Title:

Reservoir computing networks to classify ventricular heartbeat based on echo state network (ESN)

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Chapter 1: Introduction

Background analysis

Cardiovascular disease (CVD) is a condition impacting the cardiovascular system, which includes the heart and blood vessels. According to the World Health Organization (WHO), CVD is the leading risk factor amounting to about 17.9 million deaths every year around the world (Sahin and Ilgün, 2020). Around 32% of deaths are caused by CVDs and according to the centre for diseases control and prevention (CDC), heart diseases cause one death every 36 seconds in the United States of America (Ishaq et al., 2021). WHO further states that CVD causes 38% of the premature deaths caused by noncommunicable diseases in people under age 70.

With CVD claiming 659,000 lives in the United States alone, several researchers intend to provide solutions to prevent deaths due to CVDs. To understand the causes of death it is important to know the most common cardiovascular diseases. The heart and blood disorders under CVD comprise numerous disorders associated with obstruction of blood flow through blood vessels supplying the heart, brain and other parts of the body.

Cardiovascular disease	Causes	Incidents and deaths
Coronary heart diseases	Caused by obstruction of blood vessels flowing to the heart.	126 million patients and 9 million deaths in 2017 (Khan et al., 2020)
Cerebrovascular disease	Disease in the blood vessels carrying blood to the brain. It causes Stroke.	12.2 million incidents and 6.55 million deaths in 2019 (Khan et al., 2020)
Peripheral arterial disease	Obstructions in the blood vessels carrying blood to arms and legs.	113,443,017 incidents and 74,063 deaths in 2019 (Lin et al., 2022)
Rheumatic heart disease	A condition caused by rheumatic fever (Streptococci bacterial infection) that affects the heart muscles and valves.	33,194,900 cases and 319,400 deaths in 2015 (Manpreet and Kalia, 2020)

Congenital heart disease	A birth defect resulting in abnormal development of the heart.	13.3 million patients and 985, 000 deaths in 2019 (Manpreet and Kalia, 2020)
Deep vein thrombosis	Blood clots in the leg veins can slowly move to the heart ad cause blockage.	900,000 incidents and 100,000 deaths in 2022 (Wang et al., 2022)

Table 1: CVD disease causes and impact worldwide

The primary causes of CVD mortality are sudden, premature heart attacks and strokes. Premature heart attacks come with slight variations in the functioning of the heart that accentuates over time. Intricate, early prediction of abnormalities in medical tests could help avert untimely deaths. Electrocardiogram (ECG) is a generic electronic device employed to analyze overall heart health. For decades ECG remains the main source of accessing and analyzing coronary health. Due to its simplicity, ease of use, cost-effectiveness and noninvasiveness, ECG is largely preferred to do basic or initial heart health monitoring.

ECG measures the rhythmic activity of the heart over a particular duration. To perform an ECG, 12 sensors are connected to the chest and limbs to measure the electrical signals. These signals coordinate with proper blood flow throughout the body. Thus, ECG is a straightforward way to measure abnormality in heartbeats. An ECG can detect heart problems, enlarged heart chambers and abnormal heart rhythm. This study focuses on an abnormal heartbeat problem medically called arrhythmia. An arrhythmia occurs when the electrical signals are asynchronous to the heartbeat signifying that the heartbeat is to slow or too fast. Arrhythmia remains as one of the primary signs of heart ailments. Not all arrythmias are fatal but when undetected they may lead to sudden heart failure and subsequent deaths. Usually, the illness progresses over time and causes sudden cardiac arrests (De Chazal, O'Dwyer, & Reilly, 2004)(Alonso-Atienza, Morgado, Fernandez-Martinez, Garcia-Alberola, & Rojo-Alvarez, 2014). According to (Srinivasan & Schilling, 2018), of the 17 million deaths caused by heart ailments, sudden cardiac arrests (SDC) aaccountto 25%. With ECG being the direct way to predict real time heart function variations, several researches have been conducted over the years to exploit pattern identification.

Establishing a real time pattern identification will predict even the smallest variations in the ECG over time, thus helping avert SDCs.

Research Gap

Over the past decade, novel algorithms have been performed over the ECG data to predict the variations in heart functions. Previous researches have undertaken learning algorithms like decision trees, k nearest neighbor (Castillo, Melin, Ramírez, & Soria, 2012)(Saini, Singh, & Khosla, 2013), support vector machines (Raj, Ray, & Shankar, 2016) (Ye, Kumar, & Coimbra, 2016), neural networks (Dokur & Ölmez, 2001) (Martis, Acharya, & Min, 2013) (Inan, Giovangrandi, & Kovacs, 2006) and deep learning models. Several research have also researched upon ECG signal acquisition and processing using signal processing techniques like, time domain analysis (Zhang, Dong, Luo, Choi, & Wu, 2014)(Huang, Liu, Zhu, Wang, & Hu, 2014), filter banks, frequency domain analysis (Zidelmal, Amirou, Ould-Abdeslam, & Merckle, 2013)(Garcia, Moreira, Menotti, & Luz, 2017)(Qurraie & Afkhami, 2017) and wavelet transformation (Ye, Kumar, & Coimbra, 2012) (Ye, Kumar, & Coimbra, 2016) (Elhaj, Salim, Harris, Swee, & Ahmed, 2016)(Mar, Zaunseder, Martínez, Llamedo, & Poll, 2011) to detect arrhythmia.

Need for the research

Previous research has classified irregularity of the heartbeats automatically (Arvanaghi, Danishvar and Danishvar, 2022). However, the learning ability of the automated classifier was not optimized and the database used was imprecise. Manipulating the real-world scenario is imperative to get accurate predictions. Similarly, Al-Turjman, Nawaz and Ulusar (2020) discuss the analysis of the data outputs of medical instruments, however, measurements can be imprecise and time-consuming. Using support vector machines (SVM) as discussed by (Martinez-Alanis et al., 2020) requires inputting an optimal set of RR intervals and wavelets. Shi et al. (2019) discuss a hierarchical classification scheme that implements Extreme Gradient boosting (XGboost) classifier to classify a single heartbeat. Despite the speed and accuracy provided by XGboost in supervised learning environments, it affects the impact balance. In addition, class sensitivity was not obtained in the outputs discussed. More heartbeat data should be inputted in the subject-oriented analysis. The clustering algorithm discussed by Yang and Wei (2020) additionally inputs morphological errors to lessen interpretation dissimilarities, however, there were real-time data constraints. The analysis of various research suggests that there is no existing algorithm that provides better detection rates for various arrhythmia stages.

The outcomes of the research intended to achieve accurate classification of the heartbeat could be applied to monitor the health scenario of patients with ease. With the augmenting risk of cardiovascular illness and the corresponding deaths, early interpretation of abnormalities proves the best way forward in diagnosing illness. Providing a learning algorithm that could extract the ECG data and accurately predict abnormalities will pave way for early therapies that could save lives. In addition, the time spend on diagnosing the problem will be reduced.

Research Aim

The project aims to construct an effective heartbeat classification method to accurately classify heartbeats based on echo state networks a part of reservoir computing.

Research Objective

1. The primary objective is to classify the heart rate based on the QRS complex. The research process intended is as follows.
2. To preprocess the ECG to get the baselines signal to ensure accurate classification.
3. To segment the ECG signal and extract the temporal and wave features associated with the QRS complex.
4. Classify the extracted features using the reservoir computing-based echo state network, a part of the recurrent neural network.
5. Obtain high accuracy with enhanced features to solve ventricular classification problems.

Research Questions

The research will follow quantitative analysis trying to solve the following questions.

1. How important is the research on ventricular heart rate classification in heart failure identification?
2. What are the different algorithms that have rendered acceptable results on ECG classification?
3. What are the disadvantages identified in the algorithms employed in previous research?
4. How does echo state network classification improve the accuracy of ventricular heart rate classification?

Research Method

The research will follow a quantitative analysis to develop a classification scheme to retrieve, enhance and analyze ECG data to detect ventricular heart rate variabilities. Classification is the primary way to optimize the detection of arrhythmia. The objective of the project is to develop an effective classification method using the echo state network part of the reservoir computing framework.

The methodology adopted to pursue the research include four steps: Preprocessing the ECG signal, heartbeat segmentation, extracting features and classification. Variegated ECG signals are the input that will be preprocessed to extract the signal from noise. The baseline will be removed in the signal preprocessing to move into the segmentation phase. Signal preprocessing is necessary to remove the unwanted sections of the input signal to ensure relevance and accuracy during feature extraction and classification. In the segmentation phase, the heartbeat will be segmented based on the QRS complex, the deflections noted apparently in an ECG. The QRS complex represents ventricular depolarization, which represents the conduction of electrical impulses into the ventricles. The segmented output will be subjected to feature extraction where the ECG wave features will be extracted. The temporal features like the pre-RR intervals, local average RR interval, post-RR interval and global average RR interval will be included in feature extraction. The wave features that will be included are the PP interval, RR interval, PR interval, R interval and QT interval. RR intervals depict the ability of the heart to adapt to environmental changes, where the heart rate can be represented through RR intervals in a millisecond. Precisely, heart rate variability measures the time intervals between two heartbeats that are measured as RR intervals in milliseconds. The temporal and wave features will then be processed through classification, which will be performed through an echo state network. Reservoir computing-based echo state network is a part of a recurrent neural network. The importance of recurrent neural networks is that the machine learning system created will remember the input enabling it to predict accurate results on sequential data. RNN can remember inputs over time, making it reliable while working with long-time series data. With the Echo state network, it is easier to work with large non-linear data like the ECG which varies extensively with time.

Chapter 2: Literature Review

Introduction

Arrhythmia, a class of cardiovascular disease requires timely treatment. Arrhythmia constrains the blood flow to the heart and other parts of the body causing irreversible damage. In most cases, arrhythmia gradually affects the functioning of the heart, which when undetected could lead to sudden deaths (D'Errico et al., 2020). ECG is employed largely to determine the state of the heart and to routinely review the condition. Classification of heartbeat determines the irregularity of the heartbeat with time. The rhythm variations in arrhythmia could be too fast or too slow. Based on the classification of heartbeat, arrhythmia can be of two types: non-life threatening and life-threatening arrhythmia. The non-life-threatening arrhythmia leads to general heart function weakness which can be treated with therapy. Life-threatening arrhythmia causes tachycardia and ventricular fibrillation triggering untimely cardiac arrests. Bio-signals monitoring using ECG is quite challenging because of its non-stationary and nonlinear properties. Thus, various pattern recognition algorithms have been mapped with ECG analysis to effectively classify and detect abnormalities. The various kinds of literature classifying heartbeats vary in the following aspects: feature analysis, use of classifiers and evaluation techniques undertaken. The different features identified from the literature analysis include Higher order statistical features (Khoshnevis and Sankar, 2020), wavelet transformation (Tian et al., 2023), independent component analysis (Pion-Tonachini, Kreutz-Delgado and Makeig, 2019), Hermit coefficients (Brieva, Ponce and Moya-Albor, 2020) and morphological features. The classifiers identified from previous research include support vector machines (Martinez-Alanis et al., 2020), self-organizing maps (Nilashi et al., 2020), artificial neural networks (ANN) (Pandey and Janghel, 2018), linear discrimination analysis (LDA) (Liu et al., 2019), conditional random field (CRF) (Fang and Huang, 2021) and ensemble analysis. The evaluation schemes used are of two types class-oriented and subject-oriented evaluations. Class-oriented evaluation works on the generation of training and testing samples. Extensive ECG signal heartbeat segmentation results in more than a thousand individual records. When selecting random records for supervised classification there is a higher probability that the training and the testing samples belong to the same person (Cao et al., 2020). Class-oriented methods thus provide lower-quality generalization. On the contrary, subject-oriented methods as discussed in the paper by Bognár and Fridle (2020) segment the data sets as training and testing sets before the segmentation of heartbeats. With feature classification and evaluation, it is possible to completely automate the process of heartbeat classification using advanced statistical approaches.

Clinical Application of ECG

Clinical applications of patient-specific electrocardiogram (ECG) analyses are growing in prominence. Newer generation event and Holter monitor systems, texture electrocardiogram recorders, and wearable devices with ECG sensors record and monitor real-time cardiac data across periods of days or weeks (i.e., beyond the typical 48 hours), enabling thorough statistical analysis and a more nuanced picture of a patient's cardiovascular health. If an appropriate model is used to assess patient-specific diseases, real-time, individualised monitoring can also enable quick action or patient recalls. However, sophisticated automated algorithms compatible with developing hardware technology are required to manage this massive data and extract the important information for carrying out additional statistical analysis (Acharya et al. 2018).

Arrhythmia detection and heartbeat categorization have been studied for decades, and many signal processing methods including frequency analysis, template-matching, discrete wavelet, filter banks, and hidden Markov models as well as variants of neural networks have all been used. However, more improvements are required in the field of autonomous portable ECG interpretation because of the lack of a full set of algorithms compatible with new micro-device technologies, which has limited the actual exploitation of automated ECG diagnostic devices thus far (Afkhami et al. 2016).

When it comes to automated ECG monitoring activities like beat categorization, the substantial individual and group differences in the temporal course and morphology of ECG waveforms pose a significant challenge. One simple, but computationally costly, option is to use training data obtained from many people with a variety of healthy or pathological heart diseases to create a general classifier (Cuomo et al. 2016). If the data volume and complexity of the job are excessive, deep-learning-inspired algorithms will often adopt this approach to provide predictive analytic solutions. However, such a method confronts several obstacles when used for ECG diagnosis, including data collecting, beat annotation, and technological obstacles related to hardware implementations. A patient-specific classifier, in contrast to a generic model, allows the classification algorithm to be tailored to the specific characteristics of each patient's ECG records by eliminating the need to rely on data from many individuals (Farina et al. 2015).

Preprocessing

The computational advancement of microcontrollers and microprocessors has allowed for the realisation of the simplest and most generally used solution for noise reduction in ECG data, recursive digital filters of the finite impulse response (FIR) (Carnevale et al. 2017). These techniques are useful for reducing the volume of specific frequency ranges, such as those of electrical network noise (50 Hz or 60 Hz), since the reject-band filter may be applied rapidly and with little effort. The lack of certainty in the noise's frequency makes this method difficult to implement, however filtering the signal into narrower bands can help. Unnecessary filtering using high-pass and low-pass settings can alter the signal's shape and render it useless for heart illness diagnosis. To further reduce the background hum in the ECG readings, adaptive filtering architectures were also used (Garica et al. 2014). However, as stated by Li et al. (2015), this method is limited and does not provide significant benefits over the FIR digital filters. Using adaptive filters based on neural networks, Kim et al. (2016) were able to greatly enhance noise reduction by overcoming some of these challenges. When compared to the identical technique employing linearly adaptive filters, this strategy proportionally improved QRS complex identification.

Since wavelet transform-based approaches retain ECG signal features while preventing the loss of critical physiological information and are computationally straightforward, they have been widely used in the previous decade to eliminate noise. To lessen the impact of background noise and baseline shifts in the ECG signal, Llamedo et al. (2012) suggested a wavelet transform variant they named the multi-adaptive bionic wavelet transform. When compared to methods based on the classic wavelet transform, this one showed substantial improvement.

Noise reduction in other ways has also shown some promising findings. Melillo et al. (2015), used nonlinear Bayesian filters to suppress background noise in ECG signals, and their findings look promising. The greatest success to date has been achieved by a novel algorithm based on the Extended Kalman Filter, which combines the parameters of the ECG dynamic model for ECG noise reduction and signal compression. It is important to keep in mind that the signal-to-noise ratio is how the workers present their findings. A variety of preprocessing techniques for the ECG signal are investigated, however, the approach used is inextricably linked to the study's goal.

Methods that seek to automatically classify arrhythmias have a different preprocessing requirement than those that seek to segment heartbeats from the ECG signal (i.e., detection of the QRS complex, other waves, or fiducial points aimed at heartbeat delimitation).

Segmentation

Some algorithms suggest identifying other waves that occur alongside heartbeats, such as the P wave and the T wave, which can be helpful for arrhythmia classification approaches due to the additional information they provide. Although heartbeat segmentation is not the primary focus of this study, it is important to keep in mind that mistakes made at this step might have far-reaching consequences for the final categorization of the arrhythmia system and hence should not be taken lightly (Li et al. 2015). Most of the studies evaluated here used databases in which heartbeat segmentation-related events (such as the identification of the R peak or the QRS complex) are already recognised and labelled, making the segmentation step as easy as a search of a labelled event in the database. Because of this, database labelling is prone to human mistakes, yet the findings presented by these studies do not account for the influence of the segmentation stage. Consequently, comparing the effectiveness of various segmentation algorithms on automated arrhythmia classification approaches may be a fruitful line of inquiry. To determine whether their feature extraction strategy is reliable in the face of a specific segmentation problem, the R-peak mislocate error, Kim et al. (2016) suggested a test. An error was introduced to the R-peak annotations, and it was dispersed according to a Gaussian noise model. The researcher recommends that future efforts attempting automated heartbeat categorization include such a test.

Obtaining Features

The feature extraction phase is crucial to the effectiveness of cardiac arrhythmia classification using the ECG data. What constitutes a characteristic of a heartbeat is whatever information can be gleaned from it and utilised to identify its specific kind. The characteristics can be gleaned from the time-domain and/or frequency-domain morphology of the ECG signal, or from the heart rhythm itself. Feature selection and feature extraction are two distinct procedures, even though the phrases are sometimes used interchangeably (Mastoi et al. 2019). Feature selection is the process of picking a collection of features that are the most representative to enhance the classification stage, whereas feature extraction is the step characterised as the description of a heartbeat.

The RR interval, which measures the time between heartbeats, is the most often reported characteristic in the medical literature. The RR interval measures how long it takes for one pulse's R peak to occur in relation to the preceding or the following heartbeat. Apart from pacemaker patients, changes in the morphology of the curve, which are often triggered by arrhythmias, relate to changes in the breadth of the RR interval. Some writers have built their strategies on exclusively utilising the RR interval characteristics because of their high discriminatory power. Common implementations of this feature exist for noise suppression, such as averaging a patient's RR interval across a given time. The classification results can be greatly enhanced by using a normalised RR interval, as demonstrated by Ortin et al. (2019). Under the inter-patient paradigm, the results of that work are equivalent to those of the state-of-the-art approaches because only normalised RR intervals are employed. Normalized RR-intervals' efficacy was verified by feature selection methods, as demonstrated by Qurraie et al. (2017). In addition to the distances between the fiducial points of a pulse, various properties may be derived from the heartbeat intervals and can be found in the literature. The most used is the QRS interval, which is the time it takes for the QRS complex to complete. The QRS interval can be a useful diagnostic tool since it varies in response to different kinds of arrhythmias.

Researchers say that wavelet transformations are the best methodology for extracting characteristics from the ECG signal, even though many other methods have been investigated by Raj et al. (2017). In contrast to the conventional Fourier transform [98], which only provides analysis in the frequency domain, the wavelet transforms permit information extraction from both the frequency and temporal domains. Discrete wavelets transform (DWT) is the most often used type of wavelet transform for ECG signal categorization because of its simplicity of implementation.

Since continuous wavelet transform (CWT) avoids the coarse representation and instability of DWT, it has been utilised to extract features from ECG data [99]. While CWT can be useful as an analyzer, it is not often employed since its implementation and inverse are not included in common toolboxes (like the MATLAB wavelet Toolbox). Even while Ye et al. (2016) computational cost as a drawback for adopting CWT, it has been used effectively on even basic medical equipment for at least a decade already. Finally, Li et al. (2016) argue that DWT and CWT should be adopted since they are superior to current approaches, in which just one of the transforms is used by the authors.

Kim et al. (2016) state that the final performance of the classification model is highly dependent on the mother wavelet function selected for feature extraction. It is necessary to carefully consider this option so that no vital information from the ECG signal is lost. Parameters that affect arrhythmia classification outcomes include filter order and amount of decomposition in addition to the mother wavelet function selected. According to the findings of Garcia et al. (2017) using the Particle Swarm Optimization (PSO) method to fine-tune these values yields better outcomes.

To create a real-time, patient-tailored ECG beat classifier, this research makes use of the echo state network (ESN), a type of reservoir computing (RC) model. In reservoir computing, a random excitable medium is used to transform a signal from a lower-dimensional (linear transform) space into a higher-dimensional (nonlinear transform) space. RC has been proposed as a computational paradigm for "unconventional" physical or computational media, meaning those that are not based on neural network models or digital computing circuits, by researchers in computing theory and microchip technologies due to the broad applicability of the notion. Designing implantable or wearable biosensors, processors, and controllers based on this computational method is encouraging since functional reservoirs have been successfully constructed in electrical circuits, optical media, or chemical (molecule) substrates. As will be shown below, when trained and evaluated on ECG recordings chosen from the MIT-BIH arrhythmia database, the model delivers a predictive solution to the electrocardiogram (ECG) beat categorization problem that beats the existing state-of-the-art. This reservoir model is demonstrated to be compatible with the Dynap-se process- or, neuromorphic hardware used to create analogue spiking neural networks, thanks to the application of the concept of "reservoir transfer learning."

Methods of ECG Classification

Automatic ECG beat classification has made considerable use of decision-tree techniques based on numerous characteristics retrieved from each heartbeat. A typical heart rate segmentation, feature extraction, and classification module make up the backbone of such a system. Most cardiac beats are first segmented using non-overlapping sliding windows of varying sizes and shapes (Farina et al. 2015). Then, a classifier is trained using a variety of temporal features (such as the width and height of the QRS complex, the RR interval, and the area of the QRS complex), frequency domain descriptors (typically extracted using power spectral density (PSD) or discrete Cosine transform), time-frequency domain representatives (obtained using discrete Wavelet transform), and features extracted from the phase-space reconstruction of ECG recordings. The variability in ECG beat shape and temporal characteristics among patients, patient groups, and the same patient throughout activity stages presents considerable difficulty in analysing these properties. As a result, it appears that there is tremendous potential value in exploring patient adaptability.

The classification section has used a variety of methods for distinguishing between heartbeats, including ANNs, SOMs, SVMs, linear discriminators, conditional random fields, and neuro-fuzzy networks [3, 25, 26]. As far as I'm aware, this is the first study to suggest using a "mixture-of-experts" (MOE) technique to show that it's possible to make an ECG beat categorization algorithm that can be customised for each individual patient. Twenty ECG signals were randomly picked from the MIT-BIH arrhythmia database, and the overall performance parameters were reported as 94.0 per cent accuracy, 82.6 percent sensitivity, and 97.1 percent specificity. After that, a patient-specific heartbeat classification scheme was proposed using a fuzzy-hybrid neural network consisting of a fuzzy c-means classifier and an MLP neural network trained to distinguish normal from abnormal cardiac beats based on features such as the variance of the wavelet transforms, the third-order cumulant, and the autoregressive (AR) model parameters. Accuracy of 93.5 percent, sensitivity of 99.6 percent, and specificity of 95.3 percent were achieved on 7 ECG recordings from the MIT-BIH arrhythmia database. A small sample of each ECG signal was used for training and testing the classifier (i.e., 200 heartbeats). A three-class classification technique was established to identify normal beats, premature ventricular contractions (PVC) beats, and other beats in two-lead ECG recordings using cross-spectral density information retrieved in the frequency domain (Acharya et al. 2018). It was demonstrated that using the method with 40 files from the MIT-BIH arrhythmia database led to a classification accuracy of 95.51–96.12%. It has been proposed that treating ECG waveforms as data-packet streams and employing packet-processing techniques might help define ECG patterns that are unique to a patient. The technique uses wavelet analysis with adaptive thresholding to perform preprocessing and feature extraction on an electrocardiogram (ECG) based on the accurate localisation of fiducial ECG points. The MIT-BIH arrhythmia database includes 47 files, and the overall classification accuracy was reported to be 97.42% (Garcia et al. 2017).

Computing in a Reservoir

Reservoir computing is a framework for designing, training, and analysing recurrent neural networks (RNNs) for processing time-dependent information, and it was inspired by the brain's capacity to do so. You may think of a reservoir computer as having three primary components. An enormous, randomly connected recurrent neural network (the "reservoir") receives the input signal at the input layer (Wu et al. 2016). This dynamical system's internal variables perform a non-linear mapping of the input signal into a signal space with more dimensions (i.e., reservoir states). The time-varying output of the reservoir is calculated as a linear combination of the reservoir states in the output layer. Any number of all-to-all (random) feedback links between the network's output and reservoir might be incorporated into the design, depending on the specifics of the task at hand (Teijeiro et al. 2018). The RC approach recommends just adjusting the output weights to reduce the mean square error between the goal and the output signal, in contrast to more conventional (and "deep") RNN training techniques. Input weights and reservoir connection weights can be chosen arbitrarily within certain bounds to achieve optimal performance. Since only the output connections require training, and the optimization of the output layer requires just a linear regression, training techniques are computationally fast and easy to understand (Llamedo et al. 2012). Since the input signal is nonlinearly expanded into a high-dimensional (reservoir) signal space, reservoir computers can efficiently complete a wide variety of complicated tasks on time-dependent signals with little effort on the part of the user in terms of training time (Mastoi et al. 2019). Reports of successful applications of research-based computing range from nonlinear channel equalisation and time series prediction to voice recognition and robot control.

Chapter 3: Methodology

In the detection of CVDs and arrhythmias patient specific ECG analysis is highly essential. The methodology followed in the project is quantitative in nature as the techniques in machine learning algorithms are followed in conducting the research. The method will make use of ESN classifiers as they are based on RNN where the output layer weights are trained. This approach is useful to handle real-time data in the RC framework. The methods of signal processing are used in Matlab software in the project. The basic steps followed in the project method involve:

Pre-processing of ECG signal

As mentioned earlier patients' ECG forms the input for the system. ECG signals contain noise signals and contaminated signals, and they must be initially de-noised. In the approach, the variegated ECG signals are the initial input for pre-processing. Noise and unwanted signals come in ECG due to patient movement or vibration while the physiological signals are recorded. Another unwanted signal is power line interference that occurs due to the results due to respiration as it can show variations in the actual information. The noise and unwanted signals are removed in the pre-processed stage to eliminate problems in extracting hidden features of information in the raw ECG signal (Robinson et al., 2021). This pre-processing is needed to ensure accurate and relevant ECG signals to extract features and classify beats.

The removal of noisy physiological signals for high-performance data will involve the usage of a median filter to remove unwanted signals in the ECG signal. In this method, the median value is calculated by the use of two median filters of varying lengths using Matlab. The medfilt1 function in Matlab is implemented to filter the ECG signal in 1 dimension. The medfilt1 function will remove the unwanted distortions or outliers in the ECG signal. A set of differential equations are used to derive the values of the slope. Subsequently, the values obtained in output from the ECG waveforms are squared to determine R- peaks in the signal without noise. The values of the related R wave, R-location and R-wave amplitude are stored as a matrix form R^{nxm}.

Heart Beat Segmentation

The ECG recordings are segmented into heartbeats by extracting the signal surrounding each heartbeat in the annotation. In this stage of the approach, the heartbeat is segmented after detecting the peaks. The detected peaks are further determined as an R^{nxm} matrix to select the location of R as a reference point. Here, R- the peak position is determined for the sample data along with the intervals in seconds to form the single heartbeat segment. The segmented heartbeat usually will have samples gathered starting from 0.2 seconds to 0.32 seconds next to the fiducial point. The fiducial point provides the heartbeat position in the signal (Mejía-Mejía, May and Kyriacou, 2022). The heartbeats are segmented and normalized to mean as 0 and standard deviation as 1. The area segmented in the QRS-complex to indicate start-end points respectively that are shown as Q and S waves respectively, while the R wave indicates the area under the peak. The combined waves namely Q, R and S waves provide the ventricular de-polarization of a heartbeat. Ventricular depolarization indicates the electrical impulse conduction by the ventricles. The output segments are further subject to feature extraction.

Extraction of Features

The ECG wave features extracted based on normal heartbeat and abnormal heartbeat. A normal heartbeat is determined by the regular RR intervals, that has P- wave and narrow QRS complex. Contrarily abnormal heartbeat will have RR-interval in narrow form and P-wave will be absent with a wider QRS complex. The time duration between two RR intervals will represent the duration between two successive heartbeats. The RR-interval features are,

- The previous RR interval refers to the difference in time between the previous and current heartbeat.
- Subsequent RR interval provides time duration between current and subsequent heart beats respectively.
- Average RR is the average of *n* number of heartbeats from the recordings in ECG. Average is the calculation made from previous RR intervals.
- Standard Deviation of successive differences (SDSD) refers to the difference between adjacent RR intervals. This feature provides the physiological signals related to the arrhythmia condition.

The discriminant features will use the area in each heartbeat waveform. The mean('Beat') represents the averages of all values of the heartbeat that is segmented. The mean('Beat') indicates the average of absolute values obtained from the derivative in the segmented heartbeat. Here, the derivative is determined using the formula for central difference as the abnormal heartbeat will provide a broad area due to their wider QRS complex. Further, the abnormal morphology beats exhibit a rise and fall slower compared to the morphology of normal heartbeat signals. To evaluate the variability of heartbeats to distinguish between normal and abnormal beats, a patient-adaptable approach is followed. This approach involves a reference beat that is based on the estimation of normal morphology and supra-ventricular origin heartbeat of each patient.

The above quantities provide the measure of variability in heart rate as RR- intervals in milliseconds. Subsequently, the features extracted will be processed using the ESN classification algorithm.

Classification using ESN

The ESN is the classification algorithm that is the main component of the RC paradigm. The idea is the input of the random projection in a reservoir with high dimensions. Another advantage of ESN is that it will eliminate the over-fitting problem. The advantage here is that the internal connections found in input and neurons do not need training. This leads to free parameters in the system having constraints in output weights. In the case of any standard ESN, RC will involve RNN that randomly sets the weights in input, biases and connection weights in neurons found internally. ESNs will perform with topology having deterministic connections and as well as random input weights. The advantage here is that they can be implemented easily in hardware. Here, a main type of ESN architecture is selected to develop a model with efficiency for implementation in processing the real-time ECG signal. A cyclic-based ESN architecture in the form of a ring is chosen as it provides random links between neurons. The basic representation of the cyclic ESN architecture is shown in figure 1. The reservoir network input is the ECG data.

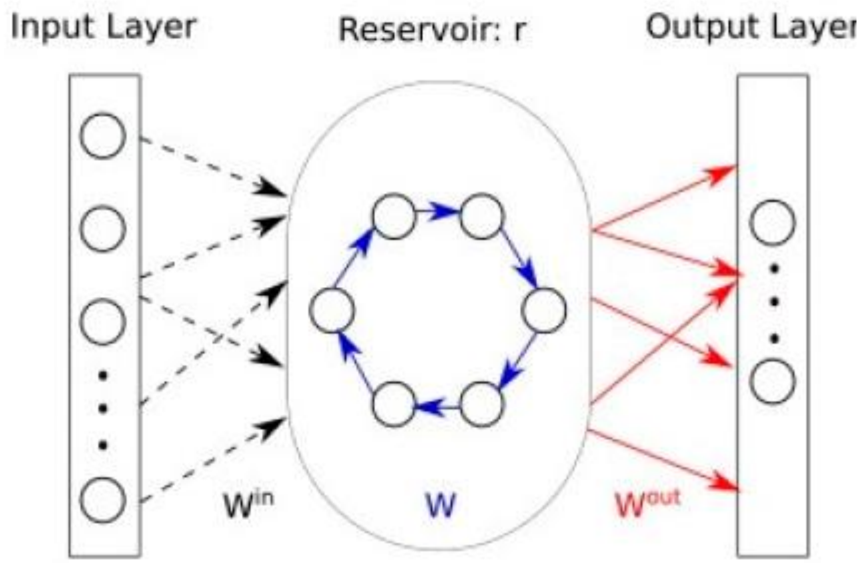

Figure 1: A standard cyclic ESN architecture (Mastoi, Wah and Raj, 2019)

The cyclic ESN model for ventricular heartbeat classification is used for its advantages in the capability of high-speed processing with low power consumption. The activation vector for ESN (Mastoi, Wah and Raj, 2019) is provided in equation (1).

$$s(n) = g(\vartheta W^{in} F(n) + \alpha W_s(n-1) \quad (1)$$

Here, $s(n) \in \mathbb{R}^{N_d}$ represents the state or the activation vector.

N_x indicates the neurons found in connection weights, and $W^{in} \in \mathbb{R}^{N_x X N_d}$ is a random matrix. N_d indicates the input vector dimension. The parameters ϑ and α represent the connection scaling inputs and *F(n)* indicates the features of the vector as input of heartbeat with dimensionality value. In ESN the activation function is referred to as the sigmoid function and made 0 by shifting it symmetrically. N_x is the linear combination of the activation function *s(n)* and ESN model output provided by equation (2).

$$y(n) = g(W^{out} s(n)) \qquad (2)$$

Here, $W^{out} \in \mathbb{R}^{N_{out} X N_x}$ is the matrix with weights to show links found in ESN neutron and different output nodes. This method is further extended to determine the weight of bias and feedback between the response function. RNN in the RC framework will remember the input thus enabling it to predict accurately over time and hence reliable when working with log time series data. Since ECG signals vary extensively with time it is easy to classify between normal and abnormal heartbeat using ESN.

The overall approach is represented by figure 2 to show the processes.

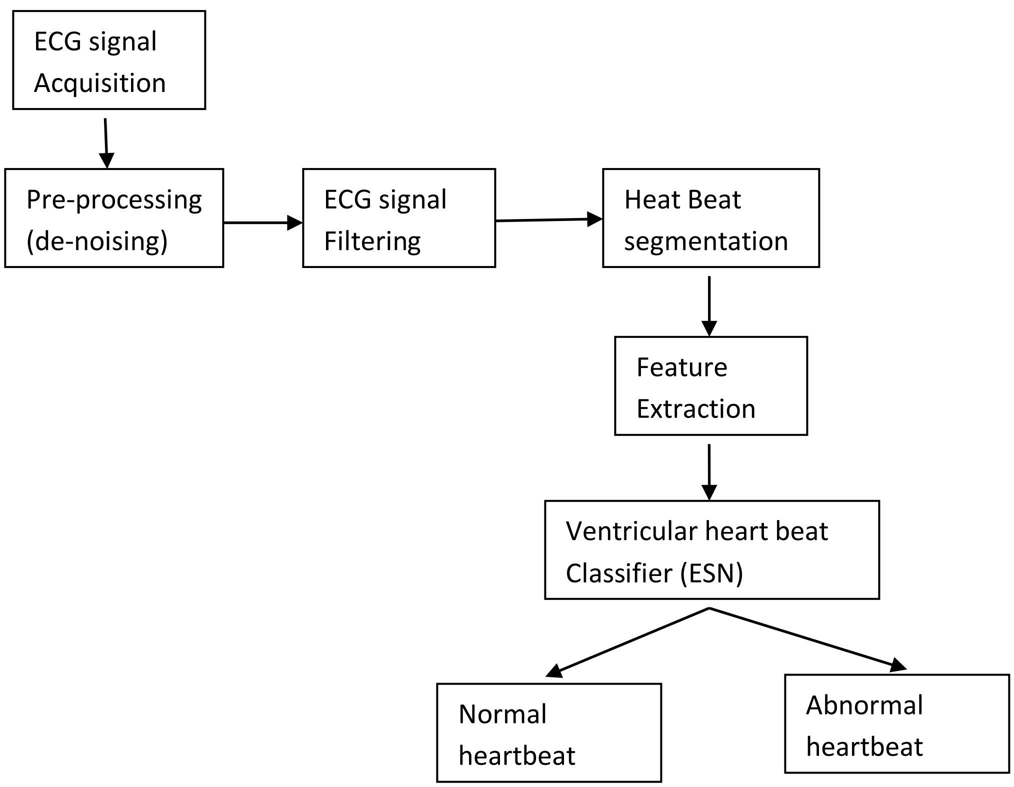

Figure 2: The steps involved in the project method

The proposed method is based on ESN. This will classify the heartbeat based on pre-processed ECG signals and will be based on morphology namely normal and supra-ventricular heartbeats. This classification is based on two stages. The first stage will obtain an ECG signal from the patient and filter followed by detecting heartbeat, segmentation and feature extraction. Here, the time difference between heartbeats in the model is included along with morphological characteristics. In the second stage the classification is done between supra-ventricular and normal heart beat is classified using ESN cyclic topology to achieve classification between abnormal and normal heart conditions.

Databases used in the project

The proposed method of heartbeat classification is evaluated using standard arrhythmia ECG databases namely MIT-BIH arrhythmia and AHA. These databases provide the standard parameters or attributes for evaluating arrhythmia classifiers. The database is considered because they contain annotations to indicate the heartbeat classes and is verified by specialists and independent researchers. The databases follow the mandate standards as in the Association for Advancement of Medical Instrumentation (AAMI) for evaluating ECG classifiers. The annotation labels consist of mainly five types namely normal heartbeat, supra-ventricular ectopic beats (SVEB), ventricular ectopic beats (VEB), fusion (F) beats and unclassified beats. Due to these reasons, the databases are considered in the project.

The American Heart Association (AHA) Ventricular Arrhythmia ECG database is used in the project as these datasets consist of ECG for testing the ESN classifier to detect heartbeats for arrhythmia condition for its effectiveness. The ECG signal recordings are classified as a ventricular-ectopic beat (VEB), supra-ventricular ectopic beat (SVEB), fusion beat (F), unclassified and paced beat (Q) and non-ectopic beat (N).

Training and Test Data

Both the MIT-BIH and AHA databases are split into separate datasets for training and testing. Here, DS1 is the training and DS2 is the testing dataset respectively used separately in both databases. The training and testing data are selected to maintain a balance between the type of heartbeats and the number of ECG waveforms in each dataset. The classifier is optimized using

DS1 and evaluated using the DS2 dataset. Further, the heartbeat of the same patients in the train and test datasets can have bias and hence the output is not replicated. For the MIT-BIH datasets, the DS1 dataset used were 22 and 44 ECG records and 22 records for DS2. In the AHA database, DS1 used 79 ECG records labelled as series=0, and 75 records for DS2 labelled as series=1.

Performance Metrics

The ESN classifier performance evaluation is based on the MIT-BIH database and AHA database with unit lead as a basis. The standard statistical measures are used namely Sensitivity (Se), specificity (Sp), positive predictive value (PPV), Accuracy (Acc) and F1 score.

The formulas for metrics are,

$$S_e = \frac{TP}{(TP + FN)}$$

$$S_p = \frac{TN}{(TN + FP)}$$

$$PPV = \frac{TP}{(TP + FP)}$$

$$Acc = \frac{(TP + TN)}{TP + TN + FP + FN)}$$

In the above equations, TP is True Positive, TN is True Negative, FN is false negative and FP is False Positive respectively. The F1 score calculation is based on the harmonic mean of Se and PPV in the formula,

$$F1\ Score = \frac{2(S_e \cdot PPV)}{(S_e + PPV)}$$

The F1 score will select the optimum parameters for the ESN classifier in the training phase.

The ESN classifier will classify the processed ECG signals based on two classes of morphology namely SVEB+ (Supra-ventricular ectopic beats), and Ventricular ectopic beats (VEB+). The SVEB+ class is further classified as N or normal and supra ventricular ectopic as S or SVEB heartbeat. The SVEB heartbeats show normal morphology with supra-ventricular origin. The

VEB+ presents ventricular origin with abnormal morphology. The VEB+ class is made up of ventricular ectopic beats VE and fusion beats (F).

The beat class distribution and scores from evaluation along with metrics are explained in the results and findings are discussed further.

Chapter 4: Findings and Results

The heartbeat classification uses the MIT-BIH arrhythmia database and the AHA database. MIT BIH is used normally by researchers in evaluating arrhythmia classifiers. MIT-BIH database consists of ECG records for 48 hours and sampled at 360 Hz with two leads. One lead consists of a waveform obtained from electrodes attached to the chest and limb, and the second lead is a modified lead of V1. Contrarily, the AHA database has ECG recordings containing 30-minute information on the beat class. The ECG records in AHA documentation mention two leads namely A and B and are sampled at 250 Hz. As indicated earlier, the ECG classifiers are evaluated using the standards of the Association for Advancement of Medical Instrumentation (AAMI) and heartbeat annotation labels indicate N, S, V, F and Q heartbeats. Here, Q beats are unclassified beats and hence not representative. With the standards of AAMI the ECG data that has paced beats are removed, also importantly the AHA data will not be able to distinguish between N and S beats.

The extraction of the ECG signal involves median filters applied in pre-processing. The lowpass filter with a cutoff frequency at k = 35 Hz is used for noise removal and outlier removal as in figure 3.

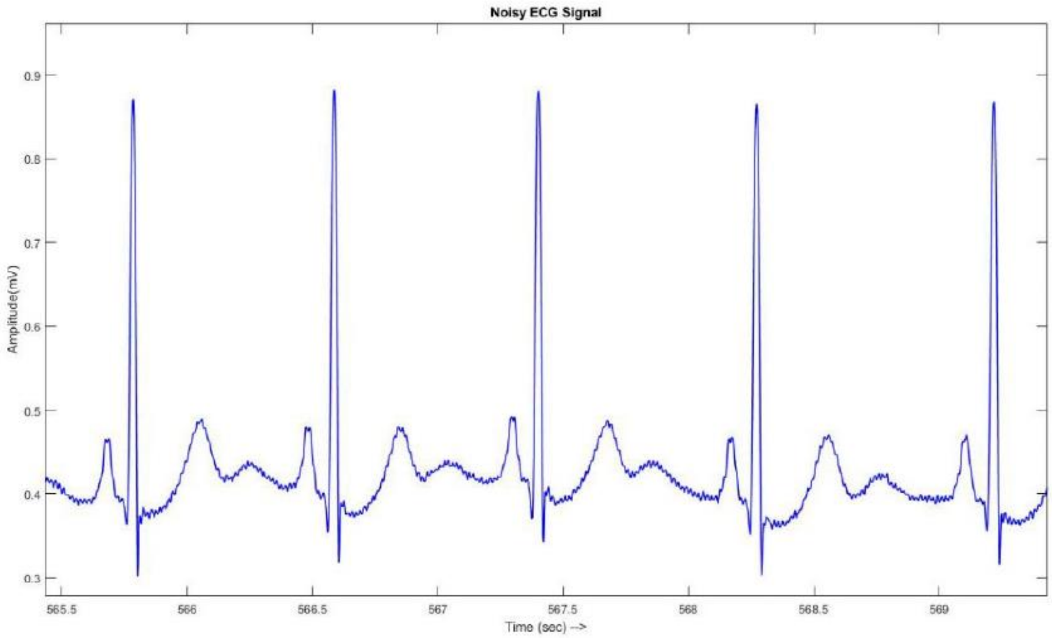

Figure 3: Representation of noisy ECG signal

After filter application, the noisy signals and outliers are removed, as represented in figure 4.

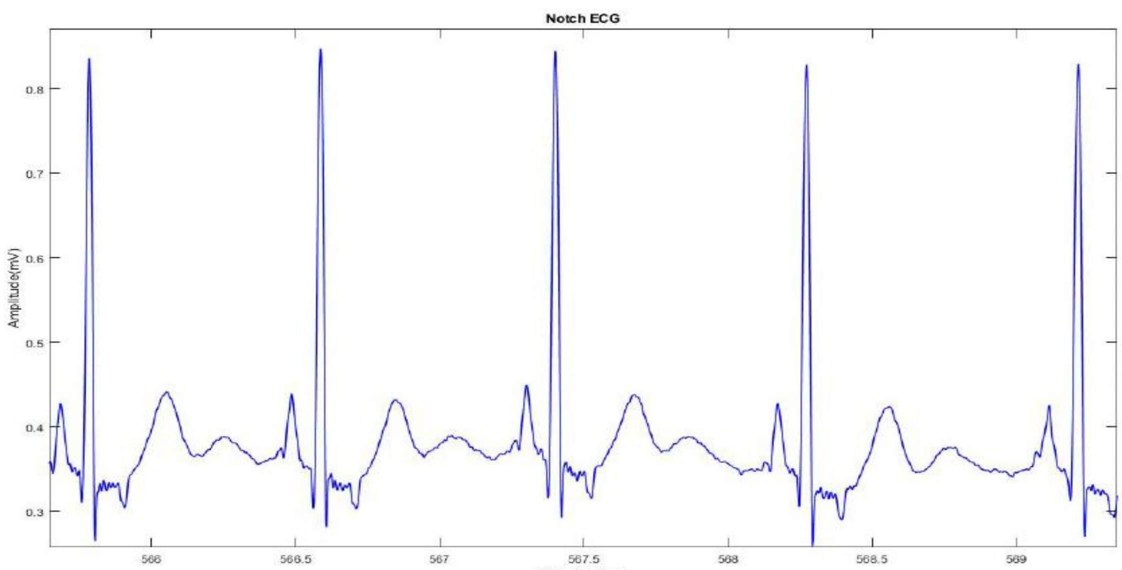

Figure 4: ECG Signal representation after noise removal

Subsequently, the peaks are detected by first obtaining high slope values using the differentiation equation. Next, the R-peaks are obtained by squaring the output signals and lastly the sum of all values was made on the slope of the R-wave. The values of R-wave, R location and amplitude are stored on the R^{nxm} matrix. The detected peaks are shown in figure 5.

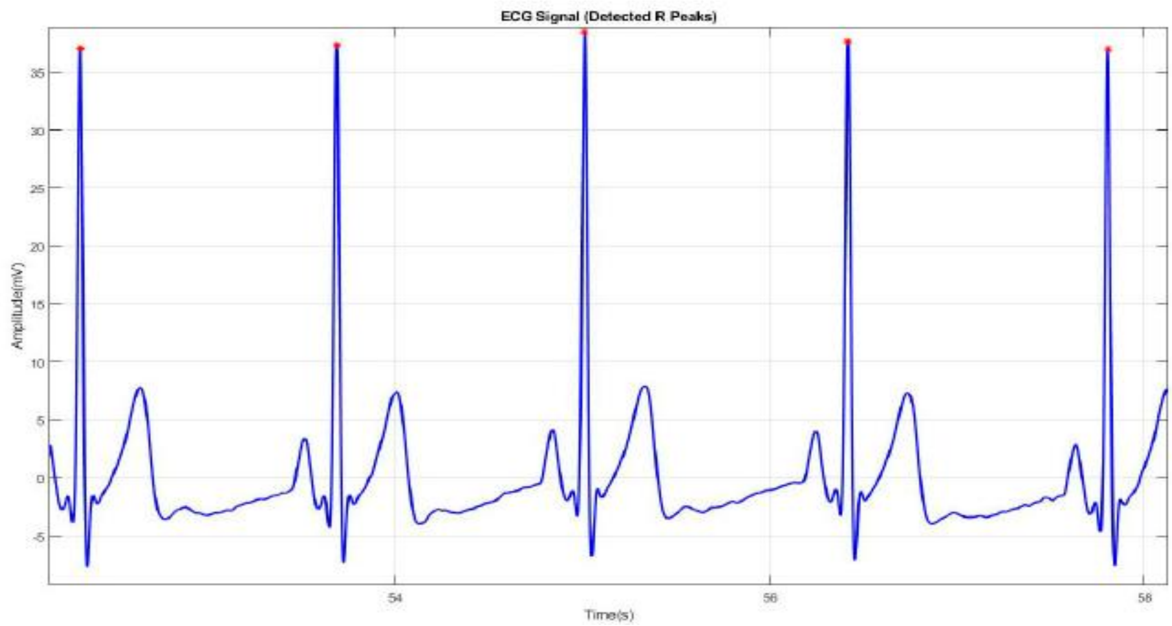

Figure 5: R- peaks detected from ECG signal are represented

Further, the heartbeat is segmented after detecting the peaks. The R^{nxm} matrix is used to choose the R location as the point of reference. After determining the position of the R-peak, the waveform is sampled for a single heartbeat. The segmented area is shown in figure 6.

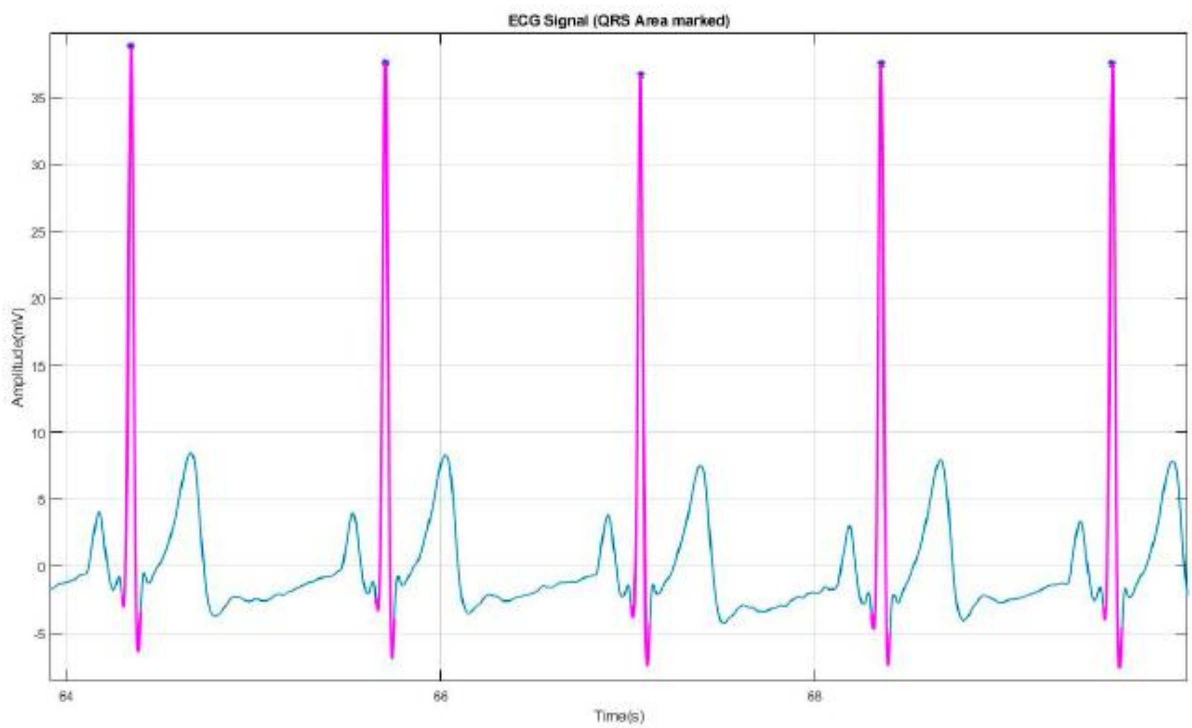

Figure 6: The QRS area is shown in pink colour

To obtain these peaks 200 samples were used from the database and to obtain the R peak, the division of points included 75 and 125 on both left and right sides respectively of R-peak. The samples were gathered in time from 0.2 seconds to 0.32 seconds. Using this approach the temporal location of waves namely Q, S, P and T waveforms are extracted from the signal.

Based on the training and testing datasets, the beat class distribution is provided in table 2.

	SVEB+ class		**VEB+ class**	
Database	**N**	**S**	**V**	**F**
MIT-BIH AR (DS1)	45,783	943	3,785	414
MIT-BIH AR (DS2)	44,179	1,834	3,216	388
AHA (DS1)	158,587		15,075	292
AHA (DS2)	156,992		15,855	437

Table 2: Beat class distribution for both the databases

The ECG records are processed in the classifier as in the following steps,

1. The ECG signals are re-sampled. The processing is done at the rate of 250 Hz, the common sampling rate. In this step, the AHA database at a frequency of 250 Hz retains the sampling rate in its original form and the MIT-BIH database is re-sampled at a frequency range - of 250 Hz from 360 Hz.
2. The ECG data is filtered to bandwidth $\nu\ (Hz) \in [0.5, 0.35]$ to remove noise and unwanted signals. In this step, a high-pass filter is used as a standard procedure.
3. The heartbeat is detected by determining the position. The databases provide annotated positions and hence those positions are used to determine the heartbeat. In the case of the MIT-BIH database, the large minimum or maximum value in QRS complex function denotes the annotated position, this is used.
4. The RR interval is determined. This interval is the time duration between two successive heartbeats. Suppose if RR interval denotes heartbeat *i*, the time difference (*i – 1*) represents the difference in time duration between *i* and the previous heartbeat (*i - 1*).

5. The heartbeat is segmented from the segmented position of data in each of the databases. The segment size is 240 ms in the project and the segment is around the annotated position.
6. Lastly, each heartbeat is normalized in the range [-1, 1]. In this manner, the signal is separate and becomes independent from the original ECG signal amplitude.

In the above processing of ECG recordings, each heartbeat must be represented as a set of features. The main reason for feature selection is to ignore complicated features that can lead to high computing costs. Hence the simple method is considered for feature extraction.

Here, the raw waveform for each heartbeat is used and the position of the heartbeat is represented. The original raw data as a waveform in each heartbeat indicates equally the number of samples having both sides as the reference point in annotating heartbeats. Further data from RR intervals are added to heartbeat features to understand characteristics related to the temporal nature of each heartbeat signal. The RR intervals are the features usually used in the arrhythmic classification of heartbeats. The heartbeat features for i^{th} heartbeat are,

(i) The original data of 60 heartbeat waveforms is centred around the annotated position for the heartbeat

(ii) The current RR- interval logarithm value is represented as $ln(RR(i))$

(iii) The next RR-interval logarithm function is represented as $ln(RR(i+1))$

(iv) The average measure of 250 RR- intervals are represented as $ln(_{mean})$. The mean is the average of n neurons with RR intervals, in this case, $n < 250$.

The process stages and feature extraction are done by representing each heartbeat as one vector with d-dimensions. Three features are found in the vector, namely RR- intervals, morphological features, and samples of ECG waveform. These features have a relation to RR- intervals. Here the vector with d-dimensional, $d = 63$ provides input for the classification algorithm.

The ESN classifier algorithm

As mentioned earlier, the ring topology is used in the ESN classifier and implemented in RC. RC is a paradigm in ML is a successful RNN approach that makes use of the layers namely input, reservoir and output layers. The ECG input stage is given to the RC network to result in a change of dimensions from $d \times H_b$ to $N \times H_b$. Here, the number of input features is indicated as d, H_b

represents the heartbeats and the neurons are denoted as N. The random input matrix represented as $W^{in}_{N\times d}$ is generated in uniform distribution that is an element of [-1, 1]. Therefore, the data features from ECG original vector, $u_{d\times Hb}$ changed as in equation $X_{N\times Hb} = (W^{in}_{N\times d} \times u_{d\times Hb})$.

The input data sent to the reservoir will proceed sequentially where further computation is made iteratively in the reservoir. Here, r is the matrix response in the reservoir for *an n*th heartbeat for classifier standard ESN is provided by expression $\boldsymbol{r}(n) = F\big(\gamma \boldsymbol{X}(n) + \eta \boldsymbol{W}\boldsymbol{r}(n-1)\big)$.

In this expression, **W** represents a square matrix with a random connection and has N x N dimensions. The activation function of ESN is represented as F. The quantities γ and η represent the scaling parameters for input and connection respectively.

In ESN, the random square matrix **W** is generated using the uniform distribution in the range [-1, 1]. This will define weights that provide connections between neurons internally. In the case of a non-linear function, the exponent and bias in the classical sigmoid function are used because sigmoid functions in reservoir computing provide outputs optimally. Using simple linear regression, the reservoir response and output connections are only optimized. The input ***r(n)*** by the ESN will calculate the output given by the quantity, $\hat{y}(n)$ as $\hat{y}(n) = \boldsymbol{W}^{out}\boldsymbol{r}(n)$. In this expression, $\boldsymbol{W}^{out}_{l\times N}$ is the quantity for output weights in the ESN. Here, *l* represents output nodes. The linear regression model is used in calculating the output nodes. Here, the error is minimized between the outputs of training data and the associated values of the target class. The output is continuous and represented as expression $\hat{y}(n)$ is converted to binary through a decision threshold. Usually, with ESN classifiers, W the connection matrix is referred to as a sparse random matrix. The ESN classifier with ring topologies performs better with the standard random connection matrix. In the study, the ring topology of ESN is used as it provides fixed connections at random in the input function $\boldsymbol{W}^{in}$ and with fixed weights having deterministic and in between internal neurons in the reservoir.

Also, the topology selected can easily explore system parameters contrarily, ESN classifiers with random topologies need more computing power. ESN ring topology is easy to implement and does not need high computing power.

Chapter 5: Analysis and Discussion

The ECG datasets were processed using an ESN classifier based on RNN that has input and connection weights at random between the neurons. RC response will be easy to classify because the input is mapped non-linearly and has high dimensions, compared to the original input through a simple linear regression technique. The classifier is evaluated using optimal parameters. The final evaluation is done using the testing dataset DS2 which is not equal to the training dataset (DS1). The classifier performance is obtained with dataset DS2. In the training phase, the parameters of individual ESN are optimized. The original ECG signal is normalized in [-1, 1]. Hence there is a similarity between the RR- intervals in the datasets. The optimum parameters for ESN are $\eta = 0.2$, $\gamma = 0.1$ and $N = 1000$ as they are found to be associated with both MIT-BIH and AHA datasets. The VEB performance measures were obtained from the dataset as in table 3.

Database	Lead	Se (%)	PPV (%)	Sp (%)	Acc (%)
MIT-BIH AR	II	84.4 (82.9)	95.8 (85.5)	99.7(98.8)	98.6 (97.7)
	V1'	81.5 (78.9)	76.2 (66.0)	98.0 (96.6)	96.8 (95.3)
AHA	A	90.4 (87.2)	94.9 (92.4)	99.5 (99.2)	98.6 (98.5)
	B	87.9 (85.8)	89.6 (83.4)	98.9 (98.2)	97.8 (97.0)

Table 3: The performance measures of VEB heartbeat using 30 ESN

The performance measures in the table obtained using two leads for both databases indicate the accuracy is above 98%. This implies lead II of the MIT-BIH dataset provides the best results. Here, the ensembles will minimize overall errors in a single ESN. The ensemble significantly reduces false negatives to result in higher PPV. The capability for generalization for both SVEB and VEB classifiers provided promising results. The generalization capability was achieved by training the AHA database for both leads A and B. This AHA dataset provided better generalization potential compared with MIT-BIH datasets. The ensemble performance and F1 score are shown in the graph, figure 7.

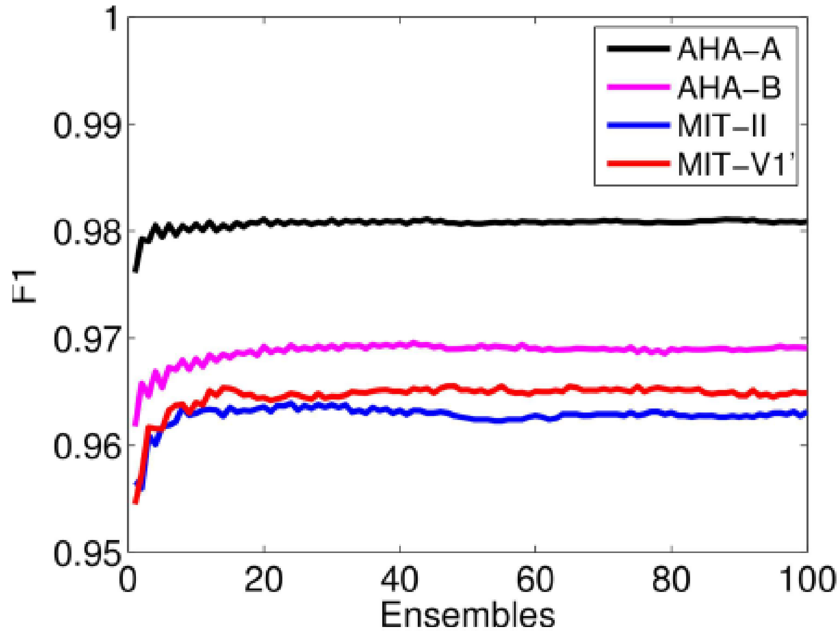

Figure 7: ESN classifier performance obtained with $\eta = 0.2$, $\gamma = 0.1$ and N = 1000

To compare the performance of the ESN classifier with another standard classifier, the classification model using CNN was explored. In this model, the datasets used were the same, MIT-BIH and AHA. The method will automatically classify VEB beats using wavelet transform of ECG and CNN. The wavelets used in this method are Morlet Wavelet, Paul wavelet and Gaussian Derivative. These wavelets were transformed as divisions of single-channel ECG waveform to the 2D image of a certain frequency. The images of time frequency were further fed into the CNN to optimize the convolution filters and are classified. This method made use of a tenfold evaluation using the arrhythmia database MIT-BIH. The AHA datasets were used separately to evaluate the trained network.

The ECG recordings from the MIT-BIH database were allocated as ten data subsets randomly. The approach of random grouping was made by gathering the numbers instead of the total heartbeats, where data of one record will not be present in both the training and testing datasets. The CNN model was provided with a 5/6 heartbeats waveform to directly train the model and 1/6 heartbeats were used to validate the learning process and optimise model parameters and prevent overfitting. The trained model was tested and the process was made using 10 iterations and results for each fold were combined.

As indicated earlier, the performance metrics namely Acc, Se, Sp, PPV and F1 scores were determined to evaluate the algorithm performance. The statistical measures were obtained and for each test fold in the datasets, the beats were identified whether they are correct or incorrect along with true positives, true negatives, false positives and false negatives.

The gross test results of the model were obtained. The F1 score was high as shown in figure 8.

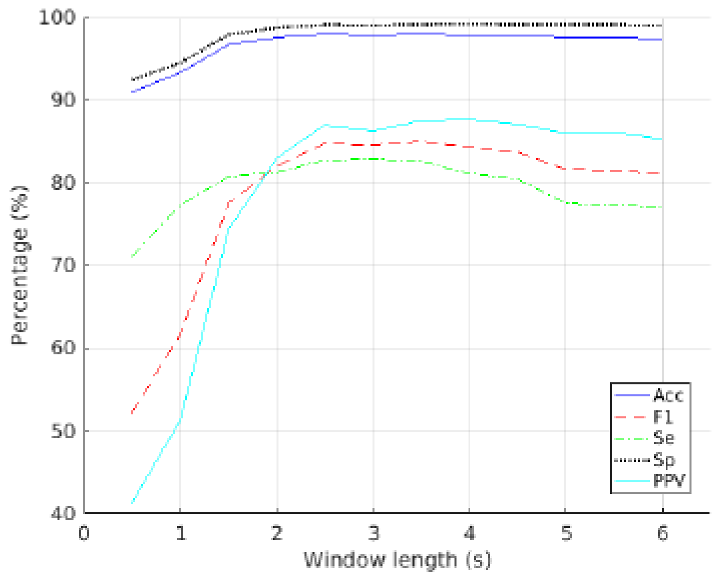

Figure 8: The gross test performance showing different metrics

The training results indicate the Paul wavelet provided the best test performance with accuracy at around 97.9%, Sp is 99.1%, and PPV at 87.2%, sensitivity at 82.6%.

With the AHA database, the algorithm could obtain 97.6% accuracy, 82.2% sensitivity, 98.8% specificity and 87.2% PPV. The results were averaged to obtain the evaluation measures, that indicate the model has the potential for good performance in classifying ECG waveforms.

Discussions

The method using the ESN classifier provides good results for VEB heartbeat with MIT-BIH and AHA databases in detecting ventricular arrhythmia. The classifier approach with ESN is found to be ideal in processing ECG signals obtained in the long term and can be used for large databases as minimum computational requirements are needed for feature extraction and the algorithm. Further ESN presents advantages over the classical methods that make use of SVM, NN, CNN or decision trees and so on. This was checked with the computational performance and performance metrics with the other model using the same databases. In the compared work a learning network using CNN was used to distinguish VEBs from ECG waveforms using the same types of input. This method is not computationally intensive and tends to show promising results during testing and validation.

The metrics value obtained from both methods is shown in Table 4.

Metrics	**ESN Classifier**		**CNN classifier model**	
	AHA	**MIT-BIH**	**AHA**	**MIT-BIH**
Accuracy (ACC)	98.15	96.1	97.5	97.3
Sensitivity (Se)	86.9	78.4	82.5	82.8
Positive Predicted Value (PPV)	93.4	79.9	82.3	87.2

Table 4: Performance metrics values obtained from both the methods

The results indicate the accuracy values obtained from ESN are slightly higher in terms of the value obtained for AHA. In the case of the MIT-BIH database, the accuracy value is slightly higher compared to the accuracy value obtained in the ESN classifier. The sensitivity values obtained from the ESN classifier are higher compared to the values of sensitivity determined using the CNN classifier model. This indicates the RC paradigm in the ESN network provides better performance in processing ECG waveforms with variations. The PPV values provide higher measures for the Aha database using the ESN classifier, whereas with MIT-BIH datasets the values for PPV are lesser compared to the PPV value obtained from the MIT-BIH dataset using the CNN model.

Based on the comparative evaluation and determination of metrics the ESN classifier provides better results in accuracy, PPV and sensitivity compared to other models based on the CNN algorithm. Therefore, it is noted that the ESN classifier based on the reservoir computing model shows good potential in classifying arrhythmia conditions from ECG waveforms.

Conclusion

The project presents the processing of ECG datasets using an ENN network based on the reservoir computing paradigm. The project aims to overcome the challenges in ECG classification due to the increase in cardiovascular diseases and related conditions. Over the years several studies highlight the use of ML models and algorithms to automatically classify heartbeat variations using ECG datasets. The project focuses on the CVD condition named arrhythmia to classify ECG heartbeats using standard ECG databases from MIT-BIH and AHA.

The ESN classifier based on the reservoir computing paradigm is considered in this study for its accuracy and low hardware requirements. The study is made by first understanding existing research related to the topic of arrhythmia classification using standard classifiers based on ML models. A comprehensive literature review is made to understand the clinical applications of ECG waveform data. The ECG waveform data must first be pre-processed to remove noisy signals from the ECG waves. This is followed by processes involving heartbeat segmentation, extracting of the features and finally classification of heartbeats. Lastly, the ESN classifier is fed with clean ECG datasets to determine between heartbeats that are normal and abnormal.

The methodology section provides the details of each step followed in the project. As mentioned in the report, the datasets from MIT-BIH and AHA databases were processed using the ESN classifier to determine heartbeat variability in each heartbeat waveform. The reprocessing steps include the use of the filter to remove noise signals and outliers before heartbeat segmentation. In the project, the techniques of signal processing are employed and used to eliminate unwanted signals in the ECG signal before it is provided as input to the classifier. This is followed by heartbeat segmentation, the heartbeat segmentation is based on the QRS complex. In this phase, the R peaks and location is determined and the QRS area in the ECG signal is obtained. The feature extraction will extract RR intervals between two successive heartbeats. It is noted the heart-rate variability measure is the time interval between two successive heartbeats measured as

RR- interval in milliseconds. The extracted features are the pre-processed ECG waveform that is fed to the ESN classifier.

In the project, the ring topology ESN architecture is used for its efficiency and less power consumption. The weight matrix is developed for the ESN model and the equations related to input and outputs are provided along with the parameters. The standard performance metrics namely accuracy, sensitivity, specificity, predictive power value, and F1 scores are determined to understand the output performance of the classifier. The temporal wave features are processed in the classifier for obtaining the performance metrics. The training and testing datasets are split from both databases to train and evaluate the model. The performance metrics were determined for the ESN classifier based on the RC paradigm.

The findings and results provide the outputs obtained from the model to highlight the different processing steps. The beat class distribution is presented and the final processing steps for the classifier are highlighted in the report. The ESN algorithm is presented for its internal workings. The performance of the ESN classifier is obtained from processing the testing dataset from both databases. The results are provided in the table.

To compare the ESN classifier, another standard model based on the CNN classifier was used to classify variations in heartbeats using the same databases. The CNN-based model made use of different signal processing methods and the same performance metric values were derived. A performance comparison is presented is made to understand the determined values. It is noted that the ESN classifier is more effective and accurate in classifying heartbeat variability compared with the standard CNN model. Hence the ESN classifier based on RC has the potential to classify different heartbeat conditions and support the diagnosis of CVD in patients.

Future work:

Future work on this topic will include processing more datasets in ESN to improve prediction accuracy using different datasets and also evaluate the system for its effectiveness using real-time data.

References

Alonso-Atienza, F., Morgado, E., Fernandez-Martinez, L., Garcia-Alberola, A., & Rojo-Alvarez, J. (2014). Detection of life-threatening arrhythmias using feature selection and support vector machines. *IEEE Trans. Biomed. Eng*, *61*, 832–840.

Al-Turjman, F., Nawaz, M.H. and Ulusar, U.D. (2020). Intelligence in the Internet of Medical Things era: A systematic review of current and future trends. *Computer Communications*, [online] 150, pp.644–660. doi:10.1016/j.comcom.2019.12.030.

Arvanaghi, R., Danishvar, S. and Danishvar, M. (2022). Classification cardiac beats using arterial blood pressure signal based on discrete wavelet transform and deep convolutional neural network. *Biomedical Signal Processing and Control*, [online] 71, p.103131. doi:10.1016/j.bspc.2021.103131.

Bognár, G. and Fridli, S. (2020). ECG heartbeat classification by means of variable rational projection. *Biomedical Signal Processing and Control*, [online] 61, p.102034. doi:10.1016/j.bspc.2020.102034.

Brieva, J., Ponce, H. and Moya-Albor, E. (2020). A Contactless Respiratory Rate Estimation Method Using a Hermite Magnification Technique and Convolutional Neural Networks. *Applied Sciences*, [online] 10(2), p.607. doi:10.3390/app10020607.

Castillo, O., Melin, P., Ramírez, E., & Soria, J. (2012). Hybrid intelligent system for cardiac arrhythmia classification with Fuzzy K-Nearest Neighbors and neural networks combined with a fuzzy system. . *Expert Syst. Appl.* , *39*.

Cao, X., Yao, J., Xu, Z. and Meng, D. (2020). Hyperspectral Image Classification With Convolutional Neural Network and Active Learning. *IEEE Transactions on Geoscience and Remote Sensing*, [online] 58(7), pp.4604–4616. doi:10.1109/tgrs.2020.2964627.

D'Errico, S., Mazzanti, A., Baldari, B., Maiese, A., Frati, P. and Fineschi, V. (2020). Sudden death in lambda light chain AL cardiac amyloidosis: a review of literature and update for clinicians and pathologists. *International journal of clinical and experimental pathology*, [online] 13(7), pp.1474–1482. Available at: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7414507/ [Accessed 22 Jan. 2023].

De Chazal, P., O'Dwyer, M., & Reilly, R. (2004). Automatic classification of heartbeats using ECG morphology and heartbeat interval features. *IEEE Trans. Biomed. Eng* , *51*, 1196–1206.

Dokur, Z., & Ölmez, T. (2001). ECG beat classification by a novel hybrid neural network. . *Comput. Methods Progr. Biomed.* , *66*.

Elhaj, F., Salim, N., Harris, A., Swee, T., & Ahmed, T. (2016). Arrhythmia recognition and classification using combined linear and nonlinear features of ECG signals. *Comput. Methods Progr. Biomed.* , *2016*, 52-63.

Fang, M. and Huang, B. (2021). Two-stage time-varying hidden conditional random fields with variable selection for process operating mode diagnosis. *Chemometrics and Intelligent Laboratory Systems*, [online] 214, p.104330. doi:10.1016/j.chemolab.2021.104330.

Garcia, G., Moreira, G., Menotti, D., & Luz, E. (2017). Inter-Patient ECG Heartbeat Classification with Temporal VCG Optimized by PSO. *Sci. Rep , 7*.

Huang, H., Liu, J., Zhu, Q., Wang, R., & Hu, G. (2014). A new hierarchical method for inter-patient heartbeat classification using random projections and RR intervals. *Biomed. Eng , 13*, 90.

Inan, O., Giovangrandi, L., & Kovacs, G. (2006). Robust neural-network-based classification of premature ventricular contractions using wavelet transform and timing interval features. *IEEE Trans. Biomed. Eng. , 56*.

Ishaq, A., Sadiq, S., Umer, M., Ullah, S., Mirjalili, S., Rupapara, V. and Nappi, M. (2021). Improving the Prediction of Heart Failure Patients' Survival Using SMOTE and Effective Data Mining Techniques. *IEEE Access*, [online] 9, pp.39707–39716. doi:10.1109/access.2021.3064084.

Khan, M.A., Hashim, M.J., Mustafa, H., Baniyas, M.Y., Al Suwaidi, S.K.B.M., AlKatheeri, R., Alblooshi, F.M.K., Almatrooshi, M.E.A.H., Alzaabi, M.E.H., Al Darmaki, R.S. and Lootah, S.N.A.H. (2020). Global Epidemiology of Ischemic Heart Disease: Results from the Global Burden of Disease Study. *Cureus*. [online] doi:10.7759/cureus.9349.

Khoshnevis, S.A. and Sankar, R. (2020). Applications of Higher Order Statistics in Electroencephalography Signal Processing: A Comprehensive Survey. *IEEE Reviews in Biomedical Engineering*, [online] 13, pp.169–183. doi:10.1109/rbme.2019.2951328.

Kuila, S., Dhanda, N. and Joardar, S. (2019). Feature Extraction and Classification of MIT-BIH Arrhythmia Database. *Lecture Notes in Electrical Engineering*, [online] pp.417–427. doi:10.1007/978-981-15-0829-5_41.

Lin, J., Chen, Y., Jiang, N., Li, Z. and Xu, S. (2022). Burden of Peripheral Artery Disease and Its Attributable Risk Factors in 204 Countries and Territories From 1990 to 2019. *Frontiers in Cardiovascular Medicine*, [online] 9. doi:10.3389/fcvm.2022.868370.

Liu, J., Song, S., Sun, G. and Fu, Y. (2019). Classification of ECG Arrhythmia Using CNN, SVM and LDA. *Lecture Notes in Computer Science*, [online] pp.191–201. doi:10.1007/978-3-030-24265-7_17.

Manpreet, S. and Kalia, R. (2020). Rheumatic Fever and Rheumatic Heart Disease. *Asian Journal of Nursing Education and Research*, 10(3), pp.360–364.

Martinez-Alanis, M., Bojorges-Valdez, E., Wessel, N. and Lerma, C. (2020). Prediction of Sudden Cardiac Death Risk with a Support Vector Machine Based on Heart Rate Variability and Heartprint Indices. *Sensors*, [online] 20(19), p.5483. doi:10.3390/s20195483.

Mar, T., Zaunseder, S., Martínez, J., Llamedo, M., & Poll, R. (2011). Optimization of ECG classification by means of feature selection. *IEEE Trans. Biomed. Eng , 58*, 2168-2177.

Martis, R., Acharya, U., & Min, L. (2013). ECG beat classification using PCA, LDA, ICA and discrete wavelet tranform. *Biomed. Signal Process. Control , 8*, 437-448.

Mastoi, Q., Wah, T. and Gopal Raj, R. (2019). Reservoir Computing Based Echo State Networks for Ventricular Heart Beat Classification. *Applied Sciences*, [online] 9(4), p.702. doi:10.3390/app9040702.

Mejía-Mejía, E., May, J.M. and Kyriacou, P.A. (2022). Effects of using different algorithms and fiducial points for the detection of interbeat intervals, and different sampling rates on the assessment of pulse rate variability from photoplethysmography. *Computer Methods and Programs in Biomedicine*, [online] 218, p.106724. doi:10.1016/j.cmpb.2022.106724.

Nilashi, M., Ahmadi, H., Manaf, A.A., Rashid, T.A., Samad, S., Shahmoradi, L., Aljojo, N. and Akbari, E. (2020). Coronary Heart Disease Diagnosis Through Self-Organizing Map and Fuzzy Support Vector Machine with Incremental Updates. *International Journal of Fuzzy Systems*, [online] 22(4), pp.1376–1388. doi:10.1007/s40815-020-00828-7.

Pandey, S.K. and Janghel, R.R. (2018). ECG Arrhythmia Classification Using Artificial Neural Networks. *Proceedings of 2nd International Conference on Communication, Computing and Networking*, [online] pp.645–652. doi:10.1007/978-981-13-1217-5_63.

Pion-Tonachini, L., Kreutz-Delgado, K. and Makeig, S. (2019). ICLabel: An automated electroencephalographic independent component classifier, dataset, and website. *NeuroImage*, [online] 198, pp.181–197. doi:10.1016/j.neuroimage.2019.05.026.

Qurraie, S., & Afkhami, R. (2017). ECG arrhythmia classification using time frequency distribution techniques. *International journal of Intelligent Engineering and Systems , 7*.

Raj, S., Ray, K., & Shankar, O. (2016). Cardiac arrhythmia beat classification using DOST and PSO tuned SVM. *Comput. Methods Progr. Biomed. , 136*, 163-177.

Robinson, Mabato, Kabari and Ledisi, G. (2021). Detection of Heart Abnormalities Using Signal Processing. *International Journal of Research and Innovation in Applied Science (IJRIAS)*, 6(11), pp.23–28.

Saini, I., Singh, D., & Khosla, A. (2013). QRS detection using K-Nearest Neighbor algorithm (KNN) and evaluation on standard ECG databases. *J. Adv. Res. , 4*, 331-344.

Şahin, B. and İlgün, G. (2020). Risk factors of deaths related to cardiovascular diseases in World Health Organization (WHO) member countries. *Health & Social Care in the Community*, [online] 30(1), pp.73–80. doi:10.1111/hsc.13156.

Shi, H., Wang, H., Huang, Y., Zhao, L., Qin, C. and Liu, C. (2019). A hierarchical method based on weighted extreme gradient boosting in ECG heartbeat classification. *Computer Methods and Programs in Biomedicine*, [online] 171, pp.1–10. doi:10.1016/j.cmpb.2019.02.005.

Srinivasan, N., & Schilling, R. (2018). Sudden Cardiac Death and Arrhythmias. *Arrhythm Electrophysiol Rev , 7* (2), 111-117.

Tian, C., Zheng, M., Zuo, W., Zhang, B., Zhang, Y. and Zhang, D. (2023). Multi-stage image denoising with the wavelet transform. *Pattern Recognition*, [online] 134, p.109050. doi:10.1016/j.patcog.2022.109050.

Wang, H., Lv, B., Li, W., Wang, S. and Ding, W. (2022). Diagnostic Performance of the Caprini Risk Assessment Model Combined With D-Dimer for Preoperative Deep Vein Thrombosis in Patients With Thoracolumbar Fractures Caused by High-Energy Injuries. *World Neurosurgery*, [online] 157, pp.e410–e416. doi:10.1016/j.wneu.2021.10.106.

Wang, H., Wu, Q.M.J., Wang, D., Xin, J., Yang, Y. and Yu, K. (2021). Echo state network with a global reversible autoencoder for time series classification. *Information Sciences*, [online] 570, pp.744–768. doi:10.1016/j.ins.2021.04.074.

Yang, H. and Wei, Z. (2020). Arrhythmia Recognition and Classification Using Combined Parametric and Visual Pattern Features of ECG Morphology. *IEEE Access*, [online] 8, pp.47103–47117. doi:10.1109/access.2020.2979256.

Ye, C., Kumar, B., & Coimbra, M. (2016). An Automatic Subject-Adaptable Heartbeat Classifier Based on Multiview learning. *IEEE J. Biomed. Health Inform , 20*, 1485.

Ye, C., Kumar, B., & Coimbra, M. (2012). Heartbeat classification using morphological and dynamic features ofECG signals. *IEEE Trans. Biomed. Eng. , 59*, 2930-2941.

Zhang, Z., Dong, J., Luo, X., Choi, K., & Wu, X. (2014). Heartbeat classification using disease-specific feature selection. *Comput. Biol. Med , 46*, 79-89.

Zidelmal, Z., Amirou, A., Ould-Abdeslam, D., & Merckle, J. (2013). ECG beat classification using a cost sensitive classifier. *Comput. Methods Progr. Biomed , 111*, 570-577