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Research Paper

AI-Enabled Clinical Decision Support for Cardiac Event Prediction

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ABSTRACT *– cardiovascular diseases represent one of the leading causes of mortality worldwide, often developing silently until an acute cardiac event occurs. Conventional clinical diagnostic workflows rely heavily on manual electrocardiogram interpretation, intermittent clinical tests, and static statistical risk-factor scoring, which are slow, reactive, and prone to human error. This study proposes an AI-enabled clinical decision support system that integrates continuous ECG waveforms with patient history, demographics, laboratory parameters, and EHR data for early cardiac event prediction. Raw ECG signals undergo preprocessing—including noise filtering, baseline wander removal, and segmentation—paired with feature selection and cross-validated training to improve reliability. Deep learning models, combining Convolutional Neural Networks for spatial waveform feature extraction and Recurrent Neural Networks/LSTMs for temporal sequence analysis, detect subtle irregularities to predict myocardial infarction and arrhythmia risks. The system produces low, medium, and high-risk scores with real-time alerts, delivered through a Flask web interface featuring interactive ECG visualizations, trend dashboards, and encrypted EHR integration. Overall, the framework supports faster triage, reduces specialist workload, and enables proactive preventive cardiology.*

KEYWORDS*: — Cardiac Event Prediction, Electrocardiogram (ECG), Deep Learning, CNN-LSTM Architecture, Clinical Decision Support.*

INTRODUCTION

cardiovascular diseases remain a leading cause of global mortality and disability, often developing silently until an acute cardiac event occurs. Conventional diagnosis relies on manual ECG reading, clinical tests, and static risk scoring, which are slow, reactive, and prone to human error or specialist delays, especially in busy or remote healthcare settings. To overcome these challenges, this

project proposes an AI-enabled clinical decision support system combining ECG signals, patient history, demographics, and EHR data for early cardiac event prediction. Raw ECG signals undergo noise filtering, baseline wander removal, and segmentation, followed by feature selection and deep learning—using CNNs for spatial waveform features and RNNs/LSTMs for temporal sequence analysis—to detect subtle irregularities and predict arrhythmia and myocardial infarction risks. A Flask-based web application delivers real-time monitoring, interactive ECG views, trend dashboards, and low, medium, and high-risk alerts with EHR integration and data security. Ultimately, this framework supports clinicians, speeds up early intervention, and enables proactive preventive cardiac care

RELATED WORK

Research in cardiac diagnostics and cardiovascular risk assessment has shifted from manual ECG reading, clinical tests, and static risk models toward deep learning and multimodal health analytics. Prior studies show that ECG waveform features—such as P-waves, QRS complexes, and T-waves—carry early diagnostic cues, while Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs)/LSTMs effectively capture spatial waveform features and temporal rhythm sequences. Combining ECG signals with patient history, demographics, laboratory data, and Electronic Health Record (EHR) information further strengthens risk prediction, although limitations such as overfitting, limited dataset diversity, and weak hospital-system integration persist. Building on these efforts, this work integrates signal preprocessing, feature selection, hybrid CNN-LSTM modeling, and EHR integration within a real-time clinical decision support system to assist clinicians.

LITERATURE SURVEY

The literature survey highlights how deep learning and multimodal data analytics enhance cardiac event prediction compared to conventional, manual clinical diagnostics and static risk-factor scoring. While traditional methods—such as visual ECG reading, clinical investigations, and statistical risk models—rely heavily on specialist expertise and reactive evaluation, deep learning models including CNNs and RNNs/LSTMs effectively extract spatial waveform features and temporal patterns from ECG signals (P-waves, QRS complexes, and T-waves). Recent studies also combine ECG waveforms with patient history, demographics, laboratory tests, and Electronic Health Record (EHR) data to improve risk assessment, while addressing challenges such as overfitting, limited dataset diversity, and weak hospital-system integration.

Furthermore, integrating signal preprocessing, feature selection, real-time risk stratification, interactive dashboards, and encrypted EHR connectivity streamlines clinical decision support, enabling faster, proactive preventive cardiac care.

EXISTING METHOD

Traditional cardiac assessment relies on manual ECG reading (P-wave, QRS complex, T-wave review), clinical tests (echocardiograms, stress tests, blood tests, angiography), statistical risk models, and standalone ECG machines without predictive analytics. These approaches are slow, error-prone under fatigue or noise, and constrained by cardiologist shortages in remote areas. Statistical models also miss non-linear patterns in large datasets, while real-time monitoring and EHR integration remain limited. Overall, existing methods are largely reactive rather than predictive, delaying early intervention.

PROPOSED METHOD

The proposed system utilizes an intelligent AI-enabled clinical decision support framework combining continuous electrocardiogram (ECG) waveforms, patient medical history, demographics, laboratory parameters, and Electronic Health Record (EHR) data to predict cardiac events early. Raw ECG signals and clinical records are ingested, preprocessed through noise filtering, baseline wander removal, normalization, and beat segmentation, and balanced using techniques such as SMOTE alongside feature selection to reduce redundancy and overfitting. The core prediction engine applies deep learning models—using Convolutional Neural Networks (CNNs) to extract spatial waveform features and Recurrent Neural Networks (RNNs)/LSTMs to capture temporal rhythm dependencies—to identify subtle irregularities and forecast arrhythmia and myocardial infarction risks. An automated risk assessment module classifies patient risk into low, medium, and high levels with real-time alerts to support timely clinical decisions. Furthermore, a web-based interface built with Flask and front-end technologies delivers interactive ECG visualizations, trend dashboards, and encrypted EHR integration for scalable deployment across hospitals, clinics, and remote settings. Ultimately, this multimodal approach reduces diagnostic delays, assists clinicians, and establishes a proactive preventive cardiology workflow.

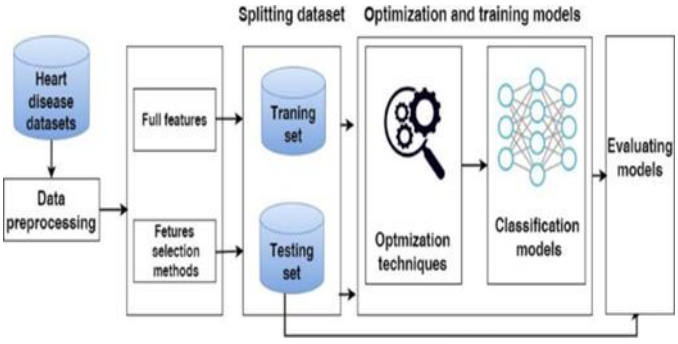

Fig. 1: Proposed Architecture of AI-Enabled Clinical Decision Support for Cardiac Event Prediction

METHODOLOGY DESCRIPTION

Data Ingestion and Clinical Integration Module: The Data Ingestion module collects continuous electrocardiogram (ECG) signals from public datasets (such as MIT-BIH Arrhythmia and PTB Diagnostic ECG) and hospital sources alongside patient medical history, demographics, laboratory parameters, cardiac imaging, and Electronic Health Record (EHR) data.

Data Preprocessing Module: The Data Preprocessing module cleans raw ECG signals and clinical data by handling missing values and outliers, applying noise filtering (for muscle and electrode artifacts), baseline wander removal, normalization, encoding, segmentation, augmentation, and SMOTE to address class imbalance.

Feature Extraction and Selection Module: The Feature Extraction and Selection module derives temporal (RR intervals, heart rate variability), spectral, and morphological (P-wave, QRS complex, T-wave) ECG features alongside clinical attributes, ranking features via correlation, chi-square, and mutual information while applying RFE, Lasso, and PCA to reduce redundancy.

Dataset Splitting and Validation Module: The Dataset Splitting module partitions preprocessed data into training, validation, and testing sets (such as 70:30 or 80:20 splits) using stratified sampling and k-fold cross-validation while preventing data leakage and supporting continuous retraining on updated clinical data.

Optimization and Regularization Module: The Optimization module tunes model hyperparameters using grid search, random search, and Bayesian optimization while applying L1/L2 regularization and adaptive learning controls to prevent overfitting and improve generalization.

Deep Learning and Classification Module: The Classification module trains and evaluates deep neural architectures—including Convolutional Neural Networks (CNNs) for spatial waveform feature extraction, Recurrent Neural Networks (RNNs)/LSTMs for temporal sequence modeling, and hybrid CNN-RNN models—alongside baseline classifiers such as Logistic Regression, Decision Tree, Random Forest, SVM, and Gradient Boosting to predict arrhythmias and myocardial infarction.

Risk Assessment and Alerting Module: The Risk Assessment module converts model outputs into actionable Low, Medium, and High risk scores and triggers real-time clinical alerts to support early, proactive intervention.

Web Application and API Controller Module: The Web Application Controller module, built with Python using Flask or Django REST APIs and WebSockets,

manages real-time data ingestion, preprocessing, feature extraction, model inference, EHR integration, logging, access control, and encryption.

User Interface and Visualization Module: The User Interface and Visualization module, built with HTML5, CSS3, JavaScript, and React.js or Angular, provides a responsive clinician dashboard displaying interactive ECG waveforms, risk-score trends, color-coded alerts, role-based access, and PDF or Excel report exports.

System Integration and Security Module: The System Integration module connects the data pipeline, deep learning models, Flask/Django back-end, EHR systems, and front-end dashboard into a scalable cloud-ready workflow with encryption, access control, and HIPAA/GDPR privacy compliance.

RESULTS AND DISCUSSION



Figure 2: User Registration Page of the AI-Enabled Clinical Decision Support System

Figure 2 shows the Sign Up page, where authorized clinicians create an account with a username and password before accessing patient data and cardiac risk predictions.



Figure 3: Home Page of the AI-Enabled Clinical Decision Support System

Figure 3 shows the home page displayed after sign-in, with options to start cardiac risk detection or sign out.

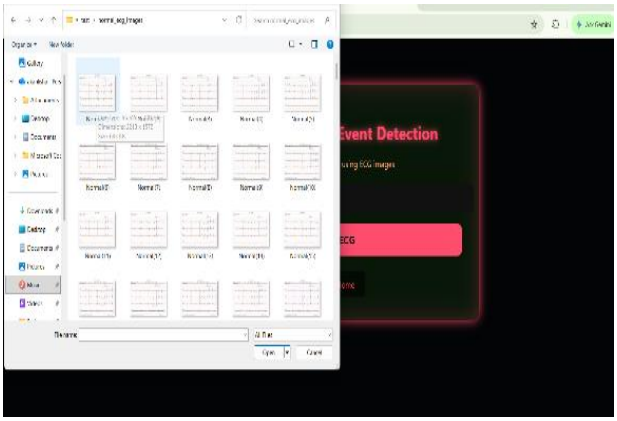

Figure 4: ECG Image Upload Screen of the AI-Enabled Clinical Decision Support System

Figure 4 shows the detection page, where the user selects an ECG image from the device for cardiac event analysis.

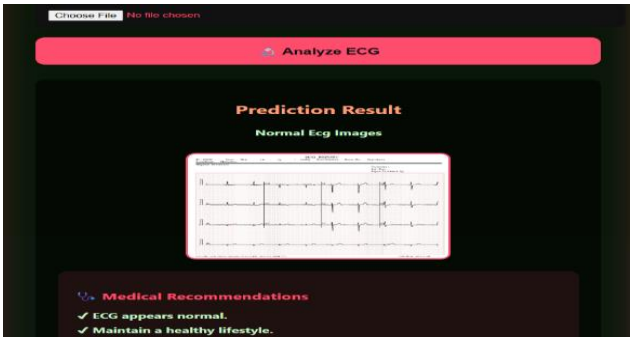

Figure 5: Prediction Result Screen of the AI-Enabled Clinical Decision Support System

Figure 5 shows the analysis output, where the uploaded ECG is classified as normal and the system displays medical recommendations.

CONCLUSION

The project provides a comprehensive clinical decision support framework for early cardiac event prediction by combining continuous electrocardiogram (ECG) signals, patient medical history, demographics, laboratory data, and Electronic Health Record (EHR) integration with machine learning and deep learning models. By pairing signal preprocessing, feature selection, and cross-validated training with hybrid CNN and RNN/LSTM architectures, real-time low, medium, and high risk scoring, and an interactive web dashboard, the system helps identify subtle electrophysiological anomalies before critical events occur. Furthermore, automated alerts, EHR connectivity, encryption, and privacy compliance reduce reliance on specialist cardiologists, speed up clinical intervention, and establish a scalable foundation for proactive cardiac care.

FUTURE SCOPE

Future developments will expand multimodal data integration by incorporating wearable devices, continuous blood pressure, and oxygen saturation alongside natural language processing of clinical notes and cardiac imaging links. Incorporating transformer-based models, ensemble learning, continual learning, and Explainable AI will further strengthen predictive reliability and clinical transparency. Additionally, enhancing alert prioritization, mobile and telemedicine integration, population-level analytics, and blockchain-based audit trails will scale the platform across hospitals, clinics, and remote care environments.

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