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Neurons to heartbeats: spiking neural networks for electrocardiogram pattern recognition

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ABSTRACT

The electrocardiogram (ECG) is one of the most significant methods of diagnostics for determining heart rhythm disorders. For this study, raw ECG signals from the Physio Bank database are subjected to an important pre-processing step that uses empirical mode decomposition (EMD) on signal denoising and distortion elimination. Establishing functioning spiking neural networks (SNN) involves figuring out the neuron's state through its activity level, challenging due to its resemblance to the human brain's data processing, yet appealing due to factors like improved unsupervised learning methods, with ten parameters chosen for the learning algorithm of SNN. A comprehensive set of 15 different time-domain features and 10 Cepstral domain features is precisely extracted to train the SNN classifier. An extensive study is conducted to analyse the learning parameters that affect SNN performance, significantly influencing result accuracy. Through a two-classification process, the differentiation between normal and abnormal ECG patterns can be achieved in this study. A maximum testing accuracy of 91.6667% and a maximum training accuracy of 99.1667% have been attained by the process. These results demonstrate the competency of the system in distinguishing between distinct ECG classes, particularly in identifying normal and abnormal cardiac rhythms through ECG classification.

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1. INTRODUCTION

Electrocardiogram (ECG) pattern recognition, crucial for diagnosing and monitoring heart diseases, provides insights into the heart's electrical activities [1], [2]. Despite advancements, accurately and efficiently interpreting ECG signals is challenging due to their inherent complexity and variability. Rafie *et al*. [3] have argued that traditional computational techniques often struggle to address these challenges, prompting the exploration of more advanced solutions. Relevant literature has highlighted significant contributions to neural network applications and machine learning algorithms in biomedical signal processing, as reviewed by Zemouri *et al*. [4]. These studies have laid the groundwork for ECG pattern recognition, noting achievements in improved accuracy and processing speed according to Siontis *et al.* [5].

However, challenges in generalizing across diverse patient datasets and the need for substantial computational resources are often encountered, according to several recent studies [6], [7].

Current methodologies have limitations in processing noisy data, consuming high power, and recognizing complex ECG patterns, underscoring the need for innovative approaches to improve the robustness and efficiency of ECG pattern recognition systems, thus introducing a novel application of spiking neural networks (SNNs) in ECG pattern recognition. Amiri *et al.* [8] inspired by the neural processing of the human brain, SNNs promise to enhance the accuracy and efficiency of pattern recognition tasks. Leveraging the temporal dynamics of SNNs aims to address the limitations of traditional neural networks, providing a more efficient and scalable solution for ECG analysis as argued by Zheng *et al.* [9]. Heart disease was among the top global health threats in 2019, according to the World Health Organization (WHO) as demonstrated by Yan *et al*. [10]. The non-invasive method of ECG serves as a significant tool for detecting cardiovascular disease, primarily identifying abnormal heartbeats within several recent studies [11], [12]. Continuous ECG monitoring on wearable devices has been proven lifesaving by detecting users' heartbeat abnormalities, increasing chances for initial intervention according to Xiaoxue *et al.* [13]. This work presents a set of ECG classification methods using SNN to classify heartbeats into normal and abnormal categories, aiming to investigate the performance of the SNN algorithm, develop a classification algorithm based on ECG data, and verify its performance through confusion tables and mean average precision.

SNNs, as the third generation of neural networks, offer a significant advantage in energy efficiency over convolutional neural networks (CNNs) by mimicking the way biological networks process information through spikes. Lower energy consumption makes SNNs ideal for applications in edge computing, robotics, and wearable devices where power efficiency is crucial as demonstrated in Yan *et al.* [10]. Guo *et al.* [14] SNNs, capable of operating with fewer layers and employing a dynamic weight model, efficiently approximate real-valued functions and provide faster computing options. Sodhro *et al.* [15] the innovative approach enhances the performance of low-power systems, particularly in sectors requiring energy-efficient intelligent systems, such as ECG classification in power-constrained wearable technology. The structure of this work includes a methodology section detailing the development and implementation of the SNN-based approach, a results section highlighting improved performance in ECG pattern recognition by SNNs with reduced computational demands, a discussion comparing the approach with existing methods and emphasizing its advantages and real-world healthcare applications, and a conclusion summarizing the contributions and future research directions, emphasizing SNNs' potential to revolutionize ECG pattern recognition.

2. RELATED WORK

This section explains the significance of ECG and heart anatomy in diagnosing cardiac conditions, emphasizing the accuracy of ECG pattern recognition. It also discusses the architecture of SNNs, highlighting their energy-efficient information processing inspired by biological neural networks. Finally, the potential applications of SNNs are explored, highlighting their adaptability in fields ranging from medical diagnostics to the development of energy-efficient wearable technologies. This discourse serves to illustrate the groundbreaking possibilities that SNNs present in improving healthcare outcomes through enhanced ECG analysis.

2.1. Electrocardiogram

An ECG can be used to diagnose cardiac disease as demonstrated in Khan *et al.* [16]. Because of its non-invasive nature, it's commonly used to identify cardiac problems. By visually reviewing recordings of ECG signals, trained cardiologists can discover abnormalities as demonstrated in Corradi *et al.* [11]. It gives information on the electrical activity of the heart in the heartbeats of patients in several recent studies [12]. ECG is gathered from cardiac muscle depolarization to repolarization by electrodes put on the patient's skin that record electric changes during the cardiac cycle according to Zheng *et al.* [17]. Several recent studies [18] have argued that heart monitoring on small devices, especially wearable devices, is now possible because of automated ECG diagnosis. The standard ECG waveform, featuring the P wave, QRS complex, and T wave, is depicted in Figure 1. Through the waveform's size and shape, information on cardiac illness or dysfunction is provided. The P wave arises from the depolarization of the atrium. When there is ventricular depolarization, the QRS complex is generally the primary and distinct waveform that is produced as demonstrated in Rana and Kim [19].

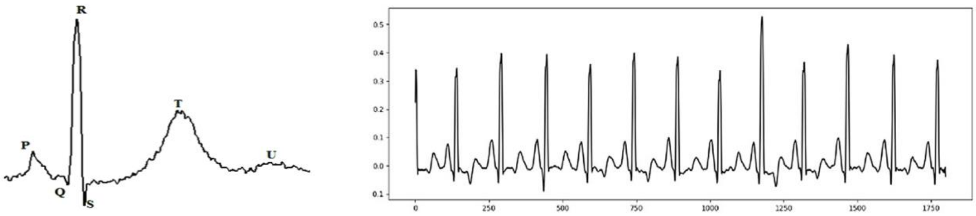


Figure 1. Normal beat [19], [20]

2.2. Heart anatomy

During a normal cardiac cycle, an electrical impulse is emitted by the sinus node. This impulse is then passed in order through the atria, atrioventricular node, and ventricle. Irregular sources of electrical impulses can lead to abnormal cardiac rhythms according to [21]. Electrode insertion on the skin of a person detects that electricity and produces a voltage-time readout that produces an ECG. The ECG signal gives human heart information which includes heart position and relative chamber size, origin and propagation of impulse, rhythmic heart and conduction, myocardial ischemia size, and location, electrolyte concentration changes, and heart effects according to Aziz *et al.* [12].

2.3. SNN architecture

In Figure 2, the architecture of the SNN, the third generation of neural networks, is depicted, showing how information is processed through spike signal propagation and timing, with synapses forming weighted connections between neurons to facilitate learning via spike-time-dependent plasticity (STDP). The STDP rule is used to determine how much each pre-synaptic spike contributes to the total weight change as demonstrated in several recent studies [22]. Binary spikes are the data transferred between layers for the SNN according to Liu *et al.* [23]. Utilizing a learning algorithm designed for multi-class tasks and extending the learning rule to handle multiclass classification efficiently. This compact architecture ensures comparable performance on multi-class classification problems.

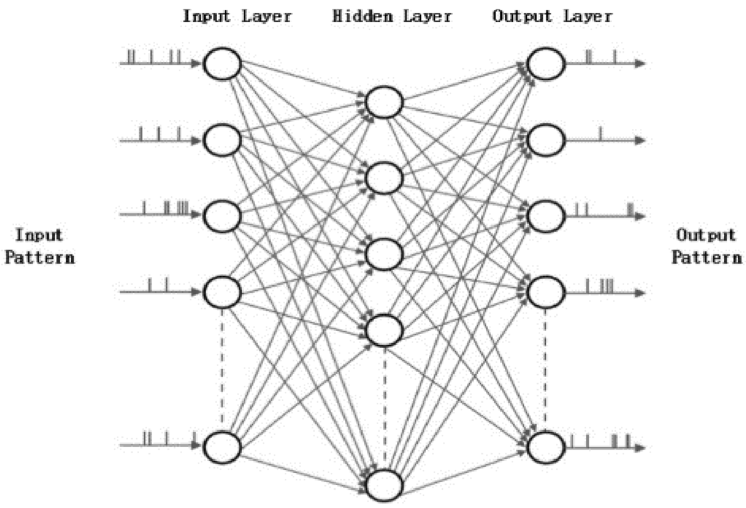


Figure 2. Architecture of SNN [19]

In Figure 3, it is illustrated that input spike timings are derived from real-valued data, where the strength of receptive field (RF) neurons in population encoding is translated into spike times. Synapses define the strength of neural connections, utilizing a time-varying weight model to enhance the dynamics of learning algorithms, including the STDP rule for weight adjustment. Sumi and Harada [24] a positive change in weight is called long-term potentiation (LTP) and a negative change in weight is for LTD. For classification tasks, SNNs are employed, where artificial neural networks, through machine learning, learn from events and make decisions by comparing them to similar past occurrences. In addition, artificial neural networks have the potential to execute several tasks at the same time as demonstrated in [25].

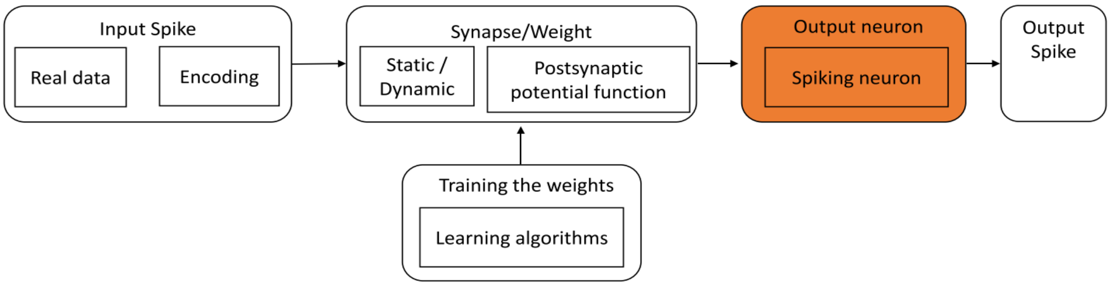


Figure 3. Mechanism of SNN [25]

2.4. Potential applications

Recent advancements in medical technology have shifted towards enabling continuous health monitoring outside the hospital, notably through wearable devices for daily use, allowing for easy tracking of vital signs like ECGs at home or on the go. Wearable ECG devices such as the Apple Watch and the Xiaomi Mi Bunny Smart Watch now can identify heart issues in real-time as demonstrated in Yan *et al* [10]. Wearable devices, focusing on health functions, have not received full food and drugs administration (FDA) approval as medical equipment, and consultation with a doctor is deemed essential for medical treatment.

3. METHOD

ECG data, sourced from the PhysioNet databases and inclusive of various cardiac conditions and healthy controls, was pre-processed to enhance signal quality and consistency. This preprocessing involved band-pass filtering, normalization, and segmentation into individual heartbeats. For ECG pattern recognition, an SNN architecture was specially designed, this architecture featured input, hidden, and output layers with leaky integrate-and-fire neurons, effectively emulating biological information processing and efficiently capturing the temporal dynamics of ECG signals.

The SNN was trained using a specific learning algorithm and modified to suit the specificities of ECG signal processing. Parameters were meticulously selected based on parameter selection of the number of RF neurons in the population encoding scheme RF, the interval between presynaptic spikes (pre (ms)), the interval between postsynaptic spikes (post (ms)), the desired postsynaptic firing time (desired post (ms)), time-step precision (precision), the weight update rate of learning (Δw), the sigma of a weight kernal that changes with time (σ (ms)), the time constant of the spike response function (τ (ms)), the maximum number of epochs (epoch), and STDP learning window of time constant (STDP (ms)), ensuring optimal network performance. The training involved a supervised learning approach with cross-validation to prevent overfitting, with performance metrics including accuracy, sensitivity, and specificity.

Experiments were conducted using MATLAB to ensure reproducibility, with the dataset divided into training and testing splits of 60%-40%, 70%-30%, and 80%-20% respectively. These experiments allowed for the comparison of results against established benchmarks for ECG pattern recognition. Chosen for their unique ability to process temporal sequences in ECG signals, SNNs demonstrated computational efficiency and performance accuracy advantages over traditional neural networks, a capability underpinned by recent advancements in neuromorphic computing. The methodology, designed to be transparent and replicable, was effectively applied to utilize innovative SNN technology for ECG pattern recognition. This approach addressed identified gaps, beginning with ECG pattern recognition, and including meticulous preprocessing, simulation, and fine-tuning of the SNN algorithm to optimize weight adjustments, culminating in a comprehensive analysis of simulation outcomes when training and testing results were unsatisfactory.

3.1. Heartbeat dataset

Utilizing the Physionet database, this study analysed 200 ECG signals, including 80 ‘normal’ and 120 ‘abnormal’, through empirical mode decomposition (EMD) for signal quality enhancement, extracting 300 features per signal to train the SNN for precise classification. Despite efforts to enhance SNN accuracy with an additional layer, the most significant improvements came from EMD-based feature refinement, underscoring its effectiveness in preprocessing for accurate ECG pattern analysis. This streamlined approach not only optimized the classification process but also demonstrated the potential of EMD in advancing ECG signal interpretation.

3.2. Pre-processing

Figure 4 shows the block diagram for pre-processing in Figure 4(a) and for the proposed method in Figure 4(b). In these methods, noise and distortions were initially removed from both normal and abnormal datasets using EMD, and weight models from IMF1 to IMF10 were selected for the SNN's learning algorithm. The ECG training and testing datasets were divided into three groups of 60%-40%, 70%-30%, and 80%-20% to accommodate the effects of low or high-frequency noise that can influence QRS detection and feature extraction during recording. This division allows for a thorough analysis of various ECG datasets, helping to identify the most suitable features for each diagnostic system by eliminating noise primarily caused by artifacts and addressing individual differences in peak and waveform shapes through further examination and preprocessing of the 12-lead ECG signals.

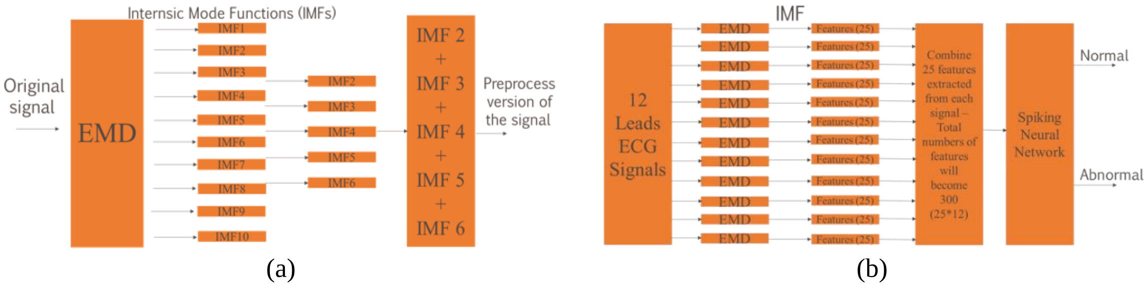


Figure 4. Block diagram for (a) pre-processing and (b) proposed method

3.3. Extraction and selection of features

For this work, 25 features were extracted, including 15-time domain features such as mean, standard deviation, and skewness, along with 10 cepstral domain features that include coefficients of the mel frequency cepstral and gammatone cepstral features (MFCC+GTCC). These features are processed through multiple operations such as fourier transform, filter bank application, and discrete cosine transform, which are executed in sequence. This combination of time-domain and cepstral features captures both statistical properties and spectral characteristics, offering benefits for various machine learning applications such as classification, clustering, or regression.

3.4. Learning algorithm parameters of SNN

In a SNN, the neuron's state is determined by its activity level, modelled as a differential equation, where an input pulse temporarily increases the current state value and then gradually decreases. Establishing a functioning SNN is challenging, as the training process resembles the human brain's data processing, but factors such as improved unsupervised learning methods make SNNs appealing. Ten parameters will be chosen for the learning algorithm parameters of SNN, including the number of RF neurons in the population encoding scheme (RF), intervals between presynaptic spikes (pre), intervals between postsynaptic spikes (post), desired postsynaptic firing time (desired post), time-step precision (precision), the weight update rate of learning (Δw), sigma of a weighted kernel that changes with time (σ), the time constant of the spike response function (τ), the maximum number of epochs (epoch), and STDP learning window of time constant (STDP).

4. RESULTS AND DISCUSSION

This study embarked on a journey to unveil the intricacies of ECG pattern recognition using SNNs. Prior investigations have delved into the realms of neural network applications and machine learning algorithms for biomedical signal processing, yet a gap persists in fully harnessing the temporal dynamics of ECG signals. Our research aims to bridge this divide, offering insights into the application of SNNs for accurate and efficient cardiac arrhythmia identification.

Our results show significant progress in ECG pattern recognition, with a testing accuracy reaching 91.6667% and training accuracy up to 99.2857%. These figures highlight the effectiveness of the SNN classifier in accurately distinguishing between normal and abnormal ECG patterns. Such performance confirms the classifier's reliability and precision in analysing cardiac rhythms.

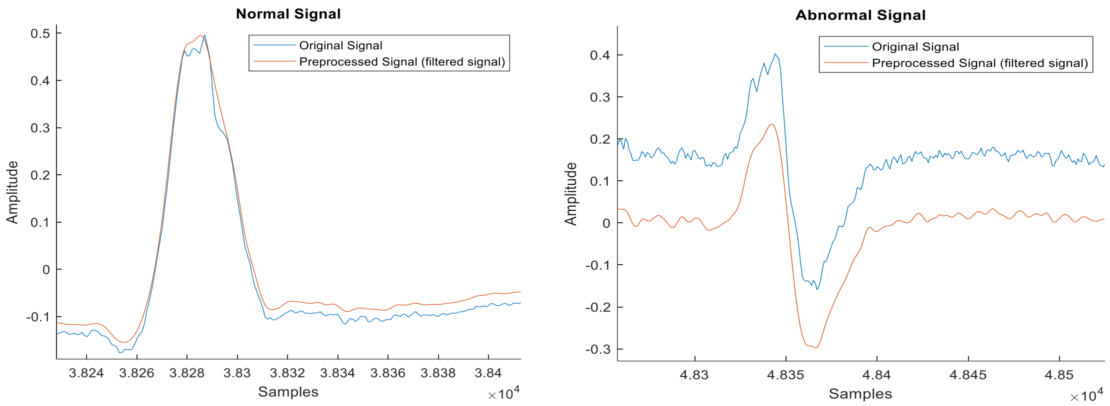
Comparatively, our study underscores the superior performance of SNNs against traditional neural networks and machine learning algorithms. The employment of SNNs capitalizes on their ability to mimic biological neural processing more closely, resulting in enhanced efficiency and lower power consumption. This approach not only aligns with but also surpasses current methodologies, particularly in recognizing the complex, temporal patterns inherent in ECG data. Our research thoroughly assesses SNNs in recognizing ECG patterns but relies heavily on pre-processed data from the PhysioNet database. It's necessary to test the model on a wider variety of datasets, especially those from real-world clinical environments where data varies more. This step will help confirm the model's effectiveness in different settings.

Our research opens up exciting possibilities for improving cardiac monitoring technologies. Future studies might look into combining SNNs with neuromorphic hardware to create hybrid models that bring together different computing techniques. Such developments could extend the use of SNNs to a wider range of tasks in biomedical signal processing, enhancing their overall effectiveness.

Our research demonstrates major improvements in using SNNs to recognize ECG patterns, which helps better identify cardiac arrhythmias and raises the accuracy standards for heart monitoring. This work addresses significant gaps in our scientific understanding and shows that advanced neural networks can substantially improve patient care. We recommend adopting these advanced technologies to develop smarter and more adaptive healthcare solutions.

4.1. Evaluation of the performance of ECGs

Figure 5 shows the pre-processing signal using EMD for normal data in Figure 5(a) and for abnormal data in Figure 5(b). Based on Figure 5, it is observed that the blue curve exhibits a higher frequency for the original signal, whereas the orange curve appears smoother for the pre-processed (filtered) signal. Figure 6 shows the effect of the optimized parameter of SNN for three groups of training and testing respectively at 60%-40%, 70%-30%, and 80%-20%, and their accuracies towards the performance of convergence based on the parameter tuning of learning rate of weight update(Δw), the sigma of a weight kernal that changes with time (σ (ms)), the time constant of the spike response function (τ (ms)), and a maximum number of epochs. Figures 6 depict learning outcomes using different training-testing data splits for 60%-40%, 70%-30%, and 80%-20% in Figures 6(a) to 6(i).



(a) (b)

Figure 5. ECG pre-processing for (a) normal signal and (b) abnormal signal

Based on Figure 6, the optimized parameters for SNNs under different training-testing splits and their respective accuracies. For training and testing accuracies, the accuracies vary across different splits. Generally, training accuracy is higher, which is expected. However, the testing accuracy shows some variance, notably being lower in the training testing ratio of 80:20 split. Most parameters of SNN like RF with the value of 15, presynaptic (pre), postsynaptic (post), desired postsynaptic (desired post) with the value of 0.2, time-step precision (precision) with the value of 0.01, and STDP remain consistent across different splits, while others like learning rate (Δw), efficacy update range (σ), Tau (τ), and epoch show variations.

Effects on convergence, such as the parameter of learning rate (Δw), particularly with a higher value (Δw = 0.5) in the 80:20 training-testing ratio split, may cause the model to overshoot the optimal solution. Resulting in lower testing accuracy, with the learning rate affecting both the speed and stability of convergence. While a high learning rate (Δw) can lead to faster convergence, it may overshoot the optimal solution, as observed in Figures 6(g), 6(h), and 6(i), indicating that both excessively low and high learning rates can adversely affect performance, suggesting that a moderate learning rate is optimal for balancing training speed and convergence stability.

Then, for the efficacy update range (σ), this parameter also increases in the training testing ratio of 80:20 split with the value of (σ = 0.55), which affects the model's generalization capability. For Tau (τ), the value in the training testing ratio of 80:20 split, which affects the model's ability to capture temporal dynamics in the data with the value of ($\tau = 1, 2,$ and 3) respectively. This shows that the value of Tau influences the model's ability to capture temporal dynamics in ECG data, which is crucial for accurately classifying heartbeats Then, for epochs maximum, the maximum number of epochs is consistent in most cases, but reduced epochs in one of the training testing ratios of 70:30 split scenarios explain the slightly lower training accuracy with the value of (epoch = 20).

In addition, for STDP (Spike-Timing-Dependent Plasticity) with the value of 1.6, this remains constant across all scenarios, suggesting that the model's ability to adapt its synaptic weights based on spike timings is unchanged. Then, for presynaptic (pre) and postsynaptic (post) parameters with the values of (pre=0.3) and (post=0.44) respectively, these parameters are mostly consistent but do show a minor change in one of the training testing ratios of 80:20 split scenarios, which could affect the model's sensitivity to input and output spikes. The role of spike-timing-dependent plasticity (STDP) in adapting synaptic weights based on the timing of incoming spikes is highlighted as a key feature of SNNs that contributes to their biological realism and effectiveness in classification tasks. The optimized parameters significantly affect the model's performance in both training and testing accuracies, with parameters such as learning rate (Δw), efficacy update range (σ), Tau (τ), and epoch playing crucial roles in the model's convergence capabilities, highlighting the importance of parameter optimization for enhancing model performance and achieving a balance between training and testing accuracies across various data splits.

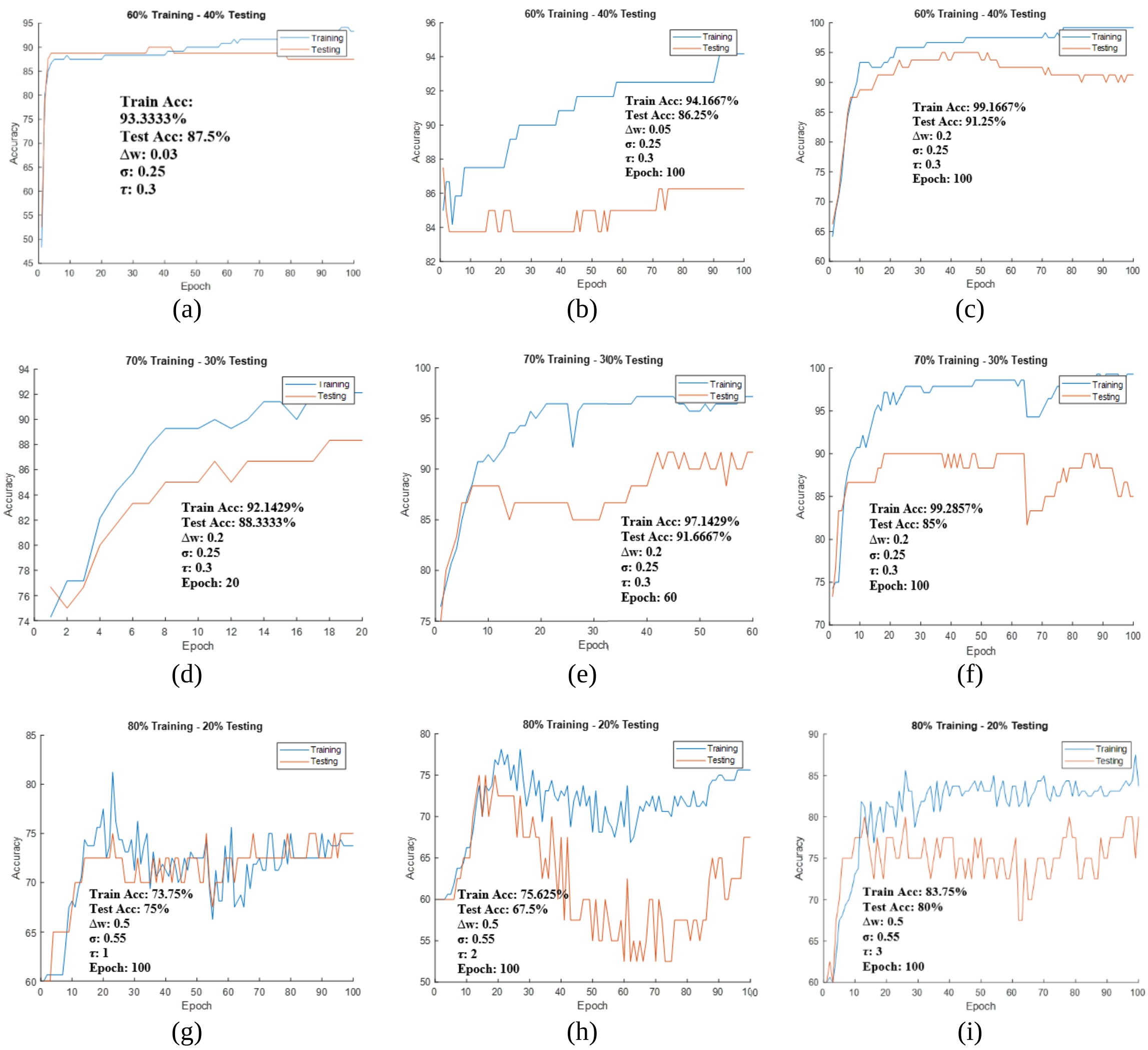


Figure 6. Convergence performance for data of: (a) 60% training-40% testing, (b) 60% training-40% testing, (c) 60% training-40% testing, (d) 70% training-20% testing, (e) 70% training-20% testing, (f) 70% training-20% testing, (g) 80% training-20% testing, (h) 80% training-20% testing, and (i) 80% training-20% testing

5. CONCLUSION

Cardiovascular arrhythmia diagnosis relies on characteristics of heartbeats and machine learning algorithms. When used in combination with an EMD ECG system, the created SNN models are capable of classifying multiple heartbeat types. SNN's learning parameters have been evaluated where the value of Tau (τ), efficacy update range (σ), learning rate (Δw), and maximum number of epochs (epoch), show significant effects for the accuracy of the training and testing data respectively. This work achieves maximum of training accuracy and testing accuracy of 99.1667% and 91.25% for training testing ratio of 60:40, 99.2857% and 91.6667% of training accuracy and testing accuracy for training testing ratio of 70:30 split, and 83.75% and 80% of training accuracy and testing accuracy for training testing ratio of 80:20 split data respectively for the classification of ECG rhythms, demonstrates the capability to classify heartbeats using SNN.

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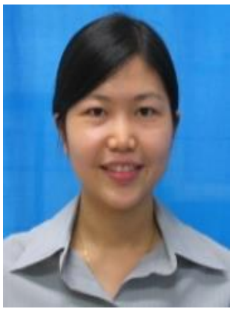

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