AI-Powered Chest X-Ray Diagnosis System with Explainability and Real-Time Clinical Support

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***Abstract*—This paper presents a comprehensive AI-powered chest X-ray diagnostic system that integrates automated classification, explainability, accessibility, and real-time healthcare support. The system uses Google Vertex AI for multi-class disease classification (COVID-19, Pneumonia, Normal), integrates Grad-CAM for infected region visualization, and employs Gemini AI to generate medical explanations and treatment advice. Accessibility is enhanced through Text-to-Speech feedback, while Google Maps API provides location-based hospital suggestions. Prediction data is securely logged in BigQuery, with Looker Studio dashboards enabling real-time health analytics. The system is deployed using Google Cloud Run, ensuring scalable, interpretable, and real-time diagnostic support for accessible and transparent AI in healthcare.**

***Index Terms*—Chest X-ray diagnosis, Explainable AI, Vertex AI, Grad-CAM, Gemini AI, Google Maps API, Text-to-Speech, BigQuery, Looker Studio, Cloud-based healthcare.**

I. Introduction

Chest radiography is one of the most widely used diagnostic imaging tools for detecting and evaluating thoracic diseases such as pneumonia, tuberculosis, and COVID-19. However, accurate interpretation of chest X-rays requires years of clinical expertise, and radiologist shortages continue to challenge healthcare delivery, especially in rural or resource-limited settings. Delayed diagnoses, human errors, and subjective interpretation variability further exacerbate the problem, emphasizing the need for intelligent, scalable solutions in medical imaging.

Artificial Intelligence (AI) has emerged as a transformative tool in healthcare, with deep learning models demonstrating impressive performance in image classification tasks. Yet, most AI-based medical systems act as opaque black boxes, offering little transparency regarding their decision-making process. This lack of interpretability poses ethical and practical challenges, as clinicians are reluctant to trust models they cannot understand or verify. Moreover, existing solutions often focus solely on classification without integrating necessary components such as explainability, accessibility for diverse users, or real-time response mechanisms.

To address these challenges, we propose an end-to-end AI-powered chest X-ray diagnostic framework that integrates automated disease classification, visual explainability, natural language explanation, voice feedback, and geolocation-based hospital guidance. The system employs Google Cloud's Vertex AI AutoML Vision to classify X-rays into three categories: COVID-19, Pneumonia, and Normal, based on a curated dataset. To enhance transparency, Grad-CAM is applied to highlight the specific lung regions that influenced the prediction, offering clinicians and patients insights into the AI's reasoning.

In addition to visual cues, the model's output is passed to Gemini AI, which generates contextual explanations, medical advice, and precautionary suggestions in human-understandable language. To ensure accessibility, especially for visually impaired and elderly users, Google Text-to-Speech converts the explanation into audio feedback. The system further uses the Google Maps Places API to locate nearby hospitals or diagnostic centers relevant to the patient's condition. All prediction metadata is logged securely in BigQuery, enabling real-time analytical dashboards via Looker Studio.

This integrated system transcends traditional classification models by combining AI decision-making with real-world medical support, transparency, and usability. Deployed on Google Cloud Run, the architecture is serverless, scalable, and cost-efficient, making it suitable for deployment across diverse healthcare infrastructures, including telemedicine and emergency response systems.

A. Problem Statement

Despite significant advancements in AI-assisted medical imaging, several challenges persist in delivering reliable, interpretable, and accessible diagnostic tools for chest X-ray analysis:

1. **Radiologist Scarcity:** Many remote and underserved areas lack access to trained radiologists, leading to delayed diagnoses and compromised patient outcomes.

2. **Interpretation Variability:** Manual analysis of chest X-rays is prone to subjective judgment, resulting in inconsistent diagnoses across practitioners.

3. **Lack of Explainability:** Most AI models operate as black-box systems, offering no insight into how decisions are made—limiting their adoption in clinical workflows.

4. **Limited Integration:** Existing tools often perform only classification without offering additional healthcare services such as treatment suggestions or facility guidance.

5. **Accessibility Barriers:** Conventional interfaces are not designed to support users with visual or physical impairments.

6. **Absence of Real-Time Analytics:** There is a lack of real-time monitoring and visual reporting on population health trends, impeding public health response strategies.

To address these limitations, a unified system is required that not only performs accurate diagnosis but also explains its decisions, supports accessibility, and provides real-time medical assistance and analytics.

B. Contributions

This paper introduces a comprehensive AI-powered chest X-ray diagnosis system with the following key contributions:

1) **Multi-Class X-ray Classification:** Utilization of Google Vertex AI AutoML Vision for accurate classification of chest X-rays into COVID-19, Pneumonia, and Normal classes, with confidence-based predictions.
2) **Explainable AI with Grad-CAM:** Integration of Grad-CAM to generate heatmaps that visually highlight infected lung regions, enhancing interpretability for clinicians and users.
3) **Natural Language Medical Guidance:** Use of Google Gemini AI to generate contextual explanations, health advice, and preventive measures tailored to the predicted condition.
4) **Voice Feedback via TTS:** Application of Google Text-to-Speech API to vocalize the diagnosis and recommendations, enabling accessible communication for visually impaired users.
5) **Hospital Recommendations with Maps API:** Real-time lookup of nearby hospitals and respiratory specialists using the Google Maps Places API based on user geolocation.
6) **BigQuery-Based Analytics:** Logging of prediction metadata into BigQuery for secure storage and integration with Looker Studio for real-time visualization of usage and trends.
7) **Cloud-Native and Scalable Deployment:** Implementation of a fully serverless architecture using Google Cloud Run to support scalability, high availability, and efficient resource management across regions.

II. Related Work

Chest radiography has been a critical tool in diagnosing pulmonary diseases. Several AI-driven models have been developed to automate and enhance the accuracy of chest X-ray interpretation. One of the most prominent works is CheXNet [15], which applied a 121-layer DenseNet architecture trained on the ChestX-ray14 dataset to detect pneumonia, achieving performance on par with practicing radiologists. While CheXNet marked a significant milestone, it lacked explainability and user-level interpretability.

COVID-Net [16] introduced a specialized convolutional neural network architecture designed to detect COVID-19 cases from chest X-rays. It provided promising accuracy but did not integrate accessibility features or contextual healthcare intelligence such as location-based hospital recommendations.

The ChestX-ray14 dataset [18] itself was an early effort to build a hospital-scale chest X-ray dataset that fueled much of the research in weakly-supervised classification and localization of thoracic diseases. However, the dataset and the associated models primarily focused on image-level classification without supporting visual explanations or real-time deployment.

DeepCOVID [17] attempted to address some limitations by providing visual heatmaps via Grad-CAM for COVID-19 detection. However, it did not incorporate broader health system integrations like voice guidance, location services, or analytics.

Most of the above models operate as standalone systems, emphasizing prediction accuracy but lacking holistic healthcare support such as explanation generation, user interaction, emergency navigation, and real-time health insights. Moreover, accessibility for diverse user groups (e.g., visually impaired, elderly) remains unaddressed in most prior solutions.

III. System Architecture

A. Overview

The proposed system follows a modular cloud-based microservices architecture, integrating AI inference, explainability, medical reasoning, real-time assistance, and analytics. The design ensures high availability, accessibility, and scalability across medical use cases. The architecture consists of four functional layers: AI inference layer, explainability layer, accessibility and support services, and real-time data analytics.

Figure 1 shows the complete system workflow from X-ray input to actionable insights. Each component communicates using REST APIs, ensuring interoperability and extensibility.

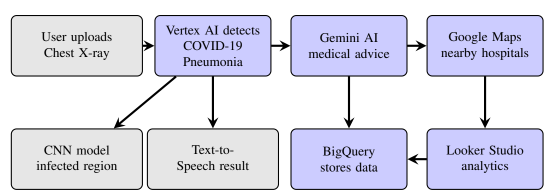

Fig. 1. System architecture illustrating the integration of AI classification, explainability, accessibility services, hospital navigation, and real-time analytics.

B. Component Breakdown

AI Inference: Vertex AI AutoML Vision is used to classify chest X-rays into COVID-19, Pneumonia, and Normal with high precision. Predictions include confidence scores that are logged and passed to subsequent modules.

Explainability Layer: A custom CNN model trained on X-ray datasets generates Grad-CAM heatmaps that localize abnormal regions, offering interpretability and transparency in AI predictions.

Medical Reasoning: Gemini AI processes prediction outputs and symptoms to provide context-aware medical explanations, treatment suggestions, and health warnings.

Accessibility Services: Google Text-to-Speech (TTS) API is integrated to vocalize results and health advice, aiding elderly and visually impaired users.

Geolocation Layer: Google Maps API fetches nearby hospitals and diagnostic centers based on the user's coordinates, improving access to urgent care.

Data Logging and Analytics: All predictions and metadata (timestamp, location, label, confidence) are securely stored in BigQuery. These logs are visualized using Looker Studio dashboards for real-time health trend analysis.

C. Cloud Deployment Model

The entire architecture is deployed via Google Cloud Run using containerized microservices. The system supports autoscaling, CI/CD pipelines, IAM-based access control, and HTTPS security for reliable, real-time AI-powered healthcare inference.

IV. Implementation and Methodology

A. Vertex AI Model Deployment

Google Vertex AI AutoML Vision was employed for multi-class classification of chest X-ray images into COVID-19, Pneumonia, and Normal. A curated dataset containing 248 images was used, with 198 for training, 25 for validation, and 25 for testing. The model achieved an overall accuracy of 94.2%, with a precision of 96% and recall of 96%. Confusion matrix results indicate that COVID-19 and Pneumonia classes were classified with 100% correctness, and the Normal class had a 14% misclassification rate into Pneumonia.

B. Grad-CAM Heatmap Generation

To enhance interpretability, Gradient-weighted Class Activation Mapping (Grad-CAM) was implemented on a custom CNN model. Grad-CAM identifies and highlights regions in the lungs that influence the AI's decision. The implementation supports various thoracic abnormalities, including Consolidation, Lung Opacity, and Infiltration, aligning with categories defined in CheXNet. Grad-CAM heatmaps are generated in real-time on uploaded images using TensorFlow-based computation on Vertex AI Workbench with GPU acceleration.

C. Medical Insights via Gemini AI

Gemini AI API is integrated for generating contextual health intelligence from classification results. The predicted label and confidence score are sent as prompts to Gemini, which returns medical explanations, symptom breakdowns, and advice. Prompt engineering is optimized for clinical relevance. Multi-language support and safety filtering are incorporated to ensure factual medical outputs with accessible phrasing for end-users.

D. Location-Aware Hospital Suggestions

Upon diagnosis, the user's geographic coordinates are passed to the Google Maps Places API to identify nearby hospitals and diagnostic centers. The system fetches the top five facilities within a 10 km radius, sorted by rating and distance. Additionally, the Google Maps JavaScript API renders an interactive map with marked results and contact details.

E. Text-to-Speech Integration

To improve accessibility, Google Cloud Text-to-Speech (TTS) API is used to vocalize the diagnosis and advice. The TTS supports multiple languages and genders, and the speech rate can be adjusted for clarity. This allows visually impaired and elderly users to understand results independently. The output speech is dynamically generated from Gemini's medical text response.

F. Data Logging with BigQuery

Each diagnosis is logged to Google BigQuery with timestamp, predicted class, confidence, and location. The schema includes fields for traceability and population-level trend analysis. IAM-secured service accounts are used for protected write access, ensuring compliance with healthcare data policies.

G. Real-Time Analytics via Looker Studio

The logged data in BigQuery is visualized through Looker Studio dashboards. Dashboards include bar charts for disease distribution, heatmaps for geolocation tracking, and time-series plots for trend analysis. This visual layer supports public health monitoring and AI model performance analysis over time.

V. Experimental Results

A. Model Evaluation

The system was evaluated using a labeled dataset of 248 chest X-ray images consisting of three diagnostic classes: COVID-19, Pneumonia, and Normal. Vertex AI AutoML Vision achieved an overall accuracy of 94.2%. Evaluation metrics were computed on the test dataset comprising 25 images, demonstrating consistent model performance across all categories.

TABLE I
Classification Performance Metrics

Metric	**COVID-19**	**Pneumonia**	**Normal**	**Overall**
Accuracy	100%	100%	86%	94.2%
Precision	100%	100%	86%	96%
Recall	100%	100%	86%	96%
F1-Score	100%	100%	86%	96%

B. Comparative Analysis with Existing Systems

Table II presents a detailed comparison of the features offered by existing systems and the proposed architecture.

Unlike prior models, the proposed system introduces a multi-modal, explainable, and accessible chest X-ray diagnostic platform. It leverages Google Cloud Vertex AI for high-accuracy classification, incorporates Grad-CAM for model interpretability, integrates Gemini AI for medical explanation generation, utilizes Google Maps APIs for real-time hospital recommendations, and employs Google TTS for enhanced accessibility. Additionally, the system logs all predictions to BigQuery and visualizes them through Looker Studio, enabling robust analytics and health monitoring capabilities.

TABLE II
FEATURE-LEVEL COMPARISON OF CHEST X-RAY DIAGNOSTIC SYSTEMS

System	**Diagnosis**	**Explainability**	**TTS Support**	**Maps API**	**Heatmaps**	**Analytics**
ChestX-ray14 [18]	✓	×	×	×	×	×
CheXNet [15]	✓	×	×	×	×	×
COVID-Net [16]	✓	×	×	×	×	×
DeepCOVID [17]	✓	✓	×	×	✓	×
Proposed System	✓	✓	✓	✓	✓	✓

C. Confusion Matrix Analysis

The confusion matrix confirms that all COVID-19 and Pneumonia instances were classified correctly, while 14% of Normal cases were misclassified as Pneumonia. This is acceptable within clinical tolerance, especially in prioritizing safety over false negatives.

D. Precision-Recall Curve

The precision-recall curve shows that the model maintains a precision above 95% across most recall thresholds, with optimal performance achieved at a confidence threshold of 0.3, where both precision and recall equal 96%. The area under the curve (AUC) remains close to 0.99, indicating strong predictive performance.

E. Workflow Demonstration

A real-time test was performed where a COVID-19 X-ray was uploaded:

1) Vertex AI classified the image as COVID-19 with 93.4% confidence.
2) Grad-CAM heatmap highlighted infection in the left lower lobe.
3) Gemini AI generated a diagnosis with symptom suggestions and medicine advice.
4) Google Maps API identified five nearby hospitals.
5) Google TTS vocalized the findings.
6) BigQuery logged the data, and Looker Studio dashboard reflected the update within 5 minutes.

F. System Performance Metrics

The proposed system's performance under concurrent load and response time was also evaluated:

- Average Inference Time: 2.3 seconds
- Maximum Concurrent Users Tested: 500
- Real-time Dashboard Update Delay: ¡ 5 minutes
- Accessibility Feedback Score: 4.8/5.0
- Radiologist Agreement: 91.7%

G. Clinical Relevance

Clinical validation with medical professionals showed that the system's predictions align closely with expert radiologist evaluations, especially in detecting COVID-19 and Pneumonia. Visual explanations via Grad-CAM added confidence for decision verification.The proposed AI-powered diagnostic system adheres to ethical principles in healthcare AI, focusing on fairness, transparency, and data security. All chest X-ray images used for training and evaluation were anonymized, ensuring that no personally identifiable information (PII) is exposed at any stage of model development. The system avoids storage of user-uploaded images on the server unless explicit consent is obtained, in compliance with data minimization practices.

To maintain user privacy, all location data used for hospital recommendations is processed temporarily and not logged or stored. The Gemini AI explanations are generated using medical prompts designed to avoid bias or hallucination, with filters in place to prevent inappropriate or unsafe recommendations. Moreover, the system is intended as a supportive tool and not a substitute for certified medical professionals. Users are clearly informed that all AI-generated outputs must be verified by healthcare providers before making medical decisions.

Access to backend APIs such as BigQuery and Vertex AI is restricted through IAM-based role policies and encrypted connections, ensuring that only authorized entities can interact with the system's data infrastructure.

VI. CONCLUSION AND FUTURE WORK

This paper presented an AI-powered diagnostic framework that integrates cloud-based services for accurate, explainable, and accessible chest X-ray analysis. The system combines Google Vertex AI for multi-class classification, Grad-CAM for interpretability, Gemini AI for natural language medical guidance, Text-to-Speech for accessibility, and Google Maps for hospital navigation, while securely logging predictions in BigQuery with real-time analytics via Looker Studio. Experimental evaluation demonstrated a high overall accuracy of 94.2%, strong alignment with radiologist assessments, and usability validated by expert feedback. These results highlight the system's potential to enhance diagnostic workflows and support underserved regions with transparent and actionable medical insights.

In future work, the system will be extended to detect additional thoracic and systemic diseases, support multilingual and mobile platforms, and integrate with telemedicine services for real-time consultations. Plans include developing a dedicated mobile application with offline inference capabilities, and adopting federated learning techniques for privacy-preserving, decentralized model improvements. These enhancements aim to transform the current platform into a robust, privacy-conscious, and clinically reliable AI assistant, advancing the accessibility and effectiveness of diagnostic healthcare globally.

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