DETECTING ECG ANOMALIES WITH AUTOENCODERS: A NOVEL APPROACH

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Abstract: Massive amounts of electronic health records, including data on vital signs and electrocardiograms (ECGs), are now accessible due to the big data revolution. These signals are now more easily obtained and are frequently captured as a time series of observations. There is a particular need to provide innovative methods that enable efficient monitoring of these signals and prompt anomaly detection given the proliferation of smart devices with ECG capabilities. However, anomaly identification is still a very difficult task because the majority of created data is not yet categorized.

Deep generative models have been used for unsupervised representation learning to develop expressive feature representations of sequences, which can improve the accuracy and ease of use of downstream tasks like anomaly detection. We suggest utilizing an autoencoder to learn representations of ECG sequences in an unsupervised manner. Then, we apply several detection algorithms to identify anomalies based on the learnt representations. We evaluated our method using the UCR time series classification archive's ECG5000 electrocardiogram dataset. Our findings demonstrate that the suggested strategy outperforms previous supervised and unsupervised techniques in identifying anomalies and learning expressive representations of ECG sequences.

keywords: cardiac arrhythmia, machine learning, time series data, signal processing, and electrocardiogram

I. INTRODUCTION:

The detection of anomalies is important to many contemporary applications and continues to be of paramount importance with the explosion of sensor use Anomaly detection in electrocardiogram (ECG) time series data has recently received considerable attention due to its impact on controlling the quality of ECG time series processes and identifying abnormal data source behavior. The process of anomaly detection in time series data involves the use of complicated algorithms and models to detect anomalous data within a selected period. An effective anomaly detector can recognize the contrasts between normal and anomalous time series data.

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.

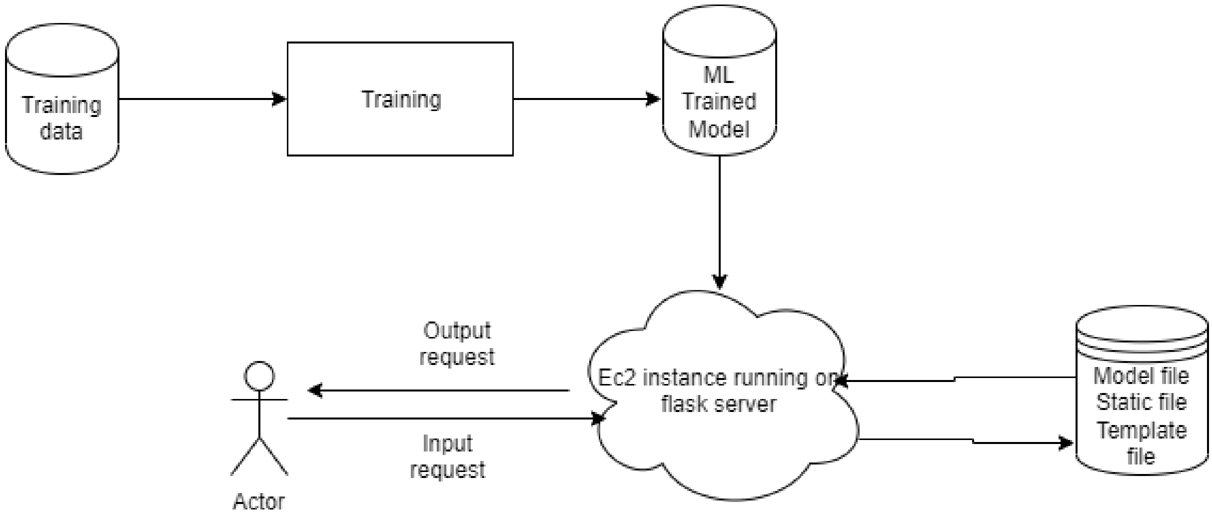

Fig.1 Architecture.

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.

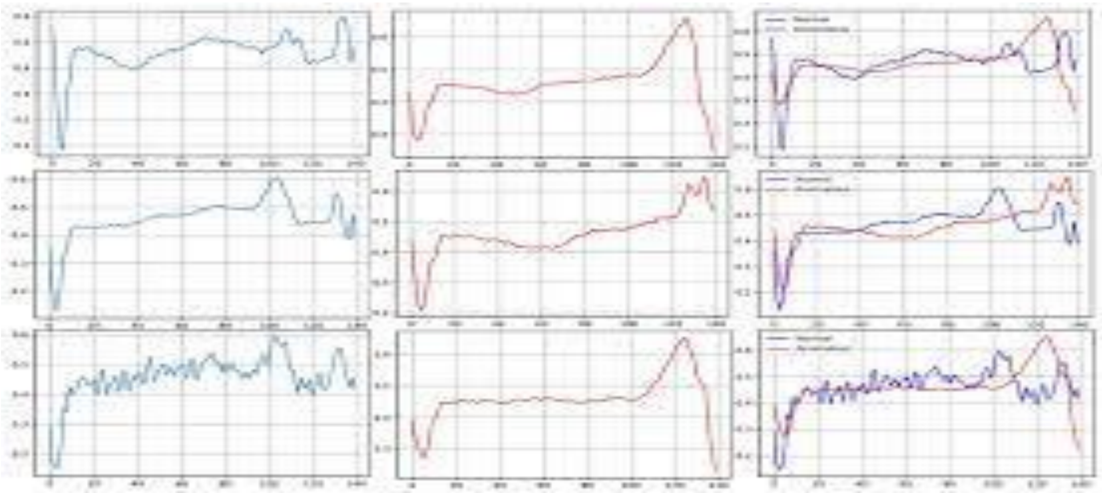

Fig.2 Graph.

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. FUTURE SCOPE:

The future scope for ECG anomaly detection using autoencoders holds great potential for further advancements. One direction is the exploration of hybrid models that combine autoencoders with other deep learning architectures, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), to leverage their respective strengths in capturing spatial and temporal dependencies in ECG signals. Additionally, the integration of transfer learning techniques can be explored to improve the performance of autoencoders by leveraging pre-trained models on large-scale ECG datasets

V. CONCLUSION:

Autoencoder-based ECG anomaly identification offers a useful and efficient method for locating anomalous patterns in ECG data. Autoencoders are able to identify variations that may indicate anomalies because they are able to learn a compact representation of normal ECG signals through the use of unsupervised learning. This technology is useful for unsupervised anomaly detection since it has the benefit of not requiring explicit labels or prior knowledge of anomalous patterns.

VI. REFERENCES:

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