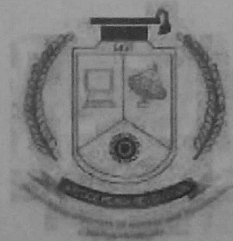


# **AI-POWERED DISEASE DIAGNOSIS FROM MEDICAL IMAGE REPORTS**

Submitted in partial fulfillment of the requirements for the award of  
Bachelor of Engineering degree in Computer Science and  
Engineering with Specialization in Artificial Intelligence

By

**KAVIRAJ L R ( Reg.No - 40731043 )**  
**JOSHUA S ( Reg.No - 40731037 )**



**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING  
SCHOOL OF COMPUTING**

## **SATHYABAMA**

**INSTITUTE OF SCIENCE AND TECHNOLOGY  
(DEEMED TO BE UNIVERSITY)**

**Category-1 University by UGC**

**Accredited with Grade "A++" by NAAC | 12B Status by UGC | Approved by AICTE**

**JEPPIAAR NAGAR, RAJIV GANDHI SALAI,**

**CHENNAI - 600119**

**APRIL - 2024**



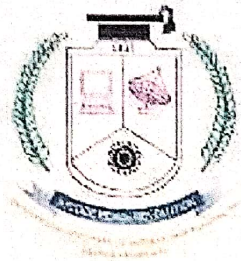


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## DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

### BONAFAIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **KAVIRAJ L R (40731043)** and **JOSHUA S (40731037)** who carried out the Project entitled "**AI-POWERED DISEASE DIAGNOSIS FROM MEDICAL IMAGE REPORTS**" under my supervision from November 2023 to April 2024.

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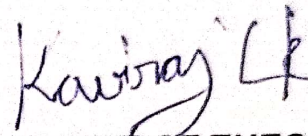


## DECLARATION

I, KAVIRAJ L R (Reg.No- 40731043), hereby declare that the Project Report entitled "AI-POWERED DISEASE DIAGNOSIS FROM MEDICAL IMAGE REPORTS" done by me under the guidance of Dr. R. RAJALAKSHMI , M.E., Ph.D., is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in Computer Science and Engineering with Specialization in Artificial Intelligence.

DATE:

PLACE: Chennai



SIGNATURE OF THE CANDIDATE



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## ABSTRACT

In the landscape of modern healthcare, the integration of data science and technology has revolutionized disease prediction and diagnosis. This project presents a cutting-edge approach to disease diagnosis by integrating advanced machine learning and deep learning architectures, namely InceptionV3 and EfficientNet-B7, within a Flask-based API framework. The targeted diseases encompass kidney stone, kidney cyst, kidney tumor, lung cancer and brain tumor. The project unfolds through several key stages. Initially, a diverse and comprehensive dataset comprising imaging data, and and subjected to rigorous preprocessing. This involves handling missing data, normalizing variables, and Data Augmentation. For each disease, state-of-the-art deep learning architectures – Transfer learning model like InceptionV3 and EfficientNet-B7 - are selected and fine-tuned to extract intricate patterns from the medical imaging data. These architectures are renowned for their ability to capture complex relationships within high-dimensional data, thus enhancing prediction accuracy. Following model training, an evaluation of accuracy and loss is performed to assess the model's performance. The Flask framework serves as the foundation for the user interface. Utilizing Flask, routes are established to handle user input and present predictions. The frontend is thoughtfully crafted to streamline the input of symptoms or medical data, ensuring a user-friendly experience. Simultaneously, the backend is designed to efficiently process user inputs, trigger the necessary prediction models, and seamlessly communicate the results back to the user interface. Advancements in medical imaging have significantly improved cancer diagnosis and treatment planning. However, accurately classifying multiple types of cancer based on CT/MRI images remains a challenging task. In this study, we propose a novel approach to cancer classification by harnessing the power of deep learning models, specifically InceptionV3 and EfficientNet-B7 architectures. The implications of our research are significant for the medical community, as it provides a powerful tool for accurate cancer classification, aiding oncologists and radiologists in making informed decisions and developing personalized treatment plans for patients with brain, kidney, and brain cancer. This approach has the potential to improve patient outcomes and contribute to advancements in the field of medical imaging and cancer diagnosis.



## TABLE OF CONTENTS

| Chapter No | TITLE                                 | Page No. |
|------------|---------------------------------------|----------|
|            | ABSTRACT                              | i        |
|            | LIST OF FIGURES                       | v        |
|            | LIST OF ABBREVIATIONS                 | vii      |
| 1          | INTRODUCTION                          | 1        |
|            | 1.1 Introduction                      | 1        |
|            | 1.2 Problem Definition                | 2        |
|            | 1.3 Aim                               | 2        |
|            | 1.4 Objective                         | 3        |
| 2          | LITERATURE SURVEY                     | 4        |
|            | 2.1 Inferences From Literature Survey | 6        |
| 3          | REQUIREMENTS ANALYSIS                 | 7        |
|            | 3.1 Software Requirements             | 7        |
|            | 3.1.1 Python                          | 7        |
|            | 3.1.2 PIP                             | 7        |
|            | 3.1.2 NumPy                           | 7        |
|            | 3.1.4 Pandas                          | 7        |
|            | 3.1.5 Anaconda                        | 8        |
|            | 3.1.6 Tensor Flow                     | 8        |
|            | 3.1.7 Keras                           | 8        |
|            | 3.2 Hardware Requirements             | 8        |
| 4          | DESCRIPTION OF PROPOSED SYSTEM        | 9        |
|            | 4.1 System Analysis                   | 9        |
|            | 4.1.1 Purpose                         | 9        |
|            | 4.1.2 Existing System                 | 9        |
|            | 4.1.3 Proposed System                 | 10       |
|            | 4.1.4 System Architecture             | 11       |



|       |                                             |    |
|-------|---------------------------------------------|----|
| 4.2   | System Overview                             | 12 |
| 4.2.1 | Use Case Diagram                            | 12 |
| 4.2.2 | Activity Diagram                            | 13 |
| 4.2.3 | Data Flow Diagram                           | 14 |
| 4.3   | Advantages                                  | 14 |
| 5     | <b>IMPLEMENTATION DETAILS</b>               | 15 |
| 5.1   | Basic Operation Of Neural Networks          | 15 |
| 5.2   | Image Acquisition And Processing            | 16 |
| 5.2.1 | Kaggle Dataset                              | 16 |
| 5.2.2 | BRaTS MICCAI dataset                        | 16 |
| 5.2.3 | Data Augmentation                           | 19 |
| 5.2.4 | Image Pre-Processing                        | 19 |
| 5.2.5 | Activation Function                         | 19 |
| 5.3   | Convolutional Neural Network –EFFIENCTNETB3 | 19 |
| 5.3.1 | Inception-v3:(LUNG)                         | 21 |
| 5.3.2 | VGG-19:(BRAIN)                              | 22 |
| 5.3.3 | Sequential Model :(Kidney)                  | 22 |
| 5.4   | Flask Framework                             | 23 |
| 6     | <b>RESULTS AND DISCUSSION</b>               | 24 |
| 6.1   | Brain Tumor Result And Analysis             | 24 |
| 6.1.1 | Prediction Output                           | 26 |
| 6.2   | Kidney Result And Analysis                  | 27 |
| 6.2.1 | Prediction Output                           | 28 |
| 6.3   | Lung Cancer Result And Analysis             | 30 |
| 6.3.1 | Prediction Output                           | 31 |
| 6.4   | User Interface                              | 33 |
| 7     | <b>SUMMARY AND CONCLUSION</b>               | 34 |
| 7.1   | CONCLUSION                                  | 34 |
| 7.2   | FUTURE SCOPE                                | 34 |



|                   |    |
|-------------------|----|
| REFERENCES        | 35 |
| APPENDIX          | 37 |
| A. SOURCE CODE    | 37 |
| B. SCREENSHOTS    | 62 |
| C. RESEARCH PAPER | 67 |
| D. CERTIFICATE    | 75 |



## LIST OF FIGURES

| FIGURE NO. | FIGURE NAME                                              | PAGE NO. |
|------------|----------------------------------------------------------|----------|
| 4.1        | System Architecture                                      | 11       |
| 4.2        | Use Case Diagram                                         | 12       |
| 4.3        | Activity Diagram                                         | 13       |
| 4.4        | Data Flow Diagram                                        | 14       |
| 5.1        | A Multi-layer Perceptron Model of Neural Network         | 16       |
| 5.2        | Brain Dataset                                            | 17       |
| 5.3        | Kidney Dataset                                           | 18       |
| 5.4        | Lungs Dataset                                            | 18       |
| 5.5        | CNN Architecture                                         | 20       |
| 5.6        | CNN Layers                                               | 20       |
| 6.1        | Accuracy of Brain Tumor Model-VGG-19                     | 24       |
| 6.2        | Loss of Brian Tumor Model-VGG-19                         | 25       |
| 6.3        | ROC Curve of Brian Tumor Model-VGG-19                    | 25       |
| 6.4        | Brain Tumor                                              | 26       |
| 6.5        | No Brain Tumor                                           | 26       |
| 6.6        | Confusion Matrix of Kidney model-Sequential model        | 27       |
| 6.7        | Training And Validation Graph of kidney model-Sequential | 27       |
| 6.8        | Normal Kidney                                            | 28       |
| 6.9        | Kidney Stone                                             | 29       |
| 6.10       | Kidney Cyst                                              | 29       |
| 6.11       | Kidney Tumor                                             | 30       |
| 6.12       | Accuracy of Lungs model - Inception V3                   | 30       |



|      |                                    |    |
|------|------------------------------------|----|
| 6.13 | Loss of Lungs Model - Inception V3 | 31 |
| 6.14 | Normal Lungs                       | 31 |
| 6.15 | Adenocarcinoma                     | 32 |
| 6.16 | Squamous Cell Carcinoma            | 32 |
| 6.17 | Large Cell Carcinoma               | 33 |
| 6.18 | User Interface                     | 33 |



## LIST OF ABBREVIATIONS

| ABBREVIATION | EXPANSION                    |
|--------------|------------------------------|
| CNN          | Convolutional Neural Network |
| CSS          | Cascading Style Sheets       |
| CT           | Computed Tomography          |
| ECG          | Electro Cardiogram           |
| EHR          | Electronic Health Records    |
| GBM          | Glioblastoma Multiforme      |
| HTML         | Hyper Text Markup Language   |
| KNN          | K Nearest Neighbour          |
| LR           | Logistic Regression          |
| MRI          | Magnetic Resonance Imaging   |
| SVM          | Support Vector Machine       |



# CHAPTER 1

## INTRODUCTION

### 1.1 INTRODUCTION

Disease diagnosis has traditionally relied on the expertise of healthcare professionals who meticulously analyze medical images and patient reports, often a time-consuming and intricate task. Advancement in computational techniques, we have the opportunity to harness the power of both medical imagery and textual reports to enhance the accuracy, speed, and efficiency of diagnostic procedures. AI technologies are now widely used in a variety of fields to aid with knowledge acquisition and decision-making. Health information systems, in particular, can gain the most from AI advantages.

Artificial intelligence (AI) encompasses multiple technologies with the common aim to computationally simulate human intelligence. Deep learning (DL) is a subgroup of ML that focuses on making predictions using multi-layered neural network algorithms inspired by the neurological architecture of the brain. Compared to other ML methods such as logistic regression, the neural network architecture of DL enables the models to scale exponentially with the growing quantity and dimensionality of data. This makes DL particularly useful for solving complex computational problems such as large-scale image classification, natural language processing and speech recognition and translation. Disease care is undergoing a shift towards precision healthcare enabled by the increasing availability and integration of multiple data types including genomic, transcriptomic and histopathologic data. Moreover, the integration of multiple data types is more resource-intensive than the interpretation of individual data types and needs modelling algorithms that can learn from tremendous numbers of intricate features. Artificial intelligence (AI) encompasses multiple technologies with the common aim to computationally simulate human intelligence. Machine learning (ML) is a subgroup of AI that focuses on making predictions by identifying patterns in data using mathematical algorithms. Deep learning (DL) is a subgroup of ML that focuses on making predictions using multi-layered neural network algorithms inspired by the neurological architecture of the brain.



Compared to other ML methods such as logistic regression, the neural network architecture of DL enables the models to scale exponentially with the growing quantity and dimensionality of data. This makes DL particularly useful for solving complex computational problems such as large-scale image classification, natural language processing and speech recognition and translation.

## **1.2 PROBLEM DEFINITION**

Traditional methods of disease prediction and diagnosis often rely on manual analysis and interpretation of medical images and data. This can be time-consuming and prone to errors. Single-disease prediction projects are highly specialized and typically focus on a specific condition. This limits their scope and utility, as they do not address the broader healthcare needs of patients who may have multiple health concerns. When healthcare professionals need to consult multiple single-disease prediction models, it can prolong the diagnostic process and increase the time it takes to reach a diagnosis. Focusing on a single disease may lead to missed opportunities for early detection or prevention of other related conditions. Without a web framework like Flask, you may not have a user-friendly interface to interact with the software.

## **1.3 AIM**

To design and implement a robust and accurate computer vision system for automated disease diagnosis from medical images using state-of-the-art deep learning techniques. The primary focus will be on achieving high precision and recall rates in the detection of [specific diseases or conditions] through the analysis of [relevant medical imaging modalities, such as X-rays, MRIs, CT scans, etc.]. The project aims to contribute to the advancement of medical diagnostics, providing a reliable tool for early detection and timely intervention. Develop an automated disease diagnosis system for healthcare specialists. Focus on extracting precise information from medical images/data with minimal errors. Optimize system phases for early diagnosis and precise disease identification. Ensuring the scalability and adaptability of the system to accommodate diverse healthcare settings and evolving medical requirements, thus promoting the widespread implementation of the diagnostic framework.



#### 1.4 OBJECTIVE

1. Gather a diverse and representative dataset of medical images relevant to the target diseases. Clean and preprocess the data to ensure consistency, removing noise and artifacts.
2. Research and select appropriate deep learning models for medical image analysis. Design a neural network architecture tailored to the specific characteristics of medical images.
3. Implement data augmentation techniques to increase the diversity of the training dataset. Train the deep learning model on the prepared dataset using appropriate loss functions and optimization techniques.
4. Collaborate with healthcare professionals to gather domain-specific insights and feedback during the development process. Incorporate feedback from medical experts to improve the model's accuracy and relevance.



## CHAPTER 2

### LITERATURE SURVEY

- [1] Pan & Yang 's survey focused on categorizing and reviewing the current progress on transfer learning for classification, regression and clustering problems. In this survey, they discussed the relationship between transfer learning and other related machine learning techniques such as domain adaptation, multitask learning and sample selection bias, as well as co-variate shift. They also explored some potential future issues in transfer learning research. In this survey article, they reviewed several current trends of transfer learning.
- [2] A Survey on Brain Tumor Detection Using Image Processing Techniques by Luxit Kapoor, Sanjeev. This paper surveys the various techniques that are part of Medical Image Processing and are prominently used in discovering brain tumors from MRI Images. Based on that research this Paper was written listing the various techniques in use. A brief description of each technique is also provided. Also of All the various steps involved in the process of detecting Tumors, Segmentation is the most significant.
- [3] S. Banerjee, S.Mitra, and B. U. Shankar reports the accuracy achieved by seven standard classifiers, viz. i)Adaptive Neuro- Fuzzy Classifier (ANFC), ii) Naive Bayes(NB), iii) Logistic Regression (LR), iv) Multilayer Perceptron(MLP), v) Support Vector Machine (SVM), vi) Classification and Regression Tree (CART), and vii) k-nearest neighbours (KNN). The accuracy reported is on the BRaTS 2015 dataset (a subset of BRaTS 2017 dataset) which consists of 200 HGG and 54 LGG cases. 56 three-dimensional quantitative MRI features extracted manually from each patient MRI and used for the classification.
- [4] In 2019, Moradi et al. compared different techniques to differentiate lung cancer nodules from nonnodules. To reduce/eliminate the false positive predictions they have come up with 3D Convolutional Neural Network Technique. Nodules exist



in different sizes and using just one CNN can result in false detections. So they divided the nodules into four groups according to their size. And they have used four different sizes of 3D CNN. They combined all those 4 classifiers to get better results. Each CNN consists of a number of 3D CNN which are all varying sizes. They have implemented logistic regression by using a decision tree classifier and gradient boosting model. LUNA16 dataset was used in this to train the complete model. LUNA16 is based on the CT images of the LIDC dataset. As a result, they saw that the result by the fused classifier is better than each of the solo classifiers.

- [5] In 2020, QINGHAI ZHANG et al. [30] proposed a method for designing of Lung nodule detection system which is automatic. The dataset used for the proposed method is LIDC-IRDI public dataset. The proposed method used for this study is Multi-Scene Deep Learning Framework which contains several steps. CT images are given as input and the probability distribution of distinct gray levels is obtained by threshold segmentation that is Histogram. Correcting the smooth lung outlines is the main aim for the lung parenchyma segmentation process. The replacement of the vein system in the lung helps to identify the nodule structure. Vessel filters are used for removing the vessels which reduce the number of false positive. The design of CNN contains a pooling layer, a convolutional layer, and a fully integrated layer. Segmentation and classification identify Class 1 and Class2 that are two class of image data and discrete images which are separated from the lung images respectively [31]. Segmentation is done to identify cancerous tumor cells in lungs. The accuracy of the determined nodules is determined by four different types of CNN architecture.



## 2.1 INFERENCES FROM LITREATURE SURVEY

The survey focuses on categorizing and reviewing the current progress in transfer learning for classification, regression, and clustering problems. It explores the relationship between transfer learning and other machine learning techniques, including domain adaptation, multitask learning, and sample selection bias. The paper surveys various techniques in Medical Image Processing used for detecting brain tumors from MRI images.

Techniques are described, and segmentation is highlighted as the most significant step in the tumor detection process. Classifiers include Adaptive Neuro-Fuzzy Classifier, Naive Bayes, Logistic Regression, Multilayer Perceptron, Support Vector Machine, Classification and Regression Tree, and k-nearest neighbors. A 3D Convolutional Neural Network (CNN) technique is proposed to handle nodules of different sizes, and classifiers for four size groups are combined for improved results. Vessel filters are used to reduce false positives, and accuracy is evaluated using four different CNN architectures.



## CHAPTER 3

### REQUIREMENT ANALYSIS

#### 3.1 SOFTWARE REQUIREMENTS

##### 3.1.1 *Python*

Python is an interpreted, high-level, general purpose programming language created by Guido Van Rossum and first released in 1991, Python's design philosophy emphasizes code Readability with its notable use of significant Whitespace. Its language constructs and object-oriented approach aim to help programmers write clear, logical code for small and large-scale projects. Python is dynamically typed and garbage collected. It supports multiple programming paradigms, including procedural, object-oriented, and functional programming.

##### 3.1.2 *PIP*

It is the package management system used to install and manage software packages written in Python.

##### 3.1.3 *NumPy*

NumPy 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

##### 3.1.4 *Pandas*

Pandas is the most popular python library that is used for data analysis. It provides highly optimized performance with back-end source code is purely written in C or Python. We can analyze data in pandas with

1. Series
2. Data frames



### **3.1.5 Anaconda**

Anaconda is a free and open-source distribution of the Python and R programming languages for scientific computing that aims to simplify package management and deployment. Package versions are managed by the package management system conda. The Anaconda distribution includes data-science packages suitable for Windows, Linux, and macOS. Anaconda distribution comes with 1,500 packages selected from PyPI as well as the conda package and virtual environment manager. It also includes a GUI, Anaconda Navigator, as a graphical alternative to the command-line interface (CLI).

### **3.1.6 Tensor Flow**

Tensor flow is a free and open-source software library for dataflow and differentiable programming across a range of tasks. It is a symbolic math library, and is also used for machine learning applications such as neural networks. It is used for both research and production at Google.

### **3.1.7 Keras**

Keras 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 Plaid ML. Designed to enable fast experimentation with deep neural networks, it focuses on being user-friendly, modular, and extensible. Keras contains numerous implementations of commonly used neural-network building blocks such as layers, objectives, activation functions, optimizers, and a host of tools to make working with image and text data easier to simplify the coding necessary for writing deep neural network code.

## **3.2 HARDWARE REQUIREMENTS**

- Processor: Intel® Core™ i3-2350M CPU @ 2.30GHz Installed memory (RAM): 4.00GB
- System Type: 64-bit Operating System
- Hard disk: 10 GB of available space or more.
- Display: Dual XGA (1024 x 768) or higher resolution monitors
- Operating system: Windows



### DESCRIPTION OF PROPOSED SYSTEM

#### 4.1 SYSTEM ANALYSIS

##### 4.1.1 Purpose

Identify diseases at an early stage when they may be more treatable and manageable. Improve patient outcomes by enabling timely interventions and reducing the progression of diseases. Enhance diagnostic accuracy by leveraging the capabilities of computer vision and deep learning algorithms. Reduce the likelihood of human error and subjective variations in interpretation.

Speed up the diagnostic process by automating the analysis of medical images. Handle a large volume of images quickly, allowing healthcare professionals to focus on treatment planning and patient care. Optimize the utilization of healthcare resources by automating routine tasks, enabling medical professionals to allocate their time more effectively. Address shortages of skilled radiologists or other specialized healthcare professionals.

##### 4.1.2 Existing System

- **Manual Diagnosis:** In the absence of an automated system, the current diagnosis of diseases heavily relies on the expertise of healthcare professionals, who assess medical reports and images manually. This process is time-consuming, prone to errors, and may vary in accuracy depending on the proficiency and experience of the healthcare practitioner.
- **Traditional Statistical Analysis:** Some healthcare facilities may utilize conventional statistical methods to analyze medical data, which may not fully capture the complex patterns and nuances present in the data.[12] These approaches often lack the sophistication and accuracy offered by advanced machine learning techniques.



- **Limited Automation:** While certain healthcare institutions may have incorporated basic automation in data management, it typically does not involve sophisticated machine learning algorithms. Automated systems might assist with data storage and retrieval but do not provide comprehensive diagnostic capabilities based on advanced data analysis.
- **Specialized Software:** There might be standalone software systems used in specific medical domains for image analysis or text processing, but these are often limited in scope and may not provide a holistic approach to disease diagnosis that incorporates both text and image data.

#### **4.1.3 Proposed System**

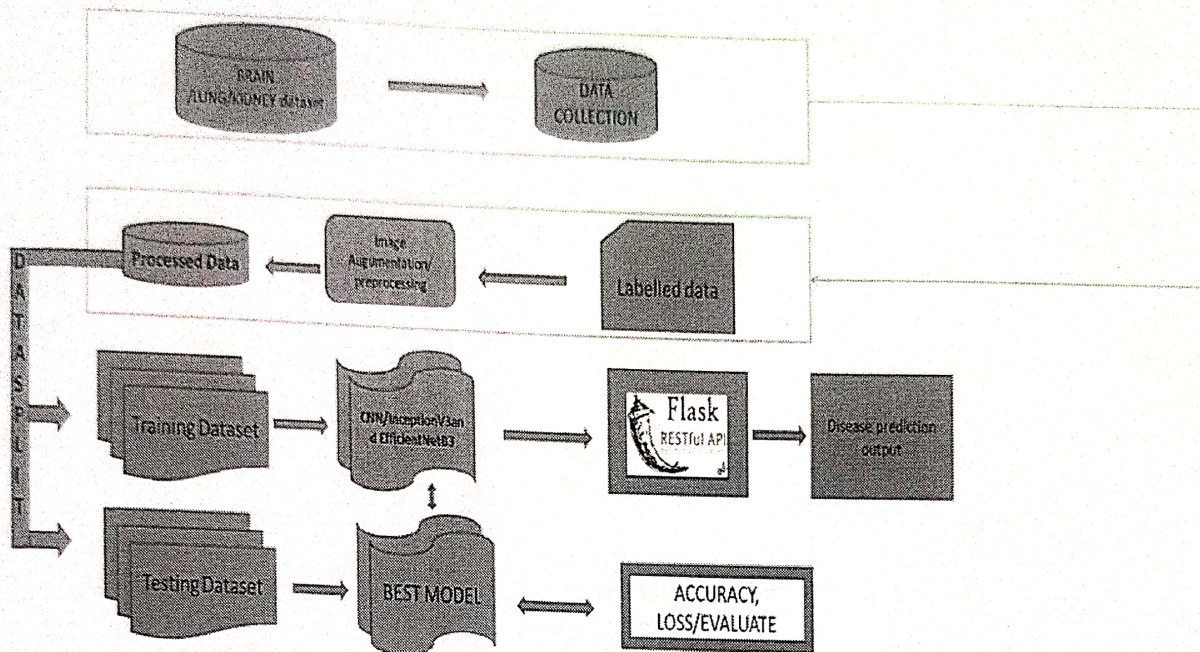
The project involves developing an integrated AI system that utilizes advanced machine learning techniques to analyze medical data and provide accurate disease diagnoses.

- **Data Collection and Preprocessing:** Gather a large and diverse dataset of medical image reports from various sources, ensuring a wide range of diseases and conditions are represented.
- **Image Analysis:** Preprocess the images to standardize resolution, remove noise, and normalize intensities. Annotate the images with labels indicating the presence or absence of the disease. Choose a deep learning architecture suitable for image classification tasks. Convolutional Neural Networks (CNNs) are commonly used for medical image analysis.
- **Disease Classification and Diagnosis:** Train machine learning models, such as convolutional neural networks (CNNs) to classify diseases based on the integrated data. Implement techniques like transfer learning and ensemble learning to enhance model performance and generalizability.
- **Validation and Clinical Trials:** Conduct rigorous validation and benchmarking of the AI system's performance against existing diagnostic methods and human experts. Collaborate with medical professionals to conduct clinical trials, evaluating the system's effectiveness in real-world healthcare scenarios.
- **Scalability and Deployment:** Design the system to handle a large volume of medical data efficiently. Optimize the algorithms and models for scalability and deploy the system on robust and scalable infrastructure to provide real-time or near-real-time diagnoses.



- User Interface and Integration: Develop a user-friendly interface that allows healthcare professionals to interact with the AI system seamlessly. Integrate the AI-powered disease diagnosis system into existing healthcare workflows to enhance clinical decision-making and improve patient outcomes.

#### 4.1.4 system architecture



**Fig:4.1 : System Architecture**

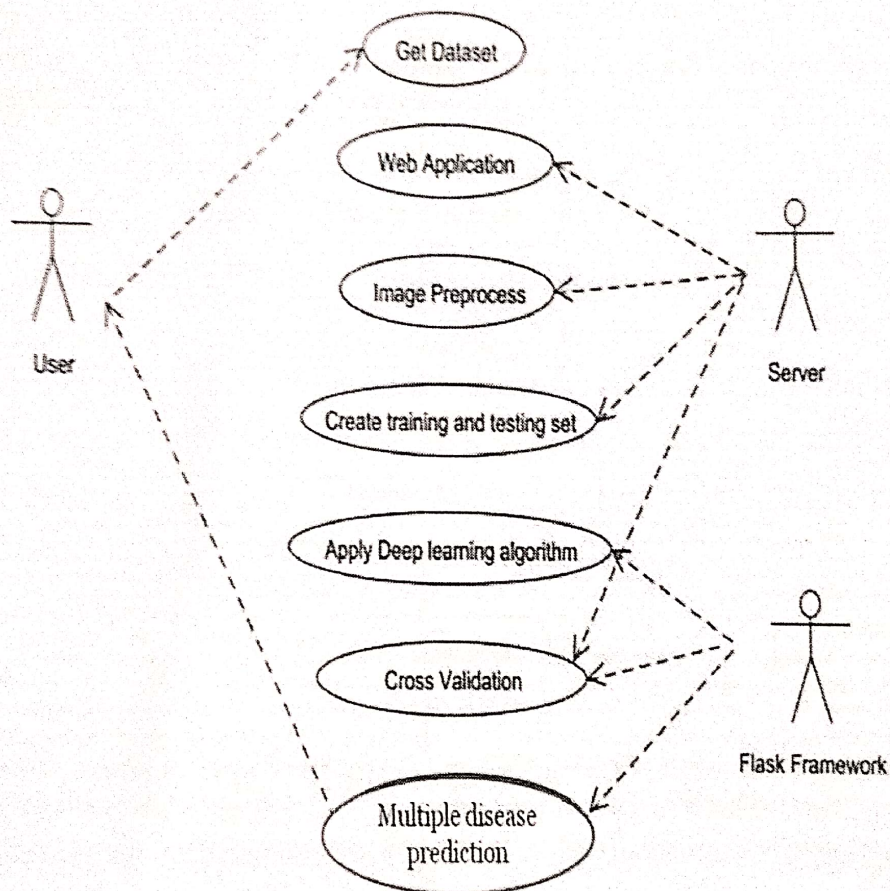
- Collect a diverse dataset of medical images relevant to the target disease(s).
- Preprocess the images to standardize resolution, remove noise, and normalize intensities. Annotate the images with labels indicating the presence or absence of the disease.
- Choose a deep learning architecture suitable for image classification tasks. Convolutional Neural Networks (CNNs) are commonly used for medical image analysis.
- Fine-tune a pre-trained model (e.g., transfer learning) on the medical image dataset to leverage features learned from large datasets like ImageNet.
- Train the model using the training set, employing techniques like data augmentation to increase the model's robustness.
- Utilize a suitable loss function (e.g., binary cross-entropy for binary classification) and optimize with an appropriate optimizer (e.g., Adam).



## 4.2 SYSTEM OVERVIEW

### 4.2.1 Use Case Diagram

A Use case Diagram is used to present a graphical overview of the functionality provided by a system in terms of actors, their goals and any dependencies between those use cases.

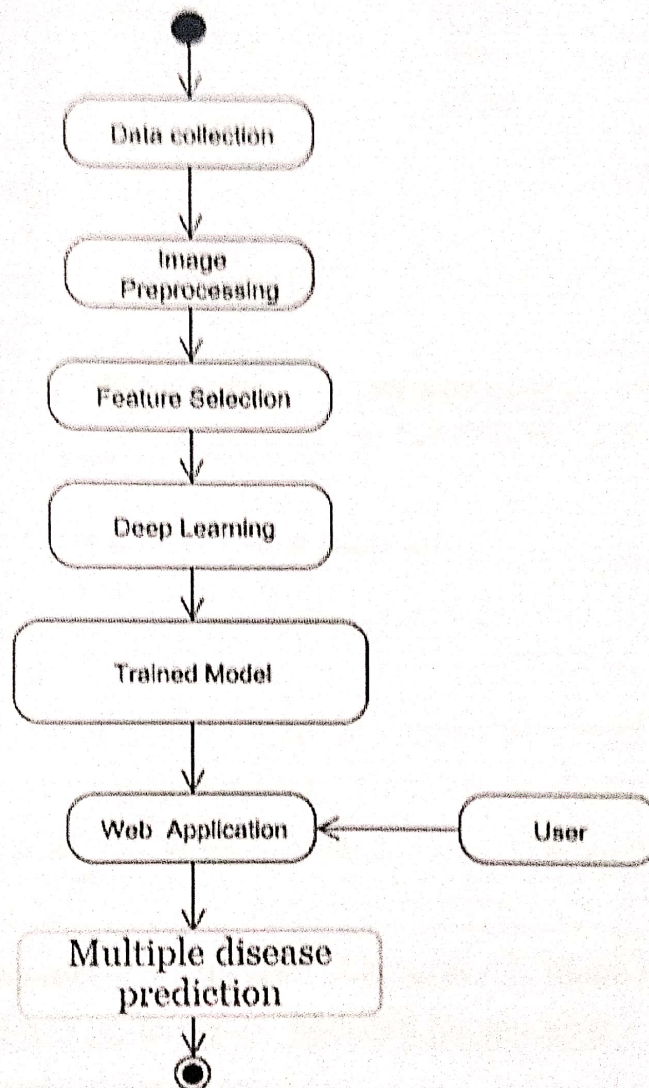


**Fig:4.2 : Use Case Diagram**



#### 4.2.2 Activity Diagram

Activity diagrams are graphical representations of workflows of stepwise activities and actions with support for choice, iteration and concurrency. In the Unified Modeling Language, activity diagrams can be used to describe the business and operational step-by-step workflows of components in a system.

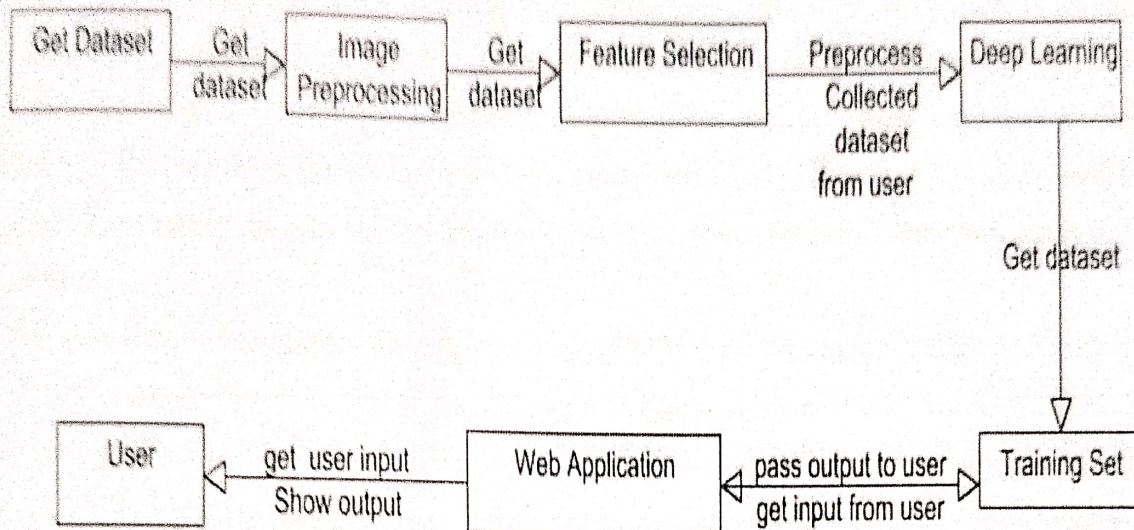


**Fig:4.3 : Activity Diagram**



### 4.2.3 Data Flow Diagram

A data flow diagram (DFD) is a graphical representation of the flow of data through a system or process. It consists of different components that show how data moves through the system. Here are the main components of a data flow diagram:



**Fig:4.4 : Data Flow Diagram**

### 4.3 ADVANTAGES

- Computer vision algorithms can analyze medical images with high precision, enabling the early detection of diseases. Early diagnosis is crucial for many medical conditions as it allows for timely intervention and improved treatment outcomes.
- Deep learning models can achieve a high level of accuracy in image recognition tasks, often surpassing human performance. Reduced human error in diagnosis can lead to more reliable and consistent results.
- Automation of disease diagnosis through computer vision can significantly speed up the diagnostic process. Faster turnaround times can lead to quicker patient treatment and better resource utilization.
- Deep learning excels at handling large datasets, which is common in medical imaging. The ability to process and learn from vast amounts of image data can enhance the model's performance and generalization.



## CHAPTER 5

### IMPLEMENTATION DETAILS

#### 5.1 BASIC OPERATION OF NEURAL NETWORKS

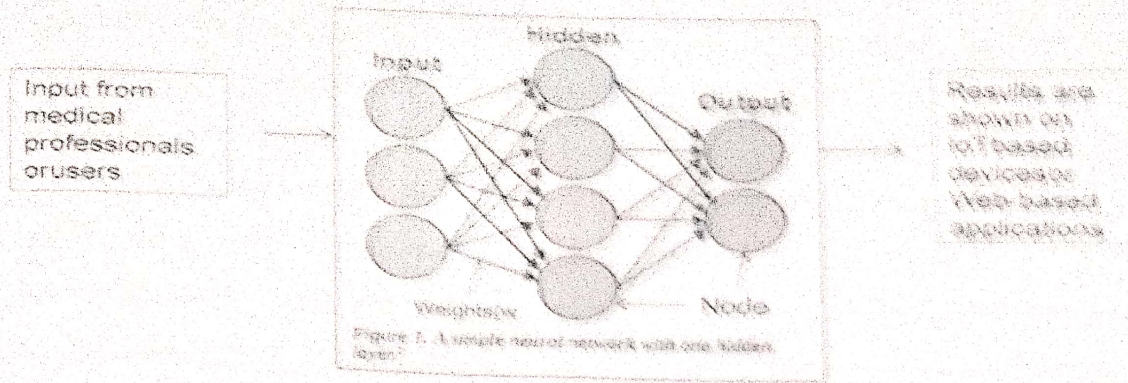
Neural Networks (NN) form the base of deep learning, a subfield of machine learning where the algorithms are inspired by the structure of the human brain. NN take in data, train themselves to recognize the patterns in this data and then predict the outputs for a new set of similar data.[18] NN are made up of layers of neurons. These neurons are the core processing units of the network. First we have the input layer which receives the input; the output layer predicts our final output. In between, exist the hidden layers which perform most of the computations required by our network.

Our brain tumor images are composed of 128 by 128 pixels which make up for 16,384 pixels.[1] Each pixel is fed as input to each neuron of the first layer. Neurons of one layer are connected to neurons of the next layer through channels. Each of these channels is assigned a numerical value known as weight'. The inputs are multiplied to the corresponding weight and their sum is sent as input to the neurons in the hidden layer. Each of these neurons is associated with a numerical value called the bias which is then added to the input sum. This value is then passed through a threshold function called the activation function'.

The result of the activation function determines if the particular neuron will get activated or not. An activated neuron transmits data to the neurons of the next layer over the channels. In this manner the data is propagated through the network this is called forward propagation'. In the output layer the neuron with the highest value fires and determines the output. The values are basically a probable.

This process continues until our weights are assigned such that the network can predict the type of tumor correctly in most of the cases. This brings our training process to an end.[3] NN may take hours or even months to train but time is a reasonable trade-off when compared to its scope. Several experiments show that after pre-processing MRI images, neural network classification algorithm was the best more specifically CNN(Convolutional Neural Network) as compared to Support Vector Machine(SVM),Random Forest Field.





**Fig:5.1 : A Multi-layer Perceptron Model of Neural Network**

## 5.2 IMAGE ACQUISITION AND PROCESSING

### 5.2.1 Kaggle Dataset

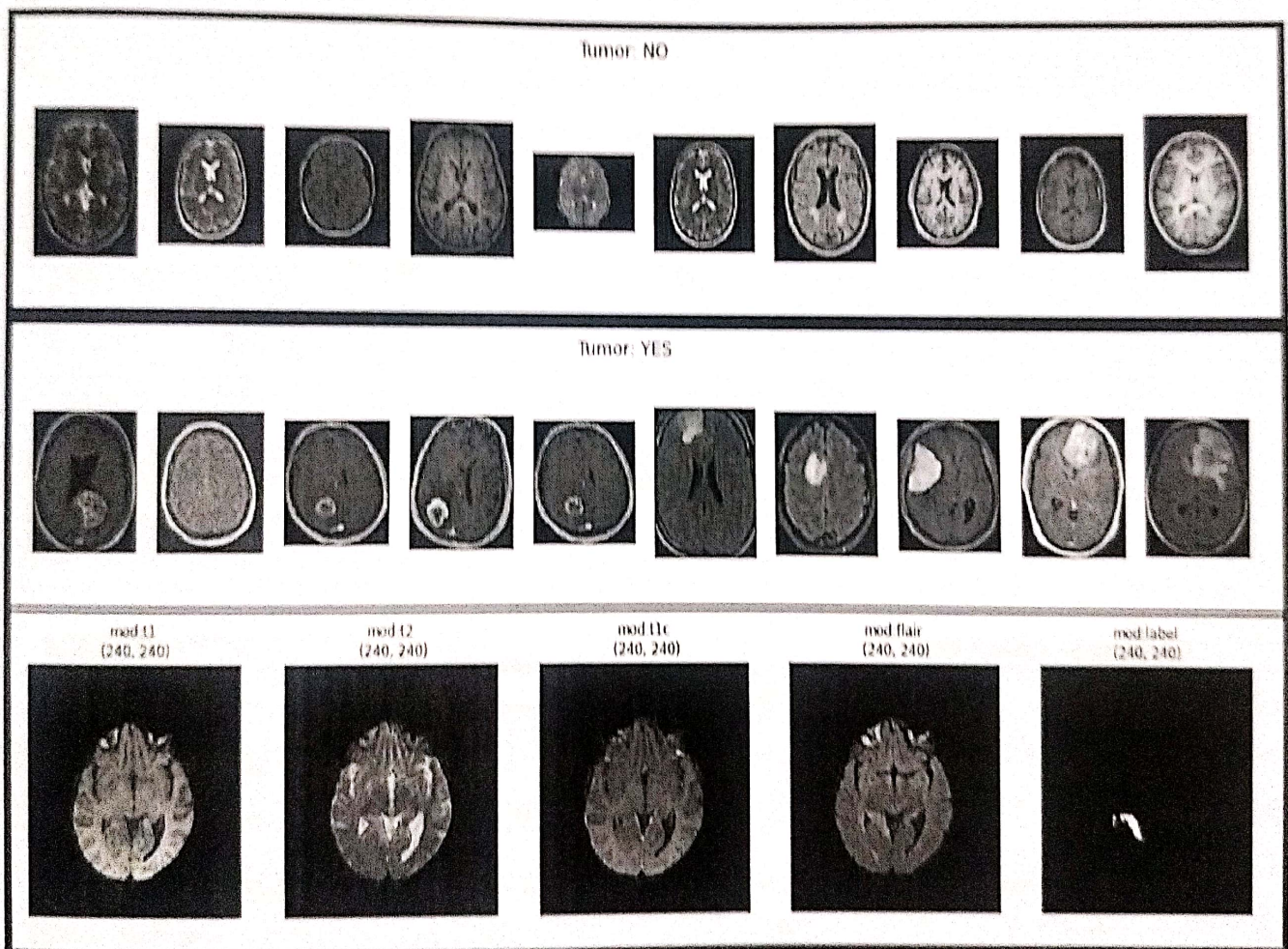
Images can be in the form of .csv (comma separated values), .dat (data) files in grayscale, RGB, or HSV or simply in .zip file as was in the case of our online Kaggle dataset. It contained 98 healthy MRI images and 155 tumor infected MRI images.

### 5.2.2 BRaTS MICCAI dataset

The Multimodal Brain Tumor Segmentation (BRaTS) MICCAI has always been focusing on the evaluation of state-of-the-art methods for the segmentation of brain tumors in magnetic resonance imaging (MRI) scans. Ample multi-institutional routine clinically-acquired multimodal MRI scans of glioblastoma (GBM) and lower grade glioma (LGG), with pathologically confirmed diagnosis and available OS, was provided as the training, validation and testing data for BRaTS 2015 challenge. All BRaTS multimodal scans are available as NIfTI files (.nii.gz) and these multimodal scans describe a) native (T1) and b) post-contrast T1- weighted (T1c), c) T2- weighted (T2), and d) T2 Fluid Attenuated Inversion Recovery (FLAIR) volumes, and were acquired with different clinical protocols and various scanners from multiple institutions.[13] They described a mixture of pre- and post-operative scans and their ground truth labels have been annotated by the fusion of segmentation results from algorithms. All the imaging datasets have been segmented manually, by one to four raters, following the same annotation protocol, and their annotations were approved by experienced neuro-radiologists. Annotations comprise the whole tumor, the tumor core (including cystic areas), and the C- enhancing tumor core.

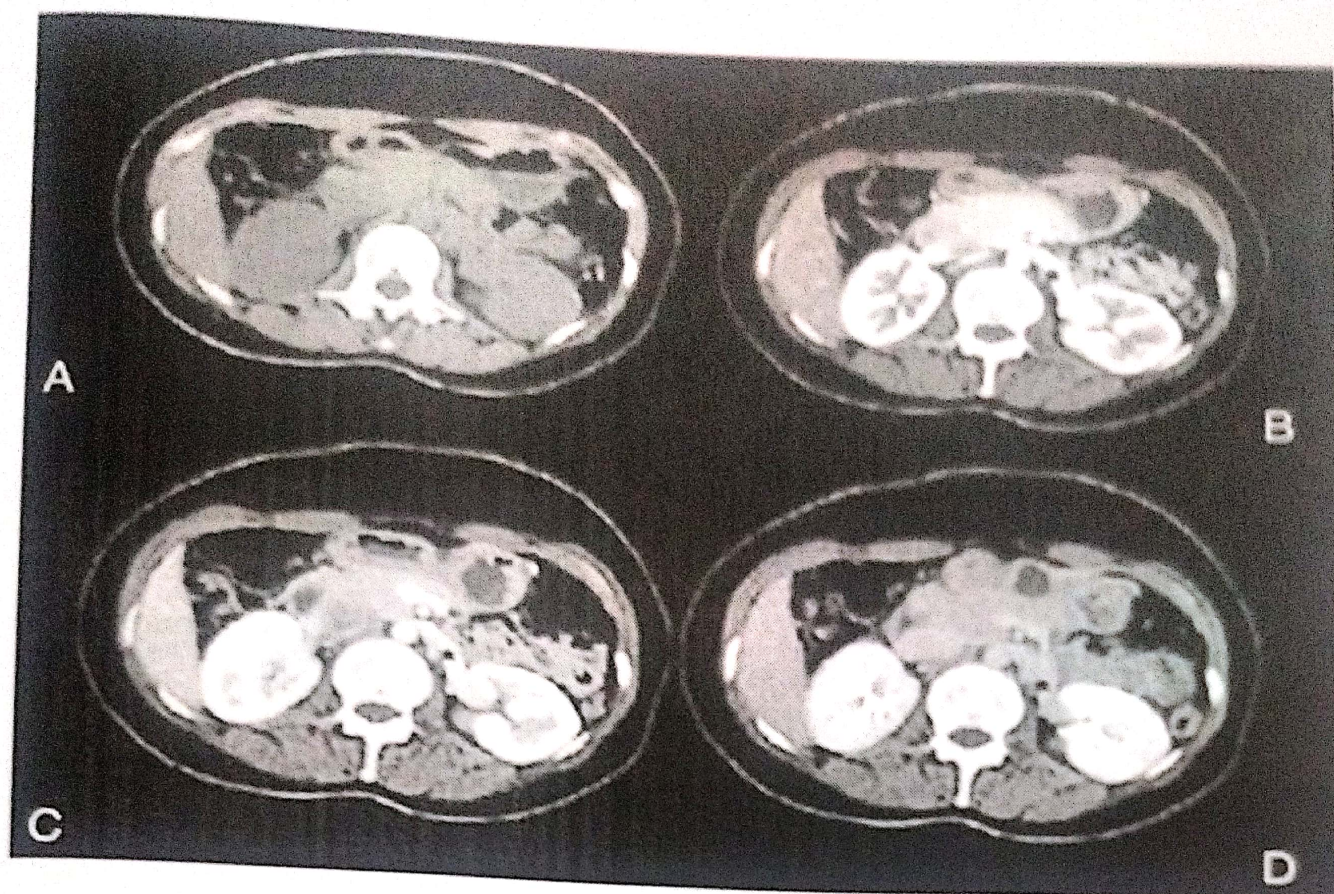


The dataset contains 2 folders for the purpose of training and testing [10]. The 'train' folder contains 2 sub-folders of HGG and LGG cases-220 patients of HGG and 27 patients of LGG.[4]. The '\_test' folder contains brain images of 110 Patients with HGG and LGG cases combined. There are 5 different MRI image modalities for each patient which are T1, T2, T1C, FLAIR, and OT (Ground truth of tumor Segmentation). All these image files are stored in .mha format and are of the size of 240x240, resolution of (1 mm<sup>3</sup>) and skull- stripped. In the ground truth images, each voxel is labelled with zeros and non-zeros, corresponding to the normal pixel and parts of tumor cells, respectively.



**Fig:5.2 : Brain Dataset**

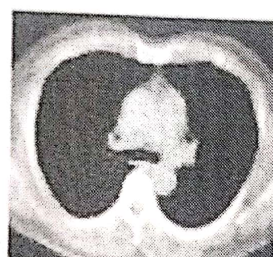




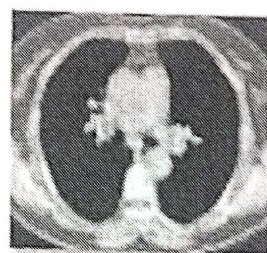
*Fig:5.3 : Kidney Dataset*



0.jpg



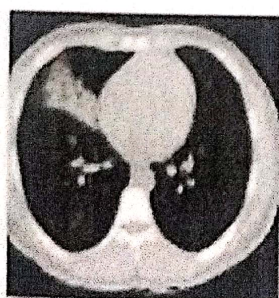
1\_0.jpg



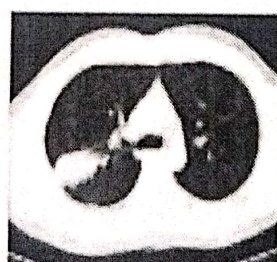
1\_1.jpg



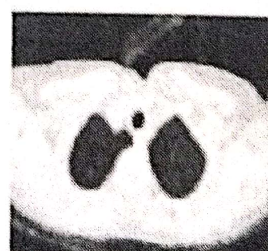
1\_2.jpg



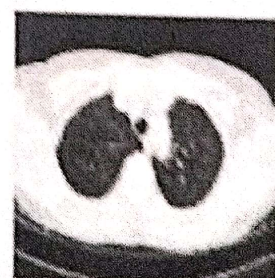
4\_5.jpg



4\_7.jpg



5\_0.jpg



5\_1.jpg

*Fig:5.4 : Lungs Dataset*



### 3.2.3 Data Augmentation

Data augmentation consists of Gray Scaling(RGB/BW to ranges of gray), Reflection(vertical-horizontal flip), Gaussian Blur(reduces image noise), Histogram equalisation(increases global contrast), Rotation(may not preserve image size), Translation(moving the image along x or y axis), linear transformation such as random rotation (0-10 degrees), horizontal and vertical shifts, and horizontal and vertical flips.[2] Data augmentation is done to teach the network desired invariance and robustness properties, when only few training samples are available.

### 3.2.4 Image Pre-Processing

In the first step of pre-processing, the memory space of the image is reduced by scaling the gray-level of the pixels in the range 0-255.

### 3.2.5 Activation Function

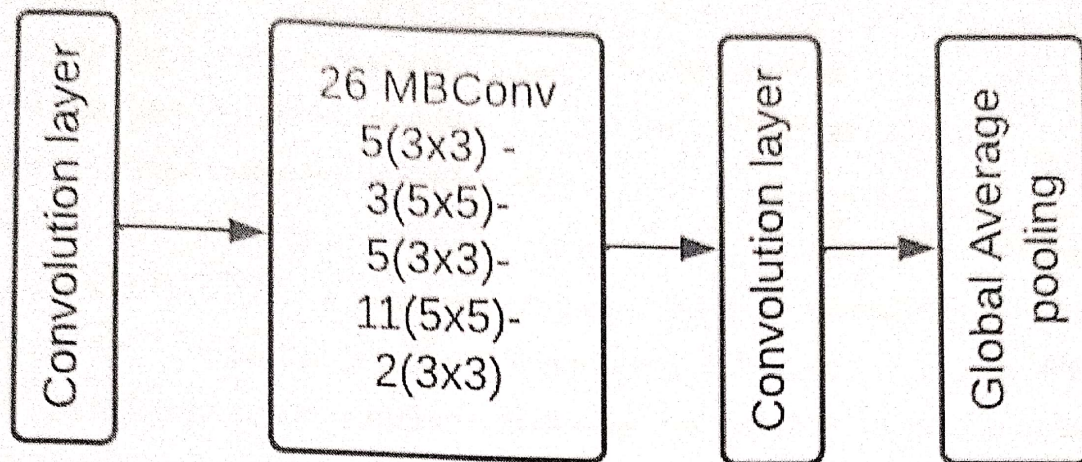
Sigmoid function ranges from 0 to 1 and is used to predict probability as an output in case of binary classification while Softmax function is used for multi-class classification. tanh function ranges from -1 to 1 and is considered better than sigmoid in binary classification using feed forward algorithm. ReLU (Rectified Linear Unit) ranges from 0 to infinity and Leaky ReLU (better version of ReLU) ranges- from -infinity to +infinity.[14] ReLU stands for Rectified Linear Unit for a non-linear operation. The output is  $f(x) = \max(0, x)$ . ReLU's purpose is to introduce non-linearity in our ConvNet.

## 5.3 CONVOLUTIONAL NEURAL NETWORK –EFFICIENTNETB3

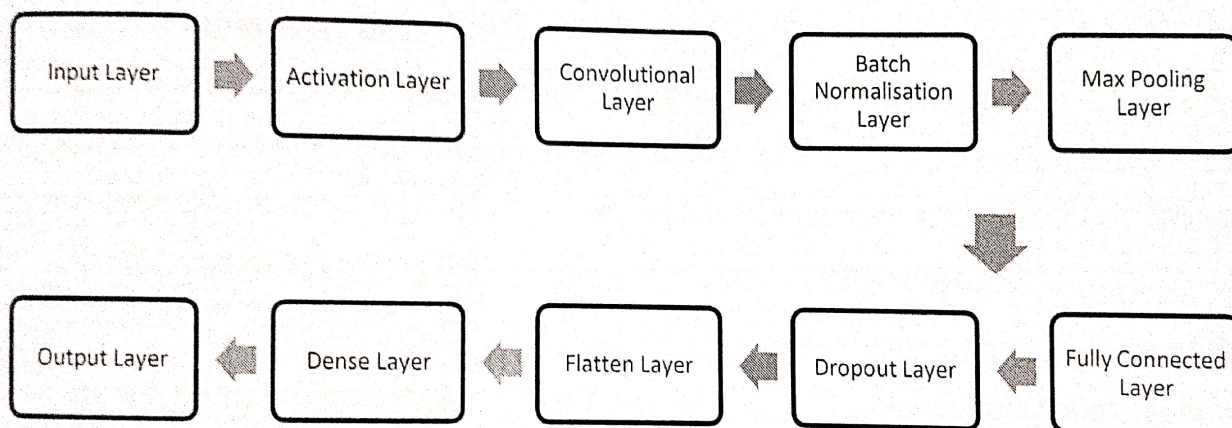
Classifier models can be basically divided into two categories respectively which are generative models based on hand-crafted features and discriminative models based on traditional learning such as support vector machine (SVM), Random Forest (RF) and Convolutional Neural Network (CNN).[11] One difficulty with methods based on hand-crafted features is that they often require the computation of a large number of features in order to be accurate when used with many traditional machine learning techniques. More efficient techniques employ lower numbers of features, using dimensionality reduction like PCA (Principle Component Analysis) or feature selection methods, but the reduction in the number of features is often at the cost of reduced accuracy. Convolutional Neural Networks (ConvNets) automatically learns



mid-level and high-level representations or abstractions from the input training data. The main building block used to construct a CNN architecture is the convolutional layer. It also consists of several other layers, some of which are described as below:



**Fig:5.5 : CNN Architecture**



**Fig:5.6 : CNN Layers**

- Input Layer-It takes in the raw pixel value of input image
- Convolutional Layer- It is the first layer to extract features from an input image. Convolution preserves the relationship between pixels by learning image features using small squares of input data.[8] It is a mathematical operation that takes two inputs such as image matrix and a filter or kernel to generate a feature map. Convolution of an image with different filters can perform operations such as edge detection, blur and sharpen by applying filters.



- Activation Layer-It produces a single output based on the weighted sum of inputs
- Pooling Layer-Pooling layers section would reduce the number of parameters when the images are too large [15] Spatial pooling (also called subsampling or down sampling) reduces the dimensionality of each map but retains important information. Spatial pooling can be of different types:
  - Max Pooling – taking the largest element in the feature map
  - Average Pooling - taking the average of elements in the feature map
  - Sum Pooling – taking the sum of all elements in the feature map
- Fully Connected Layer-The layer we call as FC layer, we flattened our matrix into vector and feed it into a fully connected layer like a neural network. the feature map matrix will be converted as column vector ( $x_1, x_2, x_3, \dots$ ). With the fully connected layers, we combined these features together to create a model. For classifying input image into various classes based on training set.
- Dropout Layer-It prevents nodes in a network from co-adapting to each other.

### 5.3.1 Inception-v3(LUNG)

Inception-v3 is a pre-trained convolutional neural network model that is 48 layers deep. It is a version of the network already trained on more than a million images from the ImageNet database.[7] It is the third edition of Inception CNN model by Google, originally instigated during the ImageNet Recognition Challenge.

This pre-trained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images.[19] The network has an image input size of 299-by-299. The model extracts general features from input images in the first part and classifies them based on those features in the second part.



### 5.3.2 VGG-19(BRAIN)

VGG-19 is a convolutional neural network that is 19 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals.

As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 224-by-224. For more pretrained networks in MATLAB®, see Pretrained Deep Neural Networks.

VGG19 is an advanced CNN with pre-trained layers and a great understanding of what defines an image in terms of shape, color, and structure.[6] VGG19 is very deep and has been trained on millions of diverse images with complex classification tasks. I didn't train VGG19 any further, only froze its layers and appended a shallow 2 layer network on top of it to perform my classification task of identifying images with and without trees.

### 5.3.3 Sequential Model(Kidney)

A Sequential model is appropriate for a plain stack of layers where each layer has exactly one input tensor and one output tensor.

A Sequential model is not appropriate when:

- Your model has multiple inputs or multiple outputs
- Any of your layers has multiple inputs or multiple outputs
- You need to do layer sharing
- You want non-linear topology (e.g. a residual connection, a multi-branch model)

Once a Sequential model has been built, it behaves like a Functional API model. This means that every layer has an input and output attribute.[9] These attributes can be used to do neat things, like quickly creating a model that extracts the outputs of all intermediate layers in a Sequential model.[20] A Sequential model can be built by using the Sequential()class. Here, we sequentially add layers to the model using the add()method.



## 5.4 FLASK FRAMEWORK

The framework is the basis upon which software programs are built. It serves as a foundation for software developers, allowing them to create a variety of applications for certain platforms.[5] It is a set of functions and predefined classes used to connect with the system software and handle inputs and outputs.

It simplifies the life of a developer while giving them the ability to use certain extensions and makes the online applications scalable and maintainable.

### Frontend Development vs Backend Development

- The front end of a website is the area with which the user immediately interacts. It contains everything that users see and interact with: text colours and styles, images and videos, graphs and tables, the navigation menu, buttons, and colours. HTML, CSS, and JavaScript are used in developing the front end.
- The backend of a website refers to the server-side of the website. It saves and organizes data and ensures that everything on the client-side of the website functions properly.[16] It is the section of the website that you are unable to interact with or access. It is the part of the software that has no direct communication with the users. Back End development is done using Java, Python, C#, and JavaScript.
- Flask is used for developing web applications using python, implemented on Werkzeug and Jinja2. Advantages of using Flask framework are:
  - There is a built-in development server and a fast debugger provided.
  - Lightweight
  - Secure cookies are supported.
  - Templating using Jinja2.
  - Request dispatching using REST.
  - Support for unit testing is built-in.



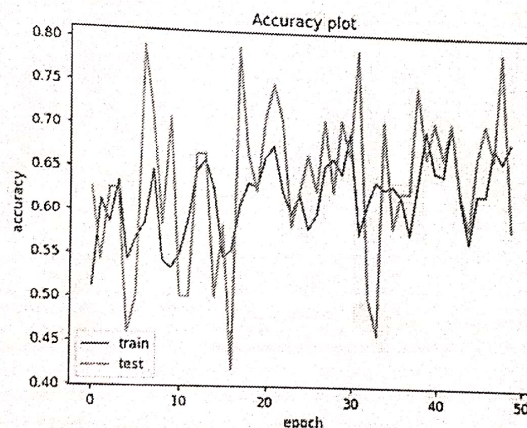
## CHAPTER 6

### RESULTS AND DISCUSSIONS

After training and evaluating the Convolutional Neural Network (CNN) algorithm for diagnosing the presence of diseases from the medical images, this phase provides valuable insights into the model's performance, strengths, limitations, and potential areas for improvement. This phase involves analyzing various metrics, comparing the algorithm's predictions against ground truth labels, and interpreting the implications of the findings.

The implementation of the model is done successfully. The results are satisfactory as we can now diagnose the disease. As mentioned all working modules are used to extract features and compare them.

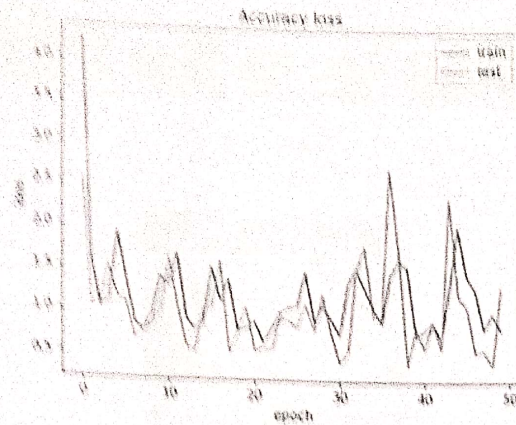
#### 6.1 BRAIN TUMOR RESULT AND ANALYSIS



**Fig:6.1 : Accuracy of Brain Tumor Model-VGG-19**

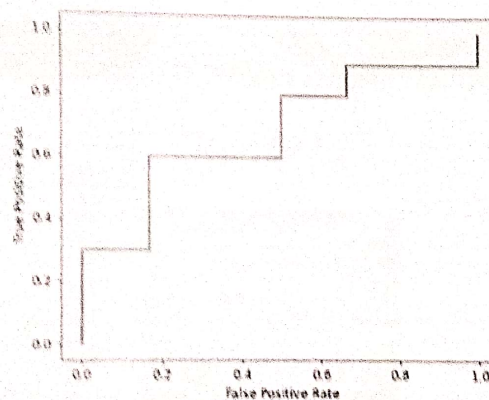
The above is the accuracy graph of trained model. Output Layer Configuration: One node with a sigmoid activation unit. Loss Function: is to Cross-Entropy, also referred to as Logarithmic loss. Loss: Used to evaluate and diagnose model optimization only.





**Fig:6.2 : Loss of Brian Tumor Model-VGG-19**

The above is the a loss graph of trained model. Metric: Used to evaluate and choose models in the context of the project. *ROC AUC*. AUC means Area Under Curve, which is calculated for the ROC curve.



**Fig:6.3 : ROC Curve of Brian Tumor Model-VGG-19**

An ROC curve is a graph plotted between Sensitivity and False positive rate. The closer the value of AUC is to 1 ,the more the model is developed. It can be calculated using functions in Python.



### 6.1.1 Prediction Output

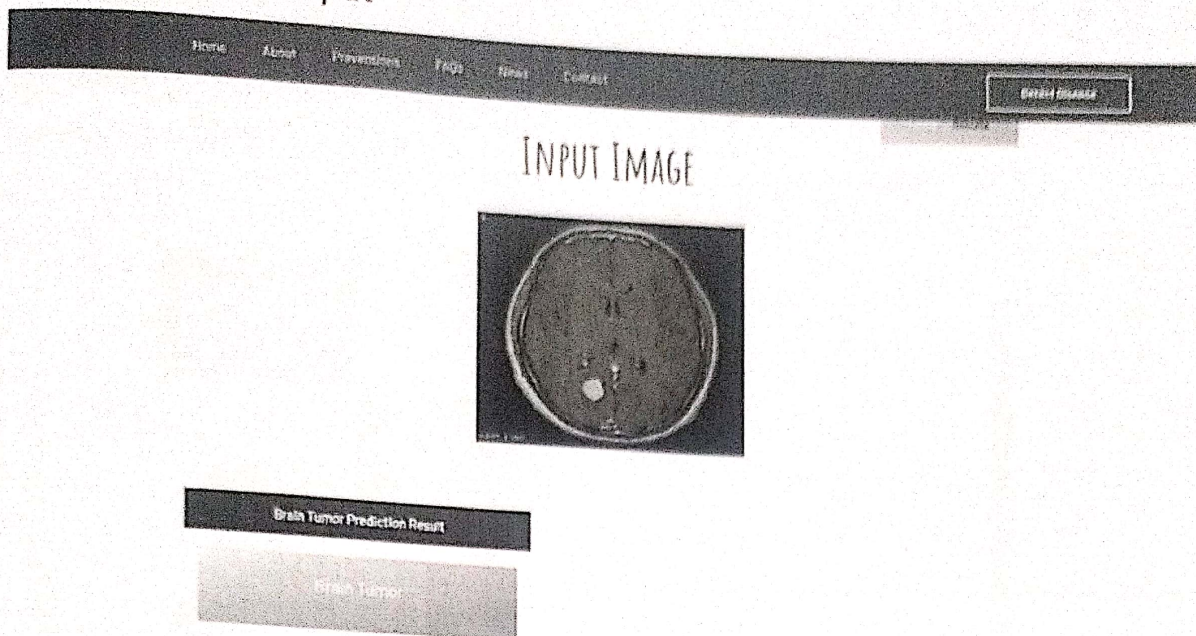


Fig:6.4 : Brain Tumor

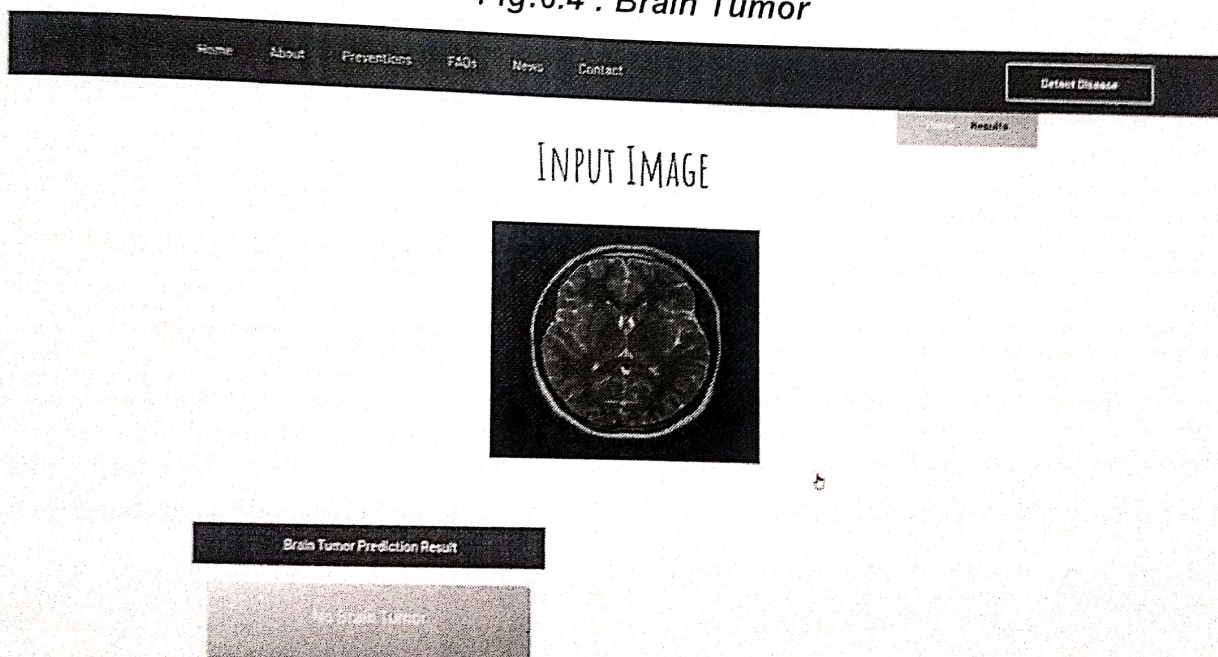
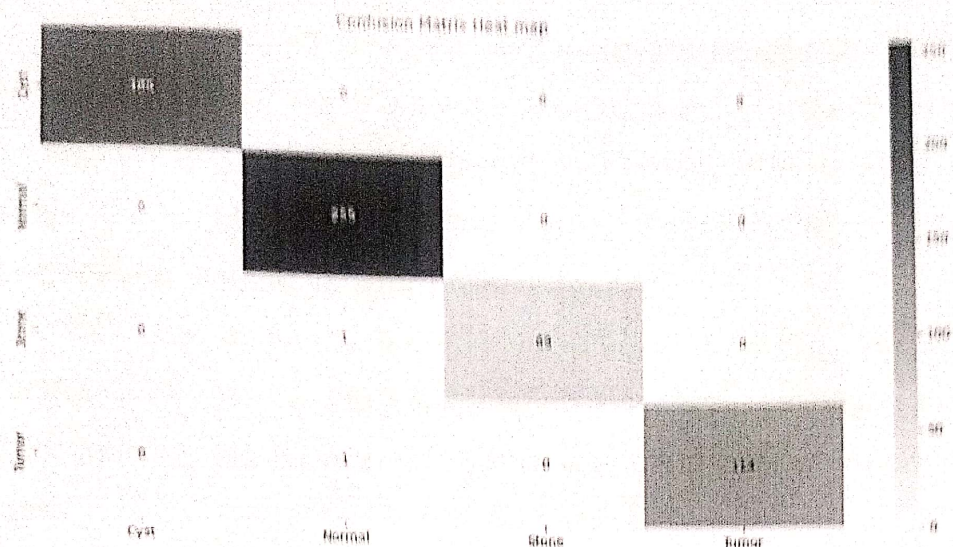


Fig:6.5 : No Brain Tumor

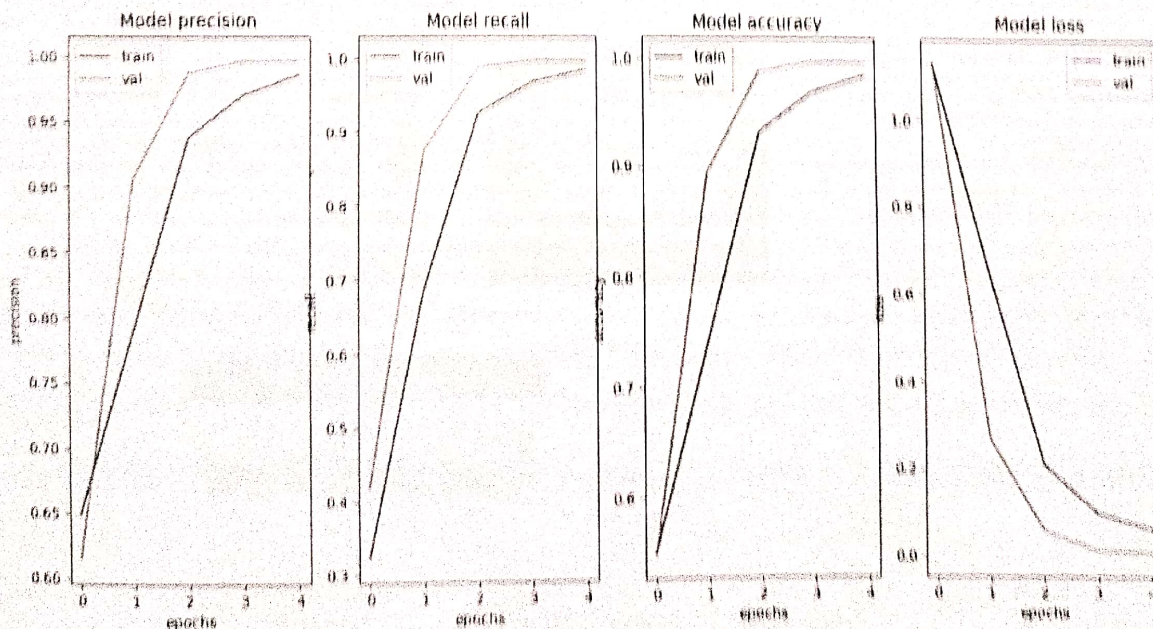


## 6.2 KIDNEY RESULT AND ANALYSIS



**Fig:6.6 : Confusion Matrix of Kidney model-  
Sequential model**

A confusion matrix is a table used in machine learning to describe the performance of a classification model on a set of data for which the true values are known.



**Fig:6.7 : Training And Validation Graph of kidney  
model-Sequential Model**



loss: 1.1325 - accuracy: 0.9489 - precision: 0.6491 - recall: 0.3229: These are metrics being tracked during training

loss: This is a measure of how well the model is doing in terms of its predictions. Lower values are generally better.

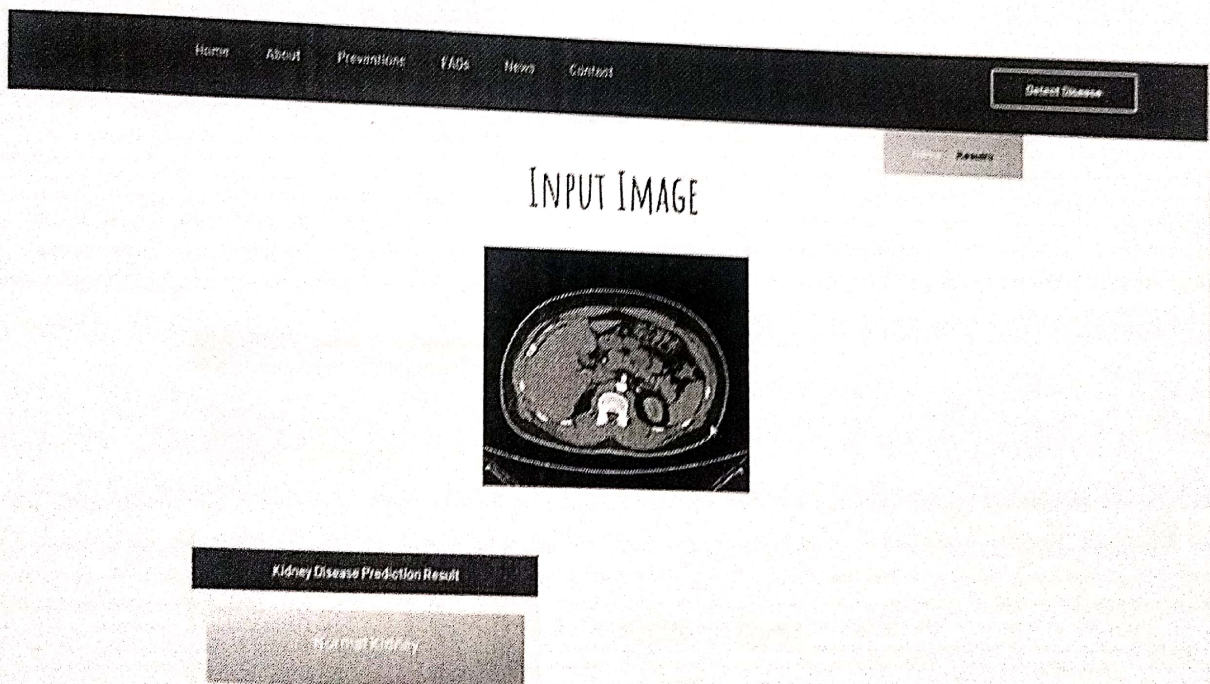
accuracy: This represents the proportion of correct predictions made by the model.

precision: This is a measure of the accuracy of the positive predictions made by the model. It's relevant in cases where you want to minimize false positives.

recall: This is a measure of how many true positives were detected by the model. It's relevant in cases where you want to minimize false negatives.

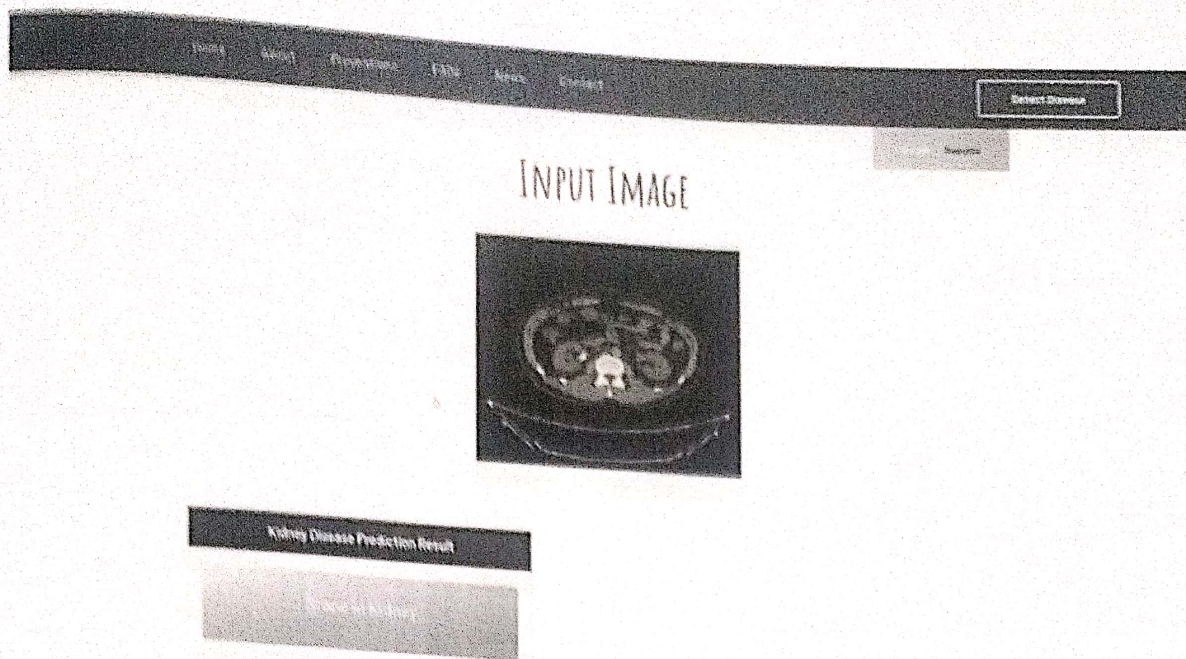
val\_loss: 1.1297 - val\_accuracy: 0.5484 - val\_precision: 0.6152 - val\_recall: 0.4177: These are the same metrics, but evaluated on a separate validation set. This set is not used for training, but for evaluating how well the model is generalizing to new, unseen data.

### 6.2.1 Prediction Output

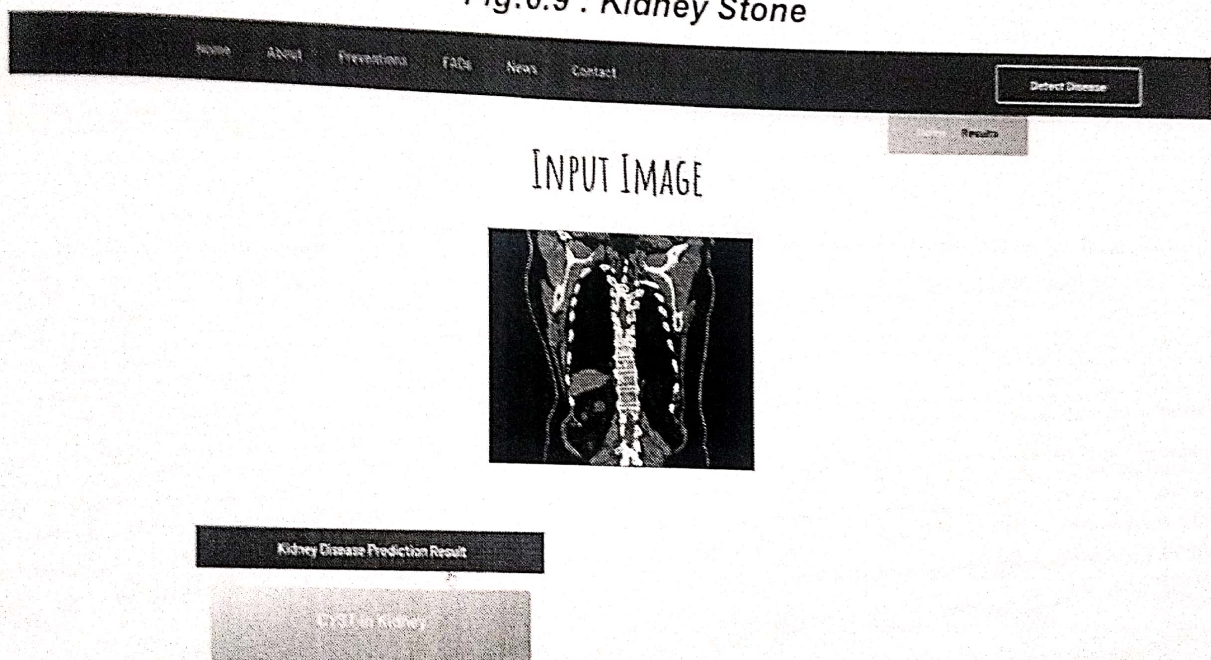


**Fig:6.8 : Normal Kidney**



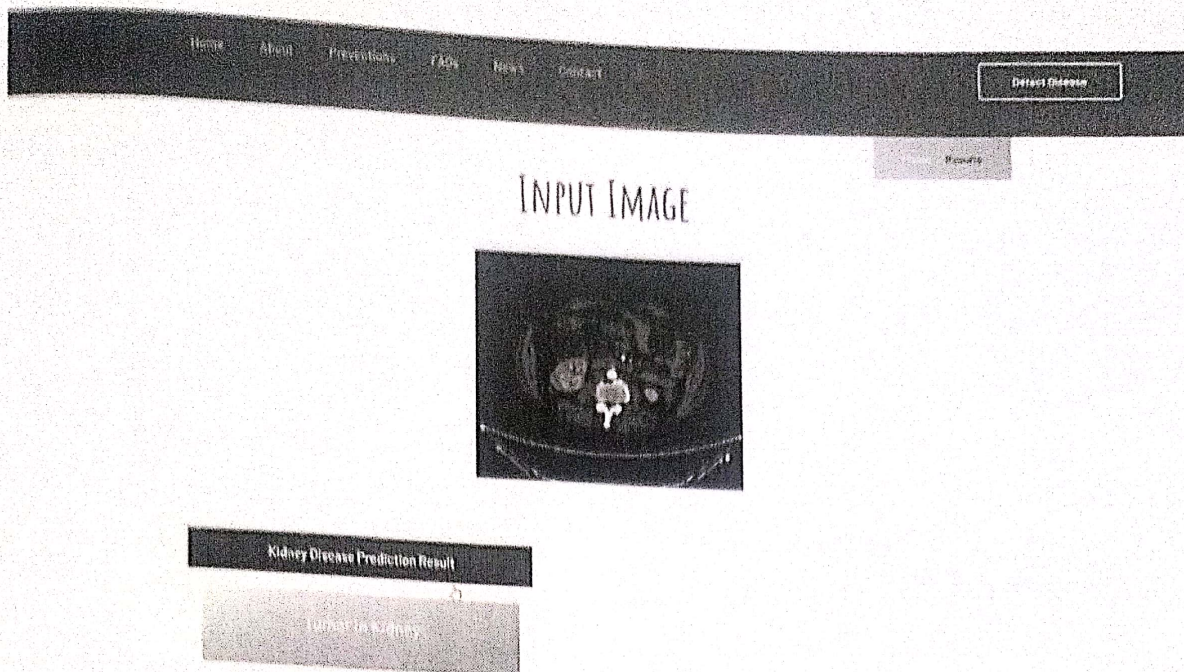


*Fig:6.9 : Kidney Stone*



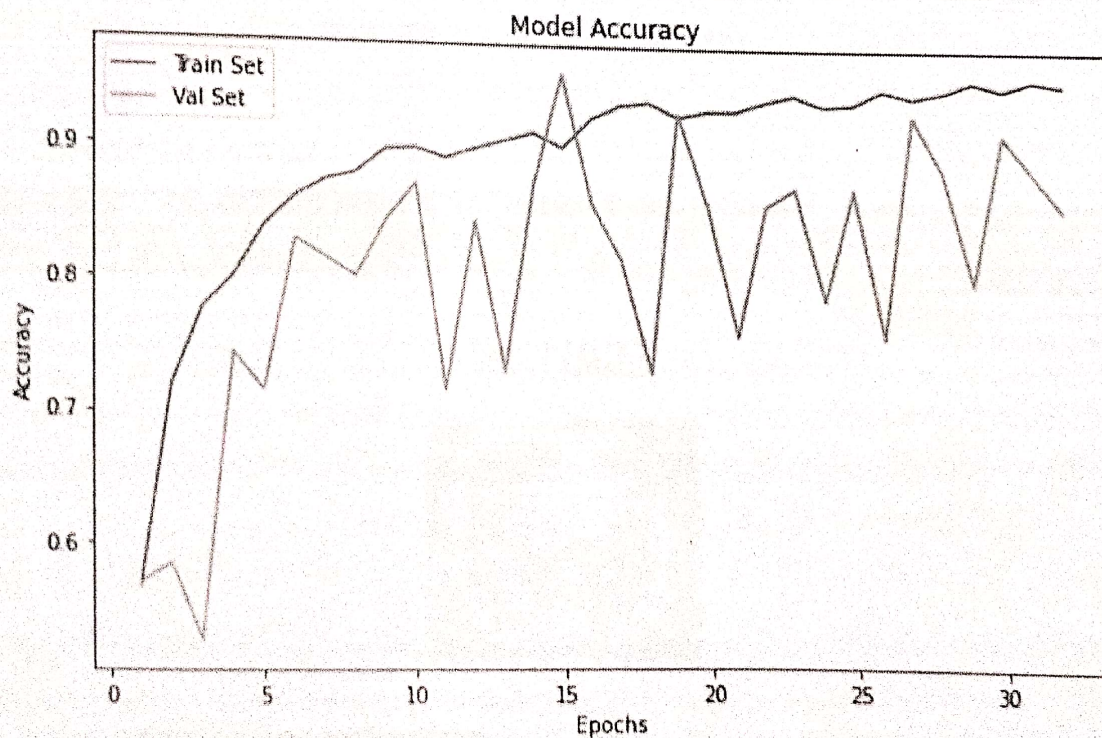
*Fig:6.10 : Kidney Cyst*





*Fig:6.11 : Kidney Tumor*

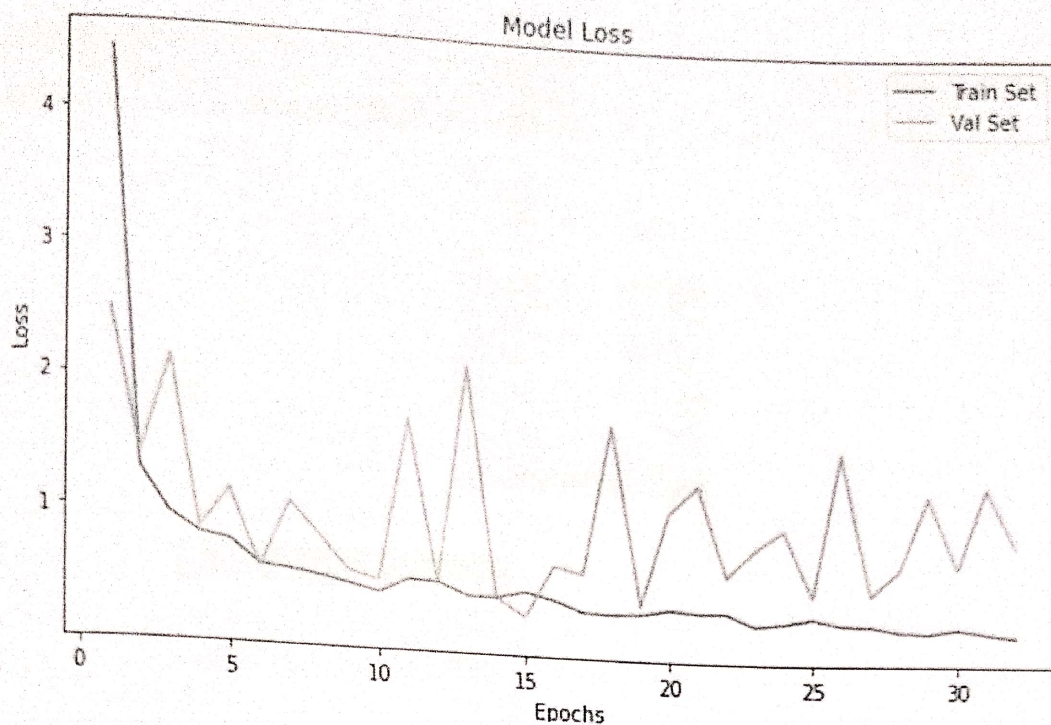
### 6.3 LUNG CANCER RESULT AND ANALYSIS



*Fig:6.12 : Accuracy of Lungs model - Inception V3*

**Result:** The graph shown above is the training model accuracy graph of Inceptional V3. The accuracy is on validation data and training data. Also, the model is trained with the accuracy of 89% on validation data; it's trained for 30 epochs.

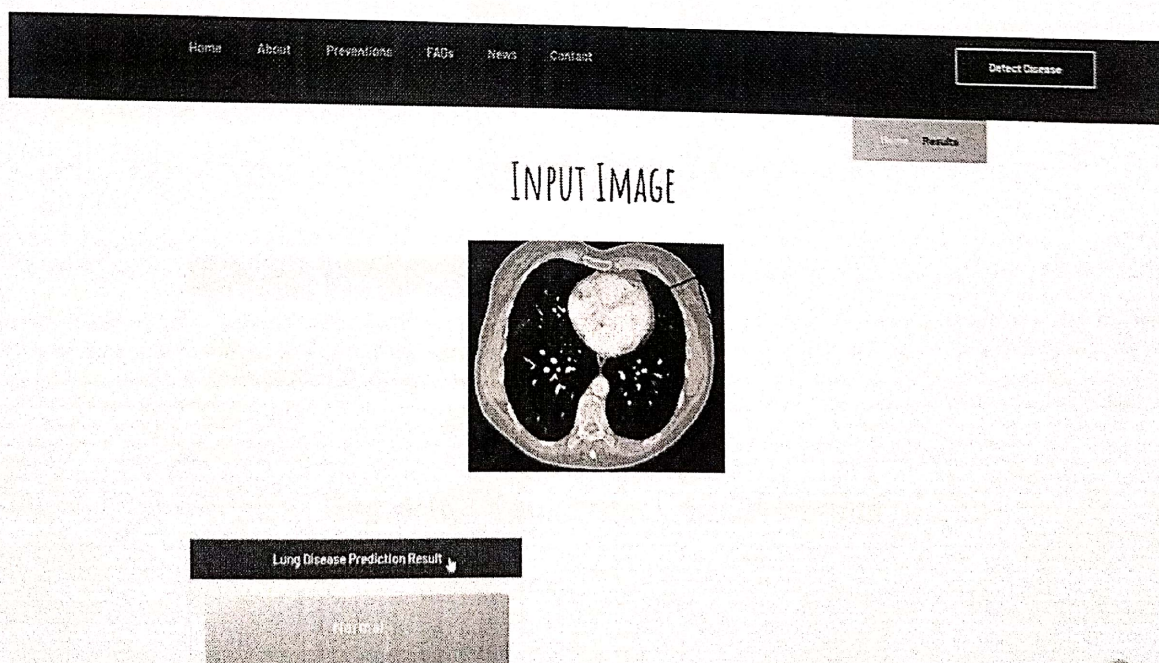




**Fig:6.13 : Loss of Lungs Model - Inception V3**

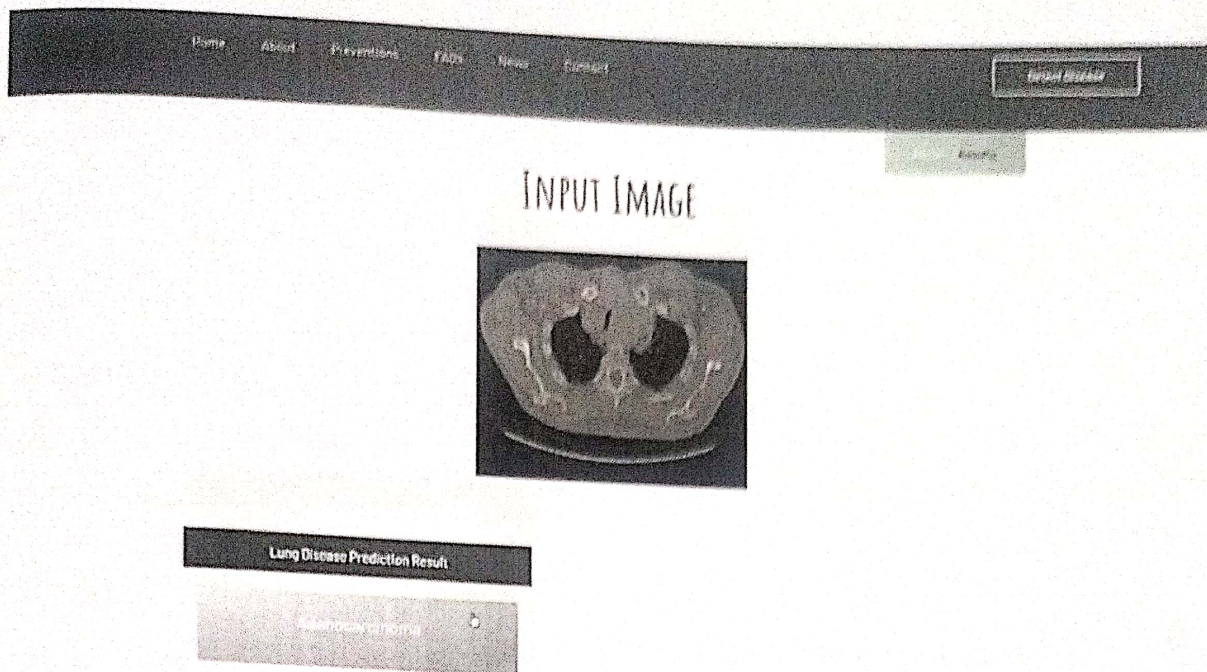
**Result:** The graph shown above is the training model loss graph of Inception V3. The loss is on validation data and training data. Also, the model is trained with the loss of 1% on validation data; it's trained for 30 epochs.

### 6.3.1 Prediction Output

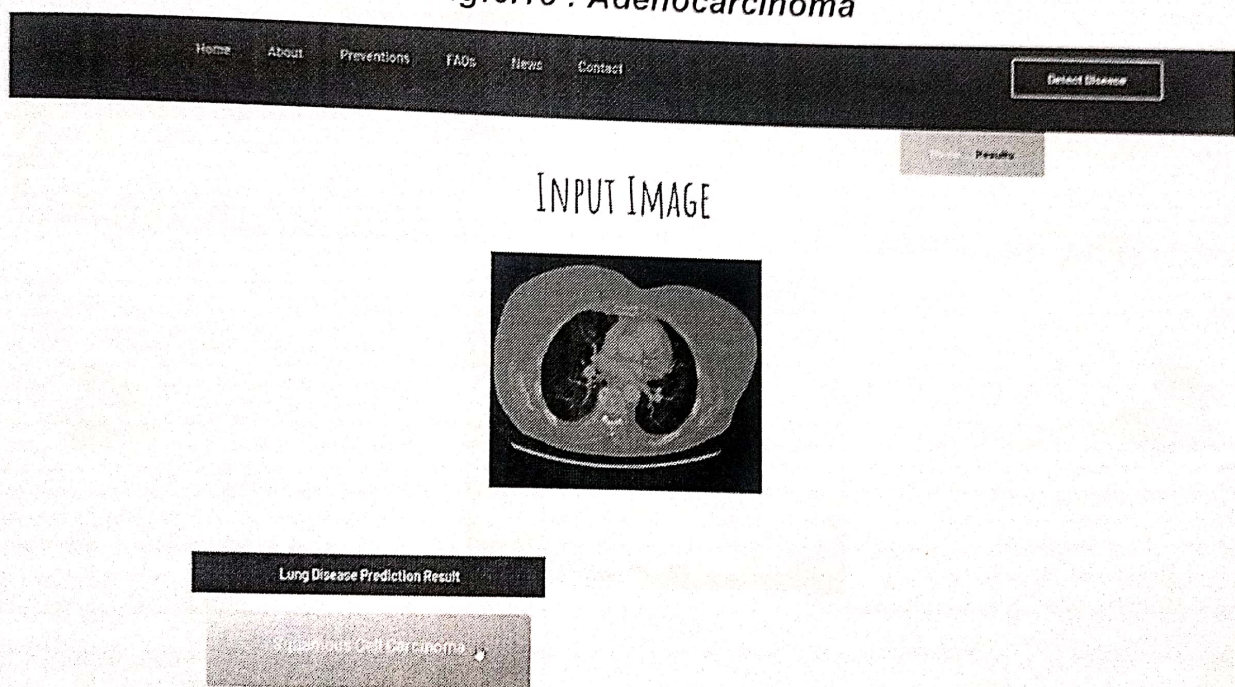


**Fig:6.14 : Normal Lungs**





**Fig:6.15 : Adenocarcinoma**



**Fig:6.16 : Squamous Cell Carcinoma**



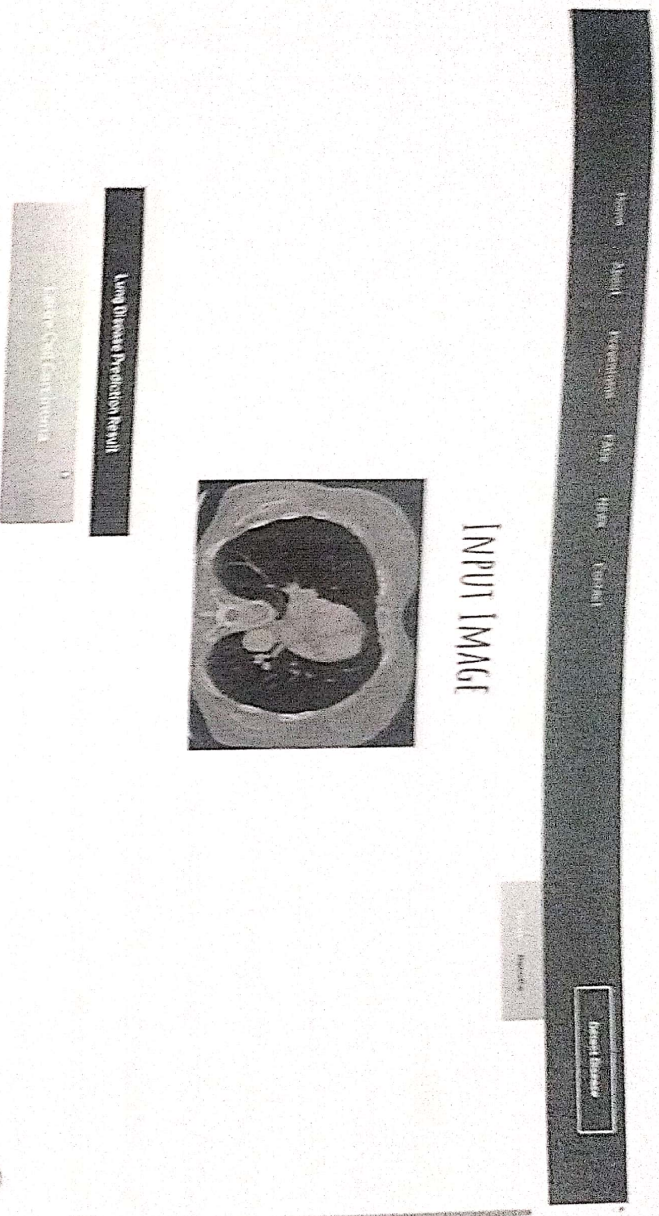


Fig:6.17 : Large Cell Carcinoma

## 6.4 USER INTERFACE

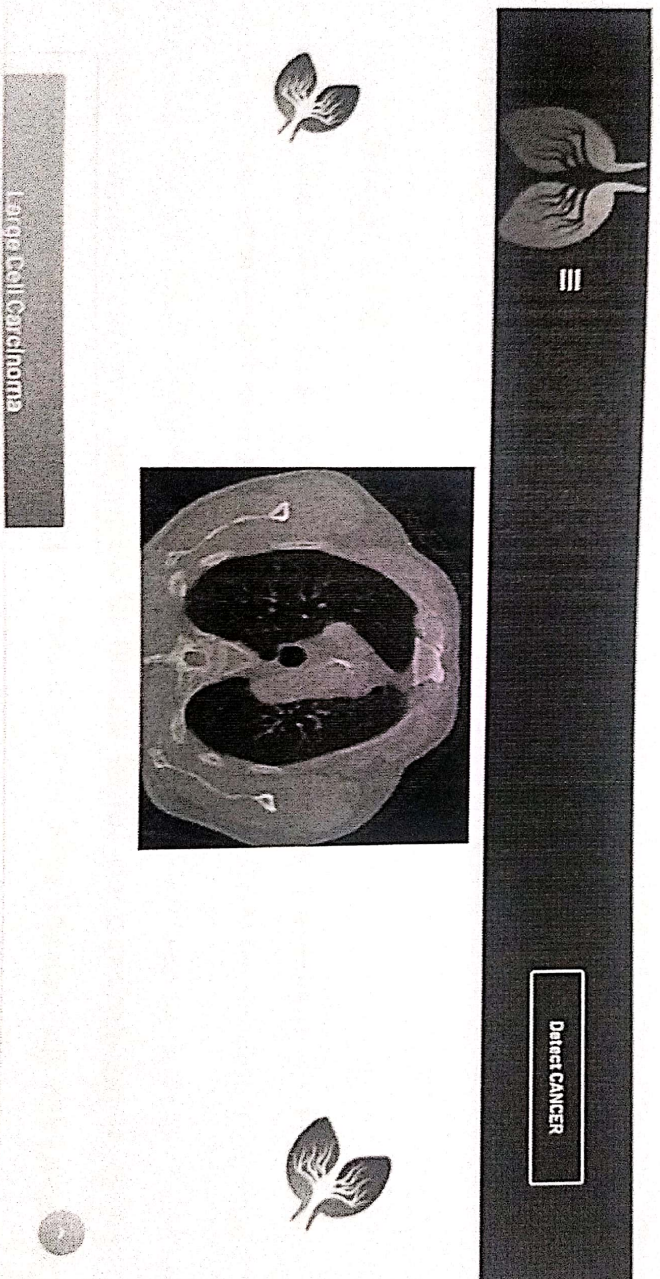


Fig:6.18 : User Interface

**Explanation:** shows the wireframe for the output of the model. It is similar to the CT scan gallery however the difference is that the user cannot select the image and will just view it. The images also are tagged with labels to see and is either tagged with cancer found or no cancer found.



## CHAPTER 7

### CONCLUSION

#### 7.1 CONCLUSION

In conclusion, the development of a disease diagnosis system using computer vision and deep learning represents a significant stride towards enhancing healthcare outcomes. This project demonstrates the potential of cutting-edge technologies to revolutionize the traditional methods of medical image analysis. By leveraging sophisticated algorithms and neural networks, the system has showcased remarkable accuracy and efficiency in identifying and classifying diseases from various medical images. We proposed a computerized method for the segmentation and identification of a Multi Disease detection using the Convolution Neural Network. The input images are read from the local device using the file path and converted into grayscale images. [17] These images are pre-processed using an adaptive bilateral filtering technique for the elimination of noises that are present inside the original image. The binary thresholding is applied to the denoised image, and Convolution Neural Network segmentation is applied, which helps in figuring out the tumor region in the input images. This phase we worked on brain tumor with transfer learning EfficientNetB3 as model and yields promising results without any errors and much less computational time.

#### 7.2 FUTURE SCOPE

- Extend the system to support multiple medical imaging modalities such as MRI, CT scans, ultrasound, and X-rays. Integrating information from various modalities can provide a more comprehensive and accurate diagnosis.
- Work towards real-time diagnosis to enable faster decision-making in critical situations. This could be particularly beneficial in emergency settings where quick and accurate diagnosis is crucial.
- Integrate the system with existing radiology workflows to automate the analysis of medical images. This can help radiologists by providing preliminary findings and reducing the time needed for diagnosis.
- Enhance the interpretability of the deep learning models used in the project. Developing methods for explaining the model's decisions can increase trust among healthcare professionals and facilitate the acceptance of AI in clinical practice.



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## APPENDIX

### A. SOURCE CODE

#### PYTHON CODE:

MODEL TRAINING FOR BRAIN TUMOR:

```
import os
from cv2 import imread
import matplotlib.pyplot as plt
from sklearn import metrics
import keras
from keras.layers import Flatten, Dense, Dropout
from keras.preprocessing.image import ImageDataGenerator
import numpy as np
from tensorflow.keras.applications import VGG19 #resnet 50
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
import warnings
warnings.filterwarnings("ignore")

path = "brain"

image_generator = ImageDataGenerator(
    rescale=1./255,
    horizontal_flip=2,
    vertical_flip=2,
    validation_split=0.1)
training_set = image_generator.flow_from_directory(batch_size=16,
                                                    directory=path,
                                                    shuffle=True,
                                                    target_size=(224,224),
                                                    subset="training",
                                                    color_mode='rgb',
                                                    class_mode='binary')
```



B. SCREENSHOTS

```

import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler

# Load data
train_data = pd.read_csv('train_data.csv')
val_data = pd.read_csv('val_data.csv')
test_data = pd.read_csv('test_data.csv')

# Preprocess data
def preprocess_data(data):
    # Standardize features
    scaler = StandardScaler()
    data[['x1', 'x2', 'x3', 'x4', 'x5', 'x6', 'x7', 'x8', 'x9', 'x10']] = scaler.fit_transform(data[['x1', 'x2', 'x3', 'x4', 'x5', 'x6', 'x7', 'x8', 'x9', 'x10']])
    return data

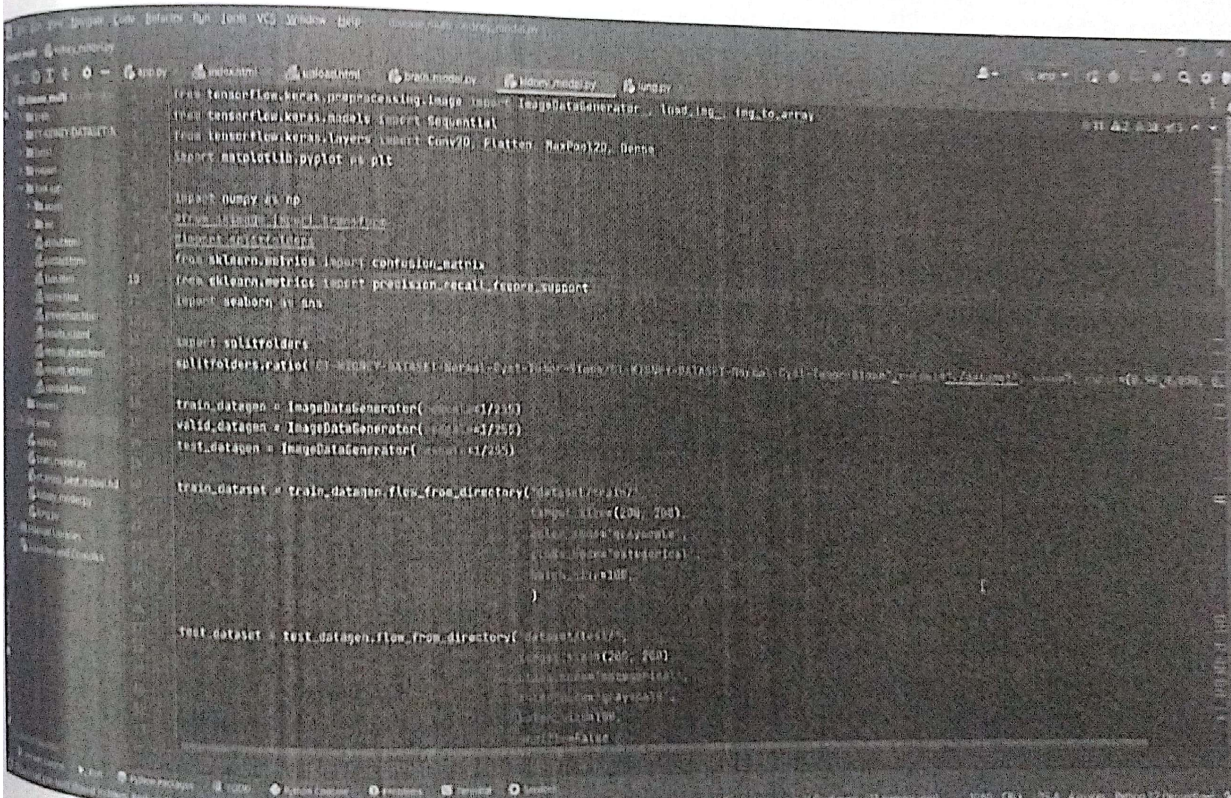
train_data = preprocess_data(train_data)
val_data = preprocess_data(val_data)
test_data = preprocess_data(test_data)

# Split data into training and testing sets
train_data = train_data[:10000]
val_data = val_data[:1000]
test_data = test_data[:1000]

# Save data to files
train_data.to_csv('train_data_preprocessed.csv')
val_data.to_csv('val_data_preprocessed.csv')
test_data.to_csv('test_data_preprocessed.csv')

```

*Fig:B.1 : Brain tumor model*



**Fig:B.2 : Kidney disease model**



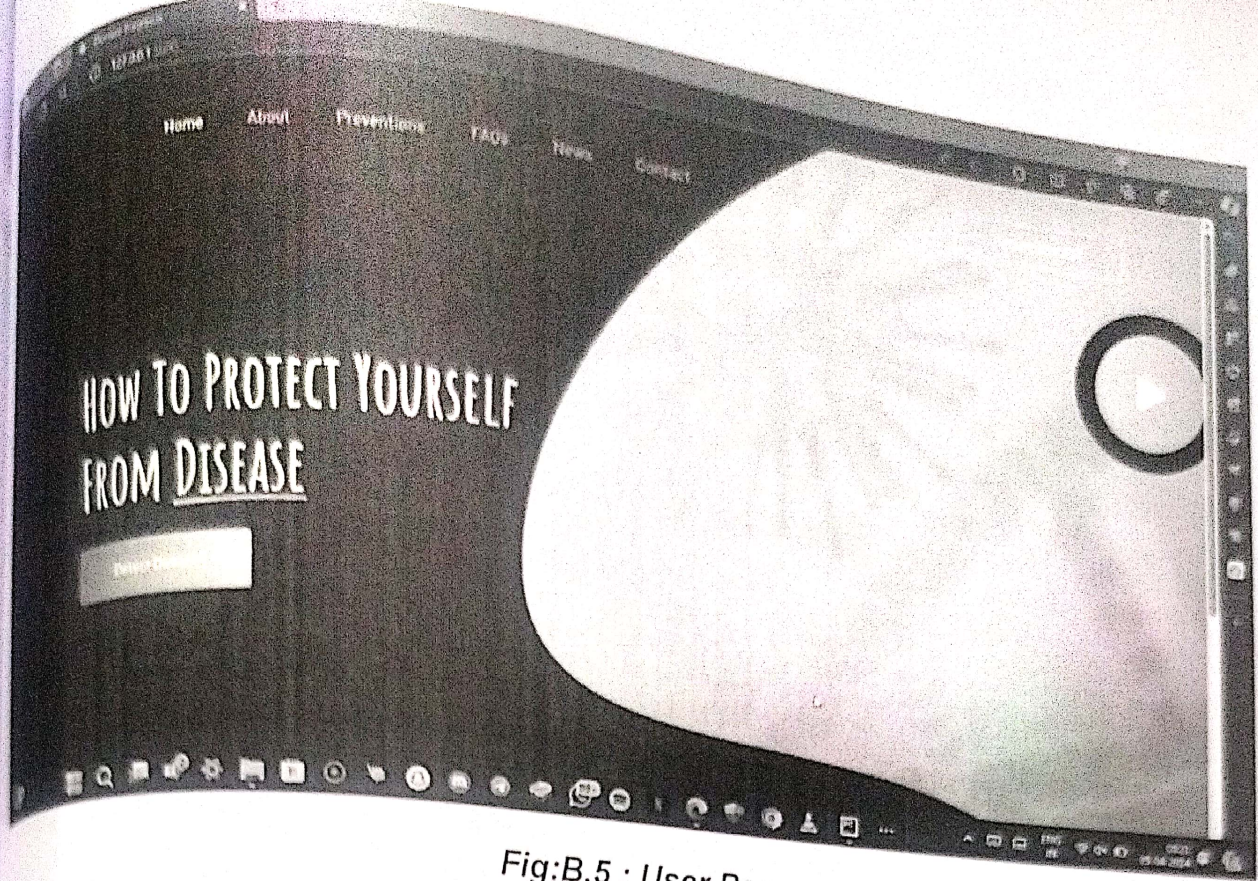


Fig:B.5 : User Page

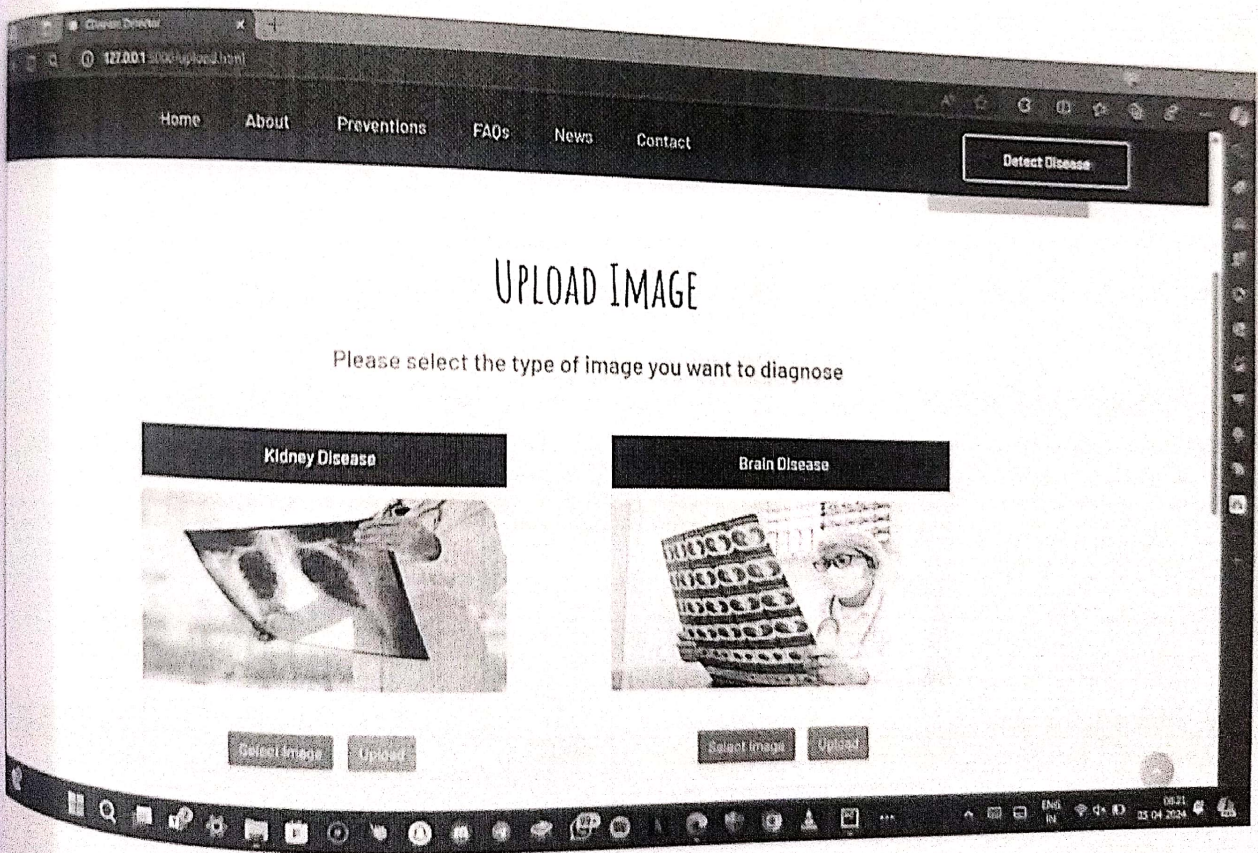


Fig:B.6 : Uploading page



# C. RESEARCH PAPER

## AI-POWERED DISEASE DIAGNOSIS FROM MEDICAL IMAGE REPORTS

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**Abstract**— The use of data science and technology in healthcare has completely changed how diseases are predicted and diagnosed. Through the integration of two state-of-the-art deep learning architectures—InceptionV3 and EfficientNet-B7—within a Flask-based API framework, this research offers a novel method for multi-disease prediction. Kidney stones, kidney cysts, kidney tumors, Lung cancer, and brain tumors are among the disorders that are being targeted. The project progresses through a number of crucial phases. first, a wide-ranging and extensive dataset made up of image data that was rigorously preprocessed. This includes data augmentation, variable normalization, and handling missing data. Modern deep learning architectures, such as Transfer learning models like InceptionV3 and EfficientNet-B7, are chosen and optimized for each disease in order to extract complex patterns from the medical imaging data. intricate connections among high-dimensional data, improving the precision of predictions. These structures are well known for improving prediction accuracy by capturing intricate linkages within high-dimensional data. The performance of the model is evaluated by calculating accuracy and loss after training. The user interface is built on top of the Flask framework. Routes are created to process user input and provide predictions using Flask. To ensure a user-friendly experience, the frontend has been painstakingly built to speed the input of symptoms or medical data. Concurrently, the backend is engineered to effectively handle user inputs, initiate the requisite prediction models, and transmit the outcomes to the user interface in a smooth manner.

**Keywords**— Deep Learning, Flask API, inceptionV3.

### INTRODUCTION

The goal of artificial intelligence (AI) development is to imitate human thought processes. Deep learning (DL), a subset of machine learning (ML), is one important method that stresses prediction using layered neural networks that are modeled after the architecture of the human brain. Because of its neural network structure, DL can process

increasingly large and complicated data inputs, unlike simpler techniques like logistic regression. This makes it useful for applications like voice translation, picture classification, and language interpretation. Precision healthcare is driving a significant transformation in the way we treat illnesses as more and more forms of health data, including genetic, tissue, and cell information, become simpler to acquire and integrate. Combining disparate data sets necessitates the use of intelligent computer algorithms that can process and learn from large amounts of complicated data simultaneously, rather than only examining each one independently. A subset of artificial intelligence called machine learning is concerned with applying mathematics to make predictions by identifying patterns in data.

### BASIC OPERATION OF NEURAL NETWORKS

Neural networks are the mainstay of deep learning, a kind of machine learning that simulates how the human brain functions. These networks use the data they already have to identify patterns and forecast the results of fresh, comparable data. Layers of neurons in neural networks process information; the input layer receives data first and generates predictions, while the output layer does the opposite. Between the input and output levels are hidden layers that house the majority of the processing. For instance, the 128 by 128 grid of 16,384 pixels that makes up our brain image.

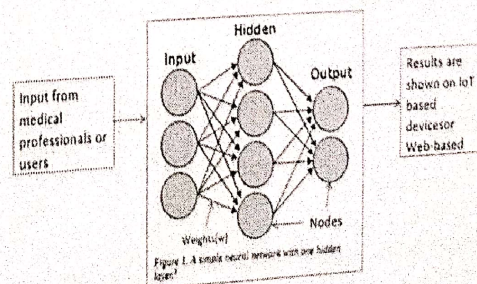


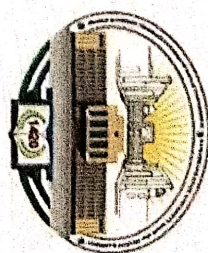
Fig 1.1 Neural network





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