

CliniScan+ : An Integrated AI – Based Lung Disease Detection Diagnosis and Smart Healthcare Support System

Rishika Sharma¹, Shiva Kumar Prajapathi H², Vedashree R³, Yudhil Krishna⁴, Dr Latha P H⁵

¹ Student, Dept of Computer Science Engineering, Rajiv Gandhi Institute of technology, Bengaluru, India

² Student, Dept of Computer Science Engineering, Rajiv Gandhi Institute of technology, Bengaluru, India

³ Student, Dept of Computer Science Engineering, Rajiv Gandhi Institute of technology, Bengaluru, India

⁴ Student, Dept of Computer Science Engineering, Rajiv Gandhi Institute of technology, Bengaluru, India

⁵ Professor, Dept of Computer Science Engineering, Rajiv Gandhi Institute of technology, Bengaluru, India

Abstract – lung diseases such as pneumonia and tuberculosis require early and accurate diagnosis to improve patient outcomes. Traditional diagnostic systems are often limited to prediction and lack interpretability and healthcare integration. This paper presents CliniScan+, an AI-based integrated healthcare support system for lung disease detection using chest X-ray images. The system employs Convolutional Neural Networks(CNN) for multi-disease classification and Grad-CAM(Gradient-weighted Class Activation Mapping) for visual explanation of model predictions, enhancing clinical trust. In addition, the system incorporates automated doctor recommendation based on disease type, consultation tracking, and geo-spatial disease risk prediction using location-based analysis. By combining diagnosis, explainability, and healthcare services into a unified platform, the proposed system aims to improve decision-making, accessibility, and real-world applicability in medical diagnostics.

Index Terms – Artificial Intelligence, Chest X-ray Analysis, Explainable AI, Geo-Spatial Disease Prediction, Healthcare Recommendation System

1. Introduction

Lung diseases are among the leading causes of mortality worldwide, making early and accurate diagnosis essential. Chest X-ray imaging is widely used for detecting diseases such as pneumonia and tuberculosis. With the advancement of artificial intelligence, deep learning models, particularly Convolutional Neural Networks(CNN), have significantly improved diagnostic accuracy.

However, most existing systems are limited to prediction and do not provide interpretability or integration with healthcare services. This lack of explainability reduces trust among medical professionals. Furthermore, current systems do not support doctor recommendation, consultation tracking, or location – based disease risk analysis.

To address these limitations, CliniScan+ is proposed as an integrated AI-based healthcare support system that combines diagnosis, explainability, and healthcare services into a unified platform.

2. Literature Survey

A. AI-Based Lung Disease Detection

Deep learning techniques, especially Convolutional Neural Networks (CNN), have been widely used for the automated detection of lung diseases from chest X-ray images. Various pre-trained models such as VGG19, ResNet50, MobileNetV2, and EfficientNet have demonstrated high accuracy in classifying diseases like pneumonia and tuberculosis. These models often use transfer learning and preprocessing techniques such as Contrast Limited Adaptive Histogram Equalization (CLAHE) to improve performance.

Although these approaches achieve high classification accuracy, they are primarily focused on prediction tasks and lack integration with clinical workflows. Most systems do not provide additional healthcare support such as doctor recommendations or patient monitoring, limited their real-world applicability.

B. Explainable AI in Healthcare

Explainable Artificial Intelligence (XAI) plays a crucial role in medical applications by increasing

Transparency and trust in AI systems. Techniques such as Grad – CAM (Gradient-weighted Class Activation Mapping) and Grad-CAM++ are commonly used to generate heatmaps that highlight the regions of interest in chest X-ray images. These visual explanations help clinicians understand the reasoning behind model predictions.

However, existing research mainly focuses on comparing different explainability techniques or improving visualization quality. These systems are not integrated with complete healthcare platforms and often lack real-time usability. Additionally, most studies do not combine multiple explainability methods to enhance interpretability further.

C. Healthcare Recommendation Systems

Healthcare recommendation systems utilize learning and artificial intelligence to suggest treatments, doctors, or medical actions based on patient data. Recent works use neural networks and data-driven approaches to analyze patient profiles and generate personalized recommendations. Some systems

also incorporate feedback mechanisms to improve recommendation accuracy over time.

Despite these advancements, most recommendation systems operate independently and are not connected with diagnostic models. They rely heavily on structured patient data and do not consider real-time diagnostic outputs such as X-ray predictions. This lack of integration reduces their effectiveness in providing end-to-end healthcare solutions.

D. Geo-Spatial Disease Prediction

Geo-spatial disease prediction involves analyzing location-based data along with temporal and environmental factors to predict disease occurrence and spread. Techniques such as spatio-temporal modeling, remote sensing, and deep learning are used to identify patterns across different regions. These systems are particularly useful for understanding disease outbreaks and risk zones.

However, most geo-spatial models are designed for large-scale epidemic analysis and are not integrated with individual medical data, limiting their application in clinical decision support systems.

E. Integrated Healthcare Systems

Recent advancements in healthcare technology focus on integrating multiple components such as AI-based diagnosis, cloud computing, IoT, and blockchain for secure and efficient healthcare delivery. These systems aim to provide end-to-end solutions including patient monitoring, data management, and clinical decision support.

While these integrated systems improve healthcare accessibility and scalability, they often lack advanced AI-based diagnostic capabilities or explainability features. Additionally, many systems do not incorporate geo-spatial disease prediction, which is essential for understanding regional health risks. This indicates a gap in developing a fully unified healthcare platform.

3. Research Gap

From the literature survey, it is observed that most existing systems focus on individual aspects of healthcare such as disease prediction, explainable AI, or recommendation systems. Deep learning models provide high accuracy in lung disease detection, but they are limited to classification and do not support further medical assistance. Similarly, explainable AI techniques improve transparency but are not integrated with complete healthcare workflows.

Healthcare recommendation systems and geo-spatial disease prediction models operate independently and are not connected with real-time diagnostic outputs. Moreover, existing integrated healthcare systems lack a combination of AI-based diagnosis, explainability, and location-based risk analysis within a single platform.

Therefore, there is a need for a unified system that integrates diagnosis, explanation, recommendation, consultation tracking,

and geo-spatial analysis to provide a comprehensive and practical healthcare solution.

4. Proposed System

The proposed system, CliniScan+, is an AI-based integrated healthcare support platform designed to provide accurate lung disease diagnosis along with intelligent healthcare services. Unlike traditional systems that focus only on prediction, this system combines multiple modules to deliver a complete end-to-end solution.

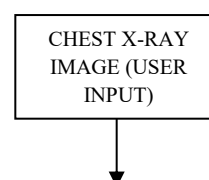
The workflow of the system begins with the input of chest X-ray images, which are processed using a Convolutional Neural Network (CNN) model for multi-disease classification. The model is trained on labeled medical datasets to identify diseases such as pneumonia and tuberculosis with high accuracy.

To enhance transparency and clinical trust, the system incorporates Explainable AI using Grad-CAM (Gradient-weighted Class Activation Mapping). This technique generated heatmaps on X-ray images, highlighting the regions responsible for the prediction, thereby assisting doctors in understanding the model's decision.

Based on the predicted disease, the system provides an automated doctor recommendation module. This module suggests suitable specialists by considering factors such as disease type, doctor ratings, and availability. In addition, a consultation tracking system is included to maintain patient records, appointment history, and follow-up details, ensuring continuity in healthcare services.

Furthermore, the system integrates a geo-spatial disease risk prediction module that analyzes location-based data to estimate the risk of lung diseases in different regions. This helps in identifying high-risk areas and supports preventive healthcare measures.

All these modules are integrated into a unified platform, making the system scalable and suitable for real-world deployment. The proposed system not only improves diagnostic accuracy but also bridges the gap between prediction and practical healthcare support by combining diagnosis, explanation, recommendation, and risk analysis in a single framework.



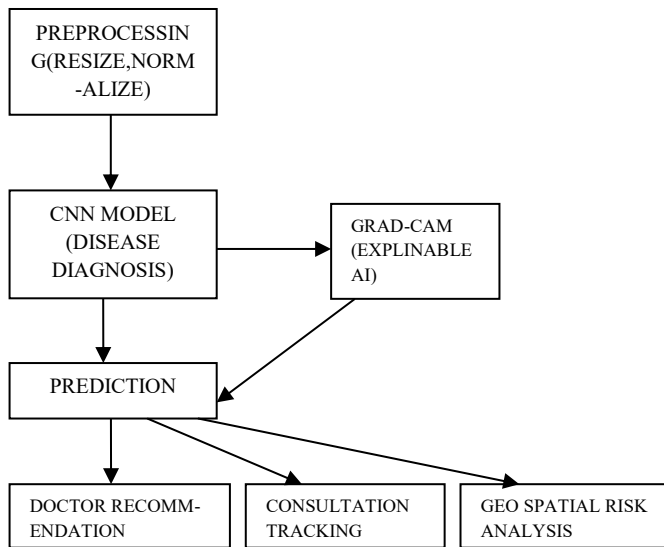


Fig 1 : Block Diagram of CliniScan+ System

5. Advantages Of Proposed System

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6. Conclusion

In this paper, an AI-based integrated healthcare support system, *CliniScan+*, has been presented to address the limitations of existing lung disease diagnostic methods. Traditional systems primarily focus on disease prediction and lack interpretability and healthcare integration, which reduces their practical usability in real-world scenarios.

The proposed system combines Convolutional Neural Networks (CNN) for accurate lung disease detection with Explainable AI techniques such as Grad-CAM to enhance transparency and clinical trust. In addition to diagnosis, the system incorporates automated doctor recommendation and consultation tracking, enabling continuous and efficient patient care. The integration of geo-spatial disease risk prediction further enhances the system by providing location-based insights, which can support preventive healthcare measures.

By unifying multiple components into a single platform, *CliniScan+* bridges the gap between AI-based prediction and practical healthcare applications. The system improves accessibility, decision-making, and reliability in medical diagnostics. In the future, the system can be extended by incorporating real-time hospital data, advanced predictive analytics, and deployment in cloud-based environments to further enhance scalability and performance.

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