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Jnana Sangama, Belagavi-590018, Karnataka



**A PROJECT REPORT
On
“A Transfer Learning Based Web App for Glaucoma Detection
Using Low-Cost Ophthalmoscopic Camera”**

*Submitted in partial fulfillment of the requirements for the award of degree of
Bachelor of Engineering in*

ELECTRONICS AND COMMUNICATION ENGINEERING

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**DEPARTMENT OF ELECTRONICS & COMMUNICATION ENGINEERING
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CERTIFICATE

This is to certify that the project work entitled "**A TRANSFER LEARNING BASED WEB-APP FOR GLAUCOMA DETECTION USING LOW-COST OPHTHALMOSCOPIC CAMERA**" is a bonafide work carried out by **SATYAM OZA R (1MJ18EC122)**, **SHANKAR S (1MJ18EC123)**, **SHIREESHA D C (1MJ18EC126)** and **VEDASHREE H A (1MJ18EC146)**, in partial fulfillment for the award of degree of Bachelor of Engineering in Electronics & Communication Engineering of the Visvesvaraya Technological University, Belagavi during the year 2021-22. It is certified that all the corrections/suggestions indicated for Internal Assessment have been incorporated in the Report. The project report has been approved as it satisfies the academic requirements

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DECLARATION

We hereby declare that the entire work of the project titled "**A Transfer Learning Based Web App for Glaucoma Detection Using Low-Cost Ophthalmoscopic Camera**" embodied in this project report has been carried out by **Satyam Oza R (1MJ18EC122)**, **Shankar S (1MJ18EC123)**, **Shreesha D C (1MJ18EC126)** and **Vedashree H A (1MJ18EC146)**, during the 8th semester of BE degree at MVJCE, Bangalore under the esteemed guidance of **Prof. Sayantam Sarkar** (Assistant Professor, ECE) affiliated to Visvesvaraya Technological University, Belagavi. The work embodied in this dissertation work is original and it has not been submitted in part or full for any other degree in any University.

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ABSTRACT

Glaucoma is the leading cause of irreversible blindness and disability worldwide. Nevertheless, the majority of patients do not know that they have the disease and detection of glaucoma progression using standard technology remains a challenge in clinical practice. Fundus evaluation is an eye exam that helps both ophthalmologists and non-ophthalmologists to provide vital diagnostic information about Glaucoma. Content-based image analysis and computer vision techniques are used in various health-care systems which are adapted in our work to detect Glaucoma. We use Transfer learning to train and screening the InceptionResNetV2 model for detection of glaucoma by using structural and functional tests which gives maximum accuracy compared to other CNN models by understanding the advancements in the particular area. In the proposed system a low-cost Ophthalmoscopic camera is used which provides the detection accuracy of 88% in true positive and false positive in order to determine the Glaucoma in the eyes. Since the present hardware used by the hospitals are fixed and expensive, we use an easy-to-use web app developed , which is intended for glaucoma detection utilizing low-cost Ophthalmoscopic cameras. It helps the patient to view the result from any part of the world.

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CHAPTER 1

INTRODUCTION

Glaucoma is the first cause of Irreversible blindness since it affects the eye's optic nerve. In most of the cases patients do not experience symptoms of vision loss until advanced stages. Content-based image analysis and computer vision techniques are used in various health-care systems to detect this disease. The abnormalities in a human eye are detected through images captured through a Ophthalmoscopic camera. The early diagnosis of glaucoma can prevent permanent loss of vision. Manual examination of the human eye is a possible solution however it is dependent on human efforts. Evaluation of the fundus is an essential component of an eye examination, providing valuable diagnostic information to both Ophthalmologists and non - Ophthalmologists.

In addition to physical examination, the fundus can also be photographed, which allows for documentation and sharing of the images for telemedicine. A study of glaucoma prevalence from worldwide published data found that by 2020, Over 11.1 million people were bilaterally blind from primary Glaucoma. Non mydriatic Ophthalmoscopic photography allows for imaging of the retina and optic nerve without pharmacologic dilation. Currently available non mydriatic cameras tend to cost thousands of dollars, and most are either table-mounted or too bulky to carry around.

Glaucoma is an optic nerve head condition caused by excessive fluid pressure in the eye. Glaucoma develops when the eye's drainage mechanism becomes clogged, allowing fluid to pool in the eye and produce pressure [1]. It's an urgent call for patients to look for treatment. Glaucoma cannot be seen or felt by the patient in its early stages. It's usually detected by the patient after a certain degree of damage has already happened during a normal eye exam. Damage manifests as a progressive shift in vision followed by vision loss. The treatment options for glaucoma include eye drops, surgeries such as laser therapy, filtering surgery, laser trabeculoplasty, and a trabecular bypass stent. All of these expenses are prohibitively expensive for most people. So, applying transfer learning techniques to detect glaucoma can be a game changer in the medical field as it has the potential to compete with the modern technologies to give precise and accurate results, hence this helps to overcome many kinds of problems faced by the patient.

The automatic detection of glaucoma by using a combination of image processing, artificial intelligence and computer vision can help to prevent and detect this disease. In this review article, we aim to present a comprehensive review about the various types of glaucoma, causes of glaucoma, the details about the possible treatment, details about the publicly available image benchmarks, performance metrics, and various approaches based on digital image processing, computer vision, and deep learning. The review article presents a detailed study of various published research models that aim to detect glaucoma from low-level feature extraction to recent trends based on deep learning.

The retina is a multi-layered structure that covers a large surface inside the eye. The function of the retina is to convert light to a neural response for further use by the brain. The retina contains two different types of photoreceptors: rods and cones. A healthy eye consists of around 60 million rods and around 3 million cones [21]. Rods are located at the peripheral part of the retina, they are responsible for peripheral vision, motion detection and the perception of light/dark contrast. Cones are mostly located in the macula luteal region of the retina, with most of the cones living at the central part of the macula lutea, the fovea centralis [22].

Cones allow for color and central vision. The retina however consists of many layers, and photoreceptors only constitute a small part of these. One could make use of several retinal imaging techniques. Examples of such techniques are Colour Fundus Photography (CF), Fundus Autofluorescence (FAF), Near-Infrared Reflectance (NIR) and Optical Coherence Tomography (OCT). CF, FAF and NIR are en-face imaging techniques while OCT is a cross-sectional imaging technique. OCT allows for accurately measuring the thickness of the retina, something that is not possible using the other imaging techniques mentioned. CT is an imaging technique to create cross-sectional views of the retina non-invasively. OCT scans are often acquired as multiple linear slices [23]. Stacking these slices, it is possible to create a 3D view of the retina and its different layers. In OCT volumes 18 different retinal layers can be identified, An OCT scan is acquired by directing a beam of near-infrared light to both a mirror and the retina [24].

Diabetic retinopathy is a condition that damages the retina. This condition affects many people that suffer from diabetes. Proper monitoring and treating the eyes can reduce symptoms at 90 percent of new cases [25].

Diabetic retinopathy may cause macula edema, resulting in vessels leaking blood in the retina. OCT can show which areas are thickened when fluid accumulates. Other effects of diabetic retinopathy that can be seen in OCT images are retinal swellings and damaged nerve tissue [26].

The Database used in this system is virtually located. Therefore the image and prediction results are then sent to the server database to visualize the results on the user interface. The predicted results will be generated and displayed in the web app interface.

A supervised classifier based on deep learning is a convolutional neural network (CNN) [27]. It consists of several convolutional layers as well as subsampling layers that are good at designing efficient filters to retrieve the classification task's sensitive image features. In this research, we adopted the CNN architecture, a 19-layer CNN model that is commonly used to address problems with image classification. The output layer was modified into a new softmax layer with two units sufficient for this task in order to distinguish healthy and glaucomatous eyes [28]. Transfer learning, on the other hand, is a method of machine learning to apply an established model to a new task domain for previous tasks.

1.1 CAUSES OF GLAUCOMA

Glaucoma is caused by high intraocular pressure, it is more likely to develop in persons who have a family history of the disease and people who have specific eye disorders such as diabetes or short-sightedness, are more prone to develop the disease. The most important effect of this disease is the loss of vision and sometimes this effect might become permanent. Glaucoma is generally found in people over age above 60. There are several causes due to which glaucoma is found, they can be poor or reduced blood flow to the optic nerve of the eye and sometimes due to the blocked or restricted drainage in the eye. Sometimes people who commonly use eye drops or medications, such as corticosteroids have more chances to get affected by this disease.

The below classification of glaucoma is based on the crucial interior of eye physique factors which are generally used to classify various types of glaucoma [2].

1. **Open-Angle Glaucoma / Chronic Glaucoma:** Open-angle or chronic glaucoma can cause vision loss by slowing down the vision. This type's indications and symptoms aren't detected until later on. It might cause permanent visual loss if not recognised and treated early.

2. **Angle-Closure Glaucoma / Acute Glaucoma:** For the most part, this is an emergency situation. High pressure in the eyes is caused by a sudden obstruction in the aqueous humor fluid. Nausea, extreme discomfort, and blurred vision are all symptoms.
3. **Congenital Glaucoma:** Congenital glaucoma is caused by a defect in the eye's angular location. This can be detected through family members or from parents to children. It inhibits the drainage mechanisms that produce excessive weeping, light sensitivity, and impaired vision.
4. **Secondary Glaucoma:** Eye surgery can cause secondary glaucoma. It can also be caused by eye diseases like cataracts or tumors. Itchy eyes and iris pain are common in this case.
5. **Normal Tension Glaucoma:** Damage of the optic nerve in the eye causes normal tension glaucoma to develop. The main cause of this type of glaucoma is a lack of blood flow to the optic nerve and increase of pressure on the fundus.

1.2 DIAGNOSIS AND TREATMENT

Some comprehensive eye examinations include:

1. Measuring intraocular pressure (tonometry).
2. Testing for optic nerve damage with a dilated eye examination and imaging tests.
3. Checking for areas of vision loss (visual field test).
4. Measuring corneal thickness (pachymetry).
5. Inspecting the drainage angle (gonioscopy).

The damage caused by glaucoma can't be reversed. But treatment and regular checkups can help slow or prevent vision loss, especially if you catch the disease in its early stages.

1.2.1 Eye Drops

Glaucoma treatment often starts with prescription eye drops. These can help decrease eye pressure by improving how fluid drains from your eye or by decreasing the amount of fluid your eye makes.

Depending on how low your eye pressure needs to be, more than one of the eye drops below may need to be prescribed. Carbonic anhydrase inhibitors, like Trusopt (dorzolamide) and Azopt (brinzolamide).

1.2.2 Oral Medications

If eye drops alone don't bring your eye pressure down to the desired level, doctors may also prescribe an oral medication, usually a carbonic anhydrase inhibitor.

Possible side effects include frequent urination, tingling in the fingers and toes, depression, stomach upset, and kidney stones.

1.2.3 Surgery and other therapies

Other treatment options include laser therapy and various surgical procedures. The following techniques are intended to improve the drainage of fluid within the eye, thereby lowering pressure:

1. **Laser Therapy:** Laser Trabeculoplasty is an option if you have open-angle glaucoma. Doctors use a small laser beam to open clogged channels in the trabecular meshwork. It may take a few weeks before the full effect of this procedure becomes apparent.
2. **Filtering Surgery:** With a surgical procedure called a trabeculectomy, the surgeon creates an opening in the white of the eye (sclera) and removes part of the trabecular meshwork.
3. **Drainage Tubes:** In this procedure, an eye surgeon inserts a small tube shunt in the eye to drain away excess fluid to lower the eye pressure.
4. **Minimally Invasive Glaucoma Surgery (MIGS):** Doctor may suggest a MIGS procedure to lower your eye pressure. These procedures generally require less immediate postoperative care and have less risk than trabeculectomy or installing a drainage device. They are often combined with cataract surgery.

1.3 PROBLEM STATEMENT

Glaucoma is a condition that damages the eye's optic nerve. It gets worse over time. It's often linked to a buildup of pressure inside our eye. As per the current available medical technologies, there are more chances to create a system which is based on Image Processing, Computer Vision and Transfer Learning techniques based on InceptionResNetV2 CNN. Architecture to accurately detect the disease and to get detailed reports on various prediction metrics of a test eye image which is fed by the user. The system also aims to collect datasets of glaucoma patients from trusted sources and then train a transfer learning based model on this dataset, the trained model is then stored and embedded with the web-app in later stages, the system also aims to build a low cost camera design which is capable enough to take retinal images which can be directly connected to a responsive web interface based on virtual servers and python-flask based web scripting to predict glaucoma results and provide users with report which will be accessible on the same web interface.

1.4 ADVANTAGES, DISADVANTAGES AND APPLICATIONS

1.4.1 ADVANTAGES

1. High Focal length and magnification.
2. Implemented low cost camera.
3. One can view the result from any part of the world by accessing a web app.
4. True image is captured.
5. It permits binocular vision with depth perception (stereoscopic vision).
6. It has a wider field of view.
7. It is not affected by the refractive state of the patient' eye.
8. It may be used in the operating room without contamination.

1.4.2 DISADVANTAGES

1. Inverted and reversed image.
2. Relatively lack of magnification.
3. Difficult to master the camera setup.
4. Small movements alter significantly the size and clarity.
5. Impossible to take images with small pupils.

6. More uncomfortable to patients.

1.4.3 APPLICATIONS

1. Can be utilized by medical experts, as an inexpensive preliminary testing tool.
2. Common people can also use it to periodically test family members.
3. Researchers can use this as a base to create more accurate and inexpensive tools to detect glaucoma.

CHAPTER 2

LITERATURE SURVEY

With the use of transfer learning and deep learning techniques, Serener and Serte [3], presented deep learning algorithms to classify early and advanced glaucoma on fundus images. This classification's accuracy performance for ResNet50 is 86 percent, while its accuracy performance for the GoogLeNet model is 85 percent. The model's downside was that it was less accurate than other methods for detecting Glaucoma illness. To improve accuracy, the models can be substituted with alternative CNN (Convolutional Neural Network) models.

The estimation of people who have been affected with Glaucoma disease worldwide under age groups, Rohit Varma, et al.'s [4] found to reintegrate epidemiologic data with some of the economic and individual pressure of glaucoma which highlights the cause of glaucoma on individuals, health systems, and societies. The prevalence of POAG (Primary Open - Angle Glaucoma), is considered to be 16 times greater among those people aged 80 years compared to those aged between 40 to 49 years and 13 times higher than those aged 50 to 59 years. The disadvantage of this approach was that glaucoma therapy was extremely cost effective when diagnostic costs were omitted and optimistic treatment efficacy assumptions were applied.

J. Ayub, et al. [5] , highlights the treatment of glaucoma disease by utilizing cup and disc segmentation using RGB (Red, Green & Blue) and HSV (Hue - Saturation Value) color models with K-mean Clustering Techniques. This approach has an accuracy rate of 86 percent. This model does not account for the circulatory system that runs throughout the disc, which overlaps basically with the precision of detecting the proper segments which belong to the disc.

A. Sallam et al. [6], presented the detection of glaucoma by using Transfer Learning from Pre-trained CNN Models such as Pre-trained AlexNet, VGG11, VGG19, and VGG16 models using Deep learning techniques, with accuracy of 81.4 percent, 80 percent, 82.2 percent, and 80.9 percent on the LAG (Large Scale Attention based Glaucoma) dataset. Patil and Nikam [7] presented a MATLAB GUI (Graphical User Interface) for glaucoma identification using fundus images. To diagnose a sickness. Image processing techniques of the CDR (Cup - to - Disc Ratio) type and ellipse methods are utilized. The optic cup and the optic disc's boundaries are detected in this case. The segmentation and the precision of the disc and cup is inefficient.

Dhumane and Patil [8] had presented glaucoma detection automated using CDR by super pixel segmentation. This technique does not require patience at the time of testing as only the retinal image is sufficient by the method of Superpixel Segmentation Techniques. This uses a simple linear iterative clustering algorithm where High Sensitivity values are generated, therefore signifying the role of image based classification. From a minimal number of components, a fully working, affordable, handheld, nonmydriatic fundus camera can be easily made. A camera like this with a combination of transfer learning based web app could be beneficial for a range of healthcare practitioners, especially those who work in places where a standard table-mounted nonmydriatic fundus camera would be uncomfortable and not at all user friendly to carry around.

CHAPTER 3

DEEP TRANSFER LEARNING

Deep Transfer Learning originates by combining two types of Machine Learning Techniques which are, Deep Learning and Transfer Learning.

3.1 DEEP LEARNING

Definition: Deep Learning is a class of Machine Learning algorithms that uses multiple layers to progressively extract higher-level features from the raw input. For example, in image processing, lower layers may identify edges, while higher layers may identify the concepts relevant to a human such as digits or letters or faces.

Deep learning (also known as deep structured learning) is part of a broader family of machine learning methods based on artificial neural networks with representation learning. Learning can be supervised, semi-supervised or unsupervised.

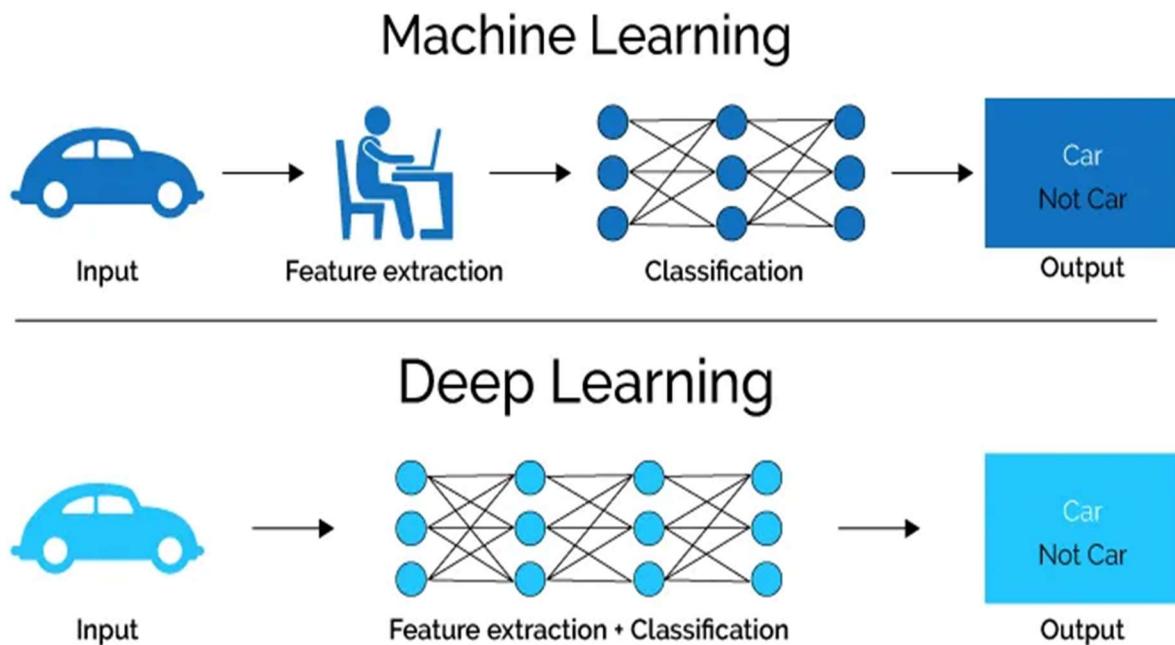


Fig. 3.1 Difference between classic Machine Learning & Deep Learning

Deep learning architectures such as deep neural networks and convolutional neural networks have been applied to fields including computer vision, speech recognition, natural language processing, machine translation, bioinformatics, drug design, medical image analysis, material inspection and board game programs, where they have produced results comparable to and in some cases surpassing human expert performance.

In Deep learning, each level learns to transform its input data into a slightly more abstract and composite representation. From Fig 3.1, the raw input may be a matrix of pixels; the first representational layer may abstract the pixels and encode edges; the second layer may compose and encode arrangements of edges; the third layer may encode features of object; and the fourth layer may recognize that the image contains a specific class object. Importantly, a deep learning process can learn which features to optimally place in which level on its own.

3.2 TRANSFER LEARNING

Definition: Given a specific Domain $D = \{ X, P(X) \}$, a task consists of two components: a label space Y , and an objective predictive function $f(\cdot)$, which is learned from labeled data pairs $\{x_i, y_i\}$ and can be used to predict the corresponding label $f(x)$ of a new instance x . The task therefore can be expressed as $T = \{ y, f(\cdot) \}$, Then, given a source domain D_s , and a learning task T_s , a target domain D_t , and a learning task T_t , transfer learning aims to help improve the learning of the target predictive function $f_t(\cdot)$ in D_t , using knowledge in D_s and T_s .

Transfer learning (TL) is a research problem in machine learning (ML) that focuses on storing knowledge gained while solving one problem and applying it to a different but related problem. For example, knowledge gained while learning to recognize cars could apply when trying to recognize trucks. From the practical standpoint, reusing or transferring information from previously learned tasks for the learning of new tasks has the potential to significantly improve the sample efficiency of a reinforcement learning agent.

Algorithms are available for transfer learning in Markov logic networks and Bayesian networks. Transfer learning has also been applied to cancer subtype discovery, building utilization, general game playing, text classification, digit recognition, medical imaging and spam filtering.

Fig 3.2 shows perfect data flow and need for Transfer Learning algorithms where the pre-trained CNN is reused, but with new weights for predicting new results for objects pointed by normalized and fine-tuned models.

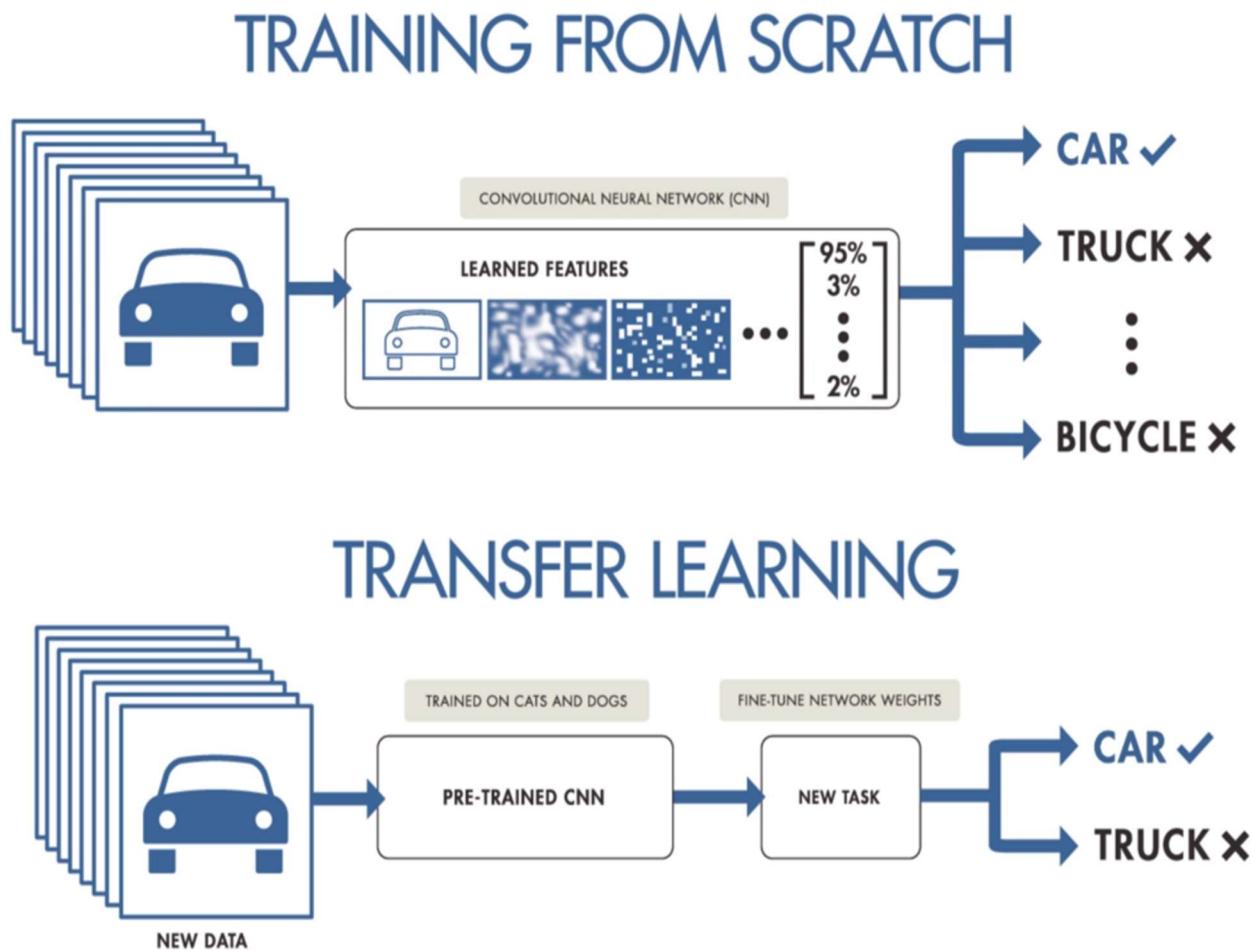


Fig. 3.2 Difference between Training from scratch and Transfer Learning

CHAPTER 4

HARDWARE USED

4.1 RASPBERRY PI

Raspberry Pi is a small single board computer. By connecting peripherals like Keyboard, mouse, display to the Raspberry Pi, it will act as a mini personal computer. Raspberry Pi is popularly used for real time Image/Video Processing, IoT based applications and Robotics applications.

Raspberry Pi is slower than laptop or desktop but is still a computer which can provide all the expected features or abilities, at a low power consumption.

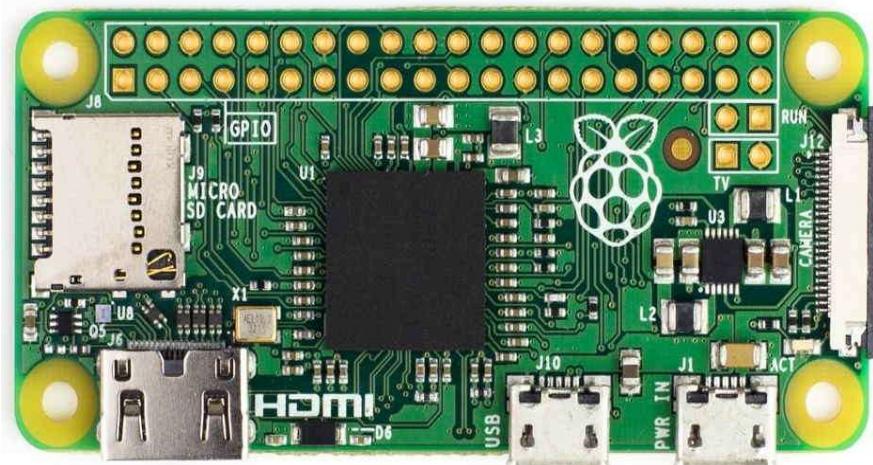


Fig. 4.1 Raspberry Pi Zero W Board [20]

The go-to choice for those running the Zero W as a computer is Raspbian, the Pi's official operating system. Raspbian is a custom-version of Debian that has been optimized to run on the Pi's hardware, has recently had a graphical overhaul, and includes an office suite, programming tools, educational games, and other software.

Raspberry Pi Zero 2 W features a mini HDMI port, a micro USB port, and a micro USB power port. Raspberry Pi offers a wide range of high-quality, low-cost cables and adapters to get you up and running on your Raspberry Pi Zero 2 W.

At the heart of Raspberry Pi Zero 2 W is RP3A0, a custom-built system-in-package designed by Raspberry Pi in the UK. With a quad-core 64-bit ARM Cortex-A53 processor clocked at 1GHz and 512MB of SDRAM, Zero 2 is up to five times as fast as the original Raspberry Pi Zero. Also One of the smallest and cheapest machines available.

Specifications:

1. Broadcom BCM2835, ARM11 running at 1GHz, 512MB RAM.
2. 40-pin GPIO.
3. Full-size HDMI.
4. Micro USB.
5. CSI camera port.
6. MicroSD card.

4.2 RASPBERRY PI NOIR CAMERA

The Raspberry Pi NoIR Camera v2 is the official “night vision” camera board released by the Raspberry Pi Foundation. The Raspberry Pi NoIR Camera Module v2 is a high quality 8 megapixel Sony IMX219 image sensor custom designed add-on board for the Raspberry Pi, featuring a fixed focus lens.



Fig. 4.2 Raspberry Pi NoIR Camera V2 Module [19]

Featuring the same 8-megapixel image sensor as the standard Raspberry Pi camera with the infrared cut-off filter removed to increase IR light sensitivity. The Pi NoIR is compatible with all Raspberry Pi models and provides high definition, high sensitivity, low crosstalk, and low noise image capture in an ultra small and lightweight design.

(NoIR = No Infrared Filter) This means that pictures you take by daylight will look decidedly curious, but it gives users the ability to see in the dark with infrared lighting. Noir is a dual high-tech spy camera and USB charger with a discreet and low-profile structure. The camera can function as a standard phone charger that sits on a socket and offers an accurate recording of every movement in its coverage area.

Specifications:

1. Raspberry Pi Camera NOIR V2
2. Resolution - 8 Megapixel
3. Sensor - Sony IMX219PQ CMOS
4. Video Modes - 1080p30, 720p60, 640x480p
5. Dimensions in mm (LxWxH) - 25 x 20 x 9
6. Weight (gm) – 4

Features of NOIR Camera:

1. Fixed focus lens on-board
2. 8 megapixel native resolution sensor-capable of 3280 x 2464 pixel static images
3. Supports 1080p30, 720p60 and 640x480p90 video
4. Size 25mm x 23mm x 9mm
5. Weight just over 3g
6. Connects to the Raspberry Pi board via a short ribbon cable (supplied)
7. Camera v2 is supported in the latest version of Raspbian.

4.3 20-Diopter ASPHERIC LENS



Fig. 4.3 20 Dioptre Aspheric Lens [18]

This lens is used for general examination of the fundus using “Binocular Indirect Ophthalmoscope (BIO)”.

This provides a high resolution image of the retina in the OPD or the operating room. A 45 degree field of view helps in visualization up to the mid peripheral region. A dynamic examination with patients eye movements helps in visualization of the peripheral retina as well. A working distance of 50mm makes lens manipulation very easy for the user.

Higher magnification than 28D is Ideal for pediatric examination, when scleral indentation is required and for patients with nystagmus. Useful when slit lamp examination is not possible.

CHAPTER 5

SOFTWARE USED

5.1 Python 3

Python is a great object-oriented, interpreted, and interactive programming language. It is often compared to Lisp, Tcl, Perl, Ruby, C#, Visual Basic, Visual FoxPro, Scheme or Java.

Python combines remarkable power with very clear syntax. It has modules, classes, exceptions, very high level dynamic data types, and dynamic typing. There are interfaces to many system calls and libraries, as well as to various windowing systems. New built-in modules are easily written in C or C++ (or other languages, depending on the chosen implementation). Python is also usable as an extension language for applications written in other languages that need easy-to-use scripting or automation interfaces.



Fig. 5.1 Python Symbol

Below are few advantages of using Python:

1. Readable and Maintainable Code
2. Multiple Programming Paradigms
3. Compatible with Major Platforms and Systems
4. Robust Standard Library
5. Many Open Source Frameworks and Tools
6. Simplify Complex Software Development
7. Adopt Test Driven Development

5.2 TensorFlow



Fig. 5.2 TensorFlow Symbol

TensorFlow is a free and open-source software library for machine learning. It can be used across a range of tasks but has a particular focus on training and inference of deep neural networks.

Tensorflow is a symbolic math library based on dataflow and differentiable programming. It is used for both research and production at Google.

Advantages of TensorFlow:

- 1. Open-source platform:** It is an open-source platform that makes it available to all the users around and ready for the development of any system on it.
- 2. Data visualization:** TensorFlow provides a better way of visualizing data with its graphical approach. It also allows easy debugging of nodes with the help of TensorBoard. This reduces the effort of visiting the whole code and effectively resolves the neural network.
- 3. Keras friendly:** TensorFlow has compatibility with Keras, which allows its users to code some high-level functionality sections in it. Keras provides system-specific functionality to TensorFlow, such as pipelining, estimators, and eager execution.
- 4. Scalable:** Almost every operation can be performed using this platform. With its characteristic of being deployed on every machine and graphical representation of a model allows its users to develop any kind of system using TensorFlow. Hence TensorFlow has been able to develop systems like Airbnb, Dropbox, Intel, Snapchat, etc.

- 5. Compatible:** It is compatible with many languages such as C++, JavaScript, Python, C#, Ruby, and Swift. This allows a user to work in an environment they are comfortable in.
- 6. Parallelism:** TensorFlow finds its use as a hardware acceleration library due to the parallelism of work models. It uses different distribution strategies in GPU and CPU systems. A user can choose to run its code on either of the architectures based on the modeling rule.
- 7. Architectural support:** TensorFlow also has its architecture TPU, which performs computations faster than GPU and CPU. Models built using TPU can be easily deployed on a cloud at a cheaper rate and executed at a faster rate.
- 8. Graphical support:** Deep learning uses TensorFlow for its development as it allows building neural networks with the help of graphs that represent operations as nodes. TensorFlow acts in multiple domains such as image recognition, voice detection, motion detection, time series, etc hence it suits the requirement of a user.

5.3 Google Colaboratory

The screenshot shows the Google Colaboratory interface. At the top, there's a navigation bar with 'File', 'Edit', 'View', 'Insert', 'Runtime', 'Tools', and 'Help'. On the right side of the bar are 'Share', 'Settings', and a profile picture. Below the bar, there's a 'Table of contents' sidebar on the left containing links to 'Getting started', 'Data science', 'Machine learning', 'More Resources', 'Machine Learning Examples', and 'Section'. The main content area displays a notebook titled 'What is Colaboratory?'. The notebook content includes a brief introduction, a bulleted list of features (Zero configuration required, Free access to GPUs, Easy sharing), and a note for students, data scientists, and AI researchers. Below this, there's a section titled 'Getting started' with a description of what a Colab notebook is and an example of Python code in a code cell. The code cell shows the calculation of seconds in a day:

```
[ ] seconds_in_a_day = 24 * 60 * 60  
seconds_in_a_day
```

 followed by the output:

```
86400
```

.

Fig. 5.3 Google Colaboratory Interface

Colaboratory, or “Colab” for short, is a product from Google Research. Colab allows anybody to write and execute arbitrary python code through the browser, and is especially well suited to machine learning, data analysis and education. More technically, Colab is a hosted Jupyter notebook service that requires no setup to use.

5.4 Python-Flask

Flask is a micro framework offering basic features of web apps. This framework has no dependencies on external libraries. The framework offers extensions for form validation, object-relational mappers, open authentication systems, uploading mechanism, and several other tools.

Fig. 5.4 Python-Flask Symbol



Features of Flask :

1. Integrated support for unit testing.
2. RESTful request dispatching.
3. Uses a Jinja2 template engine.
4. It is based on the Werkzeug toolkit.
5. Support for secure cookies (client-side sessions).
6. Extensive documentation.
7. Google app engine compatibility.
8. APIs are nicely shaped and coherent
9. Easily deployable in production

Advantages of using Python-Flask :

1. **Scalable:** Applications are often running in containers or using cloud computing with auto-scaling. Applications do not typically “scale” themselves. The infrastructure scales. With a smaller application, it's easier to deploy instances across thousands of servers easily to handle increased traffic/load. That's part of the reason why Pinterest needed to migrate from Django to Flask as they grew to support more of a microservices pattern.
2. **Flexibility:** There are very few parts of Flask that cannot be easily and safely altered because of its simplicity and minimality.
3. **Performance:** It is a micro framework being slightly more “low-level” than something like Django. There are fewer levels of abstraction between user and the database, the requests, the cache, etc. So performance is inherently better from the start.
4. **Modularity:** Modular code provides a huge number of benefits. With Flask, users have the ability to create multiple Flask applications or servers, distributed across a large network of servers, each with specific purposes. This creates more efficiency, better testability, and better performance.

5.5 VNC Viewer

VNC stands for Virtual Network Computing. It is a cross-platform screen sharing system that was created to remotely control another computer. This means that a computer's screen, keyboard, and mouse can be used from a distance by a remote user from a secondary device as though they were sitting right in front of it. VNC works on a client/server model. A server component is installed on the remote computer (the one you want to control), and a VNC viewer, or client, is installed on the device you want to control from. This can include another computer, a tablet, or a mobile phone. When the server and viewer are connected, the server transmits a copy of the remote computer's screen to the viewer.

Not only can the remote user see everything on the remote computer's screen, but the program also allows for keyboard and mouse commands to work on the remote computer from afar, so the connected user has full control (after being granted permission from the remote computer).

Features:

The main advantage of VNC is the use of encryption to ensure the secure transfer of information between the client and the server.

1. VNC allows users to access a remote computer's display.
2. VNC allows users to execute shell commands on a remote computer in the same way as if they were sitting in front of the physical computer. Using VNC commands and scripts, administrators can view, remove, or move files, create new folders, files, and directories, and download files.
3. The VNC connection layer allows multiple data streams through a single TCP connection. This ability is called multiplexing and means fewer TCP connections are needed, which allows scarce resources to be shared and also reduces overhead.
4. The ability of VNC to use port tunneling and forwarding can be used to bypass restrictive firewalls.
5. SSH allows network administrators to remotely limit user access to a network.

CHAPTER 6

DATASET

The Singapore Malay Eye Study's Online RetinalFundus Image Dataset for Glaucoma Analysis and Research(ORIGA) database has 650 images (SiMES). The SingaporeEye Research Institute is in charge of SiMES (SERI) [17].

Retinal fundus image is an important modality to document the health of the retina and is widely used to diagnose ocular diseases such as glaucoma, diabetic retinopathy and age-related macular degeneration. However, the enormous amount of retinal data obtained nowadays is mostly stored locally; and the valuable embedded clinical knowledge is not efficiently exploited. In this project we present an online depository, ORIGA(-light), which aims to share clinical groundtruth retinal images with the public; provide open access for researchers to benchmark their computer-aided segmentation algorithms. An in-house image segmentation and grading tool is developed to facilitate the construction of ORIGA(-light). A quantified objective benchmarking method is proposed, focusing on optic disc and cup segmentation and Cup-to-Disc Ratio (CDR). Currently, ORIGA(-light) contains 650 retinal images annotated by trained professionals from Singapore Eye Research Institute. A wide collection of image signs, critical for glaucoma diagnosis, are annotated. We will update the system continuously with more clinical ground-truth images. ORIGA(-light) is available for online access upon request.

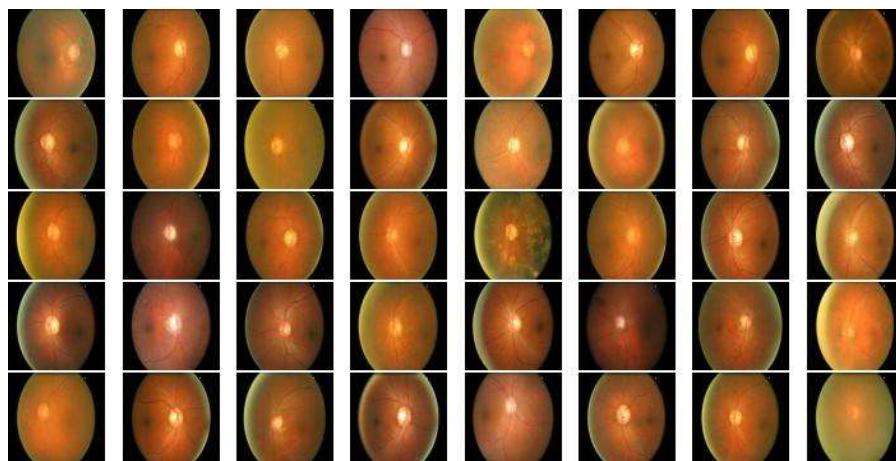


Fig. 6.1 Images in Dataset

CHAPTER 7

PROPOSED SYSTEM

7.1 PROPOSED SYSTEM DESIGN

The sample of the eye is roughly 2.3cm in diameter and is almost a spherical ball filled with some fluid captured from the patient for undergoing the test [9]. An ophthalmoscopic camera is used to filter out undesired light reflected from the cornea of a patient's eye. The NoIR camera sensor is set up with a 20-dioptral lens to capture the patient's test image [10]. The test image is sent to the controller unit for further processing. In the pre-processing stage, the test image then goes through various segmentation and filtering processes to enhance the image to increase the prediction accuracy. The test image is fed to the pretrained InceptionResNetV2 model [11] to get the prediction metrics after passing through various mathematics-based pictorial manipulation layers. Then predictions are made to obtain a boolean binary value (i.e, either True or False) for a given set of features of a classification process as shown in Fig. 7.1. This helps in predicting the results. The Database used in this system is virtually located therefore the image and prediction results are then sent to the server database to visualize the results on the user interface. The predicted results will be generated and displayed in the web app interface.

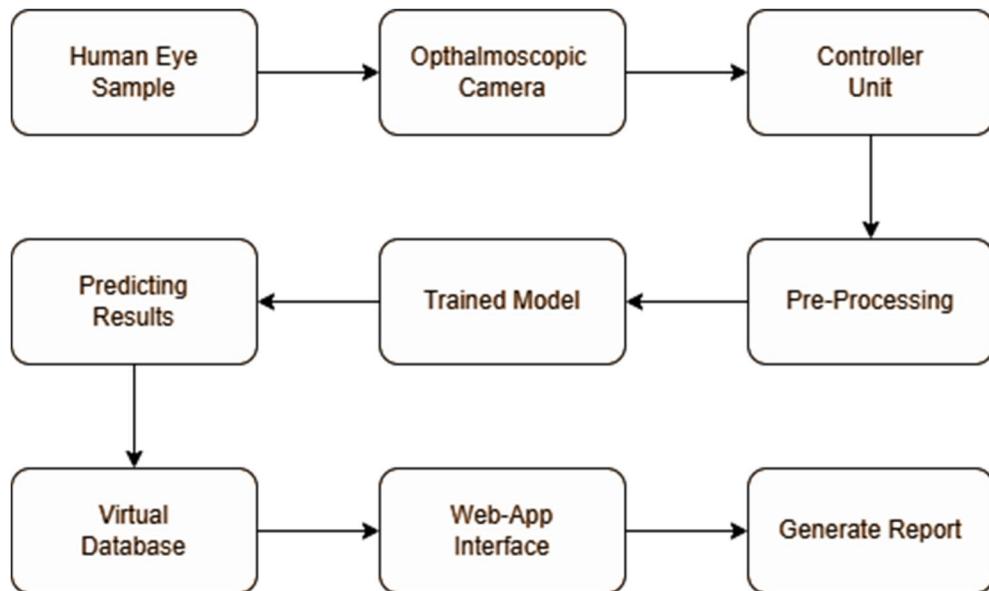


Fig. 7.1 Proposed System Design

7.2 STEPS INVOLVED IN FLOWCHART

7.2.1 Human Eye Sample

The sample of eye which is roughly 2.3cm in diameter and is almost a spherical ball filled with some fluid is captured from the patient for undergoing the test [9] as shown in Fig. 7.2. The human eye is an essential organ, which interacts with light and is necessary for the sense of sight or vision. There are two kinds of cells in the eye i.e. rods and cones. Conscious light perception, color differentiation and perception of depth are done by these cells. The human eye can differentiate between about 10 million colors, and it can also detect a single photo. The human eye is a part of the sensory nervous system. The eyes of all mammals have a non-image-forming photosensitive ganglion in the retina which receives light, adjusts the size of the pupil, regulates the supply of melatonin hormones, and also entertains the body clock. The eye is one of the most significant and sophisticated sense organs that we have as humans.

It aids in object visualization as well as the perception of light, color, and depth. Furthermore, these sense organs are comparable to cameras in that they assist humans in seeing objects when light from the outside enters them. That so, learning about the structure and operation of the human eye is fascinating. It also assists us in comprehending the operation of a camera. Six muscles are in the eye. They are responsible for controlling the movement of the eye. The most common kinds of muscles that are in the eye are the lateral rectus, medial rectus, inferior oblique, or superior rectus.

The eyes of all mammals have a non-image-forming photosensitive ganglion in the retina which receives light, adjusts the size of the pupil, regulates the supply of melatonin hormones, and also entertains the body clock. Human eyes are a specialized sense organ that is capable of receiving visual images, thereby producing the sense of sight in us. The eye receives direct oxygen through the aqueous humor. The aqueous humor nourishes the cornea, lens, and iris, by carrying nutrients, removing wastes materials excreted by the lens, and maintaining the shape of the eye. The aqueous humor is responsible for providing shape to the eye. It must be clear to function properly. Therefore the sample of the Eye is captured through the ophthalmoscopic camera.

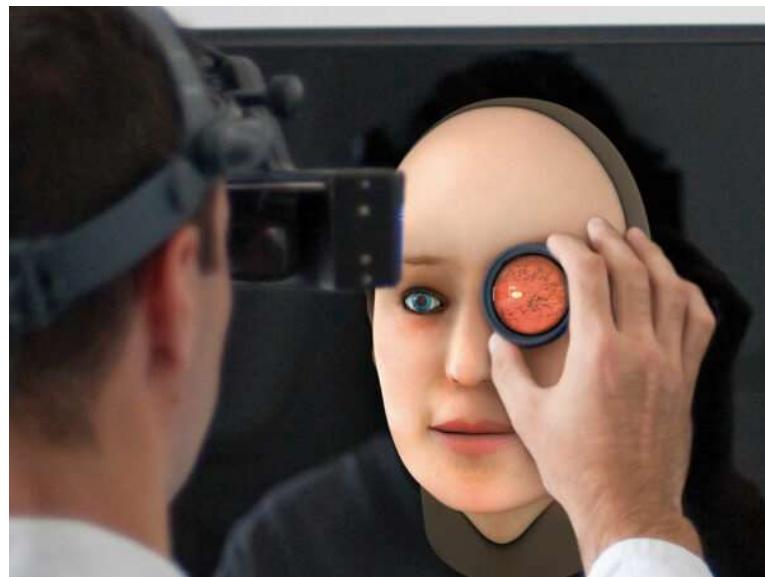


Fig. 7.2 Eye Sample Gathering

7.2.2 Ophthalmoscopic Camera

Ophthalmoscopic camera is used to filter out undesired light reflected from the cornea of a patient's eye. The NoIR camera sensor is set up with the 20-dioptre lens to capture the patient's test image [10]. An ophthalmoscopic camera is provided which can eliminate undesired light reflected from the cornea of an eye to be examined and the front and back surfaces of a front objective through which the illumination light passes by interposing a ring-shaped aperture between a plane reflecting mirror and a condenser lens arranged next to the reflecting mirror and a small shield between said condenser lens and the next condenser lens so as to shield a small area in the vicinity of and including the optical axis. The optical system for photography includes no such shield as described above and said photographic objective is of biconvex, thereby increasing the picture angle to 45 degree.

A device for the photography of a fundus, particularly a retina of an eye, comprising, a main optical viewing system including a bi-convex photographic objective placed on an optical axis of the eye for forming an intermediate image of the retina, and an aperture stop placed at a position conjugate with the cornea of the eye with respect to the photographic objective; an illuminating system comprising a light source and an illuminating optical arrangement for projecting an image of said light source on the cornea of the eye sequentially including said photographic objective.

Apertured inclined mirror placed between said photographic objective and said aperture stop for reflecting the illuminating light rays toward the optical axis of an optical system, whereby the optical axis of optical system is arranged transversely to the axis of photographic objective, mirror is centrally positioned with respect to both the viewing system and optical system axes.

An ophthalmoscopic camera comprising a photographing optical system including an objective lens adapted to be positioned opposite to a patient's eye with a working distance and an image plane on which an image of fundus of the patient's eye is formed, an illuminating optical system for projecting a beam of illuminating light to the patient's eye, a focus detecting optical system including a mark projecting system having a mark plate formed with at least one mark and located conjugate with the image plane of the photographing optical system with respect to the objective lens and an optical system for optically projecting the mark through the pupil of the patient's eye to the eye fundus. The mark projecting system includes a beam rotating device for rotating the mark projecting beam about the mark projecting optical axis.

Optical system further including first condenser lens proximate said light source followed by first and second positive lens means, a ring-shaped aperture having a central obscuring portion, said Ring-shaped aperture being provided on a surface of said second positive lens means and positioned with respect to said photographic objective and said photographic objective and said inclined mirror to produce an intermediate image of said ring aperture in substantial coincidence with said cornea, a center obscuring spot diaphragm placed on the optical axis of said optical system between said light source and said ring aperture, said spot diaphragm being provided on a surface of said first positive lens means with the lens elements of said illuminating optical arrangement so positioned as to form an intermediate image of said spot diaphragm on the rear surface of said photographic objective, whereby the curvature of the objective acts as a convex mirror for further forming said intermediate image of said spot diaphragm on said aperture stop. An ophthalmoscopic camera can view the retina and optic nerve despite pharmacologic dilation. There are numerous ways to do this, but one common one is to focus infrared light on the fundus, which does not cause the pupil to contract, and then flash white light quickly to get a color retinal image before the pupil constricts. Because the eye does not perceive the infrared light needed to focus the camera on the fundus, ophthalmoscopic photography, even with the white flash, is often more comfortable for the patient than manual examination of the fundus with white light in indirect ophthalmoscopy.

Unfortunately, the majority of ophthalmoscopic cameras on the market now cost thousands of dollars and are either table-mounted or too heavy to easily travel. An ophthalmoscopic camera is provided that may minimize unwanted light reflected off the cornea of the eye being examined, as well as the front and back surfaces of a front objective through which the illuminating light flows through a 20-Dioptre lens. The NoIR (No-Infrared filter) camera sensor [12] is connected and configured to capture the image of the patient's eye.

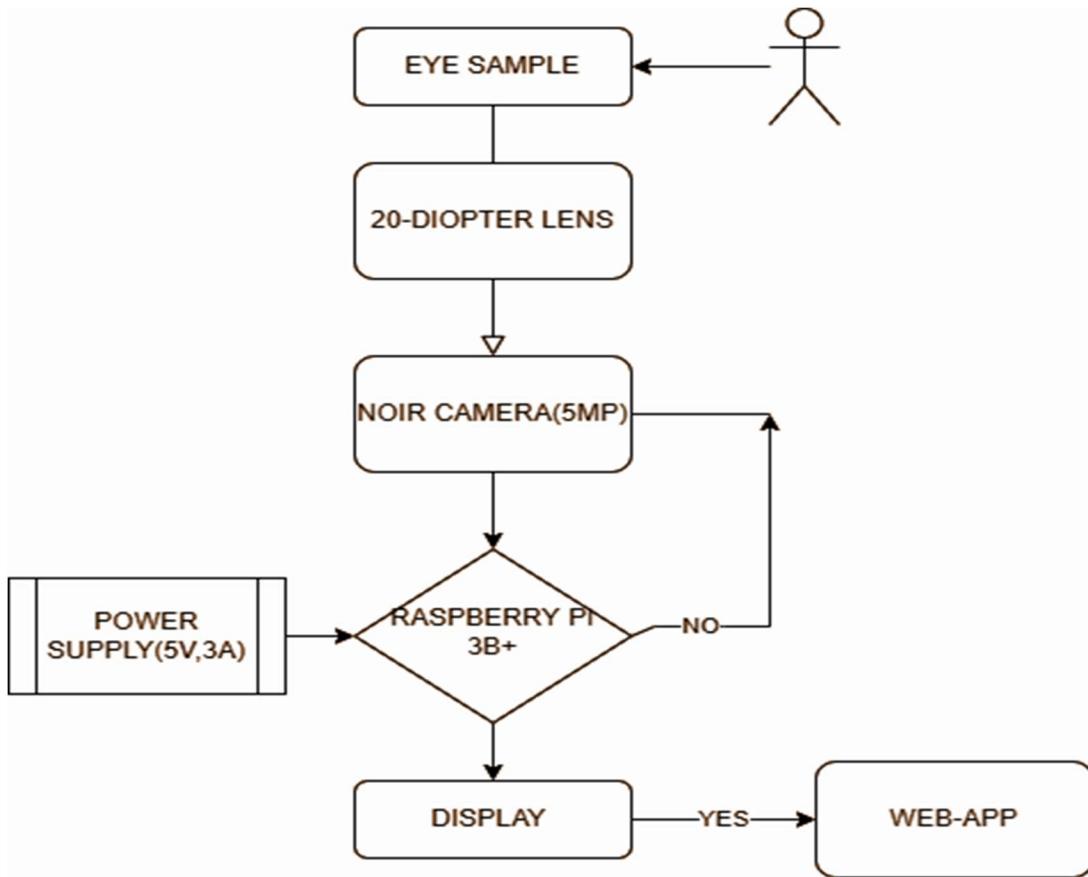


Fig. 7.3 Flowchart of Ophthalmoscopic Camera

From Fig. 7.3 & 7.4, Initial step is to take an eye sample image of the patient undergoing the test. The NoIR (No-Infrared filter) camera sensor attached with 20-Dioptre also known as ophthalmoscopic camera is set up to capture the test image of the patient eye. The test image is sent to the controller unit by means of physical connection for further processing. The test image then goes through various segmentation and filtering processes to enhance the image to increase the prediction accuracy.

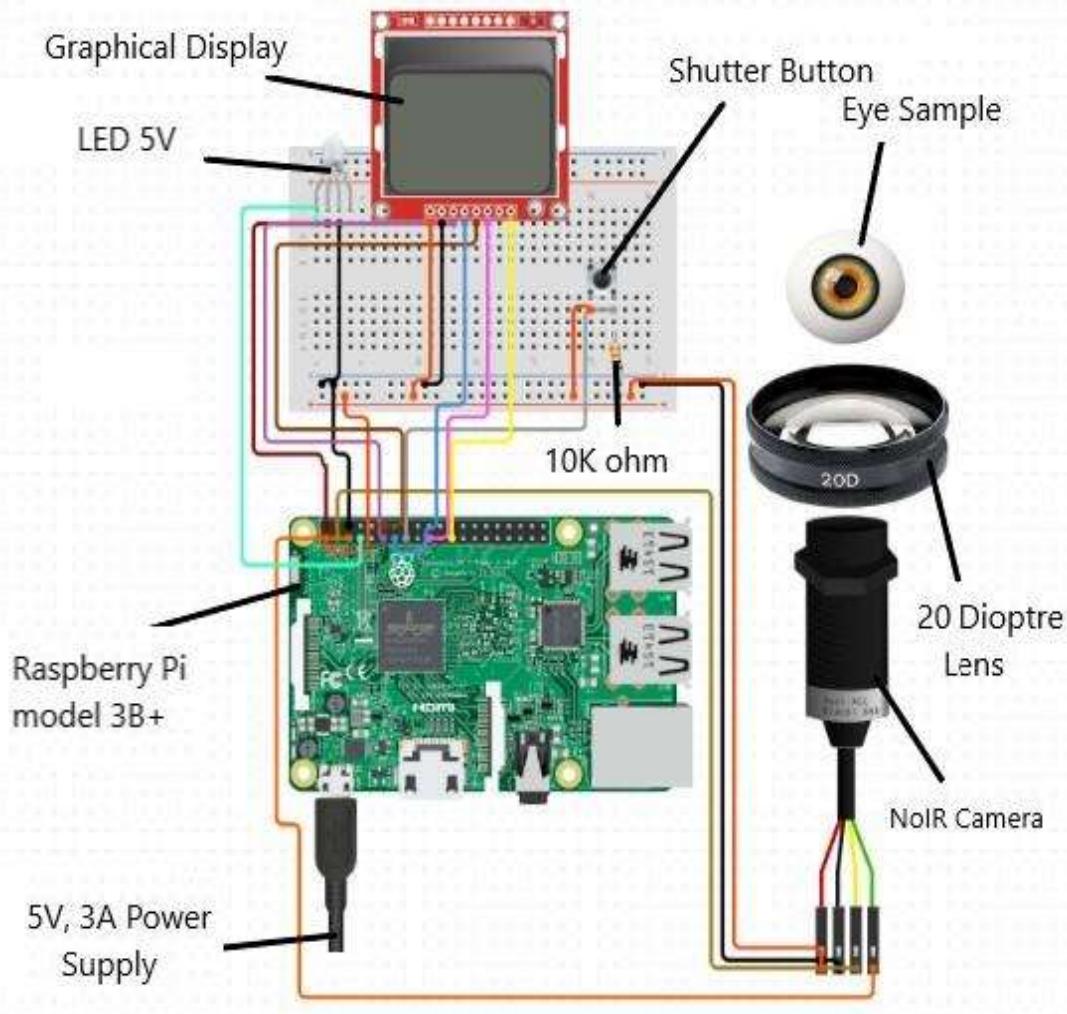


Fig. 7.4 Circuit diagram of Ophthalmoscopic Camera

7.2.3 Data Pre-Processing and Data Augmentation

Data preprocessing is a data mining technique that involves transforming raw data into an understandable format. Real-world data is often incomplete: lacking attribute values, lacking certain attributes of interest, or containing only aggregate data, Noisy: containing errors or outliers. Inconsistent: containing discrepancies in codes or names. Data preprocessing is a proven method of resolving such issues.

Real-world data are generally incomplete: lacking attribute values, lacking certain attributes of interest, or containing only aggregate data. Noisy: containing errors or outliers. Inconsistent: containing discrepancies in codes or names.

The Data pre-processing steps listed in Fig. 7.5 can be utilized to get these errors removed from image datasets, the impact of this step plays a very crucial role in terms of prediction accuracy in this case.

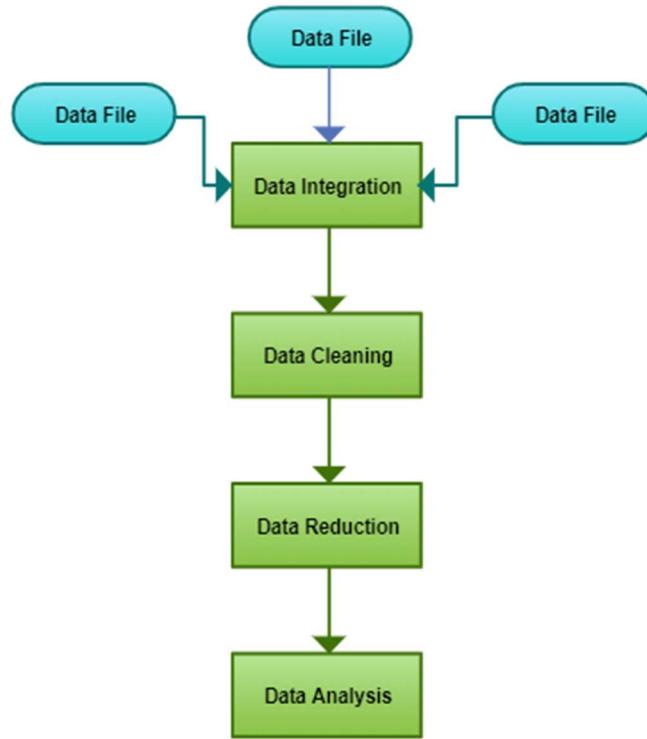


Fig. 7.5 Data Pre-Processing Flowchart

Steps Involved in Data Preprocessing:

1. Data Cleaning:

The data can have many irrelevant and missing parts. To handle this part, data cleaning is done. It involves handling of missing data, noisy data etc.

2. Missing Data:

This arises when some data is missing in the data. It can be handled in various ways.

Some of them are:

- a. **Ignore the tuples:** This approach is suitable only when the dataset is quite large and Multiple values are missing within a tuple.

- b. **Fill the Missing values:** There are various ways to do this task. You can choose to fill the missing values manually, by attribute mean or the most probable value [7].

3. Noisy Data:

Noisy data is meaningless data that can't be interpreted by machines. It can be generated due to faulty data collection, data entry errors etc. It can be handled in following ways :

- a. **Binning Method:** This method works on sorted data in order to smooth it. The whole data is divided into segments of equal size and then various methods are performed to complete the task. Each segment is handled separately. One can replace all data in a segment by its mean or boundary values can be used to complete the task.
- b. **Regression:** Here data can be made smooth by fitting it to a regression function. The regression used may be linear (having one independent variable) or multiple (having multiple independent variables).
- c. **Clustering:** This approach groups the similar data in a cluster. The outliers may be undetected or it will fall outside the clusters.

4. Data Transformation:

This step is taken in order to transform the data in appropriate forms suitable for the mining process. This involves following ways:

- a. **Normalization:** It is done in order to scale the data values in a specified range (-1.0 to 1.0 or 0.0 to 1.0).
- b. **Attribute Selection:** In this strategy, new attributes are constructed from the given set of attributes to help the mining process.
- c. **Discretization:** This is done to replace the raw values of numeric attributes by interval levels or conceptual levels.
- d. **Concept Hierarchy Generation:** Here attributes are converted from lower level to higher level in hierarchy. For Example-The attribute "city" can be converted to "country".

5. Data Reduction: Since data mining is a technique that is used to handle huge amounts of data. While working with a huge volume of data, analysis became harder in such cases. In order to get rid of this, we can use data reduction techniques. It aims to increase the storage efficiency and reduce data storage and analysis costs. The various steps to data reduction are:

- a. **Attribute Subset Selection:** The highly relevant attributes should be used, rest all can be discarded. For performing attribute selection, one can use the level of significance and p- value of the attribute having p-value greater than significance level can be discarded.
- b. **Data Cube Aggregation:** Aggregation operation is applied to data for the construction of the data cube.
- c. **Numerosity Reduction:** This enables us to store the model of data instead of whole data, for example: Regression Models.
- d. **Dimensionality Reduction:** This reduces the size of data by encoding mechanisms. It can be lossy or lossless. If after reconstruction from compressed data, original data can be retrieved, such reduction is called lossless reduction, else it is called lossy reduction. The two effective methods of dimensionality reduction are: Wavelet transforms and PCA (Principal Component Analysis).

7.2.3.2 Data Augmentation

Data augmentation is the strategy of manipulating existing data to create new data objects. Rotating, resizing, cropping, and other techniques can be utilized to augment new image samples from the existing set. It is critical to investigate the process's resilience in preserving the same label after transformation while using data augmentation. Rotations and flips, for example, are usually resilient on detection tests like cat vs. dog, but not on digit identification tasks like 6 vs. 9. In image classification, object recognition, and segmentation, data augmentation may be utilized entirely to train deep learning models. Image augmentation is manipulations applied to images to create different versions of similar content in order to expose the model to a wider array of training examples. Image augmentation manipulations are forms of image preprocessing, but there is a critical difference: while image preprocessing steps are applied to training and test sets, image augmentation is only applied to the training data.

7.2.3 InceptionResNetV2 CNN Architecture

An InceptionResNetV2 custom classifier is used to take fundus images and classify them into normal and positive glaucoma. The Inception-Resnet-V2 architecture [13] with pretrained weights was employed for transfer learning. In the custom model, we froze the weights of the first 100 layers. The settings of the frozen layers are not changed by the trained network. To speed up network training and avoid dataset over fitting, several early layer weights might be frozen. The CNN model Inception-ResNet-v2 was trained using the ImageNet dataset, which contains over a million images. The network has 164 layers and can categorize roughly 1000 item categories. As a result, the network model can learn complex attribute representations for a wide range of images. The Inception-Resnet block combines multiple-sized convolutional filters and residual connections.

In the last few years of the IT industry, there has been a huge demand for a once particular skill set known as Deep Learning. Deep Learning is a subset of Machine Learning which consists of algorithms that are inspired by the functioning of the human brain or the neural networks.

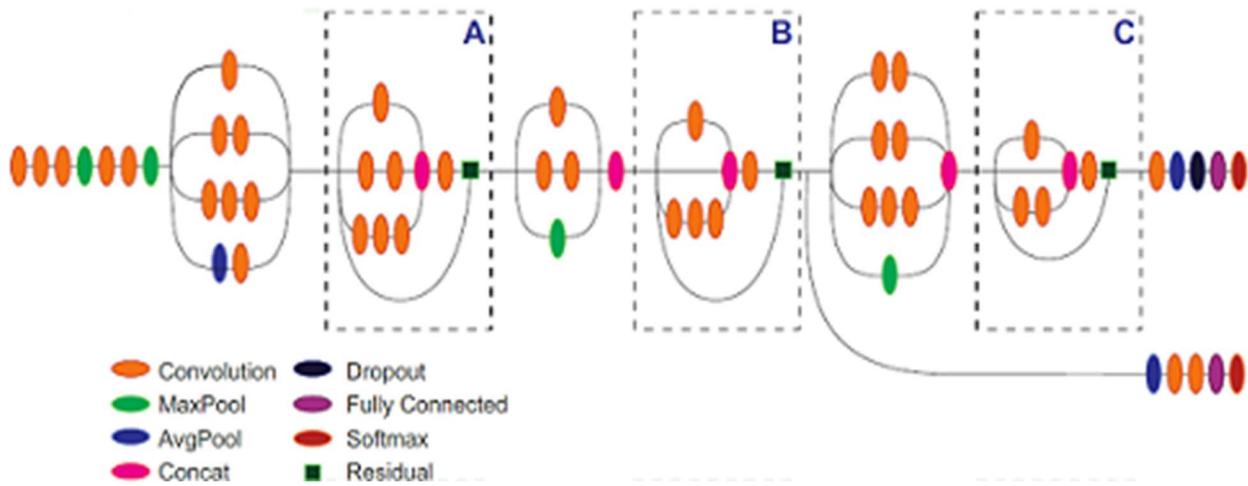


Fig. 7.6 Block Diagram of Convolution Neural Network

These structures are called Neural Networks. It teaches the computer to do what naturally comes to humans. Deep learning, there are several types of models such as the Artificial Neural Networks (ANN), Autoencoders, Recurrent Neural Networks (RNN) and Reinforcement Learning.

But there has been one particular model that has contributed a lot in the field of computer vision and image analysis which is the Convolutional Neural Networks (CNN) or the ConvNets.

CNNs are a class of Deep Neural Networks that can recognize and classify particular features from images and are widely used for analyzing visual images. Their applications range from image and video recognition, image classification, medical image analysis, computer vision and natural language processing.

The term “Convolution” in CNN denotes the mathematical function of convolution which is a special kind of linear operation wherein two functions are multiplied to produce a third function which expresses how the shape of one function is modified by the other. In simple terms, two images which can be represented as matrices are multiplied to give an output that is used to extract features from the image.

Inception-ResNet-V2 contains 11 A-blocks, 20 B-blocks, and 10 C-blocks. The decision to use this architecture was influenced by experimental findings and a comparison to other prominent deep learning models (presented in Section 4). Model performance (accuracy) and resource needs are properly balanced in Inception-ResNet-V2. Other resource-intensive, bulky models could not be used because the model was designed to work in an edge environment. The Fig. 7.6 Depicts model layered architecture considered.

With the exception of the Inception module, the completely linked layer was replaced with global average pooling. This was done in order to cut down on the amount of variables. At the same time, batch normalization (BN) is a member of the network. As it progresses up to a neural network layer, the BN layer will make each mini-batch constellation map the same, preventing gradients from fading. It's a group of constellations that act as a training ground for any other constellation. We must additionally calculate Jacobians in the backpropagation process. These are just partial derivations of the variables a and x's norms.

$$\frac{\delta \text{Norm}(a, \chi)}{\delta a} \text{ and } \frac{\delta \text{Norm}(a, \chi)}{\delta \chi} \quad \text{----Equa. 7.1}$$

Adam Optimizer [18] is employed in the network to optimize the network parameter and minimize the loss. The method is highly efficient when dealing with huge situations with a lot of data or parameters. It's quick and doesn't take up a lot of memory.

$$\theta_x := \theta_{x-1} - \alpha \cdot \frac{\widehat{m}_x}{\sqrt{v_x + \epsilon}} \quad \text{----Equa. 7.2}$$

Here $\alpha \in R$ and $\theta, \widehat{m}_x, \widehat{v}_x, \varepsilon \in R$ for some n.

Dropout may be useful as a regularization strategy to avoid overfitting. Dropout, for the most part, refers to the fact that a neuron in a neural network is shut off with a specific probability p during training.

The following is the dropout equation for probability p_i ($1 \leq i \leq t$):

$$E_R = \frac{1}{2} (X - \sum_{i=1}^t p_i \omega_i I_i)^2 + p_i(1-p_i)\omega_i^2 I_i^2 \alpha \quad \text{----Equa. 7.3}$$

The test image is fed to the pretrained InceptionResNetV2 model to get the prediction metrics after passing through various mathematics based pictorial manipulation layers. Predicting Results : The complete prediction metric is processed to obtain a boolean binary value (i.e, either True or False) for a given set of features of a classification process. The Database used in this system is virtually located therefore the image and prediction results are then sent to the server database to visualize the results on the user interface. The UI/UX part of the Web-App is creatively designed as per modern trends to increase use case of the utility. Based on the prediction metrics and feature metrics, a brief report about the test is generated which can also be viewed and downloaded by the user from the Web-App.

CHAPTER 8

RESULTS

Using a Web-App [16], the suggested system may diagnose Glaucoma disease simply by taking live Ophthalmoscopic camera images. The web-app is powered by a well trained InceptionResNetV2 model.

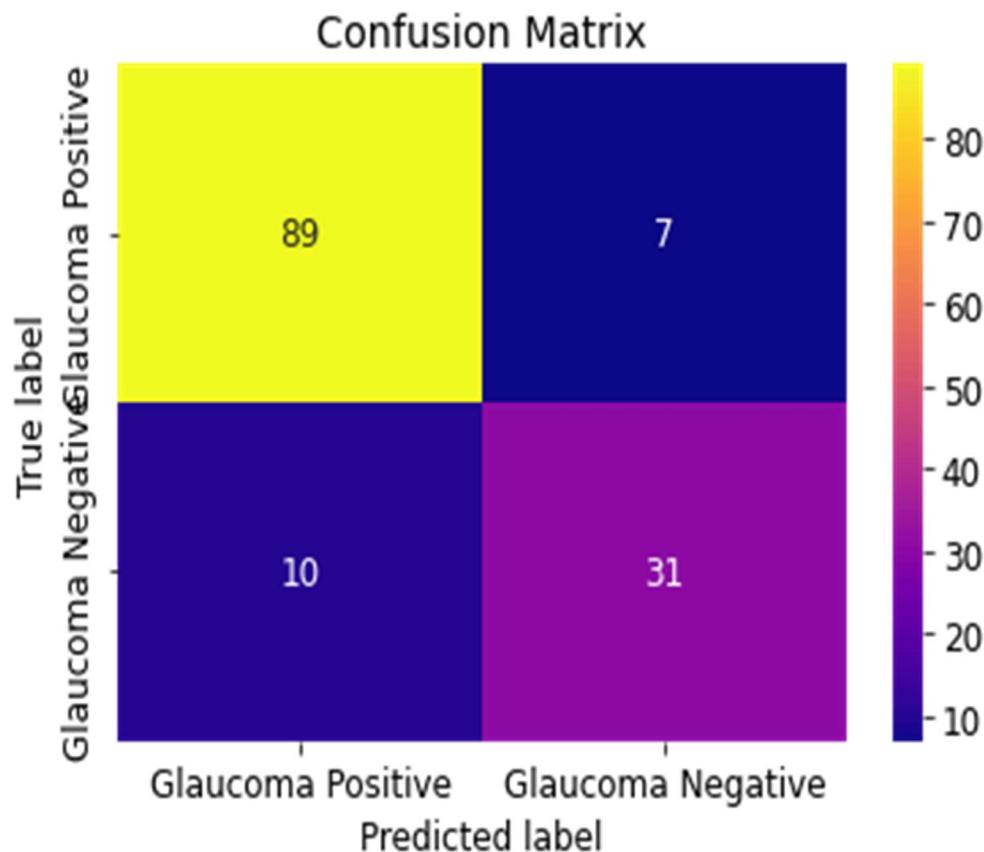
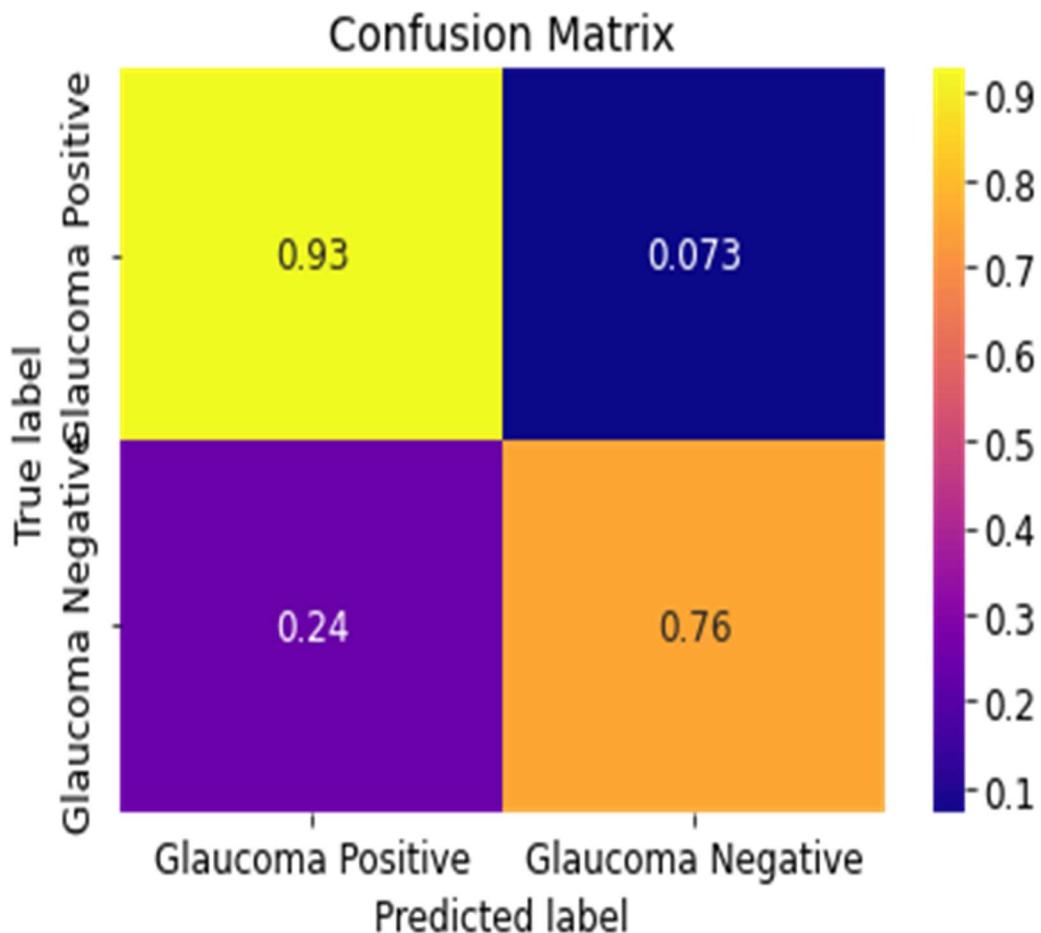


Fig. 8.1 Confusion Matrix plot without Normalization

From the Fig. 8.1 and 8.2, The confusion matrix without normalization, shows the matrix with number of images classified in each case. Sum of all the images in each case is equal to the total number of images.

Confusion matrix with normalization, shows the matrix with binary values (ratio of number of images predicted for each case to the total number of images) classified in each case.

**Fig. 8.2 Confusion Matrix plot with Normalization**

$$\text{Accuracy} = (TP + TN) / (P + N)$$

----Equa. 8.1

P - Total Positive Images

N - Total Negative Images

TP - True Positive Images after Prediction

TN - True Negative Images after Prediction

The numerator (TP + TN) is the sum of the diagonal.

The denominator (P + N) is the sum of all cells in the confusion matrix.

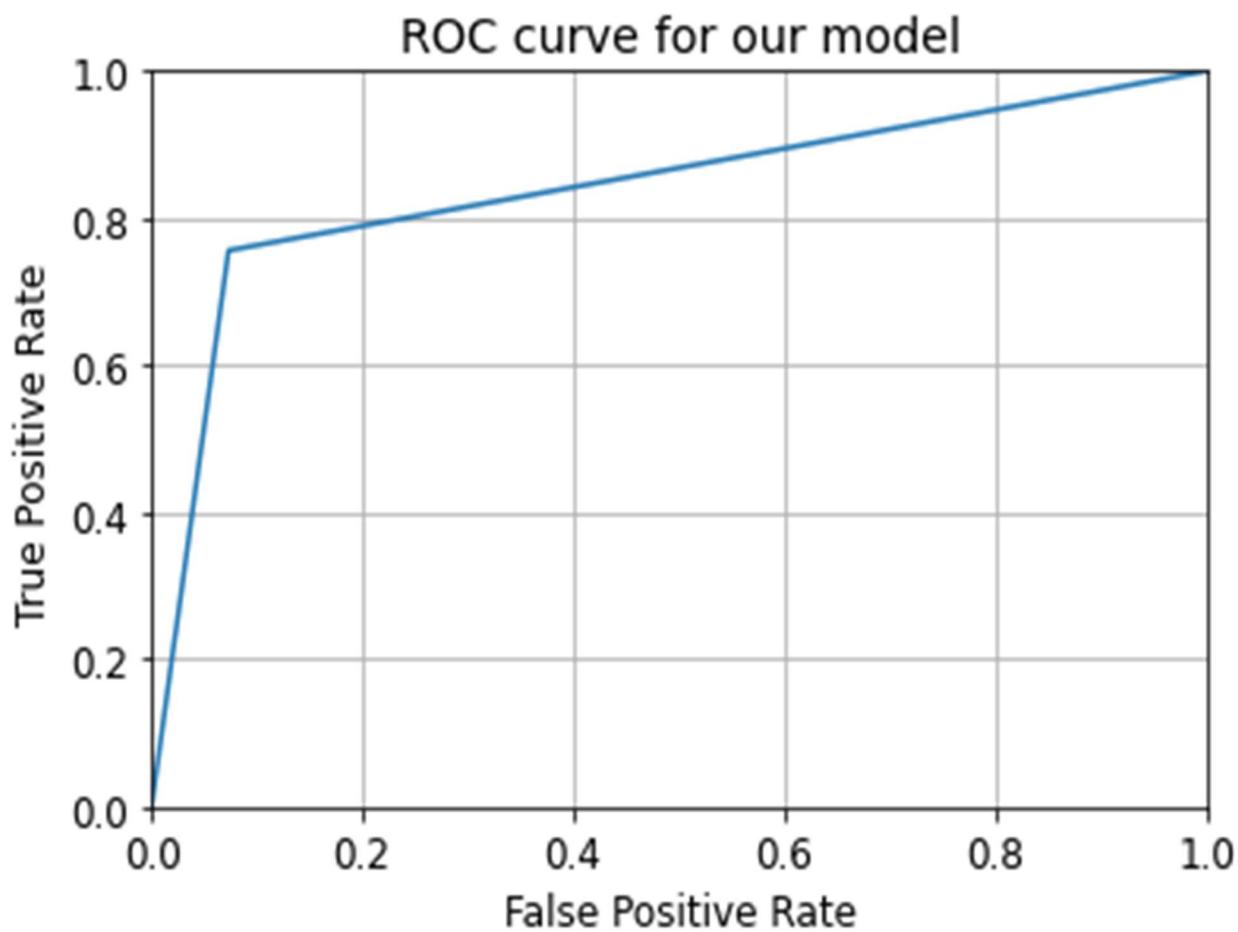


Fig. 8.3 ROC Curve Of CNN Model

From Fig.8.3 ROC Curve (Receiver Operating Characteristic Curve) [17] is the plot between True Positive Rate and False Positive Rate during the training period.

The true-positive rate is also known as sensitivity, recall or probability of detection.[9] The false-positive rate is also known as probability of false alarm[9] and can be calculated as $1 - \text{specificity}$. It can also be thought of as a plot of the power as a function of the Type I Error of the decision rule (when the performance is calculated from just a sample of the population, it can be thought of as estimators of these quantities).

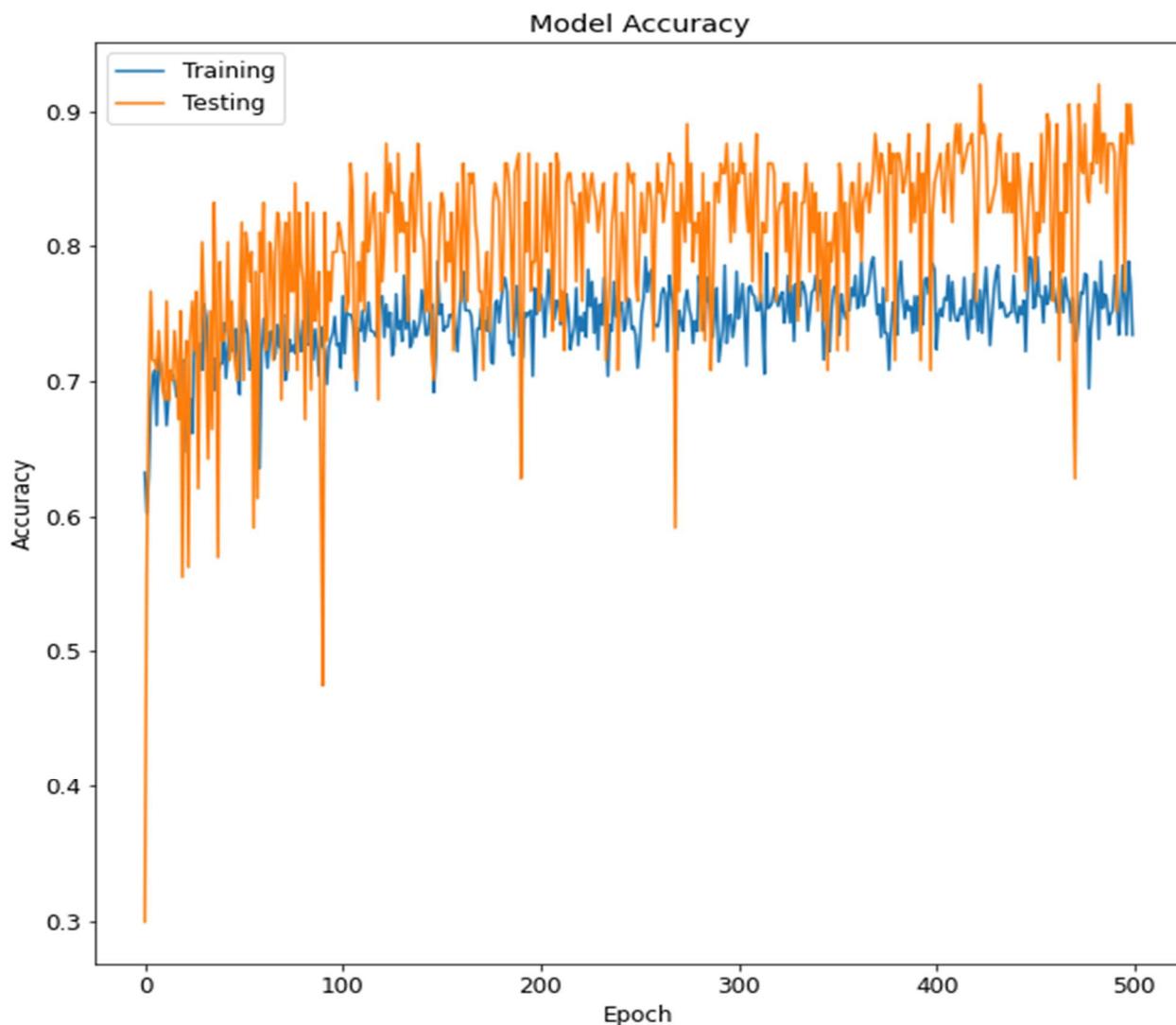


Fig. 8.3 CNN Model Training & Testing Accuracy

From the Fig.8.3, The graph summarized all the 3 points, that can be seen the training starts from the higher points when transfer learning is applied to the model which reaches higher accuracy. The results we obtained for testing and training can be observed from the above graph.

Table 8.1 CNN Model Training Report

	Precision	Recall	f1-score	Support
Negative	0.90	0.93	0.91	96
Positive	0.82	0.76	0.78	41
Accuracy			0.88	137
Macro avg.	0.86	0.84	0.85	137
Weighted avg.	0.87	0.88	0.87	137

From the Table 8.1, The CNN model training report shows us the accuracy of 88%. Which is better than any other model. As a result of their improved performance, ophthalmologists should be able to make better clinical decisions.

CHAPTER 9

CONCLUSION AND FUTURE SCOPE

Glaucoma affects a vast number of people, and the burden of ophthalmologists has increased dramatically. The expert's fatigue may considerably enhance the rate of inaccuracy in these manual diagnostics and conclusions. From the above literature survey we have seen that the maximum accuracy was upto 87%, so our proposed system reached 88% accuracy and increased its effectiveness using InceptionResnetv2 which is newly developed transfer learning supportive models. As the current Ophthalmoscopic camera in the market is high priced and which is not affordable for everyone, the proposed project aims to build a low-cost Ophthalmoscopic camera using Raspberry-Pi. Developing a Web-App can be more helpful as it gives widespread access to the users to use it and get the earlier detections in the modern day world.

To overcome this challenge, it goes without saying that a resolution which supports the systems is essential. The proposed arrangement employs a Web-app based on Python and Flask to forecast Glaucoma using low-cost ophthalmoscopic camera images. As a result, anyone with access to the internet can obtain predictions in minutes. As a result of their improved performance, ophthalmologists should be able to make better clinical decisions. This study demonstrates how a Web-App based on deep transfer learning can be used to diagnose Glaucoma in its early stages. The results might not be precise when compared to those which are obtained in the physical world because the study was conducted on a small dataset and the method has not yet been medically confirmed.

In addition, the outcome will be compared with other learning models. Apart from that, the conclusions of the study will be compared to data from a variety of sources. In the future, an attempt can be made to upgrade the performance of the model by training them on real-world scenarios with additional datasets. Increased data volume and validation with data from several sources allows for the development of more dependable systems. Which can have an increased efficiency to it. It may also be scaled to a bigger audience by connecting this Web-App to a larger, high-performance host server. This will speed up the Web-response App in high-traffic situations.

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APPENDIX

A Transfer Learning Based Web App for Glaucoma Detection Using Low-Cost Ophthalmoscopic Camera

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Abstract — *Glaucoma is the most fundamental cause of irreversible blindness in persons over a few decades. The condition is extremely prevalent in several nations, and in the worst-case situation is that many countries do not have enough ophthalmologists. According to data from a global glaucoma research, roughly 12 million individuals would be symbiotically blind from early-stage glaucoma by 2020. To evaluate the disease in the eye, fundus photography is used. Fundus photos require a lengthy visual inspection. The transfer-learning based web-app for glaucoma detection utilizing low-cost ophthalmoscopic cameras is presented in this paper. Fundus evaluation is an important part of an eye exam that helps the web-app provide vital diagnostic information to both ophthalmologists and non-ophthalmologists. The vision impairment occurs over time because it is not a rapid consequence. Only in the later stages those signs are noticed. The optic nerve was studied using 2-Dimensional retinal fundus pictures, which is a difficult task that can result in a significant cost for detecting regular glaucoma. There are a variety of different tests that can be used to rule out glaucoma, including tonometry which signifies pressure on eye, gonioscopy which examines angle is closed or open, OCT - Optical Coherence Tomography, Ophthalmoscopic Imaging to visualize retina as well as optic nerve and Fundus Copying. In this paper, an effective embedded based eye testing architecture is presented.*

Keywords — Glaucoma Detection, Transfer Learning, Ophthalmoscopic Camera and Fundus Imaging.

I . INTRODUCTION

Glaucoma is an optic nerve head condition caused by excessive fluid pressure in the eye. Glaucoma develops when the eye's drainage mechanism becomes clogged, allowing fluid to pool in the eye and produce pressure [1]. It's an urgent call for patients to look for treatment. Glaucoma cannot be seen or felt by the patient in its early stages. It's usually detected by the patient after a certain degree of damage has already happened during a normal eye exam. Damage manifests as a progressive shift in vision followed by vision loss. The treatment options for glaucoma include eye drops, surgeries such as laser therapy, filtering surgery , laser trabeculoplasty, and a trabecular bypass stent. All of these expenses are prohibitively expensive for most people. So, applying transfer learning techniques to detect glaucoma can be a game changer in the medical field as it has the potential to compete with the modern technologies to give precise and accurate results, hence this helps to overcome many kinds of problems faced by the patient.

1. Causes

Glaucoma is caused by high intraocular pressure, it is more likely to develop in persons who have a family history of the disease and people who have specific eye disorders such as diabetes or short-sightedness, are more prone to develop the disease. The most important effect of this disease is the loss of vision and sometimes this effect might become permanent. Glaucoma is generally found in people over age above 60. There are several causes due to which glaucoma is found, they can be poor or reduced blood flow to the optic nerve of the eye and sometimes due to the blocked or restricted drainage in the eye. Sometimes people who commonly use eye drops or medications, such as corticosteroids have more chances to get affected by this disease. The below classification of glaucoma is based on the crucial interior of eye physique factors which are generally used to classify various types of glaucoma [2].

A. Open-Angle Glaucoma / Chronic Glaucoma: Open-angle or chronic glaucoma can cause vision loss by slowing down the vision. This type's indications and symptoms aren't detected until later on. This is the most common and can be the initial stage of glaucoma. It might cause permanent visual loss if not recognised and treated early.

B. Angle-Closure Glaucoma / Acute Glaucoma: For the most part, this is an emergency situation. High pressure in the eyes is caused by a sudden obstruction in the aqueous humor fluid. Nausea, extreme discomfort, and blurred vision are all symptoms.

C. Congenital Glaucoma: Congenital glaucoma is caused by a defect in the eye's angular location. This can be detected through family members or from parents to children. It inhibits the drainage mechanisms that produce excessive weeping, light sensitivity, and impaired vision.

D. Secondary Glaucoma: Eye surgery can cause secondary glaucoma. It can also be caused by eye diseases like cataracts or tumors. Itchy eyes and iris pain are common in this case.

E. Normal Tension Glaucoma: Damage of the optic nerve in the eye causes normal tension glaucoma to develop. The main cause of this type of glaucoma is a lack of blood flow to the optic nerve and increase of pressure on the fundus.

II. LITERATURE SURVEY

With the use of transfer learning and deep learning techniques, Serener and Serte [3], presented deep learning algorithms to classify early and advanced glaucoma on fundus images. This classification's accuracy performance for ResNet50 is 86 percent, while its accuracy performance for the GoogLeNet model is 85 percent. The model's downside was that it was less accurate than other methods for detecting Glaucoma illness. To improve accuracy, the models can be substituted with alternative CNN (Convolutional Neural Network) models. The estimation of people who have been affected with Glaucoma disease worldwide under age groups, Rohit Varma, et al.'s [4] found to reintegrate epidemiologic data with some of the economic and individual pressure of glaucoma which highlights the cause of glaucoma on individuals, health systems, and societies. The prevalence of POAG (Primary Open - Angle Glaucoma), is considered to be 16 times greater among those people aged 80 years compared to those aged between 40 to 49 years and 13 times higher than those aged 50 to 59 years. The disadvantage of this approach was that glaucoma therapy was extremely cost effective when diagnostic costs were omitted and optimistic treatment efficacy assumptions were applied. J. Ayub, et al. [5], highlights the treatment of glaucoma disease by utilizing cup and disc segmentation using RGB (Red, Green & Blue) and HSV (Hue - Saturation Value) color models with K-mean Clustering Techniques. This approach has an accuracy rate of 86 percent. This model does not account for the circulatory system that runs throughout the disc, which overlaps basically with the precision of detecting the proper segments which belong to the disc. A. Sallam et al. [6], presented the detection of glaucoma by using Transfer Learning from Pre-trained CNN Models such as Pre-trained AlexNet, VGG11, VGG19, and VGG16 models using Deep learning techniques, with accuracy of 81.4 percent, 80 percent, 82.2 percent, and 80.9 percent on the LAG (Large Scale Attention based Glaucoma) dataset. Patil and Nikam [7] presented a MATLAB GUI (Graphical User Interface) for glaucoma identification using fundus images. To diagnose a sickness. Image processing techniques of the CDR (Cup - to - Disc Ratio) type and ellipse methods are utilized. The optic cup and the optic disc's boundaries are detected in this case. The segmentation and the precision of the disc and cup is inefficient. Dhumane and Patil [8] had presented glaucoma detection automated using CDR by super pixel segmentation. This technique does not require patience at the time of testing as only the retinal image is sufficient by the method of Superpixel Segmentation Techniques. This uses a simple linear iterative clustering algorithm where High Sensitivity values are generated, therefore signifying the role of image based classification. From a minimal number of components, a fully working, affordable, handheld, nonmydriatic fundus camera can be easily made. A camera like this with a combination of transfer learning based web app could be beneficial for a range of healthcare practitioners, especially those who work in places where a standard table-mounted nonmydriatic fundus camera would be uncomfortable and not at all user friendly to carry around.

III. PROPOSED SYSTEM

The sample of eye which is roughly 2.3cm in diameter and is almost a spherical ball filled with some fluid is captured from the patient for undergoing the test [9]. Ophthalmoscopic camera is used to filter out undesired light reflected from the cornea of a patient's eye. The NoIR camera sensor is set up with the 20-dioptral lens to capture the patient's test image [10]. The test image is sent to the controller unit for further processing. In the pre-processing stage, the test image then goes through various segmentation and filtering processes to enhance the image to increase the prediction accuracy. The test image is fed to the pretrained InceptionResNetV2 model [11] to get the prediction metrics after passing through various mathematics based pictorial manipulation layers. Then predictions are made to obtain a boolean binary value (i.e, either True or False) for a given set of features of a classification process. This helps in predicting the results. The Database used in this system is virtually located therefore the image and prediction results are then sent to the server database to visualize the results on the user interface. The predicted results will be generated and displayed in the web-app interface.

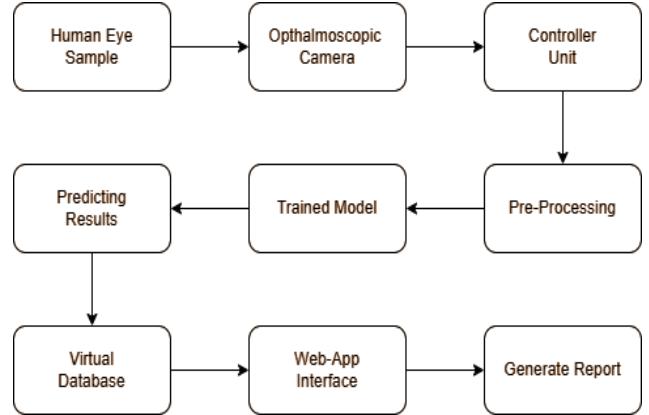


Fig. 1. Proposed System Workflow

1. Data Set

The Singapore Malay Eye Study's Online Retinal Fundus Image Dataset for Glaucoma Analysis and Research (ORIGA) database has 650 images (SiMES). The Singapore Eye Research Institute is in charge of SiMES (SERI) [16].

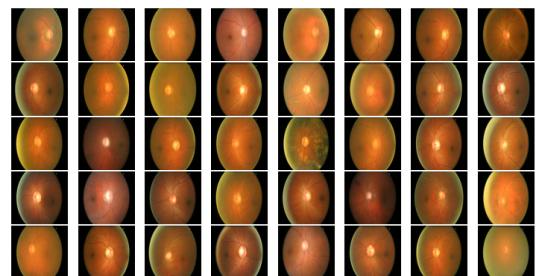


Fig. 2. Images in Dataset

Experts assigned labels to the photographs. There are 168 glaucomatous photos and 482 non-glaucoma images in this dataset.

2. Ophthalmoscopic Camera

An ophthalmoscopic camera can view the retina and optic nerve despite pharmacologic dilation. There are numerous ways to do this, but one common one is to focus infrared light on the fundus, which does not cause the pupil to contract, and then flash white light quickly to get a color retinal image before the pupil constricts. Because the eye does not perceive the infrared light needed to focus the camera on the fundus, ophthalmoscopic photography, even with the white flash, is often more comfortable for the patient than manual examination of the fundus with white light in indirect ophthalmoscopy.

Unfortunately, the majority of ophthalmoscopic cameras on the market now cost thousands of dollars and are either table-mounted or too heavy to easily travel. An ophthalmoscopic camera is provided that may minimize unwanted light reflected off the cornea of the eye being examined, as well as the front and back surfaces of a front objective through which the illuminating light flows through a 20-Dioptre lens. The NoIR (No-Infrared filter) camera sensor [12] is connected and configured to capture the image of the patient's eye.

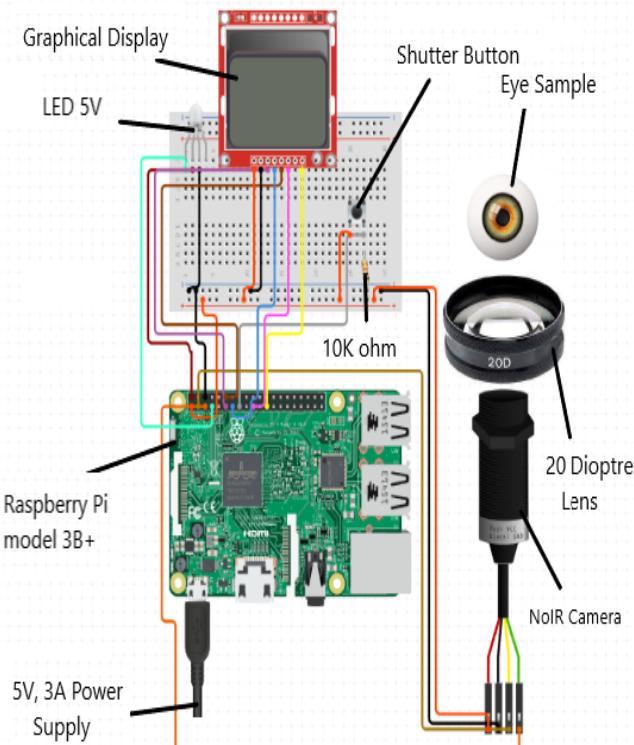


Fig. 3. Circuit diagram of Ophthalmoscopic Camera

Initial step is to take an eye sample image of the patient undergoing the test. The NoIR (No-Infrared filter) camera sensor attached with 20-Dioptre also known as ophthalmoscopic camera is set up to capture the test image of the patient eye. The test image is sent to the controller unit by means of physical connection for further processing. The test image then goes through various segmentation and filtering processes to enhance the image to increase the prediction accuracy.

3. Transfer Learning

In this technique, train a base network on a dataset and task, and then reuse or transfer the acquired features and weights to a second target network that will be trained on the similar dataset and task. It is a popular sort of deep learning that is commonly utilized in tasks such as neural language processing and computer vision.

An InceptionResNetV2 custom classifier is used to take fundus images and classify them into normal and positive glaucoma. The Inception-Resnet-V2 architecture [13] with pretrained weights was employed for transfer learning. In the custom model, we froze the weights of the first 100 layers. The settings of the frozen layers are not changed by the trained network. To speed up network training and avoid dataset over fitting, several early layer weights might be frozen. The CNN model Inception-ResNet-v2 was trained using the ImageNet dataset, which contains over a million images. The network has 164 layers and can categorize roughly 1000 item categories. As a result, the network model can learn complex attribute representations for a wide range of images. The Inception-Resnet block combines multiple-sized convolutional filters and residual connections.

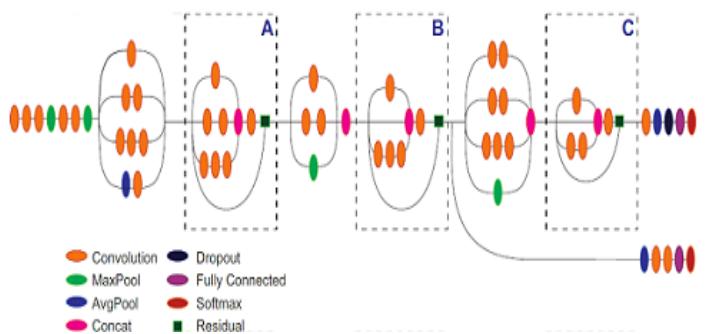


Fig. 4. CNN Model Architecture

Inception-ResNet-V2 contains 11 A-blocks, 20 B-blocks, and 10 C-blocks

The decision to use this architecture was influenced by experimental findings and a comparison to other prominent deep learning models (presented in Section 4). Model performance (accuracy) and resource needs are properly balanced in Inception-ResNet-V2. Other resource-intensive, bulky models could not be used because the model was designed to work in an edge environment. The Fig 4. depicts model layered architecture considered.

With the exception of the Inception module, the completely linked layer was replaced with global average pooling. This was done in order to cut down on the amount of variables. At the same time, batch normalization (BN) is a member of the network. As it progresses up to a neural network layer, the BN layer will make each mini-batch constellation map the same, preventing gradients from fading. It's a group of constellations that act as a training ground for any other constellation. We must additionally calculate Jacobians in the backpropagation process. These are just partial derivations of the variables a and x's norms.

$$\frac{\delta \text{Norm}(a, \chi)}{\delta a} \text{ and } \frac{\delta \text{Norm}(a, \chi)}{\delta \chi} \quad (1)$$

Adam Optimizer [15] is employed in the network to optimize the network parameter and minimize the loss. The method is highly efficient when dealing with huge situations with a lot of data or parameters. It's quick and doesn't take up a lot of memory.

$$\theta_x := \theta_{x-1} - \alpha \cdot \frac{\hat{m}_x}{\sqrt{\hat{v}_x} + \epsilon} \quad (2)$$

Here, $\alpha \in R$ and $\theta, \hat{m}_x, \hat{v}_x, \epsilon \in R$ for some n.

Dropout may be useful as a regularization strategy to avoid overfitting. Dropout, for the most part, refers to the fact that a neuron in a neural network is shut off with a specific probability p during training. The following is the dropout equation for probability pi ($1 \leq i \leq t$):

$$E_R = \frac{1}{2} (\mathbf{x} - \sum_{i=1}^t p_i \omega_i I_i)^2 + p_i (1-p_i) \cdot \omega_i^2 \cdot I_i^2 \cdot \alpha \quad (3)$$

The test image is fed to the pretrained InceptionResNetV2 model to get the prediction metrics after passing through various mathematics based pictorial manipulation layers. Predicting Results : The complete prediction metric is processed to obtain a boolean binary value (i.e, either True or False) for a given set of features of a classification process. The Database used in this system is virtually located therefore the image and prediction results are then sent to the server database to visualize the results on the user interface. The UI/UX part of the Web-App is creatively designed as per modern trends to increase use case of the utility. Based on the prediction metrics and feature metrics, a brief report about the test is generated which can also be viewed and downloaded by the user from the Web-App.

IV. RESULTS

Using a Web-App [16], the suggested system may diagnose Glaucoma disease simply by taking live Ophthalmoscopic camera images. The web-app is powered by a well trained InceptionResNetV2 model.

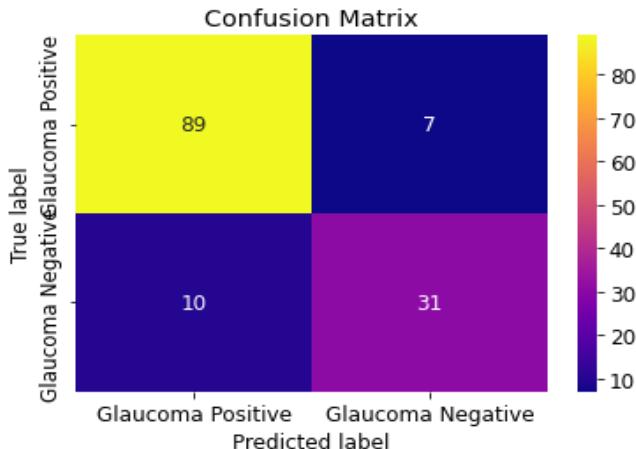


Fig. 5. Confusion Matrix plot without Normalization

Confusion matrix without normalization, shows the matrix with number of images classified in each case. Sum of all the images in each case is equal to the total number of images.

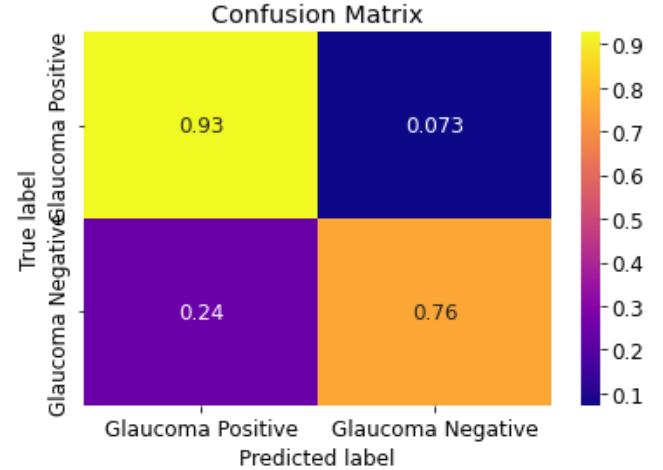


Fig. 6. Confusion Matrix plot with Normalization

Confusion matrix with normalization, shows the matrix with binary values (ratio of number of images predicted for each case to the total number of images) classified in each case.

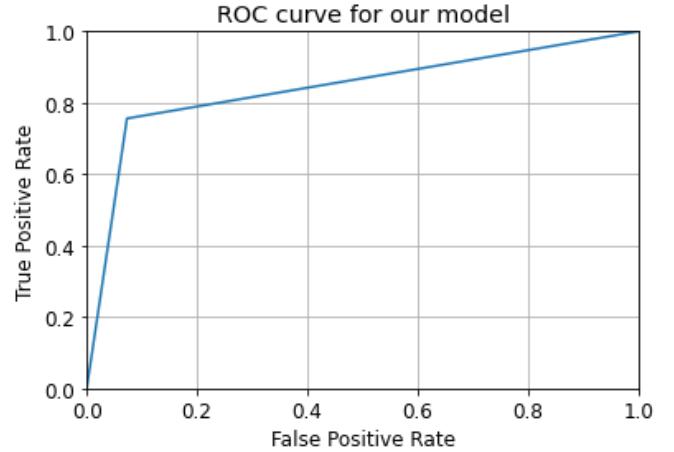


Fig. 7. ROC Curve Of CNN Model

ROC Curve (Receiver Operating Characteristic Curve) [17] is the plot between True Positive Rate and False Positive Rate during training period.

$$\text{Accuracy} = (TP + TN) / (P + N) \quad (4)$$

P - Total Positive Images

N - Total Negative Images

TP - True Positive Images after Prediction

TN - True Negative Images after Prediction

The numerator (TP + TN) is the sum of the diagonal. The denominator (P + N) is the sum of all cells in the confusion matrix.

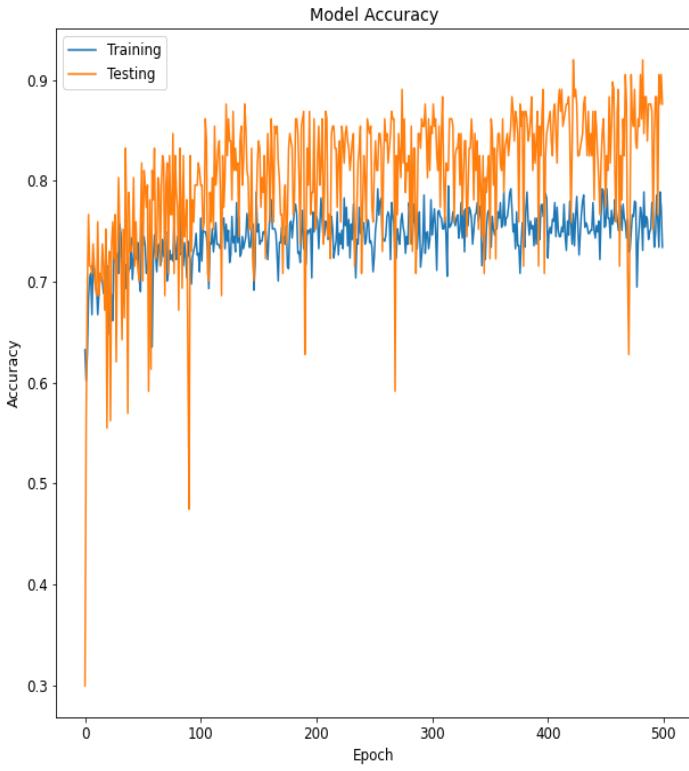


Fig. 8. CNN Model Training & Testing Accuracy

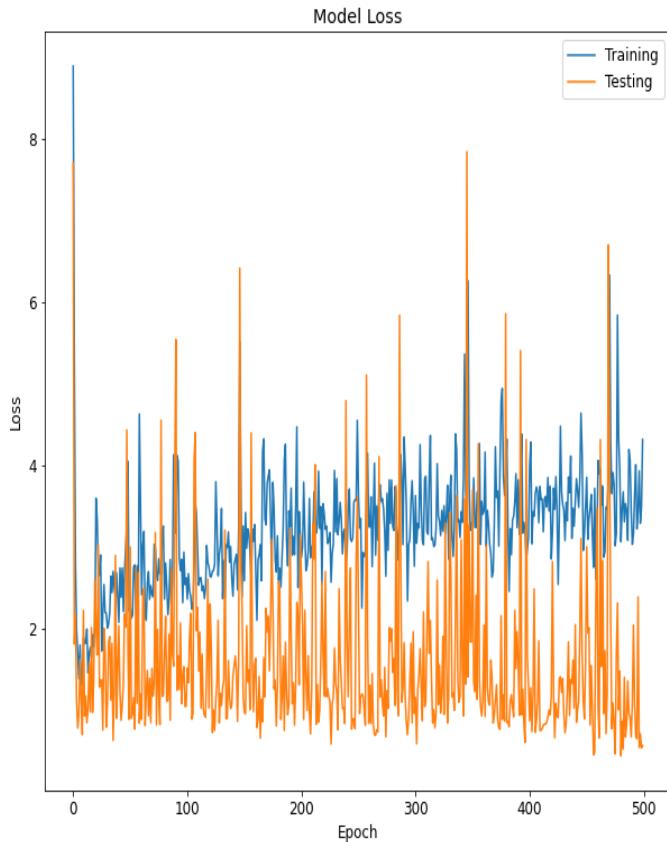


Fig. 9. CNN Model Training & Testing Loss

Fig. 8. and Fig. 9. Represents the variation of Accuracy and Loss values during Training and Testing phases.

TABLE I . CNN MODEL TRAINING REPORT

	precision	recall	f1-score	support
0	0.90	0.93	0.91	96
1	0.82	0.76	0.78	41
accuracy			0.88	137
macro avg	0.86	0.84	0.85	137
weighted avg	0.87	0.88	0.87	137

V. CONCLUSION AND FUTURE SCOPE

Glaucoma affects a vast number of people, and the burden of ophthalmologists has increased dramatically. The expert's fatigue may considerably enhance the rate of inaccuracy in these manual diagnostics and conclusions. To tackle this challenge, it goes without saying that a resolution which supports the systems is essential. The proposed arrangement employs a Web-app based on Python and Flask to forecast Glaucoma using low-cost ophthalmoscopic camera images. As a result, anyone with access to the internet can obtain predictions in minutes. As a result of their improved performance, ophthalmologists should be able to make better clinical decisions. This study demonstrates how a Web-App based on deep transfer learning can be used to diagnose Glaucoma in its early stages. The results might not be precise when compared to those which are obtained in the physical world because the study was conducted on a small dataset and the method has not yet been medically confirmed.

In addition, the outcome will be compared with other learning models. Apart from that, the conclusions of the study will be compared to data from a variety of sources. In the future, an attempt can be made to upgrade the performance of the model by training them on real-world scenarios with additional datasets. Increased data volume and validation with data from several sources allows for the development of more dependable systems which can have an increased efficiency to it. It may also be scaled to a bigger audience by connecting this Web-App to a larger, high-performance host server. This will speed up the Web-response App in high-traffic situations and provide quick results.

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at the Sixth International Conference on Design Innovations for 3Cs Compute-Communicate-Control organized by the Department of ECE and EEE on 24th and 25th June 2022, held at MVJ College of Engineering, Bengaluru.

A handwritten signature in black ink, appearing to read 'M. Brindha'.

Dr. M Brindha
Vice Principal

A handwritten signature in black ink, appearing to read 'P. Mahabaleshwarappa'.

Dr. P Mahabaleshwarappa
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