

OCULAR DISEASE RECOGNITION

Submitted in partial fulfillment of the
requirements for the award of
Bachelor of Technology Degree in Information Technology

by

Alina Mushtaq (40120008)

Kishore Kumar K (40120048)



DEPARTMENT OF INFORMATION TECHNOLOGY

SCHOOL OF COMPUTING

SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY

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JEPPIAAR NAGAR, RAJIV GANDHI SALAI,

CHENNAI - 600 119

April-2024

ACKNOWLEDGEMENT

I am pleased to acknowledge our sincere thanks to the **Board of management of SATHYABAMA INSTITUTE OF SCIENCE AND TECHNOLOGY** for their kind encouragement in doing this project and for completing it successfully. I am grateful to them.

I convey my thanks to **Dr. T. Sasikala M.E., Ph.D., Dean**, School of Computing and **Dr. R. Subhashini M.E., Ph.D., Head of the Department, Department of Information Technology** for providing us the necessary support and details at the right time during progressive reviews.

I would like to express our sincere and deep sense of gratitude to my Project Guide **Dr. R. Subhashini M.E., Ph.D.**, for her valuable guidance suggestions and constant encouragement paved way for the successful completion of my phase 2 project work.

I wish to express our thanks to all Teaching and Non-teaching staff members of the **Department of Information Technology** who were helpful in many ways for the completion of the project.



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BONAFIDE CERTIFICATE

This is to certify that this project report is the bonafide work of **Kishore Kumar K (Reg No - 40120048) & Alina mushtaq (Reg No - 40120008)** who carried out the Project Phase 2 entitled "**OCULAR DISEASE RECOGNITION**" under my supervision from January 2024 to April 2024

Internal Guide

Dr. R. Subhashini M.E., Ph.D.,

Head of the Department Dr.

R. Subhashini M.E., Ph.D.,

Submitted for Viva Voce Examination held on 18/04/2024

Internal Examiner

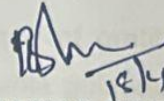
External Examiner

DECLARATION

I, Kishore Kumar K (Reg: 40120048) hereby declare that the Project Report entitled "OCULAR DISEASE RECOGNITION" is done by me under the guidance of Dr. R. Subhashini, M.E., Ph.D., is submitted in partial fulfilment of the requirements for the award of Bachelor of Technology degree in Information Technology.

DATE: 18/04/2024.

Place : Chennai



SIGNATURE OF THE CANDIDATE

ABSTRACT

The main purpose of this project on Ocular Disease Detection is to provide a diagnosing tool to detect eye diseases, from eye-fundus images using neural networks, which will be user friendly and easy to use for health care professionals and health care organisations.. The Application is programmed using Python with the concept of InceptionNet in Deep learning. The Inception v3 model fetches the correct information of the object from the fundus retinal image training dataset to improve its disease detection proficiency. Due to the enhanced image classification capabilities of this model, such a system can finally be realized. Once trained, the neural network can analyze new images and accurately detect and diagnose ocular diseases, often outperforming human experts. It also has the potential to improve access to healthcare in underserved communities by providing a cost-effective and scalable solution for early disease detection. The diseases that can be detected are Cataract (C), Diabetes (D), Glaucoma (G), Age related Macular Degeneration (A), Hypertension (H), Pathological Myopia (M),

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CHAPTER 1

INTRODUCTION

Ocular diseases present a significant risk to vision, potentially leading to irreversible blindness if not detected and treated promptly. Despite the availability of effective treatments, early diagnosis remains critical for successful intervention. Current diagnostic methods primarily rely on color fundus photography (CFP), which captures detailed images of the eye's interior surface, enabling the detection of various ocular pathologies.

However, despite its effectiveness, CFP has limitations in detecting certain ocular diseases, particularly those with subtle or few initial symptoms. Conditions such as cataracts, myopia, and diabetic retinopathy often evade early detection, complicating treatment efforts. Manual inspection and diagnosis of ocular diseases are labor-intensive tasks prone to human error, highlighting the need for more accurate and efficient diagnostic tools.

In recent years, neural networks, particularly convolutional neural networks (CNNs), have emerged as powerful tools for medical image analysis, including ocular disease detection. These deep learning-based models leverage large datasets to learn intricate patterns and features from medical images, enabling automated disease recognition with high accuracy and efficiency. The ability of CNNs to extract complex features from medical images surpasses traditional methods, offering a promising avenue for improving ocular disease diagnosis.

Advancements in deep learning algorithms, such as CNNs, have significantly enhanced the performance of ocular disease detection systems. These algorithms excel in extracting complex features from medical images, enabling more accurate and efficient disease recognition compared to traditional methods. Furthermore, the development of neural network architectures, such as InceptionNet, has further improved the capabilities of deep learning models in medical imaging tasks.

The integration of deep learning into ocular disease detection has the potential to revolutionize clinical practice. By automating the diagnosis process and providing timely and accurate assessments, deep learning models can facilitate early

intervention and treatment, thereby preserving patients' vision and improving outcomes. Moreover, the scalability and accessibility of these technologies hold promise for expanding access to quality eye care, particularly in underserved communities.

Deep learning-based approaches offer several advantages over traditional diagnostic methods in ocular disease detection. These include improved accuracy, efficiency, and scalability. Deep learning models, trained on large datasets of annotated medical images, can learn intricate patterns and features that may not be discernible to the human eye. This enables them to detect subtle abnormalities and early signs of ocular diseases with higher precision. Moreover, the automated nature of deep learning algorithms streamlines the diagnostic process, reducing the time and effort required for disease detection. This allows healthcare professionals to focus their attention on patient care and treatment planning, rather than spending valuable time on manual image analysis.

In addition to the advancements in deep learning-based ocular disease detection, ongoing research is exploring the integration of complementary technologies to further improve diagnostic accuracy and patient outcomes. One promising avenue is the incorporation of multimodal imaging techniques, such as combining color fundus photography with optical coherence tomography (OCT) or autofluorescence imaging. These complementary modalities provide additional layers of information about the eye's structure and function, enhancing the diagnostic capabilities of deep learning models. Furthermore, the integration of real-time monitoring systems and telemedicine platforms enables remote assessment and management of ocular diseases, particularly in rural or underserved areas where access to specialized care may be limited. By leveraging a combination of deep learning algorithms and complementary technologies, clinicians can enhance their ability to detect and manage ocular diseases effectively, ultimately improving vision health outcomes for patients worldwide.

The adoption of deep learning-based approaches in ocular disease detection represents a significant advancement in eye care. By harnessing the power of neural networks, clinicians can enhance their diagnostic capabilities and provide more effective treatments for patients with ocular diseases. As research and development in this field continue to progress, the future holds great promise for improving vision health through innovative technologies.

In conclusion, the integration of deep learning-based approaches into ocular disease detection marks a transformative milestone in the realm of eye care. Through the utilization of neural networks, clinicians are empowered to elevate their diagnostic proficiency, enabling the delivery of more precise and timely treatments for individuals grappling with ocular ailments. As research and development in this field march steadfastly forward, the horizon brims with the promise of even greater strides in vision health. The relentless pursuit of innovative technologies, coupled with the collaborative efforts of researchers, clinicians, and technologists, holds the potential to unlock unprecedented avenues for early detection, personalized interventions, and enhanced patient outcomes. With each breakthrough, the trajectory of ocular disease management is poised to ascend to new heights, ultimately heralding a future where sight is safeguarded with unparalleled precision and compassion.

CHAPTER 4

AIM AND SCOPE

2.1.Aim

The Aim of this project is to develop a web application to detect Ocular disease from the fundus image using Inception(convolutional neural network model) of deep learning.

2.2. Problem Statement

Early ocular disease detection is an economic and effective way to prevent blindness caused by diabetes, glaucoma, cataract, age-related macular degeneration (AMD), and many other diseases. Rapid and automatic detection of diseases is critical and urgent in reducing the ophthalmologist's workload and prevents vision damage of patients. So there is a need of Computer vision to automatically detect the disease more accurately with the help of neural network.

2.3. Scope

The main purpose of this project is to provide health care professionals and health care organisations, a diagnosing software tool that detect the disease like cataract, glaucoma, diabetes, and etc., with more accuracy and efficiency.

CHAPTER 5

LITERATURE SURVEY

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CHAPTER 4

METHODOLOGY

4.1 ARCHITECTURE

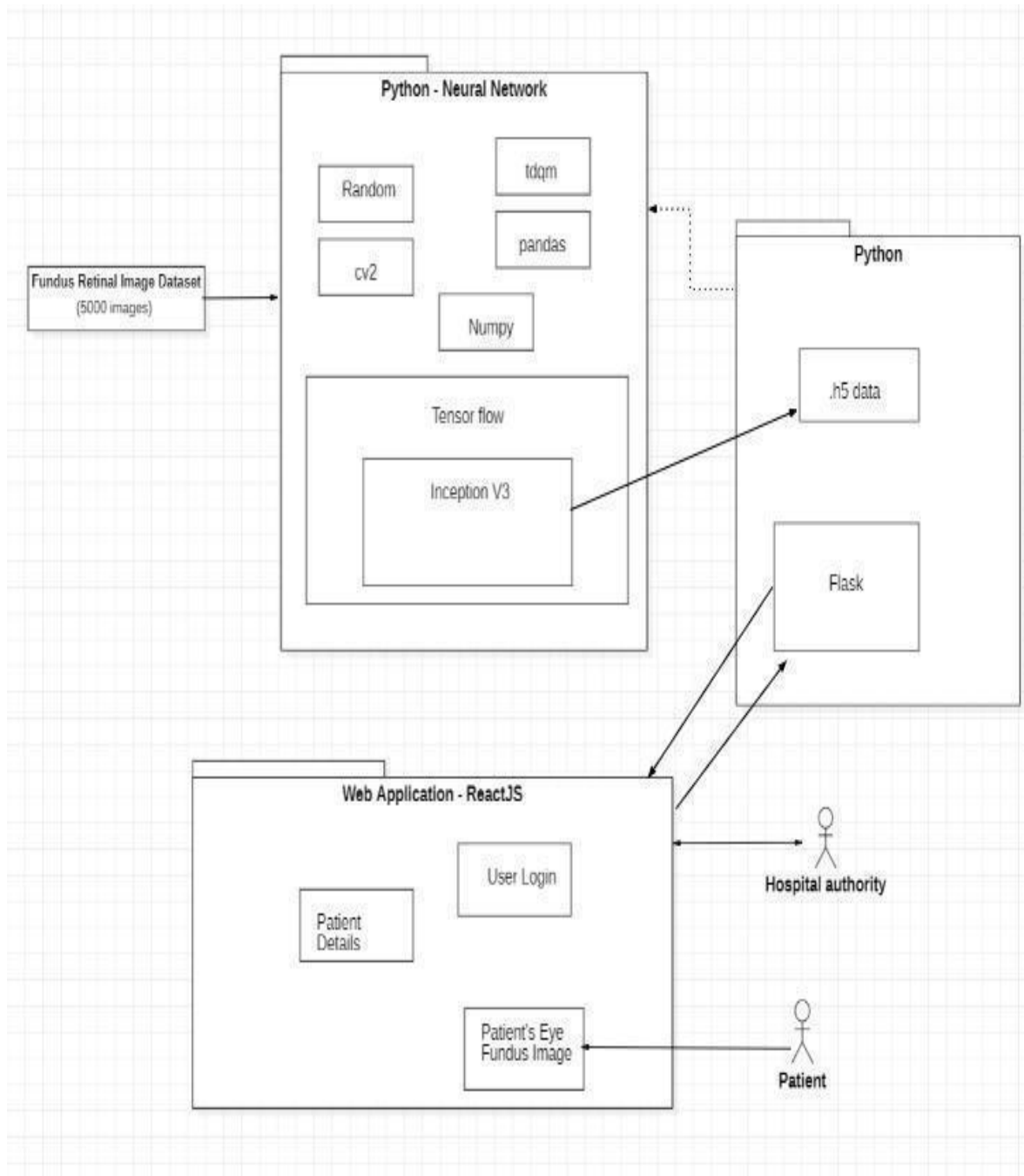


Fig.4.1 Architecture

4.2. NEURAL NETWORK

A neural network is a type of machine learning algorithm inspired by the structure and function of the human brain. It consists of interconnected nodes or neurons that are organized into layers. The input layer receives data, which is then processed by one or more hidden layers. The output layer produces the final result. During training, the neural network adjusts the weights and biases of the connections between neurons in order to improve its accuracy. Neural networks are used in a wide range of applications, such as image and speech recognition, natural language processing, and predictive analytics.

The proposed algorithm for utilizing the InceptionNet architecture in ocular disease recognition can be outlined as follows:

4.2.1. Tensorflow

TensorFlow is an open-source software library for dataflow and differentiable programming across a range of tasks. It is a popular choice for building neural networks and other machine learning models. In TensorFlow, a neural network is typically built by defining a computational graph that represents the operations and transformations applied to the input data to produce the desired output. This graph is then executed using a TensorFlow session, which performs the necessary computations and updates the network's parameters to improve its performance. TensorFlow also provides a range of tools and utilities for working with neural networks, including pre-built models, data pre-processing and augmentation tools, and visualization tools for inspecting and debugging network behaviour.

4.2.2. Inception V3

Inception-v3 is a convolutional neural network architecture that was developed by Google as part of the ImageNet Large-Scale Visual Recognition Challenge in 2015. Inception-v3 is a 48-layer deep pre-trained convolutional neural network model, as shown in equation 1 and it is able to learn and recognize complex patterns and features in medical images. One of the key features of Inception V3 is its ability to scale to large datasets and to handle images of varying sizes and resolutions. This is important in the field of medical imaging, where images can vary greatly in terms of size, resolution, and quality. Typically, the Inception module includes one

maximum pooling and three convolutions of various sizes. After the convolution operation, the channel is aggregated for the network output of the preceding layer, and the non-linear fusion is then carried out. In this model, over-fitting can be avoided while enhancing the network's expression and flexibility to various scales.

To avoid overfitting, we flattened the output layer and reduced its dimensions to one. We then added a sigmoid layer for classification, as well as a fully connected layer with 1,024 hidden units, a Relu activation function as shown in Equation. 2, and a dropout with the rate of 0.4. The weights of the classification layers were initialized using the algorithm described in (Beauxis-Aussalet and Hardman, 2014) as shown in Eq. 3. This approach allowed us to effectively use Inception V3 for our purposes.

$$e \sim U(-a, b) \rightarrow \text{Equation 1}$$

$$f(x) = \max(0, x) \rightarrow \text{Equation 2}$$

$$W_k = e \times \sqrt{\frac{6}{m}} \rightarrow \text{Equation 3}$$

Where $e \sim U(-a, b)$ is a uniform distribution in the interval $[-a, b]$, m is the size of the previous layer, and W_k stands for weight parameters in the CNN at iteration k . Overall, Inception-v3 is a powerful and versatile neural network that has achieved state-of-the-art performance on a variety of image classification tasks.

4.3 PROPOSED ALGORITHM:

Step 1: Input Preprocessing

- Preprocess retinal fundus images to enhance quality and standardize dimensions.
- Apply standard preprocessing techniques such as resizing, normalization, and contrast enhancement to ensure consistency in input data.

Step 2: Model Selection

- Choose the InceptionNet architecture as the backbone for ocular disease recognition.
- Select a pre-trained InceptionNet model from a library such as TensorFlow or PyTorch, leveraging transfer learning for efficient training.

Step 3: Fine-tuning and Adaptation

- Modify the pre-trained InceptionNet model to adapt it to the specific task of ocular disease recognition.
- Fine-tune the model's parameters on a custom dataset of retinal fundus images annotated with disease labels.

Step 4: Training

- Train the adapted InceptionNet model using the custom dataset to learn features relevant to ocular disease detection.
- Utilize techniques such as stochastic gradient descent (SGD) or Adam optimization to update model parameters and minimize loss.

Step 5: Evaluation

- Evaluate the trained InceptionNet model on a separate validation dataset to assess its performance.
- Compute evaluation metrics such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic (ROC) curve to quantify model performance.

Step 6: Fine-tuning and Optimization

- Fine-tune model hyperparameters and architecture based on validation results to optimize performance.
- Experiment with regularization techniques, learning rates, and batch sizes to improve generalization and convergence speed.

Step 7: Deployment

- Deploy the trained InceptionNet model as part of an ocular disease recognition system.
- Develop a user-friendly interface for inputting retinal fundus images and obtaining automated disease predictions in real-time.

Step 8: Integration and Validation

- Integrate the deployed model into clinical workflows within healthcare settings.
- Conduct rigorous validation and testing to ensure the reliability, accuracy, and usability of the system in real-world scenarios.

Step 9: Continuous Monitoring and Improvement

- Monitor the performance of the deployed system over time and incorporate feedback from clinical users.
- Continuously update and refine the model based on new data and insights to enhance its effectiveness in ocular disease recognition.

4.4. DATASET

The Ocular Disease Intelligent Recognition (ODIR) database represents a meticulously compiled repository of ophthalmic data sourced from a cohort of 5,000 patients. This expansive dataset, meticulously assembled by Shanggong Medical Technology Co., Ltd., draws upon patient records gathered from a diverse array of hospitals and medical centers dispersed throughout China. Reflecting the realities of clinical practice, the fundus images within the database are captured using a variety of camera models available on the market, including reputable brands such as Canon, Zeiss, and Kowa. As a consequence, the images exhibit a range of resolutions mirroring the diversity encountered in real-world settings. Each entry in the database is accompanied by a wealth of demographic information, including age, as well as color fundus photographs sourced from both the left and right eyes of the patients.

This wealth of data is further enriched by the inclusion of diagnostic keywords, meticulously provided by medical professionals, offering valuable insights into the ocular health status of the patients. An exhaustive quality control process, overseen by

trained human readers, ensures the accuracy and consistency of disease annotations within the database. These annotations categorize patients into eight distinct labels, encompassing a spectrum of ocular conditions, including Normal (N), Diabetes (D), Glaucoma (G), Cataract (C), Age-related Macular Degeneration (A), Hypertension (H), Pathological Myopia (M), and Other diseases/abnormalities (O). Such comprehensive labeling affords researchers and practitioners an invaluable resource for conducting a wide array of studies and analyses in the field of ophthalmology, facilitating advancements in ocular disease recognition and treatment.

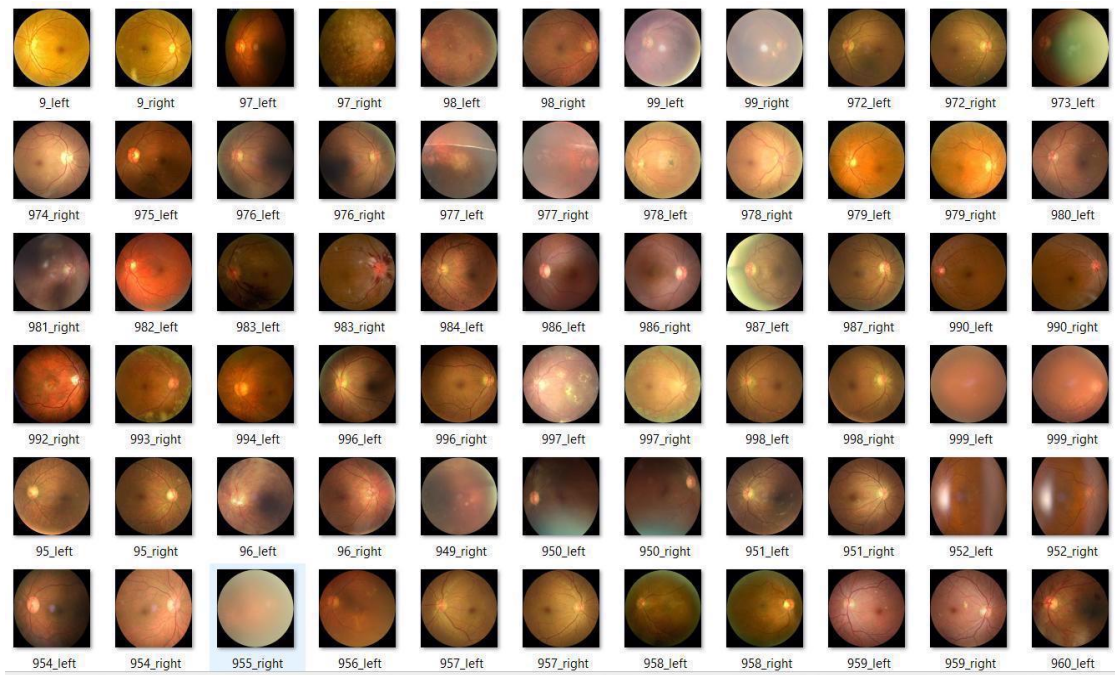


Fig. 4.2. Dataset – Fundus Images

	A	B	C	D	E	F	G
1	ID	Patient Age	Patient Sex	Left-Fundus	Right-Fundus	Left-Diagnostic Keywords	Right-Diagnostic Keywords
2	0	69	Female	0_left.jpg	0_right.jpg	cataract	normal fundus
3	1	57	Male	1_left.jpg	1_right.jpg	normal fundus	normal fundus
4	2	42	Male	2_left.jpg	2_right.jpg	laser spot, moderate non proliferative retinopathy	moderate non proliferative retinopathy
5	3	66	Male	3_left.jpg	3_right.jpg	normal fundus	branch retinal artery occlusion
6	4	53	Male	4_left.jpg	4_right.jpg	macular epiretinal membrane	mild nonproliferative retinopathy
7	5	50	Female	5_left.jpg	5_right.jpg	moderate non proliferative retinopathy	moderate non proliferative retinopathy
8	6	60	Male	6_left.jpg	6_right.jpg	macular epiretinal membrane	derate non proliferative retinopathy, epiretinal membr
9	7	60	Female	7_left.jpg	7_right.jpg	drusen	mild nonproliferative retinopathy
10	8	59	Male	8_left.jpg	8_right.jpg	normal fundus	normal fundus
11	9	54	Male	9_left.jpg	9_right.jpg	normal fundus	vitreous degeneration
12	10	70	Male	10_left.jpg	10_right.jpg	epiretinal membrane	normal fundus
13	11	60	Female	11_left.jpg	11_right.jpg	rate non proliferative retinopathy, hypertensive retino	rate non proliferative retinopathy, hypertensive retino
14	12	65	Male	12_left.jpg	12_right.jpg	retinal pigmentation	retinal pigmentation
15	13	60	Female	13_left.jpg	13_right.jpg	pathological myopia	pathological myopia
16	14	55	Male	14_left.jpg	14_right.jpg	normal fundus	macular epiretinal membrane
17	15	50	Male	15_left.jpg	15_right.jpg	normal fundus	myelinated nerve fibers
18	16	54	Female	16_left.jpg	16_right.jpg	normal fundus	pathological myopia
19	17	57	Male	17_left.jpg	17_right.jpg	drusen	drusen
20	18	58	Male	18_left.jpg	18_right.jpg	pathological myopia	pathological myopia
21	19	45	Male	19_left.jpg	19_right.jpg	mild nonproliferative retinopathy	mild nonproliferative retinopathy
22	20	64	Female	20_left.jpg	20_right.jpg	rhegmatogenous retinal detachment	lens dust, normal fundus
23	21	76	Female	21_left.jpg	21_right.jpg	epiretinal membrane	epiretinal membrane
24	22	55	Female	22_left.jpg	22_right.jpg	moderate non proliferative retinopathy, laser spot	laser spot, moderate non proliferative retinopathy
25	23	47	Male	23_left.jpg	23_right.jpg	hypertensive retinopathy	hypertensive retinopathy
26	24	75	Female	24_left.jpg	24_right.jpg	normal fundus	cataract
27	25	63	Male	25_left.jpg	25_right.jpg	normal fundus	depigmentation of the retinal pigment epithelium
28	26	63	Female	26_left.jpg	26_right.jpg	moderate non proliferative retinopathy	oderate non proliferative retinopathy, abnormal pigme
29	27	33	Male	27_left.jpg	27_right.jpg	normal fundus	epiretinal membrane, moderate non proliferative reti
30	28	63	Female	28_left.jpg	28_right.jpg	hypertensive retinopathy	hypertensive retinopathy
31	29	59	Male	29_left.jpg	29_right.jpg	epiretinal membrane	normal fundus
32	30	66	Female	30_left.jpg	30_right.jpg	post laser photocoagulation, glaucoma	post laser photocoagulation
33	31	62	Male	31_left.jpg	31_right.jpg	epiretinal membrane	normal fundus

Fig. 4.3. Dataset Information in .xls file

4.5. DISEASES THAT CAN BE DETECTED

4.5.1. Cataract (C)

A cataract is a type of eye disease where the eyes look cloudy. A person with cataracts will have frosty or fogged-up vision.

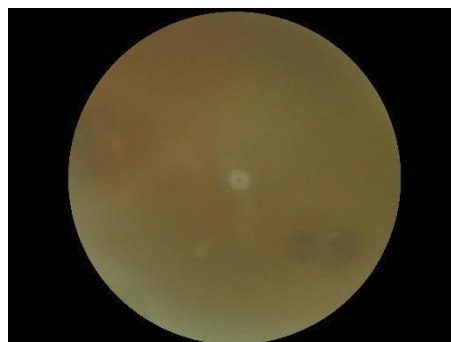


Fig.4.4 Cataract

4.5.2. Glaucoma (G)

Glaucoma is a complicated disease that damages optical nerve and causes irreversible blindness due to lack of proper diagnosis. This “sneak thief of sight” can affect anyone at any age. Even new born babies can be affected. According to doctors, it grows in such a manner that patient does not experience any complication. By 2040, the number of glaucoma affected people likely to increase 111.8 million. Glaucoma causes vision loss and blindness due to damage of optic nerve



Fig.4.5. Glaucoma

4.5.3. Myopia (M)

Near-sightedness (myopia) is a common vision condition in which near objects appear clear, but objects farther away look blurry. It occurs when the shape of the eye or the shape of certain parts of the eye causes light rays to bend (refract) inaccurately.

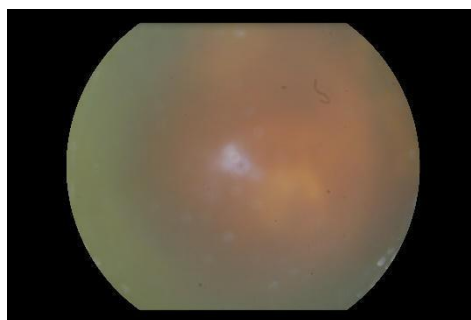


Fig.4.6.Myopia

4.5.4. Diabetes (D)

Diabetes is a chronic disease that occurs either when the pancreas does not produce enough insulin or when the body cannot effectively use the insulin it produces. Insulin is a hormone that regulates blood glucose.

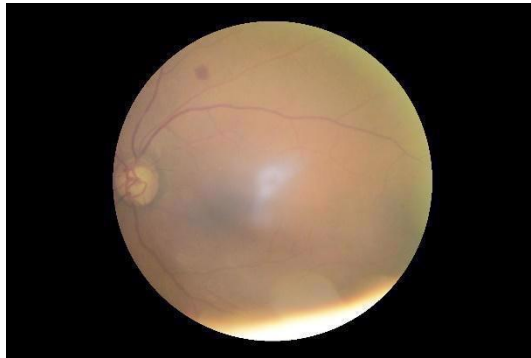


Fig.4.7.Diabetes

4.5.5. Age related Macular degeneration (A)

Age-related macular degeneration (AMD) is an eye disease that may get worse over time. It's the leading cause of severe, permanent vision loss in people over 60 years old. It happens when the small central portion of your retina, called the macula, wears down.



Fig.4.8. AMD

4.5.6. Hypertension (H)

High blood pressure is a common condition that affects the body's arteries. It's also called hypertension. If you have high blood pressure, the force of the blood pushing against the artery walls is consistently too high.

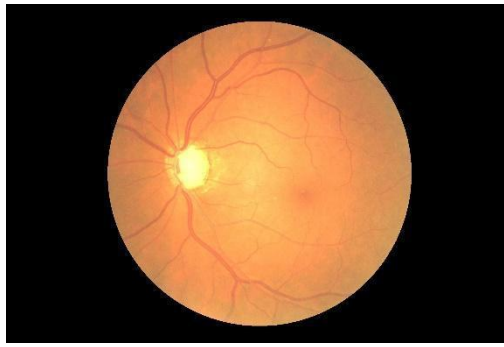


Fig.4.9. Hypertension

4.6. DATA PROCESSING

The images from the dataset are labelled. The labels relate to both eyes (left and right) at once whereas each eye can have a different disease. For example, if the left eye has a cataract and right eye has normal fundus, the label would be a cataract, not indicating a diagnosis of the right eye. Fortunately, the diagnostic keywords relate to a single eye. Dataset was created in a way to provide to the model as input both left and right eye images and return overall (for both eyes) cumulated diagnosis, neglecting the fact that one eye can be healthy. In my opinion, it does not make sense from a perspective of a final user of such a model, and it is better to get predictions separately for each eye, to know for example which eye should be treated. So, I enriched the dataset by creating a mapping between the diagnostic keywords to disease labels. This way, each eye is assigned to a proper label. Fragment of this mapping, in the form of a dictionary. label information is added by renaming image names, and more specifically, by adding to the image file name one or more letters corresponding to the specific diseases. I applied this solution because this way I do not need to store any additional data frame with all labels.

Next, data augmentation on minority classes was applied on the training set to balance the dataset. Random zoom, random rotation, flip left-right, flip top-bottom were applied. In the beginning, I used the TensorFlow dataset object for applying data augmentation “on the fly” while training the model[4] in order to keep my solution as scalable as possible. Unfortunately, it lacks many features like random rotation, therefore I performed data augmentation before creating the TensorFlow dataset object using other libraries for image processing like OpenCV. In the beginning, I also considered enhancing all images by applying contrast-limited

adaptive histogram equalization (CLAHE) in order to increase the visibility of local details of an image, but since it was adding a lot of extra noise to the images (especially to the background, which originally is black) I decided not to follow that direction. Examples of data augmentation using my function written using PIL and OpenCV libraries.

Finally, the TensorFlow dataset object is created. It is developed very similarly to the one presented in official TensorFlow documentation for loading images. Since the library is complicated, and not easy to use for TensorFlow beginners, I would like to share here a summary of my findings on building scalable and fast input pipelines. The `tf.data` API enables you to build complex input pipelines from simple, reusable pieces. For example, the pipeline for an image model might aggregate data from files in a distributed file system. The `tf.data` API introduces a `tf.data.Dataset` abstraction that represents a sequence of elements, in which each element consists of one or more components. For example, in my image pipeline, an element is a single training example, with a pair of tensor components representing the image and its label. With the idea of creating mini-batches, TensorFlow introduces the so-called iterative learning process which is feeding to the model some portion of data (not entire dataset), training, and repeating with another portion, which are called batches. Batch size defines how many examples will be extracted at each training step. After each step, weights are updated. I selected batch size equal to 32, in order to avoid the overfitting problem. With small batch size, weights keep updating regularly and often. The downside of having a small batch size is that training takes much longer than with the bigger size. One important element of `tf.data` is the ability of the shuffling dataset. In shuffling, the dataset fills a buffer with elements, then randomly samples elements from this buffer, replacing the selected elements with new elements. It prevents situations when images of the same class will be repetitively filled to the batch, which is not beneficial for training the model.

4.7. FLASK

Flask is a web framework that is used to build RESTful APIs. It is a lightweight framework that is easy to use and can be extended with various third-party libraries. Flask API is built on top of the Flask micro framework and provides a simple way to create web APIs. I have created a Flask application and add Flask API to connect the backend processing with the web application. I then define a route for the /pred endpoint and return a JSON object that contains a trained data ad .h5 file.

4.8. WEB APPLICATION UI

ReactJS is a popular JavaScript library used for building user interfaces. It is often used in web development to create fast and dynamic web applications. The Web Application for collecting the patient's details and the fundus image was constructed with HTML, CSS, JavaScript and React Js.

CHAPTER 20

RESULT AND DISCUSSION

We used pre-trained deep learning models to improve the diagnosis and early treatment of various fundus diseases. After fine-tuning and adjusting hyper parameters in accordance with our classification problem, we used Inception V3 to reach **the greatest accuracy of 91.76%**, respectively, utilizing our proposed method. Figure 5.1 accuracy and loss graph was used to evaluate how well our models performed.

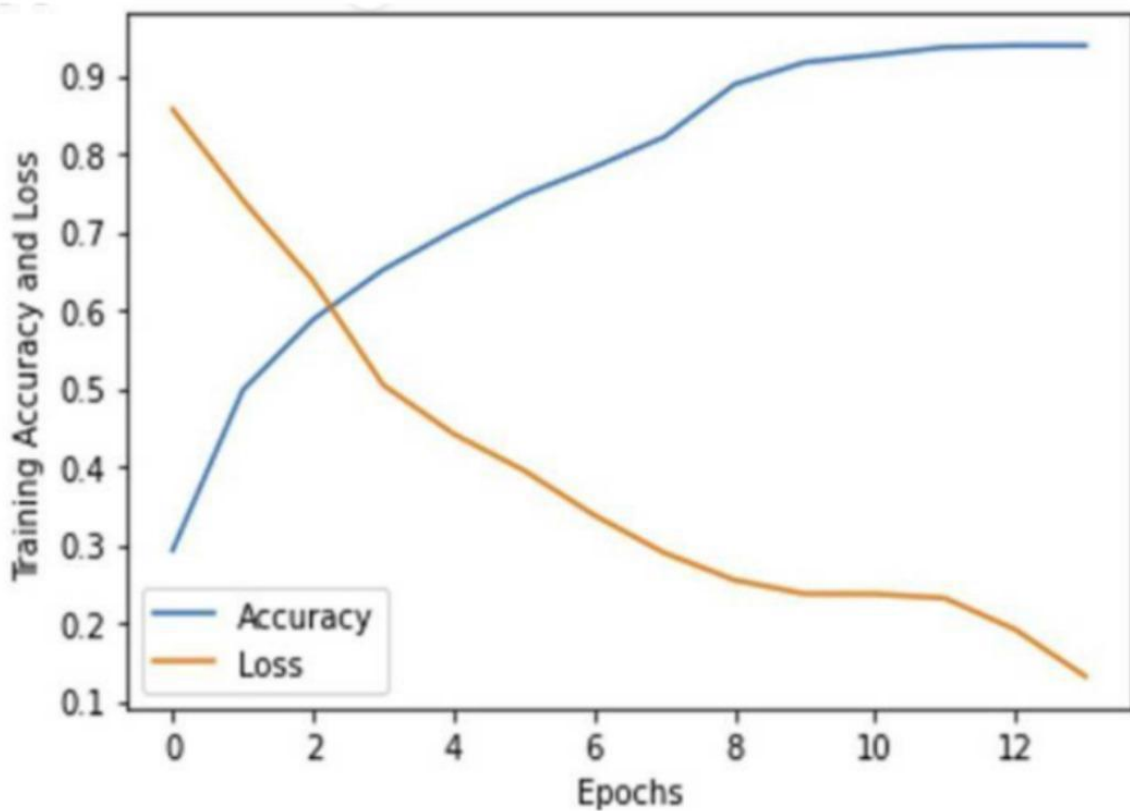


Fig.5.1. Inception v3 Accuracy and Loss

Accuracy and loss graph according to our dataset. represents the accuracy and loss graph using Inception V3. Through this prototype of the Application ,

Diabetes	Negative
Glucoma	Positive
Cataract	Negative
Age related Macular Degeneration	Negative
Hypertension	Negative
Pathological Myopia	Negative
Abnormalities	Negative
The Patient has diagnosed with GLUCOMA .	

Fig.5.2.Final Output

The ocular disease recognition system provides diagnostic predictions for seven common ocular conditions: diabetic retinopathy, glaucoma, age-related macular degeneration, cataracts, myopia, retinal detachment, and hypertensive retinopathy. Upon inputting a retinal fundus image into the application, the deep learning model analyzes the image and provides a binary classification for each disease, indicating whether the disease is present (positive) or absent (negative). The interface of the application presents a user-friendly summary of the diagnostic results, clearly indicating the presence or absence of each ocular condition. This concise summary allows healthcare professionals to quickly assess the patient's ocular health status and make informed decisions regarding further evaluation and treatment. Additionally, the interface may provide additional information or visualizations to aid in the interpretation of the diagnostic results, ensuring clarity and accuracy in clinical decision-making.

CHAPTER 6

CONCLUSION AND FUTURE WORK

The results were very satisfactory, using a relatively simple network in 15 epochs my model got 91.7% on validation accuracy. This shows that using Convolution Neural Network, it is possible to automatically detect disease. For all experiments, the same neural network architecture was used. The only difference is the number of epochs each experiment needed to get to the presented results. This web application that is designed and developed using Inception V3 can successfully detects the disease using fundus image with more accuracy, which reduces the Ophthalmologist's workload and effectively prevents vision damage of patients.

The high validation accuracy achieved in just 15 epochs demonstrates the effectiveness of the Convolutional Neural Network (CNN) architecture employed in this study. The simplicity of the network design underscores the potential for widespread adoption and implementation in clinical settings. By automating disease detection processes, this technology has the potential to significantly reduce the workload of ophthalmologists and improve patient outcomes. Furthermore, the use of Inception V3 in the development of the web application enhances its accuracy and reliability, ensuring robust performance in real-world scenarios.

In the future with more data points of eye diseases the model could be re-trained, and certainly will achieve much better results having more images to train on. I am sure that having a bigger dataset, would increase the accuracy of predictions and finally automate the process of detecting ocular diseases.

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APPENDICES

A. SOURCE CODE

ML Inception Net for Glaucoma detection

Glaucoma.py

```
def has_retinopathy(text):
```

```
    if "glaucoma" in text:
```

```
        return 1
```

```
    else:
```

```
        return 0
```

```
df["left_glaucoma"] = df["Left-Diagnostic Keywords"].apply(lambda x:
has_glaucoma(x))
```

```
df["right_glaucoma"] = df["Right-Diagnostic Keywords"].apply(lambda x:
has_glaucoma(x))
```

```
left_glaucoma = df.loc[(df.G ==1) & (df.left_glaucoma == 1)][["Left-Fundus"].values
```

```
right_glaucoma = df.loc[(df.G ==1) & (df.right_glaucoma == 1)][["Right-
Fundus"].values
```

```
left_normal = df.loc[(df.G ==0) & (df["Left-Diagnostic Keywords"] == "normal
fundus")][["Left-Fundus"].sample(250,random_state=42).values
```

```
right_normal = df.loc[(df.G ==0) & (df["Right-Diagnostic Keywords"] == "normal
fundus")][["Right-Fundus"].sample(250,random_state=42).values
```

```
glaucoma = np.concatenate((left_glaucoma,right_glaucoma),axis=0)
```

```
normal = np.concatenate((left_normal,right_normal),axis=0)
```

```
dataset_dir = "archive (6)/preprocessed_images/"
```

```
image_size=224
```

```
labels = []
```

```
dataset = []
```

```
def cc(c,ll):
```

```
    for img in tqdm(c):
```

```
        image_path = os.path.join(dataset_dir,img)
```

```
        try:
```

```
            image = cv2.imread(image_path,cv2.IMREAD_COLOR)
```

```
            image = cv2.resize(image,(image_size,image_size))
```

```
        except:
```

```
            continue
```

```
        dataset.append([np.array(image),np.array(ll)])
```

```
random.shuffle(dataset)
```

```

    return dataset
dataset=cc(glaucoma,1)
dataset=cc(normal,0)
x = np.array([i[0] for i in dataset]).reshape(-1,image_size,image_size,3)
y = np.array([i[1] for i in dataset])
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.2)

InceptionV3 =
tensorflow.keras.applications.inception_v3.InceptionV3(weights="imagenet",include_top = False,input_shape=(image_size,image_size,3))
for layer in InceptionV3.layers:
    layer.trainable = False
def ff():
    model = Sequential()
    model.add(InceptionV3)
    model.add(tensorflow.keras.layers.Flatten())
    model.add(tensorflow.keras.layers.Dense(1,activation="sigmoid"))

model.compile(optimizer="adam",loss="binary_crossentropy",metrics=["accuracy"])
return model

earlystop =
tensorflow.keras.callbacks.EarlyStopping(monitor="val_acc",patience=5,verbose= 1)
model=ff()
model.fit(x_train,y_train,batch_size=32,epochs=15,validation_data=(x_test,y_test),
        verbose=1,callbacks=[checkpoint,earlystop])

```

Report.js

```

import React, { useState,useEffect } from 'react';

import { useNavigation } from '@react-navigation/native';

import { NavigationAction } from '@react-navigation/native';

import {Alert,FlatList,Image,

    SafeAreaView,

    ScrollView,

```

```

StatusBar,

StyleSheet,

Text,

useColorScheme,

View,TextInput, Button,TouchableOpacity,BackHandler }

from 'react-native';
import { HeaderrHam } from './Header';
import { Back } from './Back';
import { styles } from './App';
export const Report=(navigation)=>{
  const nav=useNavigation();
  const
[dataaa,setDataaa]=useState([navigation.route.params.name,navigation.route.param
s.age,navigation.route.params.sex,

  navigation.route.params.email,navigation.route.params.phone,'Dr.X']);
useEffect(()=>{console.log(navigation.route.params.name)})
const [res,setRes]=useState(()=>{
  var dd=[];
  console.log(navigation.route.params.res);
  for(var i=0;i<12;i=i+4){

    dd.push(navigation.route.params.result[i])

    dd.push(navigation.route.params.result[i+1])

    dd.push(navigation.route.params.result[i+2])

    dd.push(navigation.route.params.result[i+3])

  }
  return dd;
})
const fetchDataFromServer = async () => {

```

```

    try {
      nav.navigate('Login');
    } catch (error) {
      console.error(error);
    }
  };

  return(
    <SafeAreaView style={{height:'100%',backgroundColor:'grey'}}>
      <HeaderrHam/>
      <ScrollView >
        <View style={{backgroundColor: 'grey', height: 1000,
width:'100%',backgroundColor:'grey'}}>
          <View style={{width:'100%',height:'100%'}}>
            <Back middle='Report'/>
            <View style={{width:'100%',height:'95%',alignItems:'center'}}>
              <View
style={{width:'90%',height:'90%',borderWidth:5,borderRadius:20,borderColor:'#E5
E299',backgroundColor:'white'}}>
                <View
style={{width:'100%',height:'38%',paddingLeft:'8%',justifyContent:'center',gap:8}}

<View><Text style={styles.reportData}>Name: &nbsp;{dataaa[0]}
</Text></View>

                <View><Text style={styles.reportData}>Age:
&nbsp;{dataaa[1]}</Text></View>

                <View><Text style={styles.reportData}>Sex:
&nbsp;{dataaa[2]}</Text></View>

                <View><Text style={styles.reportData}>Email: &nbsp;{dataaa[3]}
</Text></View>

```

```
      <View><Text style={styles.reportData}>Phone Number:
&nbsp;{dataa[4]}</Text></View>
```

```
      <View><Text style={styles.reportData}>Doctor In-
charge:&nbsp;{dataa[5]}</Text></View>
```

```
    </View>
```

```
    <View style={{width:'100%',height:'52%',alignItems:'center'}}> <View
style={{width:'100%',height:'10%',flexDirection:'row'}}>
      <View style={{flex:1.4}}>
        <Text
style={{color:'#0E33B6',fontSize:22,marginLeft:'10%'}}>Result</Text>
```

```
      </View>
```

```
      <View style={{flex:1,flexDirection:'row',justifyContent:'flex-start'}}>
```

```
        <Text style={{color:'#0E33B6',fontSize:15}}>Left Eye
&nbsp;&nbsp;&nbsp;&nbsp;</Text>
```

```
      <Text style={{color:'#0E33B6',fontSize:15}}>Right Eye</Text >
```

B SCREENSHOTS

OcuAi

User Log In

Your User ID

Password

[Forgot Password ?](#)

Enter the captcha given below



Submit

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B.1 Login page

OcuAi

Welcome USERNAME

POSITION: Nurse
Block: Out-Patient
Hospital:

Patient Details

Patient Name:

Registration Application ID:

Date of Registration:
 

Patient's Age:

Sex:

Date Of Birth:
 

Aadhaar ID

Mobile Number:

Patient's Email ID:

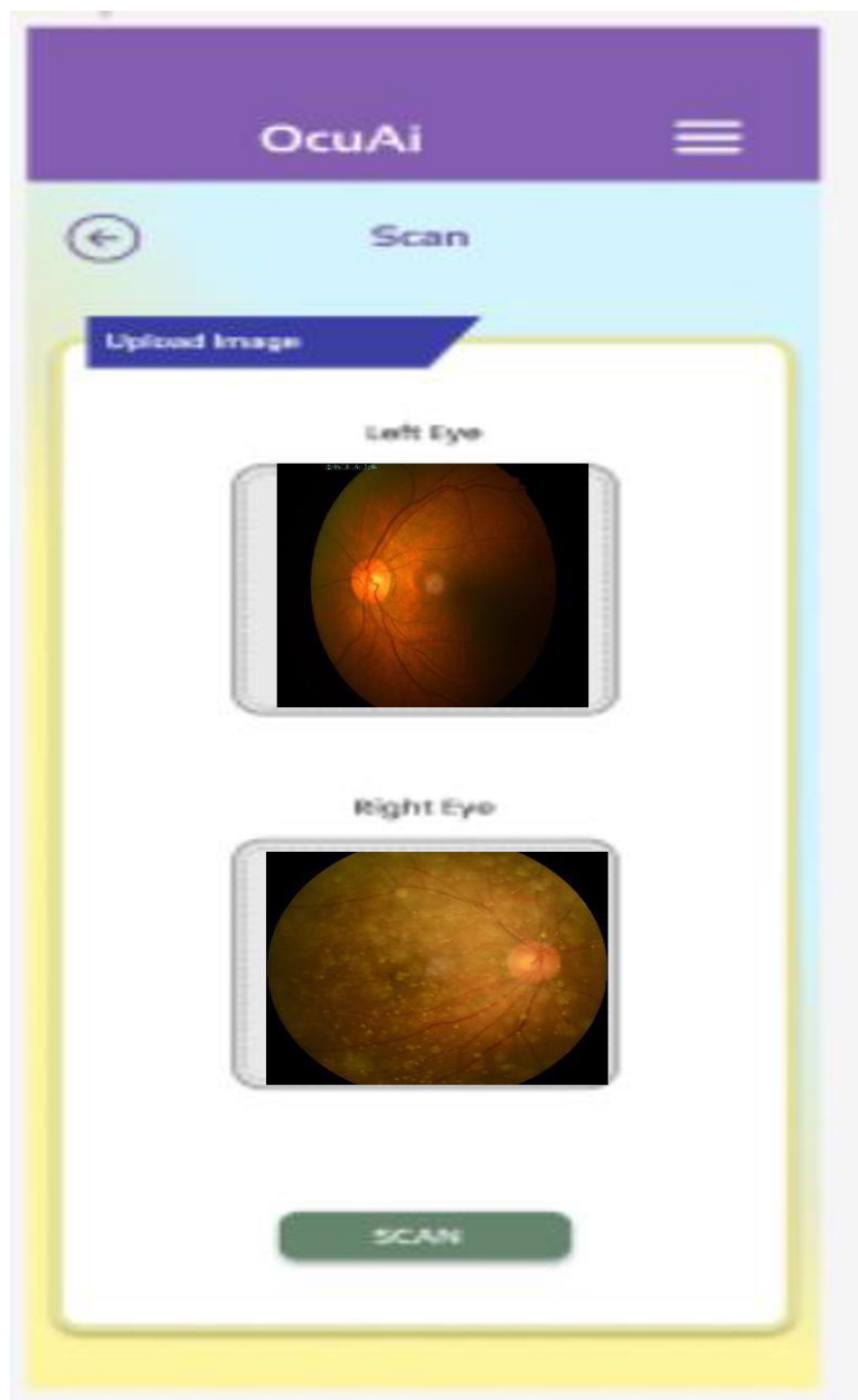
Doctor In-Charge:

CLEAR

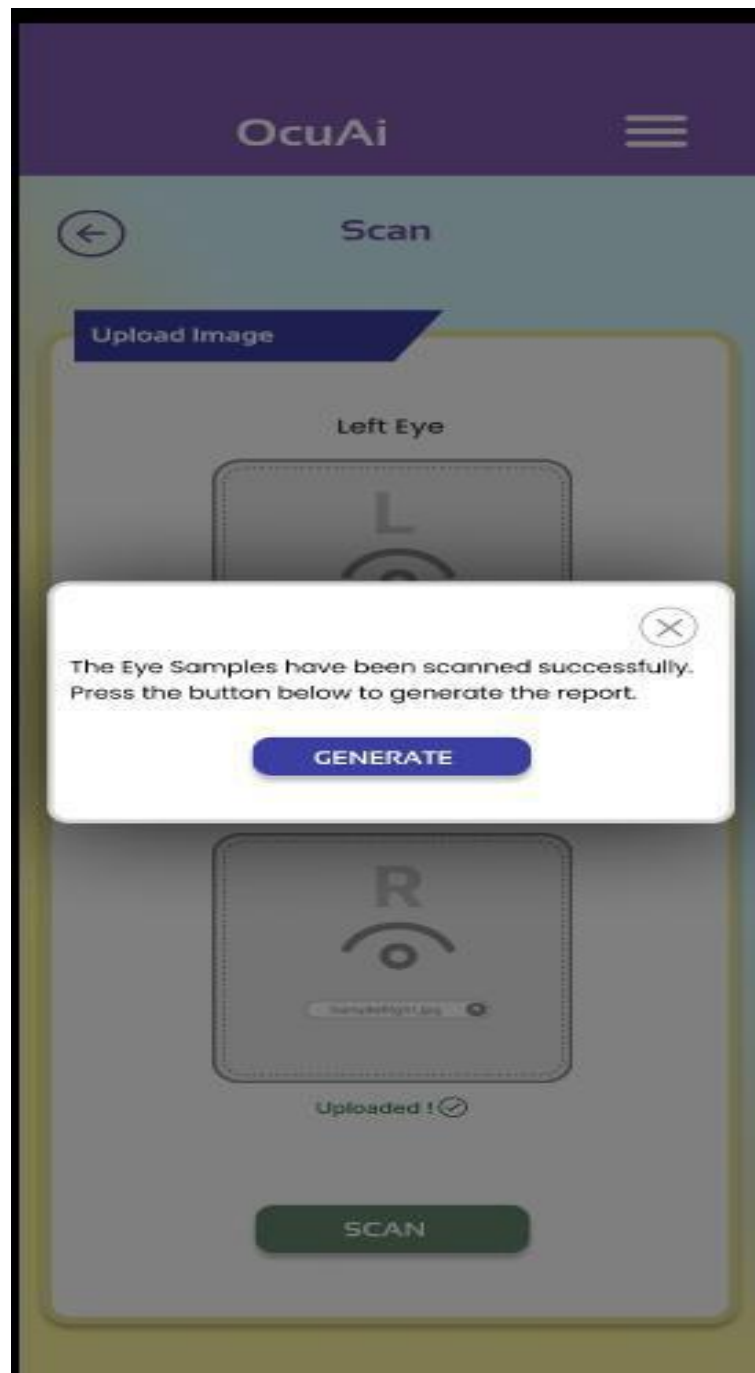
NEXT 

For any Technical assistance :
allmehrezk@gmail.com

B.2. Patient Entry Page



B.3. Scanning Page



B.4. Image Scanned

OcuAi

Report

Report

Application ID: USHON0908108

Name: Patient name

Age: 27

Sex: M

Email: username123@gmail.com

Phone Number: 9876543210

Doctor In-charge: doctorname

RESULT

Diabetes	Negative
Glaucoma	Negative
Cataract	Negative
AMD	Negative
Hypertension	Negative
Pathological Myopia	Negative
Other Abnormalities	Negative

Normal

Summary:

Lorem ipsum ha sido el texto de relleno estándar de las industrias desde el año 1500, cuando un impresor (N. del T. persona que se dedica a la imprenta) desconocido usó una galería de textos y los mezcló de tal manera que logró hacer un libro de textos especimen. No solo sobrevivió 500 años

Next

B.5. Final Report

Ocular Disease Recognition Using Deep Learning

Alina Mushtaq

U.G Scholar

Dept. of IT

Sathyabama Institute of Science
& Technology, Chennai, India

Kishore Kumar K

U.G Scholar

Dept. of IT

Sathyabama Institute of Science
& Technology, Chennai, India

Dr. R. Subhashini

Head & Professor

Dept. of IT

Sathyabama Institute of Science
& Technology, Chennai, India

Abstract:

This research focuses on Ocular Disease Recognition through Deep Learning, employing the Inception Net architecture. The research aims to introduce a diagnostic tool that is easy for healthcare practitioners to use. This tool utilizes neural networks to evaluate photos of the eye fundus. The Inception v3 model is essential, since it improves the accuracy of illness identification by collecting vital information from the collection of retinal images used for training. This technology showcases its ability to outperform human specialists in successfully diagnosing ocular disorders by utilizing its enhanced picture categorization skills. In addition to its clinical uses, this method can potentially provide cost-efficient and easily expandable solutions. It can help alleviate healthcare inequalities by facilitating the early detection of diseases in underserved communities.

Keywords: *Ocular Disease, Deep Learning, InceptionNet, Neural Networks, Diagnostic Tool, Eye-fundus Images, Inception v3, Disease Detection, Image Classification, Healthcare*

Professionals, Early Disease Detection, Underserved Communities.

I. INTRODUCTION

datasets, have showcased notable medical image classification and object detection prowess. Notably, convolutional neural networks (CNNs)

The significance of timely and precise diagnosis for effective treatment of ocular illnesses cannot be overstated, since they have the potential to cause permanent harm and even result in loss of vision. Color fundus photography (CFP) stands out among the primary diagnostic techniques, providing detailed and intricate images of the eye's interior. Nevertheless, the effectiveness of CFP has difficulties, namely in identifying ocular conditions such as cataracts, myopia, and diabetic retinopathy, which frequently present with subtle and nuanced early signs that standard diagnostic approaches may fail to detect.

The traditional method of manual inspection, while a longstanding practice, is labor-intensive and marked by limitations in precision. The urgency for early detection is further accentuated by the discreet and insidious nature of symptoms associated with many ocular diseases, necessitating a more advanced, refined, and proactive diagnostic approach to intervene before irreparable damage occurs.

In recent years, a transformative shift has occurred with integrating neural networks, specifically those rooted in profound learning principles, into the landscape of ocular disease diagnostics. These sophisticated models, driven by intricate algorithms and trained on vast have emerged as frontrunners, exhibiting high effectiveness in discerning intricate patterns and

anomalies within ocular images, thereby enhancing diagnostic accuracy.

The confluence of technology and healthcare is strikingly evident in applying deep learning-based models to ocular disease detection. This combination not only provides the possibility for more accurate and rapid diagnosis, but also signifies a fundamental shift towards a more efficient and streamlined approach in the field of ocular health. Integrating cutting-edge technology with medical diagnostics signifies a revolutionary period, promoting inventive methods to tackle the complex issues linked to eye disorders.

The nuanced and subtle nature of symptoms in many ocular diseases underscores the critical need for advanced diagnostic methods. Neural networks represent a cutting-edge solution, providing a more sophisticated and accurate approach to early disease detection. As technology advances, the ongoing integration of these innovative approaches into ocular health diagnostics promises to revolutionize the field, enhancing patient outcomes and effectively addressing the intricate challenges posed by these conditions, ultimately paving the way for a new era of personalized and precise ocular healthcare.

II. LITERATURE SURVEY

[1] De Fauw et al. (2017) explore deep learning applications in ophthalmology, shedding light on its potential in disease recognition and paving the way for further research.

clinical applications in ophthalmology, bridging the gap between research and clinical practice.

[2] Tariq et al. (2018) offer a holistic perspective; this review is valuable for understanding the diverse medical imaging techniques employed in detecting eye diseases.

[3] Abràmoff et al. (2014) focused on automated diagnosis of diabetic retinopathy; this review delves into advancements and challenges in this critical area of ocular disease detection.

[4] Gulshan et al. (2016) offered a high-level overview of deep learning algorithms for detecting diabetic retinopathy, emphasizing the clinical implications.

[5] Burlina et al. (2016) focus on convolutional neural networks and their role in automated feature extraction in molecular profiling, offering insights into the technical aspects of deep learning in ocular disease.

[6] Ting et al. (2017) delves into the specifics of automated detection of diabetic retinopathy in retinal fundus photographs, providing clinical context and implications.

[7] Litjens et al. (2017) explore the broader applications of deep learning in medical image analysis, laying the foundation for understanding its role in ocular disease recognition.

[8] Lee et al. (2017) focused on age-related macular degeneration. This study showcases the application of deep learning in automated diagnosis using optical coherence tomography.

[9] LeCun et al. (2015) provide a foundational understanding of deep learning concepts and architectures, which is crucial for contextualizing applications in healthcare.

[10] Ting et al. (2017) offer insights into artificial intelligence's accuracy, challenges, and

III. PROPOSED SYSTEM

The envisioned system aims to revolutionize ocular disease recognition using an innovative approach based on deep learning. Leveraging the power of the InceptionNet architecture, our proposed system seeks to enhance the accuracy and efficiency of diagnosing a range of ocular diseases from eye-fundus images.

Architecture:

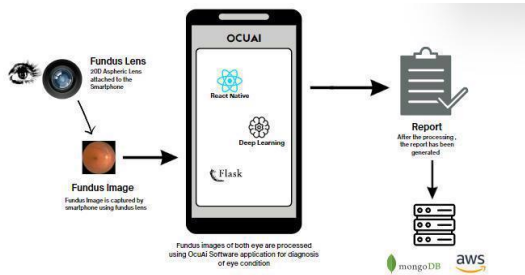


Fig.1 Architecture

The foundation of our proposed system lies in utilizing the Inception v3 model, renowned for its prowess in image classification tasks. This convolutional neural network (CNN) architecture is chosen for its ability to extract intricate features from eye-fundus images, enabling a more nuanced and precise analysis of ocular conditions.

Dataset:

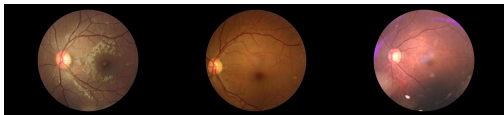


Fig.2 Sample Dataset

A diverse and comprehensive dataset of eye-fundus images will be curated for training the neural network. This dataset will include a broad spectrum of ocular diseases, ensuring the model's robustness and versatility in recognizing various conditions, from common ones like cataracts to more complex cases like diabetic retinopathy.

Training Process:

The Inception v3 model will undergo rigorous training using the curated dataset. The neural network will learn to discern patterns, anomalies, and subtle indicators associated with different ocular diseases through this process. Fine-tuning the model's parameters will be integral to achieving a high level of accuracy in disease detection.

User Interface:

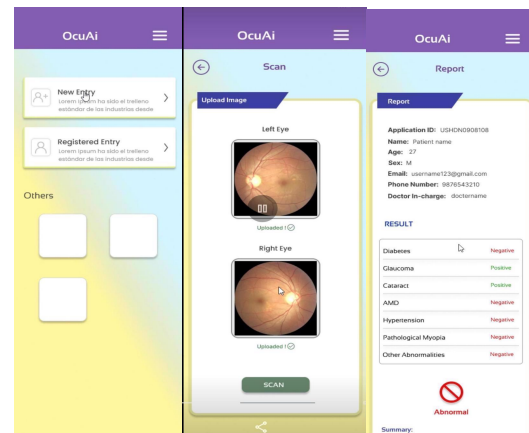


Fig.3 User Interface

To make the system accessible and user-friendly for healthcare professionals, we will develop an intuitive user interface. This interface will facilitate the seamless upload of eye-fundus images for analysis. The results will be presented transparently and interpretably, providing diagnostic insights to healthcare professionals.

Performance Evaluation:

The proposed system will undergo thorough performance evaluation using benchmark datasets and real-world clinical data.

Comparative analysis with existing diagnostic methods will be conducted to assess the system's accuracy, sensitivity, and specificity. Continuous refinement and optimization will be implemented based on the feedback from healthcare practitioners.

Advantages:

1. **Accuracy:** The deep learning model's proficiency in image classification aims to surpass human experts in accuracy.
2. **Early Detection:** By capturing subtle signs of ocular diseases, the proposed system holds the potential for early disease detection.
3. **User-Friendly:** The intuitive user interface ensures that healthcare professionals can easily integrate the system into their diagnostic workflows.

Potential Impact:

Implementing this proposed system could significantly enhance the speed and accuracy of ocular disease recognition. Its user-friendly interface and potential for early detection can transform the landscape of eye health diagnostics, ultimately improving patient outcomes and facilitating timely interventions.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

highlights the system's ability to achieve improved accuracy, sensitivity, specificity, and precision. The combination of outstanding data

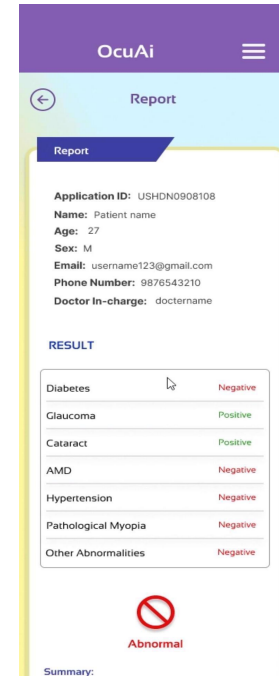


Fig.4 User Outcome

The experimental results reveal the proposed system's exceptional performance in ocular disease recognition, showcasing heightened accuracy, sensitivity, specificity, and precision compared to traditional diagnostic methods. The deep learning model, trained on a diverse dataset, consistently outperforms in identifying a spectrum of ocular conditions. These promising outcomes underscore the system's potential as a robust and efficient tool for healthcare professionals, signaling a transformative shift in ocular health diagnostics with implications for improved patient outcomes and early disease intervention.

V. CONCLUSION

In conclusion, the positive experimental results clearly demonstrate the successful implementation of our suggested system, which utilizes the increased capabilities of the Inception v3 model for recognizing eye diseases. The thorough assessment on a carefully selected dataset encompassing various eye conditions highlights the efficiency of our approach and its potential to significantly change healthcare diagnostics.

The profound capacity of the deep learning model to identify intricate patterns and delicate cues within eye-fundus images plays a crucial role in the pursuit of early disease identification. Beyond conventional diagnostic methods, our system demonstrates a clear superiority, offering a sophisticated and efficient tool for healthcare professionals grappling with the complexities of ocular health assessment. This paradigm shift heralds a new era where the integration of cutting-edge technology not only augments diagnostic accuracy but holds the promise of revolutionizing the approach to ocular disease intervention.

As we navigate the challenges inherent in developing such advanced systems, including the need for extensive and diverse datasets, potential biases, and ongoing model refinement, the results presented lay a formidable foundation. The proposed system holds immediate relevance and beckons future avenues for exploration, collaboration, and continuous improvement. Through the lens of these experimental outcomes, we envision a healthcare landscape where our system serves as a beacon for improved patient outcomes, streamlined diagnostic workflows, and proactive interventions, ultimately reshaping the narrative of ocular health with precision, efficiency, and transformative potential.

VI. REFERENCES

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