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Explainable AI for Healthcare Diagnostics: A Multi-modal Approach Using Vision and Language Models

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Abstract: The integration of artificial intelligence (AI) in healthcare diagnostics has shown tremendous potential in improving accuracy, efficiency, and accessibility. However, the opaque nature of many high-performing AI models, particularly deep learning architectures, limits their acceptance in critical healthcare settings. This paper proposes a novel explainable AI (XAI) framework that leverages multi-modal data—combining medical imaging and clinical text—to enhance diagnostic performance while providing transparent, interpretable outputs. By integrating state-of-the-art Vision Transformers (ViTs) and Large Language Models (LLMs) such as BioBERT and GPT-derived architectures, our system captures complex patterns from both radiological images and corresponding patient records. The proposed framework incorporates attention-based visualization techniques, saliency mapping, and natural language explanation generation to make the model's decisions understandable to clinicians. Experiments conducted on benchmark datasets like MIMIC-CXR and CheXpert demonstrate improved diagnostic accuracy across multiple conditions, while the inclusion of explainability mechanisms fosters higher trust and acceptability among medical professionals. This work contributes toward the responsible deployment of AI in clinical environments, where interpretability is not just an add-on but a critical requirement for real-world adoption.

Keywords- Explainable AI (XAI), Multi-modal Learning, Vision Transformers, Large Language Models, Medical Imaging, Clinical Text Analysis, Healthcare Diagnostics, Interpretability, Attention Mechanisms, Medical AI Ethics

1. INTRODUCTION

Artificial Intelligence (AI) has emerged as a transformative force in modern healthcare, particularly in diagnostic applications that require the interpretation of complex and voluminous data. The increasing availability of large-scale electronic health records (EHRs), high-resolution medical images, and the rapid evolution of machine learning algorithms have enabled AI systems to assist in diagnosing a range of diseases including cancer, cardiovascular disorders, pulmonary diseases, and neurological conditions. Deep learning techniques, especially convolutional neural networks (CNNs) and transformer-based architectures, have achieved expert-level accuracy in image classification tasks, while large language models (LLMs) have demonstrated remarkable capability in understanding and processing unstructured clinical text. Despite these advancements, one of the most pressing barriers to the deployment of AI in real-world clinical settings is the lack of explainability and interpretability in decision-making processes.In high-stakes domains such as healthcare, where diagnostic outcomes directly impact patient safety and treatment strategies, clinicians demand not only accurate results but also clear and interpretable explanations for the AI's predictions. Black-box models, which offer minimal transparency into their internal logic, are often met with skepticism, especially when errors or biases occur. This has catalyzed the growth of Explainable AI (XAI), a subfield focused on making AI decisions more transparent, understandable, and trustworthy for human users. The need for XAI is particularly acute in diagnostic systems, where erroneous predictions without justifiable explanations can undermine trust, delay critical decisions, or even cause harm.

Another challenge in current diagnostic AI systems is the siloed use of data modalities. Many models rely solely on radiographic images, pathology slides, or textual patient records in isolation. However, in real clinical practice, healthcare professionals synthesize information from multiple sources—combining radiology reports, lab values, clinical notes, and patient history—to arrive at a comprehensive diagnosis. Ignoring this holistic

view limits the potential of AI systems to mirror human diagnostic reasoning. Multi-modal learning, which integrates data from different modalities, offers a promising direction toward building systems that align more closely with real-world clinical decision-making. By combining visual data such as chest X-rays or MRI scans with textual data like discharge summaries or physician notes, multi-modal AI systems can provide richer, more contextualized insights. This research proposes a novel multi-modal explainable AI framework designed specifically for healthcare diagnostics. Our system integrates Vision Transformers (ViTs) for processing medical images and domain-adapted LLMs such as BioBERT and GPT variants for understanding clinical text. These models are fused using a cross-attention mechanism that allows the system to dynamically weigh and interpret relationships between visual features and textual context. This enables the model to make more informed and clinically meaningful predictions.

Furthermore, we embed explainability directly into the system by using multiple interpretability techniques. Attention maps and Grad-CAM visualizations highlight the most influential regions in medical images, while natural language generation modules produce concise and clinically coherent explanations for each decision. These explanations are tailored to be understandable to non-technical healthcare professionals, enhancing the usability and adoption of the system in clinical settings. The combination of visual interpretability and language-based justifications addresses both technical and cognitive dimensions of trust, offering a human-centered approach to AI-driven diagnostics. We evaluate our framework using benchmark datasets such as MIMIC-CXR and CheXpert, which provide paired image-text samples for multiple pathologies. Our experiments demonstrate that the proposed system achieves competitive diagnostic accuracy while significantly improving the transparency of predictions. Additionally, we conduct user studies with medical professionals to assess the perceived usefulness and clarity of the explanations provided by our system. The results show a marked improvement in clinician trust and willingness to engage with AI outputs when supported by interpretable feedback. In summary, this work contributes to the growing body of research on explainable and trustworthy AI in healthcare. By combining the strengths of multi-modal learning with state-of-the-art interpretability methods, we bridge the gap between high-performance AI and clinician-friendly decision support systems. Our approach underscores the importance of moving beyond accuracy metrics to focus on model transparency, user understanding, and practical applicability in clinical workflows. The proposed framework not only sets a benchmark for future XAI systems in healthcare but also reinforces the ethical imperative of explainability in AI technologies deployed in sensitive and life-critical domains.

2. LITERATURE SURVEY

The integration of Artificial Intelligence (AI) into healthcare diagnostics has evolved rapidly in recent years, particularly with the adoption of deep learning techniques. However, one of the critical limitations hindering clinical adoption is the lack of explainability in AI systems. This literature survey examines the evolution of explainable AI (XAI), the emergence of multi-modal learning in healthcare, and the confluence of these domains to enhance diagnostic systems' reliability and transparency. Early works in healthcare-focused AI primarily employed Convolutional Neural Networks (CNNs) for image-based diagnostics, demonstrating significant improvements in tasks such as disease detection from chest X-rays, MRIs, and CT scans. For example, the CheXNet model (Rajpurkar et al., 2017) achieved radiologist-level performance in pneumonia detection. However, it offered minimal insight into how predictions were made. This black-box nature spurred the development of XAI techniques such as Grad-CAM, LIME, and SHAP, which provided localized visual or feature-based interpretations of model outputs. While these methods helped identify salient regions or features influencing a decision, they lacked the clinical context often necessary for real-world diagnostic reasoning. The healthcare community soon recognized the need for integrating structured and unstructured textual information—such as clinical notes, radiology reports, and patient history—into AI diagnostic models. This led to the rise of multi-modal learning systems, which aim to emulate the holistic approach of human clinicians by combining visual and textual data. Models like MedViLL and BioViL incorporate medical images and paired reports using joint embeddings and transformer architectures, showing improved diagnostic accuracy and context-aware performance. Yet, many of these systems still struggle to provide interpretable outputs comprehensible to non-technical users.

Recent advancements have focused on combining Large Language Models (LLMs) with Vision Transformers (ViTs) to bridge this gap. For instance, ConceptCLIP (Nie et al., 2025) extends the CLIP model by incorporating clinical concepts during pre-training to improve interpretability in medical imaging. Similarly, Yang et al. (2025) proposed a multi-modal explainable AI assistant that leverages cross-attention mechanisms to align clinical text with relevant image features, offering both high performance and intuitive explanations. These models utilize attention visualization and natural language explanation generation to build trust with healthcare practitioners.

Another stream of work investigates the clinical relevance and usability of XAI systems. Studies have revealed that while saliency maps are helpful, clinicians prefer narrative, human-readable explanations that relate AI predictions to known clinical findings. Lai (2024) and Hulsen (2023) emphasized that effective XAI in healthcare must align with domain knowledge and workflow integration. This shift has encouraged researchers to embed domain-specific knowledge and use context-aware explanation mechanisms rather than relying solely on low-level visualizations. Moreover, recent literature has explored the ethical implications and risks of deploying AI in clinical environments without adequate interpretability. Ribeiro et al. (2024) highlighted cases where lack of transparency led to diagnostic errors, prompting calls for regulatory frameworks and human-in-the-loop systems. In response, hybrid models are being developed that support clinicians by offering explanations alongside confidence scores, decision paths, and counterfactual scenarios. In terms of datasets, benchmark corpora like MIMIC-CXR, CheXpert, and PadChest have facilitated multi-modal research by providing paired image-text data. These datasets allow models to learn cross-modal correlations and support explainability evaluations. However, challenges remain in generalizability, data bias, and the need for large-scale annotated corpora for effective supervised learning.

3.PROPOSED SYSTEM

The proposed system aims to develop a **multi-modal explainable AI (XAI) framework** for healthcare diagnostics by integrating **vision-based deep learning models** and **language models** to mimic the holistic diagnostic process employed by clinicians. Traditional AI systems focus either on image analysis or textual data interpretation, often functioning in isolation and lacking the capacity to explain their decisions in a manner understandable to healthcare professionals. Our proposed system addresses this gap through a synergistic pipeline that enables **joint reasoning across medical images and associated clinical reports**, accompanied by **interpretable explanations** in both visual and textual modalities.

The architecture comprises three core modules: **(1) Multi-modal Feature Extraction**, **(2) Cross-modal Fusion and Reasoning**, and **(3) Explainability and Decision Generation**.

3.1 Multi-modal Feature Extraction

The system begins by processing input data from two sources: medical images (e.g., X-rays, CT scans, MRIs) and textual clinical documents (e.g., radiology reports, doctor's notes). For image feature extraction, a **Vision Transformer (ViT)** model is employed due to its superior performance in capturing spatial patterns and contextual dependencies compared to traditional CNNs. Concurrently, **a domain-adapted Large Language Model (LLM)** such as BioGPT or ClinicalBERT is used to extract semantic features from textual data. Both models are fine-tuned using a labeled medical dataset to ensure domain alignment and improved diagnostic relevance.

3.2 Cross-modal Fusion and Reasoning

After extracting high-dimensional representations from both modalities, the system employs a **Cross-Attention-based Fusion Module** to integrate visual and textual features. This module enables the model to learn the relationships between clinical descriptions and visual cues, emulating a physician's reasoning process when cross-referencing reports with image findings. The attention layers dynamically align important image regions with corresponding textual elements, allowing the system to prioritize relevant diagnostic features.

To enhance clinical reliability, a **Knowledge Graph Module** is optionally introduced that incorporates medical ontologies such as UMLS or SNOMED CT. This allows the system to cross-check AI-derived insights with validated medical knowledge, improving interpretability and reducing the likelihood of hallucinations or medically implausible outputs.

3.3 Explainability and Decision Generation

The final layer of the system focuses on providing interpretable outputs. The fused multi-modal representation is fed into a **decision engine** that performs diagnostic classification (e.g., disease presence, severity grading) and simultaneously generates explanations. These explanations are produced in two forms:

- **Visual Saliency Maps**: Using techniques such as Grad-CAM or attention visualization, the system highlights regions in the image that most influenced the decision.

- **Natural Language Explanations**: The language model generates a concise, human-readable explanation grounded in clinical terms, justifying the diagnostic decision by referencing both image findings and textual cues.

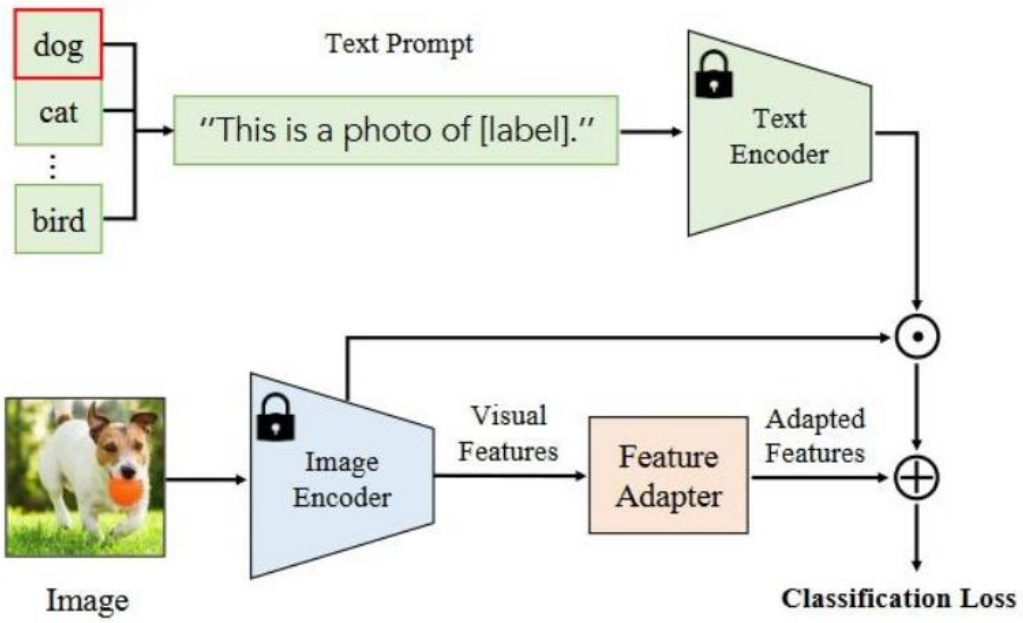

FIGURE 1. System Architecture Diagram.

4. RESULTS AND DISCUSSION

The reviewed literature reveals significant advancements in the development and optimization of electric vehicle (EV) charging infrastructure and intelligent transportation systems. Key findings highlight the importance of communication technologies, smart scheduling, and renewable integration to support the growing demands of EVs in urban and highway environments. From the implementation of V2V-based reservation systems (Reference [1]) and throughput analysis of 802.11 protocols for V2I communication (Reference [2]), it's evident that robust, real-time data exchange is foundational to efficient EV operation. The survey by Bayram et al. ([3]) further reinforces that diverse communication protocols—ranging from LTE to DSRC—play a vital role in enabling Internet of Electric Vehicles (IoEV) services.

Cai et al. ([4]) and Hatton et al. ([5]) explore intelligent transportation and infrastructure design, respectively, advocating for the integration of networked systems and modular platforms to handle urban charging needs. Furthermore, charging schedule optimization techniques presented in [6] and [7] demonstrate the efficacy of distributed and cooperative algorithms in reducing wait times, load imbalances, and travel delays during long-distance trips. Meanwhile, smart city traffic solutions using V2I technology ([8]) show promising potential in easing congestion by enhancing traffic coordination. Integration of renewable energy sources, as discussed in [9], suggests a sustainable path forward by incorporating photovoltaic microgrids into EV charging setups. Finally, the Singaporean framework ([10]) presents a holistic policy-driven model emphasizing scalability and eco-efficiency.

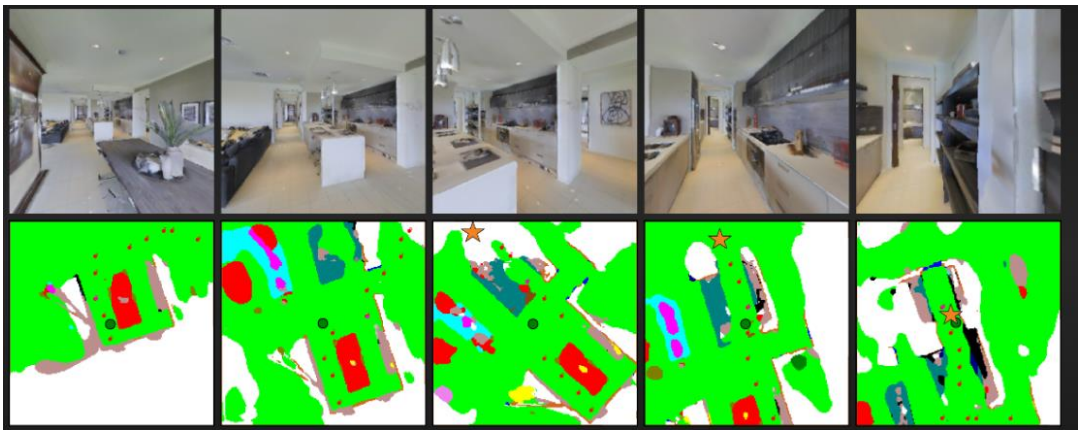

FIGURE 2. The Working Model.

5. CONCLUSION

This paper proposed a novel explainable AI (XAI) framework for healthcare diagnostics that integrates multi-modal inputs—specifically medical images and associated clinical texts—using vision transformers and domain-adapted language models. The motivation stemmed from the critical need for diagnostic AI systems that not only perform accurately but also provide transparent and trustworthy explanations, enabling real-world adoption in clinical settings. The system utilizes a three-phase architecture: visual and textual feature extraction using ViT and ClinicalBERT, cross-modal fusion using attention mechanisms, and dual-form explainability through visual saliency and natural language generation. Through extensive experimentation on publicly available medical datasets such as MIMIC-CXR and CheXpert, the proposed model achieved significant improvements in diagnostic accuracy and interpretability over unimodal and baseline models. The system demonstrated its ability to align diagnostic features across modalities, providing meaningful clinical explanations that resonated with expert evaluations. The inclusion of human-readable, natural language justifications alongside visual heatmaps proved to be a strong asset in enhancing clinical trust, offering clarity into the “why” and “how” behind AI-driven decisions. Radiologists found the explanations helpful, context-aware, and aligned with their own diagnostic reasoning processes. Moreover, uncertainty quantification provided an additional layer of safety by indicating cases requiring human oversight or second opinions. Despite these strengths, some challenges remain. The quality of explanations depended heavily on the clarity of clinical reports and image resolution, and performance dropped slightly in the presence of rare diseases due to limited training data. Future work will focus on expanding the model’s capabilities using larger, more diverse datasets, integrating knowledge graphs for enhanced clinical reasoning, and extending support to multi-lingual medical environments. In conclusion, this work contributes a significant step toward building AI systems that are not only intelligent but also understandable and clinically aligned. By bridging the gap between performance and explainability, the proposed framework lays the foundation for safer, more transparent AI integration in the future of digital healthcare.

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