



**Faculty of Electronic and Computer Engineering**



**Saw Chia Yee**

**Master of Science in Electronic Engineering**

**2023**

**NEUROMORPHIC LEARNING MACHINE BASED ON STOCHASTIC  
RESERVOIR COMPUTING FOR TIME SERIES DATA PROCESSING AND  
CLASSIFICATION**

**SAW CHIA YEE**

**A thesis submitted  
in fulfillment of the requirements for the degree of Master of Science  
in Electronic Engineering**



**Faculty of Electronic and Computer Engineering**

**UNIVERSITI TEKNIKAL MALAYSIA MELAKA**

**2023**

## DECLARATION

I declare that this thesis entitled “Neuromorphic Learning Machine Based on Stochastic Reservoir Computing for Time Series Data Processing and Classification” is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

Signature :  .....

Name : Saw Chia Yee .....

Date : 12 Jan 2023 .....

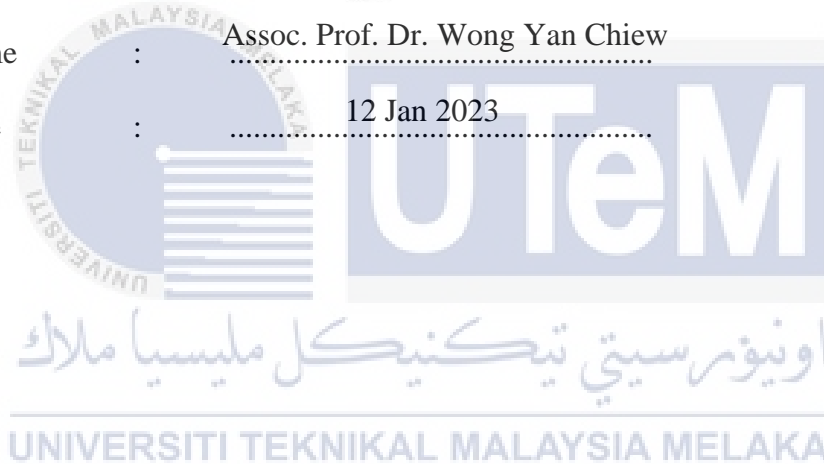


اونيورسيتي تيكنيكل مليسيا ملاك  
UNIVERSITI TEKNIKAL MALAYSIA MELAKA

## APPROVAL

I hereby declare that I have read this thesis and in my opinion this thesis is sufficient in terms of scope and quality for the award of Master of Science in Electronic Engineering.

Signature :   
Name : Assoc. Prof. Dr. Wong Yan Chiew  
Date : 12 Jan 2023



## DEDICATION

This project is dedicated to my beloved parents and Profesor Madya Dr. Wong Yan Chiew  
who for their never-ending moral support in my academic life.



## ABSTRACT

Neuromorphic computing is a potential alternative to conventional von Neumann computers for specialised sensory-processing or classification applications. Neuromorphic systems replicate the biophysics of neurobiological networks by replicating the information processing mechanism of biological neurons and synapses, resulting in high connection and parallelism on a smaller footprint. These characteristics contribute to the implementation of neuromorphic architectures in hardware development for time series data classification and recognition. However, hardware implementation of neural network suffers from resource constraints because of the typically large number of nodes utilised in RC networks and the high chip area required for each processing node. Moreover, a high number of features in time series data classification introduces computational burden and leads to excessive hardware calculation overhead. In this work, a reservoir computing based stochastic spiking neural network (SSNN) has been proposed for time series data processing and classification, enabling a more efficient hardware implementation with low computation overhead caused by minimum extracted features. The proposed neuron reservoir is implemented in two applications including ventricular heartbeat classification and human activity recognition (HAR). The 43 recordings of Electrocardiogram (ECG) signals that included both normal and arrhythmic beats from MIT-BIH arrhythmia database obtained from Physio-Net were used in this work for heartbeat classification. Baseline drift and power line interference that are frequently emphasized in ECG readings are minimized by signal denoising. The single feature, QRS complexes, was extracted and fed into the neural reservoir with 20 neurons in cyclic topology for arrhythmias' similarity calculation and classification. The HAR is evaluated in order to further validate the proposed SSNN approach. This work proposes feature extraction based on subcarrier correlation and pseudocolor variations caused by human movements depicted in the images using convolution neural network (CNN) without preprocessing applied and enabling low computational complexity and visual observation of entire pattern changes. The extracted features are fed into the neural reservoir for activities recognition. A two-input stochastic neuron is developed for complex machine learning using the stochastic computing (SC) theory. The 20 stochastic neurons are then arranged into a simple cycle reservoir (SCR) architecture to create the SSNN. The proposed system has been implemented in Xilinx Zynq-7000 field-programmable gate array (FPGA) to demonstrate the hardware efficiency leads by the minimum feature size used. The proposed stochastic spiking reservoir achieves an accuracy of 96.91% in heartbeat classification and 92.94% and 93.91% for features based on subcarrier correlation and pseudocolor plot in HAR, demonstrating that the system is accurate and effective at classifying time series data.

# **MESIN PEMBELAJARAN NEUROMORFIK BERASASKAN PENGKOMPUTERAN TAKUNGAN STOKASTIK UNTUK PEMROSESAN DAN PENGELASAN DATA SIRI MASA**

## **ABSTRAK**

Pengkomputeran neuromorfik ialah alternatif yang berpotensi kepada komputer von Neumann konvensional untuk pemprosesan deria atau aplikasi klasifikasi. Sistem neuromorfik mereplikasi biofizik rangkaian neurobiologi dengan mereplikasi mekanisme pemprosesan maklumat neuron biologi dan sinaps, menghasilkan sambungan yang tinggi dan selari pada jejak yang lebih kecil. Ciri-ciri ini menyumbang kepada pelaksanaan seni bina neuromorfik dalam pembangunan perkakasan untuk pengelasan dan pengecaman data siri masa. Walau bagaimanapun, pelaksanaan perkakasan rangkaian saraf mengalami kekangan sumber kerana bilangan nod yang biasanya besar digunakan dalam rangkaian RC dan kawasan cip tinggi yang diperlukan untuk setiap nod pemprosesan. Selain itu, bilangan ciri yang tinggi dalam klasifikasi data siri masa memperkenalkan beban pengiraan dan membawa kepada overhed pengiraan perkakasan yang berlebihan. Dalam kerja ini, rangkaian neural spiking stokastik (SSNN) berasaskan pengkomputeran takungan telah dicadangkan untuk pemprosesan dan pengelasan data siri masa, membolehkan pelaksanaan perkakasan yang lebih cekap dengan overhed pengiraan rendah disebabkan oleh ciri yang diekstrak minimum. Takungan neuron yang dicadangkan dilaksanakan dalam dua aplikasi termasuk klasifikasi degupan jantung ventrikel dan pengecaman aktiviti manusia (HAR). 43 rakaman isyarat Elektrokardiogram (ECG) yang merangkumi kedua-dua rentak normal dan aritmik daripada pangkalan data aritmia MIT-BIH yang diperolehi daripada Physio-Net telah digunakan dalam kerja ini untuk klasifikasi degupan jantung. Hanyutan garis dasar dan gangguan talian kuasa yang kerap dititikberatkan dalam bacaan ECG diminimumkan dengan penyahtandaan isyarat. Ciri tunggal, kompleks QRS, telah diekstrak dan dimasukkan ke dalam takungan saraf dengan 20 neuron dalam topologi kitaran untuk pengiraan dan klasifikasi persamaan aritmia. HAR dinilai untuk mengesahkan lagi pendekatan SSNN yang dicadangkan. Kerja ini mencadangkan pengekstrakan ciri berdasarkan korelasi subcarrier dan variasi pseudocolor yang disebabkan oleh pergerakan manusia yang digambarkan dalam imej menggunakan rangkaian neural convolution (CNN) tanpa prapemprosesan yang digunakan dan membolehkan kerumitan pengiraan rendah dan pemerhatian visual terhadap keseluruhan perubahan corak. Ciri yang diekstrak dimasukkan ke dalam takungan saraf untuk pengecaman aktiviti. Neuron stokastik dua input dibangunkan untuk pembelajaran mesin yang kompleks menggunakan teori pengkomputeran stokastik (SC). 20 neuron stokastik kemudiannya disusun menjadi seni bina takungan kitaran mudah (SCR) untuk mencipta SSNN. Sistem yang dicadangkan telah dilaksanakan dalam Xilinx Zynq-7000 FPGA untuk menunjukkan kecekapan perkakasan diterajui oleh saiz ciri minimum yang digunakan. Takungan spiking stokastik yang dicadangkan mencapai ketepatan 96.91% dalam pengelasan degupan jantung dan 92.94% dan 93.91% untuk ciri berdasarkan korelasi subcarrier dan plot pseudocolor dalam HAR, menunjukkan bahawa sistem adalah tepat dan berkesan dalam mengklasifikasikan data siri masa..

## ACKNOWLEDGEMENTS

I am highly indebted to the Faculty of Electronic and Computer Engineering for their ongoing supervision as well as for providing necessary information regarding the writing the thesis and also their support in completing this project.

A special thanks to my supervisor Profesor Madya Dr. Wong Yan Chiew who rendered help during the period of my project work, which I have found enjoyable and fulfilling. Her extensive experience in neuromorphic learning machine technology design, extensive knowledge and expertise have enabled me to successfully complete this research. I can't find the appropriate words that could properly describe my appreciation for her contribution in stimulating suggestions to achieve desired project outcome, encouragement to coordinate my project especially in writing this report and permission to use all the electronic components and software tools for practice.

I cannot express enough thanks to my very supporting co-supervisor that assigned, Dr. Muhammad Idzdiyar Bin Idris, whose have invested their full effort in guiding me in carrying out project work. A special gratitude I give to co-supervisor for his patience, enthusiasm, insightful comments, valuable suggestions, useful information, practical advice, and constant thoughts which have been given great ideas in my research and writing of this thesis. Apart from that, thanks again for his excellent guidance in my project work no matter in practice or during report completion.

I acknowledge my sincere indebtedness and gratitude to my parents, family and special mate of mine for their constructive counsel and helpful assistance. Deepest thanks again to all my friends who went out their way and offered me open-hearted assistance and guidance. They were a source of inspiration for me and helped me in the learning process with their experience and knowledge. I would like to express my deepest appreciation for their sacrifice, patience, and understanding that were inevitable during project completion.



## TABLE OF CONTENTS

	<b>PAGE</b>
<b>DECLARATION</b>	
<b>APPROVAL</b>	
<b>DEDICATION</b>	
<b>ABSTRACT</b>	<b>i</b>
<b>ABSTRAK</b>	<b>ii</b>
<b>ACKNOWLEDGEMENTS</b>	<b>iii</b>
<b>TABLE OF CONTENTS</b>	<b>iv</b>
<b>LIST OF TABLES</b>	<b>viii</b>
<b>LIST OF FIGURES</b>	<b>ix</b>
<b>LIST OF ABBREVIATIONS</b>	<b>xiii</b>
<b>LIST OF SYMBOLS</b>	<b>xvii</b>
<b>LIST OF PUBLICATIONS</b>	<b>xix</b>
<b>CHAPTER</b>	
<b>1. INTRODUCTION</b>	<b>1</b>
1.1 Background of Project	1
1.2 Problem Statement	4
1.3 Objective	5
1.4 Scope of Project	6
1.5 Significant Contribution of Work	6
1.5.1 Ventricular heartbeat classification	7
1.5.2 Human activity detection	8
1.6 Thesis Outline	9
<b>2. LITERATURE REVIEW</b>	<b>11</b>
2.1 Introduction	11
2.2 Neuromorphic computing system	11
2.3 An Outlook of Neuromorphic Computing	13
2.3.1 State-of-the-art Neuromorphic Chips	14
2.3.1.1 SpiNNaker	14
2.3.1.2 TrueNorth	15
2.3.1.3 Loihi	17

2.3.1.4	BrainScaleS	17
2.3.1.5	NeuroGrid / Braindrop	18
2.3.1.6	DYNAP	18
2.3.1.7	ODIN	19
2.4	Artificial Neural Networks (ANNs)	20
2.4.1	Artificial Neuron	22
2.4.2	Network architectures	23
2.4.2.1	Feedforward Neural Network	23
2.4.2.2	Recurrent Neural Network	24
2.4.3	Neural Network in Hardware	26
2.5	Spiking Neural Network (SNN)	26
2.5.1	Biological neuron	31
2.5.1.1	Neural Dynamics	32
2.5.2	Neuron models	33
2.5.2.1	Leaky Integrate-and-Fire (LIF) model	33
2.5.2.2	Hodgkin-Huxley Model	35
2.5.2.3	Izhikevich Model	37
2.5.3	The discrete-time neuron	37
2.6	Reservoir computing	38
2.6.1	Echo state network	41
2.6.1.1	Reservoir topology	42
2.6.2	Liquid state machine	43
2.7	Template matching	44
2.8	Summary	46
<b>3.</b>	<b>METHODOLOGY</b>	<b>47</b>
3.1	Introduction	47
3.2	Circuit design of Artificial Neuron	47
3.2.1	The format of numerical representation	48
3.3	Stochastic spiking neural network	50
3.4	Stochastic computing	50
3.4.1	Correlation Effect	52
3.4.2	Scaled Subtraction	53
3.4.3	Multiplication	54

3.4.4	Binary-to-pulse conversion (B2P)	54
3.4.5	Pulse-to-binary converter (P2B)	55
3.4.6	Random number generator	56
3.5	Stochastic neuron design	58
3.6	Implementation of the SSNN architecture	58
3.7	Output layer	62
3.8	Summary	63
<b>4.</b>	<b>VENTRICULAR HEARTBEAT CLASSIFICATION</b>	<b>65</b>
4.1	Introduction	65
4.2	Arrhythmia classification	65
4.3	The cardiac cycle and heart defect	66
4.4	The proposed ventricular heartbeat classifier	68
4.4.1	Pan-Tompkins Algorithms	70
4.4.1.1	Bandpass Filter	71
4.4.1.2	Derivative	72
4.4.1.3	Squaring Function	73
4.4.1.4	Moving Window Integration	73
4.4.2	Peak Detection	74
4.4.3	QRS Segmentation	74
4.5	Temporal Feature Extraction	75
4.6	SSNN activity	76
4.7	Results and Discussion	77
4.7.1	Performance of R-peak Detection	77
4.7.2	Arrhythmia classification Performance	78
4.7.3	Comparison with previous ventricular classifier research	81
4.8	Summary	84
<b>5.</b>	<b>HUMAN ACTIVITY RECOGNITION</b>	<b>85</b>
5.1	Introduction	85
5.2	Human activity recognition (HAR)	85
5.3	Channel state information	87
5.3.1	CSI based localization and motion detection	89
5.3.2	CSI based Micro-Activity Recognition	89

5.3.3	CSI based Macro-Activity Recognition	89
5.4	Effect of human motion on wireless channel	90
5.5	The Proposed HARSSNN Architecture	94
5.5.1	Feature Extraction	96
5.5.1.1	Proposed features based on pseudocolor plot	100
5.5.1.2	Proposed features based on subcarrier correlations	101
5.5.2	Output layer	104
5.5.2.1	Reservoir output	104
5.5.2.2	Template matching for time series HAR	105
5.6	Results and Discussion	106
5.6.1	HAR based on partial input signals of pseudocolor plot	107
5.6.2	HAR based on partial input signals of subcarrier correlation	110
5.6.3	Recognition performance comparison	112
5.6.4	Hardware resource comparison	114
5.7	Summary	116
<b>6.</b>	<b>CONCLUSION AND FUTURE WORKS</b>	<b>117</b>
6.1	Research Outcome	117
6.1.1	Ventricular heartbeat classification	118
6.1.2	Human activity recognition	118
6.2	Future Works	119
	<b>REFERENCES</b>	<b>120</b>

## LIST OF TABLES

TABLE	TITLE	PAGE
2.1	Summary of related work of SNN	27
3.1	Examples of binary representation (X) of real quantities unsigned integer	49
3.2	LFSR values corresponding to the clock cycles	57
4.1	ECG signal description	67
4.2	Evaluation result of R peak detection	78
4.3	Confusion matrix of SSNN classification	80
4.4	Feature size compared with previous research	82
4.5	Hardware resource utilization compared with previous research	83
5.1	Previous HAR studies	86
5.2	Performance comparison with previous research work	114
5.3	HAR Hardware resource comparison	115

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

## LIST OF FIGURES

<b>FIGURE</b>	<b>TITLE</b>	<b>PAGE</b>
2.1	(a) von Neumann computing system and (b) neuromorphic computing system (Bai and Yi, 2019)	12
<u>2.2</u>	Evolution of the neuromorphic hardware (Park, 2020)	14
<u>2.3</u>	Principle architectural component of SpiNNaker node (Furber et al., 2014)	15
<u>2.4</u>	TrueNorth architecture (Cassidy et al., 2013)	16
<u>2.5</u>	DYNAP die photo (Moradi et al., 2017)	19
<u>2.6</u>	Crossbar architecture ODIN SNN (Frenkel et al., 2018)	20
2.7	Overview of ANN	21
2.8	Artificial Neuron structure	22
2.9	Structure of (a) Single Layer Perceptron (b) Multilayer Perceptron	24
2.10	Biological neural model	32
2.11	Digital modelling of the sigmoidal neuron	33
2.12	Leaky-integrate-and-fire neuron model (Barceló, 2017)	34
2.13	Example simulation of a LIF neuron (Barceló, 2017)	35
2.14	Basic components of Hodgkin–Huxley-type models (Zhu, Wang and Zhu, 2018)	36
2.15	Digital modelling of the sigmoidal neuron	38
2.16	(a) General RNN architecture (b) RC system	39
2.17	General architecture of a reservoir computer	41
2.18	Alternative topologies: (a) DLR (b) DLRB (c) SCR (Rodan and Tino, 2010)	43
2.19	The structure of LSM	44
2.20	Taxonomy of the template-matching strategy (Okawa, 2019)	46
3.1	Schematic diagram of a two-input sigmoid neuron	48
3.2	Stochastic computing system's fundamental stages	50

3.3	Stochastic computation basic circuit (a)AND (b) NOR (c) XNOR (d) NOT (e)B2P (f)MUX (g)P2B	52
3.4	Correlation effect (a) both bit streams are the same (b) both bit streams are inverse of each other	53
3.5	Scaled subtraction of stochastic computing	54
3.6	Multiplication in stochastic computing	54
3.7	B2P converter block	55
3.8	P2B converter block	56
3.9	Example of 8-bit linear LFSR circuit for generating pseudo-random sequences that cycle through 255 values	57
3.10	SC-based two-input stochastic neuron	58
3.11	Simple cycle reservoir (SCR) topology	59
3.12	SSSN that composed of 20 stochastic neurons with cyclic topology	61
3.13	An example of template matching	62
4.1	A General ECG Waveform	67
4.2	Flowchart of ventricular heartbeat classifier	69
4.3	Schematic representation of ventricular heartbeat classifier	70
4.4	Block diagram of The Pan-Tompkins algorithm	71
4.5	ECG (a) Raw signal (b) LPF signal (c) HPF signal	72
4.6	Derivative output	72
4.7	Squaring output	73
4.8	MWI output	73
4.9	R-peak detection	74
4.10	QRS segmented area in the ECG signal	74
4.11	Template matching of segmented heartbeat	75
4.12	Temporal evolution of the different signals in the SNN model	76
4.13	Three chosen neurons' output from the reservoir along with QRS complex input signal	77
4.14	RTL of proposed SSNN	79
4.15	ECG classification performance	80
5.1	Three-dimensional distribution of CSI amplitude in (a) selected environment for (b) Antenna 1 (c) Antenna 2 (d) Antenna 3	88
5.2	Three antennas' CSI amplitude varies in response to motion	91
5.3	Comparison of sensitivity of different antennas. CSI signals (a) formed by	93

	PCA fusion of 30 subcarriers (b) after moving variance based on (a) when person is walking	
5.4	Flowchart of the proposed SSNN-based human activity recognition	95
5.5	Overall architecture of the proposed HARSSNN approach	96
5.6	(a) Pseudocolor plot and (b) Subcarrier correlation variation of each segment during walking activity	98
5.7	2D-CNN structure for feature extraction based on (a) pseudocolor plot and (b) subcarrier correlation	100
5.8	Pseudocolor pattern across 90-dimensional CSI amplitude vector for different human activities	101
5.9	Correlation matrix of 30 subcarriers of a randomly selected antenna pair	102
5.10	Subcarrier correlation matrix of an antenna with 30 subcarriers for different human activity	103
5.11	Dynamic distribution of subcarrier correlation matrix in static and dynamic scenarios	104
5.12	The output of three selected neurons from a reservoir in response to extracted features based on (a) subcarrier correlation (b) pseudocolor plot	105
5.13	Template of seven activities per segment	106
5.14	Cross correlation (a) between a given query extracted features and template (b) results with lags indices	106
5.15	Every three pseudocolor plot based extracted feature segments cross-correlated with the corresponding templates	108
5.16	Accuracy distribution of pseudocolor plot-based features with 3 segments of the test signal	108
5.17	Cross-correlation between different segments of pseudocolor plot based extracted features and a template	109
5.18	Classification accuracy distribution of the pseudocolor plot-based features with different segments of the test signal for (a) CNN (b) Proposed method – TM	110
5.19	Every three subcarrier correlation based extracted feature segments cross-correlated with the corresponding templates	110
5.20	Accuracy distribution of subcarrier correlation-based features with 3 segments of the test signal	111
5.21	Cross-correlation between different segments of subcarrier correlation-	111



	based extracted features and a template	
5.22	Classification accuracy distribution of the subcarrier correlation-based features with different segments of the test signal for (a) CNN (b) Proposed method – TM	112
5.23	Confusion matrix of template matching for features based on (a) subcarrier correlation (b) pseudocolor plot	113



## LIST OF ABBREVIATIONS

ALU	-	Arithmetic and Logic Unit
ANN	-	Artificial Neural Network
ASIC	-	Application-Specific Integrated Circuit
B2P	-	Binary-to-pulse converter
Bi-LSTM	-	Bidirectional Long Short-Term Memory
BNN	-	Binarized Neural Network
BPNN	-	Back propagation neural network
BPTT	-	Backpropagation through time
BW	-	Baseline wander
CDC	-	Centers for Disease Control and Prevention
CMOS	-	Complementary metal-oxide-semiconductor
CNN	-	Convolution neural network
CoNN	-	Continuous neural network
CPU	-	Central processing unit
CI	-	Cumulative statistical index
CSI	-	Channel state information
DLR	-	Delay line reservoir
DLRB	-	Delay line reservoir with feedback
DNN	-	Deep neural network

DVS	-	Dynamic Vision Sensor
DWT	-	Discrete wavelet transform
DYNAP	-	Dynamic Neuromorphic Asynchronous Processors
ECG	-	Electrocardiogram
ELM	-	Extreme learning machines
EPSPs	-	Excitatory Postsynaptic Potentials
ESN	-	Echo state network
FF	-	Flip-flop
FFNN	-	Feedforward Neural Networks
FN	-	False negative
FNR	-	False negative rate
FP	-	False positive
FPGA	-	Field programable gate array
FPR	-	False positive rate
FSHNN	-	Fully Spiking Hybrid Neural Network
HAR	-	Human activity recognition
HARSSNN	-	Stochastic spiking neural network based human activity recognition
HICANN	-	High Input Count Analog Neural Network
HPF	-	High pass filter
I/O	-	Input/output
ICA	-	Independent component analysis
IPSPs	-	Inhibitory Postsynaptic Potentials
kNN	-	k-Nearest Neighbours
LDPC	-	Low-density parity-check

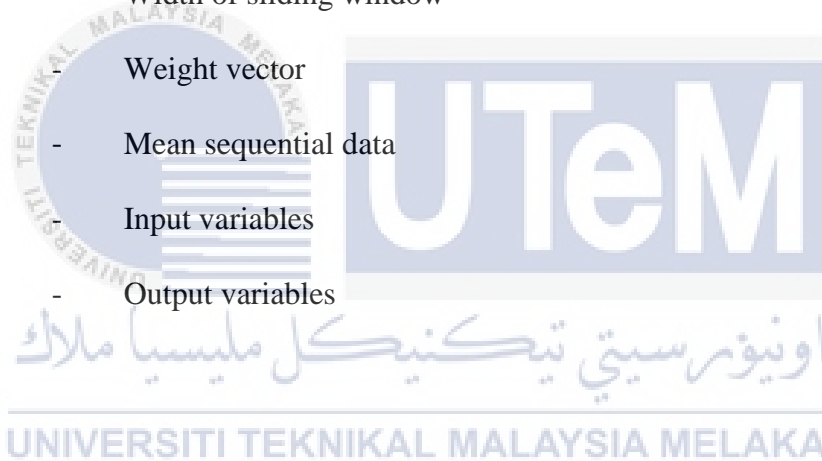
LFSR	-	Linear-feedback shift register
LIF	-	Leaky-Integrate-and-Fire
LM-SNN	-	Lattice map spiking neural network
LPF	-	Low pass filter
LSTM	-	Long Short-Term Memory
LUT	-	Lookup tables
MAC	-	Multiply-and-accumulate
MIMO	-	Multiple-input-multiple-output
MIoT	-	Medical Internet of Things
MLP	-	Multilayer Perceptron
MNIST	-	Modified National Institute of Standards and Technology
MUX	-	Multiplexer
MWI	-	Moving Window Integration
NOC	-	Network-on-Chip
ODE	-	Ordinary Differential Equation
ODIN	-	Online-learning Digital Spiking Neuromorphic
OFDM	-	Orthogonal frequency division multiplexing
P2B	-	Pulse-to-binary converter
PCA	-	Principal Component Analysis
PPV	-	Positive predictive value
RC	-	Reservoir computing
RNG	-	Random number generator
RNN	-	Recurrent Neural Network
RTL	-	Register Transfer Level
RTRL	-	Real-time recurrent learning

SC	-	Stochastic computing
SCNN	-	Spiking Convolutional Neural Network
SCR	-	Simple cycle reservoir
SDSP	-	Spike-Driven Synaptic Plasticity
SEN	-	Sensitivity
SLP	-	Single Layer Perceptron
SNGs	-	Stochastic Number Generators
SNN	-	Spiking neural network
SNs	-	Stochastic Numbers
SRAM	-	Static Random Access Memory
SSNN	-	Stochastic spiking neural networks
STDP	-	Spike Time-Dependent Plasticity
SVM	-	Support Vector Machines
TN	-	True negative
TP	-	True positive
WiGeR	-	WiFi-based hand gesture recognition device

## LIST OF SYMBOLS

$\varphi$	-	Activation function
$\sigma$	-	Variance
$\emptyset$	-	Matrix with empty set
$\delta(.)$	-	Dirac function
$\vartheta$	-	Threshold value
$acc$	-	Accuracy
$b$	-	Bias
$C$	-	Capacitor
$I, i$	-	Current
$f$	-	Nonlinear function
$f_{extract}$	-	Extracted features
$g$	-	Conductance
$L$	-	Length
$M$	-	Matrix
$N$	-	Number of reservoirs
$N_c$	-	Clock cycles
$P$	-	Probabilities
$r$	-	Reservoir
$R$	-	Resistor

$S(.)$	-	Spiking neuron's output
$S_{CSI}$	-	CSI's sequential data
$step$	-	Step size of window movement
$t$	-	Time
$T_{eval}$	-	Evaluation duration
$T_{clk}$	-	Clock duration
$u$	-	Membrane potential
$U$	-	Recovery of the membrane
$v, V$	-	Variance
$\omega$	-	Width of sliding window
$W, w$	-	Weight vector
$\bar{x}$	-	Mean sequential data
$x$	-	Input variables
$y$	-	Output variables



## LIST OF PUBLICATIONS

1. Saw, C.Y., 2022. Neuromorphic Computing based on Stochastic Spiking Reservoir for Heartbeat Classification. *Jordanian Journal of Computers and Information Technology*, 8(2).

