

ABSTRACT

Cardiovascular diseases remain one of the leading causes of global mortality, necessitating the development of robust and intelligent diagnostic systems. Electrocardiogram (ECG) signals, long utilized for monitoring heart function, are now being revolutionized by the integration of Artificial Intelligence (AI). This project proposes a comprehensive AI-powered ECG signal analysis system, designed to enhance the capabilities of cardiac biosensors for both anomaly detection and predictive modeling.

The objectives include the early identification of irregular cardiac patterns and the forecasting of ECG signal trends to assist clinicians in proactive decision-making. The methodology involves the use of the MIT-BIH Arrhythmia Database, a widely recognized dataset that offers a diverse range of ECG signals annotated for various cardiac conditions. Preprocessing steps such as noise filtering, signal segmentation, and normalization prepare the data for machine learning.

For anomaly detection, the study employs two approaches: autoencoders and k-means clustering. Autoencoders reconstruct normal ECG patterns, allowing deviations to be identified as anomalies, while k-means clustering segments the data into normal and abnormal clusters through unsupervised learning. Predictive modeling is achieved through Random Forest Regressors and Long Short Term Memory (LSTM) networks. The Random Forest model captures complex interactions in ECG features, whereas LSTM excels in learning temporal dependencies. These models are evaluated using appropriate metrics: Area Under the Curve (AUC), precision, recall, and F1-score for anomaly detection, and Mean Squared Error (MSE) and R-squared (R^2) for predictive modeling.

The autoencoder achieved an AUC of 100% in anomaly detection, and the Random Forest regressor obtained an R^2 score of 0.976, demonstrating high accuracy and effectiveness. The outcomes of this project underscore the potential of AI-integrated ECG biosensors in real-time, smart healthcare diagnostics. With high-performance models, the system ensures reliable anomaly detection and accurate ECG prediction, paving the way for personalized and scalable solutions in cardiac health monitoring.

The fusion of traditional ECG technology with advanced AI models highlights a transformative shift in biomedical engineering, focusing on preventive care and early intervention

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