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Prediction of Flood in Barak River using Hybrid Machine Learning Approaches: A Case Study

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ABSTRACT

Flooding causes several threats with outcomes which include peril to human and animal life, damage to property, and adversity to agricultural fields. Therefore, flood prediction is of prime importance for reducing loss of life and devastation to property. To model complex nature of hydrologic processes artificial neural network (ANN) tool is effectively being utilized for modelling different nonlinear relationships, and has proved to be an appropriate method for flood prediction. Present study investigated relative accuracy of radial basis function neural network (RBFNN) and support vector machine (SVM) models combined with Firefly Algorithm (FA) in predicting river flood discharge and contrasted with that of regular ANN, RBFNN and SVM models. Monthly river flow data of Silchar and Dholai stations located in Cachar district of Assam, India are utilized for the present study. For assessing model performance, coefficient of determination (R^2), mean square error (MSE) and root mean square error (RMSE) were measured. Evaluation of outcomes shows that both RBF-FA (radial basis function - firefly algorithm) and SVM-FA (support vector machine - firefly algorithm) hybrid models give more precise forecasting results than RBFNN, FFBPNN (feed forward back propagation neural network) and SVM models. Yet, it can be observed that SVM-FA model give better forecasting outputs with R^2 value 0.9818 than RBF-FA model. Results also reveal that simple SVM model performs marginally better than simple ANN model.

INTRODUCTION

Flood causes lot of destruction, damaging roads and buildings, agricultural lands etc. Therefore, for reducing vulnerability, prevention and safeguard strategies are essential. Consistent and precise flood forecasting is very crucial for flood prone areas in particular. Magnitude of impact and irretrievable amount of destructions caused by flooding makes application of flood control and deterrence processes inevitable (Billa et al., 2006; Hu et al., 2014). Application of hydrological and hydraulic tools that give data and statistics regarding degree of flood inundation, water level and velocity on basis of 1-D or 2-D hydraulic models are most common flood peril and threat analysis techniques (Mazzoleni et al., 2014; Gharbi et al., 2016). Yet, 1-D or 2-D models are mostly used in small scale ventures, as application of these necessitate massive extent of data with greater accuracy. Furthermore, physical models that integrates hydrological and hydraulic approaches entails a large processing control and is highly time consuming making these models less attractive analytical tools for regional study (Shrestha et al., 2013; Buahin and Horsburgh, 2015). Physical recognition structures utilize models for predicting flood conditions on the basis of various constraints (Elsafi, 2014). Among these models, ANNs are one such tool and may provide a promising alternative to forecast many hydrologic processes. Use of ANNs have been found as most preferred machine learning (ML) techniques as these techniques outperforms most customary approaches (Ghumman et al. 2011).

Chang et al. (2001) constructed a rainfall–runoff model for forecasting one-hour, two-hour, and three-hour ahead flood flows using a modified RBFNN model with fuzzy – clustering. Results exhibited that projected model effectively helped in constructing a rainfall–runoff model and gave high precision in predicting flood flow. Kisi et al. (2011) applied ANN, adaptive-network-based fuzzy inference system (ANFIS) and SVM to forecast daily sporadic stream flow of Thrace County situated in north-west Turkey and also compared the outcomes with those of local linear regression (LLR) and dynamic LLR. Outcomes showed that performance of ANN, ANFIS and SVM were better in comparison to LLR and DLLR models in estimating daily sporadic stream flow. Kisi and Cimen (2011) examined accuracy of wavelet and SVM hybrid model to forecast monthly stream flow of Goksudere river, Turkey and compared its performance with single SVM. Test results showed that wavelet transform significantly increased accuracy of SVM model and also served as a better alternative to develop input-output simulations in forecasting monthly stream flows. Zounemat-kermani et al. (2013) applied multi-layer FFBPNN utilizing Levenberg–Marquardt learning algorithm, RBFNN, multiple linear regression (MLR) model for predicting one day ahead daily stream flow of Cahaba watershed, Alabama. Results indicated that ANN approaches outperformed MLR in predicting stream flow dynamics. Hipni et al. (2013) utilized SVM for forecasting daily dam water level of Klang reservoir located in Kualumpur, Malaysia and compared the results with ANFIS model. Based on performance evaluation parameters, SVM showed better results with different input combinations in forecasting dam water level. Tehrany et al. (2015) proposed a new hybrid technique by combining SVM and frequency ratio (FR) for assessing flood susceptibility spatial model of Kelantan river situated in Malaysia. Results obtained ascertained the efficacy of projected hybrid technique as fast, precise and equitable in assessing flood susceptibility. Yan et al. (2018) developed a model framework combining MIKE FLOOD with SVM for forecasting flood alert and maximum flood depth of Jinlong River Basin, Hangzhou, China. Combination of a numerical model with SVM proved to be very useful in urban flood forecast. Results indicated that SVM showed its potential for early flood warning system and forecasting flood depth. Mosavi et al. (2018); Jain et al. (2017) demonstrated various facets of flood forecasting, comprising of previously used models, developing methods for input collection, exhibiting outcomes, uncertainties, and flood warnings. Also they introduced best favorable prediction approaches for long and short term floods and investigated key trends for improving quality of prediction models.

Adnan et al. (2015); Ruslan et al. (2013) proposed RBFNN and an upgraded RBFNN to predict flood water level using water stage data from Kelang river, Kuala Lumpur. Results indicated that upgraded RBFNN model was more dependable and enhanced prediction of flood water level significantly as compared to original RBFNN based on

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performance indices. Yaseen et al. (2015) proposed FFBPNN and RBFNN to forecast daily stream flow at Johor river, Malaysia, for a period of 1999–2008. Results demonstrated that RBFNN performed better compared to FFBPNN and provided accurate and reliable daily stream flow forecasting. Tehrany et al. (2015) assessed and evaluated the ability of SVM technique with linear, polynomial, RBFNN, and sigmoid kernel functions for spatially predicting flood occurrence at Kuala Terengganu river basin, Malaysia. Result demonstrated that SVM served as a proficient and dependable approach in assessing flood susceptibility. Ghorbani et al. (2016) explored usefulness of multilayer perceptron (MLP), RBFNN and SVM models to predict river flow time series of Zarrinehrud River situated in north-west Iran. Results indicated that uncertainty in predicting monthly river flow was less in SVM as compared to RBF and MLP models.

Li et al. (2016) presented an SVM model on basis of kernel principal component analysis and boosting algorithm for flood forecasting of Huaihe river, China. Results indicated that the SVM conjunction model effectively improved flood forecasting accuracy at the proposed study area. Tayyab et al. (2017) applied FFBPNN and RBFNN models combined with discrete wavelet transform (DWT), for forecasting monthly stream flow at Jinsha River, China and analyzed effect of high-frequency constituents on model performance. Comparative study revealed that conjunction of RBFNN with DWT has enhanced forecasting abilities in comparison to other proposed models. Ahmed and Shah (2017) utilized RBFNN and MLP for analyzing Surma River flow located in north-east Bangladesh and estimated its peak flow rate for flood related study on basis of five input parameters. Results revealed that MLP and RBFNN predicted peak flow in Surma river with adequate accuracy but RBFNN showed slightly better performance than MLP. Hong et al. (2018) projected a new approach by employing fuzzy weight of evidence (fuzzy-WofE) and combined it with logistic regression (LR), random forest (RF) and SVM for mapping flood vulnerability region in Poyang Province and JiangXi area, China. Based on outcomes and flood prone map, hybrid fuzzy WofE-SVM approach showed best results with maximum predictive performance and likewise found to be of statistically substantial as compared to other predictive models. Panigrahi et al. (2018) applied MLP, RBFNN, Local Linear RBFNN (LLRBFNN) and ANN with Whale Optimization for predicting flood situation in terms of various input parameters from contextual study of Daya and Bhargavi rivers, India and improving accuracy in prediction of flood events. Results obtained showed that LLRBFNN is found to be most effective in flood forecasting based on its performance as compared to other ANN models. Kartika et al. (2019); Sanubari et al. (2018) proposed RBFNN model for predicting flood at different locations of Indonesia. RBFNN was found to be helpful in predicting one-month, two-month ahead flood using previous flood-instigating constraints such as rainfall and river water level data as inputs with greater accuracy and precision. Sankaranarayanan et al. (2019) applied SVM, k-nearest neighbors (KNN), Bayes and deep neural network (DNN) for predicting flood at 10 major districts of Bihar and Odisha. Proposed techniques were validated and performance of the models were compared which indicated that DNN can be competently utilized to forecast flood with highest accurateness on basis of monsoon parameters. Faruq et al. (2019) employed non-linear auto regressive exogenous (NARX) and RBFNN technique for forecasting multi-step ahead flood water level at Kelantan river, Malaysia. Outcomes revealed that NARX showed better performance in forecasting flood level as compared to RBFNN.

Zhao et al. (2019) applied weakly labeled SVM (WELLSVM), LR, ANN, and SVM for assessing the flood susceptibility of cosmopolitan regions in Beijing with limited flood inventories. Results showed that WELLSVM utilized unlabeled data, outperformed all proposed models as well as developed high-quality flood susceptibility map for efficient urban flood management. Bafitlhile and Li (2019) applied ε-SVM and ANN to simulate and forecast stream flow of Changhua, Chenhe and Zhidan catchments under different geo-climatic conditions. Performance of two models was contrasted, and outcomes indicated that ε-SVM model mostly performed better than ANN in forecasting stream flow for all watersheds. Various ANN techniques namely BPNN, RBFNN, SVM, Recurrent neural network were applied with different input combinations for hydrological constraints at different watersheds of Odisha district, India. Performance of the proposed models were compared based on statistical parameters for finding the best suitable model (Samantaray and Sahoo 2019 a, b; Samantaray et al. 2019; Sahoo et al. 2019). Awchi (2018) examined and evaluated the application of FFBPNN, generalized regression neural network (GRNN), and RBFNN to forecast water flow level of upper and lower Zab rivers in north province of Iraq and compared outcomes with MLR. Based on performance evaluation criteria FFBPNN performed best followed by RBFNN and GRNN respectively.

ChePa et al. (2016) urbanized firefly optimization algorithm (FA) and web-based mobile app for reallocating victims and resources of evacuation centre at time of worst situation during an extreme flood disaster in Kelantan district, Malaysia. Soleymani et al. (2016) developed a novel RBF-FA model for prediction of water level of Selangor River, Malaysia and validated the proposed model with SVM and MLP. Obtained results showed that developed hybrid model provides more precise predictions and can be utilized as a competent method for precise prediction of river water level compared to SVM and MLP. Khatibi et al. (2017) used hybrid ANN model integrating MLP and Levenberg–Marquardt (MLP-LM) along with MLP and FA (MLP-FA) for predicting monthly stream flow of Bear river, USA. Results indicated that integrated MLP-FA model provided substantial development over customary MLP-LM method. Mehr et al. (2018) developed an integrated regression model combining SVM and FA to forecast 1-month ahead precipitation at Tabriz and Urmia stations, situated in semi-arid region of Iran. Results revealed that SVM-FA model significantly performed well and forecast monthly rainfall with better accuracy as compared to simple SVM, FA and Multigene genetic programming models. Hammid et al. (2018) suggested a robust FA on basis of k-fold cross validation of BPNN for predicting data to keep rapid learning and for improving a competent method to predict problems discovering effective solutions at high convergence speed of Himreen Lake dam. Suggested hybrid FA model outperformed other projected models in terms of rapidness and prediction accuracy. Darbandi and Pourhosseini (2018) used integrated models namely MLP–FA and MLP–ANN for forecasting monthly river flow of Ajichay watershed, east Azerbaijan. Results showed that MLP–FA hybrid model satisfactorily forecast river flow level based on best input combination with greater accuracy and precision in study area.

Huang et al. (2014) investigated accuracy of developed hybrid model integrating empirical mode decomposition (EMD) with SVM to forecast monthly stream flow of Wei river, China. Outcomes showed that hybrid EMD–SVM model has good consistency, great representative nature and high prediction accuracy. Kisi et al. (2015) urbanized a novel amalgam model integrating SVM and FA for predicting daily water level of Urima lake located in northwest region of Iran and compared the results with GP and ANN. Results showed that conjunction of SVM-FA model improved prediction accuracy and ability to generalize in 1 day ahead lake level forecast. Samantaray and Sahoo (2019) employed RBFNN and hybrid SVM-FA model to predict climatic parameter of a watershed in Odisha, India. Results indicated that SVM-FA showed better performance than RBFNN. Mohamadi et al. (2019) used ANFIS, MLP, RBFNN models along with six conjunctive models namely RBF-SA (Shark Algorithm), MLP-SA, MLP-FA, ANFIS-SA, ANFIS-FA, and RBF-FA for predicting monthly evaporation in Mianeh and Yazd stations, Iran. Results

Table 1. A review of applications of machine learning models for flood forecasting.

Authors (year of publication)	Methods	Major findings
Chang et al. (2001)	Modified RBFNN model with fuzzy – clustering	Constructed rainfall–runoff model for forecasting one-hour, two-hour, and three- hour ahead flood flows
Cimen (2011)	SVM and Hybrid wavelet-SVM	Forecast monthly stream flow of Goksudere River, Turkey
Kisi et al. (2011)	ANN, ANFIS, SVM, LLR and dynamic LLR	Forecast daily sporadic stream flow of Thrace County, Turkey
Hipni et al. (2013)	SVM and ANFIS	Forecasting daily dam water level of Klang reservoir located in Kualumpur, Malaysia
Zounemat-kermani et al. (2013)	Multi-layer FFBPNN utilizing LM learning algorithm, RBFNN, (MLR)	Predicting one day ahead daily stream flow of Cahaba watershed, Alabama
Huang et al. (2014)	EMD–SVM	Forecast monthly stream flow of Wei River, China
Yaseen et al. (2015)	FFBPNN and RBFNN	Forecast daily stream flow at Johor River, Malaysia
Tehrany et al. (2015)	Hybrid SVM and frequency ratio (FR)	Assessing flood susceptibility spatial model of Kelantan River situated in Malaysia.
Tehrany et al. (2015)	SVM technique with linear, polynomial, RBFNN, and sigmoid kernel functions	Predict flood occurrence at Kuala Terengganu river basin, Malaysia
Adnan et al. (2015); Ruslan et al. (2013)	RBFNN and improved RBFNN	Predict flood water level Kelang river, Kuala Lumpur
Kisi et al. (2015)	GP, ANN, SVM-FA	Predicting daily water level of Urima Lake located in North-West region of Iran
ChePa et al. (2016)	FA and web-based mobile app	Reallocating victims and resources of evacuation centre during an extreme flood disaster in Kelantan district, Malaysia
Li et al. (2016)	SVM	Flood forecasting at Huaihe River, China
Soleymani et al. (2016)	SVM, MLP, RBF-FA	Water level prediction of Selangor River, Malaysia
Ghorbani et al. (2016)	MLP, RBFNN and SVM	Predict river flow time series of Zarrinehrud River
Ahmed and Shah (2017)	RBFNN and MLP	Estimated its peak flow rate of Surma River for flood related study
Jain et al. (2017)	Review papers on NN	Review on flood forecasting models
Khatibi et al. (2017)	MLP-LM and MLP-FA	Predicting monthly stream flow of Bear River, USA
Tayyab et al. (2017)	FFBPNN and RBFNN models combined with DWT	Forecasting monthly stream flow at Jinsha River, China
Mosavi et al. (2018)	Review papers on NN	Review on flood forecasting models
Yan et al. (2018)	MIKE FLOOD with SVM	Forecasting flood alert and maximum flood depth of Jinlong River Basin, Hangzhou, China
Hong et al. (2018)	Fuzzy-WofE and combined it with LR, RF and SVM	Mapping flood vulnerability region in Poyang Province and JiangXi Area, China
Panigrahi et al. (2018)	MLP, RBFNN, LLRBFNN and ANN with Whale Optimization	Predict flood situation of Daya and Bhargavi rivers, India
Mehr et al. (2018)	SVR and FA	Forecast 1-month ahead precipitation at Tabriz and Urmia stations, situated in semi-arid region of Iran
Darbandi and Pourhosseini (2018)	MLP–FA and MLP–ANN	Forecasting monthly river flow of Ajichay watershed, East Azerbaijan.
Awchi (2018)	FFBPNN, GRNN, RBFNN and MLR	Forecast water flow level of Upper and Lower Zab Rivers in North province of Iraq
Sankaranarayanan et al. (2019)	SVM, KNN, Bayes and DNN	Predict flood at 10 major districts of Bihar and Odisha
Kartika et al. (2019); Sanubari et al. (2018)	RBFNN	Predict flood at different locations of Indonesia
Faruq et al. (2019)	NARX and RBFNN	Forecasting multi-step ahead flood water level at Kelantan River, Malaysia
Bafitlhile and Li (2019)	-SVM and ANN	Simulate and forecast stream flow of Changhua, Chenhe and Zhidan catchments
Samantaray and Sahoo (2019)	RBFNN and hybrid SVM-FA	Predict climatic parameter of a watershed in Odisha, India
Mohamadi et al. (2019)	ANFIS, MLP, RBFNN, MLP-SA, MLP-FA, ANFIS-SA, ANFIS-FA, and RBF-FA	Predicting monthly evaporation in Mianeh and Yazd stations, Iran
Zhao et al. (2019)	WELLSVM, LR, ANN, and SVM	Assessing flood susceptibility of cosmopolitan regions in Beijing

demonstrated that developed ANFIS-SA model was considered as the commanding method to predict evaporation with better prediction accuracy. A summary of highlighting major finding for each study are given in Table 1;

Objective of present research is to explore capability of RBF and SVM models combined with FA to predict flood discharge. Also a comparison of the hybrid models with that of regular ANN and SVM models is done. This study presents a comparison of prediction ability of SVM and ANN models combined with FA to predict flood at two selected gauge stations which is a novel application in field of flood prediction.

STUDY AREA

Assam (Fig. 1B) has two major rivers – Brahmaputra and Barak. Each year these two rivers and their tributaries cause floods in vast areas of Assam which leads to devastation. The destruction of properties and loss of life is visible every passing year, hence affecting the economic condition of the state.

Barak river emerges from Liyai Kullen Town of Manipur, India and passes in to plains near Lakhimpur with a basin size of 52,000 sq km. During its flow, it drains largely through Manipur, Nagaland, Mizoram and Assam states of India (Fig.1A). Total river length from its starting point to meeting at Bay of Bengal through Bangladesh is around 900 km and 524 km of the total length flows through India, 31 km on India and Bangladesh border and rest in Bangladesh. Barak basin surroundings have a varied diversity of flora and fauna. Physiographic regions of Barak basin are highly inhabited. Laterite, red and yellow soils are major soil types found in this region. For present study two gauging stations Silchar and Dholai are considered as shown in Fig.1C.

METHODOLOGY

Artificial Neural Network

In recent years, artificial intelligence approaches have been utilized and applied in numerous fields with a greater deal of accomplishments. Like a data processing arrangement, ANN comprises of several non-linear, arbitrary and solid interrelated processing components known as neurons that are structured in sets called layers. Elementary advantages of ANNs are that they do not need info on complex nature of primary processes under reflection that are evidently designated in precise mathematical forms. ANN is a recognized and a proficient way to model miscellaneous and multifaceted input–output combinations in many hydrological time series analysis.

ML utilizes innovative algorithms which analyze data, acquires knowledge from it, and utilize this knowledge for discovering meaningful interest patterns. However a NN comprises of a collection of algorithms applied in ML to model data utilizing neurons graphs. While ML models make assessments in accordance to whatever it has learned from data, NN organizes algorithms in a suitable manner so that it can make effective verdicts on its own. As ML models learn from data in preliminary phases, they may need certain human involvement. On the other hand, NNs need no human interventions because nested layers present within transfer data via hierarchies of different concepts, eventually making them able to learn from their personal errors. ML models can be classified into two categories i.e.

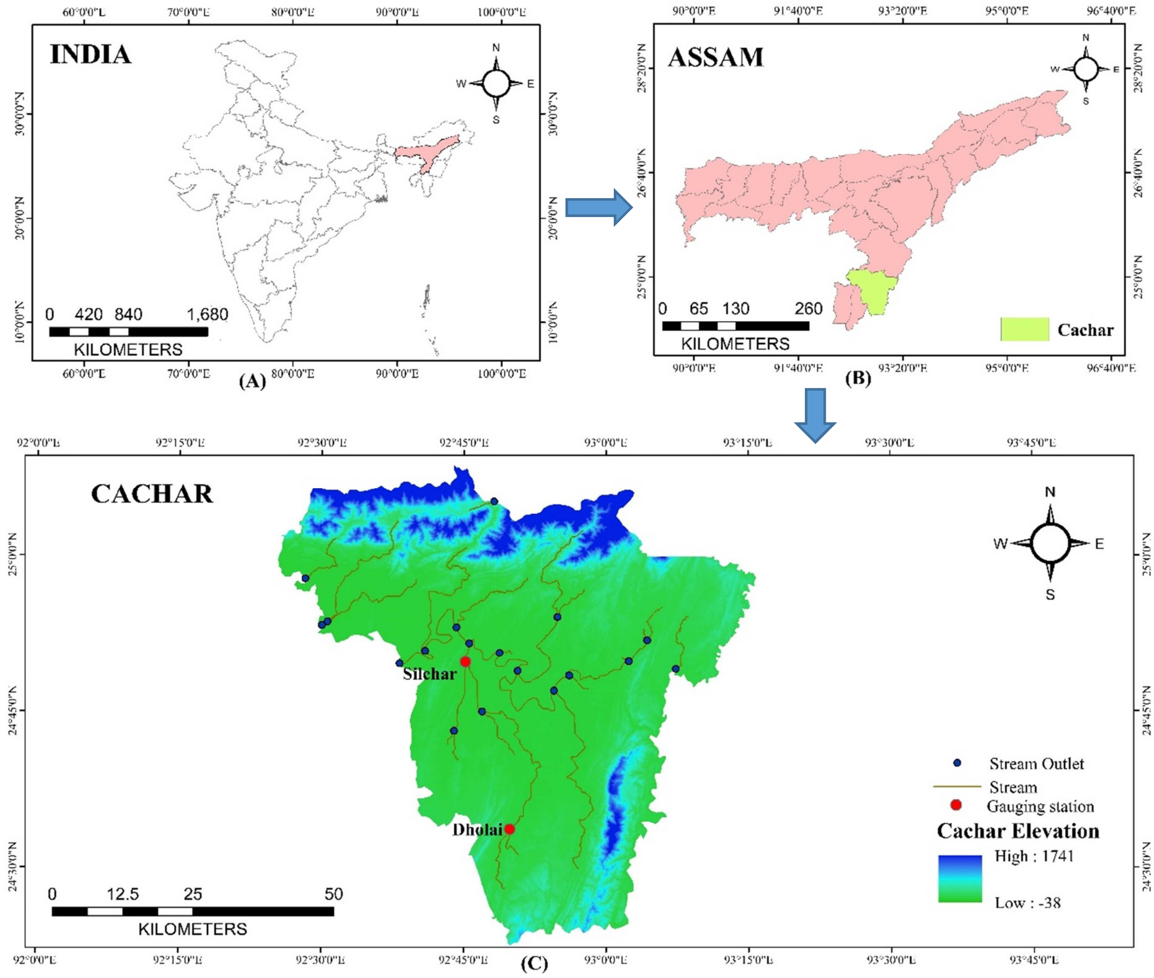

Fig.1. Digital Elevation Map of **(a)** India, **(b)** Assam, **(c)** Cachar

supervised and unsupervised learning models. But, NNs can be categorized into feed-forward, modular, recurrent, and convolutional NNs. As ML models are adaptive in nature, they are constantly growing by learning, using fresh model data and understandings. Hence, these models can recognize different patterns in data. In ML models, data is the solitary input layer. But, even in a modest NN model, there exists multiple layers.

Feed Forward Back Propagation Neural Network

BPNN is most characteristic learning model for ANN. Process of BPNN involves error at output layer that back-propagates to input layer via hidden layer in network for obtaining ultimate desired output. In a BPNN (Wilde 1997), usually there exist an input layer which acts as a circulation arrangement for data being offered to network. Any kind of processing is not done in input layer. Hidden layer follows after input layer which is used to serve as one or several processing layers. Last processing layer is known as output layer. FFBPNN utilizing BP as training algorithm is contemplated as most eminent training technique among different neural networks, is frequently applied to model hydrological processes. A general representation of a three-layer FFBPNN is displayed in Figure 2. As displayed in figure, the network consists of single input layer, where data are familiarized for modelling networks, single hidden layer comprising of 'n' neuron numbers, where data are administered or processed and single output layer, where results of specified inputs are shaped. Various input Y1, Y2, Y3,…, Yn (for input constraint section 3.5) are the n numbers of input parameters used for model development. This is the generalized architecture of FFBPNN, so we use up to Yn as input parameter. In mathematical terms, FFBPNN can be specified as in Eq. 1:

$$y = f\left(\Sigma_{i=1}^{n} w_i x_i + b\right) \tag{1}$$

where y is produced output, f is transfer function, w_i is weight vector, x_i is input vector, and b is bias. Hence, training algorithm consisting of runoff forecasts is mandatory for optimizing w and b.

In present study, a three-layer FFBPNN model skilled using tan-sigmoid function which helps to define and select number of neurons of hidden layer while linear function is utilized to calculate number of neurons of output layer.

Radial Basis Function Neural Network

Broomhead and Lowe (1988) introduced RBFNNs into ANN. Radial basis function (RBF) is contemplated as an authoritative method to interpolate various functions in a multi-dimension space. A RBF function is built into it a distance condition w.r.t a center. These can be utilized very competently for data smoothening and interpolation. RBFs can be applied in different ANN scenarios where they are utilized for

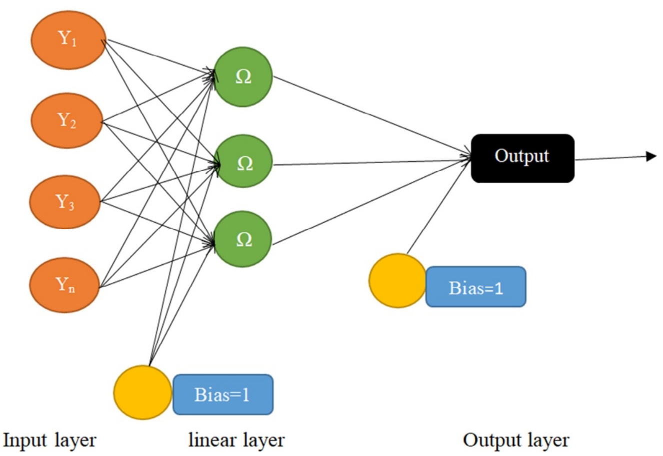

Fig.2. Architecture of FFBPNN

sigmoidal transfer function as a replacement. RBFs have three layers; input, hidden with RBF nonlinearity and a linear output layer. In view of complexity in nature of flood process that is generally very nonlinear, most appropriate ANNs to model the process must have capability for approximating any continuous function. RBFNN have many benefits as compared to other ANNs. These networks are quick in functioning as it utilizes symmetric RBF, i.e., Gaussian function and does not experience complications like local minima because RBF gives a good ability to generalize with a least number of nodes as opposite to MLP training techniques (Moradkhani et al. 2004). Architecture of RBF is presented in Fig.3.

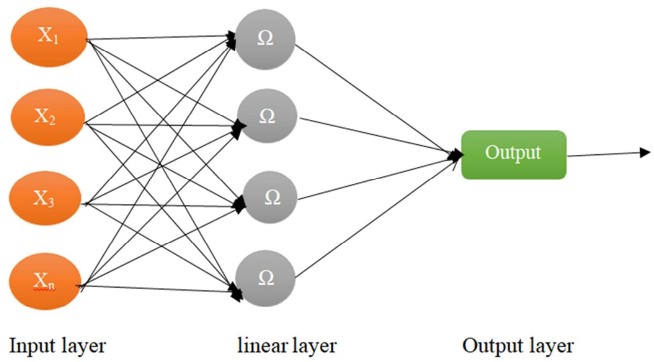

Fig.3. Architecture of RBFNN

Input layer links different inputs to network. Hidden layer relates a nonlinear transfer function from input to hidden whereas output layer relates a linear transfer function from hidden to output space. RBFs $\varphi 1$, $\varphi 2$, φN are called hidden functions whereas $\{\varphi i\ (x)\}_{i=1}^{N}$ is known as hidden space. Basic function numbers (N) is characteristically fewer compared to total data points existing in input dataset. Amid many RBFs, most frequently utilized is the Gaussian that is represented in following manner in its one-dimensional form:

$$\varphi(x, \mu) = e^{\frac{\|x-\mu\|^2}{2d^2}} \tag{2}$$

where μ is center of Gaussian function (mean value of x) and d is distance (radius) from center of $\varphi(x, \mu)$, giving an extent of spreading of Gaussian curvature.

RBF Parameters Selection Using FA

Present investigation uses FA to interpolate RBFs. Speaking differently, the researchers trained RBF using FA as an optimization technique for forecasting river flood taking the river water level. FA was employed in present analysis for optimizing connected weights in RBF system.

Description of experimental use of RBF–FA model is revealed in this section. Kernel RBF numbers were taken as 10. Likewise, MSE was utilized as a cost function in FA. Best assortment of input constraints relates to the capability of RBF-FA in making good predictions. River water level is taken as inputs for RBF-FA model where training of RBFs using FA is very essential to improve accuracy in predicting river flood. Structural architecture of RBF-FA is shown in Fig. 4. In RBFN training process, it used FA for obtaining optimal RBF parameters. Training steps involved are as follows:

Step 1: Input standardized matrix and parameters utilized in RBF-FA

Step 2: Produce preliminary FA population arbitrarily within (0 to 1) intervals and modify individuals in FA becoming bias and weight in RBF.

Step 3: Compute MSE with RBF procedure to determine initial fitness of FA.

Step 4: Examine if MSE value achieved is smaller than extent of error or if it has stretched to maximum limit of iteration. If obtained MSE is smaller or iteration has stretched to maximum limit, then individual fireflies are considered as optimum. Otherwise, the procedure continues by computing fitness value of every single firefly and maximizes fitness values to determine light intensity of firefly. Fitness value for every single one of them is found by Eq. (3).

$$f(x) = 1 / (1 + \text{MSE}) \tag{3}$$

Step 5: Compare one firefly light intensity value with another firefly. Firefly having brighter light intensity will be approached by other firefly having less intensity value. After that compute fireflies' movement value among fireflies having values of higher brightness intensity.

Step 6: Determine firefly with worst intensity value and set as preliminary solution in simulated strengthening procedure.

Step 7: Transform worst firefly and compute light intensity firefly.

Step 8: Compare intensity of light of new solution with initial solution. If new solution is enhanced, progress to step 9; otherwise, a real number 'r' is produced arbitrarily within 0 to 1. Compute probability of acceptance (P). If P ≥ r then fresh solution is recognized as a provisional solution.

Step 9: Reduce river flow. If it extents till maximum iterations, procedure halts and carry on to step 10. If not, then go back to step 7.

Step 10: Assimilate all obtained solutions.

Step 11: Determine preeminent firefly i.e. firefly with highest intensity of light.

Step 12: Make preeminent firefly to move and it will acquire a new firefly population, then repeat step (3) once more.

Step 13: Examine whether obtained MSE value is smaller than maximum iteration or error limit. If it has met maximum iteration or error limit, then bias and weight are optimum, otherwise step (4) is repeated.

Support Vector Machine

SVM is a computer based algorithm which trains by pattern for finding best function of hyper-plane for separating two stages in an input space. It analyzes two types of data, i.e. linear and non-linear discrete data. Illustration of linear discrete data is presented in Fig.5. Finest hyper-plane amid two stages can be established by determining hyper-plane margin and by getting maximum points. Margin is demarcated as distance amid hyper-plane and adjoining outline of every class known as support vector (Vapnik, 1998).

In a SVM, a hyper-plane is described as:

$$f(x) = \beta_0 + \beta^T X \tag{4}$$

Where β_0 as bias and β is expressed as weight vector. A hyper-plane can be denoted in various means as it is explained by scale of and. Orthodoxly, a hyper-plane can likewise be described as:

$$\beta_0 + \beta^T X = 1 \tag{5}$$

where symbol X signifies nearest training value examples. A canonical hyper-plane denotes to hyper-plane containing training values nearby to boundaries. This is predominantly observed in support vectors. At this point, distance amid X and a hyper-plane is computed as:

$$distance = | \beta_0 + \beta^T X | / \beta \tag{6}$$

Subsequent to application of SVM model utilizing a separate hyper-plane on specified dataset, it becomes categorized into various classifications which is dependent on dimensions. Utilizing this, we fine prediction accurateness. During computation, a misperception matrix is generated which is a method for reiterating algorithm efficiency and is characterized as a false positive, false negative, true positive, and true negative values. On basis of values attained from matrix, accurateness is computed utilizing function precision score that is provided by quantity of right predictions. It can be a fraction as well. This function provides accurateness of a subset in a multi-label categorization. This accurateness is generally considered as 1.0 for all set of labels that has been correctly predicted as true and otherwise calculated as 0 (Gereon 2018).

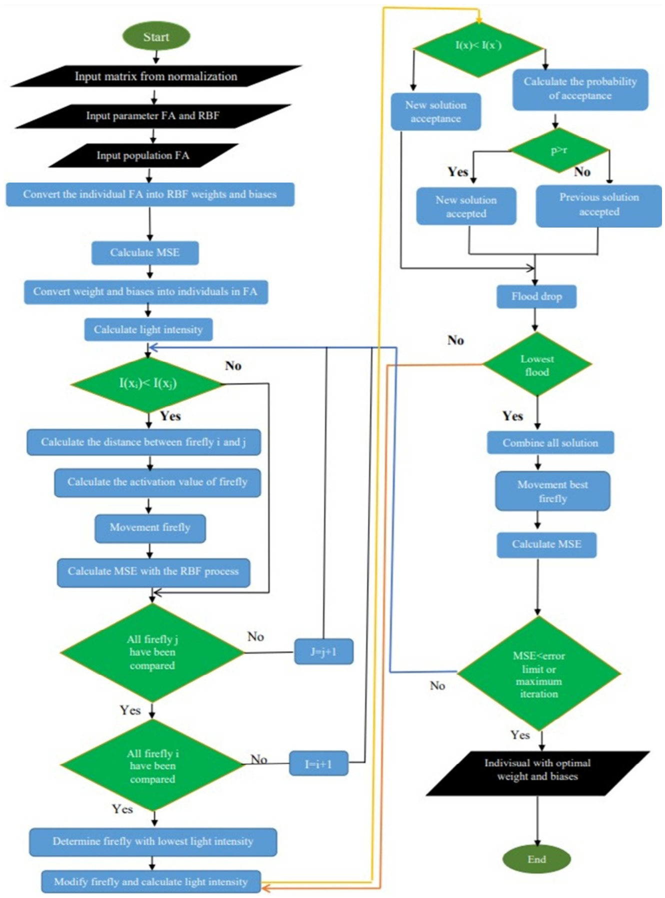

Fig.4. Architecture of RBF-FA

$$accuracy\,(Y, \hat{y}) = 1 / (n_{samples}) \sum_{i=1}^{n_{samples}-1} 1(\hat{y}_i = y_i) \tag{7}$$

Here, the accuracy, also identified as true value, is computed by assessing fraction of right predictions in n samples when i^{th} sample is taken into consideration.

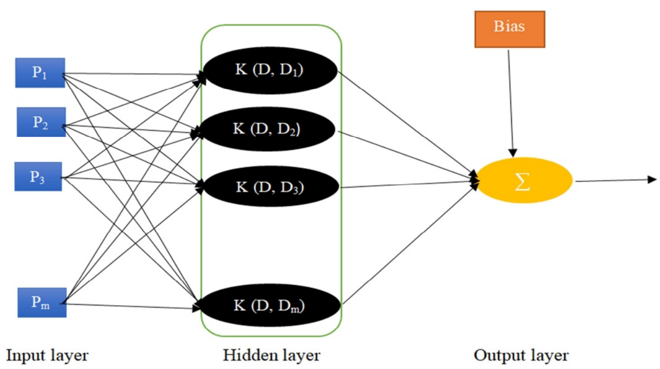

Fig.5. Architecture of SVM.

SVM parameters selection using FA

FA is based on a certain communicative outline, more specifically as perceived in flashing actions of fireflies. FA has been regarded as most robust and effective in pursuit of global and local optima in comparison to other nature-stimulated optimization systems (Fister et al. 2013; Pal et al. 2012; Yang 2013). There are few essential norms for developing FA. Type of encrypted cost function alters glare of each firefly and glare proportion w.r.t objective function. These are assumed to be unisex; hence, any of the fireflies can fascinate other irrespective of its gender. Attractiveness of one to another firefly is relational to luminous intensity that descents as the distance between them rise. Thus, those fireflies having fewer glares are attracted to firefly with more luminous intensity. Difference of light strength and preparation of objective function are key difficulties in developing FA. Subsequently, as fireflies move apart from one another, light intensity diminishes, resulting in discrepancy of intensity and hence attractiveness diminishes among them. Intensity of light with varying distance is signified in Eq. (8).

$$I(r) = I_0\, e^{-\gamma r^2} \tag{8}$$

Where, I_0 is primary light intensity, I is light intensity of firefly from distance 'r', γ signifies light immersion coefficient which lies amid 0.1 and 10 (= 0) (Ch et al. 2014). Since light intensity is relative to attractiveness of neighboring firefly, attractiveness β at distance 'r' as of a firefly is given by:

$$\beta(r) = \beta_0\, e^{-\gamma r^2} \tag{9}$$

where β_0 is attractiveness at $r = 0$.

Cartesian distance between any 2 i and j fireflies is computed by Eq. (10).

$$r_{ij} = x_i + x_j = \sqrt{\Sigma_{k=1}^{d} (x_{i,k} - x_{j,k})} \tag{10}$$

Figure 6a summarizes the basic phases of Firefly Algorithm development and also represents how FA works for selecting the optimal SVM parameters. SVM model performance is dependent on suitable assortment of constraints that are calculated by FA. Figure 6b portrays flow chart to obtain optimum SVM constraints. In SVM training procedure, it used FA for obtaining optimal SVM parameters. Training steps are as follows:

Step 1: Input the parameters used in SVM-FA.
Step 2: Initialize parameters of firefly
Step 3: Train SVM
Step 4: Calculate fitness function
Step 5: Rank fireflies in accordance to attractiveness
Step 6: Classify fireflies' category
Step 7: Stop if criterion is satisfied
Step 8: Obtain optimal parameters of SVM. If not, repeat the process from step 3 till optimum parameters attained.

Start
Define Objective function, $f(x)$, $x = (x_1, x_2, x_3, ..., x_d)^T$
Generate initial population of fireflies x_i (i = 1,2,3, ..., n)
Light intensity I_i at x_i is determined by $f(x_i)$
Define light absorption coefficient γ
While t<max generation **do**
for i = 1 : n all n fireflies **do**
for j=1 : j all n fireflies **do**
if $I_j > I_i$ then
Move firefly i toward j in d-dimension;
end if
Attractiveness varies with distance r via exp[$-\gamma r$]
Evaluate new solution update light intensity
end for
end for
Rank the fireflies and find the current best
end while
Post processor results and visualization
end

Fig. 6a. Pseudo-code for FA

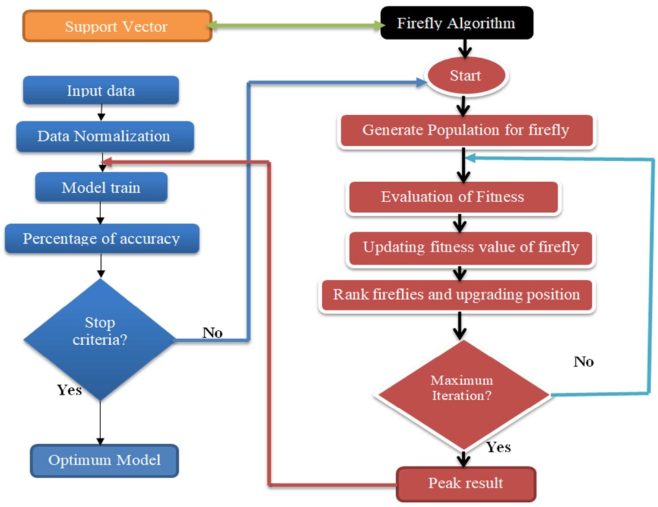

Fig.6b. Flow chart for SVM-FA

Model Performance Evaluation

The daily flood discharge data is collected from IMD, Guwahati, India for monsoon months (May to October), from 1992-2019. Data collected from 1992-2011 (70% of data set) are utilized for training and from 2012-2019 (30%) are utilized for testing desired network. Monthly data are obtained by converting daily data, which finally helps in training and testing the model. Input and output data are put into order in such a way that every data falls inside the quantified range before training. This procedure is known as normalization where normalized values are confined within range (0-1). Normalization equation which is used for putting data in order is

$$Y_i = \frac{Y - Y_{min}}{Y_{max} - Y_{min}} \tag{11}$$

Where Y_i transformed data series, Y = original input data series, Y_{min} minimum of original input data series, Y_{max} maximum of original input data series.

Input	Model Name				
	FFBPNN	RBFNN	SVM	RBF-FFA	SVM-FFA
F_{t-1}	FFBPNN-1	RBFNN-1	SVM-1	RBF-FA-1	SVM-FA-1
F_{t-1}, F_{t-2}	FFBPNN-2	RBFNN-2	SVM-2	RBF-FA-2	SVM-FA-2
$F_{t-1}, F_{t-2}, F_{t-3}$	FFBPNN-3	RBFNN-3	SVM-3	RBF-FA-3	SVM-FA-3
$F_{t-1}, F_{t-2}, F_{t-3}, F_{t-4}$	FFBPNN-4	RBFNN-4	SVM-4	RBF-FA-4	SVM-FA-4
$F_{t-1}, F_{t-2}, F_{t-3}, F_{t-4}, F_{t-5}$	FFBPNN-5	RBFNN-5	SVM-5	RBF-FA-5	SVM-FA-5

Where F_{t-1} : One month lag flood discharge; F_{t-2} : Two month lag flood discharge; F_{t-3} : Three month lag flood discharge; F_{t-4} : Four month lag flood discharge; F_{t-5} : Five month lag flood discharge.

Evaluating Criteria

R^2, MSE and RMSE are considered as evaluating standards to determine the best model. To select the perfect model for this area of study, RMSE must be minimum and coefficient of determination must be maximum.

$$R^2 = 1 - \frac{(\sum_{i=1}^{N} a - \bar{a})^2}{(\sum_{i=1}^{N} b - \bar{b})^2} \tag{12}$$

The R^2 value specifies percentage of variation in one variable described by other variable.

$$\text{MSE} = (1/n)\ \Sigma_{j=1}^{n}\ (a - b)^2 \tag{13}$$

$$\text{RMSE} = \frac{\sum_{i=1}^{N}(a-\bar{a})(b-\bar{b})}{\sqrt{\sum_{i=1}^{N}(a-\bar{a})^2\ (b-\bar{b})^2}} \tag{14}$$

Where N = Number of data; a = Predicted data; b = Observed data; = Mean predicted data; = Mean observed data

RESULTS AND DISCUSSIONS

Various inputs (F_{t-1}, F_{t-1}, F_{t-2}, F_{t-1}, F_{t-2}, F_{t-3}, F_{t-1}, F_{t-2}, F_{t-3}, F_{t-4}, F_{t-1}, F_{t-2}, F_{t-3}, F_{t-4}, F_{t-5}) are employed for Silchar and Dholai gauge station to evaluate performance of model with the help of five different approaches (FFBPNN, RBFNN, SVM, RBF-FA, SVM-FA). The results with respect to both training and testing phases are given below.

Results for FFBPNN, RBFNN, SVM, RBF-FA, SVM-FA

The FFBPNN results are discussed below for proposed gauge station. For Dholai, best model architecture is found to be FFBPNN-5 possessing MSE training and testing value 0.00378 and 0.00698, RMSE training and testing value 0.04399 and 0.03311 and R^2 training and testing value 0.8693 and 0.8821 respectively. Similarly for Silchar gauge station model FFBPNN-5 shows best value of performance. Detailed results for Silchar and Dholai are tabulated below in Table 2.

Similarly results of RBFNN are given in Table 3 with various models considered for simulation. It is found that with a model RBFNN-5, it shows best performance with all scenarios which possess MSE training and testing value 0.00446 and 0.00698, RMSE training and testing value 0.04354 and 0.02898 and R^2 training and testing value 0.8941 and 0.9081 respectively. Similarly for Dholai gauge station model RBFNN-5 shows best value of performance. Details performance value of two stations is given in Table 3.

Among five model, SVM-5 model shows best result with R^2 0.9385 and 0.9478 for training and testing period respectively while SVM-5 are considered as input parameter for Silchar gauge station. Similarly for Dholai station model SVM5 gives best R^2 value for both phases out of five simulations. In case of station Dholai preeminent R^2 value for training and testing period is 0.9397 and 0.9455 for model SVM-5. The result for SVM model based on MSE, RMSE, R^2 for testing and training period is presented in

Here five different models are used to estimate MSE, RMSE, R^2 value for five projected watershed. When RBF-FA-5 is used as input scenario, R^2 value provides the most excellent result. Considering Silchar, best value for R^2 is 0.9619 and 0.9731 for training and testing period respectively. The result of PSR-SVM-FFA model for both testing and training phase are represented in Table 5.

Here five different models are used to estimate MSE, RMSE, R^2 value for five projected watershed. When SVM-FA-5 is used as input scenario, R^2 value provides the most excellent result. Considering Silchar, best value for R^2 is 0.9807 and 0.9812 for training and testing period respectively. The result of SVM-FFA model for both testing and training phase are represented in Table 6.

Simulation

The graphs with best values of R^2 for flood using FFBPNN, RBFNN, SVM, RBF-FA, SVM-FA at Silchar in the course of testing phases is presented in Fig.7. For Dholai gauge station, the best values for flood model during testing phases are presented in Fig.8. Graphs below demonstrate how the best values leads to variation amid actual flood and predicted flood.

Comparison of Model Performance

At Silchar station among five networks with evaluation criteria MSE, RMSE, and R^2, SVM-FA performs best for SVM-FA-5 input. Similarly for Dholai SVM-FA performs best amid five networks with

Table 2. Results of FFBPNN

Station	Input	MSE		RMSE		R^2	
		Training	Testing	Training	Testing	Training	Testing
Silchar	FFBPN-1	0.00208	0.00543	0.06642	0.04887	0.8433	0.8573
	FFBPN-2	0.00297	0.00576	0.05976	0.04112	0.8479	0.8634
	FFBPN-3	0.00319	0.00599	0.05436	0.03879	0.8521	0.8687
	FFBPN-4	0.00335	0.00624	0.05243	0.03843	0.8607	0.8756
	FFBPN-5	**0.00371**	**0.00686**	**0.05076**	**0.03332**	**0.8688**	**0.8806**
Dholai	FFBPN-1	0.00212	0.00554	0.06806	0.04833	0.8478	0.8597
	FFBPN-2	0.00305	0.00581	0.06214	0.04101	0.8518	0.8668
	FFBPN-3	0.00322	0.00605	0.05991	0.03828	0.8557	0.8701
	FFBPN-4	0.00339	0.00629	0.04954	0.03796	0.8626	0.8779
	FFBPN-5	**0.00378**	**0.00698**	**0.04399**	**0.03311**	**0.8693**	**0.8821**

Table 3. Results of RBFNN

Station	Input	MSE		RMSE		R^2	
		Training	Testing	Training	Testing	Training	Testing
Silchar	RBFNN-1	0.00278	0.00564	0.05978	0.03998	0.8754	0.8838
	RBFNN-2	0.00322	0.00599	0.05576	0.03679	0.8796	0.8899
	RBFNN-3	0.00356	0.00657	0.05265	0.03364	0.8868	0.8912
	RBFNN-4	0.00389	0.00679	0.05005	0.03076	0.8915	0.8984
	RBFNN-5	**0.00446**	**0.00698**	**0.04354**	**0.02898**	**0.8941**	**0.9081**
Dholai	RBFNN-1	0.00297	0.00594	0.06265	0.04609	0.8778	0.8856
	RBFNN-2	0.00342	0.00632	0.05786	0.03998	0.8803	0.8911
	RBFNN-3	0.00388	0.00688	0.05014	0.03656	0.8887	0.8969
	RBFNN-4	0.00401	0.00701	0.04799	0.03407	0.8923	0.9002
	RBFNN-5	**0.00465**	**0.00709**	**0.04201**	**0.03091**	**0.8982**	**0.9095**

Table 4. Results of SVM

Station	Model	MSE		RMSE		R^2	
		Training	Testing	Training	Testing	Training	Testing
Silchar	SVM-1	0.00282	0.00575	0.05967	0.03934	0.9198	0.9218
	SVM-2	0.00331	0.00603	0.05546	0.03663	0.9237	0.9267
	SVM-3	0.00364	0.00665	0.05223	0.03321	0.9276	0.9321
	SVM-4	0.00391	0.00689	0.04998	0.03055	0.9339	0.9357
	SVM-5	**0.00453**	**0.00701**	**0.04365**	**0.02887**	**0.9385**	**0.9478**
Dholai	SVM-1	0.00301	0.00599	0.06223	0.04576	0.9201	0.9237
	SVM-2	0.00357	0.00647	0.05767	0.03975	0.9256	0.9295
	SVM-3	0.00396	0.00696	0.05002	0.03643	0.9291	0.9347
	SVM-4	0.00421	0.00726	0.04779	0.03385	0.9344	0.9399
	SVM-5	**0.00477**	**0.00754**	**0.04189**	**0.03088**	**0.9397**	**0.9455**

Table 5. Results of RBF-FA

Station	Input	MSE		RMSE		R^2	
		Training	Testing	Training	Testing	Training	Testing
Silchar	RBF-FA-1	0.00291	0.00589	0.05923	0.03912	0.9409	0.9514
	RBF-FA-2	0.00345	0.00634	0.05512	0.03647	0.9475	0.9569
	RBF-FA-3	0.00378	0.00687	0.05209	0.03311	0.9511	0.9604
	RBF-FA-4	0.00408	0.00699	0.04978	0.03028	0.9579	0.9633
	RBF-FA-5	**0.00468**	**0.00723**	**0.04354**	**0.02867**	**0.9619**	**0.9731**
Dholai	RBF-FA-1	0.00309	0.00612	0.06205	0.04558	0.9422	0.9531
	RBF-FA-2	0.00365	0.00664	0.05743	0.03962	0.9486	0.9578
	RBF-FA-3	0.00413	0.00704	0.04984	0.03623	0.9518	0.9618
	RBF-FA-4	0.00439	0.00741	0.04756	0.03367	0.9597	0.9654
	RBF-FA-5	**0.00491**	**0.00776**	**0.04144**	**0.03078**	**0.9629**	**0.9712**

Table 6. Results of SVM-FA

Station	Model	MSE		RMSE		R^2	
		Training	Testing	Training	Testing	Training	Testing
Silchar	SVM-FA-1	0.00303	0.00598	0.05907	0.03887	0.9599	0.9623
	SVM-FA-2	0.00359	0.00643	0.05498	0.03621	0.9656	0.9669
	SVM-FA-3	0.00387	0.00689	0.05187	0.03298	0.9667	0.9701
	SVM-FA-4	0.00434	0.00712	0.04965	0.03002	0.9781	0.9789
	SVM-FA-5	**0.00485**	**0.00754**	**0.04337**	**0.02856**	**0.9807**	**0.9812**
Dholai	SVM-FA-1	0.00323	0.00643	0.06197	0.04526	0.9602	0.9645
	SVM-FA-2	0.00387	0.00689	0.05704	0.03944	0.9673	0.9689
	SVM-FA-3	0.00434	0.00718	0.04943	0.03605	0.9687	0.9713
	SVM-FA-4	0.00456	0.00764	0.04712	0.03351	0.9789	0.9795
	SVM-FA-5	**0.00528**	**0.00792**	**0.04139**	**0.03064**	**0.9811**	**0.9818**

Table 7. Comparison of results for two watersheds

Station	Techniques	MSE		RMSE		R^2	
		Training	Testing	Training	Testing	Training	Testing
Silchar	FFBPNN	0.00371	0.00686	0.05076	0.03332	0.8688	0.8806
	RBFNN	0.00446	0.00698	0.04354	0.02898	0.8941	0.9081
	SVM	0.00453	0.00701	0.04365	0.02887	0.9385	0.9478
	RBF-FA	0.00468	0.00723	0.04354	0.02867	0.9619	0.9731
	SVM-FA	**0.00485**	**0.00754**	**0.04337**	**0.02856**	**0.9807**	**0.9812**
Dholai	FFBPNN	0.00378	0.00698	0.04399	0.03311	0.8693	0.8821
	RBFNN	0.00465	0.00709	0.04201	0.03091	0.8982	0.9095
	SVM	0.00477	0.00754	0.04189	0.03088	0.9397	0.9455
	RBF-FA	0.00491	0.00776	0.04144	0.03078	0.9629	0.9712
	SVM-FA	**0.00528**	**0.00792**	**0.04139**	**0.03064**	**0.9811**	**0.9818**

model input SVM-FA-5 during both training and testing phases. For both the gauge station FFBPNN shows less performance among all the machine learning approaches. The detailed result is tabulated below (Table 7). Since SVM-FA shows best efficiency the model will be utilized for predicting flood of future uses nearest to the watershed and recommended for irrigation, and water resources department of Assam. Figure 9 shows the comparison value for all the techniques for both Silchar and Dholai gauge station.

Assessment of actual flood versus simulated flood at and during testing phase

The variation of actual flood vs. simulated or predicted flood is

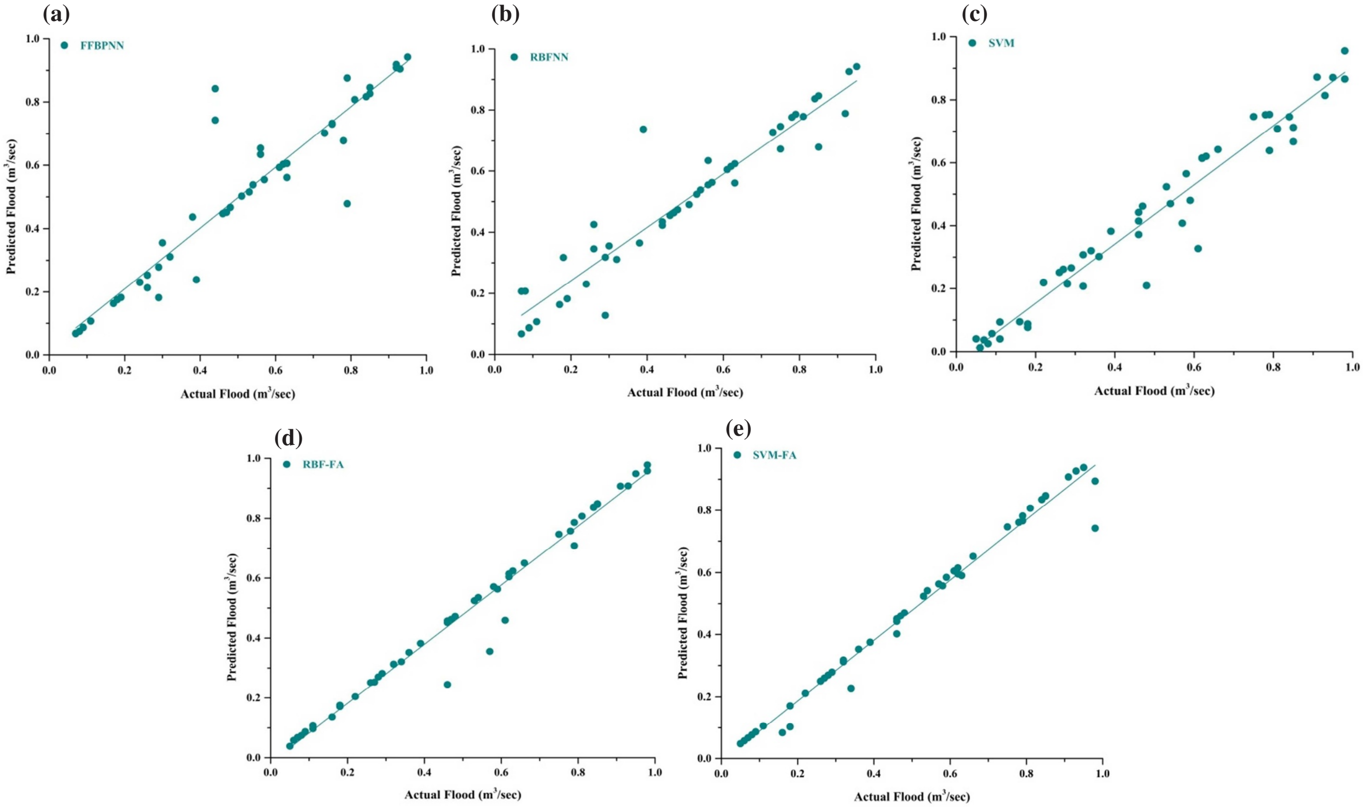

Fig.7. Observed vs Predicted flood model using **(a)** FFBPNN, **(b)** RBFNN, **(c)** SVM, **(d)** RBF-FA, **(e)** SVM-FA in testing phase (Silchar)

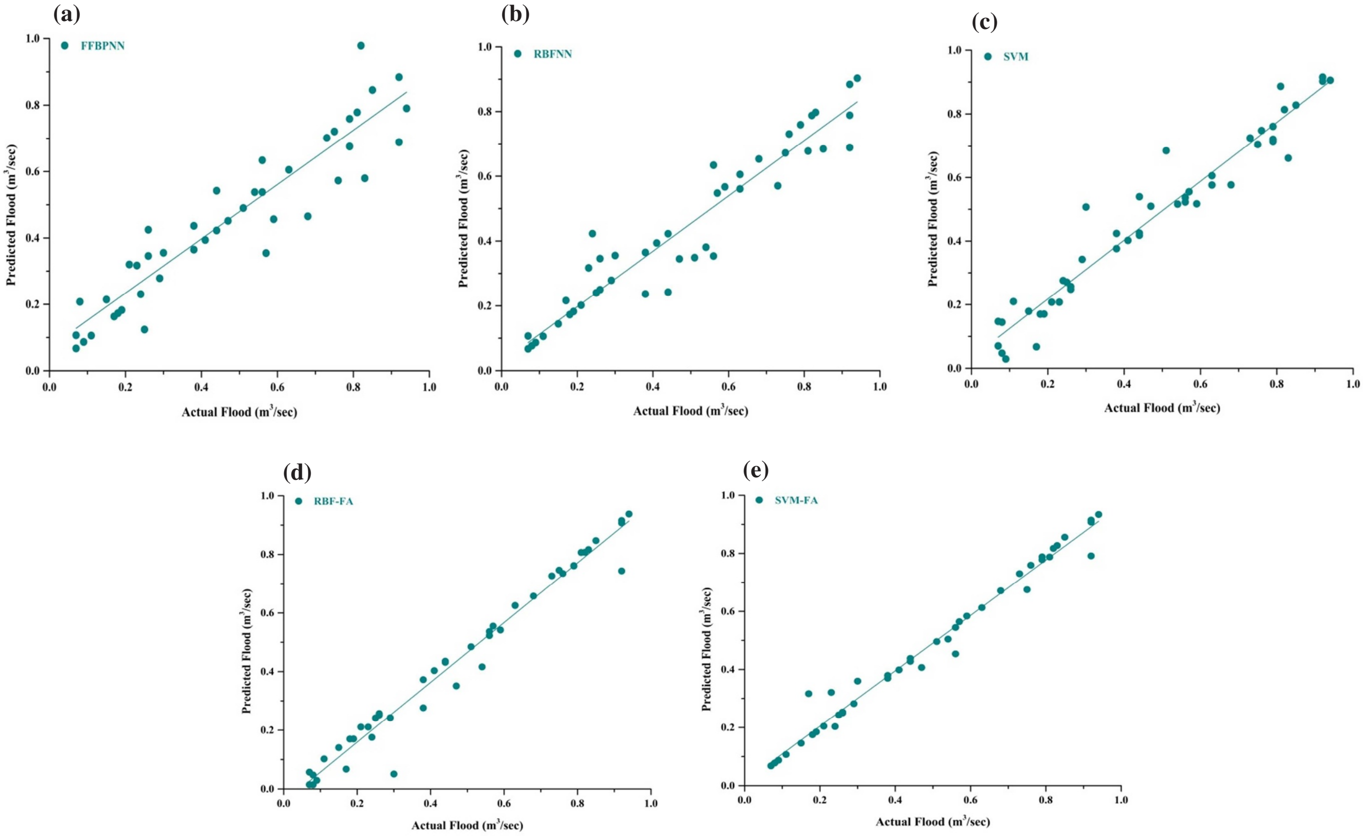

Fig.8. Observed vs Predicted flood model using **(a)** FFBPNN, **(b)** RBFNN, **(c)** SVM, **(d)** RBF-FA, **(e)** SVM-FA in testing phase (Dholai)

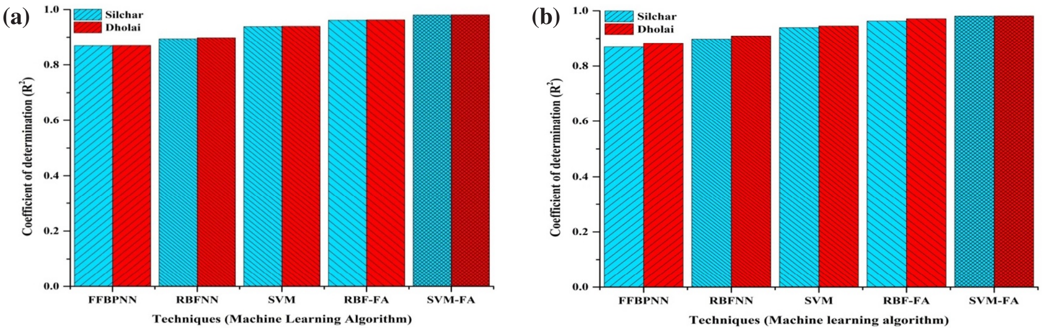

Fig. 9. Comparison graph of Silchar and Dholai gauge station for **(a)** training **(b)** testing phase

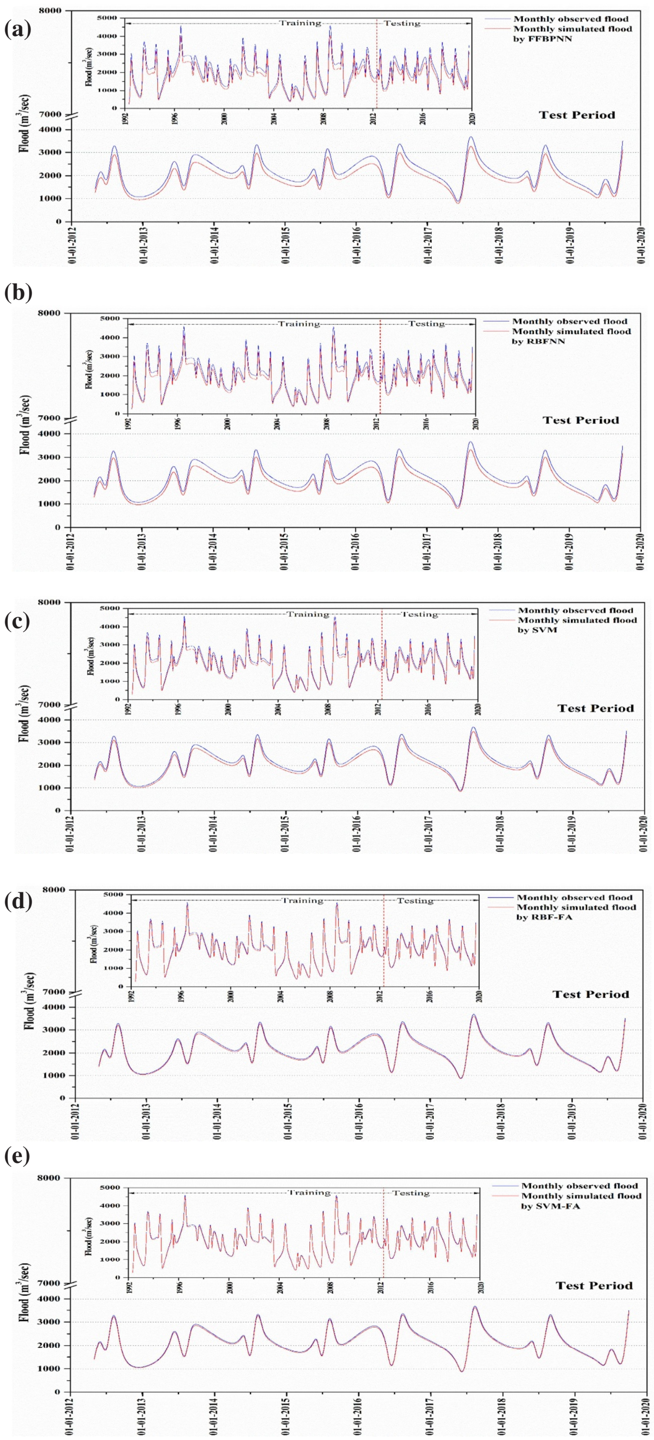

Fig.10. Actual v/s simulated flood using **(a)** FFBPNN, **(b)** RBFNN, **(c)** SVM, **(d)** RBF-FA, **(e)** SVM-FA at Silchar in testing phase.

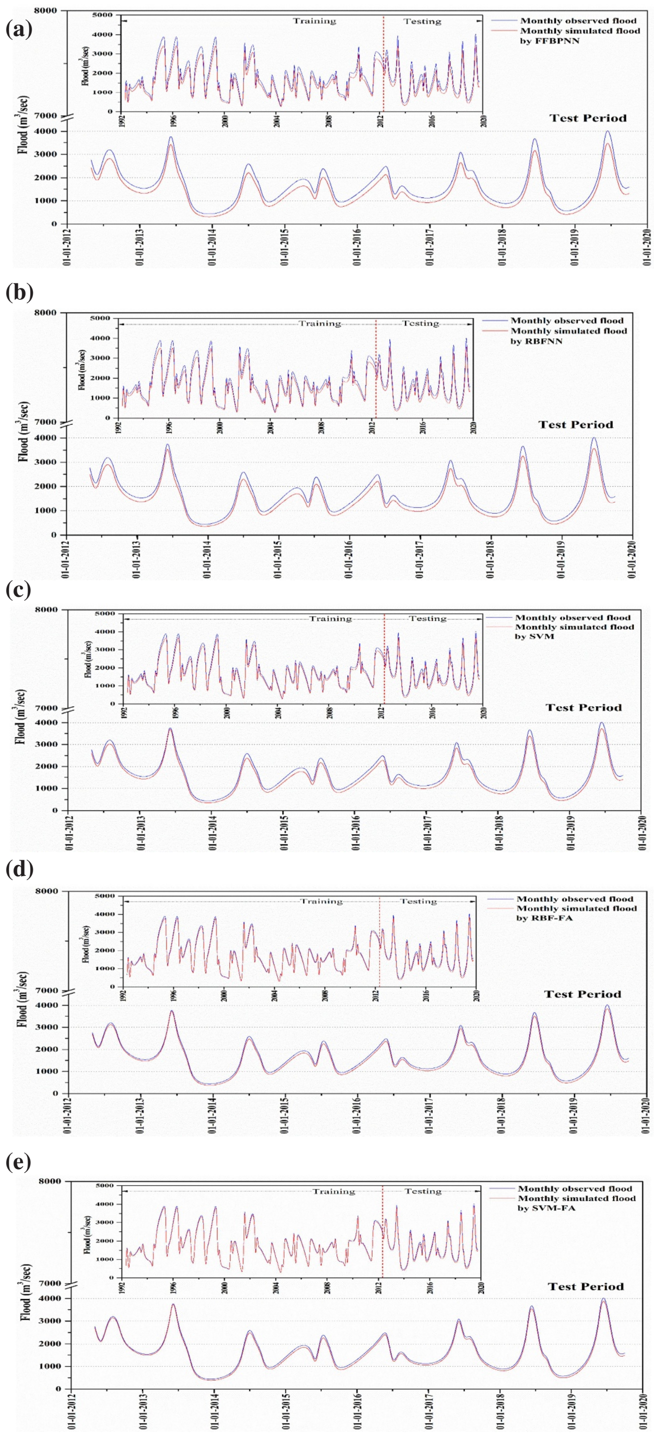

Fig.11. Actual v/s simulated flood **(a)** FFBPNN, **(b)** RBFNN, **(c)** SVM, **(d)** RBF-FA, **(e)** SVM-FA at Dholai in testing phase

revealed in figure 10. Results show that, the estimated peak floods are 4669.938m^3/s, 4702.12m^3/s, 4748.74m^3/s, 4773.23m^3/s, 4801.56m^3/s for FFBPNN, RBFNN, SVM, RBF-FA, SVM-FA against the actual peak 4840.785m^3/s for the gauge station Silchar. For Dholai station, the estimated peak runoffs are 4704.623m^3/s, 4750.265m^3/s, 4767.714m^3/s, 4794.376m^3/s, 4846.887m^3/s for FFBPNN, RBFNN, SVM, RBF-FA, SVM-FA against the actual peak of 4873.938m^3/s shown in figure11. This shows the significant potential of flood and found to be useful for flash flood region with the predicted flood index.

CONCLUSION

Present study examined accuracy of RBF-FA and SVM-FA models for river flood prediction. RBF-FA and SVM-FA models were urbanized by conjoining FA with RBF and SVM, respectively. This research employed two resolution levels. Monthly river flow data of Silchar and Dholai were used to test RBF-FA and SVM-FA models. Statistical indicators utilized to evaluate performance of projected models shows lower values of RMSE and higher values of R^2 as in contrast with regular SVM and RBF models considering all nodes. While considering **SVM-FA-5** as input best value of MSE, RMSE and R^2 are 0.00792, 0.03064, and 0.9818 for SVM-FFA algorithm. But in case of RBF-FFA best values of MSE, RMSE and R^2 are 0.00776, 0.03078 and 0.9712 respectively. While using FFBPN algorithm prominent value of MSE, RMSE and R^2 are 0.00698, 0.03311, and 0.8821 for same input. Results demonstrated that both RBF-FA and SVM-FA models give more precise prediction outcomes compared to regular FFBPN, RBFN and SVM models. Assessment outcomes also revealed that both SVM-FA and SVM models performed better as of RBF-FA and RBF models in predicting river flood.

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