```

Figure 24 : Code snippet showing the confusion matrix

The following codes are snippets from Google Colab for processing fundus images with VGG19.

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.2)
```

Figure 25: The code snippet shows the test-train split

```
for layer in vgg.layers:
    layer.trainable = False
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Flatten,Dense
model = Sequential()
model.add(vgg)
model.add(Flatten())
model.add(Dense(1,activation="sigmoid"))
model.summary()
```

Figure 26: The code snippet shows the different layers

```
model.compile(optimizer="adam",loss="binary_crossentropy",metrics=["accuracy"])
from tensorflow.keras.callbacks import ModelCheckpoint,EarlyStopping
checkpoint = ModelCheckpoint("vgg19.h5",monitor="val_acc",verbose=1,save_best_only=True,
                             save_weights_only=False,period=1)
earlystop = EarlyStopping(monitor="val_acc",patience=5,verbose=1)
history = model.fit(x_train,y_train,batch_size=32 ,epochs=15,validation_data=(x_test,y_test),
                    verbose=1,callbacks=[checkpoint,earlystop])
```

Figure 27: The code snippet shows the optimizers and other adjustments

```
from mlxtend.plotting import plot_confusion_matrix
cm = confusion_matrix(y_test,y_pred)
plot_confusion_matrix(conf_mat = cm,figsize=(8,7),class_names = ["Normal","Cataract"],
                      show_normed = True);
```

Figure 28: The above code snippet shows the confusion matrix for fundus images with VGG19

The following are code snippets from Android Studio.

```java
package com.example.imageclassify;

import android.Manifest;
import android.content.Intent;
import android.content.pm.PackageManager;
import android.graphics.Bitmap;
import android.media.ThumbnailUtils;
import android.net.Uri;
import android.os.Build;
import android.os.Bundle;
import android.provider.MediaStore;
import android.view.View;
import android.widget.Button;
import android.widget.ImageView;
import android.widget.TextView;

import androidx.annotation.Nullable;
import androidx.appcompat.app.AppCompatActivity;

import com.example.imageclassify.ml.Model1;

import org.tensorflow.lite.DataType;
import org.tensorflow.lite.support.tensorbuffer.TensorBuffer;

import java.io.IOException;
import java.nio.ByteBuffer;
import java.nio.ByteOrder;

public class MainActivity extends AppCompatActivity {

    Button camera, gallery;
    ImageView imageView;
    TextView result;
    int imageSize=224;
```

Figure 29 MainActivity.java

```java
package com.example.imageclassify;

import android.content.Intent;
import android.os.Bundle;
import android.view.View;
import android.widget.Button;
import android.widget.EditText;
import android.widget.ProgressBar;

import androidx.appcompat.app.AppCompatActivity;

import com.hbb20.CountryCodePicker;

public class SendOTP extends AppCompatActivity {


    CountryCodePicker countryCodePicker;
    EditText phoneInput;
    Button sendOtpBtn;
    ProgressBar progressBar;

    @Override
    protected void onCreate(Bundle savedInstanceState) {
        super.onCreate(savedInstanceState);
        setContentView(R.layout.activity_send_otp);

        countryCodePicker = findViewById(R.id.login_countrycode);
        phoneInput = findViewById(R.id.inputMobile);
        sendOtpBtn= findViewById(R.id.buttonGetOTP);
        progressBar= findViewById(R.id.login_progress_bar);

        progressBar.setVisibility(View.GONE);


        countryCodePicker.registerCarrierNumberEditText(phoneInput);
        sendOtpBtn.setOnClickListener((v) ->{
            if(!countryCodePicker.isValidFullNumber()){
```

Figure 30 SendOTP.java

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