GenAI Hackathon 2025

Team: Bit Wizards

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Problem Statement

In many hospitals, especially in rural or under-resourced settings, radiologists are overwhelmed or unavailable to interpret Chest X-rays quickly. This delay leads to slower diagnosis and treatment for conditions such as pneumonia, tuberculosis, or heart failure. Manual interpretation is time-consuming and susceptible to variability between practitioners. As patient volumes rise and access to specialists remains limited, the healthcare system faces a significant bottleneck in medical imaging interpretation. Automating the diagnostic reporting process can not only reduce turnaround time but also improve consistency and accuracy, especially in critical or emergency care situations. Solving this problem would have direct benefits on patient outcomes, operational efficiency, and access to quality care.

Target Audience & Context

This solution targets frontline healthcare facilities, radiology departments, diagnostic imaging centers, and telemedicine platforms—especially those in low-resource or high-volume environments. In many developing regions, one radiologist may be responsible for interpreting hundreds of images daily, causing delays and fatigue. Even in urban hospitals, AI augmentation can reduce workload and support faster triage. The proposed solution provides clinical decision support to both specialists and general physicians, enhancing diagnostic capabilities and reducing dependency on scarce human expertise. With increased adoption of digital health tools, there's a strong context for integrating AI into radiology workflows.

Use of Generative AI

Generative AI, specifically large language models (LLMs) like GPT-4, is used to automate the diagnostic report creation process from Chest X-ray predictions. After a deep learning model detects diseases such as pneumonia, cardiomegaly, or pleural effusion from an image, these findings are passed to the LLM, which generates a clinically relevant and human-readable report. This approach is ideal for radiology, where reports are descriptive, semi-structured, and rich in medical context. Generative AI ensures consistency, reduces reporting time, and produces outputs that are easy for doctors to interpret. It can also adapt to different clinical tones and reporting formats. Using Gen-AI this way allows scalable and context-aware automation of medical documentation, addressing the high demand and complexity of radiologist workflows.

Solution Framework

Our solution has a modular AI pipeline combining image classification and text generation:

1. Chest X-ray Classification: We use a pre-trained convolutional neural network (CNN) like DenseNet121, trained on datasets such as NIH ChestX-ray14 or MIMIC-CXR. The model performs multi-label classification to detect conditions like pneumonia, lung nodules, or heart enlargement.

2. Report Generation with LLM: The detected conditions are passed to a large language model (e.g., GPT-4), which constructs a radiologist-style diagnostic summary. The prompt includes clinical context and ensures medically accurate, structured output.

3. Web Interface or Integration: The final report, along with a visual heatmap (using Grad-CAM for explainability), is displayed in a user-friendly web app (Streamlit/Flask) or integrated into hospital PACS systems.

Workflow:

Input: Chest X-ray → CNN detects abnormalities → LLM writes report → Output: Final radiology-style report with visual cues.

This system reduces the cognitive and operational load on radiologists while maintaining interpretability and trust. It's designed for plug-and-play use in both rural clinics and large hospitals, making it highly practical and scalable.

Feasibility & Execution

The model can be built using PyTorch and trained with publicly available datasets like ChestX-ray14. We use pre-trained CNNs for fast deployment and OpenAI's GPT-4 via API for natural language report generation. Tools like Grad-CAM enable visual explainability. The web interface can be deployed using Streamlit or Flask. With basic cloud infrastructure (AWS/GCP), the system can be scaled securely and integrated with medical imaging workflows. Implementation is feasible within hackathon constraints and can be expanded with domain-specific fine-tuning for clinical use.

Scalability & Impact

The solution's modular architecture allows easy scaling across hospitals, diagnostic labs, and telemedicine providers. Once deployed, it can process thousands of scans daily, helping triage patients faster and reducing misdiagnosis risks. It empowers healthcare workers in underserved regions by providing instant radiology support. Long-term, it can be extended to handle CTs, MRIs, and other imaging modalities. This can transform diagnostic medicine by reducing dependence on specialists, improving access to care, and enabling 24/7 automated interpretation of routine imaging studies globally.

Conclusion & Minimum Lovable Product (MLP)

We present a minimum lovable product that combines AI-driven image classification with Gen-AI-powered report generation to automate Chest X-ray diagnosis. It reduces delay in radiology reporting, improves accuracy, and empowers clinicians. Its uniqueness lies in the seamless blend of visual and language models, offering a powerful, scalable, and practical solution with clear real-world impact—especially in radiologist-scarce healthcare environments.

AI Assistance Declaration

This submission includes support from external Generative AI tools during the ideation and documentation phases. Tools used include OpenAI's ChatGPT for structuring content, refining technical descriptions, and drafting text. All AI-generated content has been reviewed and validated by the team for accuracy and relevance to the proposed solution.