Research paper Journal Volume 11, Iss 09, 2022

ECG ANOMALY DETECTION USING AUTOENCODERS

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ABSTRACT: *While the big data revolution takes place, large amounts of electronic health records, such as electrocardiograms (ECGs) and vital signs data, have become available. These signals are often recorded as a time series of observations and are now easier to obtain. In particular, with the rise of smart devices that can perform ECG, there is the quest for developing novel approaches that allow monitoring these signals efficiently, and quickly detect anomalies. However, since most data generated remains unlabeled, the task of anomaly detection is still very challenging.*

Unsupervised representation learning using deep generative models has been used to learn expressive feature representations of sequences that can make downstream tasks, such as anomaly detection, easier to execute and more accurate. We propose an approach for unsupervised representation learning of ECG sequences using an autoencoder and use the learned representations for anomaly detection using multiple detection strategies. We tested our approach on the ECG5000 electrocardiogram dataset of the UCR time series classification archive. Our results show that the proposed approach is able to learn expressive representations of ECG sequences, and to detect anomalies with scores that outperform other both supervised and unsupervised methods.

keywords *– ECG(Electrocardiogram), Machine Learning,Time series data , Signal Processing, Cardiac arrhythmia.*

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.

ISSN PRINT 2319 1775 Online 2320 7876

 Journal Volume 11, Iss 09, 2022

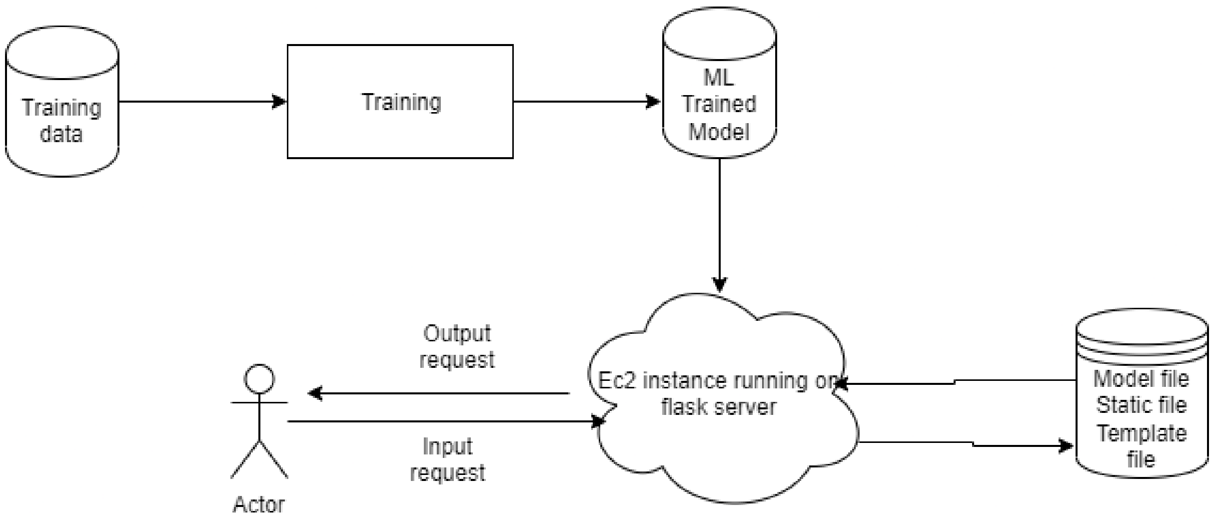

Fig.1 Architecture.

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.

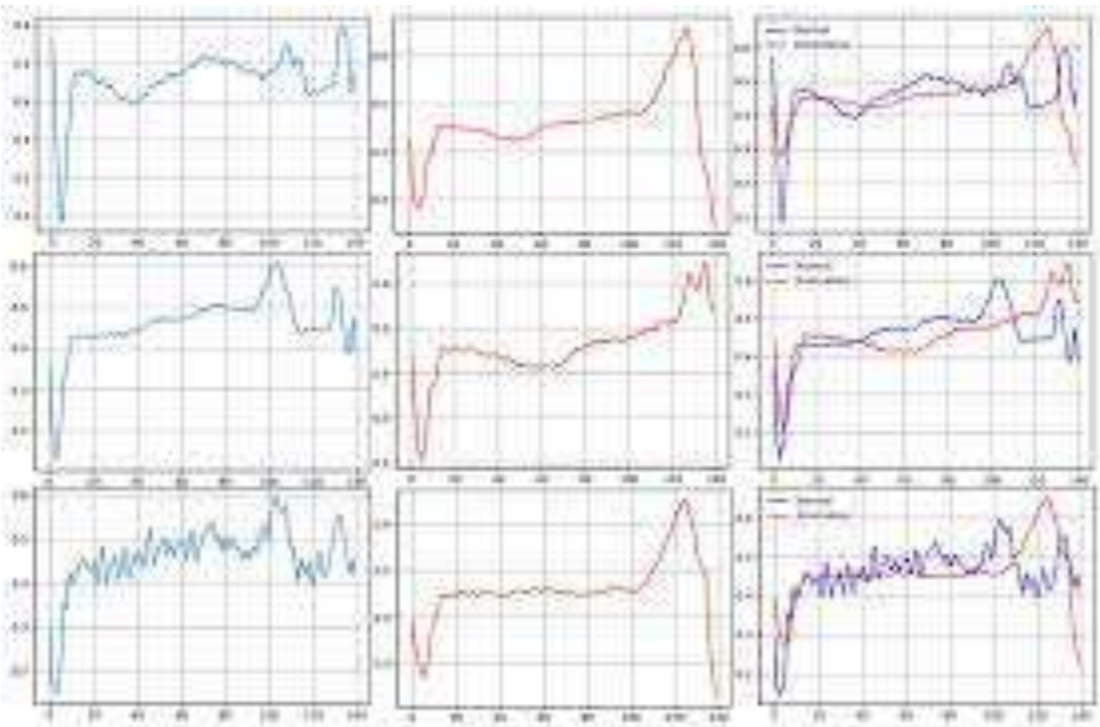

Fig.2 Graph.

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:

ECG anomaly detection using autoencoders presents a valuable and effective approach for identifying abnormal patterns in electrocardiogram data. By leveraging unsupervised learning, autoencoders learn a compact representation of normal ECG signals, enabling them to detect deviations indicative of anomalies. This methodology offers the advantage of not requiring explicit labels or prior knowledge of abnormal patterns, making it suitable for unsupervised anomaly detection.

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 Journal Volume 11, Iss 09, 2022

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