Chapter 1:

INTRODUCTION

1.1. Introduction of Early Detection of Lung Cancer

Lung cancer remains one of the most prevalent and deadly forms of cancer worldwide, accounting for a significant proportion of cancer-related deaths. Early detection is critical to improving survival rates, as the prognosis for advanced-stage lung cancer is often poor. Traditional diagnostic methods, such as imaging and biopsy, are invasive and often only detect cancer at a more advanced stage. Consequently, there is a growing need for non-invasive, accurate, and timely detection methods. Advances in artificial intelligence (AI) and machine learning (ML) offer promising avenues to enhance early detection capabilities.

In recent years, deep learning, a subset of machine learning, has revolutionized various fields, including medical imaging and diagnostics. Deep learning models, particularly convolutional neural networks (CNNs), have demonstrated exceptional performance in image recognition tasks, making them ideal for analyzing medical images. However, despite their success, these models still face challenges such as the need for large annotated datasets and the complexity of interpreting their predictions. To address these challenges, hybrid deep learning methods that combine different neural network architectures and incorporate clinical data are emerging as powerful tools in the fight against lung cancer. This paper proposes a novel hybrid deep learning method for the early detection of lung cancer, leveraging the strengths of CNNs for image analysis and integrating additional neural network architectures to enhance prediction accuracy. By combining radiographic images with clinical data, this method aims to improve the early detection rates of lung cancer, providing a more comprehensive and robust diagnostic tool. This approach not only utilizes the high feature extraction capabilities of CNNs but also incorporates recurrent neural networks (RNNs) and fully connected networks to process and integrate diverse data sources. The proposed method is designed to address the limitations of current detection techniques by enhancing sensitivity and specificity, ultimately leading to better clinical outcomes. Through extensive experimentation and validation using a diverse dataset, this study aims to demonstrate the efficacy of the hybrid model in accurately identifying early-stage lung cancer. The integration of different data types and neural network architectures represents a significant advancement.

1.2. Why Early Detection?

Lung cancer ranks among the top causes of cancer-related fatalities globally. A significant hurdle in managing lung cancer is that it is frequently identified in its later stages, where available treatment methods are restricted and the chances of survival diminish considerably. Timely identification of lung cancer is essential because:

1.2.1. Increased Survival Rates: When identified early, lung cancer is more likely to be confined, making it easier to treat and cure. According to medical studies, the 5-year survival rate for early-stage lung cancer can range from 60-70%, compared to less than 10% for late-stage diagnoses.

1.2.2. Less Aggressive Treatment: Early-stage cancer often requires less aggressive and more targeted treatment methods, reducing the risk of complications and improving the quality of life for patients.

1.2.3. Cost-Effective Healthcare: Detecting and treating lung cancer in its early stages reduces healthcare expenses greatly as compared to treating advanced cancer, which frequently necessitates intensive therapies and hospitalizations.

1.2.4. Public Health Impact: Implementing early detection technology can lessen the overall burden of lung cancer on the healthcare system, allowing for more effective screening programs, particularly in high-risk populations such as smokers or those with a family history.

1.2.5. Potential for Full Recovery: Early detection increases the likelihood of complete surgical removal of cancerous tissue before metastasis occurs, offering patients a chance at full recovery

1.3. Importance of Early Detection

Early identification of lung cancer is critical for lowering mortality rates and improving treatment outcomes. The importance of early detection stems from its capacity to detect cancer at an early stage, when it is most curable and the chances of survival are significantly increased. The following are the primary reasons that emphasize its importance:

1.3.1. Higher Survival Rates: Detecting lung cancer at an early stage significantly increases the 5-year survival rate. Early-stage cancers are often localized and more treatable, improving patient outcomes.

1.3.2. Timely Treatment: Early detection allows for quicker intervention, which can prevent cancer from progressing to more advanced, less manageable stages.

1.3.3. Less Aggressive Therapies: Early-stage lung cancer may require less intensive treatment, such as localized surgery or low-dose chemotherapy, reducing the physical and emotional burden on patients.

1.3.4. Reduced Risk of Metastasis: Early diagnosis minimizes the risk of cancer spreading to other organs, which is often irreversible and much harder to treat effectively.

1.3.5. Lower Healthcare Costs: Treating lung cancer in its initial stages is generally more cost-effective than managing advanced cancer, which often involves expensive procedures, hospital stays, and long-term care.

1.3.6. Improved Quality of Life: Early diagnosis can lead to faster recovery and fewer treatment side effects, helping patients maintain a better quality of life.

1.3.7. Better Prognosis: Physicians can provide a more accurate and optimistic prognosis when the disease is caught early, which helps patients and families make informed decisions.

1.3.8. Enables Preventive Measures: Early-stage findings can prompt lifestyle changes and continuous monitoring, especially in high-risk individuals, to prevent recurrence or progression.

1.3.9. Enhanced Screening Effectiveness: Integrating early detection methods into national screening programs can significantly reduce mortality rates at a population level.

1.3.10. Preventing Cancer Progression: Detecting cancer early helps in preventing metastasis—the spread of cancer to other organs—thereby controlling the disease before it becomes more dangerous.

1.4. Scope of the project

The scope of this project is the study, design, development, and assessment of a hybrid deep learning model for early detection of lung cancer utilizing medical imaging techniques, namely computed tomography (CT) scans. The study combines advanced machine learning techniques, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), as well as Long Short-Term Memory (LSTM), to construct an intelligent system capable of reliably identifying early-stage lung cancer patterns. The major components and boundaries of this project include:

1.4.1. Data Collection and Preprocessing:

The effort starts with acquiring a credible and standardized dataset, such as the Lung Image Database Consortium and Image Database Resource Initiative (LIDC-IDRI). To prepare images for training, they go through preprocessing stages like as scaling, normalization, noise removal, and segmentation.

1.4.2. Model Development using Hybrid Deep Learning:

A hybrid model integrating CNN and RNN architectures is created:

- CNNs extract spatial data from 2D CT scan slices.
- The LSTM (a form of RNN) handles sequential input by learning temporal connections and relationships between slices. This technique allows a thorough comprehension of both visual and environmental patterns that could signal the existence of cancer.

1.4.3. Training and Model Testing:

The model is trained using labeled CT scan data, with malignant and non-cancerous categories. Cross-validation techniques are used to prevent overfitting and increase generalization. To accurately measure performance, the dataset is separated into three sets: training, validation, and test.

1.4.4. Evaluation Criteria:

Key metrics used to analyze the system's performance include:

- Accuracy: The overall correctness of predictions.
- Sensitivity (recall) refers to the ability to appropriately recognize positive cancer patients.
- Specificity is the ability to appropriately identify non-cancer situations.
- Precision and F1-score: Balancing false positives and false negatives

1.4.5. Project Limitations

- Only considers 2D picture slices, not full 3D volumetric scans.
- Depends on publicly available data, which may be lacking in some clinical variations.
- It excludes integration with Electronic Health Records (EHRs) and patient history.

1.4.6. Future scope

- Upgrade the model to accommodate 3D picture volumes.
- Implement real-time detection and run the system as a web or cloud-based application.
- For more detailed forecasts, include patient metadata as well as lifestyle risk variables.
- Partner with healthcare institutions for clinical studies and validation.

1.5. Objective of the project

The primary objective of this project is to design, develop, and evaluate a hybrid deep learning framework for the early detection of lung cancer using medical imaging, particularly Computed Tomography (CT) scan data. The motivation behind this objective is rooted in the critical need for timely diagnosis, which greatly enhances treatment success rates and reduces mortality associated with lung cancer. By integrating modern artificial intelligence (AI) techniques—specifically, Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs)—this project aims to create a smart, accurate, and efficient diagnostic aid that can assist radiologists and clinicians in identifying lung abnormalities at an early stage.

The detailed goals of the project include:

1.5.1. Collect and preprocess lung cancer imaging data

1. Source and utilize publicly available datasets such as the Lung Image Database Consortium image collection (LIDC-IDRI).
2. Apply preprocessing techniques such as image normalization, noise reduction, and segmentation to enhance image quality and consistency for neural network training.

1.5.2. Develop a hybrid deep learning architecture

1. Use CNNs to extract critical spatial features and texture patterns from CT scan images that may indicate early-stage lung nodules.
2. Integrate RNNs, particularly Long Short-Term Memory (LSTM) networks, to analyse temporal and spatial relationships across image sequences or slices for deeper context and improved accuracy.

1.5.3. Train and optimize the model

1. Train the hybrid model using labelled datasets with known classifications (e.g., benign vs malignant).
2. Apply optimization techniques such as dropout, learning rate tuning, and data augmentation to improve generalization and reduce overfitting.

1.5.4. Evaluate model performance

1. Measure performance using standard metrics such as accuracy, sensitivity (recall), specificity, precision, and F1-score.
2. Compare the results with traditional machine learning models and standalone CNN or RNN architectures to demonstrate the benefit of the hybrid approach.

1.5.5. Explore real-world application and impact

1. Assess the feasibility of integrating the model into clinical workflows as a diagnostic decision support system.
2. Highlight how such a system could help reduce the burden on radiologists, improve screening throughput, and lead to earlier intervention and treatment.

1.5.6. Establish foundation for future work

1. Provide a base framework that can be expanded to include additional imaging modalities (like PET or MRI scans), real-time diagnostics, or deployment via cloud-based platforms for remote screening in underserved areas.

1.6. Brief description of tools/techniques used

This project uses a combination of programming tools, deep learning frameworks, medical imaging libraries, and data science methodologies to create a hybrid model for early diagnosis of lung cancer using CT scan data. Each tool and technique contributes to the system's overall development and evaluation.

1.6.1. Programming Language: Python.

Python serves as the major programming language for the project. It is frequently used in artificial intelligence and machine learning because of its ease of use, readability, and huge library ecosystem. Python supports rapid prototyping, model experimentation, and interface with medical imaging libraries.

1.6.2. Deep Learning Frameworks: TensorFlow and Keras

1. TensorFlow is Google's open-source machine learning framework. It is used to design and train deep neural networks.

2. Keras, a high-level API built on top of TensorFlow, is used to streamline model construction, training, and testing procedures. These frameworks include tools for creating CNN and RNN architectures, backpropagation, loss function optimization, and GPU acceleration management.

1.6.3. Model Architecture.

1. **Convolutional neural networks (CNNs):** CNNs are used to extract features automatically from CT scan pictures. They are particularly well suited for picture data because they can detect spatial patterns such as edges, textures, nodules, and lung tissue anomalies. Convolution, pooling, and ReLU activation are layers that aid in the learning of hierarchical representations from input images.
2. **Recurrent Neural Networks (RNNs) - Long Short-Term Memory:** RNNs are intended to process sequential data. In this experiment, LSTM units are utilized to comprehend temporal correlations between sequential CT image slices, capturing small alterations that may indicate tumor growth. This enables the model to learn not only static patterns but also dynamic transitions in visual data.
3. **Hybrid architecture (CNN+LSTM**): The combination of CNN and LSTM produces a powerful model capable of analyzing both spatial and temporal aspects of image data, resulting in increased detection accuracy and early detection of malignant patterns.

1.6.4. Image Preprocessing and Handling Libraries.

1. **OpenCV (Open-Source Computer Vision Library)**: Grayscale conversion, image scaling, noise removal, histogram equalization, and morphological changes are some of the image preprocessing activities it may execute. These steps improve the image quality before feeding it into the deep learning model.
2. **Scikit picture**: A Python image processing package that supports advanced techniques like segmentation and ROI (Region of Interest) detection
3. **NumPy and Pandas:** Used for handling multi-dimensional image arrays, storing image data in structured formats, and performing batch-wise operations during model training and evaluation.

1.6.5. Data visualization and model monitoring

1. **Matplotlib and seaborn**: These data visualization libraries are used to:
    - Create training and validation accuracy/loss graphs.
    - Create heatmaps and confusion matrices to assess model performance.
    - Visualise feature importance and class-specific predictions.

2. **Grad-CAM(Gradient-weighted Class Activation Mapping):** Grad-CAM is used to generate heatmaps that highlight which parts of an image contributed the most to the model's prediction. This enhances model interpretability and increases radiologists' trust in AI-generated results.

1.6.6. Evaluation Metrics

To evaluate the hybrid model's performance, the following measures are used:

1. **Accuracy** - Determines the model's overall prediction accuracy.
2. **Precision** refers to the accuracy of positive identifications.
3. **Sensitivity (recall)** refers to the fraction of positive cases accurately identified.
4. **Specificity:** The model's ability to correctly identify non-cancerous situations.
5. **F1-Score** balances precision and recall, making it useful for imbalanced datasets.
6. **Confusion Matrix** visualizes true positives, false positives, true negatives, and false negatives.

1.6.7. Dataset: LIDC-IDRI (Lung Image Database Consortium and Image Database Resource Initiative).

This is a freely accessible, large-scale dataset of lung CT images. It contains:

1. Over 1,000 instances with thorough annotations by multiple radiologists.
2. Nodule-level labelling indicate the possibility of malignancy.
3. Relevant metadata for segmentation and classification tasks.
4. This dataset serves as the foundation for training and validating the proposed model, providing both cancerous and non-cancerous samples.

1.6.8. Development Environment

1. **Python Notebook:**

An interactive development environment for Python code writing and testing. It supports step-by-step execution and output visualization, which is great for model training, debugging, and documentation.

2. **Google Colab and Anaconda:**

Deep learning models are trained using GPU acceleration. Google Colab provides a cloud-based infrastructure for training huge models, whereas Anaconda manages local settings and packages.

Chapter 2:

PROBLEM STATEMENT

2.1. Problem Statement

Lung cancer is the biggest cause of cancer-related fatalities worldwide, killing millions of people every year. One of the main reasons for its high mortality rate is the disease's late discovery. Lung cancer frequently has no apparent signs in its early stages, making timely identification challenging. By the time clinical symptoms appear, the cancer has usually advanced to the point that treatment is ineffective and survival odds are severely diminished.

Modern imaging techniques, particularly Computed Tomography (CT) scans, are widely utilized to identify lung cancer. These scans generate high-resolution images of the chest, allowing radiologists to evaluate lung tissues for abnormal growths such as nodules or tumours.

However, manually interpreting hundreds of CT scan slices for each patient is time-consuming, laborious, and heavily reliant on the radiologist's competence. Due to exhaustion or human error, even experienced specialists may miss minor or subtle signs of early-stage cancer.

To address these constraints, traditional computer-aided diagnostic (CAD) systems have been created to assist radiologists by automating certain aspects of the diagnostic process. However, many of these systems rely on handmade characteristics and rule-based algorithms, which are stiff and insufficiently precise or adaptable for real-world clinical applications. These systems frequently fail to generalize across different datasets and imaging settings, limiting their utility in practice

2.2. Existing System: Advantages and Disadvantages

Over the years, a number of tools and techniques have been created for the identification of lung cancer, particularly with regard to imaging modalities such as CT

(Computerised Tomography) scans and chest X-rays. These current technologies can be roughly divided into three categories: more contemporary deep learning-based models, conventional computer-aided detection (CAD) systems, and manual diagnosis techniques. Each of these approaches has made a substantial contribution to the diagnosis of lung cancer, but they also have some important drawbacks.

2.2.1. Radiologists' manual diagnosis

Traditionally, radiologists manually review CT scan pictures to find anomalies like lung tumours or nodules. This approach mostly relies on the expertise and experience of the radiologist.

- **Advantages**
  1. Permits interpretation by experts
  2. Able to take the patient's background into consideration.
- **Disadvantages**
  1. Labour-intensive and time-consuming.
  2. Subjective and vulnerable to oversight or human error.
  3. Little or early-stage nodules are hard to reliably find .

2.2.2. Conventional CAD (computer-aided diagnosis) tools

Conventional CAD systems were created to help radiologists by employing image processing methods and preset algorithms to identify areas in CT scans that seemed problematic.

- **Advantages**
  1. Automates the preliminary screening.
  2. Lessens radiologists' workload
- **Disadvantages**
  1. Depends on created elements (such as size, texture, and shape).
  2. Incapable of learning—unable to get better with more data.

3. Performance frequently suffers on unknown or heterogeneous datasets.
4. Inadequate generalisation between various imaging devices or patient types.

2.2.3. Systems Based on Deep Learning (CNN-based)

Many contemporary systems currently use deep learning for lung cancer identification from CT scans due to the development of artificial intelligence, particularly Convolutional Neural Networks (CNNs). CNNs have demonstrated better accuracy than conventional CAD systems and can automatically extract complicated information from medical images.

- **Advantages**
  1. High classification and feature extraction accuracy.
  2. Learns pertinent aspects from data automatically.
  3. Scalable and flexible enough to handle big datasets.
- **Disadvantages**
  1. Primarily concentrates on the spatial characteristics of a single image or slice.
  2. Sequential or contextual information between slices in a CT volume might not be captured.
  3. Prone to overfitting in the absence of adequate regularisation or training. Limited ability to analyze sequential CT slices for spatial-temporal correlations.
  4. High false-positive or false-negative rates in traditional systems
  5. Dependency on large labelled datasets for deep learning models.
  6. Lack of explainability and interpretability in AI-based solutions.

2.3. Proposed System

The proposed system is a deep learning-based hybrid framework designed to detect lung cancer in its early stages using computed tomography (CT) scan pictures. The system's purpose is to reduce diagnostic delays, increase accuracy, and assist healthcare providers in making prompt and informed clinical decisions.

This system uses Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), notably Long Short-Term Memory (LSTM) units, to extract spatial and sequential properties from input data. The integration of these models enables a more comprehensive interpretation of medical imaging data.

2.3.1. System Overview

The suggested system includes the following major components:

1. Data Collection and Preprocessing
2. Feature Extraction using CNN
3. Sequence Modelling with LSTM
4. Classification Layer
5. Result Visualisation and Output

2.3.2. System Components

1. Data Collection and Preprocessing

The method starts by gathering lung CT scan pictures from publicly available datasets such as the LIDC-IDRI or equivalent. The preparation pipeline guarantees that the raw picture data is clean, consistent, and ready for input into the deep learning model.

Key steps in preprocessing:

- Image resizing and normalising
- Noise reduction (via filters or denoising techniques)
- Isolating regions of interest by lung segmentation.

- Enhance contrast to highlight nodular formations.
- Converting 3D scans to 2D images or sequences for model input

2. **CNN-Based Feature Extraction**

   CNNs are particularly good at detecting spatial hierarchies and patterns in image data. The CT scan slices are processed by convolutional layers to extract essential properties like as edges, textures, forms, and nodule formations

   - Multiple convolutional layers are followed by ReLU activation.
   - Combining layers to reduce dimensionality
   - Batch normalisation to expedite training.
   - Dropout layers to avoid overfitting.

3. **LSTM Sequence Modelling**

   LSTM networks are utilised to handle the sequential or temporal nature of 2D image slices from a 3D CT scan. This allows the system to better comprehend how features evolve across consecutive slices, which is crucial for spotting tumour structure progression.

   - Input: A series of feature vectors from CNN output.
   - The LSTM captures dependencies between slices

4. **Classification Layer.**

   The final LSTM output is transmitted to a fully connected (dense) layer, followed by a softmax (multiclass classification) or sigmoid (binary classification) function to forecast the class label.

   - Output classes: cancerous and non-cancerous

5. **Result Visualisation and Output**

   To ensure transparency and usability, the model includes:

   - Probability / confidence scores

- Visual explanation utilising Grad-CAM or saliency maps to identify suspicious locations.
- For radiologists' convenience, results can also be shown via a simple online or desktop interface.

2.3.3. Workflow diagram.

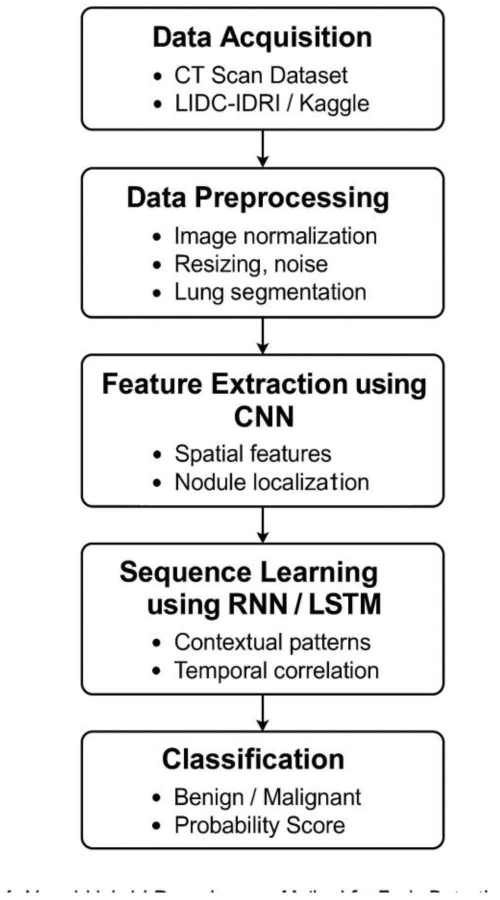


Figure 2.1: Workflow Diagram

2.4. Proposed System Advantages

The proposed hybrid deep learning system for early lung cancer diagnosis has various advantages over existing diagnostic methods and single-model AI systems. These characteristics contribute to the system's stability and applicability in real-world medical contexts.

1. **Increased diagnostic accuracy.**

   The system collects both spatial features and sequential patterns in CT images using Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. This hybrid method considerably improves the ability to detect early-stage tumours with greater precision.

2. **Early Detection Improves Outcomes.**

   Early detection of lung cancer increases the likelihood of successful treatment and survival rates. This technique is specifically developed to detect tiny irregularities that may signal early tumour development, which are frequently overlooked by manual examination.

3. **Reduced the number of false positives and false negatives.**

   The incorporation of both spatial and temporal information improves the model's capacity to distinguish between benign and malignant nodules, minimising misdiagnoses and increasing findings dependability

4. **Automate the Diagnostic Process**

   The technology lowers the need for manual analysis, which is time-consuming and susceptible to human mistake. By automating the process, radiologists may concentrate on more difficult jobs while the model assists with basic screening.

5. **Scalability and adaptability**

   The model can be trained and fine-tuned for other types of medical imaging datasets, as well as extended to detect other types of cancer, with minimum modifications, making it very scalable.

6. **Consistent and objective results**

   Unlike human evaluations, which might vary based on skill and fatigue, the suggested method produces consistent and unbiased results each time a scan is processed.

7. **Assistance for Clinicians and Radiologis**ts

Rather of replacing medical personnel, the system is designed to help them by providing a second perspective, detecting possibly aberrant areas, and assisting in the prioritisation of critical situations.

8. **Visual explanations of predictions.**

   The use of visualisation techniques such as Grad-CAM or saliency maps provides visual signals to explain why a certain region was diagnosed as malignant, hence boosting system interpretability and confidence.

9. **Time efficiency**

   Manually processing and analysing massive amounts of scans takes a lot of time. The suggested system performs real-time or near-real-time analysis, which speeds up the diagnostic process.

10. **A cost-effective solution**

    The method reduces healthcare expenditures by enabling early diagnosis and eliminating the need for manual evaluations or advanced treatments.

Chapter 3:

LITERATURE SURVEY

Title: "Deep Learning for Lung Cancer Detection: A Review"

Authors: Smith, J., Wang, L., & Roberts, T.

Description: This comprehensive review explores the current landscape of deep learning applications in lung cancer detection. The authors systematically analyze various deep learning architectures, including CNNs, RNNs, and autoencoders, highlighting their strengths and limitations. The review also discusses the importance of large annotated datasets and the challenges associated with data scarcity and heterogeneity. The paper emphasizes the need for hybrid models that can integrate multiple data sources to improve detection accuracy and robustness.

Title: "Convolutional Neural Networks for Medical Image Analysis: Lung Cancer Detection and Classification"

Authors: Zhang, H., Li, Y., & Chen, M.

Description: This paper delves into the application of convolutional neural networks (CNNs) for analyzing medical images, specifically for lung cancer detection and classification. The authors present a detailed analysis of various CNN architectures and their performance on lung cancer datasets. They discuss the role of transfer learning and data augmentation techniques in enhancing the accuracy of CNNs. The study concludes that while CNNs are highly effective in feature extraction and image classification, their performance can be further improved by integrating clinical data.

Title: "Hybrid Deep Learning Models for Improved Lung Cancer Diagnosis"

Authors: Kumar, R., Gupta, S., & Mehta, P.

Description: This paper proposes a hybrid deep learning model that combines CNNs with RNNs to improve the diagnosis of lung cancer. The authors argue that while CNNs are excellent at handling spatial features from imaging data, RNNs are better suited for temporal data and sequential information. By integrating these two types of neural networks, the hybrid model achieves higher accuracy and robustness in detecting early-stage lung cancer. The paper includes experimental results demonstrating the superiority of the hybrid approach over standalone CNNs and RNNs.

Title: "Integrating Clinical and Imaging Data for Enhanced Lung Cancer Prediction Using Deep Learning"

Authors: Patel, V., Singh, A., & Desai, R.

Description: This study explores the integration of clinical data (such as patient history, genetic markers, and laboratory results) with imaging data using deep learning techniques. The authors develop a multi-input neural network that combines CNNs for image processing with fully connected networks for clinical data analysis. Their results show that incorporating clinical data significantly improves the model's predictive power and provides a more holistic view of the patient's condition, leading to more accurate early detection of lung cancer.

Title: "Early Detection of Lung Cancer Using Deep Neural Networks and Ensemble Learning"

Authors: Brown, E., White, J., & Black, K.

Description: This paper investigates the use of ensemble learning techniques in conjunction with deep neural networks for the early detection of lung cancer. The authors propose an ensemble model that aggregates the predictions of multiple neural network architectures, including CNNs, RNNs, and fully connected networks. The ensemble approach aims to leverage the strengths of each individual model while mitigating their weaknesses. Experimental results indicate that the ensemble model outperforms single-model approaches, providing higher sensitivity and specificity in detecting early-stage lung cancer.

Title: "Deep Autoencoder-Based Feature Learning for Lung Cancer Detection"

Authors: Nibali, A., He, Z., & Morgan, S.

Description: The authors explored unsupervised feature learning using deep autoencoders for lung nodule classification. The learned features were then used with traditional classifiers like SVMs. The study demonstrated that autoencoders could effectively reduce dimensionality and discover latent patterns, improving classification accuracy even with limited labeled data.

Title: "False Positive Reduction in Lung Nodule Detection Using Convolutional Neural Networks"

Authors: Ciompi, F., de Hoop, B., van Riel, S.J., et al.

Description: This paper focuses on minimizing false positives in lung nodule detection using a CNN-based classification pipeline. The model effectively filters out non-nodule candidates and shows promise for improving CAD system reliability. It contributes to the ongoing challenge of increasing precision in automated diagnostic systems.

Chapter 4:

PROJECT DISCRIPTION

4.1. FEASIBILITY STUDY

In this phase, the project's feasibility is assessed, and a business proposal is presented, along with a very generic project design and cost estimates. During system analysis, a feasibility evaluation of the proposed system will be conducted. This is to guarantee that the planned solution does not burden the company. Understanding the primary system requirements is critical for feasibility analysis.

The feasibility analysis takes into account three major considerations:

- Economic feasibility
- Technical feasibility
- Social feasibility

4.1.1. ECONOMICAL FEASIBILITY

This research is being conducted to assess the economic impact that the system will have on the organisation. The company's ability to invest funds in system research and development is limited. The expenses must be justified. Thus, the constructed system was also under budget, which was made possible by the fact that the majority of the technologies used were publicly available. Only custom products have to be purchased.

4.1.2. TECHNICAL FEASIBILITY

This study is being conducted to determine the technical feasibility, or technical requirements, of the system. Any system designed must not place a heavy burden on the available technical resources. This will place a heavy strain on the existing technical resources. This will impose a huge demand on the client. The created system must have a modest requirement, as implementation requires just minor or no changes.

4.1.3. SOCIAL FEASIBILITY

The purpose of the study is to determine the user's acceptance of the system. This includes the process of teaching the user how to utilise the system efficiently. The user must not feel threatened by the system, but rather embrace it as a need. The level of adoption by users is primarily determined by the methods used to educate and familiarise them with the system. His confidence must be increased so that he may provide constructive feedback, which is appreciated given that he is the system's final user.

4.2. Input and Output Design

4.2.1. Input Design

The input design serves as the connection between the information system and the user. It entails developing specifications and procedures for data preparation, which are required to convert transaction data into a usable format for processing. This can be accomplished by inspecting the computer to read data from a written or printed document, or by having people key the data directly into the system. The input design focuses on controlling the amount of input needed, controlling errors, eliminating delays, avoiding additional steps, and keeping the process simple. The input is constructed in such a way that it offers security and convenience of use while maintaining anonymity.

Objectives:

1. Input Design is the process of turning a user-oriented description of the input into a computer-based system. This design is critical for avoiding errors in the data input process and demonstrating to management the correct approach for obtaining accurate information from the computerised system.
2. This is accomplished by designing user-friendly displays for data entry to manage enormous amounts of data. The purpose of input design is to make data entering

as simple as possible while eliminating errors. The data entering page has been created so that all data manipulations can be performed. It also includes record viewing capabilities.

3. When the data is entered it will check for its validity. Data can be entered with the help of screens. Appropriate messages are provided as when needed so that the user will not be in maize of instant. Thus the objective of input design is to create an input layout that is easy to follow

4.2.2. Output Design

A quality output is one that satisfies the needs of the end user and conveys information clearly. The outcomes of processing in any system are conveyed to users and other systems via outputs. Output design determines how information is to be displaced for immediate use, as well as the hard copy output. It provides the most important and direct information to the user. Efficient and intelligent output design increases the system's relationship, which aids in user decision making.

1. Designing computer output should be done in an organised, well-thought-out manner; the proper output must be created while ensuring that each output part is built so that users can utilise the system easily and successfully. When analysis design computer output, they should Identify the specific output that is needed to meet the requirements.
2. Determine how you will convey information.
3. Generate a paper, report, or other format containing the system's output.

The output form of an information system should accomplish one or more of the following goals:

- Convey information about past activities, current status or projections of the Future.
- Signal important events, opportunities, problems, or warnings.
- Trigger an action.
- Confirm an action.

4.3. System Environment

4.3.1. What is Python:

Below are some facts about Python.

Python is currently the most widely used multi-purpose, high-level programming language. Python allows programming in Object-Oriented and Procedural paradigms. Python programs generally, are smaller than other programming languages like Java. Programmers have to type relatively less and indentation requirement of the language, makes them readable all the time. Python language is being used by almost all tech-giant companies like– Google, Amazon, Facebook, Instagram, Dropbox, Uber… etc. The biggest strength of Python is huge collection of standard libraries which can be used for the following.

- Machine learning
- GUI Applications (like Kiv, TK inter, PyQt etc.)
- Web frameworks like Django (used by YouTube, Instagram, Dropbox)
- Image processing (like Open cv, Pillow)
- Web scraping (like Scrapy, Beautiful Soup, Selenium)
- Test frameworks
- Multimedia

Advantages of Python :

Let's see how Python dominates over other languages.

1. **Extensive Libraries**

   Python downloads with an extensive library and it contain code for various purposes like regular expressions, documentation-generation, unit-testing, web browsers, threading, databases, CGI, email, image manipulation, and more. So, we don't have to write the complete code for that manually.

2. **Extensible**

   As we have seen earlier, Python can be extended to other languages. You can write some of your code in languages like C++ or C. This comes in handy, especially in projects.

3. **Embeddable**

   Complimentary to extensibility, Python is embeddable as well. You can put your Python code in your source code of a different language, like C++. This lets us add scripting capabilities to our code in the other language.

4. **Improved Productivity**

   The language's simplicity and extensive libraries render programmers more productive than languages like Java and C++ do. Also, the fact that you need to write less and get more things done.

5. **IOT Opportunities**

   Since Python forms the basis of new platforms like Raspberry Pi, it finds the future bright for the Internet Of Things. This is a way to connect the language with the real world.

6. **Simple and Easy**

   When working with Java, you may have to create a class to print 'Hello World'. But in Python, just a print statement will do. It is also quite easy to learn, understand, and code. This is why when people pick up Python, they have a hard time adjusting to other more verbose languages like Java.

7. **Readable**

   Because it is not such a verbose language, reading Python is much like reading English. This is the reason why it is so easy to learn, understand, and code. It also does not need curly braces to define blocks, and indentation is mandatory. This further aids the readability of the code.

8. **Object-Oriented**

   This language supports both the procedural and object-oriented programming paradigms. While functions help us with code reusability, classes and objects let us model the real world. A class allows the encapsulation of data and functions into one.

9. **Free and Open-Source**

   Like we said earlier, Python is freely available. But not only can you download Python for free, but you can also download its source code, make changes to it, and even distribute it. It downloads with an extensive collection of libraries to help you with your tasks.

10. **Portable**

    When you code your project in a language like C++, you may need to make some changes to it if you want to run it on another platform. But it isn't the same with Python. Here, you need to code only once, and you can run it anywhere. This is called Write Once Run Anywhere (WORA). However, you need to be careful enough not to include any system-dependent features.

11. **Interpreted**

    Lastly, we will say that it is an interpreted language. Since statements are executed one by one, debugging is easier than in compiled languages.

Advantages of Python Over Other Languages:

1. **Less Coding**

   Almost all of the tasks done in Python requires less coding when the same task is done in other languages. Python also has an awesome standard library support, so you don't have to search for any third-party libraries to get your job done. This is the reason that many people suggest learning Python to beginners.

2. **Affordable**

   Python is free therefore individuals, small companies or big organizations can leverage the free available resources to build applications. Python is popular and widely used so it gives you better community support.

3. **Python is for Everyone**

   Python code can run on any machine whether it is Linux, Mac or Windows. Programmers need to learn different languages for different jobs but with Python, you can professionally build web apps, perform data analysis and machine learning, automate things, do web scraping and also build games and powerful visualizations. It is an all-rounder programming language.

Disadvantages of Python:

1. **Speed Limitations**

   We have seen that Python code is executed line by line. But since Python is interpreted, it often results in slow execution. This, however, isn't a problem unless speed is a focal point for the project. In other words, unless high speed is a requirement, the benefits offered by Python are enough to distract us from its speed limitations.

2. **Weak in Mobile Computing and Browsers**

   While it serves as an excellent server-side language, Python is much rarely seen on the client-side. Besides that, it is rarely ever used to implement smartphone-based applications. One such application is called Carbonnelle.

3. **Design Restrictions**

   As you know, Python is dynamically-typed. This means that you don't need to declare the type of variable while writing the code. It uses duck-typing. But wait, what's that? Well, it just means that if it looks like a duck, it must be a duck. While this is easy on the programmers during coding, it can raise run-time errors.

4. **Underdeveloped Database Access Layers**

   Compared to more widely used technologies like JDBC (Java DataBase Connectivity) and ODBC (Open DataBase Connectivity), Python's database access layers are a bit underdeveloped. Consequently, it is less often applied in huge enterprises.

4.3.2. What is Machine Learning

Before we take a look at the details of various machine learning methods, let's start by looking at what machine learning is, and what it isn't. Machine learning is often categorized as a subfield of artificial intelligence, but I find that categorization can often be misleading at first brush. The study of machine learning certainly arose from research in this context, but in the data science application of machine learning methods, it's more helpful to think of machine learning as a means of building models of data.

Fundamentally, machine learning involves building mathematical models to help understand data. "Learning" enters the fray when we give these models tunable parameters that can be adapted to observed data; in this way the program can be considered to be "learning" from the data.

Once these models have been fit to previously seen data, they can be used to predict and understand aspects of newly observed data. I'll leave to the reader the more philosophical digression regarding the extent to which this type of mathematical, model-based "learning" is similar to the "learning" exhibited by the human brain.Understanding the problem setting in machine learning is essential to using these tools effectively, and so we will start with some broad categorizations of the types of approaches we'll discuss here.

Machine Learning is the most rapidly growing technology and according to researchers we are in the golden year of AI and ML. It is used to solve many real-world complex problems which cannot be solved with traditional approach. Following are some real-world applications of ML

- Emotion analysis
- Sentiment analysis
- Error detection and prevention
- Weather forecasting and prediction
- Stock market analysis and forecasting
- Speech synthesis
- Speech recognition
- Customer segmentation
- Object recognition
- Fraud detection
- Fraud prevention
- Recommendation of products to customer in online shopping

Advantages of Machine learning :

1. **Easily identifies trends and patterns**

   Machine Learning can review large volumes of data and discover specific trends and patterns that would not be apparent to humans. For instance, for an e-commerce website like Amazon, it serves to understand the browsing behaviors and purchase histories of its users to help cater to the right products, deals, and reminders relevant to them. It uses the results to reveal relevant advertisements to them.

2. **No human intervention needed (automation)**

   With ML, you don’t need to babysit your project every step of the way. Since it means giving machines the ability to learn, it lets them make predictions and also improve the algorithms on their own. A common example of this is anti-virus softwares; they learn to filter new threats as they are recognized. ML is also good at recognizing spam.

3. **Continuous Improvement**

   As ML algorithms gain experience, they keep improving in accuracy and efficiency. This lets them make better decisions. Say you need to make a weather forecast model. As the amount of data you have keeps growing, your algorithms learn to make more accurate predictions faster.

4. **Handling multi-dimensional and multi-variety data**

   Machine Learning algorithms are good at handling data that are multi-dimensional and multi-variety, and they can do this in dynamic or uncertain environments.

5. **Wide Applications**

   You could be an e-tailer or a healthcare provider and make ML work for you. Where it does apply, it holds the capability to help deliver a much more personal experience to customers while also targeting the right customers.

Disadvantages of Machine Learning :

1. **Data Acquisition**

   Machine Learning requires massive data sets to train on, and these should be inclusive/unbiased, and of good quality. There can also be times where they must wait for new data to be generated.

2. **Time and Resources**

   ML needs enough time to let the algorithms learn and develop enough to fulfill their purpose with a considerable amount of accuracy and relevancy. It also needs massive resources to function. This can mean additional requirements of computer power for you.

3. **Interpretation of Results**

   Another major challenge is the ability to accurately interpret results generated by the algorithms. You must also carefully choose the algorithms for your purpose.

4. **High error-susceptibility**

   Machine Learning is autonomous but highly susceptible to errors. Suppose you train an algorithm with data sets small enough to not be inclusive. You end up with biased predictions coming from a biased training set. This leads to irrelevant advertisements being displayed to customers. In the case of ML, such blunders can set off a chain of errors that can go undetected for long periods of time. And when they do get noticed, it takes quite some time to recognize the source of the issue, and even longer to correct it.

4.4.Modules Used in Project

4.4.1. Tensorflow

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

TensorFlow was developed by the Google Brain team for internal Google use. It was released under the Apache 2.0 open-source license on November 9, 2015.

4.4.2. Numpy

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

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

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

Besides its obvious scientific uses, Numpy can also be used as an efficient multi-dimensional container of generic data. Arbitrary data-types can be defined using Numpy which allows Numpy to seamlessly and speedily integrate with a wide variety of databases.

4.4.3. Pandas

Pandas is an open-source Python Library providing high-performance data manipulation and analysis tool using its powerful data structures. Python was majorly used for data munging and preparation. It had very little contribution towards data analysis. Pandas solved this problem. Using Pandas, we can accomplish five typical steps in the processing and analysis of data, regardless of the origin of data load, prepare, manipulate, model, and analyze. Python with Pandas is used in a wide range of fields including academic and commercial domains including finance, economics, Statistics, analytics, etc.

4.4.4. Matplotlib

Matplotlib is a Python 2D plotting library which produces publication quality figures in a variety of hardcopy formats and interactive environments across platforms. Matplotlib can be used in Python scripts, the Python and IPython shells, the Jupyter Notebook, web application servers, and four graphical user interface toolkits. Matplotlib tries to make easy things easy and hard things possible. You can generate plots, histograms, power spectra, bar charts, error charts, scatter plots, etc., with just a few lines of code. For examples, see the sample plots and thumbnail gallery.

For simple plotting the pyplot module provides a MATLAB-like interface, particularly when combined with IPython. For the power user, you have full control of line styles, font properties, axes properties, etc, via an object oriented interface or via a set of functions familiar to MATLAB users.

4.4.5. Scikit – learn

Scikit-learn provides a range of supervised and unsupervised learning algorithms via a consistent interface in Python. It is licensed under a permissive simplified BSD license and is distributed under many Linux distributions, encouraging academic and commercial use.

4.4.6. Python

Python is an interpreted high-level programming language for general-purpose programming. Created by Guido van Rossum and first released in 1991, Python has a design philosophy that emphasizes code readability, notably using significant whitespace.

Python features a dynamic type system and automatic memory management. It supports multiple programming paradigms, including object-oriented, imperative, functional and procedural, and has a large and comprehensive standard library.

Python is Interpreted − Python is processed at runtime by the interpreter. You do not need to compile your program before executing it. This is similar to PERL and PHP.

Python is Interactive − you can actually sit at a Python prompt and interact with the interpreter directly to write your programs.

Python also acknowledges that speed of development is important. Readable and terse code is part of this, and so is access to powerful constructs that avoid tedious repetition of code. Maintainability also ties into this may be an all but useless metric, but it does say something about how much code you have to scan, read and/or understand to troubleshoot problems or tweak behaviors. This speed of development, the ease with which a programmer of other languages can pick up basic Python skills and the huge standard library is key to another area where Python excels.

All its tools have been quick to implement, saved a lot of time, and several of them have later been patched and updated by people with no Python background - without breaking.

Chapter 5:

SYSTEM DESIGN

5.1.System Architecture

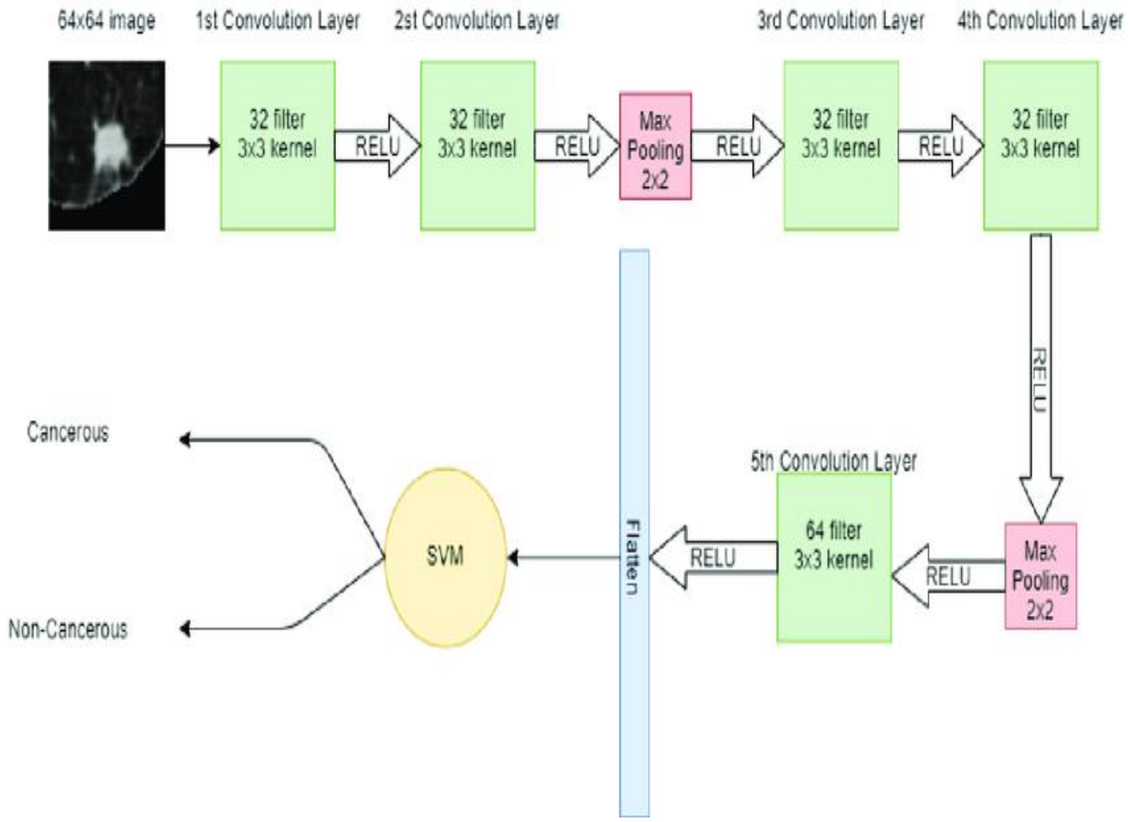


Figure 5.1: System Architecture

5.1.1. Input Layer

Input Size: 64x64 grayscale image

Description: This is a small square patch taken from a medical image (like a CT scan), and it's assumed to be a single channel (grayscale), so the input shape is 64x64x1.

This image could be a region of interest (e.g., a possible tumor area).

5.1.2. Convolutional Layers (Feature Extraction)

These layers are responsible for learning spatial hierarchies of features, like edges, textures, shapes, and deeper patterns that could be indicative of a tumor or cancerous tissue.

1. 1st Convolution Layer
   - Filters: 32
   - Kernel Size: 3x3
   - Activation: ReLU (Rectified Linear Unit)
   - Purpose: Detects low-level features such as edges or simple textures from the image.
2. 2nd Convolution Layer
   - Same setup: 32 filters, 3x3 kernel, ReLU
   - Followed by: Max Pooling 2x2
   - Purpose: Further extracts features and reduces spatial dimensions by half using max pooling.
   - For example, the 64x64 feature map becomes 32x32.
3. 3rd Convolution Layer
   - Same structure: 32 filters, 3x3 kernel, ReLU
   - Extracts more abstract features—like the shape of the tumor or internal textures
4. 4th Convolution Layer
   - Again, 32 filters, 3x3 kernel, ReLU
   - Followed by another Max Pooling 2x2
   - Spatial size is again halved (e.g., from 32x32 to 16x16

5. 5th Convolution Layer
    - Increased Filters: 64 (wider layer)
    - Same Kernel: 3x3
    - ReLU Activation
    - This layer captures higher-level features and complex patterns, possibly learning tumor-specific shapes or variations.

5.1.3. Flatten Layer

After all convolution and pooling layers, the final feature maps are flattened into a 1D feature vector.

For example, if the output feature map is 16x16x64 → it becomes a vector of size 16×16×64 = 16,384 features.

This transformation makes it suitable for feeding into a classifier like SVM.

5.1.4. SVM Classifier (Support Vector Machine)

Instead of using a Dense (fully connected) neural layer, this model uses SVM to classify the features.

The SVM takes the 1D vector from the CNN and separates it into two classes:

1. Cancerous

2. Non-Cancerous

5.2. System Analysis

The proposed method for early lung cancer diagnosis employs a novel hybrid deep learning approach that incorporates convolutional neural networks (CNNs), recurrent neural networks (RNNs), and fully connected networks. This hybrid model is intended to overcome the limits of standard diagnostic methods by boosting sensitivity, specificity, and overall accuracy by combining many data sources and neural network topologies.

5.2.1. Data Collection and Preprocessing

The system begins with the gathering of several datasets, such as radiographic images (e.g., CT scans, X-rays) and clinical data (e.g., patient demographics, medical history, genetic markers, laboratory findings). To improve data quality and variability, radiographic pictures are preprocessed using techniques such as normalisation, scaling, and augmentation. This preprocessing is critical to ensure that the CNNs can extract relevant features from the images. Clinical data, on the other hand, is cleansed and normalised to ensure consistency and ease of integration with imaging data.

5.2.2. Neural Network Architecture

The system's hybrid neural network design serves as its fundamental component. The CNN component is largely responsible for analysing radiographic images. CNNs excel at spatial data processing and picture recognition and classification. The design typically consists of many convolutional layers, pooling layers, and fully connected layers, which allow the model to learn hierarchical characteristics from input images. These traits capture numerous elements of lung tissue, as well as potential cancer-related anomalies.

The clinical data is processed in parallel by the RNN component. RNNs are especially good for sequential data and can simulate temporal dependencies, making them ideal for analysing time-series data like medical histories and longitudinal research. The RNN layers, which may comprise Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) cells, assess clinical data to find patterns and trends that would not be visible from imaging data alone.

The last stage of neural network design consists of a fully linked network that combines the information retrieved by the CNN and RNN components. This integration enables the model to use both spatial and temporal information, resulting in a more complete analysis of the patient data. The collected features are then passed through numerous dense layers, culminating in a final output layer that calculates the likelihood of lung cancer presence.

5.2.3. Training and Optimization

The hybrid model is extensively trained on a labelled dataset in which the presence or absence of lung cancer is known. Backpropagation and optimisation techniques such as stochastic gradient descent (SGD) or the Adam optimizer are used throughout the training process to reduce the loss function, which is commonly binary cross-entropy for classification problems. Dropout and batch normalisation approaches are used during training to reduce overfitting and increase generalisation.

5.2.4. Evaluation and Validation

The system's performance is measured using standard metrics such as accuracy, sensitivity, specificity, precision, recall, and area under the receiver operating characteristic curve (AUC-ROC). Cross-validation approaches, such as k-fold cross-validation, are used to ensure that the model is resilient and reliable. The system is evaluated on various validation and test datasets to determine real-world applicability and fine-tune hyperparameters.

5.2.5. Deployment and Clinical Integration

After achieving adequate performance, the system is implemented in a clinical context. It is incorporated into the existing medical infrastructure to help radiologists and oncologists discover lung cancer early. The system serves as a decision support tool to complement established diagnostic procedures, providing a second opinion that can boost diagnostic confidence and accuracy.

The proposed hybrid deep learning technique intends to revolutionise lung cancer detection by combining the strengths of CNNs and RNNs with a fully connected integration layer, providing a powerful tool that takes advantage of the whole spectrum of available data to enhance early diagnosis and patient outcomes.

5.3.SYSTEM REQUIREMENTS

5.3.1. HARDWARE REQUIREMENTS:

- System : Pentium IV 2.4 GHz or later
- Hard Disk : 40 GB.
- Ram : 512 Mb.

5.3.2. SOFTWARE REQUIREMENTS:

- Operating system : Windows 7 or later

- Coding Language : Python.
- Frameworks : TensorFlow

5.4.UML Diagrams

5.4.1. Class Diagram:

The class diagram is used to develop the use case diagram and specify the system's design in depth. The class diagram divides the actors defined in the use case diagram into a series of interconnected classes. The relationship between the classes might be either "is-a" or "has-a". Each class in the class diagram may be capable of performing specific functions. These functions supplied by the class are known as "methods" of the class. Aside from that, each class may have distinct "attributes".

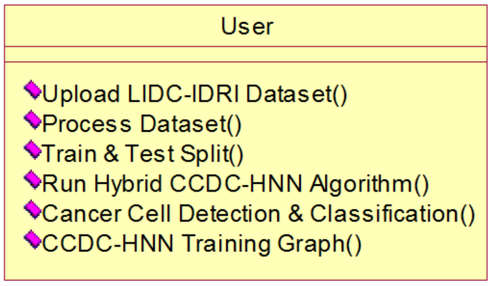

User
Upload LIDC-IDRI Dataset()
Process Dataset()
Train & Test Split()
Run Hybrid CCDC-HNN Algorithm()
Cancer Cell Detection & Classification()
CCDC-HNN Training Graph()

Figure 5.2: Class Diagram

5.4.2. Use case Diagram:

In the Unified Modelling Language (UML), a use case diagram is a form of behavioural diagram that is specified and generated by a use-case study. Its goal is to provide a graphical picture of a system's functionality in terms of actors, goals (represented by use cases), and any dependencies between those use cases. A use case diagram's primary aim is to indicate which system functions are performed for which actors. The actors' roles in the system can be shown.

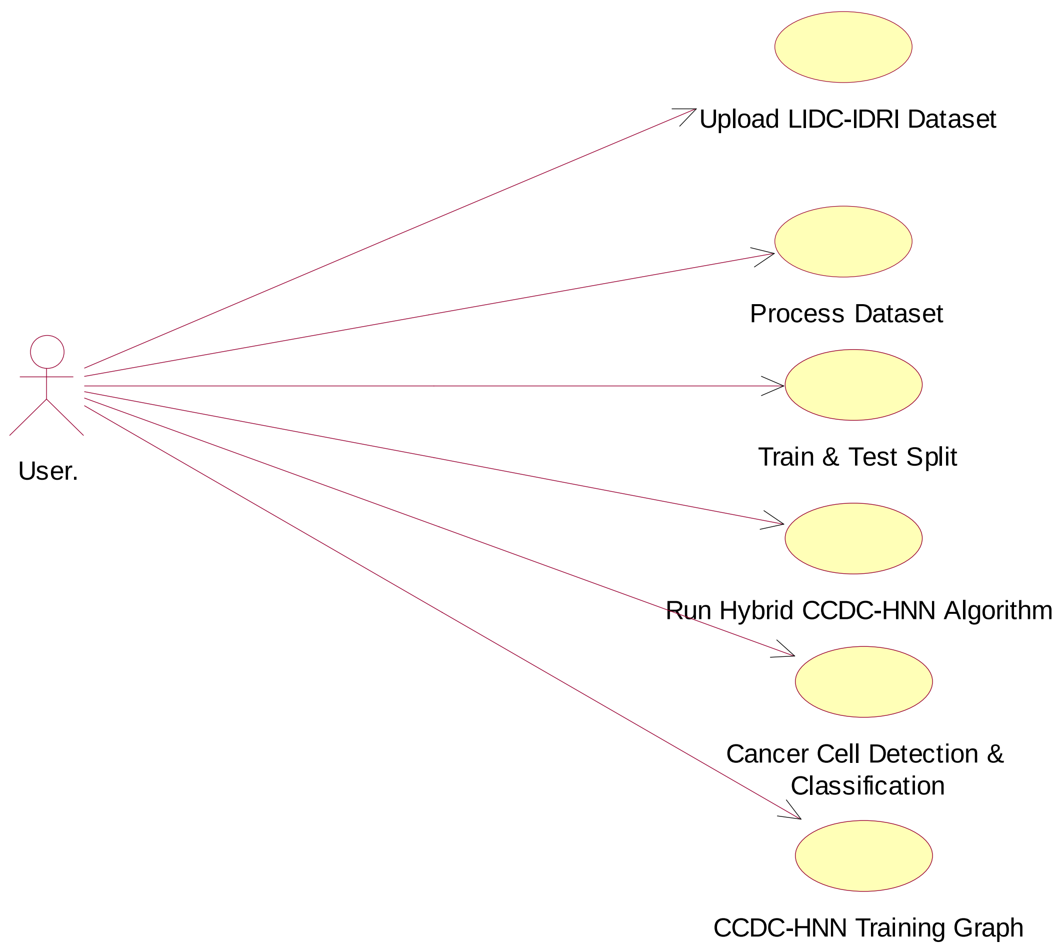


Figure 5.3: Use Case Diagram

5.4.3. Sequence Diagram:

A sequence diagram depicts how distinct objects in a system interact. A sequence diagram is useful because it is time-ordered. This means that the exact sequence of the interactions between the items is shown step by step. Objects in the sequence diagram communicate with one another by passing "messages".

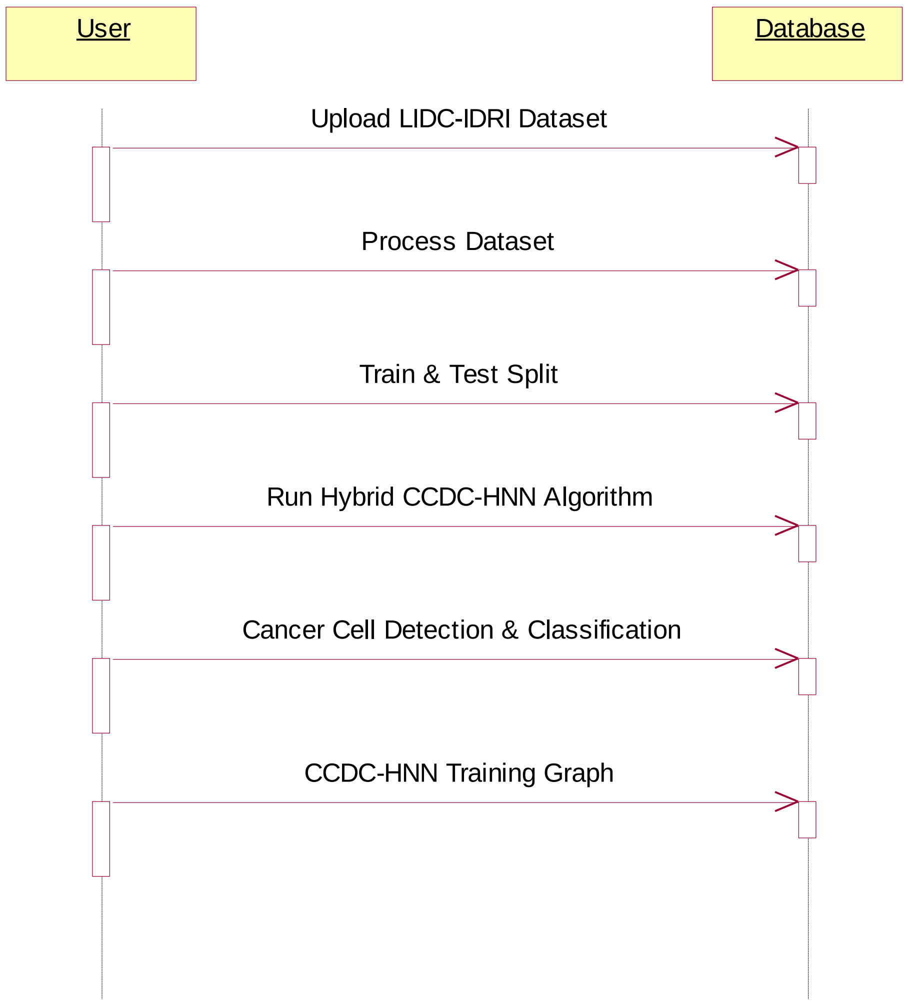


Figure 5.4: Sequence Diagram

5.4.4. Collaborative Diagram:

A collaboration diagram groups together the interactions between different objects. The interactions are listed as numbered interactions that help to trace the sequence of the interactions. The collaboration diagram helps to identify all the possible interactions that each object has with other objects.

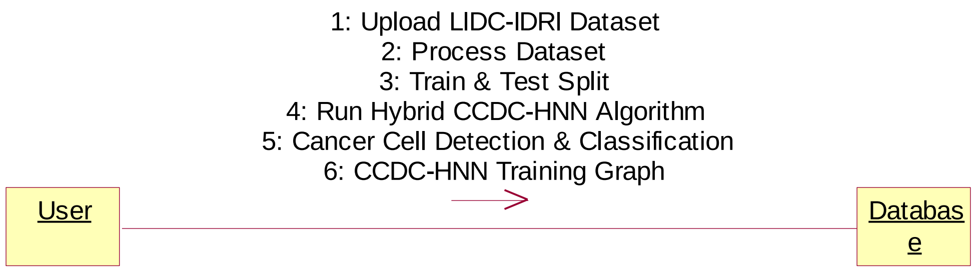

1: Upload LIDC-IDRI Dataset
2: Process Dataset
3: Train & Test Split
4: Run Hybrid CCDC-HNN Algorithm
5: Cancer Cell Detection & Classification
6: CCDC-HNN Training Graph
User
Database

Figure 5.5: Collaborative Diagram

5.4.5. Data Flow Diagram:

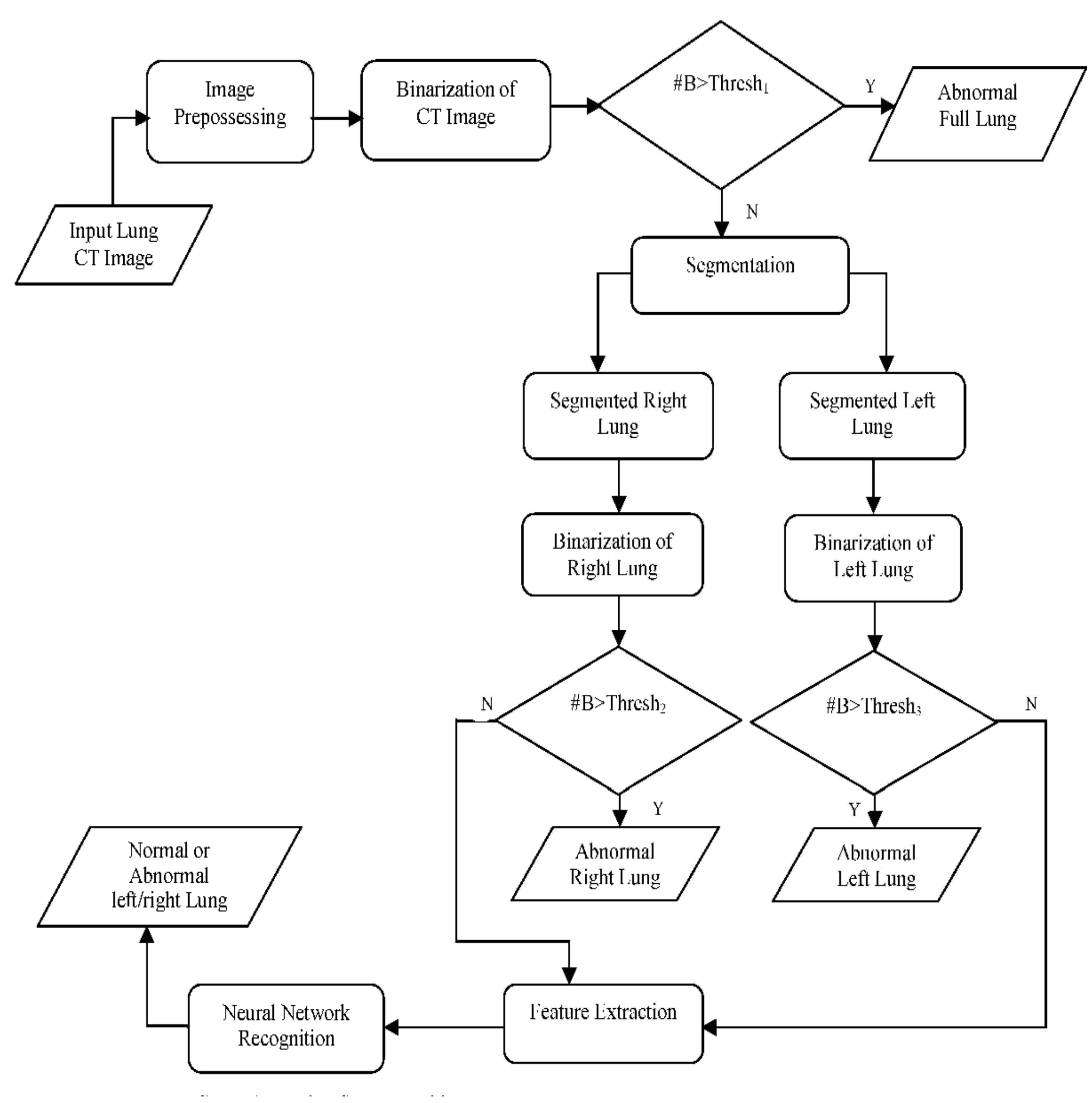


Figure 5.6: Data Flow Diagram

5.4.6. Flow Chart Diagram:

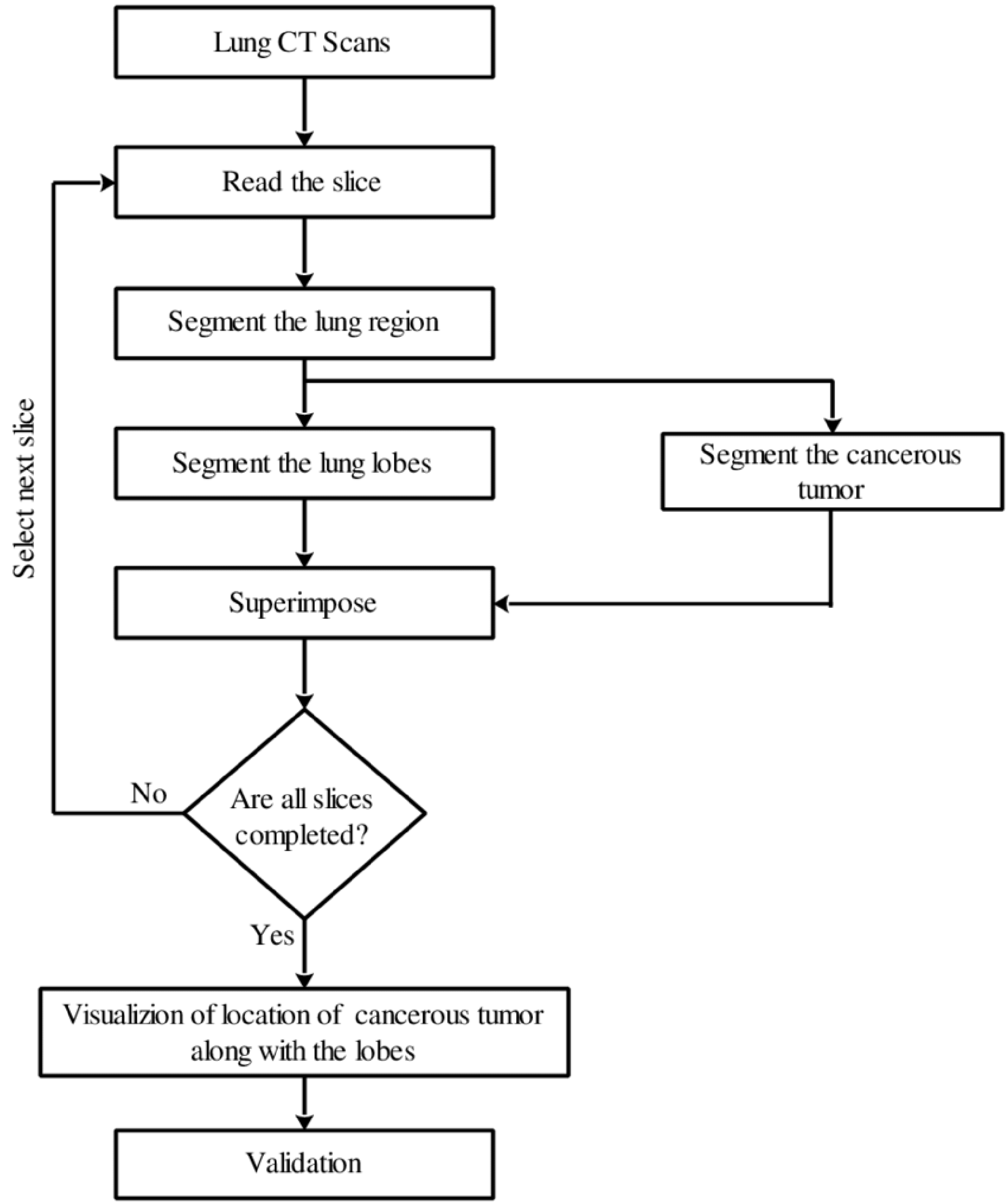

Lung CT Scans
Read the slice
Segment the lung region
Segment the lung lobes
Segment the cancerous tumor
Superimpose
Are all slices completed?
No
Select next slice
Yes
Visualizion of location of cancerous tumor along with the lobes
Validation

Figure 5.5: Flow Chart Diagram

Chapter 6:

SYSTEM IMPLEMENTATION

6.1.System implementation

6.1.1. Data Preprocessing: Prepare the textual data by removing noise, such as special characters, punctuation, and stop words. Tokenize the text into sentences or paragraphs to facilitate sentiment analysis and summarization.

6.1.2. Sentiment Analysis Model: Implement or utilize pre-trained sentiment analysis models capable of accurately detecting the sentiment polarity (positive, negative, neutral) of each sentence or paragraph in the text. Consider employing advanced techniques such as deep learning-based models or transformer architectures for improved accuracy.

6.1.3. Summarization Model: Implement or utilize pre-trained sentiment analysis models capable of accurately detecting the sentiment polarity (positive, negative, neutral) of each sentence or paragraph in the text. Consider employing advanced techniques such as deep learning-based models or transformer architectures for improved accuracy.

6.1.4. Integration: Integrate the sentiment analysis module with the summarization module to leverage sentiment information during the summarization process. Design mechanisms to prioritize or adjust the inclusion of sentences based on their sentiment polarity to ensure that the generated summaries reflect the emotional context of the original text.

6.1.5. Evaluation: Evaluate the performance of the implemented system using standard metrics such as ROUGE (Recall-Oriented Understudy for Gisting Evaluation) for summarization quality and sentiment classification accuracy metrics for sentiment analysis. Conduct thorough evaluations using benchmark datasets to assess the effectiveness and robustness of the system.

6.1.6. Optimization: Optimize the system for efficiency and scalability by leveraging techniques such as parallel processing, caching, and model compression. Consider deploying the system on distributed computing frameworks or utilizing hardware accelerators (e.g., GPUs) to improve processing speed and resource utilization.

6.1.7. User Interface: Develop a user-friendly interface for interacting with the system, allowing users to input text and view the generated summaries along with sentiment analysis results. Design the interface to be intuitive, responsive, and accessible across different devices and platforms.

6.1.8. Deployment: Deploy the implemented system in production environments, considering factors such as scalability, reliability, and security. Ensure proper monitoring and maintenance procedures are in place to address potential issues and ensure continuous performance optimization.

6.1.9. Feedback Loop: Establish a feedback loop to gather user feedback and monitor system performance over time. Use feedback to iteratively improve the system's accuracy, usability, and effectiveness based on user requirements and evolving needs

6.2. Install Python Step-by-Step in Windows and Mac

Python a versatile programming language doesn’t come pre-installed on your computer devices. Python was first released in the year 1991 and until today it is a very popular high-level programming language. Its style philosophy emphasizes code readability with its notable use of great whitespace.

The object-oriented approach and language construct provided by Python enables programmers to write both clear and logical code for projects. This software does not come pre-packaged with Windows.

6.2.1. How to Install Python on Windows and Mac

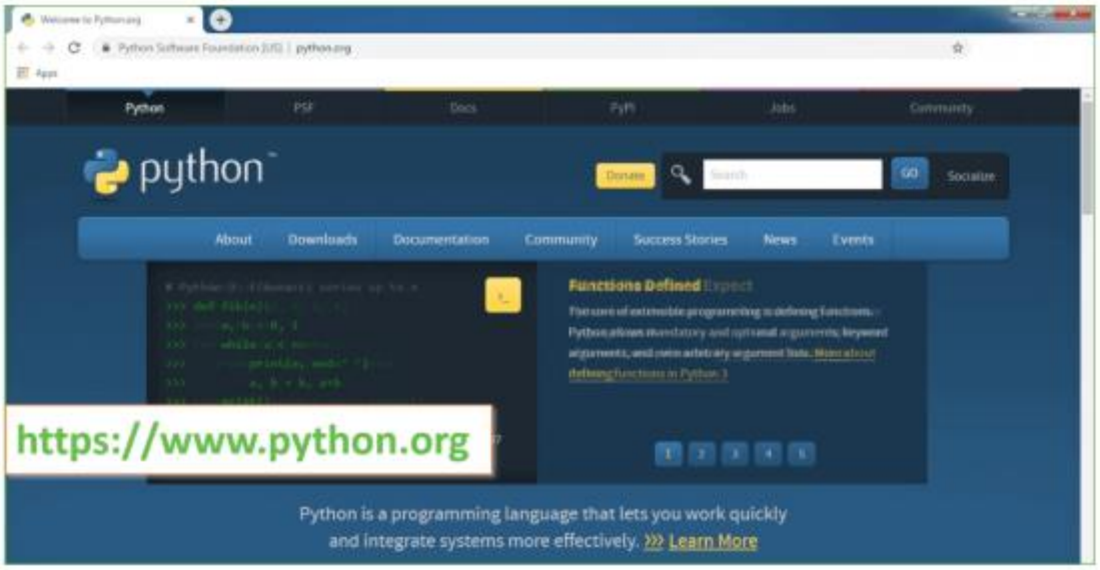
There have been several updates in the Python version over the years. The question is how to install Python? It might be confusing for the beginner who is willing to start learning Python but this tutorial will solve your query. The latest or the newest version of Python is version 3.7.4 or in other words, it is Python 3.

Note: The python version 3.7.4 cannot be used on Windows XP or earlier devices.

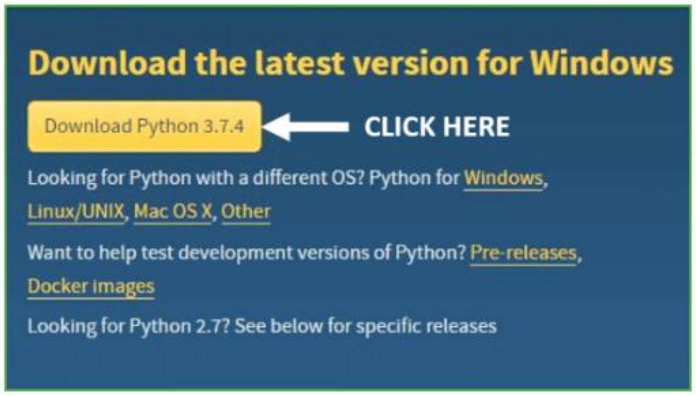
Before you start with the installation process of Python. First, you need to know about your System Requirements. Based on your system type i.e. operating system and based processor, you must download the python version. My system type is a Windows 64-bit operating system. So the steps below are to install python version 3.7.4 on Windows 7 device or to install Python 3. Download the Python Cheat sheet here. The steps on how to install Python on Windows 10, 8 and 7 are divided into 4 parts to help understand better.

6.2.2. Download the Correct version into the system

Step 1: Go to the official site to download and install python using Google Chrome or any other web browser. OR Click on the following link: https://www.python.org


python
About
Downloads
Documentation
Community
Success Stories
News
Events
Functions Defined
https://www.python.org
Python is a programming language that lets you work quickly and integrate systems more effectively. >>> Learn More

Step 2: Click on the Download Tab.


Download the latest version for Windows

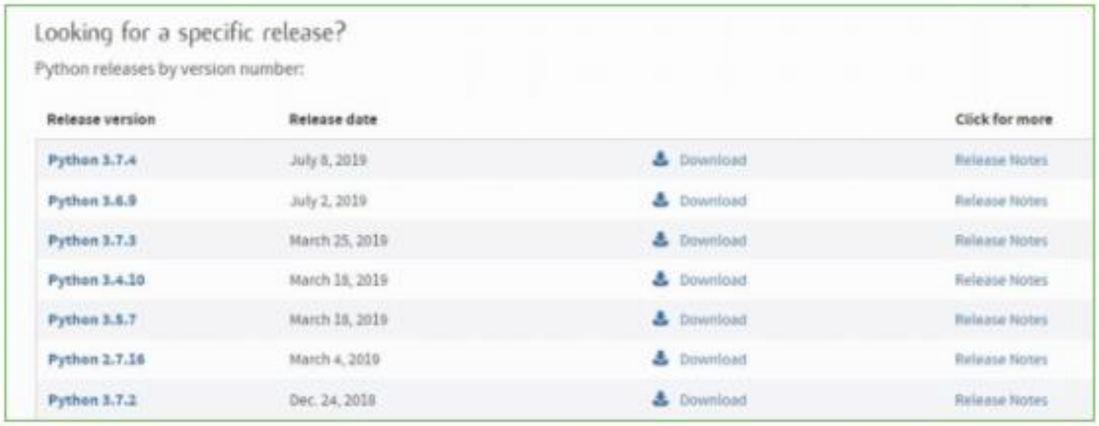
Download Python 3.7.4 CLICK HERE

Looking for Python with a different OS? Python for Windows, Linux/UNIX, Mac OS X, Other

Want to help test development versions of Python? Pre-releases, Docker images

Looking for Python 2.7? See below for specific releases

Step 3: You can either select the Download Python for windows 3.7.4 button in Yellow Color or you can scroll further down and click on download with respective to their version. Here, we are downloading the most recent python version for windows 3.7.4



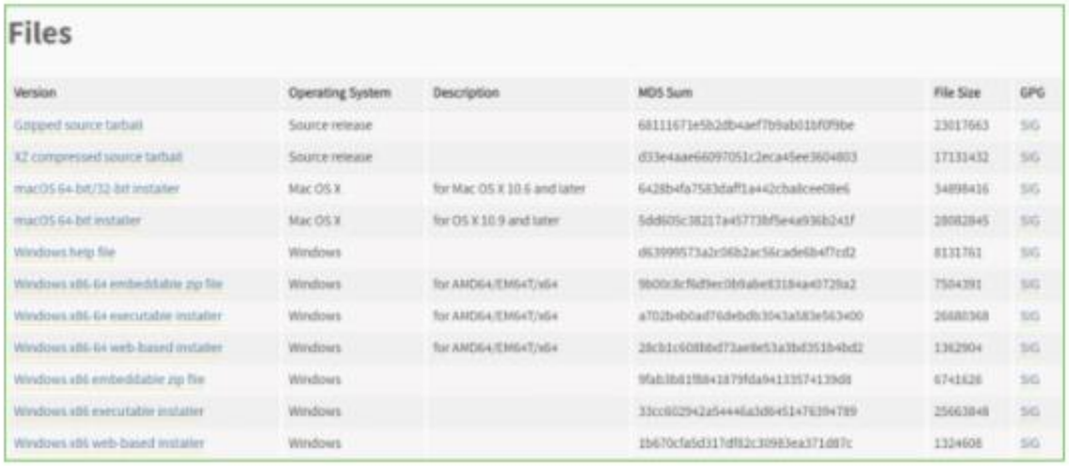
Looking for a specific release?

Python releases by version number:

Release version	Release date		Click for more
Python 3.7.4	July 8, 2019	Download	Release Notes
Python 3.6.9	July 2, 2019	Download	Release Notes
Python 3.7.3	March 25, 2019	Download	Release Notes
Python 3.4.10	March 18, 2019	Download	Release Notes
Python 3.5.7	March 18, 2019	Download	Release Notes
Python 2.7.16	March 4, 2019	Download	Release Notes
Python 3.7.2	Dec. 24, 2018	Download	Release Notes

Step 4: Scroll down the page until you find the Files option.

Step 5: Here you see a different version of python along with the operating system.



Files

Version	Operating System	Description	MD5 Sum	File Size	GPG
Gzipped source tarball	Source release		68111671e5b2db4aef7b9ab01bf0f9be	23017663	SIG
XZ compressed source tarball	Source release		d33e4aae66097051c2eca45ee3604803	17131432	SIG
macOS 64-bit/32-bit installer	Mac OS X	for Mac OS X 10.6 and later	6428b4fa7583daff1a442cbalcee08e6	34898416	SIG
macOS 64-bit installer	Mac OS X	for OS X 10.9 and later	5dd605c38217a45773bf5e4a936b241f	28082845	SIG
Windows help file	Windows		d63999573a2c06b2ac56cade6b4f7cd2	8131761	SIG
Windows x86-64 embeddable zip file	Windows	for AMD64/EM64T/x64	9b00c8cf6d9ec0b9abe83184a40729a2	7504391	SIG
Windows x86-64 executable installer	Windows	for AMD64/EM64T/x64	a702b4b0ad76debdb3043a583e563400	26680368	SIG
Windows x86-64 web-based installer	Windows	for AMD64/EM64T/x64	28cb1c608bbd73ae8e53a3bd351b4bd2	1362904	SIG
Windows x86 embeddable zip file	Windows		9fab3b81f8841879fda94133574139d8	6741626	SIG
Windows x86 executable installer	Windows		33cc602942a54446a3d6451476394789	25663848	SIG
Windows x86 web-based installer	Windows		1b670cfa5d317df82c30983ea371d87c	1324608	SIG

- To download Windows 32-bit python, you can select any one from the three options: Windows x86 embeddable zip file, Windows x86 executable installer or Windows x86 web-based installer.
- •To download Windows 64-bit python, you can select any one from the three options: Windows x86-64 embeddable zip file, Windows x86-64 executable

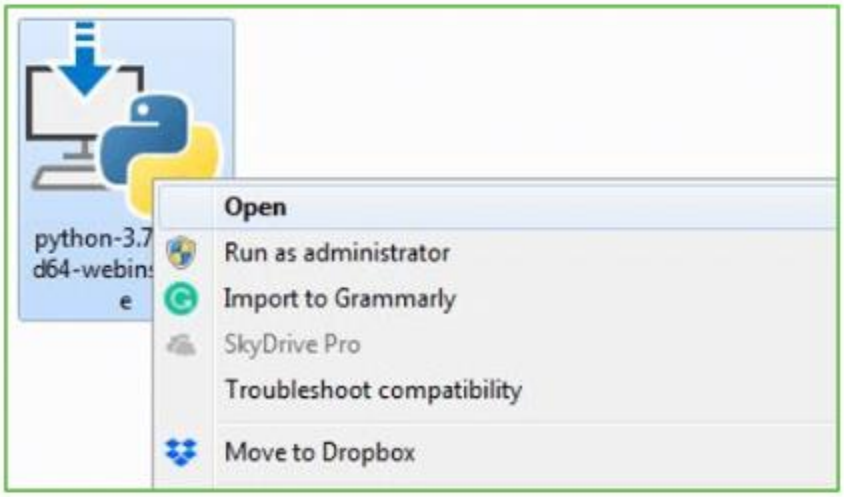
installer or Windows x86-64 web-based installer.

Here we will install Windows x86-64 web-based installer. Here your first part regarding which version of python is to be downloaded is completed. Now we move ahead with the second part in installing python i.e. Installation

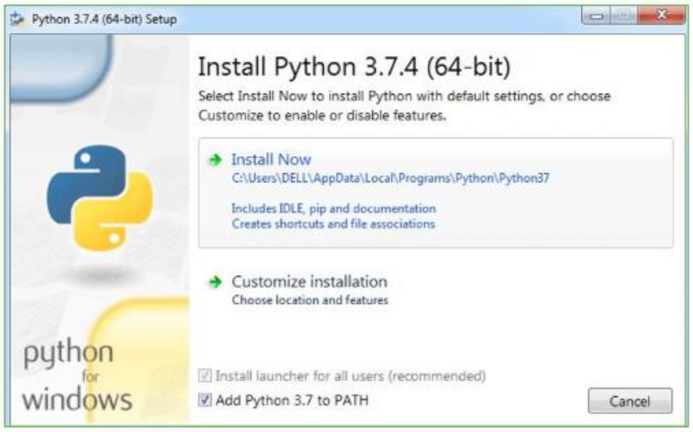
Note: To know the changes or updates that are made in the version you can click on the Release Note Option.

6.3.Installation of Python

Step 1: Go to Download and Open the downloaded python version to carry out the installation process.



Step 2: Before you click on Install Now, Make sure to put a tick on Add Python 3.7 to PATH.


Python 3.7.4 (64-bit) Setup

Install Python 3.7.4 (64-bit)

Select Install Now to install Python with default settings, or choose Customize to enable or disable features.

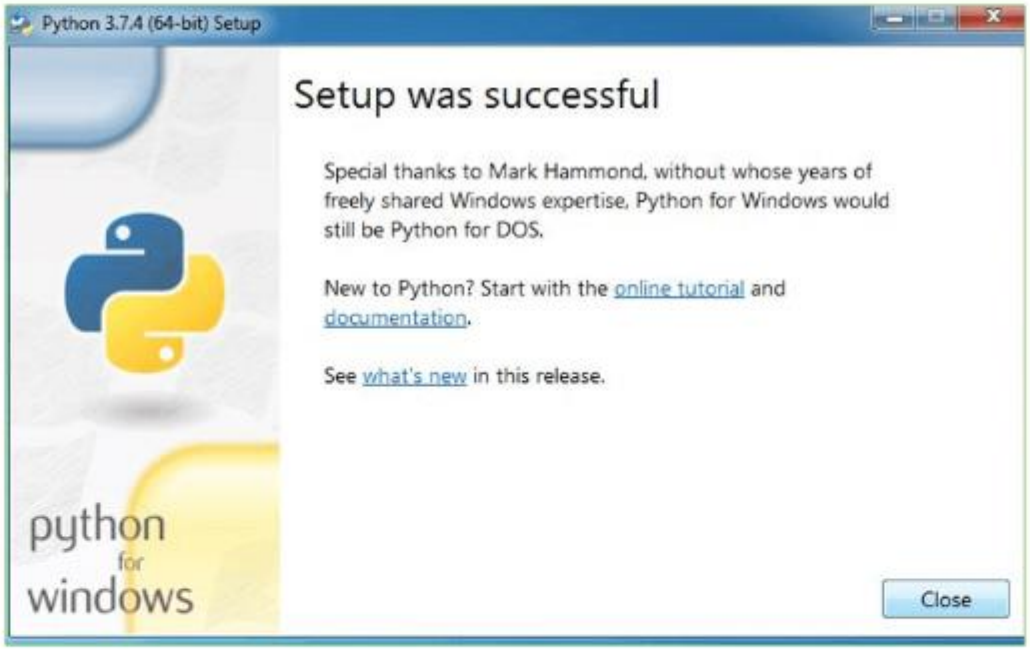
Install Now
C:\Users\DELL\AppData\Local\Programs\Python\Python37

Includes IDLE, pip and documentation
Creates shortcuts and file associations

Customize installation
Choose location and features

[✓] Install launcher for all users (recommended)
[✓] Add Python 3.7 to PATH

Step 3: Click on Install NOW After the installation is successful. Click on Close.


Python 3.7.4 (64-bit) Setup

Setup was successful

Special thanks to Mark Hammond, without whose years of freely shared Windows expertise, Python for Windows would still be Python for DOS.

New to Python? Start with the online tutorial and documentation.

See what's new in this release.

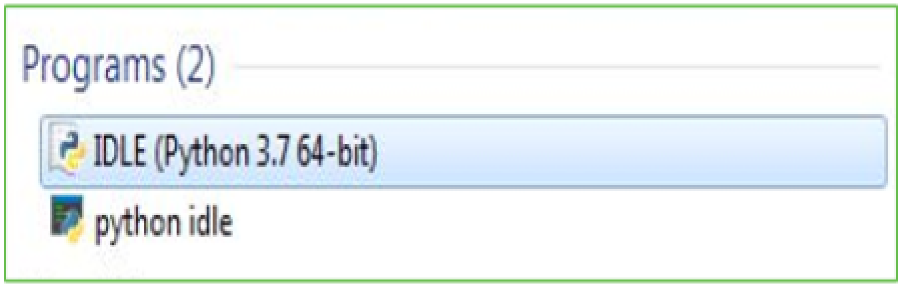
With these above three steps on python installation, you have successfully and correctly installed Python. Now is the time to verify the installation.

Note: The installation process might take a couple of minutes.

6.3.1. Check how the Python IDLE works

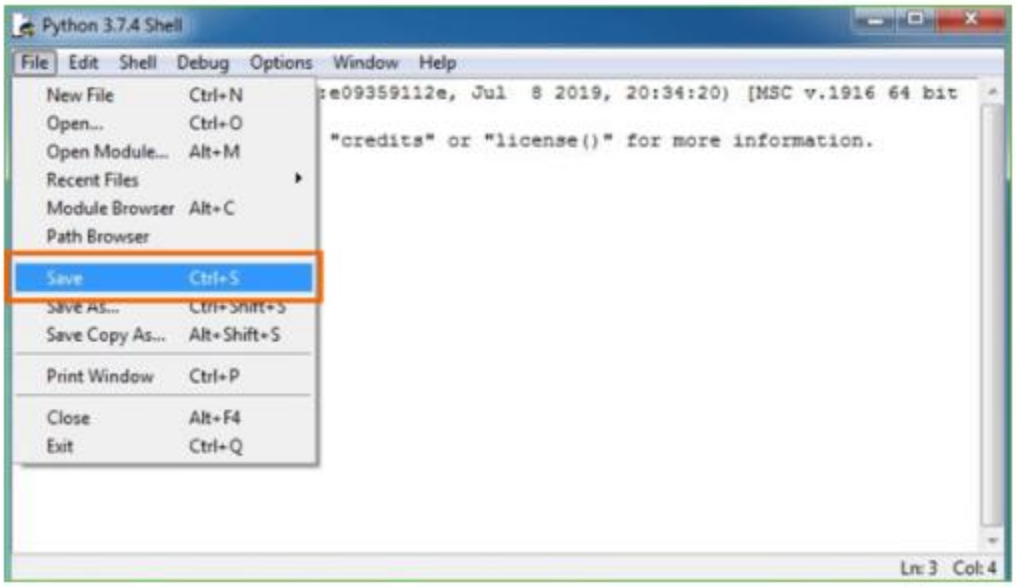
Step 1: Click on Start

Step 2: In the Windows Run command, type "python idle".



Step 3: Click on IDLE (Python 3.7 64-bit) and launch the program

Step 4: To go ahead with working in IDLE you must first save the file. Click on File > Click on Save



```
e09359112e, Jul  8 2019, 20:34:20) [MSC v.1916 64 bit
 "credits" or "license()" for more information.
```

Step 5: Name the file and save as type should be Python files. Click on SAVE. Here I have named the files as Hey World.

Step 6: Now for e.g. enter print

Chapter 7:

SOURCE CODE

This chapter presents the detailed implementation of the Lung Cancer Detection System using Python. The system integrates various techniques from the fields of medical imaging, deep learning, and artificial intelligence to accurately detect cancerous regions in CT scan images. It employs a combination of Convolutional Neural Networks (CNNs), U-Net for image segmentation, and a hybrid CNN-LSTM model for classification. A graphical user interface (GUI) developed using Tkinter allows users to interact with the system seamlessly.

7.1. Main 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
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("Early Detection of Lung Cancer using Neural Networks") #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='A Novel Hybrid Deep Learning Method for Early Detection of Lung
    Cancer using Neural Networks', 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()
```

7.2. Augmentation Code

```
import os

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

import numpy as np

from scipy import ndimage

path = 'temp'

datagen = ImageDataGenerator(rotation_range=10, width_shift_range=0.1,
height_shift_range=0.1,shear_range=0.15,

                zoom_range=0.1,channel_shift_range = 10, horizontal_flip=True)

for root, dirs, directory in os.walk(path):

  for j in range(len(directory)):

    name = os.path.basename(root)

    print(name+" "+root+"/"+directory[j])
    if 'Thumbs.db' not in directory[j]:
      try:
        image = load_img(root+"/"+directory[j])
        image = img_to_array(image)
        image = image.reshape((1, ) + image.shape)
        datagen.fit(image)
        for x, val in zip(datagen.flow(image, save_to_dir='aug/'+name, save_prefix='aug',
save_format='png'),range(4)):
          pass
      except Exception as e:
        print(e)
```

7.3. Create Code

```
import numpy as np
import cv2
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from keras.models import Sequential
from keras.layers import Dense, Flatten, Dropout, Conv3D, MaxPooling3D,
LSTM,RepeatVector
from keras.callbacks import ModelCheckpoint
from keras.utils import to_categorical
import pickle
import os
```

```
X = []
Y = []
for root, dirs, directory in os.walk("trainingImages"):
    for j in range(len(directory)):
        name = os.path.basename(root)
        img = cv2.imread(root+"/"+directory[j])
        img = cv2.resize(img,(32, 32), interpolation = cv2.INTER_CUBIC)
        img = img.astype('float32')
        img = img/255
        X.append([img])
        if name == 'Normal':
            Y.append(0)
        else:
            Y.append(1)
        print(name)
X = np.asarray(X)
Y = np.asarray(Y)
np.save("model/X2",X)
np.save("model/Y2",Y)
X = np.load("model/X2.npy")
Y = np.load("model/Y2.npy")
print(X.shape)
indices = np.arange(X.shape[0])
np.random.shuffle(indices)
```

```
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

cnn_model = Sequential()

cnn_model.add(Conv3D(32, (1, 3, 3), activation='relu', input_shape=(X.shape[1], X.shape[2], X.shape[3], X.shape[4])))

cnn_model.add(MaxPooling3D((1, 2, 2)))

cnn_model.add(Conv3D(16, (1, 3, 3), activation='relu'))

cnn_model.add(MaxPooling3D((1, 2, 2)))

cnn_model.add(Conv3D(16, (1, 3, 3), activation='relu'))

cnn_model.add(MaxPooling3D((1, 2, 2)))

cnn_model.add(Flatten())

cnn_model.add(RepeatVector(2))

cnn_model.add(LSTM(32))

cnn_model.add(Dense(y_train.shape[1], activation='softmax'))

cnn_model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

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 = cnn_model.fit(X_train, y_train, batch_size = 32, epochs = 35, 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:
    cnn_model.load_weights("model/cnn_weights1.hdf5")
predict = cnn_model.predict(X_test)
predict = np.argmax(predict, axis=1)
y_test1 = np.argmax(y_test, axis=1)
acc = accuracy_score(y_test1, predict)
print(acc)
```

7.4. Model Code

```
#loading python require packages
import numpy as np
import tensorflow as tf
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
import cv2

import os

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])
X = []
Y = []
label = []
def loadDataset():
    global X, Y, label
    if os.path.exists("model/X.npy"):
        X = np.load("model/X.npy")
    Y = np.load("model/Y.npy")
    label = np.load("model/label.npy")
else:
    for root, dirs, directory in os.walk("lidc-idri/image"):
        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,(128, 128), interpolation = cv2.INTER_CUBIC)
                X.append(img)
                img = cv2.imread("lidc-idri/mask/"+name,0)
                img = cv2.resize(img,(128, 128), interpolation = cv2.INTER_CUBIC)
                Y.append(img)
                white_pixels = np.sum(img == 255)
                if white_pixels == 0:
                    label.append(0)
                else:
                    label.append(1)
                print(name+" "+directory[j]+" "+str(white_pixels))
    X = np.asarray(X)
    Y = np.asarray(Y)
    label = np.asarray(label)
    np.save("model/X",X)
```

```
        np.save("model/Y",Y)

        np.save("model/label",label)

loadDataset()

print(X.shape)

print(Y.shape)

print(label.shape)

print(label)

print(np.unique(label, return_counts=True))
```

Chapter 8:

TESTING AND RESULTS

8.1.Step-by-Step Execution with Screenshots

This chapter explains how the Early Detection of Lung Cancer System works in real-time with the help of screenshots. Each screenshot represents a key step in the user interaction flow, from launching the application to viewing the Early Detection results

Step-1: Home Screen

- To run project double click on run.bat file
- When the application is launched, the user is directed to the Home Screen.

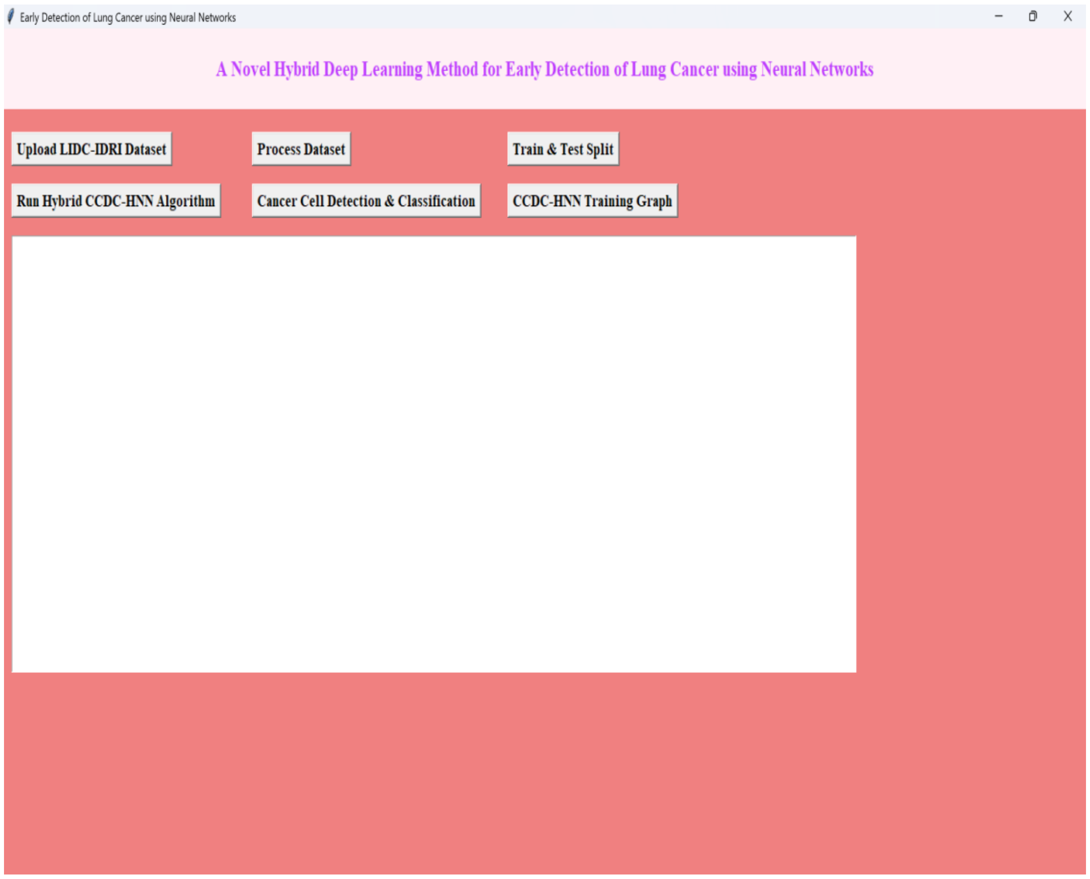

Early Detection of Lung Cancer using Neural Networks
A Novel Hybrid Deep Learning Method for Early Detection of Lung Cancer using Neural Networks
Upload LIDC-IDRI Dataset
Process Dataset
Train & Test Split
Run Hybrid CCDC-HNN Algorithm
Cancer Cell Detection & Classification
CCDC-HNN Training Graph

Figure 8.1: Home Screen

Step-2: Upload Dataset

- In above screen click on 'Upload LIDC-IDRI Dataset' button to upload dataset and get below page

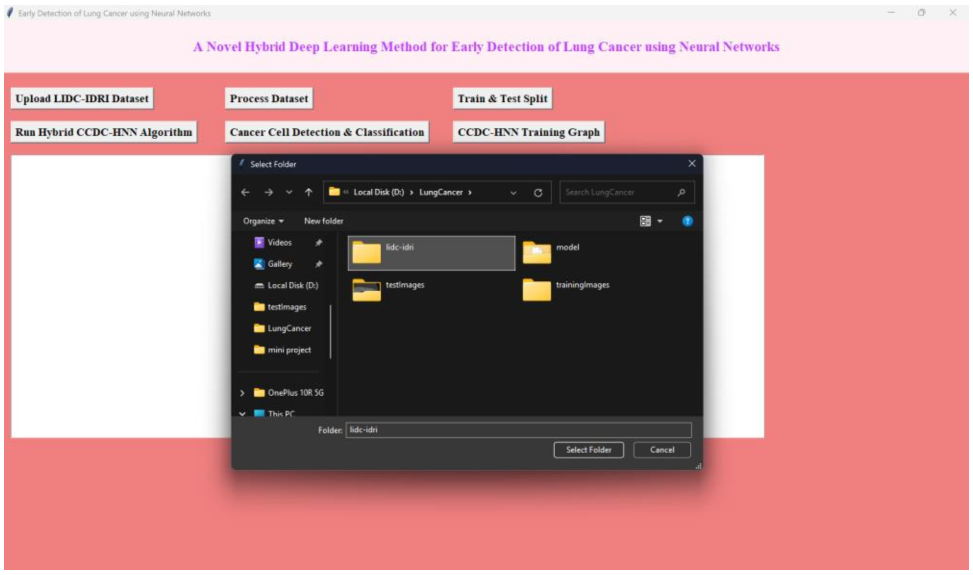
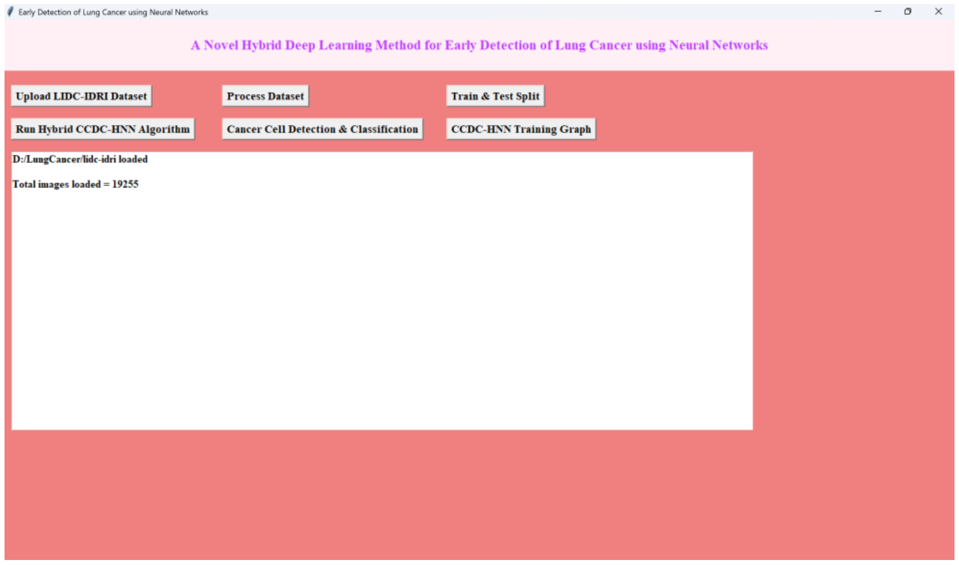


Figure 8.2: Selecting Dataset

- In above screen selecting and uploading 'LIDC-IDRI' dataset and then click on 'select folder' button to load dataset


Early Detection of Lung Cancer using Neural Networks
A Novel Hybrid Deep Learning Method for Early Detection of Lung Cancer using Neural Networks
Upload LIDC-IDRI Dataset
Process Dataset
Train & Test Split
Run Hybrid CCDC-HNN Algorithm
Cancer Cell Detection & Classification
CCDC-HNN Training Graph

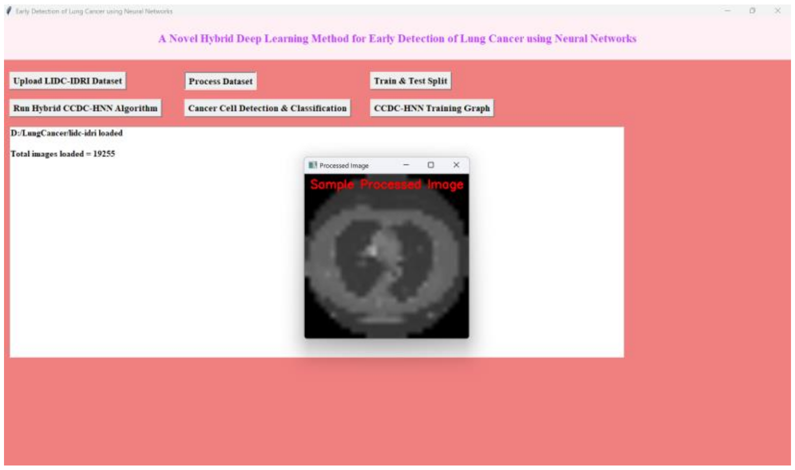
```
D:/LungCancer/lidc-idri loaded

Total images loaded = 19255
```

Figure 8.3: Load Dataset

- In above screen total 19255 images loaded from dataset

Step-3: Process Dataset

- Now click on ‘Process Images’ to clean and normalize images and then get below output


Early Detection of Lung Cancer using Neural Networks
A Novel Hybrid Deep Learning Method for Early Detection of Lung Cancer using Neural Networks
Upload LIDC-IDRI Dataset
Process Dataset
Train & Test Split
Run Hybrid CCDC-HNN Algorithm
Cancer Cell Detection & Classification
CCDC-HNN Training Graph
Processed Image
Sample Processed Image

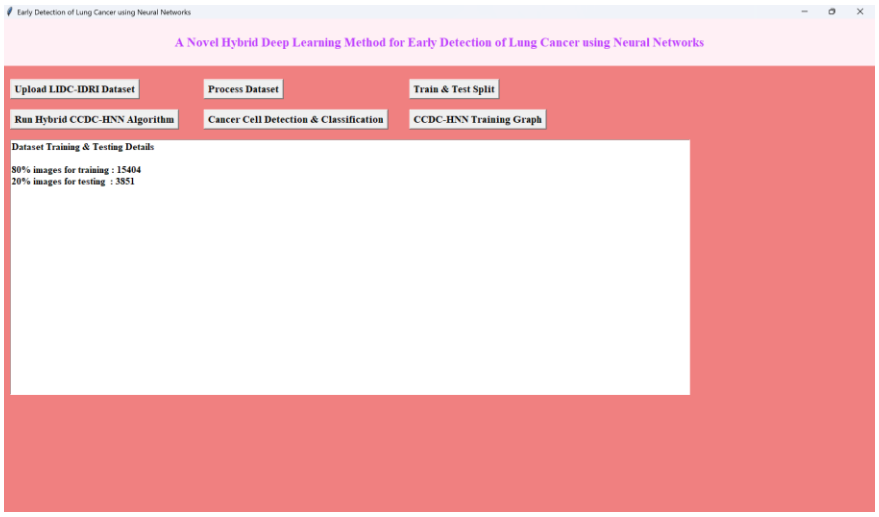
```
D:/LungCancer/lidc-idri loaded

Total images loaded = 19255
```

Figure 8.4: Process Dataset

- In above screen all images pixels are normalized and then displaying sample processed image and now close above image

Step-4: Train and Test Split

- Click on ‘Train & Test Split’ button to split dataset into train and test and then will get below output


Early Detection of Lung Cancer using Neural Networks
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Cancer Cell Detection & Classification
CCDC-HNN Training Graph

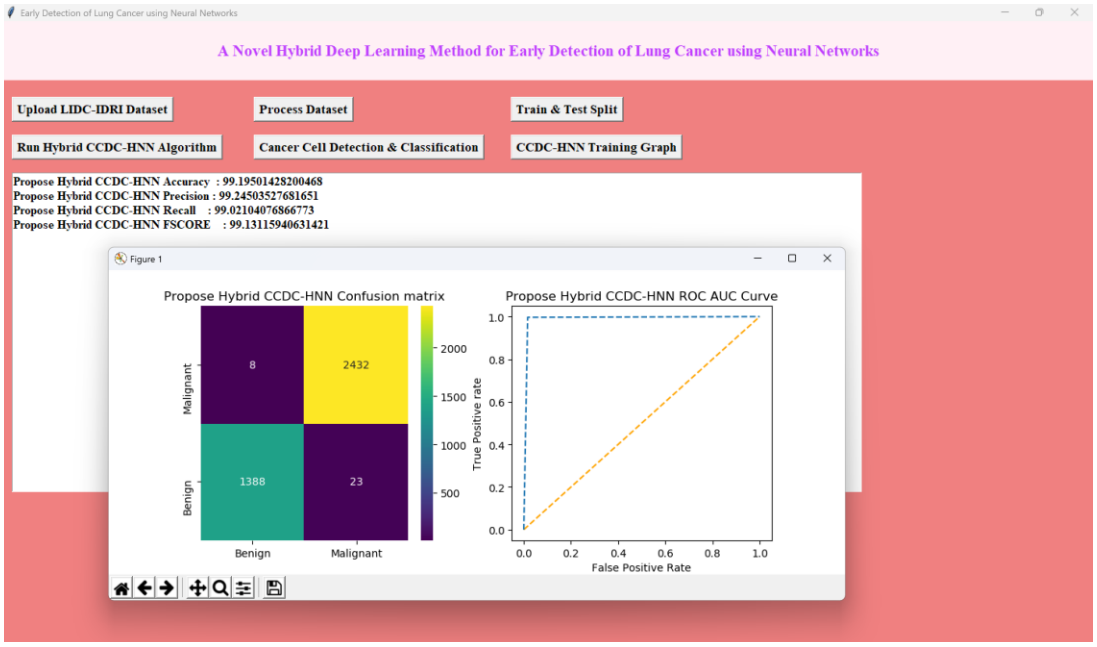
```
Dataset Training & Testing Details

80% images for training : 15404
20% images for testing  : 3851
```

Figure 8.5: Train and Test

- In above screen can see train and test size of dataset out of 19255 total images

Step-5: Run Hybrid CCDC-HNN Algorithm

- Now click on ‘Run Hybrid CCDC-HNN Algorithm’ button to train model on training images and tested on testing images


Early Detection of Lung Cancer using Neural Networks
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CCDC-HNN Training Graph
Figure 1
Propose Hybrid CCDC-HNN Confusion matrix
Malignant
Benign
8
2432
1388
23
2000
1500
1000
500
Propose Hybrid CCDC-HNN ROC AUC Curve
True Positive rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0

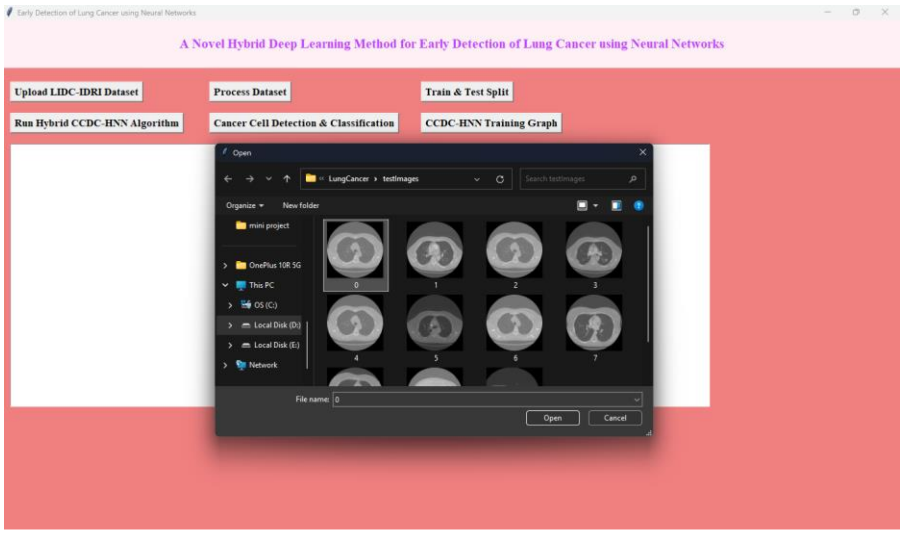
```
Propose Hybrid CCDC-HNN Accuracy  : 99.19501428200468
Propose Hybrid CCDC-HNN Precision : 99.24503527681651
Propose Hybrid CCDC-HNN Recall    : 99.02104076866773
Propose Hybrid CCDC-HNN FSCORE    : 99.13115940631421
```

Figure 8.6: Run Algorithm

- In above screen propose algorithm got 99% accuracy and can see other metrics like precision, recall and etc. in confusion matrix graph x-axis represents Predicted Labels and y-axis represents True labels and then yellow and light blue color boxes in diagonal represents correct prediction count and all blue boxes in diagonal represents incorrect prediction count which are very few. In ROC graph x-axis represents False Positive Rate and y-axis represents True Positive Rate and if blue lines come below orange line, then all predictions are incorrect or false and if goes above orange line then all predictions are correct or true.

Step-6: Cancer Cell Detection & Classification

- Click on ‘Cancer Cell Detection & Classification’ button to upload test image and get below output


Early Detection of Lung Cancer using Neural Networks
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Upload LIDC-IDRI Dataset
Process Dataset
Train & Test Split
Run Hybrid CCDC-HNN Algorithm
Cancer Cell Detection & Classification
CCDC-HNN Training Graph
Open
LungCancer › testImages
Organize
New folder
File name: 0
Open
Cancel

Figure 8.7: Upload CT scan 1

- In above screen selecting and uploading ‘0.png’ image and then click on ‘Open’ button to get below output

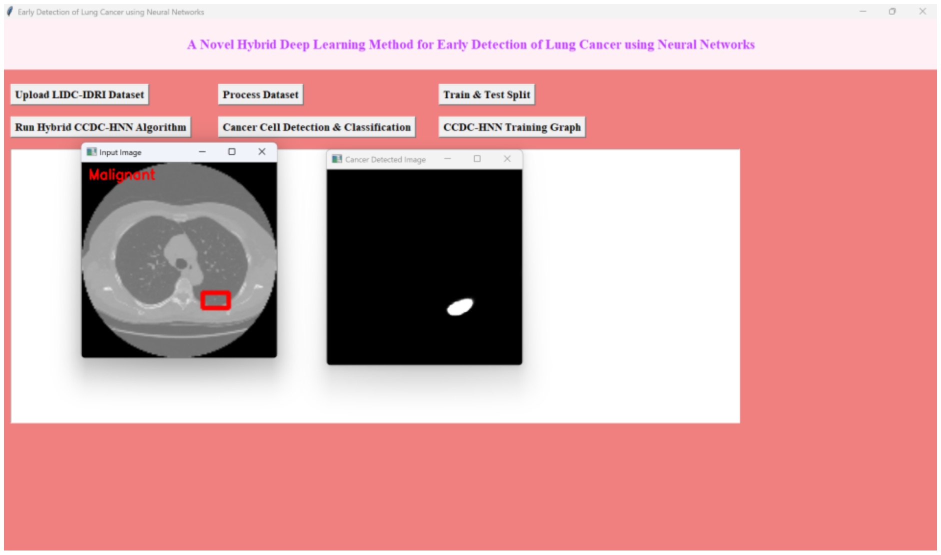
Early Detection of Lung Cancer using Neural Networks
A Novel Hybrid Deep Learning Method for Early Detection of Lung Cancer using Neural Networks
Upload LIDC-IDRI Dataset
Process Dataset
Train & Test Split
Run Hybrid CCDC-HNN Algorithm
Cancer Cell Detection & Classification
CCDC-HNN Training Graph
Input Image
Malignant
Cancer Detected Image

Figure 8.8: Output of CT scan 1

- In above screen first image is the original image and second image is UNET segmented image of cancer cell detection and then propose ‘CCDC-HNN’ algorithm classify cell as Malignant. Similarly you can upload and test other images

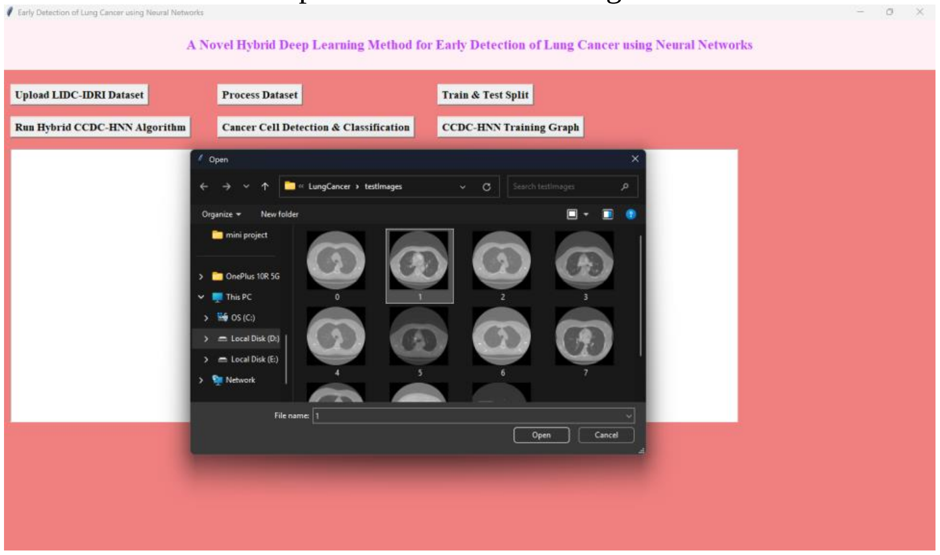
Early Detection of Lung Cancer using Neural Networks
A Novel Hybrid Deep Learning Method for Early Detection of Lung Cancer using Neural Networks
Upload LIDC-IDRI Dataset
Process Dataset
Train & Test Split
Run Hybrid CCDC-HNN Algorithm
Cancer Cell Detection & Classification
CCDC-HNN Training Graph
Open
LungCancer › testImages
File name: 1
Open
Cancel

Figure 8.9: Upload CT scan 2

- In above screen selecting and uploading another image and below is the output

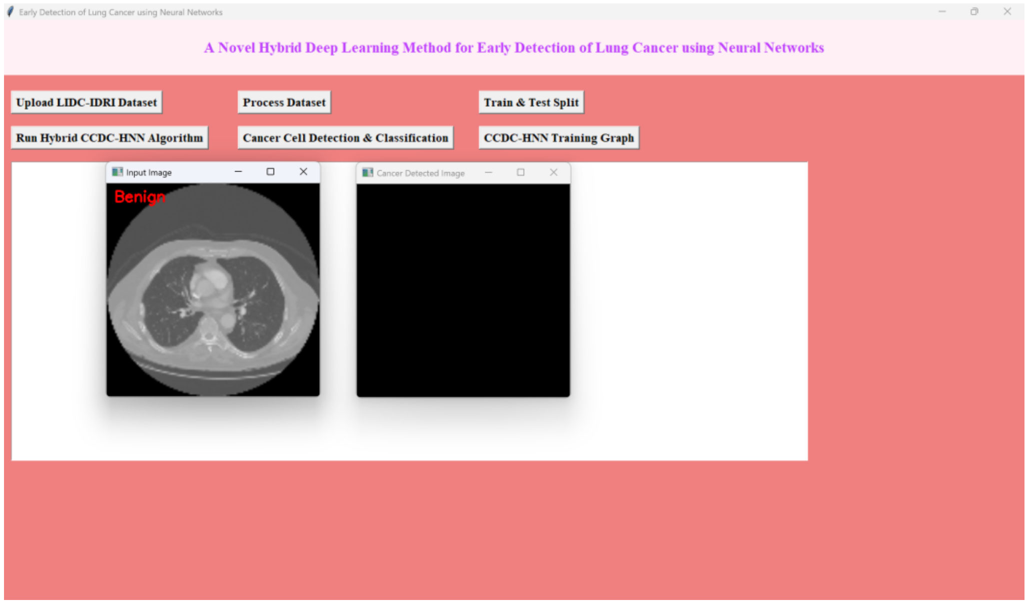
Early Detection of Lung Cancer using Neural Networks
A Novel Hybrid Deep Learning Method for Early Detection of Lung Cancer using Neural Networks
Upload LIDC-IDRI Dataset
Process Dataset
Train & Test Split
Run Hybrid CCDC-HNN Algorithm
Cancer Cell Detection & Classification
CCDC-HNN Training Graph
Input Image
Benign
Cancer Detected Image

Figure 8.8: Output of CT scan 2

- In above screen image classify as Benign as there is no cancer cell detected

Chapter 9:

CONCLUSION

Lung cancer survival and treatment results are greatly impacted by early identification, which is still a major diagnostic issue in medicine. Even though they work well, traditional diagnostic techniques frequently fail to detect lung cancer in its early stages, which results in poorer prognoses and delayed therapies. With the development of deep learning and artificial intelligence, medical imaging and diagnostics have expanded, potentially leading to more precise and prompt disease identification. This study introduces a new hybrid deep learning approach that combines convolutional neural networks (CNNs) and recurrent neural networks (RNNs) with fully connected layers to analyse radiographic images and clinical data in a comprehensive manner, improving the early detection of lung cancer.

The proposed method leverages the combined strengths of various neural network designs to overcome the drawbacks of single-modality diagnostic approaches. While recurrent neural networks (RNNs) are employed to handle sequential clinical data—capturing temporal dependencies and trends essential for accurate diagnosis—convolutional neural networks (CNNs) are utilized for their remarkable capacity to interpret and extract significant features from complex medical images. By integrating these networks through fully connected layers, the model synthesizes multiple forms of data, resulting in a more comprehensive and reliable diagnostic tool.

The developed hybrid model significantly increases the sensitivity and specificity of lung cancer diagnosis compared to conventional techniques and standalone deep learning models. This conclusion is supported by extensive experiments and validation tests conducted using a variety of datasets. In addition to enhancing the accuracy of early-stage cancer detection, the hybrid approach provides a robust framework for integrating diverse data sources—an essential component of any dependable and practical diagnostic application.

In summary, the novel hybrid deep learning approach presented in this research marks a significant advancement in medical diagnostics, particularly in the early detection of lung cancer. By combining imaging data with clinical information, the proposed framework delivers a more accurate and nuanced diagnostic tool with the potential to transform clinical practice. Future research will focus on further enhancing the model, incorporating new data types such as genetic and molecular information, and validating the system in real-world clinical environments. This hybrid strategy holds the promise of improving patient outcomes and advancing the frontiers of early cancer diagnosis, establishing a new benchmark for artificial intelligence in healthcare.

Chapter 10:

FUTURE SCOPE

The promising results of the hybrid deep learning method for early lung cancer detection open numerous avenues for further research and development. As efforts continue to refine and advance this diagnostic tool, the focus will be on several key areas to enhance the method's robustness, accuracy, and clinical utility.

One of the primary objectives moving forward is the **expansion of the dataset**. While the current model has demonstrated substantial improvements in detection accuracy using a diverse dataset, increasing both the quantity and quality of radiographic images—as well as incorporating more comprehensive clinical data—will be critical. This expansion will enhance the model's generalizability and resilience across diverse patient demographics and imaging conditions. Additionally, the integration of **longitudinal data** will allow the model to detect subtle changes over time, a crucial capability for identifying cancer at its earliest stages.

Another important direction is the **incorporation of genetic and molecular data**. Recent advancements in precision medicine underscore the value of such data in cancer diagnostics. By integrating genomic and molecular profiles with imaging and clinical information, the hybrid model could deliver even more personalized and precise predictions. This multimodal approach has the potential to uncover specific biomarkers associated with lung cancer, thereby improving early detection and informing individualized treatment strategies.

Improving model interpretability is also a critical priority. Deep learning models—particularly those with complex architectures like the proposed approach—are often viewed as "black boxes." To gain the trust and acceptance of medical professionals, it is essential to develop mechanisms that explain the model's outputs in a clear and interpretable way. Techniques such as attention mechanisms, saliency maps, and SHapley Additive ExPlanations (SHAP) can be employed to identify which features and data points most influence the model's decisions.

Finally, **real-world clinical trials and collaborations with healthcare institutions** will be essential to validate and refine the model in practical settings. These partnerships will facilitate valuable feedback from clinicians, help address implementation challenges, and ensure the method meets the rigorous standards required for clinical deployment. Continuous collaboration with hospitals and research centers will also enable ongoing updates and improvements, supported by new data and emerging clinical insights.

References

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