A

Major Project

On

LUNG CANCER PREDICTION USING DEEP LEARNING

(Submitted in partial fulfillment of the requirements for the award of Degree)

BACHELOR OF TECHNOLOGY

In

COMPUTER SCIENCE AND ENGINEERING

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April, 2025.

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

CERTIFICATE

This is to certify that the project entitled "**LUNG CANCER PREDICTION USING DEEP LEARNING**" being submitted by **G. SRUTHI (217R1A05M8), E.PAVANI (217R1A05M5) AND T.NAGALAXMI (217R1A05R0)** in partial fulfillment of the requirements for the award of the degree of B.Tech in Computer Science and Engineering to the Jawaharlal Nehru Technological University Hyderabad, during the year 2024-25.

The results embodied in this project have not been submitted to any other University or Institute for the award of any degree or diploma.

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Submitted for viva voice Examination held on _____

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To Impart quality education in serene atmosphere thus strive for excellence in Technology and Research.

INSTITUTE MISSION:

1. To create state of art facilities for effective Teaching- Learning Process.
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ABSTRACT

This project is titled as “LUNG CANCER PREDICTION USING DEEP LEARING”. Lung cancer is the most important cause of cancer death for both men and women. Early detection is very important to enhance a patient’s chance for survival of lung cancer. This system provides a Computer Aided Diagnosis System (CAD) for early detection of lung cancer nodules from the chest Computer Tomography (CT) images. They are image pre-processing, extraction of lung region from chest computer tomography images, segmentation of lung region, feature extraction from the segmented region, classification of lung cancer as benign or malignant. Initially total variation based denoising is used for image denoising, and then segmentation is performed using optimal thresholding and morphological operations. Textural features extracted. For classification, SVM classifier is used. The main aim of the method is to develop a CAD (Computer Aided Diagnosis) system for finding the lung cancer.

Deep learning models, particularly convolutional neural networks (CNNs), are widely used for image-based lung cancer prediction, such as analyzing CT scans or X-rays. These models can extract features from medical images that are otherwise difficult to detect through manual analysis. By training on labeled datasets of lung cancer images, deep learning models can learn to identify patterns corresponding to different of lung cancer. Additionally, deep learning models can be used in combination with clinical data, such as patient demographics, medical history, and genetic markers, to further refine the accuracy of lung cancer.

LIST OF FIGURES

LIST OF TABLES

LIST OF TABLES

LIST OF TABLES

TABLE OF CONTENTS

1. INTRODUCTION

1. INTRODUCTION

The project, titled "Lung Cancer Prediction Using Deep Learning" is designed to develop a robust hybrid deep learning-based Computer-Aided Diagnosis (CAD) system for predicting lung cancer using chest CT images and patient data. Lung cancer remains one of the leading causes of cancer-related mortality worldwide, underscoring the urgent need for effective early detection methods. Conventional diagnostic approaches, such as chest X-rays and traditional imaging techniques, often fall short in identifying tumors at their nascent stages, which can significantly affect patient prognosis. Recent advancements in artificial intelligence and deep learning have opened new avenues for enhancing diagnostic accuracy. This system presents a novel hybrid deep learning method that combines the strengths of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to address these challenges. CNNs excel at extracting high-level features from complex medical imaging data, such as CT scans, while RNNs are adept at analyzing sequential data and capturing temporal dependencies. By integrating these two neural network paradigms, our approach aims to improve the sensitivity and specificity of lung cancer detection. This introduction of a hybrid model not only leverages the complementary strengths of CNNs and RNNs but also represents a significant advancement in computational diagnostic techniques, offering new potential for early and more accurate detection of lung cancer.

1.1 PROJECT PURPOSE

The purpose of this project is to develop a Computer-Aided Diagnosis (CAD) system for the early detection of lung cancer using a hybrid deep learning approach. By integrating Convolutional Neural Networks (CNNs) for feature extraction from chest CT images and Recurrent Neural Networks (RNNs) for analyzing sequential patient data, the system enhances diagnostic accuracy. Traditional methods often struggle with sensitivity and specificity, leading to misdiagnosis, but this hybrid model aims to overcome such limitations by combining image-based insights with historical medical data. The proposed system applies advanced image preprocessing techniques, including total variation-based denoising and optimal thresholding for segmentation, ensuring high-quality input for feature extraction.

Using a diverse dataset of medical images and patient records, the system adapts to different clinical scenarios, enabling real-time analysis and improved detection accuracy. This

approach not only aids in the timely identification of lung cancer but also facilitates seamless integration into existing diagnostic workflows, ultimately contributing to better patient outcomes and increased survival rates.

1.2 PROJECT FEATURES

Advanced Image Preprocessing: Uses total variation-based denoising and optimal thresholding for segmentation to enhance image quality.

Hybrid Deep Learning Model: Combines **CNNs** for feature extraction from CT scans and **RNNs** for analyzing sequential patient data.

Automated Classification: Predicts whether lung nodules are benign or malignant with high accuracy.

Explainability with Heatmaps: Implements Grad-CAM to highlight important regions in lung images for better interpretability.

Real-time Analysis: Provides quick and efficient diagnosis for timely medical intervention.

Diverse Dataset Utilization: Trained on various imaging datasets to improve adaptability across different clinical settings.

Improved Sensitivity & Specificity: Reduces false positives and negatives, enhancing diagnostic reliability.

Seamless Healthcare Integration: Designed to integrate smoothly into existing hospital diagnostic workflow.

2. LITERATURE SURVEY

2.LITERATURE SURVEY

The detection of lung cancer has greatly improved with the adoption of deep learning technologies, offering higher diagnostic accuracy compared to traditional methods like chest X-rays and CT scans. Convolutional Neural Networks (CNNs) have shown significant success in analyzing medical images, extracting critical features, and classifying them effectively. Additionally, Recurrent Neural Networks (RNNs) have been employed to analyze sequential patient data, uncovering temporal patterns and aiding in identifying cancer progression over time. Combining these approaches into hybrid models has demonstrated potential in detecting complex patterns, leading to more accurate and earlier lung cancer diagnoses.

Chen et al. (2019) utilized CNNs to analyze CT scans for predicting lung cancer and achieved high accuracy using the TensorFlow framework. Their research emphasized the importance of early detection, showing that deep learning can outperform traditional diagnostic methods. Esteva et al. (2020) advanced this concept by integrating CNNs and RNNs to analyze both imaging and clinical data, using Python's Keras library. By incorporating factors such as age, smoking history, and genetic markers, their model further improved prediction accuracy, particularly for early cancer detection.

Hussein et al. (2018) explored 3D-CNNs for analyzing volumetric CT scans, highlighting the value of three-dimensional imaging in improving lung cancer. Using PyTorch, their model demonstrated superior accuracy compared to conventional machine learning techniques, emphasizing the importance of volumetric data for robust classification. Similarly, Shen et al. (2017) developed an automated system utilizing CNNs to detect lung nodules and classify their malignancy, offering a practical tool for clinicians.

Xu et al. (2021) introduced transfer learning into lung cancer prediction by fine-tuning pre-trained models like ResNet and DenseNet. Their approach reduced the need for large labeled datasets while maintaining high accuracy in distinguishing between early and advanced lung

cancer. Implemented using PyTorch, this method demonstrated the efficiency and adaptability of transfer learning in medical applications. Together, these studies illustrate the transformative potential of deep learning techniques in improving lung cancer detection and enhancing patient outcomes.

2.1 REVIEW OF RELATED WORK

The early detection of lung cancer has been extensively studied in the fields of medical imaging, machine learning, and deep learning. Several approaches have been proposed to improve diagnostic accuracy, ranging from traditional radiological assessments to advanced AI-driven models. This review explores existing methodologies, highlighting their strengths and limitations in lung cancer prediction.

1. Traditional Content Moderation Approaches

Early lung cancer detection primarily relied on manual interpretation of chest X-rays and CT scans by radiologists. While effective, this approach was time-consuming and prone to human error, often leading to missed early-stage tumors. To assist radiologists, Computer-Aided Diagnosis (CAD) systems were introduced, incorporating basic image processing techniques and heuristic-based decision-making. However, these systems lacked the ability to accurately differentiate between benign and malignant nodules, limiting their reliability.

2. Machine Learning-Based Approaches

With advancements in artificial intelligence, researchers developed machine learning models utilizing classifiers like Support Vector Machines (SVMs), , and Decision Trees. These methods extracted handcrafted features such as texture, shape, and intensity from lung images to predict cancer presence. While they showed improved accuracy over traditional methods, they struggled with feature selection, generalization across diverse datasets, and the ability to capture complex patterns in medical images.

3. Deep Learning-Based Approaches

Recent advancements in deep learning have revolutionized lung cancer detection. Convolutional Neural Networks (CNNs) have been widely used for medical image analysis, providing automated feature extraction and significantly improving classification accuracy. Studies have demonstrated the effectiveness of pre-trained CNN models such as VGG-16, ResNet, and EfficientNet in detecting lung nodules. However, CNNs primarily focus on spatial features and do not consider temporal dependencies in patient medical history, which is crucial for accurate diagnosis.

To address this, researchers have explored the combination of CNNs with Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, for sequential data analysis. This hybrid approach improves sensitivity and specificity by integrating both image-based insights and historical patient data. Despite their success, these models require large-scale annotated datasets and high computational resources, limiting their real-time clinical applicability.

4. Recent Advances: Attention Mechanisms & Transformer-Based Models

To enhance detection accuracy and clinical adaptability, recent studies have proposed hybrid deep learning models that integrate CNNs for spatial feature extraction and RNNs for sequential data interpretation. By leveraging patient history alongside imaging data, these models provide a more comprehensive diagnostic framework. Furthermore, techniques like attention mechanisms and transfer learning have been incorporated to improve feature selection and reduce the need for extensive labeled datasets. However, existing hybrid models still face challenges in scalability and real-time implementation in healthcare settings.

5. Comparison with the Proposed Approach

While existing methods have made significant progress in lung cancer detection, challenges remain in terms of accuracy, scalability, and real-time applicability. The proposed system introduces an innovative hybrid deep learning approach that integrates CNNs for medical image analysis and RNNs for sequential patient data

interpretation. By fusing spatial and temporal information, the model enhances sensitivity and specificity, reducing false diagnoses. Additionally, it is trained on diverse datasets, improving adaptability across different clinical settings. Unlike traditional CAD and machine learning methods, this deep learning approach offers real-time analysis, early detection capabilities, and seamless integration into existing hospital workflows, making it a more effective and practical solution for lung cancer prediction.

This review highlights the evolution of lung cancer detection techniques, emphasizing the shift from manual and machine learning approaches to deep learning-based models. The proposed system aims to address the limitations of previous research by offering a highly accurate, scalable, and clinically adaptable AI-driven solution for early lung cancer detection.

2.2 DEFINITION OF PROBLEM STATEMENT

The primary goal of this project is to develop a robust and scalable deep learning-based system for the early detection and classification of lung cancer using CT scan images and patient medical history. The project aims to overcome the limitations of traditional diagnostic methods, such as manual radiological assessments and conventional machine learning techniques, which often suffer from low sensitivity, high false detection rates, and a lack of sequential data analysis.

By integrating Convolutional Neural Networks (CNNs) for spatial feature extraction and Recurrent Neural Networks (RNNs) for sequential patient data interpretation, the proposed system enhances accuracy, sensitivity, and specificity in lung cancer prediction. Additionally, the system is designed to handle real-time diagnosis, adapt to diverse patient datasets, and seamlessly integrate into existing clinical workflows. Ultimately, this approach aims to improve early detection rates, facilitate timely medical intervention, and contribute to better patient outcomes.

2.3 EXISTING SYSTEM

The existing systems for lung cancer detection predominantly rely on traditional imaging techniques and machine learning methods. Conventional approaches, such as chest X-rays and computed tomography (CT) scans, are frequently used in clinical settings to identify abnormalities, but they often lack the sensitivity required for early-stage detection. Recent advancements have seen the application of machine learning algorithms, including support vector machines (SVMs) and decision trees, to analyze imaging data and patient records. These methods have improved diagnostic accuracy to some extent but still face limitations in terms of feature extraction and pattern recognition capabilities. More recently, deep learning models, particularly convolutional neural networks (CNNs), have demonstrated significant improvements by automating feature extraction from images and enhancing classification performance. Despite these advancements, many systems still operate in isolation, focusing solely on either image analysis or patient data. The integration of recurrent neural networks (RNNs) with CNNs into a hybrid framework represents a novel and promising approach. This hybrid model aims to combine the image-processing strengths of CNNs with the temporal and sequential analysis capabilities of RNNs, addressing the limitations of existing systems and offering a more comprehensive solution.

Limitations of Existing System

The existing system suffers from the following challenges:

- Inability to capture contextual meaning: Limited Sensitivity and Specificity: Traditional imaging techniques, such as chest X-rays and CT scans, often struggle with low sensitivity and specificity, particularly in detecting early-stage tumors. This can lead to false positives or false negatives.

- Manual Feature Extraction: Conventional machine learning methods, including support vector machines (SVMs) and random forests, rely on manually extracted features from imaging data, which can miss subtle patterns indicative of cancer.

- Lack of Integration: Existing systems often analyze imaging data and patient records separately. This separation can lead to missed opportunities for combining insights from both data types, potentially impacting diagnostic accuracy.

- Inadequate Temporal Analysis: Convolutional neural networks (CNNs) excel at image analysis but do not typically handle temporal or sequential data effectively. They may overlook important patterns in patient history or changes over time.

2.4 PROPOSED SYSTEM

The proposed system introduces an innovative hybrid deep learning method aimed at advancing the early detection of lung cancer through the integration of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). This hybrid approach combines the strengths of CNNs in extracting intricate features from medical imaging data, such as CT scans, with the RNNs' ability to analyze and interpret sequential patient data over time. By leveraging CNNs for detailed image analysis and RNNs for understanding temporal patterns and historical medical records, the system offers a comprehensive diagnostic tool that addresses the limitations of existing methods. The unified model enhances detection accuracy by integrating image-based insights with contextual information from patient histories, thereby improving both sensitivity and specificity. Trained on a diverse dataset that includes varied imaging modalities and patient records, the hybrid model is designed to adapt to different clinical scenarios and provide real-time analysis. This approach not only aims to detect lung cancer at its earliest stages but also seeks to offer a practical solution that can be seamlessly integrated into existing diagnostic workflows, ultimately contributing to better patient outcomes through more timely and accurate detection.

To further enhance performance, the model incorporates attention mechanisms, particularly in the RNN component. This enables the system to focus on the most relevant historical data points, prioritizing critical medical events, such as prior diagnoses, smoking history, and genetic predispositions. The CNN module, on the other hand, utilizes transfer learning with pre-trained architectures like ResNet, EfficientNet, or VGG16, fine-tuned for medical imaging tasks. This approach not only improves feature extraction efficiency but also mitigates the challenges of limited labeled medical datasets.

For training and validation, the hybrid model leverages a carefully curated dataset comprising a diverse range of lung cancer cases across different demographics and risk factors. The dataset includes annotated CT scans, biopsy results, and patient medical histories, ensuring robust generalization across real-world clinical settings. A stratified cross-validation strategy is employed to prevent overfitting and enhance model reliability.

Advantages of the Proposed System:

- Enhanced Accuracy: By integrating Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), the system leverages advanced image processing and temporal analysis to improve diagnostic accuracy, reducing the likelihood of false positives and false negatives.

- Comprehensive Analysis: The hybrid approach combines spatial features extracted from CT scans (via CNNs) with sequential data from patient histories (via RNNs), providing a more holistic view of the patient's condition and capturing patterns that might be missed by image-based or sequential analysis alone.

- Early Detection: The system's ability to analyze both current imaging data and historical patient records enhances its capability to identify early tumors, potentially leading to earlier intervention and improved patient outcomes.

- Real-Time Capability: Designed for integration into clinical workflows, the model can provide real-time analysis, enabling prompt decision-making and timely diagnosis.

- Adaptability: The hybrid model is trained on a diverse dataset, which helps it generalize across various patient demographics and imaging conditions, making it adaptable to different clinical settings.

2.5 OBJECTIVES

- Develop an AI-Based Diagnostic System – Design and implement a hybrid deep learning model integrating CNNs for image analysis and RNNs for sequential data processing to improve lung cancer detection accuracy.

- Enhance Early Detection Accuracy – Improve the ability to identify lung cancer in early by leveraging CT scan images and patient medical history, reducing false positives and false negatives.

- Automate Feature Extraction – Utilize CNNs to automatically extract relevant features from medical images, eliminating the need for manual feature selection and improving detection efficiency.

- Analyze Temporal Patient Data – Incorporate RNNs to process historical medical records, ensuring a comprehensive diagnosis that considers both current imaging and past health trends.

- Enable Real-Time Diagnosis – Develop a system capable of real-time processing, allowing for faster clinical decision-making and integration into hospital workflows.

2.6 HARDWARE & SOFTWARE REQUIREMENTS

2.6.1 HARDWARE REQUIREMENTS:

Hardware interfaces specifies the logical characteristics of each interface between the software product and the hardware components of the system. The following are some hardware requirements,

- Processor : Pentium –IV
- Hard disk : 20GB.
- RAM : 4GB.

2.6.2 SOFTWARE REQUIREMENTS:

Software Requirements specifies the logical characteristics of each interface and software components of the system. The following are some software requirements,

- Operating system : Windows 7 and above.
- Language : Python 3.7.0

3. SYSTEM ARCHITECTURE & DESIGN

3. SYSTEM ARCHITECTURE & DESIGN

Project architecture refers to the structural framework and design of a project, encompassing its components, interactions, and overall organization. It provides a clear blueprint for development, ensuring efficiency, scalability, and alignment with project goals. Effective architecture guides the project's lifecycle, from planning to execution, enhancing collaboration and reducing complexity.

3.1 PROJECT ARCHITECTURE

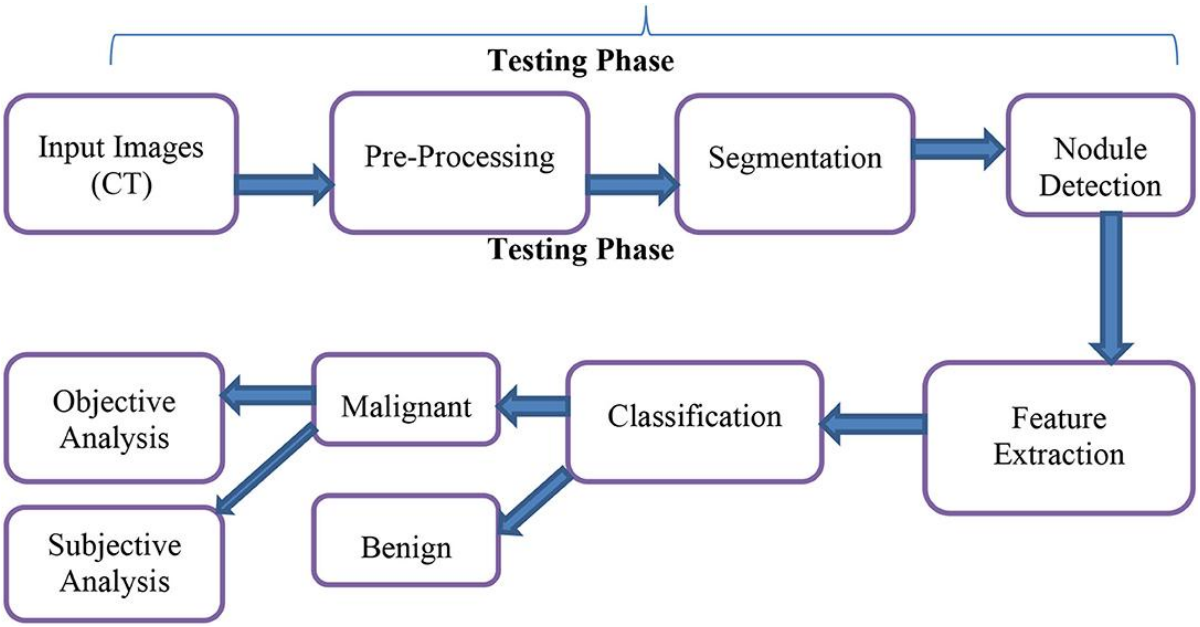

Figure 3.1: Project Architecture of Lung Cancer Prediction Using Deep Learning.

3.2 DESCRIPTION

Input Data : The project utilizes chest CT scan images as input data, focusing on detecting lung cancer at an early stage. The dataset consists of annotated CT scans, including cases of benign and malignant nodules.

Reading Data: The CT images undergo pre-processing using image enhancement techniques to remove noise and improve clarity for better analysis.

Feature Extraction : Convolutional Neural Network (CNN) extracts high-dimensional spatial features from the CT scan images, capturing crucial characteristics of lung nodules.

Temporal Pattern Learning : Extracted features are passed through a Recurrent Neural Network (RNN) to analyze sequential patient data, considering medical history to improve diagnostic accuracy.

Classification Layer : The processed features are fed into a fully connected classification layer, where the system determines whether the detected nodule is benign or malignant.

Training and Evaluation : The model is trained using a diverse dataset of CT scans, ensuring high accuracy, sensitivity, and specificity. The evaluation metrics include precision, recall, F1-score, and overall classification accuracy to validate model performance.

Feedback : Expert radiologist feedback is incorporated to refine detection algorithms and enhance model accuracy, ensuring continuous improvement in cancer prediction and diagnosis.

3.3 DATA FLOW DIAGRAM

A Data Flow Diagram (DFD) visually represents how CT scan data moves through the lung cancer detection system, showcasing key processes, data stores, and interactions between system components. It is essential for understanding data movement, optimizing workflows, and identifying inefficiencies in the system.

A Data Flow Diagram comprises Four primary elements:

- External Entities: Represent sources or destinations of data, such as medical imaging centers, hospitals, and radiologists.
- Processes: Transformations applied to data, including image pre-processing, segmentation, feature extraction, and classification.
- Data Flows: The movement of CT scan images and extracted features between system components.
- Data Stores: Storage locations for raw CT scan images, extracted features, and patient medical history.

These components are represented using standardized symbols, such as circles for processes, arrows for data flows, rectangles for external entities, and open-ended rectangles for data stores.

Benefits:

Clear Visualization: Helps stakeholders understand how data flows through the lung cancer prediction system.

Process Optimization: Identifies inefficiencies in image processing, feature extraction, and classification steps.

Security & Data Management: Ensures secure storage and handling of sensitive patient data.

Levels of DFD:

DFDs are structured hierarchically:

- Level 0 (Context Diagram): Provides a high-level overview showing interactions between hospitals, imaging centers, and the lung cancer detection system.

- Level 1: Breaks down major processes like CT image pre-processing, segmentation, feature extraction, and classification.

- Level 2+: Provides deeper insights into specific operations, such as denoising techniques, CNN feature extraction, and RNN-based historical analysis.

Figure 3.2: Dataflow Diagram of Lung cancer prediction using Deep Learning.

4. IMPLEMENTATION

4. IMPLEMENTATION

The implementation phase of a project involves executing the planned strategies and tasks. It requires meticulous coordination, resource allocation, and monitoring to ensure that objectives are met efficiently. Effective implementation is crucial for achieving project goals and delivering expected outcomes within the set timeline and budget constraints.

4.1 ALGORITHMS USED

3D CNN (Three-Dimensional Convolutional Neural Network)

- Extracts spatial and volumetric features from 3D CT scan images.
- Identifies patterns in lung tissues for detecting abnormalities.

Advantages of 3D **CNN** Models:

- Captures depth information, improving tumor localization.
- More accurate than 2D CNNs for medical imaging.
- Can detect structural patterns and variations in lung tissues.

Disadvantages of 3D **CNN** Models:

- Computationally expensive due to large 3D data processing.
- Requires a large labeled dataset for training effectively
- More prone to overfitting compared to 2D CNNs.

LSTM (Long Short-Term Memory - a type of RNN)

- Captures temporal changes in medical images over time
- Analyzes sequential frames of CT scans to monitor cancer progression.

Advantages of LSTM Models:

- Effective at detecting changes in images over time.
- Prevents vanishing gradient problems seen in standard RNNs.

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Disadvantages of LSTM Models:

- Requires a large amount of sequential data for training.
- Computationally intensive and slow compared to CNNs.
- May struggle with very long sequences due to memory constraints.

UNET (U-Net Convolutional Neural Network)

- Performs segmentation of cancerous cells in CT scans.
- Separates the region of interest (ROI) from the lung CT image.

Advantages of UNET Models:

- Highly accurate for medical image segmentation.
- Works well with a small dataset due to data augmentation capabilities.
- Captures both global and local contextual information.

Disadvantages of UNET Models:

- Requires precise annotations for effective training.
- Struggles with segmenting small objects in complex backgrounds.
- Computationally expensive when processing high-resolution images.

CCDC-HNN (Cancer Cell Detection using Hybrid Neural Network)

- A hybrid deep learning approach combining CNN and LSTM for lung cancer detection.
- Uses CNN for feature extraction and LSTM for temporal pattern analysis.

Advantages of CCDC-HNN Models:

- Improves classification accuracy by combining spatial and temporal analysis.
- More robust in detecting cancer cell changes over time.
- Reduces false positives and enhances specificity in cancer diagnosis.

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Disadvantages of CCDC-HNN Models:

- Requires high computational power due to its hybrid nature.
- Needs careful hyperparameter tuning for optimal performance.
- Training time is longer compared to individual CNN or LSTM models.

In the past many automation algorithms and bio-markers based algorithms are introduced to detect cancerous cells from Lung CT-scan images but all those techniques or algorithms detection accuracy is not accurate. To overcome from this issue author of this paper employing Hybrid (combination of CNN and LSTM) algorithm is utilized to detect cancer cells. 3DCNN algorithm is best known for features extraction and classification and then RNN (LSTM long short term memory) algorithm is used to detect changes in images over different time, so by combining both this algorithms application can detect changes of cancer cell over time.

In propose paper before classifying cancer cell author employing UNET algorithm to segment cancel cell and then applying propose CCDC-HNN (Cancer Cell Detection using Hybrid Neural Network) algorithm to classify cancer cell. Based on detected cancel cell size physician can easily understand stage of cancer.

To train propose algorithm author has utilized LIDC-IDRI (Lung Image Database Consortium and Image Database Resource Initiative) which can be downloaded from below KAGGLE URL.

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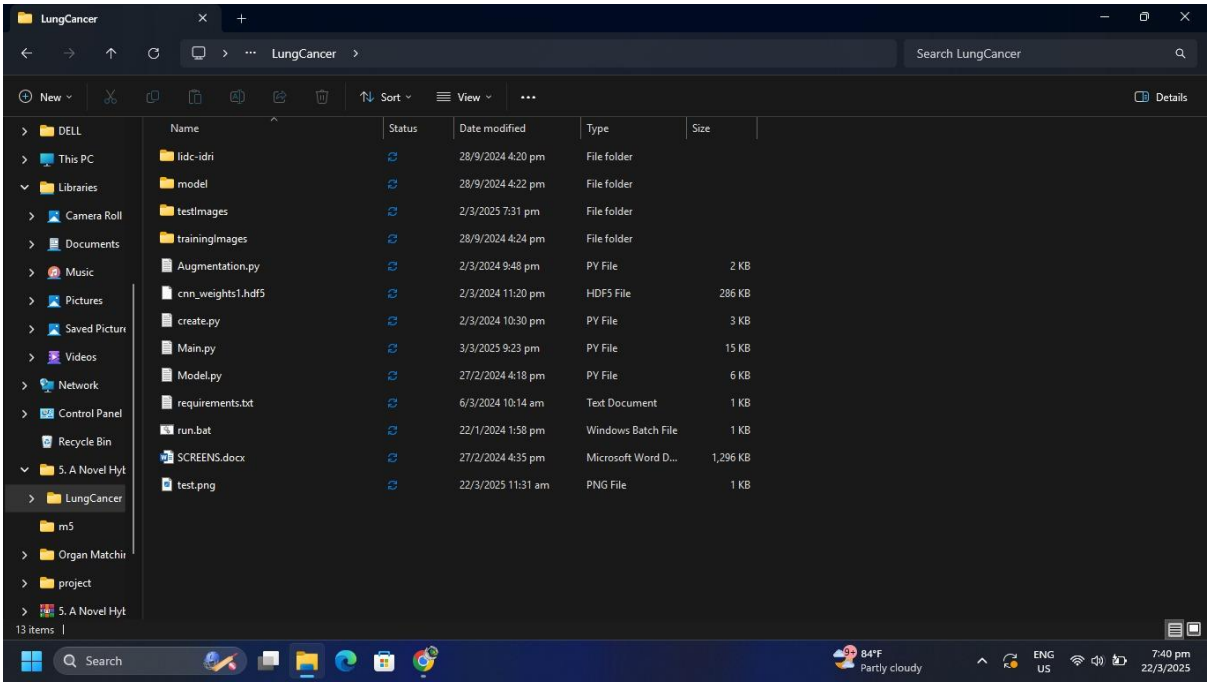

Figure 4.1: Dataset directory structure with folders ‘Training images and Testing images’ having all the examples

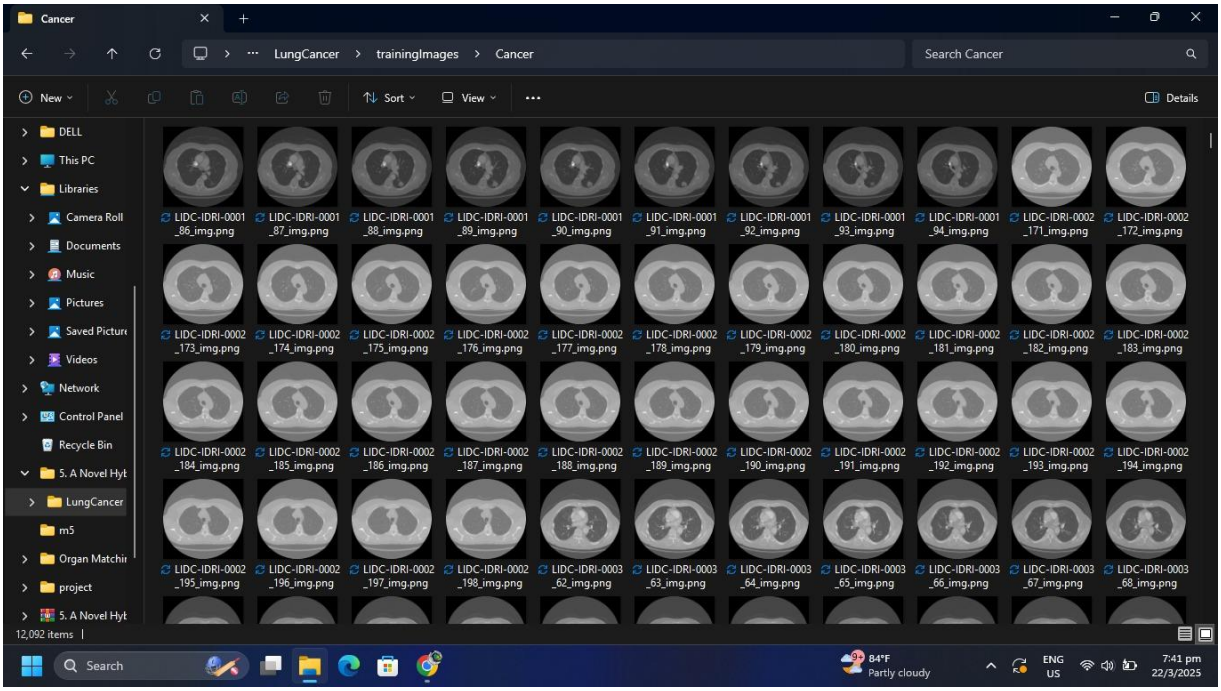

Figure 4.2: Screenshot of the "Training Images" Folder Showing Sample Image Files

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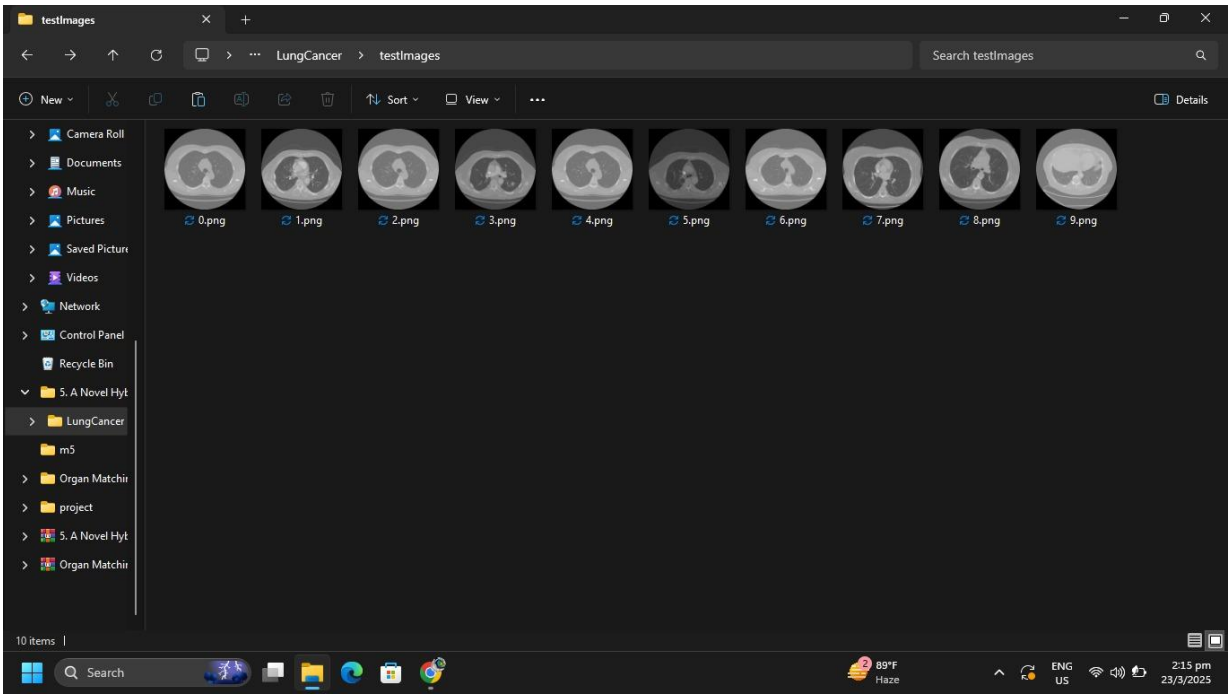

Figure 4.3: Screenshot of the "Testing Image" Folder Showing Sample Image Files.

To implement this project we have designed following modules:

1) Upload Lung Cancer Dataset: using this module we will upload dataset to application **(Figure 4.1).**
2) Preprocess Dataset: using this module we will read images and then normalize, shuffle and resize images.
3) Split Dataset Train & Test: using this module we will split dataset into train and test application where 80% dataset images will be using for training CNN algorithm and 20% dataset images to calculate prediction accuracy.
4) Run CNN Algorithm: using this module we will train CNN algorithm and then calculate its prediction accuracy.
5) CNN Training Graph: using this module we will plot CNN training accuracy and loss graph.
6) Predict Lung Cancer : using this module we will upload test image and then CNN will predict cancer.

4.2 SAMPLE CODE

```
from tkinter import *
import tkinter
from tkinter import filedialog
import numpy as np
from tkinter import simpledialog
from tkinter import ttk
from tkinter.filedialog import askopenfilename
import cv2
import os
import numpy as np
#loading python require packages
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from keras.models import *
from keras.layers import *
from keras.optimizers import *
from keras import backend as keras
from keras.preprocessing.image import ImageDataGenerator
from keras.callbacks import ModelCheckpoint, LearningRateScheduler
from keras.callbacks import ModelCheckpoint, LearningRateScheduler, EarlyStopping,
ReduceLROnPlateau
from keras.optimizers import Adam
import pickle
from keras.callbacks import ModelCheckpoint
import pickle
import seaborn as sns
from sklearn.metrics import accuracy_score
from keras.models import Sequential
```

```
import seaborn as sns
from sklearn.metrics import accuracy_score
from keras.models import Sequential
from keras.layers import Dense, Flatten, Dropout, Conv3D, MaxPooling3D, LSTM,RepeatVector
from keras.utils import to_categorical
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
from sklearn import metrics
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix


main = tkinter.Tk()
main.title("Lung cancer Prediction using deep learning") #designing main screen
main.geometry("1000x650")


global filename, X, Y
global X_train, X_test, y_train, y_test, unet_model, ccdc_model

def loadDataset():
    global X, Y, label
    if os.path.exists("model/X2.npy"):
        X = np.load("model/X2.npy")
        Y = np.load("model/Y2.npy")
    else:
        for root, dirs, directory in os.walk(filename):
            for j in range(len(directory)):
```

```
                name = directory[j]
            name = name.replace("img", "mask")
            if os.path.exists("lidc-idri/mask/"+name):
                img = cv2.imread("lidc-idri/image/"+directory[j])
                img = cv2.resize(img,(32, 32), interpolation = cv2.INTER_CUBIC)
                img = img.astype('float32')
                img = img/255
                X.append([img])
                img = cv2.imread("lidc-idri/mask/"+name,0)
                img = cv2.resize(img,(128, 128), interpolation = cv2.INTER_CUBIC)
                white_pixels = np.sum(img == 255)
                if white_pixels == 0:
                    Y.append(0)
                else:
                    Y.append(1)
                print(name+" "+str(white_pixels))
        X = np.asarray(X)
        Y = np.asarray(Y)
        np.save("model/X1",X)
        np.save("model/Y1",Y)

def uploadDataset():
    global filename, X, Y, labels
    filename = filedialog.askdirectory(initialdir=".")
    text.delete('1.0', END)
    text.insert(END,filename+" loaded\n\n")
    X = []
    Y = []
    loadDataset()
    text.insert(END,"Total images loaded = "+str(X.shape[0]))

def processDataset():
```

```
    global X, Y, labels
    text.delete('1.0', END)
    dim = 128
    img = X[0]
    img = img[0]
    print(img.shape)
    text.insert(END,"Dataset Processing & Normalization Complated")
    img = cv2.resize(img, (300, 300))
    cv2.putText(img, "Sample Processed Image", (10, 25),
cv2.FONT_HERSHEY_SIMPLEX,0.7, (0, 0, 255), 2)
    cv2.imshow('Processed Image', img)
    cv2.waitKey(0)
    cv2.destroyAllWindows()

def trainTestSplit():
    global X, Y
    global X_train, X_test, y_train, y_test
    text.delete('1.0', END)
    indices = np.arange(X.shape[0])
    np.random.shuffle(indices)#shuffle all images
    X = X[indices]
    Y = Y[indices]
    Y = to_categorical(Y)
    X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2) #split dataset
into train and test
    text.insert(END,"Dataset Training & Testing Details\n\n")
    text.insert(END,"80% images for training : "+str(X_train.shape[0])+"\n")
    text.insert(END,"20% images for testing  : "+str(X_test.shape[0])+"\n")

#function to calculate all metrics
def calculateMetrics(algorithm, testY, predict):
    p = precision_score(testY, predict,average='macro') * 100
```

```
  r = recall_score(testY, predict,average='macro') * 100
    f = f1_score(testY, predict,average='macro') * 100
    a = accuracy_score(testY,predict)*100
    text.insert(END,algorithm+" Accuracy  : "+str(a)+"\n")
    text.insert(END,algorithm+" Precision : "+str(p)+"\n")
    text.insert(END,algorithm+" Recall    : "+str(r)+"\n")
    text.insert(END,algorithm+" FSCORE    : "+str(f)+"\n")
    labels = ['Benign', 'Malignant']
    conf_matrix = confusion_matrix(testY, predict)
    fig, axs = plt.subplots(1,2,figsize=(10, 3))
    ax = sns.heatmap(conf_matrix, xticklabels = labels, yticklabels = labels, annot =
True, cmap="viridis" ,fmt ="g", ax=axs[0]);
    ax.set_ylim([0,len(labels)])
    axs[0].set_title(algorithm+" Confusion matrix")

    random_probs = [0 for i in range(len(testY))]
    p_fpr, p_tpr, _ = roc_curve(testY, random_probs, pos_label=1)
    plt.plot(p_fpr, p_tpr, linestyle='--', color='orange',label="True classes")
    ns_tpr, ns_fpr, _ = roc_curve(testY, predict, pos_label=1)
    axs[1].plot(ns_tpr, ns_fpr, linestyle='--', label='Predicted Classes')
    axs[1].set_title(algorithm+" ROC AUC Curve")
    axs[1].set_xlabel('False Positive Rate')
    axs[1].set_ylabel('True Positive rate')
    plt.show()

def dice_coef(y_true, y_pred):
    y_true_f = keras.flatten(y_true)
    y_pred_f = keras.flatten(y_pred)
    intersection = keras.sum(y_true_f * y_pred_f)
    return (2. * intersection + 1) / (keras.sum(y_true_f) + keras.sum(y_pred_f) + 1)
def dice_coef_loss(y_true, y_pred):
```

```
 return -dice_coef(y_true, y_pred)

def getUnetModel(input_size=(128,128,1)):
    inputs = Input(input_size)

    conv1 = Conv2D(32, (3, 3), dilation_rate=2, activation='relu', kernel_initializer='he_normal', padding='same')(inputs)
    conv1 = Conv2D(32, (3, 3), activation='relu', padding='same', dilation_rate=2)(conv1) #adding dilation rate for all layers
    conv1 = Dropout(0.1) (conv1)
    pool1 = MaxPooling2D(pool_size=(2, 2))(conv1)

    conv2 = Conv2D(64, (3, 3), dilation_rate=2, activation='relu', kernel_initializer='he_normal', padding='same') (pool1)
    conv2 = Conv2D(64, (3, 3), activation='relu', padding='same', dilation_rate=2)(conv2)
    conv2 = Dropout(0.1) (conv2)
    pool2 = MaxPooling2D(pool_size=(2, 2))(conv2)

    conv3 = Conv2D(128, (3, 3), dilation_rate=2, activation='relu', padding='same')(pool2)#adding dilation to all layers
    conv3 = Conv2D(128, (3, 3), activation='relu', padding='same', dilation_rate=2)(conv3)
    pool3 = MaxPooling2D(pool_size=(2, 2))(conv3)

    conv4 = Conv2D(256, (3, 3), dilation_rate=2, activation='relu', padding='same')(pool3)
    conv4 = Conv2D(256, (3, 3), activation='relu', padding='same', dilation_rate=2)(conv4)
    pool4 = MaxPooling2D(pool_size=(2, 2))(conv4)
    conv5 = Conv2D(512, (3, 3), dilation_rate=2, activation='relu', padding='same')(pool4)
```

```
conv5 = Conv2D(512, (3, 3), activation='relu', padding='same')(conv5)

    up6 = concatenate([Conv2DTranspose(256, (2, 2), strides=(2, 2), padding='same')(conv5), conv4], axis=3)
    conv6 = Conv2D(256, (3, 3), dilation_rate=2, activation='relu', padding='same')(up6)
    conv6 = Conv2D(256, (3, 3), activation='relu', padding='same')(conv6)

    up7 = concatenate([Conv2DTranspose(128, (2, 2), strides=(2, 2), padding='same')(conv6), conv3], axis=3)
    conv7 = Conv2D(128, (3, 3), dilation_rate=2, activation='relu', padding='same')(up7)
    conv7 = Conv2D(128, (3, 3), activation='relu', padding='same')(conv7)

    up8 = concatenate([Conv2DTranspose(64, (2, 2), strides=(2, 2), padding='same')(conv7), conv2], axis=3)
    conv8 = Conv2D(64, (3, 3), dilation_rate=2, activation='relu', padding='same')(up8)
    conv8 = Conv2D(64, (3, 3), activation='relu', padding='same')(conv8)

    up9 = concatenate([Conv2DTranspose(32, (2, 2), strides=(2, 2), padding='same')(conv8), conv1], axis=3)
    conv9 = Conv2D(32, (3, 3), dilation_rate=2, activation='relu', padding='same')(up9)#adding dilation
    conv9 = Conv2D(32, (3, 3), activation='relu', padding='same')(conv9)

    conv10 = Conv2D(1, (1, 1), activation='sigmoid')(conv9)#not adding dilation to last layer

    return Model(inputs=[inputs], outputs=[conv10])

def runCNN():
    text.delete('1.0', END)
    global unet_model, ccdc_model
    global X_train, X_test, y_train, y_test
    unet_model = getUnetModel(input_size=(128, 128, 1))
```

```
unet_model.compile(optimizer=Adam(learning_rate=1e-4), loss=[dice_coef_loss], metrics = [dice_coef, 'binary_accuracy']) #compiling model
    unet_model.load_weights("model/unet_weights.hdf5")
    ccdc_model = Sequential()
    #creating CNN3d layer with 1 X 3 X 3 matrix to filtered features using 32 neurons
    ccdc_model.add(Conv3D(32, (1, 3, 3), activation='relu', input_shape=(X.shape[1], X.shape[2], X.shape[3], X.shape[4])))
    #max pool to collect relevant features from CNN3D layer
    ccdc_model.add(MaxPooling3D((1, 2, 2)))
    #adding another layer
    ccdc_model.add(Conv3D(16, (1, 3, 3), activation='relu'))
    ccdc_model.add(MaxPooling3D((1, 2, 2)))
    ccdc_model.add(Conv3D(16, (1, 3, 3), activation='relu'))
    ccdc_model.add(MaxPooling3D((1, 2, 2)))
    ccdc_model.add(Flatten())
    ccdc_model.add(RepeatVector(2))
    ccdc_model.add(LSTM(32))
    ccdc_model.add(Dense(y_train.shape[1], activation='softmax'))
    #compile the model
    ccdc_model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
    #train and load the model
    if os.path.exists("model/cnn_weights1.hdf5") == False:
        model_check_point = ModelCheckpoint(filepath='model/cnn_weights1.hdf5', verbose = 1, save_best_only = True)
        hist = ccdc_model.fit(X_train, y_train, batch_size = 32, epochs = 15, validation_data=(X_test, y_test), callbacks=[model_check_point], verbose=1)
        f = open('model/cnn_history1.pckl', 'wb')
        pickle.dump(hist.history, f)
        f.close()
    else:
        ccdc_model.load_weights("model/cnn_weights1.hdf5")
    #perform prediction on test data
```

```
  predict = ccdc_model.predict(X_test)
    predict = np.argmax(predict, axis=1)
    y_test1 = np.argmax(y_test, axis=1)
    #call this function to calculate accuray and other metrics
    calculateMetrics("Propose Hybrid CCDC-HNN", y_test1, predict)

def values(filename, acc, loss):
    f = open(filename, 'rb')
    train_values = pickle.load(f)
    f.close()
    accuracy_value = train_values[acc]
    loss_value = train_values[loss]
    return accuracy_value, loss_value

def graph():
    train_acc, train_loss = values("model/cnn_history.pckl", "accuracy", "loss")
    val_acc, val_loss = values("model/cnn_history.pckl", "val_accuracy", "val_loss")

    plt.figure(figsize=(10,6))
    plt.grid(True)
    plt.xlabel('EPOCH')
    plt.ylabel('Accuracy')
    plt.plot(train_acc, 'ro-', color = 'green')
    plt.plot(train_loss, 'ro-', color = 'blue')
    plt.plot(val_acc, 'ro-', color = 'red')
    plt.plot(val_loss, 'ro-', color = 'pink')
    plt.legend(['Training Accuracy', 'Training Loss', 'Validation Accuracy', 'Validation
Loss'], loc='upper left')
    plt.title('CCDC-HNN Algorithm Training Accuracy & Loss Graph')
    plt.tight_layout()
    plt.show()

def predict():
```

```
  text.delete('1.0', END)
   global unet_model, ccdc_model
   filename = filedialog.askopenfilename(initialdir="testImages")
   img = cv2.imread(filename,0)
   image = img
   img = cv2.resize(img,(128, 128), interpolation = cv2.INTER_CUBIC)
   img = (img-127.0)/127.0
   img = img.reshape(1,128,128,1)
   preds = unet_model.predict(img)#predict segmented image
   preds = preds[0]
   cv2.imwrite("test.png", preds*255)
   img = cv2.imread(filename)
   img = cv2.resize(img,(128, 128), interpolation = cv2.INTER_CUBIC)
   mask = cv2.imread("test.png", cv2.IMREAD_GRAYSCALE)
   mask = cv2.resize(mask,(128, 128), interpolation = cv2.INTER_CUBIC)
   contours, hierarchy = cv2.findContours(mask, cv2.RETR_EXTERNAL,
cv2.CHAIN_APPROX_SIMPLE)
   bounding_boxes = [cv2.boundingRect(contour) for contour in contours]
   output = "Benign"
   for bounding_box in bounding_boxes:
      (x, y, w, h) = bounding_box
      if w > 6 and h > 6:
         cv2.rectangle(img, (x, y), (x + w, y + h), (0, 0, 255), 2)
         w = w + h
         output = "Malignant"
   img = cv2.resize(img, (300, 300))
   mask = preds*255
   mask = cv2.resize(mask, (300, 300))
   cv2.putText(img, output, (10, 25), cv2.FONT_HERSHEY_SIMPLEX,0.7, (0, 0,
255), 2)
   cv2.imshow('Input Image', img)
   cv2.imshow('Cancer Detected Image', mask)
   cv2.waitKey(0)
```

```
 cv2.destroyAllWindows()

font = ('times', 16, 'bold')
title = Label(main, text='Lung Cancer Prediction Using Deep Learning', justify=LEFT)
title.config(bg='lavender blush', fg='DarkOrchid1')
title.config(font=font)
title.config(height=3, width=120)
title.place(x=100,y=5)
title.pack()

font1 = ('times', 13, 'bold')
uploadButton = Button(main, text="Upload LIDC-IDRI Dataset",
command=uploadDataset)
uploadButton.place(x=10,y=100)
uploadButton.config(font=font1)

processButton = Button(main, text="Process Dataset", command=processDataset)
processButton.place(x=330,y=100)
processButton.config(font=font1)

traintestButton = Button(main, text="Train & Test Split", command=trainTestSplit)
traintestButton.place(x=670,y=100)
traintestButton.config(font=font1)

cnnButton = Button(main, text="Run Hybrid CCDC-HNN Algorithm",
command=runCNN)
cnnButton.place(x=10,y=150)
cnnButton.config(font=font1)

predictButton = Button(main, text="Cancer Cell Detection & Classification",
command=predict)
predictButton.place(x=330,y=150)
predictButton.config(font=font1)
```

```
graphButton = Button(main, text="CCDC-HNN Training Graph", command=graph)
graphButton.place(x=670,y=150)
graphButton.config(font=font1)


font1 = ('times', 12, 'bold')
text=Text(main,height=22,width=140)
scroll=Scrollbar(text)
text.configure(yscrollcommand=scroll.set)
text.place(x=10,y=200)
text.config(font=font1)

main.config(bg='light coral')
main.mainloop()
```

5. RESULTS & DISCUSSION

5. RESULTS & DISCUSSION

The following screenshots showcase the results of our project, highlighting key features and functionalities. These visual representations provide a clear overview of how the system performs under various conditions, demonstrating its effectiveness and user interface. The screenshots serve as a visual aid to support the project's technical and operational achievements.

5.1 GUI/Main Interface :

In below screen, click on ‘Upload LIDC-IDRI Dataset’ button to upload dataset.

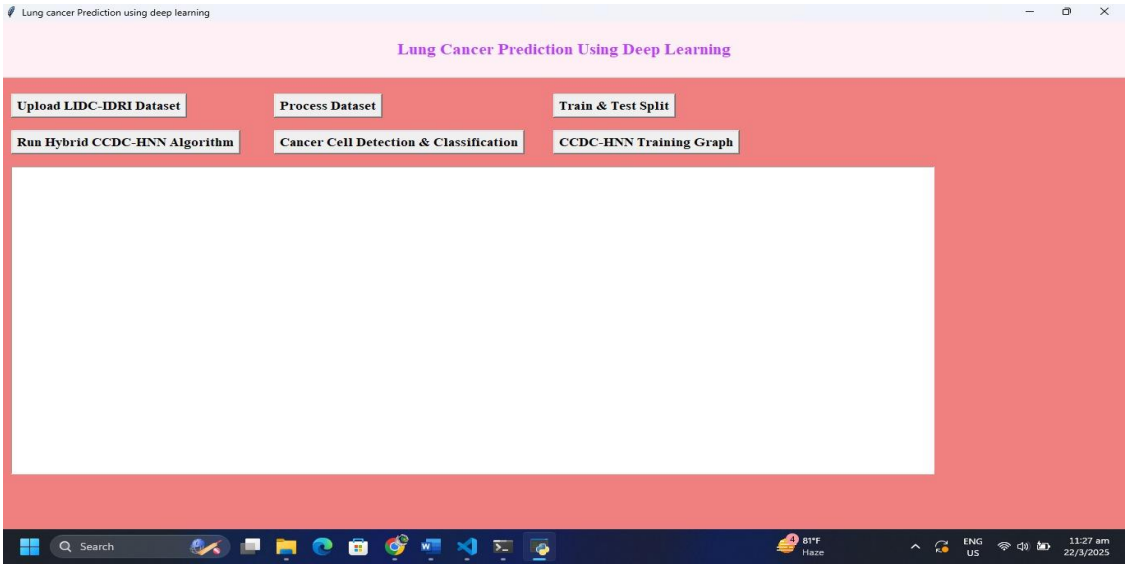

Figure 5.1 : GUI/Main Interface of Lung Cancer Prediction using Deep Learning.

5.2 Total No. of images loaded :

In below screen, It shows Total no. Of images loaded in this project, there are 19255 images are loaded.

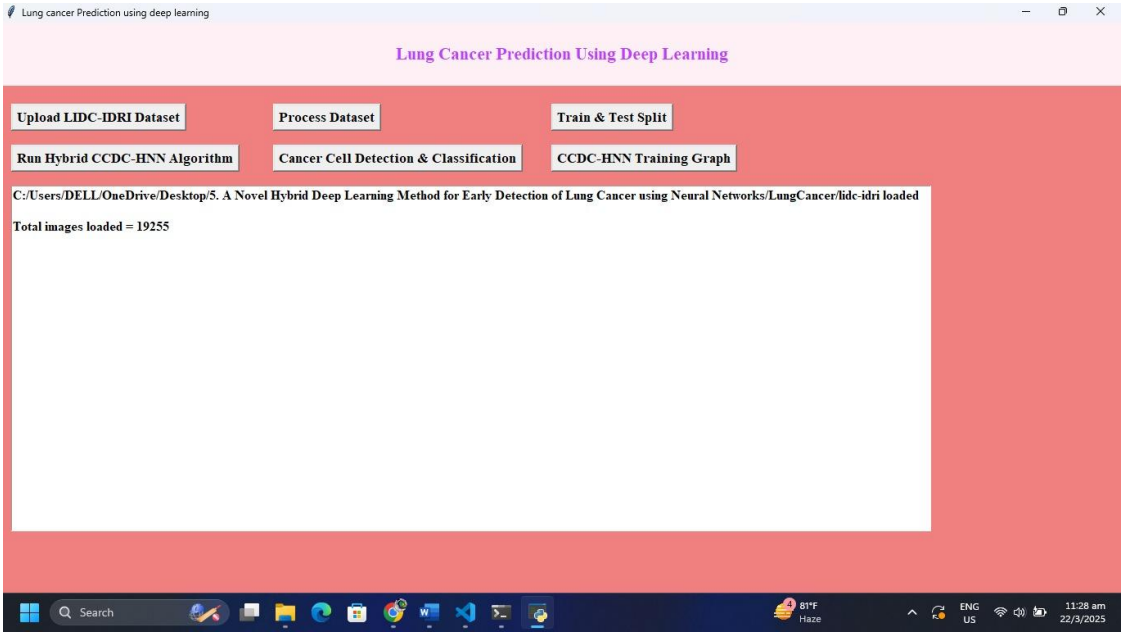

Figure 5.2 : Total No. Of Loaded of Lung Cancer Prediction using Deep Learning

5.3 Dataset :

In below screen, dataset loaded and now click on ‘Dataset Preprocessing’ button to read all images and then processes those images for training.

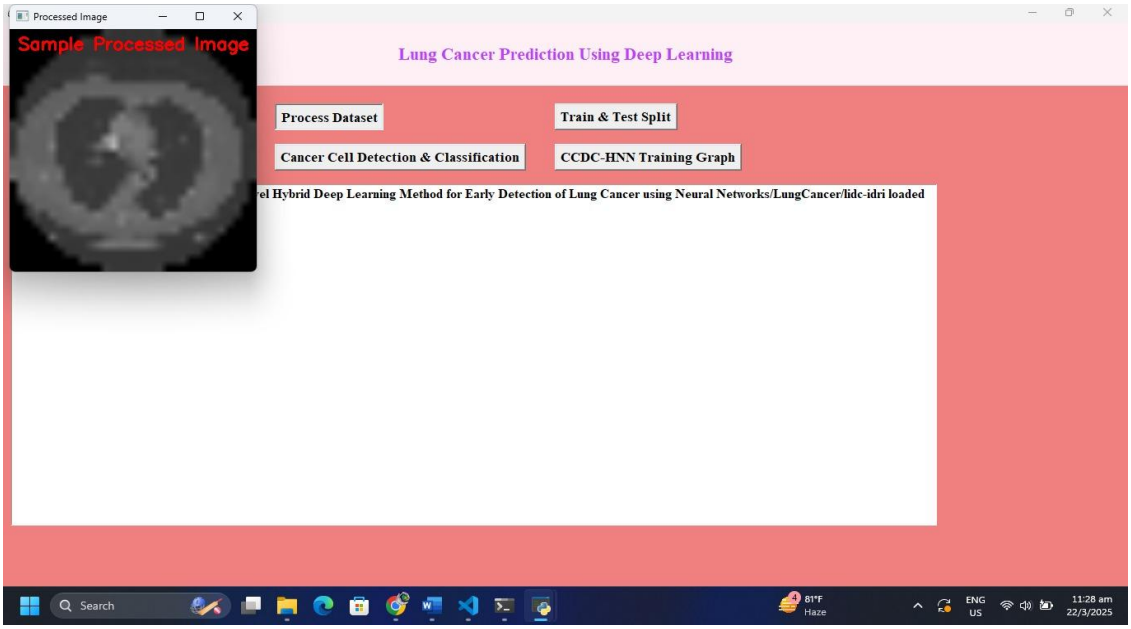

Figure 5.3 : Dataset of Lung Cancer Prediction using Deep Learning.

5.4 Dataset processing & Normalization Completion:

In below screen, we can see dataset processing and normalization was completed.

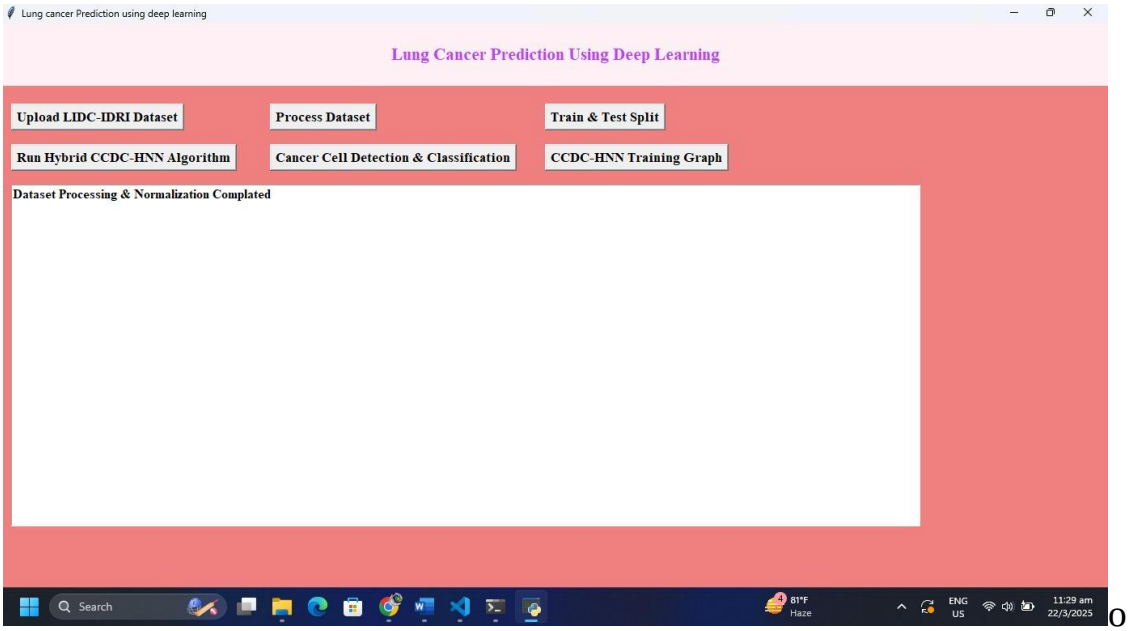

Figure 5.4 : Dataset processing & Normalization Completion of Lung Cancer Prediction using Deep Learning

5.5 Train & Test Split:

In below screen, when we click “Train & Test Split” button we get training and testing dataset details as per the screen 80% images for Training is 15404 and 20% images for testing is 3851 and Now click “Run Hybrid CCDC-HNN Algorithm”.

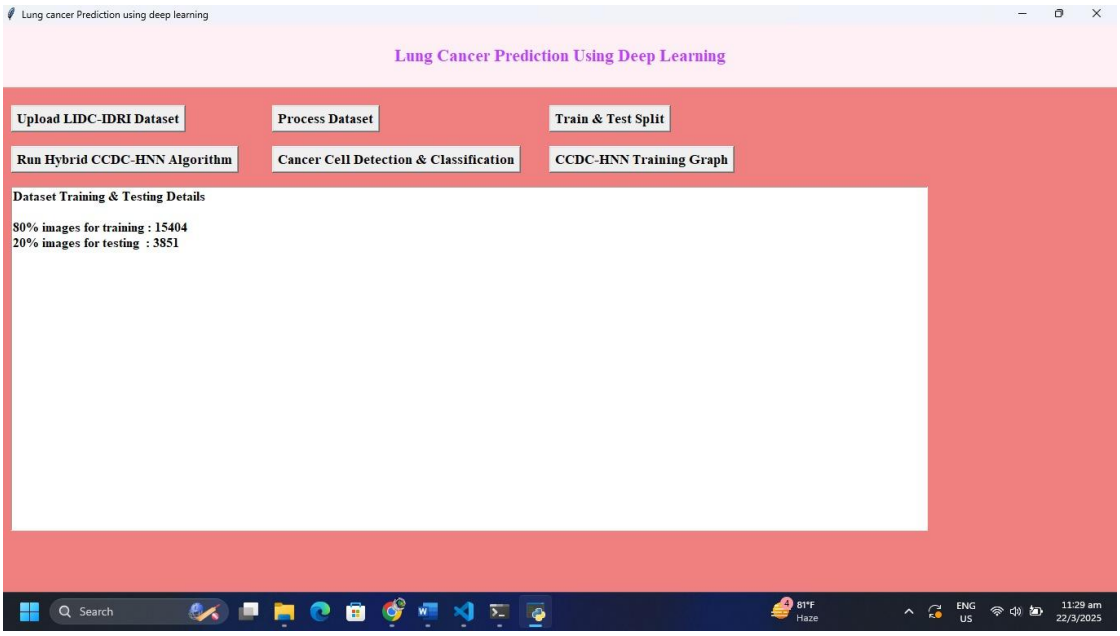

Figure 5.5 : Train & Test Split of Lung Cancer Prediction using Deep Learning

5.6 Confusion Matrix of the proposed Hybrid CCDC-HNN Model :

In below screen, Evaluation metrics for a lung cancer prediction model based on deep learning will appear when we click on “Run Hybrid CCDC-HNN Algorithm”. Two key visualizations are provided: a Confusion Matrix and an ROC AUC Curve. These metrics help in understanding how well the model distinguishes between benign and malignant cases.

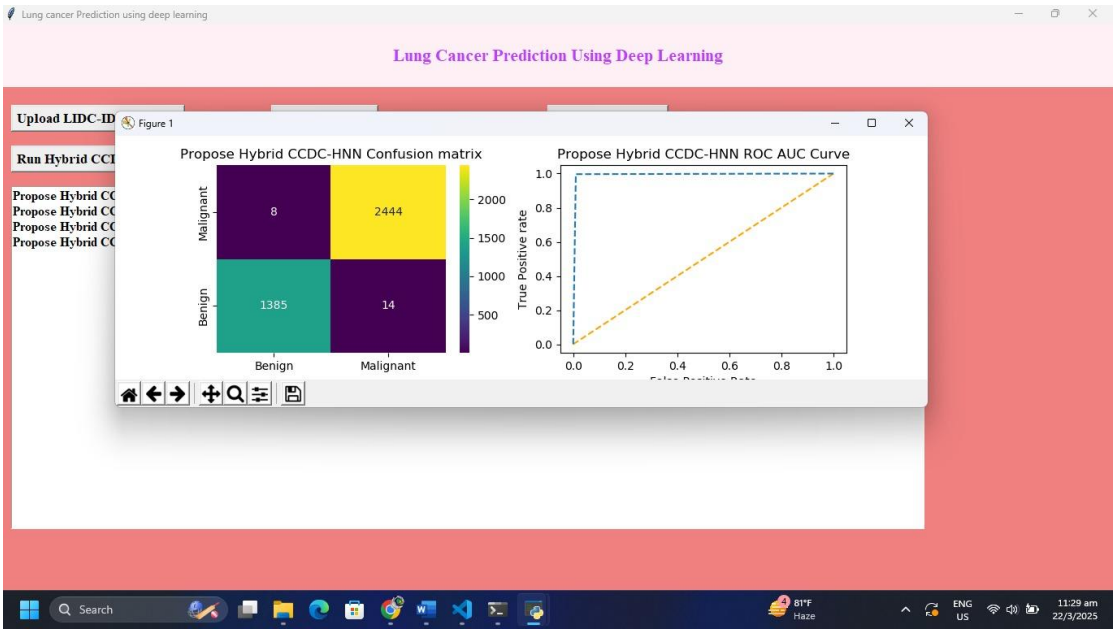

Figure 5.6 : Confusion Matrix of the proposed Hybrid CCDC-HNN Model of Lung Cancer Prediction using Deep Learning

5.7 Evaluation Metrics of the proposed Hybrid CCDC-HNN Model :

In below graph, The Lung Cancer Prediction Using Deep Learning system utilizes a Hybrid CCDC-HNN model to classify lung nodules as benign or malignant. The workflow includes dataset uploading, preprocessing, training, and classification. The model achieves 99.42% accuracy, 99.42% precision, 99.34% recall, and a 99.39% F1-score, indicating high reliability and the model demonstrates high effectiveness.

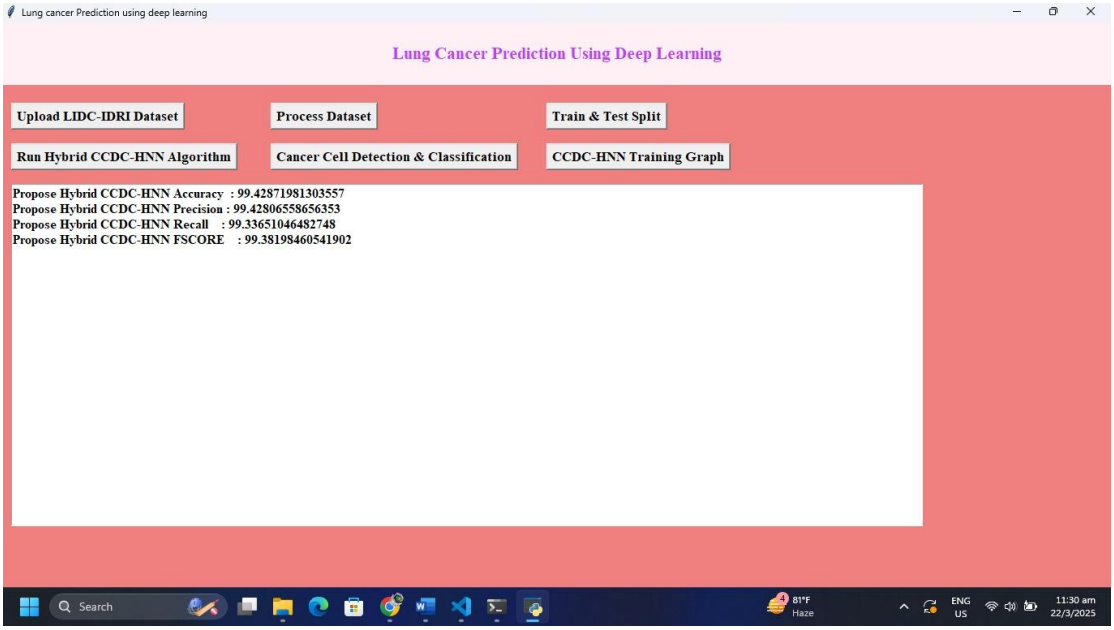

Figure 5.7 : Evaluation Metrics of the proposed Hybrid CCDC-HNN Model of Lung Cancer Prediction using Deep Learning

5.8 Upload Testing image:

In below screen, Now click “Cancer Cell Detection & Classification” selecting and uploading test image and then click on “Open’ button to perform classification.

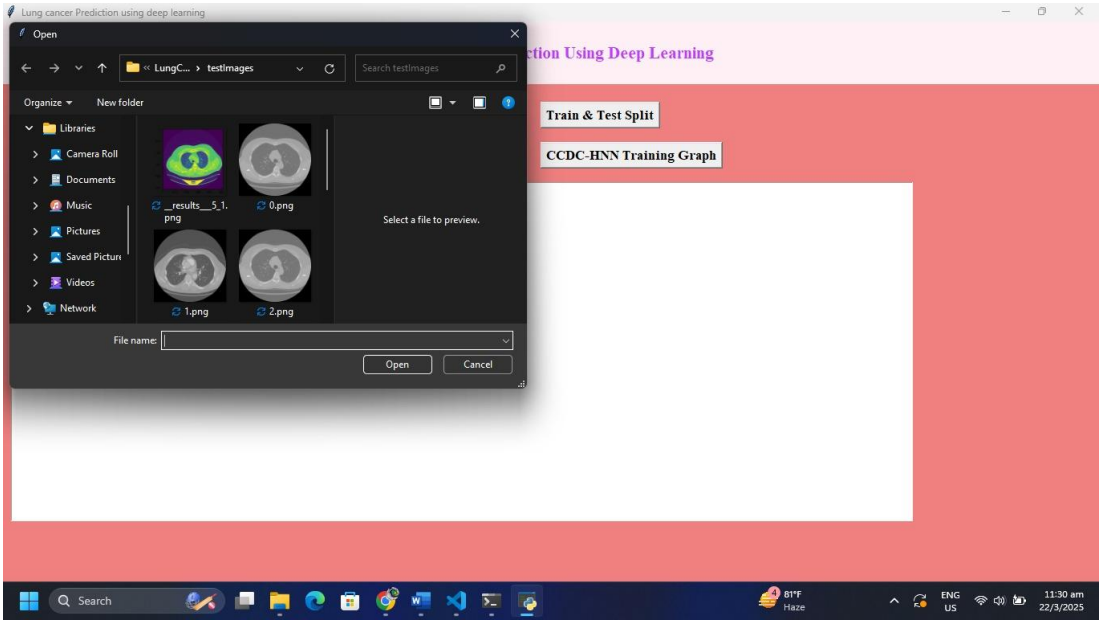

Figure 5.8 : Upload Testing image for Lung Cancer Prediction using Deep Learning

5.9 "Malignant" Prediction Result Displayed In the System:

In below screen, we got classification output result as Malignant where the system uses deep learning to identify cancerous regions in CT scan images. The left image shows a CT scan of the lungs, where a red box highlights a detected malignant (cancerous) area. The right image presents a processed version, isolating the detected cancerous region for better analysis. This system helps in early detection and diagnosis, improving treatment planning and patient outcomes.

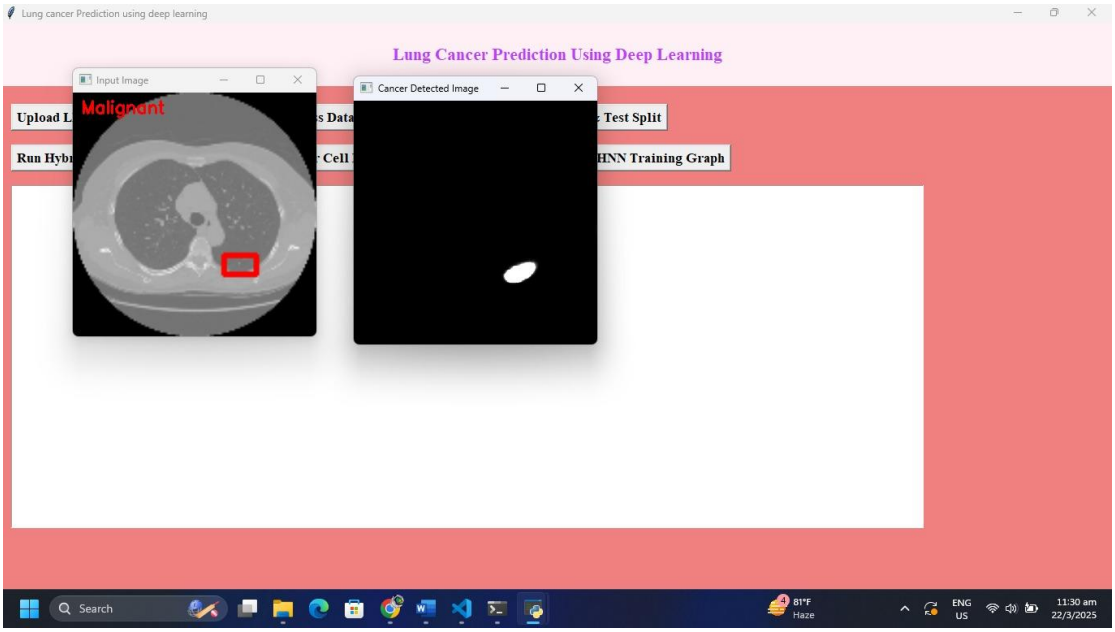

Figure 5.9 : "Malignant" Prediction Result Displayed In the System Lung Cancer Prediction using Deep Learning

5.10 "Benign" Prediction Result Displayed In the System Interface :

In below screen, we got classification output result as benign where the system uses deep learning to analyze CT scans and classify lung nodules as benign or malignant. In the given image, the left side shows a lung CT scan where the system has identified a benign (non-cancerous) region, highlighted with red text. The right side displays the processed result, which remains blank, indicating the absence of malignant (cancerous) cells. This classification helps in early diagnosis, reducing unnecessary treatments and ensuring accurate medical assessments.

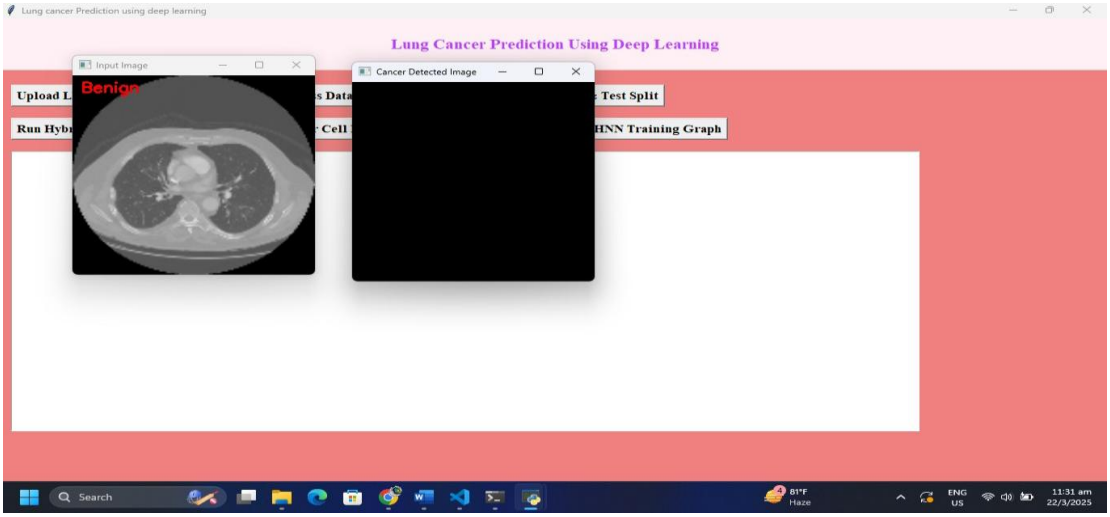

Figure 5.10 : "Benign" Prediction Result Displayed In the System for Lung Cancer Prediction using Deep Learning

5.11 CCDC-HNN Algorithm Training Accuracy & Loss Graph :

In below screen, When we click “CCDC-HNN Training Graph” we got training accuracy and loss graph. The graph represents the model's performance over several epochs. The increasing training accuracy(green) and validation accuracy(red) indicate improved learning, while the decreasing training loss(blue) and validation loss(pink) suggest a reduction in errors. This trend confirms that the model is effectively learning and enhancing its ability to detect lung cancer accurately.

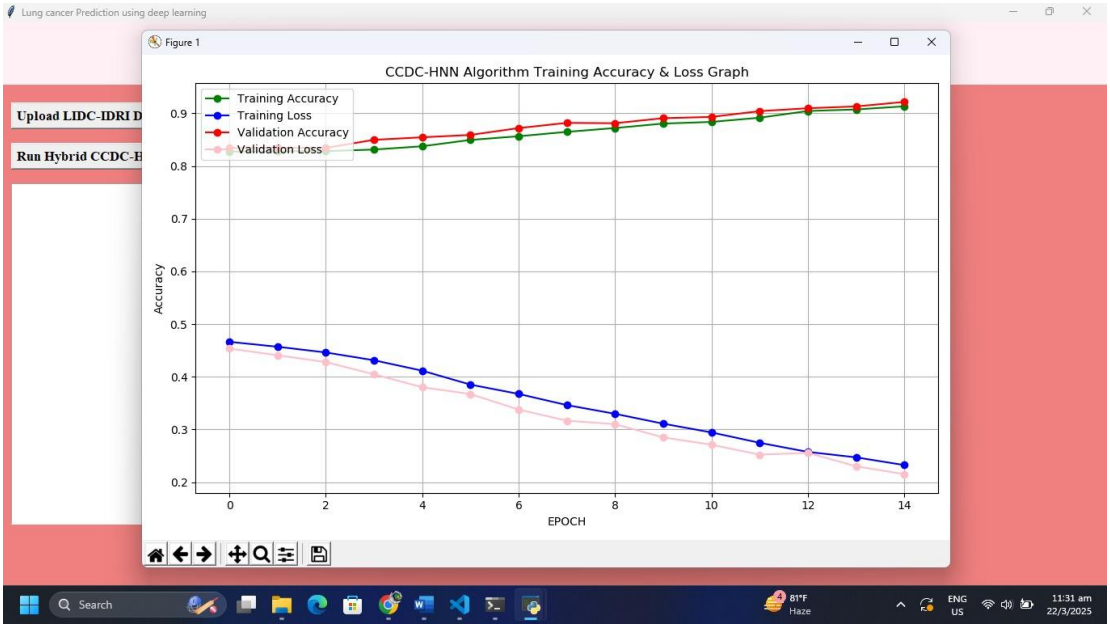

Figure 5.11 : CCDC-HNN Algorithm Training Accuracy & Loss Graph for Lung Cancer Prediction using Deep Learning

6. VALIDATION

6. VALIDATION

The validation of this project is crucial to ensuring the accuracy and robustness of the lung cancer detection system. A structured validation approach is adopted, including dataset validation, model performance evaluation, and real-world testing. The primary objective is to verify that the hybrid deep learning approach (CNN + RNN) effectively detects and classifies lung cancer cells while minimizing false positives and false negatives.

6.1 INTRODUCTION

First, the LIDC-IDRI dataset is divided into training and testing sets, typically following an 80-20 split. The training set is used to develop the deep learning model, while the testing set evaluates its performance on unseen data. To ensure generalization, K-fold cross-validation is applied, allowing the model to be tested across different data partitions. This approach prevents overfitting and ensures that the model can adapt to diverse lung cancer cases.

The performance of the proposed CCDC-HNN (Cancer Cell Detection using Hybrid Neural Network) algorithm is measured using key evaluation metrics such as:

- Accuracy: Measures the overall correctness of predictions.
- Precision: Ensures that detected malignant cases are truly malignant.
- Recall (Sensitivity): Evaluates the model’s ability to identify all malignant cases.
- F1-score: Balances precision and recall for better classification assessment.
- Confusion Matrix: Analyzes correct and incorrect classifications of benign and malignant cases.

Finally, real-world testing is conducted using unseen patient CT scan images to ensure the model performs accurately under clinical conditions. The continuous refinement of the model based on test results ensures that the system remains reliable, scalable, and suitable for real-world lung cancer diagnosis.

TEST CASES

TABLE 6.3.1 UPLOADING DATASET

Test case ID	Test case name	Purpose	Test Case	Output
1	User uploads Dataset.	Use it for lung cancer prediction.	The user uploads the Dataset, on which the lung cancer is detected.	Dataset successfully loaded.

TABLE 6.3.2 CLASSIFICATION

Test case ID	Test case name	Purpose	Input	Output
1	Classification test 1	To check if the classifier performs its task	Lung cancer image is selected	Malignant.
2	Classification test 2	To check if the classifier performs its task	Lung non-cancer image is selected.	Benign.

7. CONCLUSION & FUTURE ASPECTS

7. CONCLUSION & FUTURE ASPECTS

In conclusion, the project has successfully achieved its objectives, showcasing significant progress and outcomes. The implementation and execution phases were meticulously planned and executed, leading to substantial improvements and insights. Looking ahead, the future aspects of the project hold immense potential. Future developments will focus on expanding the scope, integrating new technologies, and enhancing sustainability. These advancements will not only strengthen the existing framework but also open new avenues for growth and innovation, ensuring the project remains relevant and impactful in the long term. This strategic approach will drive continuous improvement and success.

7.1 PROJECT CONCLUSION

The integration of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) provides a powerful and efficient approach for lung cancer stage prediction by leveraging the strengths of both deep learning architectures. CNNs are highly effective in extracting spatial features from medical imaging data, such as CT scans, by detecting intricate patterns, textures, and abnormalities within lung tissues. Their ability to automatically learn hierarchical representations ensures that crucial features relevant to cancer diagnosis are captured with high precision.

By In conclusion, the CNN-RNN hybrid model represents a promising step forward in the field of medical imaging and cancer diagnosis. By combining the feature extraction power of CNNs with the sequential learning capability of RNNs, this approach enhances lung cancer stage prediction accuracy, leading to earlier detection, more effective treatment strategies, and improved patient outcomes**.** As deep learning techniques continue to evolve, further optimizations and real-world clinical validations of this model could pave the way for more reliable and scalable in deep learning.

7.2 FUTURE ASPECTS

The future scope of the proposed hybrid deep learning method for early detection of lung cancer is promising and multifaceted. As the system continues to evolve, there are several key areas for expansion and enhancement. First, the integration of additional data types, such as genomic information or biomarkers, could further refine the model's predictive accuracy and personalized diagnostic capabilities. Advancements in imaging technologies and data acquisition methods may also provide richer datasets, enabling the model to detect a wider range of cancerous conditions and improve generalizability.

Furthermore, incorporating longitudinal data and patient outcomes could enhance the model's ability to predict disease progression and treatment responses, offering a more comprehensive view of patient health. Collaborative efforts with clinical practitioners and researchers will be essential to validate and adapt the system across diverse populations and settings, ensuring its robustness and reliability in real-world applications.

Additionally, ongoing improvements in computational power and algorithms may lead to more efficient training processes and real-time analysis capabilities. Overall, the hybrid model has the potential to drive significant progress in early cancer detection and personalized medicine, setting the stage for future innovations that can transform diagnostic practices and improve patient care more accurately and speedy recovery.

8. BIBLIOGRAPHY

8. BIBLIOGRAPHY

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8.2 GITHUB LINK

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https://github.com/sathvikvajrala/Inappropriate-content-detection-and-classification-of-youtube-videos-using-DL