Interactive X-ray Diagnosis with Multi-Modal Fusion, Modular Blocks, and Prescription Feedback Learning

---

1. Problem Statement

Accurate diagnosis of thoracic diseases from chest X-rays remains a major challenge, particularly in low-resource healthcare environments. Existing AI models often rely solely on visual data and lack the flexibility to adapt or learn from real-world clinical workflows. Moreover, they do not benefit from doctors' contextual understanding and prescription reasoning. Our solution addresses this by providing a **default disease detection model for X-rays**, while enabling interactive training using **modular model blocks** (VGG, ResNet, etc.), and supports learning from **doctor-edited prescriptions**. The platform integrates clinical metadata (age, sex, symptoms) and builds a **self-improving system** that updates its knowledge base using expert-verified prescriptions to improve future diagnostics.

---

2. Target Audience

Our platform targets **healthcare practitioners**, **AI researchers**, **hospitals**, and **startups** working in digital diagnostics. Doctors in rural hospitals or overloaded clinical setups benefit from AI-assisted diagnostics that adapt to local data. Medical AI developers and researchers gain a flexible experimentation tool. By allowing **manual edits of AI-generated prescriptions** and using them as future training signals, the system becomes increasingly accurate and personalized over time — improving both **clinical adoption** and **model trustworthiness**.

---

3. Use of Gen-AI

Generative AI is used for:

- **Synthetic data generation**: Create rare-case X-rays or augment metadata like symptoms or histories.
- **Prescription simulation**: Based on imaging + patient metadata, GenAI can generate initial treatment suggestions.
- **Natural language to model builder**: Users can build custom architectures using prompts like *"build a shallow CNN with batch norm and dropout"*.
- **Auto-improvement through editing**: When doctors manually edit AI-generated prescriptions, those are stored with patient features and labelled outcomes. GenAI processes these corrections to refine future suggestions — essentially becoming a co-learning assistant.

This makes GenAI not just a content generator, but a feedback-driven model refinement engine that integrates human expertise into AI learning cycles.

---

4. Solution Framework

The system comprises several interconnected modules:

Core Components:

- **Default X-ray Model**: A ResNet-based pretrained classifier on pneumonia and normal X-rays.
- **Image Encoder**: CNN blocks (VGG, ResNet, Inception, etc.) extract visual features.
- **Clinical Metadata Processor**: A parallel MLP handles age, sex, symptoms, and history.
- **Fusion Module**: Combines visual and tabular features into a unified feature space.

Interactive & Modular AI:

- Drag-and-drop or prompt-based model builder using standard CNN blocks.
- Users can upload their own datasets (X-ray or other modalities) and build custom classifiers.

Doctor Feedback Loop:

- Each AI-generated prescription can be manually edited by the doctor.
- These edits are saved with patient metadata (age, sex, symptoms, history).
- Over time, the model uses this edited data to refine future predictions and prescriptions via supervised fine-tuning and GenAI prompt engineering.

Explainability:

- Grad-CAM and saliency heatmaps offer visual interpretability.
- Prescriptions include justification referencing image + metadata.

Datasets Supported:

- ChestX-ray14, COVIDx, MIMIC-CXR, plus user-uploaded formats (DICOM/JPG + CSV metadata).

---

5. Feasibility & Execution

The platform will use:

- **TensorFlow/Keras** for modelling
- **Streamlit or React** for the front-end UI
- **MongoDB or PostgreSQL** to store patient data and prescription edits
- **Flask/FastAPI** for backend APIs

Initial development will start with ChestX-ray14 and a simulated prescription-edit loop. Data privacy and security protocols (e.g., HIPAA compliance) will be implemented for real clinical environments. The architecture is modular, making it easy to extend to other domains like ophthalmology or pathology.

---

6. Scalability & Impact

By enabling interactive training and doctor-in-the-loop learning, the solution can adapt across hospitals and domains. Clinical teams can add more diseases or new input features (e.g., CT scans, lab tests). Over time, this builds a **knowledge graph of prescriptions and patient profiles**, improving both **accuracy** and **personalization**. Its scalability lies in its **flexibility**, **feedback loop**, and **low compute requirements** (can start on Colab or local machines).

---

7. Conclusion / Minimum Lovable Product (MLP)

The platform uniquely blends **multi-modal fusion**, **interactive deep learning**, **GenAI** augmentation, and **feedback learning from doctor-edited prescriptions**. It's designed to evolve with use, making it a true assistant—not just a tool. The MLP includes a working pneumonia classifier, metadata fusion support, and a feedback training loop — deployable in both clinical and educational settings.