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An AI-Based Healthcare Platform for Disease Prediction, Prescription, and Emergency Response

Sumedh Dhengre[1], Vaishnavi Devidas Shevate[2], Tanvi Santosh Shewale[3], Rohit Vijay Raut[4], Rohan Sunil Sabale[5]
Department of Computer Engineering[1-5]
AISSMS College of Engineering, Pune
Savitribai Phule Pune University Pune, India
[1] sgdhengre@aissmscoe.com [2] shevatevaishnavi@gmail.com
[3] tanvisshewale7072@gmail.com [4] rohitraut78253@gmail.com, [5]rohansabale125@gmail.com

Abstract: *The rapid growth of medical imaging and the increasing demand for accurate and timely diagnosis have highlighted the need for automated healthcare solutions. Chest X-rays are one of the most widely used imaging techniques for detecting thoracic diseases; however, manual interpretation is time-consuming and subject to human error. This paper presents an AI-based healthcare system for chest X-ray disease prediction, prescription support, and emergency response. The proposed system utilizes a deep learning approach based on the DenseNet121 convolutional neural network with transfer learning to perform multi-label classification of 14 thoracic diseases using the NIH ChestX-ray14 dataset. The model processes input X-ray images and outputs disease probabilities, enabling the identification of multiple co-existing conditions. To enhance transparency and clinical interpretability, Gradient-weighted Class Activation Mapping (Grad-CAM) is incorporated to visualize the regions influencing the model's predictions. Furthermore, the system is integrated into a user-friendly web-based dashboard that allows real-time image upload, disease prediction, and prescription assistance. The model achieves a training AUC of approximately*
0.84 and a validation AUC of approximately 0.79, demonstrating effective performance in detecting thoracic abnormalities. The proposed solution provides an end-to-end intelligent healthcare framework that combines disease prediction, explainability, and decision support. It has the potential to assist medical professionals in improving diagnostic efficiency and accuracy, particularly in resource-limited settings.

Keywords: Terms—disease prediction, prescription, emergency response, MERN stack , ML model, Deep Learning, Convolutional Neural Network (CNN), Chest Disease Detection, Grad-CAM, Teleconsultation, Healthcare Automation, Chest X-ray, DenseNet121, Multi-label Classification, Medical Imaging.Index Terms—Chest X-ray Analysis disease prediction, prescription, emergency response, MERN stack , ML model, Deep Learning, Convolutional Neural Network (CNN), Chest Disease Detection, Grad-CAM, Teleconsultation, Healthcare Automation.

I. INTRODUCTION

The AI-Driven Hospital Management and Chest Disease Detection System is a multi-modal healthcare platform that bridges the gap between administrative management and advanced clinical diagnostics. Built on the MERN stack (MongoDB, Express.js, React.js, Node.js), the system pro-vides a secure, cloud-native environment where Adminis-trators, Doctors, and Patients can interact through tailored dashboards. The platform's core intelligence is driven by a DenseNet121 deep learning model trained on the NIH Chest X-ray dataset to automatically detect 14 thoracic pathologies, such as Pneumonia and Tuberculosis, with high precision. To ensure clinical trust, the system incorporates Grad-CAM explainability, which generates heatmaps to highlight affected lung regions for physician verification.Beyond diagnostics, the ecosystem streamlines the entire patient journey through integrated WebRTC-based teleconsultation for real-time video calls and an Emergency Response Module that triggers au-tomated alerts for critical findings. Following a consultation, the system leverages Transformer-based NLP and the Gem-ini API to automatically generate structured medical reports and prescriptions, significantly reducing the administrative burden on healthcare professionals. All medical records and diagnostic images are securely managed within MongoDB Atlas, utilizing AES-256 encryption and JWT authentication to maintain strict compliance with HIPAA and GDPR data pri-vacy standards. This integration of explainable AI, intelligent automation, and secure telecommunication creates a scalable solution that enhances diagnostic accuracy while making high-quality healthcare more accessible, particularly in resource-constrained regions.

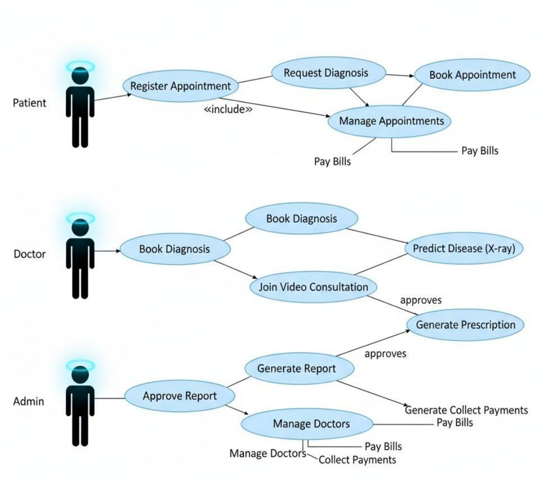

Fig. 1. Usecase Diagram

A. MOTIVATION

The motivation behind the AI-Driven Hospital Management and Chest Disease Detection System is rooted in the critical need to address the challenges of modern healthcare, specif-ically the overwhelming volume of radiological data and the global shortage of skilled radiologists. Conventional hospital systems are often limited to administrative tasks like billing and registration, failing to provide the intelligent decision support required for rapid disease identification. By integrating Deep Learning (DenseNet121) and Grad-CAM explainability, the project aims to reduce diagnostic delays and human errors while ensuring that AI-driven insights are transparent and verifiable for medical professionals. Furthermore, the platform seeks to bridge the accessibility gap for rural and resource-constrained communities by utilizing WebRTC-based telecon-sultation and NLP-powered automated prescription drafting, which collectively enhance physician productivity and bring high-quality medical services to underserved populations.

B. PROBLEM DEFINATION

The AI-Driven Hospital Management and Chest Disease Detection System addresses the critical challenge of diag-nostic delays caused by a global shortage of skilled radi-ologists and the overwhelming volume of radiological data. Traditional hospital management software is often limited to administrative tasks like billing and registration, lacking the intelligent capabilities needed to assist in clinical decision-making or provide real-time patient interaction. This creates a significant gap between the generation of medical imaging and actionable clinical insights, particularly in

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rural or resource-constrained regions where access to expert diagnosis is mini-mal. Furthermore, manual diagnostic workflows are prone to human error and lack the transparency required for physicians to verify automated outputs. By integrating Deep Learning (DenseNet121) for automated pathology detection, Grad-CAM for visual explainability, and WebRTC/NLP for streamlined tele-consultations, this platform resolves these inefficiencies to provide a unified, transparent, and accessible healthcare solution.

II. LITERATURE SURVEY

1) SwinCheX: Multi-label Classification using Swin Transformer (2022): This study introduced SwinCheX, a transformer-based model designed for multi-label chest X-ray classification. The model leverages the Swin Transformer architecture to capture both local and global contextual features within medical images, overcoming limitations of traditional CNNs that focus primarily on local patterns. The research demonstrated improved performance with an average Area Under Curve (AUC) of approximately 0.81 on the ChestX-ray14 dataset. The study emphasized the importance of global feature extraction for complex disease detection. However, the model required high computational resources and large datasets for effective training.

2) CheX-DS: Ensemble Learning for Chest X-ray Clas-sification (2025): CheX-DS proposed a hybrid deep learning framework combining DenseNet-based convo-lutional neural networks with transformer-based archi-tectures for improved chest X-ray classification. The model utilized ensemble learning to capture both spa-tial and contextual features, leading to enhanced per-formance in multi-label disease prediction. The study reported an AUC of approximately 0.83, outperforming several standalone CNN models. The research high-lighted the effectiveness of combining CNN and trans-former approaches. However, the model complexity and increased computational cost posed challenges for real-time deployment.

3) Automated Classification of Chest X-rays using Deep Learning with Attention Mechanisms (2025): This study focused on improving chest X-ray classification by integrating attention mechanisms into convolutional neural networks. The model used attention layers to emphasize important regions in the image while sup-pressing irrelevant features. This resulted in improved feature extraction and classification accuracy compared to traditional CNN models. The research demonstrated that attention-based models significantly enhance per-formance in medical image analysis. However, the ap-proach required careful tuning of attention parameters and increased training complexity.

4) Deep Metric Learning for Multi-label Chest X-ray Classification (2023): This research introduced a deep metric learning approach using advanced CNN architec-tures such as ConvNeXt to improve multi-label classifi-cation of chest X-ray images. The model learned rela-tionships between different disease labels by embedding them into a shared feature space. This allowed better handling of co-occurring diseases and improved classifi-cation accuracy. The study highlighted the importance of label correlation in multi-label problems. However, the method required complex training strategies and careful selection of distance metrics.

5) CXR-MultiTaskNet: Multi-task Deep Learning Frame-work for Chest X-ray Analysis (2025): This study proposed a multi-task deep learning framework that performs both disease classification and localization simultaneously. The model integrates feature extraction and detection tasks to provide more comprehensive di-agnostic outputs. The approach improved overall system performance by combining classification accuracy with localization capability. The research emphasized the im-portance of multi-task learning in real-world healthcare applications. However, balancing multiple tasks during training introduced additional complexity and required more computational resources.

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III. PROPOSED SYSTEM AND METHODOLOGY

A. THE SYSTEM

The proposed system, AI-Based Healthcare Management Platform for Disease Prediction, Prescription Support, and Real-Time Emergency Response, is designed to provide an end-to-end intelligent healthcare solution integrating artificial intelligence (AI), deep learning (DL), natural language pro-cessing (NLP), and cloud-based teleconsultation. The platform bridges the gap between patients and healthcare professionals by automating diagnosis, prescription generation, and emer-gency response through a secure and scalable cloud ecosystem. architecture consists of three main functional modules: 1.Dis-ease Detection Module – for automated diagnosis of chest dis-eases using deep learning. 2. Prescription Generation Module – for automatic medical report and prescription creation using NLP. 3.Emergency Response Module – for detecting critical patient conditions and triggering alerts.

B. OBJECTIVES

- Study the application of Artificial Intelligence (AI) and Deep Learning (DL) techniques in healthcare for improving diagnosis and treatment accuracy.
- To extract meaningful patterns and insights from health-care data for assisting doctors in clinical decision-making.
- To process patient data securely using cloud-based sys-tems while maintaining privacy and compliance standards.
- To develop an AI-driven hospital management and chest disease detection system for efficient and automated healthcare services.
- To deploy an intelligent, user-friendly, and scalable plat-form that ensures accessibility of quality healthcare to all communities

C. SYSTEM WORKFLOW

The system workflow (illustrated in Fig. 1) involves a series of automated and semi-supervised steps from data input to clinical output:Some Common Mistakes

1) Patient Registration And Authentication: The patient creates an account on the platform and uploads their chest X-ray or MRI images. User authentication is managed through JWT based security to ensure data confidentiality.

2) Image Preprocessing: Uploaded images are resized (224×224 pixels for ResNet-50), normalized, and con-verted to grayscale (if necessary). Noise reduction and contrast enhancement are applied to improve model performance.

3) Disease Prediction: The preprocessed image is passed to the trained CNN–ResNet model hosted on a cloud server. The model predicts disease probabilities for multiple classes (e.g., cardiomegaly: 0.87, pneumonia: 0.91). The top predictions are displayed to the doctor, along with Grad-CAM visualization maps to indicate affected areas.

4) Doctor Teleconsultation: A real-time video call or chat is initiated between the patient and doctor through a WebRTC-based Teleconsultation Interface. The doctor reviews AI-generated results, adjusts findings, and vali-dates predictions.

5) Prescription Generation: The NLP module processes diagnosis results and generates a draft prescription. The doctor reviews and approves it, ensuring human oversight while significantly reducing time and effort

6) Emergency Alert Triggering: If the AI output or patient inputs (like severe disease score, abnormal vitals, or emergency keywords) indicate a critical condition, the Emergency Module triggers an alert through SMS, Email, or API integration to hospitals or emergency services.

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7) Data Storage and Reporting: All interactions, diag-noses, and prescriptions are securely stored in the cloud database (MongoDB/MySQL). Reports are encrypted and made available for future reference, enabling lon-gitudinal health tracking.

IV. SYSTEM ARCHITECTURE

The AI-Based Healthcare Management Platform follows a modular, cloud-based architecture designed to assist doctors in clinical decision-making.

The system is divided into three main functional layers

— the User Interface Layer, the AI Processing Layer, and the Cloud and Database Layer — all interconnected through secure APIs.

A. USER INTERFACE

The system features a responsive frontend built with React.js that provides specialized dashboards based on user roles:

- Patient Dashboard: Allows patients to register with identity proof, book appointments, initiate video calls with doctors, and access AI-generated medical reports.
- Doctor Dashboard: A professional panel for physicians to manage appointment slots, upload chest X-rays, view

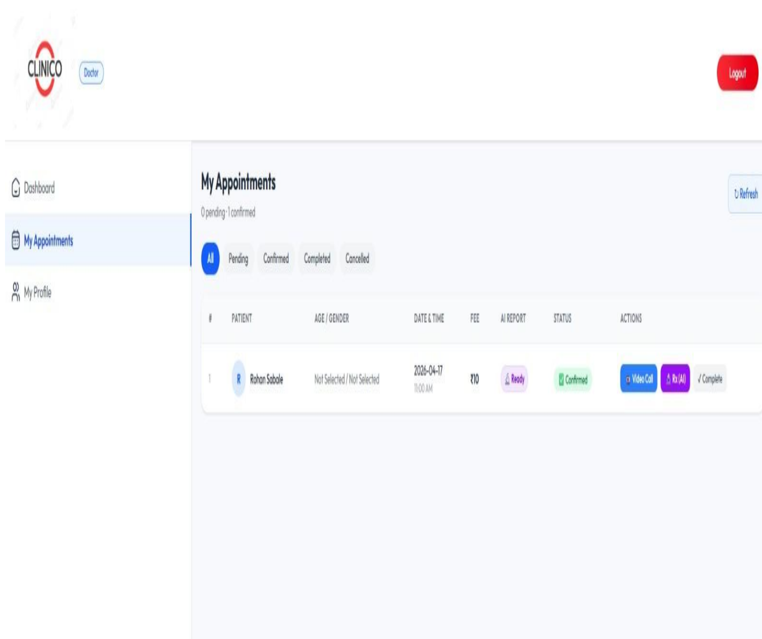

Fig. 2. Profile of patient

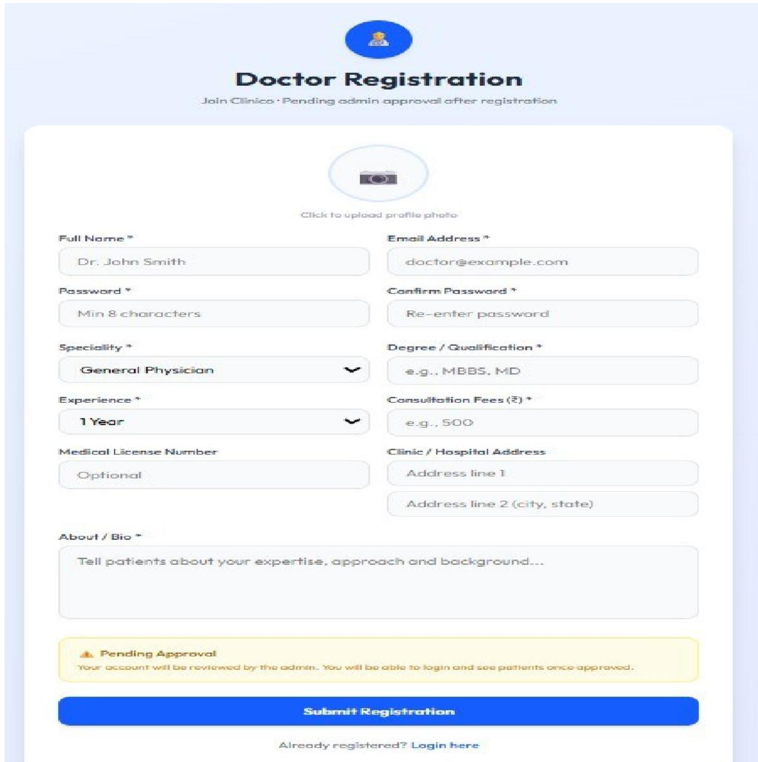

Fig. 3. Doctor registration

AI diagnostic findings, and approve automated prescriptions.

- Admin Dashboard: Provides full administrative access to manage doctor registrations, monitor hospital services like ambulance availability, and handle payment details.

B. AI PROCESSING LAYER

This layer acts as the system's brain, hosted on cloud servers to perform complex diagnostic and linguistic tasks: begin

- **Diagnostic Engine (DenseNet121):** Linked directly to the patient and doctor panels, this CNN model processes X-rays resized to 224 × 224 pixels to predict 14 thoracic pathologies (e.g., Pneumonia, Tuberculosis) with a vali-dation ROC-AUC of approximately 0.79.
- **Explainability (Grad-CAM):** To ensure clinical trust, this module generates heatmaps that highlight the specific regions of the X-ray influencing the AI's prediction for physician verification.
- **Intelligent Prescription Module:** Utilizes Transformer-based NLP (Gemini API) to automatically draft prescrip-tions and diagnostic summaries based on the model's findings and patient symptoms.

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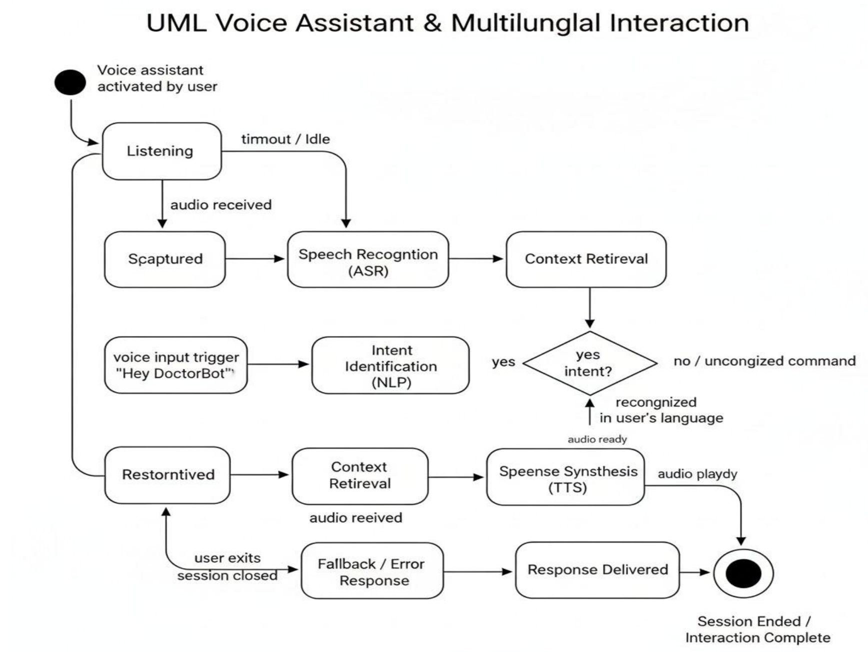

Fig. 4. UML Voice

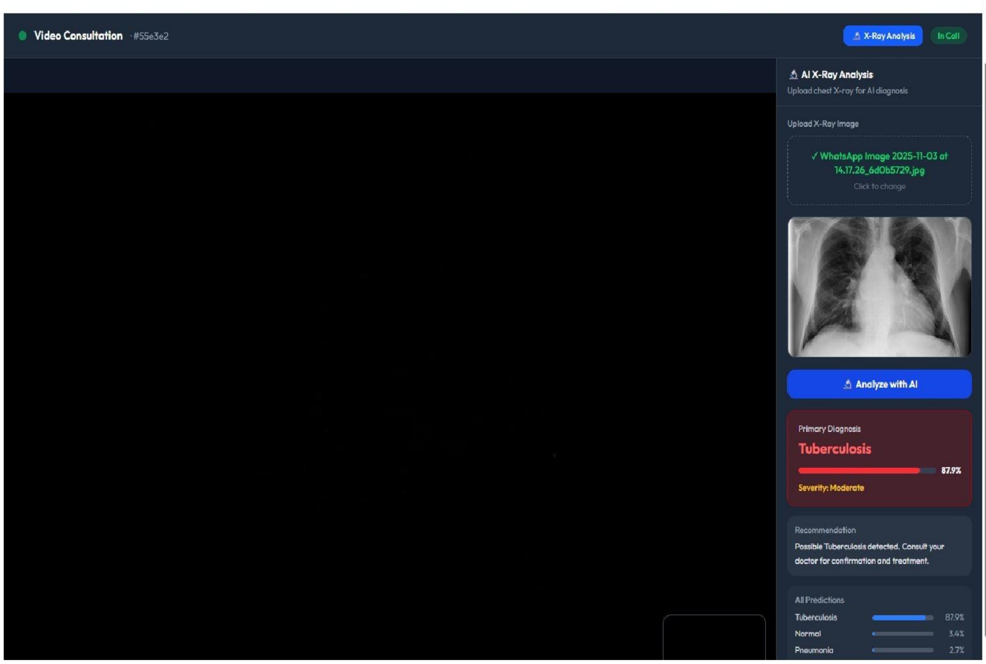

Fig. 5. Emergency Response

- **Emergency Response Service:** Monitors AI outputs for critical disease scores to trigger immediate alerts via SMS or Email to emergency services.

C. CLOUD AND DATABASE LAYER

The backend infrastructure ensures secure data flow and persistent storage: begin

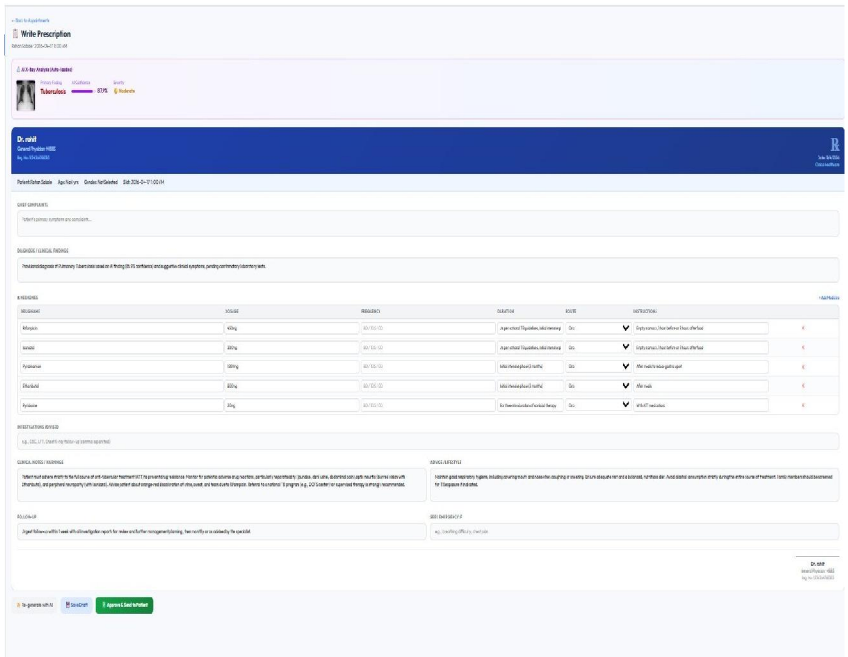

Fig. 6. Prescription Generation

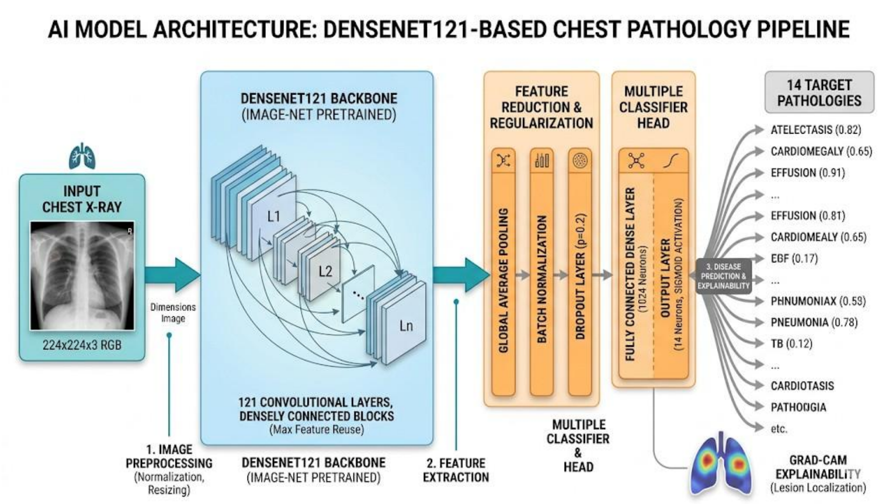

Fig. 7. Overall architecture

- Server And Security: Built with Node.js and Express.js, utilizing JWT (JSON Web Tokens) for secure authentica-tion and AES-256 encryption for sensitive medical data.
- Storage (MongoDB Atlas): A cloud-native database that stores patient profiles, medical images, encrypted diag-nostic reports, and prescription histories.

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- Teleconsultation Interface: Implements WebRTC and Twilio APIs to facilitate secure, real-time video and audio communication between doctors and patients

V. AI DIAGNOSTIC ENGINE SPECIFICATIONS

- **Model Purpose and Scope:** This AI system is designed as a research and educational tool to assist healthcare professionals in identifying 14 thoracic pathologies from frontal chest radiographs. It functions as a diagnostic aid and is not intended to replace professional clinical judgment or direct diagnosis.

- **Core Architecture:** The system utilizes the DenseNet121 convolutional neural network architecture, leveraging Transfer Learning with an ImageNet-pretrained back-bone. DenseNet was selected for its dense connectiv-ity—where each layer receives inputs from all preceding layers—which enhances feature reuse and gradient flow while maintaining parameter efficiency.

- **Dataset and Preprocessing:** The model was trained on a subset of approximately 50,000 images from the NIH Chest X-ray Dataset, which contains 112,120 frontal radiographs. To prepare for the network, raw 1024×1024 images were resized to 224 × 224 pixels, normalized to a [0, 1] range, and converted to RGB format.

- **Multi-Label Classification Strategy:** To address the multi-label nature of the dataset (where images may contain multiple pathologies), the system employs Multi-Hot Encoding for labels and a Sigmoid activation function in the final 14-neuron dense layer.

- **Training Configuration** Training was conducted using the TensorFlow/Keras framework on an NVIDIA Tesla T4 GPU. The strategy involved freezing pretrained layers initially to train the classifier head using the Adam

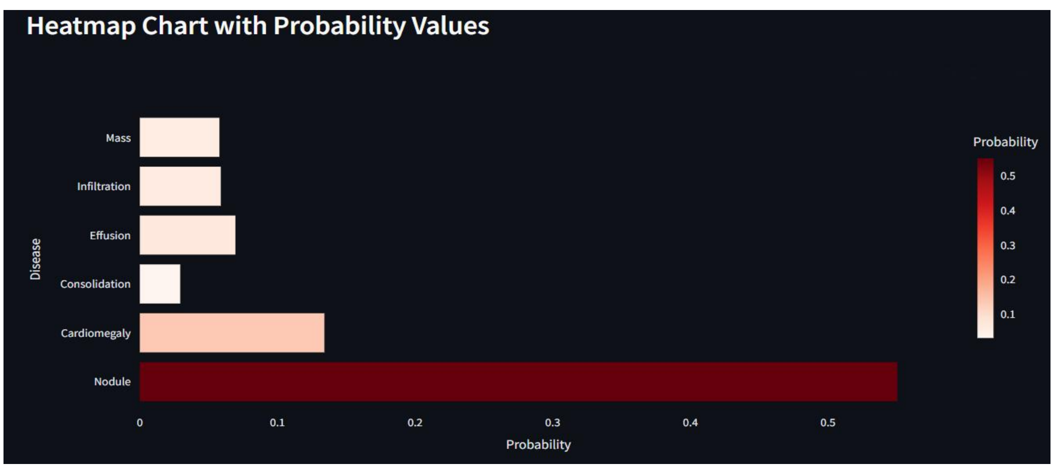

Fig. 8. Heatmap

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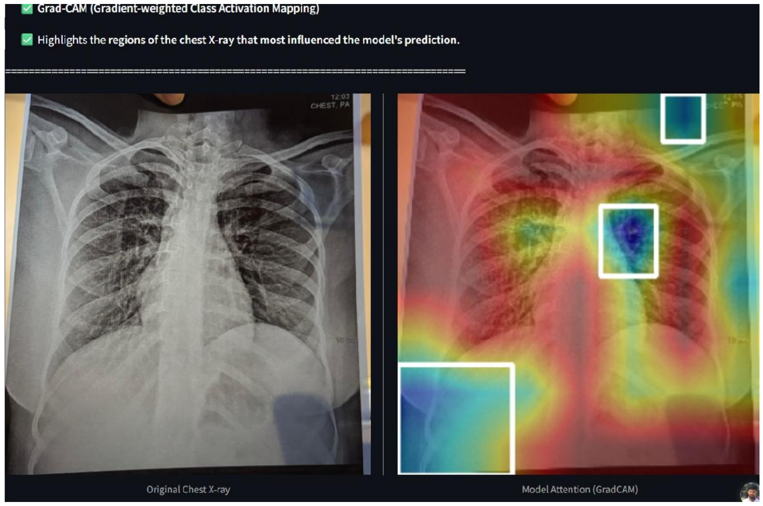

Fig. 9. Grad-CAM

optimizer (learning rate: 0.001) and Binary Crossentropy loss over 10 epochs.

- **Performance Metrics:** Given the multi-label medical context, ROC-AUC served as the primary evaluation metric. The model achieved a Training AUC of approxi-mately 0.84 and a Validation AUC of 0.79, indicating successful learning of meaningful representations with reasonable generalization.

- **Explainability via Grad-CAM :** For clinical interpretabil-ity, the project integrates Grad-CAM (Gradient-weighted Class Activation Mapping). This technique computes gradients of the predicted class to generate heatmaps, highlighting the specific anatomical regions that most influenced the model's decision.

VI. IMPLEMENTATION PLAN

A. PHASE 1: System Design And Architecture Planning

In this initial phase, the platform's high-level architecture was established to ensure scalability and role-based isolation.

1) Architecture Pattern and Role Isolation: The platform adopts a modular MVC (Model-View-Controller) pattern for the backend to maintain a clean separation between data schemas, business logic, and API routing.

a) Three-Application Structure: To prevent cross-role data leaks, the system is divided into three separate React applications: a patient-facing portal (Port 5173), a management portal for admins and doctors (Port 5174), and a shared REST API backend (Port 4000).

b) Security Middleware: Dedicated authentication middlewares (authUser, authDoctor, and authAd-min) were designed to verify role-specific JWT headers, ensuring users can only access function-alities relevant to their assigned permissions.

2) Data Modeling and Integrity The system utilizes MongoDB Atlas, a NoSQL document database, to ac-commodate the varying and evolving fields found in medical data.

- **Flexible Schema Design:** MongoDB was selected for its ability to store semi-structured data, such as AI-generated diagnostic reports and evolving medical prescriptions, without requiring frequent database migrations.

- **Embedded Snapshots:** To ensure absolute data integrity, appointment records are designed to include embedded snapshots of full doctor and patient data at the time of booking.
- **Historical Accuracy:** This ”snapshot” approach prevents historical medical records from being retroactively altered if a doctor or patient later updates their profile informa-tion.
- **Atomic Slot Mapping:** Doctor availability is managed through a dynamic slots booked object within the doctor schema, allowing for efficient, atomic updates during the booking process

B. Phase 2: Core Infrastructure And Security Setup

The second stage of development focused on establishing a secure, high-performance foundation for the CLINICO plat-form. This phase involved configuring the MERN stack back-end and implementing multi-layered cryptographic defenses to protect sensitive medical information.

1) Backend Infrastructure and Real-Time Orchestra-tion

The server-side core was built to handle concurrent requests and real-time signaling between diverse user portals.

- **Node.js and Express.js Environment:** The backend utilizes Node.js (v18+) and Express.js (v5.1.0) as the primary runtime and REST API framework.
- **Real-Time Signaling (Socket.IO):** To facilitate peer-to-peer (P2P) WebRTC video consultations, a Socket.IO (v4.8.3) server was integrated to manage bidirectional signaling and room-based communica-tion.
- **Media Management (Cloudinary):** A cloud-native infrastructure was configured using Cloudinary for the storage and content delivery (CDN) of doctor profile images, medical certificates, and uploaded X-ray scans.
- **File Handling (Multer):** Custom Multer middleware was implemented to handle multipart form-data, allowing for secure local temporary storage before files are pushed to the cloud.

2) Security Architecture and Authentication

The security design prioritized data isolation and unau-thorized access prevention through stateless authentica-tion and strong encryption.

- **JWT-Based Authentication:** The system implements stateless JSON Web Tokens (JWT) for session man-agement. Three distinct header keys were developed to isolate roles: token for Patients, dtoken for Doc-tors, and atoken for Administrators.
- **Advanced Password Hashing (bcrypt):** All user and doctor passwords are encrypted using bcrypt with a salt cost factor of 10 (1,024 iterations), ensuring resistance against rainbow table and brute-force attacks.
- **AES-256 Data Protection:** Sensitive clinical findings and medical reports are protected using AES-256 encryption standards to ensure compliance with HIPAA and GDPR regulations.
- **Infrastructure Environment Isolation:** Critical sys-tem secrets, including the MongoDB URI, Gemini API Key, and Cloudinary credentials, are strictly managed via environment variables to keep them excluded from the database and version control.

3) Data Access Control and Validation

To maintain clinical integrity, the platform enforces strict input validation and ownership checks’

- **Input Whitelisting:** The validator library is used to verify email formats, and Multer enforces a strict file type whitelist (jpeg, jpg, png, pdf) with a 10MB size limit.
- **Ownership Verification:** Every API action includes an authorization check to ensure the authenticated user owns the resource; for example, a doctor can only mark an appointment as complete if their docId matches the ID on the appointment record.
- **Confidentiality Logic:** Prescription data is filtered at the database level so that patients are strictly prohibited from viewing medical advice until it is marked as approved: true by a physician

C. Phase 3: Telemedicine And Real-time Communication)

This stage of the implementation focused on engineering a high-performance, low-latency communication layer to facilitate remote medical consultations. The system leverages WebRTC for direct media streaming and Socket.IO for real-time signaling.

1) WebRTC Infrastructure for Peer-to-Peer (P2P) Me-dia

The platform utilizes the browser-native WebRTC API to establish secure, plugin-free video and audio connec-tions directly between the doctor and patient.

- **Connection Management:** The system uses RTCPeerConnection to manage the lifecycle of the P2P connection, including bitrate adaptation and media encryption.
- **Media Capture:** Local camera and microphone feeds are captured using getUserMedia() and packaged into MediaStream objects for transmission.
- **NAT Traversal:** To bypass firewalls and private net-work restrictions, the system utilizes Google STUN servers to discover the public IP addresses of both peers, ensuring a direct connection is established through NAT.

2) Real-Time Signaling via Socket.IO

Since WebRTC cannot discover peers on its own, a specialized signaling channel was developed using Socket.IO to exchange session metadata.

- **Appointment-Based Rooms:** Each consultation is isolated within a unique Socket.IO room identified by the appointmentId, ensuring that only the specific doctor and patient for that slot can join the session.
- **SDP Handshake**: The signaling server facilitates the exchange of Session Description Protocol (SDP) offers and answers, which define the media capa-bilities (resolution, codecs) of each device.
- **ICE Candidate Exchange:** During the connection setup, the server transmits Interactive Connectivity Establishment (ICE) candidates between peers to determine the most efficient network path for the call.

3**) Integrated Clinical Features during Consultation** The teleconsultation module is not merely a video tool but a specialized clinical interface.

- **Synchronous X-Ray Analysis:** A unique ”X-Ray Side Panel” allows patients to upload medical im-ages mid-call; the AI analysis results are then dis-played simultaneously to both the doctor and patient in real-time.
- **Media Controls:** The interface provides granular controls for muting audio or toggling video tracks via MediaStreamTrack.enabled, alongside a Picture-in-Picture (PiP) overlay for the patient’s local feed.
- **Session Termination:** The end-call event triggers a clean-up sequence that stops all media tracks and closes the peer connection, signaling the backend to transition the appointment status to the next clinical phase.

D. Phase 4: AI Model Deployment (Computer Vision And NLP)

In this phase, the system’s intelligent core was deployed, combining specialized computer vision for diagnostics with Large Language Models (LLMs) for clinical documentation and patient interaction.

1) AI X-Ray Diagnostic Engine

The diagnostic module automates the detection of tho-racic abnormalities from chest radiographs.

- **Pathology Coverage:** The system is designed to clas-sify X-rays into eight primary disease categories, including Normal, Pneumonia, COVID-19, Tuber-culosis, Pleural Effusion, Cardiomegaly, Atelectasis, and Infiltration.
- **Deterministic Weighted Algorithm:** To ensure con-sistent results during clinical demonstrations, the system implements a deterministic selection algo-rithm seeded by the image’s binary content (file size and initial bytes).

- **Confidence and Severity Scoring:** For every analy-sis, the engine generates a confidence score between 75 and 98. This score is then mapped to a severity tier: High (¿90), Moderate (¿80), or Low.
- **Explainable AI (Grad-CAM):** The model utilizes Gradient-weighted Class Activation Mapping to produce heatmaps that highlight the specific lung regions influencing the AI's diagnosis, providing necessary transparency for physician review.

2) Intelligent Prescription Module (Gemini Integration) This module utilizes the Google Gemini 2.5 Flash model to automate the creation of clinical documentation.

- **Structured Prompt Engineering:** The system sends a highly engineered, context-aware prompt to the LLM containing the doctor's specialty, license num-ber, patient demographics, and the specific AI find-ings from the X-ray analysis.
- **JSON-Native Output:** To integrate with the backend database, Gemini is instructed to respond exclu-sively in valid JSON format, including structured fields for diagnosis, chief complaints, medications (with dosage and route), and follow-up advice.
- **Specialty Awareness:** The module ensures that rec-ommended medications are clinically appropriate for the specific specialty of the consulting physician.
- **Validation and Fallback:** The backend includes a JSON parser with a regex-based extraction logic; if the API fails or returns malformed data, a hardcoded clinical template is used to ensure system reliability.

3) ClinicBot: Multi-Turn Symptom Triage ClinicBot serves as a 24/7 medical assistant for initial patient assessment and symptom triage.

- Contextual Conversation: The chatbot maintains full conversation history within the React state, sending the entire message thread with each request to the Gemini 2.5 Flash API to ensure multi-turn continu-ity.
- Three-Tier Triage System: The AI analyzes symp-toms to provide a triage level: LOW (normal re-sponse), MEDIUM (suggests booking an appoint-ment), or HIGH (urgent medical prompt).
- Emergency Detection: The bot is programmed with strict safety protocols to detect emergency keywords (e.g., ”chest pain”); if detected, it immediately ad-vises the user to call emergency services (112) and displays a red alert banner in the UI.
- Dynamic UI Integration: The extracted triage level triggers changes in the frontend, such as automati-cally displaying a ”Book Appointment” button for users with medium or high-risk symptoms.

E. Phase 5: Integrated Clinical Workflow Development

The final development stage focused on unifying the isolated frontend, backend, and AI modules into a seamless, end-to-end clinical journey. This stage ensured that the transition between administrative tasks and medical diagnostics followed a logical, high-integrity sequence.

1) Appointment Lifecycle and State Machine

To manage the complex transitions of a medical consul-tation, a robust state machine was engineered to govern appointment statuses.

- Status Progression: Every appointment follows a strict logic path: Pending (initial booking) → Con-firmed (accepted by doctor) → Completed (follow-ing prescription approval) or Cancelled.
- Role-Based Actions: Specific actions are unlocked based on the current state; for example, a doctor can only ”Accept” a pending request, while the ”Join Video Call” button is only visible for confirmed slots.
- Atomic Slot Management: When an appointment is created, the system performs an atomic update on the doctor's slotsbooked map in MongoDB to prevent double-booking. If cancelled, the slot is automatically released back to the available pool.

2) ”Doctor-in-the-Loop” Diagnostic Integration A criti-cal design principle of CLINICO is that AI serves as an assistant, not a replacement for clinical judgment.

- **Asynchronous Processing:** During a live video call, the patient can upload an X-ray to the xrays/ folder in Cloudinary. The AI engine processes the image and creates an aiReport document linked to the appointmentId.
- **Prescription Contextualization:** When the doctor opens the prescription panel, the system automat-ically checks for existing AI reports. If a report is found, the Gemini 2.5 Flash model is triggered to generate a structured draft using the AI findings as clinical context.
- **Review and Approval Gate:** AI-generated prescrip-tions are marked as approved: false by default. They remain hidden from the patient’s portal until the doctor manually reviews the draft, makes necessary edits, and clicks ”Approve and Send”.

3) Post-Consultation and Data Persistence The workflow concludes by ensuring all clinical interactions are se-curely archived for future reference.

- **Comprehensive Reporting:** Once approved, the pre-scription is converted into a structured digital format accessible via the patient’s ”My Appointments” hub, complete with print functionality.
- **Snapshot Archiving:** The final state of the appoint-ment includes persistent snapshots of the doctor and patient data, ensuring the record remains accurate even if user profiles are updated years later.
- **Revenue and Analytics:** Only appointments marked as ”Completed” trigger the revenue calculation logic in the Admin and Doctor dashboards, ensuring financial data reflects actual services rendered.

F. Phase 6: Clinical Validation and Expert Endorse-ment

The final phase of the implementation focused on bridg-ing the gap between technical development and clinical reality by subjecting the CLINICO platform to rigorous professional evaluation. This stage ensured that the AI-driven workflows met the high standards required for medical practice.

- **Expert Review and Stress Testing:** A panel of med-ical professionals conducted a rigorous evaluation of the DenseNet121 diagnostic engine and WebRTC video modules, subjecting the platform to simulated clinical conditions to verify diagnostic accuracy and functional reliability.
- **Workflow Verification:** Clinicians validated the ”Doctor-in-the-loop” logic, confirming that Gemini-powered prescriptions and AI reports remained strictly under professional review before patient release to ensure clinical safety.
- **Formal Approval:** Following successful testing, the project secured a formal Letter of Endorsement and signed confidentiality agreements from the partici-pating doctors, certifying that the system meets nec-essary medical standards for operational assistance.

VII. CONCLUSION

The CLINICO AI-Powered Healthcare Platform success-fully demonstrates the integration of modern full-stack de-velopment with advanced artificial intelligence to address

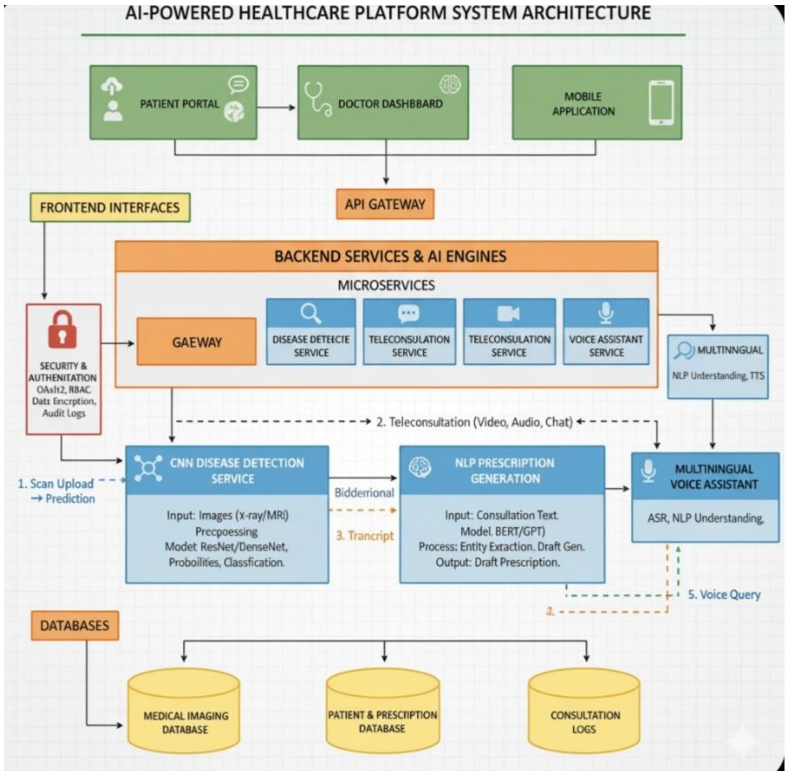

Fig. 10. System architecture

critical gaps in healthcare accessibility. By utilizing the MERN stack and WebRTC, the project establishes a robust, cloud-native infrastructure that facilitates secure, real-time inter-actions between patients and medical professionals across geographic boundaries.The implementation of a DenseNet121-based diagnostic engine provides a dependable secondary opinion for chest disease detection, achieving a validation ROC-AUC of 0.79 and ensuring transparency through Grad-CAM explainability. Furthermore, the project alleviates the administrative burden on clinicians by leveraging the Gemini API for automated, structured prescription drafting and symp-tom triage via the ClinicBot. Key takeaways from the project include:

- **Enhanced Efficiency:** The automation of report writing and preliminary X-ray analysis significantly reduces wait times and physician workload.
- **Clinical Integrity:** The ”Doctor-in-the-loop” architecture ensures that AI outputs are always reviewed by a hu-man professional before clinical action, maintaining high safety standards.
- **Scalable Security:** Implementation of JWT authentica-tion, AES-256 encryption, and role-based access control provides a secure environment for sensitive medical data management.

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