DENSENET POWERED LUNG CANCER PREDICTION

A PROJECT REPORT

Submitted by

DHANUSH S (310620106027)

GOKUL M (310620106032)

in partial fulfilment for the award of the degree of

BACHELOR OF ENGINEERING

in

ELECTRONICS AND COMMUNICATION ENGINEERING

EASWARI ENGINEERING COLLEGE, CHENNAI
(Autonomous Institution)

affiliated to

ANNA UNIVERSITY: CHENNAI - 600025

APRIL 2024

EASWARI ENGINEERING COLLEGE, CHENNAI

(AUTONOMOUS INSTITUTION)

AFFILIATED TO ANNA UNIVERSITY, CHENNAI 600025

BONAFIDE CERTIFICATE

Certified that this project report **"DENSENET POWERED LUNG CANCER PREDICTION"** is the bonafide work of "**DHANUSH S (310620106027) & GOKUL M (310620106032)**" who carried out the project work under my supervision.

SIGNATURE	**SIGNATURE**
Dr. R.SENTHAMIZH SELVI	**Dr. K. RAHIMUNNISA**
HEAD OF THE DEPARTMENT	**SUPERVISOR**
Associate Professor	Associate Professor
Department of Electronics and	Department of Electronics and
Communication Engineering	Communication Engineering
Easwari Engineering College	Easwari Engineering College
Ramapuram, Chennai 600089	Ramapuram, Chennai 600089

Submitted for Semester Examination held on _______________.

INTERNAL EXAMINER **EXTERNAL EXAMINER**

ACKNOWLEDGEMENT

We owe deep gratitude to numerous individuals who played pivotal roles in executing our project, providing invaluable assistance from its conceptualization to its documentation. Foremost, we would like to convey our sincere gratitude **to Dr. T R PAARIVENDHAR, the Founder Chairman of SRM Group of Institutions**, whose unwavering support was indispensable for the successful completion of our project.

We would also like to thank **Dr. R SHIVA KUMAR, Chairman, SRM Group of Institutions, Ramapuram Campus** for providing us with the required assistance and **Dr. R S KUMAR, Principal, Easwari Engineering College** for his continuous encouragement that led us to where we are right now.

We feel glad to express our sincere thanks to **Dr. R.SENTHAMIZH SELVI, Head of the Department, Electronics and Communication Engineering** for her suggestions, support, and encouragement towards the completion of the project with perfection.

We express our sincere gratitude to our **Project Coordinator** and **Supervisor, Dr. K. RAHIMUNNISA, Associate Professor, Electronics and Communication Engineering** for her intellectual guidance and valuable suggestions in making the project a successful one.

We would extend our hearty thanks to all **our panel members** for their valuable suggestions in completing this project.

DHANUSH S
GOKUL M

ABSTRACT

Lung cancer has the potential to be life-threatening. Detecting cancer remains a significant hurdle for medical professionals, with the complete understanding of its origins and optimal treatment still elusive. However, timely identification of cancer can greatly enhance treatment prospects. Image processing techniques, including noise reduction, feature extraction, identification of affected areas, and potentially correlating with medical records pertaining to lung cancer history, are employed to pinpoint regions of the lung affected by the disease. This research demonstrates the precise classification and prediction of lung cancer through the utilization of machine learning and image processing technology. Computed Tomography images are utilized for identifying the lung cancer. A computerized tomography (CT) scan utilizes multiple X-ray images captured from various angles around the body, employing computer processing to generate cross-sectional images (slices) that reveal the internal structures, including bones, blood vessels, and soft tissues. A dataset containing thousands of high-resolution lung scans, gathered from Kaggle. The preprocessing phase transforms raw data into a usable format, while a deep learning algorithm assigns significance to the data. In the final stage, a Dense Net is employed to determine the health status of the lung, distinguishing between normal and abnormal conditions.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATION

S.NO	ABBREVIATION	EXPANSION
1	DL	Deep Learning
2	CT	Computed Tomography
3	ML	Machine Learning
4	AI	Artificial Intelligence
5	CNN	Convolutional Neural Network
6	NSCLC	Non-Small-Cell-Lung Cancer
7	SCLC	Small-Cell-Lung Cancer
8	LUAD	Lung Adenocarcinoma
9	LUSC	Lung Squamous Cell Carcinoma
10	PET	Positron Emission Tomography
11	SVM	Support Vector Machine
12	MATLAB	Matrix Laboratory
13	IOT	Internet of Things
14	CAD	Computer-aided Design
15	NLP	Natural Language Processing
16	TN	True Negative
17	FN	False Negative
18	FP	False Positive
19	TP	True Positive

CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

Deep learning is the field of study that gives computers the capability to learn without being explicitly programmed. Deep learning is one of the most exciting technologies that one would have ever come across. As it is evident from the name, it gives the computer that makes it more similar to humans: The ability to learn. Deep learning is actively being used today, perhaps in many more places than one would expect.

Deep learning, as a powerful approach to achieve Artificial Intelligence, has been widely used in pattern recognition, a very basic skill for humans but a challenge for machines. Nowadays, with the development of computer technology, pattern recognition has become an essential and important technique in the field of Artificial Intelligence. The pattern recognition can identify letters, images, voice or other objects and also can identify status, extent or other abstractions.

Since the computer was invented, it has begun to affect our daily life. It improves the quality of our lives; it makes our life more convenient and more efficient. A fascinating idea is to let a computer think and learn as a human. Basically, Deep learning is to let a computer develop learning skills by itself with given knowledge. Pattern recognition can be treated like computer being able to recognize different species of objects. Therefore, Deep learning has close connection with pattern recognition.

Deep learning is a scientific research of statistical procedures and methods which they are used by computer systems designed to perform such functions without specific instructions, rather than trusting in the models and conclusions. This is believed to be part of an artificial intelligence. Deep learning algorithms sets up a mathematical model based on data examples called "training data" to make predictions without the completion of a task being explicitly programmed.

1.2 PURPOSE OF DEEP LEARNING

Deep learning is an application of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed. Deep learning focuses on the development of computer programs that can access data and use it learn for themselves.

Nowadays, with the development of computer technology, pattern recognition has become an essential and important technique in the field of Artificial Intelligence. The pattern recognition can identify letters, images, voice or other objects and also can identify status, extent or other abstractions.

The process of learning begins with observations or data, such as examples, direct experience, or instruction, in order to look for patterns in data and make better decisions in the future based on the examples that we provide. The primary aim is to allow the computers learn automatically without human intervention or assistance and adjust actions accordingly.

1.3 PROBLEM STATEMENT

With the rapid increase in population rate, the rate of diseases like cancer, chikungunya, cholera, etc., is also increasing. Among all of them, cancer is becoming a common cause of death. Cancer can start almost anywhere in the human body, which is made up of trillions of cells. Normally, human cells grow and divide to form new cells as the body needs them. When cells grow older or become damaged, they die, and new cells take their place. When cancer cells develop, however, this orderly process breaks down. As cells become more and more abnormal, old or damaged cells survive when they should die, and new cells form when they are not needed. These extra cells can divide without stopping and may form growths called tumors. These tumors start spreading to different parts of the body. Tumors are of two types: benign and malignant, where benign (non-cancerous) is the mass of cells which lack the ability to spread to other parts of the body, and malignant (cancerous) is the growth of cells which have the ability to spread to other parts of the body. This spreading of infection is called metastasis. There are various types of cancer like lung cancer, leukemia, and colon cancer, etc. The incidence of lung cancer has significantly increased from the early 19th century. There are various causes of lung cancer like smoking, exposure to radon gas, secondhand smoking, and exposure to asbestos, etc.

1.4 OBJECTIVE

Lung cancer remains one of the leading causes of cancer-related mortality worldwide, necessitating the development of advanced diagnostic tools for early detection and intervention. Computed Tomography (CT) imaging has emerged as a powerful modality for detecting pulmonary abnormalities, offering detailed anatomical information crucial for diagnosing lung cancer. With the advent of deep learning techniques, particularly DenseNet architecture, there is a growing opportunity to enhance the accuracy and efficiency of lung cancer detection from CT images.

DenseNet, short for Dense Convolutional Network, is a state-of-the-art deep learning architecture known for its dense connectivity pattern, wherein each layer is connected to every other layer in a feed-forward fashion. This architecture promotes feature reuse and gradient flow throughout the network, facilitating better information propagation and enabling the extraction of intricate patterns from medical images.

In this study, we aim to leverage the capabilities of DenseNet architecture for the automated detection of lung cancer from CT images. By exploiting the rich spatial information encoded in CT scans, our proposed approach seeks to overcome the challenges associated with traditional image analysis methods, such as manual interpretation and subjective variability.

The primary objective of this research is to develop a robust and accurate lung cancer detection system that can assist radiologists in screening and diagnosing pulmonary nodules and lesions. By training the Dense Net model on large-scale annotated datasets comprising diverse cases of lung abnormalities, we aim to create a versatile framework capable of detecting various types and sizes of tumors with high sensitivity and specificity.

Furthermore, we emphasize the importance of early detection in improving patient outcomes and reducing mortality rates associated with lung cancer. By enabling the timely identification of suspicious lesions and nodules, our proposed method holds the potential to facilitate prompt clinical intervention, thereby enhancing the chances of successful treatment and survival.

Through rigorous evaluation and validation using independent datasets, we aim to demonstrate the efficacy and generalization of our Dense Net-based lung cancer detection system. We envision that our research findings will not only contribute to advancing the field of medical image analysis but also translate into tangible benefits for patients by enabling more accurate and efficient screening for lung cancer.

1.5 INFORMATION ABOUT LUNG CANCER

Lung cancer is a type of cancer that starts in the lungs. It is one of the most common cancers worldwide and is a leading cause of cancer-related deaths. There are two main types of lung cancer: non-small cell lung cancer (NSCLC) and small cell lung cancer (SCLC). NSCLC is the most common type, accounting for about 85% of lung cancer cases, while SCLC accounts for the remaining 15%.Lung cancer is a disease characterized by the uncontrolled growth and proliferation of abnormal cells within the lung tissue. These cells deviate from normal cellular function due to DNA mutations induced by various factors such as smoking, exposure to air pollutants, and genetic predispositions. According to the American Cancer Society, lung cancer accounts for approximately 14% of all newly diagnosed cancers. In 2018, it was estimated that there were approximately 234,030 new cases of lung cancer in the United States, resulting in approximately 154,050 deaths. Presently, lung cancer surpasses prostate, colon, and breast cancers combined as a leading cause of mortality . Lung cancer is a prevalent and often fatal condition, claiming an estimated 422 lives worldwide each day. Predominantly afflicting individuals over the age of 50, the incidence of lung cancer continues to rise steadily. Due to its challenging detect-ability compared to other ailments, lung cancer stands as a leading cause of mortality. The primary impediment lies in the minute size of the initial lesion, commonly referred to as a nodule. Initially characterized by diminutive cancer cell dimensions, these lesions progressively evolve into malignancy over time. Hence, early detection plays a pivotal role in disease management. Timely identification significantly enhances survival rates. Recently, advancements in computer vision technology have yielded sophisticated networks capable of autonomously discerning and delineating healthy and tumorous regions

.Deep learning algorithms can identify affected nodules in lung cancer by analyzing the size, shapes, textures, and intensities of highly detailed images provided by CT scans. 3D CT images, offering a complete imaging of lung capacity, provide a more comprehensive examination of the lungs than their 2D counterparts. Here the input data are consists of three type's especially benign case, malignant case and Normal case. Now see about that image in Detail for Lung cancer detection.

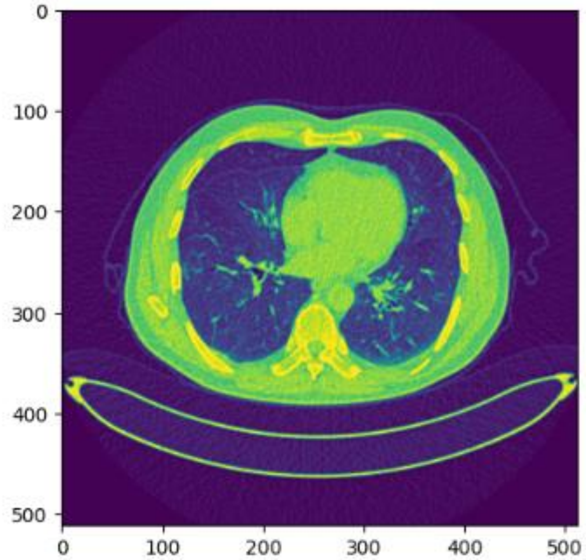


Figure 1.1: Benign Case Lung Cancer image

In lung cancer imaging, distinguishing between benign and malignant lesions is crucial. Benign lung nodules, while potentially resembling malignant ones on CT scans, typically exhibit smooth margins, a round or oval shape, and may contain calcifications with specific patterns. They often demonstrate stable size or regression over time and may have distinctive histological types like hamartomas or granulomas. Contextual clues such as location within the lung parenchyma and patient history also aid in differentiation. However, accurately discerning benign from malignant nodules can be challenging, requiring comprehensive evaluation integrating imaging, clinical, and pathological data for optimal diagnosis and management .

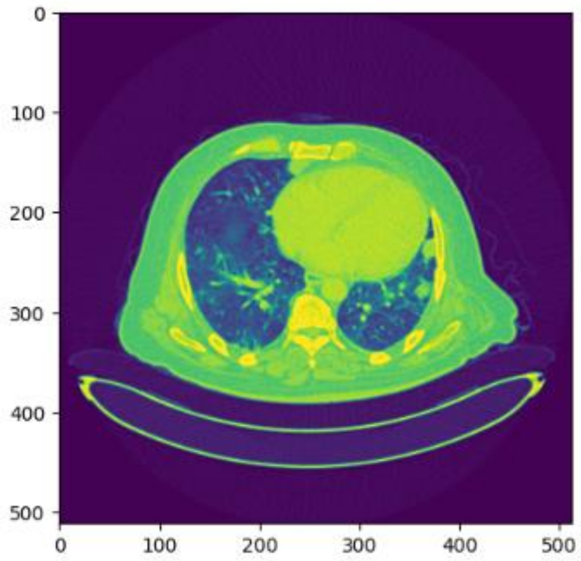


Figure 1.2: Malignant case lung cancer image

Malignant lung cancer CT images typically exhibit several characteristic features that aid in their identification and differentiation from benign lesions. These features include irregular or spiculated margins, often indicative of invasive growth, as opposed to the smooth margins commonly seen in benign nodules. Malignant nodules may also appear heterogeneous in density, reflecting the presence of necrosis, hemorrhage, or varying degrees of cellular proliferation. Additionally, they often demonstrate rapid growth over time, with evidence of increasing size or development of satellite lesions. Malignant lung tumors frequently exhibit associated findings such as adjacent lung consolidation, pleural effusion, or mediastinal lymphadenopathy, indicating local invasion or metastasis. Moreover, certain imaging characteristics, such as the presence of a "halo sign" or "air bronchogram," may suggest specific histological subtypes of lung cancer. Overall, the recognition of these malignant features on CT imaging plays a crucial role in guiding further diagnostic and therapeutic interventions for patients with lung cancer.

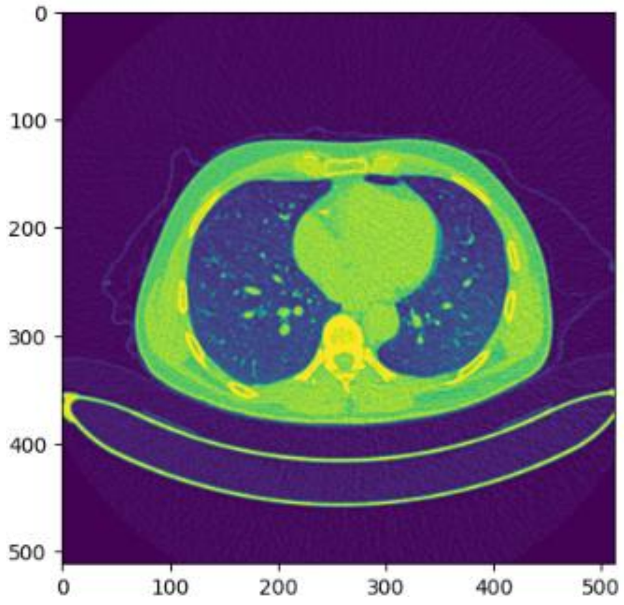


Figure 1.3: Normal Case Lung cancer image

Normal lung CT images depict healthy lung parenchyma characterized by a distinct pattern of air-filled spaces (alveoli) surrounded by thin walls. These images typically exhibit symmetric lung fields with a homogeneous appearance, showing no evidence of focal abnormalities such as nodules, masses, or consolidations. The lung vasculature, including pulmonary arteries and veins, appears well-defined and proportionate to the surrounding lung tissue. Trachea, bronchi, and bronchial branches are also visualized, demonstrating patent airways without any signs of obstruction or luminal narrowing. Pleural surfaces appear smooth and continuous, with no evidence of pleural effusion, pneumothorax, or pleural thickening. Normal lung CT images may exhibit subtle variations in lung density due to differences in regional ventilation and perfusion, but these variations remain within the expected range for healthy lung tissue. Overall, normal lung CT images serve as a reference for comparison when evaluating patients for respiratory conditions, providing a baseline assessment of lung anatomy and function.

CHAPTER 2

LITERATURE SURVEY

2.1 LITERATURE SURVEY

In the 21st century, cancer is still considered a serious disease as the mortality rates are high. Among all cancer types, lung cancer ranks first regarding morbidity and mortality . There are two main categories of lung cancer: non-small-cell lung cancer (NSCLC) and small cell lung cancer (SCLC). For non-small-cell lung cancer, a subcategorization into lung squamous cell carcinoma (LUSC) and lung adenocarcinoma (LUAD) is further used. These types of cancers account for approximately 85% of lung cancer cases. Compared with the diagnosis of benign and malignant, further fine-grained classification of lung cancers such as LUSC, LUAD, and SCLC is of great significance for the prognosis of lung cancer. Accurately determining the category of lung cancer in the early diagnosis directly influences the effect of the treatment and thus the patients' survival rate. Positron emission tomography (PET) and computed tomography (CT) are both widely used noninvasive diagnostic imaging techniques for clinical diagnosis in general and for the diagnosis of lung cancer in particular. Immuno histochemical evaluation is considered the gold standard for lung cancer classification.

Advances in artificial intelligence research enabled numerous studies on the automatic diagnosis of lung cancer. The use of data in lung cancer-type classification is roughly divided into three categories: CT and PET image data as well as pathological images . The well-known data science community Kaggle provides high-quality CT images for participants with the task to distinguish malignant or benign nodules from pulmonary nodules. Kaggle competitions repeatedly produce excellent deep learning approaches for these tasks . With the progresses in the research of automatic lung cancer diagnosis, studies are no longer limited to the classification of benign and malignant nodules and data sets are no longer limited to

CT images .

Wu et al. use quantitative imaging characteristics such as statistical, histogram-related, morphological, and textural features from PET images to predict the distance metastasis of NSCLC, which shows that quantitative features based on PET images can effectively characterize intratumor heterogeneity and complexity. Two recent publications propose the application of deep learning to pathological images to classify NSCLC and SCLC [10] and to classify transcriptome subtypes of LUAD . The complexity of the clinical diagnosis of lung cancer is also characterized by the wide range of imaging modality, which is employed in the diagnosis

Previous research already proved that deep learning approaches can not only use the feature distribution patterns from different pulmonary imaging modalities but even merging different features to achieve the computer-aided diagnosis. Liang et al. employ multichannel techniques to predict the IDH genotype from PET/CT data using a convolutional neural network (CNN), while other approaches use a parallel CNN architecture to extract several features of different imaging modalities .

Compared with the classification of the benign and malignant, the classification of the three types of lung cancer from medical images are more suitable to constitute a fine-grained image recognition problem as diverse distributions of features and potential pathological features need to be considered. Because the fine-grained features which need to extract in images, and meanwhile the lesion region is a small part of the whole image, the deep learning framework is susceptible to feature noise. At present, most methods based on various deep learning frameworks have proved to have certain bottleneck in fine-grained problems. In order to solve this problem, the previous research mainly implements the attention mechanism from the two dimensions (channel and spatial) of the feature representation. The channel attention mechanism models the relationship between feature channels, while the spatial attention mechanism ensures that noise is suppressed by weighting feature representation spatially . So far, spatial attention mechanism has been used in medical image processing to enhance extracted features . The channel attention mechanism has been used in the detection and classification of pulmonary disease . The presentation of these attention mechanisms illustrates the source of characteristic noise from different perspectives. There are few related studies on how to use the attention mechanism more effectively on images with different imaging modalities, so the deep learning model based on the multimodality dataset still has problems in fine-grained problems.

Many works has already been proposed for prediction of cancer by various researchers among then Palani et al., has proposed IoT based predictive modeling by using fuzzy C mean clustering for segmentation and incremental classification algorithm using association rule mining and decision tree for classification for classifying the tumor sets and based on the output generated by incremental classification model convolutional neural network has been applied with other features for predicting benign or malignant.

Lynch et al., Various machine learning algorithm are implemented for predicting the survivability rate of person, performance is measured based on root mean square error. Each model is trained using 10-fold cross validation, as the parameters are preprocessed by assigning default value so cross

validation is used for avoiding over fitting.

FENWA et al., proposed a model whether feature like contrast, brightness from the image dataset is extracted using texture based feature extraction and on that two type of machine learning algorithm are applied one is artificial neural network another one is support vector machine and then performance has been evaluated on both the algorithm to compare which algorithm is giving more accuracy.

Öztürk et al., proposed a model where a five type of feature extraction techniques were used in individual classification algorithm to predict at which features extraction technique which machine learning algorithm is giving more accuracy.

Jin et al., proposed a model where the original image is first converted into binary image the erosion and dilution has been operated on that image after that image has been segmented on the segmented image region of interest extraction is applied to identify volume or size of the tumor and after extraction convolutional neural network is applied with softmax classification layer to recognize the tumor is cancerous or not.

Sumathipala et al., proposed a model where the image data are taken from LIDC-IDRI, after collecting the image data image filtration has been implemented, filtration is done based on the patient who went through biopsy and module level is equal to 30 and then images whose module level is equal to 30 is segmented and then Logistic regression and random forest has been applied for prediction.

Bhatia et al. developed a preprocessing pipeline using UNet and ResNet models to enhance feature extraction from lung CT images for cancer detection. They then combined XGBoost and random forest classifiers in an ensemble approach to assess malignancy likelihood, resulting in an 84% increase in accuracy compared to conventional techniques, as shown on the LIDC-IRDI dataset.

Joon et al. utilized an active spline model for lung cancer segmentation analysis in X-ray images. Pre-processing involved median filtering for noise reduction, followed by segmentation using K-means and fuzzy C-means clustering. Feature extraction was conducted post-segmentation, and classification employed a Support Vector Machine (SVM) model in MATLAB to detect and classify lung cancer in both normal and malignant images.

Faruqui et al. developed LungNet, a deep-CNN model integrating CT-scan images with wearable sensor-based MIoT data for enhanced CAD of lung cancer. LungNet achieved 96.81% accuracy and a low false positive rate of 3.35% when classifying lung cancer into five classes, outperforming similar CNN-based classifiers. It accurately classified stage-1 and stage-2 lung cancers into subclasses with 91.6% accuracy and a false positive rate of 7.25%. Trained on a balanced dataset of 525,000 images and operating from a centralized server, LungNet shows promise for automated lung cancer diagnosis systems.

Hasan and Al Kabir developed algorithms to determine lung cancer spread using image processing and statistical learning. Their approach achieved 99.42% accuracy, significantly higher than previous methods, with recall, precision, and F-score reaching 99.76%, 99.88%, and 99.82% respectively, highlighting its superiority.

Lakshmanaprabu et al. developed OODN (Optimal Deep Neural Network) to improve lung cancer detection in CT scans by reducing features and comparing its performance with other algorithms. Automated classification streamlined human labeling, reducing time and errors. The study showed significant improvements in accuracy and precision, achieving a peer specificity of 94.56%, accuracy of 96.2%, and sensitivity of 94.2% in classifying lung images, demonstrating enhanced cancer detection feasibility in CT scans.

CHATPER 3

THEORITICAL BACKGROUND

The proposed system describes the step by step process of the glaucoma and gives a detailed view and illustration of the entire process.

3.1 DATA COLLECTION

To create a successful Deep learning learning model, it is imperative that an organization has the ability to train, test, and validate them prior to deploying into production.

Websites

Kaggle , Data towards science

3.2 FEATURE SELECTION TECHNIQUES

3.2.1 DATA SET SELECTION

Data is the most import part when you work on prediction systems. It plays a very vital role your whole project i.e., you system depends on that data. So selection of data is the first and the critical step which should be performed properly, For our project we got the data from the government website. These data sets were available for all. There are other tons of websites who provide such data. The data set we choose was selected based on the various factors and constraints we were going to take under the consideration for our prediction system.

3.2.2 DATA CLEANING AND DATA TRANSFORMATION

After we have selected the data set. The next step is to clean the data and transform it into the desired format as it is possible the data set we use may be of different format. It is also possible that we may use multiple data sets from different sources which may be in different file formats. So to use them we need to convert them into the format we want to or the type that type prediction system supports. The reason behind this step is that it is possible that the data set contains the constraints which are not needed by the prediction system and including them makes the system complicated and may extend the processing time. Another reason behind data cleaning is the data set may contain null value and garbage values too. So the solution to this issue is when the data is transformed the garbage values are replaced. There are many methods to perform that.

3.2.3 DATA PROCESSING

After the data has been cleaned and transformed it is ready to process further. After the data has been cleaned and we have taken the required constraints. We divide the whole data set into the two parts that can be either 70-30 or 80-20. The larger portion of the data is for the processing. The data set obtained will now be subjected to various data mining techniques.

Data Preprocessing is a technique that is used to convert the raw data into a clean data set. In other words, whenever the data is gathered from different sources it is collected in raw format which is not feasible for the analysis.

- Importing the required

  Libraries

- Importing the dataset

- Handling the Missing Data
- Encoding categorial data
- Splitting the dataset
- Feature scaling.

3.3 ALGORITHM- DENSENET

3.3.1 INTRODUCTION

The Dense Net architecture, short for Densely Connected Convolutional Networks, represents a breakthrough in deep learning architecture design, introduced by Huang et al. in 2017. Dense Net addresses the challenge of information flow and feature reuse in deep neural networks by introducing dense connectivity patterns among layers. This innovative architecture promotes richer feature representations, alleviates vanishing gradient problems, and enhances model interpretability.

At the core of Dense Net is the concept of dense connectivity, where each layer receives feature maps from all preceding layers as input and passes its own feature maps to all subsequent layers. This dense interconnection facilitates direct communication between layers, enabling information to flow more efficiently throughout the network. Unlike traditional architectures, where feature maps are combined through summation or concatenation at specific intervals, DenseNet connects each layer to every other layer in a feed-forward fashion.

Dense connectivity encourages feature reuse and fosters feature propagation, allowing the network to learn more discriminative representations with fewer parameters. By leveraging the collective knowledge from preceding layers, each layer can access a rich hierarchy of features extracted from earlier stages of the network. This promotes deeper understanding of the input data and enables the network to capture intricate patterns and relationships. In addition to dense connectivity, DenseNet incorporates transition layers between dense blocks to manage the growth of feature maps and control computational complexity. These transition layers typically consist of batch normalization, 1x1 convolutional layers, and down sampling operations, which compress feature maps and spatial dimensions while preserving important information.

The Dense Net architecture offers several advantages over traditional convolutional neural networks (CNNs), including parameter efficiency, improved gradient flow, and enhanced feature propagation. By facilitating dense connections among layers, Dense Net enables deeper networks with reduced vanishing gradient effects, leading to more stable training and better generalization performance.

Dense Net has demonstrated state-of-the-art results on various computer vision tasks, including image classification, object detection, and semantic segmentation. Its ability to capture rich feature representations and exploit feature reuse makes it a powerful tool for tackling complex visual recognition tasks.

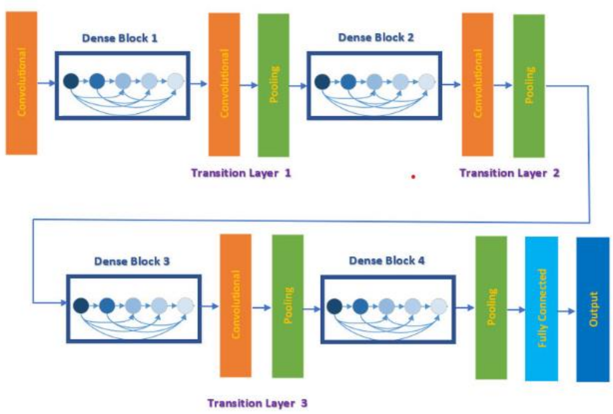


Figure 3.1: Dense Net Architecture

3.3.2 LAYERS OF DENSENET

Dense Blocks:

DenseNet is characterized by the presence of dense blocks, which are the building blocks of the architecture. Each dense block comprises multiple densely connected convolutional layers. In a dense block, each layer receives feature maps from all preceding layers as input and passes its own feature maps to all subsequent layers. This dense connectivity pattern fosters extensive feature reuse and facilitates the learning of highly discriminative representations.

Transition Layers:

Transition layers are inserted between dense blocks to manage the growth of feature maps and control computational complexity. A transition layer typically consists of three main components: a batch normalization layer to standardize the input, a 1x1 convolutional layer to reduce the number of feature maps, and a downsampling operation (e.g., average pooling) to compress the spatial dimensions. These operations help maintain a balance between model complexity and representational power.

Composite Layers:

Within each dense block, composite layers are responsible for extracting hierarchical features from the input data. A composite layer typically consists of a sequence of operations, including convolutional filters (e.g., 3x3 convolutions), batch normalization to stabilize the training process, and activation functions (e.g., ReLU) to introduce non-linearity. These operations iteratively refine the input features and capture increasingly abstract representations as information flows through the network.

Global Average Pooling Layer:

At the end of the network, a global average pooling layer is commonly employed t aggregate spatial information across feature maps. This layer computes the average value of each feature map, resulting in a compact feature vector that encapsulates the most salient information from the input data. The pooled representation serves as input to a fully connected layer or softmax classifier for making predictions.

By integrating these interconnected layers, DenseNet architectures achieve remarkable parameter efficiency, enabling deeper networks with fewer parameters compared to traditional architectures. This design choice, coupled with dense connectivity and feature reuse, empowers DenseNet models to achieve state-of-the-art performance on various computer vision tasks, including image classification, object detection, and semantic segmentation.

3.3.3 APPLICATIONS OF DENSET-NET

DenseNet, or Densely Connected Convolutional Networks, has found applications across various domains within computer vision and beyond. Some notable applications of DenseNet include:

1. **Image Classification:** DenseNet has been widely used for image classification tasks, where the goal is to classify input images into predefined categories. Its dense connectivity pattern enables efficient feature reuse, allowing the network to capture intricate patterns and relationships within the input data. DenseNet architectures have achieved state-of-the-art performance on benchmark datasets such as ImageNet.

2. **Object Detection:** DenseNet architectures have been adapted for object detection tasks, where the objective is to identify and localize objects of interest within images. By

leveraging dense connections among layers, Dense Net-based object detection models can effectively extract hierarchical features and improve detection accuracy. These models are employed in applications such as autonomous driving, surveillance, and medical imaging.

3. **Semantic Segmentation:** Dense Net has been successfully applied to semantic segmentation tasks, which involve partitioning input images into meaningful segments and assigning semantic labels to each segment. The dense connectivity within Dense Net facilitates the propagation of spatial information across layers, enabling accurate pixel-level predictions. Dense Net-based segmentation models are used in medical imaging, satellite image analysis, and scene understanding.

4. **Medical Image Analysis:** Dense Net architectures have been employed in various medical image analysis tasks, including tumor detection, disease diagnosis, and organ segmentation. The dense connectivity pattern helps capture subtle patterns and abnormalities within medical images, leading to improved diagnostic accuracy. DenseNet-based models are utilized in radiology, pathology, and other medical specialties to assist healthcare professionals in clinical decision-making.

5. **Video Analysis:** DenseNet architectures have been extended to video analysis tasks, such as action recognition, activity detection, and video captioning. By exploiting temporal dependencies across frames, DenseNet-based models can capture motion information and temporal context, leading to more robust video understanding. These models find applications in surveillance, video content analysis, and human-computer interaction.

6. **Natural Language Processing (NLP):** While originally designed for computer vision tasks, DenseNet architectures have also been adapted for certain NLP applications, such as text classification and sentiment analysis

CHAPTER 4

SYSTEM DESIGN

4.1 PROPOSED WORK

Based on the literature survey a novel model has been proposed which consist of pre- processing block, segmentation block, feature extraction block and then classification block. In prediction of cancer CT scan report is basically used. But CT scan report is full of noise which cannot be seen by human eye for that reason various digital image processing plays a important role to get a noise free image. Digital image processing is the process where the analysis and manipulation of image is used to extract some useful information from the image. Digital image processing involve various step like image pre-processing where we can enhance the image using histogram equalization, spatial filter etc. Then image restoration can be done where various kind of noise like salt and pepper noise, Gaussian noise etc are applied and filter like median filter, mean filter can be applied on the pre-processed image. After that color conversions is applied only if the image is colored image then convert it to gray level. Fig. shows the proposed novel framework. Image segmentation is a process which divides the image into several segment based on the pixel, once the image segmentation is over the feature extraction can be applied. Feature extraction is a type of dimensionality reduction where a set of raw data is reduced to more manageable group image data for extracting the feature like region and texture. After extracting the feature different machine learning technique is used to classify the image.

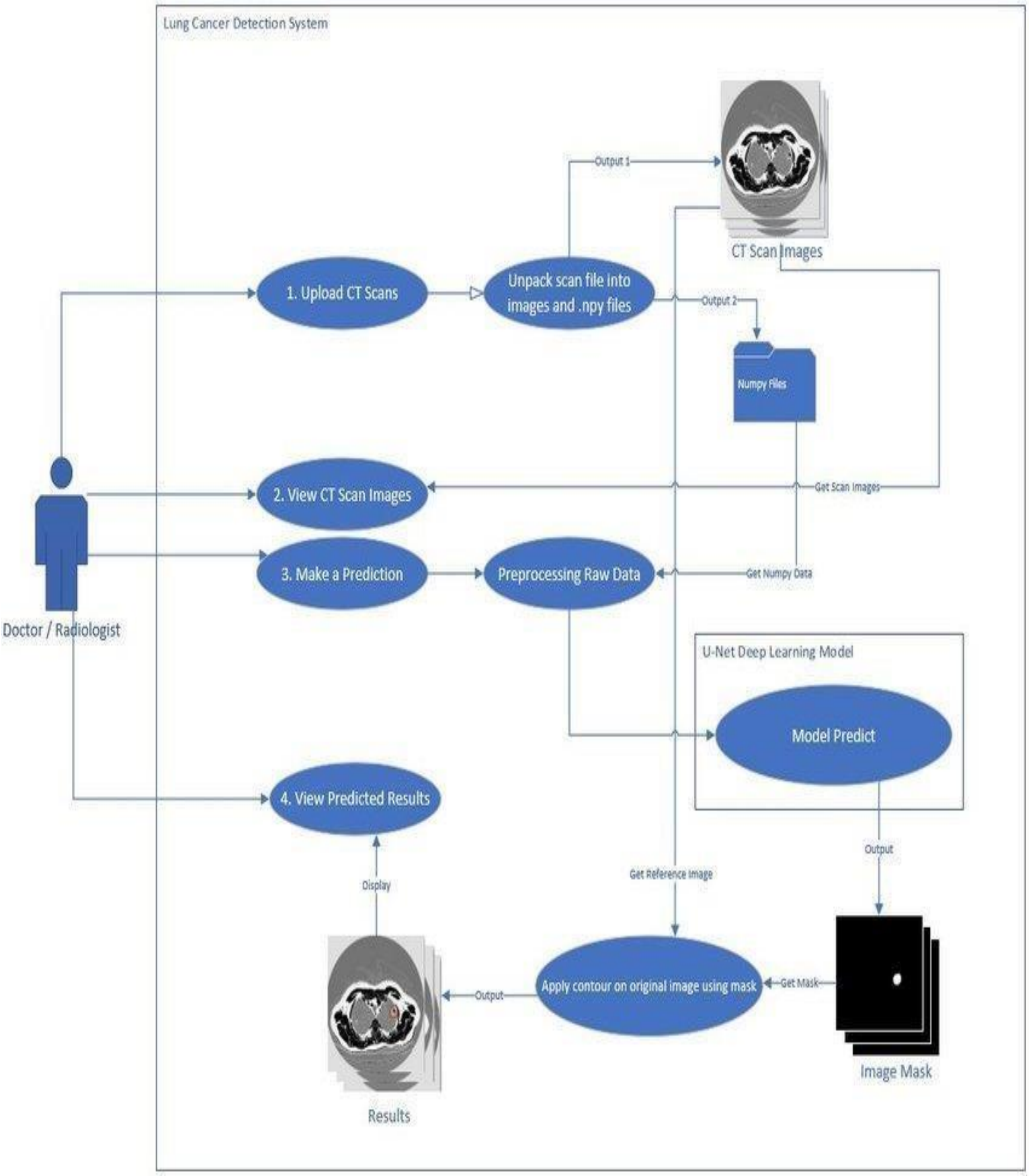


Figure 4.1: Flow Diagram of Proposal Model

4.2 ARCHITECTURE DIAGRAM

The following algorithm describes the step by step approach for the proposed model.

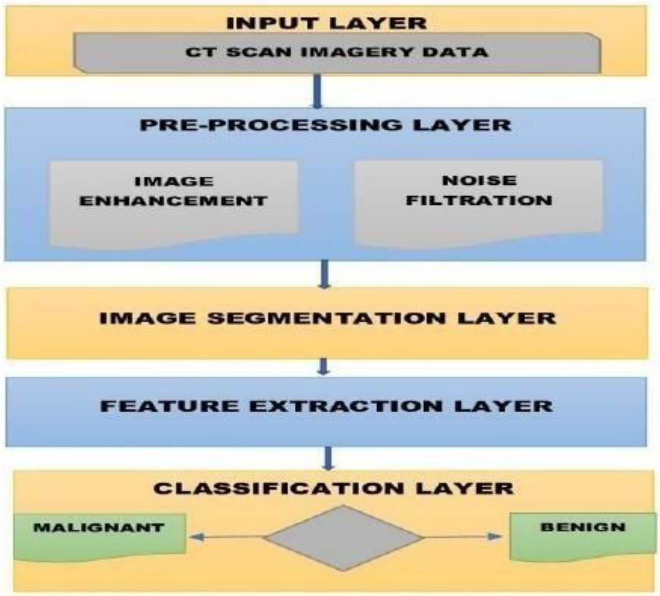


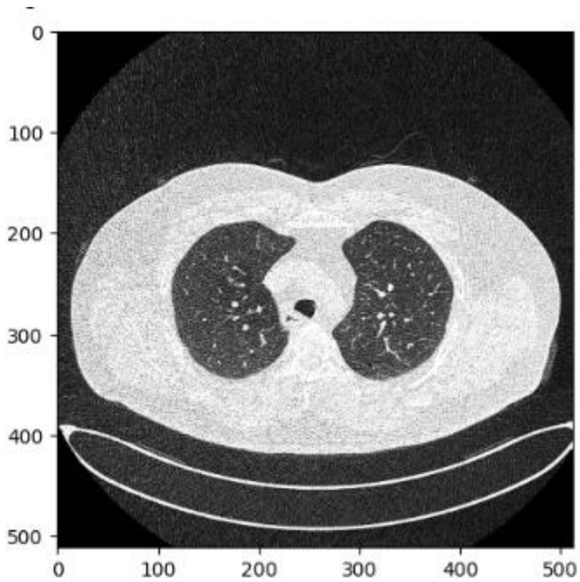
Fig 4.2: Implementation Model

.

4.3 MODULES

4.3.1 PRE-PROCESSING LAYER

Image has been collected from Kaggle. The original image was full of noise and for that first we have applied histogram equalization on the image to enhance the image and then on the equalized image median filter has been applied to remove the noise which was already present in the image after getting the noise free image we have applied some more noise in the image yield more clearer picture then again noise has been removed using median filter. Generally median filter is non linear digital filtering technique and it is also used as smoothing of images as it don't blur the edges completely as compare to other filtration technique like Gaussian filter or average filter.



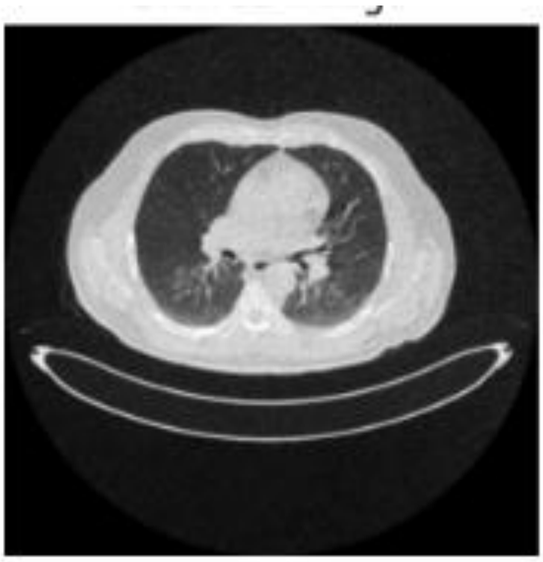


Figure 4.3 Gray scale image Figure 4.4 Noise removal image

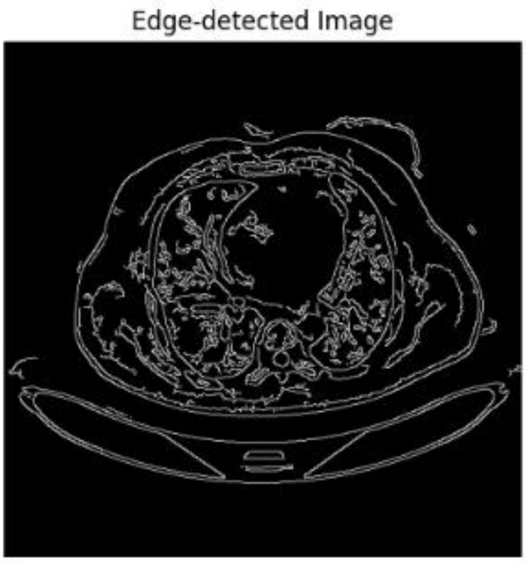


Figure 4.5 Edge Detected image

4.3.2 SEGMENTATION LAYER

Image segmentation is a method of partitioning the image into various parts. After pre- processing the image on the pre-processed image segmentation is applied to acquire the information from the image. For image segmentation first we have applied edge detection technique through edge detection we can segment the boundary of the image for edge detection prewitt operator has been used, on that operator threshold has been applied so that after edge detection the intensity value which is less than threshold is removed and the intensity value which is higher than or equal to threshold will consider for further segmentation after getting the segmented image by edge detection we will apply watershed segmentation on the output image. Watershed segmentation takes the concept topographical landscape with ridge and valley which is defined by a gray level with respective pixel or gradient magnitude. There exist various ways to segment using watershed segmentation here we have used watershed segmentation using gradient. The gradient magnitude is used to preprocess the gray scale image; it has high pixel value along the object edge and low pixel value in another left region. And through this we can get the final segmented image through which we can extract features.

4.3.3 FEATURE EXTRACTION LAYER

The output generated by segmentation is used for feature extraction. By doing feature extraction we have extracted two types of feature one is region based another is texture based region based we have extracted feature like area in context to image means pixel of the image, perimeter in context image mean vector containing the distance around the boundary of each region in the image, centroid means the centre of mass of the region and it is in 1 X 2 vector form, image and based on texture we have extracted feature like mean is used to find average intensity, standard deviation is used to measure average contrast, smoothness used to measure relative smoothness of the intensity in the region, entropy is used to measure randomness using statistical approach of texture based.

In machine learning, particularly in image processing tasks, an image mask serves as a binary filter used to isolate specific regions or features within an image for further analysis. These masks are instrumental in guiding the feature extraction process by either highlighting regions of interest or suppressing background noise. For instance, in medical imaging, masks can be crafted to emphasize anomalies like tumors while minimizing irrelevant structures. Additionally, they aid in image segmentation tasks by delineating boundaries between different objects or structures, facilitating the extraction of features from each segment. During feature extraction, masks are applied to restrict analysis to designated regions, allowing for the extraction of pertinent features such as texture or shape. Ultimately, image masks play a critical role in enhancing the accuracy and effectiveness of machine learning algorithms by focusing attention on relevant areas of the image while filtering out extraneous information.

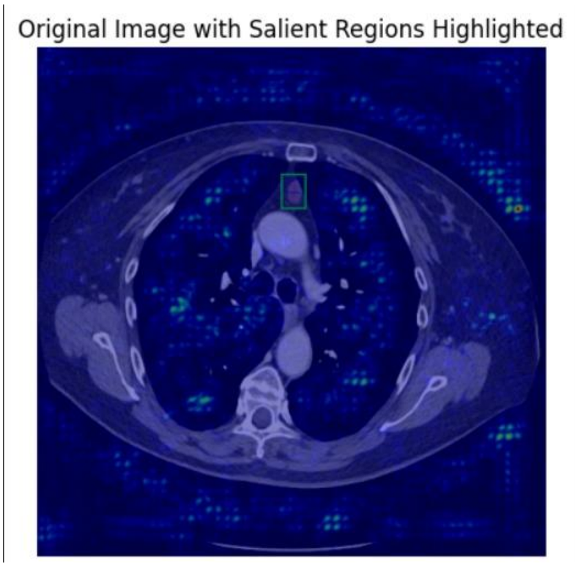


Figure 4.6: Feature Extracted Image

4.3.4 CLASSIFICATION LAYER

After feature extraction we will apply classification technique on both the feature to compare at which feature extraction which deep learning algorithm is giving more accuracy. Deep learning algorithm which has been used is Dense Net and Resnet architecture. After applying classification technique, it can be predicted that the tumour is cancerous or not and at which feature we are getting more accurate prediction.

4.4 HARDWARE SYSTEM CONFIGURATION

Processor	: Pentium Processor and Above
Ram	: 4GB
Hard disk capacity	: 500 GB

4.5 SOFTWARE SYSTEM CONFIGURATION

Operating system	: Windows 10
Programming Language	: Python 3
IDE	: Google Colab
DL Libraries	: Numpy, Pandas

CHAPTER 5

RESULTS AND DISCUSSIONS

5.1 ACCURACY TESTING

A. Confusion Matrix

Confusion matrix gives a detail description of classification or misclassification in a form of matrix. It consists of true positive (correctly predict the positive class), true negative (correctly predict the negative class), false positive (incorrectly predict the positive class), false negative (incorrectly predict the negative class).

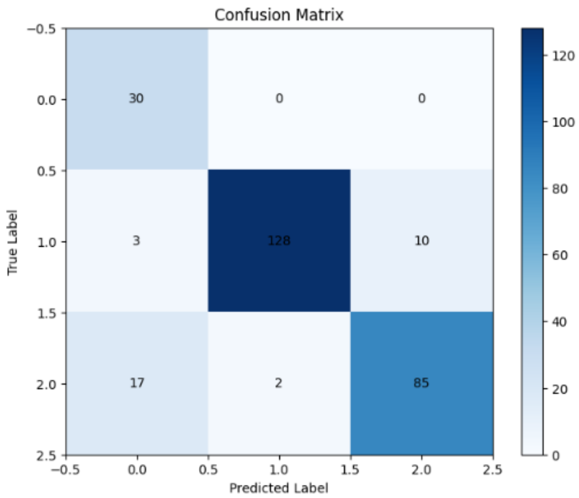


Figure 5.1: Confusion Matrix

CLASS\METRICES	TP	FP	TN	FN
BENIGN	30	20	225	0
MALIGNANT	128	2	132	13
NORMAL	85	10	161	19

5.1 Evaluation Values

B. Classification Accuracy

It is used to measure the performance of our prediction. It can be measure by correct prediction by overall prediction made.

$$\mathbf{Accuracy} = \frac{\mathbf{TP + TN}}{\mathbf{TP + TN + FP + FN}} \rightarrow (\mathbf{1})$$

Accuracy for Benign cases:

Formula: (30 +225/ (30 + 20+225+0)) * 100

Value: 92.72%

Accuracy for Malignant cases:

Formula: (128+132 / (128 + 132+2+13)) * 100

Value: 94.5%%

Accuracy for Normal cases:

Formula: (85+161 / (85 + 161+10+19)) * 100

Value: 89.45%

Average Accuracy=92.2%

C. Recall

It measures the proportion of actual positive that are correctly identified.

$$\mathbf{sensitivity} = \frac{\mathbf{TP}}{\mathbf{TP + FN}} \rightarrow (\mathbf{2})$$

Sensitivity for Benign cases:

Formula: (30 / (30 + 0)) * 100

Value: 100.00%

Sensitivity for Malignant cases:

Formula: (128 / (128 + 13)) * 100

Value: 90.78%

Sensitivity for Normal cases:

Formula: (85 / (85 + 19)) * 100

Value: 81.73%

Average Sensitivity=90.83%

D. Precision

It measure the proposition of positive identification is actually correct.

$$\textbf{Precision} = \frac{\textbf{TP}}{\textbf{TP} + \textbf{FP}} \rightarrow (\mathbf{3})$$

Precision for Benign cases:

Formula: (30 / (30 + 20)) * 100

Value: 60.00%

Precision for Malignant cases:

Formula: (128 / (128 +2)) * 100

Value: 98.46%

Precision for Normal cases:

Formula: (85 / (85 + 10)) * 100

Value: 89.47%

Average precision=82.64%

E. Specificity

It is the proportion of true negative predictions (correctly identified negative instances) out of all actual negative instances.

$$\mathbf{specificity} = \frac{\mathbf{TN}}{\mathbf{TN + FP}} \rightarrow (\mathbf{4})$$

Specificity for Benign cases:

Formula: (225 / (225 + 20)) * 100

Value: 91.84%

Specificity for Malignant cases:

Formula: (132 / (132 + 2)) * 100

Value: 98.51%

Specificity for Normal cases:

Formula: (161 / (161 + 10)) * 100

Value: 94.15%

Average Specificity=94.83%

In the realm of lung cancer detection, a confusion matrix serves as a fundamental tool for evaluating the performance of classification models. It presents a tabular representation of model predictions versus ground truth labels, particularly distinguishing between true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN).

5.2 MODEL GRAPH

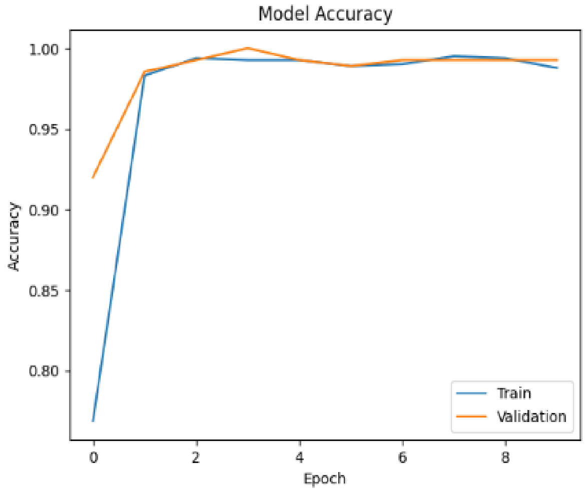


Figure 5.2: Model Accuracy Graph

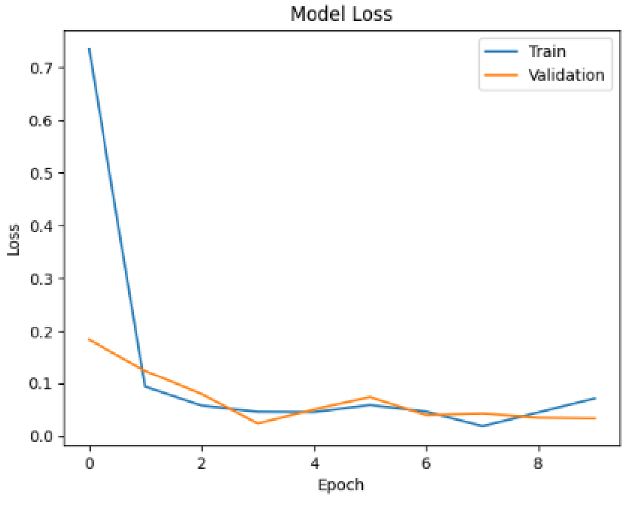


Figure 5.3: Model Loss Graph

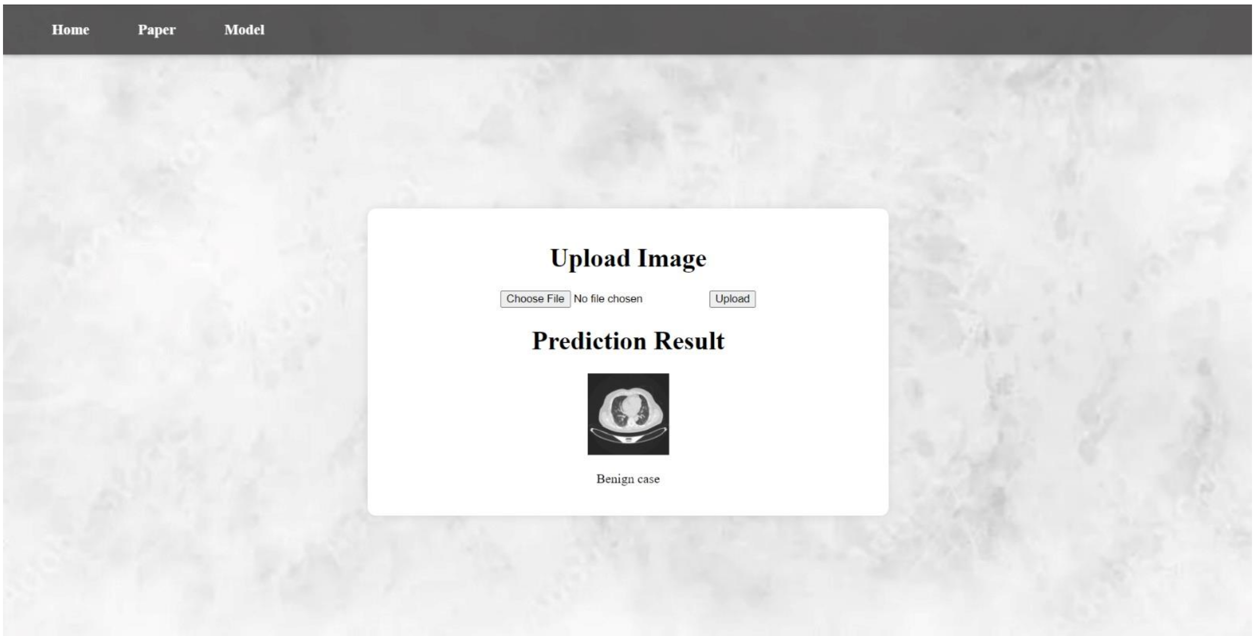


Figure 5.4 Final web image

In machine learning, model accuracy and loss graphs serve as crucial tools for evaluating the performance of models during training. The model accuracy graph tracks the model's ability to correctly predict target variables, such as class labels in classification tasks, over successive epochs or iterations. This graph displays accuracy on the y-axis against the number of epochs or iterations on the x-axis. Ideally, accuracy should increase or stabilize at a high level as training progresses, while fluctuations or sudden drops may signal issues like over fitting or under fitting. On the other hand, the loss graph depicts the value of the loss function, which measures the disparity between predicted and actual values. Lower loss values indicate better model performance. Typically, loss is plotted on the y-axis against epochs or iterations on the x-axis. A steady decrease in loss over time is desirable, although sudden spikes or fluctuations may indicate problems such as poor hyper parameter choices or noisy data. Both graphs provide insights into the model's learning process, enabling practitioners to optimize performance and address potential issues like over fitting. Additionally, monitoring both training and validation sets is crucial to ensure the model generalizes well to unseen data.

Fig .5.1 shows the confusion matrix for model which describes how many images are correctly classified among the test images. Fig .5.2 and Fig .5.3 Upon close observation of the accuracy graph, it's noticeable that initially, the validation accuracy exceeds the training accuracy for several epochs, with the x-axis representing the number of model training epochs, indicating the number of training cycles through the full dataset, and the y-axis denoting the loss and accuracy, respectively. Fig 5.4 shows the final web page for the lung cancer prediction using dense net, whenever uploading the image to that website it has capability to find out the images is benign or malignant or normal lung cancer image.

CONCLUSION

The proposed model shows the overview of prediction of lung cancer at an early stage. After prediction of the tumor begins malignant or benign, we generate a confusion matrix for each machine learning technique and based on the confusion matrix we calculate accuracy, Recall, precision and F1 score. From the result we can say that our proposed model can distinguish between benign and malignant, and it can be seen that dense net is providing more accuracy in both texture based, as well as from the recall value we can say that it has correctly indentified maximum number of malignant tumor In near future deep learning shall outperform deep learning learning in the field of image classification, object recognition and feature extraction. .In conclusion, the utilization of Dense Net architecture for lung cancer detection using CT images represents a significant advancement in medical imaging and deep learning research. The Dense Net model offers superior performance in feature extraction and classification tasks, thereby enabling accurate and efficient identification of lung cancer from CT scans. The integration of DenseNet with CT imaging not only enhances diagnostic accuracy but also holds promise for early detection and personalized treatment planning, ultimately improving patient outcomes. However, further research is warranted to address challenges such as data scarcity, model interpretability, and clinical validation. With continued innovation and collaboration, the integration of Dense Net-based models into clinical practice has the potential to revolutionize lung cancer diagnosis and management, leading to better patient care and outcomes.

REFERENCES

[1] A. Jemal, F. Bray, M. M. Center, J. Ferlay, E. Ward, and D. Forman, "Global cancer statistics," CA: A Cancer Journal for Clinicians, vol. 61, no. 2, pp. 69–90, 2013.

[2] A. K. Alzubaidi, F. B. Sideseq, A. Faeq, and M. Basil, "Computer aided diagnosis in digital pathology application: review and perspective approach in lung cancer classification," in Proceedings of the New Trends in Information & Communications Technology Applications, pp. 219–224, IEEE, Baghdad, Iraq, March 2017.

[3] A. Teramoto, H. Fujita, O. Yamamuro, and T. Tamaki, "Automated detection of pulmonary nodules in PET/CT images: ensemble false-positive reduction using aconvolutional neural network technique," Medical Physics, vol. 43, no. 6, pp. 2821–2827, 2016.

[4] A. Teramoto, M. Tsujimoto, T. Inoue et al., "Automated classification of pulmonary nodules through a retrospective analysis of conventional CT and two-phase PET images in patients undergoing biopsy," Asia Oceania Journal of Nuclear Medicine Biology, vol. 7, no. 1, pp. 29–37, 2019.

[5] A. Teramoto, T. Tsukamoto, Y. Kiriyama, and H. Fujita, "Automated classification of lung cancer types from cytological images using deep convolutional neural networks," BioMed Research International, vol. 2017, Article ID 4956063, 9 pages, 2017.

[6] C. I. Henschke, D. I. Mccauley, D. F. Yankelevitz et al., "Early lung cancer action project: overall design and findings from baseline screening," The Lancet, vol. 354, no. 9173, pp. 99–105, 1999.

[7] C. Yan, J. Yao, R. Li, Z. Xu, and J. Huang, "Weakly supervised deep learning for thoracic disease classification and localization on chest X-rays," in Proceedings of the 2018 ACM International Conference on Bioinformatics, Computational Biology, and Health Informatics, pp. 103–110, ACM, Washington, DC, USA,

2018.

[8] D. Nie, H. Zhang, E. Adeli, L. Liu, and D. Shen, “3D deep learning for multi-modal imaging-guided survival time prediction of brain tumor patients,” in Medical Image Computing and Computer-Assisted Intervention-MICCAI 2016, pp. 212–220, Springer, Berlin, Germany, 2016.

[9] Daoud, Maisa, and Michael Mayo. "A survey of neural network-based cancer prediction models from microarray data." Artificial intelligence in medicine (2019).

[10] F. Ye, P. Jian, J. Wang, Y. Li, and H. Zha, “Glioma grading based on 3D multimodal convolutional neural network and privileged learning,” in Proceedings of the IEEE International Conference on Bioinformatics & Biomedicine, pp. 759–763, IEEE, Kansas City, MO, USA, November 2017.

[11] Fenwa, Olusayo D., Funmilola A. Ajala, and A. Adigun. "Classification of cancer of the lungs using SVM and ANN." Int. J. Comput. Technol. 15.1 (2016): 6418-6426.

[12] G. Litjens, C. I. Sánchez, N. Timofeeva et al., “Deep learning as a tool for increased accuracy and efficiency of histopathological diagnosis,” Scientific Reports, vol. 6, no. 1, Article ID 26286, 2016.

[13] G. Narsimha, Krishnaiah, V, and Dr N. Subhash Chandra. "Diagnosis of lung cancer prediction system using data mining classification techniques." International Journal of Computer Science and Information Technologies 4.1 (2013): 39-45.

[14] H. Gao, L. Zhuang, L. V. D. Maaten, and K. Q. Weinberger, “Densely connected convolutional networks,” in Proceedings of the IEEE Conference on Computer Vision And Pattern Recognition, pp. 4700–4708, Honolulu, HI, USA, July 2017.

[15] H. Jie, S. Li, and S. Gang, “Squeeze-and-excitation networks,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 7132–

7141, Salt Lake City, UT, USA, June 2018.

[16] Jin, Xin-Yu, Yu-Chen Zhang, and Qi-Liang Jin. "Pulmonary nodule detection based on CT images using convolution neural network." 2016 9th International symposium on computational intelligence and design (ISCID). Vol. 1. IEEE, 2016.

[17] J. Schlemper, O. Oktay, C. Liang et al., “Attention-gated networks for improving ultrasound scan plane detection,” 2018,

[18] J. Shuiwang, Y. Ming, and Y. Kai, “3D convolutional neural networks for human action recognition,” IEEE Transactions on Pattern Analysis & Machine Intelligence, vol. 35, pp. 221–231, 2013.

[19] J. Wu, T. Aguilera, D. Shultz et al., “Early-stage non-small cell lung cancer: quantitative imaging characteristics of 18F fluorodeoxyglucose PET/CT allow prediction of distant metastasis,” Radiology, vol. 281, no. 1, pp. 270–278, 2016.

[20] K. Kuan, M. Ravaut, G. Manek et al., “Deep learning for lung cancer detection: tackling the kaggle data science bowl 2017 challenge,” 2017

[21] K. Venkatalakshmi and Palani, D "An IoT based predictive modelling for predicting lung cancer using fuzzy cluster based segmentation and classification." Journal of medical systems 43.2 (2019): 21.

[22] L. A. Jemal, R. L. Siegel, and A. Jemal, “Lung cancer statistics,” in Lung Cancer and Personalized Medicine, vol. 893, pp. 1–19, Springer, Berlin, Germany, 2016.

[23] L. Gong, S. Jiang, Z. Yang, G. Zhang, and L. Wang, “Automated pulmonary nodule detection in CT images using 3D deep squeeze-and-excitation networks,” International Journal of Computer Assisted Radiology and Surgery, vol. 14, no. 11, pp. 1969–1979, 2019.

[24] M. Al-Shabi, B. L. Lan, W. Y. Chan, K.-H. Ng, and M. Tan, “Lung nodule classification using deep local–global networks,” International Journal of Computer Assisted Radiology and Surgery, vol. 14, no. 10, pp. 1815–1819, 2019.

[25] Öztürk, Şaban, and Bayram Akdemir. "Application of feature extraction and

classification methods for histopathological image using GLCM, LBP, LBGLCM, GLRLM and SFTA." Procedia computer science 132 (2018): 40-46.
[26] R. Dey, Z. Lu, and Y. Hong, "Diagnostic classification of lung nodules using 3D neural networks," in Proceedings of the IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018), pp. 774–778, IEEE, Washington, DC, USA, April 2018.
[27] R. L. Siegel, K. D. Miller, and A. Jemal, "Cancer statistics, 2018," CA: A Cancer Journal for Clinicians, vol. 68, no. 1, pp. 7–30, 2018.
[28] Sumathipala, Yohan, et al. "Machine learning to predict lung nodule biopsy method using CT image features: A pilot study." Computerized Medical Imaging and Graphics 71 (2019): 1-8.
[29] S. Lakshmanaprabu, S. N. Mohanty, K. Shankar, N. Arunkumar, and G. Ramirez, "Optimal deep learning model for classification of lung cancer on CT images," Future Generation Computer Systems, vol. 92, pp. 374–382, 2019.
[30] S. Liang, R. Zhang, D. Liang et al., "Multimodal 3D DenseNet for IDH genotype prediction in gliomas," Genes, vol. 9, no. 8, p. 382, 2018.
[31] T. Jin, C. Hui, Z. Shan, and X. Wang, "Learning deep spatial lung features by 3D convolutional neural network for early cancer detection," in Proceedings of the International Conference on Digital Image Computing: Techniques & Applications, pp. 1– 6, Sydney, Australia, November 2017.
[32] V. A. A. Antonio, N. Ono, A. Saito, T. Sato, M. Altaf-Ul-Amin, and M. Kanaya, "Classification of lung adenocarcinoma transcriptome subtypes from pathological images using deep convolutional networks," International Journal of Computer Assisted Radiology and Surgery, vol. 13, no. 12, pp. 1905–1913, 2018.
[33] W. Fei, M. Jiang, Q. Chen et al., "Residual attention network for image classification," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 3156–3164, Honolulu, HI, USA, July 2017.
[34] W. Guo, Z. Xu, and H. Zhang, "Interstitial lung disease classification using

improved DenseNet," Multimedia Tools and Applications, vol. 78, no. 21, pp. 30615–30626, 2019.

[35] W. Sun, B. Zheng, and Q. Wei, "Computer aided lung cancer diagnosis with deep learning algorithms," in Proceedings of the Medical Imaging: Computer-Aided Diagnosis, vol. 9785, p. 97850Z, San Diego, CA, USA, March 2016.

[36] X. Zhang, Y. Zou, and S. Wei, "Dilated convolution neural network with LeakyReLU for environmental sound classification," in Proceedings of the International Conference on Digital Signal Processing, pp. 1–5, IEEE, London, UK, August 2017.

[37] Zhang, Junjie, et al. "Pulmonary nodule detection in medical images: a survey."Biomedical Signal Processing and Control 43 (2018): 138- 147.