A PROJECT REPORT ON
GLAUCOMA DETECTION USING DEEP LEARNING

A Main Project Submitted to Jawaharlal Nehru Technological University, Kakinada in Partial fulfillment of Requirements for the award of the degree of

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CERTIFICATE

This is to certify that the project work entitled "**GLAUCOMA DETECTION USING DEEP LEARNING**" is a bonafide work carried out by **BILLA SRAVANA KUMARI (19KT1A0509), AVULA SAI HITESH YADAV (19KT1A0506), MUKKALA TEJASWINI (19KT1A0539), MANAM SAI KUMAR (19KT1A0534).** Fulfillment for the award of the degree of Bachelor of Technology in **COMPUTER SCIENCE AND ENGINEERING** of Jawaharlal Nehru Technological University, Kakinada during the year **2019-2023**. It is certified that all corrections and suggestions indicated for internal assessment have been incorporated in the report. The project report has been approved as it satisfies the academic requirements in respect of the project work prescribed for the above degree.

Project Guide **Head of the Department**

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DECLARATION

This is to declare that the project entitled "**GLAUCOMA DETECTION USING DEEP LEARNING**" submitted by us in the partial fulfillment of requirements for the award of the degree of **Bachelor of Technology in Computer Science & Engineering** in **Potti Sriramulu Chalavadi Mallikarjuna Rao College of Engineering and Technology**, is bonafide record of project work carried out by us under the supervision and guidance of **Mrs. V. Navya Sree, M. Tech, (Ph.D.) Associate Professor of CSE**. As per our knowledge, the work has not been submitted to any other institute or university for any other degree.

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ABSTRACT

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Glaucoma is the term used to describe either the accumulated loss of retinal cells inside the optic nerve or the gradual visual loss brought on by optic neuropathy. Glaucoma is a disease that relates to the vision of the human eye. This disease is considered an irreversible disease that results in vision deterioration. They don't have any early warning indications of this glaucoma. We might not notice a change in your vision because the effect is so subtle. Many deep learning (DL) models have been developed for the proper detection of glaucoma so far. So, we present an architecture for proper glaucoma detection based on deep learning by making use of the convolutional neural network (CNN). The differentiation between the patterns formed for glaucoma and non-glaucoma can find out with the use of CNN. The CNN provides a hierarchical structure of the images for differentiation. Utilizing the current method, the sickness is detected. Whether a patient has glaucoma or not is determined by the optic cup to the disc ratio. The diagnosis is enhanced by the integration of an image data generator method of data augmentation. The outcomes demonstrate that the proposed model, which outperformed many other existing algorithms, attained 98% accuracy.

Keywords: feature extraction, deep learning, CNN, Image Data Generator, Glaucomatous, optic disc, optic cup.

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ABBREVIATIONS

ABBREVIATION	FULL FORM
IOP	Increase of intra Ocular Pressure
CCT	Central Corneal Thickness
DCNN	Deep Convolutional Neural Network
ODRGNET	Optic Disk Localisation and Glaucoma Diagnosis Network
OD	Optic Disk
OC	Optic Cup
RES-NET	Residential Energy Services Network
VGG-NET	Visual Geometric Group Network
VCDR	Vertical Cup Disc Ratio
ONH	Optic Nerve Hypoplasia
CAD	Coronary Artery Disease
FD's	Fractal Dimensions
G-net	Global Network of Environmental and Technology
ROI	Region of Interest
SVM	Support Vector Machine
NRR	Neural Network Rim
RELU	Rectified Linear Activation Unit
TCAv	Time Controlled Adaptive Ventilation
KNN	K-Nearest Neighbor
SBC	Session Border Controller
MLAP	Multilayer Mean Pooling

GLAUCOMA DETECTION USING DEEP LEARNING

INTRODUCTION

1. INTRODUCTION

1.1 About Project Problem

Glaucoma is a group of eye diseases that result in damage to the optic nerve (or retina) and causes vision loss. Open-angle glaucoma develops slowly over time and there is no pain. Peripheral vision may begin to decrease, followed by central vision, resulting in blindness if not treated. Closed-angle glaucoma can present gradually or suddenly. The most common type is open-angle (wide angle, chronic simple) glaucoma, in which the drainage angle for fluid within the eye remains open, with less common types including closed-angle (narrow-angle, acute congestive) glaucoma and normal-tension glaucoma. The sudden sight may involve severe eye pain, blurred vision, mid-dilated pupils, redness of the eye, and nausea. Vision loss from glaucoma, once it has occurred, is permanent. Eyes affected by glaucoma are referred to as being glaucomatous.

Figure 1.1: Optic nerve in advanced glaucoma disease

Risk factors for glaucoma include increasing age, high pressure in the eye, a family history of glaucoma, and use of steroid medication. For eye pressures, a value of 21 mmHg or 2.8 kPa above atmospheric pressure (760 mmHg) is often used, with higher pressures leading to greater risk. However, some may have high eye pressure for years and never develop damage. Conversely, optic nerve damage may occur with normal pressure, known as normal-tension glaucoma. The mechanism of open-angle glaucoma is believed to be the slow exit of humor through the trabecular meshwork, while in closed-angle glaucoma the iris blocks the trabecular meshwork. Diagnosis is achieved by performing a dilated eye examination. Often, the optic nerve shows an abnormal amount of cupping.

If treated early, it is possible to slow or stop the progression of the disease with medication, laser treatment, or surgery. The goal of these treatments is to decrease eye pressure. Several different classes of glaucoma medication are available. Laser treatments may be effective in both open-angle and closed-angle glaucoma. Several types of glaucoma surgeries may be used in people who do not respond sufficiently to other measures. Treatment of closed-angle glaucoma is a medical emergency.

About 70 million people have glaucoma globally, with about two million patients in the United States. It is the leading cause of blindness in African Americans. It occurs more commonly among older people, and closed-angle glaucoma is more common in women. Glaucoma has been called the "silent thief of sight" because the loss of vision usually occurs slowly over a long period. Worldwide, glaucoma is the second-leading cause of blindness after cataracts. Cataracts caused 51% of blindness in 2010, while glaucoma caused 8%. The word "glaucoma" is from the Ancient Greek *glaucous*, which means "shimmering." In English, the word was used as early as 1587 but did not become commonly used until after 1850, when the development of the ophthalmoscope allowed doctors to see optic nerve damage.

There are a large number of types of glaucoma which occurs in the human eyes both at the primary level, secondary level & at tertiary level, which is termed as the normal, moderate & the re level in context the of severity of the disease. Here, in this section, different types of glaucoma are discus as below. These are marked by an increase of intraocular pressure (IOP) or pressure inside the eye.

- Open-Angle Glaucoma
- Angle-Closure
- Normal Tension Glaucoma
- Congenital Glaucoma
- Primary Glaucoma
- Secondary Glaucoma
- Neo-vascular glaucoma
- Neo-vascular glaucoma
- Exfoliate Glaucoma
- Pigmentary Glaucoma
- Chronic Glaucoma
- Traumatic Glaucoma

The research work that we are going to take up further is going to deal with the primary glaucoma detection along with the hardware implementation of the same so that both at the simulation level & at implementation level, it would have been validated.

1.1.1 Signs and Symptoms

As open-angle glaucoma is usually painless with no symptoms early in the disease process, screening through regular eye exams is important. The only signs are gradually progressive visual field loss and optic nerve changes (increased cup-to-disc ratio on fundoscopic examination).

About 10% of people with closed angles present with acute angle closure characterized by sudden ocular pain, seeing halos around lights, red eye, very high intraocular pressure (>30 mmHg (4.0 kPa)), nausea and vomiting, sudden decreased vision, and a fixed, mid-dilated pupil. It is also associated with an oval pupil in some cases. Acute angle closure is an emergency. Opaque specks may occur in the lens in glaucoma, known as glaukomflecken.

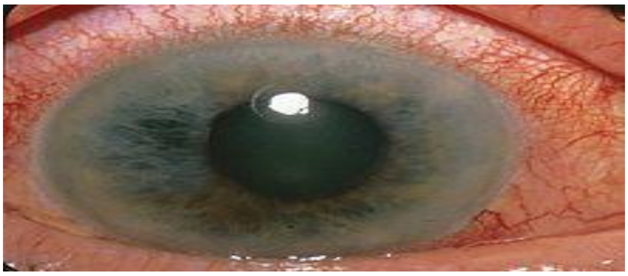


Figure 1.2: Photo showing conjunctival vessels dilated at the cornea edge and hazy cornea characteristics of acute closure glaucoma

1.1.2 Causes

Ocular hypertension (increased pressure within the eye) is the most important risk factor for glaucoma, but only about 50% of people with primary open-angle glaucoma have elevated ocular pressure. Ocular hypertension—an intraocular pressure above the traditional threshold of 21 mmHg (2.8 kPa) or even above 24 mmHg (3.2 kPa)—is not necessarily a pathological condition, but it increases the risk of developing glaucoma. One study found a conversion rate of 18% within five years, meaning fewer than one in five people with elevated intraocular pressure will develop glaucomatous visual field loss over that period. It is a matter of debate whether every person with elevated intraocular pressure should receive glaucoma therapy; currently, most ophthalmologists favor the treatment of those with additional risk factors.

Open-angle glaucoma accounts for 90% of glaucoma cases in the United States. Closed-angle glaucoma accounts for fewer than 10% of glaucoma cases in the United States, but as many as half of glaucoma cases in other nations (particularly East Asian countries).

1.1.3 Other

Other factors can cause glaucoma, known as "secondary glaucoma", including prolonged use of steroids (steroid-induced glaucoma); conditions that severely restrict blood flow to the eye, such as severe diabetic retinopathy and central retinal vein occlusion (neovascular glaucoma); ocular trauma (angle-recession glaucoma); and inflammation of the middle layer of the pigmented vascular eye structure (uveitis), known as uveitis glaucoma.

1.1.4 Diagnosis

Screening for glaucoma is usually performed as part of a standard eye examination performed by optometrists and ophthalmologists. Testing for glaucoma includes measurements of the intraocular pressure using tonometry, anterior chamber angle examination, or gonioscopy as well as an examination of the optic nerve to discern visible damage, changes in the cup-to-disc ratio, rim appearance, and vascular change. In figure 1.3, we can observe the cross-sectional view of an eye. A formal visual field test is performed. The retinal nerve fibre layer can be assessed with imaging techniques such as optical coherence tomography, scanning laser polarimetry, or scanning laser ophthalmoscopy (Heidelberg retinal tomogram). Visual field loss is the most specific sign of the condition, though it occurs later in the course of the disease.

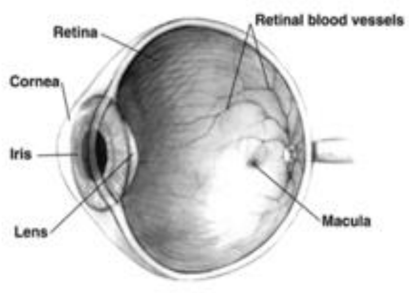


Figure 1.3: Human eye cross-sectional view

As all methods of tonometry are sensitive to corneal thickness, methods such as Goldmann tonometry may be augmented with pachymetry to measure the central corneal thickness (CCT). A thicker cornea can result in a pressure reading higher than the true pressure but a thinner cornea can produce a pressure reading lower than the true pressure.

Because pressure-measurement error can be caused by more than just CCT (such as by corneal hydration or elastic properties), it is impossible to adjust pressure measurements based only on CCT measurements. The frequency-doubling illusion can also be used to detect glaucoma with the use of a frequency-doubling technology perimeter.

1.1.5 Data Pre-processing

Data pre-processing is a process of preparing the raw data and making it suitable for a machine learning model. It is the first and crucial step while creating a machine-learning model. Image pre-processing is the term for operations on images at the lowest level of abstraction. These operations do not increase image information content but they decrease it if entropy is an information measure. The aim of pre-processing is an improvement of the image data that suppresses undesired distortions or enhances some image features relevant for further processing and analysis tasks.

Geometric transforms permit the elimination of geometric distortion that occurs when an image is captured. When creating a machine learning project, it is not always the case that we come across clean and formatted data. And while doing any operation with data, it is mandatory to clean it and put it in a formatted way. So, for this, we use a data pre-processing task.

1.1.6 Data Augmentation

Data augmentation is a technique of artificially increasing the training set by creating modified copies of a dataset using existing data. It includes making minor changes to the dataset or using deep learning to generate new data points.

Image Augmentation

Geometric transformations: randomly flip, crop, rotate, stretch, and zoom images. You need to be careful about applying multiple transformations on the same images, as this can reduce model performance.

Color space transformations: randomly change RGB color channels, contrast, and brightness.

Kernel filters: randomly change the sharpness or blurring of the image.

Random erasing: delete some part of the initial image.

Mixing images: blending and mixing multiple images.

Image Data Generator

ImageDataGenerator is used to determine the source of the data, after which it randomly alters the data and produces an output result that only contains the freshly altered data. No new information is provided. To increase the generality of the model as a whole, data augmentation is also carried out using the Keras picture data generator class. Data augmentation conducts random operations such as translations, scale changes, shearing, rotations, and horizontal flips using an image data generator. Image data generators are employed to produce batches of data from tensor images in the field of actual data augmentation. We can cycle through the input in batches while using Keras' picture data generator. The picture data generator class has a number of methods and arguments that aid in defining the data generation's behaviour. Only the newly changed data is returned by the ImageDataGenerator after accepting the original data and randomly transforming it.

Operations in data generator

a. Randomly Zoomed

The image is zoomed using the zoom augmentation technique. With this technique, the image is randomly zoomed in or enlarged by adding pixels all around it. The zoom range argument from the ImageDataGenerator class is used in this method. The same boundary values apply to zoom as they do in the case of the brightness parameter. The figure is zoomed in when the magnification value is lesser than l1.0 and out when it is larger than 1.0. The supplied image's actual class designation will remain unchanged once these changes are applied.

b. Random Brightness

The image's brightness fluctuates erratically. Additionally, it is a really helpful augmentation strategy as our item won't always be under ideal illumination. It is crucial to develop our model on photographs taken in various lighting scenarios. Accordingly, depending on the argument we supply to the ImageDataGenerator class function Object() { [native code] }, this method may make the images a little bit brighter, darker, or both. This is possible thanks to the brightness range setting. The maximum and minimum values are sent as floats, which treat them as percentages to be applied to the image. One boundary value, 1.0, determines how bright things are and how dark things are. In contrast to [0.5,1.0], where a number greater than 1.0 brightens the image, a value less than 1.0 will cause it to become darker.

c. Random Flips

The pixels will be turned around, either row-wise or column-wise, depending on whether the flip is vertical or horizontal. The vertical flip and horizontal flip arguments will be used to call this method within the ImageDataGenerator class. A horizontal flip effectively rotates both columns and rows simultaneously. A vertical flip, in essence, turns both columns and rows vertically. The mirror image of the sector in the vertical line across the centre of the image can then be used to define the updated coordinates of each corner. For the mathematically interested, the vertical bisector of the line connecting the old corner and the new, changed corner would be the vertical line going through the centre.

d. Random Shifts

When a picture is shifted, all of its pixels are moved in a single direction—such as horizontally or vertically—while maintaining its original dimensions. This implies that some pixels will be removed from the image and that new number of pixels will need to be given for a portion of the image. The pixels of the image move horizontally when a horizontal shift amplification is used, but the image's dimensions remain unchanged. New pixels would be added to a region that already contains pixels in order to keep the same image dimension.

e. Random Rotations

Picture rotation, which makes the image autonomous of the object's orientation, is one of the often used methods of augmentation. You can rotate images arbitrarily over any angle from 0 to 360 degrees using the ImageDataGenerator course by providing an integer value in the rotation limit argument. Certain pixels will rotate outside the image, producing a void that needs to be filled up. The augmentation object also selects a value between zero and the highest (which we defined). Once these modifications are made, the actual class classification of the supplied image will not change. The training model will, however, treat each changed image as if it were a brand-new image, thus in this manner, we are performing a different kind of regularisation procedure. Additionally, you can apply this technique to a future deep learning project.

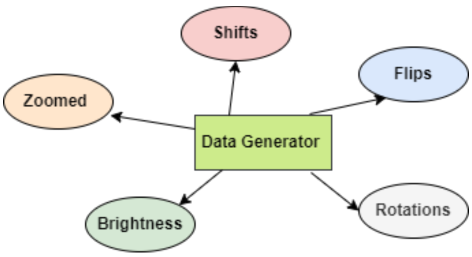


Figure 1.4: Operations in data generator

1.1.7 Classification

Classification predictive modeling involves assigning a class label to input examples. Classification is the process of finding or discovering a model or function which helps in separating the data into multiple categorical classes i.e. discrete values. In classification, data is categorized under different labels according to some parameters given in input and then the labels are predicted for the data.

The derived mapping function could be demonstrated in the form of “IF-THEN” rules. The classification process deal with the problems where the data can be divided into binary or multiple discrete labels. Convolutional neural networks receive images as input and use them to train a classifier. The network employs a special mathematical operation called a “convolution” instead of matrix multiplication. The architecture of a convolutional network typically consists of four types of layers: convolution, pooling, activation, and fully connected.

1.2 Scope

Using Convolutional Neural Networks will achieve good results, as CNN is used for learning complex features efficiently as the model has many layers and CNN performs intensive computational tasks simultaneously. We are using individual datasets to make a large dataset. So, we included CNN doesn't need any manual power i.e. human supervision. We can determine the stage of glaucoma of an individual using the amount of ocular pressure, optic disc, and optic cup. Data augmentation can be applied for small datasets. Another advantage of Data Augmentation is it multiples the images so that detection is performed more productively.

1.3 Purpose

From the literature surveyed in section 2, it is found that most of the researchers have worked with a relatively small number of images, fundus images from private datasets and datasets that lack real time variations in image quality. This hampers the robustness of the system. There is a need to develop a model which works for images acquired under different environmental conditions. Also, there is scope in enhancing the classification accuracy as much as possible.

Although there have been a significant number of techniques proposed in the literature, it is required to develop an efficient algorithm using a maximum number of subjects.

1.4 Motivation

Being the second largest cause of blindness worldwide, it can lead the person towards complete blindness if an early diagnosis does not take place. Concerning this underlying issue, there is an immense need of developing a system that can effectively work in the absence of excessive equipment, skilled medical practitioners and also is less time consuming. As a result, clinicians in rural areas can also be able to efficiently use this application for their diagnosis. As glaucoma diagnosis is a time-consuming procedure and requires skilled professionals, no special skills are required to work with developed applications

1.5 Problem Statement

The eyes are important sensory organs that provides sight. Glaucoma is a neuro-degenerative eye disease developed due to an increase in the Intraocular Pressure inside the retina. When the cup-to-disc ratio is greater than the normal range, the patient's eye is suspected as glaucomatous eye. Doctors need to perform many tests such as: Ophthalmic Test, Tonometry, Ophthalmoscopy, Perimetry, Pachymetry, Gonioscopy. After getting results from different test, doctor have to decide whether it is a glaucomatous eye or not. Careful evolution is important to detect glaucoma and there is a high chance of not getting accurate result due to lack of skill. Being the second largest cause of blindness worldwide, it can lead the person towards complete blindness if an early diagnosis does not take place. With respect to this underlying issue, there is an immense need of developing a system that can effectively work in the absence of excessive equipment, skilled medical practitioners and also is less time consuming.

LITERATURE REVIEW

2. LITERATURE REVIEW

2.1 Related work

Jahanzaib Latif et al [1] proposed a novel two-phase Optic Disk localization and Glaucoma Diagnosis Network (ODGNet). In the first phase, a visual saliency map incorporated with shallow CNN is used for effective OD localization from the fundus images. In the second phase, the transfer learning-based pre-trained models are used for glaucoma diagnosis. The transfer learning-based models such as AlexNet, ResNet, and VGGNet incorporated with saliency maps are evaluated on five public retinal datasets to differentiate between normal and glaucomatous images. A sliding window approach is used to train the shallow CNN model by sliding the whole image to select the patches with or without OD and the saliency map target the next salient region in case of the non-OD region. The proposed approach yields 95.75% accuracy, which can assist the ophthalmologists in reducing the burden on mass screening.

Partha Sarathi Mangipudi et al [2] presented an effective system for optic disc and cup segmentation using deep learning architecture. Modified Ground Truth is utilized to train the proposed model. It works as fused segmentation marking by multiple experts that helps in improving the performance of the system. Extensive computer simulations are conducted to test the efficiency of the proposed system. The authors used a modified segmentation measure for accuracy and in representing the subsequent loss function. The intersection/union of two binary maps is now transformed into multiplication of two probability masks, which make more sense. The logarithm of the modified IOU function was chosen to be minimized for the purpose of optimization. The proposed algorithm utilizes the power of the encoder-decoder network which is trained on three different datasets. But there were some images where the optic cup was small or on images in which the contrast between optic disc and its background was low, the proposed algorithm produced poor results. This is where salient point detection algorithms could be put to good use along with CNNs to improve upon the model accuracy.

Ruben Hemelings et al [3] propose a methodology that advances explainable deep learning in the field of glaucoma detection and vertical cup-disc ratio (VCDR), an important risk factor. Colour fundus images were subject to a series of pre-processing steps prior to model input. First, the images were cropped to a square shape, Subsequently, a widely-used local contrast enhancement through background subtraction was used to correct uneven illumination. The authors present a sound methodology that conclusively supports that deep learning can reliably identify glaucoma-induced damage outside the ONH. The researchers did not explicitly assess the influence of myopic changes, did not analyze the role of the disease stage.

Mamta Juneja et al [4] presents an Artificially Intelligent glaucoma expert system based on segmentation of optic disc and optic cup. A Deep Learning architecture is developed with CNN working at its core for automating the detection of glaucoma. The proposed system uses two neural networks working in conjunction to segment optic cup and disc. The CAD system comprises three basic steps such as Pre-processing, Segmentation, and Classification. Preprocessing the input images for removal of outliers. Feeding the filtered images to a neural network is used to segment the optic disc to remove the unnecessary part of the image as the optic cup resides inside the optic disc and cropped image is used for cup segmentation. A modified version of U-net is used for segmentation of optic disc and cup. In order to determine which color channels provide the highest accuracy, the G-Net model was trained and validated several times on the RGB images, red channel images, blue channel images, and green channel images.

Rutuja Shinde [5] proposes an offline Computer-Aided Diagnosis (CAD) system for glaucoma diagnosis using retinal fundus images. This application is developed using image processing, deep learning and machine learning approaches. Le-Net architecture is used for input image validation and Region of Interest (ROI) detection is done using the brightest spot algorithm. Further, the optic disc and optic cup segmentation is performed with the help of U-Net architecture and classification is done using SVM, Neural Network and Adaboost classifiers. The proposed algorithm uses three features namely CDR, ISNT ratio of Neuro-retinal Rim (NRR) and blood vessels as the decision criteria for glaucoma detection. A majority voting system developed using SVM and NN classifiers and adaboosting technique has been used in an attempt to classify the input to be either normal or glaucomatous. 10- fold cross validation was performed.

Lamiaa Abdel-Hamid [6] presents a novel two-branched deep convolutional (TWEEC) for computer-aided glaucoma diagnosis. The TWEEC network is designed to simultaneously extract anatomical information related to the optic disc and surrounding blood vessels which are the retinal structures most affected by glaucoma progression. The spatial retinal images and wavelet approximation sub-bands are compared as inputs to the proposed network. TWEEC's performance is compared to three implemented convolutional networks, one of which employs transfer learning. Experiments showed that the introduced TWEEC network achieved accuracies of 98.78% and 96.34% for the spatial and wavelet inputs, respectively. In each branch, batch normalization and dropout were used as regularization techniques in order to avoid overfitting, speed up training, and to improve the generalization of the network. The training of freshly initialized networks using the wavelet images was found to require significantly less training time.

Surya M et al. [7] proposed a method for automated Glaucoma disease diagnosis using novel blood vessel tracking and bend point detection. This algorithm is resistant to noise and illumination. While acquiring images, noise evolves, leading to incorrect detections of objects. Boundary segmentation is complicated by the existence of some bright or dark pixels across the optic disc boundary. To overcome this, the authors used various thresholds and geometrical feature frameworks to avoid at least some false positives. Cup to disc ratio is an essential clinical value in detecting Glaucoma, i.e., if CDR >0.3 or 0.4, it is a glaucomatous or a normal eye. The proposed vessel bend method gives CDR values on datasets that lie closer to ground truth values. So, the technique obtained great accuracy. Thresholded methods are not appropriate for detecting low contra glaucoma images.

M Tabassum et al. [8] The researchers presented a deep convolution neural network-based technique for the early identification of Glaucoma. Preprocessing and post-processing steps are avoided to reduce the computational cost of the system. There are no more images in the considered dataset, so augmenting the data with rotations ranging from 0 to 360 degrees is done, and brightness is increased and decreased to counter the contrast issue. The stochastic gradient descent with momentum with l2 regularization of weight decay = 0.005 for the training model, and a learning rate = 0.0001 was used for the segmentation network. This model resulted in a higher dice value for optical cup segmentation, which is difficult because of the blood vessels' presence. However, it can be trained with fewer epochs and few parameters and is 99.6 accurate on both datasets. The limitation of this model is that the dice value on the DRISHTI dataset is comparatively less than others.

Kaveri A. et al. [9] proposed a Convolution neural network architecture for glaucoma detection in optical coherence tomography images which use test concept activation vectors(TCAVs). This model is an end-to-end deep learning algorithm composed of pre-trained CNN, fine-tuned pre-trained CNN layers, and a fine-tuned fully connected classifier. Data augmentation, 30 epochs with a batch sized 1, is used for training. Fine-tuned classifiers consist of a Flattening Layer, dense layers, ReLU activation, 0.5 unit probability dropout for regularization to avoid overfitting the model, and sigmoid activation. TCAVs exhibit higher accuracy than models trained just on retinal nerve fibre layer probability map input images. This model was 90% accurate on considered datasets.

Hamid A [10] proposed a Glaucoma detection algorithm using Statistical and Textural Wavelet Features. In this study, images are first preprocessed (by enhancing the contrast of the red channel), followed by wavelet decomposition and feature extraction on the green and blue channels. The grey-level co-occurrence matrices were used to calculate all features in four angles (00, 450, 900, 1350). The suggested model demonstrated that wavelet statistical features perform better in the feature selection stage than wavelet texture features. In addition, statistical characteristics extracted from the green and blue channels produced better outcomes. The significant benefit is that this model only needs 3 seconds per image for a data set of high-resolution retinal images. The proposed method, which used the KNN classifier (k ranged from 1-15) and five-fold cross-validation, achieved an accuracy of 96.7%.

Raghavendra et al. [11] suggested a machine-learning-based CAD tool for glaucoma identification. Pixels were resized from 1024*1024 to 64*64(optimal size for the proposed study) to reduce the expenses of high-resolution images. The suggested Sparse auto-encoder model comprises two layered encoders, one of which works predominantly to minimize the dimensionality of data points created from images. With a maximum epoch of 400, the second encoder will extract essential features only to match secondary features and reduce the processing time of the model soft-max. Instead of image segmentation, the model collects essential features for classification. Compared to CNN, it needs fewer tuning parameters, and since preprocessing is not essential, the model may be used independently with little configuration. Here, gradient-based techniques are used for fine-tuning the model parameters where the performance of such models depends on the number of training samples provided, which may not always result in the best features. The best outcomes are not achieved when applying these algorithms to uncertain clinical data.

Patil N et al. [12] proposed a CADx framework for glaucoma disease treatment utilizing hand-crafted feature-based segmentation of images based on a deep learning approach and machine learning models. In this model, region of interest of pixel size(150*150) with radius 100 is extracted using DL. Then deep features are extracted using CNN and are optimized using CNN and Deep belief network. Image size 64*64 with a learning rate of 0.001 achieved the highest performance and 98% accuracy. This technique overlooks the contemporary design of the hand-crafted elements by first capturing the complete image, filtered to remove the problematic area. An Unbalanced dataset of 20% glaucoma images and 80% normal images is used, which is a drawback of this method.

Serner A et al. [13] Presented an early and advanced glaucoma detection system based on deep learning algorithms and transfer learning. The final output image was then categorized using ResNet and GoogleNet neural networks and fine-tuned using transfer learning after being preprocessed into three separate channels (red, green, and blue). Data augmentation is used to increase the number of fundus photographs. According to ROC curves, the GoogleNet algorithm (average accuracy of 83%) outperforms the ResNet method (average accuracy of 79%). The drawback of this system is that it is expensive and time-consuming and may be utilized for early detection only.

Deepak Parashar et al. [14] proposed an automatic diagnostic tool for glaucoma identification. It starts with extracting the green channels from RGB images and then decomposes them using the flexible analytic wavelet transform method. The classification of images into normal/mild/severe Glaucoma is done using the supervised machine learning technique LS-SVM. The SBC algorithm extracts fractal dimension features, normalizes the features, and selects 13 features for the model training phase. The suggested model outperformed current models when it came to 93.40% accuracy at the 8th level decomposition, with the p-value obtained at this level being the lowest.

Javier Civit-Masot et al. [15] suggested an image segmentation and transfer learning based diagnostic tool for glaucoma identification. In this study, the proposed model consists of two subsystems: (1) Segmentation Subsystem using U-Net in which data from both datasets are split individually into training and testing datasets, and training datasets are combined, testing datasets are combined. Disc Segmentation and Cup Segmentation are applied to the combined training dataset and tested separately with the Disc testing dataset and Cup testing dataset, and features are extracted. (2) The Direct Classification Subsystem consists of a light-weighted network MobileNet v2 that has been pre-trained with ImageNet and an extra classifier network. The outcomes of both subsystems are combined to produce the diagnostic aid tool's ultimate result. Compared to the results generated by the heavier networks for individual datasets, the suggested light-weighted method performed well for mixed datasets.

W Liao et al. [16] presented a deep learning strategy, a new ConvNet architecture that can be interpreted clinically. This study introduces a model that offers a region of interest (ROI), refines images using the model's backbone architecture, and extracts features. Multi-layer Mean

Pooling (M-Lap) is used to activate and discover evidence. A novel method of producing refined activation maps (EAM) with accurate information on spatial evidence is used to obtain coarse and discriminative features. The authors found that an increased accuracy leads to better segmentation of optic discs. In addition, ResBlocks are removed in each batch normalization layer and modify the dropout rate to 0.2 to reduce the overfitting of the model. The model was 88% accurate on the ORIGA dataset. Unfortunately, this model is employed only on the ORIGA dataset, which is an unbalanced dataset (which contains 20% glaucoma eye images and 80% normal eye images); also, this dataset is not publicly available all the time.

Deepak Parashar et al. [17] presented a glaucoma detection method using a 2d tensor empirical wavelet transform. This study uses preprocessed images for quality enhancement to eliminate unnecessary variations (noise, low contrast), and decomposition is performed with 2D-T-EWT. Decomposed images extract texture-based features, and robust features are selected. A multi-class LS-SVM was used to classify the images as normal, early, and advanced stages of Glaucoma. Using tenfold cross-validation, this model is 93.65 accurate with just 12 characteristics. However, the proposed model does not work well when tested on multiple data sets.

R Ali et al. [18] proposed a methodology based on a fuzzy broad learning system for glaucoma detection. In this work, region of interest is extracted and data augmentation is done on them to increase the amount of data for model training. Fuzzy broad learning system is applied to the red channel and green channel images for segmentation and then classification. The red channel image of the RGB image is less influenced by the blood vessels so used for OD segmentation. The Green channel is used for OC segmentation as contrast and brightness is more in OC are very high in this channel. The advantage of this method is that training is done faster than state of art techniques and also it can be trained on machines without GPU. But the model requires preprocessing and post-processing for giving accurate results and individual channels for OC/OD segmentation.

D R Nayak et al. [19] proposed a non-handcrafted extraction of features method. In this work Feature is applied on the dataset sigmoid activation is applied to one dimension flattened image to get the final feature vector. SVM classifier outperformed many other classification methods under ten-fold cross-validation. The advantage of this is it requires a very less number of learning parameters for model training compared with other CNN models. This model is trained on a machine with 48GB ram and a Xenon 2.4GHz processor which is costly.

A D Pinto et al. [20] proposed a methodology of semi-supervised learning for glaucoma detection based on DCGAN. In this work no preprocessing, and no data augmentation was applied. A publicly available huge data set is used for model training. Spherical interpolation was found to be better than linear interpolation for finding the path between two samples. The proposed system is capable of producing auto-cropping images used by the DCGAN model and classified labels are associated with images.

J Afolabi et al. [21] et al. proposed a technique using the deep learning model and machine learning algorithm for glaucoma detection. Image segmentation is achieved using a U-Net lite network with two layers: an up-sampling decoding layer and a down-sampling encoding layer. The initial step is to crop the fundus images based on the optic disc, apply spline interpolation to the fundus images and histogram equalization, and rescale images to 1 or 0. Through image segmentation, the vertical CDR values are acquired by using a formula CDR=OC/ OD length. Optic cup(OC),Optic disk(OD) lengths are used to train XGBoost classifier. Using a stochastic gradient optimizer with a learning rate of 0.001 (for OC segmentation) and 0.0001 (for OD segmentation), Nesterov = true, momentum = 0.95, and momentum = 0.95 in the training classifier with epochs = 65, the model was able to achieve 96% accuracy. The proposed model does not work on low-quality images.

Cheng et al. [22] presented a technique for segmenting the optic disc and the optic cup using super pixel classification. The proposed model uses various hand-crafted visual features at the super pixel level for better detection accuracy. However, due to the trained classifier's slight bias towards medium-sized cups, the proposed cup segmentation method underestimates huge cups while overestimating tiny cups when pallor is not apparent. In addition, the proposed algorithm also largely depends on hand-crafted visual features that are predominantly based on the color difference between the optic cup and the neuroretinal rim.

Marriam Nawaz et al. [23], propose. methodology that advances explainable deep learning in the field of efficient glaucoma detection and vertical cup-disc ratio The primary logic of the suggested solution is demonstrated in as part of the data preparation process, the researches explored annotations by pinpointing the RoIs with the aid of a bounding box. with an equidistant spaced range from 15_60% Researchers are using DL-based techniques in the field of medical image analysis because of its usefulness. CNN obtained a benchmark 93.22% the proposed approach step, the key points calculator of the EfficientDet-D0 network namely EfficientNet-B0 the BiFPN module performs the top-down and bottom-up key points fusion several times for the resultant features of Level 3–7 in Efficient Net. The final localized region with the associated class is predicted and results are computed for all modules as per evaluation parameters Glowworm Swarm Optimization algorithm The approach is not robust to scale and rotation alterations.

S. Sankar Ganesh et al [24], propose a methodology that advances explainable deep learning in the context aware segmentation and classification framework for glaucoma detection Every framework is assessed. The best glaucoma detection accuracy with eleven CNNs the REFUGE dataset, a result of 99.53% is attained by the second Pretrained dense net model in a framework extractor of features range [0-255]. Layer of residual block is designed to learn the residual of the last layer and the layer itself. Concerns that need to be addressed in prospect. The first restriction relates to the ResNeXt blocks' architectural design. Intensity of the ResNext's cardinality blocks are randomly taken to be 32. group convolutions and varied cardinalities in layer CAM the four mathematical and computational approaches to medicine 3 To get a single categorization score, streams are averaged assembled. When compared to traditional and deep learning-based glaucoma screening models, this network delivers the greatest results on the SCES and SINDI datasets, accordingly.

Anindita Septiarini et al [25], proposes a methodology that advances explainable deep learning in automatic glaucoma detection by applying statistical images on fundus images on the basis of the ONH,several texture extraction techniques have been developed. The most often used techniques for extracting features are wavelet and higher-order spectra (HOS) methods. based on observation of the ONH in fundus pictures and the classification outcomes of our method employing three features of glaucoma detection provided by an expert (mean, smoothness, and 3rd moment). The ONH in several retina pictures of the normal and glaucoma classes were used to derive the results. To extraction method Higher order spectra, Grey level co-occurrence matrix, Contour feature based on the cup area. To evaluate the effectiveness of the proposed strategy, the researchers compared the outcomes with those of other methods. The proposed model had a 95.24% accuracy rate.

Dheeraj Kumar Agrawal et al [26],propose methodology that advances the explainability in automatic glaucoma detection using quasi bivariate mode decomposition from fundus images are structural changes in the eye and genetics , a medical test of ONH , and eye check - up . Computer-based glaucoma detection methods have made it easy. Scanning laser ophthalmoscope, optical coherence tomography, and Heidelberg retina tomography are widely used imaging technologies for glaucoma detection. Green images are enhanced using contrast limited adaptive histogram equalization (CLAHE) to enhance contrast and dynamic range. The median filter is used to remove noise content and accuracy of 80% was reported using SVM. Range of β parameter from 10 to 1000 and a value of 100 has been found suitable. limitations for image decomposition, non-adaptive approaches like DWT, WPD, OHAWT, and CWT are not especially suited. The model produced various SBIs using the same frequency range. Only low-frequency SBI is employed for the subsequent level of breakdown in the higher level of decomposition.

Mark Christopher et al. [27], propose methodology that advances the explainable effects of study population labelling and training on glaucoma detection Despite variations in fundus camera resolution or sensor types, strategies can be successful. The capacity of deep learning-based approaches to exploit complex visual cues in fundus images for the assessment was found to enable them to attain high accuracy on unseen datasets. testing datasets, performance was best across all models on the dataset (AUCs of 0.95–0.99), MRCH datasets, glaucoma labelling was performed by three expert graders assessing fundus photographs as well as additional clinical information diagnostic accuracy for detecting glaucoma in the eyes with high myopia (the AUC ranged between 0.94 and 0.98) and lower diagnostic accuracy in eyes without high myopia (the AUC ranged between 0.81 and 0.92),likely owing to the more severe glaucoma in the eyes with high myopia. The differences between the glaucoma definitions and labelling employed in the various datasets, particularly between the DIGS/ADAGES, MCRH/Iinan, and ACRIMA datasets, are the study's weaknesses an additional performance metric and race-stratified sensitivity for all datasets.

Yasmeen George et al [28], proposed methodology that advances the explainable in attention guided 3D-CNN framework for glaucoma detection and structural functional association volumetric images methods are utilized jointly to determine the severity of glaucoma and monitor its progression. One of the functional tests utilized is called visual field test (VFT), and it is used to evaluate vision loss due to glaucoma and other optic nerve diseases. is greatly affected by cataracts, visual acuity, glaucoma medications, severity of glaucoma, learning effect, distraction and other factors method achieved a dice coefficient of 0.959 for S-net and an accuracy of 85.4% for D-net. The 3782 OCT volumes are split into training, validation and testing subsets, containing 3031 The proposed model is trained using Adam optimizer with a learning rate of le . The researchers also use weighted cross entropy loss to avoid biased training due to the class size imbalance in the data. Training is performed with a batch of size 12 through 100 epochs, the highest weights along this dimension more than two-third of the voxels of input volumes are discarded.

Ozer Can Devecioglu et al [29], proposed methodology that advances the explainability in attention in guided real time glaucoma detection from fundus images using self -ONNs using digital image processing techniques as a detecting strategy. The OD, blood vessels, and feature computation can be done automatically using pre-processing, structural procedures, and thresholding. By categorizing the photographs of the normal and glaucoma fundus, these features are verified of the ESOGU dataset, applied SVM to classify the wavelet features of the segmented OD image, achieving 94.7% accuracy for glaucoma detection from local dataset. Results demonstrated by self-ONNSnot only achieve superior detection performance the proposed Self-ONN-based framework for the ESOGU, normalized by linear scaling to the range of [−1,1], highly heterogeneous and composed of highly diverse neuron types with distinct biochemical and electrophysiological properties

Soheila Gheisari et al [30], propose methodology that advances the explainable in combined convolutional and recurrent neural network for enhanced glaucoma detection it can be defined by the method of data collected for fundus images clinical setting mainly due to high performance of false positive rates and low precision values of accuracy and precision without compromising on false positive rates, accuracy of the stand-alone VGG16 and ResNet50 compared to other research reports. It can be observed on the delated stereoscopic examining on the optic nerve head with or without concordant visual field defects on conventional white-on-white standard automated perimetry Humphrey Field Analyzer, 24-2 SITA-Standard Glaucomatous visual field defects were not attributable to other diseases. In this researchers observed that retinal structures are static in nature reasoning for improved performance on the combined model dynamic changes on the retinal vasculator specificity and sensitivity of these models range between 85 to 95%, with the transfer-trained models.In order to further support findings, a bigger and more diverse sample is necessary.

Liu Li, Mai Xu et al. [31], propose methodology that advances the explainable in a large scale database and a CNN model for attention based glaucoma detection these methods are divided into 2 categories heuristic and deep learning hand crafted features for the vertical optic disk ratio segmentation such methods achieving the end to end training and testing most of those lack of sufficient training data accuracy of the 5 experts from tier 2 is 88.4%, 87.7%, 90.0%, 87.0% and 92.7%, accuracy by 0.9% and 0.2%, with and without the pathological area localization subnet the LAG database can be obtained from Chinese glaucoma study alliance(CGSA) the guided back-propagation (BP) method to locate the tiny pathological area based on the predicted attention maps. The attention maps can be refined and then used to highlight the most critical region for glaucoma detection, CC results averaged over 5,824 fundus images. AUC results are also reported in 0.886 so these are the features that can be added by the researchers in their proposed methods.

Ahmed Almazroa et.al.in [32], propose methodology that advances the explainable in automatic image processing system for glaucoma screening.The proposed methods can be featured by the diagnosing glaucoma structurally associated with loss of tissue in the neuroretinal rim of the optic disc and that will lead to increase in the size of the optic cup. The researchers observed between the markings by ophthalmologists numbers one and five, where the markings were in 251 of 550 images observed for the HCDR. white spots of less than 50 pixels were eliminated to reduce the chance of errors when selecting the cup. Then the image was converted to binary after deciding about the brightest spot ophthalmologists as well as the algorithm ranged from 1250 to 1400 in total, except for the ophthalmologist highest percentage of accuracy (76.6%). The algorithm was the second best with 74.6% accurately segmented. Markings by ophthalmologists had the most outliers.

WangMin Liao et al [33], propose methodology that advances the explainable in Clinical Interpretable Deep Learning Model for Glaucoma Diagnosis in these models a novel scheme for aggregating features from different scales to promote the performance of glaucoma diagnosis to the pyramid structure of a CNN, the flow of information and the region of interest imprecable a CNN model provides diagnosis result meanwhile giving the evidence where the optic disk is That the EAMNet can deal with the challenging optic disc segmentation task even though the image-level labels are used for training our model. It is worth noticing that the existing methods always achieve state-of-the-art results based on the supervised model with pixel-level labels. High-resolution feature maps are hard to be represented by GAP. Besides, the optic cup is also important and related to glaucoma diagnosis. Further studies need to be carried out to design a more empirical model to deal with the clear cup segmentation by weakly-supervised evidence exploring.The model resulted Area Under Curve (AUC) of 0.88, the remove normalisation in each RESblocks and change the dropout rate to 0.2 to overfit the model.

Mukil Alagirisamy et al. in [34], propose methodology that advances the explainability in micro statistical descriptors for glaucoma diagnosis using neural networks. The automatic disc localization method based on rules is used to extract the OD features from the retinal fundus picture. Using Deep Convolutional Neural Network (DCNN), the image is then classified as either healthy or glaucomatous. The generation of optical disc features for retinal glaucoma.

errors and a high prevalence of false negatives when analysing medical pictures and signals. Many CAD systems have been proposed to automatically identify glaucoma, and the majority of them are based on characteristics derived from various domains and classification techniques. The system achieves 95.05% accuracy whereas it is 85.38% and 96.18% for ORIGA and RIM-ONE database images. proposed method automates the extracts the ROI and micro statistical glaucoma disease

Bhupendra Singh Kirar et al.in [35],propose methodology that advances the explainable in Glaucoma Detection Using Image Channels and Discrete Wavelet Transform for glaucoma detection from fundus images have been proposed using power spectral and fractal dimensions (FDs) features complex wavelet transform (CWT), wavelet packet decomposition (WPD), optimal hyper analytic wavelet transform (OHAWT) on ICs to remove the unwanted lighting effect and enhance the visibility of the image. After that, images are filtered using median filter (MF) to remove noiseICs and DWT from fundus images has used C-RGBGs-IF from the same 505 images of RIM-1 image database detection accuracy of the proposed method is 84.95% which is more than the existing methods using the same image database.So these are the methods the researches can be replaced by proposed methodology

ADI ORBACH et al.in [36], propose methodology that advances the explainable in Qualitative Evaluation of the 10-2 and 24-2 Visual Field Tests for Detecting Central Visual Field Abnormalities in Glaucoma those methods are Eyes with a glaucomatous optic nerve appearance or ocular hypertension and healthy eyes were included as cases and control subjects, eyes in the case and control groups were required to also have a best corrected visual acuity of 20/40 or better, Values presented as median interquartile range 25th-75th percentile the researchers identified by the some dataset used range will be changed automatically .These results might be explained by the fact that the visual field results, even at the 10-2 test's sample density, do not have enough spatial resolution to allow a qualitative analysis to uncover patterns that are known to be indicative of glaucoma damages. The accuracy will be very high performance 94.1 The ability of the 10-2 and 24-2 visual field tests to distinguish between healthy and eyes with glaucoma-like optic nerve appearance of this study.

Sibghatullah I. Khan, et al in [37], propose methodology that advances the explainable in Automated glaucoma detection from fundus images using wavelet-based denoising and machine learning elementary form of glaucoma is known diagnosis of glaucoma are anatomical transformations in the retina and genetics the ONH investigative test mainly as open-angle glaucoma like EMD and VMD worthwhile to mention that the LS-SVM classifier is used with

10% outlier removal. Without outlier removal, the researchers observed a decrease in classification performance by 4%–5%. It is defined as the measure of uniformity in the range [0, 1]. The limitations of out-of-sample dataset can be included to enable real-time implementation. in future studies, advanced image processing and classification methods could be utilized for better classification

Mir Islam et al.in [38] described deep learning-based glaucoma detection with cropped optic cup and disc and blood vessel segmentation. Glaucoma is one of the most well-known causes of irreversible blindness across the globe. This paper proposed a unique attention-based convolutional neural network named AG-CNN. The impressive results obtained from the proposed system are believed to help ophthalmologists examine and detect glaucoma more quickly and economically. The researchers have used four different deep learning algorithms, EfficientNet, MobileNet, DenseNet, and GoogLeNet, to diagnose glaucoma from the cropped ocular cup and disc fundus images. The proposed system and eye fundus photographs can be utilized to diagnose more complex ocular diseases, such as diabetic retinopathy. Dataset-1 consists of 210 glaucoma samples and 369 normal samples. The cup and disc are placed in the middle, and the CDR ratio is set to 1:1.

Ozer Devecioglu et al.[39] report that this is the first study where Self-ONNs are evaluated against deep CNNs over a classification problem. The proposed classifier achieved a significant performance gap of 8-12% F1 score over equivalent CNN and even deep CNN models for the three benchmark glaucoma datasets. In this study, the researchers propose compact Self-Operational Neural Networks for glaucoma detection. The superior performance of Self-ONN with an even higher gain is observed for the RIM-ONE dataset. Deep CNN models are used for pre-training the model and applied transfer learning. The study involved 3 benchmark datasets. The performance of the proposed technique is assessed against state-of-the-art CNN-based approaches.

Xiong Luo et al. [40] noted that this article proposes a deep learning-based CAD model to deal with a challenging issue in classification of ophthalmic images, through the analysis of retinal fundus images. For glaucoma and cataract classification tasks, the method does not achieve the best accuracy and sensitivity. The specificity, Kappa, and AUC have been significantly improved as a result of the incorporation of the proposed loss function. Among all those deep learning models implemented to detect three eye diseases including glaucoma, AMD, and cataract, FCL-EfficientNet-B3 model outperforms other baseline methods. 21 ophthalmologists were involved in the analysis. The authors suggest that the experimental results validate the performance of the proposed method, and indicate that glaucoma and AMD are two hard diseases for machine learning recognition. To address this problem, the research on further feature extraction technologies is the future work.

Mijung Kim et al. [41] described web-applicable computer-aided diagnosis of glaucoma using deep learning. The revival of convolutional neural networks (CNNs) and the public availability of large-scale datasets like ImageNet have led to significant performance improvements in computer vision. CNN-based predictive models have shown to be highly successful in medical image analysis. The authors introduced a predictive model for computer-aided diagnosis of glaucoma, leveraging CNNs and Grad-Class Activation Mapping. The authors advocate that in this paper, they introduced a predictive model for computer-aided diagnosis of glaucoma. The model has been developed by making use of a small-sized dataset of fundus eye images. The authors integrated the model into a publicly available prototype web application.

Ko Kim et al. [42] proposed a deep learning system for diagnosing glaucoma using Optical Coherence Tomography The group developed and validated a deep learning system for glaucoma diagnosis using OCT deviation and thickness maps of RNFL and GCIPL analyses. Deep learning systems using only the RNFL thickness map showed the best diagnostic performance. Despite no significant difference in diagnostic performance between VGG-19 (AUROC 0.987, 95% CI 0.971–0.995) and ResNet-34, the VGG-19 showed diagnostic patterns more compatible with those of glaucoma specialists. The glaucoma group had significantly higher mean age, lower retinal nerve fiber layer and ganglion cell–inner plexiform layer thicknesses, and lower mean deviation values compared to the control group. The strength of the study is that model employed on all the currently available RNFL and GCIPL deviation and thickness maps. 1822 eyes were involved in the research.

Manal Abdel-Mottaleb et al.[43] presented an automatic glaucoma diagnosing framework based on convolutional neural network (CNN) models. The researchers compared proposed model performances with the performance of trained ophthalmologists. The lowest performance was achieved by the TCNN model because the transfer learning and the fine-tuning of the pre-trained network layers utilized a small set of labeled samples. The transfer learning model is based on convolutional neural networks pre-trained with non-medical data and fine-tuned using domain specific labeled data. Unlike the previous works where the optic disc features were handcrafted, the presented models automatically extract the key features of the disease from raw images. The initial sizes of A and B were chosen to be 30 and 39 samples, respectively. With more iterations, the classifier performance improves, thus, these two sizes were increased during the learning process.

Yidong et al.[44] proposed a method for classifying microcalcification clusters in mammograms. Models report that glaucoma is an eye disease of the major nerve of a vision, called the optic nerve. It is often associated with elevated intraocular pressure, in which damage to the optic nerve is progressive over a long period of time. The method used here is an optic nerve that gives an accuracy of 99.2464, specificity of 93.5895 and sensitivity of 97.9178. This work is mainly for Glaucoma detection in patients using multimodalities including simple linear iterative clustering (SLIC) algorithm, K-Means clustering, and Gabor wavelet transformation of the color fundus camera image to obtain accurate boundary delineation. The accuracy of the proposed method is much better than the IOP measurement, abnormal visual field and previous GLCM based CNN Classification methods Glaucoma detection.

Huazhu Fu et al. [45] reported in ‘Glaucoma Detection Based on Deep Learning Network in Fundus Image that glaucoma is the leading cause of irreversible blindness worldwide. The balanced region helps avoid the overfitting during the model training and improves the segmentation performance. M-Net and Disc-aware Ensemble Network obtains the satisfied performances. Early detection is essential to preserve vision and life quality. The M-Net obtains better performance than the Disc-aware Ensemble Network (DENet). There were 168 glaucomatous eyes involved in the study. The researchers advocate that for this case, all the methods fail to produce accurate OC segmentation. This issue could potentially be addressed in future work through the use of more powerful networks or additional image enhancement pre-processing.

JinAhn et al.[46] proposed a deep learning model for the detection of both advanced and early glaucoma using photography. The researchers noted that both advanced and early glaucoma could be correctly detected via machine learning, using only fundus photographs. Transfer-learned GoogleNet Inception v3 model achieved accuracy and area under the receiver operating characteristic curve of 99.7%. Machine learning is a system of artificial computer intelligence that provides computers with the ability to automatically learn without being programmed. Transfer-learned GoogleNet Inception v3 model achieved accuracy and AUROC of 99.7% and 0.99 on training data. This study demonstrates that deep learning techniques can be combined with fundus photography as an effective approach to distinguish between normal controls and glaucoma patients.

Guangzhou An et al. [47] proposed a method on glaucoma diagnosis with machine learning based on optical coherence tomography and color fundus images. Machine learning technologies and deep learning, in particular, have seen dramatic progress and have enabled the development of new algorithms to automate eye disease diagnosis. The researchers describe a new machine learning algorithm for diagnosing glaucoma based on OCT-derived data, including disc fundus images as well as thickness and deviation maps of the macula and the optic disc. Glaucoma is a chronic, neurodegenerative ocular disease characterized by optic neuropathy and visual disturbance that corresponds to optic disc cupping and optic nerve fiber degeneration. Glaucomatous structural changes preceed functional changes.

Zhixi Li et al. [48] have developed a machine-learning system to detect glaucoma nodules (GON), a leading cause of blindness worldwide. This work includes 48,116 fundus photographs for the development and validation of a deep learning algorithm. The algorithm showed a robust performance (AUC, 0.986; sensitivity, 95.6%; and specificity, 92.0%) for the detection of referable GON. As glaucoma advances from the early to late stage, care costs increase by 4-fold. As a result of population growth and ageing, this figure is expected to increase to 112 million by 2040. Most vision loss resulting from glaucoma is avoidable through early detection and treatment strategies. Approximately 85% of cases among the Singapore Chinese, the same rate for the African American population of the United States are undiagnosed. There were 21 trained ophthalmologists involved in the study.

Felix Grassmann et al.[49]developed an automated classification strategy based on training deep learning models to predict the Age-related macular degeneration stage in color fundus images. The team reported linear weighted and unweighted k measures, overall accuracy, as well as top 2 accuracy, which indicates that the true class of a fundus image is among the 2 classes that are predicted by the convolution neural nets. The researchers included 120,656 manually graded color fundus images from 3654 Age-Related Eye Disease Study (AREDS) participants and presented an automated classification scheme based on the AREDS 9-step plus 3 severity scale and ungradable fundus image with high classification accuracy. The F1 score was similar for all 6 neural net architectures across all AREDS classes, but differed significantly for class 12. The researchers believe that this is the result of 3 factors: class 12 contained the fewest samples, so the networks were not able to learn from many different training examples.

Feng Li et al.[50] presented a deep learning-based automated detection of glaucomatous optic neuropathy on color fundus photographs. Glaucoma is the collective name of a group of eye conditions which can cause vision loss and eventually result in blindness. The model was tested on 2371 adult patients for the detection of glaucoma using fundus images,which showed high accuracy compared to human experts. In a multi-class comparison between glaucomatous optic neuropathy-confirmed, GON-suspected, and NORMAL eyes, the model obtained an accuracy of 0.941. ResNet101was used to automatically and reliably detect GON from fundus images. The proposed model showed a superior performance compared with the human experts in identifying normal eyes.

Nahida Akter et al.[51] presented a deep learning model to segment the cup surface area of the ONH OCT B-scan images of 60 eyes, including 30 normal and 30 glaucoma patients. The statistically significant features were trained using two machine learning algorithms, a LR and DL technique. This study suggested that segmentation and measurement of cross-sectional ONH cup area could be a novel clinical imaging feature. The researchers aimed to facilitate the current diagnostic assessment of glaucoma by analyzing multiple features. The researchers introduced a new cross-sectional optic nerve head feature from optical coherence tomography images. The DL model trained from the optimal features achieved significantly higher diagnostic performance compared to previous models.

Juan Gomez-Valverde et al. [52] presented a model for automatic glaucoma classification using color fundus images based on convolutional neural networks and transfer learning. Three data sets were used for training the model. It is remarkable that DENET DISC TL and fine-tuned from ORIGA data set did not outperform RESNET50 TL fine-tuned from ImageNet. The results show that CNNs is a valuable alternative for CAD systems. The transfer learning of CNN models pre-trained with different image data sets and fine-tuned to solve a specific medical imaging task. The model shows the different behavior of the network with the different data sets.

2.2 Research Gaps

There are some research gaps in the papers, we reviewed. So, we address some of the gaps in the existing approaches with our proposed model. It is also important to get the best results with the model we propose. Some of the research gaps are mentioned below.

- Many researchers used small size dataset which led them underfitting of their model.
- Many researchers didn’t consider the poor-quality images (contrast, cropping) and they are removed as noise.

- Existing models are somehow able to detect the presence of Glaucoma but fail to identify the Stage of Glaucoma
- Researchers used RGB images so when red channel is used, retinal image are most affected.
- The papers we reviewed had the most unbalanced datasets which lead to improper training and effected the truthfulness of the system.

2.3 Objective of the study

- The major objective of this study is to improve the concept of prediction of glaucoma disease with the help of data augmentation techniques.
- Developing a robust system by training the model with different kinds of datasets containing varied characteristics of fundus images and increasing the number of training and testing images.
- The proposed approach is applied on large dataset.
- The proposed image augmentation techniques are the usage of image data generator.
- Instead of using images as it is, we convert them into binary as it results in higher classification with less memory consumption.
- Using CNN for feature extraction and classification to achieve higher accurate results.

2.4 Methodology

Many pretrained models like AlexNet, ResNet, VGGNet, etc. are used. The saliency maps are produced from these models on the considered data then these maps are used for further steps of the process. Most of the proposed models used ground truths and modified ground truths for the detection of glaucoma. Some researchers have used UNet for Image Segmentation, which slows down the middle layers of the model. Some of the existing methods used imbalanced data where, imbalance data caused disturbance in the results or detection. So balancing should be applied. Very few researchers used many parameters, it'll definitely effect the performance of the model. In this we propose a model consisting of a combined dataset of ACRIMA, DRISTI and RIMONE. The proposed methodology uses an image data generator for data augmentation. The original images have increased due to augmentation and a large dataset is prepared. The dataset is split intlo 80:10:10 for training data, testing and validation data. Later the augmented images have been sent for feature selection using CNN. The images are classified using binary classification as it has two outcomes. The model can predict the glacumatous eye accurately.

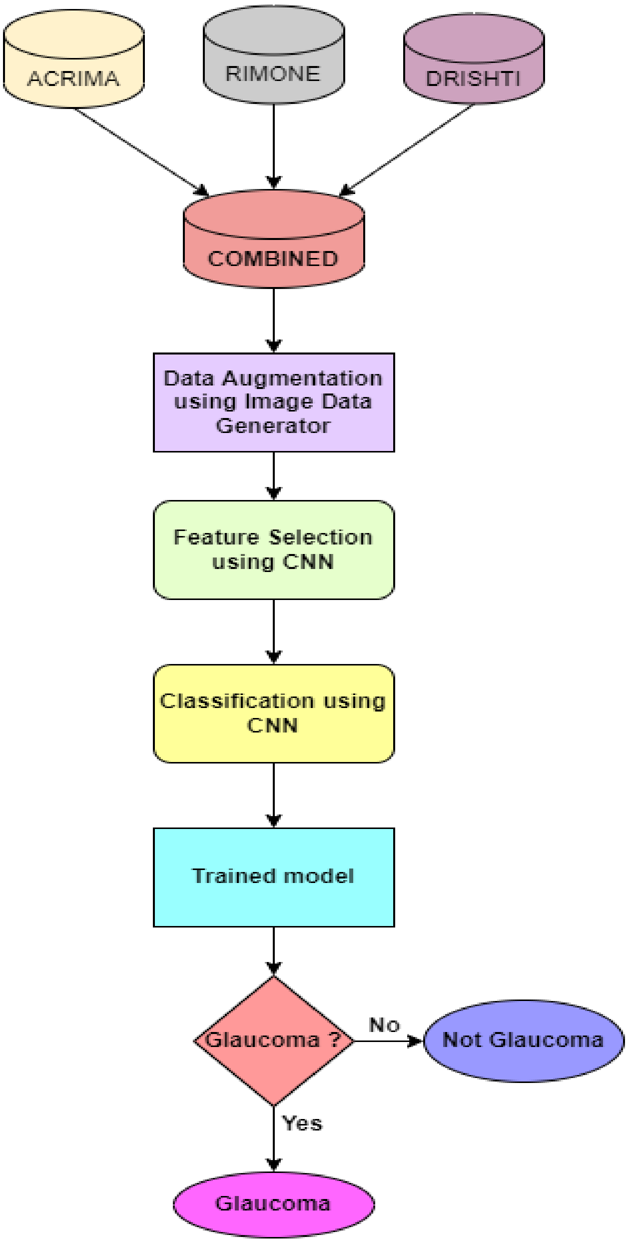


Figure 2.1 Architecture diagram for system

2.5 Data Source and Data Collection

Kaggle is a free-source to download datasets. We have taken our datasets from that only. We can have access to Use over 50,000 public datasets.

a. ACRIMA

Source:

https://www.kaggle.com/datasets/sshikamaru/glaucoma-detection?select=ACRIMA

b. DRISHTI-GS

Command to download:

kaggle datasets download -d lokeshsaipureddi/drishtigs-retina-dataset-for-onh-segmentation

Source:

https://www.kaggle.com/datasets/lokeshsaipureddi/drishtigs-retina-dataset-for-onh-segmentation

c. RIMONE

Command to download:

kaggle datasets download -d lucascunhadecarvalho/rimone-glaucoma

Source:

https://www.kaggle.com/datasets/lucascunhadecarvalho/rimone-glaucoma

2.6 Data set description & Dataset Analysis

a. ACRIMA

ACRIMA database is composed by 705 fundus images (396 glaucomatous and 309 normal images). They were collected at the FISABIO Oftalmología Médica in Valencia, Spain, from glaucomatous and normal patients with their previous consent and in accordance with the ethical standards laid down in the 1964 Declaration of Helsinki. All images from ACRIMA database were annotated by glaucoma experts with several years of experience. They were cropped around the optic disc and renamed.

b. DRISHTI-GS

This Dataset contains 50 train images and 51 test Images. In Each Directory there are two folders one is images and the second one is GT. The later folder contains Optic Disk and Cup masks associated with the images in the Images folder.

c. RIMONE

The RIM-ONE database contains 169 optic nerve head images. Each image has 5 manual segmentations from ophthalmic experts. A gold standard for each image was created from its corresponding segmentations.

SYSTEM ANALYSIS

3. SYSTEM ANALYSIS

System Analysis is the process of analyzing a system with the potential goal of improving or modifying the system. The analysis is breaking down the problem into smaller elements for study and ultimately provides a better solution. During the process of system development, Analysis is an important aspect. This involves gathering and interpreting facts, diagnosing the problem, and using the information to recommend improvements to the system. Ultimately, the goal is to give a computerized solution.

3.1 System Study

3.1.1 Feasibility Study

A feasibility study is an important phase in the software development process. It enables the developer to have an assessment of the product being developed. It refers to the feasibility study of the product in the product in terms of outcomes of the product, operational use, and technical support required for implementing it. The feasibility study should be performed based on various criteria and parameters. Here the feasibility study can be performed in four ways such as operational feasibility, technical feasibility, economic feasibility, and behavioural feasibility.

3.1.2 Operational Feasibility

It refers to the feasibility of the product’s operation. Some products may work very well at design and implementation but may fail in the real-time environment. It includes the study of additional human resources required and their technical expertise. This application will also work in any environment without any problem since we are implementing this project using Python, which is Operating System independent.

3.1.3 Technical Feasibility

It refers to whether the software that is available in the market fully supports the present application. It studies the pros and cons of using particular software for development and its feasibility. It also studies the additional training needed to be given to the people to make the application work. For this project Image Super Resolution and Contrast Enhancement Using Curvelets with Cycle Spinning, we need not recruit any additional staff to make use of this application. If we train our staff for one hour then it will be enough to work with the application.

3.2 Requirement Analysis

We are overcoming the tedious manual procedure with this approach involving automatic report generation and providing the required information.

3.2.1 Functional Requirements

This section describes the functional requirements of the system which are expressed in a natural language style. They are as follows:

While non-functional requirements describe system restrictions and properties, functional requirements describe how the system works. The expected behavior of the system is captured in the functional requirements. This Behaviour can be described in terms of services, tasks, or the requirements the system must meet to carry out. This explains key ideas and covers functional capturing. Such that they can influence architectural choices and be used to validate the structure. Features may add functionality or be different from the fundamentals. Functioning about a desirable quality. The suggested approach uses concert to evaluate the analysis of a workflow's compliance using the five specified criteria for ensuring that workflow rules are followed: actions, data, location, resources, and time restrictions. A regulation outlines what actions are permitted, required, and prohibited.

- Read the data from the datasets.
- Perform Pre-processing of the input dataset by adjusting the contrast, edges, image quality.
- To perform image augmentation to increase the image set, to detect the correct affected area from the image, apply binarization to the images to secure them from being affected by various other colours.
- Perform feature extraction and classification using CNN.
- Generation of evaluation metrics
- Assessment of results.

3.2.2 Non-Functional Requirements

1. Security

The system must be able to restrict user access and sessions. Data must also be stored in a secure manner and location. It necessitates a safe path for data transmission.

2. Concurrency and Capacity

Multiple calculations should be able to run on the system. Concurrently and maybe in interaction with one another.

3. Performance

Most people associate performance with a timeline. These are some of the most significant factors, particularly when the project is in the architecture phase.

4. Reliability

It is necessary to ensure and notify about the system transactions and processing as simple as keeping a system log will increase the time and effort to get it done from the very beginning. Data should be transferred reliably and using trustful protocols.

5. Maintainability

A well-designed system is intended to be operational for a long time. Consequently, it will Preventive and corrective maintenance are frequently required. Maintenance could mean the system's potential to expand and upgrade its features and functionalities.

6. Usability

One of the main pillars that supports a product is end-user approval and pleasure in project achievement. The user experience needs should be taken into account from the project's inception onward. This will significantly save time when the project is released. The user won't request adjustments or, in the worst-case scenario, clarifications.

7. Documentation

All projects require a minimum of documentation at different levels. In many cases the users might even need training on it, so keeping good documentation practices and standards will do this task spread along the project development; but as well this must be established since the project planning to include this task in the list.

3.3 System Requirement Specification

The System Requirements Specification (SRS) begins the translation process that converts the software requirements into the language the developers will use. The SRS draws on the use cases from the User Requirement Document (URD) and analyzes the situations from several perspectives to discover and eliminate inconsistencies, ambiguities, and omissions before development progress significantly under mistaken assumptions.

3.3.1 Software Specifications

The minimal software specifications of the proposed system are,

- Operating System : Windows XP
- Technology : Python3
- Tools / Libraries : Tensor flow, Keras
- Dataset : Image data

3.3.2 Hardware Specifications

The minimal hardware specifications of the proposed system are,

- Processor : Intel I5
- RAM : 8 GB
- Hard Disk : 64 GB

3.4 Software Design Process Model

The Agile methodology is a way to manage a project by breaking it up into several phases. It involves constant collaboration with stakeholders and continuous improvement at every stage. Once the work begins, teams' cycle through a process of planning, executing, and evaluating. Continuous collaboration is vital, both with team members and project stakeholders.

Agile Methodologies Overview

The Agile Manifesto of Software Development put forth a ground breaking mindset on delivering value and collaborating with customers when it was created in 2001. Agile's four main values are:

- Individuals and interactions over processes and tools.
- Working software over comprehensive documentation.
- Customer collaboration over contract negotiation.
- Responding to change over following a plan.

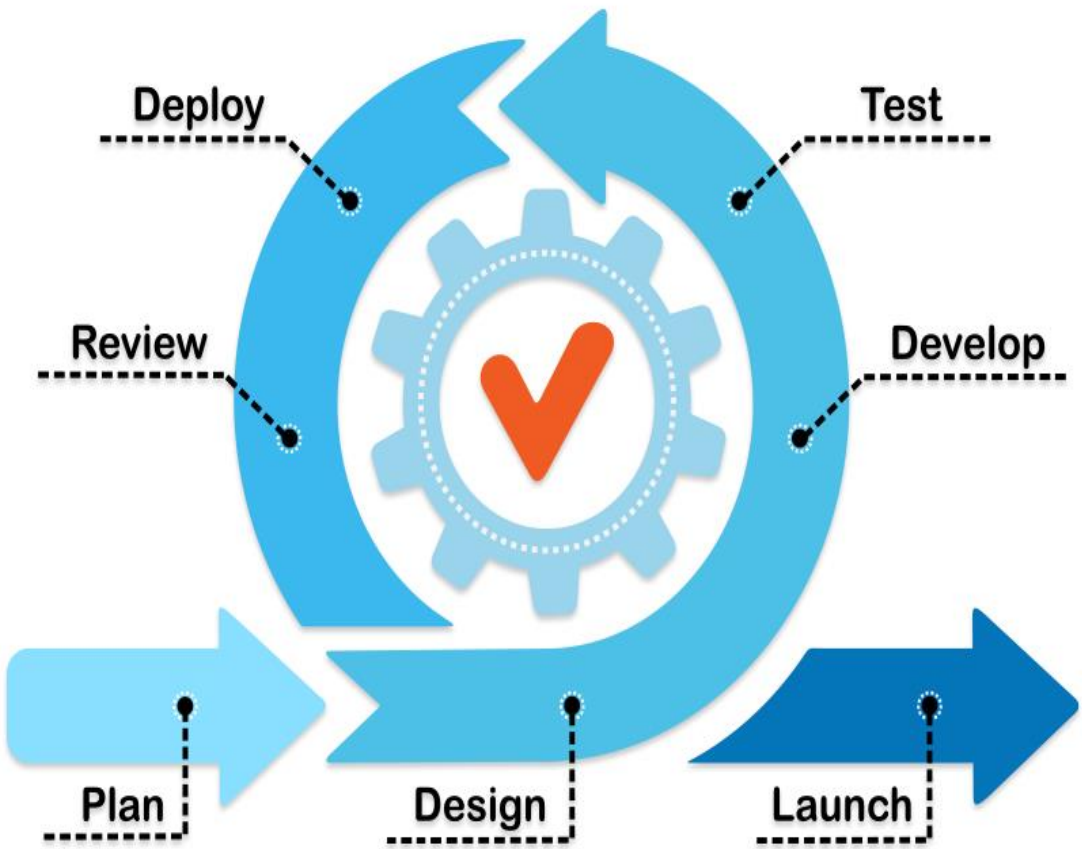


Figure 3.1 Agile Methodology

Agile project management works off the basis that a project can be continuously improved upon throughout its life cycle, with changes being made quickly and responsively. The Agile methodology enables to re-evaluate their work and make adjustments in small increments. The number of images trained to the model will fluctuate based on the step it is going through. The agile model helps in iterative process to make the required changes from the design phase. In glaucoma detection, we can add a new dataset which does not affect the requirement phase so only changes are made in the design phase.

SYSTEM DESIGN

4. SYSTEM DESIGN

4.1 About System Design

System design is the process of designing the elements of a system such as the architecture, modules, components, the different interfaces of those components, and the data that goes through that system. The purpose of the System Design process is to provide sufficient detailed data and information about the system and its system elements to enable the implementation consistent with architectural entities as defined in models and views of the system architecture.

Elements of a System:

- Architecture - This is the conceptual model that defines the structure, behavior, and views of a system. We can use flowcharts to represent to illustrate the architecture.
- Modules - These are components that handle one specific task in a system. A combination of the modules makes up the system.
- Components - This provides a particular function or group of related functions. They are made up of modules.
- Interfaces - This is the shared boundary across which the components of the system exchange information and relate.
- Data - This management of the information and data flow.

4.1.1. Initialize design definition

- Plan for and identify the technologies that will compose and implement the systems elements and their physical interfaces.
- Determine which technologies and system elements have a risk to become obsolete, or evolve during the operation stage of the system. Plan for their potential replacement.
- Document the design definition strategy, including the need for and requirements of any enabling systems, products, or services to perform the design.

4.1.2. Establish design characteristics

- Define the design characteristics relating to the architectural characteristics and check that they are implementable.

- Define the interfaces that were not defined by the System Architecture processor that need to be defined as the design details evolve.
- Define and document the design characteristics of each system element2.

4.1.3. Assess alternatives for obtaining system elements

- Assess the design options.
- Select the most appropriate alternatives.
- If the decision is made to develop the system element, the rest of the design definition process and the implementation process are used.
- If the decision is to buy or reuse a system element, the acquisition process may be used to obtain the system element.

4.1.4. Manage the design

- Capture and maintain the rationale for all selections among alternatives and decisions for the design, and architecture characteristics.
- Assess and control the evolution of the design characteristics.

4.2 System Architecture

A system architecture or systems architecture is the conceptual model that defines the structure, behavior, and more views of a system. An architecture description is a formal description and representation of a system, organized in a way that supports reasoning about the structures and behaviors of the system. An architecture description also indicates how non-functional requirements will be satisfied.

For Example:

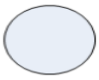
- Safety integrity: Elements of the design that reduce the risk that the system will cause (or allow causation of) harm to property and human beings.
- System availability: For example, elements of the design that enable a system to operate 24/7.
- Fault tolerance: Elements of the design that allow the system to continue to operate if some components fail (e.g. no single point of failure).

4.2.1 Data Flow Diagram

A data flow diagram (DFD) maps out the flow of information for any process or system. It uses defined symbols like rectangles, circles and arrows, plus short text labels, to show data inputs, outputs, storage points and the routes between each destination. Data flowcharts can range from simple, even hand-drawn process overviews, to in-depth, multi-level DFDs that dig progressively deeper into how the data is handled.

External entity: An outside system that sends or receives data, communicating with the system being diagrammed. They are the sources and destinations of information entering or leaving the system. They might be an outside organization or person, a computer system or a business system. They are also known as terminators, sources and sinks or actors. They are typically drawn on the edges of the diagram.

Process: Any process that changes the data, producing an output. It might perform computations, or sort data based on logic, or direct the data flow based on business rules. A short label is used to describe the process.



Data store: files or repositories that hold information for later use, such as a database table or a membership form. Each data store receives a simple label.

Data flow: the route that data takes between the external entities, processes and data stores. It portrays the interface between the other components and is shown with arrows, typically labeled with a short data name.

Data Flow Diagrams:

DFD Level 0 is also called a Context Diagram. It’s a basic overview of the whole system or process being analyzed or modeled. It’s designed to be an at-a-glance view, showing the system as a single high-level process, with its relationship to external entities. It should be easily understood by a wide audience, including stakeholders, business analysts, data analysts and developers.

Figure 4.1: Data Flow Diagram Level 0 for the system

Level 1 DFD breaks down the main process into subprocesses that can then be seen on a deeper level. Also, level 1 DFD contains data stores that are used by the main process. A level 1 DFD notates each of the main sub-processes that together form the complete system. We can think of a level 1 DFD as an “exploded view” of the context diagram.

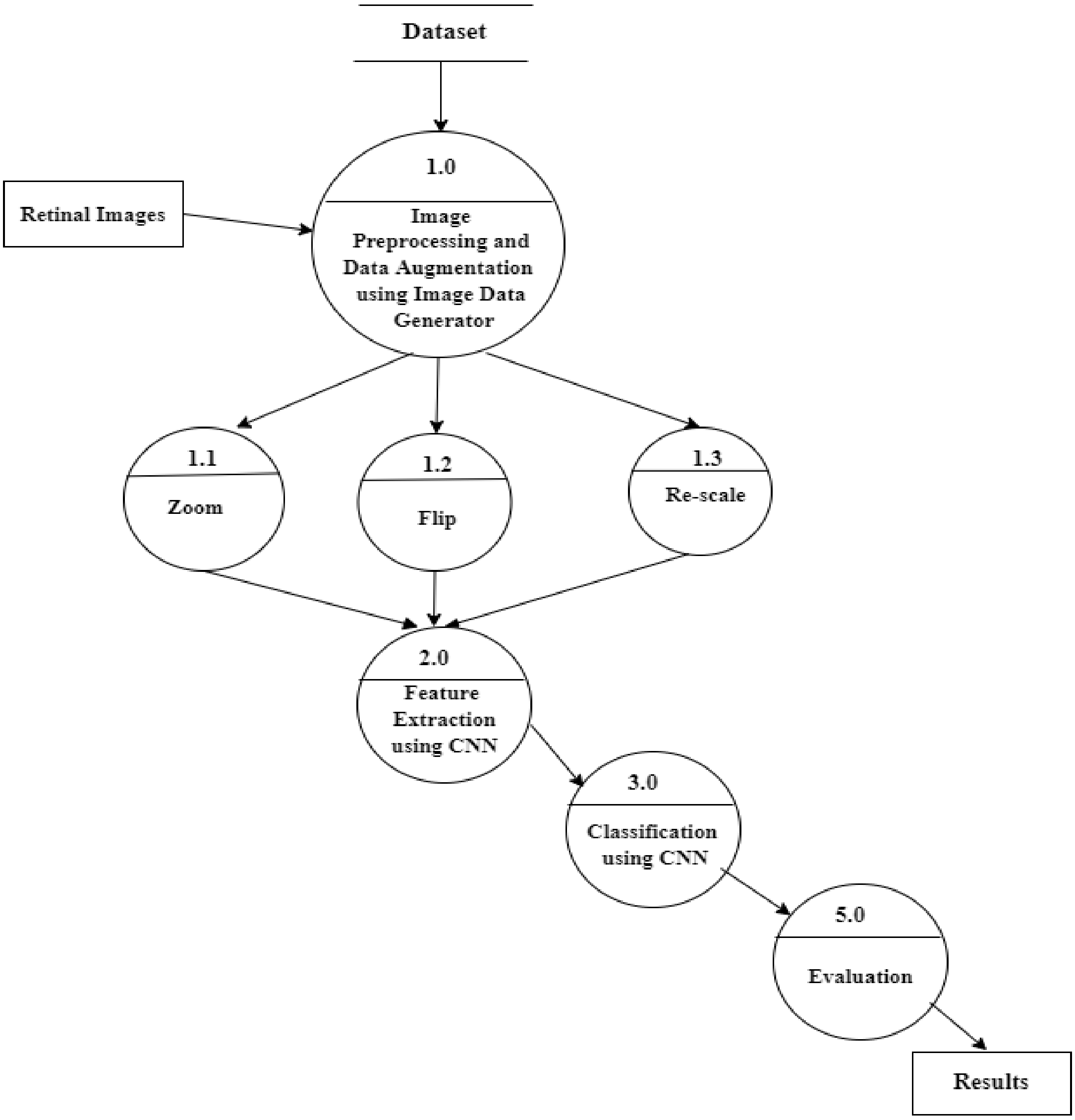


Figure 4.2: Data Flow Diagram Level 1 for the system

A DFD may look similar to a flow chart. However, there is a significant difference with the data flow diagram. The arrows in DFDs show that there is a flow of data between the two components and not that the component is sending the data that must be executed in the following component. A component in DFD may not continue execution when sending data and during execution of the component receiving the data. The component sending data can send multiple sets of data along several connections. In fact, a DFD node can be a component that never ends.

Rules

- In DFDs, all arrows must be labelled.
- The information flow continuity, that is all the input and the output to each refinement, must maintain the same in order to be able to produce a consistent system.

Strengths and Weaknesses

Strengths

- DFDs have diagrams that are easy to understand, check and change data.
- DFDs help tremendously in depicting information about how an organization operates.

Weaknesses

- Modification to a data layout in DFDs may cause the entire layout to be changed.
- The number of units in a DFD in a large application is high. Therefore, maintenance is harder, more costly and error prone.

4.3 Unified Modeling Language (UML) Diagrams

UML stands for Unified Modelling Language. UML is a standardized general-purpose modeling language in the field of object-oriented software engineering. The standard is managed and was created by, the Object Management Group. The goal is for UML to become a common language for creating models of object-oriented computer software. In its current form, UML is comprised of two major components: a Meta-model and a notation. In the future, some form of method or process may also be added to; or associated with, UML. The Unified Modeling Language is a standard language for specifying, Visualization, Constructing, and documenting the artifacts of a software system, as well as for business modeling and other non-software systems. The UML represents a collection of best engineering practices that have proven successful in the modeling of large and complex systems. The UML is a very important part of developing object-oriented software and the software development process. The UML uses mostly graphical notations to express the design of software projects.

Goals:

The Primary goals in the design of the UML are as follows:

1. Provide users a ready-to-use, expressive visual modeling Language so that they can develop and exchange meaningful models.
2. Provide extendibility and specialization mechanisms to extend the core concepts.
3. Be independent of particular programming languages and development process.
4. Provide a formal basis for understanding the modeling language.
5. Encourage the growth of OO tools market.
6. Support higher level development concepts such as collaborations, frameworks, patterns and components.
7. Integrate best practices.

4.3.1 Importance of UML Modelling

The unified modeling language allows the software engineer to express an analysis model using the modeling notation that is governed by a set of syntactic semantic and pragmatic rules. A UML system is represented using five different views that describe the system from distinctly different perspective. Each view is defined by a set of diagrams, which is as follows.

1. User Model View

This view represents the system from the user's perspective. The analysis representation describes a usage scenario from the end-user perspective.

2. Structural model View

In this model the data and functionality are arrived from inside the system. This model view models the static structures.

3. Behavioral Model View

It represents the dynamic of behavioral as parts of the system, depicting the interactions of collections between various structural elements described in the user model and structural model view.

4. Implementation Model View

In this the structural and behavioral as parts of the system are represented as they are to be built.

5. Environmental Model View

In this, the structural and behavioral aspects of the environment in which the system

is to be implemented are represented. UML diagrams can be used as a way to visualize a project before it takes place or as documentation for a project afterward. But the overall goal of UML diagrams is to allow teams to visualize how a project is or will be working, and they can be used in any field, not just software engineering. A model is a simplification of reality, providing blueprints of a system.

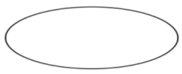
4.3.2 Use Case Diagram

Use Case diagrams identify the functionality provided by the system (use cases), the users who interact with the system (actors), and the association between the users and the functionality. Use Cases are used in the Analysis phase of software development to articulate the high-level requirements of the system. The primary goals of Use Case diagrams include:

- Providing a high-level view of what the system does.
- Identifying the users (“actors”) of the system.
- Determining areas needing human-computer interfaces.
- Graphical Notation: The basic components of Use Case diagrams are the Actor, the Use Case, and the Association.

Actor: An Actor, as mentioned, is a user of the system, and is depicted using a stick figure. The role of the user is written beneath the icon. Actors are not limited to humans. If a system communicates with another application, and expects input or delivers output, then that application can also be considered an actor.

Use Case: A Use Case is functionality provided by the system, Use Cases are depicted with an ellipse. The name of the use case is written within the ellipse.



Links: These Associations are used to link Actors. Association with Use Cases, and indicate that an Actor participates in the Use Case in some form. Behind each Use Case is a series of actions to achieve the proper functionality, as well as alternate paths for instances where validation fails, or errors occur. These actions can be further defined in a Use Case description. Because this is not addressed in UML, there are no standards for Use Case descriptions. However, there are some common templates can follow, and whole books on the subject writing of Use Case description.

Use Case Diagram:

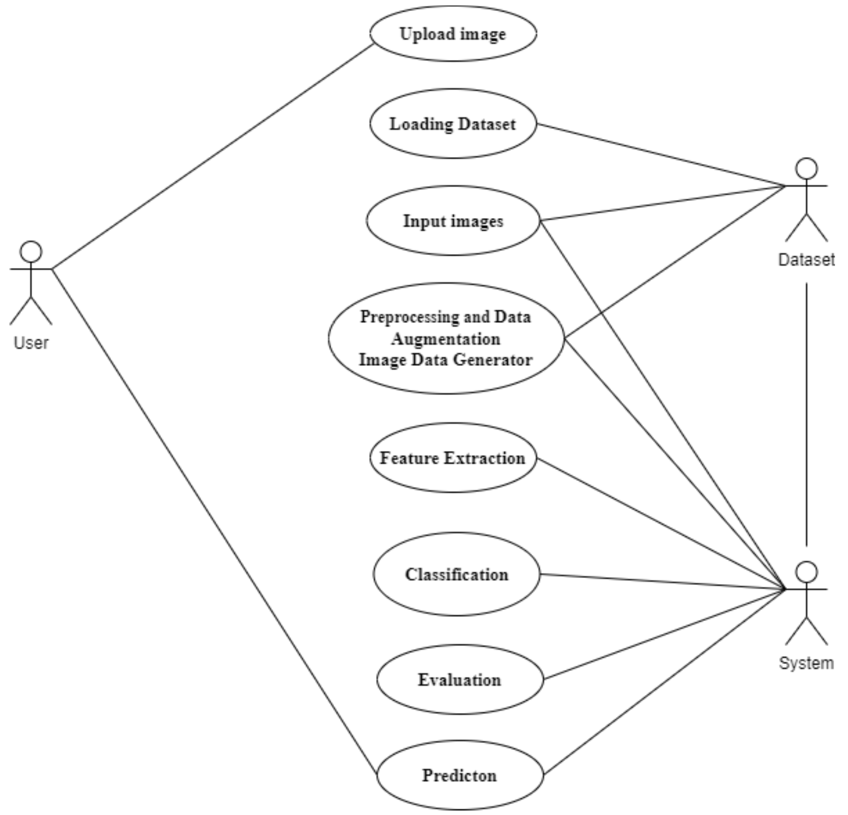


Figure 4.3: Use Case Diagram for System

4.3.3 Sequence Diagram

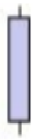
Sequence diagrams document the interactions between classes to achieve a result, such as a use case. Because UML is designed for object-oriented programming, these communications between classes are known as messages. The Sequence diagram lists objects horizontally, and time vertically, and models these messages over time.

Graphical Notation: In a Sequence diagram, classes and actors are listed as columns, with vertical lifelines indicating the lifetime of the object over time.

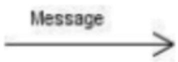
Object Objects are instances of classes and are arranged horizontally. The pictorial representation for an Object is a class (a rectangle) with the name prefixed by the object name (optional) and a semi-colon.

Lifeline The Lifeline identifies the existence of the object over time. The notation 2for a Lifeline is a vertical dotted line extending from an object.

Activation Activations, modeled as rectangular boxes on the lifeline, indicate when the object is performing an action.



Message Messages, modeled as horizontal arrows between Activations, indicate the communications between objects.



Sequence Diagram:

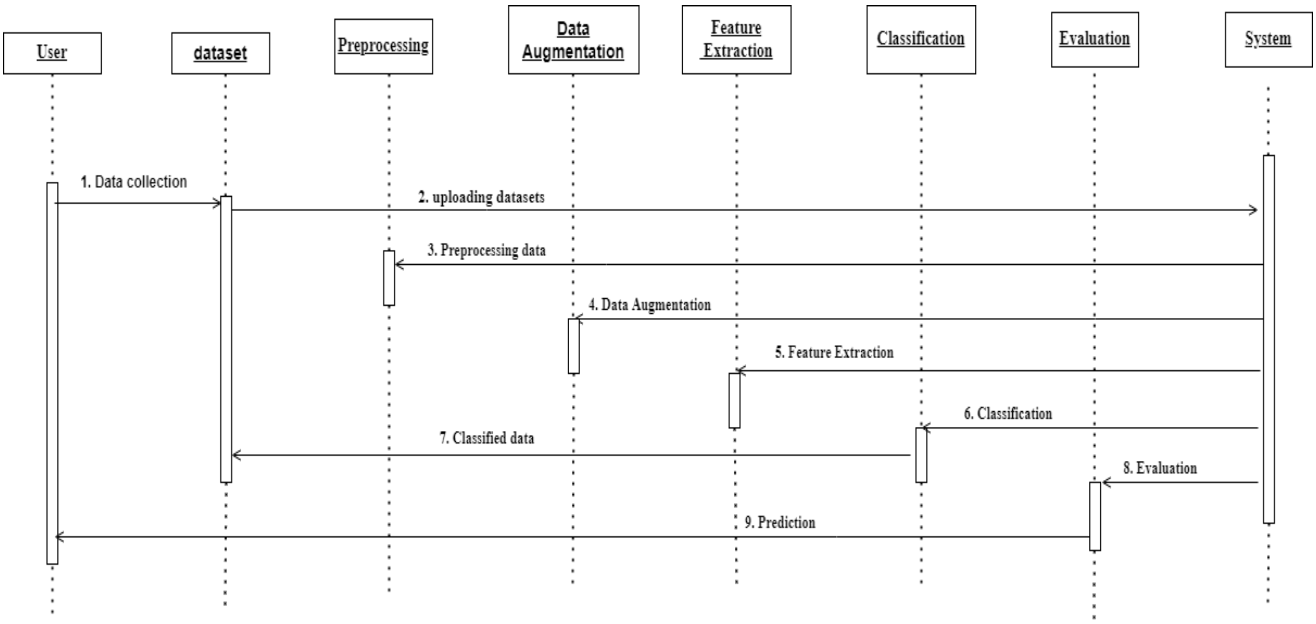


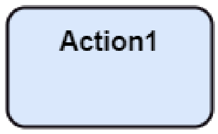
Figure 4.4: Sequence Diagram for system

4.3.4 Activity Diagram

This shows the flow of events within the system. The activities that occur within a use case or within an objects behavior typically occur in a sequence. An activity diagram is designed to be simplified look at what happens during an operations or a process.Each activity is represented by a rounded rectangle the processing within an activity goes to compilation and then an automatic transmission to the next activity occurs. An arrow represents the transition from one activity to the next. Activities are the state that represents the execution of a set of operations. These are similar to flow chart diagram and dataflow.

Initial state: Starting point of the action.

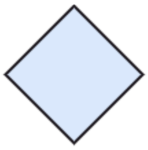
Action State: An action state represents the execution of an atomic action, typically the invocation of an operation. An action state is a simple state with an entry action whose only exit transition is triggered by the implicit event of completing the execution of the entry action.



Transition: A transition is a directed relationship between a source state vertex and a target state vertex. It may be part of a compound transition, which takes the static machine from one static configuration to another, representing the complete response of the static machine to a particular event instance.

Final state: A final state represents the last or "final" state of the enclosing composite state. There may be more than one final state at any level signifying that the composite state can end in different ways or conditions. When a final state is reached and there are no other enclosing states it means that the entire state machine has completed its transitions and no more transitions can occur.

Decision: A state diagram (and by derivation an activity diagram) expresses decision when guard conditions are used to indicate different possible transitions that depend on Boolean conditions of the owning object.



Activity Diagram:

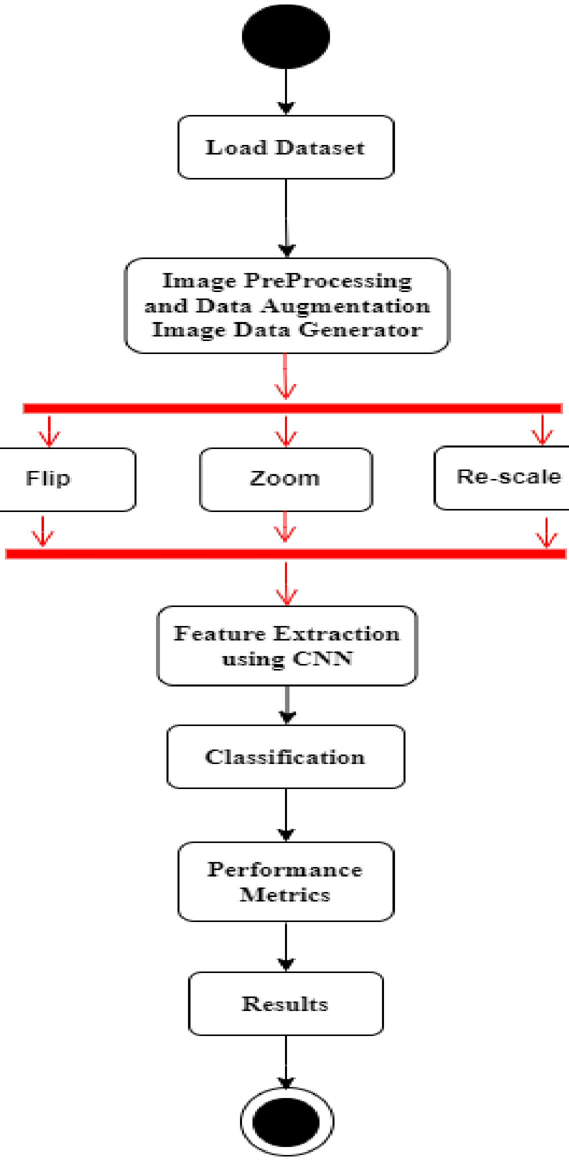


Figure 4.5: Activity Diagram for Over All System

SYSTEM IMPLEMENTATION

5. SYSTEM IMPLEMENTATION

5.1 About System Implementation

Implementation is the stage where the theoretical design is turned into a working system. The most crucial stage in achieving a new successful system and in giving confidence is implementing the system. It involves careful planning, investigation of the current system and its constraints on implementation, design of methods to achieve the change over and an evaluation of change over methods a part from planning. Two major tasks of preparing the implementation are education and training of the users and testing of the system. The more complex the system being implemented, the more involved will be the system analysis and design effort required just for implementation. The implementation phase comprises of several activities. The required hardware and software acquisition is carried out. The system may require some software to be developed. For this Programs are written and tested. The user then changes over to his new fully tested system and the old system is discontinued.

5.2 Module Description

A. Pre-Processing and Data augmentation

Preparing data for main processing or for further analysis through preliminary processing is known as data pre-processing. It is a technique for converting unclean data into clean data sets. The term refers to the modifications made to our data before we feed it to the algorithm. It may also be used to represent any first or preliminary processing stage where several steps are required to prepare data. The idea of transforming unclean data into data cleansing. Before the technique is applied, the collection is pre-processed to check for noisy data, missing values, and other anomalies. the procedure for structuring unstructured data such that it may be interpreted. It is also an important phase in data mining because to the difficulty to handle raw data. Data mining and machine learning should not be used without first assessing the quality of the data. Information from an open-source eye illness database was utilised to find and gather the datasets for the project. There were fundus photos that showed glaucoma in three datasets (Drishti, Rim-One, and Acrima datasets).

Data augmentation is a feature offered by the Keras deep learning neural network library. By using the ImageDataGenerator class, we enhanced our data. We used zooming, sheer, channel shift, rotation, width shift, and height shift, among other techniques. More picture data were produced after the augmentation technique was applied.

Image Data Generator

The Keras ImageDataGenerator receives the original data inputs and alters them at random before producing a result that solely contains the newly transformed data. The information is missing. In order to broaden the model's applicability, additional data is added using the Keras ImageDataGenerator module. Data augmentation uses an image data generator to conduct random operations on data, including translations, rotations, scale modifications, and vertical flips. In the field of real-time data augmentation, Keras ImageDataGenerator is used to create batches that contain data from tensor images. By giving the appropriate parameters and the necessary input to the ImageDataGenerator resize class, we can use it.

The picture data generator class has a number of methods, including:

flow_from_directory – This function generates batches of augmented data based on a directory path.

Apply to transform - used to apply picture transformations to the values given as arguments and gets the parameters to transform variables and x.

Fit - takes as inputs x, a seed with a default value of none, rounds (the number of rounds to be performed), and a boolean value for enhancing. The data synthesizer is adapted using this method to the supplied data sample.

B. **Feature Extraction**

With the use of feature extraction for image data, the visually appealing elements of a picture are presented as a small feature vector. This was previously accomplished using specialised, feature extraction, feature identification, and feature matching algorithms. The flexibility of deep learning to accept raw image data as input and skip the feature extraction procedure makes it a popular tool for image and video analysis at the moment. Any computer vision program that uses picture registration, object recognition, or classification must accurately reflect the image features, regardless of the approach. This representation may be implicit in the early layers of a deep network or explicit.

C. **Classification**

A form of supervised machine learning method, classification involves grouping a given set of input data into classes using one or more factors. In order to categorise fresh observations into groups or classes, classification prediction modelling uses data or observations as training input.

CNN

The convolution neural network is referred to as a machine learning subnet. It is one of many models of artificial neural networks that are used for various tasks and sets of data. For tasks like image identification and pixel data processing, deep learning algorithms use a specific kind of network design called a CNN. In deep learning, CNN is preferred over all other forms of neural networks for detecting and classifying objects. As a result, they are ideal for computer vision (CV) activities and for applications like face recognition and self-driving auto systems where accurate object detection is crucial. A particular type of neural network called a CNN can be used to find important information that may be present in both time-series data and image data. For image-based applications like object classification, pattern recognition, and image identification, this makes it very helpful. A CNN uses linear algebraic concepts like matrix multiplication to find patterns in an image. CNN may also categorise audio and signal data.

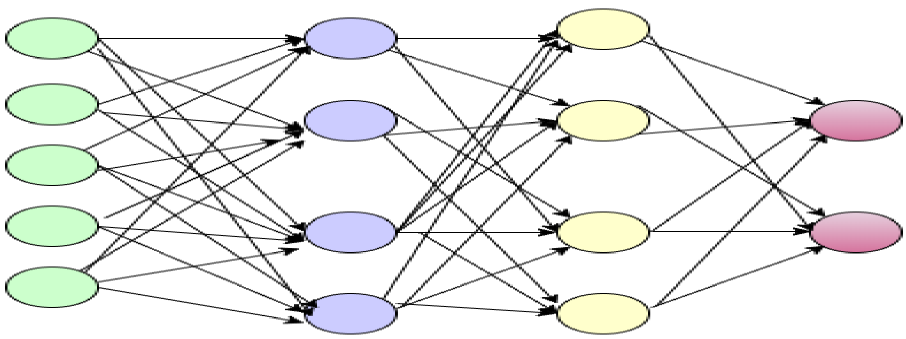


Figure 5.1: Neural Networks

CNNs have architecture resembling those of the interconnections in the human brain. The neurons in CNNs are organized differently, yet they are similar to the billions of neurons seen in the human brain. The frontal lobe of the brain, which processes visual stimuli, is actually modeled by the way CNN's neurons are organized. By overcoming the problem with standard neural networks' partial image processing that requires us to give them low-resolution images by using this design, the full visual field is protected. CNN performs better than earlier networks when given inputs that contain both speech and/or visual signals.

Convolutional layer

The convolutional layer, the life of a CNN, is where the core of processing happens. Among other things, it requires a filter, input data, and a feature map. A feature detector, sometimes referred to as kernels or filters, will examine the image's receptive fields to determine whether the attribute is present. This technique is referred to as convolution. A section of the image is represented by a 2-D array of weights acting as the feature detector.

Max pooling layer:

In the convolution process known as "Max Pooling," the Kernel extracts the most value from the region it convolves. The Convolutional Neural Network is simply informed by max pooling that we will only transmit that information ahead if it is the input with the highest possible amplitude.

Dense layer

A neural network's thick layer, which has many connections, is its typical layer. It's the most prevalent and often used layer. Before returning the outcome, the dense layer applies the following operation to the input.

output = activation (dot (input, kernel) + bias)

Flattening

The technique of flattening involves transforming data into a 1-dimensional vector for input into the layer underneath. To create a single, comprehensive feature vector, the convolutional layer's output is flattened. An image is processed more effectively by a neural network in particular architectures, such as CNN, if it is in 1D format rather than 2D.

Advantages of CNN

- The ability of CNNs to automatically extract features from data is their primary advantage over other deep learning algorithms.
- Convolutional neural networks perform at the cutting edge when it comes to unstructured data with intricate spatial patterns, including image data.
- Image data performance is at the cutting edge.
- The capacity to function with incomplete knowledge.
- There is no need to pre-process or feature the data.

The proposed CNN'S - convolutional layer uses a filter of 32 size and a kernel of 3x3. This kernel is helpful so that image of size 256x256 can be processed faster. 2 convolutional layers are used in the current model. It performs a dot product of the matrix of learning parameters or kernel and the given image. The convolutional layer is followed by a max pooling layer. ReLU activation function is used in convolutional and dense layer. Batch normalization is performed.

The dropout layer used is at ignore rate of 25%. The last output layer uses the softmax activation function. The softmax function is a good choice as it returns the chances of getting each class and it shows the higher value to the target class.

5.3 Source Code

```
import matplotlib.pyplot as plt

import numpy as np

import os

import shutil

from tensorflow import keras

import seaborn as sns

import random

from keras.models import load_model

from keras.preprocessing import image

from tensorflow.keras.preprocessing.image import load_img, img_to_array

base_dir = ’/content/drive/MyDrive/references/datasets/combine’

base_dir = pathlib.Path(base_dir)

glaucoma = [fn for fn in os.listdir(f’/content/drive/MyDrive/references/datasets/combine/glau
coma/’)]

normal = [fn for fn in os.listdir(f’/content/drive/MyDrive/references/datasets/combine/normal
’)]

data=[glaucoma,normal]

dataset_classes =[‘glaucoma’,’normal’]

image_count = len(list(base_dir.glob(‘*/*.jpg’)))+len(list(base_dir.glob(‘*/*.png’)))

print(f’Total images: {image_count}’)

print(f’Total number of classes: {len(dataset_classes)}’)

count = 0

data_count = []
```

```
for x in dataset_classes:
  print(f'Total {x} images: {len(data[count])}')
  data_count.append(len(data[count]))
  count += 1
sns.set_style('darkgrid')
sns.barplot(x=dataset_classes, y=data_count)
plt.show()
!pip install split-folders
import splitfolders #to split dataset
import pathlib
base_ds = '/content/drive/MyDrive/references/datasets/combine'
base_ds = pathlib.Path(base_ds)
img_height=256
img_width=256
batch_size=32
splitfolders.ratio(base_ds, output='images', seed=1321, ratio=(.8,.1,.1), group_prefix=None)
from keras.preprocessing.image import ImageDataGenerator
datagen = ImageDataGenerator(rescale=1./255,
shear_range = 0.15,
zoom_range = 0.15,
horizontal_flip = True)
train_ds = datagen.flow_from_directory(
    'images/train',
    target_size = (img_height, img_width),
    batch_size = batch_size,
    class_mode='categorical',
```

```
    shuffle=False)
val_ds = datagen.flow_from_directory('images/val',
    target_size = (img_height, img_width),
    batch_size = batch_size,
    class_mode='categorical',
    shuffle=False)
test_ds = datagen.flow_from_directory('images/test',
    target_size = (img_height, img_width),
    batch_size = batch_size,
    class_mode='categorical',
    shuffle=False)
from keras.models import Sequential
from keras.layers import Conv2D
from keras.layers import MaxPooling2D
from keras.layers import Flatten
from keras.layers import Dense,Dropout
from keras.layers import BatchNormalization
# Initialising the CNN
classifier = Sequential()
# Step 1 - Adding Convolution layer
classifier.add(Conv2D(32, (3, 3), input_shape = (256,256, 3), activation = 'relu'))
# Step 2 - Adding MaxPooling layers
classifier.add(MaxPooling2D(pool_size = (2, 2)))
# Adding a second convolutional layer
classifier.add(Conv2D(32, (3, 3), activation = 'relu'))
classifier.add(MaxPooling2D(pool_size = (2, 2)))
```

```
# Step 3 - Flattening
classifier.add(Flatten())
# Step 4 - Full connection
classifier.add(Dense(units = 512, activation = ’relu’))
classifier.add(BatchNormalization()),
classifier.add(Dense(256,activation=‘relu’)),
classifier.add(Dropout(0.25)),
classifier.add(Dense(units = 2, activation = ’softmax’))
# Compiling the CNN
classifier.compile(optimizer = ’adam’, loss = ’categorical_crossentropy’, metrics = [‘accuracy
’])
model_info=classifier.fit(train_ds,
steps_per_epoch = int(round(1032/32)),
epochs = 150,
validation_data = val_ds,
validation_steps = int(round(128/32)))
score=model.evaluate(test_ds)
print(“Loss:”,score[0],”Accuracy:”,score[1])
from sklearn.metrics import classification_report,confusion_matrix
import seaborn as sb
pred= np.round(model.predict(test_ds, verbose=1))
test_labels=test_ds.labels
test_pred_labels=[]
for i in range(len(pred)):
  test_pred_labels.append(np.argmax(pred[i]))
conf_matrix= confusion_matrix(test_pred_labels,test_labels)
```

```
print (conf_matrix)
sb.heatmap(conf_matrix,cmap=‘Purples’, annot=True,xticklabels=[‘glaucoma’,’normal’],
yticklabels=[‘glaucoma’,’normal’],linewidths=1, linecolor=‘green’).plot()
plt.show()
```

5.4 Results

There are several different performance metrics that can be used to evaluate a model's performance. Performance is evaluated using the Specificity, Confusion Matrix, Accuracy, Recall, Precision, and F1 score. The confusion matrix provides a detailed explanation of values such as False Negatives, False Positives, True Positives, and True Negatives.

With the use of all the training data, a neural network is trained for one cycle every epoch. In a given period, we only ever use a given piece of information. A pass is when two passes are combined, one forward and one backward. One or even more batches in each epoch are used to train the neural network using a portion of the dataset. We refer to the process of going through one batch of training samples as an "iteration." In order to train the model effectively, there are 150 epochs overall distributed across 32 batches.

Evaluation Metrics

For Evaluation of the model, we are using metrics like accuracy, F1score, recall, precision. A machine will always produce an outcome and we have no idea it is the correct one or not unless someone hints that out in our model. For calculating these metrics, we can use the confusion matrix which consist of four characteristics.

Accuracy

The model's accuracy is a measure of its performance across all classes. When each course is equally important, it helps. In order to calculate it, divide the total of forecasts by the total of guesses. Be aware that the accuracy could be misleading. When the data are unbalanced is one instance. Accuracy is simply the percentage of correctly classified items when it comes to multiclass classification.

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + False\ Positive + True\ Negative + False\ Negative} \times 100$$

Recall

The recall is calculated as the fraction of Positive observations that were correctly classified as Positive in comparison to all Positive samples. When recall is higher, there are more positive samples discovered. Recall is not affected by the quantity of incorrect sample classifications. Furthermore, if the model correctly classifies all positive data as positive, Recall equals 1.

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

Precision

The proportion of correctly classified Positive cases to all Positive samples is used to determine accuracy (either incorrectly or correctly). Precision describes how precisely the model labels a random pick as positive. Whether the model makes many inaccurate Positive classifications or only a few accurate Positive classifications, the denominator rises and the precision falls.. Yet, when the model makes numerous accurate Positive classifications in the first scenario, the precision is high (maximize True Positive). The model makes less inaccurate Positive classifications in the second scenario (minimize False Positive). The precision is useful in determining how accurate the model is when it declares that a instance is true.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Sensitivity:

Sensitivity is used to evaluate model performance because it allows us to see how many positive instances the model was able to correctly identify. A model with high sensitivity will have few false negatives, which means that it is missing a few of the positive instances.

$$Sensitivity = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

Specificity:

When sensitivity is used to evaluate model performance, it is often compared to specificity. Specificity measures the proportion of true negatives that are correctly identified by the model.

$$Specificity = \frac{True\ Negative}{True\ Negative + False\ Positive}$$

F1-score

The harmonic mean of precision and recall is the F1 score. It functions as a statistical instrument for performance evaluation. An F-score can range from zero to 1.0, which represents flawless recall and accuracy, and from zero to zero when neither recall nor precision are present. The F1 score is a common performance metric for classification and is frequently chosen over, for example, accuracy when data is imbalanced, for instance when samples belonging to one class are detected in significantly more samples than samples belonging to the other cla**ss.**

$$F1\_score = 2X \frac{Precision\ x\ Recall}{Precision + Recall}$$

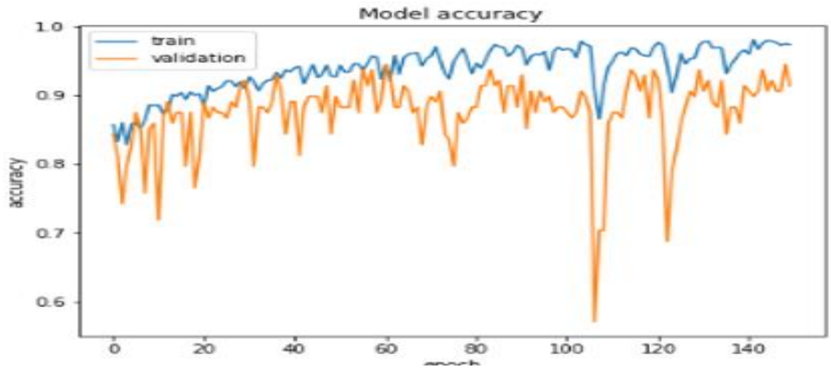


Figure 5.2: The proposed model's accuracy

From the figure, we can observe many troughs and depths in the plotted graph. Since we are having 150 epochs, the accuracy at each epoch is plotted in the graph and we can see that after 100 epochs there is a sudden drop in accuracy and when we increase the epochs there we can see a steady increase in the model's accuracy. This will give us a better insight into the model's performance.

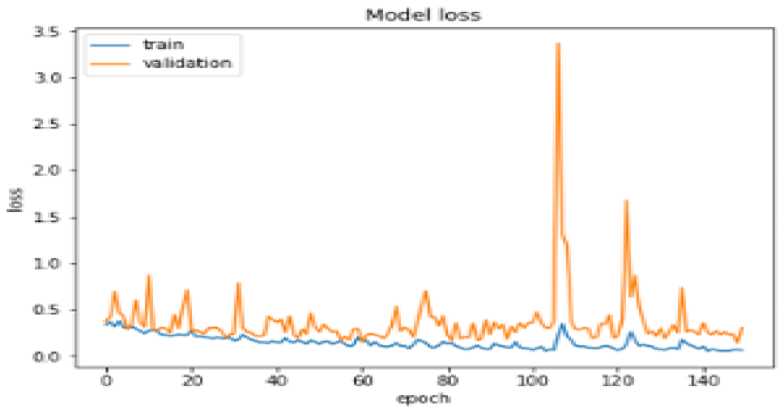


Figure 5.3: The model's loss at each epoch

The figure depicts the different values of loss at each epoch. As we have discussed earlier, there is a sudden drop in the accuracy as the loss function value is varied. This graph of loss function helps us to predict the issues that occur with learning. These issues can lead to underfitting or an overfitted model.

Table 5.1: Classification report

	Precision	**Recall**	**F1-Score**	**Support**
Glaucoma	0.984615	0.984615	0.984615	65
Normal	0.984848	0.984848	0.984848	66
Accuracy	**0.984733**	**0.984733**	**0.984733**	**0.984733**
Macro avg	0.984732	0.984732	0.984732	131
Weighted avg	0.984733	0.984733	0.984733	131

The classification report here instigates the fact that this model which achieved an accuracy of 98.47% with an integrated dataset is to be noted and this is the first ever model to achieve this. All the existing studies have achieved the results by working on small datasets whereas the proposed model has a large dataset. The CNN here can process even on low quality images. The dataset created is a balanced dataset with proportionate number of glaucoma and normal images.

Table 5.2: Comparison of Proposed method with Existing methods

Model	**Accuracy**
Proposed model	98.47
ResNet-50 [24]	94.5
EC-Net [24]	97.2
Efficient-net CNNs model [9]	88
CNN model [3]	94
Inception V3 [14]	90.4
ODG-Net [1]	95.75
KNN [10]	95.91
googleNet [18]	83
DENet [35]	91.83

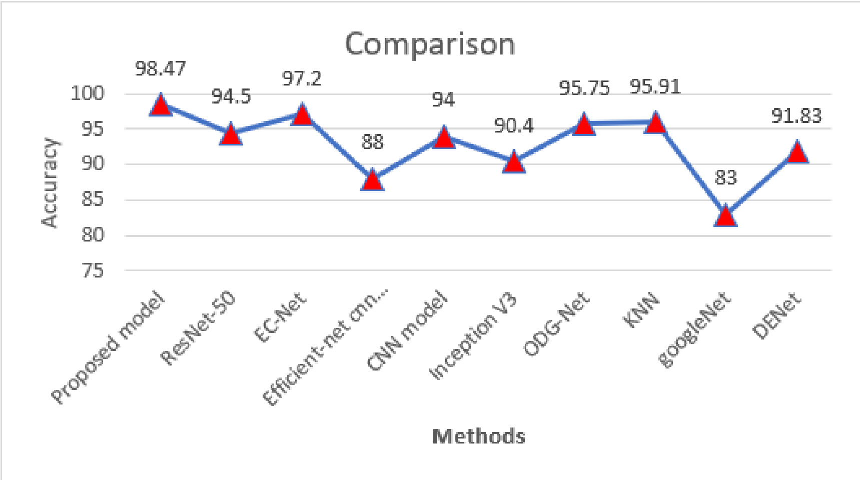


Figure 5.4: Comparative study of Performance measure.

TESTING

6. TESTING

6.1 About Testing

Software testing is a critical element of software quality assurance and represents the ultimate reviews of specification, design and coding. Testing represents interesting anomaly for the software. During earlier definition and development phases, it was attempted to build software from an abstract concept to tangible implementation. The testing phase involves the testing of the developed system using various test data. Preparation of the test data plays a vital role in the system testing. After preparing the test data the system under study was tested using those test data. While testing the system, errors were found and corrected by using the following testing steps and corrections are also noted for future use. Thus, a series of testing is performed for the proposed system, before the system was ready for the implementation. Testing is the process of detecting errors. Testing performs a very critical role for quality assurance and for ensuring the reliability of software. The results of testing are used later on during maintenance also The aim of testing is often to demonstrate that a program works by showing that it has no errors. The basic purpose of testing phase is to detect the errors that may be present in the program. Hence one should not start testing with the intent of showing that a program works, but the intent should be to show that a program doesn't work.

Testing Objectives

- Testing is a process of executing a program with the intent of finding an error.
- A successful test is one that uncovers an as yet undiscovered error.
- A good test case is one that has a high probability of finding error, if it exists.
- The tests are inadequate to detect possibly present errors

6.2 Testing Methods (levels of Testing)

In order to uncover the errors present in different phases we have the concept of levels of testing. The levels of software testing involve the different methodologies, which can be used while we are performing the software testing. In software testing, we have four different levels of testing, which are as discussed below:

1. Unit Testing

2. Integration Testing

3. System Testing

4. Acceptance Testing

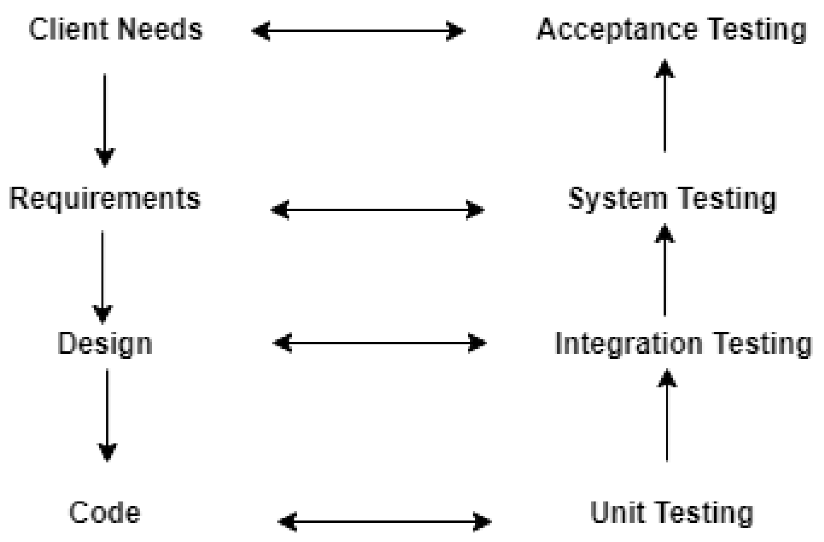


Figure 6.1: Levels of testing

6.3 Validation and Verification

Verification is the process of checking that a software achieves its goal without any bugs. It is the process to ensure whether the product that is developed is right or not. It verifies whether the developed product fulfills the requirements that we have. Verification is static testing. Verification testing is involved in the requirement gathering phase, product planning, and product development. Verification testing ensures the process is going correctly. Requirements are correct, and development is going in accordance. Verification helps to find the bugs and issues at the earlier stage of development. Verification testing is cheaper. The quality assurance team does verification testing.

Validation is the process of checking whether the software product is up to the mark or in other words product has high level requirements. It is the process of checking the validation of product that is it checks what we are developing is the right product. it is validation of actual and expected product. Validation is the dynamic testing. Validation testing is done in the testing phase of SDLC. Validation is also done at the maintenance stage. Validation testing is done to find the correct way of a process. And also ensuring that the process chosen is the best. Validation is a costlier affair. If process A is used, after that, process B is found to be better. The validation testing took the duration of finding the better approach. The product team does validation testing.

6.4 Test Cases

Unit testing

Unit testing focuses verification effort on the smallest unit of software i.e. the module. Using the detailed design and the process specifications testing is done to uncover errors within the module. All modules must be successful in the unit test before integration.

Table 6.1: Unit Testing

TEST CASE ID	TEST CASE OBJECTIVE	TEST STEPS	EXPECTED RESULT	ACTUAL RESULT	STATUS
1	Loading the image file with target shape	using "tensorflow.keras.preprocessing.image.load_img" we read image	Image loaded in target shape	Image loaded in target shape	PASS

Integration testing:

After the unit testing, we have to perform integration testing. The goal here is to see if modules can be integrated properly, the emphasis being on testing interfaces between modules. This testing activity can be considered as testing the design and testing module interactions. In this project integrating all the modules forms the main system. When integrating all the modules we have checked whether the integration effects working of any of the services by giving different combinations of inputs with which the two services run perfectly before Integration. Integration testing is a systematic technique for constructing the program structure, while at the same time conducting tests to uncover errors associated with the interface. All modules are combined in the testing step. Then the entire program is tested as a whole.

Table 6.2: Integrating Testing

TEST CASE ID	TEST CASE OBJECTIVE	TEST STEPS	EXPECTED RESULT	ACTUAL RESULT	STATUS
1	Verify that image is rescaled or not	Using keras.preprocessing.image.ImageDataGenerator images are rescaled	Normalized Images are generated	Normalized Images are generated	PASS

2	Verify that image is horizontally flipped or not	Using keras.preprocessing.image.ImageDataGenerator images are horizontally flipped	Images are generated	Images are generated	PASS
3	Verify that image is sheared at a specified angle or not	Using keras.preprocessing.image.ImageDataGenerator images are sheared	Images are generated	Images are generated	PASS
4	Verify that image is applied using zooming transformation with a specified scale factor	Using keras.preprocessing.image.ImageDataGenerator images are magnified	Images are generated	Images are generated	PASS

Acceptance testing:

Acceptance Test is performed with realistic data of the client to demonstrate that the software is working satisfactorily. Testing here is focused on external behavior of the system; the internal logic of program is not emphasized. Test cases should be selected so that the largest number of attributes of an equivalence class is exercised at once. The testing phase is an important part of software development. It is the process of finding errors and missing operations and also a complete verification to determine whether the objectives are met and the user requirements are satisfied.

Table 6.3: Acceptance Testing

TEST CASE ID	TEST CASE OBJECTIVE	TEST STEPS	EXPECTED RESULT	ACTUAL RESULT	STATUS
1	Verify that image is of type jpg,jpeg,png only	JPEG, JPG, PNG	Images are read	The result is as expected	PASS
		Other formats	Error message	The result is as expected	PASS

2	Verify that image is glaucomatous or healthy	Glaucoma Eye Image	Return output as Glaucomatous Eye	The result is as expected	PASS
		Healthy Eye Image	Return output as Healthy Eye	The result is as expected	PASS

CONCLUSION AND FUTURE WORK

7. CONCLUSION AND FUTURE SCOPE

Permanent blindness is brought on by the complication of glaucoma, which is connected to optic nerve damage. The use of glaucoma detection will expand thanks to this method of medical image processing technology. The computer-generated results from this work will help to raise the bar for clinical judgment when it comes to glaucoma identification. Because there are more normal fundus photos in the dataset, this algorithm can detect the glaucomatous images correctly. The proposed methodology uses an image data generator for data augmentation. The original images have increased due to augmentation and a large dataset is prepared. Later the augmented images have been sent for feature selection using CNN. The images are classified using binary classification as it has two outcomes. The proposed system achieved an accuracy of 98. 47% which is noteworthy in this field.

In our upcoming research, we intend to implement convolutional neural networks in the identification of numerous eye illnesses, including cataracts, retinal detachment, and diabetic retinopathy.

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8. REFERENCES

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APPENDIX

APPENDIX

Python Introduction

Python is a general-purpose high level programming language that is being increasingly used in data science and in designing machine learning algorithms.

Python is a high-level, interpreted, interactive and object-oriented scripting language. Python is designed to be highly readable. It uses English keywords frequently whereas other languages use punctuation, and it has fewer syntactical constructions than other languages.

- **Python is Interpreted** − Python is processed at runtime by the interpreter. You do not need to compile your program before executing it. This is similar to PERL and PHP.
- **Python is Interactive** − You can actually sit at a Python prompt and interact with the interpreter directly to write your programs.
- **Python is Object-Oriented** − Python supports Object-Oriented style or technique of programming that encapsulates code within objects.
- **Python is a Beginner's Language** − Python is a great language for the beginner level programmers and supports the development of a wide range of applications from simple text processing to WWW browsers to games.

History of Python

Python was developed by Guido van Rossum in the late eighties and early nineties at the National Research Institute for Mathematics and Computer Science in the Netherlands.

Python is derived from many other languages, including ABC, Modula-3, C, C++, Algol-68, SmallTalk, and Unix shell and other scripting languages.

Python is copyrighted. Like Perl, Python source code is now available under the GNU General Public License (GPL).

Python is now maintained by a core development team at the institute, although Guido van Rossum still holds a vital role in directing its progress.

Python Features

Python's features include –

- **Easy-to-learn** − Python has few keywords, simple structure, and a clearly defined syntax. This allows the student to pick up the language quickly.
- **Easy-to-read** − Python code is more clearly defined and visible to the eyes.
- **Easy-to-maintain** − Python's source code is fairly easy-to-maintain.
- **A broad standard library** − Python's bulk of the library is very portable and cross-platform compatible on UNIX, Windows, and Macintosh.
- **Interactive Mode** − Python has support for an interactive mode which allows interactive testing and debugging of snippets of code.
- **Portable** − Python can run on a wide variety of hardware platforms and has the same interface on all platforms.
- **Extendable** − You can add low-level modules to the Python interpreter. These modules enable programmers to add to or customize their tools to be more efficient.
- **Databases** − Python provides interfaces to all major commercial databases.
- **GUI Programming** − Python supports GUI applications that can be created and ported to many system calls, libraries and windows systems, such as Windows MFC, Macintosh, and the X Window system of Unix.
- **Scalable** − Python provides a better structure and support for large programs than shell scripting.

Apart from the above-mentioned features, Python has a big list of good features, few are listed below –

- It supports functional and structured programming methods as well as OOP.
- It can be used as a scripting language or can be compiled to byte-code for building large applications.
- It provides very high-level dynamic data types and supports dynamic type checking.
- It supports automatic garbage collection.
- It can be easily integrated with C, C++, COM, ActiveX, CORBA, and Java.

Python is a popular platform used for research and development of production systems. It is a vast language with number of modules, packages and libraries that provides multiple ways of achieving a task.

Python and its libraries like NumPy, SimpleITK, Tensorflow, Keras, Pandas are used in data science and data analysis. They are also extensively used for creating scalable machine learning algorithms. Python implements popular machine learning techniques such as Classification, Regression, Recommendation, and Clustering.

Python offers ready-made framework for performing data mining tasks on large volumes of data effectively in lesser time. It includes several implementations achieved through algorithms such as linear regression, logistic regression, Naïve Bayes, k-means, K nearest neighbor, and Random Forest.

Python has libraries that enable developers to use optimized algorithms. It implements popular machine learning techniques such as recommendation, classification, and clustering. Therefore, it is necessary to have a brief introduction to machine learning before we move further.

What is Machine Learning?

Data science, machine learning and artificial intelligence are some of the top trending topics in the tech world today. Data mining and Bayesian analysis are trending and this is adding the demand for machine learning. This tutorial is your entry into the world of machine learning.

Machine learning is a discipline that deals with programming the systems so as to make them automatically learn and improve with experience. Here, learning implies recognizing and understanding the input data and taking informed decisions based on the supplied data. It is very difficult to consider all the decisions based on all possible inputs. To solve this problem, algorithms are developed that build knowledge from a specific data and past experience by applying the principles of statistical science, probability, logic, mathematical optimization, reinforcement learning, and control theory.

Deep Learning

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.

Applications of Machine Learning Algorithms

The developed machine learning algorithms are used in various applications such as

- Vision processing
- Language processing
- Forecasting things like stock market trends, weather
- Pattern recognition
- Games
- Data mining
- Expert systems
- Robotics
- Steps Involved in Machine Learning
- A machine learning project involves the following steps –
- Defining a Problem
- Preparing Data
- Evaluating Algorithms
- Improving Results
- Presenting Results

The best way to get started using Python for machine learning is to work through a project end-to-end and cover the key steps like loading data, summarizing data, evaluating algorithms and making some predictions. This gives you a replicable method that can be used dataset after dataset. You can also add further data and improve the results.

Libraries and Packages and Datasets

To understand machine learning, you need to have basic knowledge of Python programming. In addition, there are a number of libraries and packages generally used in performing various machine learning tasks as listed below –

NumPy: It is a general-purpose array-processing package. It provides a high-performance multidimensional array object, and tools for working with these arrays.

It is the fundamental package for scientific computing with Python. It contains various features including these important ones:

- A powerful N-dimensional array object
- Sophisticated (broadcasting) functions
- Tools for integrating C/C++ and Fortran code
- Useful linear algebra, Fourier transform, and random number capabilities

Pandas: It is a high-level data manipulation tool developed by Wes McKinney. It is built on the Numpy package and its key data structure is called the Data Frame. Data Frames allow you to store and manipulate tabular data in rows of observations and columns of variables.

Tensorflow: TensorFlow is an end-to-end open source platform for machine learning. It has a comprehensive, flexible ecosystem of tools, libraries and community resources that lets researchers push the state-of-the-art in ML and developers easily build and deploy ML powered applications.

Keras: It is an open-source neural-network library written in Python. It is capable of running on top of TensorFlow, Microsoft Cognitive Toolkit, R, Theano, or PlaidML. Designed to enable fast experimentation with deep neural networks, it focuses on being userfriendly, modular, and extensible.

Simple ITK: It provides an abstraction layer to ITK that enables developers and users to access the powerful features of the Insight Toolkit in an easy-to-use manner for biomedical image analysis.

Datasets

A data set (or dataset) is a collection of data. In the case of tabular data, a data set corresponds to one or more database tables, where every column of a table represents a particular variable, and each row corresponds to a given record of the data set in question. The data set lists values for each of the variables, such as for example height and weight of an object, for each member of the data set. Data sets can also consist of a collection of documents or files.

- **DRISTHI**

The dataset comprises of 101 retinal fundus images with 31 normal images and 70 glaucomatous images acquired using a retinal fundus camera. The ground truth for comparison of implemented approaches comprises of the 'normal/abnormal' labels and soft segmented maps of 'disc/cup' generated by the researchers of the IIIT Hyderabad in alliance with Aravind eye hospital in Madurai, India. It also includes a .txt file for each retinal image comprising of CDR values, which is a significant diagnostic parameter for glaucoma. Further, the images in the data repository are gathered from people of varying age groups visiting the hospital, with images acquired under varying brightness and contrast. Link to dataset: (https://cvit.iiit.ac.in/projects/mip/drishti-gs/mip-dataset2/Home.php)

- **RIMONE**

The RIM-ONE DL image dataset consists of 313 retinographies from normal subjects and 172 retinographies from patients with glaucoma. These images were captured in three Spanish hospitals: Hospital Universitario de Canarias (HUC), in Tenerife, Hospital Universitario Miguel Servet (HUMS), in Zaragoza, and Hospital Clínico Universitario San Carlos (HCSC), in Madrid.

This dataset has been divided into training and test sets, with two variants:

➢ Partitioned randomly: the training and test sets are built randomly from all the images of the dataset.

➢ Partitioned by hospital: the images taken in the HUC are used for the training set, while the images taken in the HUMS and HCSC are used for testing.

- **ACRIMA**

ACRIMA database is composed by 705 fundus images (396 glaucomatous and 309 normal images). They were collected at the FISABIO Oftalmología Médica in Valencia, Spain, from glaucomatous and normal patients with their previous consent and in accordance with the ethical standards laid down in the 1964 Declaration of Helsinki. All images from ACRIMA database were annotated by glaucoma experts with several years of experience. They were cropped around the optic disc and renamed.