

Dectra: Thoracic Imaging with Deep Learning - Toward Smarter Healthcare

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Abstract— Thoracic diseases like pneumonia, tuberculosis, lung cancer, and COVID-19 are among the top causes of deaths globally. Early and correct diagnosis is essential for the successful treatment and better patient outcomes. The conventional diagnosis techniques are extremely dependent on radiologists, which is a time-consuming and incorrect process because of the massive amount of data involved in medical imaging. This project aims to design a deep learning-based thoracic imaging system that can automatically identify and diagnose chest diseases from medical images like X-rays and CT scans. The proposed system combines CNNs with secure data management systems to improve the efficiency, accuracy, and reliability of diagnoses. Moreover, the system employs blockchain technology to provide the secure storage and transparency of patients' medical information. The result shows that deep learning models have the potential to greatly improve the accuracy of identification and the speed of diagnosis, hence making a great contribution to smart healthcare systems.

Keywords— Thoracic Imaging, Deep Learning, Convolutional Neural Networks, Medical Imaging, Blockchain, Healthcare AI, Lung Disease Detection, Smart Healthcare.

I. INTRODUCTION

Thoracic imaging is an essential part of contemporary healthcare because it allows doctors to evaluate the chest area, which includes the lungs, heart, blood vessels, and ribs. It is a crucial tool in the diagnosis, management, and treatment of different chest conditions like pneumonia, lung cancer, tuberculosis, chronic obstructive pulmonary disease (COPD), and pulmonary fibrosis. The two most popular forms of thoracic imaging are chest X-rays and computed tomography (CT) scans. Chest X-rays are readily available and relatively inexpensive; hence, they are used as the primary diagnostic tool for chest conditions. CT scans, on the other hand, are more detailed and offer cross-sectional images of the chest, which enable doctors to accurately identify any abnormalities. However, manually interpreting these images is a difficult and time-consuming process that requires highly skilled radiologists. The level of accuracy in diagnosis depends on the skills and workload of the healthcare professional, and there are also delays in healthcare facilities that lack resources and specialists.

Recently, the application of artificial intelligence (AI) has been recognized as a revolutionary technology in the field of medical imaging, especially with the application of deep learning algorithms. Deep learning is a type of machine learning, which utilizes artificial neural networks modeled on the human brain's learning process. Convolutional Neural Networks (CNNs), which are highly successful in image analysis tasks, have shown outstanding performance in identifying patterns, characteristics, and irregularities in medical images.

Unlike traditional machine learning algorithms, which need manual feature extraction, deep learning algorithms can automatically learn hierarchical features from raw image data. This capability helps them to identify patterns that are not easily identifiable by the human eye. Several studies have shown that deep learning algorithms can provide a diagnostic accuracy level that is comparable to, and in some cases, superior to that of experienced radiologists, especially in tasks such as lung nodule detection, pneumonia diagnosis, and tuberculosis detection. Additionally, AI algorithms can analyze large amounts of imaging data quickly, which can reduce the pressure of workload on healthcare professionals.

However, while AI enhances diagnostic capacities, another important issue in the healthcare industry is the secure storage and sharing of confidential medical information. The confidentiality of patient imaging information must be safeguarded against unauthorized access, manipulation, or destruction, as privacy and data integrity are vital in the medical field. Blockchain technology presents an important answer to these issues by offering a secure, decentralized, and tamper-proof platform for the storage and management of medical information. Using blockchain technology, it is ensured that once information is stored, it cannot be manipulated without authorization, thus increasing trust and transparency in the healthcare system.

The combination of deep learning and blockchain technology provides a robust platform for smarter healthcare systems. In this proposed project, a deep learning-based thoracic imaging system is designed to automatically analyze chest X-ray and CT scan images for disease detection and classification. The proposed system utilizes the latest neural network architectures to extract significant features and provide precise diagnostic predictions. Simultaneously, blockchain technology is integrated to securely store patient imaging information, diagnostic results, and model predictions, ensuring data integrity, traceability, and privacy. The integration of these two technologies not only provides precise diagnostic predictions but also helps to develop a secure and trustworthy healthcare system where data can be safely shared among hospitals, laboratories, and healthcare professionals.

Finally, this proposed project will help to develop intelligent and secure medical imaging systems that can facilitate early disease detection, minimize diagnostic inaccuracies, and improve patient outcomes. By combining the analytical capabilities of deep learning with the security benefits of blockchain technology, the proposed system can facilitate node owners a public key and secret key, which enable digital signatures and verification of authenticity. Major benefits of blockchain technology include removing the need for a third-party guarantor and making it virtually impossible alter information entered. However, a major disadvantage is the massive store requirement.

Smarter healthcare decision-making and overcome both technological and medical challenges in thoracic imaging systems.

II. OVERVIEW OF BLOCKCHAIN

A. Blockchain Technology

Blockchain technology is a decentralized and distributed digital ledger system that records transactions across multiple computers in a secure and immutable way. In the medical field, blockchain technology has numerous benefits, including data integrity, privacy, secure sharing of medical information, and preventing unauthorized access.

In the proposed system, blockchain technology is employed to securely store patient imaging reports and diagnostic information. Every transaction, such as image upload and diagnosis, is stored as a block of encrypted patient information, timestamps, and hash values for verification. Once stored, the information cannot be altered, ensuring transparency and trust between healthcare providers and patients.

Blockchain technology also supports interoperability between healthcare facilities, enabling authorized medical practitioners to access patient information without undermining security.

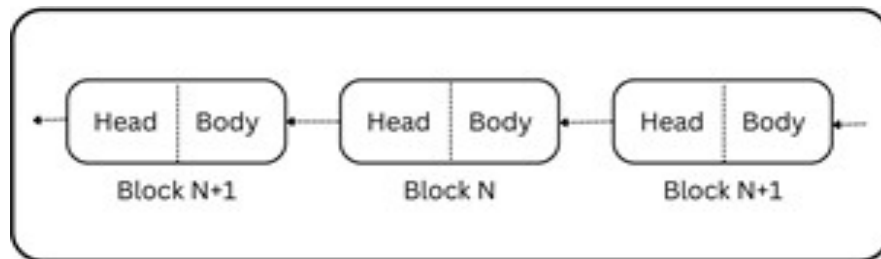


Fig 1. Blockchain Structure Diagram

III. LITERATURE SURVEY

TABLE I: LITERATURE REVIEW

Ref. No	Year of publication	Summary of a given paper	Technologies used	Challenges
[1] Li et al.	2019	Used CNN models on Chest X-ray and CT images for lung cancer detection. Achieved 91.3% accuracy in classifying nodules.	CNN, Deep Learning	Requires large labeled datasets, high computational cost
[2] Wang et al.	2020	Applied feature selection techniques with ML models to improve lung cancer classification accuracy by 6.8%.	SVM, Random Forest, XGBoost	Feature selection complexity, overfitting risk
[3] Kumar et al.	2021	Proposed hybrid model combining medical images and clinical records. Achieved 94.2% accuracy.	CNN + ML models	Integration of heterogeneous data, data preprocessing
[4] Chen et al.	2021	Developed AI-based CAD system improving early cancer detection rate by 15.4%.	Deep Learning, CAD System	Model interpretability, clinical validation
[5] Patel et al.	2022	Used transfer learning (ResNet, EfficientNet) for CT scan classification. Achieved 96.1% accuracy.	Transfer Learning, CNN	Limited medical datasets, model generalization
[6] Smith et al.	2022	Compared VGG-16, Inception-V3, DenseNet; DenseNet achieved 97.3% accuracy.	VGG-16, Inception-V3, DenseNet	Model complexity, computational requirements.
[7] Zhao et al.	2023	Proposed U-Net for tumor segmentation in CT scans. Achieved Dice score of 0.89.	U-Net (Segmentation)	Precise tumor boundary detection
[8] Gupta et al.	2023	Used ML algorithms to predict lung cancer risk using clinical data. Achieved 92.7% accuracy.	Decision Tree, KNN, GBM	Data imbalance, missing clinical data
[9] Fernandez et al.	2024	Applied Federated Learning for multi-hospital lung cancer detection with 95.4% accuracy.	Federated Learning	Data privacy, communication overhead

IV. EXPECTED OUTCOME

The final aim of Dectra is to create a support system for AI-based diagnosis and recovery for various diseases related to the chest area, including lung cancer and heart diseases. The final outcome will be as follows:

Accurate Risk Prediction:

- CNN-based image analysis for detection of lung cancer using chest X-ray images.
- SVM-based classification for heart disease diagnosis using clinical parameters.
- Risk probability scores and risk levels (e.g., Low Risk, Moderate Risk, etc.).

Efficiency:

- Preprocessing will enhance efficiency in terms of time.
- It minimizes error possibilities due to interpretation of images by humans.
- Results will be available in real-time or near real-time.

User Experience:

- Developing a user-friendly interface for both patients and doctors to use.
- Results can be easily visualized for better understanding (heat maps, probability scores, etc.).
- Personalized patient recovery recommendations (diet, exercises, medications, weekly plan, etc.).

Real-World Impact:

- Medical professionals can use Dectra to aid them in decision-making for patient recovery.
- The support system can be implemented for use in hospitals, telemedicine services, remote patient diagnosis, etc.
- It can bridge the gap between conventional diagnostic techniques and recent advancements in AI-based healthcare

V. SOFTWARE AND TOOLS

The execution of the project needs software frameworks as well as hardware components.

Programming Language: The project uses Python as the programming language because of its vast libraries for machine learning and image processing.

Deep Learning Frameworks: The project uses TensorFlow and Keras for developing and training convolutional neural networks. PyTorch can also be used as an alternative framework.

Medical Imaging Libraries: The project uses OpenCV and NumPy for image preprocessing and manipulation. Specialized medical AI frameworks like MONAI also provide domain-specific tools for medical imaging tasks.

Development Tools: The project uses Jupyter Notebook or Google Colab for experimentation and model development. Flask or Django can also be used for developing the system as a web application.

Blockchain Platform: The project uses Ethereum or Hyperledger Fabric for developing secure storage of medical records using smart contracts.

Hardware Requirements: The project requires GPU-enabled systems like NVIDIA GPUs for faster training of deep learning models.

VI. METHODOLOGY

The project was carried out in a step-by-step process to ensure technical robustness as well as usability:

Step 1: Data Collection & Preprocessing

- Chest X-ray images for lung cancer detection.
- Clinical data (blood pressure, cholesterol, ECG, etc.) for heart disease classification.
- Preprocessing techniques:
 - Normalization, denoising, contrast enhancement for images.
 - Cleaning, feature selection, scaling for clinical data.

Step 2: Model Development

- Convolutional Neural Networks (CNNs):
 - Feature learning from chest X-ray images.
 - Identification of abnormal tissue patterns.
- Support Vector Machines (SVMs):
 - Structured clinical data for heart disease classification.
 - Leveraging patient history for image classification results.

Step 3: Integration

- A unified prediction system that uses CNN as well as SVM outputs.
- Probability score calculation for cancer/heart disease risk.
- Evaluation metrics: Accuracy, Sensitivity, Specificity, Confusion Matrix.

Step 4: User Interface Design

- Built with popular web development frameworks (Flask/Django + React).
- Stepwise user interface for a smooth user experience:
 - Patient Information
 - Upload Reports
 - AI Analysis Results
 - Care Recommendations

Step 5: Personalization

- Personalized recovery plans according to the risk level of the patient:
- Diet Plans (Antioxidant-rich foods).
- Exercise Plans (Breathing techniques, yoga, cycling).

VII. IMPLEMENTATION

A. System Architecture

Frontend: Interactive web interface for patients and doctors. **Backend:** Python-based server for AI models and data processing.

Database: Secure storage of patient information and diagnostic logs.

AI Models: CNN for images, SVM for clinical data, under a unified platform.

Deployment Environment: Cloud-based for scalability and accessibility.

B. Modules & Workflows Patient Info Module

Collects information from patients and doctors. Report Upload Module

Validates and preprocesses medical reports received from doctors.

AI Analysis Module

Uses CNN and SVM models to obtain probability scores. Results Dashboard

Displays the results to the user with explanations.

Care Recommendation Module

Provides diet plans, exercises, medicines, and weekly Plans.

C. Challenges & Solutions

- Challenge: Image Quality
- Solution: Image preprocessing techniques such as denoising and normalization were employed.
- Challenge: Accuracy vs Interpretability
- Solution: Image visualization techniques such as heatmap generation and region highlighting were incorporated.
- Challenge: Data Security
- Solution: Data encryption mechanisms were implemented to ensure security standards were met. Users have access to a comprehensive history.

The 'Uploading Page' is divided into two main sections. The 'Patient Information' section on the left has a subtitle 'Enter patient and doctor details to begin the analysis'. It contains input fields for 'Patient Name' (with a person icon) and 'Doctor Name' (with a stethoscope icon), both with placeholder text 'Enter patient's full name' and 'Enter treating doctor's name' respectively. Below these is a 'Select Cancer Type for Prediction' section with two buttons: 'Chest Cancer' (with a heart icon) and 'Lung Cancer' (with a lung icon). Both buttons have a note: 'Requires blood report & ECG'. The 'Upload Medical Reports' section on the right has a subtitle 'Upload the required documents for chest cancer analysis'. It contains two upload areas: 'Blood Report' and 'ECG Report'. Each area has an upload icon and text: 'Upload the patient's recent blood test report (PDF, JPG, PNG)' and 'Drag and drop or click to browse'.

Fig 2. Uploading Page

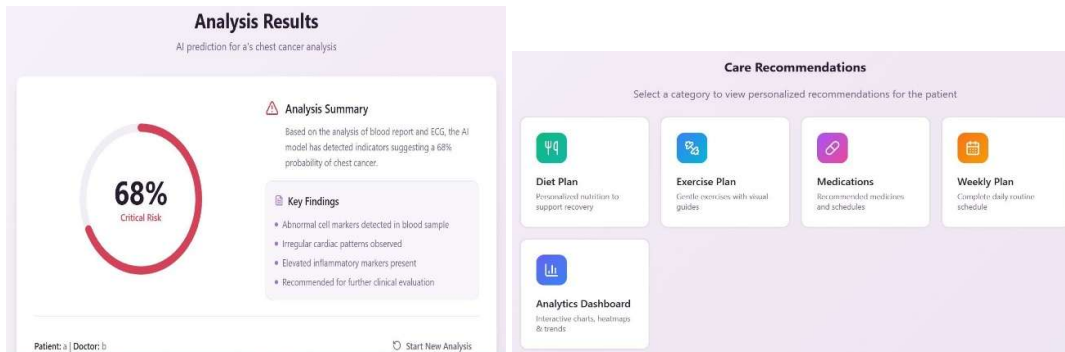


Fig. 3: Prediction

Fig 4: More Recommendations

VIII. CONCLUSION

The successful implementation of the proposed AI-based model for the detection of thoracic diseases proves the application of deep learning algorithms as well as machine learning algorithms within the domain of healthcare diagnostics. The application of the integrated model for the detection of lung cancer, heart disease, and other thoracic diseases is ensured through the integrated application of the CNN-based model for the detection of lung cancer using X-ray images, as well as the SVM-based model for the detection of heart disease using clinical parameters. The application of the proposed model is ensured through the results obtained from the experimental evaluation of the model.

The AI-based model is effective in reducing the dependency, eliminating the diagnostic errors, and improving the diagnostic process. The modularity of the AI-based model is effective in integrating the model with the existing infrastructure, ensuring the application of the model for the detection of thoracic diseases within the domain of healthcare diagnostics. The successful implementation of the AI-based model for the detection of thoracic diseases is effective in ensuring the application of the model within the domain of artificial intelligence, where the model is applied to assist medical professionals with informed decisions to enhance the survival probability.

FUTURE SCOPE

The project has laid a strong foundation and can be taken to the next level:

Advanced Imaging Integration:

- Move from X-rays to include CT, MRI, and PET scans.
- Include multi-modal data to increase accuracy.

Explainable AI (XAI):

- Include SHAP and LIME to increase model decision transparency.
- Increase clinician confidence through feature importance visualization.

Scalability & Cloud Deployment:

- Complete integration with existing hospital information systems.
- Telemedicine-ready to enable remote diagnostics.

Predictive Analytics:

- Track patient health over time.
- Determine disease progression and recovery rates.

Global Applications:

- Modify the system to be used in resource-scarce countries.
- Enable large-scale population screening programs.

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