

A Comparison Review based on Classifiers and Regression Models for the Investigation of Flash Floods

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Abstract—Several regions of the world have been affected by one of the natural disasters named as flash floods. Many villagers who live near stream or dam, they suffer a lot in terms of property, cattle and human lives loss. Conventional early warning systems are not up to the mark for the early warning announcements. Diversified approaches have been carried out for the identification of flash floods with less false alarm rate. Forecasting approaches includes some errors and ambiguity due to the incompetent processing algorithms and measurement readings. Process variables like stream flow, water level, water color, precipitation velocity, wind speed, wave's pattern and cloud to ground (CG) flashes have been measured for the robust identification of flash floods. A vibrant competent algorithm would be required for the investigation of flash floods with less false alarm rate. In this research paper classifiers have been applied on the collected data set so that any researcher could easily know that which classifier is competent and can be further enhanced by combining it with other algorithms. A novel comprehensive parametric comparison has been performed to investigate the classification accuracy for the robust classification of false alarms. For the better accuracy more than one process variables have been measured but still contained some false alarm. Appropriate combination of sensor was integrated to increase the accuracy in results as multi-modal sensing device has been designed to collect the data. Linear discriminant analysis, logistic regression, quadratic support vector machine, k-nearest neighbor and Ensemble bagged tree have been applied to the collected data set for the data classification. Results have been obtained in the MATLAB and discussed in detail in the research paper. The worst accuracy of the classification (62%) has been achieved by the coarse k-NN classifier that means coarse k-NN produced 38% false negative rate that is not acceptable in the case of forecasting. Ensemble bagged trees produced best classification results as it achieved 99 % accuracy and 1% error rate. Furthermore, according to the comprehensive parametric comparison of regression models Quadratic SVM found to be the worst with mean square error of 0.5551 and time elapsed 13.159 seconds. On the other hand, Exponential Gaussian process regression performed better than

the other existing approaches with the minimum root mean squared error of 0.0002 and prediction speed of 35000 observations per second.

Keywords—Flash floods; classification; SVM; k-NN; logistic regression; quadratic SVN; ensemble bagged trees; exponential GPR

I. INTRODUCTION

Low cost effective solution has been designed using Android phone and Arduino. Echolocation strategy has been applied to measure the water level [1]. Bunch of sensors were deployed from the upper stream to the village. Sensors nodes were designed to observe the data. Supervisor control data acquisition (SCADA) based system was designed to forecast the floods on real time basis [2]. Torrential downpour can be considered as the main cause of flash floods. Heavy precipitation for the short time known as torrential downpour. Two meteorological radars have been used to observe the torrential downpour in Czech Republic [3]. Ultrasonic sensor based observations have been analyzed to determine the dam level [4]. Data from 2007 to 2010 were collected from three stations of Selangor to design a novel model for the prediction of flash floods using ANN. Feed forward back propagation with the tangent sigmoid function was proposed to estimate the floods. The process variables like humidity, rainfall, and temperature were taken as input and the rainfall data from the stations were set as the targets. The proposed model best results [4]. Another research elaborated a novel method by measuring the magnetic field lines by tesla meter or magnetometer to predict the flash floods. Research proved by showing the results that during the flash floods magnetic field line reduced abruptly therefore magnetic field lines that are radiated from the center of the earth can be regarded as the significant yardstick to measure the flash floods [5]. A practical early warning system must detect the flash floods in appropriate timings as there is no use of the system if the flood

is detected after the starting of the event. Keeping in the mind the time constraint a flood prediction model using hybrid approach NNARX (Neural Network Autoregressive with Exogenous Input) with EKF (extended Kalman Filter) was developed. 120 samples of the data set were tested and results showed that hybrid approach worked better [6]. In a previous method a novel solution was suggested by measuring the carbon dioxide levels in the environment and soil flux as the newly discovered phenomena proved that plants take less water due to the increased amount of carbon dioxide levels. Multi-layer perceptron was applied on the collected data set to reduce the false alarms in determining the flash floods [7]. IT based flash flood monitoring was performed for the immediate emergency rescue of the affected people in Jeddah [8]. Majority casualties happen due to the lack of the data and information regarding the propagation of the flash flood. Therefore, an urban flash flood monitoring was performed to know the actual and predicted flow of the flash floods for the evacuation announcement [9]. Kalman filtering, fuzzy logic, clustering, Neural network autoregressive model with exogenous input (NNARX), Particle swarm optimization (PSO) and Support vector machine have been applied for the prediction and estimation of flash floods [10]. Fuzzy logic based a disaster management device has been designed for the announcement of exit routes during the hazard [11]. Ensemble learning model has also been designed for the better generalization model of classification [12]. The false positive rate (FP) is the data values which have been estimated wrong due to the presence of error. The negative false rate (FN) is the data that is defined falsely as negative [13]. False alarm ratio relies on the relation of the complexity and anisotropy of the sea-floor Williams et al. [14] [15]. Gaussian process regression model can be acknowledged as the competent approach for solving non-linear regression issues. It performs regression in a simple way parameterization and Bayesian. It also removes ambiguity and uncertainty in the prediction of event [16]. Data driven approaches are usually capable to determine the complex and non-linear data to be transformed for the prediction of the event [17]. Support vector machine was developed in 1990s and became popular among the classification model to its better learning generalization [18]. Signal attenuation and distortion in Television satellites due to the rainfall was observed and flooding was mapped. It has been analyzed that Ku band frequencies varied due to rain fall and climate change. Simulated maps of flash floods were compared with the existing mapping methods to validate the approach [22].

Table I demonstrates the tabular chart for the comparison of AI based algorithms. Root mean square error has been a yardstick to estimate the performance of the algorithms. The results of actual run time data using existing approach of MLP-PSO show probability of 95.15%. The proposed algorithm of ANN-PSO has performed the investigation of flash flood with 0.0047 error probability and enhanced accuracy [20].

TABLE. I. COMPARATIVE ANALYSIS OF VARIOUS APPROACHED FOR THE FLASH FLOOD INVESTIGATION [20]

Performance Indices	ANN	SVM	ANFIS	NNARX	ANN-PSO
RMSE	0.194	0.390	0.116	0.090	0.0047
Best Fit	73	64	78	80.10	98.7
Results	Satisfactory	Unsatisfactory	Satisfactory	Satisfactory	Satisfactory
Hourly Data	6 hrs	6 hrs	3 hrs	3 hrs	3 hrs
Accuracy	73	64	78	80.16	98.99
Precision	Medium	Low	High	High	High
Reliability	Medium	Low	High	High	High
Power Utilisation	Limited	Limited	Limited	Limited	Limited

II. PROBLEM STATEMENT

It has been highlighted in the literature review that sensors and transducers produce false alarms. Errors are generated usually in instrumentation and measurement [10]. Sometime prediction of flash floods can be wrong due to the incompetent decision algorithms and poor sensitivity of sensors. Due to the increased number of false alarms a competent and vigorous classifier and regression model was required for the discrimination of true positive value and false positive value. Sensors data values may contain false alarms and missed values [21].

III. MATERIALS AND METHODS

Multi-modal sensing device was developed to collect the data from any sea shore. The data has been collected from the sea shore of Kund Malir, Pakistan. Selection of transducers was not an easy task as appropriate combination of competent sensors was needed. According to the literature review almost all the parameters have been used for the flash floods investigation.

A. Multi-Resolution Sensing Device for Data Collection

Fig. 1 shows that a device has been developed for the investigation of flash flood as a hazard monitoring device. Multi-modal sensing device comprised of the following sensors: (a) pressure (b) temperature (c) water level (d) gas sensor for detecting CO₂ and (e) ultrasonic sensor. Selection of sensors was very complex task as bunch of appropriate sensors must be used for the accurate and precise results without any false alarm rate [21].

B. Fundamental Flow Diagram

In Fig. 2, Ultrasonic sensor, Passive infrared sensor, MQ2 sensor, humidity sensor, pressure and temperature sensors have been used to measure the data near the sea shore of Kund Malir, Pakistan. Data labeling was performed. The data may contain random, missed and repetitive values it must be filtered or normalized before the processing. Therefore, robust classification and regression model were needed.



Fig. 1. Multi-Resolution Data Collection Device.

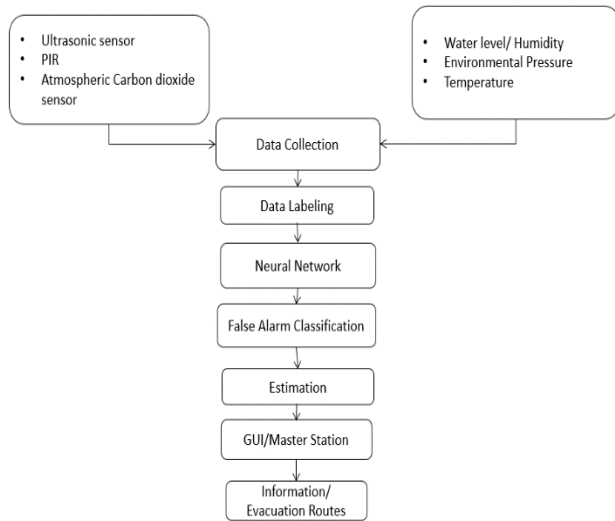


Fig. 2. Main Flow Diagram.

C. Collected Data Set

Table II shows that the data set has been collected and all the values have been saved in parallel at the same time. All the sensors have been correlated to each other. More than ten thousand number of instances were recorded and observed for the data processing having total six attributes. Six attributes are the different sensor data values that have been represented in the Table I.

D. Threshold

Table III represents the threshold and range related to the sensor values. All of the sensors must exceed the threshold in order to activate the trigger function. Moreover, all the sensors have been interfaced to each other. Sensors produced random results due to the high wind speed. Change of venue for data collection requires modification in threshold of sensors depending on the meteorology of location.

TABLE II. COLLECTED DATA SET FROM THE MULTI-MODAL SENSING DEVICE [21]

PIR	Distance (mm)	Rainfall	CO ₂ (ppm)	Temperature (°C)	Pressure (hectopascal)
0	300	0	0	30.13	100270.6
0	37.42	458	539	29.95	100268.4
0	37.18	459	533	29.71	100277.5
0	3661.34	453	418	29.6	100279.8
0	3654.66	453	397	29.46	100277.5
0	3691.18	450	356	37	100280.1
0	3691.18	450	356	29.4	100280.1

1	4.51	504	355	28	110424.2
1	4.39	494	412	23	110424.2
1	4.96	485	399	23	110424.2
1	4.84	479	382	23	100283.5
1	5.06	476	349	23	110424.2
1	4.66	483	400	23	110424.2
1	4.66	478	387	23	110424.2
1	32.45	551	392	23	110424.2
0	22.45	512	387	23	110424.2
0	29.64	518	388	23	110424.2
1	3619.3	529	389	23	110424.2
1	78.39	498	386	23	110424.2
0	0	491	385	23	110424.2
0	30.13	517	397	23	110424.2
0	36.96	501	395	23	110424.2
0	31.92	496	392	23	110424.2
0	32.95	497	390	23	110424.2
0	41.18	503	387	23	110424.2
0	135.14	494	385	23	110424.2
0	3846.76	496	385	23	110424.2
0	6.47	519	393	56	110424.2
0	104.96	506	389	23	110424.2
0	103.76	498	387	23	110424.2
0	31.2	488	385	25	110424.2
0	104.63	486	386	25	110424.2
0	34.51	535	389	25	110424.2
1	6.72	530	1014	25	110424.2
1	20.91	527	1012	25	110424.2
0	101.85	511	1010	25	110424.2
0	3749.04	499	347	25	110424.2
0	36.96	493	303	25	110424.2
0	9.3	492	324	25	110424.2
0	0	493	388	25	110424.2
0	110.74	492	363	25	110424.2
0	105.54	495	341	25	110424.2
0	23.86	496	392	25	110424.2
0	99.76	498	1012	25	110424.2
0	3279.56	502	1012	25	110424.2
0	75.99	510	1012	25	110424.2
0	3259.63	536	1010	25	110424.2
0	37.8	534	1010	25	110424.2
0	3279.9	522	1010	25	110424.2
0	35.02	517	1011	25	110424.2
0	3223.39	516	1011	25	110424.2
0	30.96	543	1010	25	110424.2
0	3244.81	557	1009	25	110424.2
0	32.29	571	1009	25	110424.2
0	3233.67	553	1010	25	110424.2
0	35.19	530	1010	23	110424.2
0	35.79	521	1010	23	110424.2
0	3300.48	522	1010	23	110424.2
0	29.72	549	1009	23	110424.2

TABLE III. THRESHOLD VALUES FOR SENSORS

	MINIMUM LIMIT	MAXIMUM LIMIT
PIR	1	
DISTANCE	0	50
RAINFALL	>300	
CO ₂	> 600	
TEMPERATURE	0	50
PRESSURE	>5000	
ALTIMETER	>1000	

IV. EXTENSIVE PARAMETRIC COMPARISON OF DATA CLASSIFIERS

Table IV demonstrated that Comprehensive parametric comparison has been performed to investigate the classification accuracy for the robust classification of false alarm in predicting flash floods. Linear discriminant analysis, logistic regression, quadratic support vector machine, k-nearest neighbor and Ensemble bagged tree have been applied to the collected data set for the data classification. Initially seventy-five percent of the data were used as a training and other 25 percent data was saved for the testing purpose. Both of the data files training and testing were converted into the variable so that it may utilized in the MATLAB as all the simulations have been performed in the MATLAB. MATLAB based simulations produced the confusion matrix and all the parametric results which have been presented in the table. The worst accuracy of the classification (62%) has been achieved by the coarse k-NN classifier that means coarse k-NN produced 38% false negative rate that is not acceptable in the case of forecasting. Ensemble bagged trees produced best classification results as it achieved 99 % accuracy and 1% error rate.

A. Linear Discriminant Analysis

Fig. 3 explains that data set was trained for the linear discriminant classification and it produced confusion matrix and other results. Confusion matrix showed that LDA achieved 89% true positive rate and 11 false negative rate with 97% accuracy. Prediction speed and training time was found to be 12000 observation/seconds and 1.5238 seconds respectively. This classification model was up to the mark but accuracy can be further improved. Data can be regularized in discriminant analysis classifier for the robust classification model.

B. Logistic Regression Classification Model

Fig. 4 represents that Logistic regression classification model was developed in the MATLAB using the collected data set. The classification model achieved 96.4% accuracy. Prediction time and training time was found to be 15000 observation/second and 3.9633 seconds. It took almost double time to classify the faulty data compared to the linear discriminant analysis with slight less accuracy.

C. Quadratic Support Vector Machine Classification Model

Fig. 5 illustrates that Quadratic support vector machine classifier has been applied to the collected data set form the sea shore of Kund Malir. The model is based on predict SVM model in which predictors have been defined in the matrix and then comparison would be performed between the observed and predicted. The trained Quadratic SVM model may be compact or full. The trained model has been exported for the testing purpose. $y_{out} = \text{predict}(\text{QSVMModel}, X)$. Quadratic support vector machine classifier model achieved 93% true positive rate and 7% False negative rate in the confusion matrix. 96.8% accuracy achieved by Q-SVM in 0.9237 seconds of training time. Prediction speed was found to be 40000 observations per second.

TABLE IV. PARAMETRIC COMPARISON OF LDA, LR, QSVM, K-NN AND ENSEMBLE

Classification Models	True Positive rate (%)	False Negative rate (%)	Accuracy (%)	Prediction speed per second	Training Time (s)
Linear Discriminant	89	11	97.0	12000	1.5238
Logistic Regression	93	7	96.4	15000	3.9633
Quadratic SVM	93	7	96.8	40000	0.9327
Fine k-NN	96	4	98.6	9600	1.5307
Medium k-NN	91	9	96.6	19000	0.927
Coarse k-NN	62	38	89.3	16000	0.90243
Ensemble Bagged Trees	99	1	99.4	2800	6.4101

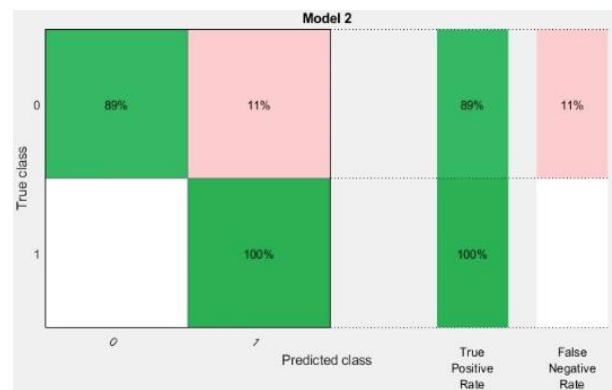


Fig. 3. Linear Discriminant Analysis Confusion Matrix.

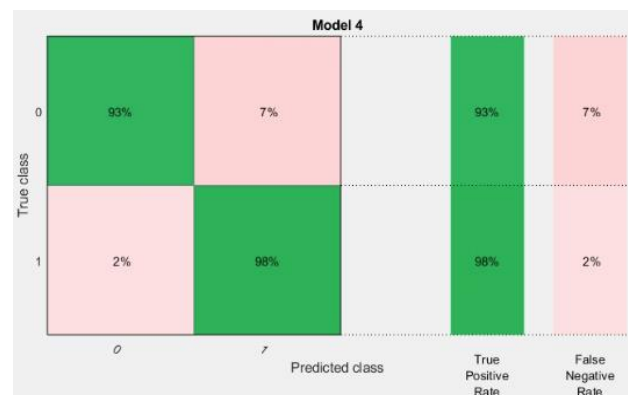


Fig. 4. Logistic Regression Confusion Matrix.

D. Fine k-Nearest Neighbor Classification Model

Fig. 6 shows the confusion matrix for the Fine k-nearest neighbor algorithm. Fine k-nearest neighbor classification model has been developed by measuring the standardized Euclidian distance.

$$E = (u_u - V_v)B^{-1}(u_u - V_v) \quad (1)$$

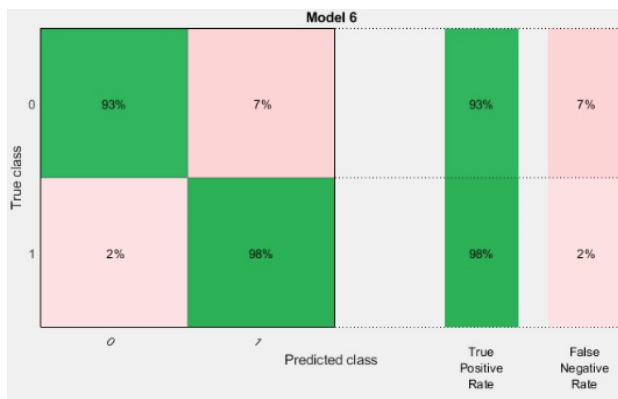


Fig. 5. Q-SVM Confusion Matrix.

Where, U and V are the data matrix. B can be considered as the diagonal matrix and S can be acknowledged as scaling factor. Model was trained in the MATLAB using collected data set. 96% true positive rate and 4% of false negative rate was achieved in this classification model. The fine k-NN classification model achieved 98.6% accuracy with training time of 1.5307 second and prediction speed of 9600 observations per second.

E. Medium k-Nearest Neighbor Classification Model

Fig. 7 explains that medium k-NN classifiers have been used widely as a bench mark for learning. k-NN classifier has the capability to be modified easily as well. X can be considered as the numeric data for the training. Moreover, Chebychev distance, Euclidean distance, city block distance and Minkowski distance can be measured for determining the kd-Tree. Medium k-nearest neighbor classification model produced 19% true positive rate and 9% false negative rate. 96.6% accuracy was achieved with training time of 0.927 second and 19000 observations per second.

F. Coarse k-Nearest Neighbor Classification Model

In Fig. 8, the worst accuracy of the classification (62%) has been achieved by the coarse k-NN classifier that means coarse k-NN produced 38% false negative rate that is not acceptable in the case of forecasting.

G. Ensemble Bagged Trees Classification Model

Fig. 9 represented the confusion matrix of Ensemble Bagged Trees. The Ensemble bagged trees has been applied to the data set for the better decision. The motive of the ensemble is to construct a better learning model which can produce better classification performance on the applied data set. $Y_{fit} = ensemblebaggedtree(B, X)$ returns a vector of forecasted responses for the predictor data in the table or matrix X, based on the ensemble of bagged decision trees B. Y_{fit} is a cell array of character vectors for classification and a numeric array for regression. By default, predict takes a democratic (non-weighted) average vote from all trees in the ensemble. X can be considered as a numeric Matrix. Ensemble Bagged Tree learning model for classification achieved best performance accuracy of 99.4% with prediction speed of 2800 observations/second and training time is 6.4101 seconds. 99% True positive rate and

1% false negative rate was achieved by the Ensemble Bagged Trees.

H. Graphical Illustration of Model

Fig. 10 displays the Graphical analysis of ensemble bagged tree prediction model has been represented in figure no. 9. Blue color shows the output value of “zero” and orange color represents “one”. It can be easily observed from the results that Ensemble bagged tree performed better than the other existing classifiers.

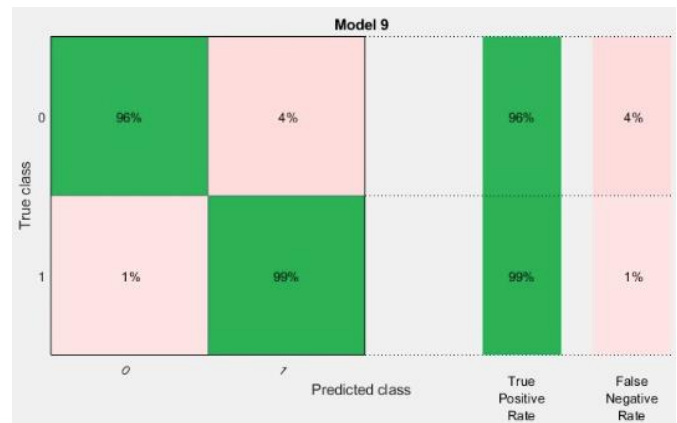


Fig. 6. Fine k-Nearest Neighbor Confusion Matrix.

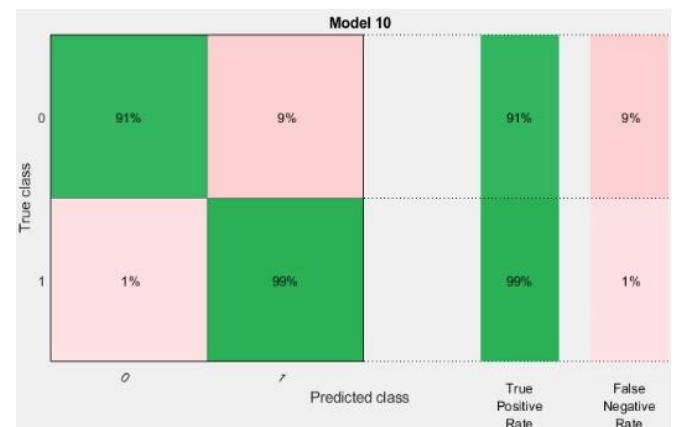


Fig. 7. Medium k-NN Confusion Matrix.

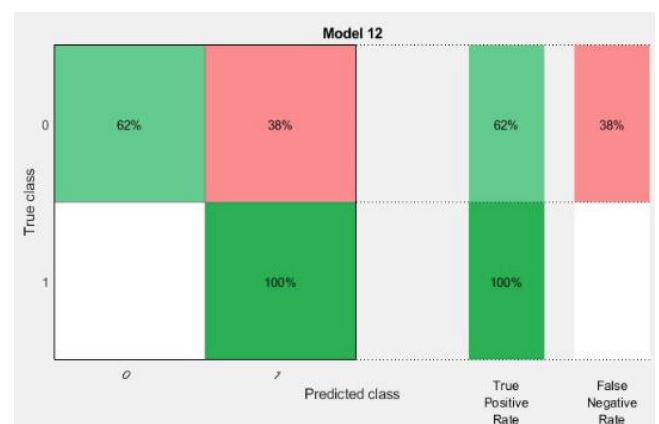


Fig. 8. Coarse k-NN Confusion Matrix.



Fig. 9. Ensemble Bagged Trees Confusion Matrix.

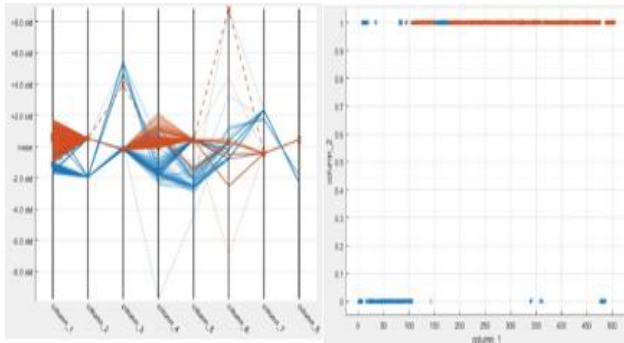


Fig. 10. Graphical Analysis of Prediction Model.

V. EXHAUSTIVE PARAMETRIC COMPARISON OF REGRESSION MODELS

Table V shows the comprehensive parametric comparison for finding out the best performer regression model. LR, interactions linear, robust linear, step wise linear, linear support vector machine, Quadratic SVM, Gaussian SVM, Rational quadratic GPR, Exponential GPR and ensemble bagged trees regression models have been developed for the prediction of flash floods. These regression models have been applied on the collected data set. According to the comprehensive parametric comparison of regression models Quadratic SVM found to be the worst with mean square error of 0.5551 and time elapsed 13.159 seconds. On the other hand, Exponential Gaussian process regression performed better than the other existing approaches with the minimum root mean squared error of 0.0002 and prediction speed of 35000 observations per second.

A. Graphical Illustration of Linear Regression, Interactions Linear, Robust Linear and Step Wise linear

Fig. 11 demonstrates the graphical illustration of model 1 (Linear Regression), Model 2 (Interactions Linear), Model 3 (Robust Linear) and Model 4 (step wise linear). Moreover, Blue color represents the true data and yellow color depicts the predicted data. The graphs have been plotted between number of records and flood response (hurricane response).

TABLE. V. PARAMETRIC COMPARISON OF REGRESSION APPROACHES

Predictive Models	RMSE	R ²	MSE	MAE	Prediction speed per second	Training Time (s)
Linear Regression	0.1900	0.82	0.0361	0.113	11000	4.5756
Interactions Linear	0.1087	0.94	0.0118	0.044	39000	0.8332
Robust Linear	0.267	0.65	0.0712	0.071	80000	0.898
Step Wise Linear	0.1118	0.94	0.0125	0.046	70000	3.779
Linear SVM	0.2316	0.73	0.0536	0.127	47000	11
Quadratic SVM	0.5551	-0.53	0.0308	0.322	73000	13.159
Gaussian SVM	0.0721	0.97	0.0052	0.045	140000	0.818
Rational Quadratic GPR	0.0006	1	3×10 ⁻⁷	9×10 ⁻⁵	22000	1.1555
Exponential GPR	0.0002	1	4×10 ⁻⁸	3×10 ⁻⁵	35000	2.1752
Ensemble Bagged Trees	0.0750	0.97	0.0056	0.0222	34000	2..3892

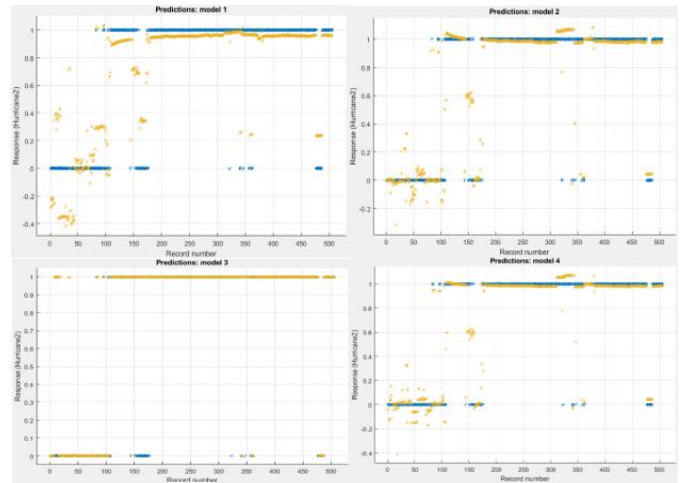


Fig. 11. Graphical Illustration of Prediction Model 1, Model 2, Model 3, Model 4.

B. Graphical Illustration of Linear SVM, Quadratic SVM, Gaussian SVM and Rational Quadratic GPR

Fig. 12 demonstrated the graphical illustration of model 5 (Linear SVM), Model 6 (Quadratic SVM), Model 7 (Gaussian SVM) and Model 8 (Quadratic GPR). Moreover, Blue color represents the true data and yellow color depicts the predicted data. The graphs have been plotted between number of records and flood response (hurricane response).

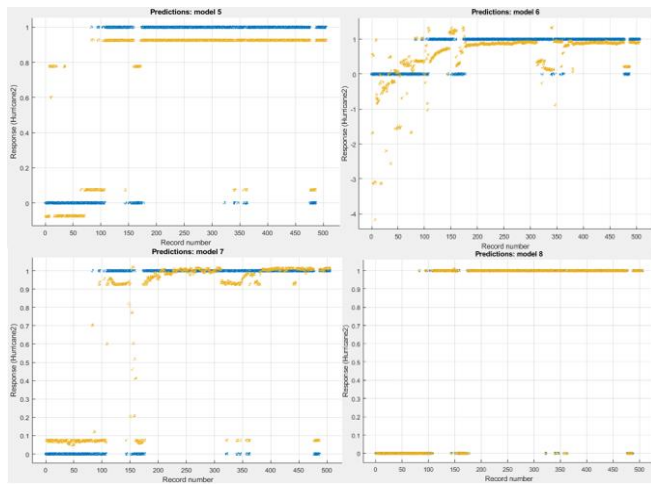


Fig. 12. Graphical Illustration of Prediction Model 5, Model 6, Model 7, Model 8.

C. Graphical Illustration of Exponential GPR and Ensembled Bagged Trees

Fig. 13 portrayed the graphical analysis of model 9 (Exponential GPR) and model 10 (Ensemble Bagged Trees). Moreover, Blue color represents the true data and yellow color depicts the predicted data. The graphs have been plotted between number of records and flood response (hurricane response). (Gaussian Processes). For set S , mean function $\mu : S \rightarrow R$ and any covariance function (also called kernel) $k : S \times S \rightarrow R$, there exists a GP $f(x)$ on S ,

$$\text{s.t. } E[f(x)] = \mu(x), \text{Cov}(f(x_s), f(x_t)) = k(x_s, x_t), x, x_s, x_t \in S \quad (2)$$

It denotes $f \sim GP(\mu, k)$. For a regression problem $y = f(x) + \varepsilon$, by Gaussian process method the unknown function f is assumed to follow a $GP(\mu, k)$. Given n pairs of observations $(x_1, y_1), \dots, (x_n, y_n)$,

we have

$$y = f(X) + \varepsilon \quad (3)$$

where $y = [y_1, y_2, \dots, y_n]^T$ are the outputs, $X = [x_1, x_2, \dots, x_n]^T$ are the inputs, and $\varepsilon = [\varepsilon_1, \varepsilon_2, \dots, \varepsilon_n]^T$ are independent identically distributed Gaussian noise with mean 0 and variance σ^2 [19].

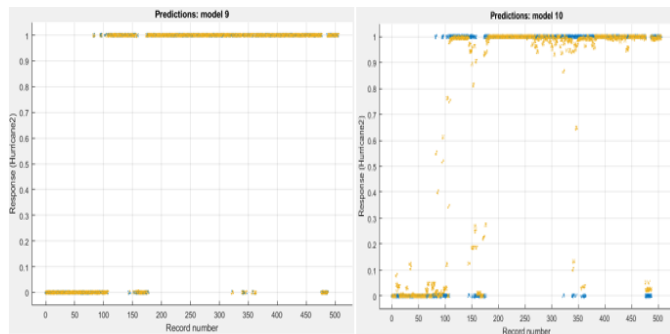


Fig. 13. Graphical Analysis of Prediction Model 9 and Model 10.

VI. CONCLUSION AND FUTURE WORK

In this research paper various classification model and regression model have been investigated to determine the competent approach for the identification of flash floods with less false alarm rates. Parametric comparison has been shown so that researchers may have an idea about the technical and practical implications related to the flash flood research. Actually the collected data or observed data may contain inconsistent, missed or random values. Therefore, vigorous classification and predictive model is required for the accurate and precise identification of the flash floods. Moreover, Bayesian regularization and scaled conjugate gradient were applied to the data set. Results showed that scaled conjugate gradient performed better. Comprehensive parametric comparison of classifiers and regression models has been performed and compare to find out the better classification and regression model. It can be concluded that the worst accuracy of the classification (62%) has been achieved by the coarse k-NN classifier that means coarse k-NN produced 38% false negative rate that is not acceptable in the case of forecasting. Ensemble bagged trees produced best classification results as it achieved 99 % accuracy and 1% error rate. According to the comprehensive parametric comparison of regression models Quadratic SVM found to be the worst with mean square error of 0.5551 and time elapsed 13.159 seconds. On the other hand, Exponential Gaussian process regression performed better than the other existing approaches with the minimum root mean squared error of 0.0002 and prediction speed of 35000 observations per second.

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