INTELLIGENT FLOOD FORECASTING MODEL USING COMMITTEE MACHINE LEARNING FOR EARLY WARNING SYSTEM

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DEDICATION

This thesis is dedicated to my father, Ridwan who taught me that the best kind of knowledge to have is that which is learned for its own sake. It is also dedicated to my late mother, Amanah who taught me that even the largest task can be accomplished if it is done one step at a time. I came to this point also through the prayers of both my parents. My sister I'a Natus Sholihah, my wife, Rizki Aulia Rahmah and my children, Abram Xavier El Fawwaz, Zaydan Vishal Alfarez, Ruby Almahyra Feiyaz who always supporting me in any kind of situations.

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ABSTRACT

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 level and flow are crucial for flood forecasting in early warning systems and disaster risk reduction. Although some computational models achieved good prediction accuracy in particular problems, they might not perform well in different datasets. Thus, this study proposed a novel intelligence system using an ensemble committee machine-based framework to solve the "unstable" performance of the computational model to forecast flood with individual base learners by simple averaging and weighted averaging method. In addition, the use of simple averaging in the ensemble method is compromised by the worst-performing individual models in a collective forecast. The weights of different individuals should be tuned to find the optimal weight combination. This weight tuning algorithm can be treated as an optimisation problem. Thus, the genetic algorithm (GA) and K-nearest neighbour (K-NN) optimisation method were chosen for their flexibility and performance to improve the model's generalisability. The applied base learners using various machine learning algorithms include radial basis function neural network (RBFNN), adaptive-neuro fuzzy inference system (ANFIS), support vector machine (SVM), and long short-term memory network (LSTM). The committee machine model was employed to forecast the river water level at the downstream area in different lead times addressed for the three various datasets in different areas, including Kelantan river, Terengganu river in Malaysia, and Mekong river in Cambodia. Performance comparison of the models is evaluated and analysed using various performance metrics, including mean percentage error (MPE), root mean square error ($RMSE$), mean absolute error (MAE), and correlation coefficient (R). The results showed that the proposed Intelligent Committee Machine Learning (ICML) outperformed the individual base models for most performance indicators. Specifically, its $MPE, RMSE,$ and MAE of ICML by GA produced 2% - 70% smaller than the best individual and ICML-KNN-based model in the Kelantan dataset. Likewise, R values are 0.01% - 0.24% higher than the best ANFIS model and ICML by K-NN. The proposed ICML-GA based model has improved $MAEs$ performance in the Terengganu dataset, 0.26% - 4.5% smaller than the best individual model (LSTM). While R performance of ICML-GA model produced 0.01% - 0.06% better in all steps ahead forecasting horizons. While in the Mekong dataset, the ICML-GA model outperformed all performance indicators. Specifically, its $MPEs$ are 2% - 11% smaller than the best ANFIS and RBF model, 2% - 7% smaller in $RMSEs$, and 1% - 10% smaller in $MAEs$ than those ANFIS and RBF. In addition, R values improved 0.01% - 0.07% better than other individual models. In sum, the proposed ICML-GA model can robustly forecast river water levels to predict floods for early warning and disaster risk reduction and outperformed individual models and the ICML-KNN model for the case studies investigated in this work.

ABSTRAK

Hujan lebat di kawasan hulu sungai sering mengakibatkan peningkatan paras air sungai, yang membawa kepada bencana banjir yang teruk di kawasan tadahan hilir. Oleh itu, pemantauan secara intensif terhadap paras dan aliran air sungai adalah penting untuk ramalan banjir dalam sistem amaran awal dan pengurangan risiko bencana. Walaupun sesetengah model pengiraan mencapai ketepatan ramalan yang baik dalam masalah tertentu, model tersebut mungkin tidak berfungsi dengan baik dalam set data yang berbeza. Oleh itu, kajian ini mencadangkan sistem perisikan baru menggunakan rangka kerja berasaskan mesin jawatankuasa berkelompok untuk menyelesaikan prestasi "tidak stabil" model pengiraan untuk meramal banjir dengan pelajar asas individu dengan kaedah purata dan wajaran. Di samping itu, penggunaan purata mudah dalam kaedah kelompok terjejas oleh model individu yang berprestasi paling teruk dalam ramalan kolektif. Berat individu yang berbeza harus ditala untuk mencari kombinasi berat yang optimum. Algoritma penalaan berat ini boleh dianggap sebagai masalah pengoptimuman. Oleh itu, kaedah pengoptimuman algoritma genetik (GA) dan K-jiran terdekat (K-NN) telah dipilih untuk fleksibiliti dan prestasi baiknya untuk meningkatkan kebolehgeneralisasian model. Algoritma pembelajaran asas yang digunakan menggunakan pelbagai algoritma pembelajaran mesin termasuk rangkaian saraf fungsi asas jejarian (RBF), sistem inferens kabur neuro adaptif (ANFIS), mesin vektor sokongan (SVM) dan rangkaian memori jangka pendek yang panjang (LSTM). Model mesin jawatankuasa digunakan untuk meramalkan paras air sungai di kawasan hiliran dalam masa pendahuluan yang berbeza, ditujukan untuk tiga pelbagai set data di kawasan berbeza, termasuk sungai Kelantan, dan sungai Terengganu di Malaysia, dan sungai Mekong di Kemboja. Perbandingan prestasi model dinilai dan dianalisis menggunakan pelbagai metrik prestasi, termasuk ralat peratusan min (MPE), ralat min kuasa dua akar ($RMSE$), ralat mutlak min (MAE), dan pekali korelasi (R). Keputusan menunjukkan bahawa pembelajaran mesin jawatankuasa perisikan (ICML) yang dicadangkan mengatasi model asas individu untuk kebanyakan penunjuk prestasi. Khususnya, $MPE, RMSE$ dan MAE ICML-FF oleh GA menghasilkan 2% - 70% lebih kecil daripada model individu terbaik dan ICML-KNN dalam set data Kelantan. Begitu juga, nilai R adalah 0.01% - 0.24% lebih tinggi daripada model ANFIS terbaik dan ICML-KNN. Dalam set data Terengganu, model berasaskan ICML-GA yang dicadangkan telah bertambah baik dalam prestasi MAE, di mana 0.26% - 4.5% lebih kecil daripada individu terbaik (LSTM). Manakala prestasi R model ICML-GA menghasilkan 0.01% - 0.06% lebih baik dalam semua langkah ke hadapan ramalan ufuk. Semasa dalam set data Mekong, model ICML-GA mengatasi prestasi dalam semua penunjuk prestasi. Secara khususnya, MPEnya adalah 2% - 11% lebih kecil daripada model ANFIS dan RBF terbaik, dan 2% - 7% lebih kecil dalam $RMSE$, juga 1% - 10% lebih kecil dalam MAE daripada ANFIS dan RBF tersebut. Di samping itu, nilai R meningkat 0.01% - 0.07% lebih baik daripada model individu lain. Secara ringkasnya, model mesin jawatankuasa pintar ICML-GA yang dicadangkan mampu meramalkan paras air sungai yang mantap dan mengatasi model individu dan model ICML-KNN untuk meramalkan banjir untuk amaran awal dan pengurangan risiko bencana untuk kajian kes yang disiasat dalam kerja ini.

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LIST OF ABBREVIATIONS

ANN	-	Artificial Neural Network
GA	-	Genetic Algorithm
PSO	-	Particle Swarm Optimization
ICML	-	Intelligent Committee Machine Learning
CM	-	Committee Machine
FFP	-	Flood Forecasting Point
ANFIS	-	Adaptive Neuro Fuzzy Inference System
K-NN	-	K-Nearest Neighbour
SVM	-	Support Vector Machine
SVR	-	Support Vector Regression
LSTM	-	Long Short-Term Memory Network
RBF-NN	-	Radial Basis Function Neural Network
EPS	-	Ensemble Prediction System
PSA	-	Pattern Search Algorithm

LIST OF SYMBOLS

δ	-	Minimal error
D, d	-	Diameter
Y	-	Output River Water Level
Q	-	River Discharges
p	-	Pressure
$RMSE$	-	Root Mean Squared Error
MAE	-	Mean Absolute Error
MPE	-	Mean Percentage Error
R	-	Coefficient of Correlation
R^2	-	Coefficient of Determination

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CHAPTER 1

INTRODUCTION

1.1 Overview and Motivation

Nowadays, in many parts of the world, frequent floods have become part of people's lives, with increasing numbers and frequencies, which people have adapted for hundreds of years. These floods are usually expected and welcomed in some locations since they enrich the land and improve livelihoods (WMO and GWP, 2013). Floods are the world's most considerable damage potential compared to other natural catastrophes and affect the largest number of people. There is evidence of rising rates of the number of individuals impacted by floods which correspond to an increase in economic loss. The river flows in the local communities are increasing, becoming increasingly intense and less predictable. Building natural catastrophe resilience is one of this region's most significant problems for sustainable development. Floods are one of the most frequent natural disasters in Asia-Pacific, with devastating impacts on the poor and vulnerable populations who live along river basins and are dependent on agriculture for their livelihoods (UNESCAP, 2015).

Research on the advancement of flood forecasting models contributes to flood early warning and risk reduction, disaster management, minimising the loss of human life, and reducing property damage. Data-driven machine learning methods have been widely used in classification and regression tasks in inter-disciplinary studies, involving many engineering fields, hydroinformatics, and environmental studies. Innovative techniques and solutions based on machine learning methods have been developed with adequately published results. Emerging advances in computing technologies coupled with big-data mining have boosted data-driven applications. Machine learning technology has modernised scientific thinking and predictive applications with its flexibility and scalability in pattern extraction. This study investigates recent machine learning algorithms for flood water level forecasting to improve the model’s performance by combining individual models to form an advanced intelligent committee machine learning framework.

1.2 Research Background

Flood disasters continue to occur in many countries around the world due to the dynamic climate change condition. Among the natural hazards, flood disasters are the most destructive. Massive floods cause tremendous casualties to human life, properties and agriculture and disrupt a country’s socio-economic system. Governments, therefore, are under pressure to develop and provide accurate and robust flood forecasting for disaster risk management to reduce the impact of this disaster (Khalid and Shafiai, 2015). 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 (Jain *et al.*, 2018). 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 (UNISDR, 2015). 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.

Flood forecasting models are an essential component in many flood warning and emergency response systems. Models can assist by providing warnings of the likely timing and peak flow of the flooding in advance and helping to understand the complexities of flood events as they develop. Models output may also be used in decision support systems for flood event management. In addition, 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 (Sene, 2008).

To date, several flood forecasting models are mainly data-specific and involve simplified various input assumptions (Lohani *et al.*, 2014). Thus to mimic the complex mathematical expression of physical processes and river behaviour, such models benefit from specific techniques, e.g., empirical black-box models, stochastic and hybrids (Zhao *et al.*, 2018). These physically and statistically based models boost the usage of advanced data-driven methods, e.g., Machine Learning (ML) and Deep Learning (DL) techniques. Data-driven forecasting methods using ML are promising tools as they are less time consuming to develop with minimal inputs. ML technique is one of the most significant current discussions in Artificial Intelligence (AI) fields. Among them, the most well-known works of flood forecasting modelling include artificial neural networks (ANNs) (Napolitano *et al.*, 2010; Elsafi, 2014; Yaseen *et al.*, 2018), support vector machines (SVM) (Zhu *et al.*, 2016; Hong, 2008) and adaptive neuro-fuzzy inference system (ANFIS) (Lohani *et al.*, 2014; Ashrafi *et al.*, 2017). 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 (Guo *et al.*, 2018; He *et al.*, 2019; Qu *et al.*, 2019), respectively, for power load and probability density forecasting, traffic flow forecasting and rainfall forecasting. In addition, Cai *et al.* (2019) reported that deep learning performed better than the traditional ANN models in their work.

Previous methods are indicative of all individual models being capable of forecasting floods. Different AI models provide a similar acceptable efficiency but with different strengths and weaknesses. So that, exploiting the synergy among better performing models is an attractive proposition if the positive aspects of individual modelling techniques can be combined. One such technique is the Intelligence Committee Machine (ICM) or Committee Machine with Intelligent System (CMIS) models. This technique was explored in various disciplines, including river flow forecasting, gas reservoirs, and rock permeability predictions (Abrahart and See, 2002; Goswami and O'Connor, 2007; Bagheripour, 2014; Tatar *et al.*, 2014). These works typically use AI-based multi-model interfaces to exploit their synergy. Outputs from different AI models are used to reach the overall decision, thereby achieving better performance (Nadiri *et al.*, 2016). Researchers have successfully employed an ensemble committee-based data intelligent approach to generate soil moisture forecasts (Prasad *et al.*, 2018). The CMIS combines AI models by simple ensemble averaging or by weighted averaging, which is adopted via optimisation methods such as Genetic Algorithm (GA) (Kadkhodaie-Ilkhchi *et al.*, 2009). Gholami *et al.* (2018) compared GA and simple ensemble averaging method as combiners and concluded that the GA is more efficient. Notably, the term committee is understood to refer generally to the synergic combination of a few models and machine to be another word for artificial. The advantage of the CMIS is a capability for a nonlinear combination of AI models under supervision, leading to improvements in the performance of CMIS over individual AI models.

The forecasting of flood lead-time and location occurrence is fundamentally complex due to the dynamic nature of the monsoon phenomenon. Although extensive studies have been carried out on hydrological-flood forecasting models, very few identified AI approaches apply to all types of modelling (e.g., forecasting, optimisation, classification, etc.). Previously published studies are limited to one flood forecasting model employed in one reservoir. There was not a single AI technique suitable for all specific problems in general (Yaseen *et al.*, 2018). However, the nature of the presented models remains unclear, and flood peak needs to be forecasted more accurately. With this growth of forecasting techniques in hydrological data, these applied models still have a notable degree of shortcoming about their generalisation and implementation as an expert system. Therefore, the design of flood modelling remains a complex challenge that continues to be undertaken by researchers or scientists.

Investigating multi-model integration is a continuing concern within the field of advanced machine learning methods. It has been reported that the integration of intelligent systems and the committee machine concept can improve and optimise the performance of individual models (Kadkhodaie-Ilkhchi *et al.*, 2009). Although studies have recognised the idea of committee networks (Mosavi *et al.*, 2018; Fotovatikhah *et al.*, 2018), the use of CMIS based machine learning models is mainly unnoticed in engineering-hydrological science, especially for flood forecasting. Yaseen *et al.*

(2019) suggested that a further study then is needed focusing on using advanced-soft computing methods. Integration of individual machine learning-based models are largely unobserved in developing flood forecasting model. They are worth investigating in future research study. Based on these findings, the CMIS technique looks very promising and will be developed further in this study to obtain an improved flood forecasting model. A CMIS has a parallel framework that produces a final output by combining the results of individual models. Individual models include those widely employed in ML methods, including ANN, a hybrid neural network and fuzzy system, and support vector machine. Finally, the more recent ANN paradigm called deep learning will also be examined as an individual expert member in that particular committee machine network.

Committee machine-based model is designed by combining various types of machine learning algorithms or individual experts. It is essential to find suitable machine learning algorithms developed to create committee-based models. Therefore, the literature study reviewed the most successful machine learning models, including single and hybrid models developed for flood forecasting problems. Mosavi *et al.* (2018) reported many machine learning models developed in the literature for flood forecasting. Among them, ANN models, including multilayer perceptron and radial basis function, were the most successful model in the current development. In addition, SVM based model has increasingly been applied in this particular problem, as reported by Fotovatikhah *et al.* (2018). Despite the success story from the decision tree and random forest based model (Khosravi *et al.*, 2018; Muñoz *et al.*, 2018), the ANFIS model as part of the hybrid algorithm was effectively developed for the flood forecasting problem (Rezaeianzadeh *et al.*, 2014). The use of LSTM as part of the deep learning technique is selected as an individual expert to develop ICML based model since this model has received limited attention in the literature (Song *et al.*, 2019). Hence, combining their strengths could produce better generalisability to improve the model performances in the advanced ensemble machine learning technique.

The approach's usefulness is evaluated using real case studies for Malaysia's two (2) major rivers, Kelantan River and Terengganu River, as a representative flood forecasting point (FFP). In addition, one river across Cambodia, namely Mekong river, will also be considered as a case study. These reservoirs are among the most frequent seasonal flood disasters in Malaysia and Cambodia. Two significant types of flood occur in Malaysia are flash flood and monsoon flood. Some districts and states in Malaysia suffer from floods during the monsoon season, which this study will consider, especially in Kelantan and Terengganu. While flash flood reportedly occurs occasionally in Kuala Lumpur region (Abu Bakar *et al.*, 2017).

The applications in flood forecasting can be classified according to flood resource variables. These variables include river water level, flood peak discharge, urban flood, plain flood, river flood, precipitation, river inflow, peak flow, river flow, rainfall-runoff, flash flood, rainfall, streamflow, seasonal streamflow, soil moisture, rainfall-discharge, groundwater level, rainfall stage, flood frequency analysis, flood quantiles, surge level, extreme flow, storm surge, typhoon rainfall, and daily flows (Maier *et al.*, 2010). Among these critical influencing flood resource variables, rainfall and the streamflow river water level had the most significant role in flood modelling (Toukourou *et al.*, 2011), which will be considered more in this study.

1.3 Problem Statements

Data-driven modelling and computational intelligence, in general, have proven their applicability to various water-related problems. These include modelling, short and long-term forecasting, data classification, reservoir optimisation and building flood severity maps based on aerial or satellite photos (Ghaderi *et al.*, 2019). However, since natural processes are complex, it is sometimes impossible to build a single global model that adequately captures the overall system behaviour. According to Mosavi *et al.* (2018), in hydrological flood forecasting, data-driven machine learning methods were the most popular in improving the quality of the flood forecasting models. However, such individual machine learning models are helpful only when the model architecture and parameters are chosen correctly (Chen and Lin, 2006). Inappropriate models cannot learn the problem well and can easily lead to overfitting or poor generalisation. Hence, it affects their predictive performance.

Despite the developments of flood forecasting methods, there is still an increasing concern over the performance and ability of these models when used in various flood-prone areas. There are, however, issues with the accuracy of such models. For example, they may be quite accurate on average, where some error measures might be low. Still, they miss the extreme values (peaks or low values), which are essential in actual situations, e.g. flood early warning applications. Hence, using a single global model for a complex process is often inadequate (Mosavi *et al.*, 2018). In this case, machine learning algorithms lose their estimation abilities, and the results are poor if not invalid. Moreover, as recently reported by Yaseen *et al.* (2019) and Luo He *et al.* (2019), 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.

In addition to the ensemble of committee machines, combination methods among the individuals were essential to producing the final result, and over there, simple averaging is the most popular one (Kadkhodaie-Ilkhchi *et al.*, 2009). However, the disadvantage is that the important contribution of the individuals cannot be emphasised due to giving equal weights to all the individuals. Likewise, the overall model performance is compromised by the worst performing models (Prasad *et al.*, 2018). One another approach is by aggregating the individual models. A number of aggregating methods have been proposed, such as boosting (Li *et al.*, 2016), bagging (Yariyan *et al.*, 2020), stacking (Zhan *et al.*, 2018), and majority vote (Xie *et al.*, 2017). Among these combining methods, majority voting is widely used due to its simple implementation procedure. However, majority voting also has some disadvantages, for example, the majority voting decision rules often neglect a winning expert that obtains only a minority of correct results, and this downgrades the diversity of the ensemble, which is the primary reason for using the ensemble method (Jafari Kenari and Mashohor, 2013).

On the other hand, Ekbal and Saha (2011), and Zhang and Wang (2021) implemented a weighted majority vote to produce high prediction accuracy in their particular problems. Moreover, studies have been reported that weighted voting schemes can enhance the accuracy and robustness of the individual model compared with the simple majority vote (Ekbal and Saha, 2011a; Kim *et al.*, 2011). When using weighted voting, the weights of different base learners should be tuned to find the optimal weight combination. This weight tuning algorithm can be treated as an optimisation problem, which can be addressed using metaheuristic algorithms such as the genetic algorithm (GA). Thus, GA is then implemented in this study due to its robustness and good applicability for solving different complex optimisation problems (Esmaeili-Jaghdan *et al.*, 2016).

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 optimise it via GA for a collective forecast. This overcomes the weaknesses of conventional simple averaging forecast combinations as well as the majority vote. Consequently, according to the problems stated above, the following three research questions were posed:

(a) How to design and develop an improved committee machine model using intelligent systems (ANN, ANFIS, SVM and deep learning) for flood forecasting?

(b) How to determine an ensemble committee machine method that can improve the time series forecasts of the individual experts?

(c) How to identify the strengths of four individual experts and synergise them to improve the committee machine framework?

1.4 Objectives of Study

The primary goal of this study is to propose an enhanced design of a flood forecasting model utilising a committee machine with intelligent systems and observe how the consensus among these models can produce improvement to get better and robust performance. These individuals' intelligent system includes ANN, hybrid ANFIS, SVM and LSTM model. For further investigation, the specific objectives in this study were stated as follows;

(a) This study aims to design and develop an improved model, namely intelligent committee machine learning - flood forecasting (ICML-FF), based on four different intelligent systems, namely ANN, ANFIS, SVM and LSTM.

(b) This study seeks to determine and assess the generalisability of the ensemble ICML-FF based approach in order to improve accuracy by tuning the hyperparameters of individual models using the genetic algorithm.

(c) This study aims to investigate the capabilities of the individual model's contribution to improve the ensemble ICML-FF based framework in terms of forecasting accuracy.

1.5 Scopes of Study

This study's emphasis will be on designing and developing an intelligent committee machine model for flood forecasting in two major river basins in Malaysia, namely Kelantan and Terengganu rivers. Likewise, another river in Cambodia, Mekong river, will also be used as a case study. Four models will be developed as individual experts: an artificial neural network of the radial basis function kind, a hybrid neuro-fuzzy model, a support vector machine, and a long short-term memory network model. The simple averaging method is implemented as the aggregation strategies to combine the weights of the individual models. Finally, the weights are further tuned using the genetic algorithm optimisation method to produce the final forecasting result. In addition, the proposed ICML-FF was also compared with the existing committee machine model established for the flood forecasting problem. In this case, K-nearest neighbour (K-NN) is examined as the committee machine applied for flood peak discharge in Azmi *et al.* (2010). Furthermore, it is within the scope of this study to examine the performance comparison of individual intelligent experts and ICML-FF based models, as well as the comparison analysis with the existing committee machine model used for flood forecasting problem.

It was observed that the ML methods' characteristics varied significantly according to the period of prediction. Thus, dividing the study based on short-term and long-term was essential. Short-term forecasting for floods often refers to hourly, daily, and weekly predictions, and they are often used as warning systems. On the other hand, long-term forecasts are primarily used for policy analysis purposes. Furthermore, if the forecast leading time to flood is three days longer than the confluence time, the forecasting is considered to be long-term. From this perspective, according to Mosavi *et al.* (2018), a multi-step ahead of time forecasting horizon was set to hourly (from one to six hours ahead) for Kelantan River dataset. In contrast, a daily flood forecasting model (from one to six days ahead) was developed for Mekong river dataset. Thus, the lead time greater than three steps ahead considered as long-term forecasting in this present study. Hence, this study investigated the importance of advanced systems for both target tasks, consisting of short-term and long-term flood periods. However, only three steps ahead of time forecasting horizon was used for flood warning and risk reduction analysis.

1.6 Significance of Study

This study contributes to the existing knowledge of computational intelligence methods, particularly for machine learning techniques. This study aims to provide a significant opportunity to advance the understanding of this growing research area by exploring more soft-computing prediction methods. The proposed method can produce an applicable flood forecasting system, and it expects more robust and accurate forecasting of the flood to reduce the disaster impact. This new understanding should help to improve the forecasting model, particularly in flood disasters. Furthermore, this approach will prove helpful in expanding the proposed model into another study in a different flood-prone location. In general, the proposed model is expected to exhibit itself as a very optimistic predictive model that can be utilised as a viable alternative to the state-of-the-art soft computing methods for flood forecasting.

1.7 Thesis Organisation

This thesis consists of five chapters. The contents of each chapter are described as follows. Chapter 1 provides an introduction involving the overview and motivation conducted in this research study, including the background of the research, problem of the research, objectives of the study, the scopes and focus of the study, and the significance of the research study.

Chapter 2 explains existing researchers' fundamental knowledge and previously published studies about flood forecasting models utilising a data-driven machine learning-based approach. It also mentioned the strategy conducted to search the literature in the online databases. This chapter also describes the state of the art machine learning techniques in flood forecasting problems, including flood resource variables used, machine learning algorithms and its model's performances. Reviews of the most suitable machine learning models utilising as ICML-FF based model comprising RBF-NN, ANFIS, SVM and LSTM were discussed in this chapter. Furthermore, this chapter also explored the use of committee machines based on artificial intelligent algorithms. Moreover, the ensemble methods in constructing committee machine-based models to improve a model's performance are also explained. In addition, this chapter also reviews the benefit of the developed flood forecasting models for flood warning and risk reduction.

Chapter 3 provides a proposed ICML-FF framework to accomplish the objectives of the present study. This chapter starts with a general proposed research design and procedure. Then, the datasets of Kelantan River, Terengganu River, and Mekong River comprises the resources of river water level data, rainfall, and streamflow used as input and output variables of the proposed ICML-FF model are presented. The data preparation and model development process is described in this chapter. Furthermore, the evaluation matrices were addressed to measure the model's performances, which are root mean square error (RMSE), mean absolute error (MAE), mean percentage error (MPE), and coefficient of correlation value, R. The proposed ICML-FF framework was constructed by utilising individual experts, including RBF-NN, ANFIS, SVM, and LSTM model. Lastly, this chapter has also proposed the scenario of general flood warning for disaster risk reduction to final validation of the ICML-FF model.

Chapter 4 discusses research findings and analysing the simulation results of the proposed model. The research findings comprise the model's simulation results, including all mentioned individual experts in three different datasets. Furthermore, this chapter also discusses the proposed ICML-FF simulation results and their findings as well as comparison analysis using existing ensemble model by K-NN for flood forecasting problem. The comparison between the individual experts model's performances and the ICML model were discussed. All details about the evaluation matrices ($RMSE$, MAE, MPE, and R) performances were explained. In addition, this chapter investigated the effectiveness of the proposed ICML-FF model in applying flood warning and disaster risk reduction analysis.

Chapter 5 concludes the research accomplishment of the present study and describes the significant achievement and contributions of the study. In addition, this chapter summarised the successful completion of the research objectives and scopes. Finally, suggestions for improvements are provided, which can be used as directions for future research.

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LIST OF PUBLICATIONS

A. Indexed Journal Articles

1. **Faruq, A**., Marto, A., Izzaty, N.K., Kuye, A.T., Hussein, S.F.M. and Abdullah, S.S., 2021. 'Flood disaster and early warning: application of ANFIS for river water level forecasting'. *Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control*, pp.1-10.
2. **Faruq, A**., Marto, A. and Abdullah, S.S., 2021. 'Flood Forecasting of Malaysia Kelantan River using Support Vector Regression Technique'. *Computer Systems Science and Engineering*, *39*(3), pp.297-306. *(Scopus/ISI-Q3).*
3. **Faruq, A**., Arsa, H.P., Hussein, S.F.M., Razali, C.M.C., Marto, A. and Abdullah, S.S., 2020. 'Deep Learning-Based Forecast and Warning of Floods in Klang River, Malaysia'. *Ingénierie des Systèmes d Inf.*, *25*(3), pp.365-370. *(Scopus).*
4. **Faruq, A**., Abdullah, S.S., Marto, A., Abu Bakar, M.A., Mohd Hussein, S.F. and Che Razali, C.M., 2019. 'The use of radial basis function and non-linear autoregressive exogenous neural networks to forecast multi-step ahead of time flood water level'. *International Journal of Advances in Intelligent Informatics*, *5*(1), pp.1-10. *(Scopus).*

B. Indexed Conference Proceedings

1. **Faruq, A.**, Abdullah, S.S., Marto, A., Razali, C.M.C. and Hussein, S.F.M., 2020, June. 'Flood Forecasting using Committee Machine with Intelligent Systems: a Framework for Advanced Machine Learning Approach'. In *IOP Conference Series: Earth and Environmental Science* (Vol. 479, No. 1, p. 012039). IOP Publishing.
2. **Faruq, A.**, Abdullah, S.S., Marto, A., Bakar, M.A.A. and Mubin, A., 2020, April. 'River water level forecasting for flood warning system using deep learning long short-term memory network'. In *IOP Conference Series:*

Materials Science and Engineering (Vol. 821, No. 1, p. 012026). IOP Publishing.

C. Indexed Book Chapter

1. **Faruq, A.,** Marto, A., Abdullah, S.S., 'Intelligence Flood Forecasting Models for Disaster Risk Reduction'. In Understanding Systemic Risk, Investing in Disaster Resilience, (Vol. 2, No. 12), DPPC MJIIT, 2021, UTM Press.