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Cloud-based disaster management architecture using hybrid machine learning approach in IoT

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Abstract
Natural disasters are becoming more frequent and more severe as a result of global warming. It is critical to take precautions before disasters, to gather and analyze information simultaneously while they are happening, and to make accurate assessments after them given that the deaths and injuries brought on by such disasters both leave lasting traumas in the life of society and damage the economy. Internet of Things (IoT) technology, is a young field that can assist intelligent safety-critical systems with data collection, processing in cloud edge data centers, and application of prediction methodologies for discovering key points and unexpected patterns using 5G technology. With the use of a cloud-based prediction algorithm for disaster management in the IoT environment, this study seeks to quickly process the data that is gathered during disasters and to speed up the analysis that will be done both during and after the disasters. An Optimized Ensemble Bagged Tree (OEBT) algorithm with ANOVA-based feature selection is developed for this aim. The experimental results show that accuracy, F1-Score, precision, and recall of the proposed OEBT algorithm utilizing the US Natural Disasters Dataset are 97.9%, 78.3%, 98.7%, and 78.9%, respectively. Comparisons with decision tree, logistic regression, and the traditional ensemble techniques are made. The suggested algorithm outperforms them all in terms of success rates.

Keywords Internet of Things (IoT) · Machine learning · Feature selection · Sustainable disaster management · Classification

1 Introduction

Currently, Internet of Things (IoT) is a required portion of information technology and intelligent communications since it affords several conveniences, such as 5G technology, intelligent sensors, smart software applications and actuators [1]. The existing technologies

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collaborate in an intelligent connectivity by supporting various problem statements including Quality of Service (QoS) factors, functional properties, accessibility and data transmission in the cloud-edge services [2]. On the other hand, intelligent sensors and actuators cannot save more information for a smart connectivity in the IoT environment with respect to low capacity storage and very limited battery cells. Therefore, data transmission procedure is useful to move data flow from IoT layer to cloud-edge layer for processing and storage. Based on many research studies, the IoT architecture is applied for managing safety-critical case studies such as wildfire, earthquake, flooding, blizzard, hurricanes, seasonal tornadoes, and landslides for disaster management.

According to the data released by NOAA (National Oceanic and Atmospheric Administration) [3], the global temperature increase between 1901 and 2020 was 1 °C. As a result, sea levels began to rise at almost twice the normal rate and glaciers began to melt rapidly.[1] As stated by NASA, such changes have negative effects on the natural disasters we experience, both in terms of diversity and frequency.[2] In the IMF (International Monetary Fund) report, it was stated that these negative effects especially affected low-income countries.[3]

The knowledge that we will experience more and more diverse and more frequent natural disasters shows us that more work needs to be done on disaster management. In many countries, a significant part of the population lives in big cities and natural disasters complicate the recovery process after a disaster with infrastructure damage in such big cities. In order to prepare for disasters, collect information during them and return to daily life quickly after them, there is a need to use modern technology as well as classical methods. Sustainable disaster management is needed for sustainable city life. Conventional methods can be used for prediction of potential hazards in a disaster-affected environment [4]. Artificial Intelligence (AI) approaches [5] can also be useful for predicting and optimizing the safety-critical case studies for disaster management. However, the emerging topics of the AI methods such as meta-heuristic algorithms and machine learning methods did not provide the fundamental aspects of prediction models for enhancing disaster management abilities in real-time IoT environments [6]. An example is given in [7], where fire management was considered using devices in the cloud.

This study was carried out in order to classify the natural disasters experienced using machine learning methods. The data processed here were collected with the help of sensors in previously installed stations. This type of study serves to create fast decision mechanisms, as these types of problems can be solved quickly by using computers. It is also a good strategy to determine which attributes will be the most relevant ones in case of a disaster and justify them as the valid features for the problem [8]. The following are this paper's main contributions:

- Proposing a new cloud-based prediction architecture for crisis and disaster management in an IoT setting.
- Providing a feature selection approach to identify the most appropriate collection of features from the disaster management dataset's accessible attributes.
- Presenting an Optimized Ensemble Bagged Tree (OEBT) algorithm to predict the type of disaster for ongoing crucial disaster actions.

[1] https://www.noaa.gov/education/resource-collections/climate/climate-change-impacts

[2] https://earthobservatory.nasa.gov/features/RisingCost/rising_cost5.php

[3] https://www.imf.org/en/Blogs/Articles/2017/11/16/climate-change-will-bring-more-frequent-natural-disasters-weigh-on-economic-growth

- Comparing the proposed machine learning algorithm to other state-of-the art machine learning algorithms and evaluating it using scientific prediction criteria.

The paper is structured as follows: The related research on IoT and disaster management is summarized in Section 2. The recommended methodology for categorizing disasters is presented in Section 3. The experiments conducted for this work are described in Section 4. The conclusions are drawn in Section 5.

2 Related work

The extensive literature study on current Artificial Intelligence (AI)-based prediction and optimization techniques for sustainable disaster management in the Internet of Things is illustrated in this part. The type of applied dataset determines how AI-based prediction algorithms are split into two categories, according to several review and survey papers that have been published. The first category offers image-based data analysis for disaster operations, and past case studies have used Unmanned Aerial Vehicle (UAV)-based data flow for images in various crucial situations including flooding, earthquakes, and wildfires. For the first category, a few image processing and computer vision methods are used to assess how well the optimized and new models perform. The second category depicts the statistical and non-image data flow for each disaster activity in accordance with the key features of each activity, such as the location, disaster type, time, date, the degree of devastation, and emergency status.

For example, in [9] a comprehensive review of existing disaster activities based on mapping critical points such as hazard and susceptibility points using Geographic Information Systems (GIS) was provided. Use cases are related to data analysis of images from risky locations. A machine-learning model using decision tree to predict flood destructive aspects in disaster management was proposed in [10]. They evaluated existing prediction factors in comparison with other machine learning algorithms, for example Support Vector Machine (SVM) and linear regression. According to the main experimental results, the decision tree algorithm provided a higher accuracy than other classical algorithms. The main weakness of this work is applying training method for only three features and the lack of a testing method.

In another research, a machine learning method based on image processing for flood forecasting architecture in disaster management using Artificial Neural Network (ANN) algorithm was [11]. Authors have used crowdsourcing strategy with geospatial data flow and apply training methods without feature selection approach.

On the other hand, in [12] a new image-based machine learning strategy with logistic regression and random forest algorithms for wildfire spread in smart remote sensing was presented. This work ignored data segmentation for each image to classify main critical points of wildfire spread. In [13] a new image processing model based on the UAV data flow for predicting main critical positions of flood area in disaster management was proposed. On the other hand, authors prepared a question-based dataset according to some critical questions and answers. Authors applied existing image processing method and semantic segmentation approach for training and test results. The main weakness of this work is that authors just evaluated accuracy factor for flooding areas. Some other prediction factors such as recall and precision can be useful for evaluating results.

In another research, a new machine learning model based on regression classification method with a Principal Component Analysis (PCA) test for predicting flood aspects of households was [14]. A real numerical dataset with a 6-year flood in Bangladesh was used. The main weakness in the experimental results is that existing accuracy and precision of prediction model with regression algorithm was ignored.

Finally in another research, a new flood prediction strategy using Convolutional Neural Network (CNN) algorithm with existing UAV-based image data flow was presented [15]. Authors have investigated machine learning strategy for two sets of pre-image flood and post-image flood classes for some critical locations in Pakistan. The main limitation of this research is that authors just evaluated the proposed method and did not compare their results with other powerful classifications algorithms.

3 Methodology

Here, the suggested architecture for cloud-based machine learning disaster management is shown. The applied disaster management dataset's pre-processing procedure is then briefly described. The disaster management dataset is processed using normalization techniques before crucial and highly effective features are extracted using an ANOVA-based feature selection technique. The basic prediction approach using the suggested optimized Ensemble Bagged Tree (OEBT) algorithm is provided for the training and testing phases.

3.1 Cloud-based machine learning disaster-management architecture

The suggested cloud-based decision-making disaster management system's architecture is shown in Fig. 1. As can be seen in this picture, data is continuously gathered by IoT devices at the Environmental IoT Layer from multiple sources and stored in cloud data centers using a service repository. The cloud's pre-processing unit receives the collected data, which is later standardized. To secure the best feature assignment out of the available data attributes, feature selection is done. The training and test sets are used to classify the data based on its features. The Cloud Computing Layer verifies the accuracy of the results, and the Decision-Making Disaster Management Layer determines whether the data falls into the categories of Major Disaster, Fire Management, Emergency Management, or a safe situation. If the decision signals an emergency, the authorities are notified. Both the decision repository and the cloud data center record the final decision.

3.2 Pre-processing phase

The data pre-processing achieved by the normalized co-simulation technique is used to filter the right data and eliminate the spontaneous content [16]. Initially, a circular search radius is planned for the purpose of selecting relevant data. Undefined characters in the data file have been manually removed.

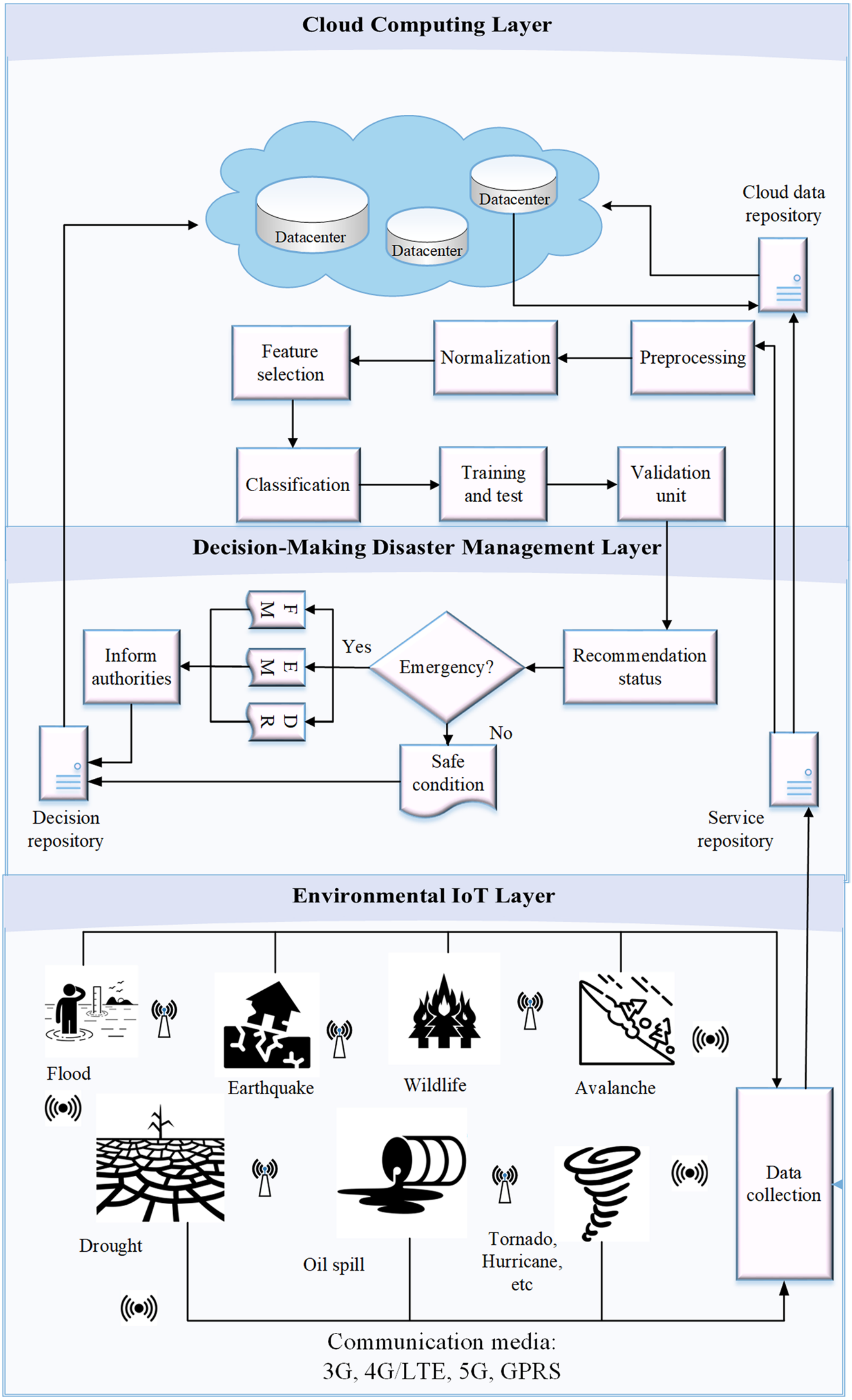


Fig. 1 The architecture of the cloud-based disaster management system

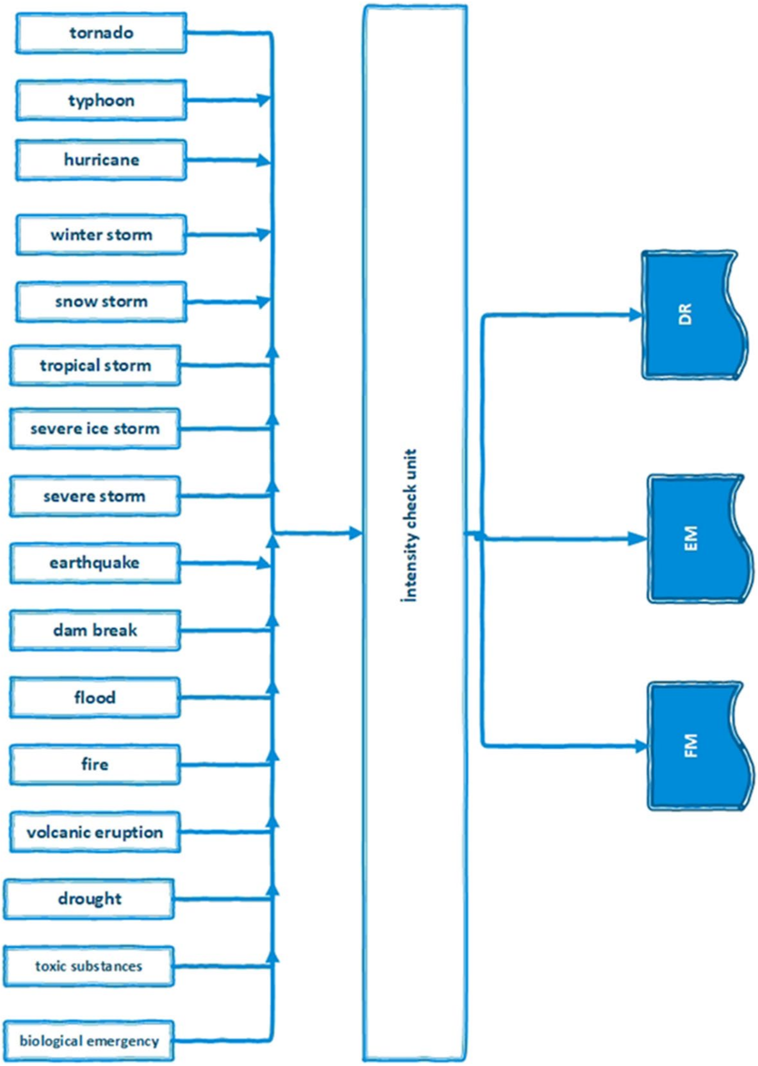


Fig. 2 The categorization of disaster activities based on US Natural Disaster Dataset

3.3 Feature selection

The US Natural Disaster Dataset [17] divides the major disaster types into categories based on their intensities. Figure 2 lists 16 different categories of disaster-related activity. The existing disaster activities are classified into three main classes including Major Disaster (DM), Emergency Management (EM) and Fire Management (FM).

Table 1 Selected features and their explanation using machine learning search algorithm

Feature Name	Type
last_refresh	Date of record update by FEMA
id	Assigned number for the record
hash	MD5 Hash of the record
last_ia_filing_date	Last individual assistance program filing date
incident_begin_date	Beginning date of the incident
hm_program declared	Binary flag for the declaration of the "Hazard Mitigation program"
pa_program_declared	Binary flag for the declaration of the if the "Public Assistance program"
ia_program_declared	Binary flag for the declaration of the "Individual Assistance program"
ih_program_declared	Binary flag for the declaration of the "Individuals and Households program"
declaration_title	Title of the disaster
incident_type	Type of the event ("Fire," "Flood," or "Biological")
fy_declared	Fiscal year for the declaration of the disaster
declaration_date	Date the disaster was declared
disaster_number	Order of the disaster
fema_declaration_string	Agency standard method for uniquely identifying Stafford Act declarations

There are 23 attributes per record in the data file. 15 of them are utilized as the most effective features in MATLAB using the Analysis of Variance (ANOVA) [18] technique. The ANOVA algorithm provides a helpful statistical criterion to be used in choosing the most pertinent characteristics to describe as the problem's features. The optimal features obtained for our dataset and their descriptions are given in Table 1.

3.4 Optimized ensemble bagged tree prediction mechanism

A brief description about the enhanced bagged algorithm is provided according to the following definitions. An improved ensemble bagged tree algorithm can receive a training dataset with a 2D-structure $D_k = ((m_1, n_1), (m_2, n_2), (m_3, n_3), \ldots, m_k, n_k)$ where $m_i \in M$ shows a set of features from dataset and $n_i \in$ (classifier_1, classifier_2, classifier_3) shows a set of the weak current classifiers in training method. The OEBT algorithm can apply a weak learning in parallel with Classification and Regression Trees (CART) [19] for identifying the bootstrap redundancy and performance. In the CART procedure [20], the existing features are applied based on recursive segmentation using Decision Tree (DT) algorithm. This algorithm categorizes the set of latest instances into two sub-sample as a binary solution to reach optimum accuracy and precision. In the OEBT algorithm, a Bayesian optimization method is applied for bagging procedure with parallel training with respect to decision tree algorithm respectively. Bagging can be applied for minimizing discrepancy of the DT algorithm. In Bagging method [21], existing dataset is divided to some sub-classes and each class is selected randomly to train with the DT algorithm. The main procedure of this method is very useful in comparison to other classifiers, such as decision tree and random forest algorithms. Algorithm 1 shows a brief procedure of OEBT algorithm with a parallel sub-set selection for training approach.

Algorithm 1 OEBT Algorithm

1. **Start**
2. **Initialize** $F(i) = (f_1, f_2, f3, \dots \dots f_{15})$ using ANOVA from the dataset;
3. AB = { $e_1, e_2, e_3, e_4, \dots e_m$}, the set of ensemble classifiers in Bayesian-based bagged tree;
4. B = {$b_1, b_2, b_3, b_4, \dots b_n$}, the set of Boosted classifiers;
5. X = the training set of bagged ensembles for B classifiers with iteration 30;
6. $L = n(X)$;
7. **For** $i = 1$ to Iteration = 30
8. **Process**
9. Initialize Random samples from $F(i)$;
9. $S(i)$ = Bagging with replacement ensemble L ;
10. $T(i)$ = trained with L (i) on S (i);
11. AB = AB (i);
12. **Next** i;
13. **for** $i = 1$ to Iteration = 30;
14. $K(i)$ = classified by AB (i);
15. **Next** i;
16. Calculated class = max $(K(i)$: $i = 1,2, 3, 4 \dots, n)$;
17. **Finish**;

4 Experimental results and technical discussion

Here, first a short description in relation to the dataset's already-existing disaster labels is provided. Second, the prediction criteria that are presently in use are explained in order to assess performance using machine learning techniques. The proposed prediction approach for real-time disaster management in the IoT environment is then illustrated through discussion of performance analysis and comparison. The simulations are implemented in PC along Intel-Core i5, 2.50 GHz central processing unit, 8 GB random access memory, and Windows 10.

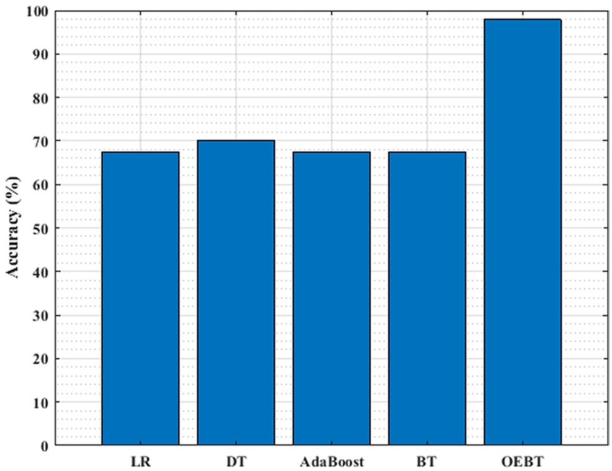
4.1 Dataset description

The effectiveness of the suggested prediction system is validated using a dataset of US natural disasters. It includes 63,788 instances of tornadoes, hurricanes, severe storms, typhoons, winter storms, tropical storms, snowstorms, severe ice storms, dam breaks, floods, earthquakes, fires, droughts, volcanic eruptions, toxic materials, and biological emergencies, which represent the three main types of disasters: Major Disaster (DM), Emergency Management (EM), and Fire Management (FM). Eighty percent of the available data are randomly selected for training, and twenty percent are selected for testing.

4.2 Performance evaluation

For the best classifier selection, measuring performance is a crucial task. Performance parameters including accuracy, F1-score, Positive Predictive Value (PPV), False Discovery Rate (FDR), Area Under Curve (AUC), and computation time are assessed and compared with other machine learning techniques in order to assess the performance. The following confusion matrix parameters are required in order to calculate the performance metrics

Fig. 3 Evaluation of accuracy metric for existing machine algorithms in disaster management



with True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values [22]:

Accuracy is computed by Eq. (1);

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN} \tag{1}$$

PPV (Positive Predictive Value) as precision factor is computed by Eq. (2);

$$PPV = \frac{TP}{TP + FP} \tag{2}$$

TPR (True Positive Rate) as recall factor is calculated by Eq. (3);

$$TPR = \frac{TP}{TP + FN} \tag{3}$$

F1-Score is determined by Eq. (4);

$$F1\ Score = 2 * \frac{PPV * TPR}{(PPV + TPR)} \tag{4}$$

AUC (Area under Curve) is calculated using Eq. (5);

$$AUC = 0.5\left(\frac{TP}{TP + FN} + \frac{TN}{TN + FP}\right) \tag{5}$$

4.3 Performance analysis

We can observe the experimental results of the OEBT approach. Then, the suggested OEBT algorithm is compared with currently used techniques like Logistic Regression

Fig. 4 Evaluation of precision metrics for three types of disaster activities

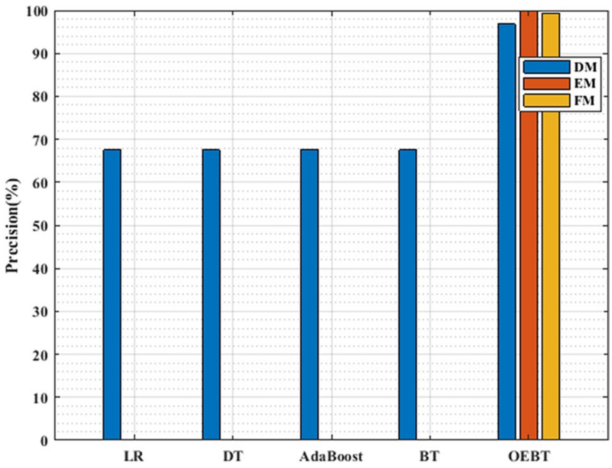
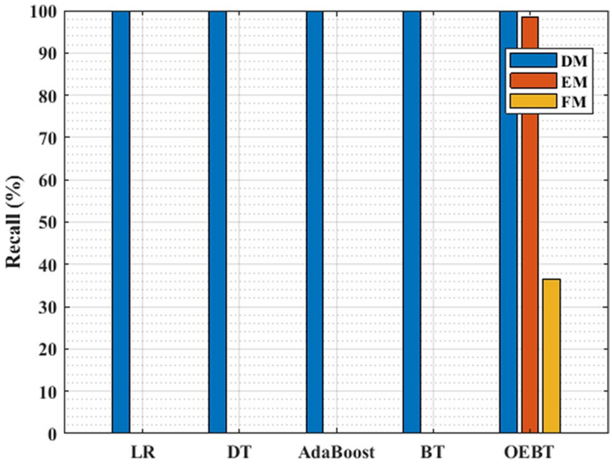


Fig. 5 Evaluation of recall metrics for three types of disaster activities



[23], Decision Tree (DT), Bagged Tree (BT) and AdaBoost [24]. The performance study of accuracy factor is shown in Fig. 3 for current machine learning methods. Experimental results show unequivocally that the OEBT algorithm provides the highest level of accuracy with 97.9% compared to other methods. Since the decision tree algorithm achieves higher accuracy than AdaBoost, Bagged Tree and linear regression algorithms.

According to Fig. 4, it is also obvious that the OEBT algorithm delivers a somewhat better result as the precision factor. The proposed OEBT algorithm achieved 96.8% for precision of DR activities, 100% for precision of EM activities, and 99.3% for precision of FM activities in disaster management system. After that, other algorithms outperform same precision factor with 67.5% just for DR activities.

In Fig. 5, the OEBT algorithm outperforms 100% of recall for DR activities, 98.6% of recall for EM activities, and 36.4% of recall for FM activities in disaster management system. For DT, BT, AdaBoost and LR algorithms, they achieved 100% of recall just for major disasters.

Fig. 6 Evaluation of F1-Score metric for disaster management system

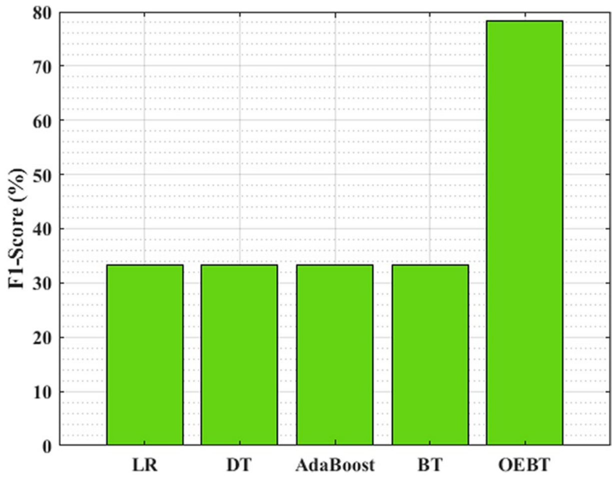


Fig. 7 ROC analysis for the OEBT algorithm in disaster management system

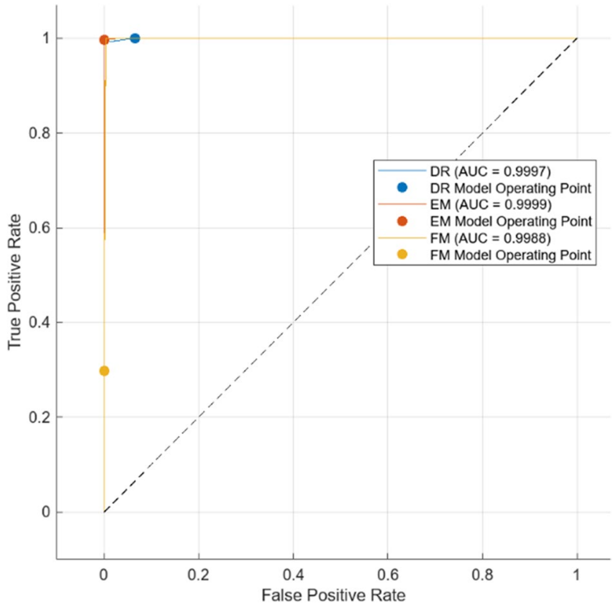


Figure 6 shows F1-scoer factor for current machine learning algorithms. Experimental results show that the OEBT algorithm provides the highest level of F1-score with 78.3% compared to other methods. Since the other machine learning algorithms achieved 33.3% of F1-score.

The ROC analysis for the OEBT algorithm is shown in Fig. 7. For the three main categories of disaster management approaches, this analysis clearly displays True Positive Rate (TPR) and False Positive Rate (FPR) numbers. It can be seen that the OEBT algorithm

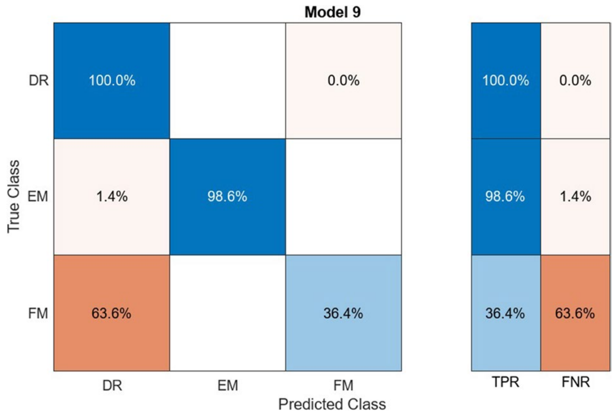


Fig. 8 The confusion matrix analysis for OEBT algorithm in disaster management system

Table 2 Computation time analysis for disaster management activities

Algorithm	Computation time (s)
Logistic Regression	815.1
AdaBoost	500.5
Decision Tree	231.05
Ensemble Bagged Tree	382.35
the OEBT algorithm	4463.7

provides the highest Area Under Curve (AUC) value for activities related to Major Disaster Management (DM) and Emergency Management (EM). Obviously, as this figure illustrates, EM activities have lower FPR values than DM activities. It is evident that the OEBT algorithm only predicts Fire Management (FM) operations with an accuracy of 0.998 since it achieves a lower Area under Curve value.

The Confusion Matrix analysis for the OEBT algorithm is shown in Fig. 8. The matrices reveal that while Fire Managements are identified with only 36.4% accuracy, Emergency Managements with 98.6% and Major Disasters are classified precisely with 100% true positive rate for. It is obvious that there is some open challenges to optimize the accuracy, precision and recall metrics in fire management actions.

The computation time metric for running the applied disaster management dataset's machine learning algorithms is shown in Table 2. This table shows the suggested OEBT algorithm offers a high calculation time value.

5 Conclusion

In this paper, a new cloud-based machine learning architecture is proposed for prediction of disaster management using the OEBT algorithm with ANOVA feature selection method to improve some critical aspects of prediction approaches in the IoT environment. The proposed OEBT algorithm was executed in MATLAB and validated with certain performance metrics. The proposed OEBT algorithm attains 97.9% accuracy, 99.81% F1-Score, and 98.8% PPV. The achieved scores are higher than decision tree, AdaBoost and logistic regression algorithms, respectively. Also, the proposed OEBT algorithm has minimum 1.8% for FDR metric than the other machine learning methods. The main limitation of this research is related to the prediction of fire management activities. This part of the problem needs a better solution. In the future work, some other meta-heuristic algorithms can be applied for feature selection method to focus on improving fire management aspect in the disaster management dataset and improve the prediction results. This work's architecture may be useful for disaster management, when a quick and accurate response is essential to save lives and lessen damage.

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Data availability Data sharing does not apply to this article as no new data has been created or analysed in this study.

Declarations

Ethical approval and consent to participate This article does not contain any studies with human participants performed by any of the authors.

Consent for publication Not Applicable.

Competing interests Not Applicable.

Human and animal ethics Not Applicable.

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