ECG classification based on brain-inspired spiking neural network
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Keywords: Electrocardiogram; classification; spiking neural network

ABSTRACT – Electrocardiogram (ECG) is one of the most significant diagnostic methods of heart rhythms. In this work, raw ECG signals from Physio Bank are pre-processed with empirical mode decomposition (EMD). EMD is used in this study as a pre-processing method. Through Empirical Mode Decomposition (EMD), the proposed technique first denoises the signal and removes distortions. To train the SNN Classifier, 15 different time-domain features and 10 Cepstral Domain Features are extracted. Two classifications, normal and abnormal, are employed and maximum accuracy of training at 99.1667% and maximum accuracy of testing at 91.6667% is attained. Signals are classified using Spiking Neural Network (SNN) classification algorithms by extracting features with excellent discriminative abilities. This result demonstrates that it is a competent system capable of differentiating between distinct classes for ECG classification which is for normal and abnormal classes.

1. INTRODUCTION
According to the WHO, among the top global health threats in the year 2017 was heart disease [1]. A non-invasive method known as an electrocardiogram (ECG) stands to utilized as for the detection of cardiovascular disease, the most significant method towards identifying abnormal heartbeats [2]. The detection of the users’ heartbeat abnormalities on wearable devices with continuous ECG monitoring that increases initial intervention chances was proven to be life-saving [3]. In this paper, a set of ECG classification methods with a Spiking Neural Networks (SNN) is presented. The ECG signal is used to classify heartbeats into two categories which is normal and abnormal.

2. SNN ARCHITECTURE
Neuronal network within the third generation are known as SNN. Synapses link the neurons in the dense network. A synapse connects each neuron in the first layer to all neurons in the second layer [4]. The most popular learning method used to train the SNN is spike-time-dependent plasticity (STDP). A STDP rule is used to determine how much each pre-synaptic spike contributes to the total weight change [5-6]. Binary spikes are the data transferred between layers for the SNN [7].

3. PROPOSED METHOD
Figure 1 indicates block diagram for the proposed method. The proposed technique first removes the noise and distortions for both the normal and abnormal datasets. Through EMD, there is a selection from a combination of IMF1 to IMF10 as the weight models for SNN’s learning algorithm. ECG train and test datasets are stored in three groups which are 60%-40%, 70%-30%, and 80%-20% for training and testing respectively.

3.1 Extraction and selection of features
25 features have been extracted for this work. There are the first 15 features for Time Domain Features, and 10 features are Cepstral Domain Features which is Coefficients of the Mel frequency cepstral and Gammatone Cepstral Features (MFCC +GTCC) [8].

4. EVALUATION OF THE PERFORMANCE OF ELECTROCARDIOGRAPHS (ECG)
Figure 2 illustrates the pre-processing signal through EMD for normal and abnormal data. Table 1 shows the optimizes parameter of SNN for three groups of training and testing respectively at 60%-40%, 70%-30%, and also 80%-20% and their accuracies. The effect of the optimized parameter towards the performance of convergence presented in Figure 3.
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Figure 2 ECG pre-processing for (a) normal signal and (b) abnormal signal.

Table 1 Optimized parameter for SNN of 60% Training - 40% Testing, 70% Training Testing - 30% Testing, and 80% Training - 20% Testing.

<table>
<thead>
<tr>
<th>Data for</th>
<th>60% Training - 40% Testing</th>
<th>70% Training - 30% Testing</th>
<th>80% Training - 20% Testing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training accuracy (%)</td>
<td>93.3333</td>
<td>92.1429</td>
<td>73.75</td>
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<tr>
<td>Testing accuracy (%)</td>
<td>87.5</td>
<td>88.3333</td>
<td>75</td>
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<td>Parameters of SNN</td>
<td></td>
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<td>RF</td>
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<td>15</td>
<td>15</td>
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<td>0.3</td>
<td>0.3</td>
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<tr>
<td>Postsynaptic</td>
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<td>0.44</td>
<td>0.44</td>
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<tr>
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<td>0.2</td>
<td>0.2</td>
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<td>Precision</td>
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<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>Learning rate</td>
<td>0.03</td>
<td>0.05</td>
<td>0.2</td>
</tr>
<tr>
<td>Efficacy update range</td>
<td>0.25</td>
<td>0.25</td>
<td>0.25</td>
</tr>
<tr>
<td>Tau</td>
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<td>0.3</td>
<td>0.3</td>
</tr>
<tr>
<td>Epochs maximum</td>
<td>100</td>
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<tr>
<td>STDP</td>
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</tr>
</tbody>
</table>

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 can classify multiple heartbeat types. This work achieves maximum of training accuracy and testing accuracy of 99.1667% and 91.25% for 60% training and 40% testing data, 99.2857% and 91.6667% of training accuracy and testing accuracy for 70% training and 30% testing data, and 83.75% and 80% of training accuracy and testing accuracy for 80% training and 20% testing data respectively for the classification of ECG rhythms, demonstrates the capability to classify heartbeats using brain inspired SNN.

ACKNOWLEDGEMENT
The authors acknowledge the technical and financial support by Universiti Teknikal Malaysia Melaka and the Ministry of Higher Education, Malaysia, under the research grant no. FRGS/1/2020/FKEKK-CETRI/F00421.

REFERENCES


**Figure 3** Convergence performance for data of: 60% Training - 40% Testing: (a) Training accuracy: 93.3333% Testing accuracy: 87.5% (b) Training accuracy: 94.1667% Testing accuracy: 86.25% (c) Training accuracy: 99.1667% Testing accuracy: 91.25%, 70% Training - 20% Testing: (d) Training accuracy: 92.1429% Testing accuracy: 88.3333% (e) Training accuracy: 97.1429% Testing accuracy: 91.6667% (f) Training accuracy: 99.2857% Testing accuracy: 85%, and 80% Training - 20% Testing: (g) Training accuracy: 73.75% Testing accuracy: 75% (h) Training accuracy: 75.625% Testing accuracy: 67.5% (i) Training accuracy: 83.75 % Testing accuracy: 80%.