Faculty of Cognitive Sciences and Human Development

Performance Measurement on Deep Spiking Neural Network (DSNN) Algorithm in Flood Prediction Environment

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Master of Science
2023

Performance Measurement on Deep Spiking Neural Network (DSNN) Algorithm in Flood Prediction Environment

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A thesis submitted

In fulfillment of the requirements for the degree of Master of Science

(Intelligent System)

Faculty of Cognitive Sciences and Human Development
UNIVERSITI MALAYSIA SARAWAK
2023

DECLARATION

I declare that the work in this thesis was carried out in accordance with the regulations of Universiti Malaysia Sarawak. Except where due acknowledgements have been made, the work is that of the author alone. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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Date : 7 August 2023

ACKNOWLEDGEMENT

I want to extend my sincere gratitude to the remarkable individuals and institutions whose contributions played a pivotal role in the resounding success of my study work. Foremost, I am indebted to my esteemed supervisor, Dr. Abdulrazak Yahya Saleh, whose unwavering guidance, invaluable advice, and constant encouragement were instrumental throughout my master's program. His mentorship has shaped me into a better researcher and academic.

In addition, I express my profound thanks to the management of the Universiti Malaysia Sarawak and Zamalah Scholarship for their unwavering support and assistance. Their dedication to fostering an enriching academic environment has been a driving force behind my accomplishments.

Finally, I would like my gratitude knows no bounds when it comes to acknowledging the unwavering support and love of my parents and siblings. Their understanding, patience, and unconditional love have been my pillars of strength, providing the necessary emotional support throughout this journey. Thank you all.

ABSTRACT

There are several algorithms used to predict floods, including LSTM, BP, MLP, SARIMA, and SVM. While shallow neural networks are simple and efficient, they have limited memory and may not accurately capture long-term patterns or large-scale data. LSTM has gained attention among researchers in flood prediction for its ability to preserve historical data and solve complex time series problems. However, the study of this area is ongoing, with potential for further improvement. In current studies, researchers are exploring new directions by developing hybrid algorithms. The SNN, a third generation ANN, has been created to handle more complex data with a higher decision-making firing rate than ML and DL. In this study, a new hybrid DSNN algorithm will be utilised to predict floods in Kuala Baram, Miri, Sarawak. Rainfall data from 30 years (1989-2019) was collected from DID to evaluate the effectiveness of the DSNN algorithm compared to traditional and shallow neural networks algorithms. Performance was measured using ACC, RMSE, SPE, SEN, PPV, NPV, and ASP. A comprehensive analysis of the proposed DSNN algorithm was conducted. Four different training batch ratios were used to validate: 80:10:10, 70:15:15, 60:20:20, and 50:25:25. The results of the study showed that the DSNN algorithm outperformed the other algorithms with a higher ACC rate of 98.10%, an RMSE of 6.5%, a SEN of 93.50%, an SPE rate of 79.00%, and ASP of 89.60%. Overall, the DSNN algorithm with an 80:10:10 training sample ratio performed the best.

Keywords: Deep Spiking Neural Network (DSSN), Flood Prediction, Leaky Integrate and Fire (LIF), Long Short-Term Memory (LSTM), Spiking Neural Network (SNN).

Pengukuran Prestasi Algoritma Deep Spiking Neural Network (DSNN) dalam Ramalan Banjir

ABSTRAK

Terdapat beberapa algoritma yang digunakan untuk meramal banjir, termasuk LSTM, BP, MLP, SARIMA, dan SVM. Walaupun rangkaian neural adalah mudah dan cekap, ia mempunyai ingatan terhad dan mungkin tidak dapat mengesan corak jangka panjang atau data berskala besar secara tepat. LSTM telah menarik perhatian penyelidik dalam ramalan banjir kerana keupayaannya untuk mengekalkan data sejarah dan menyelesaikan masalah rangkaian masa yang kompleks. Walau bagaimanapun, kajian dalam bidang ini masih berterusan dengan potensi untuk peningkatan lebih lanjut. Dalam kajian semasa, para penyelidik sedang mengeksplorasi arah baru dengan membangunkan algoritma hibrid. SNN, generasi ketiga ANN, telah dicipta untuk mengendalikan data yang lebih kompleks dengan kadar keputusan yang lebih tinggi daripada ML dan DL. Dalam kajian ini, satu algoritma hibrid baru DSNN akan digunakan untuk meramal banjir di Kuala Baram, Miri, Sarawak. Data hujan selama 30 tahun (1989-2019) telah dikumpulkan dari DID untuk menilai keberkesanan algoritma DSNN berbanding dengan algoritma rangkaian neural tradisional. Prestasi diukur menggunakan ACC, RMSE, SPE, SEN, PPV, NPV, dan ASP. Analisis menyeluruh terhadap algoritma DSNN yang dicadangkan telah dijalankan. Empat nisbah latihan yang berbeza digunakan untuk pengesahan: 80:10:10, 70:15:15, 60:20:20, dan 50:25:25. Hasil kajian menunjukkan bahawa algoritma DSNN memberikan prestasi lebih baik berbanding algoritma lain dengan kadar ACC yang lebih tinggi, iaitu 98.10%, RMSE sebanyak 6.5%, SEN sebanyak 93.50%, kadar SPE sebanyak 79.00%, dan ASP sebanyak 89.60%. Secara keseluruhannya, algoritma DSNN dengan nisbah sampel latihan 80:10:10 memberikan prestasi terbaik.

Kata kunci: *Deep Spiking Neural Network (DSNN), Leaky Integrate and Fire (LIF), Long Short-Term Memory (LSTM), Ramalan banjir, Spiking Neural Network (SNN).*

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LIST OF ABBREVIATIONS

ACC	Accuracy
ACF	Auto-Correlation Function
AER	Address Event Representation
AEs	Autoencoders
AHP	Analytic Hierarchy Process
ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
ASP	Average Site Performance
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AUC	Area Under the Curve
BILSTM	Bidirectional Long Short-Term memory
BN	Bayesian Networks
BP	Backpropagation
CC	Coefficient Correlation
CGS	Centre for Graduate Studies
CNN	Convolutional Neural Network
ConvNets	Convolutional Neural Networks
CRBM	Conditional Restricted Machine
DBN	Deep Belief Network
DEM	Digital Elavation Model

DID	Department of Irrigation and Drainage
DL	Deep Learning
DRNN	Deep Recurrent Neural Networks
DSSN	Deep Spiking Neural Network
DSLM	Deep Liquid State Machine
DVS	Dynamic Vision Sensor
EBF	Evidential Belief Function
ELM	Extreme Learning Machine
FN	False Negative
FP	False Positive
FR	Frequency Ratio
FRCBM	Factored Conditional Restricted Boltzmann Machine
GEE	Google Earth Engine
GFI	Geomorphic Flooding Index
GIS	Geographic Information System
GPS	Global Positioning System
GRU	Gated Recurrent Unit
GSM	Global System for Mobile Communications
IoT	Internet of Things
KNN	K-Nearest Neighbours
Landsat TM	Landsat Thematic Mapper
LeNet-5 CNN	LeNet – 5 Convolutional Neural Network
LIF	Leaky Integrate and Fire
LME	Legate McCabe Efficiency Index
LoRaWan	Long Range Wide Area Network

LSTM	Long Short-Term Memory
LULC	Land Use and Land Cover
MAE	Mean Absolute Error.
MAPE	Mean Percentage Error
MDEL	Multiscale Deep Feature Learning
ML	Machine Learning
MLP	Multilayer Perceptron
MSE	Mean Squared Error
NARX	Nonlinear AutoRegressive with Exogenous inputs
NDWI	Normalised Difference Water Index
NM	Numerical Model
NPV	Negative Predictive Value
NSE	Nash-Sutcliffe Efficiency
OLI	Operational Land Image
OWA	Ordered Weight Average
PACF	Partial Auto-Correlation Function
PC	Personal Computer
PDBM	Predictive Boltzmann Machine
PPV	Positive Predictive Value
PSO	Particle Swam Optimization
r	Coefficient Correlation
R^2	R-Squared
RAM	Random Access Memory
RBFNN	Radial Basis Function Neural Network
RBM	Restrictive Boltzmann Machine

ResNet	Residual Neural Network
RGB	Red, Green, Blue
RMSE	Root Mean Square Error
RNN	Recurrent Neural Networks
ROC	Receiver Operating Characteristic
RWL	Reservoir Water Level
SAE	Stacked Autoencoders
SAR	Synthetic Aperture Radar
SARIMA	Seasonal Autoregressive Integrated Moving Average
SDAE	Stacked Denoising Auto Encoder
SDWI	Shadow Difference Water Index
SEN	Sensitivity
SMS	Short Message Service
SNN	Spiking Neural Network
SPE	Specificity
SRM	Spike Respond Model
SVM	Support Vector Machine
TN	True Negative
TNR	True Negative Rate
TP	True Positive
TRP	True Positive Rate
UNIMAS	Universiti Malaysia Sarawak
VE	Validation Epoch
VGG Net	Visual Geometry Group Network
WOA	Whale Optimisation Algorithm

XAJ	Xinanjiang Model

CHAPTER 1

INTRODUCTION

1.1 Study Background

In 2021, Malaysia's massive floods resulted in an estimated total loss of RM6.1 billion, with Selangor being the worst hit state (Abdullah, 2018; Bedi, 2022; Mohammed et al., 2018; Safiah Yusmah et al., 2020). According to an article in the New Straits Times by Dr. Mohd Uzidin (Bernama, 2022), the annual floods have adverse impacts on various aspects of life, including loss of lives, destruction of public assets, houses, transportation, infrastructure, manufacturing, and agriculture industries. These floods cause financial losses not only to business operators but also to citizens in general. The total loss due to floods adds up to more than RM2 billion, with houses (RM1.6 billion), automobiles (RM1.0 billion), the manufacturing sector (RM0.9 billion), commercial real estate (RM500 million), and agriculture (RM90.6 million) being the most affected.

Flood is a natural disaster that hinders a country's development (Elias et al., 2013; Kourgialas & Karatzas, 2011). Flooding typically happens when swollen water from rivers or lakes overflows the levees, but it can also occur when rainwater collects on saturated ground with insufficient areas for infiltration. Some floods develop slowly, whereas flash floods can happen very fast. Floods are becoming more frequent due to climate change, and transformation of the earth's physical infrastructure as a consequence of technical and economic improvements (Elias et al., 2013). Serious attention must be given to flood control measures and solutions developed to mitigate the negative impact of this disaster. Past research has run several statistical tests and analyses in Malaysia, including Sabah and Sarawak; the results show that since the 1920s, floods have been the most common natural calamity, hitting many locations, particularly the low-lying areas (Pirah & Roslee, 2021; Tew et al., 2022). The expansion of the areas causes almost 9% of the entire disaster, while floods bring direct damages to nearly 22% of the total population (Yusoff et al., 2018). Furthermore, Malaysia's climate is experiencing an increase in the frequency of rainfall, with an average of roughly 2,500 mm per year in Peninsula Malaysia, 3,000 mm per year in Sabah, and 3,500 mm per year in Sarawak (Aliagha et al., 2015; Othman et al., 2014; Salleh et al., 2013; Tan et al., 2015).

During the monsoon seasons, most Malaysian states receive considerable rainfall every year, resulting in flooding in numerous locations, particularly those in and around central business districts. The district of Baram River in Sarawak is vulnerable to flooding due to its proximity to the river mouth fronting the South China Sea. The Baram River is the second longest river in Sarawak with its source located hundreds of kilometres inland in the mountains near the Sarawak-Indonesia border (Ling et al., 2017). The river begins in Long Lamai and ends at Baram with water flowing into the South China Sea (KessLer & Jong, 2015). Few studies on flood event prediction have used physical modelling techniques such as regression (Fenglin et al., 2023; Panahi et al., 2021; Rezaeianzadeh et al., 2018; Tsakiri et al., 2018; Viteri López & Morales Rodriguez, 2020) and hydrodynamic modelling (Boota et al., 2023; Fitzpatrick et al., 2023; Huang et al., 2023; Karim et al., 2023; Timbadiya & Krishnamraju, 2023).

High-performance models can assist in predicting impending flooding events and mitigate the damaging effects. One of the most effective techniques is to use computer modelling. Computer modelling has been frequently utilised in research to tackle physical difficulties. Researchers can easily and quickly evaluate changes in real-life situations and their impacts over time. With the advent of high-speed computers and sophisticated software packages, many digitalised models have been developed to forecast outcomes of floodings (Fotovatikhah et al., 2018; Jajarmizadeh et al., 2014; Teng et al., 2017).

Deep Artificial Neural Network (ANN), also known as Deep Learning (DL), is the most well-known computerised modelling that solves problems using algorithmic techniques (Schmidhuber, 2015). Shallow and deep neural networks, with different credit assignment paths, link actions and outcomes utilising pattern recognition, generalisation, perception, and machine learning. DL consists of deep supervised learning, which encompasses recapitulating the history of Back-propagation, unsupervised learning, reinforcement learning and evolutionary computation, and indirect search for short programs encoding deep and large networks (Hinton, 2007; LeCun et al., 2015; Liu et al., 2017). Spiking Neural Network (SNN), the third generation of Artificial Neural Network (ANN), plays a vital role in biological information processing (Maass, 1997). The SNN model provides an in-depth description of biological neuronal behaviour. Researchers have used additional data to analyse the average firing rate for neuron computations. The structure of SNNs is optimised for the efficient processing of firing times; the transmission of information between neurons occurs via action potentials or spikes.

In contrast, ANN models average individual spikes over time, dividing all interactions by the average neuron firing rate (Ikeda & Manton, 2009). They are also more computationally robust than ANN, which uses a mean firing rate (Ignatov et al., 2015). Therefore, due to the robustness of DL and SNN models, this study fits and integrates the DL model’s spike trains and hybrid training into Deep Spiking Neural Network (DSNN).

The study area is the Baram River, in Miri Division of Sarawak, and north-western Borneo. The Baram River flows around the Miri District, as shown in Figure 1.1 shows Baram river flow around the Miri, Sarawak. Figure 1.2 illustrate topographic map of Kuala Baram, Miri in 1960. Meanwhile, Figure 1.3 illustrates the city of Miri city in 1960. The Baram River basin, covering an area of approximately 10,000 square miles, has been a part of Sarawak since it was surrendered to the White Rajah of Sarawak by the then Sultan of Brunei in 1882. (30,000 km2). Figure 1.4 shows a closer view of the Batang Baram anchorage area, and Figure 1.5 shows the location of the Baram Miri Basin.

Figure 1.1: Baram River Flow around the Miri, Sarawak (Dandot, 2006)

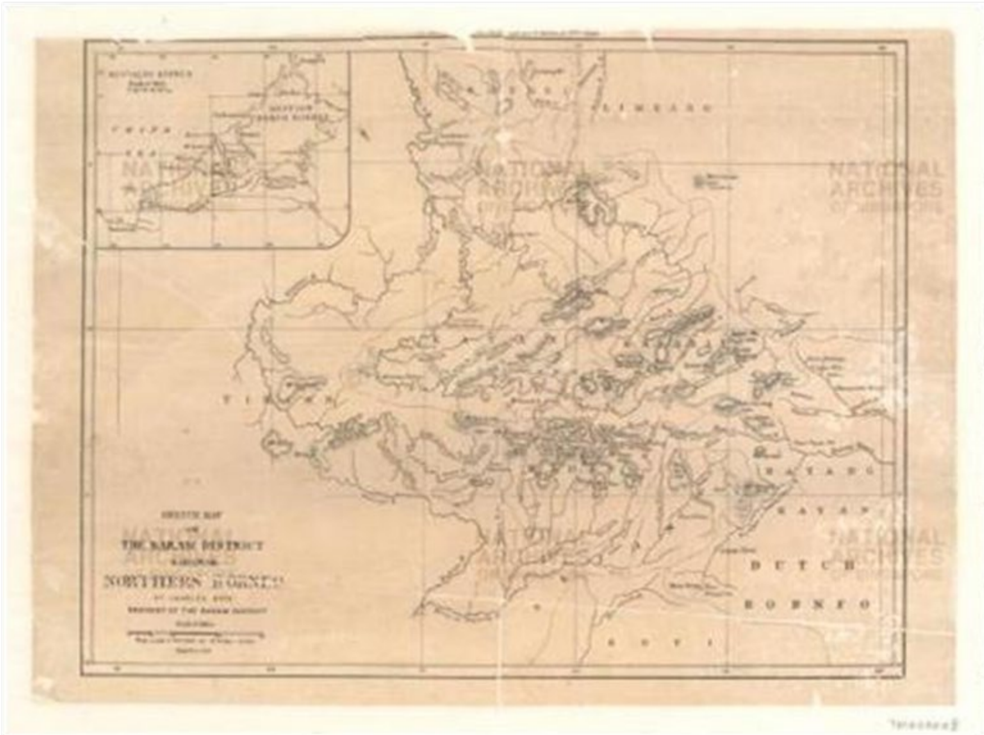

Figure 1.2: Topographic Map of Kuala Baram, Miri in 1960 (Dandot, 2006)

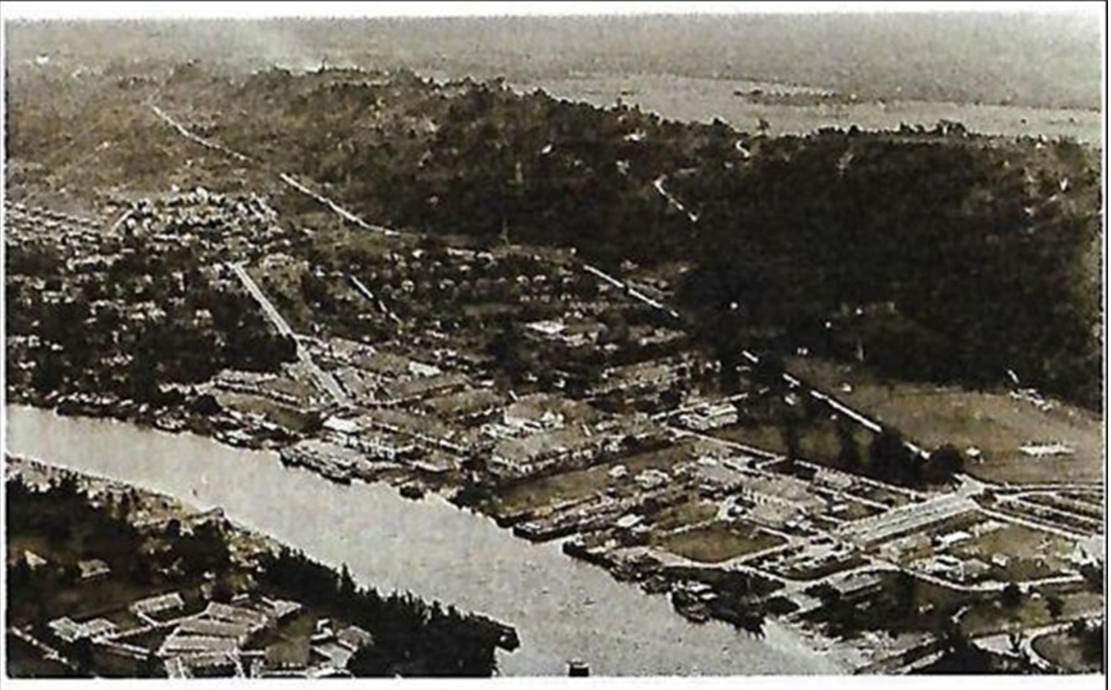

Figure 1.3: Miri City in 1960 (Dandot, 2006)