GEN AI HACKATHON T$0 – 2025

LUNG-LENS

- AI ALCHEMISTS

1. Problem Statement

The number of radiologists is very small as to the requirement, especially in rural areas. Because of this, many diseases that require medical imaging diagnosis, such as X-rays, CT scans, MRI, etc, go undetected until too late. So, build an AI tool to analyze X-rays and detect diseases like tuberculosis, pneumonia, and cancer for faster and accurate results. As AI models can now match or exceed human performance in interpreting medical images. This will help in the early detection of disease and thereby save lives. This will solve the problem of shortage in the number of radiologists and will also aid radiologists in diagnosis for faster decision-making.

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2. Target Audience & Context

Our product aims to help detect tuberculosis, pneumonia, and cancer by analysing X-ray images using an AI model. This will result in faster and more accurate decision-making. This product is mainly targeted at the healthcare industry to assist doctors in identifying the mentioned diseases. Under this industry, we mainly target rural clinics, followed by diagnostic labs and hospitals. Our product is accessible even in low-resource settings. Our main purpose is to solve the shortage of radiologists, speed up and accurately interpret disease, and make it accessible to all.

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3. Use of Gen-AI

We use Gen-AI for better interpretation of X-rays for diagnosis. First, disease is detected using Vision Transformer (ViT), which has been trained on multiple datasets (NIH ChestX-ray14, CheXpert, Montgomery TB Set). The ViT architecture is particularly effective for medical imaging because it can analyze images in patches and understand complex spatial relationships between different regions of the chest. Then, its result is passed onto the OpenAI GPT API. Then GPT curates personalised results based on the passed disease name, confidence score, and other user input. And the result is in a form which is easy to understand even for a doctor not-specialist in radiology and suggests further steps to be taken. This Gen-AI layer transforms medical data into personalized recommendations, increasing trust, accessibility, and adoption.

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4. Solution Framework

Our system consists of four major components:

1. Data Ingestion & Training: We utilize open datasets specifically for tuberculosis, pneumonia, and lung cancer detection. These datasets help us train Vision Transformers (ViT) models, which have proven superior performance in medical imaging. Each dataset is used to create disease-specific classifiers that can identify particular conditions with high accuracy.
2. Multi-Model Evaluation: Our system runs predictions across all trained models for every chest X-ray uploaded. When any disease is detected above our set confidence threshold, it gets checked for review. This ensures comprehensive screening without missing potential diagnoses.
3. Gen-AI Interpretation: The detected results are processed through the OpenAI GPT API to generate clear explanations. This curates personalized reports based on the disease identified, confidence scores, and additional patient information. The output is designed to be understandable for healthcare providers who may not specialize in radiology.
4. Continual Learning: Continual learning means our AI model doesn't just stop learning after its initial training. Instead, it keeps improving by regularly updating itself with new X-ray data and feedback from doctors. This way, it stays accurate, adapts to new disease patterns, and becomes even more reliable over time, making sure our tool always delivers the best possible results for patients and healthcare providers.

5. Frontend Interface: We have developed a user-friendly web application using React that allows easy image upload and result display. The interface shows confidence scores alongside the AI-generated interpretations, making it practical for use in various healthcare settings, including rural clinics.

We have already developed a working prototype that is accessible via our live demo. In future iterations, we plan to integrate additional features such as real-time feedback and a chatbot interface for clarification.

Protype: https://lung-lens.vercel.app / https://github.com/Aryamitra95/LungLens

HuggingFace Api: asutoshp10/Lungs-space at main

Datasets: https://www.kaggle.com/datasets/nih-chest-xrays/data/data

https://www.kaggle.com/datasets/mimsadiislam/chexpert

Model: https://huggingface.co/asutoshp10/Lungs-desease/tree/main

YouTube Link: https://youtu.be/dbXbSNWDIcA?si=Z1Xi869PqDAgMpw3

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5. What makes our solution different?

Our solution stands out by combining Vision Transformers for precise disease detection with GPT-based AI for clear, personalized reports, making results easy to understand for any healthcare provider. It supports simultaneous screening for multiple lung diseases with tailored confidence thresholds, works efficiently on low-resource devices for rural clinics, and offers explainable results through visual heatmaps and simple summaries. Its modular design allows for rapid expansion to new diseases, and a continual learning framework ensures the model improves over time by incorporating clinician feedback and new data.

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6. Feasibility & Execution

The implementation of this project is highly feasible due to several factors. Most of the required datasets are publicly available and already labelled, which greatly reduces the preprocessing workload. We plan to use cloud-based GPU services like Google Colab, Kaggle, or Azure for model training and fine-tuning. The interpretability component can be built using existing APIs from OpenAI and visualization libraries like Grad-CAM. A functional MVP can be completed within 4-6 weeks. The frontend deployment will be done as a web application with minimal computational power requirements. For low-resource environments, we will consider ONNX or TensorFlow Lite versions.

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7. Scalability & Impact

The trained model can operate efficiently on low-power devices and cloud instances once deployed. The modular design allows for easy integration of additional diseases such as COVID-19 or cardiomegaly. The potential impact includes early disease detection, aiding doctors to detect disease who may not be radiology specialists, solving the issue of the shortage of radiologists, and making this diagnosis available to a larger population.

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8. Conclusion / Bonus: MLP

Our Minimum Lovable Product includes a functional web application where users can upload X-ray images, receive disease predictions, and obtain AI-generated interpretations. The tool combines diagnostic accuracy with clear communication and practical usability. It serves as a diagnostic assistant rather than a replacement for medical professionals. We aim to improve early detection capabilities, simplify diagnostic processes, and make healthcare more accessible across different settings.