Deep Learning Techniques for Flood Forecasting

Siti Azirah Asmai^{1,*}, Muhammad Hafizi Mohd Ali¹, Z Zainal Abidin¹, Zuraida Abal Abas¹, Nurul Akmar Emran¹,

¹Fakulti Teknologi Maklumat Dan Komunikasi, Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, 76100 Durian Tunggal, Melaka, Malaysia

*Corresponding author's email: azirah@utem.edu.my

ABSTRACT: A flood is a natural and seasonal phenomenon, which occurs from heavy rainfall or storm surge due to the cycle of the moon moves around the earth. However, global climate change causes a flood to be an unpredictable and unseasonal disaster. It is a challenge to predict a flood. Therefore, flood prediction is vital for emergency response, and several forecasting techniques are studied, for instance, ANN, RNN, and LSTM. This study aims to develop a flood forecasting model based on deep learning techniques to predict floods. A dataset from the river water level in one of the highest flood occurrences in Malaysia uses in this research. Results from LSTM and RNN techniques are compared and it showed that Recurrent Neural Network (RNN) performed well in flood forecasting model compared to Long Short-Term Memory (LSTM) in predicting river level in terms of accuracy performance. The significance of the proposed flood forecasting model brings a proactive flood prediction,

Keywords; Deep Learning; Flood Prediction, RNN, LSTM

1. INTRODUCTION

Floods are natural phenomena geo-hazards triggering the natural disasters that cause fatalities, damages, and severe impacts to social and economic [1]. There are many classifications of flood for instance, flash floods, coastal floods, river floods, ponding [2]. The purpose of this paper is to propose a solution in predicting flood occurrence in advance by applying a Deep Learning technique to get better accuracy in time series forecasting.

Studies have shown that the deep learning model has been applied in many fields, such as weather prediction [3], natural language processing [4], computer vision [5], and audio recognition [6], since they provide a promising outcome comparing to human experts. A common technique of the deep learning model uses Long Short-Term Memory (LSTM) and Recurrent Neural Network (RNN). This study discusses related work regarding to those techniques. For example [7] apply an LSTM technique to predict the flood by using dataset from Klang River. LSTM is very effective in modeling enormous time-series data. However, there is a drawback of LSTM, which is based models only provide good accuracy prediction at specific locations. In general, LSTM is a data-driven model that results in inadequate simulation [8]. Nagesh [9] applies the RNN model to predict the river flow in the month to prevent floods.

Additionally, Paul and Das [10] demonstrate groundwater forecasting for modeling and managing coastal flooding using the RNN model. Meanwhile, Paul and Das [11] have shown that an Artificial Neural Network (ANN) predicts flood water levels 24 hours ahead of time by using rainfall and present river level data. According to their study, the ANN approach works well because it uses non-linear problems . Nonetheless, ANN is less accurate due to the dependency of the trained model. Therefore, this paper aims to present the reliability and accuracy of the deep learning model in flood forecasting to predict the occurrent in advance.

2. METHODOLOGY

a. Data preparation

A dataset of river level Sungai from Golok at Rantau Panjang, Kelantan is used from 2013 until 2018. The data set contains the date and river level. This dataset is obtained from a river water level station. Those data undergo a set of the preparation process, pre-processing, filtering, and transformation.

b. Data extraction and integration

In this analytical study, the python 3 program was used in developing the proposed method. The process of extracting features for flood-related data tasks have be performed. In the feature extraction, the structured data from sensory data is arranged with the targeted flood measure. The structure data is divided into two, which training data and testing data. 80% is allocated for training data and 20% for testing data to evaluate the accuracy.

c. Flood Prediction Model Generation

The flood prediction model is developed based on the river level features data using RNN and LSTM techniques as illustrated in Figure 1. By using the concept of learning through experience, RNN and LSTM gather the information and detect patterns and the relationship in the data. An RNN and LSTM architecture constitute a computational model that contains hundreds of artificial neurons and is connected with coefficients known as weights. This computational model is used to generate the desired output based on learning the information process from connecting neurons in the network. In general, RNN and LSTM have the same architecture. The implementation of RNN and LSTM in flood prediction requires the input data to be arranged in sequence and segmented for constructing prediction outputs.

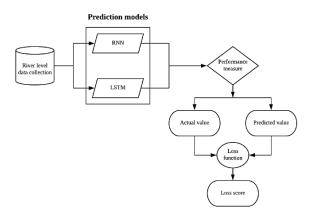


Figure 1: Prediction model generation

To apply RNN and LSTM, several key parameters need to be considered, namely the number of hidden layers, the number of nodes, and the activation functions. Deciding the number of input and hidden nodes has always been an issue, which is having a smaller number of hidden nodes tended to have less adequate performance. In this stage, the difference between RNN and LSTM is RNN use sequences as inputs in the training phase, while LSTM has a cell gate, which has the ability to remove or add information to the cell and act as a memory cell when the information is added in the training phase. Once the optimized RNN and LSTM model is completely obtained, the testing datasets are fed into the model and compared with the actual measures for performance measure in terms of accuracy.

3. RESULTS AND DISCUSSION

The result for each performance model evaluates by using mean absolute error (MAE). MAE measures the average magnitude of errors in a set of predictions, without considering the direction. MAE is a good in produce better performance when using a single test sample. From Table 1, results have shown that RNN is the best model to be applied because this model produces a high accuracy model with little loses compared to the LSTM. Therefore, RNN model is used in predicting river level for flood prediction.

Table 1 Individual performance model

Model	MAE
RNN	0.4518
LSTM	0.5133

4. CONCLUSION

This study empirically evaluates the performance of the RNN and LSTM model in terms of mean absolute error. Based on the MAE result, findings indicate that the RNN model is the best model to be applied because little loss happened within testing the data. For future improvement, several additional datasets are demand to improve the accuracy model, and the dataset needs to add more features to get a better prediction model.

ACKNOWLEDGEMENT

Authors are grateful to Universiti Teknikal Malaysia Melaka for the financial support through PJP/2020/FTMK/PP/S01802 and Fakulti Teknologi Maklumat Dan Komunikasi, Universiti Teknikal Malaysia Melaka for supporting us in accomplishing this study.

REFERENCES

- [1] A. Deshmukh, E. H. Oh, and M. Hastak, "Impact of flood damaged critical infrastructure on communities and industries," *Built Environ. Proj. Asset Manag.*, vol. 1, no. 2, pp. 156–175, 2011, doi: 10.1108/20441241111180415.
- [2] O. Water, N. River, and S. On, "Four common types of flood explained," 2020.
- [3] A. Dharmalingam, "A Research on Deep Learning in Weather forecasting Cardiff Metropolitan University Assignment Cover Sheet," no. December 2019, pp. 0–15, 2020, doi: 10.13140/RG.2.2.26091.77608.
- [4] D. W. Otter, J. R. Medina, and J. K. Kalita, "A Survey of the Usages of Deep Learning for Natural Language Processing," *IEEE Trans. Neural Networks Learn. Syst.*, vol. 32, no. 2, pp. 604–624, 2021, doi: 10.1109/TNNLS.2020.2979670.
- [5] S. A. Asmai, Z. Z. Abidin, Z. A. Abas, A. F. N. A. Rahman, and M. H. M. Ali, "Aedes mosquito larvae recognition with a mobile app," *Int. J. Adv. Trends Comput. Sci. Eng.*, vol. 9, no. 4, pp. 5059–5065, 2020, doi: 10.30534/ijatcse/2020/126942020.
- [6] L. Schoneveld, A. Othmani, and H. Abdelkawy, "Leveraging recent advances in deep learning for audio-Visual emotion recognition," *Pattern Recognit. Lett.*, vol. 146, pp. 1–7, 2021, doi: 10.1016/j.patrec.2021.03.007.
- [7] A. Faruq, H. P. Arsa, S. F. M. Hussein, C. M. C. Razali, A. Marto, and S. S. Abdullah, "Deep Learning-Based Forecast and Warning of Floods in Klang River, Malaysia," *Ing. des Syst. d'Information*, vol. 25, no. 3, pp. 365–370, 2020, doi: 10.18280/isi.250311.
- [8] X. H. Le, H. V. Ho, G. Lee, and S. Jung, "Application of Long Short-Term Memory (LSTM) neural network for flood forecasting," *Water (Switzerland)*, vol. 11, no. 7, 2019, doi: 10.3390/w11071387.
- [9] D. Nagesh Kumar, K. S. Raju, and T. Sathish, "River Flow Forecasting using Recurrent Neural Networks," 2004.
- [10] B. Bowes, J. Goodall, J. Sadler, M. Morsy, and M. Behl, "Toward Forecasting Groundwater Table in Flood Prone Coastal Cities Using Long Short-term Memory and Recurrent Neural Networks," *Earth Sp. Sci. Open Arch.*, 2019.
- [11] A. Paul and P. Das, "Flood Prediction Model using Artificial Neural Network," *Int. J. Comput. Appl. Technol. Res.*, vol. 3, no. 7, pp. 473–478, 2014, doi: 10.7753/ijcatr0307.1016.