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Enhancing flood forecasting accuracy through improved SVM and ANFIS techniques

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Extreme rainfall in upstream watersheds often results in the rise of river water levels, leading to severe flood disasters in the downstream catchment. Therefore, monitoring river water levels and flow is crucial for flood forecasting in early warning systems and disaster risk reduction. However, forecasting river water levels remains a challenging task that cannot be easily captured with classical time-series approaches. This paper explores the potential of improving flood forecasting accuracy by combining two forecasting techniques: Support Vector Machine (SVM) and Adaptive Neuro-Fuzzy Inference System (ANFIS) by simple averaging and weighted averaging methods and optimizing their contributions. To tune different individuals' weights the genetic algorithm and K-nearest neighbors' algorithm (K-NN) were used to find the optimal weight combination. The committee machine model was employed to forecast the river water level in different lead times from 1 hour to 6 hours applied to the Selangor River. Model performance was evaluated and analyzed using various performance metrics, including mean percentage error (MPE), root mean square error (RMSE), mean absolute error (MAE), and correlation coefficient (R). The results show that the proposed Intelligent Committee Machine Learning (ICML) outperformed SVM and ANFIS for most performance indicators. This method aims to develop a robust and accurate time series forecasting model by combining multiple forecasting techniques and optimizing their contributions, ultimately leading to improved prediction performance.

Keywords: *flood; genetic algorithm; forecasting; Selangor River; ANFIS; SVM.*

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1. Introduction

Floods are among the most harmful and destructive natural disasters, causing significant damage to infrastructure, agriculture, human life, and the socioeconomic system. Heavy and excessive rainfall and inadequate drainage systems are typically associated with flooding. Because of these problems, governments are under pressure to create accurate and reliable flood risk maps and make more plans for flood risk management and protection. For this reason, flood forecasting is one of the few feasible options to manage flood disasters [1]. Many flood forecasting models rely on specialized data and incorporate simplified input assumptions [2]. Linear techniques, such as linear regression are one of the commonly used methods for flood forecasting. These techniques involve using linear regression models to analyze and predict the behavior of water levels in a particular location. These models assume a linear relationship between the input parameters and the output, namely, the water level. One of the advantages of linear techniques is their simplicity and ease of implementation. However, linear techniques are limited in accounting for complex hydrological processes that may affect flood behavior. They assume a linear relationship between the input parameters, which may not always hold. Additionally, linear techniques may not be suitable for long-term predictions. In addition, they cannot account for the inherent non-linearity in the rainfall-runoff process. The ANN model provides considerable flexibility in solving non-linear problems, and it has been successfully applied in various hydrological areas [3, 4]. Modern ANN approaches, sometimes called hybrid models, such as ANFIS, have also been particularly effective in improving flood forecasting techniques due to their high accuracy and capability [5]. Hence, several non-linear Reduced Finite Frequency Analysis techniques (RFFA) have been proposed, including Adaptive Neuro-Fuzzy Inference Systems (ANFIS) [6, 7], Artificial Neural Networks (ANN) [8, 9], Support Vector Machine (SVM) [10,11], and Machine Learning Models (MLMs) [12]. ANFIS has been used to identify non-linear relationships between chaotic data [13]. For example, using 21 years of data from 33 catchments, Bozchaloei and Vafakhah [14] applied artificial neural networks (ANN), nonlinear regression (NLR), and adaptive neuro-fuzzy inference system (ANFIS) to study flow duration curves at Namak Lake catchment in Iran. They found that ANFIS performed better than ANN and the NLR. However, by recognizing and extending the patterns in past data, SVM models offer precise flood condition forecasts. Because of SVM algorithms' versatility and demonstrated effectiveness in recognizing the numerous causes contributing to floods, flood analysts are better equipped to make well-informed recommendations [15]. Using data from 55 hydrometric stations with 20 years of flood discharge data, ANFIS, ANN, and SVM models were applied in the RFFA at Namak Lake. It was discovered that the ANFIS and SVM models performed better than the ANN model because it addresses many of the shortcomings of ANN. In many scientific and technical applications, the SVM model has gained popularity as a computational technique in recent years [16]. Even in the field of hydrological modeling, investigators have extensively applied SVM. Han et al. [17] described the applicability of SVM over the Bird Creek watershed, USA. Study results showed that SVM could be a reliable technique for different rainfall inputs and performed well under different evaluation criteria. Although the ANFIS and SVM models are effective and reliable technologies [18, 19], they might perform poorly in some problems because of producing irrational output values in some points [20–23]. Employing evolutionary algorithms is one of the most effective approaches to improve the prediction performance of single models in complex scenarios. By exploring the search space of a problem and optimizing potential solutions, they can generate accurate and adaptive models that can handle large amounts of data and changing environments. Nikam and Insom et al. [24] applied a novel method to develop an improved SVM model based on particle filter to estimate suitable model parameters for an enhanced good classification system. The results indicated that the proposed method provided a more accurate analysis and performed better than the standard SVM model. As [25] applied Grey Wolf Optimizer (GWO) to adjust and optimize parameters of ANFIS, results showed that the hybrid of ANFIS-GWO significantly improved the prediction accuracy. The Harris Hawks optimization (HHO) algorithm was also used to optimize the parameters of ANFIS to check for the possibility of performance improvement [26]. Results also demonstrated the superior performance of the hybrid ANFIS-HHO model over the least-squares support vector regression (LS-SVR) and ANFIS models. The Genetic Algorithms GA is one of the most recently introduced optimization techniques [27]. Genetic algorithms are considered one of the essential techniques in searching for the optimal option from a set of available solutions for a specific design. Numerous studies have employed this algorithm to produce acceptable output data [28–30]. Thus, in this study, the potential of the evolutionary algorithm, GA, is investigated to boost the prediction performance of ANFIS and SVM and present a reliable good prediction model. Also, one of the algorithms widely used in the optimization field is the nearest neighbor algorithm, a statistical technique used to classify a variable's value according to the closest training examples in a feature space. It is used to determine the optimal weights based on the performance of the models on the nearest data points. A study [31] by Liu, Yao and Chen al. (2017) explored the performances of three real-time updating models in improving flood forecasting accuracy. The first model is the K-nearest neighbor (K-NN) algorithm. The two other updating models are the Kalman filter (KF) and a combined model incorporating both the KF and K-NN procedures. used the middle reaches of the Huai River in East China. Statistical results show that the KNN model can provide excellent forecasts with an 8-h lead time in both the calibration and validation periods. In this work, optimization techniques known as GA and K-NN algorithms are introduced to predict flood discharge, and the performance of the models is evaluated based on quantitative statistical measures. Also, a comparison is made between improved models and conventional approaches. Here, two traditional techniques, ANFIS and SVM, are applied to predict flood discharge and compared with the results of enhanced models by GA and

K-NN algorithms. This method aims to develop a robust and accurate time series forecasting model by combining multiple forecasting techniques and optimizing their contributions, ultimately leading to improved prediction performance.

2. Study area and data used

The Selangor River is located in Malaysia, which runs from Kuala Kubu Bharu in the east and empties into the Straits of Malacca at Kuala Selangor in the west. It plays a significant role in both the ecological and socio-economic landscape of the region as it is a crucial source of water for domestic, agricultural, and industrial uses. It supplies water to the densely populated areas in the state of Selangor. Historically, the river served as an important transportation route for trade and commerce. Although its commercial navigation has declined, it still holds cultural significance and offers recreational activities such as boating and fishing. Its surrounding areas are home to a variety of flora and fauna, contributing to the region's biodiversity and supporting various economic activities, including agriculture and aquaculture. The river plays a role in flood management for the surrounding areas. Proper management of its waters can help mitigate flood risks during heavy rainfall and contribute to effective drainage systems. The study area's location is depicted in Figure 1. The data used in this study comes from the gauging station Sg.Damansara di Batu3. For the 11 days, from 00:00 on 01/11/2023 to 00:00 on 12/11/2023, the hourly values of water level and precipitation with delays of 1, 2, and 3 hours were considered input variables. For modeling, 265 data samples were taken into account. Various input scenarios were created by combining the aforementioned variables, and machine learning models were used to predict the river water level. In this study, 70% of the data was used for model training, while the rest was used to test the models

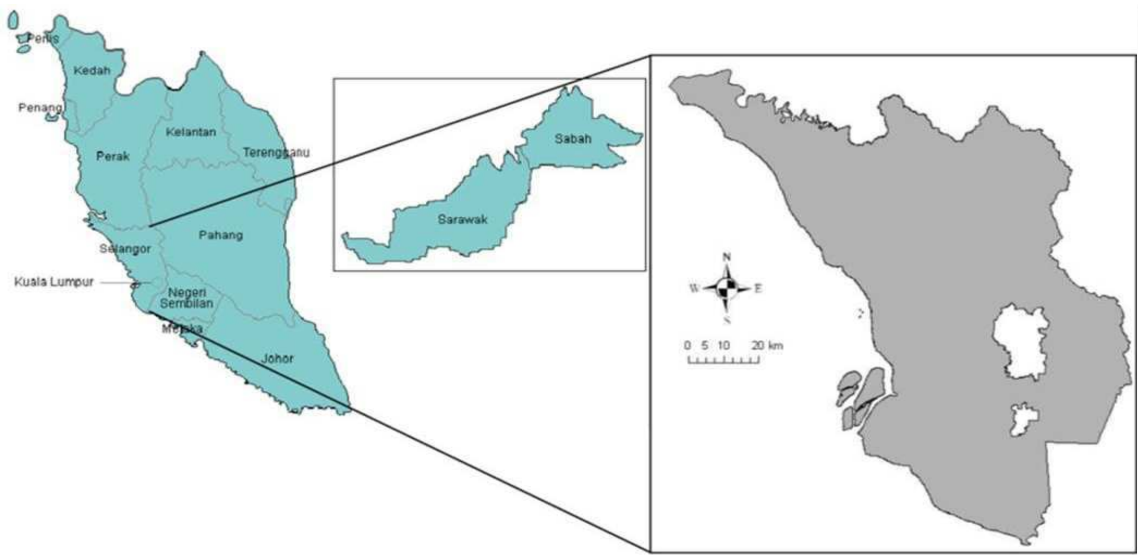


Fig. 1. The location of the study area.

3. Research methods

To ensure a continuous dataset, this research begins with a literature review to better understand the issue. Next, data (rainfall and water level) is collected and pre-processed by filling in the gaps with a linear approximation and developing lagged variables to record temporal correlations. This study considered various historical inputs using autocorrelation and partial autocorrelation functions. In particular, the water level (wl) data lagged by 1, 2, and 3 hours; rainfall data were lagged by 1 and 24 hours. This makes it possible for the models to use past values as predictors. Data normalization, the final stage of preprocessing, scales the data between 0 and 1, improving machine learning model performance.

Thus, an innovative intelligence system was presented in the study, which employed ensemble intelligent committee machine learning (ICML) to address the "unstable" performance of the computational model used to forecast floods utilizing individual models and weighted average techniques. Furthermore, the ensemble method's use of simple averaging is jeopardized by the lowest-performing individual models in a collective forecast. The ideal weight combination should be determined by adjusting the weights of various people. This weight-tuning procedure can be approached as an optimization issue.

To increase the model's generalizability, the optimization techniques, K-nearest neighbor (K-NN) and genetic algorithms (GA) were selected because of their effectiveness and adaptability. Support Vector Machine (SVM) and Adaptive Neuro-Fuzzy Inference System (ANFIS) are the two separate models used as base machine learning models. These modeling techniques were implemented using the RStudio 2024 environment.

4. Support vector machine (SVM)

Support vector machines are supervised learning models used for classification and regression tasks. Support vector regression (SVR) is an extension of support vector machines (SVM) for regression problems. Like SVM, SVR aims to find a function that approximates the relationship between input variables and the output. SVR is an application for the case of regression, the difference between SVM and SVR is the application of SVM to find the best separator function (hyperplane) between an infinite number of functions to separate two objects. SVR has an application to find a function as a hyperplane (dividing line) in the form of a regression function that matches all input data with an error ε and makes ε as thin as possible [32]. The regression function of the SVR method is

$$f(x)=\sum_{i=1}^{l}(\alpha-\alpha^{*}I)\langle x,x_i\rangle+b. \tag{1}$$

Loss function: A function that shows the relationship between errors and whether the error is penalized is called a loss function. The loss function is the ε-insensitive loss function, which has the following formulation:

$$L_{\varepsilon}(y)=\begin{cases}0, & |f(x)-y|\leqslant\varepsilon\\ |f(x)-y|-\varepsilon, & \text{otherwise.}\end{cases} \tag{2}$$

Critical features of SVM:

- **Kernel functions:** SVMs can use different kernel functions (e.g., linear, polynomial, radial basis function, sigmoid) to transform the input data into higher-dimensional spaces, making it easier to find a separating hyperplane. These kernels are used to solve both linear and non-linear problems and can be expressed as follows:
  1. **Linear kernel function:**
  $$k(x_i,x_j)=x_i\cdot x_j. \tag{3}$$
  2. **Polynomial kernel function:**
  $$k(x_i,x_j)=(1+x_i\cdot x_j)^q,\quad q=1,2,3,\ldots,n. \tag{4}$$
  3. **Radial basis kernel function:**
  $$k(x_i,x_j)=\exp\left(-\frac{\|x_i-x_j\|^2}{2\sigma^q}\right). \tag{5}$$
  4. **Sigmoid kernel function:**
  $$k(x_i,x_j)=\tanh(k\cdot x_j^T x_i+\theta). \tag{6}$$
- **Regularization parameter (C):** This parameter controls the trade-off between achieving a low error on the training data and minimizing the model complexity to avoid overfitting.
- **Hyperparameter tuning:** A grid search is used to find the optimal hyperparameters for SVM.

SVM Model training: this work has trained an SVM model using the `caret` package in R with a radial basis function kernel, cross-validation, and hyperparameter tuning. Cross-validation with 3 folds is used to evaluate the model's performance.

Application in Flood Forecasting: the choice of parameters and kernels is crucial for achieving the best performance in different applications. In flood forecasting, SVMs model the relationship between historical rainfall, water, and future water levels. By capturing these relationships, SVMs can provide accurate future water-level forecasts based on current and past data.

5. Adaptive neuro-fuzzy inference system (ANFIS)

Adaptive neuro-fuzzy inference system (FIS), or so-called ANFIS, is a more advanced form of neuro-fuzzy based on the Takagi–Sugeno (TS) FIS. The architecture of ANFIS was proposed by Jang (1993). It is a well-known approach for neuro-fuzzy systems, which embed FIS and the ANN.

ANFIS has two parameters, namely the premise parameter and the consequent parameter. In this algorithm, hybrid training is carried out with steps, such as steps forward and steps backward backward [32].

For a network with a radial baseline function to be equivalent to a fuzzy rule-based Sugeno first-order model, limitations are needed:

1. Both must have the same aggregation method (weighted average or weighted sum) to derive all outputs.
2. The number of activation functions must be equal to the number of fuzzy rules (IF-THEN).
3. If there are multiple inputs based on the rules, then each activation function must be the same as the membership function of each input.
4. The activation function and fuzzy rules must have the same function for neurons and the rules on the output side backward [32].

In the Neuro-Fuzzy system, there are five layers of processes in which the functions and equations of each layer is described as layer-1 as input nodes, layer-2 as rule nodes, layer-3 as average nodes, layer-4 as consequent nodes, and layer-5 as output nodes [32].

Layer 1: **Fuzzification Layer** – Fuzzification Layer, at this layer a fuzzy set will be formed using the membership function. Several membership functions can be used including, Bell (bell), Gaussian, trap, triangle, etc. The output at layer 1 can be expressed as Equation (7):

$$O_{1,i} = \mu_{A_i}(x) = \frac{1}{1 + \left|\frac{x-c}{a}\right|^2}. \tag{7}$$

Layer 2: **Product Layer** – At this layer, the transmission of information with layer 1 is synthesized, and the multiplication of all incoming signals is performed. The output at this layer can be stated by Equation (8):

$$O_{2,i} = \mu_{A_i}(x) \cdot \mu_{B_i}(y) = W_i. \tag{8}$$

Layer 3: **Normalization** – The results of layer 2 are then normalized. Output at layer 3 is stated in Equation (9):

$$O_{3,i} = \frac{W_i}{\sum W}. \tag{9}$$

Layer 4: **Defuzzification** – Output at layer 4 can be calculated using the formula in Equation (10):

$$O_{4,i} = \tilde{W}_i \cdot Y_i = \tilde{W}_i(p_i x_1 + q_i x_2 + r_i), \tag{10}$$

where $\{p_i, q_i, r_i\}$ is a set of consequent parameters.

Layer 5: **Total Output Layer** – At this layer, the results of layer 4 will be calculated using Equation (11):

$$O_{5,i} = \sum \tilde{W}_i Y_i = \frac{\sum \tilde{W} Y_i}{\sum \tilde{W}_i}. \tag{11}$$

In this work, this algorithm is implemented using the `frbs.learn` function from the `frbs` package in RStudio for ANFIS training with two fuzzy sets and `GAUSSIAN` as membership functions, the Weighted Average Method for defuzzification, and `MIN` as the determinant for the type of t-norm used for fuzzy logic operations.

6. Combining models by intelligent committee machine learning (ICML)

The ICML framework leverages the strengths of both SVM and ANFIS by combining their forecasts to improve overall prediction accuracy. The combination of models, also known as an ensemble, helps to reduce the biases and variances associated with individual models, leading to more robust and reliable predictions. Hence, this step is the main contribution of this work.

The proposed methodology comprises three significant steps:

1. Individual models (ANFIS and SVM) first forecast the flood water level.
2. A committee machine with the mentioned individual models is constructed to achieve better generalization functions based on the machine learning approach.
3. After creating individual intelligent models, it is necessary to find a suitable method to combine the individual results. This includes ensemble averaging and optimized weighted averaging tuned by Genetic Algorithm (GA) and K-NN algorithm to extract the optimum weights of individual models.

A final forecast output y is then achieved as $y = n + t$, where n is the forecasted data, and t is the time ahead forecasting horizons (1 to 6 hours ahead).

7. Ensemble methods

Simple averaging: in this method, the arithmetic mean of the predictions from the SVM and ANFIS models is taken. Simple averaging is straightforward and effective when the individual models are diverse and uncorrelated,

$$\text{(ENS-AVG) Prediction} = 0.5 \cdot \text{SVM Prediction} + 0.5 \cdot \text{ANFIS Prediction}. \tag{12}$$

The disadvantage of simple averaging is the equal weight for every committee member, i.e., there is no difference between the weights of two committee members with low and high generalizations. There are two methods to determine weights for ICML-based models: simple ensemble averaging using equal weights and weighted averaging using optimized weights.

Optimized weighted averaging: this method assigns different weights to the predictions from each model based on their performance. Therefore, the weights are optimized using optimization methods to minimize the overall prediction error.

Weighted optimization by genetic algorithm (GA)

GA is used to find the optimal weights by simulating the process of natural evolution. It iterates through a population of potential solutions, selecting and recombining them based on their fitness until the best weights are found. The genetic algorithm operates by first generating an initial population, with each individual indicating a solution to the problem. Then, the nobility of each individual is evaluated by an objective function that signifies the constraints of the problem. Next, the population is sorted based on the fitness of each individual. Finally, by applying crossover and mutation to the best individual, the next generation is constructed. This process continues until reaching the finishing criteria. In this study, the GA parameters setting was set with a population size of 50, a maximum number of iterations of 100, and the initial constraint of the random vector population is $[0, 1]$. The fitness function is designed to minimize both the forecasting error and maximize the correlation coefficient as shown in Equation (13):

$$\text{Fitness} = \alpha \cdot \text{MPE} + \beta \cdot (1 - R), \tag{13}$$

where $\alpha = 0.3$ and $\beta = 0.7$ are weighting factors.

Weighted optimization by K-nearest neighbors algorithm (K-NN)

It is a simple, yet powerful, method used for classification and regression tasks. In this study, the K-nearest neighbor (K-NN) algorithm is proposed as another combination strategy in ensemble learning for flood forecasting problems. It has been used to determine the optimal weights based on the performance of the models on the nearest data points. The optimized weighted averaging approach is designed to maximize the strengths of each model while minimizing its weaknesses. The K-NN method, used as weighted averaging, uses the similarity (neighborhood) between the observation of predictors (input dataset) and similar sets of historical observations (successor) to obtain the best estimate for a dependent variable (target value). The K-NN algorithm needs to calculate the distance between the forecasted data point and the observed data point. The distance between the current and historical conditions is calculated using Euclidean distance. Hence, the Euclidean distance D_i, between the forecasted data points, $\hat{y}^j$, and the observed data points, y, was calculated by Equation (14):

$$D_i = \sqrt{\sum\nolimits_{j=1}^{k} (\hat{y}^j - y)^2}. \tag{14}$$

The weights for each forecasted data point and each multi-time step ahead forecasting, W_i, were calculated by the reciprocal of the distance as shown in Equation (15):

$$W_i = 1/D_i. \tag{15}$$

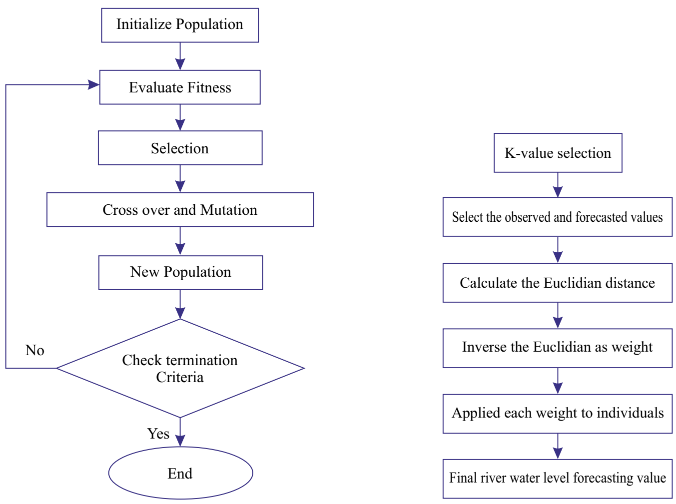
The combined forecast is then calculated as Equation (16):

$$\text{Ensemble Prediction} = \sum\nolimits_{i=1}^{k} W_i \cdot \text{Forecast}_i, \tag{16}$$

where W_i is the weight of the i-th model's forecast.

Selection of the K value in K-NN plays a significant role in determining the efficacy of the model. A large K value has benefits which include reducing the variance due to noisy data, though it could suffer from the underfitting situation. However, choosing a small value of K leads to unstable decision boundaries. Therefore, in general applications of the K-NN algorithm, the value of K is often set as a relatively small integer value.

The ICML framework can provide more accurate and reliable flood forecasts by adjusting the weights based on the performance metrics. Figure 2b illustrates the flowchart of the applied K-NN algorithm.



a ***b***

Fig. 2. Genetic algorithm and K-nearest neighbors algorithm flow charts for optimization processes.

8. The models evaluation

Four different performance measures will be used to demonstrate the efficiency of both the individual models (SVM & ANFIS) and the ICML model. The four quantitative performance indicators used were the root mean square error (RMSE), mean absolute error (MAE), mean percentage error (MPE), and correlation coefficient (R). The formulation of four performance indicators can be expressed as

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}, \tag{17}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|, \tag{18}$$

$$\mathrm{MPE} = \frac{1}{n}\sum_{i=1}^{n} \frac{(y_i - \hat{y}_i)}{y_i} \cdot 100\%, \tag{19}$$

$$R = \frac{\sum_{i=1}^{n}(y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2 \sum_{i=1}^{n}(\hat{y}_i - \bar{\hat{y}})^2}}, \tag{20}$$

where n is the number of data points, $\hat{y}_i$ is the forecasted value, y_i is the actual value, and $\bar{y}$ is the average value of the actual or observed records. RMSE indicates overall agreement in actual units with the deviations squared, so the assessment favors higher magnitude events. MAE indicates overall agreement in actual units. The mean percentage error is the computed average percentage error of the forecasted value to the observed records. In contrast, the R-value describes the proportion of the variance in the observed dataset that the model can explain. Figure 3 shows the flow chart.

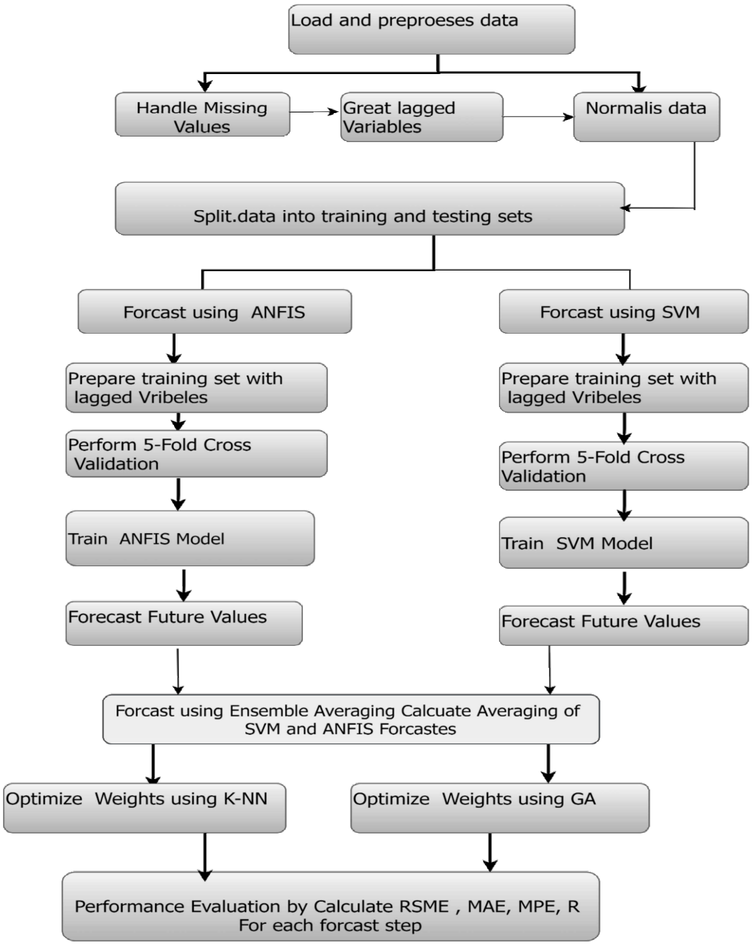


Fig. 3. Flow chart.

9. Results and discussion

Evaluating the performance of various models and ensemble methods for flood forecasting is crucial to determine their efficacy in predicting water levels. The results are compared across several metrics: root mean square error (RMSE), mean absolute error (MAE), mean percentage error (MPE), and the correlation coefficient (R). These metrics provide insights into the accuracy, reliability, and robustness of individual models and ensemble models (Intelligent Committee Machines Learning). The following sections detail the performance of each model across forecasting steps from 1 to 6 hours.

Table 1. Individual models and Ensemble Model (Intelligent Committee Machines Learning) performance through error measurements and coefficient correlation.

	Step 1	Step 2	Step 3	Step 4	Step 5	Step 6
SVM	RMSE: 0.0220	0.0205	0.0188	0.0203	0.0280	0.0595
ANFIS	RMSE: 0.0870	0.0708	0.0478	0.0844	0.0518	0.0455
ENS-(AVG)	RMSE: 0.0517	0.0431	0.0315	0.0504	0.0382	0.0472
ENS-(GA)	RMSE: 0.0159	0.0184	0.0236	0.0171	0.0210	0.0237
ENS-(K-NN)	RMSE: 0.0490	0.0534	0.0595	0.0500	0.0566	0.0540
	Step 1	Step 2	Step 3	Step 4	Step 5	Step 6
SVM	MAE: 0.0150	0.0139	0.0126	0.0146	0.0222	0.0442
ANFIS	MAE: 0.0851	0.0687	0.0458	0.0828	0.0499	0.0435
ENS-(AVG)	MAE: 0.0497	0.0407	0.0289	0.0483	0.0355	0.0423
ENS-(GA)	MAE: 0.0093	0.0133	0.0203	0.0101	0.0149	0.0196
ENS-(K-NN)	MAE: 0.0476	0.0521	0.0583	0.0484	0.0550	0.0518
	Step 1	Step 2	Step 3	Step 4	Step 5	Step 6
SVM	MPE: -15.02	-14.31	-13.43	-15.16	-21.51	-39.03
ANFIS	MPE: -67.52	-54.64	-36.37	-65.46	-39.51	-34.78
ENS-(AVG)	MPE: -41.27	-34.47	-24.90	-40.31	-30.51	-36.91
ENS-(GA)	MPE: -0.52	3.24	8.50	-0.04	3.73	-3.58
ENS-(K-NN)	MPE: 29.01	32.46	37.18	29.52	34.41	31.52
	Step 1	Step 2	Step 3	Step 4	Step 5	Step 6
SVM	R: 0.7155	0.7279	0.7636	0.7808	0.6706	0.0657
ANFIS	R: 0.5001	0.4814	0.5103	0.5561	0.5103	0.5167
ENS-(AVG)	R: 0.7579	0.7525	0.7268	0.7442	0.7151	0.4113
ENS-(GA)	R: 0.7710	0.7836	0.7680	0.7854	0.7880	0.2448
ENS-(K-NN)	R: 0.7581	0.7535	0.7269	0.7443	0.7152	0.4113

10. Summary of results

In evaluating the performance of different forecasting models across various metrics, optimized weighted averaging ENS-(GA) consistently demonstrates superior accuracy with the lowest RMSE and MAE values, indicating minimal prediction errors and high reliability. It also shows the least bias with MPE values close to zero and maintains strong correlations with high R-values in the early steps. SVM performs well initially, with low RMSE and MAE values and high R-values, but its performance declines by Step 6, as evidenced by increased RMSE, MAE, and a drop in the R-value, alongside a tendency to underpredict, reflected in its negative MPE. Ensemble Averaging (ENS-AVG) delivers moderate performance, with RMSE and MAE values lower than those of ANFIS and ENS-(K-NN) but higher than those of SVM and ENS-(GA). It also shows a consistent underprediction trend with moderately negative MPE values and maintains moderate R-values. ANFIS exhibits the least accuracy, with the highest RMSE and MAE values, significant negative MPE indicating strong underprediction, and consistently low R-values, reflecting weaker linear relationships. On the other hand, optimized weighted averaging ENS-(K-NN) shows fluctuating RMSE values and higher MAE, with positive MPE values indicating a tendency to overpredict, resulting in moderate overall performance compared to the other models.

Figures 4 through 9 respectively present the forecasted and actual river water levels for 1-hour, 2-hour, 3-hour, 4-hour, 5-hour, and 6-hour ahead predictions, illustrating the time series results of flood water level forecasting for the Selangor dataset using two individual models and an ensemble ICML-based model. In these figures, the X-axis represents the test dataset, while the Y-axis shows the river water level of the Selangor River. The results indicate that both the ICML model and the individual models effectively capture the peak curves of the experimental data. Notably, the ICML model optimized by the Genetic Algorithm (GA) outperformed all other machine learning models across all forecasting steps.

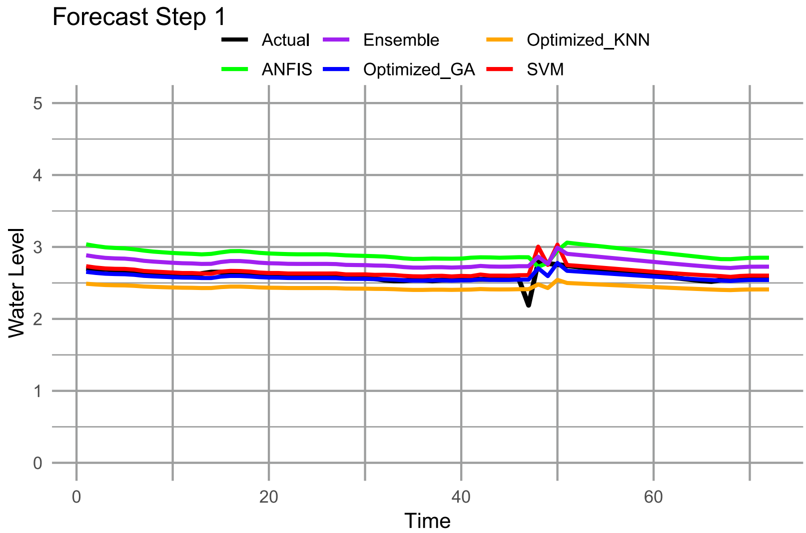


Fig. 4. Sample of 1 hr ahead flood water level forecasting by individual models and committee machine models.

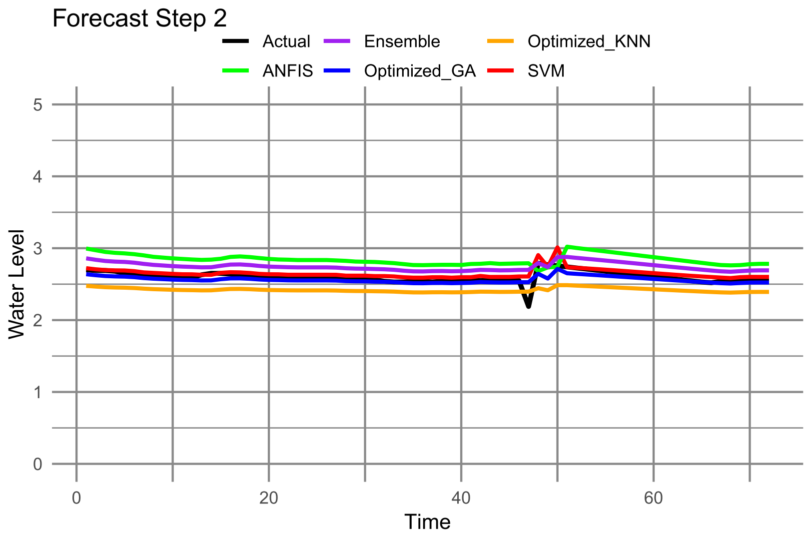


Fig. 5. Sample of 2 hr ahead flood water level forecasting by individual models and committee machine models.

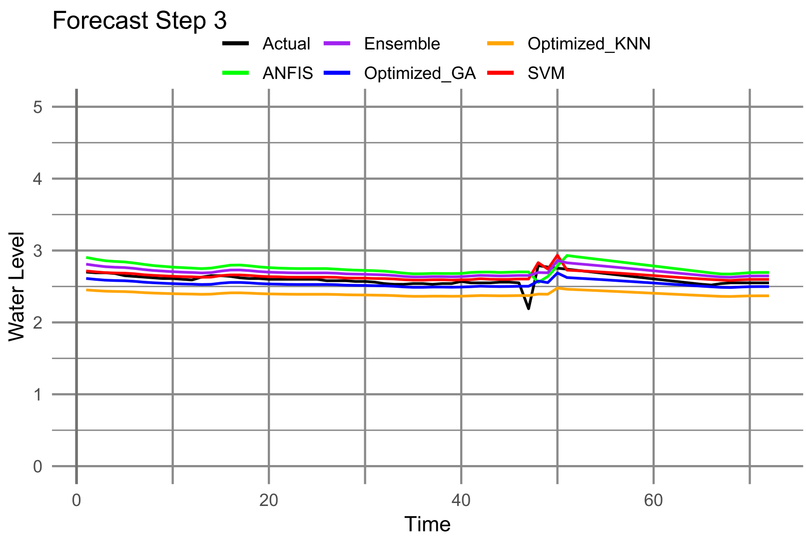


Fig. 6. Sample of 3 hr ahead flood water level forecasting by individual models and committee machine models.

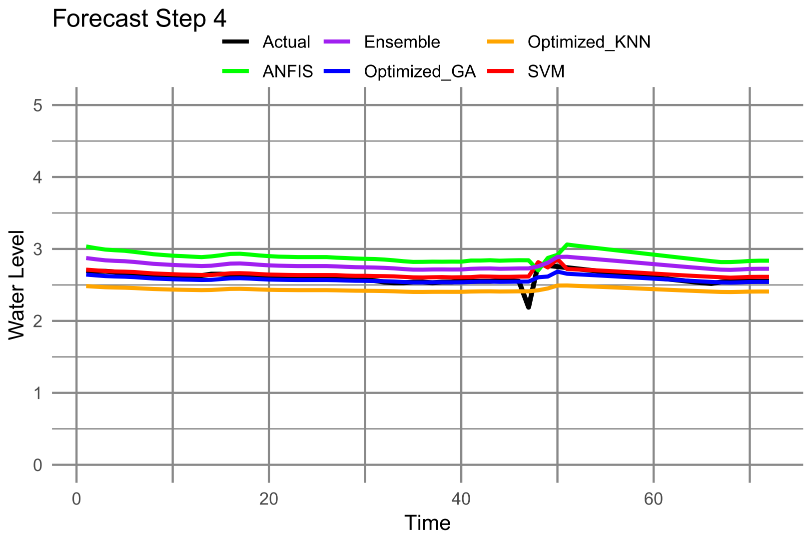


Fig. 7. Sample of 4 hr ahead flood water level forecasting by individual models and committee machine models.

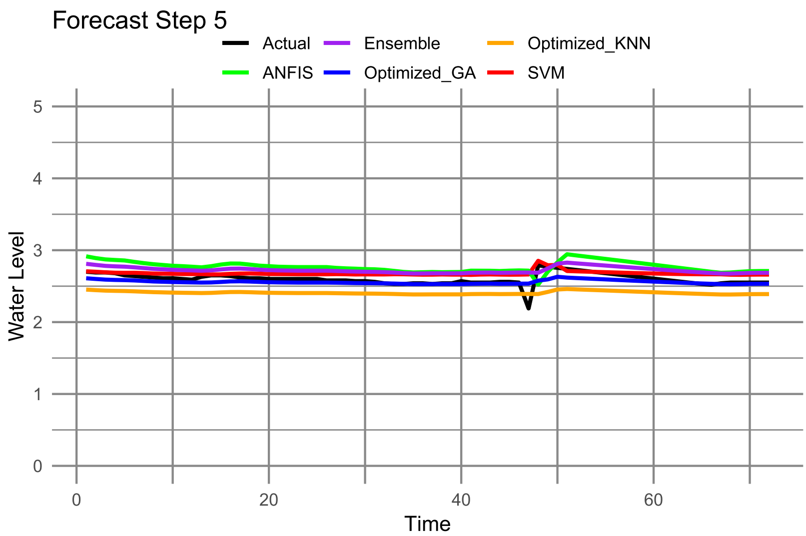


Fig. 8. Sample of 5 hr ahead flood water level forecasting by individual models and committee machine models.

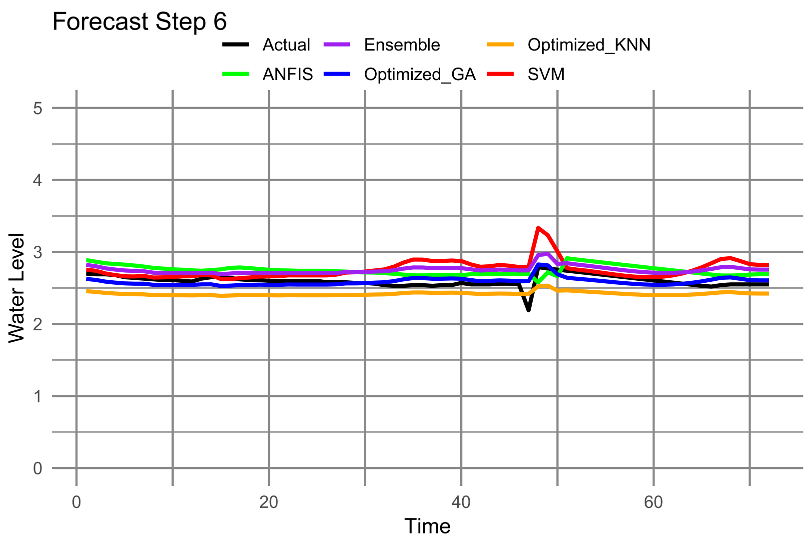


Fig. 9. Sample of 6 hr ahead flood water level forecasting by individual models and committee machine models.

11. Conclusion

The results of the updated models reinforce the effectiveness of optimized weighted averaging(GA) and SVM as the most accurate and reliable forecasting models. Optimized weighted averaging (GA) particularly stands out with the lowest error metrics (RMSE and MAE), minimal bias (MPE), and strong correlations (R-values). The SVM model performs well in early steps but shows increased errors and reduced correlation in the later stages. Ensemble averaging performs moderately well, balancing error minimization and bias. Optimized weighted averaging (K-NN) shows fluctuating performance, with higher errors and biases than GA, but still maintains a reasonable level of accuracy. ANFIS, however, consistently underperforms across all metrics, confirming its unsuitability for accurate and reliable forecasting in this context. These findings emphasize the importance of using robust ensemble methods, particularly Optimized Weighted Averaging (GA), to achieve optimal forecasting performance.

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Підвищення точності прогнозування повеней завдяки вдосконаленим методам SVM та ANFIS

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Екстремальні опади у водозбірних басейнах, розташованих вище за течією, часто призводять до підвищення рівня води в ріках, наслідком чого є сильні повені у водозбірних басейнах, які розташовані нижче за течією. Тому моніторинг рівнів води річок та потоків має вирішальне значення для прогнозування повеней у системах раннього попередження та зменшення ризику стихійних лих. Класичні методи аналізу часових рядів виявляються недостатньо ефективними для вирішення складного завдання прогнозування рівня води в річках. У цій статті досліджується можливість підвищення точності прогнозування повеней шляхом поєднання двох методів — методу опорних векторів (SVM) та адаптивної нейронечіткої системи логічного висновку (ANFIS) — з використанням простого та зваженого усереднення, а також оптимізації вагового внеску кожної моделі. Для налаштування ваг окремих моделей використовувалися генетичний алгоритм та алгоритм K-найближчих сусідів (K-NN) з метою знаходження їх оптимального поєднання. Запропонована ансамблева модель (Intelligent Committee Machine Learning) застосовувалась для прогнозування рівня води у річці Селангор з інтервалом у 1–6 годин. Порівняння продуктивності моделей було оцінено та проаналізовано за допомогою різних показників продуктивності, включаючи середню відсоткову похибку (MPE), середньоквадратичну похибку (RMSE), середню абсолютну похибку (MAE) і коефіцієнт кореляції (R). Результати показали, що запропонована ансамблева модель машинного навчання (ICML) перевершила SVM та ANFIS за більшістю показників ефективності. Завдяки поєднанню кількох моделей і налаштуванню їх взаємодії, метод демонструє значне покращення точності прогнозування часових рядів.

Ключові слова: *повінь; генетичний алгоритм; прогнозування; ріка Селангор; ANFIS; SVM.*