Anomaly Detection in Electrocardiogram Sensor Data

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Contributor: Ana Minic , Luka Jovanovic , Nebojsa Bacanin , Catalin Stoean , Miodrag Zivkovic , Petar Spalevic , Aleksandar Petrovic , Milos Dobrojevic , Ruxandra Stoean

Monitoring heart electrical activity is an effective way of detecting existing and developing conditions. This is usually performed as a non-invasive test using a network of up to 12 sensors (electrodes) on the chest and limbs to create an electrocardiogram (ECG). By visually observing these readings, experienced professionals can make accurate diagnoses and, if needed, request further testing. However, the training and experience needed to make accurate diagnoses are significant.

electrocardiogram diagnosis particle s

particle swarm optimization

optimization

recurrent neural networks

1. Introduction

Cardiovascular health is a global concern as the leading cause of death globally ^[1]. Many factors contribute to this, among which is the more static lifestyle that has become a standard for most people, and this is especially troublesome as the lack of physical activity leads to various health issues. Other factors include age, stress, and diet irregularities. People who smoke and drink alcohol regularly are also found to be more prone to heart-related diseases ^[2]. All these factors can be attributed to personal choices and, as Keeney et al. ^[3] suggest, around 25% of cardiovascular diseases can be avoided just by altering personal choices without even considering genetics and other factors that influence an individual's health. Long periods of time are usually required for health conditions regarding cardiovascular health to develop. This is due to their nature, as cardiovascular problems develop over time and increase in severity. Furthermore, such illnesses are harder to spot, which jeopardizes the health of the patient.

Traditional ways of monitoring cardiovascular health are open to improvements, with the emphasis being on the time it takes to diagnose a disease. The heart emits electrical signals that can be monitored by instruments, and the most applied principle is the electrocardiogram (ECG) ^[4]. The standard system consists of 10 sensors ^[5] distributed over the human body for a precise reading, but other variations with more sensors exist as well. The primary point for the placement of the sensors is the chest due to the position of the heart. The rest are distributed over the limbs. For example, the standard system with 10 electrodes produces 12 leads, which are represented by waveforms. The activity of the heart from specific angles is represented by leads ^[6]. The ECG provides a graph of the heartbeat and its rhythm, allowing medical personnel to detect possible irregularities that can be indicators of

diseases. The results of the ECG are visual and readable by professionals only, but this is not the only hindrance, as the data can have imperfections due to the nonlinearity and complexity of signals, as well as the low amplitude of recordings, and noise [I].

Considering the previously mentioned shortcomings of ECG systems, possible solutions are being explored to improve the determination of cardiovascular health. As artificial intelligence (AI) techniques are beginning to improve daily aspects of humans' lives, the medical field is not an exception in this trend ^[2]. Improvements in ECG systems aim for faster recognition of patterns, leading to quicker diagnoses. This is of great importance as it allows patients to begin treatment sooner and reduces the risk of improper medication, which can occur with manual result interpretation. The ECG data problem is formulated as a time-series task, which makes it suitable for AI applications. As Wolpert et al. ^[9] state in the "no free lunch theorem" (NFL), not one model is perfect and provides equally optimal results for all problems. For this particular type of problem neural networks provide the best results, as they are suited for time-series problems due to their architecture being modeled after the human nervous system. Regardless of their previously achieved exceptional performance in this field, such solutions are not without shortcomings. This is usually solved by applying an optimization technique that can tune the performance of the main solution by providing the optimal subset of its configuration parameters. Every problem requires customized frameworks as the NFL states, and the combinations of such solutions are vast.

The utilization of AI in the field of medicine has gained significant attention from researchers, primarily driven by various compelling factors. Among these factors, the continually growing demand for healthcare services and the increasing need for rigorous scrutiny during the diagnostic process serve as powerful motivators for researchers to explore the integration of automation into the medical domain ^{[10][11]}. Moreover, the evolving landscape of networking and the internet of things (IoT) ^[12] has generated a heightened demand for enhanced security measures. Applications of IoT networks in combination with AI have shown admirable outcomes when applied to issues associated with healthcare ^{[13][14]}.

One intriguing area where AI finds practical application is in the realm of time-series analysis. These algorithms enable the observation and prediction of trends within continuous datasets, facilitating the determination of data patterns, directions, and correlations. Algorithms that can effectively account for temporal aspects within data have exhibited promising results when applied to complex real-world challenges ^{[15][16]}. Furthermore, advanced data decomposition techniques have been combined with time-series data, further enhancing their performance by breaking down signals into a series of component signals. This approach often leads to improved forecasting outcomes, as complex signals are inherently challenging to predict, while a series of simpler signals can be more readily managed and analyzed ^{[17][18]}.

2. Al Approaches in Electrocardiogram Analysis

Al methods have been increasingly employed in the analysis and interpretation of ECGs to aid in the diagnosis of cardiovascular diseases ^{[19][20]}. CNNs are effective for image-based tasks, and ECG signals can be treated as 1D

images. CNNs can automatically learn hierarchical features from ECG data and can be useful in routine clinical practice, as shown by ^{[21][22][23]}.

RNNs, and their variant long short-term memory networks (LSTMs), are useful for capturing temporal dependencies in ECG signals, making them suitable for tasks such as arrhythmia detection. These models are typically lightweight, simple, and show promising efficiency and accuracy, as discussed by ^{[24][25]}. Hybrid methods have also been considered, such as the CNN-LSTM approach introduced in ^[26].

Machine learning algorithms have been considered for this problem as well ^{[27][28]}. Random forests and decision trees may be used for classification tasks, such as identifying different types of arrhythmia ^{[29][30][31]}. On the other hand, support vector machines (SVMs) may be effective for binary classification tasks and have been applied to identify specific cardiac conditions in ECGs ^[32].

3. Recurrent Neural Networks

With the goal of creating a neural network that is more suitable for problems that require sequential data analysis, the RNN was created. The difference from the basic neural network is the existence of recurrent connections between neurons, allowing for future inputs memory storage. Sequential layers with neurons are connected similarly to the basic neural network, as well as the weights and biases for connection input evaluation, decision-making, and output generation. RNNs require optimization in terms of architecture in addition to the control parameters for optimal performance. The benefits of using RNNs less complex in their structure are observable in data interpretation and training. More complex architecture is required for problems that have to keep track of complex nonlinear relationships.

The hidden state in the previous time step ht-1

is combined with the current at the time step *t*. The process is described by Equation (1).

$$a_t = b + Wh_{t-1} + Ux_t,$$

where *at* is the input activation, *b* the bias term, and *W* and *U* represent the weight matrices of recurrent and input connections, respectively.

Equation (2) describes the process of the alteration of the hidden state after every input with the ϕ activation function over the *at*.

$$h_t = \phi\left(a_t\right)$$

Based on the prediction goal, different functions can be used as ϕ . The output of the network is derived from the hidden state. The previously described process is mathematically formulated by Equation (3).

$$y_t = Wh_t$$

While RNNs have a unique ability of working with and reacting to changes in sequential data, certain drawbacks can be observed in the basic model. This class of networks is particularly sensitive to vanishing and exploding gradients ^[33], making good models difficult to construct. Furthermore, RNNs can only retain an influence of one previous input, which can limit their applicability for longer term forecasts. Certain methods have been developed to deal with these issues. such as the gated recurrent unit (GRU) and long short-term memory networks (LSTMs). However, while these versions of RNNs offer some advantages, they come at the cost of an increased complexity relative to the base algorithm.

4. Metaheuristics

The field of metaheuristic algorithms became popular due to the algorithms' proficiency in solving NP-hard problems. The main challenge is to find solutions to these problems within a reasonable timeframe, while also maintaining reasonable hardware requirements. The algorithms can be divided further into subgroups, but there is no formal definition. The grouping that is recognized by most researchers includes the differentiation by the phenomena used for inspiration of the algorithm. In this manner, the different groups include swarm, genetic, physics, human, and the most novel group of these, the mathematically inspired algorithms.

Swarm-inspired solutions take inspiration from species that live in large groups and the aspects of their lives that benefit from group behavior ^[34]. This is often the case when a single unit is incapable of completing a task on its own, and that is where other units of the same species come into play. The swarm group of algorithms has provided excellent results with solutions to NP-hard problems, but to reach their maximum potential, hybridization with similar solutions is advised. The issue of these stochastic population-based algorithms is that they usually favor one of the two phases between exploration and exploitation, which can be overcome by incorporating a mechanism from a different solution. Notable algorithms from the swarm family include PSO ^[35], genetic algorithm (GA) ^[36], sine cosine algorithm (SCA) ^[37], firefly algorithm (FA) ^[38], grey wolf optimizer (GWO) ^[39], reptile search algorithm (RSA) ^[40], as well as the COLSHADE ^[41] algorithm.

Swarm metaheuristics find application in a wide range of real-world problems. Some of the implementations include glioma MRI classification ^[42], detection of credit card fraud ^{[43][44]}, global optimization problems and engineering optimization ^{[45][46][47]}, cloud computing ^[48], prediction of the number of COVID-19 cases ^[49], feature selection ^[50], and wireless sensor networks ^{[51][52]}.

Ahmadpour et al. ^[53] developed a genetic-algorithm-based solution to track subjects' blood pressure, significantly improving their overall quality of life and allowing for the early detection of preventable diseases. Khan et al. ^[54]

explore an IoT environment that enables all-day monitoring of patients' conditions and greatly improves their cardiovascular health.

Examples of AI-assisted medical diagnosis include diabetic retinopathy detection ^[55], skin lesion classification ^[56], lung cancer classification ^[57], and magnetic resonance imaging (MRI), among diverse other applications in medicine.

Although it is one of the first metaheuristics algorithms, proposed over twenty years ago, PSO is still considered a very powerful optimizer. Recently, the PSO algorithm has been successfully implemented, either in a basic or modified version, to tackle numerous problems in the medical and other domains. Notable examples include tuning LSTM for ECG-based biometric analysis ^[58], CNN-based classification of cardiac arrhytmias and healthcare monitoring ^{[59][60]}, and RNN-based cloud balancing ^[61], to mention a few.

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