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Flood River Water Level Forecasting using Ensemble Machine Learning for Early Warning Systems

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Abstract. Flood forecasting is crucial for early warning system and disaster risk reduction. Yet the flood river water levels are difficult and challenging task that it cannot be easily captured with classical time-series approaches. This study proposed a novel intelligence system utilised various machine learning techniques as individual models, including radial basis function neural network (RBF-NN), adaptive neuro-fuzzy inference system (ANFIS), support vector machine (SVM), and long short-term memory network (LSTM) to establish intelligent committee machine learning flood forecasting (ICML-FF) framework. The combination of these individual models achieved through simple averaging method, and further optimised using weighted averaging by K-nearest neighbour (K-NN) and genetic algorithm (GA). The effectiveness of the proposed model was evaluated using real case study for Malaysia's Kelantan River. The results show that ANFIS outperforms as individual model, while ICML-FF-based model produced better accuracy and lowest error than any one of the individuals. In general, it is found that the proposed ICML-FF is capable of robust forecasting model for flood early warning systems.

1. Introduction

Flood forecasting models are essential in hazard assessment and disaster management. The research on the advancement of flood forecasting will increase since it contributes to disaster risk reduction, which is a difficult task, challenging and highly complex to model [1]. According to the Sendai frameworks 2015-2030, disaster risk reduction (DRR) is given priority numbers three and four. The framework states "investing in disaster risk reduction for resilience" and "enhancing disaster risk preparedness for effective response" among its priorities [2]. In connection with these viewpoints, hence flood modelling and forecasting is crucial for disaster risk management. In many regions of the world, flood forecasting is one of the few feasible options to manage flood disasters. Moreover, flood forecasting is essential for an early warning system (EWS), in which such EWS is an integral component of disaster risk management. A flood forecasting system provides the operating environment within which the flood forecasting model can be operated and is sometimes called the system environment [3].

The most well-known works of flood forecasting modelling include artificial neural networks (ANNs) [4], [5] support vector machines (SVM) [6], [7] and adaptive neuro-fuzzy inference system (ANFIS) [8], [9]. These models were effectively employed for both short-term and long-term flood forecasting. As a new method in ANN models, deep learning is a significant subject of interest in AI methods. Deep learning is being studied in many problems, such as image processing, speech recognition, and natural language processing. In the subject of forecasting, recent studies have reported the successful use of deep learning in various fields [10]–[12], respectively, for power load and probability density forecasting, traffic flow forecasting and rainfall forecasting.

As recently reported by Yaseen *et al*. [13] and Luo He *et al*. [12], the most successfully implemented flood forecasting model include both single and hybrid model. However, few published studies have systematically examined the concept of committee machine intelligent system technique in hydrological-engineering problems, especially for flood forecasting. Hence, there is a need to investigate the effectiveness of committee machines for flood forecasting in various flood-prone areas. More specifically, in the case of Malaysia, the committee model approach has not been applied so far in the flood forecasting problem. This combination methods among the individuals were essential to produce final result, and over there, simple averaging is the most popular one [14]. Though, the disadvantage is the important contribution of the individuals cannot be emphasized due to giving equal weights to all the individuals.

In response to these problems, this study proposes to design intelligent flood forecasting models and develop committee machine learning based methods for further improvement and advancement of flood forecasting methods. The notion is to extract the pertinent information simulated by individual models and further optimize it via weighted averaging methods. Moreover, comparison analysis of the effectiveness of the K-NN and GA as ensemble method were further investigated in this study with a case study from Kelantan River, located in Kelantan State, Peninsular Malaysia.

2. Methodology

2.1. Data Source and Case Study

The case study used is dataset from Kelantan River as the flood forecasting point (FFP). This reservoir is among the most frequent occurrence of seasonal flood disasters in Malaysia. The state of Kelantan belongs to the eastern region and is located in the northeast of peninsular Malaysia, with Kota Bharu as its capital city. About twenty-seven months of data in January 2013 – March 2015 were collected through department of irrigation and drainage (DID) supervisory control and data acquisition systems. There are 19,672 records datasets were used, employed for training and validation test. As shown in Figure 1. and Table 1., three variables indicating the river water level (WL), rainfall (RF), and river streamflow (SF) were used as independent variables, while one WL as target output used as dependent variable. The proposed intelligent machine learning network requires these input data, while the observed water level becomes the system's output/target data.

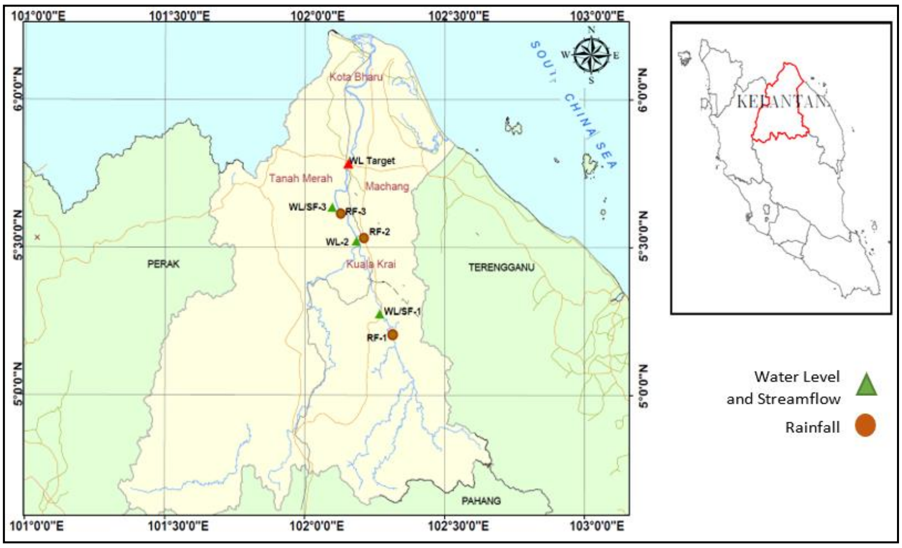


Figure 1. Kelantan river basin at Peninsular Malaysia (DID, Malaysia)

Table 1. List of hydrological observations stations of Kelantan River basin

Station ID	Station name	Observation items	Location (District)
5222452	Lebir river	Water Level-1 (WL-1)	Tualang (Kuala Krai)
5521444	Kelantan river	Water Level-2 (WL-2)	Kuala Krai
5621401	Sokor river	Water Level-3 (WL-3)	Tegawan village (Tanah Merah)
4922001	Rkt. Lebir	Rainfall-1 (RF-1)	Tualang (Kuala Krai)
5522047	JPS Kuala Krai	Rainfall-2 (RF-2)	Kuala Krai
5621051	Kenneth farm	Rainfall-3 (RF-3)	Tanah Merah
5222452	Lebir river	Streamflow-1 (SF-1)	Tualang (Kuala Krai)
5621401	Sokor river	Streamflow-2 (SF-2)	Tegawan village (Tanah Merah)
5721442	Kelantan river	Water Level (Observed/ Target)	Guillemard Bridge (Tanah Merah)

2.2. Model Development

Three (3) past inputs were considered in this study based on autocorrelation and partial autocorrelation functions, to develop intelligent-based flood forecasting models. Hence, the general flood forecasting model M, which includes input variables at upstream and downstream stations, is denoted in equation (1). Where t is variables value at t time, and i is 1, 2, 3, to 6 steps ahead of time forecasting. While Y is water level at target river, and W, R, and Q respectively are river water level, rainfall, and streamflow at upstream stations. Finally, f is the intelligent model that can be either RBFNN, ANFIS, SVM, or LSTM algorithms.

$$M(t+i) = f\left\{\begin{array}{c} Y(t), Y(t-1), Y(t-2), \\ W(t), W(t-1), W(t-2), \\ R(t), R(t-1), R(t-2), \\ Q(t), Q(t-1), Q(t-2) \end{array}\right\} \tag{1}$$

2.3. Proposed ICML-FF

Individual expert intelligent systems (RBFNN, ANFIS, SVM and LSTM) will first forecast the flood water level. In this study, the ensemble method based on ICML-FF design includes ensemble averaging and optimised weighted averaging tuned by K-NN and GA to extract the optimum weights of individual models is investigated. A final forecast output is then achieved, $Y = n + t$, where n is the forecasted data, and t is time ahead forecasting horizons (1 to 6 step ahead). A schematic diagram of ICML can be illustrated in Figure 2.

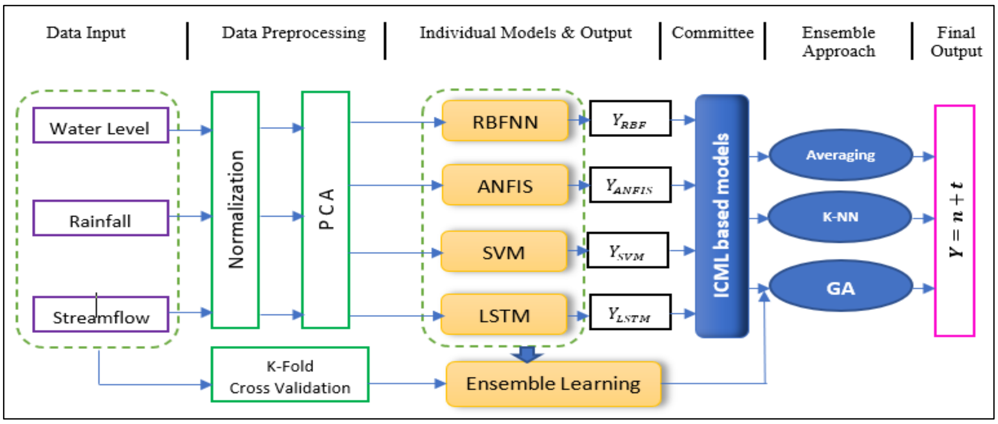
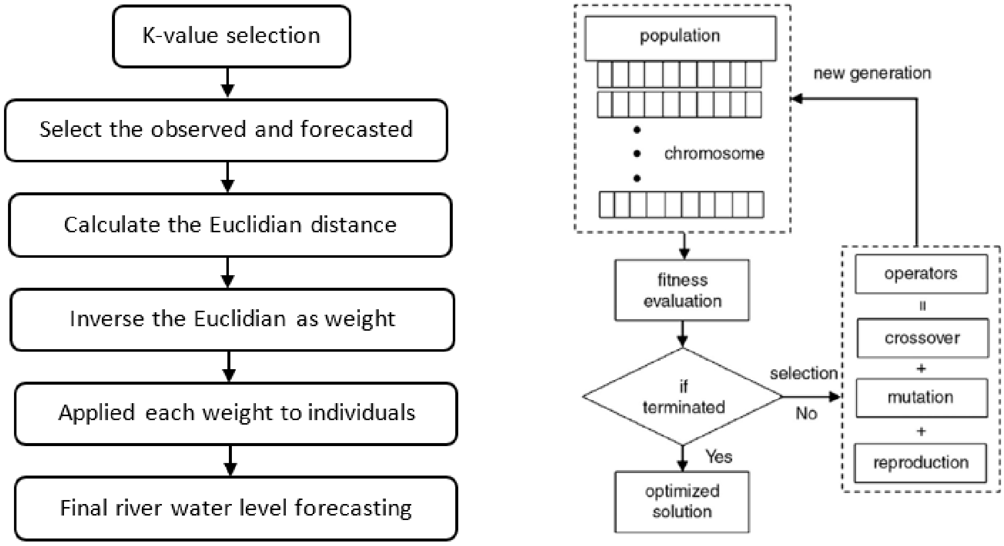


Figure 2. Proposed ensemble ICML-FF based model

2.4. Ensemble Machine Learning by K-NN and Genetic Algorithm
The Euclidian distance, D_i, between the forecasted data points, Y_j and the observed data points, X_t was calculated by equation (2). The weights for each forecasted data point and each multi-time step ahead forecasting, $\mathcal{W}_i$, were calculated by the reciprocal of the distance:

$$D_i = \sqrt{\sum_{j=1}^{K}(Y_j - X_t)^2} \quad ; \quad \mathcal{W}_i = \frac{1}{D_i} \tag{2}$$

The idea of the K-NN as weighted average method in ensemble learning is demonstrated in Figure 3 (a) [15], [16] and while Figure 3 (b) is GA optimisation algorithm used to tune the hyperparameters of the ensemble learning [17].



(a) (b)

Figure 3. Flow chart of ensemble machine learning by (a). K-NN and (b). GA

3. Result and Discussion
As a result, in the simple averaging method, any one of the individual intelligent models has an equal contribution in constructing ICML. The four individual base learners simply have their weight value set to 0.25. Thus, the calculated flood water level from ICML could be obtained using equation (3):

$$\begin{aligned} &EnsembleAveraging\ (E - AVG)_{(T-hr)} = \\ &\quad 0.25\left(Forecasted_{RBF(T-hr)}\right) + 0.25\left(Forecasted_{ANFIS(T-hr)}\right) + \\ &\quad 0.25\left(Forecasted_{SVM(T-hr)}\right) + 0.25\left(Forecasted_{LSTM(T-hr)}\right) \end{aligned} \tag{3}$$

Here, $T - hr$ represents each time hour ahead forecasting horizons, including one to six-hour lead-time. Applying this formula for forecasting the final output of individual models has provided the correlation coefficient value, R, and error value, mean percentage error (MPE), in each step ahead of time forecasting.

The last step of ensemble learning combines the output of individual intelligent models to get the final output using optimised weights by the genetic algorithm optimisation technique. It should be noted that the hyperparameters were tuned on the training stage using a 5-Fold cross-validation set. The average percentage error and coefficient correlation of 5-Fold cross-validation were then used as the objective function of GA. The MPE and R-value were then selected as the fitness (cost) value of GA. Thus, with a constant weight of fitness (Wcf) value of 0.5, the objective function as stated:

$$f_{GA} = 0.5\ MPE + 0.5\ (1 - R) * 100 \quad (4)$$

To extend the comparison analysis, the forecasted results emitted by individual models in this present study is examined using K-NN method as ensemble learning to produce final flood water level forecasting. However, only Kelantan dataset is selected to evaluate the compared committee machine-based model since its more complex and more features used rather than other two case studies. With the value of K-nearest neighbor set to 2, the flood forecasting performance results of committee machine-based model comprise three ensemble methods include simple averaging, genetic algorithm, and K-NN method is depicted in Table 2.

Table 2. ICML flood water level forecasting result, the best model is marked in bold.

Hour	MPE						
	RBF	**ANFIS**	**SVM**	**LSTM**	**E-AVG**	**E-GA**	**E-KNN**
1	1.7210	**0.1047**	0.4953	0.3523	0.5221	0.1969	0.1976
2	0.7575	**0.1586**	0.4637	0.9578	0.3457	0.1678	0.2223
3	2.0847	0.2605	0.6237	0.6055	0.6361	**0.2518**	0.2845
4	1.6412	0.4084	1.0490	0.9916	0.6964	**0.3886**	0.6423
5	6.8516	0.5331	1.4158	1.0052	2.2748	**0.5210**	1.1655
6	2.4323	0.6561	1.7325	1.1198	1.1942	**0.6016**	1.0065
Hour	**R**						
	RBF	**ANFIS**	**SVM**	**LSTM**	**E-AVG**	**E-GA**	**E-KNN**
1	0.9922	**0.9999**	**0.9999**	0.9996	0.9996	**0.9999**	**0.9999**
2	0.9984	**0.9999**	0.9998	0.9987	0.9997	**0.9999**	**0.9999**
3	0.9806	0.9996	0.9996	0.9992	0.9992	0.9997	**0.9998**
4	0.9740	0.9977	0.9984	0.9944	0.9981	0.9986	**0.9992**
5	0.8533	0.9961	0.9968	0.9939	0.9834	**0.9980**	0.9970
6	0.8929	0.9946	0.9950	0.9945	0.9948	0.9974	**0.9978**

As a result, committee machine-based GA demonstrates the adequacy with outperform other ensemble methods in MPE performances. Even though, R results are varied in multi-step ahead forecasting, and K-NN based method could compete with the GA. In addition, the weighted averaging ensemble method based on K-NN shows improvement over simple averaging method. This result signifies that every individual model in ICML has its own strength and domain knowledge with their proper weights related to generalisation ability [18]. This observation agrees with Azmi *et al.* [15] and Fan *et al*. [16] which has similar to that investigated in this present study.

Table 3. summarised the optimised weights attained using GA and K-NN ensemble learning-based method. In GA, the achieved weights are dominated by ANFIS model, in which ANFIS model also shows outperforms other individual in this Kelantan dataset, hence, the ANFIS's weights are contributed significantly in improving the committee machine model. This finding denotes that K-fold cross validation technique used in ensemble-GA training could benefit in generalised the committee machine model. In contrast, the weights obtained by K-NN are achieved depending on the distance of the forecasted and observed (actual) river water value. In K-NN, the nearer the distance, the greater weights assigned. Results showed that ANFIS's weights are larger than other in one to three ahead forecasting. This observation is also supported with the findings in the simulation results, in which ANFIS model is outperforms other individual in short-term ahead forecasting indicated by lowest MPE and R values.

Table 3. Optimised weights obtained by GA and ***K***-NN

Hour	Weights by GA				Weights by *K*-NN			
	RBF	ANFIS	SVM	LSTM	RBF	ANFIS	SVM	LSTM
1	0.0653	0.8896	0.0179	0.0272	0.0277	0.2286	0.1868	0.0862
2	0.0149	0.9351	0.0169	0.0331	0.0705	0.3908	0.1875	0.0353
3	0.0100	0.9000	0.0100	0.0800	0.0129	0.1568	0.1356	0.0723
4	0.0100	0.8167	0.0113	0.1620	0.0125	0.0569	0.0717	0.0278
5	0.0100	0.7700	0.0100	0.2100	0.0076	0.0435	0.0503	0.0252
6	0.0101	0.7184	0.0104	0.2611	0.0090	0.0374	0.0404	0.0247

4. Flood Early Warning System

In connection with disaster risk management and flood warning system, according to DID [19] and Sulaiman [20] for river water level data-above sea level, it can be classified into three main categories, including “alert level”, “warning level”, and “danger level”. The river water level at Guillemard bridge, located in the Kelantan River, was selected as a flood forecasting point in the first dataset. The alert level for the Guillemard bridge station is 12 meters, while for warning level is 14 meters, and the danger level is 16 meters – above sea levels [21].

Occurrences of heavy rainfall would flow into the reservoir and are expected to increase in river water level in just a couple of hours. It indicates when the river water level is more than the maximum observed value, it can be assumed flood will occur in that area since it could reach a dangerous level. According to Wu-Jian [22], the forecast lead time of predictions, at the very least, should be set to three hours since flood managers can issue flood warnings and notify the public to prepare for the possibility of floods. Thus, representing ensemble ICML based time series results with the flood water level threshold of the Kelantan River datasets were respectively illustrated in Figure 4. This result expressed the important things of the proposed ICML-FF. Hence, the accurate forecast models are expected to be useful for early warning systems for disaster risk reduction.

These simulation results illustrated that when the river water level significantly above the normal level, it indicates an alert level, and the flood operation room should be activated (flood warning issues). Likewise, when the river water level is near the flooding (above alert level), it’s entering the warning, and hence the district flood operation room should be activated. At the end, when danger level, it shows that the river water level can cause considerable flooding, indicating that evacuation may be needed (flood commences).

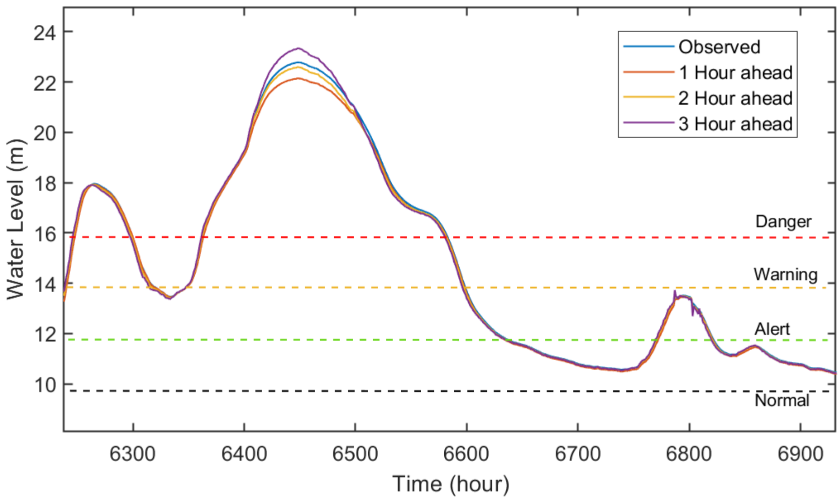


Figure 4. Water Level Threshold at Guillemard bridge in Kelantan River as a FFP using ICML Model

5. Conclusion

This study has offered a framework for exploring flood forecasting systems using an advanced ensemble machine learning approach. Returning to the purposes posed at the beginning of this study, it is now possible to state that advanced machine learning-based methods for flood forecasting problems have been developed, and their performances have been investigated. Final test results found that the ANFIS model has the best performance in the short-term forecasting horizon, for one and two hours ahead in the Kelantan River dataset. Overall, the results in multi-step ahead of time forecasting from the Kelantan River datasets show that the developed ICML-FF has a simple structure and has an easy way of constructing it. Moreover, since there are multiple directions to solve a problem, it could improve the model's performance with a high correlation coefficient value and provides smaller errors than averaging all individual experts by combining their outputs.

In addition to the flood forecasting model for early warning system and disaster risk reduction, the developed ICML-FF model consistently produces more accurate prediction results according to the designated levels criteria of flood warning analysis, including normal level, alert level, warning level, and danger level. A better prediction result is essential towards achieving better flood early warning system and disaster risk management for major problems in urban floods. Furthermore, the developed data-driven based on machine learning methods could be an alternative in terms of prediction improvement and the robustness of the models.

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