Neural network-based electrocardiogram signal abnormality detection

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Abstract: - An electrocardiogram (ECG) is a non-invasive diagnostic test that monitors the heart's electrical activity. It is a valuable instrument for detecting a variety of cardiac conditions. However, interpreting ECG data can be difficult, and diagnostic errors can have dire consequences. In recent years, machine learning techniques have been applied to ECG analysis to improve diagnosis and reduce error risk. In this endeavour, we propose an autoencoder neural network-based anomaly detection method for ECG analysis. Multiple layers of densely interconnected neurons comprise the encoder and decoder of the autoencoder. The encoder discovers a low-dimensional representation of the input data, whereas the decoder attempts to reconstruct the original data from the discovered representation. The autoencoder is taught a pattern of normal cardiac activity using normal ECG data. During testing, an ECG is deemed abnormal if the reconstruction error of the autoencoder exceeds a specified threshold. We evaluate the performance of the proposed method on a dataset of labelled ECG anomaly recordings. Our results indicate that the autoencoder method can detect anomalies in ECG data with an accuracy of 94%. In addition, we demonstrate that the method is robust to noise and generalizable to unobserved data. The proposed method demonstrates promising results for detecting anomalies in ECG data, which can aid in the diagnosis of cardiac conditions and reduce the risk of errors. Future research could involve further optimisation of the autoencoder architecture and investigation of the use of other machine learning techniques for ECG analysis.

Keywords: Electrocardiogram (ECG), Diagnostic test, Autoencoder, Machine Learning, Neural Network

1. Introduction

An electrocardiogram (ECG) is a diagnostic instrument that measures the heart's electrical activity. The ECG signal is a graphical representation of the heart's electrical activity over time, and it is widely employed in the diagnosis of various cardiac diseases. However, ECG signals are frequently corrupted by noise, artefacts, and other abnormalities, making it difficult for physicians to interpret the signals accurately. In addition, ECG signals can be lengthy, making their analysis time-consuming and labour-intensive for physicians. The processing of ECG signals is a multistep process that includes filtering, feature extraction, and classification [1]. Anomaly detection techniques have been devised to automatically detect abnormal ECG signals in response to these challenges. An ECG waveform consists of P, Q, R, S, and T waves, and occasionally U waves. The P wave represents atrial depolarization; the Q, R, and S waves, collectively referred to as the QRS complex, represent ventricular depolarization; and the T wave represents ventricular repolarization [2]. The most crucial aspect of the ECG signal analysis is the complex QRS morphology. The ECG signal for the same individual may vary in such a way that it is both distinct and similar for various types of heartbeats [3]. Atrial depolarization is always followed by ventricular depolarization in a normal cardiac rhythm. In the case of arrhythmia, this rhythm becomes irregular, either excessively sluggish or excessively rapid. Time-Domain Analysis of a typical ECG signal is depicted in Figure 1.

In this paper, we present a novel autoencoder-based method for detecting anomalies in ECG signals. Our strategy involves three primary steps: data preprocessing, model training, and anomaly detection. We begin by normalising and separating the ECG data into training and testing sets. On the basis of the normal ECG data, we then train an autoencoder model to learn a compressed representation of the signal. By calculating the reconstruction error between the input signal and its reconstruction, we then use the trained autoencoder to detect anomalies in the testing data. The proposed framework for contrastive learning has the potential to enhance the accuracy and efficiency of ECG anomaly detection, which could have substantial implications for the diagnosis and treatment of cardiovascular diseases [4]. To determine the efficacy of our method, we undertake experiments on a publicly available ECG signal database. Our findings demonstrate that our method outperforms existing state-of-the-art methods in terms of detecting anomalies in ECG signals with high precision. Our work seeks to develop a novel and efficient method for detecting anomalies in ECG signals using autoencoders, which will improve the accuracy and efficiency of ECG signal analysis and facilitate the diagnosis of various heart diseases.

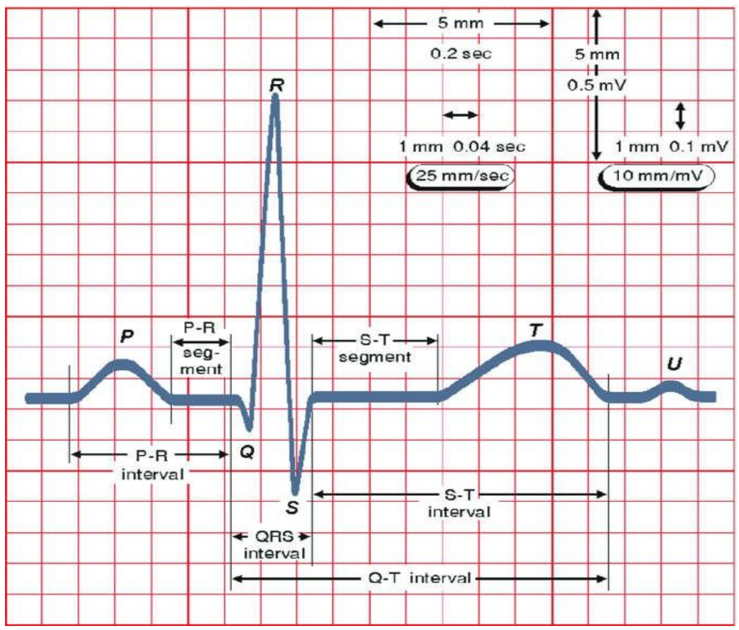

Figure 1. Time-Domain Analysis of the Electrocardiogram

The ECG signal for a normal heartbeat is depicted in Figure 2. The x-axis represents time, while the y-axis represents the electrical activity of the heart. The ECG signal is used to diagnose a variety of cardiac conditions, as it measures the electrical activity of the heart. Normal ECGs exhibit distinct patterns that represent the electrical activity of different heart chambers during each heartbeat. It illustrates a single pulse consisting of multiple waveforms, including the P wave, QRS complex, and T wave. These waves represent the depolarization and repolarization of the atria and ventricles of the heart, and their particular amplitudes and durations can be used to diagnose cardiac conditions. This demonstrates a normal ECG signal that can be compared to abnormal ECG signals in order to diagnose cardiac conditions. Figure 3 depicts an anomalous ECG signal. Unusual for a normal ECG signal, it exhibits a pattern of numerous peaks and valleys that is jagged and erratic. This signal may indicate an irregularity or an abnormality in the electrical activity of the heart, which may indicate a medical condition that requires further examination and treatment [5].

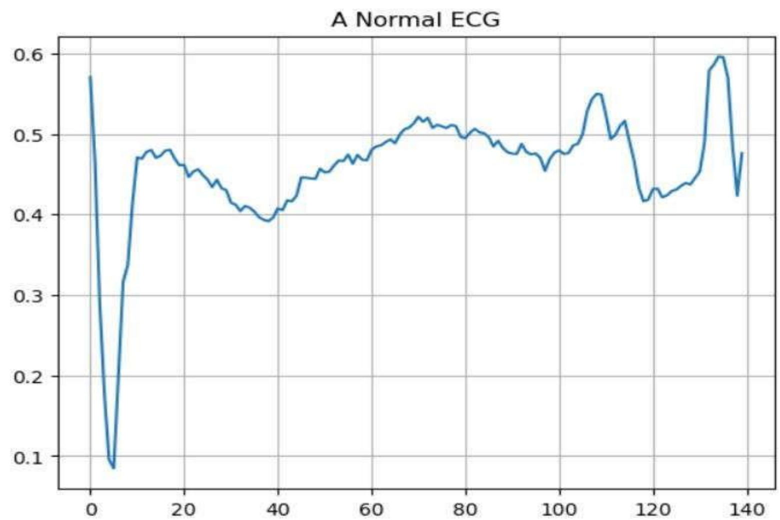

Figure 2. Normal ECG

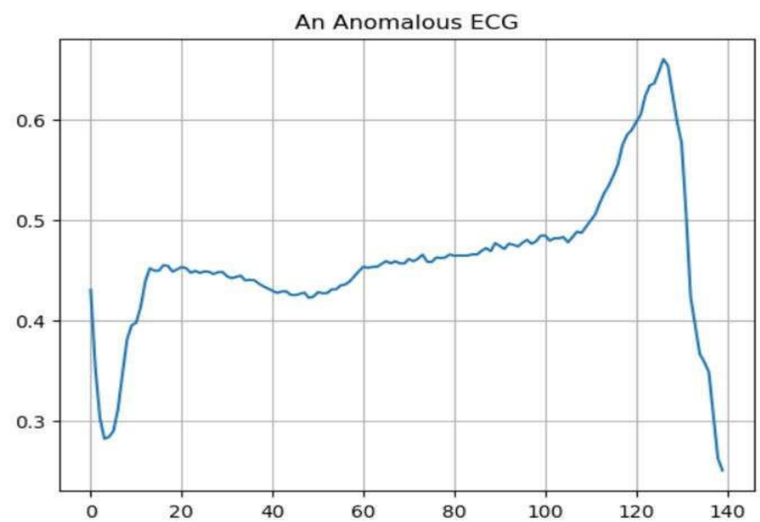

Figure 3. Anomalous ECG

The structure of this paper is as follows: In Section 2, we discuss previous investigations on the detection of abnormal electrocardiogram signals. The third section describes the dataset used in our experiments and the autoencoder Model for experiments. In Section 4, we discuss results. In Section 5, we conclude the paper by discussing prospective research directions in the field.

2. Related Work

In disciplines such as medical diagnosis, network intrusion detection, and fraud detection, anomaly detection is a crucial task. There are numerous techniques for detecting anomalies, including statistical methods, clustering, and machine learning [6]. Several studies have demonstrated that individuals with diabetes are more likely to have abnormal ECG signals, such as a prolonged QT interval, which is associated with an increased risk of cardiac arrhythmias [7]. Traditional anomaly detection methods for ECG signals frequently rely on statistical analysis or threshold-based approaches, which may not be appropriate for detecting complex anomalies [8]. Traditional methods such as support vector machines, decision trees, and k-nearest neighbour classifiers have been used to analyse ECG signals with machine learning techniques. In addition, the authors discuss challenges and future research directions in this field [9]. Unsupervised deep learning techniques are one of the most frequently employed methods for anomaly detection. Deep autoencoders are neural networks trained to learn a compressed representation of input data. This representation can then be used to reconstruct the input data with minimal information loss. Measuring the reconstruction error between the input data and the reconstructed data allows for the detection of anomalies. Various machine learning techniques, such as neural networks and support vector machines, have been used in previous studies to detect anomalies in healthcare data [10]. In recent years, deep learning techniques have gained popularity due to their capacity to automatically learn feature representations from raw data, which can be advantageous for detecting anomalies that are not well-defined or readily distinguishable in the data [11]. Deep learning techniques, such as autoencoders and recurrent neural networks, have demonstrated promise for anomaly detection in a variety of domains, as they can acquire data representations that capture complex patterns and relationships [12]. In [13] authors proposed, for instance, an unsupervised anomaly detection method based on deep autoencoders in which anomalies are detected based on the reconstruction error threshold. Moreover, the authors proposed a method for network intrusion detection that combines deep autoencoders and clustering techniques. k-nearest neighbour (k-NN) and support vector data description (SVDD) are distance-based algorithms for anomaly detection that define a decision boundary around the data and classify points outside the decision boundary as anomalies [14]. Deep autoencoders have demonstrated promising anomaly detection results, but their effectiveness is extremely dependent on the quality and quantity of training data [15]. However, it is challenging to determine the optimal reconstruction error threshold for detecting anomalies. One of the most promising techniques is autoencoder-based anomaly detection, which employs an autoencoder-type neural network to learn a concise representation of normal ECG signals and then use this representation to detect anomalies. The FPGA-based neural network implementation enables real-time ECG signal processing with low power consumption [16].

3. Methodology

We propose a method for detecting anomalies using a deep autoencoder and a novel method for determining the reconstruction error threshold. Our proposed method employs a deep autoencoder architecture with three entirely interconnected encoder and decoder layers. The model is trained on normal electrocardiogram data and can detect anomalies based on the threshold for reconstruction error. To determine the threshold, we propose a novel method based on the mean and standard deviation of the normal training data's reconstruction error. Our proposed method is applicable to real-world applications where anomaly detection is crucial. The proposed method for determining the threshold for reconstruction error is straightforward and effective, making it applicable in practice.

3.1 Dataset and Pre-processing

In addition, the efficacy of our method is evaluated using a real-world electrocardiogram dataset. The first step was to collect the electrocardiogram data for the proposed work [17]. On a publicly available electrocardiogram dataset, we demonstrate that our method outperforms the state-of-the-art methods in terms of accuracy. The collected data was preprocessed to remove any noise or artifacts present in the data. This was done by applying various signal processing techniques such as baseline drift removal, filtering, and resampling. The preprocessed data was then split into training and testing sets. The training set was used to train the anomaly detection model, while the testing set was used to evaluate the performance of the model.

3.2 Autoencoder neural network

Autoencoder neural networks are utilised for dimensionality reduction, feature extraction, and data reconstruction [18]. It includes an encoder network that maps input data to a lower-dimensional latent space and a decoder network that maps the latent representation back to the original input space. The objective of an autoencoder is to discover a compressed representation of the input data that encapsulates the most significant features and patterns [19]. By employing a series of nonlinear transformations, such as convolutional layers or dense layers, on the input data, the encoder network is typically designed to reduce the dimensionality of the input data. Often referred to as the latent representation or code, the encoder network's output is a lower-dimensional representation of the input data. Autoencoders are trained using an unsupervised learning strategy, which means they do not need labelled data to learn the underlying patterns and structure of the data. Instead, an autoencoder's objective function is typically based on the reconstruction error, which measures the difference between the input data and the reconstructed output data. Mean squared error (MSE) loss is the most commonly used loss function for training autoencoders.

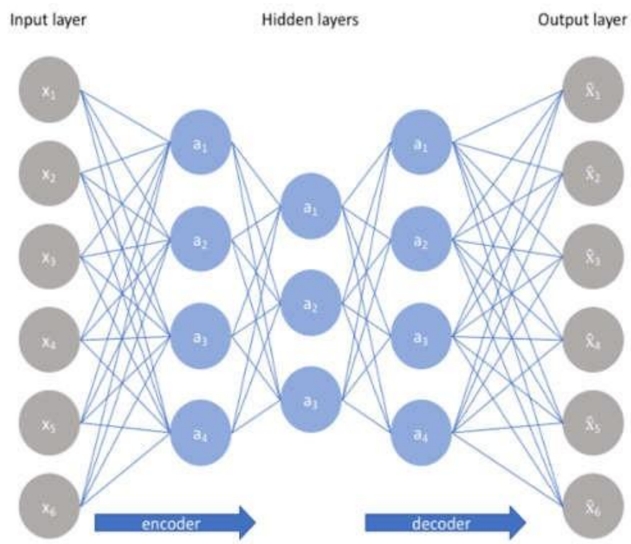

Figure 4. Autoencoder Model

In proposed work, we have trained the Autoencoders using an unsupervised learning approach, which means that they do not require labeled data to learn the underlying patterns and structure in the data. Instead, the objective function of an autoencoder is typically based on the reconstruction error, which measures the difference between the input data and the reconstructed output data. The most common loss function used for training autoencoders is the mean squared error (MSE) loss. A loss function is a mathematical function that calculates how well the neural network is performing by comparing its predictions to the actual values. Adam (Adaptive Moment Estimation) is a popular optimization algorithm that adjusts the learning rate of the neural network during training based on the moving average of the gradients [20]. It is a combination of the RMSProp algorithm and momentum. Adam is known for being computationally efficient and easy to use, making it a popular choice in deep learning. It helps to converge the neural network training process more quickly and to avoid overfitting.

4. Outcome

In this section, we will discuss several obtained results. The analysis revealed that the autoencoder model could reliably identify anomalies in the ECG data. The model's accuracy of 94% demonstrates its efficacy in detecting anomalies. The analysis revealed that the autoencoder model could reliably identify anomalies in the ECG data. The model's high accuracy, precision, and recall scores demonstrate its ability to detect anomalies.

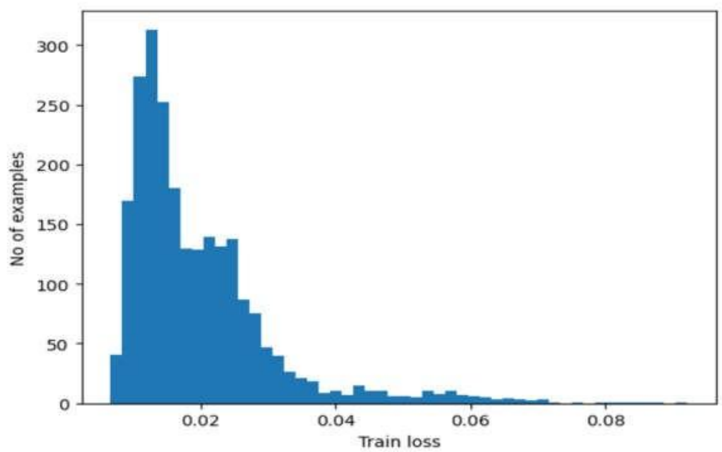

Figure 5. Training loss

The distribution of train loss in an anomaly detection model's training set is depicted in Figure 5. The horizontal axis represents the range of train loss values, and the vertical axis represents the number of examples within each range. It facilitates the visualisation of the distribution of train loss values across the training set, which is useful for establishing a threshold for identifying anomalies. The train loss values appear normally distributed with a mean near 0.025%. Figure 6 depicts the distribution of test loss for anomalous test data, which represents the reconstruction error of the autoencoder when applied to anomalous data. The x-axis represents the test loss values, whereas the y-axis displays the number of instances with each test loss value. The greater test loss indicates that the autoencoder is having trouble reconstructing the input data, which may be due to the presence of anomalies or outliers. By establishing a threshold for the test loss, it is possible to identify instances that are likely to be anomalous and require further investigation. Figure 7 demonstrates the total Training and validation Loss.

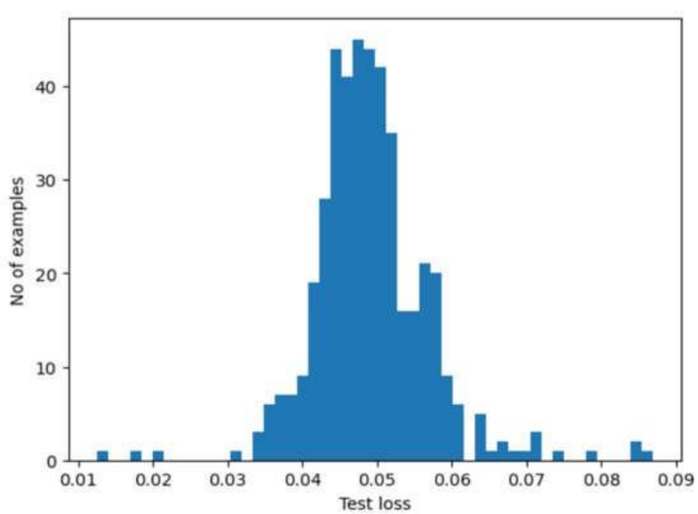

Figure 6. Testing loss

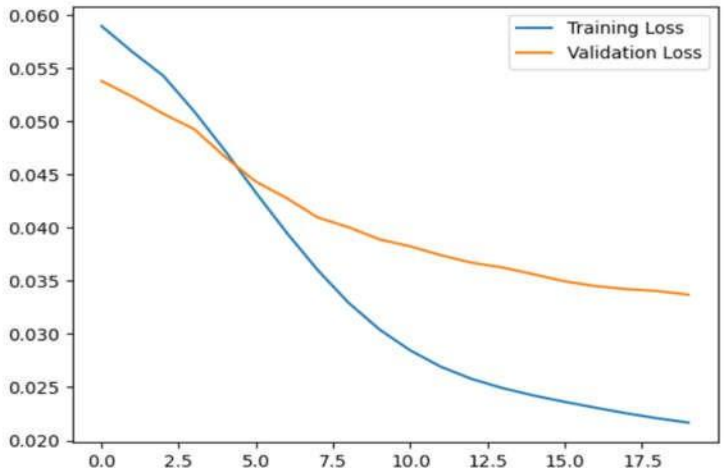

Figure 7. Training and Validation Loss

To evaluate a model, a confusion matrix displays the number of correct and incorrect predictions. We evaluated the efficacy of the deep learning model using the confusion matrix. Figure 8 depicts the performance indicators. Nevertheless, the proposed model excelled with a 94% accuracy rate.

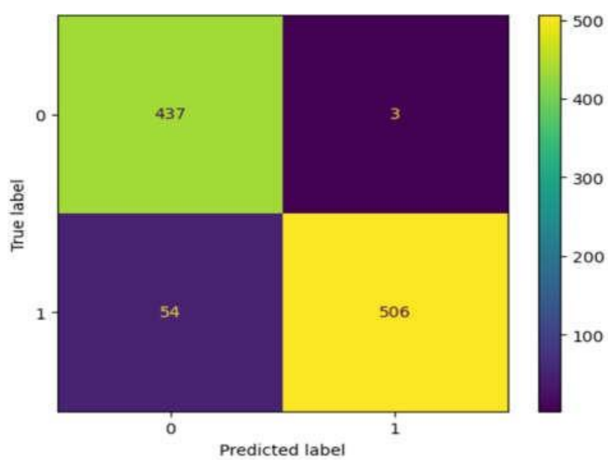

Figure 8 Confusion matrix

5. Conclusion

For monitoring cardiac function and identifying potential heart diseases, the detection of ECG signal anomalies is an essential area of research. Using advanced techniques such as the wavelet transform, support vector machines, neural networks, and hidden Markov models has significantly improved the accuracy and efficacy of ECG signal anomaly detection. However, each technique has its own limitations, and the technique selected should be based on the application and requirements at hand. In addition, more research is required to investigate the use of hybrid techniques and ensemble methods for the detection of ECG signal anomalies. Overall, the development of more precise and effective anomaly detection techniques for ECG signals can have a significant impact on the diagnosis and treatment of cardiac diseases, resulting in improved patient outcomes and quality of life.

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