Analyzing Natural Disasters' Severity With Artificial Intelligence And Machine Learning

P. Das[1], N. Simiran[2], T. Pattnaik[3]

[1]Assistant Professor, Dept of CSE, GITAM, Bhubaneswar - 752054.

[2] Assistant Professor, Dept of CSE, GITAM, Bhubaneswar - 752054.

[3] Assistant Professor, Dept of CSE, GITAM, Bhubaneswar - 752054.

ABSTRACT

Disaster management platforms like emergency services offer important information for helping during disasters. Machine learning can be used to find this information. However, using social media data for emergency response has many challenges. These include reliability, measuring performance, deception, focus, and turning observations into useful information. During the Haiti earthquake, many volunteers worldwide tried to help by sending SMS messages with mapping, translation, and resource allocation. But these platforms couldn't handle the huge amount of urgent information. Organizations weren't prepared to use data from outside their networks, especially not at this scale. They lacked technical staff and tools to make sense of the data. To solve this, we suggest using a method called domain adaptation, which learns from existing labeled data. Our method uses the Linear SVC Algorithm with a Self-Training strategy. Tests show that this method can classify emergency messages effectively during disasters.

1. INTRODUCTION

Natural disasters are unavoidable events that have a profound impact on the economy, environment, and human lives. They result in the collapse of buildings, the spread of diseases, and can devastate entire nations, as seen with tsunamis, earthquakes, and forest fires. For example, when earthquakes strike, millions of buildings collapse due to seismic activity. In recent decades, machine learning methods have been increasingly utilized for predicting wildfires. A study conducted in Italy utilized the random forest technique to map wildfire susceptibility. Floods, on the other hand, are the most damaging natural disasters, causing destruction to properties, infrastructure, and loss of human lives. To predict flood susceptibility, a combination of machine learning techniques including random forest, random subspace, and support vector machine have been employed.

The rapid growth of the population necessitates the acquisition of land for habitation, leading to disturbances in the ecosystem, which contribute to global warming and the escalation of natural disasters. Particularly in underdeveloped countries, populations cannot afford the damages caused by disasters to their infrastructure.

The aftermath of disasters often leaves humans in dire situations, with rescue operations hampered by geographical factors. Identifying victims becomes challenging in such scenarios. Forest fires, especially in densely populated areas, spread rapidly, making firefighting efforts difficult. Therefore, developing strategies to predict and prevent such disasters is imperative. With advancing technology, aviation systems are incorporating smart technologies to deploy unmanned aerial vehicles (UAVs) equipped with cameras. These UAVs can reach remote areas to assess the impact of disasters on human life, infrastructure, and transmission lines by capturing images and videos.

1.1 Problem statement

At the onset of crises, the issues mentioned occur when emergency responders and organizations activate their internal processes to address the situation (Munro, 2011). Over the years, these organizations have functioned with a centralized command structure, standard procedures, and internal evaluation standards to determine the best responses to emergencies. Although these methods may not meet today's demands for speed, efficiency, and knowledge, they have effectively delivered rescue, response, and recovery efforts to millions of people.

1.2 Objective

Towards optimizing current organizational mechanisms in terms of speed, efficiency and knowledge, machine learning algorithms have been used to help responders sift through the big crisis data, and prioritize information that may be useful for response and relief.

2. SYSTEM ANALYSIS

2.1 Existing System

During the November 2015 Paris attacks, eyewitnesses or their friends used Twitter to quickly share information about gunfire and dangerous locations, alerting people moments after attacks occurred in various places. Parisians also started the hashtag #PorteOuverte (meaning "open door") on Twitter to provide safety and refuge to those impacted by the attacks.

As a result, microblogging data from platforms like Twitter is considered valuable for both responder organizations and victims because of its widespread use, rapid communication, and accessibility across different platforms.

a) Disadvantages of Existing System

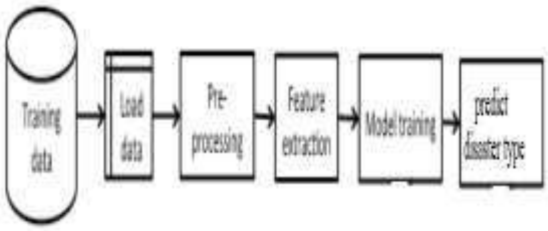
- One problem became apparent during the earthquake in Haiti when thousands of technical volunteers from around the world suddenly attempted to provide responders with mapping capabilities, translation services, people and resource allocation, all via SMS at a distance.
- Despite the good will of field staff, their institutions' policies and procedures were never designed to incorporate data from outside their networks, especially at such an overwhelming flow. In addition, the organizations did not have the technical staff, or the analytical tools, to turn the flow of data into actionable knowledge.

2.2 Proposed System

We propose to use a domain adaptation approach, which learns classifiers from available dataset, with labeled data. Our approach uses the Linear SVC Algorithm, together with an Self-Training strategy. Experimental results on the task of identifying emergency messages classification relevant to a disaster of interest show that the domain adaptation classifiers.

3. SYSTEM DESIGN

3.1 System architecture



The automatic classification of tweets begins with the manual classification of a dataset which serves as the ground truth for evaluating the performance of two machine classifying algorithms, Naive Bayes (NB) and Support Vector Machine (SVM). The following sub-sections describe the dataset and the approach used in the study.

3.2 Data Source

Habagat hit the Philippine's capital Manila and its neighboring provinces last August 1-8, 2012. The monsoon brought about eight days of torrential rain and thunderstorms which caused flooding in several areas and consequently caused massive damages and loss of properties and lives. At the onset of the Habagat until its aftermath, subscribers of Twitter used this social medium to send relevant or personal messages to their intended recipients. A sample of Habagat tweets were collected by the researchers of Ateneo de Manila University using the Twitter API. The sample has a total of 612,622 tweets, of which 373,771 are unique tweets and 238,851 are retweets. Unique tweets are the original messages that are sent by the author of a tweet which can be viewed by his or her followers and followees. Retweets on the other hand are messages received by a subscriber and are forwarded to another user or set of users.

3.3 Manual Classification

From the collected Habagat tweets, a sample of 4,000 tweets was randomly selected. Annotators initially classified the randomly selected tweets as to whether they are encoded in English, Tagalog, combination of English-Tagalog or other languages or dialects. The annotators further classified the English tweets as informative or uninformative based on the given definitions. Informative tweets are tweets that provide useful information to the public and are relevant to the event, while uninformative tweets are tweets that are not relevant to the disaster and these do not convey enough information or are personal in nature and may only be beneficial to the family or friends of the sender.

3.4 Information Extraction

Using conditional probability and Bayes' theorem, information can be extracted from the statistics of manually classified tweets. Conditional probability is defined as $P(A|B) = P(A \cap B)/P(B)$, provided $P(B) > 0$. Bayes' theorem , also known as Bayes' rule or Bayes' law, is a result in probability theory that relates conditional probability. If A and B denote two events, P(A|B) denotes the conditional probability of A occurring, given that B occurs [22]. Bayes theorem is mathematically defined as:

$$P(A|B) = P(B|A)\,P(A)/P(B)$$

where:

P(A) is the prior probability or marginal probability of A.

It is ‖prior‖ in the sense that it does not take into account any information about B

P(A|B) is the conditional probability of A, given B

P(B|A) is the conditional probability of B given A

P(B) is the prior or marginal probability of B, and acts as a normalizing constant

In the context of this study, *P(A)* is the probability of a tweet being informative, while *P(B)* is the probability of a tweet being unique. Therefore, information of the probabilities of tweets being informative or not informative, given that these are unique or are re tweets were then extracted.

4. IMPLEMENTATION

4.1 Machine Learning Algorithms for Classification

a) Supervised Learning

Supervised learning was employed to train a machine to differentiate between informative and non-informative tweets. In supervised learning, the dataset has known class attribute values (labeled data) before the algorithm runs [24]. This method builds a model that links x to y, where x represents a vector of features and y is the class attribute. The model is created by running the supervised learning algorithm on a training set, which maps feature values (x) to class attribute values (y). After training, the model is tested on a dataset to predict class attributes. In this study, x represents the vector of features and y includes categories like "informative" and "uninformative."

To reduce bias associated with data sampling, the study employed stratified 10-fold cross-validation to assess the model's performance. In 10-fold cross-validation, the dataset is divided into 10 mutually exclusive subsets (DS1, DS2...DS10) of roughly equal sizes, ensuring proportional representation of tweet classes. The classification model is trained and tested 10 times using this dataset, with 9 subsets used for training and the remaining subset for testing. The Naive Bayes and Support Vector Machine (SVM) algorithms were compared based on various evaluation metrics.

Naive Bayes and Support Vector Machine are two commonly used machine learning algorithms for classification. The Naive Bayes classifier is robust and performs well in various real-world classification tasks. It's a simple probabilistic classifier based on Bayes' theorem, making strong (naive) independence assumptions [25]. Essentially, it assumes that the presence or absence of one feature in a class is unrelated to the presence or absence of any other feature [26]. Support Vector Machine is a binary classification method that finds a hyperplane to optimally separate the d-dimensional data into its two classes [26]. However, since real-world data is often not linearly separable, SVM uses kernel-induced feature space to project data into a higher-dimensional space where separation is easier [27].

b) Evaluation of the Machine Learning Algorithms:

In this study, accuracy, recall, precision, area under curve (AUC) and F-measure were used as metrics in the empirical evaluation of the classification algorithms Naive Bayes and Support Vector Machine. Table I presents the description of each metric of evaluation, as described in Rapid miner.

Table I: Metrics of Evaluation

Metric	Description
Accuracy	Relative number of correctly classified examples or in other words percentage of correct predictions.
AUC	AUC is the Area Under the Curve of the Receiver Operating Characteristics (ROC) graph which is a technique for visualizing, organizing and selecting classifiers based on their performance.
Precision	Relative number of correctly as positive classified examples among all examples classified as positive
Recall	This parameter specifies the relative number of correctly as positive classified examples among all positive examples
F-measure	This parameter is a combination of the *precision*and the *recall*i.e. $f=2pr/(p+r)$where f,$r$and $p$are f-

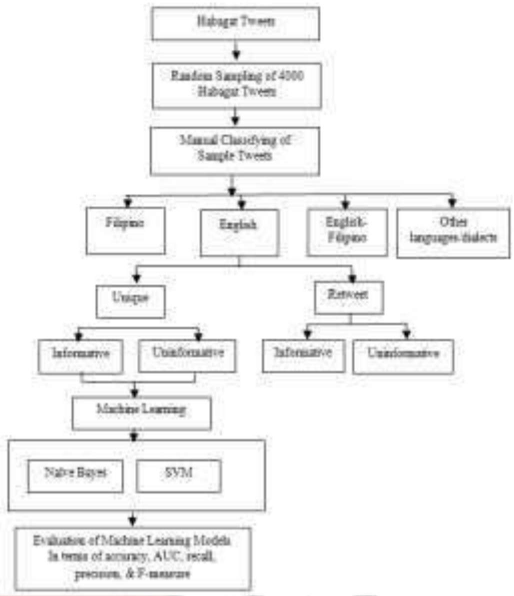


Figure: Methodology Structure

5. RESULTS AND DISCUSSION

5.5 Manual Classification of Habagat Tweets

Out of the 4000 randomly selected tweets, there were 1,563 in English, 1,393 in Tagalog, 913 using a combination of English and Filipino, and 121 in other languages or dialects. Table III provides a summary of the manually classified English tweets.

Based on the annotations, the computed ICC or multi-rater Kappa coefficient is 0.671, indicating a substantial level of agreement among annotators in determining whether a tweet is informative or not.

If there was disagreement in labeling, the three annotators discussed to resolve differences and agreed on a specific label for the tweet after thorough deliberation.

5.2 Extracted Information

By applying conditional probability and Bayes' theorem, data was extracted from the manually classified tweets. According to these statistics, uninformative tweets outweighed informative ones by a ratio of 65% to 35%. An example of an uninformative tweet is: "Stay safe everyone!!! #PrayForThePhilippines #TrustGOD”.

Unique tweets are more likely to be uninformative (71.72%) compared to informative ones, which have a probability of 28.28%. Additionally, the probabilities of retweeted tweets being uninformative and informative are almost equal, at 49.22% and 50.78% respectively.

Although uninformative tweets are more numerous, informative tweets are more likely to be retweeted (41.99%) compared to uninformative ones (21.67%). This suggests that retweeted informative tweets hold significance and urgency, potentially enhancing public awareness and disaster response.

The findings also indicate that subscribers primarily used Twitter to share subjective messages and emotions regarding the Habagat event. These results align with previous studies on hurricanes by Hughes and Palen, flooding and wildfires by Starbird and Palen, and the Haiti earthquake by Starbird and Palen. These studies reveal that users use Twitter to share crisis information, express opinions and emotions, and offer aid to those in need.

5.2 Evaluation of Machine Learning Algorithms:

Table IVpresents the results of the 10-fold cross validation for all folds for all the metrics of evaluation. Using the Kolomogorov-Smirnov and Shapiro Wilk for normality testing, the data is normally distributed and this is true to all the five evaluation metrics. The normality of these variables has also been validated by their Normal Probability Plots.

Since the data are normally distributed, parametric testing was performed. The parametric t-test was specifically used to determine the significant differences between Naive Bayes and SVM. Table Vpresents the results of the experimentation.

The paired t-test results shown in Table V demonstrate that there is a significant difference between Naive Bayes and SVM ($p<0.001$). This is true to all the five parameters namely, accuracy, AUC, precision, recall, and F-measure. In particular, SVM is significantly higher than Naive Bayes in accuracy, AUC, recall, and F-Measure, though Naive Bayes is significantly higher than SVM in precision. Table VI shows the mean values for the paired sample statistics.

	Informative Tweets	Uninformative Tweets	Total
Unique	315	799	1114
Retweets	228	221	449
Total	543	1020	1563

5.3 Evaluation of Machine Learning Algorithms

Table IVpresents the results of the 10-fold cross validation for all folds for all the metrics of evaluation. Using the Kolomogorov-Smirnov and Shapiro Wilk for normality testing, the data is normally distributed and this is true to all the five evaluation metrics. The normality of these variables has also been validated by their Normal Probability Plots.

Since the data are normally distributed, parametric testing was performed. The parametric t-test was specifically used to determine the significant differences between Naive Bayes and SVM. Table Vpresents the results of the experimentation.

The paired t-test results shown in Table V demonstrate that there is a significant difference between Naive Bayes and SVM ($p<0.001$). This is true to all the five parameters namely, accuracy, AUC, precision, recall, and F-measure. In particular, SVM is significantly higher than Naive Bayes in accuracy, AUC, recall, and F-Measure, though Naive Bayes is significantly higher than SVM in precision. Table VI shows the mean values for the paired sample statistics.

Table IV: Results Of 10-Fold Validation

	ACCURACY		AUC		PRECISION		RECALL		F-MEASURE	
FOLD	NB	SVM	NB	SVM	NB	SVM	NB	SVM	NB	SVM
1	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
2	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
4	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1.0000	[illegible]	[illegible]
5	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
6	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
8	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
10	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
MEAN	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

TABLE V: Paired T-Test Results

					95% Confidence Interval of Difference				
		Mean	Std Deviation	Std Error Mean	Lower	Upper	T	df	Sig(2-tailed)
Pair 1	Accuracy (SVM-NB)	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	9	<0.001
Pair 2	AUC (SVM-NB)	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	11.346	9	<0.001
Pair 3	Precision (SVM-NB)	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	9	<0.001
Pair 4	Recall (SVM-NB)	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	9	<0.001
Pair 5	F-measure (SVM-NB)	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	15.292	9	<0.001

Table VI: Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	NB_Accuracy	0.60172	10	0.5014710	0.0158579
	SVM_Accuracy	0.80207	10	0.0265764	0.0084042
Pair 2	NB_AUC	0.72350	10	0.0954443	0.0310821
	SVM_AUC	0.86880	10	0.0620767	0.0196304
Pair 3	NB_Precision	0.86546	10	0.0648431	0.0205052
	SVM_Precision	0.79652	10	0.0186738	0.0059052
Pair 4	NB_Recall	0.51856	10	0.0510700	0.0161498
	SVM_Recall	0.96747	10	0.0253584	0.0080190
Pair 5	NB_F-Measure	0.64702	10	0.0479798	0.0151726
	SVM_F-Measure	0.87349	10	0.0162222	0.0051299

Confusion matrices of SVM and Naive Bayes as shown in Table VII and Table VIII respectively. Using the same trainingdata set for both algorithms, the SVM model achieved an average accuracy of 80%, while Naive Bayes had 57% average accuracy. This indicates that the SVM model returned 892 correct classifications out of 1,114 unique tweets while Naive Bayes model correctly classified only 633 tweets.

In terms of recall, the SVM model correctly classified 780 uninformative tweets and only 19 labeled uninformative tweets as informative resulting to a recall value of 97.62% for the uninformative class. For Naive Bayes, the model correctly classified 396 uninformative tweets over 799 uninformative tweets yielding a 49.56% recall value.

AUC is a measure of quality of a probabilistic classifier. A random classifier has an area under curve 0.5, while a perfect classifier has 1. Binary classifiers used in practice should therefore have an area somewhere in between, preferably close to 1 [41]. In this experiment, SVM demonstrated an average AUC of 0.884 which indicates that the classifier ranked positive examples higher than the negative examples.

6. CONCLUSION

We compared two classification algorithms: Support Vector Machine (SVM) and Naïve Bayes. After testing with a 10-fold cross validation, SVM showed better accuracy, recall, AUC, and F-measure, while Naïve Bayes was more precise.

In the future, we plan to explore different features and weights to create word vectors and see how they affect the evaluation metrics. We'll also focus on selecting the best features, optimizing parameters, and considering the meaning of words. Additionally, we'll evaluate other machine learning algorithms based on different metrics besides accuracy, recall, precision, AUC, and F-measure. It's important to prioritize these metrics to help data mining researchers choose the right algorithm for specific tasks.

We'll also work on classifying tweets in multiple languages, which will help extract relevant information for better situational awareness during disasters. Finally, we aim to develop a real-time system that can detect and filter relevant information from disaster-related tweets, improving disaster response management.

REFERENCES

1. Mignan A., Broccardo M. Neural network applications in earthquake prediction (1994–2019): Meta-analytic and statistical insights on their limitations. *Seism. Res. Lett.* 2020;**91**:2330–2342. doi: 10.1785/0220200021

2. Tonini M., D'Andrea M., Biondi G., Degli Esposti S., Trucchia A., Fiorucci P. A Machine Learning-Based Approach for Wildfire Susceptibility Mapping. The Case Study of the Liguria Region in Italy. *Geosciences.* 2020;**10**:105. doi: 10.3390/geosciences10030105.

3. Islam A.R.M.T., Talukdar S., Mahato S., Kundu S., Eibek K.U., Pham Q.B., Kuriqi A., Linh N.T.T. Flood susceptibility modelling using advanced ensemble machine learning models. *Geosci. Front.* 2021;**12**:101075.

4. Schlemper J., Caballero J., Hajnal V., Price A.N., Rueckert D. A deep cascade of convolutional neural networks for dynamic MR image reconstruction. *IEEE Trans. Med. Imaging.*

5. Tang C., Zhu Q., Wu W., Huang W., Hong C., Niu X. PLANET: Improved convolutional neural networks with image enhancement for image classification. *MathProbl.Eng.* 2020;**2020** doi: 10.1 155/2020/1245924.

6. Ashiquzzaman A., Oh S.M., Lee D., Lee J., Kim J. *Smart Trends in Computing and Communications, Proceedings of the SmartCom 2020, Paris, France, 29–31 December 2020.* Springer; Berlin/Heidelberg, Germany: 2021. Context-aware deep convolutional neural network application for fire and smoke detection in virtual environment for surveillance video analysis; pp. 459–467.

7. Li T., Zhao E., Zhang J., Hu C. Detection of Wildfire Smoke Images Based on a Densely Dilated Convolutional Network. *Electronics.* 2019;**8**:1131. doi: 10.3390/electronics8101131.

8. Mangalathu S., Burton H.V. Deep learning- based classification of earthquake-impacted buildings using textual damage descriptions. *Int. J. Disaster Risk Reduct.* 2019;**36**:101111. doi: 10.1016/j.ijdrr.2019.101111.

9. Hartawan D.R., Purboyo T.W., Setianingsih C. Disaster Victims Detection System Using Convolutional Neural Network (CNN) Method; Proceedings of the 2019 IEEE International Conference on Industry 4.0, Artificial Intelligence, and Communications Technology (IAICT); Bali, Indonesia. 1–3 July 2019; pp. 105–111.

10. Amit S.N.K.B., Aoki Y. Disaster detection from aerial imagery with convolutional neural network; Proceedings of the 2017 International Electronics Symposium on Knowledge Creation and Intelligent Computing (IES-KCIC); Surabaya, Indonesia. 26–27 September 2017; pp. 239–245.

11. Yang S., Hu J., Zhang H., Liu G. Simultaneous Earthquake Detection on Multiple Stations via a Convolutional Neural Network. *Seism. Res. Lett.* 2021;**92**:246–260. doi: 10.1785/0220200137.

12. Madichetty S., Sridevi M. Detecting informative tweets during disaster using deep neural networks; Proceedings of the 2019 11th International Conference on Communication Systems & Networks (COMSNETS); Bangalore, India. 7–11 January 2019; pp. 709–713.

13. Nunavath V., Goodwin M. The role of artificial intelligence in social media big data analytics for disaster management-initial results of a systematic literature review; Proceedings of the 2018 5th International Conference on Information and Communication Technologies for Disaster Management (ICT-DM); Sendai, Japan. 4–December 2018; pp. 1–4.

14. Boonsuk R., Sudprasert C., Supratid S. An Investigation on Facial Emotional Expression Recognition Based on Linear-Decision-Boundaries Classifiers Using Convolutional Neural Network for Feature Extraction; Proceedings of the 2019 11th International Conference on Information Technology and Electrical Engineering (ICITEE); Pattaya, Thailand. 10–11 October 2019; pp. 1–5.

15. Zhou F., Huang J., Sun B., Wen G., Tian Y. Intelligent Identification Method for Natural Disasters along Transmission Lines Based on Inter-Frame Difference and Regional Convolution Neural Network; Proceedings of the 2019 IEEE International Conference on Parallel & Distributed Processing with Applications, Big Data & Cloud Computing, Sustainable Computing & Communications, Social Computing & Networking (ISPA/BDCloud/SocialCom/SustainCom);

Xiamen, China. 16–18 December 2019; pp. 218–222.

16. Sulistijono I.A., Imansyah T., Muhajir M., Sutoyo E., Anwar M.K., Satriyanto E., Basuki A., Risnumawan A. Implementation of Victims Detection Framework on Post Disaster Scenario; Proceedings of the 2018 International Electronics Symposium on Engineering Technology and Applications (IES-ETA); Bali, Indonesia. 29–30 October 2018; pp. 253–259.

17. Padmawar P.M., Shinde A.S., Sayyed T.Z., Shinde S.K., Moholkar K. Disaster Prediction System using Convolution Neural Network; Proceedings of the 2019 International Conference on Communication and Electronics Systems (ICCES); Coimbatore, India. 17–19 July 2019; pp. 808–812.

18. Chen Y., Zhang Y., Xin J., Wang G., Mu L., Yi Y., Liu H., Liu D. UAV Image-based Forest Fire Detection Approach Using Convolutional Neural Network; Proceedings of the 2019 14th IEEE Conference on Industrial Electronics and Applications (ICIEA); Xi'an, China. 18–21 June 2019; pp. 2118–2123.

19. Gonzalez A., Zuniga M.D., Nikulin C., Carvajal G., Cardenas D.G., Pedraza M.A., Fernández C., Munoz R., Castro N., Rosales B., et al. Accurate fire detection through fully convolutional network; Proceedings of the 7th Latin American Conference on Networked and Electronic Media (LACNEM 2017); Valparaiso, Chile. 6–7 November 2017.

20. Samudre P., Shende P., Jaiswal V. Optimizing Performance of Convolutional Neural Network Using Computing Technique; Proceedings of the 2019 IEEE 5th International Conference for Convergence in Technology (I2CT); Pune, India. 29–31 March 2019; pp. 1–4.

21. Lee W., Kim S., Lee Y.-T., Lee H.-W., Choi M. Deep neural networks for wild fire detection with unmanned aerial vehicle; Proceedings of the 2017 IEEE International Conference on Consumer Electronics (ICCE); Las Vegas, NV, USA. 8–11 January 2017; pp. 252–253.

22. Nguyen D.T., Ofli F., Imran M., Mitra P. Damage assessment from social media imagery data during disasters; Proceedings of the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining; Sydney, NSW, Australia. 31 July–3 August 2017; pp. 569–576.

23. Direkoglu C. Abnormal Crowd Behavior Detection Using Motion Information Images and Convolutional Neural Networks. *IEEE Access.* 2020;**8**:80408–80416. doi: 10.1109/ACCESS.2020.2990355.

24. Yuan F., Zhang L., Xia X., Huang Q., Li X. A wave-shaped deep neural network for smoke density estimation. *IEEE Trans. Image Process.* 2019;**29**:2301–2313. doi: 10.1109/TIP.2019.2946126

25. Layek A.K., Poddar S., Mandal S. Detection of Flood Images Posted on Online Social Media for Disaster Response; Proceedings of the 2019 Second International Conference on Advanced Computational and Communication Paradigms (ICACCP); Gangtok, Sikkim, India. 28–28 February 2019; pp. 1–6.

26. Amezquita-Sanchez J., Valtierra-Rodriguez M., Adeli H. Current efforts for prediction and assessment of natural disasters: Earthquakes, tsunamis, volcanic eruptions, hurricanes, tornados, and floods. *Sci. Iran.* 2017;**24**:2645–2664. doi: 10.24200/sci.2017.4589.

7. Zhang X.Y., Li X., Lin X. The data mining technology of particle swarm optimization algorithm in earthquake prediction. *Adv. Mater. Res.* 2014;**989–994**:1570–1573. doi: 10.4028/www.scientific.net/AMR.989-994.1570.

28. Adeli H., Panakkat A. A probabilistic neural network for earthquake magnitude prediction. *Neural Netw.* 2009;**22**:1018–1024. doi: 10.1016/j.neunet.2009.05.003.

29. Kradolfer U. SalanderMaps: A rapid overview about felt earthquakes through data mining of web-accesses; Proceedings of the EGU General Assembly Conference; Vienna, Austria. 7–12 April 2013; pp. EGU2013–6400.

30. Merz B., Kreibich H., Lall U. Multi-variate flood damage assessment: A tree-based data- mining approach. *Nat. Hazards Earth Syst. Sci.* 2013;**13**:53–64. doi: 10.5194/nhess-13-53- 2013.

31. Sahay R.R., Srivastava A. Predicting monsoon floods in rivers embedding wavelet transform, genetic algorithm and neural network. *Water Resour. Manag.* 2014;**28**:301–317. doi: 10.1007/s11269-013-0446-5.

32. Venkatesan M., Thangavelu A., Prabhavathy P. An improved Bayesian classification data mining method for early warning landslide susceptibility model using GIS; Proceedings of the Seventh International Conference on Bio-Inspired Computing: Theories and Applications (BIC-TA 2012); Springer, Gwalior, India. 12–16 December 2012; pp. 277–288.

33. Korup O., Stolle A. Landslide prediction from machine learning. *Geol. Today.* 2014;**30**:26–33. doi: 10.1111/gto.12034.

34. Di Salvo R., Montalto P., Nunnari G., Neri M., Puglisi G. Multivariate time series clustering on geophysical data recorded at Mt. Etna from 1996 to 2003. *J. Volcanol. Geotherm. Res.* 2013;**251**:65–74. doi: 10.1016/j.jvolgeores.2012.02.007.

35. Das H.S., Jung H. An efficient tool to assess risk of storm surges using data mining. *Coast. Hazards.* 2013:80–91. doi: 10.1061/9780784412664.008.

36. Chatfield A.T., Brajawidagda U. Twitter early tsunami warning system: A case study in Indonesia's natural disaster management; Proceedings of the 2013 46th Hawaii International Conference on System Sciences; Maui, HI, USA. 7–10 January 2013; pp. 2050–2060.

37. Khalaf M., Alaskar H., Hussain A.J., Baker T., Maamar Z., Buyya R., Liatsis P., Khan W., Tawfik H., Al-Jumeily D. IoT-enabled flood severity prediction via ensemble machine learning models. *IEEE Access.* 2020;**8**:70375–70386. doi: 10.1109/ACCESS.2020.2986090.

38. Zhai C., Zhang S., Cao Z., Wang X. Learning-based prediction of wildfire spread with real-time rate of spread measurement. *Combust. Flame.* 2020;**215**:333–341. doi: 10.1016/j.combustflame.2020.02.007.

39. Tan J., Chen S., Wang J. Western North Pacific tropical cyclone track forecasts by a machine learning model. *Stoch. Environ. Res. Risk Assess.* 2020:1–14. doi: 10.1007/s00477-020-01930-w.

40. Liu Y.Y., Li L., Liu Y.S., Chan P.W., Zhang W.H., Zhang L. Estimation of precipitation induced by tropical cyclones based on machine-learning-enhanced analogue identification of numerical prediction. *Meteorol. Appl.* 2021;**28**:e1978. doi: 10.1002/met.1978.

41. Meadows M., Wilson M. A Comparison of Machine Learning Approaches to Improve Free Topography Data for Flood Modelling. *Remote Sens.* 2021;**13**:275. doi: 10.3390/rs13020275.

42. Nisa A.K., Irawan M.I., Pratomo D.G. Identification of Potential Landslide Disaster in East Java Using Neural Network Model (Case Study: District of Ponogoro) *J. Phys. Conf. Ser.* 2019;**1366**:012095. doi: 10.1088/1742-6596/1366/1/012095.

43. Chen X., Xu Y., Wong D.W.K., Wong T.Y., Liu J. Glaucoma detection based on deep convolutional neural network; Proceedings of the 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC); Milan, Italy. 25–29 August 2015; pp. 715–718.

44. Asaoka R., Murata H., Iwase A., Araie M. Detecting preperimetric glaucoma with standard automated perimetry using a deep learning classifier. *Ophthalmology.* 2016;**123**:1974–1980. doi: 10.1016/j.ophtha.2016.05.029.

45. Salam A.A., Khalil T., Akram M.U., Jameel A., Basit I. Automated detection of glaucoma using structural and non structural features. *Springerplus.* 2016;**5**:1519. doi: 10.1186/s40064-016-3175-4.