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A Machine Learning Approach to Predicting Community Engagement on Social Media During Disasters

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A Machine Learning Approach to Predicting Community Engagement on Social Media During Disasters

by

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A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy
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# TABLE OF CONTENTS

LIST OF TABLES iv  
LIST OF FIGURES v  
ABSTRACT vi  

## CHAPTER 1 INTRODUCTION  
1.1 Motivation and Problem Statement 1  
1.2 Research Scope and Thesis Statement 4  
1.3 Research Questions and Research Methods 6  
1.4 Research Methods 10  
1.5 Publications 11  
1.6 Dissertation Organization 12  

## CHAPTER 2 BACKGROUND AND RELATED WORK 13  
2.1 Role of Social Media in Real-World Crisis 13  
2.1.1 Social Media 14  
2.1.2 Microblogging (Twitter) 14  
2.1.3 Community 16  
2.1.3.1 Online Community 17  
2.1.3.2 Community Engagement 17  
2.1.4 Situational Awareness 17  
2.1.5 Crowdsourcing 18  
2.2 Emergency Response Management 19  
2.3 Disaster, Disaster Categories and Sub-Categories 20  
2.4 Communication During Disasters Events 20  
2.4.1 Supervised Classification 21  
2.4.2 Unsupervised Clustering 22  
2.4.3 Types of Disasters 23  
2.5 Summary 25  

## CHAPTER 3 TOPIC MODELING AND EVENT DETECTION IN TWITTER 26  
3.1 Introduction 26  
3.2 Method 28  
3.2.1 Tweets Collection 28  
3.2.2 Data Preprocessing 29  
3.2.3 Topic Modeling 29  
3.2.4 Topics Identification 30  
3.2.5 Events Analysis 30  
3.3 Results and Discussion 30
3.3.1 Topic Analysis 30
3.3.2 Events Analysis 31
  3.3.2.1 Temporal Analysis 31
  3.3.2.2 Sentiment Analysis 31
  3.3.2.3 Spatial Analysis 32
3.4 Summary 33

CHAPTER 4 PREDICTING COMMUNITY ENGAGEMENT ON TWITTER 34
4.1 Introduction 34
4.2 Method 35
  4.2.1 Framework 35
    4.2.1.1 Data Collection and Filtering 36
    4.2.1.2 Data Preprocessing 36
    4.2.1.3 Binary and Multi-class Classifications 37
4.3 Experimental Setup 37
  4.3.1 Crowdsourced Annotation 37
  4.3.2 Feature Sets 38
    4.3.2.1 TF-IDF Feature 38
    4.3.2.2 Psychometric Features 38
    4.3.2.3 Linguistic Features 39
    4.3.2.4 Twitter Features 39
    4.3.2.5 Sentiment Feature 39
  4.3.3 Feature Selection 39
  4.3.4 Classifiers 40
  4.3.5 Performance Measurements 40
4.4 Experiment 41
4.5 Results and Discussion 42
  4.5.1 Annotation Results 42
  4.5.2 Experiment Results 43
4.6 Summary 44

CHAPTER 5 DETECTING SITUATIONAL AWARENESS DURING DISASTER 47
5.1 Introduction 47
5.2 Dataset and Annotation 49
5.3 Method 50
  5.3.1 Framework 51
  5.3.2 Data Preprocessing 51
  5.3.3 Binary Classification 51
  5.3.4 Ensemble Learning 52
5.4 Feature Sets, Classifiers and Performance Measurements 53
  5.4.1 Feature Sets 53
  5.4.2 Feature Selection 54
  5.4.3 Classifiers 55
  5.4.4 Performance Measurements 56
5.5 Results 56
5.6 Discussion 57
5.7 Summary 59
CHAPTER 6 PREDICTING HIGH PRIORITY TWEETS DURING DISASTER 60
  6.1 Introduction 60
  6.2 Dataset and Annotation 62
    6.2.1 Data Collection 62
    6.2.2 Amazon Mechanical Turk Annotation 63
  6.3 Method 66
    6.3.1 Clustering 66
      6.3.1.1 Topic Modeling 67
    6.3.2 Multi-class Classification 67
      6.3.2.1 Data Preprocessing 68
      6.3.2.2 Feature Extraction and Selection 68
      6.3.2.3 Classifiers and Performance Measurements 70
    6.3.3 Ranking 71
  6.4 Results and Discussion 72
    6.4.1 Clustering Results 73
    6.4.2 Multi-class Classification Results 75
    6.4.3 Ranking Results 76
  6.5 Summary 77

CHAPTER 7 CONCLUSIONS 79
  7.1 Discussion 81
  7.2 Contributions 82
  7.3 Limitations and Future Work 82

LIST OF REFERENCES 85

APPENDICES 96
  Appendix A Copyright Permissions 97
**LIST OF TABLES**

Table 2.1  Clustering techniques used in disaster scenario.  
Table 3.1  Environmental topics in Barbados with statistics.  
Table 4.1  Binary results of using (80%) training data and (20%) evaluation.  
Table 4.2  Multi-class results using (80%) training data and (20%) evaluation.  
Table 4.3  Top 10 ranked attributes for extracting relevant tweets.  
Table 5.1  Relevant tweets and irrelevant tweets.  
Table 5.2  Examples of feature types used in our model.  
Table 5.3  Performance metrics for evaluating our model.  
Table 6.1  Multi-class results of three proposed classifiers.  
Table 6.2  Ranking model results.
LIST OF FIGURES

Figure 1.1 Research scope. 4
Figure 1.2 Challenges of adopting social media during a time-critical emergency. 7
Figure 1.3 Research method. 11
Figure 2.1 Types of Twitter data and methods of collecting tweets. 15
Figure 2.2 Emergency management cycle. 19
Figure 2.3 Types of disasters. 20
Figure 3.1 Twitter topic modeling and event detection framework. 28
Figure 3.2 Important topics discussed during the disaster. 32
Figure 3.3 Sentiment analysis comparison water vs. zika. 33
Figure 4.1 Twitter community engagement detection framework. 36
Figure 4.2 Best F1 score of models for the binary classification. 44
Figure 4.3 Best F1 score of models for the multi-class classification. 45
Figure 5.1 Two stages Twitter situational awareness detection framework. 51
Figure 5.2 Best accuracy of each classification model. 58
Figure 5.3 Best area under the curve of each classification model. 58
Figure 6.1 Hurricane Michael tweets volume. 63
Figure 6.2 Twitter clustering, classification, ranking model. 66
Figure 6.3 Topic waves during hurricane Michael. 73
Figure 6.4 Distribution of daily sentiment for hurricane Michael. 74
Figure 6.5 Accuracy measures for the comparison of classifiers. 75
Figure 6.6 F1 measures for the comparison of classifiers. 77
ABSTRACT

The use of social media is expanding significantly and can serve a variety of purposes. Over the last few years, users of social media have played an increasing role in the dissemination of emergency and disaster information. It is becoming more common for affected populations and other stakeholders to turn to Twitter to gather information about a crisis when decisions need to be made, and action is taken. However, social media platforms, especially on Twitter, presents some drawbacks when it comes to gathering information during disasters. These drawbacks include information overload, messages are written in an informal format, the presence of noise and irrelevant information. These factors make gathering accurate information online very challenging and confusing, which in turn may affect public, communities, and organizations to prepare for, respond to, and recover from disasters. To address these challenges, we present an integrated three parts (clustering-classification-ranking) framework, which helps users choose through the masses of Twitter data to find useful information. In the first part, we build standard machine learning models to automatically extract and identify topics present in a text and to derive hidden patterns exhibited by a dataset. Next part, we developed a binary and multi-class classification model of Twitter data to categorize each tweet as relevant or irrelevant and to further classify relevant tweets into four types of community engagement: reporting information, expressing negative engagement, expressing positive engagement, and asking for information. In the third part, we propose a binary classification model to categorize the collected tweets into high or low priority tweets. We present an evaluation of the effectiveness of detecting events using a variety of features derived from Twitter posts, namely: textual content, term frequency-inverse document frequency, Linguistic, sentiment, psychometric, temporal, and spatial. Our framework also provides insights for researchers and developers to build more robust socio-technical disasters for identifying types of online community engagement and ranking high-priority tweets in disaster situations.
CHAPTER 1
INTRODUCTION

1.1 Motivation and Problem Statement

From natural disaster to pandemics to intentional or accidental man-made actions, no part of the country is protected from disaster. When a crisis hits, chaos tends to follow. People collect information from the sources most immediately accessible to them: those in their immediate environment, friends, and families by phone, broadcast alerts, radio, television, online communities, and social media. Based on this information, people decide whether to quickly evacuate from the disaster area, seek shelter, or prepare in a way that keeps them away from risk [1].

In recent years, social media has become a common channel in responding to emergency situations. Two-way conversation is the core idea of social media [2]. Information collected from social media can be utilized as one of the essential sources from which emergency responders and social media content analysts can extract meaningful information to help classify and rank new concerns or afford more detail about observed issues [3]. When affected or eyewitness people adopt social media to send notifications and updates, ask for or offer help, or report the situation around them, they contribute to information streams that both residents and emergency responders depend on during a disaster [4].

Twitter, as a form of social media, is a fast emerging tool for expressing opinions, spreading news, and facilitating intercommunication between individuals and organizations to help them to gain situational awareness during times of mass emergency.

People tend to use various devices (e.g., tablets, cell phones, etc.) to disseminate information and record real-life situations as they occur around them. For example, Hurricans Sandy in 2012, Harvey and Irma in 2017, and Michael in 2018 were extensively reported by Twitter users [5], [6]. Another case where Twitter was used as a resource for the U.S. Department of Health to interact
with residents, was the outbreak of the Zika virus (2015-2016), where the Centers for Disease Control and Prevention (CDC) and World Health Organization (WHO) utilized Twitter to post the latest updates on the pandemic [7].

Emergency management officials are adopting social media platforms in order to reach a wider audience. During disasters, community members use social media to post information regarding the situation. This information can be considered as an essential factor that affects situational awareness of the Emergency Operations Centers (EOCs) unit and impacts their decision quality [8]. People exposed to the impact of disasters no longer rely only on traditional channels to get their information. For instance, during Hurricane Sandy in 2012, Twitter users posted more than 20 million tweets about the hurricane in six days [9]. In-depth investigation of these tweets shows that during this incident and in the following hours, local participants provided details including eyewitness information, acute injuries, the effect on communities, calls for help, and expressions of worry. They thereby act as social “sensors” of terrestrial activity [10].

On the other hand, online participants outside the hurricane zone may also add to tweet (message) threads by sharing information about volunteering and donations, people’s wishes and prayers, alerts and advice, and families seeking news about their relatives’ status. These update messages improve the emergency response team’s situational awareness by supporting them in allocating supplies and coordinating rescue operations.

In contrast, officials (e.g., emergency managers) use social media to send and respond to information and to be a part of the conversation during a disaster. They supply information and directions to the affected public and reply to people’s inquiries and concerns. They further utilize social media to dismiss the spread of fake news and misinformation [11]. From the perspective of emergency services, this adoption of social media presents some complexities and challenges [12], [13].

Part of disaster response and preparedness is understanding the different types of communities where frequent disasters are increasingly affecting communities’ most vulnerable members and hindering efforts to eradicate poverty. In the case of the Zika virus outbreak, we can raise questions about what community engagement can do to tackle epidemic preparedness or response. If we think of engagement as trust building, we think of mapping the people and the institutions in a community that you would call on to play a role in an epidemic or pandemic response. What challenges and prospects do communities have in responding to disaster risk while making communities resilient?
Additionally, the size of affected areas or number of victims will be reflected over the extent and size of the interaction of people in the media.

Classifying communities depending on type of online community engagement is the key solution. For example, Barbados is a tourist island that has suffered from ongoing sewage leak issues seeping across parts of the island; hence, we expect that social media analysts or emergency managers will receive many questions from visitors asking about what is going on.

Another example is hurricanes in Florida, where residents are more exposed to posts about the disaster in order to report about the current situation or ask for help. In addition, information often arrives at a rapid rate which makes it difficult for social media analysts in the emergency center to manually filter through, monitor, and analyze such texts during a time-critical emergency [14].

People assume officials are able to instantly grab urgent requests, questions, and reports using these new communication channels. But, the emergency officials usually are not prepared to answer on time and satisfy expectations [15]. Current means employed by emergency administrators do not treat urgent messages (tweets) as more important than other things that rely on their degree of attention or situational awareness. Alternatively, they only rely on the temporal order of the information.

In this research, we focused on the information overload challenge in the adoption of social media during emergencies and how to overcome the difficulty of extracting relevant information for disasters and other hazards, which is often noisy.

Depending on the people using social media during disasters, we designed and developed a machine learning model to classify community engagement into four parts: (1) Asking for information, (2) Reporting information, (3) Positive engagement, and (4) Negative engagement. This categorization makes it easy to handle requests and queries and prioritize information. We developed a two-level classification system to predict types of tweets during disasters: binary-level, which is the task of classifying the posts of a given set into two groups (relevant and irrelevant), and multi-classification, which takes the relevant tweets and divides them into four engagement types.

I also implemented an unsupervised machine learning algorithm to discover and understand how social media is used in the discussion of environmental health situational awareness based on three features: (1) Temporal, (2) Sentiment, and (3) Spatial, in addition to other topics online users are exposed to when engaging in such conversations. I also explored the significance of various categories
of features such as N-gram features, psychometric features, linguistic features, Twitter-specific features, and sentiment features for automatically identifying situational awareness information using feature selection and supervised machine learning techniques.

1.2 Research Scope and Thesis Statement

This research lies at the intersection of four terms: social computing (social media, crowdsourcing, and social behavior), machine learning techniques, text analysis, and mass disaster events (Figure 1.1). The scope of social computing has expanded tremendously, with almost all branches of software research and practice strongly feeling its impact. The term social computing can be defined as “computational facilitation of social studies and human social dynamics as well as the design and use of information and communication technologies that consider social context” [16]. It relies on building social committees and contexts by the usage of technology, applications, and software. Therefore, social media, blogs, email, crowdsourcing, social behavior, and social networks are examples of what is often called social computing software.
By contrast, the term machine learning (ML) refers to the automated detection of meaningful patterns in data. It is no secret that ML is one of the fastest growing areas of computer science, with far-reaching applications. As [17] state, ML can be defined as “computational methods using experience (training data) to improve performance or to make accurate predictions.” In this dissertation I applied two types of machine learning techniques: (1) Supervised Learning: Here, the system is trained using past data, which includes input (also known as features) and output (also known as labels), and is able to take decisions or make predictions when new data is encountered, and (2) Unsupervised Learning: The system is able to recognize patterns, similarities and anomalies, taking into consideration only the input data, i.e., using only the features.

On the other hand, it would be impossible for us to read all the millions of research tweets on a specific disaster event, which is where text mining can help. Text mining is the process of discovering and extracting knowledge from unstructured data. It is used to help answer specific research questions by filtering large amounts of research and extracting the required relevant information. The key objective of data preparation is to transform text into a numerical format, eventually sharing a common representation with numerical data mining. Different text-mining tasks are introduced that fit within a predictive framework for machine learning. These include document classification, information retrieval, clustering of documents, information extraction, and performance evaluation [18].

Finally, a disaster is a sudden, calamitous event that seriously disrupts the functioning of a community or society and causes individual, community, government, and non-governmental agencies losses that exceed the community’s or society’s ability to cope using its own resources. The Federal Emergency Management Agency (FEMA) defines disaster as follows: “An occurrence that has resulted in property damage, deaths, and/or injuries to a community.” [19]. Unlike these selected examples, most social media posts do not include new and useful information.

Many repeat information that is already available through other channels. Many include personal impressions and/or messages that are only relevant for the user who posted them and perhaps a small circle of family and friends. However, some really interesting and important messages do get posted, sometimes providing information that is not available through other channels. Social media information is often irreplaceable immediately after a sudden onset emergency or disaster. It plays a role not only in the immediate aftermath of a disaster, but during its entire life cycle, for instance,
to coordinate donations and volunteering, or to propagate messages of safety from authorities.

Many other types of information, including photos and videos, are posted in huge amounts during large-scale crises. They all contribute to gaining a more accurate picture of a developing situation [1].

- Thesis Statement: With the existence of information overload, we can automatically identify
topic waves events in addition to continuous and disruptive events as they appear from social
media messages in a specific area and for a predefined time for better situational awareness
and decision support. At the same, we have designed a few novel methods for (1) detaching
relevant tweets from irrelevant ones, (2) predicting types of online community engagement,
and (3) ranking the social media posts that are critical for enhancing response times during
disasters.

1.3 Research Questions and Research Methods

A goal of this dissertation is to study the features of emergency-related social media messages
and how a mixture of human labeling and machine learning methods can enhance the situational
awareness of emergency first responders based on social media. We used Twitter as an example of
social media platforms that can produce valuable information during crises. Our proposal model can
possibly be employed to any other microblog data as well, such as Tumblr and Instagram. To specify
our research questions, we decided to identify the most important challenges of adopting social
media during a time-critical emergency, as shown in Figure 2. These challenges can be mapped to
(1) Scalability, (2) Content, (3) Multi-platforms, (4) Misinformation, (5) Clustering/Classification,
and (6) Ranking [20],[21],[22],[23].

- Scalability: Scalability is the capability of a system to handle a growing amount of data [24].
Massive disasters usually create an outburst of social media activity. Data volume, velocity,
and storage space requirements can be obstacles, concerning a catastrophe such as a
hurricane or oil spill that lasts for multiple days, millions of posts may be reported. Even
though the content of each message can be sorted, a Twitter message with 280 characters
includes overhead for username, date stamp, images, videos, etc. that needs to be stored.
Consequently, a Twitter gathering for a disaster can range from several hundred megabytes
to a few gigabytes. Additionally, the concept of data velocity, which is used to describe as
the speed of data creation, may be more challenging, especially considering that data does not flow at a constant rate but experiences extreme variations. Another factor that affects the system’s scalability or performance is the replication of the tweet (redundancy), which is very common among datasets collected. This issue considers it a waste to store meaningless data, which can lead to struggles with managing, processing, and analyzing data during a disaster.

- Content: Social media contains a broad diversity of content formats involving text, video, images, audio, and URL links. Twitter messages (known as tweets) are short, unstructured, and informal. Hence, Twitter users tend to use idioms, phrases that are more common in speech than writing, abbreviations in their messages, typographical errors, emojis, poor punctuation and sometimes incoherent statements, which makes the analysis of tweets very difficult [14] and [25]. Further, the quality of the content itself is a complicated process for social media analytics and includes several characteristics including opinion, emotions, and conciseness, among others. Moreover, a plurality of languages can be found in the same disaster dataset and sometimes in the same tweet. This makes it difficult to interpret or analyze messages and identify accurate and regular data patterns [1]. Finally, in the case of Twitter discussions, as a human, it is easy to read and understand the author’s intention
associated with each tweet. On the other hand, a computer is not able to make the same inferences humans do, and thus cannot obtain the equivalent level of understanding [26].

- Multi-platforms: Before working on any social identifying or predicting project, it is essential to know the social media landscape and the possibilities for data sources. Multiple social media outlets like Twitter and Facebook are used for different purposes, but shared features do exist. Hence, social media analysts and emergency managers need to follow the up to date use of each platform during events. For instance, the top three types of user engagement on Twitter are (1) tweeting about everyday routines, (2) sharing links and photos, and (3) retweeting or commenting on other users’ tweets; whereas on Facebook people (1) share pictures, (2) communicate with friends, and (3) add comments (notes) on friends’ posts. Notwithstanding being the world’s most massive social network, Facebook is infrequently utilized for social monitoring, identifying, and evaluating health and behavior issues. This is because of a variety of circumstances, inclusive of how the site is adopted by users and accessible for data gathering. In reverse, Twitter is more often used for social assessment and monitoring, because it affords a vast and nearly representative sample and the data is accessible and available [27].

- Misinformation: In today’s communication environments, it is easy to disseminate information. Ideas, opinion, or information can move from a small community to a worldwide audience in a brief moment. The challenge we are facing today is sorting out valid information from rumors or false messages. Using social media to search for and share news during an emergency has both beneficial and adverse consequences. On one hand, it is the inexpensive, accessible, and active distribution of information that drives people to investigate and use news from social media. Contrarily, it permits the wide spread of fake news with intentionally or unintentionally wrong information. This can lead to extremely negative consequences for individuals and the community. These concerns are even more challenging before, during, and after disasters. Accordingly, researchers try to learn the models and mechanisms of the spread of rumors via social media and produce algorithms to discover and eliminate misinformation as crises unfold. To reduce the spread of false information needs an understanding of the following questions: (1) What are the purposes of misinformation and what are its features?
(2) How does false information flow in social media? (3) What are the best methods to fight the spread of incorrect information? [28].

- Clustering: The clustering method cuts the data samples into groups or sets so that data samples inside each group are similar to one another and distinctive to the data that relate to other groups [20]. This grants a way to capture a dataset-level view of the major themes and decreases data dimensionality. The objective is to sort the diverse topics addressed during a crisis and find out which topics users are more likely to talk about. In the context of coping with social media posts through crises, the clustering step can support the process of reducing the number of messages that must be checked by humans, for example by demonstrating multiple related tweets as a single item rather than multiple ones. Because of the rapidity and scale at which data arrives, information overload, and the challenging language of Twitter content, the overall goal is to automatically order (group) the disaster-related messages in a stream of tweets from all the non-disaster content. Thus, the main challenge here is how to find structure in unstructured data [20].

- Classification: Social media provides a powerful lens for identifying people’s behavior, decision-making, and information sources before, during, and after wide-scope events such as natural disasters. However, so much information is generated from social media services like Twitter that filtering of noise becomes necessary. Thus, identifying relevant information in social media is challenging due to the low signal-to-noise ratio. The existence of unrelated data (noise) is a regular dilemma that presents many negative results in classification methods. Noise is an inevitable issue that disturbs the data collection and preprocesses in text mining applications, where errors generally happen. Many tweets contain too much information; some of the collected tweets are irrelevant to the affected regions during the disaster event, and not all shared tweets provide useful meaning. This dataset may be binary classified (for example, identifying whether the collected tweets are relevant or irrelevant to the affected regions during the disaster event) or it may be multi-classified (for example, categorizing the relevant tweets into subclasses such as sports, business, crisis, travel, weather, and so on) [29].
• Ranking: Latterly, with the dynamic increase of using social media platforms and the challenges in finding valuable information, efficient information retrieval methods have become more critical than ever. The ranker is in charge of the matching among processed inquiries and indexed records (tweets) [30]. In crisis situations, individuals and communities expect social media analytics and crisis management teams to immediately provide directions and assistance. Nonetheless, the information overload of social media encountered by governments and organizations, combined with their inadequate human resources, challenges them to classify and rank urgent requests or questions in a short period. This “information overload” can have severe consequences for decision making during a disaster, which relies upon the availability of relevant data. Although social media has been broadly considered during emergencies, there is insufficient work on distinguishing requests and ranking them to respond in a timely manner [31], [12].

Accordingly, the research questions in this thesis include:

1. How is Twitter used in the discussion of disaster situational awareness?
2. What types of topics are users exposed to when engaging in disaster discussions on social media?
3. How can we distinguish between relevant and irrelevant tweets?
4. How can we classify and predict the types of online community engagement on Twitter related to disasters?
5. How can we build a Model to Rank Twitter Data Requests for disaster responders?

1.4 Research Methods

In this research, we followed the process represented in Figure 3. Initially, to extract information useful for disaster response teams from tweets, we applied an unsupervised learning technique called topic modeling, which can help identify topics from collections of such disaster-related tweets. Next, we applied two types of classifications: (1) binary classification, to separate between relevant and irrelevant tweets, and (2) multi-classification, to identify and predict types of Twitter community
engagement during disasters. Through the processes of improving our model performance, we applied the ensemble method in order to create multiple models and then combine them to produce improved results. Finally, to address and prioritize requests posted on twitter, we adopted some ranking models to provide users with accurate and relevant results.

1.5 Publications

Work described in this dissertation has resulted in the following publications (permission is included in Appendix A):


1.6 Dissertation Organization

This dissertation is organized as follows: Chapter 2 covers background and literature review in the areas of social media, community engagement, disaster response, and machine learning. Chapter 3 covers the unsupervised machine learning techniques and event identifications to understanding such discussions can help with predicting early warning signs for crisis situations and to enhance situational awareness and emergency preparedness. Chapter 4 describes the supervised machine learning techniques to identify relevant information and predict the four types of online community engagement during emergency events. Chapter 5 covers the ensemble learning method for detecting situational awareness tweets during environmental hazards. Chapter 6 presents a novel study in which tweets about Hurricane Michael are classified into four categories, which can improve ranking and filtering of messages for emergency services. Finally, Chapter 7 summarizes research findings for this thesis and provides direction for future work in this area.
CHAPTER 2

BACKGROUND AND RELATED WORK

In this chapter, I provide background on the fundamental concepts of social media, emergency response phases, and a summary of relevant research on the adoption of social media channels for emergency management. I review the literature that addresses the use of social media for emergency management, apply Twitter clustering, classification, and ranking for tweet filtering in the emergency field, and introduce social media analysis methods for emergency response and event identification.

2.1 Role of Social Media in Real-World Crisis

As the use of and dependence on smartphones has increased, social media has become the most effective medium for high-speed, real-time connection through a crisis. People are increasingly adopting social media in their everyday life, and this practice is extending to crisis situations. Various studies have been conducted in this domain [32] describing how social media has been utilized via crisis together with machine learning that has been generated or expanded to assist the flow of information.

The evolution and growth of social media and social networking applications such as Twitter, Facebook, Snapchat, and Instagram have hugely affected the data broadcasting scenes. It’s no secret that social media is often used for everyday chatter; it is further correlated with sharing news and other important information [33], [34]. More than any time in the past, the public turns to social media as their source of communication [35], [36]; this is particularly true in breaking-news situations, where people want updates on events in real time. Thus, we need to define some particular concepts before we are embarking any further. These concepts will be used throughout this thesis.
2.1.1 Social Media

Danah Boyd [37] defines social media as “the sites and services that emerged during the early 2000s, including social network sites, video sharing sites, blogging and microblogging platforms, and related tools that allow participants to create and share their own content.” Social data appears in several styles. Various online outlets and websites created for different users and multiple objectives may be suited appropriately for particular disaster communication intentions.

Analysts have investigated how a diversity of social media channels have been applied through crises, including the 2015—2016 Zika virus outbreak [38] and the incident at Virginia Tech [39], where analysts studied a number of different platforms.

Previous research has examined how people explore and distribute information [8], [40], [41]. Other research has focused on the use of social media to support and organize response efforts after disasters such as the 2010 Haiti earthquake [42], [43] and Hurricanes Harvey, Irma, and Maria [44].

Inside the situation of natural or human-made crises, and particularly within crisis management, detecting messages that indicate a disturbing or threatening scenario is crucial. Similarly, messages that report ongoing news, beliefs, or disrespectful criticisms appear to be unrelated, which causes analyzing the tweet stream of knowledge in such a critical scenario to be a complex task.

In this dissertation, I concentrate on the Twitter platform for a variety of reasons: not only because it is easy to study, but also because of the range of features that make it an interesting tool for emergency response. First, almost all tweets are public (private accounts require each user to request access to their tweets). Public tweets are also searchable through a variety of application programming interfaces (APIs). Finally, Twitter enables real-time communication through features such as #hashtags, Retweet, and Replay.

2.1.2 Microblogging (Twitter)

Microblogs such as Twitter, Tumblr, and SinaWeibo are a quick and straightforward approach to chat and engage with others, thanks to high-tech connection and the development of the smartphone. Twitter is expressly prevalent in the United States, with about 47 million active users as of January 2019 [45]. Twitter messages can be up to 280 characters in length. Other platforms like Facebook
have higher length limits. Twitter is a popular way to share news, current status, beliefs, and activities of users, making it beneficial for social monitoring.

Twitter makes some of its data (approximately 1% of all tweets) publicly available and free to access. However, in Figure 2.1 there are two kinds of data: (1) historical data and (2) streaming current data. There are two ways to obtain this data: (1) Register as a Twitter developer and complete the authentication process or (2) purchase from enterprises (Twitter partners) such as Crimson Hexagon [46].

There are variety of attributes associated with every Tweet such as:

- **Retweet**: A retweet is simply a tweet reposted by another Twitter user to display it to that user’s followers. Retweets are marked by the acronym RT.

- **Favorite**: Users use favorites if they admire a tweet. By favoriting a tweet, users can permit the owners of the tweets to know that they loved their tweets. The number of times a tweet has been favorited is visible to all Twitter members.

- **Followers**: A Twitter user’s followers are different accounts that subscribe to the user’s posts and updates. When someone follows an account, it will appear in that account’s followers list. By following another user, Twitter users indicate that they want to keep up with what that person is posting. A user’s number of followers is visible to everyone.
• Following: The term “following” is a state where any Twitter user desires to obtain and read what a user is posting in real time; he or she clicks the follow button on that person’s profile. Subscribing to (following) someone additionally implies that you have allowed the person you follow approval to send you a direct message on Twitter. The number of accounts a user follows is visible to others.

• Mention: Mention facilitates interchangeable messaging by pulling attention from different members by using the symbol (@) followed by username.

• Reply: The reply is a response to a message (tweet) from one user directly and privately to another recipient and is not visible in the user’s Twitter stream.

• Hashtag (#): Hashtag is identified by the symbol (#) in front of any term. Basically, hashtags were created to streamline virtual chats by classifying tweets about a specific topic.

2.1.3 Community

There is no standard definition of a community. The term community elicits a representation of individuals in a specific terrestrial environment, socially created via the mechanism of a regional authority for the good of the individuals who remain in that area.

The primary hypothesis is that the individuals who stay within a community share fundamental interests, demands, or hopes. However, there are diverse kinds of communities, such as professional communities, scientific communities, ethnic communities, and spiritual communities. Such communities are likely to be associated with particular regions but alternatively can be connected by interests aside from geography. Furthermore, culturally or socially coordinated groups within a specific zone are often involved in many such communities within its limits.

Recently, disaster response or preparation has been correlated with a psychosomatic insight of community [47]. Using a terrestrial setting view, one might evaluate the destructive effect on the community of New Orleans following Hurricane Katrina in 2005. Of course, the knowledge gained through exposure to such an event for those from that city was considerably altered in their capability to evacuate, their experiences during the response phase, and their assistance in decision-making throughout the disaster [48].
During a disaster, emergency units are working to aid the victims. User engagement could support them by bringing public attention to the situation and identifying potential contributors of needed supplies such as food, water, and medicines. An additional question is how to identify appropriate channels of interactions between these supply providers and victims in need of resources.

### 2.1.3.1 Online Community

Online community refers to an aggregation of people in cyberspace who share the same interests using electronic means [49]. During a disaster, emergency units are working to aid the victims. The online community could support them by bringing public attention to the situation and identifying potential contributors of needed supplies such as food, water, and medicines. An additional question is how to identify appropriate channels of interactions between these supply providers and victims in need of resources. The online community could contribute to labeling the mental and social demands of affected people in the context of crises or other emergencies. Attention must be paid to the advantages and drawbacks of such shared online resources concerning the particular emergency.

### 2.1.3.2 Community Engagement

Community engagement refers to the process of working collaboratively with and through groups of people affiliated by geographic proximity, special interest, or similar situations to address issues affecting the well-being of those people (Principles of Community Engagement - Second Edition). The Centers for Disease Control and Prevention defines community engagement as “A process of working collaboratively with and for groups of people affiliated by geographical proximity, special interest, or similar situations to address issues affecting the well-being of those people” [50].

### 2.1.4 Situational Awareness

Situational awareness is a key concept in emergency response, which points to understanding what is happening around oneself, predicting how it will evolve with time, and finally, being joined with the dynamics of the environment. Emergency response processes demand quick reactions that count on accurate data linked to the situation. In disordered situations, user response is vital because once events have escalated, the effort needed for support can be higher.
It is important to not only grasp what is happening now but also to anticipate how events taking place may affect or determine the future. For instance, understanding that water bottles are sold out at stores across a city could reasonably mean that other people going to the store to purchase them would not be happy if these stores ran out. Furthermore, if this phenomenon is replicated at other stores across the city, citizens might begin to worry that their water is unsafe to drink, given the absence of water for purchase. It is essential to not only follow what is immediately occurring, but also to forecast how the crisis may change or restrict the future.

2.1.5 Crowdsourcing

Crowdsourcing is a service of getting a judgment (such as labeling) and help from large numbers of workers using online services. For example, Amazon’s Mechanical Turk service is a general-purpose place where requesters can post tasks to be completed, and other users (workers) are paid to complete the tasks [51], [52]. Crowdsourcing platforms allow for wide-ranging prospective workers to engage in projects.

Crowdsourcing commonly is a gathering of people invited to give a judgment about provided data. The decisions are generally in the shape of a binary or multi-class tag, a real value, or a short description. Crowdsourcing workers are necessary for conducting data mining duties such as classifying tweets, survey participation, ranking opinions, and categorizing images. Using crowdsourcing services such as Amazon’s Mechanical Turk is becoming a common approach for collecting and labeling data.

Mechanical Turk (MTurk) is a platform belonging to Amazon that permits any individual to create an account and submit jobs (projects) to be completed and define rates paid for performing them. Crowdsourcing is an effective way to divide time-consuming projects into small-scale tasks to get the project done efficiently and promptly when needed. MTurk is an incredible approach to reduce expenses and time expected for each stage of the Machine Learning process. It is straightforward to assemble and tag the vast volumes of data demanded for training machine learning algorithms with MTurk. Further, developing a useful machine learning prototype requires endless repetitions and revisions.
2.2 Emergency Response Management

The emergency management cycle has four main stages Figure 2.2: Mitigation, Preparedness, Response, and Recovery [53]. Mitigation involves anticipating and decreasing dangers before a crisis occurs. Preparedness includes a connected sequence of planning, organizing, and assessing actions to help officials and people to react to an incident appropriately. Both mitigation and preparedness happen before a crisis event. The next two stages happen after a crisis occurs. Response includes actions taken immediately during and after an event impact to protect lives, reduce economic damages, and relieve pain. Response actions may involve initiating the Emergency Operations Center (EOC), evacuating endangered residents, opening shelters and affording medical care, firefighting, and search and rescue. Finally, the recovery stage covers the steps needed to resume normal routines. Actions were taken to restore a community to normal conditions, including the recovery of basic services and the reconstruction of physical and social damages. Common recovery activities involve debris cleanup, money assistance to individuals and communities, the rebuilding of roads, and maintaining power lines.
2.3 Disaster, Disaster Categories and Sub-Categories

Disaster, to start with, refers to social phenomena characterized by a disruption of routine and social structure [54]. It is an unpredictable, severe, and life-threatening state that affects the entire community. According to the Center for Research on the Epidemiology of Disasters (CRED), natural disasters are categorized as geophysical, metrological, hydrological, climatological, and biological, as shown in Figure 2.3. Disasters may have natural (e.g., earthquakes, floods, or tornadoes), or human (e.g., riots) causes [1]. Through this research, we will focus on natural disasters.

2.4 Communication During Disasters Events

Researchers have been examining social media to understand its influences on users and communities. Several studies address growth in the usage of social media and its effects. Imran et al. [21] examine several types of research for processing social media in crises. Investigating disasters reveals the value of social media in how public and authorities use social media and what circumstances affect this use by interpreting tweets posted during typhoons in the Philippines [55].

<table>
<thead>
<tr>
<th>Class</th>
<th>Sub-Class</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Natural</td>
<td>Meteorological</td>
<td>Hurricane</td>
</tr>
<tr>
<td></td>
<td>Hydrological</td>
<td>Flood</td>
</tr>
<tr>
<td></td>
<td>Geophysical</td>
<td>Earthquake</td>
</tr>
<tr>
<td></td>
<td>Climatological</td>
<td>Wildfire</td>
</tr>
<tr>
<td></td>
<td>Biological</td>
<td>Epidemic</td>
</tr>
<tr>
<td>Man-made</td>
<td>Intentional</td>
<td>shooting</td>
</tr>
<tr>
<td></td>
<td>Accidental</td>
<td>Building collapse</td>
</tr>
</tbody>
</table>
The power of the number of retweets, URLs, mentions, and sentiment has been analyzed in several studies to find models concerning relevant information and commentary, such as expression of feelings, reporting, and trying to make judgments about an event. Another analysis of tweets from Hurricane Sandy demonstrates that retweet activity increased during the event [56], [57].

We intend to merge disasters, machine learning, and social media analysis to measure community engagement and situational awareness. We outline the relevant recent work in the following three areas: supervised classification, unsupervised clustering, and types of disasters. After collecting messages from various social media platforms related to a disaster event, the steps to follow are classification of the messages into multiple categories, followed by clustering and ranking the messages according to their importance.

2.4.1 Supervised Classification

Many disaster events eventually require the classification of data points into multiple categories, which further aids in analysis and summarization. Although text classification is a field that has existed for many years, our primary concern is text classification related to disaster events or topics. Adopting a classification method for disasters has different aspects based on a variety of disasters, types of public participation in disasters, and content of Twitter messages. Some research on emergency management response focuses on the content of tweets, including how volunteers express their feelings or opinions during disasters to manage and enhance collaboration between digital volunteer communities [58].

The continual extension of online data has given rise to massive amounts of information becoming available for others to review and understand. Some automatic methods have allowed researchers to discover diverse viewpoints expressed in social media messages, e.g., sentiment analysis and opinion mining [59], [22].

Another group of studies applies classification techniques based on the following types of tweets: impact phase, affected people, affected infrastructure or utilities, posts coming from eyewitnesses and reporting types of impact [60], [61], people trapped [62], victims, as well as people missing, found, or witnessed [63].

Another group of studies discusses needs (money, goods, services, water, hospitals), as well as donations and enhancing situational awareness. For example, the researchers in [64] analyzed
Table 2.1: Clustering techniques used in disaster scenario.

<table>
<thead>
<tr>
<th>Model</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>CrisisTracker [2013 - Rogstadius]</td>
<td>Collects tweets and group them into clusters then curated by humans into stories.</td>
</tr>
<tr>
<td>SaferCity [2013 - Berlingerio]</td>
<td>Uses spatio-temporal clustering approach based on [2008-Blondel]</td>
</tr>
<tr>
<td>Weibo messages clustering [2015 - Wang]</td>
<td>Clusters important topics such as loss and influence, disaster information, and weather</td>
</tr>
<tr>
<td>Human centric clustering [2016 - Granell]</td>
<td>Focuses on socio-technological issues and advanced applications</td>
</tr>
</tbody>
</table>

Twitter communications about 26 natural and man-made disasters and discovered that the reported information regarded the affected people, buildings, roads, power supplies, volunteering, warnings and directions, and prayers [65], [66].

Moreover, some researchers concentrated on investigating information sources (governmental and non-governmental). As shown by [67], where they analyzed the online discussions about Hurricane Matthew and the Louisiana floods and sorted users into two sectors (organization and non-organization). They also summarized how members in each of these sectors have novel approaches to broadcasting information; for instance, the organization members are less likely to retweet in contrast to non-organization members, who are mostly expected to retweet messages.

2.4.2 Unsupervised Clustering

Although the main agenda has been categorizing content and running supervised machine learning algorithms for automatic classification, there are still cases and volumes of data that are unlabeled. In such cases, identifying and exploring potential hidden patterns takes priority [31], [68]. Table 2.1 illustrates some examples of the clustering techniques used in disaster scenarios.
2.4.3 Types of Disasters

Some researchers focused on the types of disasters, such as meteorological, hydrological, climatological, and biological, and their effects on public health and communication [69] and [70]. In [69], the team collected 300 million tweets for approximately one year and seven months focusing on the expansion of influenza. They used Pearson correlation between sets of data to measure the estimated values and annotations. They implemented a support vector machine (SVM) classifier to distinguish between related and unrelated tweets. Their approach performed well in detecting influenza epidemics with an 0.89 correlation. Smartphone devices with a WeChat application, GPS and camera features have allowed users to monitor surface water quality and establish a tracking method using social media platforms [70] to allow users to monitor surface water quality. Outcomes show that the monitoring reports are credible if the users are qualified. Further, Antonio A. Ginart et al. [71] formed and validated a machine learning classifier to separate relevant from irrelevant tweets for understanding health behavior about marijuana.

Another study [72] investigated factors connected with engagement of U.S. federal health agencies via Twitter. They studied numbers of retweets in addition to the time between the agency’s initial tweet and both the first and last retweets. They noticed that a third of the tweets had zero retweets. Less than 1% had more than 100 retweets. The hurdle analysis shows that hashtags, URLs, and user mentions are positively associated with retweets. Sentiment has no association with retweets while tweet count has a negative association with retweets. A text analysis of 1,583 tweets, where the numbers of retweets and favorites were included as engagement signs, found that the American Heart Association, American Cancer Society, and American Diabetes Association varied in the degree to which they used the retweet, hashtag, and hyperlink features for broadcasting health information, forming relationships, and promoting efforts to enhance health [73].

As we mentioned earlier, social media performs a vital task in the management of crises such as environmental disasters and can further be utilized to build and improve environmental awareness and advance health. The primary aim of [74] is to examine health-related warning messages sent by public safety agencies via Twitter during the 2013 flooding in Boulder, Colorado. They found that tweets focused on drinking water (41%), floodwater exposure (18%), general crisis information (16%), sanitizing (14%), and sewage (8%), whereas only 6% of the tweets focused on public health.
Pascal Beaudeau et al. [75] proposed a framework to find out how climate change could affect health risks concerning drinking water. They concluded that heavy rainfall could cause combined sewer overflow events, which can increase waterborne pathogens that lead to possible gastroenteritis. Further, [76] shows that social media plays a crucial role in the estimation of air pollution levels based on collected Twitter posts that complain of poor air quality.

One study [77] investigated 13,153 tweets during the April 2009 flooding of the Red River Valley in the U.S., where the damage was enormous in some areas. The researchers found mechanisms of information production, dissemination, and coordination. In [78], the 2010 Deepwater Horizon oil spill in the Gulf of Mexico exemplifies how community engagement in social media aided situational awareness. In the largest ever marine oil spill, a group of researchers gathered Twitter posts about the crisis to evaluate how members of society came to understand the potential consequences of the tragedy, the response efforts, and more specifically the use of oil dispersants in the clean-up. The results revealed that Twitter users desired to cooperate in and contribute to response efforts, a finding with implications for future oil spill response.

Multiple studies in the area of disaster informatics have frequently claimed that the messages shared on social media from different users across a damaged area could be a reliable resource for both crisis responders and affected residents [79], [80]. More recently, emergency responders have started to adopt social media into their work as another means of communication and real-time updates for the current situation and correcting misinformation [81].

Multiple studies have used Twitter as a general way to study environmental public health issues concerning possible risk attributes for disease [82], [83]. A mixture of NLP and machine learning methods (supervised and unsupervised learning) were utilized to find out what users were posting regarding Zika. The proposed system was built to classify the tweets into four groups: symptoms, transmission, prevention, and treatment [82]. McGough et al. adopted a combination of official reports and Twitter posts to develop Zika forecasts for diverse Central and South American countries [83].

Among other uses, information from social media can aid in the early discovery of disease outbreaks. For example, through cholera disease outbreaks in 2010 in Haiti, HealthMap news media reports and Twitter posts have positively interacted with official government reports [84]. Further, Ordun et al. [85] have shown that mentions of food poisoning can be discovered in online restaurant
reviews from Twitter. A Twitter-based system named nEmesis [86] has been used as part of a program to ensure restaurants meet safety and sanitary regulations. This system led to about a 60 percent increase in detecting restaurants with health risks.

In the field of emergency administration during crises, various studies have demonstrated that possessing adequate situational awareness knowledge is crucial [87], [88], [89]. For instance, using impersonal and formal linguistic features, Verma et al. [87] were capable of distinguishing between situational and non-situational awareness tweets, achieving over 80% accuracy. Buscaldi and Hernandez-Farias [88] have also found benefits in analyzing sentiment analysis and NLP during disasters with the goal of identifying tweets that may contribute valuable information. They collected 13,530 tweets to demonstrate that tweets with a negative tone are more likely to carry information about emergencies in the context of a natural disaster. In [89] researchers studied Ebola-related tweets to present how visual analytics methods and sentiment modeling can show interesting patterns in disaster scenarios.

2.5 Summary

While these different studies highlight the utility of using social media to monitor people’s thoughts and feelings regarding specific events and disease outbreaks, our approaches in chapters 3-6 investigate different psychometric and linguistic features that have not been analyzed in previous studies. We further focus on the significance of the characteristics, behavior, and content features of each tweet to distinguish the type of feedback from differing posts and arrange them into clusters. As we know, in times of emergency, people search for or share information. They desire answers concerning what is occurring in order to ascertain what might follow. In this respect, we provide a social media annotated dataset and propose a framework to track tweets and predict the different types of user engagement during crisis. To this end, we chose two datasets related to environmental health risks such as wastewater (sewage) in Barbados and Hurricane Michael in Florida as case studies to understand what people and organizations say during crisis situations. Our study may contribute important considerations for decision-makers and other individuals in efforts to prepare for crisis situations and save time in choosing where to focus their limited resources concerning their situational assessment.
CHAPTER 3

TOPIC MODELING AND EVENT DETECTION IN TWITTER

Online users may utilize social media to discuss issues related to their environment. Understanding such discussions can help with predicting early warning signs for crisis situations and to enhance situational awareness and emergency preparedness. We adopted a method to collect and filter 30,358 tweets concerning environmental health risks in Barbados over a period of four years. In this chapter, we implemented an unsupervised machine learning algorithm to discover and understand how social media is used in the discussion of environmental health situational awareness, as well as what other topics online users are exposed to when engaging in such conversations. Our results show that there is a distinction between disruptive and ongoing events by exploring the number of tweets at a certain point of time and the sentiment of each event.

3.1 Introduction

Communities are at risk of suffering from natural disasters or disease outbreaks; some are more defenseless than others. For example, Barbados and other small island developing states (SIDS) are susceptible to hurricanes, floods, and the expanded dangers of waterborne and foodborne illness in addition to other mosquito-borne diseases. Social media platforms such as Facebook and Twitter let users share different types of content and communicate interpersonally. Due to the nature of social media, it is challenging to differentiate between disruptive and ongoing events when tracking, monitoring, and evaluating environmental health conversations.

This work adds to the understanding of crisis from the view of social media activities. We propose a framework based on Twitter activities that can be utilized to identify the progression of crises by applying unsupervised learning methods and extracting textual, sentimental, temporal, and spatial patterns of Twitter activities during sewage crises in Barbados. Millions of tweets are disseminated on Twitter, which makes it challenging for users to determine the sort of information
they want or need. Consequently, it is vital to perform computational approaches to assist humans in obtaining information that is beneficial to them.

Discovering insights within unstructured text is challenging unless we can explore, distinguish, and divide the textual data in a meaningful way. One of the common methods for detecting related topic waves within Twitter data is Latent Dirichlet allocation (LDA) [90].

Because emergency directors have come to depend on social media to communicate warnings and updates, they need to learn how users interact with disaster-related content on social media. We applied an unsupervised learning model to derive and define highly correlated tweets used by the public during known emergencies, such as mosquito-borne diseases, waterborne diseases, and wastewater emergencies.

To date, several studies have used social media platforms to explore public health issues and track environmental health risks. In 2010 [78], a group of researchers collected tweets about the Deepwater Horizon Oil Spill crisis to evaluate how members of society came to understand the potential consequences of the tragedy. The results revealed that Twitter users desired to cooperate in and contribute to response efforts. In [91], the researchers collected 206,764 tweets during the tornado that struck Joplin, Missouri (USA) and 140,000 tweets during Hurricane Sandy. Then, they sorted them into different categories, e.g., warnings and advice, losses and destruction, donations and offers, and information sources.

Much of the topic modeling and latent Dirichlet allocation (LDA) research has focused on classification [92], dataset searches [93], and recommendations [94]. Analyses of the topic models show that disaster preparedness is an integral part of disaster risk reduction by improving solid waste management and evacuation preparation. LDA and its variants are widely used statistical modeling approaches implemented in event identification tasks [95], [96]. Further, classification-clustering methods along with textual, temporal and geolocation features have been used in [97] to provide a way to detect events.

To this aim, we chose environmental health risks such as wastewater (sewage) and mosquito-borne diseases in Barbados as a case study to understand what people and organizations say during crises. Our study may contribute important considerations for decision-makers to prepare for disasters and save time.
Throughout this paper, the term event can be referred to “An incident that caused an increase in the number of text data that addresses the associated topic at a particular time.” In [10], a disruptive event can be defined as “An event that opposes another event or disrupts an ordinary event. It may happen during a day or multiple days, causing troubles and may result in anxiety, sadness, and discontinuity.” Lastly, an ongoing event can be defined as “An event that has been occurring for quite a long time and is expected to remain for some time in the future.”

3.2 Method

In our study we concentrated on Twitter. It has been widely used for sharing news and activities during crises and natural emergencies. To name the topics that have been discussed in specified location and specified time and to extract and distinguish between ongoing or disruptive event we proposed framework which is presented in Figure 3.1, where its components are split into five stages: (1) Tweets collection, (2) Data preprocessing, (3) Topic modeling, (4) Topics identification, and (5) Events analysis.

3.2.1 Tweets Collection

A large number of users rely on Twitter during disasters to search for and transfer information. A tweet broadcasts not only information, but often emotion as well. We used Crimson Hexagon [46] to collect a corpus of 3,897,789 English posts from January 1, 2014, to May 31, 2018 with the keyword “Barbados.” Then, since our main interest is understanding the different environmental issues, we adopted a filtering method with a list of the following keywords: crisis, wastewater, sewage, Water
Authority, water quality, Climate Change, Zika, mosquito, chikungunya, West Nile, malaria, disease, and health risk. The total sample size was 30,358 tweets.

3.2.2 Data Preprocessing

Data preprocessing is normally a mandatory step. This step involves processes for data cleaning, such as the elimination of noise and irregular data. In data transformation, data is transformed and consolidated into forms that are appropriate for text mining and machine learning methods. Feature aggregation and data minimization involves the selection and extraction of tweet features. Data cleaning is the process of correcting corrupt data, filtering some unreliable data out of the dataset, and decreasing additional features of the data. We also applied a data normalization step, which ensures that all the characteristics are shown in the same measurement units and use a standard range. Data normalization tries to assign all features the same weight, which is especially useful in statistical learning methods.

Twitter users tend to use colloquialisms, slang, abbreviations, and spelling and grammatical errors in their posts. We applied traditional text processing methods like stop-word removal (“the”, “a”, “an”, “in”, etc.), punctuation, Lemmatization (converting work, working, worked, workers are to the root of the word), lowercased all characters, and removal of unnecessary white spaces using the Natural Language Toolkit library available in the Python programming language.

3.2.3 Topic Modeling

In this step, we applied unsupervised learning, where topic modeling is a typical task. Topic modeling is based on two basic assumptions: (1) Each dataset consists of a mixture of topics, and (2) Each topic consists of a collection of words. As a result, the goal of topic modeling is to uncover these hidden topics that shape the meaning of our dataset. From a machine learning perspective, Latent Dirichlet allocation (LDA) [98] is a Bayesian probabilistic model used for topic modeling. It uses term frequency and inverse document frequency TF-IDF approach, which treats each document as a vector of word counts. LDA has three important parameters: number of documents (M), number of topics (K), and number of words per document (N). In our study, [M= 30,358 tweets], [k=9], and finally [N=10].
3.2.4 Topics Identification

In this step, we explore the different topics obtained from the previous step. After applying unsupervised machine learning to our data, we identified the top keywords that describe each topic. From there, we analyzed each topic and its relation to environmental health issues such as Zika.

3.2.5 Events Analysis

In this step, we hypothesize that a disruptive event can be characterized by a set of features: temporal, spatial, and sentiment features. The temporal features are related to the diffusion of tweets counts over time frames. The spatial features include location, e.g., whether tweets originate inside Barbados or outside Barbados (International). We analyzed sentiment features (positive or negative) to understand whether the sentiment expressed in each topic can help with identifying disruptive events. We assume neutral sentiment will not add any impact, so we excluded it.

3.3 Results and Discussion

To analyze the disaster situations and find out the topics which have been discussed from Twitter and to accomplish the goals set in the objectives section, we perform an extensive analysis using the collected dataset. This section presents the results of our proposed model setup and the interpretation results.

3.3.1 Topic Analysis

The (nine) topics are shown in Table 3.1 with a summary of statistics for each topic: (1) Barbados on the Water, (2) Environment in Barbados (3) Holidays in Barbados, (4) Zika in Barbados, (5) Head of Environment, (6) Environment Agency Boss, (7) Barbados Water Authority-BWA, (8) Barbados on the Water Festival, and (9) Projects in Barbados.

Each topic is a combination of weightage and keywords that contribute to the topic. For example, Topic 5 “Head of Environment” is represented as: (0.046, head) + (0.045, environmental) + (0.043, environ) + (0.043, room) + (0.043, parliament) + (0.043, Barbados) + (0.043, walking) + (0.043, unit) + (0.042, state) + (0.042, nation). As shown in the Table 3.1, the topic “Barbados on the Water (water)” has the highest number of tweets while the topic “project” has only 730 tweets.
Table 3.1: Environmental topics in Barbados with statistics.

<table>
<thead>
<tr>
<th>Summary</th>
<th>Water</th>
<th>Environment</th>
<th>Holiday</th>
<th>Zika</th>
<th>Head_Envi</th>
<th>Envi_Boss</th>
<th>BWA</th>
<th>Water Festival</th>
<th>Project</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>89</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1st Qu</td>
<td>205</td>
<td>9</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>9</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Median</td>
<td>239</td>
<td>15</td>
<td>9</td>
<td>0</td>
<td>3</td>
<td>15</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Mean</td>
<td>274</td>
<td>126.7</td>
<td>53.77</td>
<td>53.04</td>
<td>48.02</td>
<td>30.45</td>
<td>18.85</td>
<td>15.34</td>
<td>13.77</td>
</tr>
<tr>
<td>3rd Qu</td>
<td>303</td>
<td>37</td>
<td>6</td>
<td>31</td>
<td>3</td>
<td>6</td>
<td>28</td>
<td>15</td>
<td>6</td>
</tr>
<tr>
<td>Max</td>
<td>706</td>
<td>2176</td>
<td>1390</td>
<td>933</td>
<td>1897</td>
<td>926</td>
<td>73</td>
<td>284</td>
<td>517</td>
</tr>
<tr>
<td>Total Tweets</td>
<td>14520</td>
<td>6715</td>
<td>2850</td>
<td>2811</td>
<td>2545</td>
<td>1614</td>
<td>999</td>
<td>813</td>
<td>730</td>
</tr>
</tbody>
</table>

Also, we can see that most topics, including “Zika” and “BWA”, have fewer tweets in the first quarter compared to the topic “water”. These results help with identifying ongoing topics.

3.3.2 Events Analysis

To identify the difference between ongoing and disruptive event, we are analyzing three factors, temporal, sentiment, and spatial features.

3.3.2.1 Temporal Analysis

We collected data for a long duration because some valuable posts in the past may not be as critical today or in the future. The results are presented in Figure 3.2. A topic like “Barbados on the Water” was discussed 14,520 times, which might be assigned as an ordinary event. On the contrary, “Zika in Barbados” was visible as a disruptive event that has been discussed 2,811 times overall, but mostly in 2016 when the World Health Organization announced the Zika outbreak in 2016. The variation of the time (horizontal axis) per each topic is displayed in Figure 3.2, where it is demonstrated that “Barbados on the Water” continuously appears since the first day of data collection. Conversely, in 2016, the “Zika” curve rises dramatically and then falls the same way.

3.3.2.2 Sentiment Analysis

The sentiment expressed in each topic can also be a factor in identifying the type of event. Interestingly, in Figure 3.3, we observed in 2016 that disruptive topics such as “Zika” has high negative sentiment (361 tweets) compared to positive sentiment (33 tweets). Positive sentiment analysis for an ongoing topic such as ”Barbados on the Water” was continuously higher than negative sentiment except in 2016, where there were 812 tweets with positive sentiment and 1338 tweets
with negative sentiment. To sum up, negative sentiment can be a strong predictor in identifying disruptive events such as “Zika”, which can be used by governmental agencies and policymakers to understand which topics users engage with the most. Moreover, a disruptive event can occur during ordinary events. This finding is consistent with previous research [97] where tweets with a negative sentiment have a good confirmation rate for reporting disruptive events.

3.3.2.3 Spatial Analysis

The social media tool Crimson Hexagon can estimate the location of the user or the event based on various pieces of information such as their profile information. The goal is to detect real-time location estimation. Once the location has been extracted from each tweet, we aggregate them to determine two groups of tweets: those originating from Barbados and those that were not (i.e., Non-Barbados). The country with highest number of tweets is the US with 5,609 posts, Barbados comes next with 4,783 posts, and the United Kingdom (UK) comes in third with 3,423 tweets. The engagement of countries such as the UK, USA, and Canada can be justified because sewage problems drove these countries to advise their citizens to avoid the affected areas.
3.4 Summary

The effectiveness of social media in the field of environmental health risks can support decision makers and health organizations by providing assistance and measuring people’s responses to crises. Hence, this empirical study contributes to this domain by reviewing public interaction with social media platforms due to environmental health concerns. The results indicate that it is not enough to consider temporal, spatial, or sentiment in isolation. Instead, the aggregate of features leads to clearer distinctions between events. In the future, we plan to use multi-class classification to predict community engagement on Twitter during environmental health hazards.
CHAPTER 4

PREDICTING COMMUNITY ENGAGEMENT ON TWITTER

In this research, I worked to determine the time-critical message from Twitter that is valuable for incident response team, communities in danger, and other worried people in disaster situations. I developed two levels of classifications binary and multi-class using supervised machine learning techniques to help analysts view tweets based on information relevancy and divided the community based on their tweets into four components. The ultimate goal is to find the suitable combination of features and classifier algorithms that present the best accuracy. In this empirical study, a framework was developed for binary and multi-class classification of Twitter data. We first introduce a manually built gold standard dataset of 4000 tweets related to the environmental health hazards in Barbados for the period 2014 - 2018. Then, the binary classification was used to categorize each tweet as relevant or irrelevant. Next, the multi-class classification was then used to further classify relevant tweets into four types of community engagement: reporting information, expressing negative engagement, expressing positive engagement, and asking for information. Results indicate that (combination of TF-IDF, psychometric, linguistic, sentiment and Twitter-specific features) using a Random Forest algorithm is the best feature for detecting and predicting binary classification with (87% F1 score). For multi-class classification, TF-IDF using Decision Tree algorithm was the best with (74% F1 score).

4.1 Introduction

Environmental hazards like unsafe water, poor sanitation, urban air pollution and rising temperatures cause significant disease burden globally [99]. During infectious disease outbreaks, early epidemiological assessment is hindered when data, which may not be available for weeks, is only collected through official reporting structures like hospitals. To get timely estimates of disease burden and dynamics, near real-time data from informal sources (e.g. online social media) can be
used. For example, during the 2010 cholera outbreak in Haiti, HealthMap news media reports and Twitter posts were positively correlated with official government cholera cases reported [84]. This unofficial data for a water-related disease was available up to two weeks earlier than official reported cases.

Twitter has been used as a formal source of information. It has been used in the United Kingdom to share and exchange information between the public, emergency responders, and water service providers [100]. Researchers showed that within social media, residents could report, request and obtain crisis-related information, while engaging in disaster response and rescue efforts [101].

Barbados (The Case Study Site) is a country in Caribbean has experienced significant and consistent water and sewage crises, which impact incidence of many diseases, including mosquito borne diseases. In this paper we use data mining and machine learning algorithms to detect and predict community engagement on twitter about water and sewage environmental health hazards in Barbados.

To the best of our knowledge, no studies have been conducted to classify and predict the types of community engagement (reporting information, expressing negative engagement, expressing positive engagement, and asking for information) on Twitter related to water, sewage and mosquito borne disease health risks.

4.2 Method

In this section, we propose a binary and multi-class model [102] to classify online social community engagement during environmental health risks that have caused disruptions to communities. With a 280-character limit, Twitter ¹ has been widely used for sharing news, beliefs, and activities during crises and natural emergencies, and to gather support for social and public health monitoring [103].

4.2.1 Framework

Figure 4.1 presents a high-level picture of the framework used to collect a series of data over a given time-frame for a given location, Barbados to be specific. Its components are split into

¹https://twitter.com/
four stages: (1) Data (tweets) collection; (2) Data Preprocessing; (3) Binary classification; and (4) Multi-class classification.

### 4.2.1.1 Data Collection and Filtering

In this stage, we used Crimson Hexagon [46] to crawl any tweet, including the keyword Barbados from January 1, 2014, to May 31, 2018. 5,532,419 tweets were captured (all languages), of which 3,897,789 were in English. Then, a filtering method with a list of keywords containing the following was adopted: crisis, wastewater, sewage, Water, Climate Change, waterborne, Zika, mosquito, dengue fever, yellow fever, chikungunya, Aedes aegypti, West Nile, malaria, and infectious disease. After applying the aforementioned filters, the total sample size was reduced to 30,358 tweets. This much smaller sample size was likely due to (1) Barbados is a small island compared to other populations, and people might use other social media platforms like Facebook or Instagram, (2) Although English is the official language of Barbados it is not the only language used (e.g. large international tourist population speak multiple languages), and (3) this study excluded potential content concerning community engagement on this topic written in other languages.

### 4.2.1.2 Data Preprocessing

The goal behind preprocessing is to tokenize sentences into words in order to represent each tweet as a feature vector. Twitter users tend to use idioms, abbreviations, and grammatical errors in their posts. Therefore, text processing methods like stop-word removal, punctuation, stemming
(converting a word to its root), and removing unnecessary white spaces using the Natural Language Toolkit (NLTK) library available in Python were applied. Also, all characters were lowercased, and after initially saving these features all URLs and mentions were eliminated.

### 4.2.1.3 Binary and Multi-class Classifications

In this stage, a two step procedure was used for twitter community engagement classification. Step 1 used binary classification to classify the tweets as relevant or irrelevant. In our case, Irrelevant tweets include personal messages, holiday greetings, chatter, ambiguous tweets, and spam. Step 2 used multi-class classification to further describe relevant tweets as four types: (1) asking for information, (2) reporting information, (3) expressing negative engagement, and (4) expressing positive engagement.

### 4.3 Experimental Setup

In this section, we will focus on (1) the process of crowdsourcing Twitter annotations, (2) extracting and selecting features to improve algorithm performance and (3) classification of algorithms and WEKA (data mining software tool).

#### 4.3.1 Crowdsourced Annotation

A small random sample (4000 tweets) was selected and uploaded to Amazon Mechanical Turk (MTurk). To facilitate the labeling process, some guidelines and samples were provided to the annotators. The relevant tweets are divided into four types: (1) Asking for information, verification or instructions for handling specific situations; e.g., “what is going on in both sewage plants on the south coast?” (2) Reporting facts, activities, events, and observations; such as “our beaches on the south coast are full of sewage” (3) Expressing negative engagement such as complaints, frustration, or sarcasm; e.g., “Barbados in a crisis and all Kellman thinking about is an airport,” and (4) Expressing positive engagement like proposing a solution or showing satisfaction, or counter the spread of misinformation. E.g., “This is bullshit. I live in Barbados, and NOTHING happened. Take this misinformation down” If the tweet contained no content related to public health issues or

---

the sewage leak issue in Barbados, they were labeled as irrelevant. E.g., the tweet “good morning Barbados, a day spent on the water enjoying snorkeling”. The “No Agreement” tweets that belongs to Multi-class labeling were excluded from the model to avoid bias. From 4000 tweets, in binary labeling, 40% of final tweets were relevant, and 60% determined as irrelevant.

4.3.2 Feature Sets

Basically, most machine learning algorithms require features (attributes) with some characteristics to work suitably. According to our collected data, the five groups of features are: (1) TF-IDF, (2) Psychometric, (3) Linguistic, (4) Twitter, and (5) Sentiment.

4.3.2.1 TF-IDF Feature

TF-IDF is an abbreviation of Term Frequency and Inverse Data Frequency. It refers to N-gram feature, which rely on the word count for each given unigram that appears in the tweet. The three main components that affect the importance of a word in a dataset are (1) Term Frequency (TF) which presents the frequency of the word in the dataset. (2) Inverse Data Frequency (IDF): applied to calculate the weight of rare words overall tweets in the dataset. (3) TF/IDF is a technique which uses the product of TF and IDF to determine the weight of each word. In formulas (1, 2 and 3), t is a term, d is the tweet in which t occurs, and D is the dataset.

\[ TF(t) = tf(t, d) \]  \hspace{1cm} (4.1)
\[ IDF(t) = \log \left( \frac{|D|}{1 + |\{d : t \in d\}|} \right) \]  \hspace{1cm} (4.2)
\[ TF - IDF(t) = TF \times IDF \]  \hspace{1cm} (4.3)

4.3.2.2 Psychometric Features

Psychometric Features are connected more with mental abilities and behavioral characteristic. We adopted the linguistic inquiry and word count (LIWC version 2015) tool to extract these features [104]. Psychometric features involve: emotional, social words, and personal concerns. It also includes drives and needs which are represented by words related to personal power, accomplishment, reward, and risk.
4.3.2.3 Linguistic Features

Linguistic Features include the following two types: (1) Grammatical features, which produce a rate of words that are verbs, adverbs, pronouns, and other punctuation. (2) Summary variables, which include analytical thinking, and emotional tone [104]. Analytical thinking is the percentage of terms in which people use words that suggest formal and hierarchical thinking patterns. While clout refers to the social situation or leadership that people demonstrate within their writing. Lastly, with emotional tone, LIWC merges both positive emotion and negative emotion scores into a single summary variable.

4.3.2.4 Twitter Features

Twitter features refer to characteristics unique to the Twitter platform. There are various forms that users on Twitter engage: (a) Retweet ratio is a metric of fame for a tweet since it implies both endorsement and distribution [105]. (b) Mention ratio is a technique in Twitter to ask other users to engage or follow a discussion in the form of (@username). (c) Hashtag ratio is an essential characteristic of Twitter which can be injected anywhere in a message. Some hashtags are devoted mainly to events such as (#Barbados) which can be used as search key on Twitter [106]. (d) Url ratio is the number of inserted links in a tweet which used to share extra information about the situation. (e) The number of followers and followings.

4.3.2.5 Sentiment Feature

Sentiment Features are the computational study of opinions, emotions, and disturbances shown in the text [107]. In our experiment, we decided to use the sentiment labels provided by the Crimson Hexagon tool because we found it produces more accurate results than we would have had otherwise.

4.3.3 Feature Selection

Typically, any machine learning algorithm represents a model as a function $f$ that predicts the output $Y$ given the input $X \{ x_1, x_2, ..., x_R \}$ where $x_i$ is selected input features and $R$ is a real number. It is commonly right that not all input feature $x$ affords the same value of information about
the output $Y$, rather just a small subset of them $\{ x_1, x_2, ..., x_s \}$ where $(S < R)$, that addresses
important information about $Y$.

Increasing training time and risk of overfitting can causes for poor performance when we present
data with very high dimensionality and irrelevant features. Overfitting occurs when a model learns
to pick up noise and irrelevant features and counted as relevant for classification during modeling.
In our proposed model, we are identifying different types of community engagements from text data.
The number of data points in the full twitter dataset is large, so the size of available memory is
important.

The total number of initial features that we extracted was 6540. This is a very large number of
features. To optimize the features, we used the an Information Gain [108] approach for extracted
relevant features only.

Information Gain is the variation of the volume of information that can be carried to the
classification model when a feature is included or not. Therefore, to compute information gain, we
need first to determine the information entropy. The information entropy $H(T_r)$ and the information
Gain (IG) for a feature $F_i$ calculated is as follows:

$$ IG(T_r, F_i) = H(T_r) - \sum_{c \in F_i} P(c)H(c), \text{where} $$

$$ H(T_r) = -\sum_{x \in S} p(x) \log_2 p(x) $$

4.3.4 Classifiers

We split the dataset into two parts. The larger part we use for training (80%) and the smaller
part we use for evaluation (20%). An experiment was conducted to evaluate the performance of
the model under the selected 4 supervised learning classifiers using a machine learning tools named
WEKA [109]. We compared classifiers that have frequently been used in related work: Support
Vector Machine (SVM) [110]; Decision Trees (DT) [111]; Naive Bayes (NB) [112]; and Random
Forest (RF) [113].

4.3.5 Performance Measurements

More generally, to evaluate the effectiveness of our model, we used the standard classification
metrics: (1) Accuracy (total number of correct predictions); (2) F1 score (harmonic mean of Precision
(P) and (R) Recall) and (3) Area Under Curve (AUC) which describe by false positive rates on the horizontal axis and true positive rates on the vertical axis. Based on classification of True Positives (TP), True negatives (TN), False Positives (FP) and False Negatives (FN), we have the following:

\[ F1 = 2 \cdot \frac{R \cdot P}{R + P} \]  
\[ Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \]  

(4.6)  
(4.7)

4.4 Experiment

A supervised classifier is trained to predict which tweets contain environmental health risks and which do not. Then a multi-class classification is performed to identify the types of engagements during the crisis.

- **Experiment (1) Binary classification**: In this part, Our intent was to investigate if supervised machine learning models can be trained on the annotated data in our dataset so that the tweets containing environmental health risks may be automatically identified. For our qualitative text analysis, we extracted (TFIDF, Psychometric, Linguistic, Twitter-specific, and Sentiment) features from all of a users Twitter posts and saved them into five different CSV files. We then combined and ranked all features before selecting the top features that are assumed to improve the system’s performance or drive more accurate differentiation of the community engagement types by applying information gain. Next, we divided each CSV file into two sections, the larger part we use for training (80%) and the smaller part we use for evaluation (20%) so that the model may be trained and tested on different data. Finally, we ran the WEKA data mining toolkit and used four supervised classification algorithms (mentioned earlier) to evaluate the performance of automatic detection. The F1 score, AUC and Accuracy values obtained from the binary classification are presented in Table 4.1 and Figure 4.2

- **Experiment (2) Multi-class classification**: In the second part of this experiment, from our collected data, three annotators manually labeled 4,000 tweets into five classes— irrelevant, expressing negative engagement, reporting information, expressing positive engagement, and asking for information— to train our four classifiers as we mentioned previously. The
agreement between our three annotators, measured using Cohen’s kappa coefficient, was substantial (kappa = 0.64). We placed the binary classification outcomes to our multi-class model to distribute the relevant tweets into four groups. Finally, we ran the experiment using the WEKA platform. The F1 score, AUC and Accuracy values obtained from the Multi-class classification are presented in Table 4.2 and Figure 4.3. To better understand our approach, we selected Random Forest as an example to show our steps in order to predict the suggested five types of community engagement during Barbados crisis. RF made of a set of decision trees; \( h(x, \theta_k) \), where \( k = 1, 2, \ldots, n \) and \( \theta_k \) are independent identically distributed random vectors while, \( x \) is a feature extracted from the twitter data (input vector). Each decision tree predicts a class independently. A voting is performed on the results from each decision tree and finally the class which gets majority vote will be the final predicted class. The workflow of the RF algorithm with preprocessing, training and testing steps for multi-classifications is shown in Algorithm 4.1.

4.5 Results and Discussion

In this section, we present tweets annotation results and experiment results of our model for the different selected features.

4.5.1 Annotation Results

Here we present the results of Amazon MTurk’s labeling of community engagement type of the 4000 tweets according to the binary and multi-class classifications. More than half of tweets were classified as irrelevant (2245). Of the 1755 relevant tweets, reporting information (984) was the most common type of engagement. “Expressing negative engagement” was the second most common form of engagement (296). These tweets shared resulting disgust and inconvenience caused by the environmental health hazards (sewage). 95 tweets were categorized as “expressing positive engagement.” “Asking for information” was the least common type of tweet engagement (26). The inability of users to directly communicate with Barbados’ water utility on twitter may have contributed to this low type of engagement. When users asked for information they tended to direct their tweet towards a specific individual or organization.
Table 4.1: Binary results of using (80%) training data and (20%) evaluation.

<table>
<thead>
<tr>
<th>Feature set</th>
<th>RF Acc.</th>
<th>RF AUC</th>
<th>RF F1</th>
<th>SVM Acc.</th>
<th>SVM AUC</th>
<th>SVM F1</th>
<th>NB Acc.</th>
<th>NB AUC</th>
<th>NB F1</th>
<th>DT Acc.</th>
<th>DT AUC</th>
<th>DT F1</th>
</tr>
</thead>
<tbody>
<tr>
<td>TF-IDF</td>
<td>85.13</td>
<td>91</td>
<td>85</td>
<td>74.75</td>
<td>69</td>
<td>72</td>
<td>80.5</td>
<td>85</td>
<td>80</td>
<td>79.75</td>
<td>84</td>
<td>79</td>
</tr>
<tr>
<td>Psychometric</td>
<td>71.25</td>
<td>76</td>
<td>71</td>
<td>70</td>
<td>68</td>
<td>70</td>
<td>62</td>
<td>68</td>
<td>62</td>
<td>66.25</td>
<td>67</td>
<td>66</td>
</tr>
<tr>
<td>Linguistic</td>
<td>64.13</td>
<td>68</td>
<td>62</td>
<td>64.88</td>
<td>61</td>
<td>63</td>
<td>62.88</td>
<td>63</td>
<td>62</td>
<td>61.38</td>
<td>61</td>
<td>59</td>
</tr>
<tr>
<td>Sentiment</td>
<td>61.16</td>
<td>59</td>
<td>55</td>
<td>61.16</td>
<td>54</td>
<td>55</td>
<td>61.17</td>
<td>59</td>
<td>55</td>
<td>61.17</td>
<td>59</td>
<td>55</td>
</tr>
<tr>
<td>Twitter</td>
<td>72.96</td>
<td>81</td>
<td>72</td>
<td>59.66</td>
<td>50</td>
<td>45</td>
<td>66.19</td>
<td>75</td>
<td>67</td>
<td>67.91</td>
<td>70</td>
<td>68</td>
</tr>
<tr>
<td>All-Features</td>
<td>87.31</td>
<td>96</td>
<td>87</td>
<td>59.67</td>
<td>50</td>
<td>45</td>
<td>49.46</td>
<td>59</td>
<td>48</td>
<td>79.76</td>
<td>87</td>
<td>80</td>
</tr>
</tbody>
</table>

4.5.2 Experiment Results

In our results, the modeling and classification were attempted on a machine with Intel Core i5 CPU @2.7 GHz with 8GB RAM configuration. In the first experiment, the best results were reached by using Random Forests classifier with (all-features) with 87% F1 score. It is interesting to note TF-IDF feature became the second highest features which recorded an 85% F1 score. In the second experiment using the multi-class model to detect the types of community engagement, results across the training techniques were comparable; Decision Tree with TF-IDF features achieved the highest F1 score with 74%. Whereas Random Forest with (TF-IDF and All-Features) reported the second highest F1 score with 72% scores.

To determine and rank the relevant attributes of each feature, we applied information gain equation 4.4. The top 10 features with the most significant weight for each class are listed in Table 4.3. To distinguish between relevant and irrelevant tweets, as displayed in the table, the top affected feature in binary classification was Twitter-features with the following attributes: Following, Followers, Mention, and Hashtag. Whereas, in Multi-class classification, the (TF-IDF) got the most informative features among all other features where: zika, water, virus, case, and sewage recorded the majority of the weight.

Table 4.2: Multi-class results using (80%) training data and (20%) evaluation.

<table>
<thead>
<tr>
<th>Feature set</th>
<th>RF Acc.</th>
<th>RF AUC</th>
<th>RF F1</th>
<th>SVM Acc.</th>
<th>SVM AUC</th>
<th>SVM F1</th>
<th>NB Acc.</th>
<th>NB AUC</th>
<th>NB F1</th>
<th>DT Acc.</th>
<th>DT AUC</th>
<th>DT F1</th>
</tr>
</thead>
<tbody>
<tr>
<td>TF-IDF</td>
<td>76.16</td>
<td>86</td>
<td>72</td>
<td>70.82</td>
<td>63</td>
<td>64</td>
<td>40.13</td>
<td>83</td>
<td>51</td>
<td>77.12</td>
<td>80</td>
<td>74</td>
</tr>
<tr>
<td>Psychometric</td>
<td>71.25</td>
<td>76</td>
<td>71</td>
<td>61.64</td>
<td>50</td>
<td>47</td>
<td>35.75</td>
<td>64</td>
<td>43</td>
<td>60.27</td>
<td>62</td>
<td>57</td>
</tr>
<tr>
<td>Linguistic</td>
<td>64.13</td>
<td>68</td>
<td>62</td>
<td>61.64</td>
<td>50</td>
<td>47</td>
<td>36.98</td>
<td>61</td>
<td>41</td>
<td>57.81</td>
<td>60</td>
<td>56</td>
</tr>
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<td>Sentiment</td>
<td>56.67</td>
<td>49</td>
<td>41</td>
<td>56.67</td>
<td>50</td>
<td>41</td>
<td>72.37</td>
<td>48</td>
<td>61</td>
<td>56.67</td>
<td>50</td>
<td>41</td>
</tr>
<tr>
<td>Twitter</td>
<td>50.66</td>
<td>52</td>
<td>42</td>
<td>55.74</td>
<td>50</td>
<td>40</td>
<td>50</td>
<td>55</td>
<td>42</td>
<td>46.34</td>
<td>50</td>
<td>41</td>
</tr>
<tr>
<td>All-Features</td>
<td>75.93</td>
<td>87</td>
<td>72</td>
<td>70.27</td>
<td>62</td>
<td>70</td>
<td>33.5</td>
<td>80</td>
<td>41</td>
<td>72.57</td>
<td>77</td>
<td>71</td>
</tr>
</tbody>
</table>
4.6 Summary

The effectiveness of social media platforms in the field of environmental health can support decision makers and health organizations by measuring the feedback of people’s responses about crises. In this paper, a framework for binary and multi-class community engagement classifications was proposed. The framework included choosing essential features of tweets, applying feature selection algorithm and training the dataset using machine learning algorithms.

While we consider that our outcomes are encouraging, we do see that there is still some uncertainty in the efficacy of our technique for classification. The first reason is the quality of labeling, knowing there are many advantages of using MTurk, such as easy access to a vast topic pool, the low rate of performing experiments and faster with producing results. The quality of annotation
of the data can be much better if we could hire domain experts. The second reason is some types of community engagement might overlap in the meaning or might have very similar features which make the process too difficult to distinguish between tweets. For instance, we excluded 354 out of 4000 tweets because the three annotators could not agree with them (No Agreement). Based on our experiences, if the annotators are authorized to view the entire discussion preceding the tweet and are familiar with the content of the URLs this could mitigate these misunderstandings. Moreover, specifying five labels possibly caused confusion for the annotators; It may be possible to narrow the variety of the choices and make them only three for the future work. In addition, it is essential to note that our model results may not be adaptable to other fields without further examination. Knowing public opinions and beliefs towards environmental health risks topics may help academics, health agencies, and policymakers generate better strategies and guidelines for maintaining public health. In future research, we plan to employ graph theory such as community detection technique to explore other types of community engagement that may not be presented in our data. For more validation, we will work on another social media platform to predict community engagement.
Algorithm 4.1 Random forest for community-engagement prediction

Given: D is labeled Tweets
Split D to 80% Training Tweet dataset \( (T_{tr}) \) and
20% Testing Tweet dataset \( (T_{te}) \)
Features extracted from Training Tweet dataset = \( F_{tr} \)
Features extracted from Testing Tweet dataset = \( F_{te} \)
Classified Community-Engagement from Tweet= CE
Probability that feature F belong to Community-Engagement CE = P (CE|F).

Step 1 Preprocessing:
1. NLTK filters are applied to detach noise from \( T_{tr} \) and \( T_{te} \)
2. Features \( F_{tr} \) and \( F_{te} \) are chosen from processed data \( T_{tr} \) and \( T_{te} \) obtained from Step 1.

Step 2 Training:
Input: Training data set \( F_{tr} \)
Output: Random Forest model to classify different types of Community Engagement.
1. Select the training data \( T_{tr} \)
2. Apply vector-based word representations: to convert raw tweet to numbers
3. Build a decision tree (DT) using following steps:
   (a) Reduced dimensionality by select (K features) from the set of (S features) by choice an attribute selection measure.
   (b) Apply Information Gain from formula 4 and 5 among the K to pick up the best features.
   (c) Fix the number of forests with a maximum of 200 trees.

Step 3 Prediction:
Input: Testing data set \( T_{te} \) and Trained Random-Forest model from Step 2.
Output: Community Engagement prediction \( CE_{fs} \)
1. Select the same features F used for training the model from testing feature set \( F_{te} \)
2. Predict the types of engage \( CE_{fs} \) from the model using following equations:
   \[
   \text{for each DT in Forest do}
   \]
   \[
P(CE|F) = \frac{1}{L} \sum_{i=1}^{L} P(CE|F,T_i)
   \]
   \[
   \text{where } L = \text{ number of trees, and}
   \]
   \[
P(CE|F,T_i) \text{ is the conditional probability}
   \]
   \[
   \text{end for}
   \]
   \[
   CE_{fs} = \arg\max_{i \in \{1,2,...,5\}} (P(CE_i \mid F))
   \]
   \[
   \text{where } CE_i \in CommunityEngagementType_i
   \]
CHAPTER 5

DETECTING SITUATIONAL AWARENESS DURING DISASTER

In this chapter, I will focus on enhancing the current model results by implementing an ensemble learning method to improve the overall performance. In this technique, various models are utilized to produce predictions for each model. The predictions by each model are viewed as a distinct vote. The prediction which we get from the majority of the models is count as the final prediction. The shift to social media platforms like Twitter during environmental hazards and emergencies has expanded recently. Yet, the classification of situational awareness tweet based on people post is a complicated process due to the high dimensionality of features. In this empirical study, a framework using machine learning and Natural Language Processing techniques was developed for two-stage binary classification of Twitter data. The First stage consists of four models: Random Forest, Support Vector Machine, Naive Bayes and Decision Trees. Whereas, the second stage includes an ensemble learning approach. Text features - TFIDF (term frequency, inverse document frequency), psychometric, and linguistic - were analyzed as predictors of binary classification to categorize each tweet as situational relevant or irrelevant automatically. A manually built and labeled dataset of 4,000 tweets were analyzed for situational awareness of environmental health hazards in Barbados from water, mosquito-borne diseases, and sewage during the period 2014 - 2018. Based on the experiment, our model was able to achieve over 85% accuracy on classifying tweets that contribute to situational awareness. Furthermore, the results indicate that applying ensemble learning in the second stage showed superior results compared to the combined features-based classification models.

5.1 Introduction

Disasters (e.g., natural, human-made, and infectious disease outbreaks) are massive and shocking events that require ingenuity and effort from vast numbers of people. Environmental health risks, sustainability, and situational awareness are widely recognized among the major community concerns.
Communities in crisis need information whereby respondents must listen to and act on feedback from the community. Despite the fact that all communities are at risk of suffering from natural disasters or the outbreak of disease, some are more defenseless than others. For example, Small Island Developing States are susceptible to hurricanes, floods, and the expanded dangers of waterborne and foodborne illness in addition to other mosquito-borne diseases.

Social media platforms, in particular, Twitter is adopted by victims, volunteers and agencies to share information and afford different forms of aid through disaster events, for example, hurricanes, wildfire, earthquake, and acts of human-made crisis such as shooting, civil unrest [1], [64]. Twitter has been used as a formal or official source of information; a good example was the spread of Zika virus in 2016 when Centers for Disease Control and Prevention (CDC) utilized Twitter to post updates on the pandemic situation [114]. Hashtag #FlintWaterCrisis is another good example where social media were helping to put a spotlight on the Flint water crisis. This information has proven invaluable for “situational awareness” and effective emergency response.

The concept of situational awareness points to the perception of what is going on and then projects how it will unfold with time and with consideration to the dynamics of the surrounding environment [115]. Throughout this paper, the term ‘situational awareness’ refers to a tweet that involves information (awareness) about the disaster in addition to precise details about the situation such as (1) asking for information, (2) reporting information, (3) expressing negative engagement, and (4) expressing positive engagement. Recent researches [116], [117], [118] have shown the adopting of Twitter may help to enhance situational awareness for participants during disasters. Residents could offer (e.g., coordinating disaster relief efforts) and get crisis-related information, besides to engage in disaster response and rescue efforts. However, only a small portion of posts (tweets) contribute to situational awareness, while a large number of tweets solely reflect opinions, criticism or express sympathy with affected people. In our study, these terms (relevant and situational awareness) or (irrelevant and situational awareness) are used interchangeably.

Barbados, as an example, a Caribbean island with a population of 286,388 is ranked among the worlds 15th most water-scarce countries [119]. The terms #BarbadosWaterCrisis and #BarbadosWastewaterCrisis were actively trending online and in print media between 2015 and 2018. Environmental Health risks such as the discharge of untreated wastewater, mosquito, and waterborne diseases, and skin infections were amongst major concerns of citizens there. In 2018 the
Barbados Water Authority (BWA) announced a sewage leak crisis across parts of the island. The incident has produced a slew of dilemmas in different health, economy, and tourism sectors, among others. In this paper, we use twitter engagement about environmental health hazards in Barbados to see how text mining and machine learning algorithms can be used to detect and predict situational awareness.

By applying Natural Language Processing (NLP) and machine learning techniques, we propose a two-stage classification framework to distinguish between situational awareness and non-situational awareness tweets. Based on initial analyses of tweet content, we found that tweets that contribute to situational awareness are likely to be written in four different types: reporting information, expressing negative engagement, expressing positive engagement, and asking for information. We believe this study provides new insights for real-time data gathering and analysis to support situational awareness.

Machine learning classification of an instance mostly needs to be verified with other classifiers. The classification results using multiple classifiers aggregated together commonly result in better and reliable classification performance [120]. Ensemble learning is the process of combining the probability of predictions from a number of classifiers to enhance the overall prediction [121]. Dasarathy et al. proposed the first ensemble system in 1979 [122], to partition a feature space by utilizing some classifiers aggregated together. Many other researchers have used the ensemble learning technique for enhancing classification performance in different domains such as sentiment classification [123].

In this chapter, we hypothesize that by applying Ensemble Learning it is much reliable to produce better predictive performance than building a single classifier of combined features from three different types: basic features (i.e., TF-IDF), psychometric features, and linguistic features.

5.2 Dataset and Annotation

This section explains the collection of tweets related to environmental risks in Barbados from 2014 to 2018 and their substantial impacts on society, environmental, health, economics, and tourism. Twitter, one of the largest social networks sites based on active users with on average 328 million monthly active users in 2017 [45]. With a 280-character limit, twitter has been widely used for
sharing news, beliefs, and activities during crises and natural emergencies, and to gather support for social and public health monitoring [103]. People adapt Twitter platforms for diverse reasons, from real-time conversation to awareness of breaking news [124]. We used Crimson Hexagon [46] to collect every tweet that includes the keyword Barbados from January 1, 2014, to May 31, 2018. Since no language limitation was forced through data gathering, we captured 5,532,419 tweets, of which 3,897,789 were in English. Then, for the filtering stage, we worked with a domain expert in the field of Environmental Engineering to identify keyword-based matching as follows: crisis, wastewater, sewage, Water Authority, water quality, BWA, Climate Change, waterborne, contaminated, Zika, mosquito, dengue fever, yellow fever, chikungunya, Aedes aegypti, West Nile, malaria, Culex, infectious disease, skin test, and health risk. Finally, we got a total sample of tweets around 30,000.

This much smaller sample size was likely due to (1) Barbados is a small island compared to other populations, and people might use other social media platforms like Facebook or Instagram, (2) English is not the sole language spoken in Barbados, and this study excluded potential content written in other languages.

Additionally, to collect large volumes of high-quality training tweets, we chose one of the most popular crowdsourcing platform called Amazon Mechanical Turk (MTurk). A small random sample (4000 English tweets) was selected and uploaded to the platform mentioned above to get human-annotated data. Three MTurk annotators with the following criteria were requested: (1) U.S. residents with a hit approval rating of 94%, (2) classified as a master, and (3) is English language proficient. Annotators were paid USD 0.20 per tweet. Each tweet was labeled three times, 1 per annotator. Before the annotators begin the task, to facilitate the labeling process, some tweets were shown as examples of relevant situational awareness and non-situational awareness tweets (see Table 5.1). From 4000 tweets, 40% of final tweets were relevant to sewage crisis and health problems, and 60% determined as irrelevant.

5.3 Method

In this section, we developed a two-stage model for detecting and predicting situation awareness tweets by using the text classification technique.
5.3.1 Framework

Figure 5.1 presents a high-level picture of our framework used to collect a series of data over a given time frame for a given location, Barbados to be specific. Its components are split into five stages: (1) Tweets collection (see section 3); (2) Data Preprocessing; (3) Features Extraction (4) Binary classification; and (5) Ensemble Model.

5.3.2 Data Preprocessing

Preprocessing has become essential techniques in current Natural Language Processing tasks. Raw-collected tweets usually come with many imperfections such as inconsistencies, missing values, noise or redundancies. We applied text-processing methods like tokenizer (transforms texts to sequences of words), stop-word removal (a commonly used word such as “the”, “a”, “an”, “in”), remove punctuation, stemming (converting a word to its root), and eliminating unnecessary white spaces using the Natural Language Toolkit (NLTK) library available in Python programming language. Also, we lowercased all characters reduced duplicate tweets and deleted all URLs and mentions after initially saving these features.

5.3.3 Binary Classification

In this work, we applied supervised learning for classification to trains a model on known input (Tweets + Labels) and output data so that it can predict future outputs. The objective of using a classification method is to divide the dataset into two categories (1) Relevant and (2) Irrelevant tweets.
Algorithm 5.1 Ensemble learning method.

**Input:** Three classifiers results (probabilities) trained on features $f \in \{\text{tfidf, psychometric, linguistic}\}$

**Output:** Ensemble model

**Majority voting:** classifiers trained on feature set $f$:

A) Get the predicted class using probabilities $P_{\text{relevant}}$ and $P_{\text{irrelevant}}$.
B) Ensemble prediction $E_{\text{pred}} = \text{sum}(C_{1\text{pred}}, C_{2\text{pred}}, C_{3\text{pred}})$, where $C$ is the classifier model,
C) Average the summation $E_{\text{pred}}$ of prediction and threshold it at $t = 0.5$

The Relevant or situational awareness tweets can be used to estimate the present circumstances. Generally, can become into following types: (1) asking for information for the purposes of information verification or instructions for handling specific situations; (2) reporting facts, activities, events, detections, observations, and notes; (3) expressing negative engagement such as complaints, frustration, sadness, or sarcasm; (4) expressing positive engagement like proposing a solution or showing satisfaction or happiness. Differently, Irrelevant or non-situational awareness tweets are tweets contain too much noise include such as personal messages, holiday greetings, chatter, ambiguous tweets, and spam.

### 5.3.4 Ensemble Learning

Ensemble learning utilized in this paper is based on ensemble fusion approach where the probabilities $P_{\text{relevant}}, P_{\text{irrelevant}}$ of each binary classifier $C$ on feature set $S$ are used to perform the majority voting ensemble technique $E$. Where $P_{\text{relevant}}, P_{\text{irrelevant}} = F(C, S)$ is the process of fitting a trained classifier model $C$ in the test set of features $C$. Therefore, we obtained the probabilities from each classifier trained and tested using Waikato Environment for Knowledge Analysis (Weka) software. After that, we perform the majority voting as follows: if two classifiers probabilities indicate that an instance is classified as relevant, then the ensemble results for that instance is relevant. Likewise, if two classifiers probabilities indicate that an instance is classified as irrelevant, then the ensemble result of that instance is irrelevant. Algorithm 5.1 shows the ensemble learning process.
5.4 Feature Sets, Classifiers and Performance Measurements

Feature selection and extraction is a fundamental problem in mining large data sets. The primary goal of this step is to reduce the dimensionality of the dataset, making training faster and enhancing accuracy. The dissertation reviews several classification methods to detect and predict relevant situational tweets using text feature extraction, applying supervised learning models such as Random Forest, Support Vector Machine, Naive Bayes, and Decision Tree. We name three types of features based on their field: (TF-IDF), Psychometric, and Linguistic. The full list of features appears in Table 5.2.

5.4.1 Feature Sets

- Term frequency-inverse document frequency: (TF-IDF) refers to N-gram features, which rely on the word count for each given word that appears in the tweet. It consists of two parts: (1) The Term Frequency (TF) - It presents the frequency of the word per tweet in the dataset. It is the ratio of the number of occurrences the word appears in a post compared to the entire number of words in that dataset. (2) The Inverse Document frequency (IDF) – It determines the importance of rare words overall tweets in the dataset. The words that rarely occur in the dataset have a big IDF score. Therefore, (TFIDF) – It measures the weight of each term by using the product of (TF) and (IDF). Hence, if a word frequently appears in a tweet or the set of tweets, it would make sense to acknowledge the word to be important. However, the more frequently a word shows up over tweets, the less it benefits with understanding the textual content.

<table>
<thead>
<tr>
<th>Type</th>
<th>Subtype</th>
<th>Tweet</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relevant</td>
<td>Asking for information</td>
<td>(1) What’s the Reason for the Water Troubles in Barbados?</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2) What is going on in both sewage plants on south coast?</td>
</tr>
<tr>
<td></td>
<td>Reporting information</td>
<td>(1) No #zika virus cases in the Caribbean to date says Barbados health ministry.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2) The leaking sewage on the south coast has returned.</td>
</tr>
<tr>
<td></td>
<td>Positive engagement</td>
<td>(1) This is bullsht. I live in Barbados and NOTHING happened. Take this misinformation down.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2) Don’t be spreading rumors / joking about a water crisis please.</td>
</tr>
<tr>
<td></td>
<td>Negative engagement</td>
<td>(1) Absolutely disgusted! Had to cancel flights to Barbados due to Zika.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2) Out for a nice drive in Barbados sadly need masks on face as the stench of sewage bubbling.</td>
</tr>
<tr>
<td>Irrelevant</td>
<td>No content related</td>
<td>(1) Good morning Barbados, I am enjoying snorkeling.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2) I can’t sleep at the night.</td>
</tr>
</tbody>
</table>
• Psychometric Features: Psychometric Features are connected more with mental abilities and behavioral characteristic. The thought is that particular words are strong signs of people’s feelings and cognitive worlds. Psychometric Features include many features such as emotional, social words, personal concerns (like work, leisure, money, and death), Drives and Needs. In this study, we utilized the linguistic inquiry and word count (LIWC version 2015) tool to extract these features. LIWC is a text analysis tool developed within the context of Pennebaker’s work on emotional writing [104].

• Linguistic Features: Linguistic Features refer to investigating Twitter-users’ linguistic patterns in their reflective writings (typing) can help to know the scope and aspects of their thinking and communication approaches. It includes two types: (1) Grammatical features, which produce a rate of words that are verbs, adverbs, pronouns, and other punctuation. (2) Summary variables, which include: (a) analytical thinking (percentage of terms that catches the degree to which people use words that suggest formal, logical, and hierarchical thinking patterns). (b) clout (social situation, trust, or leadership). (c) authenticity (someone discloses him/her self authentically or honestly). (d) emotional tone (Negative or positive emotional self-expression)[104]

5.4.2 Feature Selection

In this part we try to answer: How do you know which features to adopt and which to discard? Machine learning algorithm represents a model as a function $f$ that predicts the output $Y$ given the input $X \{ x_1, x_2, ..., x_R \}$ where $x_i$ is selected input features and $R$ is a real number. It is commonly right that not all input feature $x$ affords the same value of information about the output $Y$, rather just a small subset of them $\{ x_1, x_2, ..., x_s \}$ where $(S < R)$, that addresses important information about $Y$.

In our proposed model, the total number of initial features that we extracted was 6540. This is a substantial number of features. To optimize the features, we used the Information Gain [108] approach for extracted relevant features only. Information Gain is the variation of the volume of information that can be carried to the classification model when a feature is included or not. Therefore, to compute information gain, we need first to determine the information entropy (measuring what our
overall uncertainty is for our an information source where the probabilities of the outcomes are unequal). The information entropy $H(T_r)$ and the information Gain (IG) for a feature $F_i$ calculated is as follows:

$$IG(T_r, F_i) = H(T_r) - \sum_{c \in F_i} P(c)H(c), \text{where}$$

$$H(T_r) = - \sum_{x \in S} p(x) \log_2 p(x)$$

5.4.3 Classifiers

We split our selected random tweets into two segments: the larger part we use for training (80%) and the smaller part we use for evaluation (20%). An experiment was conducted to assess the performance of the selected classifiers using popular machine learning tools named WEKA [109].

1. Support Vector Machine (SVM) [110] is one of the supervised machine learning algorithms that is employed for various classification problems and proved very useful in NLP applications. It initially divides instances of two classes by implementing a hyperplane to expanding the margin between the two classes.

2. Decision Trees (DT) [111] is a tree where a node describes as an input feature, each branch names a decision, and each leaf describes as output. It created using an idea of divide and conquer algorithm because it applies the feature labels to divide the data into smaller subsets of similar classes.

3. Naive Bayes (NB) [112] It uses Bayes’ theorem to calculate the likelihood that the tweet belongs to a particular class label relevant or irrelevant (a series of “yes/no” decisions). The term (naive) indicating to the hypothesis that all features are independent.

4. Random Forest (RF) [113] is a collection of decision trees trained on random splits of the training data and which are used together to classify new instances. In the case of this research, the best results on the development data set were obtained when 200 trees.
5.4.4 Performance Measurements

To evaluate the effectiveness of our model based on our suggested features, we adopted the standard classification metrics: Accuracy (total number of correct predictions); precision (how often are our predictions for a class are correct); recall (how often tweets are classified correctly as the correct class; The F-measure is a harmonic mean of precision and recall and Area Under Curve (AUC) which describe by false positive rates on the horizontal axis and true positive rates on the vertical axis for varying thresholds.

\[
\text{Precision}(P) = \frac{TP}{TP + FP} \quad (5.3)
\]

\[
\text{Recall}(R) = \frac{TP}{TP + FN} \quad (5.4)
\]

\[
F - \text{measure} = 2 \frac{R \times P}{R + P} \quad (5.5)
\]

\[
\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \quad (5.6)
\]

To get a complete picture we need to know four basic terminology: TP, TN, FP, FN refer to the number of true positive, true negative, false positive and False negatives, respectively. TP and TN tell us when the classifier is getting things right, while FP and FN tell us when the classifier is getting things wrong.

5.5 Results

Classification of tweets on our dataset to relevant (i.e., situational awareness) or irrelevant (i.e., non-situational awareness) was done on features sets described on section 5.4.2 using multiple classifiers discussed in section 5.4.3. The results show that all classifiers trained and tested on TFIDF features have the best accuracy and AUC among all other features sets. The best accuracy and AUC were 85.13% and 0.91 respectively using Random Forests classifier of TFIDF features set. The second best accuracy was 79.5% using the majority voting ensemble approach of three Random Forests classifiers trained and tested on three different feature sets. Additionally, the second best AUC was 0.78 using the majority voting ensemble approach of three Support Vector Machine classifiers trained and tested on three different feature sets. Classifiers trained on Psychometric and Linguistic features individually showed lower results compared to TF-IDF and ensemble approach results.
Relatively lower results were observed when combined features (i.e., concatenated) of TF-IDF, Psychometric and Linguistic were used as training and testing of classifiers. Table 5.3 shows the best accuracy, AUC, and F-measure of each classifier trained and tested on an individual feature set, classifiers results trained and tested on combined feature sets, and majority voting ensemble results. A comparison of best accuracy and AUC results on a feature set is shown in Figure 5.2 and Figure 5.3.

Table 5.2: Examples of feature types used in our model.

<table>
<thead>
<tr>
<th>Type</th>
<th>Feature</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unigram</td>
<td>TF-IDF</td>
<td>Weight a keyword based on the number of times it appears in the dataset</td>
</tr>
<tr>
<td>Psychometrics</td>
<td>Personal Concerns</td>
<td>Ratio of words associated with personal life (work, achievement, leisure, home, money, religion, and death)</td>
</tr>
<tr>
<td></td>
<td>Cognitive Processes</td>
<td>Ratio of word associated with insight, cause, discrepancies, tentative, and certainty differentiation</td>
</tr>
<tr>
<td></td>
<td>Core Drives and Needs</td>
<td>Ratio of words associated with personal drives as power, achievement, reward and risk</td>
</tr>
<tr>
<td></td>
<td>Perceptual process</td>
<td>Ratio of words that indicate to multiple sensory and perceptual dimensions associated with the five senses</td>
</tr>
<tr>
<td>Linguistic</td>
<td>WC</td>
<td>Total number of words in tweet</td>
</tr>
<tr>
<td></td>
<td>Words &gt; 6</td>
<td>Letters Count of words with more than six letters</td>
</tr>
<tr>
<td></td>
<td>WPS</td>
<td>Sum of words per sentence</td>
</tr>
<tr>
<td></td>
<td>QMark</td>
<td>The ratio of words holds a question mark</td>
</tr>
<tr>
<td></td>
<td>Exclam</td>
<td>Ratio of words contains exclamation mark</td>
</tr>
<tr>
<td></td>
<td>Analytical Thinking</td>
<td>A high number reflects formal, logical, and hierarchical thinking, lower numbers reflect more informal, personal.</td>
</tr>
<tr>
<td></td>
<td>Clout</td>
<td>A high number implies that the writer is talking from the perspective of high expertise and is satisfied</td>
</tr>
<tr>
<td></td>
<td>Authenticity</td>
<td>Ratio of number where higher numbers are correlated with a more honest, personal, and disclosing text.</td>
</tr>
<tr>
<td></td>
<td>Informal Speech</td>
<td>Ratio of words related to informal language markers as agents, fillers and swears words</td>
</tr>
<tr>
<td></td>
<td>Time Orientation</td>
<td>Ratio of words that refer to Past focus, present focus and future focus.</td>
</tr>
<tr>
<td></td>
<td>Grammatical</td>
<td>Ratio of words that refer to auxiliary verb, prepositions, impersonal pronouns, personal, pronouns, and articles.</td>
</tr>
<tr>
<td></td>
<td>Punctuation</td>
<td>Ratio of periods, commas, colons, semicolons etc.</td>
</tr>
</tbody>
</table>

Table 5.3: Performance metrics for evaluating our model.

<table>
<thead>
<tr>
<th>Feature Set</th>
<th>RF</th>
<th>SVM</th>
<th>NB</th>
<th>DT</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Acc.</td>
<td>AUC</td>
<td>F1</td>
<td>Acc.</td>
</tr>
<tr>
<td>TF-IDF</td>
<td>85.13</td>
<td>0.91</td>
<td>0.85</td>
<td>83.75</td>
</tr>
<tr>
<td>Psychometric</td>
<td>71.25</td>
<td>0.76</td>
<td>0.71</td>
<td>70</td>
</tr>
<tr>
<td>Linguistic</td>
<td>64.13</td>
<td>0.68</td>
<td>0.62</td>
<td>64.88</td>
</tr>
<tr>
<td>All-Features</td>
<td>69.5</td>
<td>0.69</td>
<td>0.69</td>
<td>59.64</td>
</tr>
<tr>
<td>Ensemble learning</td>
<td>79.5</td>
<td>0.75</td>
<td>0.83</td>
<td>77.25</td>
</tr>
</tbody>
</table>

5.6 Discussion

This study aims to build a classification model of environmental health issue in Barbados tweets to a relevant or irrelevant category. It is important to an early response of a disaster during a huge tweet getting posted to the Twitter platform. We found the best results using Random Forests classifier with TF-IDF features of 85.13% accuracy, 0.91 AUC and 0.85 F-measure. Majority voting ensemble approach showed higher results compared to the combination of features based models. Therefore, ensemble learning results became the second highest of 79.5% accuracy, 0.75 AUC and
Figure 5.2: Best accuracy of each classification model.

Figure 5.3: Best area under the curve of each classification model.
0.83 F-measure. Whereas, the combination of all three features got the lowest results for all different features with an accuracy of 49.88%, AUC of 0.59 and 0.46 F-measure. Combining features based model lower results because the features could have redundant and meaningless features which were selected by a feature selector. Additionally, combining the feature yield a high number of features which result in an obstacle to fit the best model. TF-IDF results remain the highest. Therefore, unigram (TF-IDF) can be hard to beat which is consistent with previous study[125].

Ensemble approach presents reliable results since it finds the agreement of at least two classifiers of an instance prediction. This approach is more interesting and helpful to utilize for better prediction model rather than combining the features based model.

5.7 Summary

Social media performs a vital task in the management of crises such as environmental disasters and can further be utilized to build and improve environmental awareness and advance health. In this paper, we analyzed Twitter data collected between 2014 to 2018 which was related to environmental health risks in Barbados. A two-stage framework for binary classification is proposed, It shows that implementing an ensemble method on a combination of (TF-IDF, Psychometric and Linguistic) features performs well at identifying tweets that contribute to situational awareness. While we consider that our outcomes are encouraging, we do see that there is still some uncertainty in the efficacy of our technique for classification. The first reason is the quality of labeling, knowing there are many advantages of using Mechanical Turk, such as easy access to a vast topic pool, the low rate of performing experiments and faster with producing results. The quality of annotation the data can be much better if we could hire domain experts. In the future direction of this research is to examine and validate the performance of our framework against other well-known machine learning methods such as deep learning. For more validation, we will work on another social media platform (Facebook or Reddit) to predict situational awareness tweets. A different direction is to incorporating other feature types such as sentiment and Twitter-specific feature such as retweet by a different user. Moreover, we will build a disaster lexicon which indicates how many environmental-health disaster words are used in the tweet.
CHAPTER 6

PREDICTING HIGH PRIORITY TWEETS DURING DISASTER

Communities and affected individuals are increasingly relying on social media outlets such as Twitter during hurricane disasters. Studies have reported the value of the data accessible on Twitter for many disaster response duties. Still, it is difficult to make judgments on social media data for a number of reasons, such as constraints of available tools to investigate the high volume of information flows during disasters. In this chapter, I describe the full final developed version of our model. By applying Natural Language Processing (NLP) and machine learning techniques, we introduce a three-level framework (Clustering-Classification-Ranking) to predict, analyze, and identify high priority tweets during a disaster. First, tweets are gathered based on features (e.g., keywords, hashtags) from Twitter’s streaming API. Then, the topic modeling algorithm, such as Latent Dirichlet Allocation, is implemented to explore the hidden topics and events being addressed during the incident period. Next, multi-class classification is adapted based on content as well as term frequency, inverse document frequency, psychometric, linguistic, sentiment, and Twitter features to further categorize tweets into four types based on user and community engagement: asking for information, reporting, requesting/offering help, and other. Finally, tweets are ranked according to their estimated level of importance.

6.1 Introduction

Social media plays a vital role in connecting citizens to all kinds of authorities, including governments and non-governmental organizations. The use of social media platforms has become a routine feature of disaster response. These platforms are utilized continuously by affected people, emergency rescue teams and the humanitarian community, and far away viewers to inquire about or deliver information, as well as afford various sorts of support such as prayers and guidance during disaster situations such as volcanic eruptions, cyclones, and acts of unrest [1], [81], [40].
Research on the social and informational phases of crises has broadly observed the possibility for this information to be beneficial to emergency responders [21], [126]. Recent research has determined that the people expect a timely response to questions and needs directed to governments and nongovernmental sectors on social media [127], [128].

However, there are some challenges, such as information overload, isolating relevant tweets from noise, and identifying similar groups of data in a dataset that need to be addressed [129]. Although there has been improvement in advancing the value of these streams, there is yet much work to be completed in supporting responders by classifying, ranking, processing, and combining social media data in their decision making. Thus, quickly prioritizing messages with aid-seeking intent that require a timely response has become a critical need for emergency operation centers [130].

When a disaster hits, time is limited and lives are at stake; therefore, people have to react immediately with as much information on the situation as is feasible. However, millions of Twitter messages ("tweets") are being spread at any given time, and knowing what information to look for is usually challenging and complicated. Clearly, we use various Artificial Intelligence techniques from Natural Language Processing and unsupervised and supervised machine learning techniques to process the data generated during disaster events and to answer the following: How can we build a Model to Rank Twitter Data Requests for disaster responders in order to extract the high-priority tweets?

Extracting and exploring themes or topic-waves in tweets is a non-trivial task due to their format and style, and because tweets typically are more irregular than traditional texts. The language used in tweets is often informal, containing grammatically creative text, slang, emoticons and abbreviations, making it more difficult to extract topics from tweets than from more formal text. Although the informal language and sparse text make it difficult to retrieve the underlying topics in tweets, [131] previously found that Latent Dirichlet Allocation (LDA) produced decent results with tweets. LDA [98] is an unsupervised probabilistic model that generates mixtures of latent topics from a collection of documents, where each mixture of topics produces words from the collection’s vocabulary with certain probabilities.

Topic models are statistical approaches applied to describe the hidden topics inside dataset collections. These probabilistic forms display topics as multinomial orders over words, considering that several tweets in a collection can be represented as a blend of topics. Additionally, we investigate
how to identify whether a Twitter message (tweet) refers to a disaster or not, in order to assist in more effective and efficient handling of unpredictable disastrous situations. Therefore, we propose a multi-class classification model to identify how people interact with Twitter during Hurricane Michael.

To our knowledge, this is the first study to formally apply a three-level model (Clustering-Classification-Ranking) to social media messages, in order to identify four types of user participation during disasters (asking for information, reporting, requesting/offering help, and other) and then prioritize messages based on importance to emergency responders.

6.2 Dataset and Annotation

Hurricane Michael, a destructive natural disaster in 2018, created catastrophic damage in the affected areas, including Florida, Mexico Beach, Georgia, and the Florida Panhandle. In addition to billions of dollars in damages and several fatalities, survivors faced significant impacts. During such life-threatening emergencies, affected and vulnerable people, humanitarian associations, and other concerned authorities search for information helpful to mitigate a crisis or to help others. People increasingly use Twitter during natural disasters and emergencies. Research studies have exposed the usefulness of the data available on Twitter for several disaster response tasks. In this study, our goal is to identify users’ posts (tweets) based on the content of the tweets.

6.2.1 Data Collection

We collected data using the Twitter streaming API, filtering on hashtag (#HurricaneMichael) and the terms: Hurricane Michael, emergency, Injured, dead, and damage. The collection began October 01 at 12:00 am EDT and ended October 31 at 11:59 pm EDT. During high volume periods, the collection was rate-limited at 50 tweets per second. Our dataset contains around 3 million English tweets where Figure 6.1 shows the volume of tweets per day. For the filtering stage to minimize the irrelevant tweets, we worked to identify keyword-based matching as follows: help or Resident or recovery or victim or Injured or dead or Infrastructure or utility or damage. Our sample included approximately 200,000 tweets.
6.2.2 Amazon Mechanical Turk Annotation

A small random sample (3037 English tweets) was selected and uploaded to Amazon’s Mechanical Turk (MTurk). Three MTurk annotators with the following criteria were requested: (1) U.S. residents with a hit approval rating of 94%, (2) classified as a master, and (3) English language proficient. Annotators were paid USD 0.20 per tweet. Each tweet was labeled three times, once per annotator. Before the annotators began the task, to facilitate the labeling process, some tweets were shown as examples. The tweets were coded into one of the following types:

1. Asking for information: These tweets ask questions that can be answered. Questions related to Hurricane Michael included: What to do? When Hurricane hit? Evacuate or stay at home? Where is the nearest shelter? Questions were asked for the purposes of information verification or instructions to handle certain situations. These tweets also mentioned the person or organization who could answer the question.
• Example 1: “A Florida won’t be opening shelters for Hurricane Michael Why?”

• Example 2: “Tropical Storm Michael is forecast to reach hurricane strength in the Gulf of Mexico and move toward the Florida panhandle. After that the question is where does it move in”

• Example 3: “@NWSNHC Is this going to be #Michael and a Central Gulf Coast Storm or a North Eastern Gulf Coast Storm? Good Question”

2. Reporting: Tweet (Message) contains the following: Tweets in this category contain information on the following: (1) injured or dead people, (2) infrastructure and utility damage (such as buildings, bridges, roads, houses and other utility services such as power lines and water pipes), (3) missing/found people, or reports of people affected due to the disaster, and (4) warnings, cautions, and advice about the disaster (may include URLs).

• Example 1: “Hurricane Michael killed at least 26 people in Florida.”

• Example 2: “Hurricane Michael hit my grandparents home in PCB that I spent my childhood summers in and holds a lot of memories for me with my family. they were able to evacuate and are safe in ATL for now prayers for them and anyone else effected””

• Example 3: “Hurricane Michael leaves 90 percent of Tallahassee homes without power.”

• Example 4: “Tree down on a home in Williamsburg this morning. Fortunately, @WilliamsburgGov says no one hurt, but a good idea of the damage left behind by #Michael.”

• Example 5: “Deborah Jones is missing from Panama City Beach. Went missing during #HurricaneMichael Her picture is below. If you have any information on her whereabouts, please contact your local police department.”

• Example 6: “More than 1,300 missing in Florida after #HurricaneMichael.”

• Example 7: “Make sure you sign up for #AlertBay before #Michael gets here so you can stay up-to-date on warnings, watches, road closures and more. You can sign up on your phone, tablet and/or desktop at https”
• Example 8: “Hurricane #Michael is expected to make landfall on the Gulf Coast Wednesday, so make sure to prepare now. Here’s what you need in your emergency prep kit.”

3. Requesting or Offering help: These tweets request or offer any kind of help, donations, medical needs, information, goods, money, food, water, shelter, volunteering, etc. These messages may also contain donation offers.

• Example 1: “@wsbtv studios in Midtown and Caring 4 Others on Browns Mill Rd. in SE Atlanta. Needs: bottled water, household cleaning supplies, non-perishable foods. Come help south GA!”
• Example 2: “Anything would help me and my family out appreciate everything and everyone through this hard time”

4. Other: Tweets in this category (1) contain nothing related to Hurricane Michael or its effects, (2) show sympathy, prayers, or emotional support, (3) express complaints, frustration, or sarcasm, (4) contain personal messages, holiday greetings, or chatter.

• Example 1: “(The Sun):#Food thrown away by supermarkets will be turned into meals for the poor, #Michael Gove announces : LEFTOVER food from supermarket giants will be turned into millions of meals for the poor, Michael Gove will reveal.”
• Example 2: “#HurricaneMichael makes landfall, our entire nation is keeping the families in the line of danger in our prayers.”
• Example 3: “Great work by Amanda and Codie this week as they survey the damage left from Hurricane Michael.”
• Example 4: “Fishing for “reds” with my little guy today- first time I have been on the water since HurricaneMichael”

From 3037 tweets, 80% of final tweets were distributed over (Asking for information, Reporting, and Requesting or Offering help) to Hurricane Michael crisis, and 20% determined as other.
6.3 Method

In this section, we developed a three-stage framework for predicting high-priority tweets during disasters. Figure 6.2 presents a high-level picture of our framework used to collect a series of data over a given time frame for a given location, the State of Florida to be specific. Its components are split into four main steps (green color): (1) Data collection, (2) Clustering, (3) Multi-class classification, and (4) Ranking. The Clustering step involves applying Topic Modeling approach. The Classification step involves four things: (1) Send tweets to Amazon Mechanical Turk for labeling, (2) Preprocessing, (3) Feature Extraction and Selection, and (4) Machine learning classifiers. Finally, the Ranking step includes building a dictionary (disaster terms) to decide whether this tweet has a high priority or not.

6.3.1 Clustering

In this step, unsupervised machine learning proposes a function to extract hidden structure from “unlabeled” data. Typical situations for applying unsupervised learning algorithms involve (1) Data Exploration (Topic Modeling), (2) Outlier Detection, and (3) Pattern Recognition. While there is a full-scale list of possible clustering algorithms, I will try to cover the fundamental ideas of the Topic Modeling algorithm.
6.3.1.1 Topic Modeling

Developing a useful process for handling the exponential growth of social media data requires adopting innovative methods or tools that deal with the conditions of a building, seeking, ordering, and querying extensive groups. Research of machine learning has evolved some ideas and models for detecting patterns of words in datasets groups such as topic model. Topic models afford a suitable way to investigate the large unclassified and disordered message. A topic comprises a cluster of terms that usually occur together. Topic modeling can correlate words with the same meanings and differentiate between uses of terms with varied meanings. Recently, the latent topic technique has become so widespread as a fully unsupervised technique for topic exploration in extensive dataset collections, including models, such as Latent Dirichlet Allocation (LDA). LDA is a text mining algorithm that is built on statistical (Bayesian) topic models, and it is very widely used. LDA is a generative model that attempts to simulate what the writing process is, so it works to generate a document given a topic. In general, all topic models are built on the same underlying hypothesis: (1) Each dataset collection consists of a variety of topics, and (2) each topic consists of a combination of terms (words). Three central parameters need to be optimized: (1) K, which gives the number of topics, (2) Alpha, which indicates how many topics a dataset potentially has, and (3) Beta, which manages the number of terms per dataset.

One of the popular methods to process textual data under LDA is TF-IDF. TF-IDF stands for “Term Frequency-Inverse Data Frequency.” Term Frequency (TF) presents the frequency of the words in each tweet in the dataset. Inverse Data Frequency (IDF) is utilized to estimate the weight of rare terms (words) overall tweets in the dataset. Words that rarely occur in the dataset become a high IDF score.

Considering we are working with tweets, we examined different values for K (number of topics). The design is challenging to train, and the outcomes require a continued dose of repetitions.

6.3.2 Multi-class Classification

In this work, we applied supervised learning for classification to train a model on known input (Tweets + Labels) and output data so that it can predict future outputs. The objective of using
a multi-class classification method is to divide the dataset into four categories: (1) Asking for information, (2) Reporting, (3) Requesting or Offering help, and (4) Other.

6.3.2.1 Data Preprocessing

Tweets usually come with many inconsistencies, missing values, noise, or redundancies. We used text-processing methods such as:

- Tokenization: Break the tweet into sentences and the sentences into words.
- Lowercase the words and eliminate punctuation.
- Discard tweets with fewer than three words.
- Exclude all stopwords. We believe that the words that arise more frequently should have a higher weight (importance) in textual data analysis. However, this is not always the case. Words such as “the”, “is”, and “you”—named stopwords—appear the most in a corpus of text, but are of very small importance. Alternatively, the rare words are the ones that support in separating between the data, and provide more weight.
- Words are stemmed (reduced to their root form).

6.3.2.2 Feature Extraction and Selection

Useful features are the heart of any machine learning technique. Dimensionality decline as an essential step to machine learning is efficient in eliminating unnecessary and repetitive tweets and improving learning accuracy. This section reviews several classification methods to predict the four types of community engagement using text feature extraction, applying supervised learning models such as Random Forest, Support Vector Machine, and Decision Tree. We name four types of features based on their field:

- Term frequency-inverse document frequency (TF-IDF) is combining term frequency and inverse document frequency by multiplying the term frequency weight by the inverse document frequency weight. TF-IDF is calculated as:

\[
TFIDF(t) = TF \times IDF
\]  

(6.1)
• Psychometric features have been selected in fields where measurements of some features of personality psychology are needed. For example, it has been utilized to find an individual’s character connection to a provided set of features. In this study, the psychometric features are included to assess the strengths and weaknesses of a person while he/she is tweeting about a disaster.

• Linguistic features are point to studying Twitter users’ linguistic attributes in their contemplative posting, which can make it easier to grasp the range and viewpoints of their thought and interaction approaches. It comprises two classes: (1) grammatical features, and (2) summary variables, which involves the following attributes: (a) analytical thinking, (b) social situation, trust, or leadership, and (c) emotional tone.

• Twitter-specific features refer to characteristics unique to the Twitter platform. There are various forms that users on Twitter engage with:

  (a) Retweet Ratio: Whereas there will be limitations, retweeting is a reasonable metric of fame for a tweet since it implies both endorsement and distribution. Retweet ratio can indicate events where users either agree with the message or wish to spread the information to more users. A post is more expected to be retweeted if its creator has multiple followers and follows many others users, or if the tweet includes a hashtag or URL.

  (b) Mention Ratio: A mention is a technique practiced in Twitter to ask other users to engage or follow a discussion in the form of (@username).

  (c) Hashtag Ratio: A hashtag is an essential characteristic of online social networks which can be injected anywhere in a message. Some hashtags are devoted mainly to events such as (#hurricane) which can be used as search key on Twitter for further tweets relating to a particular topic.

  (d) Link or URL Ratio: It is regular to include links when tweeting to point to detailed information or to share extra data. Tweets that have links to the same page may validate that these tweets refer to the same topic. Hence, the iteration of URLs is especially meaningful in crisis detection.
(e) Followees: The followers of a user are other twitter members who receive the user’s tweets and notifications. If someone follows an account, it will display in their followers list. The entire number of followers a user has is visible to everyone. Followings, on the other hand, are other people who the user engaged in their account’s topic or are a supporter of the account’s owner. The number of accounts a user follows is also apparent to everyone.

On the other hand, feature selection is one of the central ideas in machine learning that influences the performance of our model. The text features that we apply to train our machine learning models have an essential impact on the accuracy we want to accomplish. From the previous step, the total number of extracted features was around 6750. This is a significant number of features, which raises the question of how to select features. To resolve this problem, we started with reducing overfitting by eliminating repetitive tweets because less duplicated data means a lower chance of making decisions based on noise. Features that excellently partition should provide the highest amount of information. While the Irrelevant features should deliver no information, the dilemma that we encounter is to decide which attributes in a given collection of training features is valuable for segregating between the classes to be learned. To execute this, we utilize entropy and information gain. Entropy provides us with a measure of impurity in our class. To optimize the features, we also used the Information Gain [108] approach for extracted relevant features only. Information gain (IG) measures how much “information” a feature gives us about the class.

### 6.3.2.3 Classifiers and Performance Measurements

The automated classification of posts into predefined classes has seen a booming interest in recent years because of the expanded availability of social media in several areas. The main objective of Supervised Learning techniques is to learn how to predict a random variable.

- **Classifiers**: we divide the dataset into two parts. The larger part we use for training (80%) and the smaller part we use for evaluation (20%). An experiment was conducted to evaluate the performance of the model under the selected three supervised learning classifiers using a machine learning tool named WEKA [109]. We compared classifiers that have frequently
been used in related work: Support Vector Machine (SVM) [110]; Decision Trees (DT) [111]; and Random Forest (RF) [113].

- Performance Measurements: to evaluate the effectiveness of our model based on our suggested features, we adopted the standard classification metrics. The most automatic way to assess the classification problem is to measure the accuracy (see Equation 6.5), the proportion of true outcomes that the classifier was capable of obtaining. As we know, the accuracy degree individually may be slightly deceitful because it is probable to reach great accuracy by predicting all instances as Positive. Precision, recall, and F-score measures are therefore employed to gather more insight into our framework performance. Precision refers to how often our predictions for a class are correct; recall refers to how often tweets are classified correctly as the correct class; the F-measure balances the data obtained from both precision and recall, and Area Under Curve (AUC) which is described by false positive rates on the horizontal axis and true positive rates on the vertical axis for varying thresholds.

\[
\text{Precision}(P) = \frac{TP}{TP + FP} \quad (6.2)
\]

\[
\text{Recall}(R) = \frac{TP}{TP + FN} \quad (6.3)
\]

\[
F - \text{measure} = 2 \times \frac{R \times P}{R + P} \quad (6.4)
\]

\[
\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \quad (6.5)
\]

The terms TP and TN, FP and FN, match the results of the classifier facing amazon annotators decision. The terms Positive and Negative introduce to the classifier’s prediction, and the terms True and False indicate whether the classifier prediction agrees to the annotators’ judgment.

6.3.3 Ranking

Social media messages are very diverse in their intended purpose for operational response, extending from immediate calls to offers of help to emotional posts. Consequently, instantly ranking messages with the help-seeking intention that expect a quick, timely answer has become a crucial necessity for authorities in emergency administration. We study a common type of emergency requests, directly after looking at the general rules from FEMA (Federal Emergency Management
A high-priority (urgent) tweet is a message that: (1) asks for or offers help, such as food, shelter, or medicine during a disaster and (2) reports critical information about the current condition, such as flooding, dead, found, or lost people.

The essential feature of request posts is that it requires assistance that can be given or asks a question that can be easily and directly answered. For ranking messages (tweets), we recommend a supervised learning approach for automatic classification and predicting high-priority tweets. In automatic classification, the objective is to classify a message as urgent or not. In our analyses, we have studied only binary levels with the help of creating a disaster dictionary.

As we know that timely responding by sharing beneficial information before, during, and after a disaster is vital for those expected to make life-changing decisions during serious emergencies. With social media, especially Twitter, the problem of finding accurate, helpful information becomes further complicated. We intend to propose a framework for enhancing the response in the sampling of Twitter interactions that can guide us to a comprehensive situational awareness of disaster situations. Therefore, we create “a dictionary” of the 420 most frequently used disaster words on Twitter. These words are associated with hurricane disasters. Next, we used the dictionary mentioned earlier as a feature to find out which tweets need instant action and which tweets have a normal degree of urgency.

6.4 Results and Discussion

In this section, we display the results from the proposed Clustering-Classification-Ranking framework, examining their performance with the recommended features of the model. We then discuss the limitations of this model and directions for future research.
6.4.1 Clustering Results

We collect sentiment analysis to define how people’s beliefs and opinions evolve as hurricane events proceed. To assist concerned officials and emergency teams, as well as to speedily filter Twitter data, we use topic modeling methods to address different topics during each day.

![Figure 6.3: Topic waves during hurricane Michael.](image)

As an emergency responder, you need to view the whole picture of the disaster situation. As shown in Figure 6.3, Topic Modeling reveals the “topics” that have been most discussed during the time collection for Hurricane Michael from (October 01, 2018) to (October 31, 2018).

From the figure above we can see that (15) hidden topics have been generated based on word frequency. Each topic is a mixture of weight and keywords that contributes to the topic. For example, from around 91,000 tweets we extracted the following topic (Hurricane Michael Make Landfall), which is represented as: (0.050, Michael) + (0.048, Hurricane) + (0.046, Make) + (0.044, Landfall) + (0.044, atmospheric) + (0.043, floodwaters) + (0.040, zoom) + (0.039, unit) + (0.035, feeling) + (0.032, effected).

Clustering (unsupervised method) can be applied to reveal the noticeable themes in a massive dataset. Once an unsupervised model has shown the properties and contents of a dataset, then one might adopt more accurate algorithms such as supervised classification for particular topics of interest.
Figure 6.4: Distribution of daily sentiment for hurricane Michael.

On the other hand, identifying such sentiments from online social media platforms can help emergency responders understand the dynamics of the messages, e.g., the users’ anxieties, fears, and the emotional impressions of communications between members. To perform the sentiment analysis, we used Crimson Hexagon [46] tool to elicit the sentiment tags that are being expressed in the tweets. The results obtained from the preliminary analysis of sentiment are summarized in Figure 6.4.

On the other hand, identifying such sentiments from online social media platforms can help emergency responders understand the dynamics of the messages, e.g., the users’ anxieties, fears, and the emotional impressions of communications between members. To perform the sentiment analysis, we used Crimson Hexagon [46] tool to elicit the sentiment tags that are being expressed in the tweets. The results obtained from the preliminary analysis of sentiment are summarized in Figure 6.4.
One can obviously witness that the “sadness” sentiment dominated during days 9 to 15, which represents the time when the disaster hit Florida. Moreover, Fear and Anger have appeared during the same interval. Our interpretation in this matter might be related to (1) the nature of people’s fear of the hurricane and its consequences (2) the issues encountered by affected people where there is no answer from authorities or because of delayed response.

### 6.4.2 Multi-class Classification Results

The results show that the incorporation of all features (TF-IDF, Psychometric, Linguistic, and Twitter) produced the best accuracy (84.22), and F-score (77.32) by implementing the Random Forest classifier. The next best accuracy was 82.4% using TF-IDF approach of Random Forest classifiers trained and tested among all other different feature sets. Classifiers trained on Psychometric and Linguistic features individually presented lower results compared to (All Features) approach results.

Table 6.1 shows the best accuracy, AUC, and F-measure of each classifier trained and tested on a single feature set, and classifiers results trained and tested on combined feature sets. A comparison of accuracy for each classifier is shown in Figure 6.5.
Table 6.1: Multi-class results of three proposed classifiers.

<table>
<thead>
<tr>
<th>Feature set</th>
<th>RF</th>
<th>SVM</th>
<th>DT</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Acc.</td>
<td>AUC</td>
<td>F 1</td>
</tr>
<tr>
<td>TF-IDF</td>
<td>82.4</td>
<td>86</td>
<td>75</td>
</tr>
<tr>
<td>Psychometric</td>
<td>71.25</td>
<td>76</td>
<td>71</td>
</tr>
<tr>
<td>Linguistic</td>
<td>64.13</td>
<td>68</td>
<td>67.2</td>
</tr>
<tr>
<td>Twitter</td>
<td>69.65</td>
<td>59.8</td>
<td>60.43</td>
</tr>
<tr>
<td>All Features</td>
<td><strong>84.22</strong></td>
<td><strong>87</strong></td>
<td><strong>77.32</strong></td>
</tr>
</tbody>
</table>

6.4.3 Ranking Results

When a disaster makes landfall, the rescuers, police officers, firefighters, or paramedics want to know which places to go to first and which messages need to be prioritized for immediate response. In this section, a binary classification algorithm used in order to prioritize messages to help the emergency manager/social media analytics to rank tweets based on the contents.

The results show that TF-IDF feature produced the best accuracy (77.4), and F-score (70.1) by implementing the Random Forest classifier. The next best accuracy was 75% using the combination of all suggested features (All Features) using Random Forest classifiers trained and tested among all other different feature sets. Classifiers trained on Twitter features individually presented lower results. Table 6.2 shows the accuracy (Acc.), Area Under Curve (AUC), and F-measure (F1) of all suggested classifiers. At the same time, a comparison of F1 scores for each classifier is shown in Figure 6.6.
6.5 Summary

Social media performs an important task in the management of crises such as natural disasters and can further be utilized to build and improve situational awareness and decrease the time needed to respond to affected people. It is essential to an early response of a disaster during a huge tweet getting posted to the Twitter platform. In this paper, we analyzed Twitter data collected between October 01, 2018 and October 31, 2018 that was related to a natural disaster (Hurricane Michael) in Florida. A three-stage framework for clustering-classification-Ranking is proposed. It shows that implementing a multi-class method on a combination of (TF-IDF, Psychometric, and Linguistic)
features performs well at identifying the four types of community engagement posts during the disaster. Additionally, using a topic modeling approach yielded 15 hidden topics being discussed by people and organization during the data collection period. While we consider that our outcomes are encouraging, we do see that there is still some uncertainty in the efficacy of our ranking technique. To improve performance, we need to incorporate other feature types, such as the credibility of the shared URL, and apply term scoring.
CHAPTER 7

CONCLUSIONS

Social media can be handled as a central real-time method of communication. It affords several approaches to distribute information in a quick, affordable, and efficient form where both victims, volunteer groups, and authorities can place their queries and solutions at the same platform in real time. This real-time interaction assists the decision-making needs of affected people and crisis management officials through time-critical situations. Moreover, it can aid in coordinating and managing response and recovery efforts and locating experts for real-time consulting and to mentor new emergency managers.

Twitter performs a significant role in identifying affected people, obtaining their status information, and also collecting data on various rescue activities performed during both human-made disasters and natural disasters. In this dissertation we aimed to build a machine learning approach to predicting community engagement on social media during disasters. Additionally, this work proposed an automatic model to identify high-priority tweets in disaster situations. The implementation of such a model will help to minimize the workload of emergency managers during the process of obtaining, preprocessing, and extracting meaningful information in a disaster situation.

In chapter 3, we presented a topic modeling technique for exploring, identifying, and analyzing the hidden topics in our large unlabeled dataset. Topic modeling provides us with methods to organize, understand, and summarize large collections of textual information. We also implemented an event detection method to detect and distinguish between an ongoing event and disruptive event. The results indicate that it is not enough to consider temporal, spatial, or sentiment topics in isolation. Instead, the aggregate of features leads to clearer distinctions between events. Our study shows how Twitter data can be used to analyze different topics, such as the case of the sewage crisis in Barbados. This thesis presented original work to integrate several data mining techniques
for detecting events for a specific time period and place, such as data preprocessing, unsupervised machine learning, and topic clustering.

In chapter 4, we designed a binary and multi-class model to discover the related tweets that contribute to situational awareness concerning an emergency incident and to predict the types of online community engagement during the environmental hazard that occurred in Barbados. We adopted Twitter-content, linguistic-based, psychometric, and sentiment-based features to improve the performance of classification. We believe that this study is the first to design a system that attempts to classify the types of online community engagement into four categories: reporting information, expressing negative engagement, expressing positive engagement, and asking for information. We presented an extensive analysis of various features related directly to social media data and show how they can be used to distinguish between relevant tweets and irrelevant tweets.

In Chapter 5, we investigated the use of ensemble predictive modeling and its effect on combining multiple methods to enhance classification performance. Our model consists of data collection, data preprocessing, feature extraction and classification, and an ensemble model. We concluded that this approach is more interesting and helpful to utilize for a better prediction model, as opposed to combining the feature-based model. Therefore, understanding the features of social media content that single out disruptive events is a key motivation behind this work. One way to optimize the identification of the patterns and signals that indicate an event is to undertake feature selection (optimization), because not all features are expected to lead to better system performance or contribute equally towards improved machine classification and/or clustering accuracy.

In Chapter 6, we proposed a three-level clustering-classification-ranking model with three main goals: (1) identify the optimum number of independent topics present in the corpus, (2) predict the four types of online engagement of people and communities during the Hurricane Michael disaster, and (3) apply a binary classification on the dataset to classify the relevant tweets into two groups: high-priority and low-priority tweets. The major contribution of this research is the development of text mining algorithm to detect hurricane-related tweets in English languages. The other contribution is the classification of these tweets into high and low priority classes to identify tweets needing urgent attention.
7.1 Discussion

The purpose of this study was to gain an understanding of the role of social media during disasters, and how we can analyze and predict the types of online community engagement on Twitter related to disasters. We also explored how to develop a model to rank Twitter data requests for emergency responders. However, while there is a growing body of research aimed at understanding how people use social media during disaster events, we want to consider two additional questions raised by our research: (1) What are the economic factors associated with Twitter use? (2) What are the ethics of social media use? What concerns do practitioners have about using social media?

Based on one study [132], 77% of American citizens have smartphones as of 2017. This technology has given people an unprecedented ability to rapidly access, consume, and produce information. Pew Research Center [133] showed that 80% of social media usage happens through mobile technologies, and 24% of Americans are Twitter users. Twitter is an especially effective way to obtain real-time information when no information is being reported through conventional methods. If something has happened and a number of people were present, there’s probably a tweet floating around somewhere about it. This is because of the way Twitter is structured.

The demographics of Twitter users have been discussed in different fields such as race, age, income, and gender. As an example, the work in [134] analyzes the hashtag #BlackLivesMatter (created after the killing of Trayvon Martin in 2012) and found that more African-Americans engage with the hashtag; additionally, young females are more likely to actively engage in debate using the hashtag than men, yet the proportions of white and African American females are similar. Another study found that low-income respondents had higher levels of risk perception but fewer resources for engaging in preparedness actions [135]. Twitter users are younger, more highly educated and have higher incomes than U.S. adults overall. Twitter users also differ from the broader population on some key social issues [133].

The use of social media as a recruitment tool for research with humans is increasing, and likely to continue to grow. Compared to traditional platforms such as surveys or interviews, social media platforms provide researchers with a huge opportunity to gather data that would otherwise have taken much more time and resources to obtain. Although traditional ethics frameworks can inform researchers to some extent in this, social media data brings new contextual challenges that the more
traditional approaches are not equipped to deal with. The research in [136] indicates that there is no specific regulatory guidance and few resources to guide the Institutional Review Board (IRB), investigators, and others on the use of social media for research recruitment.

Some of the privacy issues offered by the practitioners were about the information that transpires across the Internet highway. Some samples of this include the fact that they are open to basically everyone. In Twitter, users “follow” other users, meaning that they subscribe to read the content of their followees. Following a user on Twitter is an asymmetric act and does not require mutual consent. In most cases uses of these sources should be classified as non-human subjects research, even when they include identifiers via videos, photos, and text [137], [27].

7.2 Contributions

The main objectives listed at the beginning of this study have been met as follows:

• This study constructed two labeled datasets. The first one is related to Barbados (Caribbean island) which contains 30,358 tweets from January 1, 2014, to May 31, 2018. The second dataset is for Hurricane Michael, which made landfall in Florida. The dataset is a collection of 200,000 tweets collected between October 01, 2018 October 31, 2018.

• Two-level model for extracting relevant tweets during disasters and to classify the online community into four sub-classification.

• A topic modeling approach attempts to extract the most important topics per dataset and event detection framework to distinguish between ongoing events and disruptive events.

• A novel three-level model to rank high-priority tweets in disaster situations.

7.3 Limitations and Future Work

Many research using platforms same Facebook or Twitter will apply keyword filtering as a beginning round because relevant tweets represent a minority number of the whole dataset. In this dissertation, we limit ourselves to a specific dataset, which is keyword filtered twitter stream. This action is capable of obtaining a considerable number of crises but does not get all crisis-related tweets, as users may address crisis or emergency situation without straightly using the keywords
in our list. The method can be logically a correct way for collecting relevant content, even though it may drop data that is relevant but uses terms are not in the keyword list, or it may extract irrelevant data that use terms in various ways.

The keyword filter may carry some possible bias in our dataset. Hence, a future direction is to enlarge the binary and multi-class crisis track classifiers to the full extent of tweets. There are some difficulties in this direction. First, many researchers do not have access to collect and process the full range of tweets stream. One trade-off might be to strategically expand the keyword filtering to include additional words that capture people behaviors before, during, and after disasters. Despite, still with this approach, it will be tough to obtain all crisis events because they can be expressed in several forms. Besides, Twitter places a capacity limit of tweets open in public streaming APIs. It is imperative to avoid this apparent bias by accurately picking keywords. Second, related crisis tweets estimated to be a small portion of public social media posts and obtaining sufficient crisis tweets examples to develop classifiers expects a tremendous amount of annotation work and time-consuming. To deal with this situation, we may train and test the classifier with the specific dataset as what we made. A different technique we might use is active learning to find various examples from the dataset to be labeled, which can be used to train a classification model.

My next goal will be designing a social media monitoring tool to bring social media analysts, emergency managers, volunteers, and officers together to support collaboration between them during disasters. I will implement machine learning and integrate it with a mapping system into the suggested tool. The framework consists of four main parts, a web application interface, data upload and storage, analytical elements which include, clustering, classifiers, tweets processing modules, ranking tweets, and tweet retrievers that collect raw data from Twitter. However, before launching the tool, it is essential to know who the target users and communities are. For local-level emergency management agencies, this may consist of looking at the demographics of the community. This will help identify the ages, languages, and educational levels of the users. If there is a diverse community or workers in the area, multilingual considerations will need to be taken into account and implemented.

There are a few other issues from the perspective of recovery that we need to caution readers about. While our current work focuses only on creating engagement opportunities between common citizens and decision makers, we do not address the specific issue of how our contributions can
impact decision making. There are related studies that attempt to do that [138]. In this context, a particular avenue of concern is a situation wherein existing disparities in communities are worsened as a result of leveraging social media data in recovery efforts. For instance, there are studies that caution that since it is likely that more frequent users of social media platforms could be higher placed in the socio-economic scale, it may happen that these people are more likely to be catered to by decision makers instead of more needy people (who could be less frequent users of social media platforms). These can worsen existing disparities [139], [140]. To compensate these, it is vital to collect data from multiple sources (e.g., 311 data), sending volunteers to more needy communities, and also other sources for superior and more fair decision making under disasters.
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