

Flood Prediction using Deep Spiking Neural Network

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Abstract— The aim of this article is to analyse the Deep Spiking Neural Network (DSNN) performance in flood prediction. The DSNN model has been trained and evaluated with 30 years of data obtained from the Drainage and Irrigation (DID) department of Sarawak from 1989 to 2019. The model's effectiveness is measured and examined based on accuracy (ACC), RMSE, Sensitivity (SEN), specificity (SPE), Positive Predictive Value (PPV), NPV and the Average Site Performance (ASP). Furthermore, the proposed model's performance was compared with other classifiers that are commonly used in flood prediction to evaluate the viability and capability of the proposed flood prediction method. The results indicate that a DSNN model of greater ACC (98.10%), RMSE (0.065%), SEN (93.50%), SPE (79.0%), PPV (88.10%), and ASP (89.60 %) is predictable. The findings were fair and efficient and outperformed the other BP, MLP, SARIMA, and SVM classification models.

Keywords— Deep Spiking Neural Network (DSNN), Deep Learning (DL), Flood Prediction, Long Short-Term Memory (LSTM), Spiking Neural Network (SNN).

I. INTRODUCTION

Flooding occurs in many places, particularly in Sarawak, and this annual flooding has had a substantial impact on casualties, property destruction, land structure, and economic losses [1], [2]. Highly accurate flood prediction could help to prevent casualties and damages cause.

According to previous research conducted in Malaysia, including Sabah and Sarawak, an increase in the area causes 9% of the entire disaster, while floods directly harm nearly 22% of the whole population [3]. Furthermore, Malaysia's climate is wet, with an average annual rainfall of roughly 3,500 mm in Sarawak, 3,000 mm in Sabah, and 2,500 mm in Peninsular Malaysia [4], [5].

To predict future flood events, past historical flood data are needed. Various models and data types emerged for forecasting flood using physical modelling such as regression model, hydrodynamic modelling, and the process in gaining data is costly and time consuming [6]. In this study, flood data are classified as a large amount of data; thus, the more layers of neurons there are, the better the network is at collecting more nuanced relationships occurring within the hidden layer.

As a result, this study proposed a DSNN model, which is a combination of DL and SNN that is trained on historical rainfall values to predict future rainfall values, increasing the accuracy of the efficiency of flood classification while successfully reducing forecast time. DL enables the computational model made from many processing layers to learn data with multiple different layers [7].

SNNs, on the other hand, transmit data via action potentials or spikes, which are effectively timed events. The strength of the spikes is derived from the synaptic accurate modelling. SNNs have been demonstrated to be computationally as powerful as traditional artificial neural networks [8].

The significance of this research is to fill the gap in the discovery of more precise and effective prediction models. The novel contribution of this approach is to bridge the gap with the DSNN model combining DL and SNN. The advantage of the suggested method is that variables and knowledge-related concepts such as hydrology are needed to describe flood dynamics.

The area of research is Baram River, Miri, Sarawak. In the state of Sarawak, district of Baram river susceptible due to its location are located near to the river mouth in the sea of South China. Baram area, Miri are utilized to experience worse flooding in the 1960 and the recent flood in February and July 2018 has become worst which cause tremendous amount of destruction property, loss of lives and school close. During this time, the residential area in Baram, Miri will not have enough of food, other necessities, and important resources electricity shutdown in the rural area [9] - [11].

The Baram River originates from the mountains at the border of the Sarawak inland for hundreds of kilometers as illustrated in Fig. 1 while Fig. 2 displays Baram river anchorage area. Meanwhile, Fig 3 depicts Baram River flow around the Miri, Sarawak. Fig. 4 shows the Baram River, Miri Basin.

The formation of the river delta created the gap in the South China Sea because of the continuously change of demographic area due to the floods [12].



Figure 1. Baram, Miri Map [13]

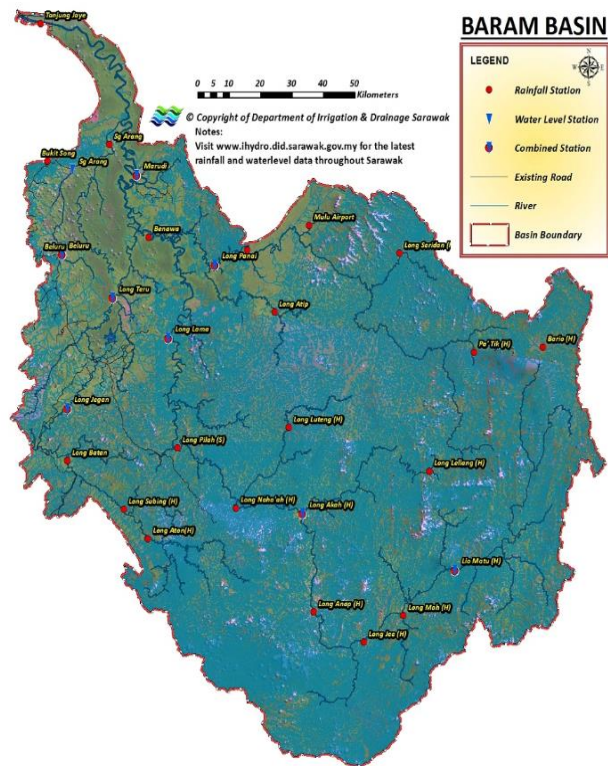


Figure 4. Baram River Basin [15]



Figure 2. Baram River Anchorage Area [13]



Figure 3. Baram River flow around the Miri, Sarawak [13]

A. Long Short-Term Memory (LSTM) Model

LSTM is a dynamic state of neural network that is utilized to train Recurrent Neural Networks (RNN) [16]. Recurrent networks can leverage their feedback connections to store representations of recent input events as short-term storage activations rather than long-term memory that is slowly embodied by weight changes. For various applications, including predicting, musical composition, speech processing and non-Markovian control, the use of feedback connections can be of potential importance. LSTM has already been applied to plenty of learning issues that vary in size and complexity from the issues on which those enhancements had been initially tested. Several research have been done using the LSTM for flood forecasting purposes. Therefore, due to the superior advantages shown in many research, LSTM will be adopted in this research [18], [19].

The network model is a memory cell that able to attain its situation. Non-linear LSTM components restrict the flow of information into and out of neuron [17]. Fig. 5 displays a thorough SRN design and Fig. 6 demonstrates a Long Short-Term Memory Block as employed in the hidden layers of a recurring neural network. In addition, Fig. 7 depicts the standard legend visual representative utilised in SRN and LSTM.

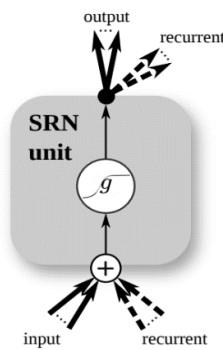


Figure 5. Schematic of Simple Recurrent Network (SRN) [17]

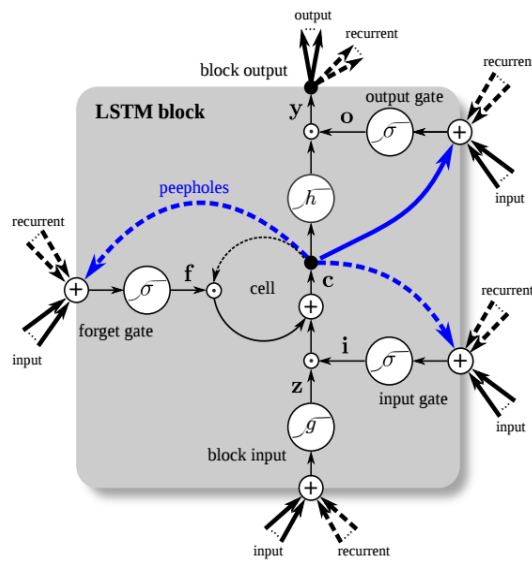


Figure 6. Long Short-Term Memory block. [17]

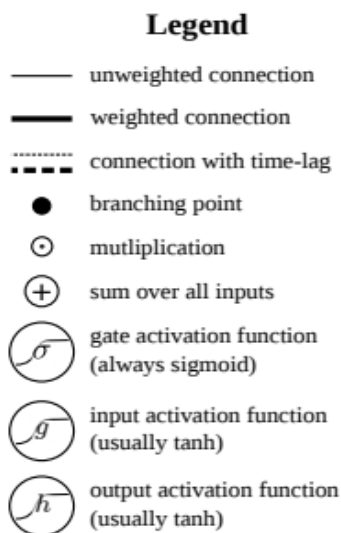


Figure 7. Legend visual representative of SRN and LSTM [17]

The LSTM comprises three gates: input, forget, exit, and block input, as well as a single cell, the output activation, and peephole connections. The block output is connected to the block input and all the gates repeatedly. The LSTM function can be observed by comprehending the three-standard step operating in LSTM. A typical LSTM network consists of many memory blocks called cells. Two states are moved to the next cell: the cell state and the hidden state. The LSTM can delete information or add it to the cell state, which is strictly managed by structures known as gates. Gates are a mechanism to pass information optionally. They consist of a sigmoid neural network layer and are spot-propagated [17].

The memory blocks are crucial for storing and processing the memory via five key techniques, named sigmoid layer, forget gate, tanh layer, input gates, update cell state and output gate. Sigmoid layer outputs values from zero to one, indicating how much each element should be allowed to do. A zero value means "Let nothing pass," while one value means "Let it all pass!" A forgotten gate is essential for erasing cell state information. The information no longer needed for the LSTM is eliminated by multiplying the filter. This is necessary to optimise the LSTM network's performance. This gate requires two inputs, one hidden from the previous cell or the previous cell output and the other input in that particular stage [20], [21].

The input gate is able to aggregate cell state information. This addition has essentially two sections of the sigmoid layer and the tanh layer. First, the "input gate layer" is called by a sigmoid layer. Next, a tanh layer provides a new candidate value vector that could be added to the state. Combined with the sigmoid layer and tanh layer of the gate, the cell state is updated and the old value is replaced.

When new values are added, the existing cell state automatically updates by combining the new values with the current cell state to produce new cell state values. Lastly, the value of the next hidden state is determined by the output gate. The hidden state is utilized for prediction and contains information from previous inputs. First, the existing and the preceding hidden states are transferred into the third sigmoid function. So the new cell state from the cell state is passed on to the tanh function [20], [21].

Data input (x_t) are fit into LSTM cell in Forget Gate Eq.1, where (f_t) control the data that is less importance. Input Gate responsible for adding new input to the cell state and containing two parts as shown in Eq. 2 and Eq. 3. First, ($i_t = \sigma$) update new value and second ($\tilde{C}_t = \tanh$), creates a vector of new values that can insert to cell. Cell State is to update the old cell state, C_{t-1} , into the new cell state (C_t). Eq.4 shows the updated equation. multiply the old state by (f_t), Output gate will depend on cell state and scale the values between -1 to 1 in Eqs. 5 and 6.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (1)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (2)$$

$$\tilde{C}_t = \tanh(W_c [h_{t-1}, x_t] + b_c) \quad (3)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (4)$$

$$O_t = \sigma(W_o [h_{t-1}, x_t] + b_o) \quad (5)$$

$$h_t = O_t * \tanh(C_t) \quad (6)$$

B. Leaky Integrate and Fire (LIF) Model

SNNs proved to be the solution for bridging the gap between computational and theoretical. SNNs communicate with each other via discrete events (spikes) instead of continuous valued activations. Such system is updated asynchronously as event arrives, thus reducing number of operations required at each time step. LIF model has been widely used due to its intensity of firing rate execution. LIF able to shorten the time of prediction and give better accuracy. LIF in Fig. 8 shows a formal spiking neuron model. Therefore, this study will adapt LIF model threshold and merge into LSTM model, the thresholds classify the flood datasets

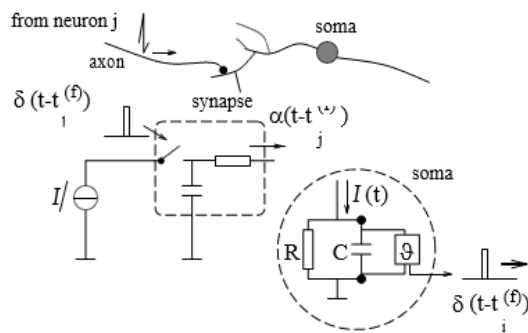


Figure 8. Schematic diagram of LIF [22].

The concepts of the neuron's potential are defined in LIF, $dv(t)$ as show in Eq. 7.

$$C_m \frac{dv(t)}{dt} = I_{leak}(t) + I_s(t) + I_{inj}(t) \quad (7)$$

Where;

- C_m capacity of the neuron
- $I_{leak}(t)$ current active neuron leak
- $I_s(t)$ effect of the synapses signal to the neurons
- $I_{inj}(t)$ injected into the neuron

The leak current of LIF is show in Eq. 8.

$$I_{leak}(t) = \frac{C_m}{\tau_m} = [v(t) - V_0] \quad (8)$$

Where;

- V_0 is the resting potential
- τ_m is the continuous active time
- $\tau_m = R_m C_m$ to the Capacity and resistance to leak

II. EMPIRICAL STUDY

To test the efficiency of the DSNN model, Multiple experiments on 35 datasets are conducted using k-fold cross validation. During k-fold cross validation, data is divided into k subsets of the same size. The framework was designed for k iterations, every cycle exits one of its train subsets and use it as testing dataset. Table I shows the details of 35 rainfall station, Baram, Miri. These are the real-world datasets given by DID, which similar in term of the number of available samples, datasets characteristics (Multivariate), and features (2).

Table I. Details rainfall station, Baram, Miri.

Type of Datasets	Station No	Station Name	Period of Data
Rainfall	4440060	Miri DID Barrack	(1989-2019) 30 Years
	3152011	Lio Matu	
	3347003	Long Akah	
	3541033	Long Jegan	
	3744009	Long Lama	
	3945017	Long Panai	
	3842034	Long Teru	
	4143004	Marudi	
	3940036	Beluru	
	4339005	Miri Airport	
	4339001	Miri MCC	
	4440001	Lutong	
	3050015	Long Moh	
	2949001	Long Jee	
	3048026	Long Anap	
	3345029	Long Naha'ah	
	3243071	Long Aton	
	3342032	Long Subing	
	3441001	Long Batan	
	3547001	Long Luteng	
	3444018	Long Pilah	
	4442001	Tanjong Jaye	
	4043059	Benawa	
	3847035	Long Atip	
	3950020	Long Seridan	
	3752001	Pa Tik	
	3754007	Bario	
	3451028	Long Lellang	
	4151017	Long Napir	
	3946001	Long Terawan	
	4047001	Long Pala	
	4049001	Mulu	
	4139064	Kebuloh	
	4239001	Bukit Lambir Micro	
	4241001	Bakong	

The division of data is a key phase in developing artificial neural networks (ANN), dividing data sets into training, testing and validation subsets in order to ensure model performance generalization [23] - [26]. Due to the fact that other factors affecting model development, such as model

structure selection, random weight initialization and training, the performance variation due to data splitting was greater than the variability [27].

Four distinct ratios have been employed in this article. The ratio described in this article has been utilised extensively in flood prediction. For the first ratio utilized in [28], the flood forecast for Sungai Isap is reliable to be used in flood forecasting in Levenberg (80 % training: 10 % validation: 10 % testing). 80% of the input data was utilised by the training network. The network ends training in the validation section when 10 percent of data is used to classify the network structure not being used in the training section. In the meantime, data validation was reviewed in a new training sequence and the number of validation errors reduced. Following completion of the training phase and validation, the remaining 10 percent data will be applicable to the testing procedure.

Second ratio is (70% training: 15% validation: 15% testing) has been used in [28]. Third ratio utilized in [29] is the investigation of a benchmarking methodology for evaluating data division strategies for modelling water resource parameters using artificial neuronal networks (50% training: 25% validation: 25% testing). The last ratio is (60% training: 20% validation: 20% testing) in Klang River flooding research utilizing artificial neural networks [30]. Table II shows the overview ratio used in this research.

Table II. Overview Ratios on Data Splitting

Ratio	Dataset
(80:10:10)	Flood
(70:15:15)	
(60:20:20)	
(50:25:25)	

The dataset has been passed through three main major mechanisms. In the training and validation of the algorithm, the selected hyper-parameter includes batch size, epoch, activation, optimization, and validation stages. Table II shows batch size, epoch, and validation steps. Table III shows the batch size, epoch, and validation steps Hyper Parameters of DSNN model and Table IV illustrates the activation and Hyper Parameters of DSNN model.

Table III. Batch Size, Epoch, and Validation steps Hyper Parameters of DSNN model

Datasets	Batch Size	Epochs	Steps per-epoch	Validation steps
Flood Dataset	32	10	200	200
	64	10	400	400
	128	10	600	600
	256	10	1000	1000

Table IV. Activation and Optimization Hyper Parameters of DSNN model

Datasets	Activation	Optimization
Flood Dataset	SoftMax	Adam

Fig. 9 briefly describes the simple schematic representation of DSNN proposed method. Spiking Recurrent Neural Networks are gaining momentum in the resolution of complicated time issues. Generally, Spiking Neural Networks are computationally robust and efficient. The LIF model threshold will integrate into the LSTM model where the thresholds will play significant role in the LSTM process by classifying the flood data, returning, and estimating the accuracy of where the threshold is dynamically learning from the datasets and determining the appropriate threshold from the start of the action. LIF able to shorten the time of prediction and give better accuracy.

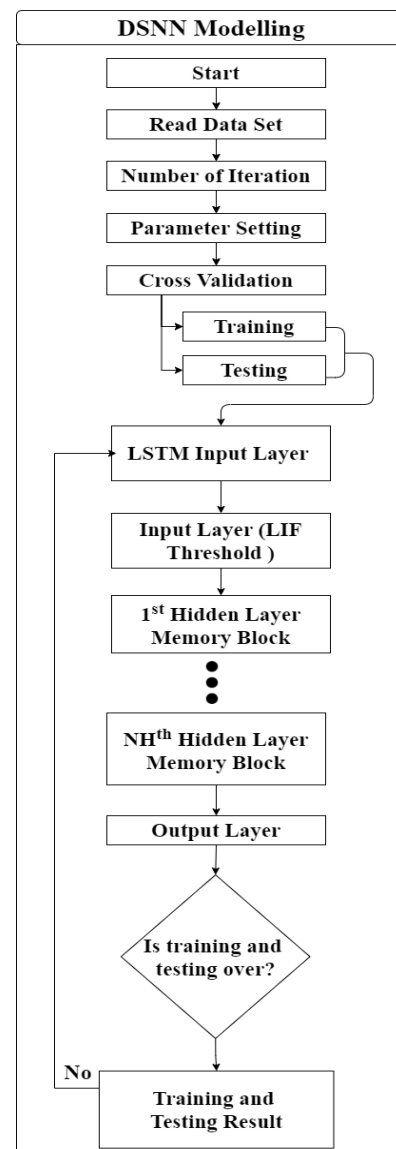


Figure 9. Simple schematic representation of DSNN proposed method

III. FINDINGS AND ANALYSIS

The following subsection indicates the methods of the performance value that are utilized to evaluate the proposed methods. Analysis is performed on flood datasets collected from DID. All experiments are evaluated and analyzed based on Accuracy (ACC), Root Mean Square Error (RMSE), Sensitivity (SEN), Specificity (SPE), Positive Predictive Value (PPV), Negative predictive value (NPV) and Average Site Performance (ASP) which are widely used in prediction and various fields as in [31] - [35]. In order to achieve a more detailed analysis, evaluation of the performance of the proposed method is compared with standard classifiers which widely used in flood prediction to explore the possibility of the proposed method and its capability in predicting flood. The proposed methods DSNN model has been compared with Backpropagation (BP), Multi-Layer Perceptron (MLP), Seasonal Autoregressive Integrated Moving Average (SARIMA), and Support Vector Machine (SVM) [36] - [43].

A. Performance Measurement

The calculation of SEN, SPE and PPV, NPV, ASP, ACC and RMSE is given in Eqs. (10) to (16).

Sensitivity (SEN)

$$TPR = \frac{TP}{(TP + FN)} (\%) \quad (10)$$

Specificity (SPE)

$$TNR = \frac{TN}{(TN + FP)} (\%) \quad (11)$$

Positive Predictive Value (PPV)

$$PPV = \frac{(TP)}{(TP + FP)} (\%) \quad (12)$$

Negative Predictive Value (NPV)

$$NPV = \frac{(TN)}{(TN + FN)} (\%) \quad (13)$$

Average Site Performance (ASP)

$$ASP = \frac{(SEN + PPV)}{(2)} (\%) \quad (14)$$

Accuracy (ACC)

$$ACC = \frac{(TP + TN)}{(TP + FP + TN + FN)} (\%) \quad (15)$$

Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (P_i - O_i)^2}{n}} \quad (16)$$

B. Results

The proposed method DSNN model was compared with BP, MLP, SARIMA, and SVM. This research applied 4 different ratios distributions (80:10:10), (70:15:15), (60:20:20) and (50:25:25) for training sample, testing sample and validation sample.

The findings of this analysis indicated that the flood can be forecast by a DSNN model with higher ACC (98.10%), RMSE (0.065), SEN (93.50%), SPE (79.00%), PPV (88.10%), ASP (89.60%). The prediction by DSNN Model with (80:10:10), training sample has shown better results compared with (70:15:15), (60:20:20) and (50:25:25) training sample. Tables V to VII have shown the results of the ratio applied in this research. Meanwhile, Fig. 10 to Fig. 13 demonstrated the performance measurement used and ratio applied.

Table V. Result Ratio (80:10:10)

Analysis Criteria	DSNN	BP	MLP	SARIMA	SVM
SEN	93.50	84.50	80.00	83.90	85.20
SPE	79.00	77.10	77.6	75.80	73.90
PPV	88.10	85.30	80.70	82.50	84.70
NPV	80.70	84.50	80.00	83.90	85.20
ASP	89.60	84.90	80.40	83.20	80.40
ACC	98.10	92.40	96.20	96.90	95.30
RMSE	0.065	0.088	0.079	0.076	0.080

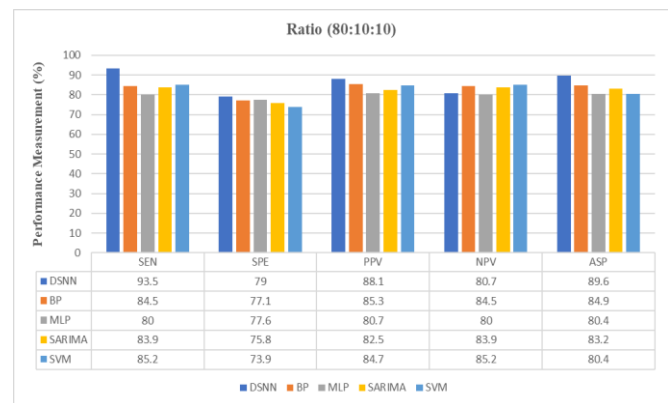


Figure 10. Performance measurement with ratio (80:10:10)

Table VI. Result Ratio (70:15:15)

Analysis Criteria	DSNN	BP	MLP	SARIMA	SVM
SEN	89.60	77.20	79.60	85.80	78.70
SPE	66.30	63.20	62.40	69.68	65.60
PPV	82.50	67.60	68.16	65.50	69.45
NPV	83.90	64.70	71.60	77.50	67.90
ASP	83.20	66.70	71.50	66.70	78.50
ACC	88.70	68.50	74.67	84.05	83.90
RMSE	0.740	0.880	0.840	0.730	0.870

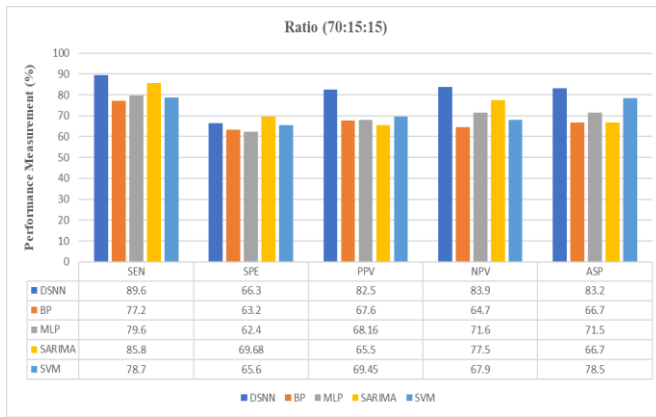


Figure 11. Performance measurement with ratio (70:15:15)

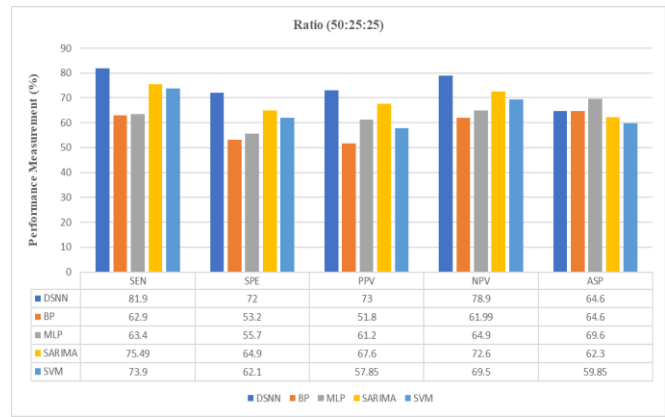


Figure 13. Performance measurement with ratio (50:25:25)

Table VII. Result Ratio (60:20:20)

Analysis Criteria	DSNN	BP	MLP	SARIMA	SVM
SEN	82.60	71.99	80.40	86.00	85.20
SPE	77.20	61.12	67.00	68.90	63.74
PPV	73.30	62.30	64.25	70.70	64.60
NPV	78.90	64.50	80.00	82.75	78.90
ASP	64.60	72.24	80.40	70.30	76.30
ACC	79.70	75.80	76.10	79.10	77.50
RMSE	0.66	0.890	0.830	0.740	0.810

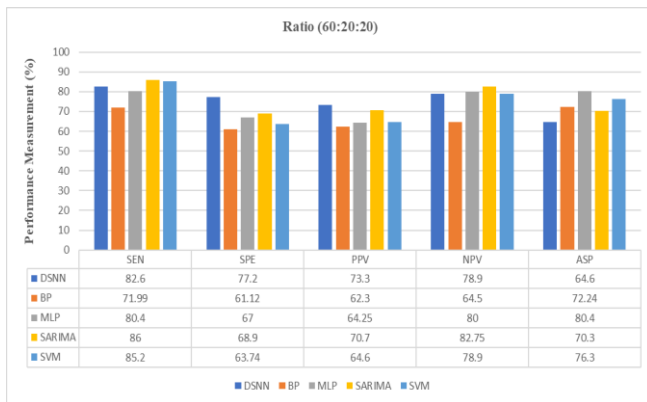


Figure 12. Performance measurement with ratio (60:20:20)

Table VIII. Result Ratio (50:25:25)

Analysis Criteria	DSNN	BP	MLP	SARIMA	SVM
SEN	81.90	62.90	63.40	75.49	73.90
SPE	72.00	53.20	55.70	64.90	62.10
PPV	73.00	51.80	61.20	67.60	57.85
NPV	78.90	61.99	64.90	72.60	69.50
ASP	64.60	64.60	69.60	62.30	59.85
ACC	77.40	69.40	70.20	75.00	72.40
RMSE	0.800	0.950	0.890	0.870	0.890

IV. COMPARATIVE STUDY AND ANALYSIS

The proposed method DSNN model was compared with BP, MLP, SARIMA, and SVM. DSNN model is an effective method for flood prediction, evidenced with a high accuracy ACC (98.10%), RMSE (0.065), SEN (93.50%), SPE (79.00%), PPV (88.10%), NPV (80.70%), ASP (89.60%) as shown in Tables IX to X and Figs. 14 to 15.

Table IX. Accuracy (ACC %)

ACC	DSNN	BP	MLP	SARIMA	SVM
(80:10:10)	98.10	92.40	96.20	96.90	95.30
(70:15:15)	88.70	68.50	74.67	84.05	83.90
(60:20:20)	79.70	75.80	76.10	79.10	77.50
(50:25:25)	77.40	69.40	70.20	75.00	72.40

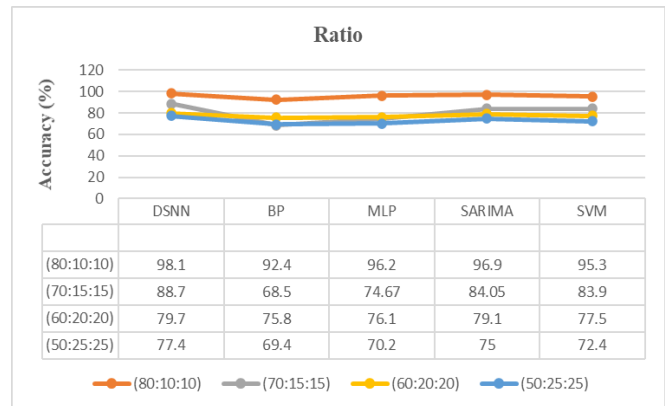


Figure 14. Accuracy Results (%)

Table X. RMSE Values

RMSE	DSNN	BP	MLP	SARIMA	SVM
(80:10:10)	0.065	0.088	0.079	0.076	0.080
(70:15:15)	0.740	0.880	0.840	0.730	0.870
(60:20:20)	0.66	0.890	0.830	0.740	0.810
(50:25:25)	0.800	0.950	0.890	0.870	0.890

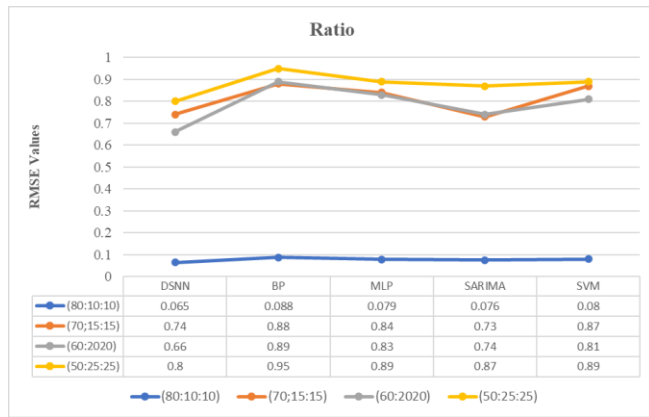


Figure 15. RMSE Values Results

A detailed examination of the results concludes that the variance in the performance of the proposed methods in a single dataset is greatly reduced compared to the variance in the performance on other datasets of the same method proposed. Consequently, the performance depends heavily on the type of the dataset. High dimensionality, samples, missing data, many classes, imbalanced classes and sound are major aspects that influence the classification of the presented approaches.

V. CONCLUSION

This research focuses on evaluating the efficiency of the DSNN model for flood prediction, as compared to LSTM and LIF. Through this study, the result shown DSNN model is an effective method for flood prediction, evidenced by a high accuracy ACC (98.10%), RMSE (0.065), SEN (93.50%), SPE (79.00%), PPV (88.10%), and ASP (89.60%). The DSNN model prediction using (80:10:10) training sample showed superior results. The DSNN model captures an important drivers of dataset demand. For understanding more insights of flood prediction, other modalities such as spatial, land-use, terrain, and time of a year such as monsoon season or time series-prediction are recommended to be explored as a future work. The flood prediction system can be utilized to develop other expert systems such as medical diagnosis, agricultural and malware detection. The model can be embedded in devices that use the mobile app platform. Early flood prediction helps government to save lives and minimize the damages to properties and the environment. In addition, more datasets with different attributes should be considered too. More comparisons with others flood forecasting approaches are also a strong suggestion.

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References

[1] Yusoff, I. M., Ramli, A., Azmi, N., Alkasirah, M., & Nasir, N. M. (2018). Exploring the managing of flood

disaster: A Malaysian perspective. *Malaysian Journal of Society and Space*, 14(3), 24–36.

[2] Elias, Z., Hamin, Z., & Othman, M. B. (2013). Sustainable management of flood risks in Malaysia: Some lessons from the legislation in England and Wales. *Procedia-Social and Behavioral Sciences*, 105, 491-497. <https://doi.org/10.1016/j.sbspro.2013.11.052>

[3] Official Website of Department of Irrigation and Drainage Sarawak (DID), May 2018. <http://publicinfobanjir.water.gov.my/>

[4] Tan, M. L., Ibrahim, A. L., Duan, Z., Cracknell, A. P., & Chaplot, V. (2015). Evaluation of six high-resolution satellite and ground-based precipitation products over Malaysia. *Remote Sensing*, 7(2), 1504-1528. <http://dx.doi.org/10.3390/rs70201504>.

[5] Khalid, M. S. B., & Shafiai, S. B. (2015). Flood disaster management in Malaysia: An evaluation of the effectiveness flood delivery system. *International Journal of Social Science and Humanity*, 5(4), 398. <https://doi.org/10.7763/IJSSH.2015.V5.488>

[6] N.N Kourgialas, G.P Karatzas, “**Flood management and a GIS modelling method to assess flood-hazard areas-A case study**”, *Hydrological Sciences Journal*. Vol. 56, PP. 212- 225. March 2011. <https://doi.org/10.1080/02626667.2011.555836>

[7] Lecun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436–444. <https://doi.org/10.1038/nature14539>

[8] Maass, W., & Markram, H. (2004). On the computational power of circuits of spiking neurons *Journal of Computer and System Sciences*, 69(4), 593 616. <https://doi.org/10.1016/j.jcss.2004.04.001>

[9] Kawi, M. R. (2018, February 9). Sarawak floods: More schools close; 4,444 at relief centres. *New Straits Times*. Kuching. Retrieved from <https://www.nst.com.my/news/nation/2018/02/333693/sarawak-floods-more-schoolsclose-4444-relief-centres>

[10] Stephen, T. (2018, February 8). Number of flood evacuees in Sarawak rises to more than 5,000. *The Star Online*. Miri. Retrieved from <https://www.thestar.com.my/news/nation/2018/02/08/floods-in-sarawak/>

[11] Abdullah, M. (2018, July 12). Flash flood strike after thunderstorm pounds Miri. *The Borneo Post*. Miri. Retrieved from <https://www.pressreader.com/malaysia/the-borneopost/20180712/281479277180572>

[12] Encyclopædia Britannica, “**Baram River**”, Encyclopædia Britannica, Inc. July 1998, available at <https://www.britannica.com/place/Baram-River>

[13] Dandot, D, W, B., Ismuni, I, H., Murang, O., Jones, D, J., Siaw, C., Dari, C., Othman, H., ... Ming, L, W. (2006). *Development in Sarawak an Aerial Perspective: Miri* (2nd ed., pp 173-208). Sarawak, Malaysia: Osacar Sdn Bhd, Malaysia

[14] Map of The Baram District, Sarawak, “**Northern Borneo: Sketch Map of The Baram District, Sarawak, Northern Borneo [Image]**”, National Archives of Singapore, March 1900. available at

https://www.nas.gov.sg/archivesonline/maps_building_plans/record-details/f9069d81-115c-11e3-83d5-0050568939ad

- [15] Resource Centre- Hydrology Stations at Baram Basin, “**Baram River Basin [Image]**”, 2018. available at <https://did.sarawak.gov.my/modules/web/pages.php?mod=webpage&sub=page&id=333>
- [16] Hochreiter, S., & Schmidhuber, U., J. (1997). Long Short-Term Memory. *Neural Computation*, 9(8). Retrieved from <http://www7.informatik.tu-muenchen.de/~hochreit>
- [17] Greff, K., Srivastava, R. K., Koutnik, J., Steunebrink, B. R., & Schmidhuber, J. (2017). LSTM: A Search Space Odyssey, 2. <https://doi.org/10.1109/TNNLS.2016.2582924>
- [18] Jin, B. O., Member, S., Che, C., Liu, Z., Zhang, S., Yin, X., & Wei, X. (2018). Predicting the Risk of Heart Failure with EHR Sequential Data Modeling. *IEEE*, 6. <https://doi.org/10.1109/ACCESS.2017.2789324>
- [19] Zhang, Q., Wang, H., Dong, J., Zhong, G., & Sun, X. (2017). Prediction of Sea Surface Temperature using Long Short-Term Memory. *Journal IEEE Geoscience and Remote Sensing Letters* Vol. 1. <https://arxiv.org/pdf/1705.06861.pdf>
- [20] Bao, W., Yue, J., & Rao, Y. (2017). A deep learning framework for financial time series using stacked autoencoders and long-short term memory. *PLoS one*, 12(7), e0180944. <https://doi.org/10.1371/journal.pone.0180944>
- [21] Graves, A. (2012). “**Supervised Sequence Labelling with Recurrent Neural Networks; Studies in Computational Intelligence**”, Springer, Berlin.
- [22] Gerstner, W., Kistler, W. M., Naud, R., and Paninski, L. (2014). *Neuronal dynamics: from single neurons to networks and models of cognition*. Cambridge University Press.
- [23] S.Gopal Krishna Patro, Pragyana Parimita Sahoo, Ipsita Panda, K. K. S. (2015). Technical Analysis on Financial Forecasting. *International Journal of Computer Science International Journal of Computer Sciences and Engineering JCSE*, 3(1), 1–6.
- [24] Abrahart, R. J., Anctil, F., Coulibaly, P., Dawson, C. W., Mount, N. J., See, L. M., ... Wilby, R. L. (2012). Two decades of anarchy? Emerging themes and outstanding challenges for neural network river forecasting. *Progress in Physical Geography: Earth and Environment*, 36(4), 480–513. <https://doi.org/10.1177/0309133312444943>
- [25] Anctil, F., & Lauzon, N. (2004). Generalisation for neural networks through data sampling and training procedures, with applications to streamflow predictions. *Hydrology and Earth System Sciences*, 8(5), 940–958. <https://doi.org/10.5194/hess-8-940-2004>
- [26] Wu, W., May, R., Dandy, G. C., Maier, H. R., Wu, W. ;, May, R. ;, & Dandy, G. C. ; (2012). A method for comparing data splitting approaches for developing hydrological ANN models ‘A method for comparing data splitting approaches for developing hydrological ANN models’ (Vol. 12). Retrieved from <https://scholarsarchive.byu.edu/iemssconference/2012/Stream-B/394>
- [27] LeBaron, B., & Weigend, A. S. (1998). A bootstrap evaluation of the effect of data splitting on financial time series. *IEEE Transactions on Neural Networks*, 9(1), 213–220. <https://doi.org/10.1109/72.655043>
- [28] Keong, K. C., Mustafa, M., Mohammad, A. J., Sulaiman, M. H., Abdullah, N. R. H., Samad, R., & Pebrianti, D. (2017). Levenberg-Marquardt flood prediction for Sungai Isap residence. *Proceedings - 2016 IEEE Conference on Systems, Process and Control, ICSPC 2016, (December)*, 160–165.
- [29] Wu, W., May, R. J., Maier, H. R., & Dandy, G. C. (2013). A benchmarking approach for comparing data splitting methods for modeling water resources parameters using artificial neural networks. *Water Resources Research*, 49(11), 7598–7614. <https://doi.org/10.1109/SPC.2016.7920722>
- [30] Hong, J. L., & Hong, K. (2016). Flood Forecasting for Klang River at Kuala Lumpur using Artificial Neural Networks. *International Journal of Hybrid Information Technology*, 9(3), 39–60. <https://doi.org/10.14257/ijhit.2016.9.3.05>
- [31] Nguyen, Q. K., Bui, D. T., Hoang, N. D., Trinh, P. T., Nguyen, V. H., & Yilmaz, I. (2017). A novel hybrid approach based on instance based learning classifier and rotation Forest ensemble for spatial prediction of rainfall-induced shallow landslides using GIS. *Sustainability (Switzerland)*, 9(5). <https://doi.org/10.3390/su9050813>
- [32] Adnan, R., Ruslan, F. A., Samad, A. M., & Zain, Z. M. (2012). Artificial neural network modelling and flood water level prediction using extended Kalman filter. *Proceedings - 2012 IEEE International Conference on Control System, Computing and Engineering, ICCSCE 2012*, 535–538. <https://doi.org/10.1109/ICCSCE.2012.6487204>
- [33] Labatut, V., & Cherifi, H. (2011). Evaluation of Performance Measure for Classifier Comparison. *Ubiquitous Computing and Communication Journal, UBICC Publishers*, 6, 21–34. Retrieved from <https://hal.archives-ouvertes.fr/hal-00653071>
- [34] Tirelli, T., Pozzi, L., & Pessani, D. (2009). Use of different approaches to model presence/absence of *Salmo marmoratus* in Piedmont (Northwestern Italy). <https://doi.org/10.1016/j.ecoinf.2009.07.003>
- [35] Fawcett, T. (2006). An introduction to ROC analysis. *Pattern Recognition Letters*, 27(8), 861–874. <https://doi.org/10.1016/j.patrec.2005.10.010>
- [36] Sankaranarayanan, S., Prabhakar, M., Satish, S., Jain, P., Ramprasad, A., & Krishnan, A. (2019). Flood prediction based on weather parameters using deep learning. *Journal of Water and Climate Change*. <https://doi.org/10.2166/wcc.2019.321>
- [37] Saleh AY, Tei R (2019), Flood prediction Using Seasonal Autoregressive Integrated Moving Average (SARIMA) Model. *International Journal of Innovative Technology and Exploring Engineering (IJITEE)*, 8 (8). ISSN 2278-3075
- [38] Saleh AY, Tei R (2018), Flood prediction of Sungai Bedup, Serian, Sarawak, Malaysia using Deep Learning.

International Journal of Engineering & Technology
7(3.22): 55–58.

DOI: 10.14419/ijet.v7i3.22.17125

- [39] Widiyari, I. R., Nugroho, L. E., & Widyawan. (2018). Deep learning multilayer perceptron (MLP) for flood prediction model using wireless sensor network based hydrology time series data mining. Proceedings - 2017 International Conference on Innovative and Creative Information Technology: Computational Intelligence and IoT, ICITech 2017, 2018-Janua, 1–5. <https://doi.org/10.1109/INNOCIT.2017.8319150>
- [40] Wang, J., Shi, P., Jiang, P., Hu, J., Qu, S., Chen, X., ... Xiao, Z. (2017). Application of BP Neural Network Algorithm in Traditional Hydrological Model for Flood Forecasting. Water, 9(1), 48. <https://doi.org/10.3390/w9010048>
- [41] Liu, F., Xu, F., & Yang, S. (2017). A Flood Forecasting Model Based on Deep Learning Algorithm via Integrating Stacked Autoencoders with BP Neural Network. Proceedings - 2017 IEEE 3rd International Conference on Multimedia Big Data, BigMM 2017, 58–61. <https://doi.org/10.1109/BigMM.2017.29>
- [42] Bustami, R., Bessaih, N., Bong, C., & Suhaili, S. (2007). Artificial Neural Network for Precipitation and Water Level Predictions of Bedup River Artificial Neural Network for Precipitation and Water Level Predictions of Bedup River. IAENG International Journal of Computer Science. 2 (34).
- [43] Bustami, R., Bessaih, N., Bong, C., & Suhaili, S. (2011). River Bedup Catchment Water Level Prediction Using Pre-developed ANN Model of Siniawan Catchment. Journal of Civil Engineering, Science and Technology, 2(1), 36–41. <https://doi.org/10.33736/jcest.86.2011>

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