Eye Disease Detection Portal

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ABSTRACT

Eye diseases and cancer, affecting millions of people in the developing world, can lead to vision loss. Tomography, a type of X-ray technique, is used for their detection, but symptoms like pain, blurriness, and redness may go unnoticed. Limited access to expertise in metropolitan areas poses a challenge for accurate diagnosis, despite the availability of scanning centers in many towns. By utilizing Deep Learning techniques, we have revolutionized the detection of eye diseases and cancer. This project involves extensive datasets obtained from previously scanned tomography scans, which are subjected to preprocessing steps to ensure optimal quality. The trained models learn from these datasets, enabling them to accurately classify eye conditions. To facilitate ease of use, we have developed an intuitive interface that allows ophthalmologists to input eye images from scans. Leveraging the power of Deep Learning algorithms, the system swiftly analyzes the images and generates comprehensive reports indicating the presence of various eye diseases and cancer. This approach addresses the limitations of traditional diagnostic methods, as it significantly reduces the time and effort required for disease identification. By incorporating advanced Deep Learning techniques, our system achieves the highest levels of accuracy in detecting and diagnosing eye diseases, ensuring prompt and effective treatment for patients. Overall, our project showcases the potential of Deep Learning in revolutionizing the detection and diagnosis of eye diseases and cancer, ensuring that patients receive prompt and accurate treatment regardless of their geographical location.

Literature Survey

The authors of this paper took an approach to detect the brain tumor using the DeepLearning. Brain Tumor is currently considered as the severe disease and can even be fatal if it is not treatedin time. In this paper, the authors have solved the problem of detecting Brain Tumor by considering CNN algorithm from the Deep Learning domain. Their approach was, They consideredthe MRI images of the brain scan as the dataset, pre-processed in a way that reducethenoise in thescan and thereby making the images suitable for more further steps. Their proposed system whichis trained using these MRI images, classifies new input image as tumorous or normal based on features extracted during the training. The authors have also used the conceptof Back Propagationwhile training the data in order to minimize the errors andthereby generatingmore accurate results.Another concept which they have used in this paper is Autoencoders, which are used to remove irrelevant features from the generated image. Further tumor image issegmented by using unsupervised learning model K-means algorithm.[1]

The authors of this paper took an approach to detect the Fovea in Retinal OCT imaging. Foveais a minor depression within the neurosensory retina , The point where the visual acuity is at itshighest level. In their study, the authors have introduced “PRE U-net” as a novel approachfor afully automated fovea centrali, thereby addressing the localization as a pixel wise regression task. In order to have a positive approach, the authors considered nearly around 5586 OCT volumes from 1541 eyes. In addition to this a 2D B scans are sampled from each images and concatenated with spatial location information to train the network. The test results included healthy people as well as patients with neovascular age-related macular degeneration (nAMD), diabetic macula edoema (DME), and macular edoema from retinal veinocclusion (RVO),whichincluded the three primary retinal illnesses that cause blindness. Theirresults show that thePREU-net outperforms state-of-the-art approaches and enhances the robustness of automatic localization, which is clinically useful. [2]

Neovascularization is a process that happens in a human body when a new blood cells grow. The prime location for happening of Neovascularization is in the eye which includes cornea andretina.The side effects of these newly grown vessels includes leak, blurry vision and most fatalvision loss. The authors of this paper has found a solution to detect the Neovascularisation.Retinopathy screening is a non- invasive approach of collecting retinal pictures, and detecting neovascularization from retinal images is important in the diagnosis and grading of diabetic retinopathy. An effective deep learning network for automated identification of neovascularization in colour fundus pictures is proposed in this article.

To identify neovascularization, the network uses the Feature Pyramid Network and Vovnet as itsbackbone.Color fundus pictures from practise are used to assess the network. According to the experimental results, the network requires less training and testing time than Mask R-CNNwhile maintaining a high accuracy of 98.6%. [3]

Reliable choroid measurements have grown in importance as a diagnostic tool for vision- threatening retinal disorders. However, automated and precise choroid segmentation remains an unsolved problem. This research introduces a revolutionary choroidsegmentationapproach based on a deep learning system that can segment images quickly andaccurately without humanparticipation. This is accomplished by integrating pixel clustering, picture enhancement, and deep learning techniques.

The superpixels were extracted using thesimple linear iterative clustering (SLIC) technique (patches).

Following that, the extracted patches areimproved by raising the contrast of the region of interest. The patches are then loaded into aconvolutional neural network, which labels the areas as choroid or non-choroid. The created algorithm's performance is evaluated using a dataset of 169 enhanced depth imaging optical coherence tomography pictures. The collected results proved the suggested segmentation method's efficacy in terms of accuracy (98.01%). [4]

OBJECTIVES

- The main objectives of the project are:
- To increase the accuracy of detection using any Deep Learning Algorithm
- To ensure that there will be faster processing throughout the process. Rightfrom input to output
- To identify the best Deep Learning Algorithm which satisfies our needs.
- To classify the previous image datasets to its highest contrast of detailing.
- To provide a web interface by abiding to golden rules of UI design.
- To implement the above-mentioned objectives using MERN stack
- To reduce the time of analysis and produce faster results.

SYSTEM DESIGN & IMPLEMENTATION

The Agile methodology emphasizes flexibility and collaboration throughout the softwaredevelopment process. It involves breaking down the project into smaller, manageable tasks or user stories, which can be developed and tested in iterations called sprints. This methodology promotes frequent communication and feedback between the development team and end-users,allowing for early detection of issues and timely adjustments. In the context of the project, theAgile methodology is adapted.

Requirements marks the first phase to gather and analyze the requirements for the multiple ocular disease diagnosis system, considering input from medical professionals and relevant stakeholders. User stories can be created to capture specific functionalities and features needed for accurate diagnosis. Design comes the second phase in which we develop a detailed design of the system, including the architecture, data models, and interfaces required for integrating tomography imaging and disease diagnosis algorithms. This phase can involve iterative design reviews to ensure the system's effectiveness and adaptability. Implementation is the third phase where coding is begun and development of the system based on the design specifications. Adopt best practices for coding standards and quality assurance, utilizing suitable programming languages and frameworks for efficient development. Verification is the fourth phase which perform rigorous testing and validation of the developed system to ensure it meets the desired functionality and accurately diagnoses multiple ocular diseases. This phase includes unit testing, integration testing, and user acceptance testing to verify that the system performs as intended. Maintenance is the final phase,

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once the system has been fully developed and deployed, it enters the maintenance phase. Regular updates, bug fixes, and enhancements can be addressed based on feedback from end-users and advancements in ocular disease diagnosis techniques.

Speech Recognition, Autonomous vehicles, Health care and many more. Specifically in healthcare the deep learning has proved its worth over the years like Medical Imaging, Disease diagnosis, Drug discovery , Electronic health record analysis and more. In this project eye medical image scans are considered to detect the type of disease present in the eye.

A total of six different disease or stages of eye are considered, which are Normal, Retinoblastoma, Myopia, Cataract, Hypertension and Glaucoma. The eye with no abnormalitiesis considered as a Normal Eye. The eye with affected retina and light sensitive tissue is considered as Retinoblastoma. Myopia is considered as the near sightedness which isdue to refractive error of the eye. Cataract is the clouding of the lens in the eye which leads to decreasein eye vision. Hypertension or Hypertensive eye is caused because of extensive hypertension. Glaucoma is caused because of increase intraocular pressure.

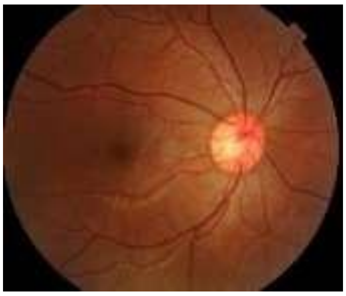

Fig 1.1: Normal Eye

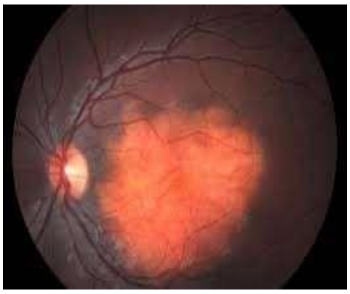

Fig 1.2: Retinoblastoma

Fig 1.3: Myopia

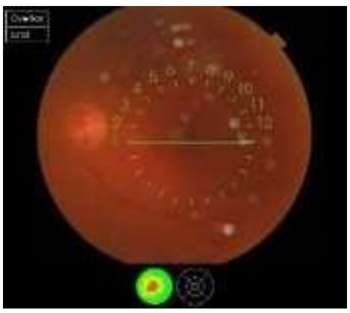

Fig 1.4: Cataract

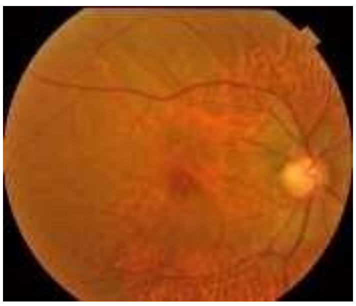

Fig 1.5: Glaucoma

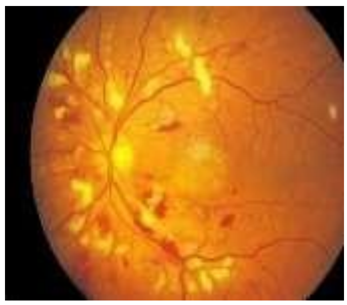

Fig 1.6: Hypertension

Ocular Coherence Tomography (OCT) is a non-invasive imaging technique that provides high-resolution cross-sectional images of the retina and other ocular structures. It utilizes low- coherence light to measure the echoes reflected back from different layers of the eye, creating detailed images. OCT allows for the visualization and evaluation of the retinal layers, optic nerve, and other structures, aiding in the diagnosis and management of various eye conditions, including glaucoma, macular degeneration, and diabetic retinopathy. It is widely used in ophthalmology due to its ability to provide valuable information about the structure andhealth of the eye in a quick and efficient manner.

Fig 1.7: Ocular Coherence Tomography Device

The Dataset for this project was obtained from Kaggle . The dataset itself had around Five Thousand pairs of images there by making Ten Thousand Images, out of which only Three Thousand pairs or Six thousand images belonged to our pre mentioned diseases hence thosewereconsidered for our project. The dataset had a csv file which consisted of image path and its respective diagnosis, A folder which consisted all of this images. These images were pre- processed as per the algorithm standards required our training.
Image pre processing involved with the process of gathering the images which belong to our pre mentioned disease type, filtering the image without compromising its features, fixing theimagesize to (224,224,3). Later the collected images of a particular disease was grouped as adata frame, from which the training , testing, validation images was derived.
This project utilizes OCT datasets sourced from Kaggle, comprising 10,000 eye images.Preprocessing involves resizing the images to 224x224 pixels with RGB channels. The VGG19deep learning algorithm is employed to train the model, recognizing patterns corresponding to eye diseases. Training, validation, and testing datasets are divided, preventing overfitting. GPU acceleration is used for faster computation. The user inputs an eye image, and the model processes it, providing a diagnosis or detecting eye diseases. Output is displayed, along with additional information. The project combines deep learning, preprocessing, and user interaction to accurately diagnose eye diseases from OCT datasets.

Convolutional Neural Networks (CNNs) are a class of deep learning models widely used for visual recognition tasks. They are designed to automatically learn hierarchical representations

from input images. A typical CNN architecture consists of multiple convolutional layers, whosemain role is to apply filters to extract local features. Pooling layers are succeeded byconvolutionlayers, whose primary responsibility is to downsample the feature maps to reducedimensionality.At the end of any CNN modes, A Fully connected layers at the end will help toclassify the extracted features into specific categories. CNNs leverage the spatial relationshipspresent in images, making them highly effective in tasks such as medical image processing. InCNN we have many architectures such as ResNet50, VGG19, LeNet5 and many more. ResNet50 and VGG19 is considered with more prominence given for VGG19 which is used forall disease detection.

ResNet50 architecture is a short for Residual Network, it consists of 50 layers. A ResNet50 hasan input layer which takes input image, 7 X 7 Convolution layers with 64 filters, Fully Connected layers for final output.ResNet50 uses another layer called Residual Blocks this is used to bypass a network by skipping connections. Due to which this provided us with lesser accuracy for this project.

VGG19 is a deep convolutional neural networks which has 19 layers, including convolutional layer, pooling layer, fully connected layers. Its simple yet effective design, utilizing 3x3 filtersand stacking layers, makes it a popular choice for image classification and transfer learning tasks. There will be skipping connections in VGG 19 as found in ResNet50 hence the accuracywill be higher, Which makes this to prefer VGG19 over ResNet50.

Considering the VGG 19 algorithm, Deep learning models was created for individual diseaseswhere average accuracy is around 85%. These models are later used for the prediction of real time data. A web based solution comprising these models and a user friendly user interface is provided to end users.

3.1.1 Agile Model

Agile methodology offers greater flexibility in project scope, enabling staged or iterative planning and continuous integration throughout the project's lifecycle. The main principle of agile project management is to maintain a flexible project scope, distinguishing it from traditional project management methods.

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Specifically relevant to the project, the agile methodology assigns relativelyhigher importance to the following aspects:

Interactions and individuals: Emphasis is placed on effective collaboration and communication among team members, stakeholders, and medical professionals involved in the project to ensure accurate diagnosis of multiple ocular diseases.

1. Project execution: Agilefocuses on deliveringproject outcomesthroughiterativedevelopment cycles, allowing for regular progress updates and adjustments based on evolving requirements and technological advancements in tomography imaging.
2. Collaboration with the customer: Close collaboration with end-users, such as doctors and clinicians, is vital to gather their inputs, validate the diagnostic accuracy, and incorporate their feedback throughout the development process.
3. Response to change: The agile methodology recognizes the dynamic nature of ocular disease diagnosis requirements and enables adaptability to evolving demands. It leverages early input on the technological aspects of tomography-based diagnostic deliverables to respond quickly and effectively to changes.

The agile methodology in this project ensures that the project scope remains flexible, avoiding the accumulation of requirementsandallowingforeffectivecommunicationwithinandoutsidetheprojectteam. By adopting an agile approach, the project can benefit from higher customer satisfaction, reduceddefects, and quicker development timelines. The iterative nature of the agile methodology facilitates ongoing improvements and adjustments, leading to accurate and efficient diagnosis of ocular diseases using tomography. The agile model, known for its effectiveness, simplicity, and reliability, is widely used in contrast to traditional models. Its application in this project allows for efficient completion of daily research tasks, enhancing the effectiveness of the team's work and promoting collaboration among team members. The agile model, in essence, represents a set ofdevelopmental procedures with a fundamental guiding principle of eliminating anything futile or unnecessary, ultimately streamlining the project's execution for successful multiple ocular disease diagnosis using tomography.

Figure 3.1: Agile Methodology

3.2 Architecture

The System Architecture consist of two servers, One for NodeJS and other is for Flask. The combination of these two servers will give us powerful and smooth user experience. A NoSQLdatabase will store the real word data and API's are used for report generation and mail sendingprocess. A local repository is used for storing deep learning models which is used for predictionby the flask server.

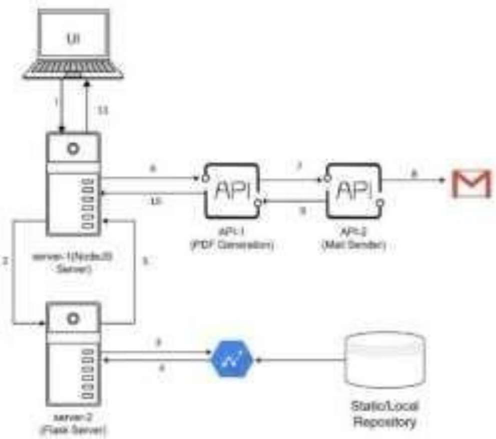

Figure 3.2: System Architecture

3.3 Functional Requirements

Deep learning models are utilised to diagnose multiple ocular eye diseases. Several deep learning algorithms have been carefully used to implement these models. Algorithms like Resnet50 and VGG19 are used.

3.3.1 Resnet50

The ResNet-50 algorithm, short for Residual Network-50, is a convolutional neuralnetwork architecture brought into light by Microsoft Research in 2015. It is part of the ResNet family ofmodels, which aimed to address the problem of vanishing gradients in deepneural networks by introducing residual connections.

The ResNet-50 architecture consists of 50 layers, that pocesses convolutional, pooling and fully connected layers respectively and shortcut connections. The key innovation of ResNet is the use of residual connections, or skip connections, which allow information to flow directly through the network without being heavily affected by multiple layers of transformations.

These residual connections are implemented as element-wise additions between the output of alayer and the input to that layer. By bypassing some layers and allowing the network to learn residual mappings, ResNet enables the training of deep networks with better accuracy and easeof optimization. In ResNet-50 specifically, the network starts with a 7x7 convolutional layer with stride 2, followed by several stages, each containing multiple residual blocks. Each residual block has multiple convolutional layers that in turn has batch normalization and ReLU activation functions, along with a shortcut connection. The network terminates with global mean pooling and the fully connected layers for classification.

ResNet-50 has been widely used and achieved state-of-the-art results in various computer visiontasks, including image classification, object detection, and image segmentation. It has 50 layers,which strikes a balance between accuracy and computational efficiency. However, there are also deeper versions of ResNet, such as ResNet-101 and ResNet-152, which have more layers and may offer even higher performance at the cost of increased computational requirements.

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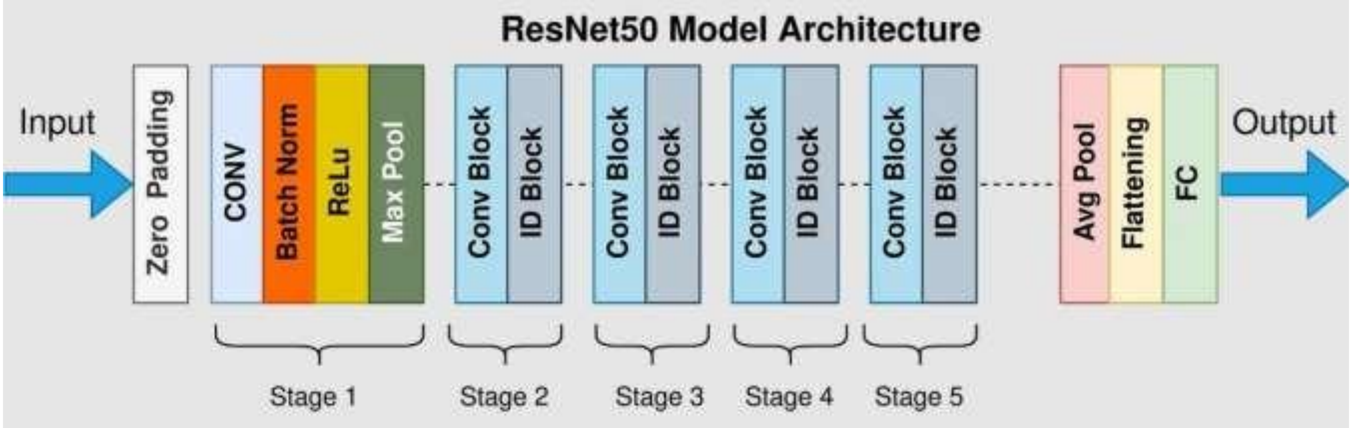

Figure 3.3: ResNet50 Architecture

How It Works?

The ResNet50 model used in the project works as follows. The objective is to build a model forclassifying eye diseases. The necessary libraries are imported, including pandas,numpy, os, random, cv2, matplotlib.pyplot, itertools, tqdm, math, and various libraries fromTensorFlow, Keras, and scikit-learn. Thecodemounts the Google Drive to access thedatasetand store the trained model. The data is loaded and preprocessed by reading a CSV file containing image details using pandas, discarding unnecessary columns, and keeping the relevant columns for analysis. The directory path of the images is stored in avariable, and the code retrieves the images and details of eye diseases from a separate CSV file. Data visualization is performed by displaying a few images of eye diseases from the dataset using matplotlib. Non-eye disease images are selected by filtering based on certainkeywords, and left and right eye images are combined and stored in a variable. Asubset of non-eyedisease images is randomly selected fortraining and testing. The modelis initialized by using the ResNet50 architecture, a pre-trained CNN, with weights pre- trained on the ImageNet dataset. Custom layers are added on top of the ResNet50 model,including a Flatten layer, Dense layers with activation functions, and the final output layer. The model is compiled with an appropriate loss function, optimizer, and metrics. Data augmentation is performedusing ImageDataGenerator to generate augmented training data. The model is then trainedusing the fit_generator function with the training data generator and testing data generatorprovided as input. The number of epochs and stepsper epoch are specified. The accuracy and loss curves during training are plotted and displayed. The model undergoes fine-tuning and transfer learning by freezing the pre- trained model's layers and training only the custom layers on top. The early stopping and model checkpoint callbacks are used to monitor the validation accuracy and save the best model weights. The trained model is evaluated on the testing data using the predict_generator function, obtaining predictions and determining the class indices. The predicted class indices are further analyzed to understand the model's performance on the testing data. Finally, the code plots and displays the accuracy and loss curves during training. Overall, the algorithm demonstrates the process of building a model for eye disease classification using transfer learning and fine-tuning, covering steps such as data loading, preprocessing, data augmentation, model training, and evaluation.

3.3.2 VGG19

VGG19, short for Visual Geometry Group 19, is a deep convolutional neural network architecture that was developed by the Visual Geometry Group at the University of Oxford. It is a variant of the VGG network, which was originally introduced by the same research group. The VGG19 architecture is composed of 19 layers, including 16 convolutional layers and 3 fullyconnected layers. The convolutional layers are primarily 3x3 filters with a stride of 1 and a padding of 1. The pooling layers are implemented using 2x2 max pooling with a stride of 2. The fully connected layers at the end of the network serve as the classifier.

The VGG19 architecture is known for its simplicity and uniformity in design, making it easier to understand and implement compared to more complex architectures. However, it has a largernumber of parameters compared to earlier models like AlexNet, which can make training the network computationally expensive.

One of the main drawbacks of VGG19 is its large memory footprint and computational requirements. The model's depth and number of parameters make it less suitable for resource- constrained environments like mobile devices compared to more lightweight architectures like MobileNet or EfficientNet. However, VGG19 remains a valuable benchmark model and a reference point for understanding deeper convolutional neural network architectures.

Convolutional Layer:

Input: X with shape (W_in, H_in, C_in), where W_in is the width, H_in is the height, and C_inis the number of input channels.

Convolution operation: Y = f(W * X + b), where Y is the output feature map, W is the convolutional filter weights, b is the bias term, and f() is the activation function (usually ReLU).**Max Pooling Layer:**

Input: X with shape (W_in, H_in, C_in).

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Max pooling operation: Y = max_pool(X, pool_size, stride), where Y is the downsampled feature map, pool_size is the size of the pooling window, and stride is the stride used for pooling.

Fully Connected Layer:

Input: X with shape (N, D_in), where N is the number of samples in the batch and D_in is the number of input features.

Linear transformation: Z = X * W + b, where Z is the output of the fully connected layer, W isthe weight matrix, and b is the bias term.

Activation function: Y = f(Z), where Y is the final output of the fully connected layer, and f() is the activation function (e.g., ReLU or softmax).

The specific architecture of VGG19 includes multiple convolutional layers with 3x3 filters, followed by max pooling layers with 2x2 pooling windows. The fully connected layers are typically used for classification at the end of the network.

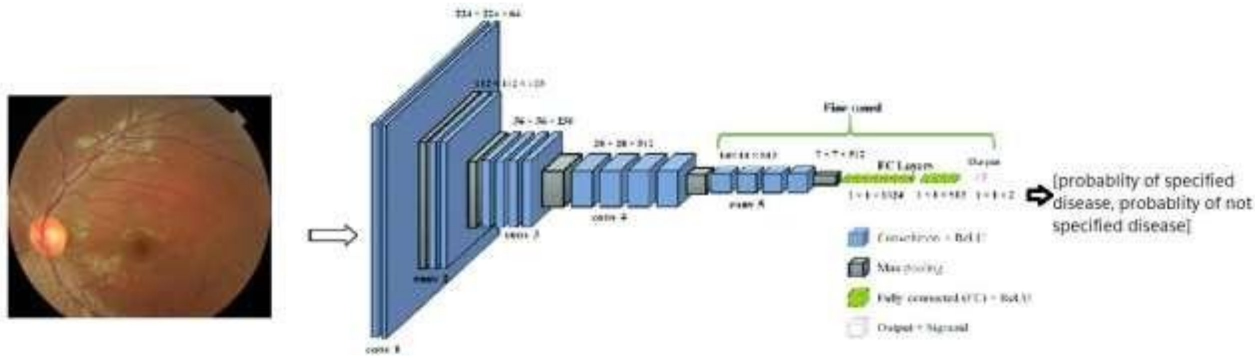

Figure 3.4: VGG19 Architecture

CONCLUSION

By developing a web application for the diagnosis of Multiple Ocular Diseases using Tomography, weenable users to access it remotely from any location. Through the utilization of existing datasets andthe implementation of advanced Deep Learning techniques, we can offer users highly precise diagnostic outcomes. The web-based solution not only enhances cost-efficiency but also ensures a seamless and intuitive user experience. By optimizing the VGG19 algorithm and fine-tuning the model, we can effectively minimize the time required for disease detection in tomography scans.

Future Scope of the project is that it has a potential future expansion for Multiple Ocular Disease Diagnosis Using Tomography in the integration of medical electronic hardware. This integration would enable the instantaneous delivery of results, eliminating the need for users to manually upload images to websites for disease prediction. By incorporating medical electronic hardware, the diagnostic process can be streamlined, saving users timeand effort.

Another exciting future prospect involves generating heat maps based on the pre-trained model. These heat maps would accurately pinpoint the precise locations or spots in the eyethat provide evidence of the presence of specific diseases. By visualizing these heat maps,clinicians and researchers can gain valuable insights into the exact areas affected by ocular diseases. This advancement would enhance the understanding and diagnosis of ocular conditions, leading to more targeted treatments and interventions