

AI Course

Capstone Project Final Report

For students (instructor review required)

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LungScanAI: AI-Powered Lung Health Diagnostics

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NextGen Diagnostics

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1. Introduction

1.1. Background Information

Lung diseases such as tuberculosis, pneumonia, lung cancer, and COVID-19 pose significant global health challenges. Accurate and timely diagnosis is critical but often hindered by limited resources and diagnostic tools, especially in underserved regions. Advances in artificial intelligence (AI) and deep learning offer innovative solutions to these challenges, enabling early detection and improved healthcare outcomes.

Artificial intelligence (AI) and deep learning offer innovative solutions to these challenges, promising early detection and improved healthcare outcomes.

1.2. Motivation and Objective

The LungScanAI project aims to develop an accessible and scalable diagnostic tool that utilizes advanced AI models to analyze chest X-rays. This system aspires to provide high-accuracy predictions for various lung diseases, improving diagnostic reliability, particularly in resource-constrained environments. By offering efficient, accurate, and user-friendly tools, this initiative seeks to bridge healthcare disparities.

1.3. Members and Role Assignments

Abdul Qayyum: As the project coordinator, Abdul Qayyum played a crucial role in the project's success. He was responsible for enhancing the dataset's diversity through data augmentation and implementing the powerful DenseNet-201 architecture. Abdul also fine-tuned the advanced Swin Transformer model, rigorously evaluated the models' performance, and developed a user-friendly web application to showcase the results.

Ume Salma: Ume Salma defined the project's objectives, sourced the relevant datasets, and implemented state-of-the-art models including CheXNet and ViT. She skillfully managed the ensemble learning process to optimize the model's performance and ensure its effectiveness in the final solution.

Muawaz Saleem: Muawaz Saleem meticulously preprocessed the datasets and implemented the efficient EfficientNet-B7 architecture. He rigorously validated the models using 10-fold cross-validation and oversaw user testing, ensuring that the final product provided a seamless user experience.

1.4. Schedule and Milestones

Phase 1 (Day 1-2): Project initiation, objective definition, and team role assignment.

Phase 2 (Day 3-4): Dataset collection, augmentation, and splitting.

Phase 3 (Day 5-7): Model implementation and fine-tuning.

Phase 4 (Day 7-8): Model validation and integration.

Phase 5 (Day 9-10): Web-based platform deployment and user feedback incorporation.

2. Project Execution

2.1. Data Acquisition

The dataset was sourced from reputable platforms such as Kaggle, NIH, and GitHub. This dataset consisted of high-quality chest X-ray images representing both healthy individuals and those afflicted with tuberculosis, pneumonia, lung cancer, and COVID-19. To address class imbalances, we employed SMOTE data balancing techniques.

2.2. Training Methodology

We utilized pre-trained models (CheXNet, DenseNet-201, ViT, EfficientNet-B7, Swin Transformer) initialized with ImageNet weights. . We further enhanced the generalization capabilities of our models by applying data augmentation techniques such as flipping, rotation, and scaling to the training data. Finally, we fine-tuned these models using the Adam optimizer and categorical cross-entropy loss to optimize their performance on our specific task. . Finally, we fine-tuned these models using the Adam optimizer and categorical cross-entropy loss to optimize their performance on our specific task.

2.3. Workflow

1. **Data Preprocessing:** To prepare the data for model training, we resized images to a standard size, normalized pixel values, and addressed class imbalance by balancing the dataset.
2. **Model Training:** We trained multiple pre-trained models, including CheXNet, DenseNet-201, ViT, EfficientNet-B7, and Swin Transformer, on augmented datasets to improve their generalization capabilities.
3. **Evaluation:** We rigorously evaluated the performance of our models using a variety of metrics, including accuracy, precision, recall, and F1-score. These metrics were derived from confusion matrices, which provide a detailed breakdown of correct and incorrect predictions.
4. **Ensemble Learning:** To further enhance the accuracy of our predictions, we employed ensemble learning, combining the predictions from multiple models to make a more informed decision.
5. **Deployment:** We developed a user-friendly web-based platform that allows users to easily upload chest X-ray images and receive accurate predictions.

2.4. System Design

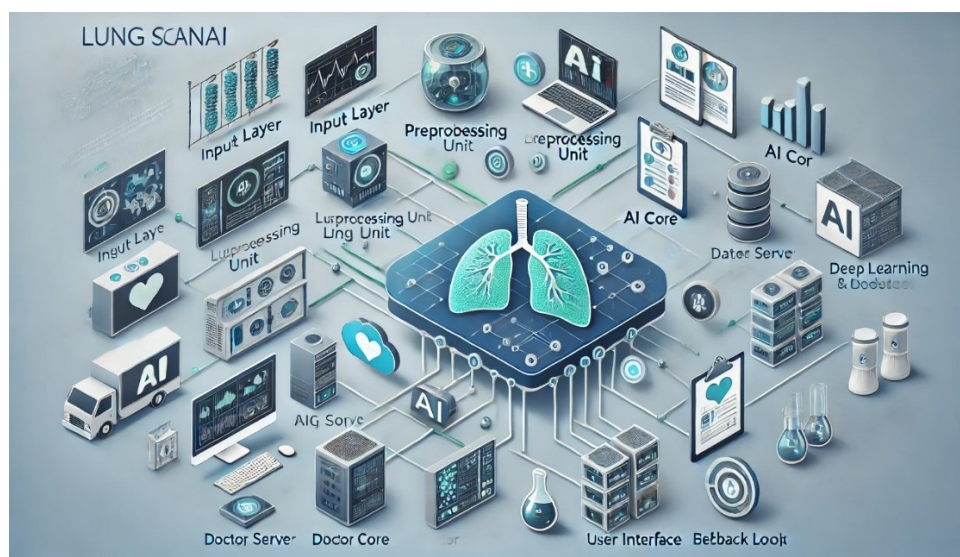


Fig 1. System Diagram

3. Results

3.1. Data Preprocessing

Data augmentation and SMOTE techniques ensured a balanced dataset. Images were resized to 150x150 pixels and normalized to improve model performance

3.2. Exploratory Data Analysis (EDA)

Train multiple pre-trained models using the augmented dataset.

3.3. Modeling

- CheXNet (DenseNet-121): Specialized in pneumonia detection.
- Vision Transformer (ViT): Performed well for tuberculosis and lung cancer.
- DenseNet-201: Balanced accuracy across all classes.
- EfficientNet-B7: Demonstrated strong performance in COVID-19 detection.
- Swin Transformer: Complemented ensemble learning with robust predictions.
- Ensemble Model: Achieved 98.7% accuracy, 98.9% precision, 98.4% recall, and 98.6% F1-score.

3.4. User Interface

A web application hosted on Streamlit enables users to upload chest X-rays and receive real-time diagnostic predictions.

3.5. Testing and Improvements

- Cross-validation ensured reliability across diverse datasets.
- Iterative feedback cycles from healthcare professionals refined the platform's usability.

4. Projected Impact

4.1. Accomplishments and Benefits

- Increased diagnostic accuracy for multiple lung diseases.
- Developed an accessible platform for under-resourced regions.
- Enhanced healthcare efficiency by reducing diagnosis time.

4.2. Future Improvements

- Incorporate additional imaging modalities like CT scans.
- Expand datasets for improved generalization.
- Integrate mobile capabilities for real-time diagnostics in remote locations.

5. Team Member Review and Comment



NAME	REVIEW and COMMENT
Abdul Qayyum	This project underscores the potential of AI to revolutionize diagnostics. I'm thrilled to have contributed to such impactful work.
Ume Salma	LungScanAI reflects our dedication to leveraging technology for meaningful change. I am deeply gratified by the achievements of our team
Muawaz Saleem	This project was a testament to the power of collaboration and AI's transformative potential in healthcare.

6. Instructor Review and Comment

CATEGORY	SCORE	REVIEW and COMMENT
IDEA	__/10	
APPLICATION	__/30	
RESULT	__/30	
PROJECT MANAGEMENT	__/10	

PRESENTATION & REPORT	--/20	
TOTAL	--/100	