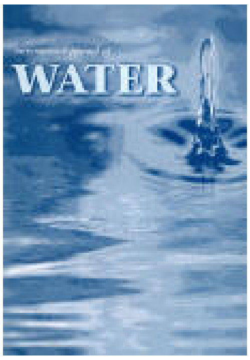

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Vikas Mittal, T.V. Vijay Kumar, Aayush Goel

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Assessing the impact of meteorological parameters for forecasting floods in the northern districts of Bihar using machine learning

Vikas Mittal and T.V. Vijay Kumar*

School of Computer and Systems Sciences,
Jawaharlal Nehru University,
New Delhi, 110067, India
Email: vikas.mittal.10@gmail.com
Email: tvvijaykumar@hotmail.com
*Corresponding author

Aayush Goel

Department of Electronics and Communication Engineering,
Bharati Vidyapeeth's College of Engineering,
New Delhi, 110063, India
Email: aayushgoel1996@gmail.com

Abstract: India is the second largest flood affected country in the world. Every year floods have a deleterious effect on people, agriculture and infrastructure. Due to its high population density and poor infrastructure, the damage caused by floods in India is exacerbated forcing millions of people to migrate from one place to other. Therefore, there is a need to devise flood mitigation strategies that would forecast future floods in real time. In this paper, machine learning techniques have been used for forecasting floods in the northern districts of Bihar. Experimental results showed that, in addition to traditional meteorological parameters rainfall and temperature, certain parameters like vapour pressure, cloud cover, wet day frequency, crop evapo-transpiration and surface evapo-transpiration had a severe impact on the performance of a flood forecasting model.

Keywords: natural hazards; floods; forecasting; artificial intelligence; machine learning; supervised learning; classification.

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Biographical notes: Vikas Mittal has completed his MTech in Computer Science and Engineering and BTech in Information Technology from Guru Gobind Singh Indraprastha University, New Delhi, India. His research interests are machine learning and disaster management.

T.V. Vijay Kumar has completed his PhD in the area of Databases from School of Computer and Systems Sciences, Jawaharlal Nehru University, New Delhi, India after completing his MPhil and MSc in Operational Research and BSc (Hons.) in Mathematics from the University of Delhi, Delhi, India. His research interests are database management and distributed databases, data warehousing and data mining, artificial intelligence and machine learning, meta-heuristic algorithms and multi-objective optimisation, data science and big data analytics, early warning systems and disaster management.

Aayush Goel has completed his BTech in Electronics and Communication Engineering from Department of Electronics and Communication Engineering, Bharati Vidyapeeth's College of Engineering, New Delhi, India. His research interests are machine learning, natural language processing and disaster management.

1 Introduction

India is the 7th largest country in the world, with an area of 3.2 million square kilometres and 7500 km long coastline (Jain et al., 2007). Thus, India is vulnerable to different natural hazards like earthquakes, tsunamis, cyclones, and floods due to its drastically varying geography and climate (NDMA, 2017). As per the *UNISDR* report on Economic Losses, Poverty, and Disasters in 2017 (Wallemacq et al., 2018), India is the 4th biggest country in terms of losses due to floods and tsunami. Frequent floods in Indian region have also resulted in malnutrition and stunted growth among children (Wallemacq et al., 2018). India is the second largest flood affected nation in the world (UNDRR, 2020). Floods in India are probably the most recurrent natural hazards (NIDM, 2018). 23 out of 35 states and union territories are prone to floods (NIDM, 2018). According to the 2016–2017 annual report (NDMA, 2017), around 12% of India's land is susceptible to flood or river erosion. During 1970–2009, natural disasters have affected more than 1.86 billion people, more than 150,000 people have lost their lives in India (Parida et al., 2021). Floods, tsunamis, cyclones and earthquakes have led to economic damages worth over 80 billion dollars (*USD*) (Wallemacq et al., 2018). Every year, floods in India have severely hit its population, agriculture and other infrastructure. From 1953 to 2016 floods affected an area of 460 million hectare, more than 2040 million people have been affected (Central Water Commission, 2018). Due to floods more than 1.05 lakh people have lost their lives and damage of 347581 crore rupees (Central Water Commission, 2018) have been recorded. Hence, floods severely threaten India's environment, its people and its economy.

To overcome the challenges posed by floods, effective disaster management is necessary. Disaster management comprises four phases *viz.* disaster mitigation phase, disaster preparedness phase, disaster response phase and disaster recovery phase (NIDM, 2002). In disaster mitigation phase, structural and non-structural measures such as designing early warning systems, building hazard resistant constructions and defining land use policies are carried out (NIDM, 2002). Early forecasting can give more time which helps in better planning and preparation for response to floods. In disaster preparedness phase, preparation of plans for dealing with disasters and training of individuals through mock drill activities takes place (NIDM, 2002). In disaster response phase, plans designed during preparedness phase are implemented for minimising the losses (NIDM, 2002). Finally, disaster recovery phase focuses on restoration of basic services and reconstruction of damaged infrastructure along with damage estimation (NIDM, 2002).

Historical data plays an important role in implementation of *ML* techniques for flood forecasting. For this study, meteorological data (1991–2002), considering seven features, of most flood affected districts of Indian state of Bihar obtained from Climatic Research Unit, University of East Anglia (Mitchell and Jones, 2005; Allen et al., 1998) were used by the *ML* algorithms for forecasting floods.

This paper is organised as follows: Section 2 provides an overview of related work. *ML* based flood forecasting model using six *ML* techniques is explained in Section 3. Experimental results and performance of *ML* techniques is analysed in Section 4 followed by concluding remarks and future scope in Section 5.

2 Related work

In India, floods prominently occur due to heavy rainfall during monsoon season and poor drainage system. Poor soil permeability and sudden occurrence of heavy rainfall often causes flash floods in various parts of the country (NIDM, 2018). In addition to this, heavy rainfall causes heavy discharge from upstream stations. Therefore, river water level at downstream stations exceeds the danger level and breaches river embankments leading to flooding in the close vicinity of the river bank.

Flood forecasting in these areas is delayed until a huge amount of water is discharged from the upstream station, which gives extremely limited time for preparation to first responders and response teams. Once rainfall forecasting and other meteorological parameters are known, we can compute whether or not rainfall will lead to flooding in the region. This information can be used to issue early flood warning. Therefore, early forecasting would enable agencies to timely devise better plans to deal with situations arising due to floods. Physical models for forecasting floods require parameters like coefficients of channel roughness, hydrological time series data and parameters in relation to river geometry for prediction of river water level (Panda et al., 2010). However, these parameters are difficult to obtain in desired affected regions (Panda et al., 2010). Therefore, data driven flood forecasting models are used for early flood warning. *ML* techniques are widely used for designing data driven flood forecasting models (Ghose, 2018; Thirumalaiah and Deo, 1998; Panda et al., 2010; Nayak et al., 2005b; Lohani et al., 2014; Tiwari and Chatterjee, 2010; Sahay and Srivastava, 2014; Nayak and Ghosh, 2013).

In Ghose (2018), a three layer back propagation neural network model was proposed for predicting runoff on a daily basis for Govindpur basin on Brahamani river, Orissa, India. In Thirumalaiah and Deo (1998), neural network was applied on storm hydrograph data to forecast floods in real time in the Bhasta river region of Maharashtra, India. This flood forecasting model was trained using error backpropagation, conjugate gradient and cascade correlation algorithm. The trained neural network model consisted of three feed forward layers. The aforementioned models provided flood warnings with a lead time of upto 3 h. In Panda et al. (2010), an artificial neural network was used to analyse historical data of Kushabhadra branch of Mahanadi delta in Orissa, India. Hourly water level data of monsoon period (2006) was used to train feed forward neural network (*FFANN*) model with Levenberg-Marquardt (*LM*) back propagation. The trained model was subsequently tested on monsoon period data of 2001. Water level was predicted with a lead time of upto 5 h. Performance of *FFANN* model was compared with the *MIKE 11HD* hydrodynamic model (DHI, 2004) and it was found that the former performed comparatively better on two performance metrics: Nash-Sutcliffe index and root mean square error (*RMSE*).

In Nayak et al. (2005b), a rainfall run-off forecasting model for floods in Kolar basin, Madhya Pradesh (India) was proposed. This model was trained using a fuzzy inference system by combining the features of fuzzy computing and artificial neural networks (*ANFIS*). Also, its performance was compared with the performance of artificial neural network based model (*ANN* model) (Nayak et al., 2005b) and fuzzy inference system (*FIS* model) (Nayak et al., 2005a) on three metrics: coefficient of efficiency, *RMSE* and coefficient of correlation, while considering hourly monsoon period data for the duration 1987–1989. The comparison showed that though *ANFIS* and *FIS* models performed equally well for shorter lead time, *ANFIS* performed comparatively better for larger lead time. In Lohani et al. (2014), Takagi Sugeno (*T-S*) fuzzy inference system (*FIS*) (Takagi and Sugeno, 1985) was modified as Threshold Subtractive Clustering based Takagi Sugeno (*TSC-T-S*) fuzzy inference system for flood forecasting. The *T-S FIS* was modified to support rare (high to very high river flow) hydrological events while supporting different member functions. The *TSC-T-S* based *FIS* was used for computing clusters to predict rare (high to very high river flow) and frequent (low to medium river flow) hydrological situations. This model forecast rare and frequent hydrological events with lead time of upto 6 h. In Tiwari and Chatterjee (2010), a wavelet-bootstrap-*ANN* (*WBANN*) based flood forecasting model was proposed. Hourly monsoon period data of five years (2001–2005) was decomposed into sub-components using wavelet transform. These sub-components were re-sampled using bootstrapping and were used to train the *WBANN* model. *WBANN* model was used for hourly flood forecasting in Mahanadi river basin with a lead time of upto 10 h. In Sahay and Srivastava (2014), a wavelet-genetic-*ANN* (*WGANN*) based flood forecasting model was proposed for floods in Kosi and Gandak rivers of India. Wavelet transform was used to decompose time-series data into sub-components. Further, genetic algorithm was used to optimise initial parameters of *ANN*. *WGANN* model was used to forecast river water level with a lead time of upto 24 h.

Focusing on urban flooding, Nayak and Ghosh (2013) proposed a support vector machine classifier which predicts extreme rainfall using meteorological parameters. This model can forecast extreme rainfall which can cause floods, with a lead time of upto 48 h. This forecasting model has low precision (0.1).

Flood forecasting models discussed above are based on rainfall-runoff data. These models forecast floods with a lead time varying from 1 h (minimum) to 48 h (maximum). This lead time is too short for first responders and response agencies. Further, the above-mentioned forecasting models only considered precipitation and temperature for forecasting floods. These models ignored parameters like vapour pressure, cloud cover, crop evapo-transpiration, surface evapo-transpiration and wet day frequency, which can have an effect on total rainfall and can be useful indicators for flood occurrences.

This paper considers these parameters along with the existing parameters used by other *ML* forecasting models for forecasting floods.

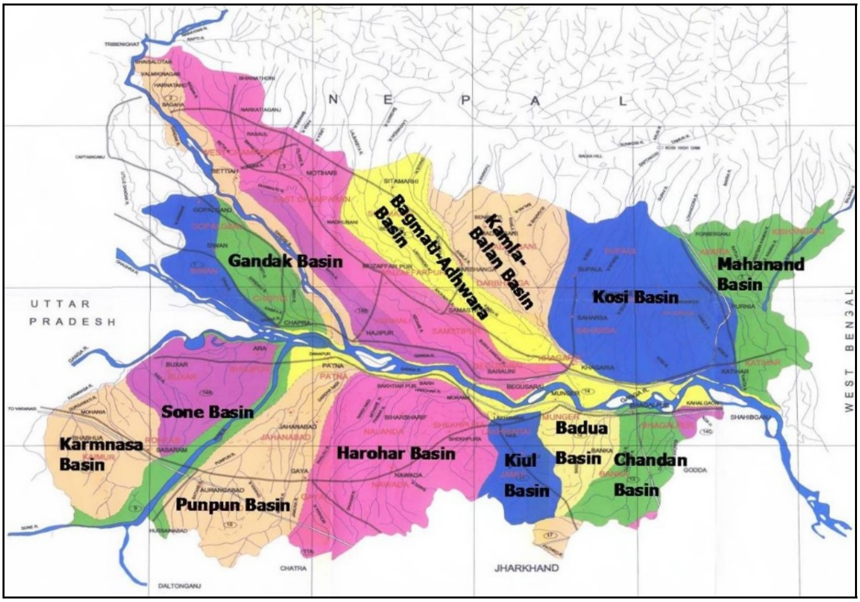
This paper focuses on designing *ML* based flood forecasting models that consider seven meteorological parameters, namely precipitation, temperature, evapo-transpiration, surface evapo-transpiration, vapour pressure, cloud cover and wet day frequency. Since these meteorological parameters can be ascertained a month in advance, forecasting of floods can be timely done. This in turn would provide ample time to first responders and response agencies to prepare and plan in order to prevent floods turning into disasters. Further, the impact of considering additional five features for forecasting floods is studied based on experimental based comparisons. The proposed *ML* based flood forecasting models are discussed next.

3 ML based flood forecasting models

In India, Bihar is the most flood prone state where 73% of its land area faces a recurrent threat of flood (Singh, 2013). High water discharge from mountain regions of Nepal causes rise in water levels of many rivers in Northern Bihar, which in turn results in drastic floods in the plains of Northern Bihar. These plains are drained by Gandak, Burhi Gandak, Bagmati, Adhwara, Kamla Balan, Kosi and Mahananda rivers. These rivers have high discharge and large volume of sediments which can cause floods. River basins of these rivers as shown in Figure 1, span across an area of 52928 km^2 out of which 40225 km^2 is prone to floods (Water Resource Department, 2021). These river basins lead to floods in districts of Northern Bihar namely East Champaran, Mujaffarpur, Samastipur, Khagaria, Bhagalpur, Madhubani, Patna, Katihar, West Champaran, Sitamarhi, Darbhanga, Begusarai, as depicted in Figure 2. The shades depict the magnitude of occurrences of floods with dark shade depicting higher occurrences and lighter shades depicting lower occurrences of floods. Distribution of flood occurrences for these districts between 1991 and 2002 has been depicted in Figure 3. During this period, a total of 201 flood occurrences were recorded across 12 districts of Northern Bihar (India). Highest number of flood occurrences were recorded in Samastipur district, whereas lowest number of flood occurrences were observed in Madhubani district.

This paper focuses on using *ML* techniques to forecast floods in such plains of Northern Bihar. For this, monthly average of historical meteorological data (1991–2002) of twelve afore-mentioned flood affected districts of Northern Bihar has been used (Climatic Research Unit, University of East Anglia) (Mitchell and Jones, 2005; Allen et al., 1998). This dataset was labelled using the data mentioning the flood occurrences in the same region for the same period available in the state's flood management portal (FMISC, http://www.fmis.bih.nic.in/). Monthly average of features like temperature, cloud cover, crop evapo-transpiration, surface evapo-transpiration, precipitation, vapour pressure and wet day frequency have been used for forecasting floods in the twelve afore-mentioned flood affected districts of Northern Bihar. This data needs to be pre-processed before *ML* models can be applied on it. Data pre-processing is discussed next.

Figure 1 River basins in Bihar (see online version for colours)



Source: http://wrd.bih.nic.in

Figure 2 Flood affected districts in northern Bihar (see online version for colours)

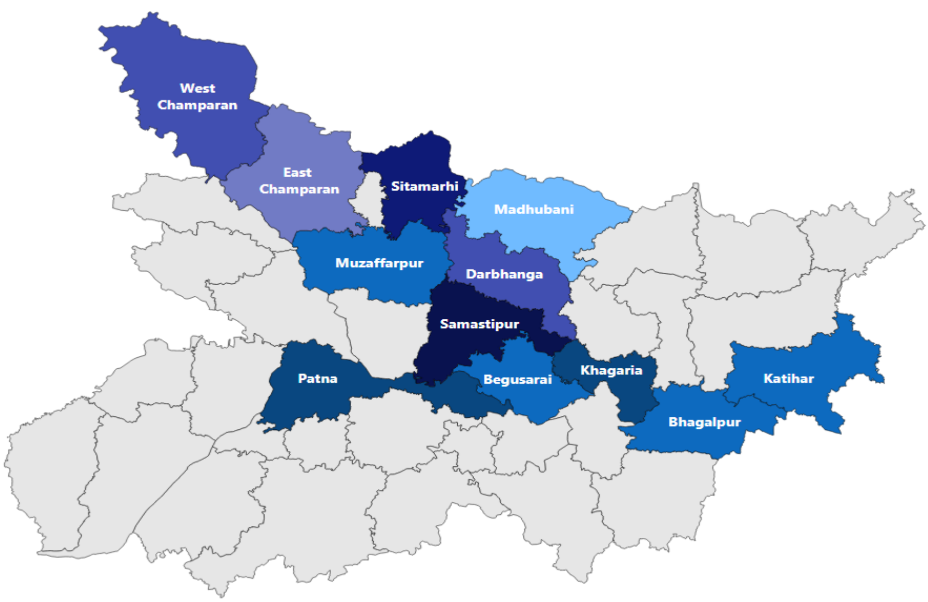
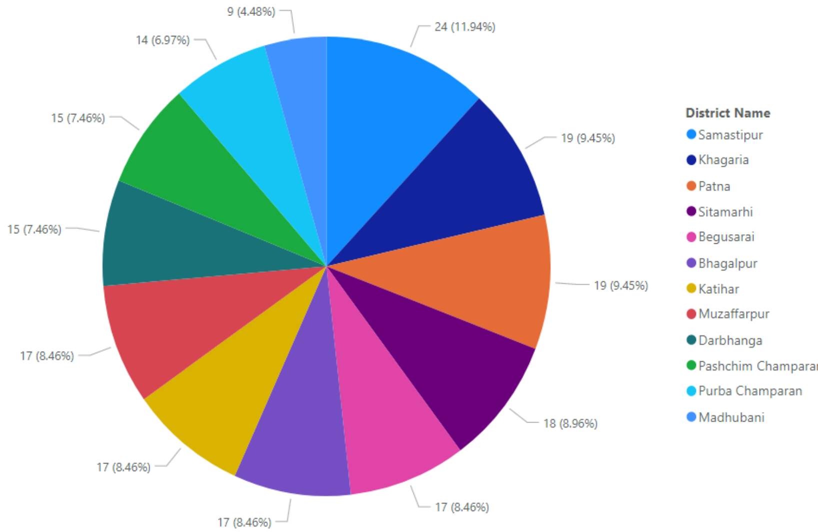


Figure 3 Flood occurrences in flood affected districts (1991–2002) (see online version for colours)



3.1 *Data preprocessing*

The dataset considered in this work has varying ranges for above mentioned features. Higher range features would influence the analysis and suppress the importance of lower range features (Singh and Singh, 2020). This would make forecasting model insensitive to certain features thereby leading to poor classification performance. Data normalisation can be used to normalise the data to a common scale. The proposed model normalises the data using using min-max scaler (Jayalakshmi and Santhakumaran, 2011). The min-max scaler is defined as given below:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

where X_{max} and X_{min} denote maximum and minimum values of feature (X) respectively. The value of X' would vary from 0 to 1.

Classification based *ML* techniques can be used for classification of flooding and non-flooding events in flood affected districts of Northern Bihar. Classification techniques used for flood forecasting model are briefly discussed next.

3.2 *Classification techniques*

Flood forecasting dataset discussed above is labelled and therefore classification techniques can be appropriately used. In this paper, classification techniques like Naive Bayes (Rish, 2001), Logistic Regression (Cabrera, 1994; Peng et al., 2002), support vector machine (*SVM*) (Evgeniou and Pontil, 2001; Zhang, 2012), Random Forest (Biau, 2012; Breiman, 2001) and *k*-nearest neighbour (Guo et al., 2003; Laaksonen and Oja, 1996) have been used to classify the above discussed flood forecasting data. These techniques are briefly discussed below:

Naive Bayes: Naive Bayes classifier is a probabilistic learning model based on the Bayes theorem (Rish, 2001). The classifier considers each pair of features independent of each other. Let there be a set X of n variables or features as $X = (x_1, x_2, x_3, \ldots, x_n)$ and y be the target class then probability of y when X has already happened can be defined as:

$$P(y \mid X) = \frac{P(X \mid y)P(y)}{P(X)}$$

where $P(y|X)$ is a probability of target class y given predictor attributes X, $P(X|y)$ is the probability of predictor attributes X given target class y, $P(y)$ is the probability of target class y and $P(X)$ is the probability of predictor attributes. In Naive Bayes technique, where predictor attributes are considered to be independent, equation (2) becomes:

$$P(y \mid x_1, \ldots, x_n) = \frac{P(x_1 \mid y)P(x_2 \mid y) \ldots P(x_n \mid y)P(y)}{P(x_1)P(x_2) \ldots P(x_n)}$$

Further, as per Naive Bayes technique, for all tuples in the dataset, $P(x_1)P(x_2)\ldots P(x_n)$ remains the same and therefore equation (3) becomes:

$$P(y \mid x_1, \ldots, x_n) \propto P(y)\prod_{i=1}^{n} P(x_i \mid y)$$

For multi-class classification problem, the maximum probability of predictor class is computed as (Rish, 2001):

$$y = argmax_y P(y)\prod_{i=1}^{n} P(x_i \mid y)$$

Logistic regression: It is a classification technique that uses a logistic function to classify data into two or more discrete classes (Cabrera, 1994; Peng et al., 2002). Logistic function $L_\theta(x)$ is defined in terms of linear function Z as: $L_\theta(x) = sigmoid\ (Z)$, where Z is a linear function defined as $Z = \beta_0 + \beta_1 X$ and $X = (x_1, x_2, x_3, \ldots, x_n)$ is a set of input features, β_0 and β_1 are the intercept and weights respectively. $L_\theta(x)$ defined above can be written as:

$$L_\Theta(X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X)}}$$

The cost function of Logistic Regression is a Sigmoid function which allows the value of the cost function strictly between 0 and 1.

Support vector machine (*SVM*)*:* It is a classification technique that maps data points into N-dimensional space (Evgeniou and Pontil, 2001; Zhang, 2012). *SVM* aims to find a hyperplane in N-dimensional space that distinctly classify the data points. Amongst the number of hyperplanes that can distinctly classify the data points, *SVM* computes the hyperplane having maximum margin or distance from data points. This optimal hyperplane is determined by maximising the margin of the *SVM* using the hinge loss function (Rosasco et al., 2004) given below:

$$c(x, y, f(x)) = \begin{cases} 0 & \text{if} \quad y * f(x) \geq 1 \\ 1 - y * f(x) & \text{else} \end{cases}$$

Random forest classifier: It is an ensemble classification technique that uses multiple decision trees to classify dataset (Biau, 2012; Breiman, 2001). Random Forest uses bootstrapping approach to build multiple decision trees using randomly selected data from the dataset. The classification of the sample data is based on voting mechanism where each decision tree classifies the given sample data and votes for the resultant output class. The class having maximum votes is chosen as the class of the sample data.

k-Nearest Neighbours (*KNN*)*:* It is a supervised classification technique that classifies a sample data using plurality of vote from its nearest *k*-neighbours (Guo et al., 2003; Laaksonen and Oja, 1996). The *k*-nearest neighbours can be computed using distance metrics like Manhattan distance, Euclidean distance etc. The class to which maximum number of k-neighbours belong is chosen as a class for the sample data.

Artificial neural network (*ANN*)*:* It is a classification technique inspired by the neural network structure in the human brain (Gurney, 1997). It is defined as a network of nodes, called artificial neurons, where each node in the network is connected with other node in the network. Synapses, which connect neurons, carry signal or information to the nodes. Weights are assigned to each synapses or connection in the network. Optimal weights are obtained through backpropagation method with the help of weight optimisation process like stochastic gradient descent.

The above mentioned classification based *ML* techniques can be used to classify the flood forecasting data. These techniques have been applied to the flood forecasting dataset which comprises 1728 instances, out of which 201 instances represent flood occurrences. Results produced by these techniques are compared on various performance metrics. These metrics are discussed next.

3.3 Performance metrics

Performance of a *ML* model can be measured with the help of different values like True Positives (*TP*)*,* True Negatives (*TN*)*,* False Positives (*FP*) and False Negatives (*FN*) which are obtained from confusion matrix or error matrix. Performance evaluation of *ML* models involves arriving at a confusion matrix using the results obtained from testing the models. Confusion matrix depicts the number of correct and incorrect predictions made by the *ML* model. In case of binary classification, confusion matrix has two rows and two columns, where the row represents actual values and the column represents predicted values or vice-versa. For the flood forecasting model, the four values present in the confusion matrix are – flooding events that were predicted as flooding events, i.e., True Positives (*TP*), non-flooding events predicted as non-flooding events, i.e., True Negatives (*TN*), non-flooding events predicted as flooding events, i.e., False Positives (*FP*) and flooding events predicted as non-flooding events, i.e., False Negatives (*FN*), as shown in Figure 4. These have been used to compute different performance metrics like accuracy, precision, recall, F-measure and *AUC-ROC* for evaluating the performance of aforementioned *ML* models after applying on both two feature dataset and seven feature dataset for forecasting floods. The performance metrics used to evaluate *ML* based forecasting models, presented in this paper, are briefly discussed below.

Figure 4 Confusion matrix for flood forecasting model

		Predicted Values	
		Positive	**Negative**
Actual Values	**Positive**	Flooding events that were predicted as flooding events (*TP*)	Flooding events predicted as non-flooding events(*FN*)
	Negative	Non-flooding events predicted as flooding events (*FP*)	Non-flooding events predicted as non-flooding events (*TN*)

Accuracy is defined as the ratio of sum of true positives and true negatives to the total number of instances, i.e., proportion of correct predictions, is given as (Liu et al., 2014):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

where *TP, TN, FP* and *FN* are true positive, true negative, false positive and false negative respectively.

Precision is defined as the proportion of positives determined that were actually correct. It is the ratio of true positive (*TP*) to the total number of positive predicted instances (*TP* + *FP*) and is given as (Liu et al., 2014):

$$Precision = \frac{TP}{TP + FP}$$

Recall is defined as a proportion of actual positives determined correctly. It is the ratio of true positive (*TP*) to the total number of actual positive instances and is given as (Liu et al., 2014):

$$Recall = \frac{TP}{TP + FN}$$

F-measure is defined as a harmonic mean of precision and recall and is given as (Liu et al., 2014):

$$F - Measure = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Area under receiver operating characteristic (*ROC*) *curve* (*AUC-ROC*) provides the aggregate performance measure across all thresholds used for the classification. It is a probability of the classification model to rank the positive instance more highly then the negative instance. It is an area under the ROC curve, i.e., area under the curve plotted between true positive rate (*TPR*) and false positive rate (*FPR*) for different threshold values, where *TPR* and *FPR* are computed as given below (Liu et al., 2014):

$$TPR = \frac{TP}{TP + FN} \text{ and } FPR = \frac{TP}{FP + TN}$$

The experimental results and analysis of applying above mentioned *ML* models on the flood forecasting dataset is discussed next.

4 Experimental results

As discussed above, *ML* models *KNN*, *LR, NB, RF, SVM* and *ANN* were applied on the normalised flood forecasting dataset with two features (*2F*): temperature and precipitation, and normalised flood forecasting dataset with seven features (*7F*): temperature, precipitation, vapour pressure, crop evapo-transpiration, evapo-transpiration, cloud cover and wet day frequency. The information related to the experiments has been given in Table 1. Experimental results were obtained for each *ML* model with *2F* and *7F* within the below mentioned experimental setup, using stratified *5*-fold cross validation (Berrar, 2018). Minimum, maximum, mean and standard deviation for Accuracy, Precision, Recall, F-measure and *AUC-ROC* were computed across the five folds.

Table 1 Experimental setup

Operating system	Windows 10
Processor	Intel i7@2.80 GHz
RAM	16 GB
Tool	Python 3.7.7
Two features (2F)	Monthly Average (Temperature and Precipitation)
Seven features (7F)	Monthly Average (Temperature, Precipitation, vapour Pressure, Crop Evapo-transpiration, Evapo-transpiration, Cloud Cover and Wet day frequency)
Number of folds	5
Learning rate in ANN	0.05
No. of decision trees in RF	20
Value of *k* in *k*-NN	5

4.1 Accuracy

Accuracy of all models for *2F* and *7F* has been given in Table 2. It can be noted from Table 2 that *SVM*(*2F*), *LR*(*2F*), *KNN*(*2F*), *ANN*(*2F*) and *RF*(*2F*) models have almost similar mean accuracy ranging between 0.893 and 0.899. However, maximum accuracy obtained by these five models exceeds 0.9. Amongst *2F* models, *SVM*(*2F*) has the least standard deviation. *NB*(*2F*) performs the worst in terms of mean accuracy. In case of all *7F* models, *KNN*(*7F*) and *RF*(*7F*) have comparatively higher mean accuracy than *SVM*(*7F*), *LR*(*7F*), *ANN*(*7F*) and *NB*(*7F*) with *NB*(*7F*) performing the worst amongst all the models. Further, *KNN*(*7F*) and *RF*(*7F*) were able to achieve maximum accuracy of 0.945 and 0.942 respectively. Furthermore, *KNN*(*7F*) and *RF*(*7F*) also have comparatively lower standard deviation amongst all the models. When comparing mean accuracy of all *2F* and *7F* models, it can be noted from the histogram, as shown in Figure 5, that the models *SVM*(*7F*), *LR*(*7F*), *KNN*(*7F*), *ANN*(*7F*), *RF*(*7F*) and *NB*(*7F*) have higher mean accuracy when compared to the respective mean accuracy obtained by them for *2F* models. Further, the accuracy of the models *SVM*(*7F*), *LR*(*7F*), *KNN*(*7F*), *ANN*(*7F*) and *RF*(*7F*) is better than accuracy of all *2F* models. Though *NB*(*7F*) model has comparatively poor mean accuracy than *SVM*(*2F*), *LR*(*2F*), *KNN*(*2F*), *ANN*(*2F*) and

RF(*2F*), its mean accuracy is comparatively better than the mean accuracy of *NB*(*2F*) model. Thus, it can be inferred that considering all features improves the overall accuracy in terms of forecasting floods. Moreover, in case accuracy is the key performance indicator, *KNN*(*7F*) and *RF*(*7F*) can be used for forecasting floods.

Figure 5 Histogram for mean accuracy of all flood forecasting models (see online version for colours)

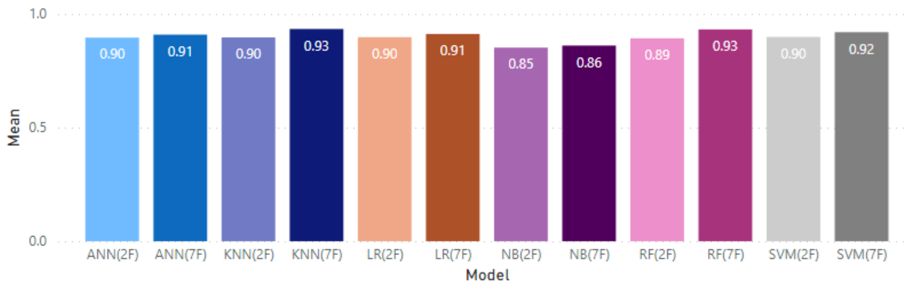


Table 2 Accuracy of all flood forecasting models

Model	*Accuracy*			
	Min	*Max*	*Mean*	*SD*
ANN(2*F*)	0.882	0.905	0.896	0.009
KNN(2*F*)	0.875	0.91	0.897	0.013
LR(2*F*)	0.887	0.91	0.898	0.008
NB(2*F*)	0.844	0.864	0.852	0.007
RF(2*F*)	0.884	0.901	0.893	0.006
SVM(2*F*)	0.89	0.908	0.899	0.005
ANN(7*F*)	0.879	0.934	0.909	0.019
KNN(7*F*)	0.925	0.945	0.934	0.008
LR(7*F*)	0.893	0.919	0.912	0.01
NB(7*F*)	0.846	0.872	0.861	0.01
RF(7*F*)	0.922	0.942	0.932	0.007
SVM(7*F*)	0.896	0.936	0.92	0.015

4.2 Precision

Precision of all models for *2F* and *7F* has been given in Table 3. High precision is desirable for flood forecasting models, as high precision is an indicator of more true positives and fewer false positives. Higher true positive value would indicate more flood occurrences are classified as floods whereas less false positives would indicate that lesser non-flood occurrences are classified as floods. Flood forecasting models having higher true positives and lower false positives would be more preferable for forecasting floods. It can be noted from Table 3 that mean precision value obtained using *SVM*(*2F*), *LR*(*2F*), *ANN*(*2F*), *KNN*(*2F*), *RF*(*2F*) and *NB*(*2F*) models range from 0.425 to 0.698 where highest mean precision value is obtained using *SVM*(*2F*) and lowest mean precision value is obtained using *NB*(*2F*). Further, mean precision value of *SVM*(*2F*) is larger than maximum precision values of *ANN*(*2F*), *KNN*(*2F*), *RF*(*2F*) and *NB*(*2F*). Further, it can also be noted from the table that minimum precision value of *SVM*(*2F*) is better than mean precision values of *KNN*(*2F*), *RF*(*2F*) and *NB*(*2F*). However, *SVM*(*2F*) model has comparatively higher standard deviation than *ANN*(*2F*), *KNN*(*2F*), *RF*(*2F*) and *NB*(*2F*) models. This may be attributed to high maximum precision value obtained using *SVM*(*2F*). Amongst all 2*F* models, *NB*(2*F*) model has worst mean precision but also least standard deviation. In case of all features, *SVM*(*7F*) and *RF*(*7F*) models have comparatively higher mean precision than *KNN*(*7F*), *LR*(*7F*), *ANN*(*7F*), *NB*(*7F*) with *NB*(*7F*) performing the worst amongst all 7*F* models. Though *SVM*(*7F*) and *RF*(*7F*) models have highest mean precision value, the standard deviation of *RF*(*7F*) is less than the standard deviation of *SVM*(*7F*) model. Further, it can be noted from the histogram, shown in Figure 6, that all 7*F* models have higher mean precision value in comparison to those obtained using *2F* models. Therefore, it can be inferred that considering all features improves the overall precision in terms of forecasting floods. Hence, if precision is used as the key performance indicator, *RF*(*7F*) model can be used for forecasting floods.

Figure 6 Histogram for mean precision of all flood forecasting models (see online version for colours)

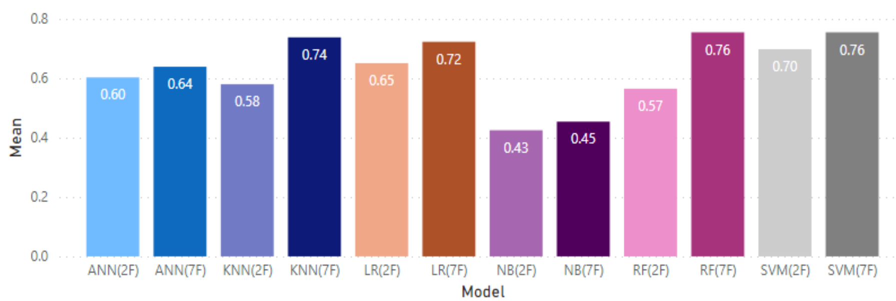


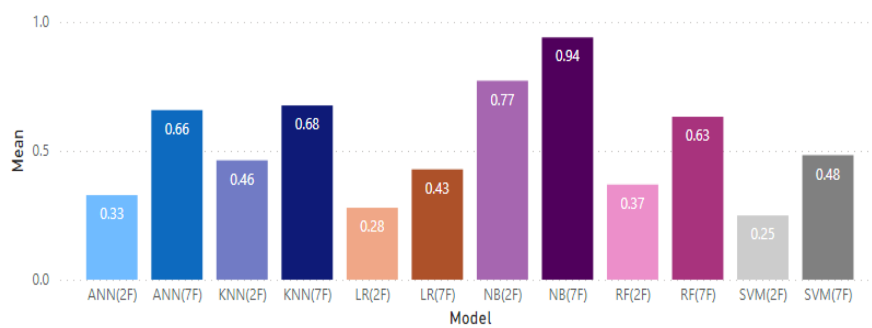
Table 3 Precision of all flood forecasting models

Model	*Precision*			
	Min	*Max*	*Mean*	*SD*
ANN(2*F*)	0.5	0.652	0.603	0.054
KNN(2*F*)	0.457	0.667	0.58	0.077
LR(2*F*)	0.529	0.846	0.651	0.11
NB(2*F*)	0.4	0.443	0.425	0.015
RF(2*F*)	0.5	0.636	0.565	0.043
SVM(2*F*)	0.6	0.833	0.698	0.089
ANN(7*F*)	0.486	0.923	0.639	0.152
KNN(7*F*)	0.674	0.778	0.738	0.035
LR(7*F*)	0.583	0.875	0.723	0.109
NB(7*F*)	0.43	0.475	0.454	0.018
RF(7*F*)	0.684	0.875	0.755	0.076
SVM(7*F*)	0.586	0.909	0.755	0.109

4.3 Recall

Recall of all models for *2F* and *7F*, has been given in Table 4. High recall is desirable for flood forecasting models, as high recall is an indicator of more true positives and fewer false negatives. More true positives would indicate more flood occurrences are classified as floods whereas fewer false negatives would indicate that fewer flood occurrences are classified as non-flood occurrences. It can be noted from Table 4 that mean recall value obtained using all *2F* models range from 0.249 to 0.772 where highest mean recall value is obtained using *NB*(*2F*) model and lowest mean recall value is obtained using *SVM*(*2F*) model. Further, minimum recall value of *NB*(*2F*) model is comparatively better than maximum recall value of *KNN*(*2F*), *RF*(*2F*), *ANN*(*2F*), *LR*(*2F*) and *SVM*(*2F*) models. However, standard deviation of *NB*(*2F*) model is also highest amongst all *2F* models. In case of all features, *NB*(*7F*) obtained highest mean recall value with least standard deviation. Minimum recall value of *NB*(*7F*) is comparatively better than maximum recall value of *KNN*(*7F*), *RF*(*7F*), *SVM*(*7F*) and *LR*(*7F*) models. Maximum recall value of *NB*(*7F*) is also highest amongst all *2F* and *7F* models. When comparing mean recall value of six models on both two features and all features, it can be noted from the histogram, shown in Figure 7, that all *7F* models have higher mean recall values in comparison to those obtained using *2F* models. Except *NB*(*7F*) model, standard deviation of *7F* models is higher in comparison to standard deviation of *2F* models. Thus, it can be inferred that considering all features improves the overall recall in terms of forecasting floods. Moreover, if recall is used as the key performance indicator, *NB*(*7F*) model can be used for forecasting floods.

Figure 7 Histogram for mean recall of all flood forecasting models (see online version for colours)



4.4 F-measure

As observed above, though *SVM*(*7F*) has the highest mean precision value, it has low mean recall value. Also, *NB*(*7F*) model has least mean precision value but highest mean recall value. Thus, in order to have a right balance between precision and recall, F-measure has been used to evaluate the performance of all the *2F* and *7F* models. F-measure of all models for *2F* and *7F*, has been given in Table 5. It can be noted from Table 5, that mean F-measure value obtained using all *2F* models range from 0.359 to 0.546 where highest mean F-measure value is obtained using *NB*(*2F*) model and lowest mean F-measure value is obtained using *SVM*(*2F*) model. Further, minimum F-measure value of *NB*(*2F*) is better than mean F-measure value of *RF*(*2F*), *ANN*(*2F*), *LR*(*2F*) and *SVM*(*2F*) models. Furthermore, minimum F-measure value of *NB*(*2F*) is better than maximum F-measure value of *SVM*(*2F*) and *LR*(*2F*) model. Standard deviation of *NB*(*2F*) is lowest amongst all *2F* models. While considering all features, mean F-measure value of *KNN*(*7F*) model is highest. Further, minimum F-measure value of *KNN*(*7F*) model is better than mean F-measure value of *NB*(*7F*), *ANN*(*7F*), *SVM*(*7F*) and *LR*(*7F*) models. When comparing mean F-measure value of six models on both two features and all features, it can be noted from the histogram, shown in Figure 8, that all *7F* models have higher mean F-measure values in comparison to those obtained using *2F* models. However, standard deviation of *SVM*(*7F*), *LR*(*7F*) and *ANN*(*7F*) models increases and standard deviation of *NB*(*7F*), *KNN*(*7F*) and *RF*(*7F*) models decreases in comparison to standard deviation of corresponding *2F* models. Among *7F* models, *LR*(*7F*) has worst mean F-measure but still its mean F-measure is comparatively better than mean F-measures of all *2F* models except *NB*(*2F*) model. Thus, it can be concluded that in case F-measure is the key performance indicator, *KNN*(*7F*) model can be used for forecasting floods.

Table 4 Recall of all flood forecasting models

Model	*Recall*			
	Min	*Max*	*Mean*	*SD*
ANN(*2F*)	0.225	0.425	0.328	0.068
KNN(*2F*)	0.375	0.55	0.463	0.065
LR(*2F*)	0.22	0.4	0.279	0.065
NB(*2F*)	0.634	0.875	0.772	0.098
RF(*2F*)	0.293	0.475	0.369	0.06
SVM(*2F*)	0.2	0.375	0.249	0.066
ANN(*7F*)	0.3	0.95	0.658	0.253
KNN(*7F*)	0.55	0.8	0.676	0.084
LR(*7F*)	0.341	0.55	0.428	0.099
NB(*7F*)	0.85	1	0.94	0.049
RF(*7F*)	0.525	0.725	0.632	0.065
SVM(*7F*)	0.3	0.725	0.483	0.139

Figure 8 Histogram for mean *F*-measure of all flood forecasting models (see online version for colours)

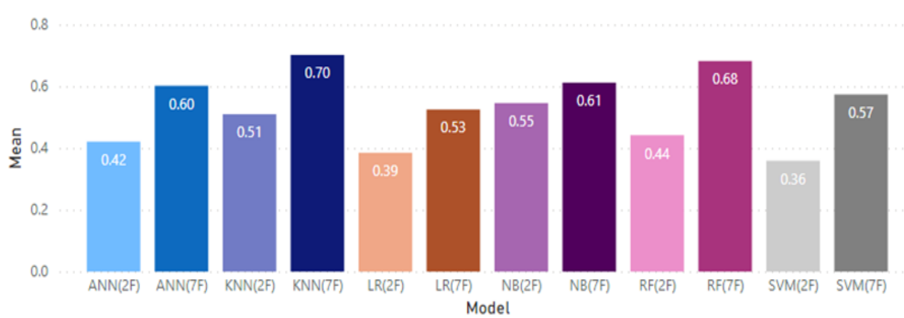


Table 5 *F*-measure of all flood forecasting models

Model	*F-measure*			
	Min	*Max*	*Mean*	*SD*
ANN(2*F*)	0.327	0.507	0.421	0.064
KNN(2*F*)	0.427	0.563	0.51	0.053
LR(2*F*)	0.316	0.478	0.385	0.061
NB(2*F*)	0.491	0.576	0.546	0.032
RF(2*F*)	0.387	0.514	0.442	0.041
SVM(2*F*)	0.314	0.462	0.359	0.058
ANN(7*F*)	0.447	0.768	0.602	0.13
KNN(7*F*)	0.638	0.771	0.702	0.047
LR(7*F*)	0.431	0.603	0.525	0.067
NB(7*F*)	0.596	0.633	0.612	0.016
RF(7*F*)	0.649	0.722	0.682	0.031
SVM(7*F*)	0.436	0.707	0.574	0.1

From the above performance comparisons of the *ML* models, it can be inferred that *RF*(*7F*) and *KNN*(*7F*) models performed comparatively better than the other *ML* models used for flood forecasting on most of the performance parameters. In order to ascertain their overall performance across classification thresholds with respect to other *ML* models were evaluated by computing area under the *ROC* curve (*AUC-ROC*). The comparison of *ML* models on *AUC-ROC* is given next.

4.5 AUC-ROC

AUC-ROC of all models for *2F* and *7F*, has been given in Table 6. It can be noted from Table 6 that mean *AUC-ROC* value obtained using all *2F* models range from 0.864 to 0.924 where highest mean *AUC-ROC* value is obtained using *NB*(*2F*) model and lowest mean *AUC-ROC* value is obtained using *KNN*(*2F*) model. Further, mean *AUC-ROC* value of *NB*(*2F*), *ANN*(*2F*), *LR*(*2F*) and *RF*(*2F*) models are almost similar. Furthermore, standard deviation of *NB*(*2F*) is better than standard deviation of all *2F* models except *ANN*(*2F*). It can be noted from the histogram, shown in Figure 9, that all *7F* models have higher mean *AUC-ROC* value in comparison to those obtained using *2F* models. Mean *AUC-ROC* value of *NB*(*7F*) model although lowest in all *7F* models, is still larger than mean *AUC-ROC* value of all *2F* models. Mean *AUC-ROC* value obtained using all *7F* models range from 0.937 to 0.965. Amongst *7F* models, *RF*(*7F*) model has highest mean *AUC-ROC* value. Further, the comparisons of the *ML* models on their *ROC* curves for maximum and minimum values, as shown in Figures 10 and 11 respectively, shows that area under the *ROC* curve for both maximum and minimum values is best for *RF*(*7F*) model. Additionally, minimum *AUC-ROC* value of *RF*(*7F*) model is larger than mean *AUC-ROC* value of *KNN*(*7F*), *LR*(*7F*), *SVM*(*7F*) and *NB*(*7F*) models. *RF*(*7F*) model also has least standard deviation amongst all *7F* models. Thus, it can be inferred that the overall performance of *RF*(*7F*), in terms of *AUC-ROC* across all classification thresholds, is best amongst all *ML* models and thus *RF*(*7F*) model can be preferred over all other *ML* models for forecasting floods.

Figure 9 Histogram for mean *AUC-ROC* of all flood forecasting models (see online version for colours)

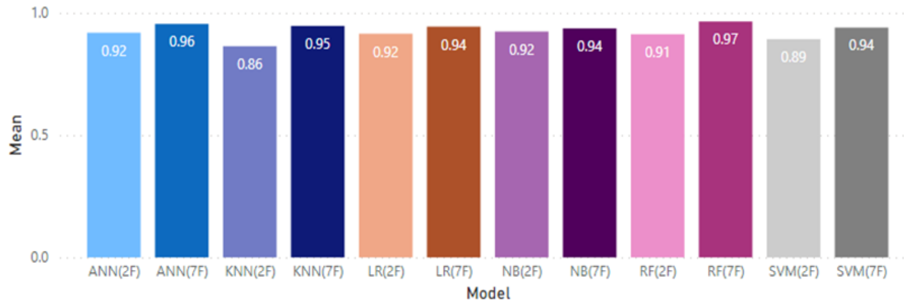


Figure 10 ROC curve for all flood forecasting models (for maximum value) (see online version for colours)

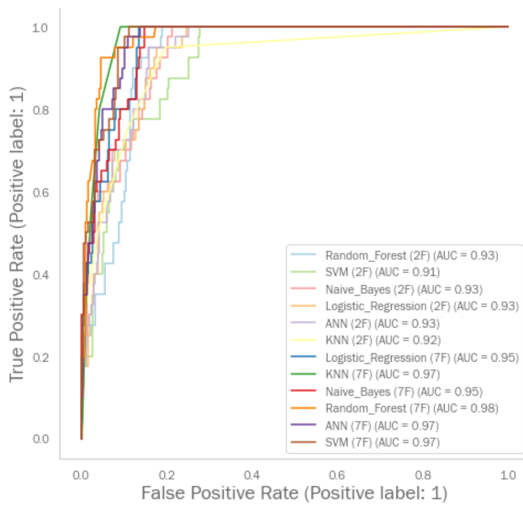


Figure 11 ROC curve for all flood forecasting models (for minimum value) (see online version for colours)

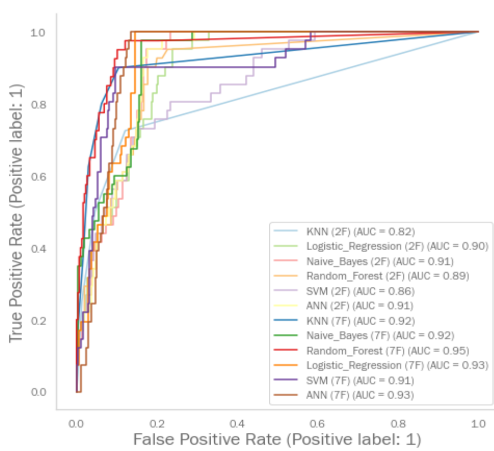


Table 6 *AUC-ROC* of all flood forecasting models

Model	*AUC-ROC*			
	Min	*Max*	*Mean*	*SD*
ANN(2*F*)	0.91	0.932	0.919	0.008
KNN(2*F*)	0.818	0.916	0.864	0.036
LR(2*F*)	0.898	0.931	0.915	0.011
NB(2*F*)	0.909	0.934	0.924	0.009
RF(2*F*)	0.89	0.926	0.913	0.013
SVM(2*F*)	0.857	0.913	0.893	0.019
ANN(7*F*)	0.931	0.966	0.955	0.013
KNN(7*F*)	0.92	0.973	0.947	0.021
LR(7*F*)	0.927	0.954	0.944	0.01
NB(7*F*)	0.923	0.953	0.937	0.012
RF(7*F*)	0.954	0.975	0.965	0.008
SVM(7*F*)	0.907	0.969	0.94	0.022

It can be noted from the above that for all performance metrics *7F* based *ML* models have performed comparatively better than their respective *2F* based *ML* models. Thus, considering features like vapour pressure, cloud cover, evapo-transpiration, crop evapo-transpiration and wet day frequency, in addition to the two features considered by earlier *ML* models, has improved the forecasting ability of the *ML* models. Further, amongst the *7F* based *ML* models, *KNN*(*7F*) and *RF*(*7F*) models have performed reasonably well in almost all performance parameters. Moreover, *KNN*(*7F*) performed the best in F-measure and *RF*(*7F*) performed the best in *AUC-ROC*. Furthermore, *SVM*(*7F*), *ANN*(*7F*) and *LR*(*7F*) have an average performance in almost all the parameters. *NB*(*7F*) performed the worst amongst all the models; however its performance is best in the case of recall.

From above, it can be inferred that all features, instead of only two features in the dataset, should be considered for forecasting floods. Further, from amongst all the above-mentioned *ML* models, *KNN*(*7F*) and *RF*(*7F*) models were able to perform comparatively better in terms of classifying floods and thus can be used for forecasting floods.

5 Conclusion

This paper focused on designing *ML* based classification models for forecasting floods. Most of the studies involving forecasting floods considered parameters like temperature and precipitation. However, parameters like vapour pressure, cloud cover, wet day frequency, crop evapo-transpiration and surface evapo-transpiration may also influence the occurrence of floods and therefore were also considered, along with the two parameters, for forecasting floods. In this study, monthly meteorological data of 12 most flood affected districts of Northern Bihar (India) for a period 1991–2002 obtained from Climatic Research Unit, University of East Anglia and state's flood management portal was considered. Classification models like *NB, LR, SVM, KNN, RF and ANN* were applied on this labelled dataset. The experimentation considered two features(*2F*), as per the existing literature, and seven features(*7F*), as proposed in this paper. Above mentioned *ML* models were trained and tested using stratified 5-fold cross validation on both *2F* and *7F* datasets. The comparison of these *2F* and *7F* models were carried out on performance parameters like accuracy, precision, recall, F-measure and *AUC-ROC* and it was observed that the *ML* models were able to forecast comparatively better when they considered seven features. Thus, it can be inferred that additional five features considered in this study lead to improvement in the effectiveness of the models in forecasting floods. Further, amongst these classification models, *RF*(*7F*) and *KNN*(*7F*) models performed comparatively better than the other *ML* models on most of the performance parameters. Furthermore, while comparing the overall performance of all the *ML* models across multiple thresholds, the performance of *RF*(*7F*) model was the best and thus *RF*(*7F*) model can be preferred over all other *ML* models for forecasting floods.

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