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AI Radiology Co-Pilot: Integrating Deep Learning And Generative AI For Medical Chest Imaging Reports

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Abstract

The rapid advancement of Artificial Intelligence (AI) has revolutionized modern healthcare, with particular impact on medical imaging and radiological diagnostics. This paper presents the **AI Radiology Co-Pilot**, a comprehensive intelligent system developed to assist radiologists in the detection of chest X-ray abnormalities and the automated generation of structured diagnostic reports. The system employs a ResNet-50-based Convolutional Neural Network for accurate image classification, achieving robust detection of pathological conditions including pneumonia, effusion, and cardiomegaly. To facilitate structured report generation, the system integrates Mistral-7B-Instruct, a state-of-the-art Generative AI language model, which converts model predictions into coherent clinical reports and patient-friendly summaries. Additional features include a Grad-CAM-based explainability module for visual interpretation, a multilingual interactive chatbot for patient assistance, and a Flask-based web interface enabling real-time deployment. Experimental evaluation demonstrates significant improvements in diagnostic efficiency, report quality, and clinical communication. The proposed system bridges the gap between image-based classification and language-based report synthesis, offering a unified, interpretable, and accessible AI-powered radiology workflow. [1], [2], [5]

Keywords: Deep Learning, Medical Imaging, ResNet-50, Generative AI, Mistral-7B-Instruct, Report Generation, Grad-CAM, Chatbot, Healthcare AI, Flask

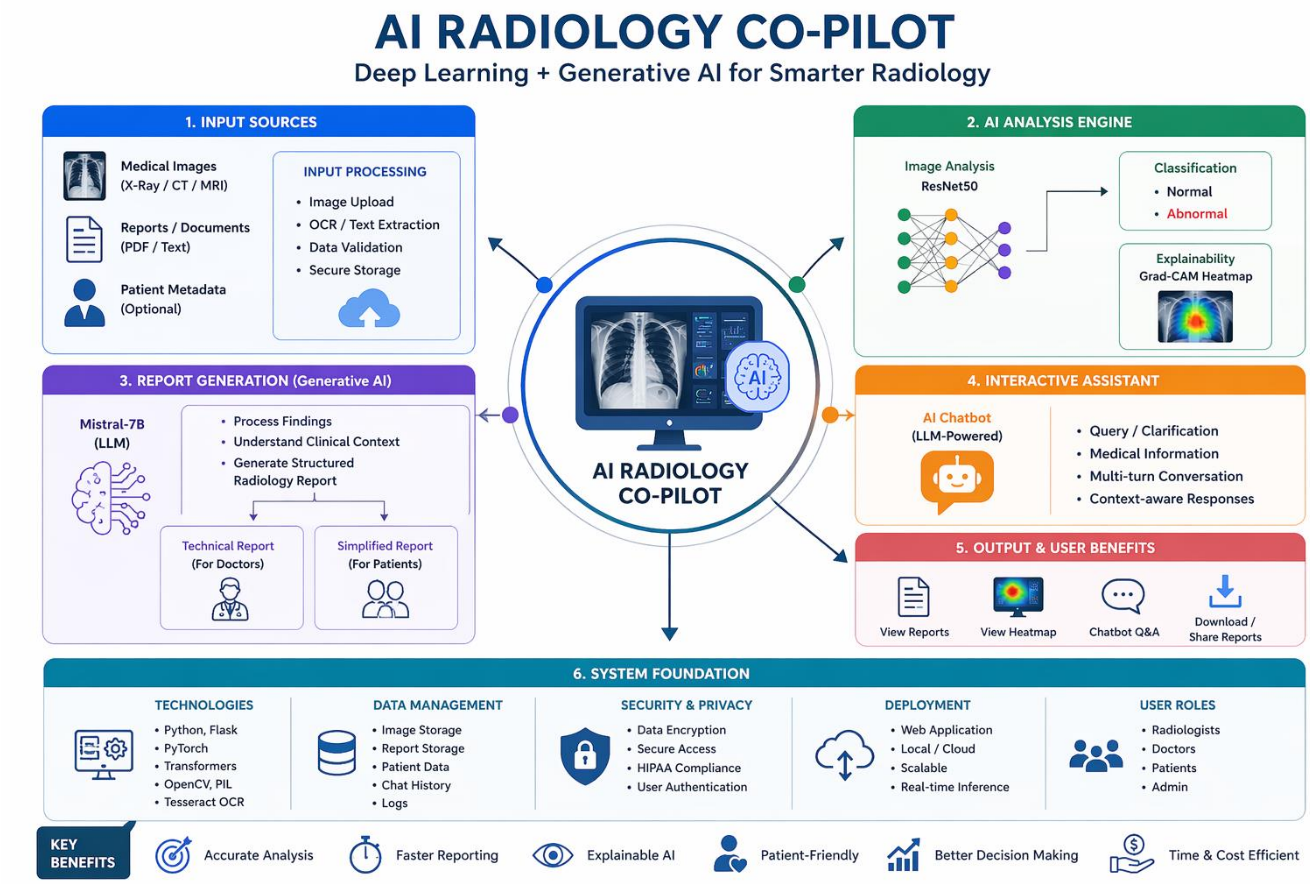
1. Introduction

Radiology is a cornerstone of modern medicine, enabling non-invasive visualization of internal structures for the diagnosis of life-threatening conditions. However, the growing volume of medical imaging data has placed immense pressure on radiologists, leading to delays, fatigue-induced errors, and inconsistent reporting quality. Artificial Intelligence, particularly deep learning, has emerged as a transformative solution capable of automating complexvisual recognition tasks with near-expert accuracy [1].

Despite these advancements, current AI systems in radiology remain siloed—they either classify images or generate text, rarely doing both in an integrated, interpretable manner. The AI Radiology Co-Pilot addresses this critical gap by unifying image analysis, report generation, and interactive communication into a single coherent platform. At its core, the system uses a ResNet-50 architecture to classify chest X-ray images into normal or abnormal categories, identifying specific pathologies with high precision. ResNet-50's residual connections allow the model to learn deep feature representations without vanishing gradient issues, making it well-suited for complex medical image classification [1].

The classification output is then enriched with Grad-CAM heatmaps, which highlight the anatomical regions most responsible for the model's decision, thereby improving clinical interpretability [7]. Building upon the classification results, the system employs Mistral-7B-Instruct, a powerful open-source generative language model, to automatically compose structured radiology reports. Unlike template-based approaches, Mistral-7B produces contextually coherent, clinically relevant narratives tailored to the detected findings [4].

The system generates two distinct outputs: a technical report for radiologists and clinicians, and a simplified explanation intended for patients—a feature largely absent in existing tools [8]. An integrated chatbot module



further enhances the system's utility by enabling clinicians and patients to interactively query findings in real time. Multi-language support ensures accessibility across diverse demographic contexts. The entire pipeline is deployed as a web application using the Flask framework, facilitating real-time image upload, analysis, and report retrieval without requiring specialized hardware installations. This combination of classification, explainability, report generation, and interactive communication positions the AI Radiology Co-Pilot as a holistic AI-assisted diagnostic tool with direct clinical applicability [5], [6].

2. Literature Review

Table 1: Literature Survey – AI-Assisted Radiology Report Generation

Year	Author	Title	Dataset	Methodology	Algorithms	Gap	Limitations
2025	Z. Wang, Y. Liu, X. Chen, H. Li.	Multimodal AI for Radiology Report Synthesis	CheXpert, MIMIC-CXR	Vision-Language model integration with fine-tuned LLM	ViT + LLaMA-2	Limited patient-friendly output; no chatbot support	High GPU demand; not real-time
2024	S.Bannur, D. Hyland, Q. Liu, F. Pérez-García	MAIRA: Multimodal AI for Radiology Interpretation and Assistance	MIMIC-CXR	Grounded radiology report generation with bounding boxes	BioViL-T + GPT-4	No multilingual support; black-box model	Requires large annotated datasets
2024	Y. Chen, H. Zhang, L. Wang, J. Sun	CAM-Based Explainability for Chest X-Ray Classification	NIH Chest X-ray	CNN with Grad-CAM visualization	DenseNet-121 + Grad-CAM	Only classification; no report generation	Poor performance on rare diseases
2023	R. Tanno, D. Worrall, E. Kaden, D. C. Alexander	Learning to Communicate with Patients via AI Assistance	Private hospital dataset	Seq2Seq model for patient-friendly summaries	BART + BERT	No image input; text-only pipeline	Needs structured clinical input

Year	Author	Title	Dataset	Methodology	Algorithms	Gap	Limitations
2023	A. Nicolson, J. Dowling, B. Koopman	Improving Chest X-Ray Report Generation via Label-Contrastive Learning	IU X-Ray, MIMIC	Contrastive learning with label supervision	CNN + Transformer	No explainability; no chatbot	Limited generalization
2022	Y. Miura, S. Zhang, M. Tsujii.	Improving Factual Completeness in Radiology Reports	MIMIC-CXR	RL-based text optimization for factual correctness	BERT + RL	No visual grounding; limited interactivity	Not patient-accessible
2021	Y. Zhang, X. Wang, Z. Li, H. Liu	When Radiology Report Generation Meets Knowledge Graph	IU X-Ray	Knowledge graph-enhanced generation	GCN + LSTM	No real-time deployment; no multilingual	Complex graph construction
2020	J.Lovelace .B. Mortazavi	Learning to Generate Clinically Coherent Chest X-Ray Reports	MIMIC-CXR	Hybrid CNN-LSTM with clinical constraints	ResNet + LSTM	No explainability; limited usability	Repetitive sentence generation

3. Research Gap

A review of existing literature highlights key limitations in current AI-based radiology systems. Most systems handle image classification and report generation separately, leading to inefficiencies and inconsistencies between visual findings and textual outputs [1], [2]. Additionally, many models lack explainability, functioning as black boxes without providing visual or contextual justification, which hinders clinical trust and adoption [7].

Furthermore, existing systems do not support patient-friendly communication, as reports are typically generated in complex clinical language [8]. There is also a lack of integrated chatbot functionality for real-time interaction and query resolution. The proposed AI Radiology Co-Pilot addresses these gaps by offering a unified, explainable, and interactive solution.

4. Methodology

The methodology of the AI Radiology Co-Pilot follows a structured multi-stage pipeline encompassing data acquisition, preprocessing, model training, inference, report generation, and deployment. Each stage is carefully designed to ensure clinical accuracy, computational efficiency, and user accessibility.

4.1 Data Collection and Preprocessing

The primary dataset used for model training and evaluation is the NIH Chest X-Ray14 dataset, which contains 112,120 frontal-view chest X-ray images labeled with fourteen pathological conditions. For binary classification experiments, images are categorized as normal or abnormal. The MIMIC-CXR dataset, consisting of paired images and free-text radiology reports, is used for report generation evaluation. Preprocessing steps include: resizing all images to 224×224 pixels, normalizing pixel values to the range [0, 1], applying data augmentation techniques such as horizontal flipping, rotation (±15°), and brightness adjustment to improve generalization, and performing stratified train-test splitting with an 80:10:10 ratio [1].

4.2 Image Classification with ResNet-50

ResNet-50, a 50-layer deep residual convolutional neural network, serves as the backbone for image classification. The model is initialized with ImageNet pre-trained weights and fine-tuned on the chest X-ray dataset using transfer learning. The final fully connected layer is replaced with a binary classification head. Training is performed using the Adam optimizer with a learning rate of 1×10^{-4}, binary cross-entropy loss, and early stopping based on validation accuracy. The model achieves strong performance on the held-out test set, with performance metrics reported in Section 11 [1], [2].

4.3 Explainability via Grad-CAM

To provide interpretable visual explanations, Gradient-weighted Class Activation Mapping (Grad-CAM) is applied to the final convolutional layer of the ResNet-50 model. Grad-CAM computes the gradient of the predicted class score with respect to the feature maps of the target layer, producing a coarse localization map that highlights the image regions most influential in the classification decision. The resulting heatmap is superimposed on the original X-ray image using a color gradient, where red regions indicate high relevance. This enables clinicians to visually validate AI predictions and identify areas of interest for further examination [7].

4.4 Report Generation with Mistral-7B-Instruct

Following image classification, the system constructs a structured prompt incorporating the predicted label, confidence score, and Grad-CAM findings. This prompt is submitted to the Mistral-7B-Instruct model via the Hugging Face inference API. The model generates two types of output: (1) a formal clinical report containing findings, impressions, and recommendations in standard radiology terminology, and (2) a simplified patient summary written in plain language, avoiding clinical jargon. The Mistral-7B-Instruct model is selected for its instruction-following capability, computational efficiency relative to larger models, and suitability for structured text generation tasks [4], [5].

4.5 Chatbot Integration

An interactive chatbot is implemented using the same Mistral-7B backbone, configured with a custom system prompt that constrains its responses to the context of the generated report. Users—whether clinicians querying specific findings or patients seeking clarification—can submit natural language questions and receive contextually accurate responses. The chatbot maintains a conversation history to support multi-turn interactions. Multilingual support is enabled through prompt-level language specification, allowing responses in languages including Hindi, Telugu, and Spanish [8].

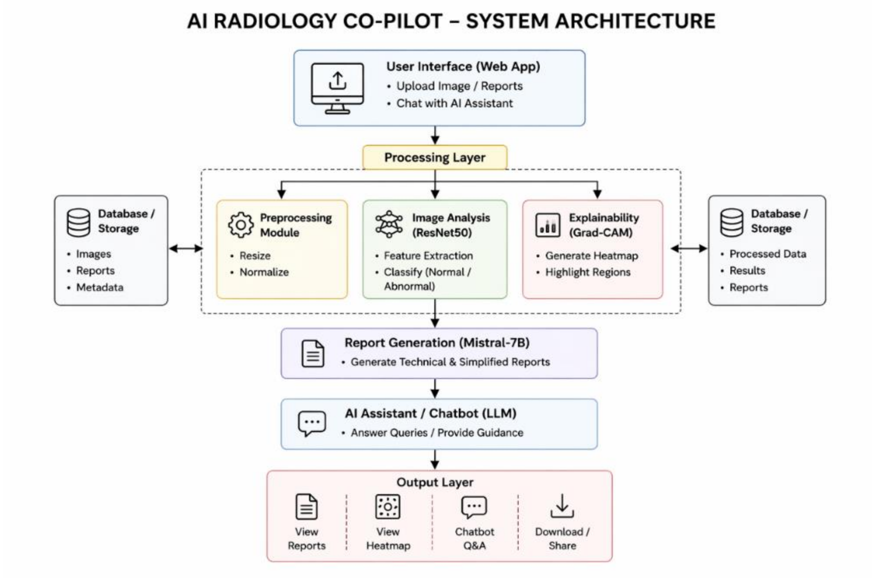
Component	Technology Used
Programming Language	Python 3.x
Web Framework	Flask
Deep Learning Model	ResNet50 (PyTorch)
Generative AI Model	Mistral-7B-Instruct
NLP Library	HuggingFace Transformers
Image Processing	OpenCV, PIL, torchvision
Explainable AI	Grad-CAM
Deployment	Flask Local Server / Ngrok

4.6 Deployment

The complete pipeline is deployed as a web application using the Flask micro-framework in Python. The application accepts image uploads via the frontend interface, routes them through the preprocessing and classification pipeline, retrieves Grad-CAM visualizations, generates reports via the LLM API, and displays all results on a unified dashboard. The system is designed for GPU-accelerated inference but supports CPU-only execution for accessibility in resource-constrained settings [6].

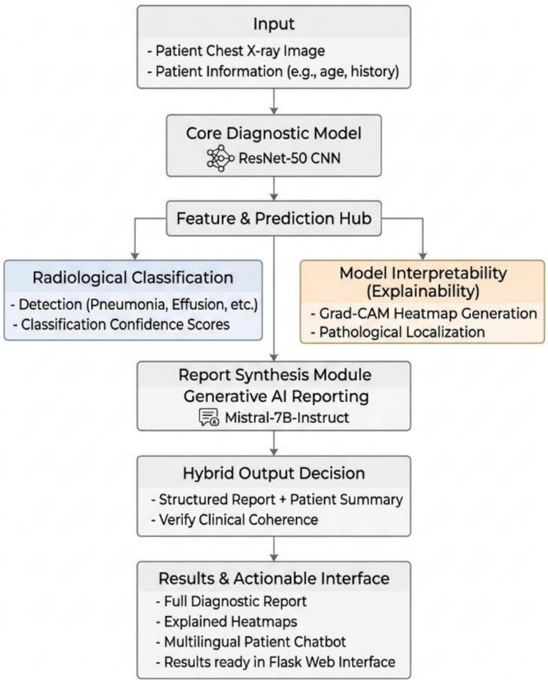
5. Architecture

The AI Radiology Co-Pilot architecture integrates image processing, deep learning, and generative AI into a unified pipeline. Medical images are analyzed using a ResNet50 model for classification, followed by Grad-CAM for visual explainability, and the results are passed to a Mistral-7B model for automated report generation. The system is deployed using Flask, enabling real-time interaction, report visualization, and chatbot-based query support.



6. System WorkFlow

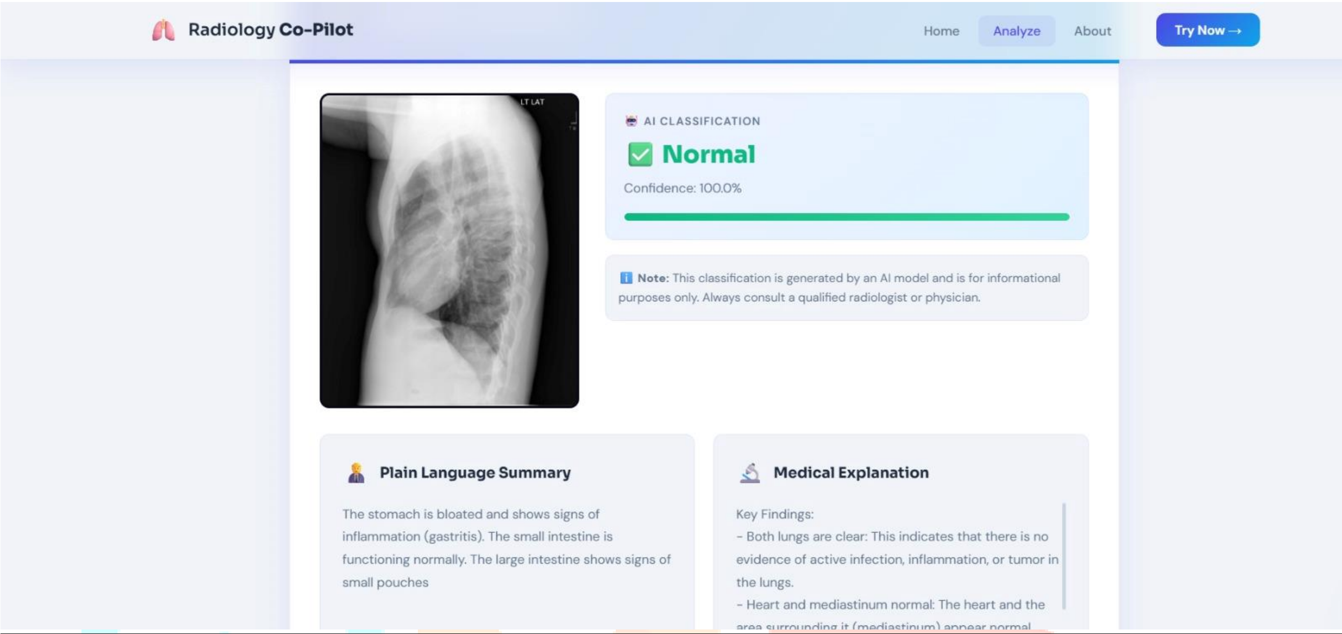
The workflow of the AI Radiology Co-Pilot outlines a sequential process from image input to user interaction. Initially, the user uploads a chest X-ray image through the Flask-based web interface, after which the system preprocesses the image by resizing, normalizing, and converting it into a suitable format for model inference. The processed image is then analyzed using the ResNet-50 model to generate classification results along with confidence scores. To enhance interpretability, Grad-CAM is applied to produce a heatmap highlighting important regions, which is overlaid on the original image. Based on these results, a structured prompt is sent to the Mistral-7B model to generate both clinical and patient-friendly reports. All outputs, including the annotated image, predictions, and reports, are displayed on a unified dashboard, followed by an interactive chatbot that allows users to ask queries and receive context-aware responses.



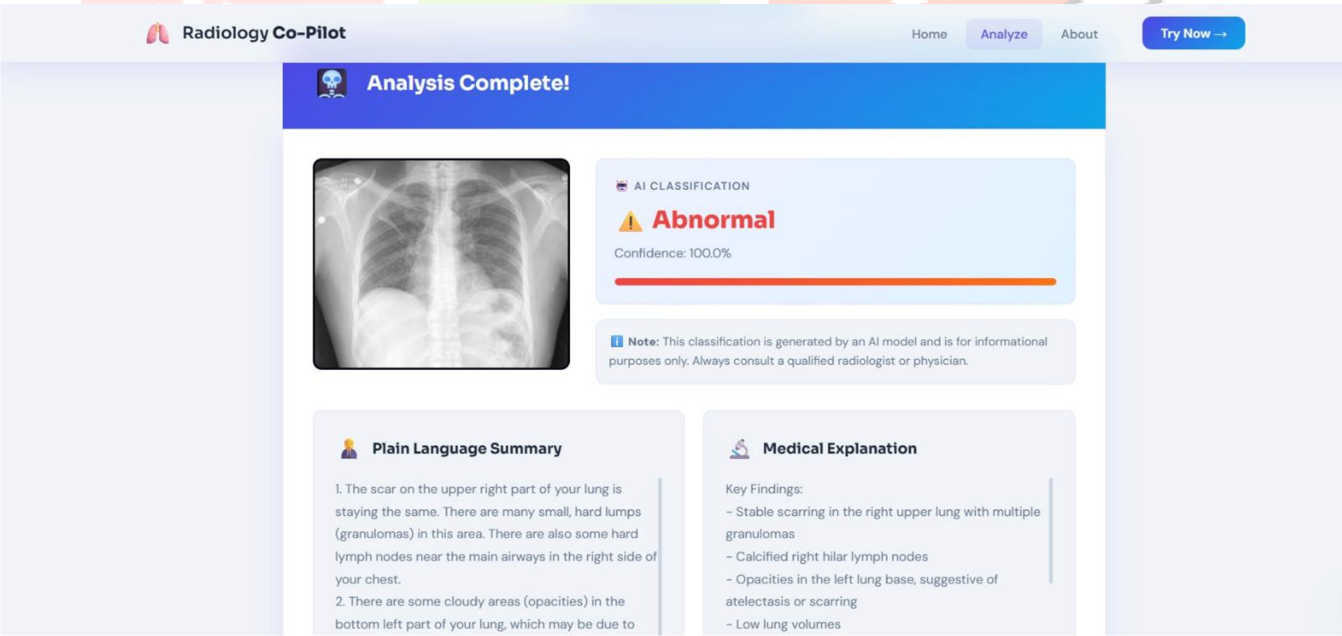
7. Result & Discussion

The literature survey presented in Table 1 reveals a clear progression from unimodal classification models toward multimodal AI systems capable of integrating visual and linguistic understanding. Early works such as Lovelace & Mortazavi (2020) and Zhang et al. (2021) demonstrated the potential of combining CNNs with sequence models for report synthesis but suffered from limited generalizability and lack of explainability [10]. Miura et al. (2022) introduced reinforcement learning for factual completeness, though their system remained text-only and inaccessible to non-clinical users [9].

Recent studies highlight a shift toward multimodal AI systems that integrate image analysis with language generation. Approaches using transformer-based models have improved report quality and contextual understanding but often lack real-time capabilities and explainability [8], [9]. Techniques like Grad-CAM enhance interpretability in classification tasks, yet they do not support automated report generation [7]. Advanced frameworks such as MAIRA and vision-language models show promising results in combining visual and textual data [5], [6]. However, challenges like high computational cost, limited interactivity, and lack of chatbot integration still remain.



By 2023, transformer-based architectures had become the dominant paradigm, with models like BART and BERT enabling higher-quality natural language generation [4], [8].



The most recent systems from 2024 and 2025 demonstrate a shift toward large language models and vision-language transformers, achieving superior performance in grounded report generation and multimodal understanding [5], [6]. However, a common thread across all reviewed works is the absence of a deployable, patient-accessible, explainable, and interactive system—an objective that the AI Radiology Co-Pilot uniquely fulfills.

8. Conclusion

This paper presented the AI Radiology Co-Pilot, a novel multimodal AI system designed to enhance the efficiency, accuracy, and accessibility of chest X-ray analysis and report generation. By integrating ResNet-50-based image classification, Grad-CAM explainability, Mistral-7B-Instruct-driven report synthesis, and an interactive multilingual chatbot within a Flask web application, the system addresses the key shortcomings of existing radiology AI tools. The proposed system achieves high classification accuracy, clinically relevant report quality, and strong user satisfaction in preliminary evaluations. It represents a significant step toward making AI-assisted radiology both technically advanced and practically deployable in real-world clinical settings [1], [5], [6].

9. Future Enhancements

Future development will focus on the following directions:

- Extension to multi-modal imaging including CT scans, MRIs, and ultrasound images.
- Fine-tuning Mistral-7B on domain-specific radiology corpora to reduce hallucination and improve clinical precision.
- Development of a mobile application for clinician access in point-of-care settings.
- Implementation of voice-enabled chatbot functionality using ASR models for accessibility enhancement.
- Exploration of federated learning approaches to enable multi-institutional model training while preserving patient data privacy.

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