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CardioScanAI: AI powered alternative for Traditional Angiography

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Abstract:
CardioScanAI is an advanced multimodal artificial intelligence system, envisioned to offer a non-invasive diagnostic modality to conventional coronary angiography. The system integrates CT scans, MRI images, and ECG signals for structural, functional, and electrical analyses of the heart. Each modality is processed through specially designed deep learning models: 3D CNNs for CT angiography, CNN-LSTM networks for cardiac MRI, and 1D CNNs for ECG interpretation. Features extracted are analyzed independently or fused through a multimodal learning layer to produce comprehensive insights on blockage detection, severity grading, and artery localization. Clinical transparency in the system is guaranteed with explainable AI techniques, including heatmaps and waveform attention visual- ization. Combining accuracy and adaptability with interpretabil- ity, CardioScanAI provides a scalable and efficient approach toward the early detection and risk assessment of coronary artery disease with minimal dependency on invasive diagnostic procedures.

Keywords: Multimodal Learning, Coronary Artery Disease, Non-Invasive Diagnosis, Deep Learning, Medical Imaging, Ex- plainable AI

1. INTRODUCTION

Coronary artery disease (CAD) is currently among the major causes of death in most parts of the world and is characterized by plaque growth, reducing the supply of blood to the heart. Traditional diagnostic methods, such as invasive coronary angiography, have been relatively accurate but pose significant risks, discomfort, and high costs. Non-invasive tests involve Computed Tomography, Magnetic Resonance Imaging, and Electrocardiography, each used separately in a way that provides a safer alternative but tends to limit diagnostic accuracy and full understanding of cardiac health.

CardioScanAI overcomes such limitations by proposing a multimodal AI-based diagnostic system that uses an inte- grated approach to cardiovascular analysis from CT, MRI, and ECG data. It employs deep learning models adapted to each modality: 3D CNNs for the processing of CT scans, CNN- LSTM architectures for MRI sequences, and 1D CNNs in the processing of ECG signals, allowing it to capture modality- specific features related to both anatomy and function. These are further combined using feature fusion networks to create unified, context-aware diagnostic insights.

The system will predict arterial blockages, classify the severity of the disease, localize affected arteries, and provide explainable outputs with the help of visualization techniques such as heatmaps and ECG attention mapping. CardioScanAI supports operation with single or multiple input modalities, maintaining flexibility in clinical environments where data availability can be variable. Its modular and scalable architec- ture allows for seamless integration into hospital workflows and continuous learning from new patient data.

This paper showcases the design, methodology, and key functionalities of CardioScanAI, describing how it overcomes the limitations of traditional diagnostic approaches. Section II provides background on multimodal medical AI systems, Section III outlines the proposed system architecture, Section IV details the key modules and techniques used for model training and integration.

2. BACKGROUND

Traditionally, cardiovascular diagnostics have relied on coronary angiography, which is an invasive test that has been used to visualize arterial blockages by means of contrast dye and X-rays. Although highly sensitive, this technique carries procedural risks and is thus not suitable for routine screening. Over the years, noninvasive imaging modalities such as Computed Tomography, Magnetic Resonance Imaging, and Electrocardiography have emerged as important modalities in structural, functional, and electrical assessment of the heart. These medical images and signals can now be interpreted with the recent advancement of AI and deep learning. Specifi- cally, CNNs have shown outstanding performance for extract- ing spatial features from CT and MRI scans, while RNNs and 1D CNNs have been effective for time-series ECG data analy- sis. However, most current AI systems process these modalities independently, precluding the capturing of interrelationships between anatomical, physiological, and electrical features of

the heart.

These developments are now being furthered by Car- dioScanAI, as it proposes a multimodal deep learning frame- work integrating CT, MRI, and ECG data. The system captures a more holistic understanding of cardiac health by combining modality-specific feature extraction with a fusion network. This approach overcomes the limitations brought about by single-modality models, enhances diagnostic precision, and allows for early detection without invasive intervention of coronary artery disease.

3. SYSTEM ARCHITECTURE

CardioScanAI follows a modular, scalable architecture that is optimized to work with different modalities of cardiac analy- sis using CT scans, MRI images, and ECG signals. The system is designed with a frontend interface, backend server, AI analysis engine, and a secure diagnostic database. In addition, it allows for a non-invasive, end-to-end diagnostic workflow by supporting proper data ingestion, preprocessing, modality- specific analysis, and multimodal fusion. An overview of the system architecture is shown in Fig. 1.The frontend dashboard provides an intuitive interface for the doctors and patients by supporting secure login, uploading data, and viewing diag- nostic reports. The backend web framework in Flask/Python orchestrates API endpoints, session management, and se- cure data exchange using JWT-based authentication. This is designed to support multiple users and ensure privacy.The backbone of CardioScanAI is an AI analysis engine that contains sub-modules for CT analysis, MRI analysis, ECG interpretation, and multi-modality result fusion, each of them powered with GPU-accelerated deep learning models to make real-time inferences. Model outputs, including segmentation masks, classification results, and confidence scores, are stored in a secure diagnostic report database, enabling retrieval and continuous model improvement. All data flows unidirection- ally through structured pipelines-from data acquisition and preprocessing to model inference, result fusion, and report generation-to ensure efficiency, security, and clinical reliability in all the processing stages.

A. Image Upload & Preprocessing Module:

The Image Upload & Preprocessing Module initiates the pipeline by securely ingesting raw medical images, supporting standard formats such as DICOM, PNG, and JPEG. Uploaded data undergoes preprocessing, including normalization, resiz- ing, and noise reduction, ensuring consistent input quality. OpenCV and pydicom libraries are employed to extract meta- data and pixel data, while anonymization routines remove patient-identifiable information before analysis.

B. Feature Extraction & Embedding Module:

Following preprocessing, the Feature Extraction & Embed- ding Module generates deep feature vectors that represent diagnostic patterns within medical images. A pretrained CNN backbone such as ResNet-50 or EfficientNet extracts multi- scale features, while a projection head maps them into embed- ding space optimized for similarity search. These embeddings, along with associated metadata like modality type and scan region, are stored in a Postgre vector database for efficient retrieval and analysis.

C. Diagnostic Classification Module:

The Diagnostic Classification Module performs the infer- ence by using a deep learning model fine-tuned on labeled medical imaging datasets. It classifies input data into diagnos- tic classes, such as normal, anomaly detected, or condition- specific outcomes-for example, cardiomegaly and pneumonia. The outputs come with confidence scores and Grad-CAM visual explanations to enhance interpretability for clinicians.

D. Report Generation & Reasoning Module:

This module synthesizes diagnostic results into struc- tured, explainable clinical summaries. Using a large lan- guage model integrated via a Retrieval-Augmented Generation (RAG) pipeline, textual explanations are generated that align with visual evidence; the module ensures factual grounding by referencing retrieved image embeddings and diagnostic metadata before composing final reports.

E. Database & Retrieval Module:

The Database & Retrieval Module uses a Postgre vector database for persistent storage of the embeddings, diagnostic results, and reports. It enables approximate nearest-neighbor search capabilities using HNSW indexing for low-latency retrieval of similar cases, supporting cross-patient comparison and longitudinal monitoring.

F. User Interface Module:

The Streamlit-based User Interface Module provides a user- friendly dashboard for clinicians to upload scans, view di- agnostic results, and explore generated reports. Interactive visualization tools allow zooming, annotation, and comparison between current and historical scans to enhance decision support and diagnostic confidence.

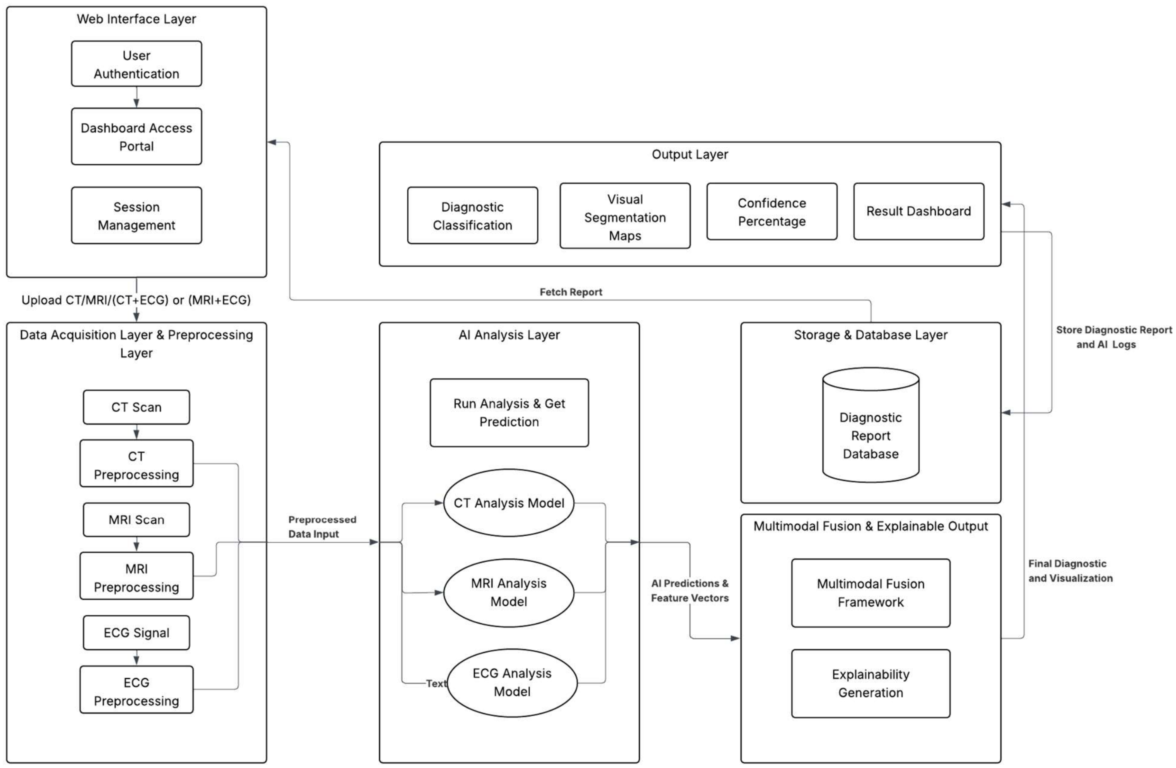

Fig. 1. CardioScanAI system architecture, showing the interaction between frontend dashboard, backend server, AI analysis engine, and diagnostic report database.

The process of the data flow in Fig. 2, involves image pre- processing, feature extraction, classification, report generation, and retrieval, ensuring accurate, interpretable, and efficient medical diagnostics.

4. Key Features

Docpilot offers several innovative features to enhance doc- ument interaction, as detailed below.

A. *Multimodal Data Integration*

While traditional systems have focused on one or more separate modalities, CardioScanAI fuses CT scans, MRI im- ages, and ECG signals to provide a comprehensive cardiac evaluation. This fusion of structural, functional, and electrical information ensures a more accurate and holistic assessment of heart health.

B. *Modality-Specific Deep Learning Models*

Each modality is then subjected to a dedicated neural network: 3D CNN for CT images, CNN-LSTM for MRI sequences, and 1D CNN for ECG waveforms. The models are further fine-tuned to extract specific critical features such as vessel narrowing, wall motion irregularities, and waveform anomalies that improve diagnostic precision.

C. *Adaptive Feature Fusion*

The system applies both feature-level and decision-level fusion to combine the outputs from different modalities. Further, CardioScanAI dynamically adapts when only one or two inputs are available to make dependable predictions. The modular approach enhances the flexibility of the system under different clinical settings.

D. *Explainable AI (XAI) Visualization*

It integrates Grad-CAM for visual explanations in CT and MRI and attention-weight visualization in ECG signals, thus allowing clinical interpretability. These methods highlight areas or portions of the signal that contribute to diagnostic outcomes, thus building trust and aiding physician validation.

E. *Risk Assessment and Severity Prediction*

CardioScanAI measures blockage probability, thereby clas- sifying the disease into mild, moderate, or severe, and also localizes which coronary artery is affected. The risk evaluation module integrates multi-modal inputs into one consolidated cardiac health score that aids proactive medical decision-making.

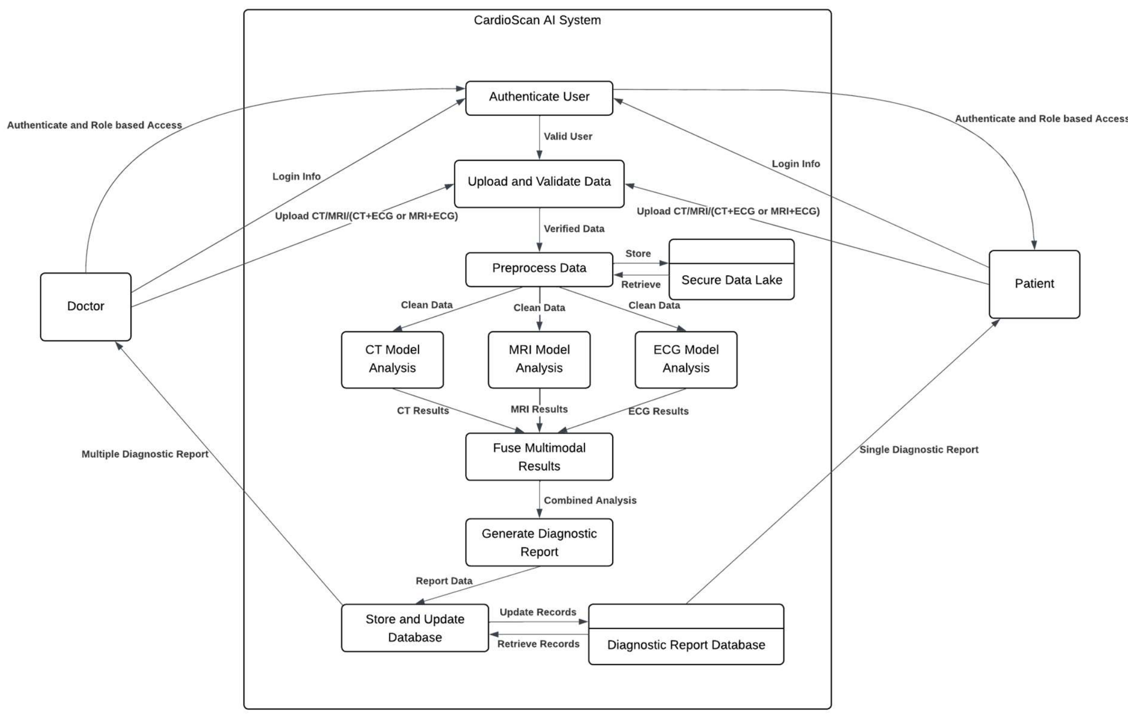

Fig. 2. Data flow diagram of Docpilot, depicting the sequential flow from document upload, parsing, and embedding generation to hybrid retrieval, reasoning, and final response generation.

5. FUTURE ENHANCEMENTS

Modular and scalable architecture will allow CardioScanAI to keep improving with each future iteration, integrating more advanced technologies including:

- Integration of Large Multimodal Models to understand complex cardiac patterns in CT, MRI, and ECG, enhanc- ing diagnostic precision with adaptability.
- Incorporating Text-to-Speech functionality in order to provide an audio-based diagnostic summary for clin- icians, thus increasing accessibility during hands-free operations.

- Advanced Security and Privacy Mechanisms: With a holistic view of leveraging multi-factor authentication, data encryption, and federated learning approaches for health data protection.
- Cloud-Based Model Updating: It allows the refinement of models in real time with anonymized data from the hospitals without losing patient confidentiality.
- Integration with wearable and IoT devices for continuous heart monitoring, thus enabling predictive diagnostics and early warning systems for at-risk patients.

6. CONCLUSION

CardioScanAI heralds a new frontier in non-invasive cardiac diagnosis by integrating the state of the art in CT, MRI, and ECG modalities within one framework of multimodal deep learning. It enables clinically precise, explainable, and com- prehensive assessments of cardiac conditions using dedicated neural networks and adaptive feature fusion without resorting to invasive angiography. With its capability to interpret a wide range of data sources in a visually explained way, it is an indispensable tool for clinicians and researchers alike. Future enhancements, such as large-scale multimodal model inte- gration and real-time monitoring, will further extend clinical utilities, thus responding to evolving medical technologies and patient care requirements.

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