



Classification of Flood Disasters Severity Levels by Employing Machine Learning Techniques

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CLASSIFICATION OF FLOOD DISASTERS SEVERITY LEVELS BY EMPLOYING MACHINE LEARNING TECHNIQUES

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Abstract

Natural disasters can happen at any time and pose a risk to individuals. Numerous disasters have the potential to affect the economy of the country as well as the people. The most frequent disaster that happens worldwide and severely affects people is flooding. The article provides machine learning classification techniques, like decision trees, Naive Bayes, support vector machines (SVM), and K-Nearest Neighbour (KNN) with severity index. The severity index was established using economic loss as a starting point. To define the damage, however, a variety of factors were taken into consideration, such as the total number of fatalities, injuries, and flood victims, as well as the costs associated with reconstruction and the overall economic losses. The study reveals that, the Ensemble and decision tree classifiers provide better ideal categorization in terms of accuracy and error.

Keywords: Natural disasters, Decision trees, Support Vector Machines, K-Nearest Neighbour Naïve Bayes and Ensemble classifiers

1. INTRODUCTION

Natural disasters have occurred mostly in recent years, usually causes significant loss to both individuals and entire nation. The big disaster that may occur mostly in India includes floods, tsunamis, earthquakes, cyclones, and famine. One of the most frequent disasters among such occurrences is flooding. The states that are most affected by flooding include Kerala, Kashmir, and Uttarakhand. Based on a study, the event has results in more than 10,000 fatalities and more than \$10 million

in economic losses. As a result of such a natural disaster, there is infrastructure damage, food and water shortages, public health difficulties, environmental impact, and economic impact [1]. Since natural disasters were unpredictable that may affect any type of concern a fuzzy keywords-driven Natural Disasters Warning is introduced for the enterprises [2]. Some real time disaster events and their analysis were discussed [3-6]. Though we have some analysis forecasting and monitoring is also essential for such disaster events there are several methods adopted [7-9]. The above mentioned article initiated to implement machine learning based classification method for the flood disaster event. However some classification method applications like fuzzy logic, support vector machines and neural networks led the further development in the work [10-13]. Apart from the other types of classification techniques decision tree classifier and KNN Classifier have given promising classification levels [14&15].

1.1 FLOOD DISASTER DATA EVENT CLASSIFICATION

The flood disaster data events were sampled and processed in three processing units. Initially the disaster events were sampled and processed using principal component analysis and classified using different types of classifiers. The entire progression of classification is revealed in the Figure.1.1.

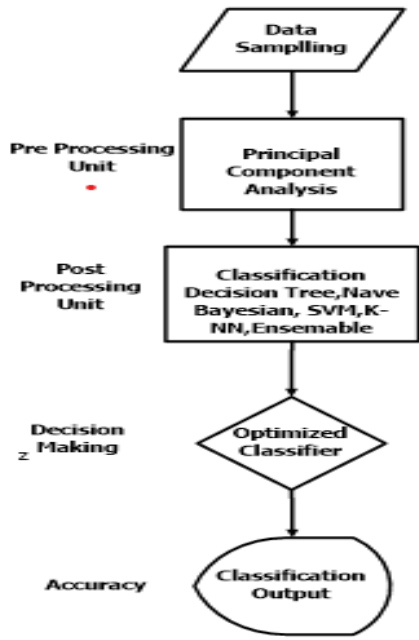


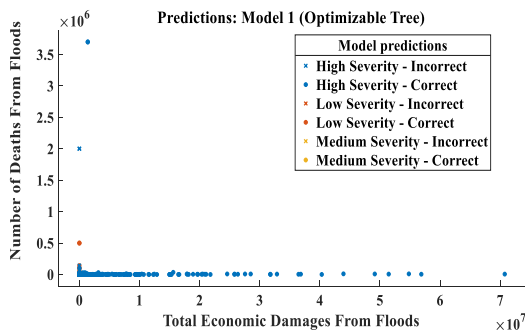
Figure.1.1.1.Process Flow Chart of Flood Disaster Event Classification

2. METHODS OF MACHINE LEARNING BASED CLASSIFICATIONS

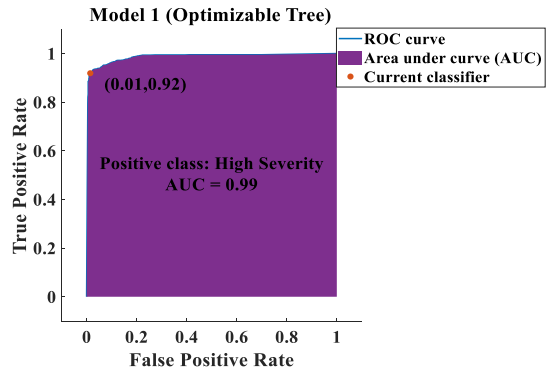
A classification model seeks to infer some significance from the values that were observed. It will attempt to forecast the value of one or more outputs given one or more inputs. Various categorization models exist. Like Logistic regression, decision trees, random forests, support vector machines, multilayer perceptron's, and Naive Bayes are some of classification models.

2.1. Decision trees

The decision tree is a technique used to create regression models in the form of a tree structure. Decision trees are frequently used in machine learning and data mining applications to divide data into small groups. The scatter plot of the Flood data, Confusion Matrix and ROC were depicted in the fig.2.1 (a-c).



(a)



(b)

Model 1 (Optimizable Tree)

	High Severity	Low Severity	Medium Severity
High Severity	1114	91	7
Low Severity	16	1730	4
Medium Severity	11	48	35
	High Severity	Low Severity	Medium Severity
	Predicted Class		

Figure 2.1. (a) Decision Tree Representation of Flood Data, (b) ROC (c) Confusion Matrix

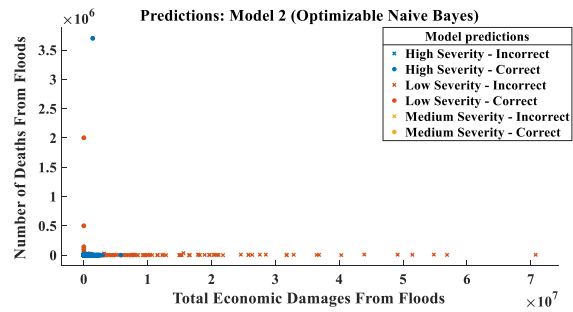
2.2. Naive Bayes Classifiers

A group of classification algorithms built on the Bayes' Theorem are known as naive Bayes classifiers. It is a family of algorithms rather than a single algorithm, and they all adhere to the same basic idea. The mathematical formulation of Bayes' theorem is given by the equation.1.

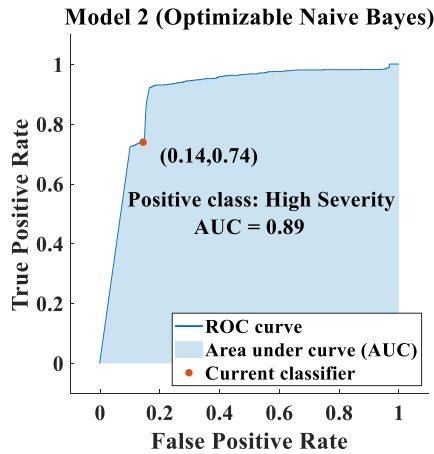
$$F(X, Y) = \frac{F(Y, X)F(X)}{F(Y)} \tag{2.1}$$

Where X and Y are events and $F(Y) \neq 0$.

The scatter plot of the Flood data, Confusion Matrix and ROC were depicted in the fig.2.2 (a-c).



(a)



(b)

Model 2 (Optimizable Naive Bayes)

	High Severity	Low Severity	Medium Severity
High Severity	897	267	48
Low Severity	242	1455	53
Medium Severity	23	61	10
	High Severity	Low Severity	Medium Severity
	Predicted Class		

Figure 2.2. (a) Naive Bayes Representation Of Flood Data, (b) ROC and (c) Confusion Matrix

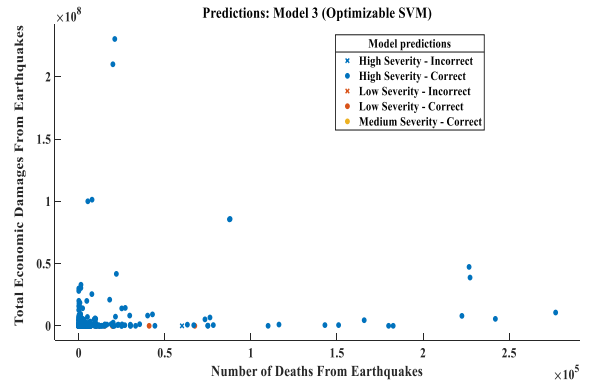
2.3. Support Vector Machines (SVM)

A SVM sorts data into classes by locating the optimal hyper plane that divides all of the data points in one class from those in the other. The hyper plane with the biggest margin between the two classes is the optimum hyper plane for a SVM. Margin is the maximum thickness of the slab that is perpendicular to the hyper plane however has no interior data points.

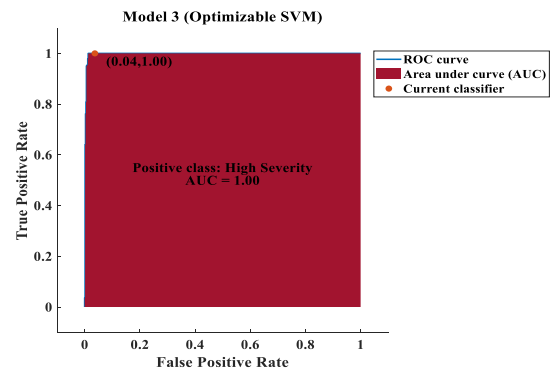
The equation of a hyper plane is given by the equation.2.2

$$F(A) = A'\gamma + b = 0 \tag{2.2}$$

where $\gamma \in R^d$ and b is a real number. The scatter plot of the Flood data, Confusion Matrix and ROC were depicted in the fig.2.3 (a-c).



(a)



(b)

Model 3 (Optimizable SVM)

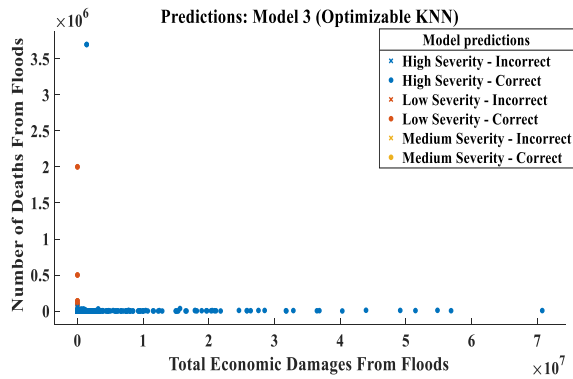
	High Severity	Low Severity	Medium Severity
High Severity	525		
Low Severity	3	596	
Medium Severity	20	1	3
	High Severity	Low Severity	Medium Severity
	Predicted Class		

Figure 2.3. (a) SVM Representation of Flood data, (b) ROC and (c) Confusion Matrix

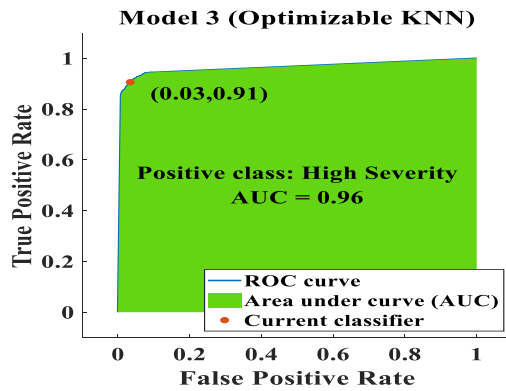
2.4. k- Nearest-Neighbor (K-NN)

The number of nearest neighbours and the distance metric may both be changed in the nearest-neighbor classification model known as K-NN. A Classification KNN classifier may be used to make reconstitution predictions since it saves training data. Alternately, employ the predict technique to categorise fresh observations using the model. The scatter plot of the

Flood data, Confusion Matrix and SOC were depicted in the fig.2.4 (a-c).



(a)



(b)

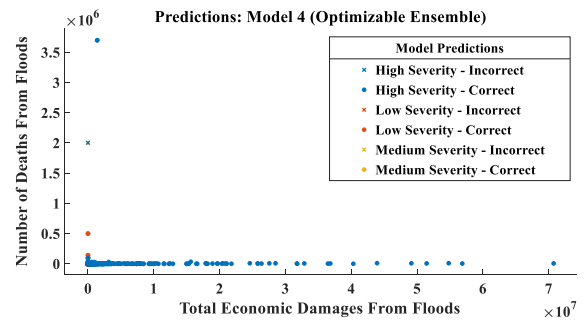
Model 3 (Optimizable KNN)

	High Severity	Low Severity	Medium Severity
High Severity	1098	97	17
Low Severity	55	1675	20
Medium Severity	8	57	29
	High Severity	Low Severity	Medium Severity
	Predicted Class		

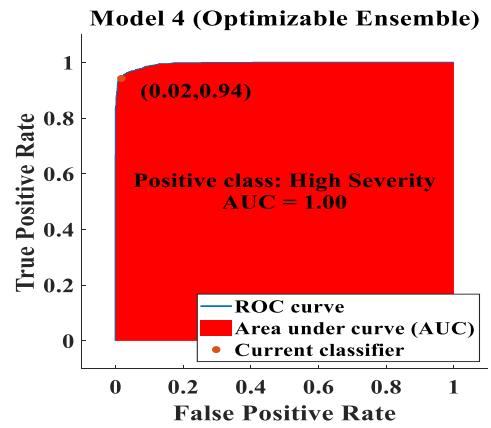
Figure 2.4. (a) K-NN Representation of Flood data, (b) ROC, (c) Confusion Matrix

2.5. Ensemble learning

A prediction model made up of a weighted mixture of many classification models is called a classification ensemble. In general, improving forecast accuracy by integrating several categorization models. The scatter plot of the Flood data, Confusion Matrix and SOC were depicted in the fig.2.5 (a-c).



(a)



(b)

Model 4 (Optimizable Ensemble)

	High Severity	Low Severity	Medium Severity
High Severity	1143	64	5
Low Severity	26	1721	3
Medium Severity	5	52	37
	High Severity	Low Severity	Medium Severity
	Predicted Class		

Figure 2.5. (a) Ensemble Learning Representation Of Flood Data, (b) ROC And (c) Confusion Matrix

3. SIMULATION RESULTS OF OPTIMIZED CLASSIFIERS

A simulation was carried out for 50 numbers of iterations. It is identified that the optimized decision tree and ensemble classifiers outperformed and SVM classifiers provided a low accuracy.

3.1 OPTIMIZED DECISION TREE CLASSIFIERS

The optimized tree classifiers provide the good accuracy level. The best point hyper parameters are achieved at the iteration range of 15. The maximum classification error plot is as shown in figure 3.1

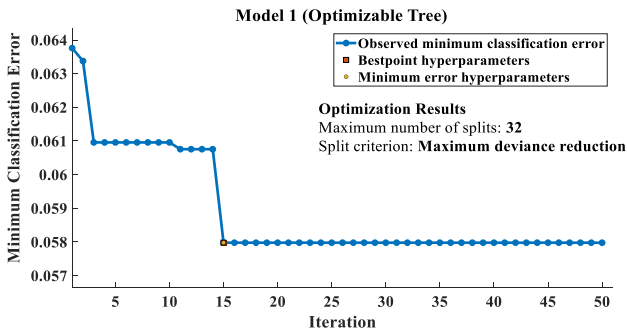
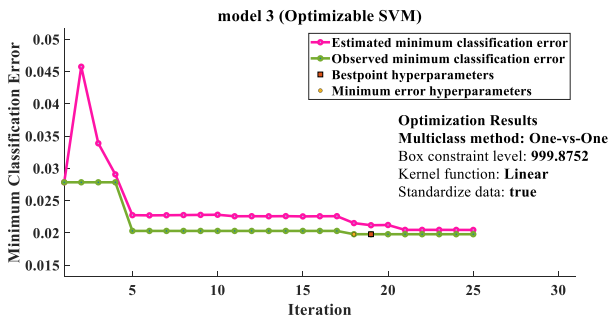


Figure 3.1. Maximum Classification Error Plot At Different Iterations

3.2 OPTIMIZED SVM CLASSIFIERS

SVM classifiers offer a poor level of accuracy in the form of classification and offer a minimum level of error classification with a greater training time. The minimum classification error obtained by the SVM classifier is as shown in figure.3.3

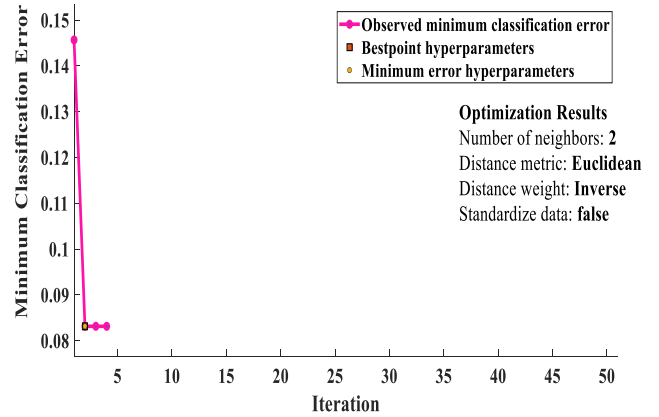


3.2. Maximum Classification Error Plot at Different Iterations

3.3 OPTIMIZED ENSEMBLE CLASSIFIERS

The optimized ensemble classifiers provide a good accuracy level with minimum number of iterations. The minimum classification error of the optimized ensemble classifier is as shown in figure3.3.

Model 3 (Optimizable KNN)



3.3. Maximum Classification Error Plot At Different Iterations

Table.1. Performance Metrics of Different Types of Classifiers

Parameters	Classifiers				
	Optimized Decision tree	Optimized Naive Bayesian	Optimized SVM	Optimized K-NN	Optimized Ensemble
Accuracy (%)	94.2	77.3	42.1	91.7	94.9
Misclassification Cost	177	694	1768	254	155
Prediction Speed (obs/Sec)	8900	1600	1800	4100	2100
Training Time	176.6	401.15	315.17	354.32	462.45

The Misclassification cost is low in optimized ensemble classifier while compared to all the other types of classifiers. The performance of the different types of classifiers is as shown in the table.1.

3.4 TECHNICAL FINDINGS

1. The accuracy differs in all the classifiers however decision tree and ensemble classifiers play a lead role.
2. The misclassification cost varies with respect to the accuracy level.
3. The prediction speed is independent with accuracy and misclassification costs.
4. Based on the training time the accuracy level got altered.

4. CONCLUSION

The article proposes different types of classifier performance metrics for a flood disaster with three severity levels. The accuracy of the various classifier shows that an optimized decision tree and ensemble classifiers provides a good level of classification in terms of accuracy, training time and prediction speed. However the optimized SVM Classifier provides has a low level of accuracy. It is predicted that the decision tree and ensemble classifiers may provide the same form of classification for other types of disasters like earthquake, Tsunami, volcano cyclones.

5. ACKNOWLEDGEMENTS

The authors alone would be responsible for said statements made in the article.

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Biographies



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