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Detection of Eye Diseases (Glaucoma & ARMD)

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Abstract: *As population aging has become a major demographic trend around the world, patients suffering from eye diseases, such as Glaucoma, ARMD are expected to increase. Early detection and appropriate treatment of eye diseases are of great significance to prevent vision loss and promote living quality. Conventional diagnosis methods are tremendously dependent on physicians, professional experience and knowledge, which lead to high misdiagnosis rate and huge waste of medical data.*

In this project, a deep learning model-based method which is inspired by the diagnostic process of human ophthalmologists is proposed to automatically classify the fundus photographs into 2 types with or without ARMD categories also, with or without Glaucoma. The project consists of two different neural network models developed to recognize the diseases, Glaucoma and ARMD.Better accuracy is obtained as we use deep learning. This project will be an aid to eye specialists in giving an efficient treatment. Eyesight is one of the most important senses, the developed project can help people all over to maintain eye care. This project uses Kaggle Glaucoma and ARMD datasets. This model predicts Glaucoma with 90% accuracy and ARMD with more than 70% accuracy.

Key Word*: Glaucoma Detection, ARMD detection, CNN Architecture of Detection of Glaucoma and ARMD*

I. Introduction

The rising prevalence of age-related eye diseases, particularly age-related macular degeneration, places an ever-increasing burden on health care providers. As new treatments emerge, it is necessary to develop methods for reliably assessing patients' disease status and stratifying risk of progression. The presence of drusen in the retina represents a key early feature in which size, number, and morphology are thought to correlate significantly with the risk of progression to sight-threatening age-related macular degeneration. The damage of optic nerve which is especially responsible for the proper eyesight, if damaged causes Glaucoma. Glaucoma is not only caused for elderly people, but also can affect people of any age. Manual labeling of drusen or any damage in the eye, on color fundus photographs by a human is labor intensive and is where automatic computerized detection would appreciably aid patient care.

This project aims to develop appropriate algorithm to detect these diseases. The retinal or fundus images of eye, are processed to recognize any symptoms of diseases, such as Glaucoma, ARMD (Age-related macular degeneration).

Based on the symptoms, the disease is identified, if any. This project will be an aid to eye specialists in giving an efficient treatment. Eyesight is one of the most important senses, the developed project can help people all over to maintain eye care.

Problem Definition: Eye sight is one of your most important senses: 80% of what we perceive comes through our sense of sight. Early detection and appropriate treatment of eye diseases are of great significance to prevent vision loss and promote living quality. The aim of the project is to develop a deep learning model which uses Convolutional Neural Networks to detect whether the given image of fundus is suffering from Glaucoma or Not and ARMD or not. Detection of Eye Diseases i.e., Glaucoma & ARMD model is built using Keras API of Tensorflow 2.0. The deep learning techniques will aid in fast and accurate diagnosis.

Project Scope: This project aims to detect the ARMD and GLAUCOMA diseases using deep learning model. In this project, a novel convolutional neural network model with the CNN architecture is trained with a transfer learning technique. The proposed model accepts fundus images as inputs and learns from their features to help to make a prediction. This project is developed with a motive to help Eye care workers, to help reduce the time taken for generating a diagnosing report of disease recognition, which would manually take upto 2 weeks of time. This system can be used for mass Eye care camps across remote areas, which would hugely benefit the people living in such areas.

Existing System: Most of diagnosis processes suggested earlier either rely on the variables manually measured by experts or put much effort into extracting handcrafted features with image processing approaches which bring extra complexity and instability. Thus, the deep-learning method with the ability to learn significant features directly from the fundus photography has aroused the attention of researchers in recent years.

Disadvantages:

- Uses machine learning approach which depends on clinically relevant variables such as micro count and abnormality in the graded retinal images labeled by human experts.
- Time Consuming

Proposed System: In this project, a deep learning model based method which is inspired by the diagnostic process of human ophthalmologists is proposed to automatically classify the fundus photographs into 2 types with or without ARMD categories also, with Or without Glaucoma.Quellecet al. proposed a system to detect referable ARMD by employing a deep .convolutional neural network (CNN) and automated segment ARMD lesions by creating heat maps of the convolutional layer which shows the potential to discover new bio markers in images.

The project consists of two different neural network models developed to recognize the diseases, Glaucoma and ARMD. The trained deep learning model extracts the features from the images dataset and learns to recognize the disease by making the prediction. When a fundus eye image is given as input, it categorizes into two categories for each disease (i.e., Glaucoma, Non-Glaucoma and ARMD, Non ARMD). Better accuracy is obtained as we use deep learning.

The proposed system consists of the following goals and advantages:

Goals:

- To build Effective model to predict Glaucoma and ARMD.
- Classification and prediction of Glaucoma and ARMD.
- To get high accuracy and precision.

Advantages:

- It doesn't require high computational power.
- It is very easy to implement.
- It is easily interpretable.
- It is very efficient
- It outputs well-calibrated predicted probabilities.
- High accuracy and precision.
- The database system is fast and can handle large data sets.

II. Literature Survey

Horta et al. reported a hybrid method- frame employing deep image features and random forest to combine di erent patient non-visual data like lifestyle, cataract, demographics with the image for classi cation. Detec-tion of the circular boundaries of the retina, normalization of intensity levellightness channel extraction from L*a*b color space and nally resizing the image for changing the resolution was done as preprocessing steps. Next, to extract deep image features, CNN (pre-trained with 1.2 million image data) was used. The deep features combined with the non-medical non-visual in-formation of the patients were used to train a Random Forest Classier to perform binary classification for higher severity AMD and lower severity of AMD.

Govindaiah et al. [71] reported an extended study of previous work on AREDS fundus AMD dataset using a modi ed VGG16 architecture. Macula was chosen as a Region of Interest and images were resized to a common reference level. For classi cation, a modi ed VGG16 architecture was implemented using 3x3 convolution layer and 2x2 pooling layer and for comparison a 50-layerKeras implementation of residual neural network was used. This architecture gave an accuracy of upto 92.5% in binary classification between no/early-stage AMD and intermediate/advanced stage ARMD.

Chen et al. [79] implemented a CNN with dropout and data augmentation on ORIGA and SCES dataset. A six layers deep CNN with 4 convolutional layers of progressively decreasing lter size (11, 5, 3, 3) followed by 2 dense layers was used to get 83.1% and 88.7% AUC on ORIGA and SCES respectively.

Table 2.1 shows the literature survey of Traffic Accidents Classification and Prediction using Logistic Regression. It contains name of author, title of proposed work, method, accuracy, objective, results of various existing systems.

Table no 1: Literature Survey of Detection of Glaucoma and ARMD

S. No	Author	Title	Dataset	Method	Accuracy	Demerits
1	Horta et al.	ARMD Detection using DCNN	AREDS	DCNN	76.9%	Used patients non-visual Data which may affect the prediction .
2	Govindaiah	ARMD Detection using	AREDS	VGG16	90%	Very much time taking To train the system.
3	Fu et al.	Glaucoma Identification Using DENet	DENet	SCES	83.2%	Complex process.
4	Fu et al.	Glaucoma Detection	DENet	SINDI	66.6%	Complex and Less accurate.
5	Muhammad et al.	Glaucoma Detection	HDLM	Private 102 images	93.1%	Use of private dataset and less number of images. The accuracy obtained is not accepted.

III. Modules in Detection of Glaucoma and Armd

The project consists of the following modules:

- Module for Glaucoma Detection
- Module for ARMD Detection

Module for Glaucoma Detection: Glaucoma is a condition that damages your eye's optic nerve. It gets worse over time. It's often linked to a buildup of pressure inside your eye. Glaucoma tends to run in families. You usually don’t get it until later in life. The increased pressure in your eye, called intraocular pressure, can damage your optic nerve, which sends images to your brain. If the damage worsens, glaucoma can cause permanent vision loss or even total blindness within a few years.

D-Eye model for Glaucoma:

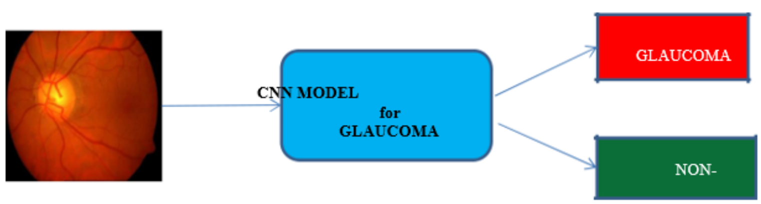

Figure no 1: Model for Glaucoma Detection

Figure no 1, depicts the block diagram of model for Glaucoma Detection, the model takesfundus image as input and predicts whether the fundus is suffering from Glaucoma or not.

The fundus eye images have been taken from kaggle and the deep learning model is then trained to recognize the presence or absence of disease by prediction, with certain accuracy, when a fundus eye image is given as input.

Module for ARMD detection: Age-related macular degeneration — also called macular degeneration, AMD or ARMD is deterioration of the macula, which is the small central area of the retina of the eye that controls visual acuity. The health of the macula determines our ability to read, recognize faces, drive, watch television, use a computer or phone, and perform any other visual task that requires us to see fine detail.

D-Eye model for ARMD:

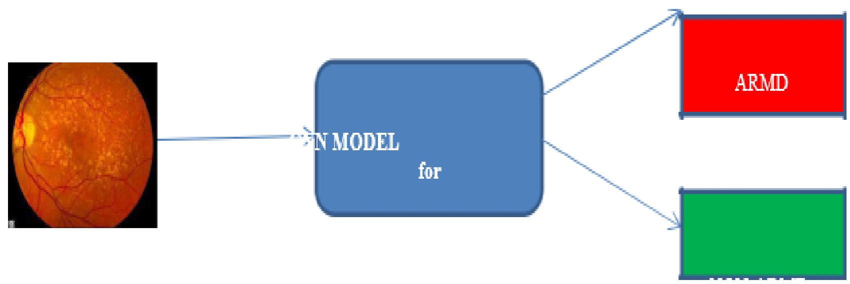

Figure no 2: Model for ARMD Detection

Figure no 2, depicts the block diagram of model for Glaucoma Detection, the model takes fundus image as input and predicts whether the fundus is suffering from ARMD or not.

The fundus eye images have been taken from stare, the deep learning model is then trained to recognize the presence or absence of disease by prediction, with certain accuracy, when a fundus eye image is given as input.

IV. Methodology of Detection of Glaucoma and Armd

Data set Analysis:

- The Glaucoma dataset is collected from Kaggle.
- The kaggle data set consists of around 500 images belonging to Glaucoma and other 500 belonging to Non-Glaucoma.
- The dataset for ARMD is taken from State Dataset.
- The stare data set consists of around 900 images belonging to ARMD disease.
- The references for dataset are mentioned below:

Data Pre-Processing:

- Preprocessing refers to all the transformations on the raw data before it is fed to the machine learning or deep learning algorithm.
- In the pre-processing, the size of all the images is fit into frame of size, (128, 128).
- Rescaling is done to transform every pixel value from range [0,255] -> [0,1].
- shearing displaces each point in the vertical direction by an amount proportional to its distance from an edge of the image.
- This transformation zooms the initial image in or out.
- It flips the image with respect to the vertical axis. One can either turn it on or off using the horizontal_flip parameter.

Converting Images to Pixels:

- Computers see an input image as an array of pixels.
- Based on the image resolution, it will see h x w x d (h = Height, w = Width, d = Dimension).
- E.g., An image of 6 x 6 x 3 array of a matrix of RGB (3 refers to RGB values) and an image of 4 x 4 x 1 array of a matrix of grayscale image.
- tf.keras.preprocessing.image.img_to_array (img, data_format=None, dtype=None)
- It returns a 3D numpy array.

CNN Architecture of Detection of Glaucoma and ARMD:

The Artificial neural networks are the computing systema vaguely inspired by biological neural networks. Such systems learn to perform tasks by considering examples. Among various Artificial neural networks, Convolutional Neural networks (CNN) are considered efficient for image classification. CNN image classification takes an input image, processes it and classifies it under certain specified categories.

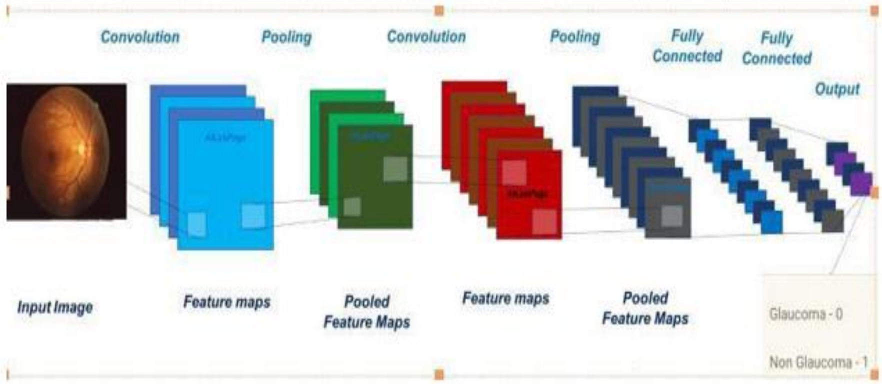

Figure no 3: CNN Architecture of Detection of Glaucoma and ARMD

Figure no 3, shows the architecture of Convolutional Neural Network used for this project, consisting of input fundus image and all the convolution and pooling layers and output predictor.

Each input image will pass through a series of convolution layers. In which a filter is used to reduce the size of the image matrix as specified. Pooling is performed in order to reduce the number of trainable parameters. Subsequently, pooling layers are added between convolution layers. In the Fully Connected layer, the results of convolution/pooling layers are used to classify the image accordingly.

- CNN image classifications take an input image, process it and classifies it under certain categories.
- Each input image will pass through a series of convolution layers.
- Pooling is performed in order to reduce the number of trainable parameters.
- Subsequently, pooling layers are added between convolution layers.
- In the Fully Connected layer, the results of convolution/pooling layers are used to classify the image accordingly.

Conv2D Layer:

conv2D: to perform convolution operation a filter is used whose size can be specified, at last a matrix is obatined, which is much smaller than the input matrix.

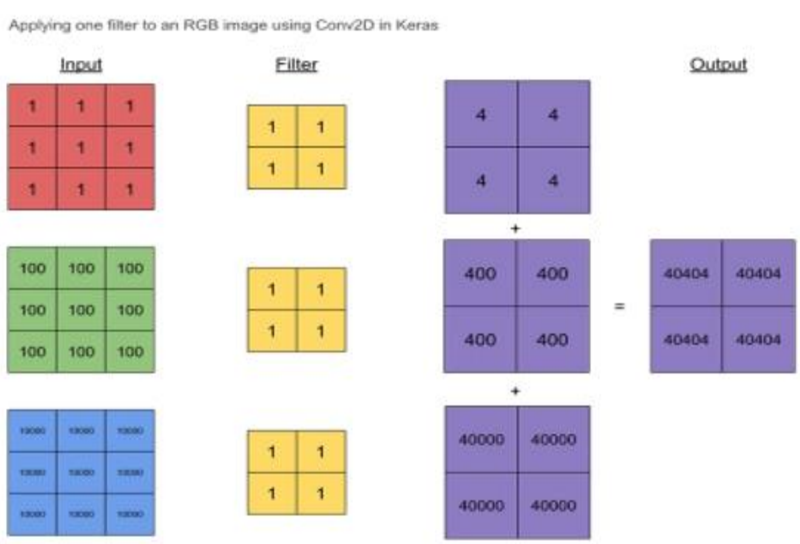

Figure no 4: Example for functioning of Convolution LayerFigure 4.2represents how the Convolution works for a given input of matrices.

MaxPooling2Layer:

Sometimes when image is too large, we would need to reduce the number of trainable parameters. subsequently we add pooling layers between convolution layers. The most common from of pooling layer generally applied is the max pooling. Pooling layers provide an approach to down sampling feature maps by summarizing the presence of features in patches of the feature map. Two common pooling methods are average pooling and max pooling that summarize the average presence of a feature and the most activated presence of a feature respectively.

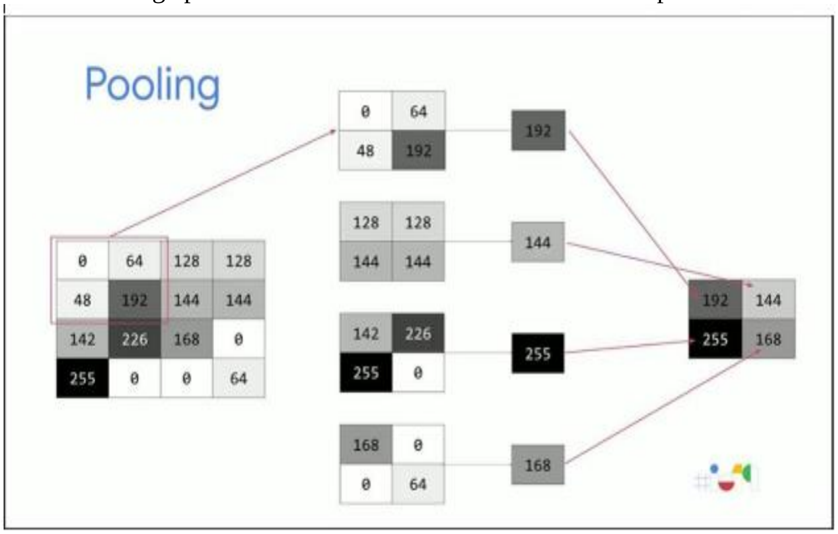

Figure no 5: Example for Maxpooling Layer

Figure no 5, shows the working of MaxPooling2D layer for a given matrix as input.

Activation Functions:

ReLu Activation Function:

- ReLU stands for rectified linear unit, and is a type of activation function. Mathematically, it is defined as y = max (0, x).
- ReLU is linear (identity) for all positive values, and zero for all negative values.

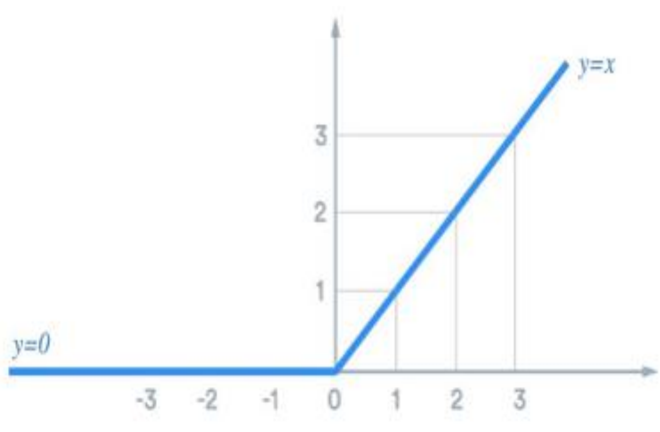

Figure no 6: Graph of ReLu Activation Function

Figure no 6, is the graphical representation of ReLu Activation Function

Sigmoid Activation Function:

- Sigmoid activation function, sigmoid(x) = 1 / (1 + exp(-x))

- For small values (<-5), sigmoid returns a value close to zero, and for large values (>5) the result of the function gets close to 1

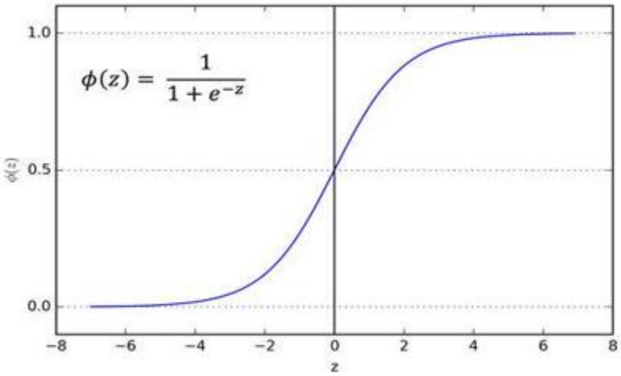

Figure no 7: Graph of Sigmoid Activation Function

Figure no 7, shows the graphical representation of Sigmoid Activation Function.

Adam Optimizer Algorithm:

Adam optimization is an extension to Stochastic gradient decent and can be used in place of classical stochastic gradient descent to update network weights more efficiently.

Momentum: When explaining momentum, researchers and practitioners alike prefer to use the analogy of a ball rolling down a hill that rolls faster toward the local minima, but essentially what we must know is that the momentum algorithm, accelerates stochastic gradient descent in the relevant direction, as well as dampening oscillations. To introduce momentum into our neural network, we add a temporal element to the update vector of the past time step to the current update vector. This gives the effect of increased momentum of the ball by some amount. This can be expressed mathematically as:

$$Vt = \gamma Vt-1 + \eta \nabla\theta J(\theta)$$
$$\theta = \theta - Vt$$

The momentum term γ is usually initialized to 0.9.

Adaptive Learning Rate: Adaptive learning rates can be thought of as adjustments to the learning rate in the training phase by reducing the learning rate to a pre-defined schedule of which we see in AdaGrad, RMSprop, Adam and AdaDelta— This is also referred to as Learning Rate Schedules.

Require: α: Stepsize
Require: $\beta_1, \beta_2 \in [0,1)$: Exponential decay rates for the moment estimates
Require: $f(\theta)$: Stochastic objective function with parameters θ
Require: θ_0: Initial parameter vector
  $m_0 \leftarrow 0$ (Initialize 1st moment vector)
  $v_0 \leftarrow 0$ (Initialize 2nd moment vector)
  $t \leftarrow 0$ (Initialize timestep)
  while θ_t not converged **do**
    $t \leftarrow t+1$
    $g_t \leftarrow \nabla_\theta f_t(\theta_{t-1})$ (Get gradients w.r.t. stochastic objective at timestep t)
    $m_t \leftarrow \beta_1 \cdot m_{t-1} + (1-\beta_1) \cdot g_t$ (Update biased first moment estimate)
    $v_t \leftarrow \beta_2 \cdot v_{t-1} + (1-\beta_2) \cdot g_t^2$ (Update biased second raw moment estimate)
    $\widehat{m}_t \leftarrow m_t/(1-\beta_1^t)$ (Compute bias-corrected first moment estimate)
    $\widehat{v}_t \leftarrow v_t/(1-\beta_2^t)$ (Compute bias-corrected second raw moment estimate)
    $\theta_t \leftarrow \theta_{t-1} - \alpha \cdot \widehat{m}_t/(\sqrt{\widehat{v}_t} + \epsilon)$ (Update parameters)
  end while
  return θ_t (Resulting parameters)

Figure no 8: Adam Optimization Algorithm

Figure no 8, shows the steps involved in Adam optimization Algorithm which is used in this project for optimization of CNN models.

This project uses Adam Algorithm for optimization as it is efficient because it is a combination of Stochastic Gradient Descent with momentum and adaptive learning. So, it gives better results than rmsprop and other algorithms.

Input and Output Design: The following some are the projects inputs and outputs.

INPUT:

- Importing the all required packages like numpy, pandas, matplotlib, scikit – learn and required machine learning algorithms packages.
- Setting the dimensions of visualization graph.
- Downloading and importing the dataset and convert to data frame.

OUTPUT:

- Pre-processing the importing data frame for imputing nulls with the related information.
- All are displaying cleaned outputs.
- After applying machine learning algorithms it will give good results and visualization plots.

INPUT DESIGN:

Input design is a part of overall system design. The main objective during the input design is as given below:

- To produce a cost-effective method of input.
- To achieve the highest possible level of accuracy.
- To ensure that the input is acceptable and understood by the user.

OUTPUT DESIGN:

Outputs from computer systems are required primarily to communicate the results of processing to users. They are also used to provide a permanent copy of the results for later consultation. The various types of outputs in general are:

- External Outputs, whose destination is outside the organization,
- Internal Outputs whose destination is within organization and they are the
- Operational outputs whose use is purely within the computer department.
- Interface outputs, which involve the user in communicating directly with the outputs were needed to be generated as a hard copy and as well as queries to be viewed on the screen. Keeping in view these outputs, the format for the output is taken from the outputs, which are currently being obtained after manual processing. The standard printer is to be used as outputmedia for hard copies.

Output Screens:

Figure no 9: The output indicating Non-Glaucoma

Figure no 9, shows the output predicted by Glaucoma detector as Non-Glaucoma correctly on server side i.e, colab notebook for given non-Glaucoma fundus image as input.

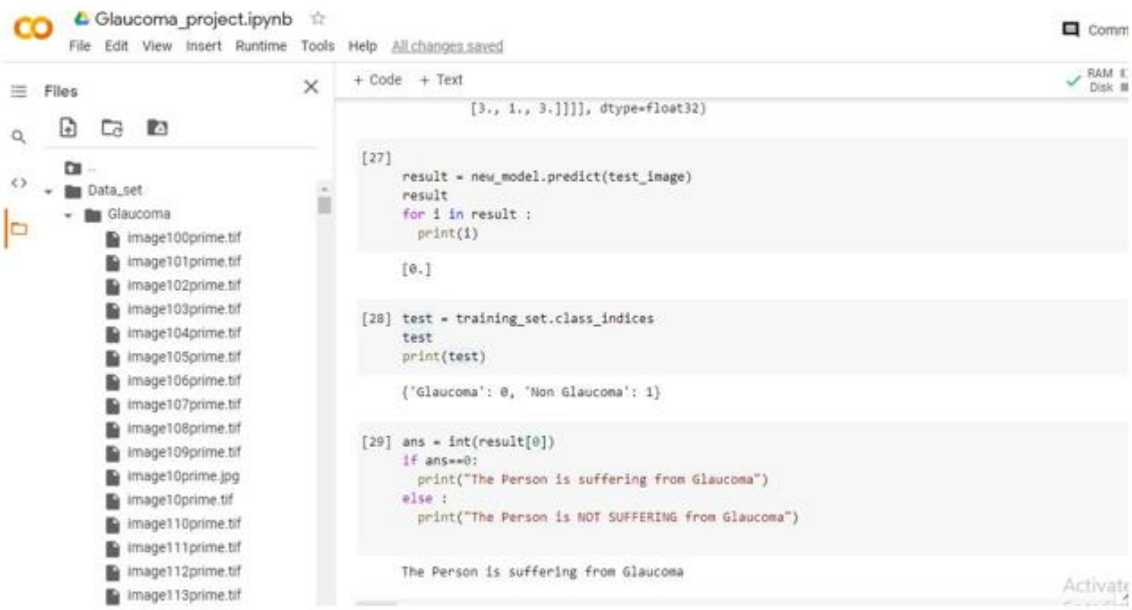

Figure no 10: The output indicating Glaucoma

Figure no 10, shows the output predicted by Glaucoma Detection Model as Glaucoma for the given fundus image on colab notebook.

```
classifier.summary()

Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 62, 62, 32)        896
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 31, 31, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 29, 29, 32)        9248
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 14, 14, 32)        0
_________________________________________________________________
flatten (Flatten)            (None, 6272)              0
_________________________________________________________________
dense (Dense)                (None, 128)               802944
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 129
=================================================================
Total params: 813,217
Trainable params: 813,217
Non-trainable params: 0
_________________________________________________________________
```

Figure no 11: The output for ARMD

Figure no 11, shows the output predicted by the ARMD model for a given fundus image as input.

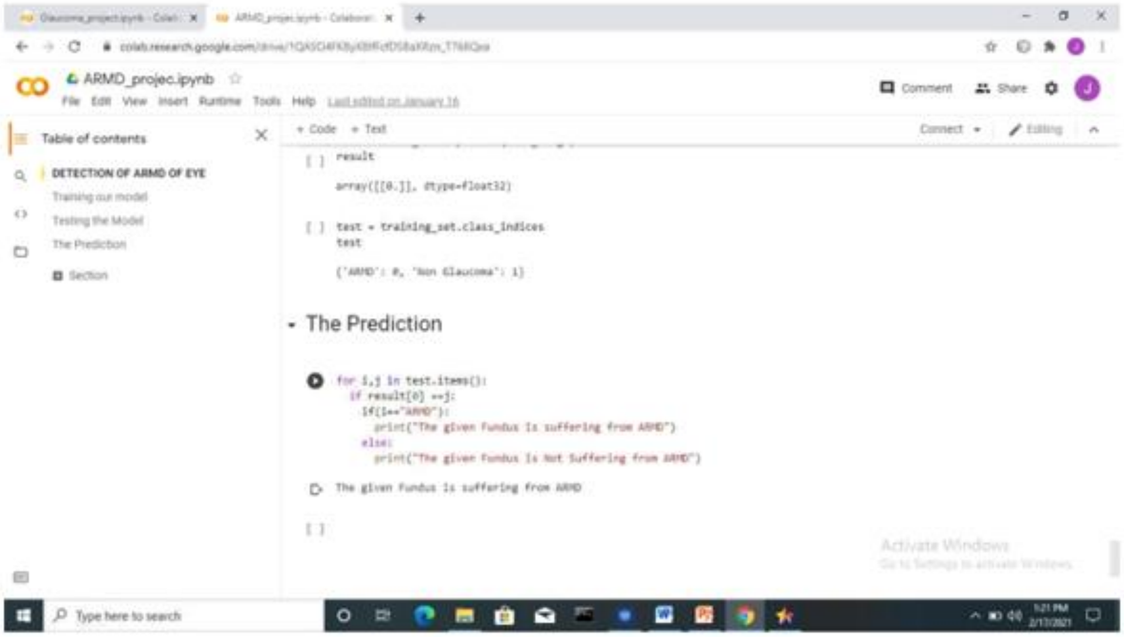

Figure no 12: The Training parameters for CNN model

Figure no 12, shows all the trainable parameters count in each layer of the Galucoma and ARMD Detection Model and output shape of each layer in CNN architecture of this project.

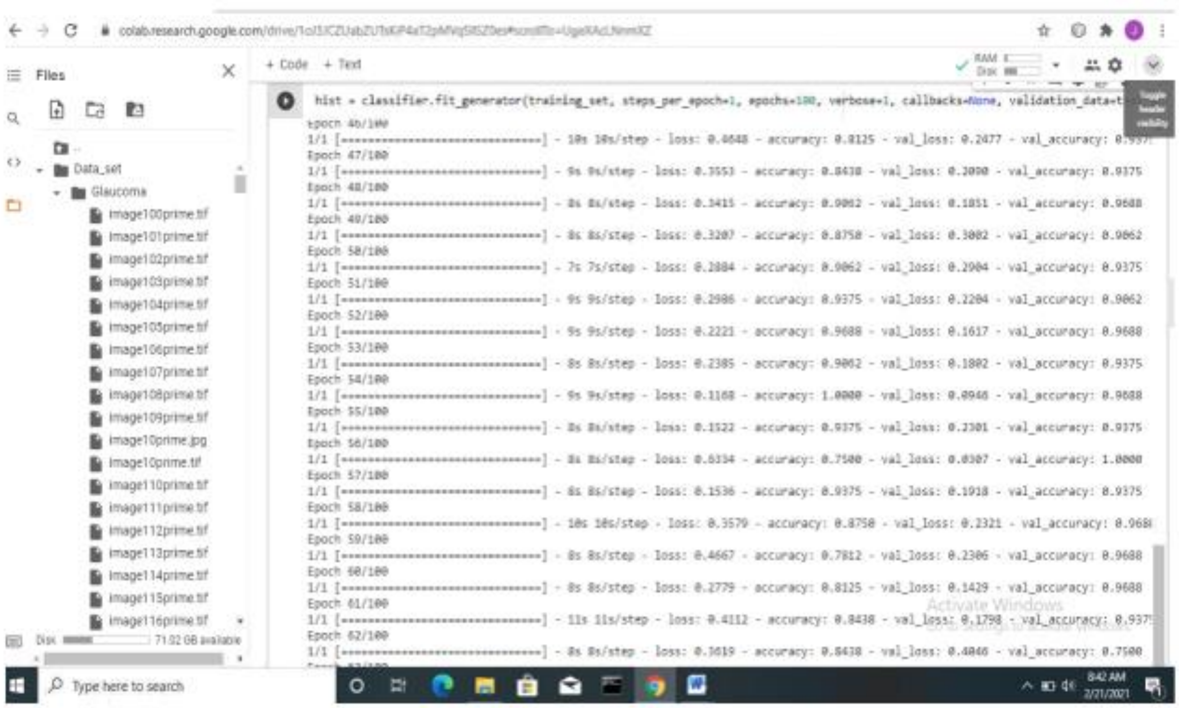

Figure no 13: The Epochs of Training DL Model

Figure no 13, shows the training of Glaucoma and ARMD model for the given training dataset usally referred as epochs. In each epoch the model goes through the entire dataset once and reports accuracy and loss values.

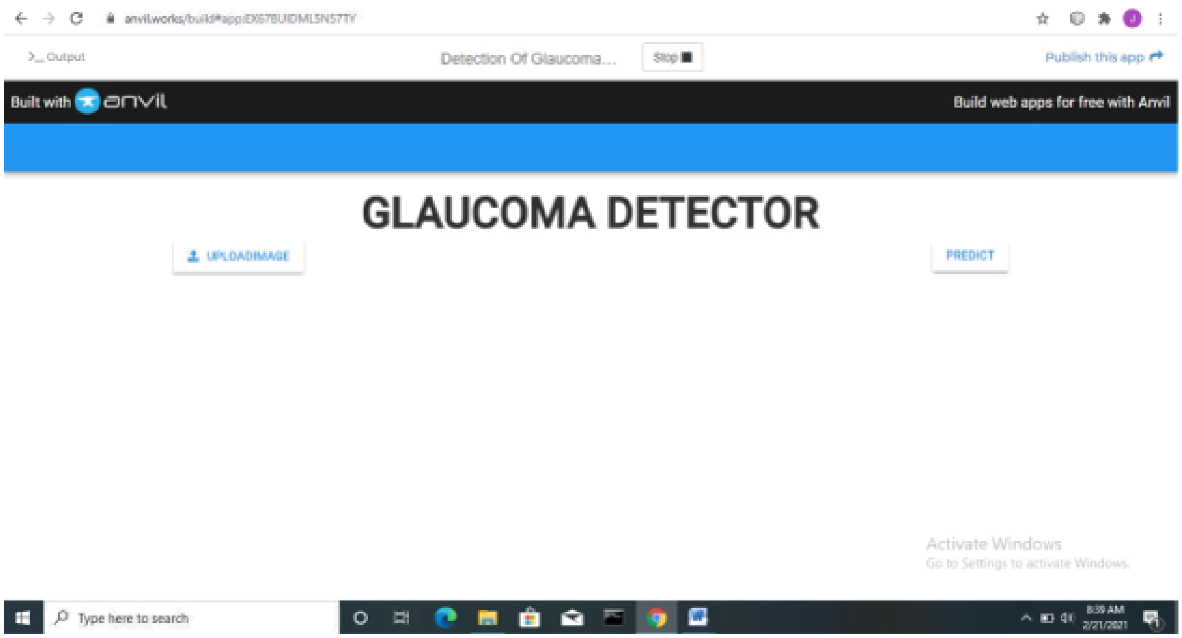

Figure no 14: The User Interface for Detection of Glaucoma

Figure no 14, shows shows the output screen of Graphical User Interface for a user to uploadhis/her fundus image and check whether it is suffering from Glaucoma or not.

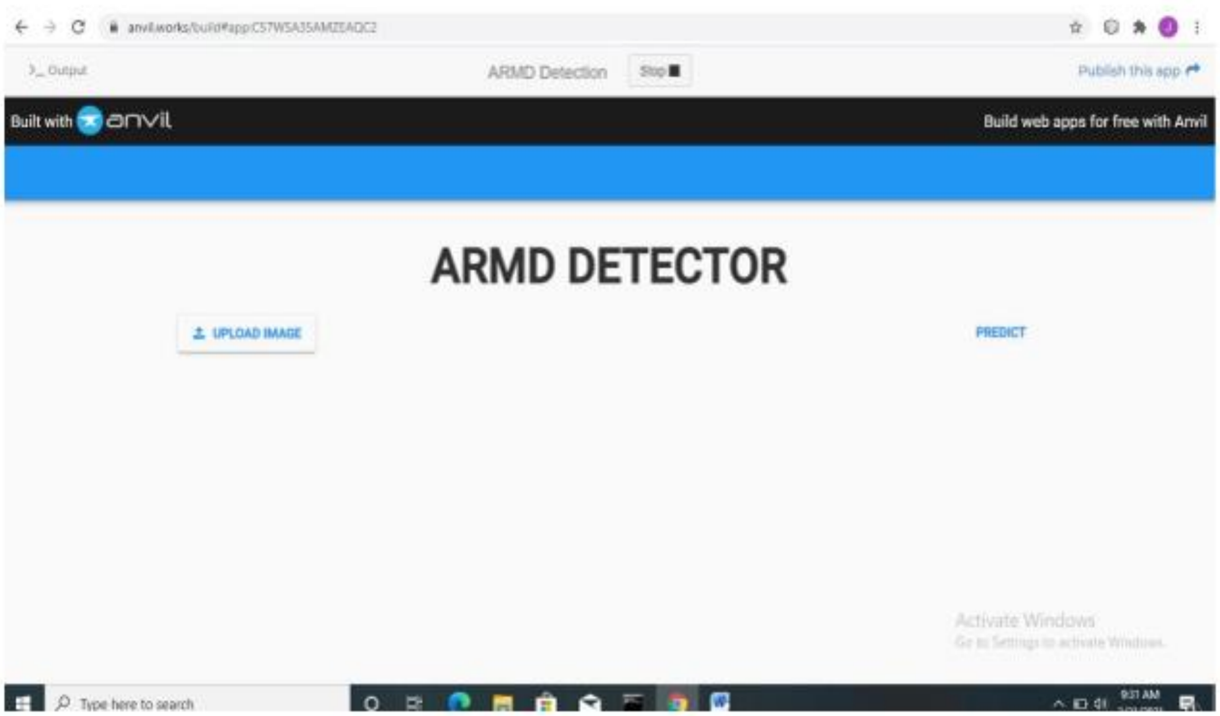

Figure no 15: The User Interface for Detection of ARMD

Figure no 15, shows the output screen of Graphical User Interface for a user to upload his/her fundus image and check whether it is suffering from ARMD or not.

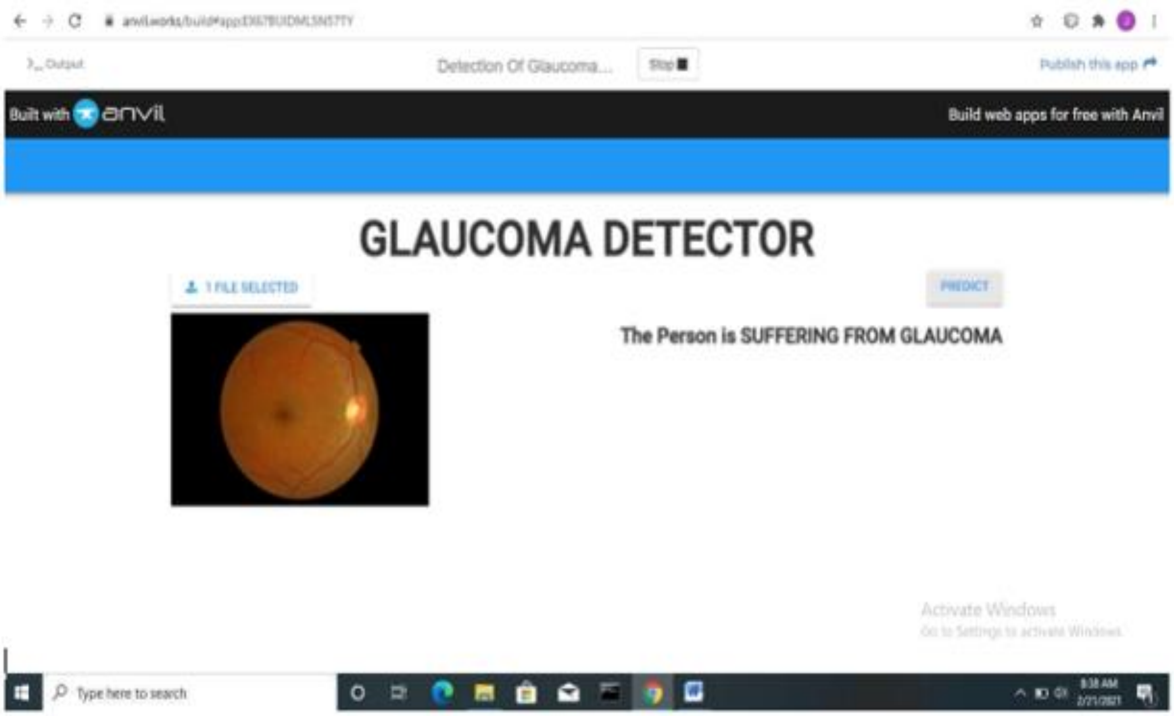

Figure no 16: The User Interface Output Screen indicating Glaucoma

Figure no 16, shows the output screen of Graphical User Interface indicating that the given fundus image is suffering from Glaucoma.

Figure no 17: The User Interface indicating NOT –Glaucoma

Figure no 17, shows the output screen that the given fundus image is not suffering from Glaucoma.

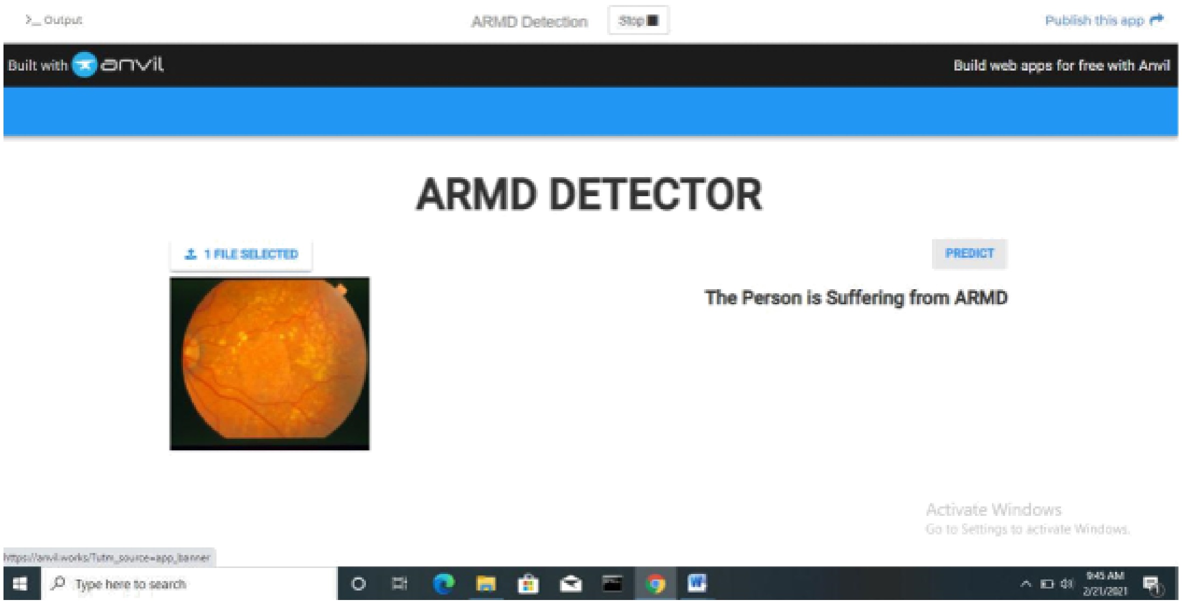

Figure no 18: The User Interface Output Screen indicating ARMD

Figure no 18, shows the user interface output screen indicating that the given fundus image is suffering from ARMD.

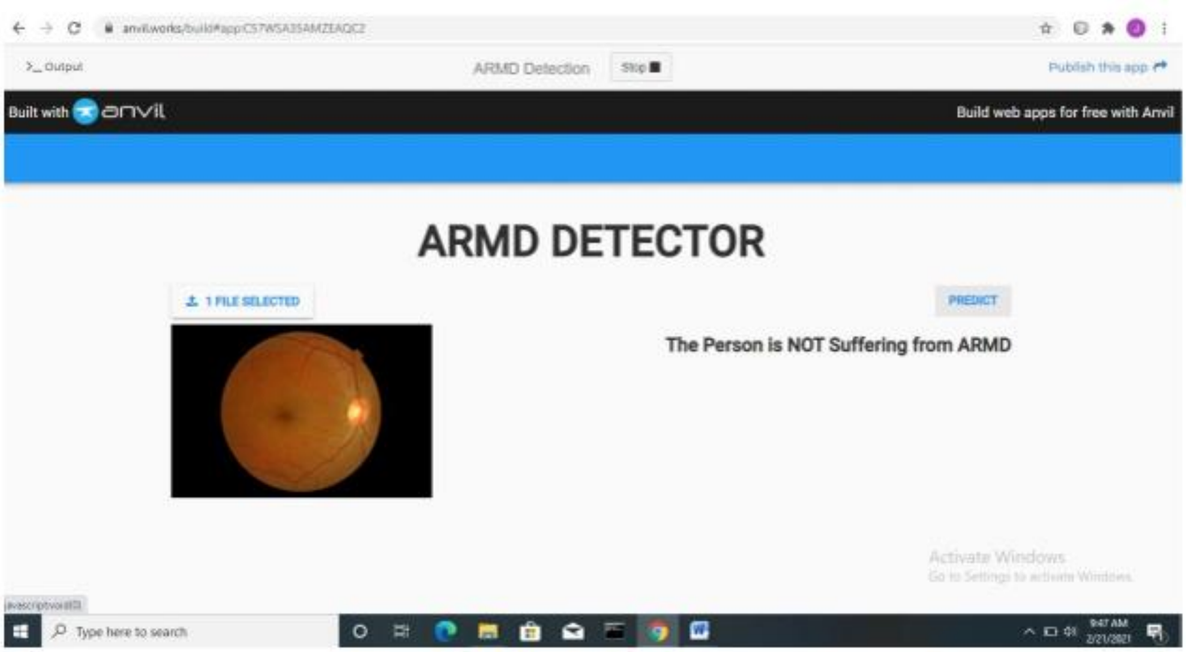

Figure no 19: The User Interface Output Screen indicating NOT-ARMD

V. Conclusion & Future Scope

Conclusion: The Detection of Glaucoma and ARMD project is developed with a motive to help Eye care workers, to help reduce the time taken for generating a diagnosing report of disease recognition, which would manually take upto 2 weeks of time. This system can be used for mass Eye care camps across remote areas, which would hugely benefit the people living in such areas. Though the system gives good efficiency, it is recommended to be used only by trained officials, under the care of ophthalmologists.

- The testing efficiency of the system in recognizing the Glaucoma disease is 0.9062
- The testing loss of the system in recognizing the Glaucoma disease is 0.1876
- The testing efficiency of the system in recognizing the ARMD disease is 0.7164
- The testing loss of the system in recognizing the Glaucoma disease is 0.2365

Future Scope: Future algorithms involving drusen detection should aim to provide useful quantification to aid screening for ARMD. A screening program should stratify patients according to optimal follow-up pathway. For automated drusen detection to contribute to the cost-effectiveness of a screening program for ARMD, it must separate individuals with drusen associated with normal aging from patients whose drusen load progresses and stratify patients with mild ARMD into those at low risk and at high risk of progression to severe ARMD. This would enable the ophthalmologist to select relevant patients for regular follow-up, thus improving the efficiency of patient care. The Datasets available are now foreign datasets, and with the help of a device which is reliable in collection the fundus eye images with HD quality would be a future scope for the further development of the project.

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