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Rainfall-Runoff Modeling Using Artificial Neural Network for Batu Pahat River Basin

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***Abstract*— This research delves into the effectiveness of Artificial Neural Networks with Multilayer Perceptron (ANN-MLP) and Nonlinear AutoRegressive with eXogenous inputs (NARX) models in predicting short-term rainfall-runoff patterns in the Batu Pahat River Basin. This study aims to predict river water levels using historical rainfall and river level data for future intervals of 1, 3, and 6 hours. Data preprocessing techniques, including the management of missing values, identification of outliers, and reduction of noise, were applied to enhance the accuracy and dependability of the models. This study assessed the performance of the models for ANN-MLP and NARX by comparing their effectiveness across various forecast timeframes and evaluating their performance in different scenarios. The findings of the study revealed that the ANN-MLP model showed robust performance in short-term prediction. On the contrary, the NARX model exhibited higher accuracy, particularly in capturing intricate temporal relationships and external impacts on river behavior. The ANN-MLP produces 99% accuracy for 1-hour prediction, and NARX yields 98% accuracy with 0.3245 Root Mean Squared Error and 0.1967 Mean Absolute Error. This study makes a valuable contribution to hydrological forecasting by presenting a rigorous and precise modeling methodology.**

***Keywords*— Rainfall-runoff simulation; artificial neural network; hydrological model; ANN; NARX.**

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I. INTRODUCTION

This research introduces a mathematical approach to determine the appropriate parameters for machine learning applications in training models utilizing historical data on rainfall and river water levels. The method under consideration is founded upon the principle of rainfall-runoff, which pertains to the quantification of water discharge originating from a hydrological catchment within a Batu Pahat River basin. Recently, artificial intelligence with machine learning offers a promising alternative to traditional rainfall-runoff modeling. It adapts to complex hydrological patterns more effectively through data-driven approaches and improves accuracy. This dynamic methodology enhances the understanding and prediction of runoff, proving advantageous in water resource management and flood forecasting. The artificial intelligence system acquired data to forecast future water levels. Subsequently, it presents comprehensive information encompassing rainfall and water level data, accompanied by predictions for the subsequent time intervals of 1, 3, and 6 hours. It is possible to optimize predictive models, even in the presence of river environment alterations or new infrastructure implementation. In such instances, the model is readily retrained by utilizing rainfall and water level data that has been gathered after any modifications. A study was undertaken to assess the precision of the novel model by employing this methodology on past river water level data, and it was verified that the prediction of water level increase can be achieved with consistent accuracy when the model is trained using rainfall data.

In recent study, the application of Artificial Neural Network (ANN) with Multilayer Perceptron (MLP) has been investigated in the analysis of week-ahead forecasts, as demonstrated by the work conducted by [1]. Results show that the use of the Scaled Conjugate Gradient Gradient-Tangent model yields superior results compared to employing the Sigmoid activation function. In a study conducted by researchers [2], a comparison was made between the Harris hawks optimizer and particle swarm optimization in the context of a rainfall-runoff model at Perak river. Research studies have demonstrated that the application of a meta-heuristic optimization technique has the potential to enhance the accuracy of measurements at Dorim stream in Seoul [3]. In recent studies, scholars have proposed the application of MLP as a predictive tool for streamflow forecasting in the Citarum river over different time intervals, including 2, 4, 6, 8, 10, 12, and 24 hours ahead [4].

A study has been conducted on predicting groundwater levels by adopting the Nonlinear AutoRegressive with eXogenous Inputs (NARX) methodology. The process of determining input and feedback delays entailed the utilization of seasonal trend decomposition and time series decomposition on the dataset. The remaining components were subjected to auto and cross-correlation algorithms to detect substantial time delays [5]. The NARX model is used in simulating rainfall-runoff patterns within the Linyi watershed[6]. In a study conducted by researchers in [7], the combination of Principal Component Analysis (PCA), Self-Organizing Map (SOM) and NARX known as PCA-SOM-NARX were used. The findings show that the PCA-SOM-NARX methodology yielded reliable and precise predictions for flood inundation depth in several steps. Additionally, it demonstrated a stronger correlation with the geographical pattern of inundation resulting from heavy rainfall events. There is a study on sea level projects that help in flood forecasting using NARX-ANN model at Kuala Terengganu [8]. The findings indicate an upward trajectory, even when considering a data intake spanning over a decade. In a recent study, researchers used historical data spanning a period of 15 years.

This paper proposes modeling rainfall-runoff using ANN-MLP and NARX based on time series rainfall and water level data. It is organized as follows: Section 2 describes the materials and methodology; Section 3 presents all results and related discussions; and finally, Section 4 presents conclusions.

II. Materials and Method

A. Research Focus and Objectives

The research focuses on developing an advanced machine-learning model for short-term rainfall-induced flood forecasting. Specifically, the study aims to leverage pre-processed data and ANN-MLP and NARX models to predict water levels 1, 3, and 6 hours ahead based on historical rainfall and river water level data input. The objective is to enhance flood forecasts' accuracy and lead time, which is crucial for effective disaster mitigation and emergency response. The research focuses on developing an advanced machine-learning rainfall-runoff model for short-term rainfall-induced flood forecasting. Explicitly focusing on ANN-MLP and NARX. The aim of the study aligns with the following objectives:

1) To identify data and pre-processing by compiling historical rainfall rate and water level data from relevant sources, implementing robust pre-processing techniques, including handling missing values, outlier detection, and ensuring time-series alignment and extracting relevant features and construct suitable input sequences to facilitate the training and evaluation of the forecasting models.

2) To develop a forecast model by designing and implementing a baseline ANN-MLP for a 1-hour prediction of water level using preprocessed data, extending the predictive capabilities to forecast water levels for 3 hours to 6 hours ahead, employing improved model architectures and training strategies and finally developing the NARX-based neural network for 1, 3 and 6 hours ahead water level forecasting, explicitly accounting for temporal dependencies within the data.

3) To evaluate the forecast model using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and correlation coefficients, conducting comparative analyses to assess the forecasting accuracy of both MLP and NARX models for different lead times (1, 3, and 6 hours).

Through these objectives, this research significantly enhances the precision and lead time of rainfall-induced flood forecasts, contributing to more effective flood risk mitigation strategies and emergency response plans.

B. Study Area and Data

This research investigates meteorological data collected from the irrigation and drainage stations located in Sungai Batu Pahat, Sungai Simpang Kanan (Parit Karjo) and Sungai Simpang Kanan (Parit Besar) as depicted in Fig. 1. The distance between station Sungai Batu Pahat and station Sungai Simpang Kanan Parit Besar is 8 km. Data used in this study consists of three years' hourly data from 2017 to 2019. TABLE I and Fig. 1 shows the location of the stations. The data consist of discernible upward trend in precipitation levels commencing in October 2018 and persisting through the conclusion of the year 2019.

TABLE I
STATION LOCATION

Station	Latitude	Longitude	Station No.
Sg Batu Pahat	1.8406483 N	102.92366 E	1829078
Sg Simpang Kanan (Parit Besar)	1.8957564 N	102.97170 E	1829054
Sg Simpang Kanan (Parit Karjo)	1.87496944 N	103.05663 E	1831080

The observed rise in precipitation levels can be attributed to the occurrence of the Southeast Monsoon, which typically takes place from May or June through September or early October. The Southeast Monsoon is observed exclusively in the southern region of Malaysia. According to Department of Meteorology Malaysia, peninsular Malaysia experiences three distinct monsoon seasons, the Northeast Monsoon, which occurs from November to March, the Southeast Monsoon and the Inter-Monsoon period, spanning from April to October. Batu Pahat experiences a significant amount of rainfall, even during the period of lowest precipitation. According to the Köppen-Geiger climate classification, the climate in this region is categorized as wet equatorial climate [9].

According to statistical data, the average temperature in the city of Batu Pahat is documented as 26.4 °C. Annually, a total of 2492 mm (98.1 inches) of precipitation is recorded. Fig. 2 shows the hourly data for rainfall and river level for Sg. Batu Pahat Station in 2019. The Batu Pahat region is situated near the equator, resulting in a challenging task of defining the warm weather season.

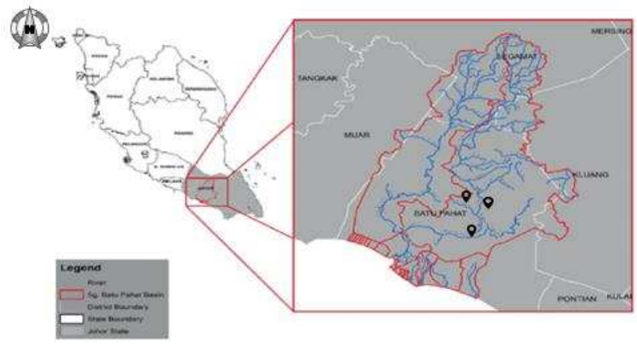

Fig. 1 Map of the stations

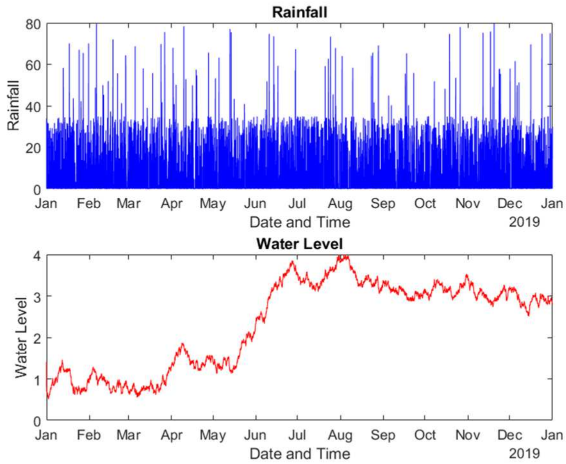

Fig. 2 Hourly data Rainfall and River level for Sg. Batu Pahat Station in 2019

C. Research Materials and Methodology

The materials and methodology for the rainfall-runoff model integrating machine learning, featuring pre-processing, ANN-MLP and NARX architecture, and comprehensive validation, encompasses a multifaceted approach. Historical rainfall and runoff data are the foundational materials, particularly the pre-processed data used to rectify missing values, detect outliers, and normalize the dataset. Relevant hydrological features are extracted to enhance model performance. The ANN-MLP and NARX model is constructed, utilizing hourly rainfall data as input and past river level runoff information as an exogenous time series. The model undergoes rigorous training through backpropagation, optimizing weights and biases to minimize errors for 1-hour, 3-hour, and 6-hour river water level predictions. Extensive validation uses various techniques, including cross-validation and time series splitting, to ensure the model's robustness. Performance is evaluated using metrics like MAE, RMSE, and correlation coefficients across different prediction horizons, thus furnishing a versatile and accurate rainfall-runoff modeling framework. This methodology enables the development of a data-driven rainfall-runoff model capable of accurately simulating hydrological processes.

1) Data Preprocess:

Data preprocessing is an essential stage for data analysis and machine learning in the pipeline. It entails cleansing, organizing, and transforming unstructured data into a format suitable for analysis or modeling [10]. Appropriate data preprocessing can have a substantial influence on the quality and performance of the analytical and machine-learning models [11]. The flow of Data Preprocessing in this study is illustrated in Fig. 3.

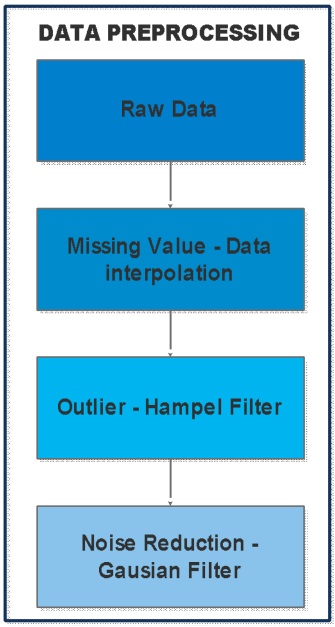

Fig. 3 Data Preprocessing Process

Data Preprocessing steps begin according to Fig. 3 by acquiring the dataset. The raw data inside the dataset refers to the unprocessed and unmodified data directly obtained from the primary sources. In this research, the dataset used is hourly river level data and rainfall data received from the Malaysia Department of Irrigation and Drainage. The following steps involve identifying and managing outliers, missing values, and noise reduction. The occurrence of missing data in water level and rainfall monitoring stations can be attributed to various sources, such as machine malfunctions, human errors, or other contributing variables. Hence, the station can fail to capture the data occasionally or for the recorded value to assume a negative value.

- Missing Value

The river level dataset presents a notable presence of negative values, contradicting the reference to mean sea level in water level measurements. This absence of data diminishes the study's statistical robustness. While it's common for data to be missing, increasing the sample size to compensate, it doesn't eliminate potential bias and attention must be given to the issue of missing data [12]. The challenge was overcome by employing a data interpolation algorithm. Interpolation, a mathematical technique, approximates function values by fitting available data points. Common in time-series analysis, it replaces missing values with preceding ones, resolving the difficulty [13]:

$$y = y1 + \frac{(y2-y1)}{(x2-x1)} * (x - x1) \quad (1)$$

where x and y are unidentified figures, that will determine through the other values. $y1$, $y2$, $x1$ and $x2$ are given variables that will help determine unknown values in (1).

- Remove Outlier

In data preprocessing, removing outliers is crucial for accurate summary statistics. Outliers, extreme data points deviating from the norm, often signal errors or rare events. In discharge measurements, inaccuracies arise from faulty water level data due to human error, recorder faults, or flow obstructions. The presence of outliers distorts statistics like mean and standard deviation, hampering accurate representation of data. This study employs a dynamic Hampel Filter, using a moving window mean or median for outlier detection. The method's adaptability enhances sensitivity to contextual variations, striking a balance between precision and broader outlier identification [14]. The approach, a moving-window version of the Hampel identifier by Davies, relies on robust estimates like median absolute deviation (MAD) for effective outlier removal [15]. This outlier detection approach relies on the use of the median and the MAD scale estimator. Specifically, the filter's response is given in (2):

$$y_k = \begin{Bmatrix} x_k \, | x_k - m_k | \leq tS_k \\ m_k \, | x_k - m_k | \rangle tS_k \end{Bmatrix} \tag{2}$$

the median value from the moving data window is denoted as m_k, whereas the MAD scale estimate is represented by s_k.

$$S_k = 1.4826 \, x \, median j \in [-K, K] \{ | x_{k-j} - m_k | \}$$

This technique proves valuable in diverse fields, from anomaly detection in data analysis to recognizing irregularities in spatial or temporal patterns. In the experimentation of rainfall and water level in this study, the best fitting to define the outliers is set to more than three local standard deviations from the local mean within a five-element window. The parameters were selected based on descriptive statistical analysis, that provide the initial values of interpolation of data pattern.

- Noise Reduction

The next steps are noise reduction. Data noise reduction is the process of reducing or eliminating random or unwanted variations in data that can hide meaningful patterns or make data analysis and modeling more difficult. A Gaussian filter smoothens data by manipulating it with a Gaussian function were used in this study in (3). This weighted average reduces noise and highlights underlying trends. The Gaussian function is defined as:

$$G\sigma(x, y) = \frac{1}{2\pi\sigma^2} exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \tag{3}$$

In this equation, the value of the Gaussian function at coordinates(x,y) which is G(x,y). σ (*sigma*) is the standard deviation of the Gaussian distribution, which controls the width or spread of the Gaussian function.

2) Artificial Neural Networks:

ANN has made big changes in many areas, such as healthcare, banking, image recognition, and natural language processing. ANN are made up of several computational components known as neurons, which process information based on how they change in reaction to outside stimuli. These neurons mimic neurons found in biology. Every neuron takes in information, processes it and then produces an output[16]. It is comprised of three layers. The initial layer is referred to as the input layer. The neural network comprises input neurons responsible for transmitting information to the hidden layer. The hidden layer is responsible for conducting computations on the input data and subsequently transmitting the resulting output to the output layer. The factors encompassed in this context are weight, activation function and cost function[17].

In the early model of ANN, feed forward neural network being introduced and established as perceptron. It uses one perceptron layer, input directly fed to the output [18]. The weakness of this method is perceptron cannot be trained to recognize many classes of pattern. Each neuron composed of 2 parts: weight coefficient and transfer function (Fig. 4). It consists of a summing function with an internal threshold and weighted inputs as shown below:

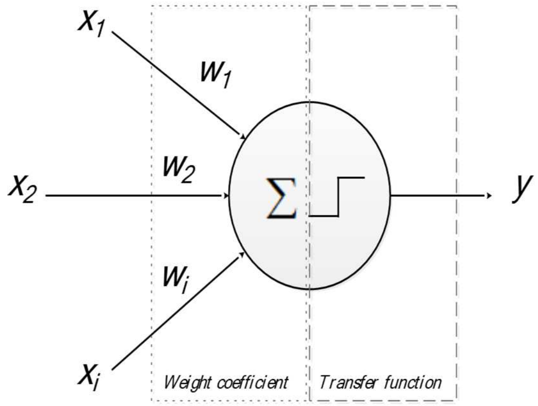

Fig. 4 Weighted input

For a neuron receiving n inputs, each input xi (i ranging from 1 to n) is weighted by multiplying it with a weight w_i . The equation (4) illustrate that the sum of the $x_i w_i$ products gives the net activation of the neuron. This activation value is subjected to a transfer function (f) to produce the neuron's output.

$$f(b + \textstyle\sum_{i=1}^{n} x_i w_i) \tag{4}$$

3) MLP or Feedforward Neural Network:

The MLP is a commonly utilized feed-forward ANN structure that finds extensive applicability across a range of machine learning tasks. MLP functions by inserting additional layers of nodes connecting the input and output nodes. These nodes are organized into an input layer, an output layer, and multiple hidden layers. The fundamental architecture of a MLP comprises an input layer, which is responsible for receiving and encoding the input features or variables from the dataset[19]. After the input layer, there exists one or more hidden layers, which consist of several neurons, also referred to as nodes or units. The concealed layers in a neural network are accountable for acquiring complex patterns and representations within the dataset via a sequence of weighted connections and activation functions. The output layer, situated at the terminal point of the network, generates the ultimate prediction or classification outcome by utilizing the acquired representations in the hidden layers. During the process of feed-forward propagation, the input data is sent across the network. At each neuron, weighted sums and activation functions are applied to the input data, resulting in the generation of the final output[20]. A simple ANN-MLP is shown in Fig. 5. The significance of the dependent variables z_i in forecasting is contingent upon the specific collection of independent variables provided $\{x_{i,\dots,}x_n\}$. The quantity of neurons in the input layer of ANN is equivalent to the total number of attributes being used in this architecture act as independent variables.

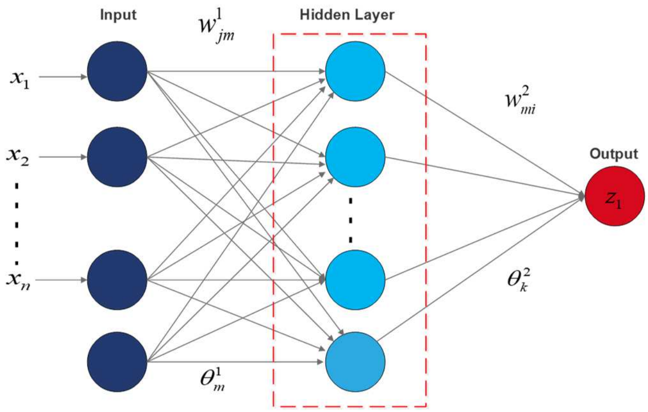

Fig. 5 Feedforward Multi-Layer Neural Network

The last layer corresponds to the output of the network. During the learning process, the weights are modified in order to reduce the error between the actual and predicted values for the dependent variables. The equation (5) illustrates the hidden node x_1^1 output is estimated by specifying the input vectors, weights and bias utilized by each neuron. The inputs $(\{x_i,\dots,x_n\})$ provided to the corresponding neuron are multiplied by their respective weights $(\{w_{11}^1,\dots,w_{n1}^1\})$ and the bias value (θ_1^1) is added to estimate the output from each neuron. The backpropagation learning algorithm is commonly employed for the computation of derivatives pertaining to the weight and bias variables, specifically in relation to the performance of the mean square error[21].

$$X_1^1 = f(\textstyle\sum_{i=1}^{n} x_i w_{il}^1 + \theta_1^1) \qquad (5)$$

In this study, ANN-MLP is in a layered architecture. Comprising input, hidden and output layers, each layer contains interconnected nodes. Input parameters are rainfall rate and river water level, the output forecast is the river water level. During training, the network adjusts weights through backpropagation, minimizing the error between predicted and actual outcomes. Activation functions introduce non-linearity, enhancing the model's capacity to learn complex patterns.

4) Recurrent Neural Network:

Recurrent Neural Networks (RNN) are a variant within the branch of Deep Learning methodologies that incorporates the concept of recurrence by allowing it to leverage historical data. RNNs are utilized for the purpose of predicting future scenarios[22]. RNN is the modification of Feedforward Neural Network with the improvement of using characteristic of feedback from output to input. Beside on relying to the output, RNN output also depends on previous state and act as memory[23]. A specific type of recurrent neural network, referred to as an RNN with Nonlinear Autoregressive Exogenous architecture, has been designed for the purpose of studying dynamic systems, particularly time-series data. The objective of using the NARX model is to forecast values of a time series, referred to as the output, by utilizing its historical values with the values of other interconnected time series, known as the exogenous inputs. The primary difference between NARX and conventional ANN is that NARX can manage time-based data compared to conventional ANN. Researchers frequently assert that NARX is superior to ANNs for predicting temporal data because it can incorporate external information, making it more effective in situations where temporal dependencies and external effects are crucial [24]. It is essential to comprehend this distinction to select the appropriate design for various time-series modelling tasks in machine learning and related disciplines. Fig. 6 is the illustration of NARX architecture.

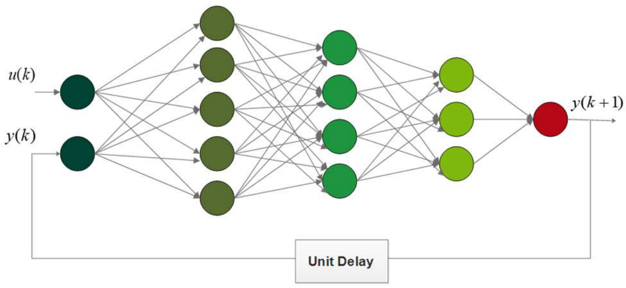

Fig. 6 NARX architecture

The NARX input-output model is commonly employed to explain a significant class of nonlinear dynamic systems that possess both input u and output y variables in discrete time.

$$y(k+1) = f(x(k)) \qquad (6)$$

In this context, ($y = k+1$) represents the anticipated output at a future time point ($k+1$), whereas $x(k)$ refers to the regressor vector. The regressor vector is composed of a limited number of historical inputs and outputs:

$$f(x(k)) = [y(k)\dots y(k-n_y+1)u(k-n_u+1]^T \quad (7)$$

where n_y and n_u : the dynamic order of the system. The challenge of nonlinear system identification requires deducing the unknown function f in (7) based on a set of sampled data sequences $\{(u(k),y(k))\}$ where $k = 1,2,\dots,N$.

In this study the NARX methodology for river water level prediction integrates with the historical river water levels and input rainfall rates to predict 1, 3 and 6 hours ahead. Unlike the ANN-MLP this approach utilizes the RNN architecture, leveraging past outputs and external factors to capture complex dependencies in river behavior.

5) Experimental design:

The experimental design used in this study is displayed in Fig. 7. The Department of Irrigation and Drainage of Malaysia provides information on rainfall and river levels. While river level is the objective statistic, input data also includes rainfall data. The data must first be preprocessed using the Gaussian Noise Reduction technique, Outlier Hamper Filters, and Spline Data Interpolation. The ANN-MLP and NARX models' imputation process is prepared by an experimental design. The network training process includes a detailed construction of hidden layers, connecting nodes, external factors for NARX and the activation function. Next, the MAE, RMSE and R were used to compare the accuracy of ANN-MLP with NARX. The predicted value must then be contrasted with the runoff threshold based on the results or outcomes.

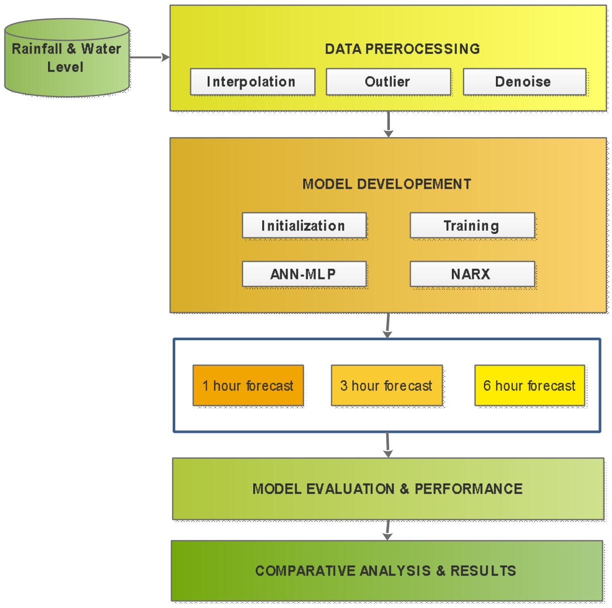

Fig. 7 Experimental Design for River Water Level forecast

D. Performance Evaluation

The model performance was evaluated by using MAE, RMSE and R.

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|y_t - \hat{y}_t| \quad (8)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2} \quad (9)$$

where y_t is the real value, $\hat{y}_t$ is forecast value and n is the number of observations. A lower RMSE indicates better model performance, as it means the squared errors are minimized. Like RMSE, a lower MAE suggests better performance. It's more robust to outliers compared to RMSE.

The correlation coefficient is used to gauge the linear relationship between two random variables, providing a measure of the strength of their association. In this context, it was utilized to evaluate the link between actual values and their corresponding forecasts. If each variable has n scalar observations, then the Pearson correlation coefficient is defined as [25]:

$$R = \frac{n\sum y_t\hat{y}_t - (\sum y_t)(\sum \hat{y}_t)}{\sqrt{n(\sum {y_t}^2)-(\sum y_t)^2} - \sqrt{n(\sum {\hat{y}_t}^2)-(\sum \hat{y}_t)^2}} \quad (10)$$

III. Result and Discussion

A. Preprocessing Data for Imputation

Data preprocessing is a critical phase in data analysis, particularly when dealing with missing data. The utilization of Spline Data Interpolation, Outlier Hamper Filters and Gaussian Noise Reduction. Fig. 8 shows the implementation of data interpolation to handle missing value. Various Exploratory Data Analysis (EDA) were conducted to visualize and analyze the distribution of data before and after preprocessing [26]. The data preprocess will enhance the quality of imputation that will contribute to accurate and meaningful outcomes.

When the imputations were created after data reprocessing, the final stage is to verify the imputed data using Gaussian Kernel Density Estimation (KDE). KDE is a non-parametric method to estimate probability density function (PDF) of a random variables [27]. It is a method used for visualizing the distribution of a dataset. The basic idea involves placing a kernel (a smooth, often Gaussian-shaped function) at each data point and then summing up these kernels to create a smooth curve, which provides an estimate of the underlying probability density. Fig. 9 shows PDF between original data and imputed data for river water level datasets is identically distributed and it can be concluded that the imputation method is satisfactory.

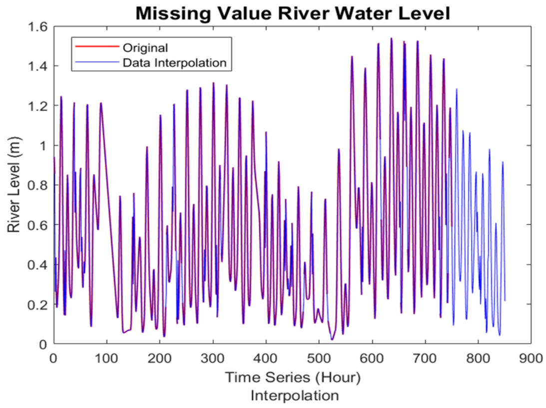

Fig. 8 Missing value with Interpolation.

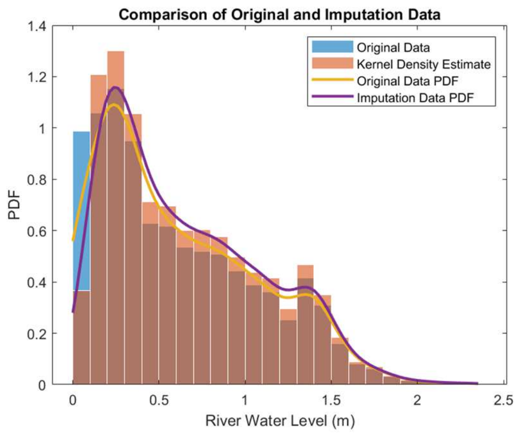

Fig. 9 Comparison of Original and Imputation Data

B. ANN-MLP

After data preprocessing was successful, the architecture of the ANN-MLP was carefully designed, with variations in hidden layers, activation functions, and optimization algorithms systematically explored. Rigorous parameter tuning and cross-validation ensure the robustness of our findings. The experimental results reveal the unparalleled performance of the ANN-MLP model across various domains. In comparison to single layer perceptron, MLPs indicate a marked improvement in accuracy, particularly in scenarios with non-linear decision boundaries. The impact of different activation functions on convergence speed and overall accuracy is thoroughly examined, providing insights into optimal choices for specific tasks. Research indicates that reducing the number of hidden layers in a neural network directly influences its accuracy. Although achieving high accuracy is a goal, it comes at the cost of increased time complexity. With fewer hidden layers, there's a risk that the network may not train adequately, potentially leading to subpar predictions in applications like rainfall-runoff modeling[28].

TABLE II
RESULTS ON ANN-MLP FOR STATION BATU PAHAT

Hour Prediction	No of Hidden Layers	Epochs	MAE	RMSE	R
1	1	1000	0.6015	0.7358	0.9998
1	5	1000	0.6016	0.7470	0.9967
1	10	1000	0.5983	0.7410	0.9982
3	1	1000	0.5176	0.5313	0.8367
3	5	1000	0.5133	0.5411	0.9355
3	10	1000	0.5244	0.5608	0.8335
6	1	1000	0.3064	0.3835	0.3665
6	5	1000	0.3002	0.4616	0.6099
6	10	1000	0.3008	0.3783	0.3968

TABLE III
RESULTS ON ANN-MLP FOR STATION PARIT KARJO

Hour Prediction	No of Hidden Layers	Epochs	MAE	RMSE	R
1	1	1000	0.4733	0.5665	0.9952
1	5	1000	0.4775	0.5658	0.9993
1	10	1000	0.4795	0.5684	0.9989
3	1	1000	0.4526	0.4964	0.9994
3	5	1000	0.4643	0.4906	0.9652
3	10	1000	0.4600	0.4849	0.9646
6	1	1000	0.4778	0.4799	0.1399
6	5	1000	0.4666	0.4697	0.1131
6	10	1000	0.4728	0.4775	0.0748

TABLE IV
RESULTS ON ANN-MLP FOR STATION PARIT BESAR

Hour Prediction	No of Hidden Layers	Epochs	MAE	RMSE	R
1	1	1000	0.8765	0.8936	0.9997
1	5	1000	0.8793	0.8961	0.9988
1	10	1000	0.8790	0.8957	0.9985
3	1	1000	0.8842	0.8879	0.9936
3	5	1000	0.8890	0.8923	0.9724
3	10	1000	0.8892	0.8931	0.9601
6	1	1000	0.8849	0.8852	0.8823
6	5	1000	0.8816	0.8841	0.1680
6	10	1000	0.8811	0.8835	0.1725

The model's performance was evaluated using R, RMSE, and MAE. According to the analysis based on these metrics, a lower MAE and RMSE indicate a lower prediction error. On the other hand, a value of R closer to 1 is preferable as it signifies a stronger linear relationship and a more accurate indication of the direction between two variables. TABLE II's result indicates that the value of R is near to 1. When the number of hidden layers increases from 1 to 10, the values of RMSE and MAE tend to slightly increase as well. With five hidden layers, the model works best for 6-hour predictions. In TABLE III, the results demonstrate a notable level of accuracy, as constant high accuracy is observed in both the 1 hour and 3 hour forecast intervals. TABLE IV displays MAE and Root RMSE values, indicating a lower level of precision in forecasting when compared to the remaining stations. Based on the conducted study, it is evident that the ANN-MLP model demonstrates strong performance in short-term prediction like presented by Fig. 10. When the value of regression showed in Fig. 11 near to 1 and the black data points are tightly clustered around the line of perfect fit, which is a positive indicator.

The accurate predictions can be achieved by allowing an RMSE of 1-hour prediction. The features that influencing the predictions were identified, with time series analysis revealing the model's proficiency in capturing temporal patterns. It is required to minimal overfitting through training and validation phases. The neural network, comprising 5 layers, showcasing its efficacy.

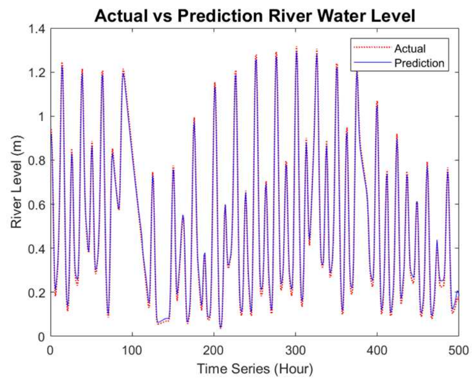

Fig. 10 Actual vs Prediction for 1 hour ahead

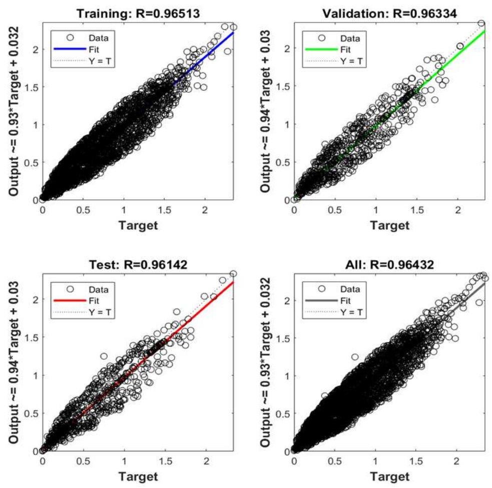

Fig. 11 ANN-MLP Regression for 1 hour ahead

C. RNN-NARX

The architecture of the RNN with NARX is thoroughly configured, with attention to parameters such as sequence length, recurrent layer depth and the influence of exogenous inputs. Rigorous cross-validation and comparative analyses ensure the reliability and generalizability of our findings. The results demonstrate the superior performance of the RNN with NARX in comparison to ANN-MLP architectures, especially in scenarios with complex temporal dependencies and external influences. The model exhibits enhanced predictive accuracy and the ability to capture long-term dependencies, making it well-suited for applications such as time-series forecasting and dynamic system modelling. Furthermore, our study investigates the impact of varying sequence lengths on the model's predictive capabilities. Surprisingly, the RNN with NARX exhibits robust performance even with shorter sequences, showcasing its resilience in scenarios with limited historical data. TABLE V illustrates that lower hour predictions, such as those for 1 hour, tend to have slightly lower values of MAE and RMSE. This suggests improved performance in these cases. The observed R values exhibit a moderate level of magnitude, indicating a moderate degree of correlation. TABLE VI routinely demonstrates the highest level of accuracy in its performance. TABLE VII has higher MAE and RMSE values, which suggest a lower level of predictive accuracy.

TABLE V
RESULTS FOR RNN-NARX FOR BATU PAHAT STATION

Hour Prediction	No of Hidden Layers	Epochs	MAE	RMSE	R
1	1	1000	0.2642	0.3620	0.8897
1	5	1000	0.2646	0.3591	0.8988
1	10	1000	0.2656	0.3603	0.8970
3	1	1000	0.2631	0.3613	0.7918
3	5	1000	0.2647	0.3604	0.7971
3	10	1000	0.2637	0.3603	0.7992
6	1	1000	0.2675	0.3611	0.5880
6	5	1000	0.2654	0.3604	0.5976
6	10	1000	0.2646	0.3612	0.5967

TABLE VI
RESULTS FOR RNN-NARX FOR PARIT KARJO STATION

Hour Prediction	No of Hidden Layers	Epochs	MAE	RMSE	R
1	1	1000	0.2034	0.3276	0.9487
1	5	1000	0.1977	0.3236	0.9621
1	10	1000	0.1967	0.3245	0.9570
3	1	1000	0.2616	0.3948	0.7532
3	5	1000	0.2558	0.3936	0.7582
3	10	1000	0.2542	0.3923	0.7557
6	1	1000	0.2979	0.4523	0.5528
6	5	1000	0.2933	0.4549	0.5569
6	10	1000	0.2899	0.4513	0.5532

TABLE VII
RESULTS FOR RNN-NARX FOR PARIT BESAR STATION

Hour Prediction	No of Hidden Layers	Epochs	MAE	RMSE	R
1	1	1000	0.3265	0.6523	0.8824
1	5	1000	0.3214	0.6259	0.8875
1	10	1000	0.3219	0.6240	0.8895
3	1	1000	0.3590	0.6409	0.7706
3	5	1000	0.3551	0.6415	0.7192
3	10	1000	0.3540	0.6415	0.7180
6	1	1000	0.3775	0.6536	0.8640
6	5	1000	0.3768	0.6543	0.7812
6	10	1000	0.3750	0.6544	0.7877

The NARX model yielded convincing outcomes in the range of river water level prediction. Employing a complex interplay of historical data and external factors, the model exhibited a commendable RMSE of 5 hidden layers, attesting to its accuracy. RMSE and correlation coefficient further validated the model's predictive ability, showcasing its ability to encapsulate the dynamics of river water fluctuations. Analysis of feature importance highlighted the significant role of certain variables, revealing the factors crucial for precise predictions. Time series evaluations underscored the model's adeptness in capturing temporal dependencies as focal aspect in water level forecasting. is the optimized predictive performance. The degree of variation between the predicted and actual values can indicate the volatility of river water levels, which can be a significant determinant of the predictive capacity of the model showed in Fig. 12. The points in Fig. 13 are grouped around the Y=T line, which represents the line of best fit, indicating that the model's predictions are fairly near to the actual targets. The lack of notable outliers suggests that the faults in the model are very moderate and stable.

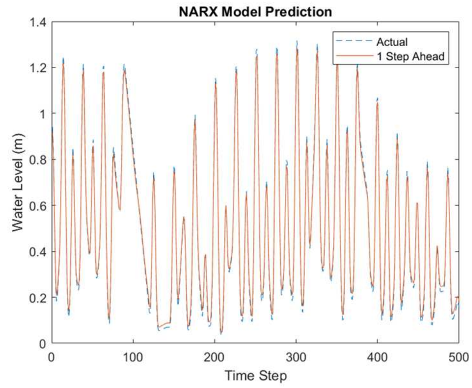

Fig. 12 NARX Actual vs Forecast for 1 hour ahead

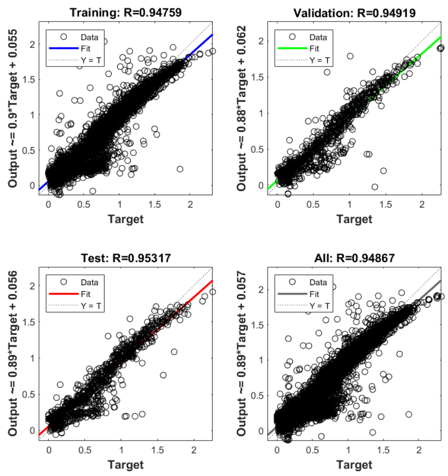

Fig. 13 NARX Regression for 1 hour ahead

D. Comparative Analysis

Comparative assessments against alternative methodologies such as ANN-MLP models, underscored the NARX model's superiority. Challenges such as sensitivity to input variations were observed, prompting consideration for robustness in real world scenarios. According to Fig. 14 and Fig. 15, the distinguishing factor between two graphs utilizing identical datasets is the variation in time steps. The temporal intervals would be interconnected inside the procedure of forecasting time-series data. In summary, the NARX model proves to be a proficient instrument for predicting river water levels, demonstrating a sophisticated grasp of dynamics and adaptability. Delving into aspects such as input sensitivity could further expand its practicality, consolidating its role as a valuable asset in hydrological forecasting. The outcome demonstrates that an hourly forecast may be made with a decent value of R that is almost equal to 1 by applying ANN-MLP. The researchers' BPN model achieves accuracy on a 3-hour timescale using only the water level parameter. In contrast to this research, the application of water level and rainfall as parameters can improve the accuracy result into an accuracy of one hour and provide a better prediction, with the prediction value closely grouped around the line of perfect fit. Similar to this study, another researcher's use of ANN-MLP for hourly river level forecasting surpassed the Adaptive Neuro Fuzzy Inference System (ANFIS), achieving RMSE (0.01740) with four hidden layers as opposed to RMSE (0.8961) with five hidden layers[29].

E. Rainfall-runoff

In rainfall-runoff forecast modeling using ANN with rainfall and historic water level data, the consideration of thresholds for runoff in three rivers in this study is crucial. ANN models excel in capturing complex, non-linear relationships inherent in hydrological systems, recognize patterns and predict runoff that offering a dynamic understanding of flood risk. The incorporation of river-specific thresholds further refines accuracy. These levels in TABLE VIII are used to keep an eye on and deal with flood threats. The "Normal" range shows normal and safe water amounts. As the levels rise to the "Alert" and "Warning" levels, people should be more careful and take steps to get ready for possible floods. The "Danger" level means that there is a high chance of floods, and that immediate action may be needed to protect people and property.

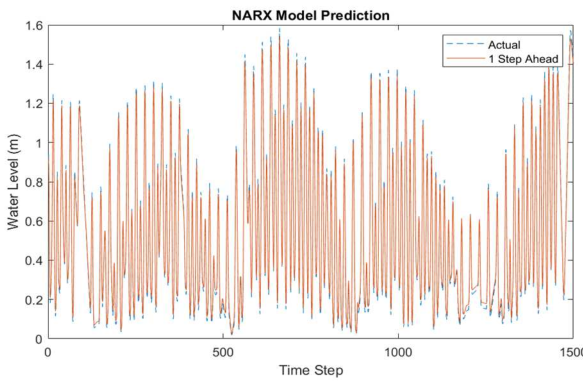

Fig. 14 Actual vs Forecast NARX

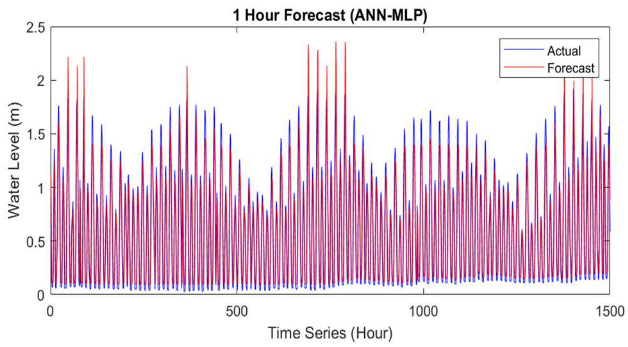

Fig. 15 Actual vs Forecast ANN-MLP

The threshold value is provided by Malaysia Department of Irrigation and Drainage [30]. From the different stations' threshold levels, Sg Batu Pahat threshold level is higher. Fig. 16 shows the distribution of river water level for Sg Batu Pahat. This means it has more capacity or a different risk profile than the other two stations. Sg Simpang Kanan (Parit Besar), on the other hand, has the lowest limits, which means it may flood more easily or not be able to handle high water levels as well. The water levels at Sg Simpang Kanan (Parit Karjo) are in the middle of the other two stations, which could mean that the risk level or potential for water levels is moderate.

TABLE VIII
THRESHOLD VALUE FOR WARNING ALERT

Station Name	Normal (m)	Alert (m)	Warning (m)	Danger (m)
Sg Batu Pahat	1.00	2.30	2.60	3.00
Sg Simpang Kanan (Parit Besar)	0.50	1.60	1.80	2.00
Sg Simpang Kanan (Parit Karjo)	1.30	2.00	2.10	2.30

The distribution of actual and forecast for river water level of Sg Batu Pahat in Fig. 16 and Fig. 17 indicate the prediction model is acceptable. The adaptability of ANNs to evolving conditions and their ability to process vast datasets swiftly make them indispensable tools for timely and reliable flood forecasts based on the runoff threshold level.

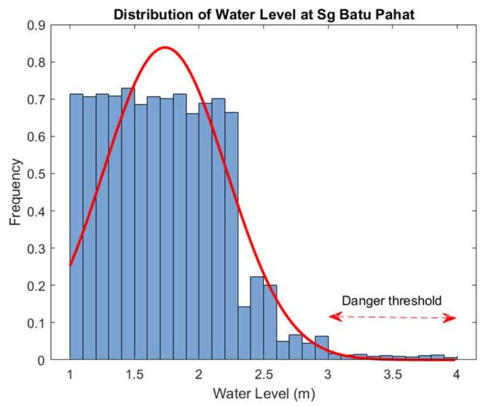

Fig. 16 Distribution of Water Level for Sg Batu Pahat River

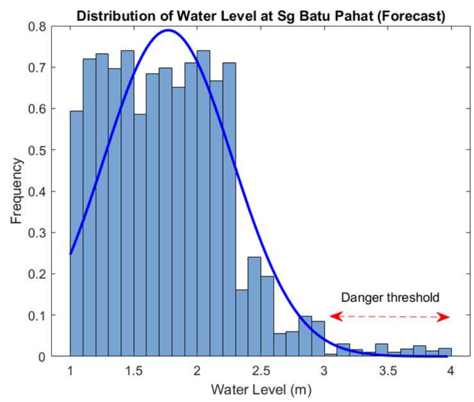

Fig. 17 Distribution of Water Level forecast for Sg Batu Pahat River

IV. Conclusion

This research explored the application of ANN-MLP and NARX models for river level prediction for 1, 3 and 6 hours ahead. Commencing with accurate data preprocessing, extensive testing involving appropriate network structures and epochs was conducted for both ANN-MLP and NARX models. Results show that ANN-MLP outperformed NARX. The ANN-MLP model has higher correlation coefficient. The NARX model has lower error metrics of RMSE and MAE, suggesting that it is better at predicting the exact values. This study faces a notable constraint linked to the reliability of the raw data acquired from the monitoring station. While gathering the data, a section was identified to have negative values resulting from errors in the data reading process. Another notable limitation of this study pertains to the process of hyperparameter tuning. Future considerations involve hybrid models of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks [31], inclusion of additional weather parameters, or improved preprocessing for enhanced flood prediction accuracy. In conclusion, computational intelligence, exemplified by models like ANN-MLP and NARX, proves pivotal in flood forecasting. Their adeptness in handling complex relationships and temporal dynamics enhances accuracy.

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References

[1] L. C. P. Velasco, R. P. Serquiña, M. S. A. Abdul Zamad, B. F. Juanico, and J. C. Lomocso, "Week-ahead rainfall forecasting using multilayer perceptron neural network," *Procedia Computer Science*, vol. 161, pp. 386–397, 2019.

[2] Y. Tikhamarine, D. Souag-Gamane, A. N. Ahmed, S. S. Sammen, O. Kisi, Y. F. Huang, and A. El-Shafie, "Rainfall-runoff modelling using improved machine learning methods: Harris hawks optimizer vs. particle swarm optimization," *Journal of Hydrology*, vol. 589, no. June, p. 125133, 2020.

[3] E. H. Lee, "Runoff prediction of urban stream based on the discharge of pump stations using improved multi-layer perceptron applying new optimizers combined with a harmony search," *Journal of Hydrology*, vol. 615, no. PB, p. 128708, 2022.

[4] L. M. F. Enung, Kasyanto H., Sari R.R., "Application of multilayer perceptron (MLP) method for streamflow forecasting (case study: Upper Citarum River, Indonesia)," 2023.

[5] A. Wunsch, T. Liesch, and S. Broda, "Forecasting groundwater levels using nonlinear autoregressive networks with exogenous input (NARX)," *Journal of Hydrology*, vol. 567, pp. 743–758, 2018.

[6] Y. Shao, J. Zhao, J. Xu, A. Fu, and M. Li, "Application of Rainfall-Runoff Simulation Based on the NARX Dynamic Neural Network Model," *Water (Switzerland)*, vol. 14, no. 13, pp. 1–16, 2022.

[7] F.-J. C. Li-Chiu Chang, Jia-Yi Liou, "Spatial-temporal flood inundation nowcasts by fusing machine learning methods and principal component analysis," *Journal of Hydrology*, vol. 612, no. Part A, 2022.

[8] O. B. Bagheri M., Ibrahim Z.Z., Wolf I.D., Akhir M.F., Talaat W.I.A.W., "Sea-level projections using a NARX-NN model of tide gauge data for the coastal city of Kuala Terengganu in Malaysia," *Environmental Science and Pollution Research*, vol. 30, no. 34, pp. 81839–81857, 2023.

[9] M. Kottek, J. Grieser, C. Beck, B. Rudolf, and F. Rubel, "World map of the Köppen-Geiger climate classification updated," *Meteorologische Zeitschrift*, vol. 15, no. 3, pp. 259–263, 2006.

[10] V. Desai and H. A. Dinesha, "A Hybrid Approach to Data Pre-processing Methods," *2020 IEEE International Conference for Innovation in Technology, INOCON 2020*, pp. 6–9, 2020.

[11] K. K. Al-jabery, T. Obafemi-Ajayi, G. R. Olbricht, and D. C. Wunsch II, "Data preprocessing," *Computational Learning Approaches to Data Analytics in Biomedical Applications*, pp. 7–27, 2020.

[12] H. Kang, "The prevention and handling of the missing data," *Korean Journal of Anesthesiology*, vol. 64, no. 5, pp. 402–406, 2013.

[13] M. Lepot, J. B. Aubin, and F. H. L. R. Clemens, "Interpolation in time series: An introductive overview of existing methods, their performance criteria and uncertainty assessment," *Water (Switzerland)*, vol. 9, no. 10, 2017.

[14] R. K. Pearson, Y. Neuvo, J. Astola, and M. Gabbouj, "Generalized Hampel Filters," *Eurasip Journal on Advances in Signal Processing*, vol. 2016, no. 1, 2016.

[15] S.-K. S. Fan, C.-Y. Hsu, C.-H. Jen, K.-L. Chen, and L.-T. Juan, "Defective wafer detection using a denoising autoencoder for semiconductor manufacturing processes," *Advanced Engineering Informatics*, vol. 46, p. 101166, 2020.

[16] A. Haidar, "Rainfall Forecasting Using Artificial Neural Networks by," no. September, 2018.

[17] A. R. Sanubari, P. D. Kusuma, and C. Setianingsih, "Flood modelling and prediction using artificial neural network," *Proceedings - 2018 IEEE International Conference on Internet of Things and Intelligence System, IOTAIS 2018*, pp. 227–233, 2019.

[18] D. N. Fente and D. K. Singh, "Weather forecasting using artificial neural network," in *2018 second international conference on inventive communication and computational technologies (ICICCT)*, 2018, pp. 1757–1761.

[19] Z. LV, J. Zuo, and D. Rodriguez, "Predicting of Runoff Using an Optimized SWAT-ANN: A Case Study," *Journal of Hydrology: Regional Studies*, vol. 29, no. April, 2020.

[20] Y. Tikhamarine, D. Souag-Gamane, A. N. Ahmed, S. S. Sammen, O. Kisi, Y. F. Huang, and A. El-Shafie, "Rainfall-runoff modelling using improved machine learning methods: Harris hawks optimizer vs. particle swarm optimization," *Journal of Hydrology*, vol. 589, no. March, p. 125133, 2020.

[21] E. Papatheocharous, H. Papadopoulos, and A. S. Andreou, "A Comparison of Feature Selection Techniques for Software Cost Modelling and Estimation," *arXiv*, no. June 2014, 2012.

[22] K. Abdel-Nasser, M., Mahmoud, "Accurate photovoltaic power forecasting models using deep LSTM-RNN.," *Neural Comput & Applic*, pp. 1–14, 2019.

[23] A. A. F. and R. A. E.-K. Salma Alhagry, "Emotion Recognition based on EEG using LSTM Recurrent Neural Network," *International Journal of Advanced Computer Science and Applications(IJACSA)*, vol. 8, no. (10), 2017.

[24] N. Zerhouni, R. Zemouri, and R. Gouriveau, "Defining and applying prediction performance metrics on a recurrent NARX time series model," *Neurocomputing*, vol. 73, no. (13-15), pp. 2506–2521, 2010.

[25] J. Hauke and T. Kossowski, "Comparison of Values of Pearson's and Spearman's Correlation Coefficients on the Same Sets of Data," *Quaestiones Geographicae*, vol. 30, no. 2, pp. 87–93, 2011.

[26] M. Al-Gabalawy, H. S. Ramadan, M. A. Mostafa, and S. A. Hussien, "Power Curve Estimation of a Wind Turbine Considering Different Weather Conditions using Machine Learning Algorithms," in *2022 23rd International Middle East Power Systems Conference (MEPCON)*, 2022, pp. 1–8.

[27] S. R. J. N. L. Hwang and A. Lippman, "Nonparametric multivariate density estimation: a comparative study," *IEEE Trans. on Signal Processing*, vol. 42, no. 10, pp. 2795–2810, 1994.

[28] M. Uzair and N. Jamil, "Effects of Hidden Layers on the Efficiency of Neural networks," *Proceedings - 2020 23rd IEEE International Multi-Topic Conference, INMIC 2020*, pp. 1–6, 2020.

[29] M. Nur Adli Zakaria, M. Abdul Malek, M. Zolkepli, and A. Najah Ahmed, "Application of artificial intelligence algorithms for hourly river level forecast: A case study of Muda River, Malaysia," *Alexandria Engineering Journal*, vol. 60, no. 4, pp. 4015–4028, 2021.

[30] R. Adnan, F. A. Ruslan, Z. M. Zain, and others, "Flood water level modelling and prediction using artificial neural network: Case study of Sungai Batu Pahat in Johor," in *2012 IEEE Control and System Graduate Research Colloquium*, 2012, pp. 22–25.

[31] M. Moishin, R. C. Deo, R. Prasad, and N. Raj, "Designing Deep-based Learning Flood Forecast Model with ConvLSTM Hybrid Algorithm," vol. XX, 2021.