Crisis Management Systems: Big Data and Machine Learning Approach

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Abstract: A crisis is defined as an event that, by its nature or its consequences, poses a threat to the vital national interests or the basic needs of the population, encourages rapid decision making, and requires coordination between the various departments and agencies. Hence the need and importance of crisis and disaster management systems. These crisis and disaster management systems have several phases and techniques, and require many resources and tactics and needs. Among the needs of these systems are useful and necessary information that can be used to improve the making of good decisions, such as data on past and current crises. The application of machine learning and big data technologies in data processing of crises and disasters can yield important results in this area. In this document, we address in the first part the crisis management systems, and the tools of big data and machine learning that can be used. Then in the second part, we have established a literature review that includes a state of the art, and a discussion. Then we established a machine learning and big data approach for crisis management systems, with a description and experimentation, as well as a discussion of results and future work.

1 INTRODUCTION

The frequency of crises and disasters around the world is changing and increasing, as well as the consequences of these different crises and disasters are numerous and cause several casualties and several losses (for example, car accidents, incidents, the Asian tsunami, the Mumbai attacks, terrorist attacks, Nepal Disasters, Afghanistan Disaster, etc.)(Boin, 2009). These Crises and disasters can get worse in some ways, and the ability to cope with some of these adverse events increases. There may be different types of social entities trying to cope with crises. Among the areas such as individuals, households, groups and societies, official organizations, both private and public (Quarantelli, 1988).

In good crisis management, special tactics and hard work are used to deal with eventualities of the present situation or that arise during an emergency. Also crisis management relies to a large extent on the application of tactics specifically adapted to unforeseen situations of a given community disaster. The change of adversity in this area poses new challenges for many organizations and individuals, such as governments, crisis management organizations, social workers, etc. It also creates a new research agenda for students and researchers. This also opens the doors and gives opportunities to apply several technical and theoretical approaches of several scientific fields, in order to solve some problems in the sector of crisis and disaster management. Among these areas that can be applied are the tools and technologies of big data and machine learning.

Big data is now developing rapidly in all areas of science and engineering. Learning this massive data offers significant opportunities and transformative potential for various sectors (Qiu et al., 2016). Especially with the use of these massive data with big data techniques, in machine learning algorithms. The field of crisis management systems is among the different fields of application of big data and machine learning (Alpaydin, 2009) (Carbonell et al., 1983), and it still need several improvements.

Problematic. Although the flow of information within a crisis and disaster management system is much greater, and decisions during times of crises may be more difficult to take. By taking into account all possible information on previous crises and disasters, we can improve the decisions that need to be made in case of crises or disasters to help decision makers in the field of crisis management.

Research Questions. During this work, we have several research questions that can be asked, and we want to try to answer them, among these questions:
What are the difficulties that can be encountered in making decisions about crisis and disaster manage-

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ment?
How can we improve the decisions of crisis management systems using machine learning and big data?
What are the machine learning and big data approaches proposed in the field of crisis management? how can we improve them?
What data are available on crisis management? How can we use them to improve the decisions of crisis management systems?

Methodology. In this work, a literature review was conducted to build a state of the art in the field of machine learning and big data in crisis management systems. Then we made a discussion based on this state of the art in this area. Then, and at the base of the literature review, we try to propose a machine learning and big data approach in this field, with a detailed description and an experiment. Then the analysis of the results and suggestion of the next works.

Collection of Papers. In order to collect documents for this work, we conducted a search in paper databases and forums for crisis management and information systems, and databases on machine learning and big data. With the documents of the international conferences in this field. In addition, we also conducted web searches to identify relevant information that did not appear in academic papers.

These documents were chosen according to their originality and their contributions in the field of crisis management systems, taking into consideration the application of the tools of machine learning and big data. In terms of the appearance of machine learning in the field of crisis management systems, we have taken the documents published since 2005 to find out the evolution of this field. But in terms of the results obtained, we have taken recently published articles and documents, for example from 2017 to the present, in order to be able to understand and compare these results obtained

2 STATE OF THE ART

2.1 Big Data in Crisis Management

The era of Big Data has begun to cover all aspects of our life. With the wide attention in the field of Big Data, a large number of new technologies have begun to emerge, and these technologies will become important tools for the acquisition, storage, and analysis of Big Data. According to the theory of Crisis Management, Big Data can lead the direction of a potential crisis management and has created opportunities for it to improve and control through the analysis of crisis information. Scientists and analysts are facing one of the biggest challenges of managing large volumes of data generated at times of disasters and crisis. Therefore, the role of big data in disaster and crisis management has been evolving.

In (Bellomo et al., 2016) N. Bellomoa et al. propose an essay concerning the understanding of human behaviours and crisis management of crowds in extreme situations using Big Data to deal with Decision Making toward Information Management and Crisis Response. They said that the overview on crowd dynamics and safety problems presented has shown that the literature in this field can give valuable contributions to the crisis management of human crowds in evacuation situations. In (Watson et al., 2017) Hayley Watson et al. present findings from a case study of big data roadmap, and supports findings from other studies in that big data is able to contribute to crisis response efforts. They said that the literature has demonstrated how the increased use of disparate datasets can positively affect preparedness and response to crises and disasters, in particular, the use of big data. So that can aid decision making within response, activities emerges as an important benefit of big data in this sector.

In (Ma and Zhang, 2017) Yefeng Maa and Hui Zhangb study the problem of information management at China's Emergency Operations Center (EOC), and aim to propose a data-driven knowledge management system (KMS) supporting decision making, coordination, and collaboration within EOCs and with the public, whose the big data analytics is employed. They said that Big data analytics is incorporated to knowledge management process in order to improve the capability of data processing and crisis situations. Their case study shows that the proposed knowledge management solution is helpful for improving situation awareness and decision making when dealing with social security incident. In (Doka et al., 2017) Katerina Doka et al. have presented a storage and processing platform, that is able to support applications and services that use the power of Big Data produced by mobile and social network users to detect and manage emergencies. This system uses collection and analysis of mobile and social networking data before, during and after a disaster. They focused on the scalability of the Big Data frameworks.

In (Akter and Wamba, 2017) Shahriar Akter and Samuel FossoWamba examine big data in Disaster Management to present main contributions, gaps, challenges and future research agenda, based on a systematic literature review. Their study aims to contribute to a better understanding of the importance of big data in disaster management. They said that decision makers need to address various challenges, such as crisis analytics platform, data governance, data quality, analytics capabilities, etc... As limitations of their work, they said that they considered only papers that satisfied some specific criteria, they considered coherent and inherent with Disaster Management. For example, they did not include unpublished works, book chapters and conference proceedings.

2.2 Machine Learning in Crisis Management

Technology changes exponentially, whereas organizations change logarithmically (Martec's law). That is, the technology in the field of crisis management is evolving very quickly and these changes seem to be accelerating. While the change of an organization, its way of thinking and behaving is always difficult and slow (Dugdale et al., 2019). There are many more other works to review and use in this field, but the most important are the most relevant ones that can give us an idea about how to improve crisis management systems by using the big data and machine learning, based on the established work. We will still need to cite some criteria that can help us to compare, or at least understand the machine learning and big data models proposed. These criteria will also be inspired by some works established in this context, namely (Zagorecki et al., 2013) and (Lin et al., 2011) and others.

In (van Someren et al., 2005) Robert de Hoog and Guido Bruinsma address the problem of selecting and distributing information to users in function of their characteristics. In particular, they propose a trainable system for information distribution and expect that this will reduce problems due to information overload, and will give more effective collaboration between all actors in the crisis management systems environment. The idea was to study the use of machine learning methods to automatically construct context-specific task profiles, and use a description of user activities to guide information distribution and system training. In (Schulz et al., 2012) Axel Schulz et al. show an approach for turning massive amounts of unstructured citizen-generated in making better informed decisions, and aims the utility of Linked Open Data and crowd sourcing for processing data from social media. Their goal was to minimize the manual efforts for filtering information by introducing machine learning methods such as clustering and trained classifiers, by taking into consideration three steps: Information collection, information classification and information enrichment.

In (Zagorecki et al., 2013) Adam T. Zagorecki et al. have discussed the application of data mining and machine learning techniques to support the decision making processes for the disaster and crisis management. They said that the challenge of applying DM and ML methods to disaster and crisis management starts at the point of the identification of useful data that can be exploited by the used methods, this data could be static when it is collected prior to the disaster event or dynamic when it is a real-time event that is produced during the disaster. Moreover, they have discussed the problem of using simulated data instead of using real data during the processing. In (Schulz et al., 2013) Axel Schulz at al. have talked about using tweets with emotions for crisis management, by showing the systematic evaluation of an approach for sentiment analysis on micro-posts that allows detecting seven emotion classes. They noted a remark from results that the accuracy and the recall of an approach using tweets labeled with a 7-class sentiment classifier are better than simply using tweet with negative sentiment using a 3-class sentiment classifier. In (Nguyen et al., 2016) Dat Tien Nguyen et al. have proposed to use Deep Neural Network (DNN) to identify informative tweets and classify them into topical classes by using a new online algorithm based on stochastic gradient descent to train DNNs in an online fashion during disaster situations. The results showed that the performance of the model in Binary Classification model is quite inconsistent as the size of the in-event training data varies and dropped when the training size is between 2200 to 3900 tweets. In addition, the performance of the model in Multi-Class Classification run provides very low accuracy at the first training and continue to drop until a good number of training examples.

In (Lanfranchi, 2017) Vitaveska Lanfranchi presents an analysis of the ethical risks and implications of using automated system that learn from social media data, to provide intelligence in crisis management, and shows a short overview on the use of social media data in crisis management and its implication of machine learning and social media data by using an example of a scenario. They reported that the most used sources of information for fast and agile crisis information are probably social media or crowd-sourced data, and the combination of social data and machine learning algorithms to understand and filter the data has high ethical implications. They said also that the system will be pretrained on an existing corpus of Twitter data related to Crisis and Emergency Management, by performing sentiment analysis, performing social network analysis, use a network visualization and starting following users that post useful contents.

In (Lagerstrom et al., 2016) Ryan Lagerstrom et al. have proposed an approach for image classification using low-level features built on pretrained classifiers, in the context of fire emergency in the Australian state. They used a convolutional neural networks for feature extraction and Random Forests for classification to detect fires on images to help managing emergencies. They showed that these methodologies could classify images into fire and not not-fire classes with a good accuracy. In (Giannakeris et al., 2018) Panagiotis Giannakeris et al. presented a detection approach for classifying objects (flood, fire, etc.) in disaster scenarios in order to build a warning system framework for detecting people and vehicles in danger. They used transfer learning to classify image in this context, and they have achieved a good accuracy. In (Muhammad et al., 2018) Khan Muhammad et al. proposed an early fire detection framework using convolutional neural networks for surveillance cameras to detect fire in the indoor and outdoor environments. They also used transfer learning based on AlexNet to classify images and detect fire disaster, which raised a good accuracy.

In (Arru et al., 2019) Maude Arru et al. present a method of data analysis that helps crisis decision makers to determine whether or not to alert the population in a likely crisis situation. The work describes four step decision support process, with the use of decision trees, which will help provide decision makers with an indication of the likely behavior of a population in response to an alert. By using this information, and by focusing on the users and analyzing the behavior of the population in the event of a crisis, they said that they can then decide whether or not to trigger an alert of crisis. In (Buettner and Baumgartl, 2019) Ricardo Buettner and Hermann Baumgarti examine how deep learning can be applied to evacuation situations. They show how artificial agents can recognize exhaust panels, such as doors and stairs for evacuation route planning. In this context, they used a network of convolutional neurons for image recognition in emergency situations, with an interesting result and a high accuracy of recognition, which surpasses the current methods.

2.3 Discussion

During the review of the work established in the field of application of machine learning in crisis management, and taking into consideration the criteria that we have talked about, we can say that there is a lot of effort and many ideas applied in this area. At the level of models and approaches built by researchers, we see that the most common machine learning models in this field are binary and multi-class classification methods (using NBB, NBM, etc..), and modern deep learning techniques such as DNN, CNN and Bi-LSTM, with other multiple techniques such as NLP, DM and role-task framework. It appears that the most frequent works are those that use a classification (binary or multi-class) and one of deep learning techniques (DNN, CNN, ...). These methods and models have been suggested in this area just in recent years, since some of them have proposed models with their experiments and results, and others have just proposed models without doing an experiment, to make them in future work.

For works that have proposed machine learning models with their experiments and results, we note that the measurements used in the experiments are not unified, standard performance measures such as precision recall, ROC and others are always present, alongside other measures such as F-Measure, AUC and F1-score, as well as general measures like average performance, Completeness, etc.. For the sources of the collected data, it appears that the most frequent source is Twitter, and this by using the tweets of the users during the crises. Also the intervention of the Volunteers and human-participation during the labelization of the data. It should also be noted that most of the datasets used in these works are not very wide, especially those containing only labeled tweets, and that large datasets usually contain simulated data and not real data. This may lead us to think about dataset types and data quality used in experiments. Also, there are works that have reported that their models and experiments can be improved, either by the good choice of datasets or by the improvement of the learning of the model or by the change and the modification of the parameters.

3 BIG DATA AND MACHINE LEARNING APPROACH ADOPTED

Seeing the approaches mentioned in these previous studies, and taking into consideration the possibility of improving each approach with the nature of crisis management systems, we can propose an approach that essentially serves to classify decisions (knowing their types previously). The datasets used in the training should preferably be the reports generated from previous real crises, with the possibility of using informative data of Twitter users for example.

In general, crisis management systems generate reports that give more information about the method of crisis management and the plan that was used, and also gives an opinion on this management method (good, bad, ...). This information includes: the level of the crisis (Response Level), the management time, the percentage of resources used, etc. This approach (Figure 1) can be rectified later in this work or in subsequent works, depending on the experimental results. The major problem that can surely be posed is the existence of a good real dataset that can help the model to have a good learning.

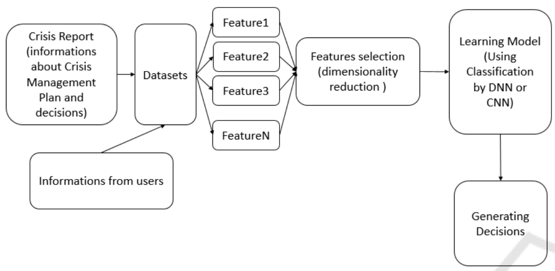

Figure 1: Machine Learning Approach.

3.1 Which Datasets to Use?

The phase of choosing the database is among the most important phases in a machine learning approach or project. It is enough that the absence of a useful database can prevent the success of the whole approach, and using a good dataset can provide an opportunity to get good results and have useful interpretations especially when the data is real. In our case, it will be preferable that the dataset has large dimensions and will be compatible with the characteristics of big data that we know. Also the databases used in this type of domain must contain real information on crisis management systems, such as crisis management plans and reports, and even decisions made by these systems.

3.2 Extracting and Selecting Features

Feature extraction is a universal problem in machine learning, because it is very critical to understand what are the important and necessary aspects of the problem to solve. In another way, we need to know what are the criteria and the essential components of the data to use and to take into account during the implementation and exploitation of the data to have a good learning. Features extraction depends heavily on the chosen database, generally, we take at the beginning the majority of the database components as features and sometimes we take them all, especially when the components are not much. In our case, where the databases can be reports from crisis management system or crisis data from the users, the features depend on the information and criteria given by these reports, so they can be like crisis management time, resources, crisis levels, type of crises, informative data, etc.

When extracting features, this extraction is more or less correct to make a good learning, because these features contain information on the data used but sometimes they contain information that is not necessarily important. Whence comes the idea that it is not necessary to take all extracted features. The most important thing is to take as much information as possible, and it will be better to do that with a few features. The idea of this step is to make a selection of a subset of input variables of a learning algorithm while ignoring the rest. In other words, we can talk about a reduction in dimension. Because the experiments shows that when we use data with very high dimension, models usually choke because the time of training increase exponentially with a high number of features, and models begin to have a risk of overfiting. In our case, the features extracted from the database usually depend on the information given by the crisis management reports, these features are related to the management time, the resources needed, the crisis levels, the types, and other variables. The reduction of the dimensions of these variables can give us only the most useful features in learning,and can give us the types of output of the model and the components of the decisions.

3.3 Learning Models?

Taking into consideration the definitions and properties of machine learning, its types and characteristics, doesn't necessarily tell us which machine learning model to use. However, it give us an intuition on how these models work which may leave us in the hassle of choosing the suitable model for our problem.

In our case, we can say that they exist several kinds of making a model from this machine learning approach. However, the closest model is to make a classification model. Because we are talking here about generation of decisions, and the method of generating these decisions, until now in our work, consists in knowing the classes of certain decisions or the components of these decisions. Provided that we know beforehand the types of the classes of the decisions (for example the level, the priority, ..). We can also do a logistic regression model, to estimate the percentage of some decisions (for example the percentage of resources needed to manage a given crisis).

4 MODEL EXPERIMENTATION

4.1 Dataset

During our search for datasets available in this area, we took into consideration the preferred type of data on crises, like reports on real crises. This type of data can be generated by crisis management organizations, and is not always free.

There are many data on crises, either natural or man-made crises. As an example, we used a database on natural crises in the country of Afghanistan in a given period of time (2016-2018 for example). These information includes assessment figures from Red Crescent Societies, national NGOs, international NGOs, and others, and are based on the reports received. This dataset provides information on natural crises in Afghanistan, such as the type of crisis, the number of people killed by each crisis, the number of homes destroyed, and so on.

Another dataset that may be useful to us, in the same context of the natural crises in the country of Afghanistan, and more precisely on the response to the floods. This dataset [1] presents information on the degree of recovery, including the level and type of coping strategies used by both assisted and unaided households since the 2014 floods.

A third dataset that we use in the same context is "Nepal - Disaster data from 1991-2010" [2] , witch includes the disasters that occurred in Nepal published by Open Database License (ODC-ODbL). This dataset gives some information on these crises in Nepal, as the type of the crises, the human victims (deaths, missing, injured ..), the destroyed houses, etc.

4.2 Generating Features, Choosing a Model

First, a classification model was used to classify the type of a crisis using the dataset that provides information on natural crises in Afghanistan. For example, we chose to classify two types of crisis using the information given. Knowing the type of crisis from certain information (such as the number of victims and houses affected) allows us to have an idea about the priority of managing this crisis, and also to have an idea about the resources needed to use during the management of this crisis. The interest of this classification is to be able to extract a component of a decision towards a crisis. This component is the type of a crisis, according to some information about natural crises such as people killed, affected people, affected families, damaged homes, destroyed homes, etc. And it is up to us to choose beforehand the classes of the types to work with (of the first case we choose two types of classes to carry out a binary classification).

Then, another classification was made based on the numeric features of the second dataset. This classification aims to classify the level of a natural crisis (i.e. low community damage, and high community damage). This classification of crisis levels allows to have an idea about the priority of such a crisis. Also, and according to the available data, it allows to give an opinion and a judgment on the intervention of the systems of crisis management towards a given crisis. The interest of this classification is to obtain another component of a decision about a crisis. This component is to know the degree of damage of a crisis on a given community, based on information obtained during an evaluation carried out on the communities affected by the crisis. Knowing the degree of damage of a crisis from some information on this crisis (such as demographics, vulnerable groups, expenses, etc.) will allow us to take into consideration the degree of damage to know the priority of each case of a crisis, and to improve reactions in a similar situation.

4.3 Results

We have chosen features, then train the model using these features and modify the choice of these according to the results obtained. The first choice, which is obvious, is to use all the numeric features. The choices that follow are based on the results obtained and the importance of the information contained in each feature in relation to the desired decisions. We chose the accuracy to measure the performance of the classification model, because it is simple and gives us the desired interpretation of the degree of performance, and it serves to know how many samples did the model correctly label among all the samples. So we can summarize the results of the classification in two stages. One for the component of the type of crises (table 1), and the other for the classification of the degree of damage on the community (table 2).

4.4 Discussion

Based on the results of the experimental part of the model, we can draw some essential remarks. The choice of the two decision components used to manage crises was or classify the type of crisis, and the degree of damage to the community, for the reasons given in the previous sections. The results obtained during the training of the models are acceptable and

[1] https://data.humdata.org/organization/reach-initiative
[2] http://www.desinventar.net/DesInventar/report.jsp

Table 1.

Dataset	Features	Accuracy
Dataset 1	All numeric features	0.3101
	Personskilled Houses-destroyed Families-displaced	0.2658
	Families-affected Individuals-affected	0.7468
Dataset 2	Deaths , Injured ,Missing ,Victims , Affected	0.7760
	Deaths ,Victims ,Affected	0.7634

Table 2.

Dataset	Features	Accuracy
Dataset 3	All numeric features	0.6539
	expenditures-health demographics-household expenditures-transport	0.6477

are different meanings. In the case where we have chosen to classify the type of crises using all numerical features, we notice a very low accuracy of the model. This is due to the large number of columns used in learning, which interferes with the model learning and that is proven in the field of machine learning.

When we chose to use a smaller number of features (which summarizes the largest amount of data) such as crisis-affected families and crisis-affected individuals in the first dataset (disasters in Afghanistan) we had acceptable results. Also in the second dataset (disasters in Nepal), when we did a learning with a small number of features that are relevant, like Deaths, Injured, Missing, Victims, Affected, we got almost the same results. So it can be said that even the two datasets used in the classification of the type of crisis are different and represent information on crises in different countries, the type classification of natural crises can be done using almost the same features. These features represent information about the individuals and families affected by these crises and the victims of these crises.

In the classification of the other component of decisions, which is the degree of damage to the community, the use during the learning of all the numeric features, and the use of a small number of these features, give almost the same results. This can be explained by the small number of columns used (which does not give a big difference even if we perform a dimension reduction), and also the large number of records that are larger than the first two datasets.

5 CONCLUSION

The application of big data tools and machine learning techniques and algorithms in several fields gives in most cases good results that are useful in each area, which give something more, and especially who is able to be improved every time. In this work, we have seen and shown that the area of crisis and disaster management is not an exception in this context. As there is a lot of work going on in this area to apply big data and machine learning, using different types of data and different data sources. These works also have the possibility to be improved to obtain better results, this is according to the researchers who published in this field, and according to the results that they obtained.

According to our knowledge in the field of machine learning, and according to the machine learning work published in this field, the results obtained by this approach remain acceptable, especially as a first attempt. And the proposed approach remains flexible to be modified and adapted to the conditions of the crisis management area. also the approach and this work in general has many prospects to be carried out as works of future. Although the datasets used in this work are real and present specific crises and disasters, we need, in the context of perspectives and future work, to use several other datasets on other crises and disasters to improve the accuracy rate of these models in order to be able to extract good decisions. And also using datasets of images of crises during training to get a good performance.

The biggest perspective in our work is to continue to look into the field of machine learning applied to crisis management systems, and to the field of crises in general. They remain a lot of things to apply at the level of management and also the prediction of crises and minimization of risks. Especially when there is the possibility to exploit dynamic and varied data such as data from social networks. In addition, there still many things to apply from big data techniques, such as massive data storage techniques, parallel and real-time processing and calculations, and massive data quality measurements.

The field of studies of car accidents and road accidents is a very interesting area to apply approaches based on machine learning and big data. This is due to several factors, such as the problem of the increase of road accidents, and also the necessity to exploit the existing data on these types of crises in several countries. we can say the same things about the fields of local and global epidemics, as well as earthquakes and floods and forest fires. It will also be interesting and useful to use these types of data and other types of data, to make a predictive model that can predict crises before they occur.

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