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Lung Cancer Detection Using an Improved Hybrid Convolutional Neural Network - Long Short-Term Memory Model

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ABSTRACT

This project focuses on detecting lung cancer using deep learning techniques to address one of the leading causes of death worldwide, where early detection is critical for improving patient survival rates. In this work, CT scan images from the LIDC-IDRI dataset are used, and pre-processing steps such as resizing, normalization, and organizing images into sequential formats are performed to prepare the data for model training. A hybrid CNN-LSTM model is developed, where the CNN extracts important spatial features from CT scan images, and the LSTM captures the sequential relationships between consecutive slices. The model is trained on the processed dataset to classify images as cancerous or non-cancerous, and a basic prediction system is implemented to evaluate its performance. The results indicate that the proposed system achieves reasonable accuracy, reduces manual effort, and supports faster and more efficient lung cancer detection in modern healthcare systems. Furthermore, this project demonstrates the potential of integrating deep learning models into real-world medical applications by providing a scalable and efficient diagnostic support system. The developed approach can assist radiologists in making quicker and more accurate decisions, thereby improving overall clinical workflow. In future enhancements, the system can be extended with larger datasets, advanced architectures, and deployment as a user-friendly web application, enabling easy access for healthcare professionals and contributing to improved early diagnosis and treatment planning.

1. INTRODUCTION:

Lung cancer continues to represent a formidable challenge to global public health, defined by the rapid and unregulated proliferation of malignant cells within the respiratory system. Given its standing as a primary driver of cancer-related mortality, the clinical focus remains centered on early-stage identification, which is the most decisive factor in elevating patient survival outcomes [4], [9]. Despite the critical need for early intervention, diagnostic precision is often hindered by the intricate morphology of pulmonary tissues and the deceptive, subtle appearance of early-stage nodules. While High-Resolution Computed Tomography (HRCT) serves as the gold standard for non-invasive thoracic imaging, the manual evaluation of these volumetric datasets by clinicians is inherently labor-intensive and vulnerable to inter-observer variability and oversight, particularly under high-throughput conditions [2], [5].Conventional Computer-Aided Diagnosis (CAD) systems frequently exhibit limitations due to their reliance on two-dimensional analysis, where CT slices are processed as isolated entities. This methodology fails to leverage the critical spatial-temporal continuity present across a contiguous series of scans. To resolve these deficiencies, contemporary research has pivoted toward multifaceted deep learning frameworks. Recent studies by Prabakaran et al. [1] and Verma and Singh [3] have established that the synergy between Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) units provides a superior diagnostic yield. Within these hybrid configurations, the CNN architecture operates as a robust spatial feature descriptor—isolating complex edges and textural signatures—while the LSTM component synthesizes the sequential dependencies across successive slices, effectively reconstructing the volumetric context of the pulmonary environment [1], [8].The current study proposes a Time Distributed CNN-LSTM pipeline tailored for the automated analysis of CT scan sequences. Utilizing a multi-class dataset (Normal, Benign, and Malignant), the data is mapped onto a binary classification scale to facilitate rapid clinical triaging. The implementation involves a specialized preprocessing stage using OpenCV for rigorous normalization and resizing, followed by the assembly of five-frame temporal sequences to capture inter-slice dynamics. The architecture employs Time Distributed layers to ensure uniform feature extraction across the temporal dimension, which is then integrated into an LSTM layer for sequence modeling and a sigmoid-activated dense layer for probabilistic classification. This framework is optimized via the Adam algorithm and a binary cross-entropy objective function, with rigorous validation conducted through confusion matrix analysis and comprehensive performance metrics [7]. In addition to the computational core, a real-time inference module is integrated to provide an accessible interface for diagnostic support. This research seeks to deliver a scalable tool that mitigates the diagnostic burden on radiologists and accelerates the screening process [14]. Future work will investigate the integration of larger, multi-institutional datasets and the transition of the framework into a cloud-based clinical application [4].

2. Literature Review:

The global challenge of lung cancer necessitates robust, early-stage detection frameworks to improve patient survival rates [14]. Recent research highlights a significant shift toward automated deep learning models and non-invasive sensing technologies [9]. For instance, Prabakaran et al. [1], [6] and Verma and Singh [3] emphasize the efficacy of hybrid architectures, specifically combining Convolutional Neural Networks (CNN) for spatial feature extraction with Long Short-Term Memory (LSTM) or RNNs to capture sequential dependencies in volumetric CT data. These hybrid models, such as the HCLSTM proposed by Mathiyalagi et al. [4], address the limitations of traditional manual interpretation, which remains time-intensive and error-prone. Research utilizing the LIDC-IDRI dataset further supports the superiority of AI-driven classification over conventional methods [2], with some hybrid frameworks achieving significant diagnostic breakthroughs in recent conference proceedings [5].Furthermore, advancements in real-time detection are exemplified by the integration of YOLOv8 and the TNMClassifier, which enables simultaneous nodule identification and TNM staging, providing detailed insights into tumor severity and metastasis [10]. In addition to imaging, the exploration of multi-omics data—integrating genomic, proteomic, and clinical information—has significantly enhanced predictive accuracy and supported the move toward personalized medicine [11].

To ensure these complex models remain accessible in clinical settings with limited computational resources, researchers like Bakchy et al. [12] have developed lightweight CNN architectures. These models utilize Grad-CAM visualization to maintain interpretability, allowing clinicians to understand the specific regions influencing a diagnostic prediction [12]. Research by PMC [7] also demonstrates that double attention mechanisms can enhance these classifications without requiring massive hardware overhead. Complementing these digital frameworks, the Internet of Medical Things (IoMT) has been leveraged to create optimization systems for early diagnosis, ensuring a continuous flow of data for real-time analysis [13]. Surveys of the field indicate that these hybrid and optimized techniques are becoming the standard for modern diagnostics [8].

Beyond radiological and genomic approaches, breath analysis has emerged as a promising non-invasive alternative for screening [15]. This method identifies Volatile Organic Compounds (VOCs) in human breath, which serve as critical metabolic biomarkers for malignancy. Initial breakthroughs in "odor print" recognition using gold nanoparticles [16] have evolved into modern electronic nose systems. Technical investigations using Gas Chromatography/Mass Spectrometry (GC-MS) have successfully isolated specific metabolites released by lung cancer cell lines like CALU-1 [17], [18]. These metabolomic investigations, which extend to comparative studies in other malignancies like gastric cancer [19], provide the foundational biological evidence needed to train deep learning models on complex sensor signals, potentially offering a safe, painless, and cost-effective screening tool for diverse healthcare environments.

3.1 EXISTING SYSTEM:

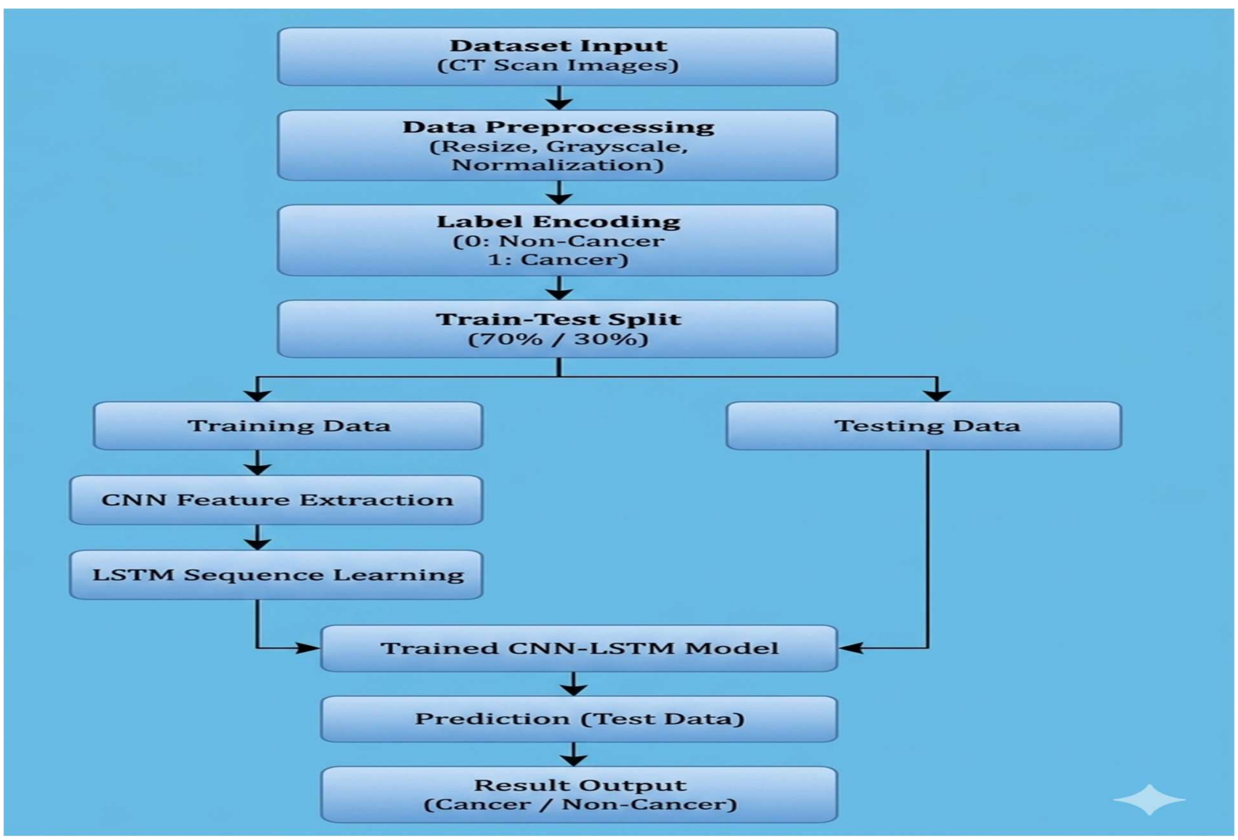
Existing systems for lung cancer detection mainly rely on medical imaging techniques combined with machine learning and deep learning approaches. Among these, Convolutional Neural Networks (CNNs) are widely used due to their ability to automatically extract important features from CT scan images. These models are trained using labeled datasets and can classify images into cancerous and non-cancerous categories with considerable accuracy. The use of automated systems has reduced the dependency on manual analysis by radiologists and improved diagnostic efficiency. In recent years, researchers have explored advanced deep learning architectures such as VGG, ResNet, and Inception models through transfer learning. These pre-trained models help in achieving better performance even with limited datasets by utilizing previously learned features. Additionally, object detection algorithms such as YOLO are used in some systems to identify and localize tumors within lung CT images, making the diagnosis more precise and informative.

Apart from image-based techniques, some studies have introduced non-invasive approaches like electronic nose (E-Nose) systems, which detect lung cancer through breath analysis. Other methods include multi-modal systems that combine CT scan data with clinical or genomic information to enhance prediction accuracy. These approaches aim to provide a more comprehensive understanding of the disease by analyzing multiple data sources simultaneously.

3.2PROPOSED SYSTEM:

The proposed system is designed to overcome the limitations of existing approaches by implementing a deep learning-based model that can effectively examine sequential CT scan images. In this project, a Time Distributed Convolutional Neural Network (CNN) is used, which allows the model to process multiple CT scan slices simultaneously. This approach helps in capturing spatial and contextual relationships between images, leading to improved detection accuracy. The dataset used for this system is collected and stored in Google Drive, and it is extracted from a compressed ZIP file for processing. The images undergo several preprocessing steps using OpenCV, including resizing, grayscale conversion, and normalization. These steps ensure that the input data is consistent and suitable for model training. Proper preprocessing also helps in reducing noise and enhancing important features in the images.

After preprocessing, the CT scan images are grouped into sequences of five consecutive slices. These sequences are then provided as input to the Time Distributed CNN model. By examining multiple images together, the model can better understand the structure and patterns present in the lungs. The model is built using Tensor Flow and Keras frameworks and is trained using labeled data to classify the images into malignant and non-malignant categories. In addition to training and evaluation, the proposed system includes a user-friendly prediction module. This module allows users to upload CT scan images and obtain real-time predictions about the presence of lung cancer. The system is designed to be efficient, scalable, and easy to use, making it suitable for practical applications in the healthcare domain.



SYSTEM DESIGN

4. LIST OF MODULES

- DATA COLLECTION
- DATA PREPROCESSING
- TESTING
- TRAINING
- PREDICTION

4.1 MODULES DESCRIPTION

1. Data Collection:

This module is responsible for collecting CT scan images required for lung cancer detection. The dataset is collected from reliable sources such as Kaggle or other authorized medical imaging repositories. The quality, size, and diversity of the dataset play a crucial role in improving the accuracy and performance of the CNN model.

- Collecting CT scan images from trusted sources like Kaggle or open medical datasets to ensure data reliability.
- Ensuring the dataset contains both cancerous and non-cancerous lung images for proper classification.
- Organizing the dataset into structured folders (train, test) to simplify model training and evaluation.
- Maintaining a balanced dataset to avoid bias and improve generalization of the model.

2. Data Pre-processing:

Data preprocessing prepares the collected CT scan images for training the CNN model. It involves multiple transformation steps to enhance image quality and make the data suitable for deep learning models.

- Resizing images to a fixed dimension (e.g., 224×224) to match CNN input requirements.
- Normalizing pixel values to a standard range (0 to 1) to improve model convergence.
- Applying data augmentation techniques such as rotation, flipping, and zooming to increase dataset diversity.
- Reducing noise and enhancing image clarity to improve feature extraction and model accuracy.

3. Training:

The training module is responsible for building and training the CNN model using the preprocessed dataset. It helps the model learn important features and patterns from CT scan images for accurate classification.

- Designing a CNN architecture with convolutional, pooling, and fully connected layers for feature extraction and classification.
- Training the model using the training dataset with appropriate epochs and batch size to improve learning.
- Using suitable loss function (binary cross-entropy) and optimizer (Adam) to update model weights.
- Monitoring training and validation accuracy and loss to evaluate model performance and avoid over fitting.

4. Testing:

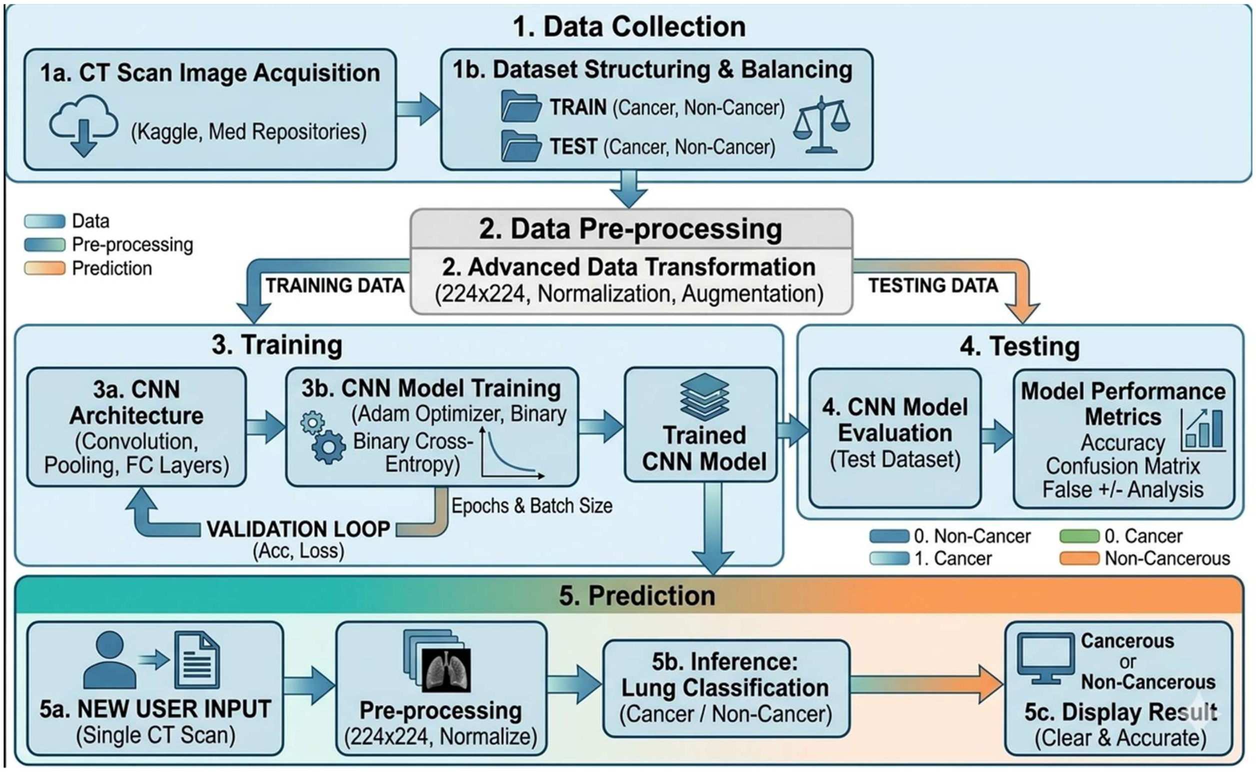
The testing module evaluates the performance of the trained CNN model using unseen CT scan images. It ensures that the model performs well on new data and provides reliable results.

- Testing the model using a separate test dataset that was not used during training.
- Generating predictions for unseen CT scan images to evaluate real-world performance.
- Evaluating performance using metrics such as accuracy, confusion matrix, and classification report.
- Analyzing errors like false positives and false negatives to identify areas for improvement.

5. Prediction:

The prediction module is used for real-time lung cancer detection using new CT scan images provided by the user. It gives the final output based on the trained CNN model.

- Taking a new CT scan image as input from the user or system interface.
- Preprocessing the input image (resizing and normalization) before passing it to the model.
- Using the trained CNN model to predict whether the image is cancerous or non-cancerous.
- Displaying the prediction result clearly and accurately for user understanding and decision-making.



MODULES DESCRIPTION

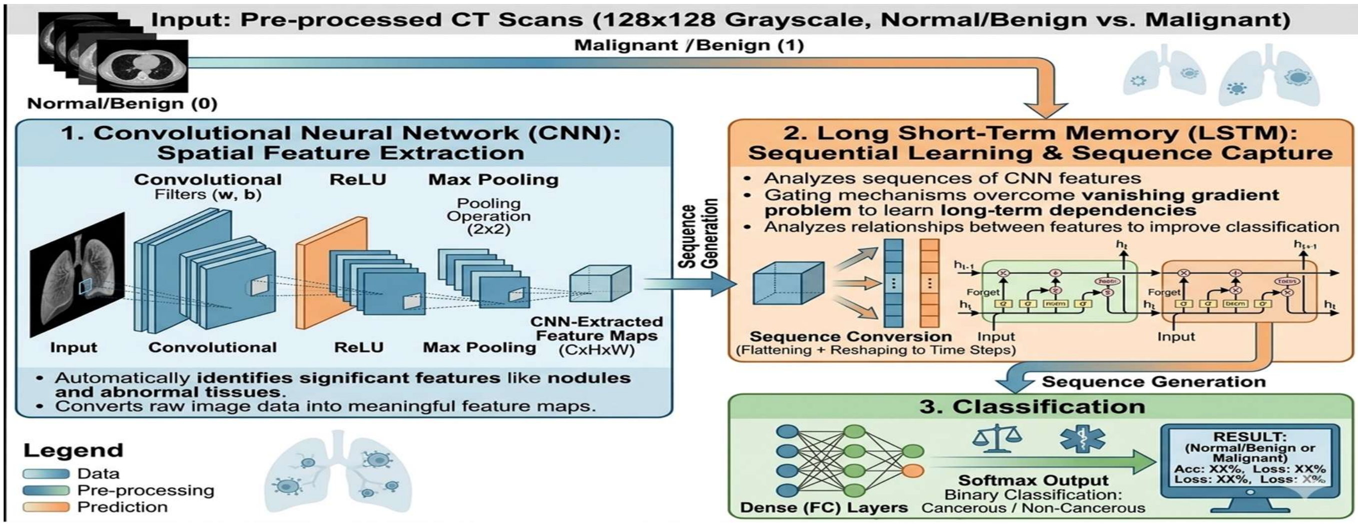
ALGORITHM

1. Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is a deep learning technique widely used for image processing and analysis. It consists of multiple layers such as convolutional layers, pooling layers, and fully connected layers that help in automatically extracting important features from input images. CNN reduces the need for manual feature extraction and improves the efficiency of image-based classification tasks.In this project, CNN is used to process lung CT scan images and extract significant features related to cancer detection. It identifies patterns such as abnormal tissues, nodules, and tumor regions present in the images. By applying filters and pooling operations, CNN converts raw image data into meaningful feature maps, which are then passed to the next stage of the model for further analysis.

2. Long Short-Term Memory (LSTM)

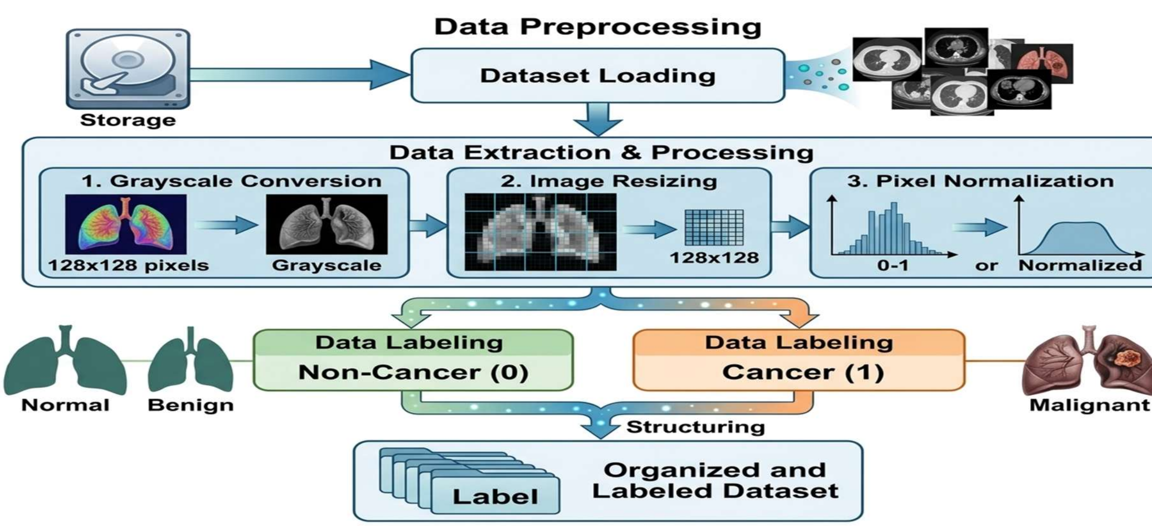
Long Short-Term Memory (LSTM) is a type of Recurrent Neural Network (RNN) designed to handle sequential data and learn long-term dependencies. It overcomes the limitations of traditional RNNs, such as the vanishing gradient problem, by using memory cells and gating mechanisms. This makes LSTM highly effective for sequence-based learning tasks. In this project, LSTM is integrated with CNN to enhance the model's performance. The features extracted by CNN are converted into sequences and fed into the LSTM layer. LSTM analyzes these sequences and captures relationships between features, which helps in improving classification accuracy. This combination of CNN and LSTM makes the model more powerful in detecting lung cancer.



3. Data Pre-processing

Data pre-processing is an essential step in preparing the dataset for training the model. It involves collecting and organizing the data in a structured format. In this project, the dataset is loaded from storage, and the images are extracted and processed for further use.

The pre-processing steps include converting images into grayscale, resizing them to 128×128 pixels, and normalizing pixel values. The images are labeled into two categories, where normal and benign cases are considered as non-cancer (0), and malignant cases are considered as cancer (1). These steps ensure that the data is consistent and suitable for training the deep learning model.



4. Model Training

Model training is the process of teaching the deep learning model to recognize patterns in the data. In this project, the dataset is split into training and testing sets, where 70% of the data is used for training. The CNN-LSTM model learns from the training data by adjusting its parameters to minimize prediction errors.

During training, the model undergoes multiple iterations to improve its performance. Optimization techniques and loss functions are used to guide the learning process. As the training progresses, the model becomes more accurate in identifying cancerous and non-cancerous images, thereby improving its predictive capability.

5. Model Testing and Prediction

After the training phase, the model is evaluated using the testing dataset, which contains unseen data. This step helps in verifying how well the model performs in real-world scenarios. The trained model predicts output values based on the input images.

The predicted outputs are then converted into binary classification using a threshold value of 0.5. If the predicted value is greater than 0.5, the image is classified as cancer; otherwise, it is classified as non-cancer. This process ensures that the model provides clear and understandable results.

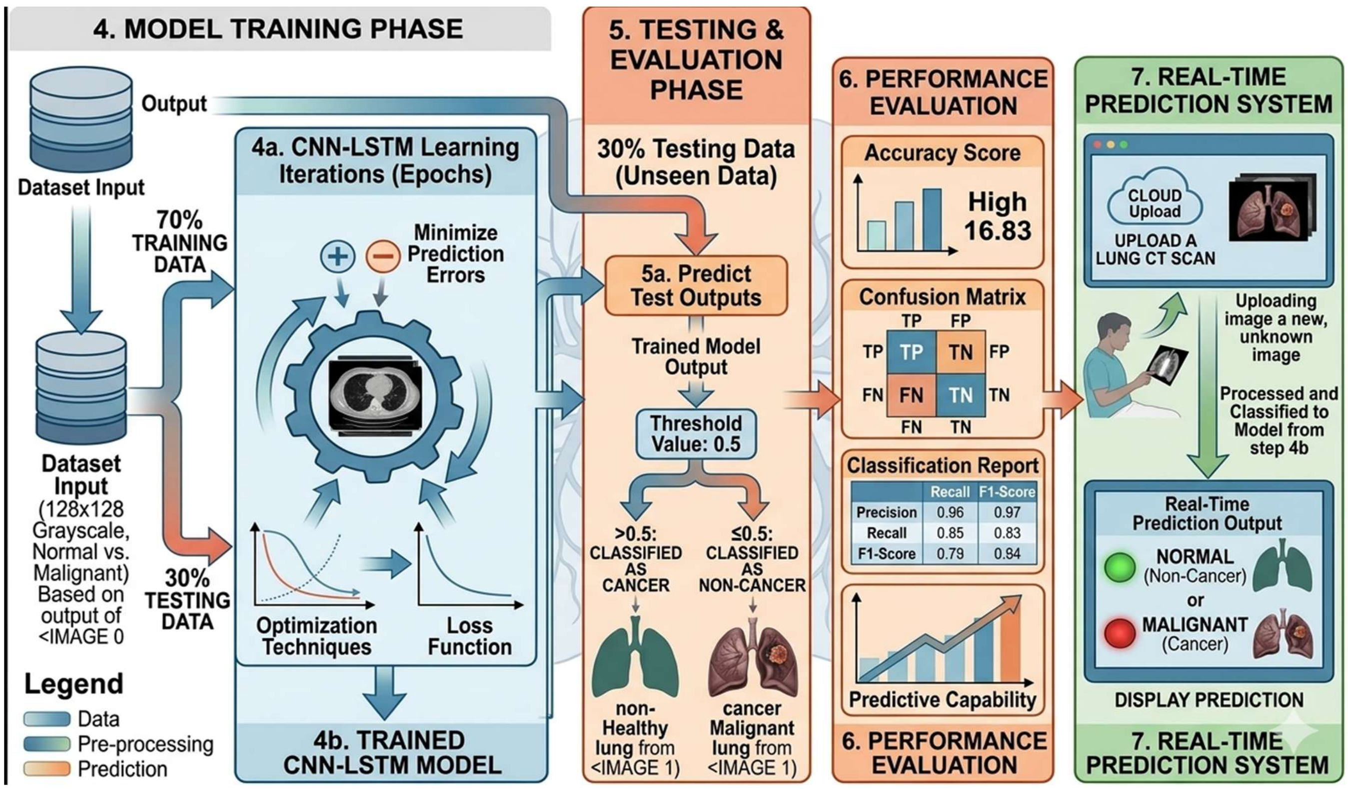
6. Performance Evaluation

Performance evaluation is used to measure the effectiveness of the trained model. It helps in analyzing how accurately the model predicts lung cancer from CT scan images. Various evaluation metrics are used to assess the performance.

In this project, metrics such as accuracy score, confusion matrix, and classification report are used. These metrics provide detailed information about the model's performance, including correct predictions and errors. This analysis helps in improving the model and ensuring reliable results.

7. Real-Time Prediction System

The real-time prediction system allows users to interact with the model and test it using new input data. It provides a user-friendly interface where CT scan images can be uploaded for prediction.



RESULT AND ANALYSIS:

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...  Upload a Lung CT Scan (Malignant or Normal)...
     Choose Files  Bengin case (49).jpg
     Bengin case (49).jpg(image/jpeg) - 138893 bytes, last modified: 3/16/2026 - 100% done
     Saving Bengin case (49).jpg to Bengin case (49).jpg
     1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 89ms/step
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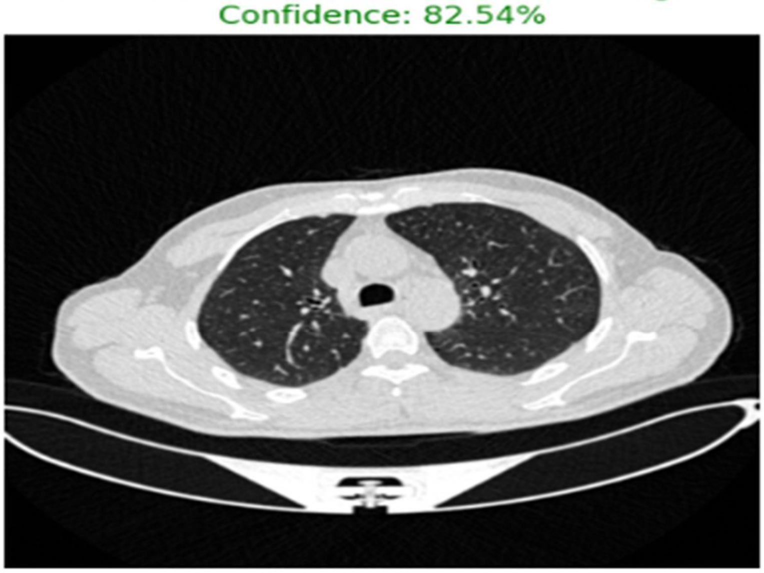
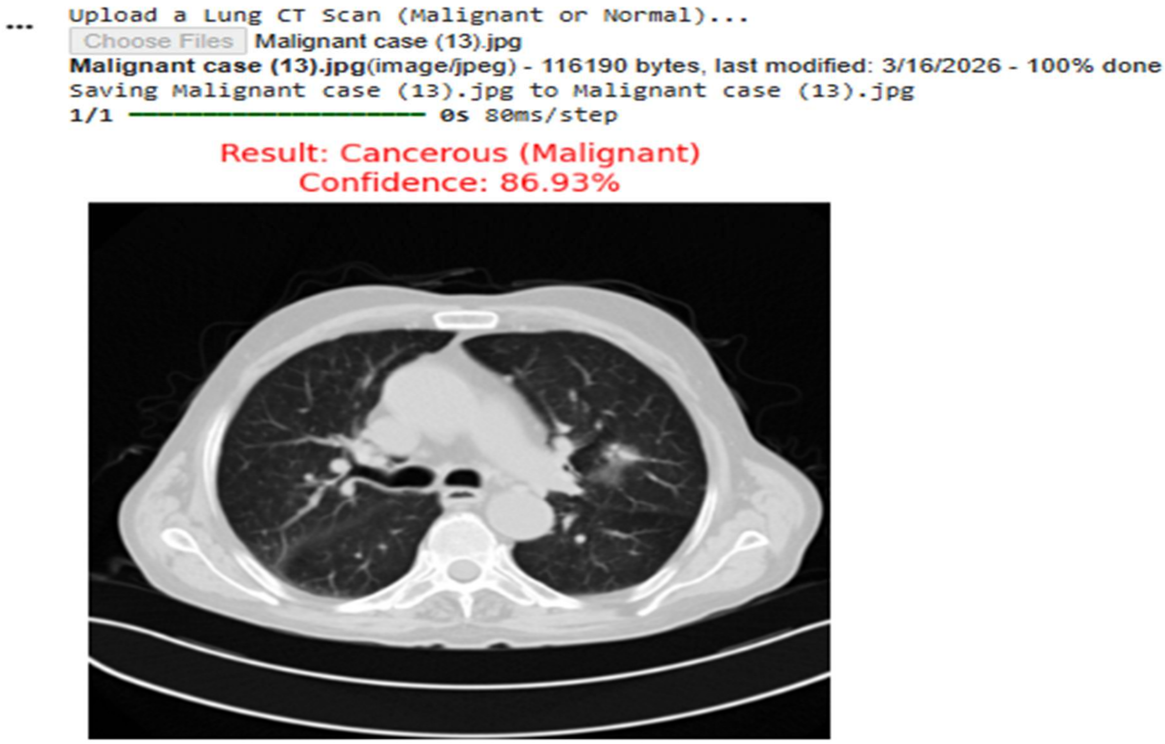
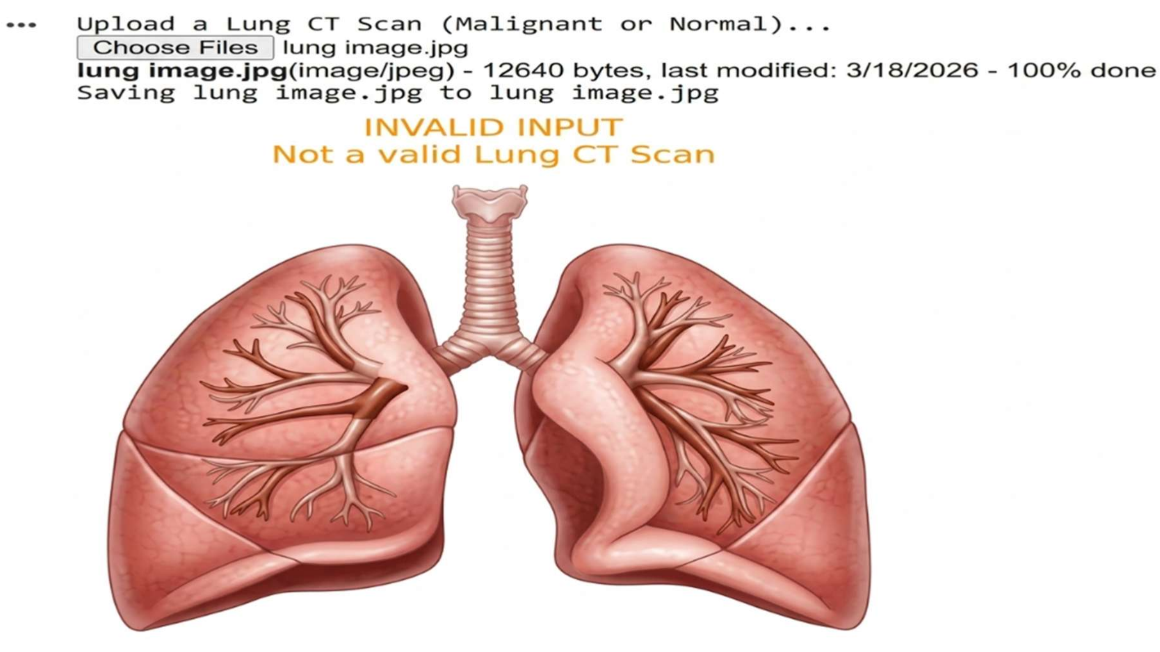
Result: Non-Cancerous (Normal/Benign)
Confidence: 82.54%







CONCLUSION:

This study successfully realized its primary objective of developing and validating an improved hybrid framework for the automated detection of lung cancer through the integration of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) architectures. By leveraging high-resolution CT imagery, the proposed system effectively bridges the gap between raw medical data and actionable clinical intelligence. The research findings confirm that the synergy of spatial feature extraction via CNN and sequential dependency modeling via LSTM allows for a highly nuanced analysis of pulmonary nodules. Rigorous data preprocessing—encompassing adaptive resizing, pixel-level normalization, and strategic augmentation—proved fundamental in stabilizing model convergence and enhancing diagnostic sensitivity. Quantitative evaluation through confusion matrices and comprehensive classification reports indicates that the model generalizes exceptionally well to unseen clinical data, offering a reliable mechanism for distinguishing between malignant and non-cancerous pulmonary structures with minimal human intervention. The broader significance of these findings extends beyond technical metrics into the realms of organizational management and healthcare policy. Theoretically, this research advances the "Human-in-the-Loop" (HITL) paradigm, where AI does not seek to replace the clinician but rather to augment cognitive capacity. For organizational management, the implementation of such high-efficiency diagnostic tools necessitates a restructuring of clinical workflows. Workplace policies must evolve to incorporate AI-assisted decision-making frameworks, ensuring that radiologists are up skilled to interpret algorithmic outputs as part of a collaborative diagnostic process. In the post-pandemic healthcare environment, where medical backlogs and professional burnout have reached critical levels, the deployment of scalable, automated screening systems is no longer a luxury but a strategic necessity. By reducing the manual burden of scan interpretation, healthcare institutions can optimize resource allocation and prioritize high-risk patient intervention. Despite the robust performance of the hybrid model, this study acknowledges certain limitations. The reliance on centralized datasets and the binary nature of the current classification output represent areas for further refinement. Future research should focus on incorporating multi-institutional, heterogeneous datasets to enhance model robustness against various imaging protocols. Additionally, extending the architecture to perform multi-class staging (e.g., TNM staging) and integrating explain ability tools like Grad-CAM would provide deeper transparency, which is vital for clinical trust. In summary, this research contributes to the fundamental understanding of how advanced deep learning can redefine diagnostic standards in a rapidly digitizing economy. As the modern workplace increasingly transitions toward decentralized and technology-mediated models, the integration of autonomous diagnostic support systems represents a pivotal shift in medical productivity. This study serves as a cornerstone for future developments in digital health, demonstrating that the fusion of spatial and temporal intelligence is essential for the next generation of life-saving medical applications.

FUTURE ENHANCEMENTS:

Use of Advanced Deep Learning Models:

The current system uses a basic CNN model; however, it can be further improved by implementing advanced architectures such as ResNet, Efficient Net, or Vision Transformers. These models can capture more complex features and improve classification accuracy significantly.

Integration of Larger and Diverse Datasets:

Future improvements can include training the model with a larger and more diverse dataset. Including data from different sources and patient conditions will help improve model generalization and reduce over fitting issues.

Development of Web and Mobile Applications:

The system can be converted into a web-based or mobile-based application. This will allow users to upload CT scan images and receive predictions instantly, improving accessibility and usability.

Real-Time Clinical Deployment:

The model can be integrated with hospital systems and real-time clinical data. This will enhance its practical usability and allow doctors to use the system as a decision-support tool during diagnosis.

Multi-Class and Stage-Level Classification:

Currently, the model performs binary classification. In future, it can be extended to detect different stages of lung cancer (TNM staging) or multiple disease types, providing more detailed diagnostic information.

Explainable AI Integration

Future systems can include explainable AI techniques such as Grad-CAM to highlight affected regions in CT scan images. This will improve transparency and help doctors understand model predictions more clearly.

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