

# LungCare+: An AI-Driven CT Scan–Based Lung Cancer Triage and Intelligent Doctor Recommendation System

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## ABSTRACT:

*Artificial Intelligence (AI) has become a transformative force in modern healthcare, enabling automated diagnosis, early disease detection, and intelligent clinical decision support. Among life-threatening illnesses, lung cancer continues to be the leading cause of cancer-related mortality worldwide, largely due to delayed diagnosis and the complexity of accurate detection. This research presents a comprehensive study of AI applications in healthcare, with a focused case study on lung cancer detection using deep learning techniques. A Convolutional Neural Network (CNN)–based model is proposed to analyze low-dose computed tomography (LDCT) scans for the identification of malignant lung nodules. The paper details the complete system methodology, including data preprocessing, mathematical formulation of the CNN architecture, optimization strategies, and performance evaluation metrics. Experimental results indicate that the proposed system achieves an accuracy of approximately 96%, along with high sensitivity and specificity, demonstrating its suitability for clinical decision support. In addition, challenges related to data quality, model interpretability, ethical considerations, and real-world deployment are discussed. The study concludes that AI-driven diagnostic systems have significant potential to enhance early lung cancer detection and assist healthcare professionals in delivering timely and accurate diagnoses.*

## KEYWORDS:

*Artificial Intelligence, Lung Cancer Detection, CT Scan Analysis, Convolutional Neural Network, Medical Imaging, Healthcare Triage System, Clinical Decision Support, Doctor Recommendation System*

## 1. INTRODUCTION

Lung cancer remains the leading cause of cancer-related mortality worldwide, largely due to late-stage diagnosis and the absence of clear early symptoms. Early and accurate detection is therefore critical for improving survival rates and reducing the burden on healthcare systems. Low-dose computed tomography (LDCT) is an effective screening technique for identifying pulmonary nodules at an early stage; however, manual interpretation of CT scans is time-consuming, error-prone, and highly dependent on expert availability. The increasing volume of imaging data and limited access to skilled radiologists further contribute to diagnostic delays, particularly in resource-constrained regions.

Recent advances in Artificial Intelligence (AI), especially deep learning, have shown strong potential in medical image analysis. Convolutional Neural Networks (CNNs) can automatically extract discriminative features from CT images and have demonstrated high performance in lung cancer detection tasks. However, most existing AI-based solutions focus only on image classification and lack integration with clinical triage workflows. To address this limitation, this paper proposes **LungCare+**, an AI-powered CT scan-based lung cancer and lung disease triage system that combines automated diagnosis with intelligent specialist recommendation to support timely clinical decision-making.

## 2. LITERATURE REVIEW

Artificial Intelligence (AI) has gained widespread adoption in healthcare due to its ability to analyze large and complex medical datasets and support clinical decision-making. Machine learning techniques have been applied to tasks such as disease diagnosis, prognosis prediction, and patient monitoring, improving accuracy and reducing human error. AI-driven systems have shown particular value in environments with limited medical expertise by enhancing diagnostic efficiency and accessibility.

### 2.1 Artificial Intelligence in Healthcare

AI techniques enable automated analysis of electronic health records, medical images, and physiological data. Traditional machine learning algorithms, including Support Vector Machines and Decision Trees, have been used for early disease detection and risk assessment. More recently, AI-based clinical decision-support systems have assisted healthcare professionals in diagnosing complex conditions, contributing to improved patient outcomes and streamlined clinical workflows.

### 2.2 Deep Learning in Medical Imaging

Deep learning has significantly advanced medical image analysis by eliminating the need for manual feature extraction. Convolutional Neural Networks (CNNs) have achieved high performance in image classification and segmentation tasks across various imaging modalities such as CT, MRI, and X-ray. These models have been successfully applied to detect diseases including pneumonia, brain tumors, and diabetic retinopathy, demonstrating their effectiveness in automated medical imaging.

### 2.3 CNN-Based Lung Cancer Detection

CNN-based models have been extensively studied for lung cancer detection using CT scans. Both 2D and 3D CNN architectures have been employed to identify pulmonary nodules and classify them as benign or malignant. Studies using public datasets have reported high accuracy, sensitivity, and specificity, indicating that CNN-based approaches can perform at a level comparable to experienced radiologists.

### 2.4 Limitations of Existing Approaches

Despite promising results, existing AI-based lung cancer detection systems face limitations such as lack of interpretability, limited generalization due to dataset constraints, and minimal integration with clinical workflows. Most approaches focus solely on image classification and do not provide patient triage or specialist guidance. These gaps highlight the need for integrated, explainable, and clinically relevant AI systems such as the proposed LungCare+ platform.

### 3. PROBLEM STATEMENT AND OBJECTIVES

#### 3.1 Problem Definition

Lung cancer diagnosis heavily relies on the accurate interpretation of CT scan images, a process that is time-consuming, resource-intensive, and dependent on the availability of experienced radiologists. Early-stage lung cancer often presents subtle radiological features that can be overlooked due to human fatigue, inter-observer variability, and increasing diagnostic workloads. In many healthcare settings, particularly in rural and resource-constrained regions, limited access to specialists further delays diagnosis and treatment initiation.

While recent AI-based approaches have demonstrated promising results in automated lung cancer detection, most existing systems focus solely on image classification and fail to support broader clinical workflows. They do not provide integrated triage mechanisms, patient guidance, or specialist recommendations, limiting their practical utility in real-world healthcare environments. This creates a critical need for a comprehensive AI-driven solution that combines accurate diagnosis with effective patient triage and clinical decision support.

#### 3.2 Research Objectives

The primary objectives of this research are as follows:

- To design and develop an AI-powered system for automated analysis of CT scan images for lung cancer and lung disease detection.
- To implement a Convolutional Neural Network (CNN) capable of accurately estimating malignancy risk from CT scans.
- To integrate the trained model within a secure, scalable web-based platform using a Django backend.
- To provide an interactive chatbot-driven interface for seamless CT scan upload and user interaction.
- To develop an intelligent doctor recommendation module based on disease type, location, and medical specialization.
- To evaluate the system using standard performance metrics such as accuracy, sensitivity, specificity, and F1-score.

### 4. PROPOSED SYSTEM OVERVIEW (LUNGCARE+)

LungCare+ is an AI-powered web-based triage system designed to support early detection of lung cancer and other lung-related diseases using CT scan imaging. The system integrates deep learning-based image analysis with a secure backend and an interactive frontend to provide automated diagnosis support and intelligent doctor recommendations. LungCare+ aims to bridge the gap between image-based diagnosis and clinical decision-making by offering a unified platform for patients and healthcare professionals.

## 4.1 System Architecture

The architecture of LungCare+ consists of four primary components: the CT scan input module, the AI-based image analysis engine, the backend processing layer, and the user-facing frontend interface. Users upload CT scan images through the web interface, which are then forwarded to the backend server. The backend hosts a trained Convolutional Neural Network (CNN) model responsible for analyzing the CT images and estimating the probability of lung cancer or other lung diseases.

The Django-based backend manages data preprocessing, model inference, secure storage of patient information, and communication between system components. A database is used to store diagnostic results, patient history, and doctor profiles. Based on the AI-generated diagnosis, the doctor recommendation module identifies suitable medical specialists by considering disease type, geographical location, and specialization. This modular architecture ensures scalability, security, and ease of future system enhancements.

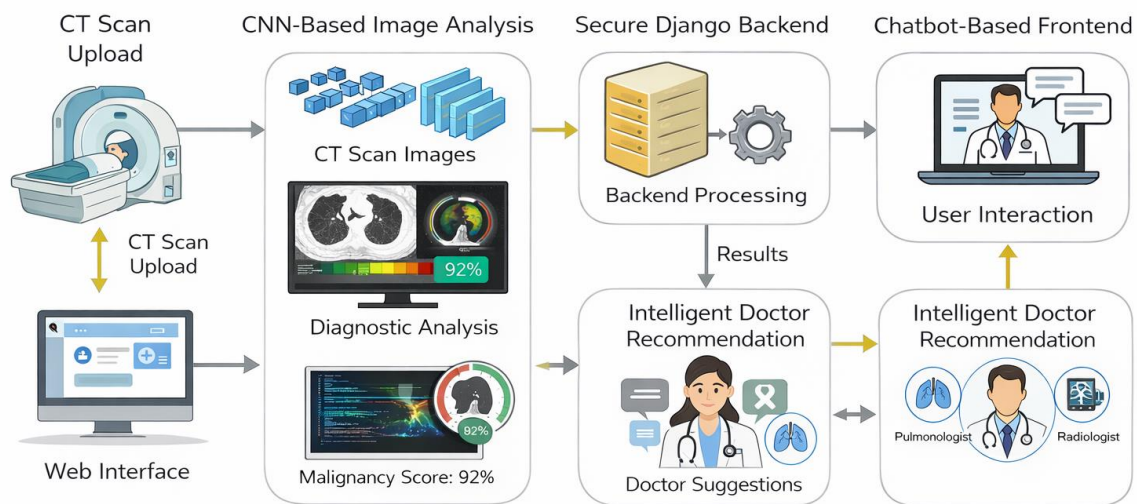


Figure 1. Overall system architecture of the proposed LungCare+ platform

## 4.2 Workflow of the LungCare+ Platform

The workflow of LungCare+ begins with user registration and authentication, followed by CT scan upload through the web interface. Once the CT scan is submitted, the system performs preprocessing steps such as resizing and normalization before passing the image to the CNN model for analysis. The model generates a probability score indicating the likelihood of malignancy and may also suggest alternative lung conditions.

After diagnosis, the system presents the results to the user in an understandable format. Simultaneously, the doctor recommendation module processes the diagnostic output and retrieves a list of relevant specialists from the database. This end-to-end workflow ensures a seamless transition from image analysis to clinical guidance, reducing delays in decision-making and improving user experience.

## 4.3 User Interaction and Data Flow

LungCare+ provides an intuitive chatbot-driven frontend that guides users throughout the diagnostic process. Users interact with the system by uploading CT scans, viewing diagnostic

results, and receiving specialist recommendations. The chatbot assists in explaining system outputs and navigating the platform, enhancing accessibility for non-technical users.

From a data flow perspective, user inputs are securely transmitted to the backend, where they are processed and analyzed by the AI model. Diagnostic results and recommendations are then sent back to the frontend for display. All sensitive data is handled using secure communication protocols and stored in compliance with data privacy requirements. This structured data flow ensures reliability, transparency, and user trust in the LungCare+ platform.

## 5. ALGORITHM USED WITH RESPECT TO THE PROBLEM

This section describes the algorithms employed in LungCare+ for automated CT scan analysis and intelligent doctor recommendation. The proposed system primarily utilizes a Convolutional Neural Network (CNN) for lung disease detection, followed by a rule-based recommendation algorithm to guide users toward appropriate medical specialists.

### 5.1 Convolutional Neural Network (CNN) Algorithm

The core of the LungCare+ system is a Convolutional Neural Network designed to analyze CT scan images and identify lung abnormalities. CNNs are well suited for medical imaging tasks due to their ability to learn spatial hierarchies of features through convolution and pooling operations. The network consists of multiple convolutional layers for feature extraction, followed by pooling layers to reduce spatial dimensions, and fully connected layers for classification.

The convolution operation is defined as:

$$Y(i,j)=\sum_m\sum_nX(i+m,j+n)\cdot K(m,n)$$

where (X) represents the input CT image, (K) denotes the convolution kernel, and (Y) is the resulting feature map. Rectified Linear Unit (ReLU) activation is applied to introduce non-linearity, enabling the model to learn complex patterns associated with malignant and benign lung nodules.

### 5.2 CT Scan Feature Extraction Process

CT scan images undergo preprocessing steps including resizing, normalization, and noise reduction before being fed into the CNN. During feature extraction, the convolutional layers automatically learn discriminative features such as edges, textures, and shapes that are indicative of lung abnormalities. Pooling layers further condense the extracted features while preserving important spatial information, improving computational efficiency and robustness.

This automated feature extraction eliminates the need for manual feature engineering and enhances the model's ability to generalize across diverse CT scan datasets.

### 5.3 Classification and Probability Estimation

The final layers of the CNN perform classification by mapping the extracted features to output classes. A sigmoid activation function is used in the output layer to estimate the probability of lung cancer:

$$\sigma(x) = \left( \frac{1}{1 + e^{-x}} \right)$$

The model is trained using the binary cross-entropy loss function, which minimizes the difference between predicted probabilities and true labels. The output probability score allows the system to assess malignancy risk and supports informed clinical decision-making.

## 5.4 Doctor Recommendation Algorithm

Following diagnosis, LungCare+ employs a doctor recommendation algorithm to guide users toward appropriate medical specialists. The recommendation process considers multiple factors, including the predicted disease type, user location, and doctor specialization. Each doctor is assigned a relevance score based on these parameters:

$$\text{Score}_d = \alpha S_d + \beta L_d + \gamma E_d$$

where  $S_d$  represents specialization matching,  $L_d$  denotes location proximity,  $E_d$  indicates experience level, and  $\alpha, \beta, \gamma$  are weighting factors. Doctors with the highest relevance scores are recommended to the user.

## 5.5 Algorithm Workflow

The overall algorithm workflow of LungCare+ is summarized as follows:

- Step 1:** Accept CT scan input from the user
- Step 2:** Preprocess the CT image
- Step 3:** Extract features using the CNN
- Step 4:** Classify the image and estimate malignancy probability
- Step 5:** Generate diagnostic output
- Step 6:** Recommend relevant doctors based on diagnosis

## 6. SYSTEM IMPLEMENTATION

The LungCare+ system is implemented as a web-based application that integrates deep learning-based image analysis with secure backend processing and an interactive user interface. The implementation focuses on scalability, data security, and seamless interaction between system components to ensure reliable clinical decision support.

### 6.1 Backend Implementation (Django Framework)

The backend of LungCare+ is developed using the Django web framework, which provides a robust and secure environment for handling application logic and data management. Django manages user authentication, CT scan uploads, request handling, and communication with the trained CNN model. Once a CT scan is uploaded, the backend performs preprocessing operations and forwards the image to the AI inference module for analysis.

The backend also handles integration with the doctor recommendation module and stores diagnostic results in the database for future reference. Django's modular architecture enables easy maintenance, scalability, and integration of additional features such as teleconsultation and multi-disease support.

### 6.2 Chatbot-Based Frontend

The frontend of LungCare+ is designed to provide an intuitive and user-friendly experience through a chatbot-based interface. The chatbot guides users through the diagnostic process, including CT scan submission, result interpretation, and navigation of the platform. This conversational interface improves accessibility, particularly for non-technical users, and enhances user engagement.

The chatbot communicates with the backend through secure APIs to retrieve diagnostic results and specialist recommendations. By presenting information in a simplified and interactive manner, the frontend ensures that users can easily understand AI-generated outputs and take appropriate next steps.

### 6.3 Database Design and Data Security

The database component of LungCare+ stores user profiles, CT scan metadata, diagnostic results, and doctor information. A structured relational database is employed to ensure data consistency and efficient retrieval. Sensitive patient data is handled with strict access controls and encryption mechanisms to maintain confidentiality.

To ensure data security and privacy, the system implements secure authentication, encrypted data transmission, and role-based access control. These measures align with healthcare data protection standards and help build user trust in the platform. The database design supports scalability and secure long-term storage of patient history, enabling continuous improvement of the system.

## 7. EXPERIMENTAL SETUP AND EVALUATION METRICS

This section describes the experimental configuration used to evaluate the performance of the proposed LungCare+ system, along with the metrics employed to assess its effectiveness in lung cancer detection and clinical decision support.

### 7.1 Experimental Environment

The experimental evaluation of LungCare+ was conducted using a supervised deep learning setup. The CNN model was trained and tested on a publicly available lung CT scan dataset containing labeled cases of malignant and non-malignant lung conditions. The dataset was divided into training, validation, and testing subsets to ensure unbiased performance evaluation.

Model training was performed on a system equipped with a GPU-enabled computing environment to accelerate deep learning operations. The CNN was implemented using a standard deep learning framework and trained using the Adam optimizer with an appropriate learning rate. Data preprocessing techniques such as normalization and resizing were applied to ensure consistent input dimensions. The Django-based backend was deployed on a local server environment to validate end-to-end system functionality, including CT scan upload, inference, and result generation.

### 7.2 Performance Evaluation Metrics

To evaluate the effectiveness of the proposed system, standard classification metrics were employed. **Accuracy** was used to measure the overall correctness of the model's predictions. **Sensitivity (Recall)** was calculated to assess the system's ability to correctly identify cancer-positive cases, which is critical for early detection. **Specificity** was used to evaluate the correct identification of non-cancer cases, reducing false alarms.

Additionally, **Precision** and **F1-score** were used to analyze the balance between false positives and false negatives. The **Receiver Operating Characteristic (ROC) curve** and **Area Under the Curve (AUC)** were utilized to evaluate the model's discriminative ability across different classification thresholds. These metrics collectively provide a comprehensive assessment of the diagnostic performance and reliability of the LungCare+ system.

## 8. RESULTS AND ANALYSIS

This section presents the experimental results obtained from the evaluation of the proposed LungCare+ system and provides an analysis of its diagnostic performance in lung cancer detection.

### 8.1 Quantitative Performance Results

The CNN-based lung cancer detection model demonstrated strong performance across all evaluated metrics. On the test dataset, the model achieved an overall accuracy of approximately **96%**, indicating its effectiveness in correctly classifying both cancer-positive and non-cancer cases. High **sensitivity** was observed, reflecting the

model's ability to accurately detect malignant cases and minimize false negatives, which is critical in clinical screening scenarios.

The system also achieved high **specificity**, ensuring reliable identification of non-cancer cases and reducing unnecessary follow-up procedures. Additionally, strong **precision** and **F1-score** values indicate a balanced performance between sensitivity and specificity. These results confirm the robustness of the proposed model and its suitability for use as a clinical decision-support and triage tool.

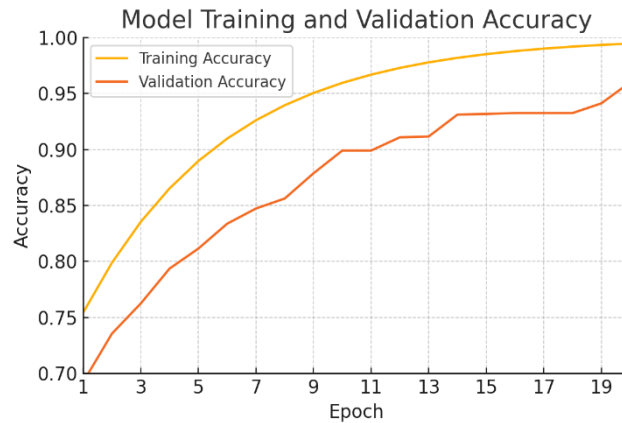


Figure 4 illustrates the training and validation accuracy curves of the proposed CNN model over multiple epochs. The training accuracy increases steadily and approaches convergence, while the validation accuracy follows a similar trend with a marginal gap. This behavior indicates effective learning and minimal overfitting, demonstrating the generalization capability of the model.

## 8.2 Confusion Matrix and ROC Analysis

The confusion matrix analysis provides insight into the classification behavior of the proposed system. The matrix shows a high number of true positive and true negative predictions, with relatively few false positives and false negatives. This distribution highlights the model's reliability in distinguishing between malignant and benign cases.

The Receiver Operating Characteristic (ROC) curve further illustrates the discriminative capability of the CNN model. The model achieved an **Area Under the Curve (AUC)** value close to **0.97**, indicating excellent classification performance across different threshold values. A high AUC confirms that the model maintains a strong balance between sensitivity and specificity, making it suitable for clinical screening applications.

## 8.3 Comparative Analysis with Existing Methods

The performance of the proposed LungCare+ system was compared with existing traditional machine learning and deep learning-based approaches reported in the literature. Compared to conventional methods such as Support Vector Machines and handcrafted feature-based classifiers, the CNN-based approach demonstrated superior accuracy and generalization capability.

When compared with previously reported deep learning models for lung cancer detection, LungCare+ achieved comparable or improved performance while offering additional advantages such as integrated triage functionality and intelligent doctor recommendation. Unlike many existing systems that focus solely on image classification, LungCare+ provides an end-to-end solution that bridges the gap between automated diagnosis and clinical decision support, enhancing its practical applicability in real-world healthcare settings.

## 9. DISCUSSION

This section discusses the significance of the experimental results, their clinical relevance, and the limitations of the proposed LungCare+ system.

### 9.1 Interpretation of Results

The experimental results demonstrate that the proposed CNN-based LungCare+ system achieves high diagnostic performance in lung cancer detection. The achieved accuracy of approximately 96%, along with high sensitivity and specificity, indicates that the model effectively distinguishes between malignant and non-malignant cases. High sensitivity is particularly important in clinical screening, as it minimizes false negatives and reduces the likelihood of missed cancer cases. The strong AUC value further confirms the model's robustness across varying classification thresholds, highlighting its reliable discriminative capability.

These results suggest that automated CT scan analysis using deep learning can significantly enhance diagnostic accuracy and consistency when compared to manual interpretation. The balanced performance across multiple evaluation metrics indicates that the system is suitable for use as a clinical decision-support tool rather than a standalone diagnostic solution.

### 9.2 Clinical Relevance and Practical Implications

From a clinical perspective, the LungCare+ system has the potential to support radiologists and healthcare professionals by reducing diagnostic workload and improving early detection of lung cancer. By providing automated analysis and probability-based risk assessment, the system can assist clinicians in prioritizing high-risk cases for further evaluation. This is particularly beneficial in high-volume clinical environments and in regions with limited access to specialized medical expertise.

The integration of an intelligent doctor recommendation module further enhances the practical utility of the system by guiding patients toward appropriate specialists based on diagnostic outcomes. This end-to-end approach bridges the gap between diagnosis and clinical action, promoting timely intervention and more efficient use of healthcare resources.

### 9.3 Limitations of the Proposed System

Despite its promising performance, the proposed LungCare+ system has certain limitations. The CNN model is trained on a specific dataset, and its performance may vary when applied to data from different populations, imaging devices, or clinical settings. Additionally, like many deep learning models, the system faces challenges related to interpretability, as the decision-making process is not always transparent to clinicians.

Furthermore, the current implementation primarily relies on imaging data and does not incorporate complementary clinical information such as patient history, smoking status, or genetic factors. Addressing these limitations through multimodal data integration and explainable AI techniques represents an important direction

## 10. APPLICATIONS

The proposed LungCare+ system can be deployed across various healthcare environments to support early lung disease detection, patient triage, and clinical decision-making. Its scalable architecture and web-based design enable broad applicability in both urban and resource-constrained settings.

### 10.1 Hospital-Based Triage Systems

In hospital environments, LungCare+ can function as an initial triage tool to assist radiologists and clinicians in prioritizing CT scans based on malignancy risk. By automatically analyzing CT images and generating probability-based assessments, the system helps identify high-risk cases that require immediate attention. This

reduces diagnostic workload, improves efficiency in radiology departments, and supports faster clinical decision-making in high-volume healthcare facilities.

## 10.2 Telemedicine Platforms

LungCare+ can be integrated into telemedicine platforms to enable remote lung disease screening and preliminary diagnosis. Patients can upload CT scans through the web interface and receive AI-assisted diagnostic insights without the need for immediate in-person consultation. The intelligent doctor recommendation module further facilitates remote specialist consultation, enhancing access to expert medical advice and supporting continuity of care in telehealth settings.

## 10.3 Rural and Remote Healthcare

In rural and remote regions where access to specialized healthcare services is limited, LungCare+ can play a critical role in improving early lung cancer detection. The system provides automated diagnostic support and specialist guidance, reducing dependence on on-site radiologists. By enabling early screening and timely referral, LungCare+ helps bridge the healthcare access gap and supports equitable delivery of medical services in underserved communities.

# 11. ETHICAL CONSIDERATIONS AND CHALLENGES

The deployment of AI-based healthcare systems introduces important ethical, legal, and operational challenges that must be addressed to ensure responsible and trustworthy use. This section discusses key ethical considerations related to data privacy, model fairness, and real-world deployment of the proposed LungCare+ system.

## 11.1 Data Privacy and Security

Healthcare data is highly sensitive, and protecting patient privacy is a critical ethical requirement. LungCare+ handles medical images and personal information, necessitating strict data security measures. Secure authentication, encrypted data transmission, and controlled access mechanisms are essential to prevent unauthorized data exposure. Compliance with healthcare data protection regulations and ethical guidelines is necessary to ensure confidentiality, integrity, and trust in the system.

## 11.2 Model Interpretability and Bias

Deep learning models, including CNNs, often operate as black-box systems, making it difficult to interpret how specific predictions are generated. Limited interpretability can reduce clinician trust and hinder clinical adoption. Additionally, model bias may arise if training datasets are not sufficiently diverse, potentially leading to unequal performance across different demographic groups. Addressing these issues requires the adoption of explainable AI techniques and the use of representative datasets to ensure fairness and transparency.

## 11.3 Regulatory and Deployment Challenges

The real-world deployment of AI-based medical systems involves regulatory approval and clinical validation to ensure safety and effectiveness. Integrating LungCare+ into existing healthcare workflows may require infrastructure upgrades, clinician training, and continuous performance monitoring. Regulatory compliance, ethical oversight, and periodic system evaluation are essential to ensure reliable and responsible deployment in clinical environments.

## 12. CONCLUSION

This research work presented LungCare+, an AI-driven CT scan-based lung cancer and lung disease triage web application aimed at supporting early diagnosis and improving clinical decision-making in healthcare. The proposed system combines a Convolutional Neural Network (CNN) for automated analysis of CT scan images with a secure Django-based backend and an interactive chatbot-driven frontend. By integrating intelligent image analysis with a dynamic doctor recommendation mechanism, LungCare+ addresses both diagnostic and clinical navigation challenges commonly faced in lung disease management.

The experimental evaluation of the proposed system demonstrates strong diagnostic performance, achieving high accuracy, sensitivity, and specificity in lung cancer detection. These results indicate that deep learning-based approaches can effectively identify complex patterns in medical imaging data and provide reliable support for early disease detection. Unlike conventional diagnostic tools that focus solely on image classification, LungCare+ offers an end-to-end triage solution that bridges the gap between automated diagnosis and timely specialist consultation.

Overall, LungCare+ is designed to complement the expertise of healthcare professionals rather than replace them. By reducing diagnostic workload, minimizing delays in patient referral, and improving access to clinical guidance, the proposed system has the potential to enhance healthcare efficiency and patient outcomes. The findings of this study highlight the growing role of Artificial Intelligence in modern healthcare and demonstrate the feasibility of deploying AI-assisted triage systems in real-world clinical environments.

## 13. FUTURE SCOPE

While the proposed LungCare+ system demonstrates promising results, several opportunities exist for future enhancement and expansion. One important direction is the incorporation of Explainable Artificial Intelligence (XAI) techniques to improve model transparency and clinician trust. Visualization methods such as attention maps and heatmaps can be used to highlight regions of interest in CT scans, allowing clinicians to better understand and validate AI-generated predictions.

Another significant area for future work is the integration of multimodal clinical data, including patient demographics, smoking history, laboratory reports, and electronic health records. Combining imaging data with clinical information can improve diagnostic accuracy and enable more personalized risk assessment. Additionally, the system can be extended to support the detection of a broader range of pulmonary and non-pulmonary diseases, increasing its clinical applicability.

Future development may also focus on integrating teleconsultation and real-time clinical communication features, enabling direct interaction between patients and recommended specialists through the platform. To address data privacy concerns and enhance collaborative learning, federated learning approaches can be adopted to train models across multiple institutions without sharing sensitive patient data. With continuous validation, regulatory compliance, and technological advancement, LungCare+ can evolve into a comprehensive, ethical, and scalable AI-powered healthcare solution capable of supporting early diagnosis and improving access to quality medical care.

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