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Recent trends in using machine learning and Twitter data for disaster management

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Abstract
The impacts of disasters are devastating on the local communities and ecosystems. Recent advances in machine learning (ML) including deep learning (DL) can cope with the complexity of disasters and have been used to develop methods that provide effective solutions in all phases of disaster management. Furthermore; social media plays a critical role in communicating disaster related information before and after a disaster strikes. ML and DL are being increasingly used to mine information from social media data and especially Twitter data. This paper aims to provide the recent trends in this field by focusing on recent research studies presenting ML and DL based methods that leverage information posted on Twitter for disaster management. The identified methods have been developed to provide solutions in the areas of disaster detection, damage assessment and post-disaster response.

Keywords: Disaster management; machine learning; deep learning; social media data; Twitter, natural disasters

1. Introduction
The number of natural disasters is on the rise with a record high 389 disasters being recorded in 2020. The climate-related disasters mainly dominated the disaster events during the same year. Furthermore, 2020 was marked with 26% more storms and 23% more floods, as well as greater economic losses (CRED& UNDRR, 2021). Adopting the United Nations Office for Disaster Risk Reduction (UNISDR) (2009) terminology, a disaster is a "serious disruption of the functioning of a community or a society involving widespread human, material, economic or environmental losses and impacts, which exceeds the ability of the affected community or society to cope using its own resources" (UNISDR, 2009).
Disaster management addresses disasters before and after they strike. The disaster management cycle widely adopted includes the phases of mitigation, preparedness, response and recovery (Alexander, 2002). Activities aiming to lessen or limit the impacts of hazards and disasters are part of the mitigation phase. The goal of preparedness is to build capacities that will be used by communities, organizations and individuals to better manage the impacts of hazards and disasters. It includes activities such as emergency planning and public information and training. Disaster response operations take place once a disaster strikes, such as emergency plan implementation, emergency search and rescue, shelter management, and distribution of supplies Recovery activities aim to

bring normalcy to the community and may take years to complete, such as rebuilding and rehabilitation, food and financial assistance and mental care.

ML and DL can enable effective and informed disaster management to address the impacts of disasters. ML and DL leverage information provided by different big data sources, such as satellite imagery, social media, wireless sensor networks and crowdsourcing, to assist disaster management operations in all disaster phases (Sun et al., 2020; Arinta & Andi, 2019; Yu et al., 2018). DL is a subclass of ML that can learn the features of a complex system directly from raw data, therefore avoiding the manual feature engineering process used by traditional ML. Convolutional Neural Networks (CNNs) have widely been used for mining information from images and Long-Short Term Memory (LSTMs) have been used for natural language processing tasks (Lecun et al., 2015).

Artificial intelligence (AI) applications in twenty six areas of disaster management have been overviewed by Sun et al. (2020). The types of big data sources used in disaster management and their role have been given in a review by Yu et al. (2018). The role of big data and ML and DL in six disaster management areas has been provided in a review by Arinta and Andi (2019). Linardos et al. (2022) have presented a review of recent developments in ML and DL methods developed for disaster management, focusing in seven areas of disaster management.

Social media is a big data source that has been used by various stakeholders, including emergency services, decision makers, non-governmental organizations (NGOs) and affected population. People located in disaster-hit areas use social media, posting both images and text to receive help from emergency responders or communicate the situation as is (Robertson et al., 2019). ML and DL methods developed to process and analyze social media data mainly rely on Twitter. Being a public social media platform, Twitter has been widely used for this purpose due to its highly accessible streaming API, in contrast to other private social media which are not easily accessible including Facebook. Moreover, Twitter contains geolocated information which is valuable in disaster relief operations, such as search and rescue and delivery of humanitarian aid. Yet, information posted on Twitter for relief and aid by disaster victims and emergency responders is not easily extracted, due to the high levels of noise and the volume of information (Varga et al., 2013).

Considering the increasing trend in mining information from Twitter platform for assisting disaster management operations this paper provides an overview of recent literature focused on ML and DL methods developed for disaster management using Twitter data and presented in the time period 2017 to 2021. For this purpose, the explored databases in this study included Elsevier, IEEE, Taylor and Francis, Wiley and Springer. The search included the keywords "natural disaster", "disaster management", "prediction", "assessment", "mitigation", "preparedness", "response", "relief", "machine learning", "deep learning", "social media". A manual search followed, based on the research experience of the researchers to eliminate unrelated studies and review articles. A section on the reviewed literature studies is presented next. A discussion of the results follows. Finally, conclusions are drawn.

2. ML and DL methods using Twitter data for disaster management

Recent ML and DL based methods presented since 2017 that have used Twitter data have been identified in the areas of damage assessment, post-disaster response and disaster detection. Damage assessment is a crucial subphase of disaster response. In this phase the impact of the disaster is identified. Post-disaster response refers to the actions that take place right after the disaster event. The effectiveness of this subphase of disaster management greatly relies on fast and accurate information that will assist search and rescue operations, resource distribution and supply route optimization, among others. During the disaster preparedness phase the ability to detect a disaster as early as possible is crucial for the effectiveness of the overall response to the disaster.

Wang et al. (2020) proposed a multi-task multimodal deep learning framework that included natural language processing and computer vision capabilities to assist damage assessment in disasters. The framework was trained on a large Twitter dataset which included tweets and images. The outcome was that the system was able to capture efficiently the correlation between relevant items of different data forms. The system outperformed other single-task single data models.

Resch et al. (2018) presented a model which analyzed tweets with Latent Dirichlet Allocation (LDA). This unsupervised, self-learning method was able to extract a semantic topic from textual content of the tweet which was then analyzed with semantic analysis to identify whether the tweet is disaster related and extract a damage subtopic. The approach showed promising results to assess damage in earthquakes and other natural disasters that were validated through comparison with official earthquake data of the US Geological Survey.

Nguyen et al. (2017) employed state of the art computer vision techniques to analyze images from social media to assist damage assessment during natural disasters. The system was able to identify three different levels of damage in disaster related images. The study concluded that fine-tuned deep CNNs are able to adapt to recognize the severity of damage in disaster related images. The authors evaluated their method using the 2015 Nepal earthquake data.

Zhang et al. (2019) proposed CrowdLearn. a hybrid system that leveraged crowdsourcing potential along with machine intelligence using Twitter data for damage assessment applications. This way the system was able to improve the performance of black-box AI algorithms. CrowdLearn yielded great results in real-time in the domain of damage assessment, outperforming DL methods.

Alam et al. (2018) presented a system called Image4Act. This end-to-end system utilizes social media to efficiently collect and process information related to disaster impact in terms of infrastructure damage. The system includes data denoising techniques to cope with the noisy nature of the data in social media platforms.

Robertson et al. (2019) applied relevance classification with multilayer perceptron (MLP) in social media posts during Hurricane Harvey. The proposed framework utilized VGG-16 to extract features from the previously classified posts. An analysis was conducted on Hurricane Harvey data to compare the system on human-coded images in order to improve the communication between people affected by disasters and emergency responders.

Huang et al. (2020) proposed a system that fused visual and textual features extracted from social media. More specifically, Inception-V3 CNN was used to extract visual features and word embedded CNN was used to extract textual features. Those features were then combined and fed into a classifier which produced the final prediction. The approach enhances robustness of classification. Various ML algorithms were used during classification, including Logistic Regression (LR), Decision Tree (DT), Support Vector Machine (SVM) and Random Forest (RF).

O'Neal et al. (2018) identified the issue of noisy data on social media platforms. A computer vision approach was used utilizing Google Vision API to extract features from social media data and then classify them between signal and noise. Furthermore, a second step of classification was proposed which identified the respondent type (rescuer, rescuee, etc.). Additionally, a stacked ML classifier was used instead of individual base classifiers such as SVM, KNN, DT and MLP to increase the image classification performance. 2017 Hurricane Harvey data was used that was collected from rescuers and rescuees, as well as data from social media posts.

An interesting conclusion came from Reynard and Shirgaokar (2019). By applying ML algorithms for sentiment analysis on Twitter posts about hurricane Irma the authors concluded that the most popular tweets were less likely to include valuable information about the disaster. The study aimed to evaluate the use of Twitter data for the effective assistance on disaster response operations.

Chaudhuri and Bose (2020) addressed the problem of lack of useful information for decision making systems during a disaster, in the context of search and rescue operations. The authors explored the impact of a deep learning system that utilized information from images of smart settlements in earthquake scenarios where the information was limited. The authors concluded that deep learning techniques based on CNN variants significantly outperformed ML methods based on ANN and SVM.

Li et al. (2018) proposed the domain adaptation methodology on Twitter data to facilitate post-disaster response operations. According to the authors both labeled data from previous disasters and newly produced unlabeled tweets from current disasters can be used to train domain adaptation classifiers. A Naïve-Bayes (NB) self-trained method was proven better than traditional ML models including RF, SVM and LR, for tweet classification regarding tweets specific to a particular disaster. The proposed method was trained with a Twitter dataset called CrisisLexT6.

Basu et al. (2019) experimented with several supervised and unsupervised methods in order to address the problem of evaluating real-time information from Twitter regarding the need and availability of resources during a disaster. The methods that employed unsupervised learning outperformed those that used supervised learning when not enough training data were available from similar prior disasters. Data from the 2015 Nepal earthquake and August 2016 earthquake in central Italy was used to evaluate the method.

Kundu et al. (2018) compared various deep learning methods for tweet classification into different actionable classes relevant to post-disaster response activities related to resource management. The proposed LSTM model was evaluated using data from the 2015 Nepal earthquake and outperformed the non-deep learning methods as well as the other deep learning models.

Sit et al. (2019) proposed a framework for the identification and analysis of tweets about hurricane Irma. A binary classification by employing LSTM network was followed by unsupervised classification for topic extraction. Finally, a clustering based on geolocation was applied to pinpoint the impacted regions.

Li et al. (2020) explored the potential of genetic algorithms for better medical rescue strategies. In this study medical features were classified for the purpose of proposing better rescue management plans during emergencies.

Layek et al (2019) proposed a system which utilized both deep CNN and color filtering. More specifically a CNN model detected images that contained floods in images in social media. Once those images were captured, the final result was verified by color-based filtering.

3. Discussion

Based on the results of this paper, Twitter has been shown to be a tool of critical importance containing valuable information for emergency responders, and other decision makers especially in the disaster response phase of disaster management, as well as in the disaster preparedness phase. Compared to other social media platforms, Twitter contains geolocational information, and therefore it can provide answers to both what happened as well as where it happened.

Based on the reviewed literature, research studies leveraging information from Twitter data focused mainly on disaster response operations. According to Figure 1, the disaster types mostly studied were hurricanes and earthquakes (29.4% each), followed by any disaster type, floods and typhoons. Figure 2 shows the distribution of research studies by disaster subphase. According to the results, in damage assessment, 60% of the studies are based on DL. In post-disaster response, 66.7% of the studies are based on ML, and in disaster detection the method was based on DL. Figure 3 shows the performance of the developed methods in terms of accuracy by disaster subphase and by disaster type.

Twitter image data has been recently used for damage assessment. Challenges of processing large volumes of image data include difficulty of obtaining sufficient number of labeled data. Pretraining was employed for a method developed for damage assessment to overcome the need of a large dataset to train the CNN (Nguyen et al., 2017). Information posted on Twitter for post-disaster response has been mainly used to improve communication between people in need and emergency responders (Robertson et al., 2019). Furthermore, Twitter data has been used for performance evaluation of disaster response operations (Reynard and Shirgaokar, 2019; Li et al., 2018), identification of resource needs and availabilities (Basu et al., 2019; Kundu et al., 2018), noise reduction of the developed methods (O'Neal et al., 2018), search operations (Sit et al., 2019) and information retrieval (Alam et al., 2017; Chaudhuri and Bose, 2020).

CNNs and its variants have been widely used to extract information from Twitter image data for both post-disaster response operations (Robertson et al., 2019; Huang et al., 2020; Reynard and Shirgaokar, 2019; Chaudhuri and Bose, 2020; Sit et al., 2019) as well as damage assessment (Wang et al., 2020; Nguyen et al., 2017; Zhang et al., 2019; Alam et al., 2017). LSTMs have been used to mine information from Twitter text data in the context of post-disaster response operations (Kundu et al., 2018; Sit et al., 2019).

The accuracy of the ML and DL based methods can be improved by using different types of data for training. O'Neal et al. (2018) used less noisy, private, and thus not easily accessible, social media data to increase the accuracy of their developed method. Moreover, developed methods should be validated and explainable for robust decision making (Holzinger et al., 2022). Future research should address the need for increased volume of labeled datasets as well as cope with the human labeling of the data. Transfer learning for feature extraction is a promising method that has been used to address the limited size of training datasets (Robertson et al., 2019). Furthermore, focus should be given on ML and DL based approaches aiming to better cope with the high levels of noise and therefore, improve the signal-to-noise ratio. Additionally, the performance of the developed methods on extracting the fine details of posted information, such as affected population and location specific information, should be improved (Sit et al., 2019).

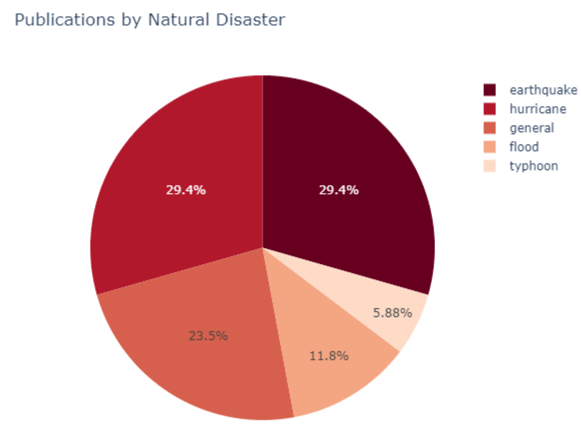

Figure 1. Research studies by disaster type

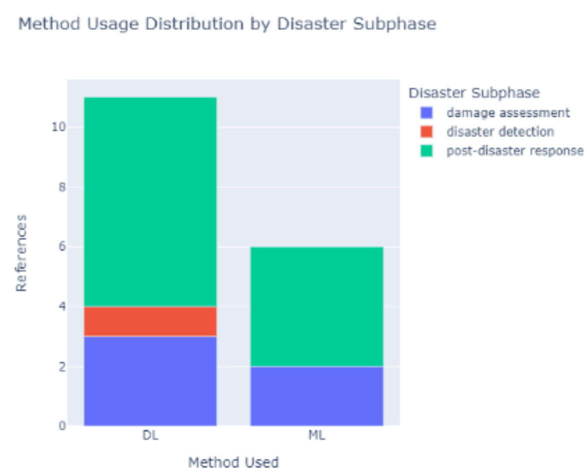

Figure 2. Percentage distribution of ML and DL in the research studies by disaster subphase

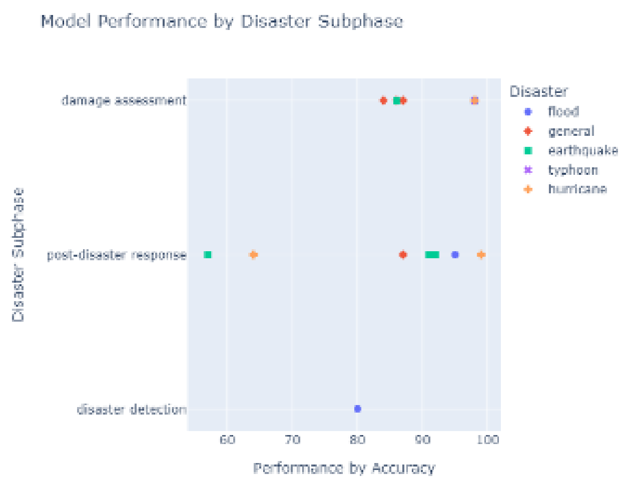

Figure 3. Performance of the ML/DL based methods in terms of accuracy for the different disaster subphases

4. Conclusions

The Twitter platform is increasingly being used by affected population, first responders and decision makers, especially during disaster response. This paper aims to provide a overview of the recent trends of using ML and DL to develop methods that process and analyze Twitter data for disaster management operations and applications. The research efforts have mainly focused on the disaster response phase, and especially in the areas of damage assessment and post-disaster response. Disaster preparedness has also been studied in terms of disaster detection. Considering the critical role of effective communication between emergency responders and affected population as well as other decision makers and the availability of geolocated data posted on the Twitter platform, more research is needed in all phases of disaster management to improve the robustness and the explainability of the developed methods.

References

Alam, F., Imran, M., Ofli, F. (2017). Image4Act: Online social media image processing for disaster response. 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2017, Sydney, Australia, 2017.

Alexander, D.E. (2002). Principles of Emergency Planning and Management; Oxford University Press, Oxford, UK, 2002.

Arinta, RR., Andi, EWR. (2019). Natural disaster application on big data and machine learning: A review. 2019 4th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE), Yogyakarta, Indonesia, 20-21 Nov. 2019.

CRED & UNDRR. (2021). Global trends and perspectives Executive Summary. Doc Publ. Published online 2021:8.

Basu, M., Shandilya, A., Khosla, P., Ghosh, K., Ghosh, S. (2019). Extracting Resource Needs and Availabilities from Microblogs for Aiding Post-Disaster Relief Operations. *IEEE Trans Comput Soc Syst.*, 6(3): 604-618.

Chaudhuri, N., Bose, I. (2020). Exploring the role of deep neural networks for post-disaster decision support. *Decis Support Syst.*, 130 :113234.

Linardos, V., Drakaki, M., Tzionas, P., Karnavas, Y.L. (2022). Machine Learning in Disaster Management: Recent Developments in Methods and Applications. *Mach. Learn. Knowl. Extr.*, 4(2): 446-473.

Holzinger, A., Dehmer, M., Emmert-Streib, F., Cucchiara, R., Augenstein, I., Del Ser, J., Samek, W. Jurisica, I., Díaz-Rodríguez, N. (2022). Information fusion as an integrative cross-cutting enabler to achieve robust, explainable, and trustworthy medical artificial intelligence. *Inf. Fusion*, 79: 263–278.

Huang, X., Li, Z., Wang, C., Ning, H. (2020). Identifying disaster related social media for rapid response: a visual-textual fused CNN architecture. *Int J Digit Earth.*, 13(9): 1017-1039.

Kundu, S., Srijith, PK., Desarkar, MS. (2018). Classification of short-texts generated during disasters: A deep neural network based approach. 2018 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM), Barcelona, Spain, 28-31 Aug. 2018.

Layek, AK., Poddar, S., Mandal, S. (2019). Detection of flood images posted on online social media for disaster response. 2019 Second International Conference on Advanced Computational and Communication Paradigms (ICACCP). Gangtok, India, 25-28 Feb. 2019.

Lecun, Y., Bengio, Y., Hinton, G. (2015). Deep learning. *Nature*. 521: 436-444. doi:10.1038/nature14539.

Li, H., Caragea, D., Caragea, C., Herndon, N. (2018). Disaster response aided by tweet classification with a domain adaptation approach. *J Contingencies Cris Manag.*, 26(1): 16-27.

Li, T., Li, Z., Zhao, W., et al. (2020). Analysis of medical rescue strategies based on a rough set and genetic algorithm: A disaster classification perspective. Int J Disaster Risk Reduct., 42: 101325.

Nguyen, D.T., Ofli, F., Imran, M., Mitra, P. (2017). Damage assessment from social media imagery data during disasters. IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2017, Sydney, Australia, 2017.

Resch, B., Usländer, F., Havas, C. (2018). Combining machine-learning topic models and spatiotemporal analysis of social media data for disaster footprint and damage assessment. *Cartogr Geogr Inf Sci.,* 45(4): 362-376.

Robertson, B.W., Johnson, M., Murthy, D., Smith, WR., Stephens, K.K. (2019). Using a combination of human insights and 'deep learning' for real-time disaster communication. *Prog Disaster Sci.*, 2: 100030. doi:10.1016/j.pdisas.2019.100030.

O'Neal, A., Rodgers, B., Segler, J., et al. (2018). Training an Emergency-Response Image Classifier on Signal Data. 2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA), Orlando, FL, USA, 17-20 Dec. 2018.

Reynard, D., Shirgaokar, M. (2019). Harnessing the power of machine learning: Can Twitter data be useful in guiding resource allocation decisions during a natural disaster? *Transp Res Part D Transp Environ*. 2019, 77:449-463.

Sit, MA., Koylu, C., Demir, I. (2019). Identifying disaster-related tweets and their semantic, spatial and temporal context using deep learning, natural language processing and spatial analysis: a case study of Hurricane Irma*. Int J Digit Earth.*, 12(11):1205-1229.

Sun, W.., Bocchini, P., Davison, BD. (2020). Applications of Artificial Intelligence for Disaster Management. *Nat Haz*, 103: 2631-2689.

UNISDR. Available online: https://www.undrr.org/publication/2020-non-covid-year-disasters.UNISDR, 2009. Available online: https://www.unisdr.org/files/7817_UNISDRTerminologyEnglish.pdf.

Varga, I., Sano, M., Torisawa, K. Hashimoto, C., Ohtake, K., Kawai, T. et al. (2013). Aid is out there: looking for help from Tweets during a large scale disaster. Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics, Curran Associates, Inc., Red Hook, NY, 1619-1629

Wang, T., Tao, Y., Chen, SC., Shyu ML. (2020). Multi-Task Multimodal Learning for Disaster Situation Assessment. 2020 IEEE Conference on Multimedia Information Processing and Retrieval (MIPR), Shenzhen, China, 6-8 Aug. 2020.

Yu, M., Yang, C., Li, Y. (2018). Big data in natural disaster management: A review. *Geosci.* , 8.

Zhang, DY., Zhang, Y., Li, Q., Plummer, T., Wang, D. (2019). CrowdLearn: A Crowd-AI hybrid system for deep learning-based damage assessment applications. 2019 IEEE 39th International Conference on Distributed Computing Systems (ICDCS), Dallas, TX, USA, 7-10 July 2019.