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Flood Forecasting using Committee Machine with Intelligent Systems: a Framework for Advanced Machine Learning Approach

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Abstract. Among many natural hazards, flood disasters are the most incisive, causing tremendous casualties, in-depth injury to human life, property losses and agriculture, therefore affected the socioeconomic system of the area. Contributing to disaster risk reduction and the property damage associated with floods, the research on the advancement of flood modelling and forecasting is increasingly essential. Flood forecasting technique is one of the most significant current discussion in hydrological-engineering area, in which a highly complex system and difficult to model. The past decade has been seen the rapid development of machine learning techniques contributed extremely within the advancement of prediction systems providing better performance and efficient solutions. This paper proposes a framework design of flood forecasting model utilizing committee machine learning methods. Previously published works employing committee machine techniques in the analysis of the robustness of the model, effectiveness, and accuracy are particularly investigated on the used in various subjects. It is found that artificial neural networks, hybridizations, and model optimization are reported as the most effective ways for the improved development of machine learning methods. The proposed framework employs four representative intelligent systems as individual members, including radial basis neural networks, adaptive-neuro fuzzy, support vector machine and deep learning networks to construct a committee machine. As a conclusion, this committee machine with intelligent systems appears to be capable of enhancing the designing of flood forecasting model for disaster risk reduction.

1. Introduction

Flood disasters keep on happening in numerous nations around the globe due to the dynamic climate change condition. Among the natural hazards, flood disasters are the most destructive. Huge flood causing tremendous casualties, extensive damage to human life, property losses, agriculture and the socioeconomic system. In order to reduce the impact of this disaster, the governments, therefore, are under pressure to develop and provide an accurate and robust flood forecasting for disaster risk management [1]. Flood forecasting models are important in hazard assessment and extreme event management. The research on the advancement of flood forecasting is increasing since it contributes to disaster risk reduction, which is a difficult task, challenging and highly complex to model [2]. According

to Sendai Frameworks 2015-2030, disaster risk reduction (DRR) is given by priority number three and four, which are 'investing in disaster risk reduction for resilience' and 'enhancing disaster risk preparedness for effective response', respectively [3]. In connection with this viewpoints, hence flood modelling and forecasting is crucial for disaster risk management. In many regions of the world, flood forecasting is one among the few feasible options to manage flood disasters.

To date, a number of flood forecasting models are mainly data-specific and involve simplified various input assumption [4]. 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 [5]. These physically and statistically based models boost the usage of advanced data-driven methods, e.g., Machine Learning (ML) and Deep Learning (DL) technique. 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 discussion in Artificial Intelligence (AI) fields. Among them, the most well-known works of flood forecasting modelling include artificial neural networks (ANNs) [6], support vector machine (SVM) [7] adaptive neuro-fuzzy inference system (ANFIS) [8], were effectively employed for both short-term and long-term flood forecasting. As a new method in ANN models, deep learning is a major subject of interest within the field of AI methods. Deep learning is being studied in many types of problems such as image processing, speech recognition, and natural language processing. In the subject of forecasting, recent studies have been reported the successful use of deep learning in various fields [9], [10], [11] respectively for power load and probability density forecasting, traffic flow forecasting and rainfall forecasting. As it developed that deep learning proven reported better result than traditional ANN model [12].

Previous methods are indicative of all individual models being capable of forecasting the floods. Different AI models provide a similar acceptable efficiency but with different characteristic strengths and weaknesses. So that, exploiting the synergy among better performing models is an attractive proposition if the positive aspects of different modelling techniques can be combined. One such technique is Intelligence Committee Machine (ICM) or sometimes called Committee Machine with Intelligent System (CMIS) models that were explored in various disciplines; river flow forecasting, gas reservoirs and rock permeability predictions [13], [14], [15], respectively. It introduces an AI-based multi-model interface to exploit their synergy. This uses outputs from different AI models and determines the interface to reach the overall decision on identifying better performing AI models. Using ensemble committee-based data intelligent approach, researchers have successfully employed for generating soil moisture forecasts [16]. The CMIS combines AI model results by simple ensemble averaging [17] or by weighted averaging, which is adopted via optimization methods such as Genetic Algorithm (GA) [18]. Gholami et., al. [19] 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 sophisticated due to the dynamic nature of the monsoon phenomenon. Although extensive studies have been carried out on hydrological-flood forecasting models, there have been very few identified approach that can generally be applied particularly in AI which was applicable for all types of modelling (e.g., forecasting, optimization, classification, etc.). Previously published studies are limited to one flood forecasting model employed in one reservoir, and there was no single AI technique that was suitable for all specific problems in general [10]. However, the nature of the presented models remains unclear and flood peak needs to be forecasted more accurately. Along with this growth of forecasting techniques in hydrological data, all of these applied models still have a notable degree of shortcoming about their generalization and implementation as an expert system. Therefore, the design of flood modelling remains a passionate challenge that continues to be undertaken by researchers or scientists.

Investigating multi-model is a continuing concern within the field of advanced machine learning methods. It has been reported that model integration of intelligent systems and the concept of committee machine can improve and optimized performance than the individual model. Although studies have recognized the concept of committee networks, as investigated recently by [20] and [21] the use of

CMIS based machine learning models are largely unnoticed in engineering-hydrological science especially for flood forecasting. A further study as suggested by [22] then to focus on the use of advance-soft computing methods. The CMIS technique in order to obtain a better result of flood forecasting, therefore, is proposed in this study. A CMIS has a parallel framework that produces a final output by combining the results of individual models. These are consist of famous models that widely employed in ML methods which include ANN, a hybrid neural network and fuzzy system, and support vector machine. To eliminate the limitation of the usage of a single ANN model, an extending model into deep learning will also be examined as an individual expert member in that particular CMIS.

2. Application of Committee Machine in Various Study

The study of hydrological data processing, which includes flood hydrograph forecasting, has grown significantly since the early 1990s where physical-based models were long used to predict hydrological events such as storm, rainfall-runoff, streamflow forecasting and including floods [23]. Although physical-based models showed great capabilities for forecasting a diverse range of flooding scenarios, they often require various types of hydro-geomorphological monitoring datasets, requiring intensive computation, which prohibits short-term forecasting [24]. Due to these constraints, a large number of forecasting models that enhanced efficiency using available historical data are developed by the researchers, which are more robust and versatile [25].

Recently, the use of advanced data-driven methods, including AI models has been attracting considerable interest in flood forecasting problems. As a result, the practical research on flood forecasting based on AI models has significantly better performance result compared to the traditional approach. Jabbari and Bae [26] enhanced the accuracy of real-time flood forecasting using artificial neural network (ANN) models. Such ML algorithms like SVM [27], and hybrid ANFIS [28] were reported to be effective techniques for flood forecasting. Furthermore, a recent investigation by Taifur, et., al. [29] which employed a number of ML forecasting models showed good forecasting result of a flood using substantially less data, such as easily measurable flow stage. In order to eliminate the limitation of using single models, an extended model such as deep learning has been derived [30]. More recently, Caihong Hu, et., al. [30] introduced a state-of-the-art of Long Short-Term Memory (LSTM) as deep learning method in hydrological time-series data forecasting. Based on the simulation performance, LSTM models outperformed existing ANN model and found to be more stable.

In order to improve the performance accuracy and to achieve better dataset management, a multiple of ML modelling options were introduced for hydrological data in the last few years. Wang Bin, et, al [31] have demonstrated multi-model ensemble (MME) schemes to forecast historical monthly rainfall and temperature with machine learning methods, the MMEs obtained a better result than any individual model and can be more efficient and useful having improved performance accuracy. On the other hand, using the term combination of ML models, Moghadam, et., al. [32] implemented the proposed approach for flood susceptibility mapping. Although many studies have recognized the use of machine learning as part of artificial intelligence algorithms, the previous published study has yet to explicitly investigate the effectiveness of committee machine with intelligent system addressing for floods modelling and forecasting. The literature related to numerous studies on improving the performance of the model by using CMIS is summarized in Table 1.

Table 1. The use of CMIS for forecasting application in various fields

Authors/year	Application	Committee Models	Findings
Monomoy Goswami; Kieran M. O'Connor/2007 [14]	Flow forecasting in the absence of quantitative precipitation	Ensemble Average, Weighted Average, and Neural Network	Used the observed rainfall together with observed river flow is seen to considerably improve the performance of the flow forecasting model. (a) Ensemble autoregressive (AR) best in one-two days forecast.

			(b) ANN is best in more than 2 days ahead.
Afshin Tatar/2014 [33]	Prognosticating residual gas saturation in water drive gas reservoirs	Individual MLP; RBF and Least Square SVM; CMIS tuned by GA	Results reveal the robustness of CMIS for modelling the residual gas saturation.
Mohammad-Taghi Faghihi-Nezhad; Behrouz Minaei-Bidgoli/2018 [34]	Prediction of Stock Market	Ensemble Average; Weighted Average; GA and PSO. CMIS tuned by GA and PSO	GA and PSO respectively are applied in order to optimize the direction of the next price movement and create a new training data set. CMIS shows better result than individual models.
Asaad Y. Shamseldin; Kieran M. O'connor./2003 [35]	River flow forecasting	Linear function and MLP ANN	The committee with WAM and AR shows better result.
Amir Dashti et al./2018 [36]	Prediction of solubility of gases within H2-selective nanocomposite membranes	MLP-ANN; ANFIS; GA-ANFIS; GP Genetic Programming. CMIS tuned by GA.	CMIS shows better with (R^2) of 0.9999, 0.9987, 0.9998, 0.9995, and 0.9997 for CMIS, GP, GA-ANFIS, ANFIS and ANN models respectively.
Noradin Ghadimi./2018 [37]	Multi-block engine load and price forecast in smart grid	ANN; RBF-NN; SVM . CMIS tuned by feature selection and tuned by chaotic shark smell optimization (C-SSO)	The improved fusion algorithm outperforms and accurate result compared with other forecasting strategy includes ANN, SVM and RBFNN.
Ali Kadkhodaie-Ilkhchi1/2009 [18]	Estimation of Total Organic Carbon Content from Petrophysical	Fuzzy; AN-FIS; ANN. CMIS tuned by GA	CMIS shows better result than individual model employed.
Parisa Bagheripour/2014 [15]	Rock permeability prediction	MLP; RBF and Generalised Regression NN. CMIS tuned by GA	CMIS shows better result comparing with individual NN models.
Ramendra Prasad, et.,al./2018 [16]	Generating soil moisture forecasts	M5 model tree; Random Forest; Extreme Learning Machine. CMIS tuned by ANN	ANN-CMIS shows better result and performance.

Amin Gholami., et.,al./2017 [19]	Estimation of wax deposition	SVR and ANN ; CMIS tuned by GA	CMIS shows better than individual models.
M Azmi et al./2010 [38]	Hydrological Forecasting	Multi Linear Regression; MLP-ANN; KNN ; CMIS tuned by ensemble average and KNN	CMIS tuned by KNN shows better than simple averaging.
Robert J. Abrahart and Linda See./2002 [13]	River flow forecasting	ANFIS, Fuzzy and ARMA models. Each of Rivers models tuned by Simple Mean for each set of forecast; Single Best performing; Neural Network and Fuzzy Logic algorithm.	CMIS data fusion with NN shows better performance than individual model performing alone.

The literature has emphasised the important finding of the effectiveness committee machine models for prediction application in various discipline of studies. Afshin Tatar et, al. [33] presented the prediction of residual gas saturation utilizing committee machine intelligent technique in water drive gas reservoirs using petrophysical data. Three intelligent systems namely radial basis function (RBF), neural network multilayer perceptron (MLP), and least square support vector machine (LSVM) were employed. Whereas Nezhad and Bidgoli are more concerned with stock market predictions [34]. To optimise the combination of the mentioned experts, genetic algorithm (GA) and particle swarm optimization (PSO) were chosen as weighted averaging technique for its flexibility and well performance. Result obtained from the developed intelligent approaches more robust and had more desirable performance. Furthermore, to enhance the precision of ultimate rock permeability prediction, Parisa [15] was constructed a committee neural network model. The values of rock permeability derived from the MLP, RBF and generalized regression neural network (GNN) models. While Gholami et, al. [19] developed a combination of intelligent models through committee machine for the quantitative estimation of wax deposition. In this paper, committee machine was constructed for combining the results of the support vector regression (SVR) and ANN models.

In the field of hydrological area, Monomoy and Kieran [14] used a multi-model approach for real-time flow forecasting in the absence of quantitative precipitation forecasts. The outputs of the models in this scenario are combined using three techniques of the combination includes simple ensemble averaging method (SAM), the weighted averaging method (WAM) and the neural network method (NNM). Azmi et, al. [38] have presented a comparative assessment of five different methods multi-model data fusion in streamflow and flood peak discharged hydrological forecasting. Data fusion by *K*-nearest neighbour (KNN) algorithm was outperformed conventional methods. While Asaad [35] previously investigated the efficacy of using a combined simulation-mode for real-time river flow forecasting model. The objective of the approach is to pool the strengths and de-emphasise the perceptible weakness of the individual models in order to produce 'consensus' lead-time flow forecasting. All of three methods of model output combination produce very similar efficiency values which are generally better than the efficiencies of the individual models used in combination.

Figure 1 shown numerous schematic diagrams of committee machine developed by the previous researchers in the various field of problems; prediction of fluoride concentration [39], estimation of total organic carbon [18], prognosticating residual gas saturation [33], prediction of solubility of gases [36].
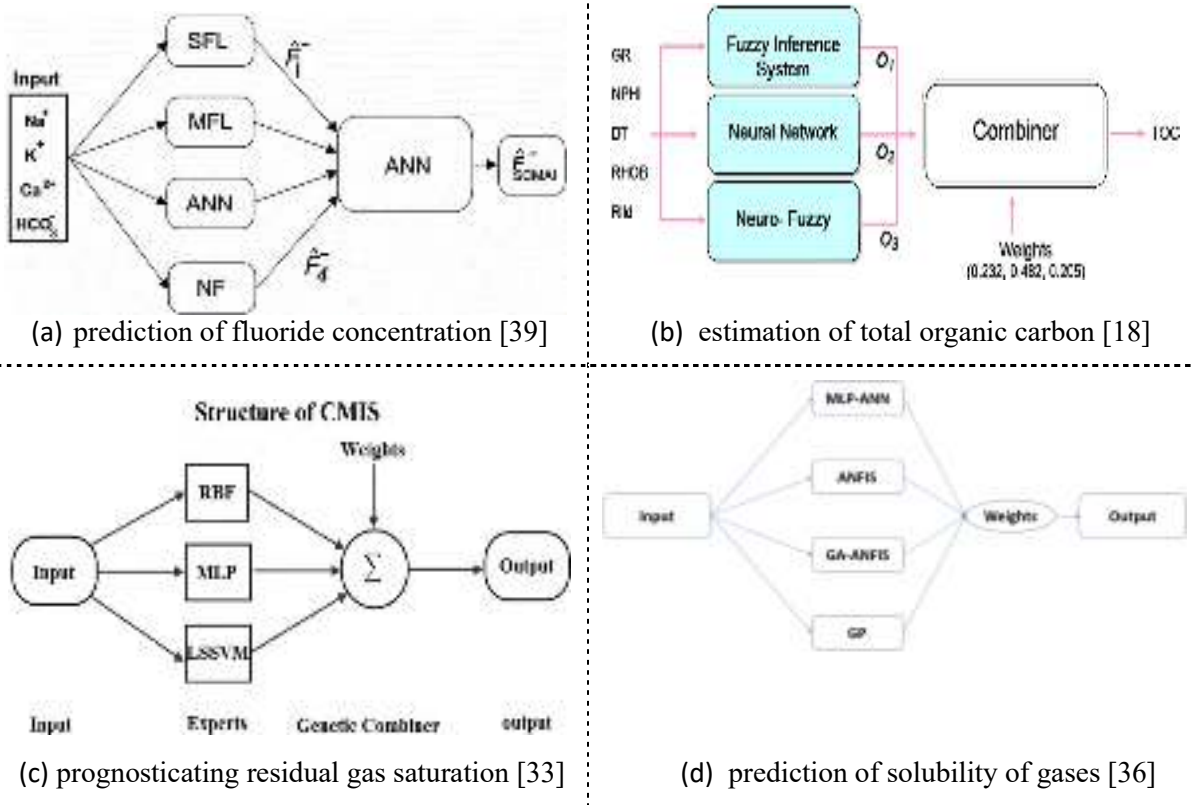
(a) prediction of fluoride concentration [39]

(b) estimation of total organic carbon [18]

(c) prognosticating residual gas saturation [33]

(d) prediction of solubility of gases [36]

Figure 1. Schematic diagram of CMIS design used in various disciplines.

3. Proposed CMIS Model Frameworks

There are some reasons for distributing a learning task among a number of individual networks. The main reason is due to improving the generalization ability because the generalization of individual is not unique. The combination of some ANNs when they do the same task is called as the ensemble of neural networks or committee of neural networks. Haykin [40] namely the combination of experts constitute a committee machine. In this terminology, the author utilizes the combination of ANN models to construct the committee machine. On the other hand, when the networks are different it is called a committee of machine, which are ensemble frameworks of single individual machine learning models [41]. Basically it fuses a knowledge acquired by experts to arrive at an overall decision that supposedly superior to the attainable by any one of them acting alone.

The proposed methodology comprises of three major steps. At the first stage, the flood water level will be forecasted from the individual expert as intelligent systems (this study, e.g. RBFNN, ANFIS, SVM and DCNN). Then a committee machine with this mentioned intelligent system is constructed to get better generalization functions based on machine learning approach. After the construction of individual intelligent models, it is necessary to find a suitable method to combine individual results. The last phase of the design CMIS is the combination of the individual outputs. In this study, ensemble method based on CMIS design includes ensemble averaging and the weighted averaging algorithm will be addressed. A schematic diagram of proposed CMIS can be illustrated in Figure 2.
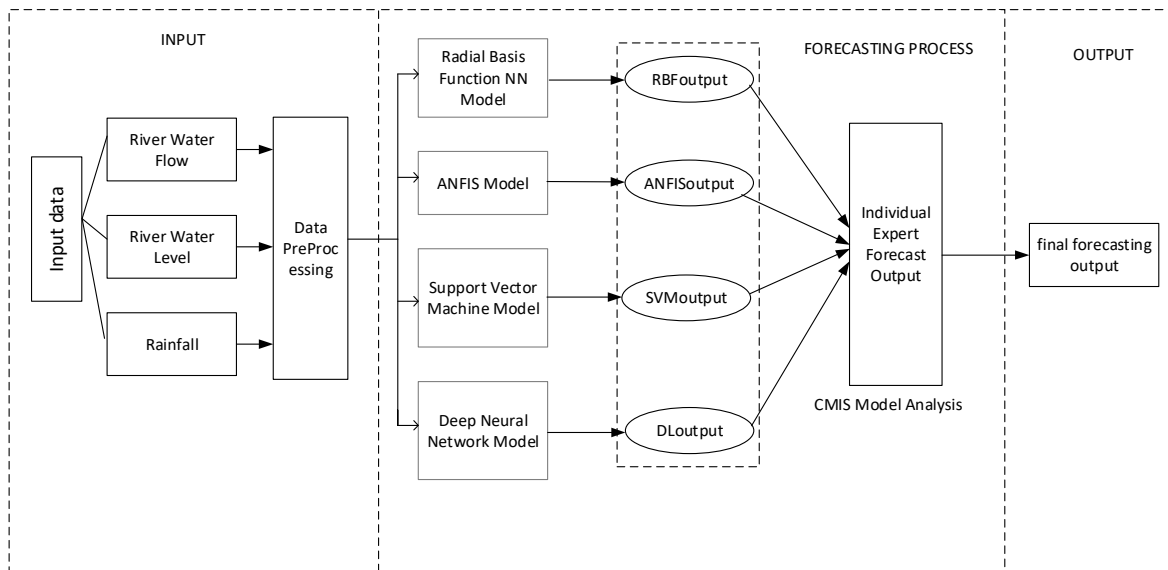
Figure 2. The schematic of the proposed CMIS flood disaster forecasting frameworks

The applications in flood forecasting can be classified according to flood resource variables, i.e., 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 [23]. Among these key influencing flood resource variables, rainfall and the streamflow river water level had the most remarkable role in flood modelling [24]. In Figure 2, three differences input data includes river water flow (streamflow), river water level, and rainfall is proposed in this study.

3.1. Ensemble Model Based on CMIS

Committee machines attempt to minimize the errors of individual learning algorithms or machines by grouping them and making them work synergistically. The ensemble is a more robust model than the model represented by any individual machine. The last phase of designing committee machine with intelligent system is the combination of the individual-intelligent outputs. Numerous examinations have been done to discover the consolidation techniques to combine the individual outputs and produce the final output values. In committee machine methods, the ensemble candidates are different. There are a number of methods to create different individual training data, the initial condition, the topology of nets, and the training algorithms. After selecting individuals and training them, their generated results will be combined with some methods.

There are two methods to determine weights for CMIS; simple ensemble averaging using equal weights and weighted averaging using optimized weights [39]. In the simple ensemble averaging approach, the outputs can just take the average as given by Equation (1), and the weighted averaging approach with the gates $g_i(x(p))$ can be generated in any convenient manner, the outputs are gated according to the inputs.

$$y(p) = \sum_{i=1}^{n} \frac{1}{n} y_i(p) \quad and \quad y(p) = \sum_{i=1}^{n} g_i(x(p)) \, y_i(p) \tag{1}$$

An ensemble average consists of a set of training models which share a common input $x(p)$ for training pattern p, and whose individual outputs $y_i(p)$ are combined to produce an overall output $y(p)$. The authors Opitz and Shavlik [42] presented the algorithm that uses genetic algorithm to explicitly search for a highly diverse set of accurately trained networks. Application on the permeability prediction

using committee machine also presented in [17], ensemble averaging method is computed according to the weight. The optimal combination of the weight for prediction is also investigated using genetic algorithm [43]. The proposed combining method using fuzzy genetic algorithm gives smallest error and highest correlation on the reliability of the permeability predictions [41]. While the authors [44] obtained optimal weight factors by using a genetic algorithm-pattern search (GA-PS) to predict Poisson's ratio. The model constructed by CMIS approach consists of radial basis neural network, Sugeno fuzzy inference system and ANFIS models.

To obtain the optimal weights for combining using GA algorithm, the fitness function as defined in the Equation (2).

$$MSE_{GA} = \sum_{i=1}^{n} \frac{1}{n} (w_1 y_{1i} + w_2 y_{2i} + \cdots w_k y_{ki} - T_i)^2; \sum_{i=1}^{n} w_i = 1 \tag{2}$$

Where, y_{1i} is the output of the first network on the $i-th$ input or $i-th$ training pattern, w_i is the weight of the ith member, T_i is the target value of ith input, and n is the number of training data.

4. Conclusion
The present formulation of developed ML modelling for flood forecasting is relatively young and in the early stage of advancement. Previous studies indicated that in the context for improving the quality of prediction, the novel ensemble and advance hybridizations methods are challenging to be studied. An applicable flood forecasting model using advance committee machine learning approach is proposed in this work. This new understanding should help to improve the forecasting technique particularly in flood disasters. In general, the proposed CMIS framework is expected to exhibit itself as very optimistic predictive model that can be utilized as a viable alternative to the state-of-the-art of advanced soft computing for flood forecasting technique.

Further work should be undertaken to develop individual machine learning algorithms, constructing the committee machine with intelligent systems model and employs these models into some considered case study. Enhance the CMIS model and algorithm to get a better result, more robustness flood forecasting model and reliable design. Examine the proposed models into the real system in term of benchmarking study can be considered. The national flood prevention and warning program as known as Program Ramalan dan Amaran Banjir Negara, Malaysia, therefore can be an option in case of benchmarking application. The potential proposed method can also be tested in diverse area flood forecasting data in a way to check the generalization capability of the CMIS model.

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