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RESEARCH ARTICLE

Forecasting Monthly Rainfall Using ANN and RNN Models: Case Study Batu Pahat, KLIA Sepang, Kuala Krai and Kuala Terengganu, Malaysia

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Abstract Accurate rainfall forecasting is vital for a country's preparedness in managing natural disasters caused by extreme weather, especially in Malaysia, which experiences catastrophic floods annually. This study focuses on forecasting rainfall in Batu Pahat, Kuala Krai, KLIA Sepang, and Kuala Terengganu - areas that have been severely affected by flooding in recent years. Two of the stations are prone to seasonal monsoon floods, while the others frequently experience flash floods. Analysing rainfall patterns in these areas is essential to evaluate how accurately forecasting models can perform across different regions. In this study, Artificial Neural Network (ANN) and Recurrent Neural Network (RNN) models were applied to monthly rainfall data from 1999 to 2021. For in-sample performance, RNN outperformed ANN at Batu Pahat and KLIA Sepang, while ANN performed slightly better at Kuala Krai and Kuala Terengganu, although the error differences were minor. This indicates that while ANN may fit certain patterns better, RNN generally showed more consistent accuracy. For out-of-sample forecasts, RNN achieved lower error measurements across most stations due to its ability to capture temporal dependencies in sequential data. Therefore, RNN presents a more robust model for rainfall forecasting, supporting the government's efforts to mitigate flood risks.

Keywords: Rainfall, forecast, time series, artificial neural network, recurrent neural network.

Introduction

Situated in Southeast Asia, Malaysia is a tropical country known for its abundant rainforests and diverse ecological systems. Due to its tropical climate, Malaysia experiences heavy rainfall nearly every year, making it prone to flooding, especially during monsoon period. In Malaysia, states such as Kelantan, Terengganu, and Johor frequently experience flooding, while flash floods are becoming increasingly common in major cities like Selangor [1]. Department of Statistics Malaysia [2, 3] stated that the catastrophic floods that the country facing cause an overall loss of RM622.4 million in 2022 and RM755.4 million in 2023, which includes losses in living quarters, vehicles, business premises, manufacturing, agriculture, public asset and infrastructure. Alias [4] states that climate change intensified in 2024, with rainfall stations showing higher intensities than those recorded during the 2014 flood. The unabated climate change will worsen the flooding, making it essential for the early-warning system to be effectively managed, particularly for communities residing near the coast and experiencing higher rainfall intensity. Natural Resources, Environment and Climate Change Minister Nik Nazmi Nik Ahmad stated that the projection rainfall can be used to assist the government in managing the flood disasters. The minister also announced that to raise the bar for disaster preparedness system, a new projection model is said to be introduced soon [5]. The projection model is crucial in order to understand the rainfall pattern, weather conditions and generation of water level data. To accomplish this, adequate rainfall modelling should be employed.

Modelling rainfall predictions in hydrology is essential for evaluating surface and groundwater resources. This process encounters challenges due to the complex interactions among factors like soil, land use,

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and rainfall [6]. Thus, a reliable forecasting model is needed to enhanced the accuracy of rainfall data. Over the years, many forecasting methods have been widely used to forecast the rainfall data including the traditional time series model, autoregressive integrated moving average (ARIMA) [7, 8, 9, 10]. However, ARIMA model is limited by the fact that it is only suitable for short-term predictions and struggle to capture the nonstationary pattern of the data [11, 12]. On the other hand, due to climate change, many of the rainfall data collected today exhibit nonlinear patterns as they are influenced by various factors. As a result, using ARIMA to model rainfall data is no longer suitable, as it may produce unreliable projections that lack accuracy, making them inappropriate for use in risk assessments. To address these limitations, machine learning model is introduced. Machine learning models like artificial neural networks (ANN) have gained popularity more than a decade due to their flexibility, nonlinearity, and ability to function with no requirement on prior knowledge of physical process governing rainfall [13,14]. For example, by analysing past rainfall data, these models can uncover hidden patterns such as seasonal variations, unusual weather trends, or the impact of specific environmental changes on precipitation. This capability enables machine learning to forecast hydrological events more effectively by identifying complex relationships within the data [15]. The advantages of machine learning methods are further supported with review articles by Thakur *et al*. [16], who concluded that machine learning outperformed ARIMA in terms of lower measurement error when comparing data from countries such as Italy, Thailand, India, Myanmar, Australia, and others. In addition, Dwivedi *et al*. [17], Grover *et al*. [18] and Jafarian-Namin *et al*. [19] reported that ANN model is more reliable than ARIMA to forecast rainfall when applied to rainfall data collected from India and Tehran, respectively.

In addition to ANN, another variant of machine learning models which is recurrent neural networks (RNN), have also been applied to rainfall prediction due to their ability to handle sequential data [20]. According to Ponnamperuma and Rajapakse [21] and Ng *et al*. [22], RNN model has better performance as compared to ARIMA in terms of long-term forecast with longer historical data. Longer historical data is crucial in generating more reliable forecast due to the unexpected risks in climate change and thus we need prior information to make better decision on the rainfall pattern in different regions. Accurate long-term projections are also critical for governments to warn authorities about potential flooding or drought in flood-prone areas. While ARIMA is effective for short-term forecasts with limited data, machine learning models are more suitable for effective risk management in the long run since the government need a new projection model for long-term forecast data. Given the limitations of ARIMA, several studies, including those by Ridwan *et al*. [23], and Kumar *et al*. [24], have focused solely on modelling rainfall using machine learning methods. Therefore, this paper will compare the performance of machine learning models to improve rainfall predictions.

As compared to ANN, RNN can better capture the spatial and time-based variations of the rainfall in a specified region [25]. Hence it is expected that RNN model should outperformed ANN in forecasting. This is supported by Apaydin *et al*. [26], Pang *et al*. [27] who has found that RNN produced better accurate prediction as compared to ANN when applied to their data. However, Khan *et al*. [28] found that ANN works better than RNN when applied to data of Hunza River Basin. Patil *et al*. [29] also found that ANN outperformed RNN and all others machine learning methods when applied to plant disease data. This suggests that the performance of ANN and RNN may vary depending on the statistical properties of the rainfall pattern. Therefore, this study will evaluate both models at selected stations in Malaysia to determine which one provides the best rainfall forecasts.

The primary objective of this research is to analyse the performance of the rainfall prediction accuracy from two machine learning methods which are artificial neural networks (ANN) and recurrent neural networks (RNN). Monthly rainfall from four stations in Malaysia are selected in this study which are Kuala Krai, KLIA Sepang, Kuala Terengganu and Batu Pahat from the period of 1999 to 2021. The performance of the developed model is assessed by comparing the predicted rainfall data with those of the actual observed data. Supporting the objectives of Sustainable Development Goal (SDG) 13 related to climate action, this study offers valuable insights to the government by generating accurate rainfall predictions, which can enhance early-risk management for natural disasters such as flooding and droughts. Additionally, precise predictions support the design of resilient infrastructure, such as drainage systems and reservoirs, reducing climate-related damage risks. The structure of this study is as follows: Section 2 outlines the machine learning methods used in this study, Section 3 discusses and compares the analysis obtained from the machine learning methods that are used in this paper which are ANN and RNN and finally in Section 4, presents the overall conclusion of the study and recommendations for future research.

Materials and Methods

Study Area and Data

This study analyses average monthly rainfall data from 1999 to 2021, obtained from Meteorological Department Malaysia. The data was collected from four stations: Batu Pahat, Johor; Kuala Krai, Kelantan; KLIA Sepang, Selangor; and Kuala Terengganu, Terengganu. These four stations were chosen due to their geographical locations, which are prone to flooding. Kuala Krai, located at 5° 32' N latitude and 102° 12' E longitude, particularly is highly vulnerable to floods because the Kelantan River, which flows through the area, is formed by the Galas and Lebir Rivers [30]. Kuala Terengganu coordinated at 5° 23' N latitude and 103° 06' E longitude near the coasts faces threats from the seasonal northeast monsoon and rising sea levels. It is expected that by 2050, the area may be divided into several islands [31]. In Johor, Batu Pahat with 1° 52' N latitude and 102° 59' E longitude is one of the most flood-prone areas, largely due to its position at the lower basin of Sungai Batu Pahat [32]. Other than that, according to Fuad *et al*. [33], factors that contributed to flooding in Batu Pahat area is caused by heavy rainfall, small drainage system with rapid and uncontrolled urbanization. Similar to Batu Pahat, flash floods are becoming more frequent in major cities such as Selangor, with KLIA Sepang (latitude 2° 44' N and longitude 101° 42' E) also affected. In 2021, flooding caused the closure of main roads leading to KLIA Sepang. The information provided highlights the importance of this study in identifying the best forecasting model to generate accurate rainfall data for early flood risk mitigation. Without proper action plans, communities in flood-prone areas will continue to face increasing losses, including lives. Therefore, this study aims to analyse the rainfall patterns from selected stations and compare the performance of both models in forecasting rainfall data. The data was split into in-sample and out-sample sets, with 80% for training (from 1999 to 2016) and 20% for testing (from 2017 to 2021). To improve data quality, interpolation and normalization is performed before applying the data to the neural network models. The performance of the models was evaluated by using two measurement errors which are Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) for in-sample and out-sample. Artificial Neural Network (ANN) and Recurrent Neural Network (RNN) models were structured based on 12 input nodes (representing 12 months of historical rainfall data), hidden layer of 50 neurons and 1 output node with 200 epochs, with the utilization of Adam optimizer.

Artifical Neural Network

The main goal of constructing an Artificial Neural Network (ANN) is to model the characteristics of the rainfall time series. Inspired by the concept of neurons in brain, the ANN consists of interconnected neurons with multiple layers. Information from one neuron is processed and pass across layers, allowing the model to learn the historical patterns of the data and thus able to adapt to any pattern changes. This enables the ANN model to capture the nonlinearity and seasonality, making it suitable for forecasting rainfall with these characteristics. To train the ANN to transfer information between units, the weights of each unit must be adjusted by minimizing the error between observed and predicted output. To compute the error, Bayesian regularization propagation is used to adjust connection weights based on the error and bias value [34]. The Bayesian regularization propagation enhanced the performance of the ANN model by incorporating the automatic adjustment of regularization term, which lessen the manual tuning and enhance the robustness of the model [34].

Figure 1 shows that the network employed in this study is a layered network where each of the circle or perceptron. In such networks, neurons connect to the subsequent layer. The network processes a problem presented as an array of real values, with each value assigned to a distinct input neuron.

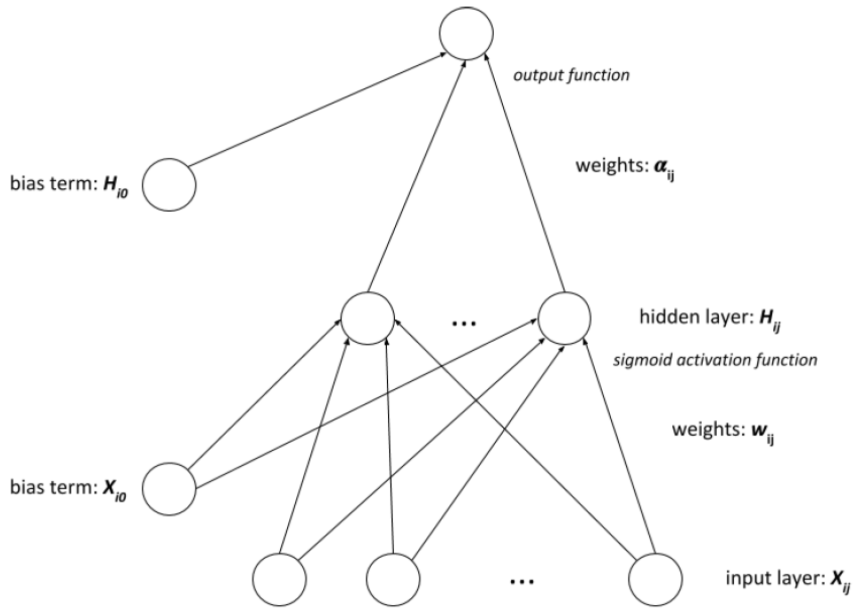

Figure 1. The ANN structure [34]

ANN is composed of three main components which are input layer, hidden layer and output layer [35] The input layer is the first step of ANN processing where the observed or historical data is received. These input neurons then transmit the values to the neurons in the next (hidden) layer. Then, hidden layer analyses the received data and learn the data pattern which makes the ANN is adaptable to data changes. Finally, the output layer generated the predicted rainfall data. The output signal is represented as follows:

$$y_j = f\left(\sum_i w_{ij} l_i + b_j\right) \tag{1}$$

where is an activation function, are the input signal of neurons , denoted as the weight that is connected between input and output and is the bias of neuron [36].

Recurrent Neural Network

Recurrent Neural Networks (RNNs) have emerged as powerful models for handling sequential data in various fields. RNN consists of a series of modules with the same basic structure. In feed-forward neural networks (FFNN), there is no capability to remember previous outputs, resulting in each output being independent. Unlike other models, RNNs can remember past information, making them better for time series predictions. In RNN, the input at each step includes both the current data and the output from the previous step, creating a feedback loop structure [34]. This allows RNN to use all available information, regardless of sequence length. The current state is determined using the following equation:

$$C_t = g\left(C_{t-1} X_t\right) \tag{2}$$

where C_t is the current state, C_{t-1} is the previous state's output, X_t is the new input at time step t, and g is a recursive function. The activation function is applied using:

$$C_t = \tanh\left(w_h C_{t-1} + w_t X_t\right) \tag{3}$$

where w_h and w_t are the weights at the recurrent and input neurons, respectively. The output is calculated with:

$$y_t = w_y C_t \tag{4}$$

where y_t is the output, and w_y is the weight at the output neuron.

Measurement Errors

The measurement errors that are used to assess the performance of ANN and RNN in this study are Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). The formula for MAE and RMSE are as follows:

$$\text{RMSE} = \sqrt{\frac{\sum_{k=k}^{t}(y_k - F_k)^2}{t}}$$

$$\text{MAE} = \frac{\sum_{k=1}^{t}|y_k - F_k|}{t}$$

where y_i represents observed rainfall data, and F represents the predicted rainfall data obtained from the model for year k, and t denoted as the number of years of rainfall data.

Results and Discussion

This section forecast the rainfall data in Malaysia by using two neural network forecasting models which are ANN and RNN models. Monthly rainfall data from the Batu Pahat, Kuala Krai, KLIA Sepang and Kuala Terengganu stations are used in this study and the descriptive statistics of the data are summarises in Table 1 below. Table 1 demonstrates that the monthly rainfall data from all stations display complex, nonlinear patterns, as evidenced by the high skewness and kurtosis, which suggest asymmetric distributions with heavy tails and outliers. This is further indicated by the mean of each station being slightly higher than the median, which indicates the presence of outliers in the data. The presence of outliers can be seen in Figure 2, where Kuala Krai and Kuala Terengganu exhibit significantly more outliers compared to the other stations. This might be due to Kuala Krai and Kuala Terengganu location that is near to the Kelantan's River and seasonal northeast monsoon, respectively which resulting in greater rainfall variability as compared to others. Additionally, the variance values across all stations, particularly at Kuala Terengganu and Kuala Krai, show significant volatility, making it difficult for linear models to capture these fluctuations. Kuala Terengganu and Kuala Krai have higher maximum rainfall and variance than Batu Pahat and KLIA Sepang due to their frequent seasonal monsoon floods. The description in Table 1 is further confirmed by the graphical plot illustrated in Figure 3. As can be seen, the monthly rainfall data in four selected stations in Malaysia are nonlinear and volatile, especially in Batu Pahat and KLIA Sepang, while Kuala Terengganu and Kuala Krai exhibits seasonality pattern due to their seasonal monsoon. Hence, ANN and RNN are employed to address this nonlinearity, given its flexibility in modelling such complex patterns. It is expected that RNN will perform better as compared to ANN in terms of in-sample and out-sample error, however, due to the vanishing gradient problem in RNN, the precision of the RNN can be reduced since the learning of the past values can be stopped if the gradient values are too small [37]. Thus, it is possible that RNN will not consistently performing better at all stations.

Table 1. Descriptive statistics for average monthly rainfall data in Malaysia

	Batu Pahat	Kuala Terengganu	Kuala Krai	KLIA Sepang
Minimum	0.60	0.00	0.00	0.13
Maximum	16.49	52.68	44.73	16.21
Mean	5.93	7.58	7.38	6.13
Median	5.66	4.83	6.05	5.30
Skewness	0.77	2.31	2.39	0.72
Kurtosis	0.78	6.12	8.16	0.52
Variance	8.84	68.60	38.09	8.52

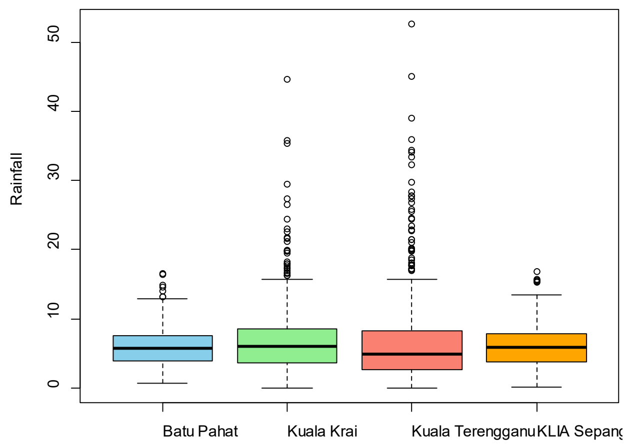

Figure 2. Boxplot of Average Monthly Rainfall Data for Selected Stations in Malaysia

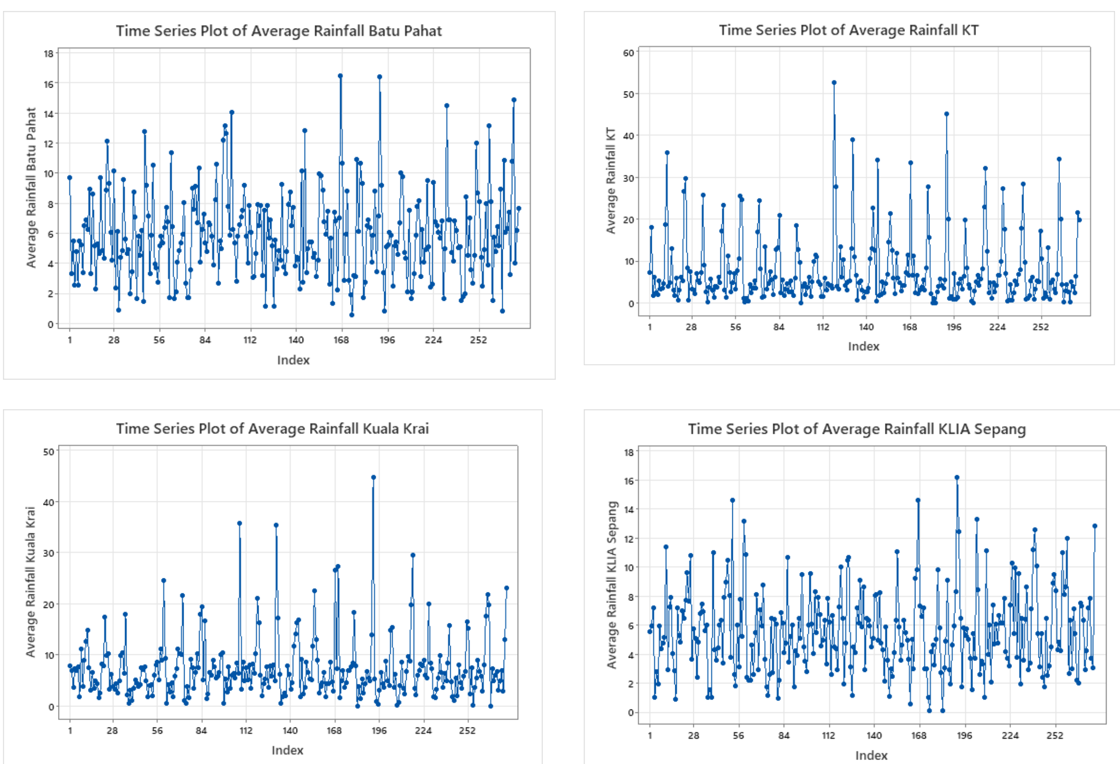

Figure 3. Time series plot of average monthly rainfall data for selected stations in Malaysia

The performance of ANN and RNN model on the four selected stations in Malaysia are presented in measurement errors form which are RMSE and MAE. The results of the measurement errors for these two models are presented in Table 2 and Table 3 below, in which Table 2 indicates for in-sample error, and Table 3 indicates for out-sample errors. Table 2 shows that RNN model outperformed ANN for Batu Pahat and KLIA Sepang stations since it has lowest measurement errors for RMSE and MAE, with the percentage difference of approximately 52.66% in RMSE and 49.19% in MAE for Batu Pahat, and by 58.88% in RMSE and 57.43% in MAE for KLIA Sepang. While for Kuala Terengganu and Kuala Krai, ANN outperformed RNN for Kuala Krai and Kuala Terengganu stations with lower error for RMSE and MAE, with percentage difference of approximately 34.74% in RMSE and 39.25% in MAE for Kuala Krai, and by 1.61% in RMSE and 2.65% in MAE for Kuala Terengganu. Although the ANN model outperformed the RNN model in Kuala Krai and Kuala Terengganu, the percentage of error difference is relatively small as compared to Batu Pahat and KLIA Sepang. This suggests that while ANN may be slightly better in certain stations, RNN can still outperform ANN, depending on the data pattern.

Table 2. Results in-sample between ANN & RNN

Model	ANN		RNN	
States	RMSE	MAE	RMSE	MAE
Batu Pahat	1.69	1.24	0.80	0.63
Kuala Krai	2.44	1.61	3.74	2.65
Kuala Terengganu	3.67	2.57	3.73	2.64
KLIA Sepang	1.97	1.48	0.81	0.63

All parameters for the four marginal distributions used are estimated from the data sets using the method Table 3 presents the results of out-sample measurement errors for ANN and RNN model. The results explains that RNN model outperformed the ANN model for all stations except for KLIA Sepang. This result differs from the findings in Table 2, where RNN performed better at KLIA Sepang, and ANN performed better at Kuala Krai and Kuala Terengganu. However, overall, RNN is the better choice for forecasting rainfall in Malaysia since the percentage difference between ANN and RNN for KLIA Sepang is relatively small which is around 20% for both RMSE and MAE.

Table 3. Results of out-sample between ANN & RNN

Model	ANN		RNN	
States	RMSE	MAE	RMSE	MAE
Batu Pahat	3.96	3.13	3.82	2.84
Kuala Krai	5.68	3.66	5.01	3.43
Kuala Terengganu	6.12	4.50	5.17	3.74
KLIA Sepang	3.48	2.87	4.38	3.76

Figures 4 to Figure 7 illustrate the fitted ANN and RNN rainfall data to the observed rainfall data for the selected stations in Malaysia based on in-sample and out-sample performances, as tabulated in Table 2 and Table 3. The green line indicates the splitting of the in-sample and the out-sample sets; which are 1991 to 2016 for in-sample, and 2017 to 2021 for out-sample.

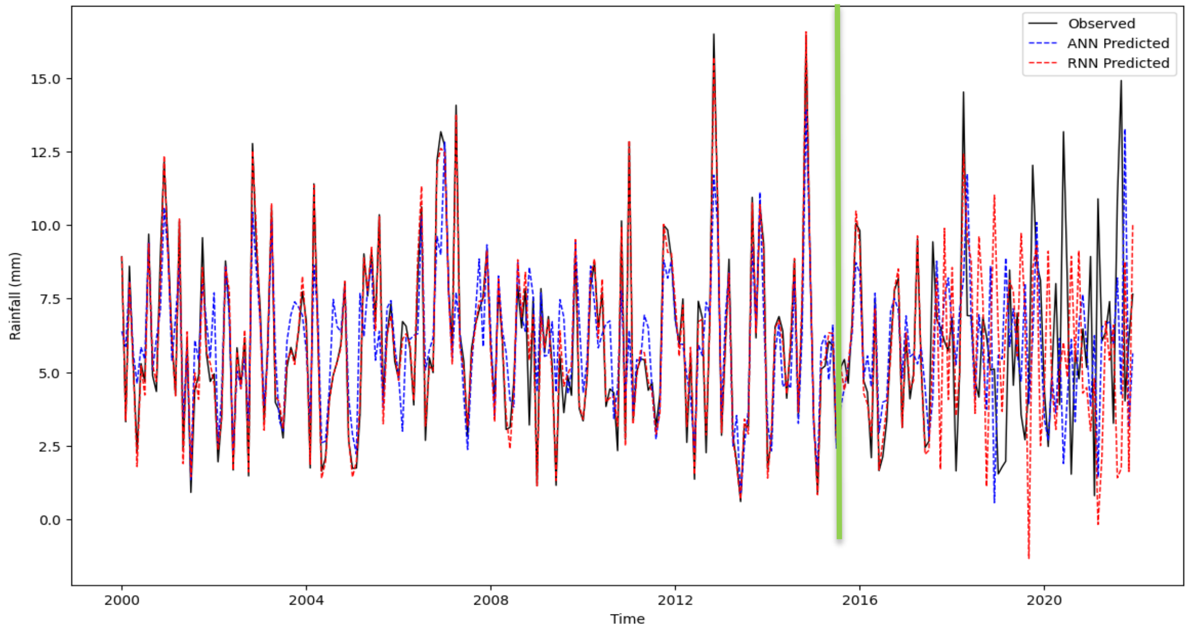

Figure 4. Comparison of actual and predicted rainfall from ANN and RNN models for Batu Pahat

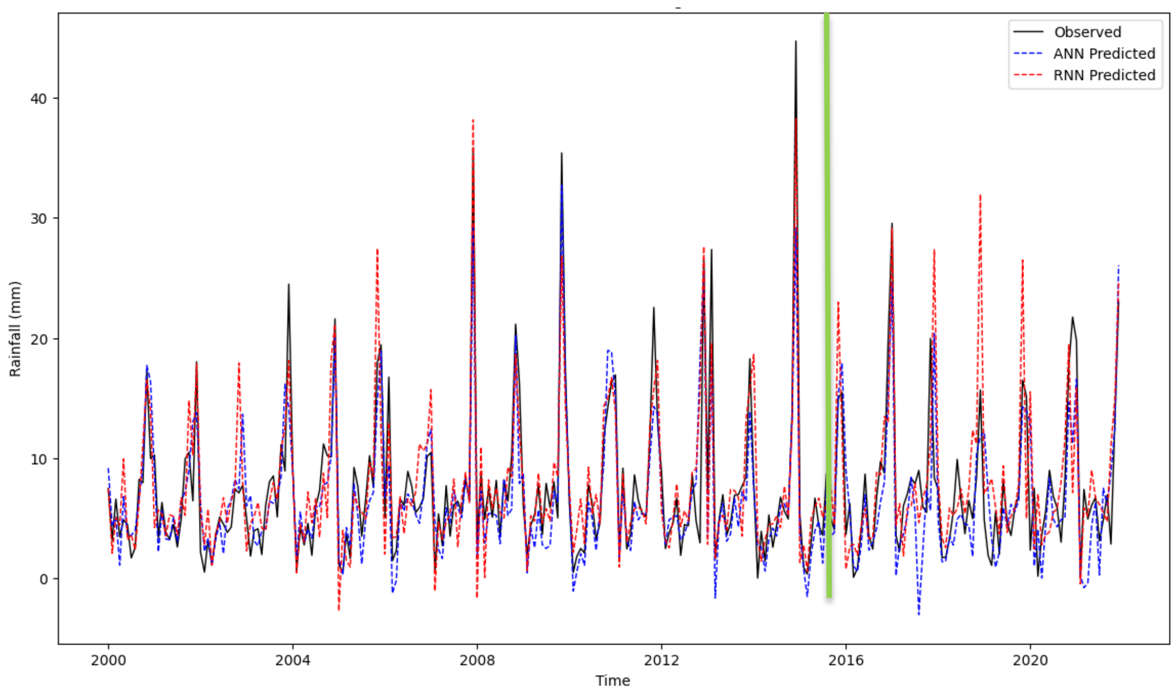

Figure 5. Comparison of actual and predicted rainfall from ANN & RNN for Kuala Krai

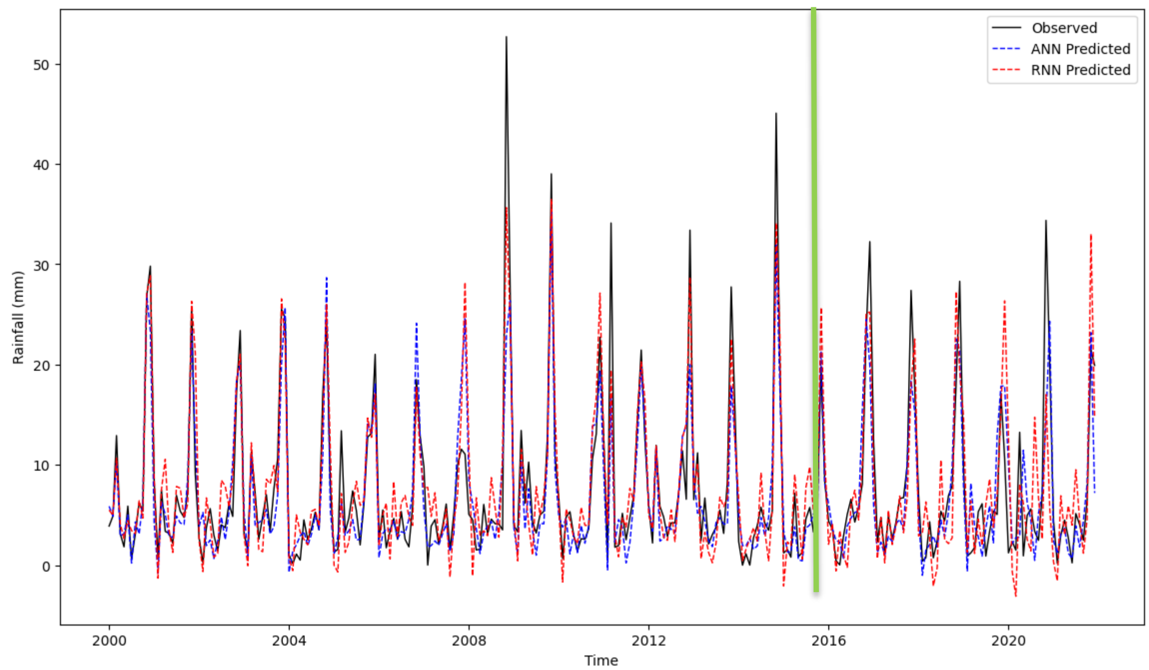

Figure 6. Comparison of actual and predicted rainfall from ANN & RNN for Kuala Terengganu

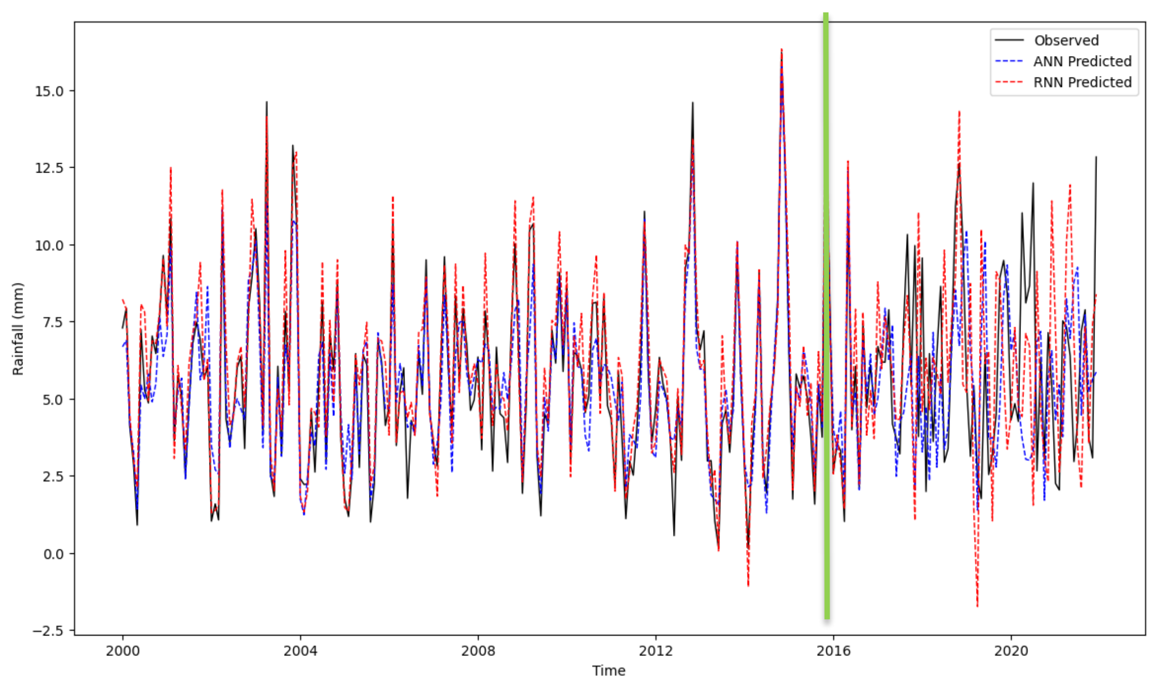

Figure 7. Comparison of actual and predicted rainfall from ANN & RNN for KLIA Sepang

According to Figures 4 to 7, there is only a small difference between RNN and ANN on the observed data. This suggests that both models can be used to model the rainfall data, but their performance may vary significantly depending on the location and data patterns. However, in this study, RNN consistently outperformed ANN in terms of measurement errors for in-sample and out-sample. Although ANN performed better at certain stations for in-sample error, the difference was relatively small compared to the cases where RNN significantly outperformed ANN. While in the out-sample, RNN outperformed ANN for all stations except KLIA with relatively small error which is around 20% only.

Based on the literature, RNN model is expected to outperform ANN model at all stations due to the RNN's ability in processing sequential data and remember past inputs. This helps RNN capture patterns over time better than ANN and makes it an effective model for rainfall prediction, where past data affects future results, leading to better forecasts. However, in this study, RNNs did not always perform better at some stations. This could be because of the vanishing gradient problem [37], which is why many researchers have created improved versions of RNN to fix it. Since this study focuses only on comparing ANN and RNN, further research is needed to find the best model for reducing flood risks in Malaysia.

Conclusions

Forecasting accurate rainfall is vital in managing risks related to extreme weather impact and helping in making better informed decision making. This study analyses the accuracy of Artificial Neural Network (ANN) and Recurrent Neural Network (RNN) models in forecasting rainfall data in Malaysia with a focus on four stations in four specific districts: Batu Pahat, Johor; Kuala Krai, Kelantan; KLIA Sepang, Selangor; and Kuala Terengganu, Terengganu from 1999 to 2021. The performance of these two models were compared and analysed by using two measurement errors which were RMSE and MAE. The data descriptives from the study show that all the four stations exhibit nonlinearity and volatility, suggesting that traditional time series models like ARIMA may not be suitable. As a result, neural network models were proposed for this study. The findings conclude that, generally, RNN performed better as compared to ANN in terms of out-sample measurement errors, while for in-sample measurement errors, ANN performed better at Kuala Krai and Kuala Terengganu, while RNN outperformed the ANN at Batu Pahat and KLIA Sepang. Although ANN showed better performance in Kuala Krai and Kuala Terengganu, the error difference was relatively small compared to RNN for Batu Pahat and KLIA Sepang. This suggests that while ANN may be slightly better at some stations, RNN can still give better performances depending on the data pattern. In conclusion, based on the in-sample and out-sample evaluations, the RNN demonstrated better accuracy performance in monthly rainfall forecasting as compared to ANN. This suggests its effectiveness in capturing complex rainfall patterns. Future research should consider incorporating additional meteorological factors like humidity and temperature. Exploring advanced techniques like hybrid RNN could address the RNN's vanishing gradient problem, leading to more accurate future rainfall generation. This study could be used as a reference for the government in building new projection model which is crucial in understanding the rainfall pattern to mitigate uncertain flood risks.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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