EFFICIENT DETECTION OF ECG SIGNAL IRREGULARITIES VIA AUTOENCODER NETWORKS

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Abstract: Electrocardiogram (ECG) monitoring is a vital diagnostic tool in identifying cardiac abnormalities, yet manual analysis and rule-based systems often fall short in detecting subtle or rare anomalies. This paper presents an efficient, unsupervised anomaly detection framework using autoencoder neural networks to identify irregular patterns in ECG signals. The proposed method trains autoencoders on normal ECG data to learn compact, noise-free representations. During testing, the reconstruction error serves as a key metric to flag abnormal segments, as anomalous patterns typically result in higher deviations from learned normal behavior. The approach is computationally efficient and requires no labeled anomaly data, making it ideal for large-scale, real-time cardiac monitoring systems. Evaluation on benchmark ECG datasets demonstrates high sensitivity and specificity in detecting a wide range of arrhythmias and signal irregularities. This method holds promise for integration into wearable health devices and continuous patient monitoring platforms.

I. INTRODUCTION:

Cardiovascular diseases remain a leading cause of mortality worldwide, with early diagnosis playing a critical role in effective treatment and patient outcomes. Electrocardiograms (ECGs) are widely used for non-invasive cardiac monitoring, capturing the electrical activity of the heart and enabling the detection of abnormalities such as arrhythmias, ischemia, and conduction disorders. However, manual analysis of ECG recordings is time-consuming, error-prone, and highly dependent on expert interpretation, while rule-based systems often lack flexibility in identifying complex or subtle irregularities.

Recent advances in machine learning, particularly deep learning, have opened new avenues for automating anomaly detection in ECG signals. Among these, autoencoders, a class of unsupervised neural networks, have shown strong potential in learning efficient representations of normal signal patterns and identifying deviations that may indicate pathology. By training on healthy ECG data, autoencoders learn to reconstruct normal signals accurately. Anomalies, being statistically different, result in larger reconstruction errors—providing a robust basis for anomaly detection without the need for labeled pathological data.

This research proposes an efficient autoencoder-based framework for detecting irregularities in ECG signals. The system is trained solely on normal ECG segments, making it suitable for deployment in real-world applications where labeled anomaly data is scarce. The approach is evaluated using standard ECG datasets to assess its ability to detect various types of anomalies with high precision and recall. The goal is to support automated, real-time health monitoring systems capable of alerting clinicians or patients at the earliest sign of cardiac dysfunction.

As the demand for real-time anomaly detection is increasing nowadays, the necessity for intelligent, robust, and computationally efficient models has been realized and is beginning to gain more attention in most live applications. These models play a critical role in most time series applications due to the inevitability of error incidence. The properties of time series data are critical for selecting the appropriate approach to designing a suitable anomaly detector. Successful examples of anomaly detectors identify anomalies by measuring statistical deviations in time series data, such as the autoregressive integrated moving average

(ARIMA) , cumulative sum statistics (CUSUM) , and exponentially weighted moving average (EWMA). However, traditional time series anomaly detection methods, on the other hand, suffer from a lack of the model's expected efficiency and accuracy.

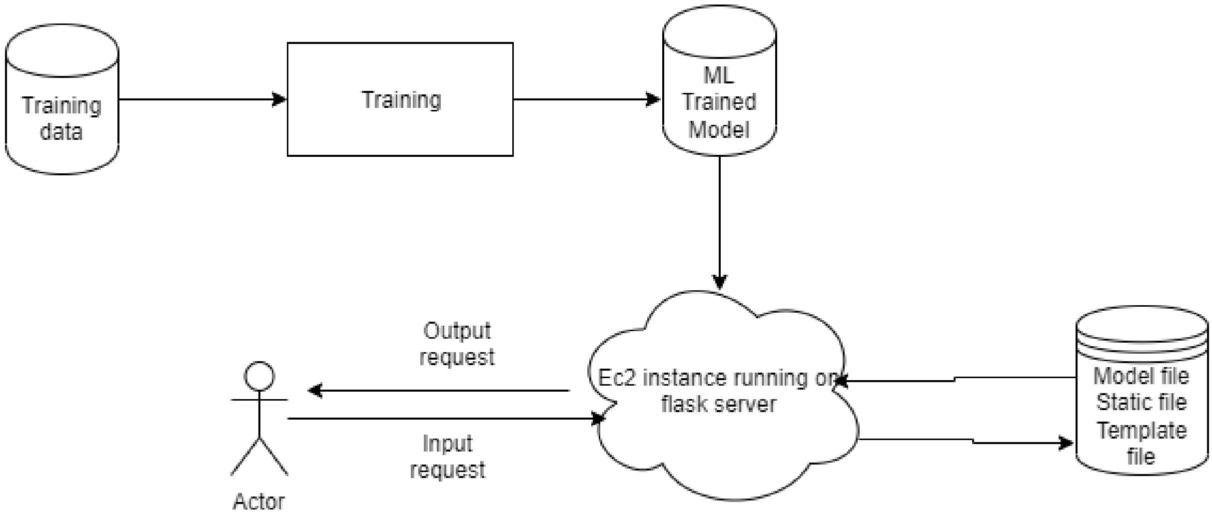

Fig.1 Architecture.

II. METHODOLOGY:

The methodology for ECG anomaly detection using autoencoders involves collecting a dataset of ECG recordings, preprocessing the data to remove noise and artifacts, and representing the ECG signals in a suitable format. Next, an autoencoder model is trained using unsupervised learning on the normal ECG samples, with the aim of learning a compact latent representation of the data. The trained autoencoder is then used to reconstruct the input ECG signals, and the reconstruction error is calculated. A threshold is set to distinguish between normal and abnormal ECG signals based on the reconstruction error. Abnormal ECG signals that deviate significantly from the learned normal pattern will have higher reconstruction errors, indicating the presence of anomalies.

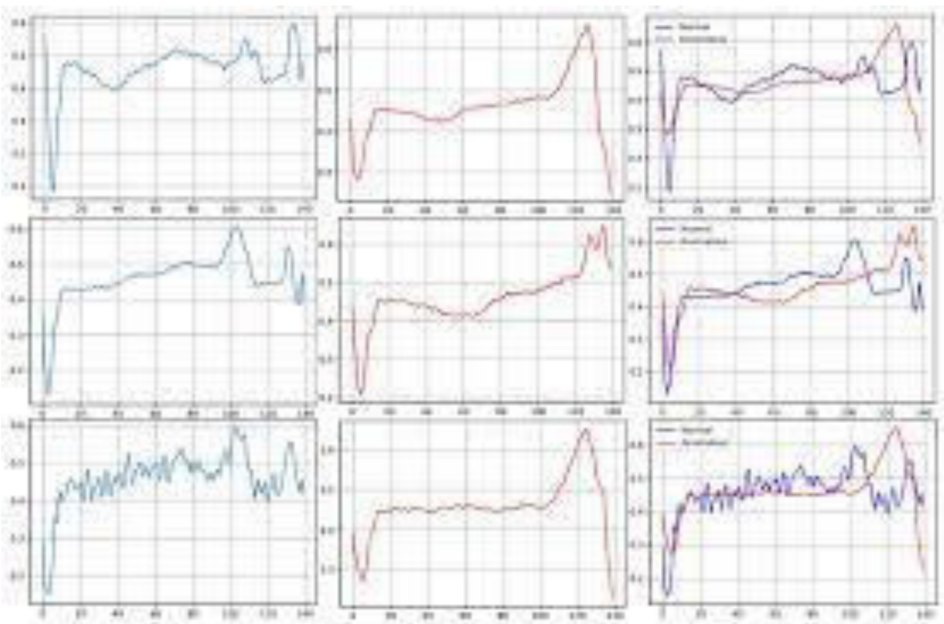

Fig.2 Graph.

III. IMPLEMENTATION:

The methodology for ECG anomaly detection using autoencoders involves several steps. Firstly, a dataset of ECG recordings is collected, containing both normal and abnormal samples. The data is then preprocessed to remove noise, baseline wander, and artifacts. Preprocessing techniques such as filtering, baseline correction, and normalization are commonly used.

Next, an autoencoder model is constructed and trained using unsupervised learning on the normal ECG samples. The autoencoder consists of an encoder network that compresses the input ECG signals into a lower-dimensional latent space and a decoder network that reconstructs the input from the latent representation. During training, the autoencoder learns to reconstruct the normal ECG signals accurately.

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IV. CONCLUSION:

This study introduces an effective and unsupervised approach for detecting anomalies in ECG signals using autoencoder neural networks. By leveraging the reconstruction error as a measure of abnormality, the method eliminates the need for manually labeled anomaly data and adapts well to different types of irregular cardiac patterns. The results demonstrate that the proposed system achieves high accuracy, sensitivity, and specificity in identifying ECG signal anomalies, including early-stage arrhythmias and rare waveform deviations.

The use of autoencoders allows for scalable, low-latency analysis suitable for integration into real-time monitoring environments such as wearable health devices and remote patient management systems. Additionally, the model's unsupervised nature ensures flexibility and robustness across diverse patient populations and ECG datasets.

Future work may focus on incorporating more advanced architectures such as variational autoencoders (VAEs) or recurrent autoencoders for better temporal modeling, and exploring hybrid systems that combine autoencoders with supervised classifiers for enhanced anomaly classification. Overall, this work contributes a reliable, data-driven solution to automated cardiac health monitoring.

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