

Research Article

Sentiment Analysis on Response of Terrorism on Social Media

Pooja N. Jain and Archana S. Vaidya

Department of Computer Engineering Gokhle Education Society's R. H. Sapat College of Engineering Management Studies and Research, Nashik, India

Received 10 Nov 2020, Accepted 10 Dec 2020, Available online 01 Feb 2021, **Special Issue-8 (Feb 2021)**

Abstract

With the very increasing number of platforms of online social media, the world has diminish even further with respect to communication and exchange of knowledge point of view. No Matter how, at times of communication, can be obstruction when misused using such extensive social media tools. The acts of terrorism become apparently suitable as the hurdle of communication is neutralized. The propagation of very unpleasant content becomes much more easier and even recruiting anti-socials gets easier. Strangely, these social media platforms are the ones that show crucial nature during such crises situations. On the use of social media during a time of terrorist attack the present study meaningfully address how to use social media for public communication with emergency organization, police or military during terrorist attack. Then how to perform post-attack social media analytic and how to detect acts of terrorism using Naive Baye's and K-means clustering for clustering of tweets and to find trends, unrest and distaste using social media analytic. With this objective, we are trying to work in this command and is service for influencing to counter attack terrorism as it is the get off the hook for our country in the wake of latest Uri and Pulwama attack.

Keywords: Sentiment analysis, social media analytics, terrorism

Introduction

Social media, plays a very essential part in a life for an individual as well as in functioning of a government. According to result of statistics, it shows that the worldwide population is about 7.72 billion where about 3.397 billion active social media accounts per person. The impact of social media on society and its people and the data that provokes in the wake of it has been argued broadly by [1]. The progress of 21st century can hardly disclose without the manifestation of the part of social media in it. It wouldnt be exaggerating to say that social media is appearing in all spheres of life, like education, health care, business, disaster management, politics, tourism industry and also in use of media sharing and entertainment needs no mention. Like benefits there are some Misuse of social media[2], On one hand this may seem to be abridging a communication gap and faster news delivery among people; however, on other hand, it is being heavily misused by many. Misuse on a level of genocide, murders, bombings, conspiracies etc.

In a study conducted by [3], they states that about 90% of terrorist activities online are conducted via social media platforms while 76% of U.K. terrorists engage in internet to research and sterilizing their actions A potent literature conducted by [4], revealed the extensive use of social media by Islamic State (ISIS) to advertise their ideology and ennoble members and

supporters. Misuse of social media has been examined by [5], who presents the social media activity and online presence of media mujahedeen who are suspected to be the supporters of jihadist groups and circulate propaganda content online. The ISIS and social media involvement have been briefly examined and presented by [6][7]. On a positive side, social media can also be of a great help for military, defence and public with regards to safety during such regrettable terrorist event as those disclosed by [8][9]. A exhaustive review of how social media tools are being used in troubles by the public, emergency organizations and academic institutions has been well reported by [10]. The behavioral side of social media has been explored by [11] to assess the evolution of social media and social networking from 1997 to 2017. Policing of terrorism using the data from social data and the counter measures to be taken against it are lucidly explained by [12][13].

An overall perspective on the goodness and evil of social media in todays global synopsis has been distinguished by [14] wherein the author examines the clearly endless welfares of social media and the superstitions that it brings with it in different wheels of life. With the ever moving use of some famous social media like Twitter, Facebook, Youtube, Instagram, LinkedIn etc. there have been a factor of other social media platform surfacing and building strong toehold on the grounds of practical world. More the number of

networking options, greater is the risk of facing such unfortunate crises. The religious hypocrisy, terrorist attacks and cultural disagreement among the people of various fields, region or country rides enough hatred to give rise to dreadful attacks. It is highly necessary to manage safety measures, peace and counter terrorism using the quickest way possible. Use of social media is one of the way in this digital generation. We are defining the graph of Terrorist attacks of India like Uri and Pulwama by using google trends that shows the graph of use of social media increases during Uri attack of 18 September 2016 and Pulwama attack of 14 February 2019. Hence the current

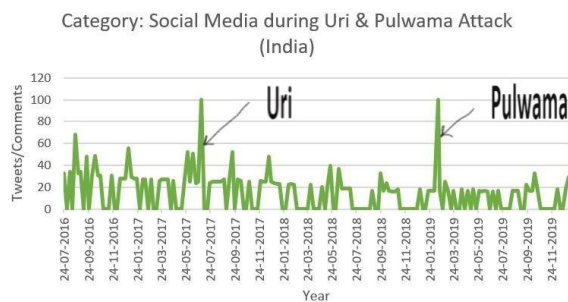


Fig. 1. Use of Social Media during platforms during Uri and Pulwama Attack of India

paper concentrates on collecting all the work and research with relevant studies, reported by various authors in last decades of years concerning the use of social media during a time of terrorist attack with a view to address following issues:

- How to use social media during terrorist attack for public communication with emergency organization and military or police
- How to identify acts of terrorism, crises and revenge using social media analytics
- How to perform post-attack social media analytics

With this objective, we also hope to inspire to work in this direction to counter attack terrorism as it is the need of the time for our country in the wake of recent Uri and Pulwama attack.

Review of Literature

M. Mirbabaie, D. Bunker, A. Deubel and S. Stieglitz defines Convergence Behaviour (CB) on social media during this crisis situation was studied in [15], demonstrates the case of Manchester Bombing of year 2017, where authors defines that the Mourners who retweets the most and create emotional content who pass the information into other communities.

D. Bunker, M. Mirbabaie, and S. Stieglitz, They proposed the case of Munich Shooting of 2016 reported by [16], who explained the behavior of individuals who choose to remain passive i.e. bystanders, The authors believe that Bystanders plays an important role due to their proximity to discord event

and their function as an eye-witness. This paper relise in the analysis of the bystander communication in both close and not so close proximity to a crisis event.

M. Mirbabaie, and E. Zapatka case study on Brussels Bombings in 2016, 2017 in [17], where work provides initial insights into analysing the tweets of top users and the retweets made by influential users for sensemaking, as it demonstrates what is worth propogating from the perspective of the key roles to support their audience in sensemaking.

A. Gupta, T. zyer, J. Rokne, and R. Alhadj case study on Paris Attacks of year 2015 in [18], Study investigated 4 keywords related to the attack: paris attacks, Bataclan, paris, and porteouverte This revealed some facts which were not reported in major newspapers. They constructed the timeline of the attack using the million of tweets.

T. Simon, A. Goldberg, L. Aharonson-Daniel shows study on Westgate Mall Terror Attack in Kenya of year 2013 in [19], here Twitter was very essential channel of communication between the emergency responders, government and the public. This highly facilitated the emergency management of the crises. TwitterMate was used to collect the data generated during tweets and also to analyze it. It also identifies the main hashtags surfaced by the crowd and specific Twitter accounts of individuals, NGOs and emergency responders. They investigated the number of tweets, geographical location of tweets and users demographics.

C. A. Cassa, R. Chunara, K. Mandl in [20][21], describes the Boston Marathon Bombing of 2013 They found specific keywords to appear regularly before the official public safety and media reports. People adjacent to the explosions posted messages within minutes via Twitter. This helped to detect the location and details of events and showcases the role of social media in the ahead of time identification and portrayal of emergency events.

P. Burnap, M. L. Williams, L. Sloan in Woolwich terrorist attack of year 2013, A model to predict information flow size and survival was developed by [22], with the help of data extracted from one of the popular social networking website Twitter. The information flow size and survival were modeled using zero truncated negative binomial (ZTNB) regression method and technique of Cox regression respectively. Data collected by systematic monitoring of twitter. They investigated a number of online behaviors with offline effects.

Martin Innes, Colin Roberts in [23], the case study on Murder of Lee Rigby of year 2013, They claimed that the Twitter data gathered after the murder of Fusilier Lee Rigby and explicate the inter and intra-community conflict dynamics.

O. Oh, M. Agrawal, and H. R. Rao in [24] case study on Mumbai Terrorist Attack of year 2011, The role of circumstantial information as an cause of terrorists opportunistic decision making in the volatile and extreme environment of the Mumbai terrorist attack has been studied. Using Situation Awareness (SA)

theory, they examined the data of Twitter posts of the Mumbai terror incident, explored the sideeffects of Twitter as a participatory emergency reporting system in the terrorism context. Also suggested a conceptual framework for evaluating information control in the linguistic context of terrorist act. Another regrettable attack on Mumbai took place on 13 July, 2011 when three serial blasts occurred [25] performed a content and activity analysis of posts on Twitter immediately after the bomb blasts. They explained that the number of URLs and @-mentions in tweets soar during the time of the crisis in comparison to what researchers have exhibited for usual situations. Furthermore, they also showed empirically that bulk of posts on Twitter during the crisis originates from non-authority users. on 26/11 Author identified how terrorists obtain and adversely use situational information, which is reported by networked citizens.

System Architecture

A. Problem Statement

Classification and clustering of tweets related to before and after an attack and performing Trend Analysis, Sentiment Analysis and Volume Analysis as per tweets. The proposed problem statement is prediction of Sentiments related to terrorism with the help of Machine Learning.

B. Architecture

The main goal and challenge of the system is analyzing Twitter/Facebook data for Terrorism related attacks to see the impact of tweeter on Indian people or particular place, situation and how people think or react about that incident. Our proposed system is analyzing system which is based on the mechanism that analyses user tweets using hashtags and Keywords. The proposed system collects tweets using this hashtags which are related to terrorism attacks. General public orientation toward these attacks can be studied using the tweets that people have posted on the Tweeter. Tweeter/Facebook is generally admired by academicians, journalists and Politicians. These tweets can be categorized on various policies such as geo-location analysis to analyses the view of peoples for that particular area which might help government to detect culprit or manage situation. The proposed system mainly focus on collection of tweets to make volume analysis to and out the popular days of attacks ; A trend analysis for trending factors or persons and a sentiment analysis to actually divide the positive and negative tweets for the attack so that making trend analysis on this tweets can help this government to act accordingly to improve their reputation at the same time it might help user to actually make a clear opinion about any attack. This will be conducted in 3 phases. To brief about it

- The phase one is connecting with tweeter/facebook and downloading the tweets.
- The second phase about loading these tweets on dataset for further analysis and
- The third phase is the actual analysis of Volume analysis, Trend Analysis and Sentiment analysis.

The architecture of the proposed system is as shown in the figure 2.

C. Algorithms

For implementation of this system following algorithms will be used:

- Algorithm 1: Tweet Processing Let T be the set of downloaded tweets.
 - Input: T
 - Output: A processed tweets with all unwanted word, space and special character removal
- Algorithm 2: Volume Analysis Let T be the set of preprocessed tweets.
 - Input : T
 - Output: A top hashtags, top active users and top trends.

Steps:

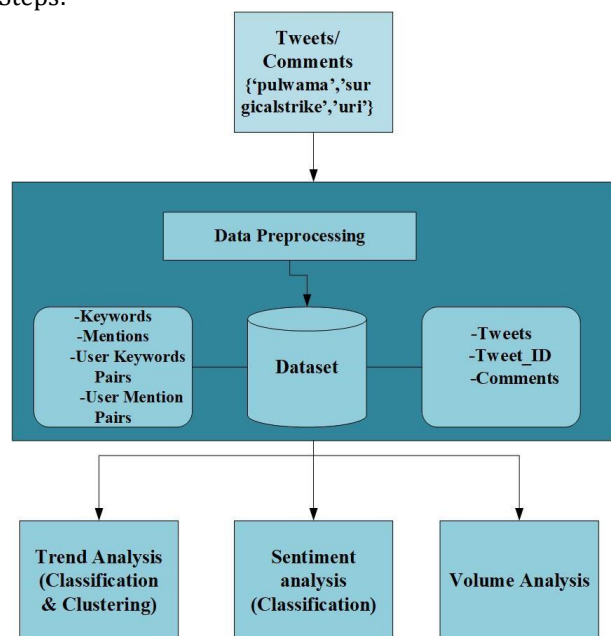


Fig. 2. Block Diagram of Proposed System

- Preprocess all tweets to remove unrecognized unicodes, garbage numbers, etc.
- Transfer all tweets from Local filesystem to HDFS.
- All tweets are split into words with whitespace as a separator and mapped to one, in map phase.
- All similar words are counted and written to dataset, in reduce phase.
- Transfer all tweets of output to local file system.
- Sort all tweets according to the count and filter all with hashtags, users and trends.

- Put all top hashtags, users and trends. - Visualize results for better prospect.
- Algorithm 3: K-Means Clustering Algorithm The tweets in dataset is given as input to K-means algorithm. firstly all attack related geolocations will be provided as centroid for Cluster. For every repetition, distance between center and tweet geolocation is checked and tweet is added to respective cluster. Distance between centroid and tweet is measured in terms difference between x,y co-ordinates. Clusters are updated at every iteration. After certain iterations, a loop is formed. For this loop we may observed that the k center change their location. This change is step by step until no more changes are done or in other words centres do not move any where. lastly these tweets are classified for identifying which tweet belongs to which phase. *K-Means Clustering*

Algorithm- Using Geo-Location

- Input: Let X be Set of geolocation points where,
 $X = \{X_1, X_2, \dots, X_n\}$
 Let V be Set of centers where,
 $V = \{V_1, V_2, \dots, V_n\}$ - Output: Formation of Clusters - Steps:
- * Pre-processing: where all tweets pre-process separately and find out unique terms and TF-IDF of each unique term.
- * Create set of tweet vectors by using dictionary of unique terms.
- * Provide the numbers of clusters to be quantified.
- * For initial Centroids of the clusters, provide the TF-IDF values for centroid from vectors randomly.
- * Transfer clusters and vectors from Local filesystem on dataset * Repeat
- Determine closeness in terms of TF-IDF of each vector with every cluster centroid, in map phase. · Assign vectors to cluster which is most closes to centroid of cluster, in reduce phase.
- * Until
- No more changes in the center of clusters or
- Cluster's object is not changed further
- Algorithm 4: Naive Bayes Classifier The orientation of users towards attacks, related topics can be analyzed from tweets. As per naive Bayes algorithm, map Reduce version will be resolved to classify tweets into positive, negative and neutral classes. Steps:
 - Create data for the classifier
- * Creation of a list of positive Words
- * Creation of a list of negative Words
- * Provide a tweet file which we have to be analysed
 - Design a Classifier
- * Extraction of the word feature list from the list with its frequency count
- * Using this words-list, create feature extractor which contains the words which will matched with a dictionary created by us showing which words are contained in the input passed

- Training the Classifier using dataset of training.
- * Generate Label of Positive-Probability which contains total number of positive words in input file
- * Generate Label of Negative-Probability which contains total number of Negative words in input file
 - Calculate the score probability for the positive and Negative word for individual tweet

$$p(t) = \sum_{k=1}^m score(w) \quad (1)$$

Here, t represents tweets, m is length of t , w is weight of t while $p(t)$ is polarity of tweets (positive, negative or neutral).

- * Calculate score of Positive tweets by total number of positive words in the tweet divided by PositiveProbability
- * Calculate score of Negative tweets by total number of Negative words in the tweet divided by Negative-Probability
 - Compare this probability to identify the tweet category as positive, negative or neutral that is anger, anxiety and sadness related to attack.

System Analysis

A: Mathematical Model

The proposed system S is defined as follows :
 Mathematical modeling of the current system can be formulated as,

$S = \{I, O, F, U\}$

I: Input

O: Output

F: Functions U: User

$I = \{U, UT, HL\}$

U = User having a tweeter or Facebook profile

UT = User Tweets

HL = Hashtags list provided as input for analyzing tweets

$O = \{UP, PT, TA, VA, SA\}$

UP = Retrieved User Profile

PT = Processed Tweets will remove unwanted data TA

= Trend analysis on processed tweets/comments will provide trending about attack

VA = Volume analysis as per date and location on processed tweets/comments

SA = Sentiment Analysis on tweets/comments will be categorizing them in positive, negative or neutral sentiments(anger, anxiety,sadness)

$F = \{TFpr, KE, KC, UC\}$

TFpr = Tweets/Facebook comments Pre-processing
 (Removing stop words, urls, unwanted tags)

KE = Keyword Extraction

KC = Keyword classification based on user view

UC = User clustering based on keywords and Hashtags

$U = \{SU, TU\}$

SU = System User

TU = Tweeter/Facebook User

B: Implementation Details

- Software Requirements:

Software Required (Server):

- OS : Windows , Linux
- Browsers : Opera , Chrome , Mozilla Firefox etc
- MODEM Drivers : For internet connections
- Developer Tools:
 - JDK 1.8 : For Java Platform
 - Eclipse-Oxysen : For Python code editing
 - Tweepy-master : For Twitter API connection
 - Setuptools : For build, install, upgrade, and uninstall packages
 - Hadoop : For storing data on map reduce
 - Latex : For Documentation
- Hardware Requirement:
 - RAM : Minimum 4MB
 - Hard Disk : Minimum 500GB
 - Processor : Minimum i5 processor

Results and Discussions

We have implemented this system based on java and Hadoop platform for MapReduce framework. For verifying the classification and clustering results will be tested. We have developed system in eclipse-oxysen environment.

- Datasets:

The dataset for the system is the terrorism attacks related downloaded tweets shown in Table I. Following steps shown how to download the tweets Steps :

- Registers on Twitter/Facebook development account to access APIs
- Issues the consumer Token and Secret key
- Enters Credentials
- Validate Credentials and issues OAuth verifier
- Request access token using OAuth verifier, Consumer Token and Secret key
- Issues Access Token and Secret key
- Request for content using access token and secret key
- Responds with requested Information

- Results:

As discussed in the system it will generate Sentiment analysis, trend analysis and volume analysis. The tweets downloaded from twitter/facebook database are processed with the help of porter stemming algorithm and users define functions. These data of filtered tweets will be used as input for various analysis modules generating the sentiment, trend, volume analysis. .

The system is able to download the tweets as shown in Table I of dataset module. Using this Tweets, System is able to identify Trending topics as well as

total counts of sentiments of total tweets and top hash-tags like who is responsible to that attack what government take actions related to that situation.

1. Accuracy comparison graph: Figure 4 shows that analysis of performance based on confusion matrix as per algorithms of existing system and proposed system, so proposed system has better accuracy upto 86% as compare to existing which has 72% of accuracy as in Table II.

Table I Tweets/Comments Related to Uri And Pulwama Attack

User	Tweets
XXXXXXXX	On the 3rd anniversary of the Uri Attack remembering our bravehearts who laid down their life for motherland.Tribute and Salute This attack changed Indias response narrative towards sponsors of terrorism. Now India will go to ANY extent against terrorists and their masters-Pak
XXXXXXXX	Uri attack: The Italian connection to Indian terror of uriattack
XXXXXXXX	BCZ NO EVIDENCE IS FOUND TO BLAME IT ON PAK: India releases 'guides' held for suspected involvement in UriAttack
XXXXXXXX	It would be helpful to mention the following: <ul style="list-style-type: none"> - 1) JeM is banned in Pakistan. - 2) Perp was a local Kashmiri. - 3) India blamed Pakistan w/o evidence in 2016 for the UriAttack.Months later, IND closed the probe having found no proof of PAK involvement.

For analysis of result following factors are considered: Confusion Matrix:

The experimental result evaluation, we have notation as

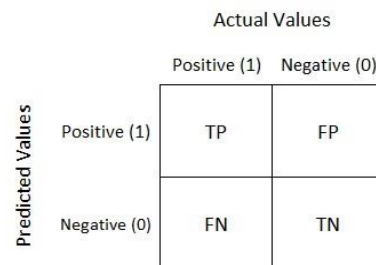


Fig. 3. Confusion matrix follows in figure 3 where Actual Values and Predicted Values assign in matrix as per following Values:

True positive: (correctly predicted number of instance)
 False positive: (incorrectly predicted number of instance), True negative: (correctly predicted the number of instances as not required)
 False negative: (incorrectly predicted the number of instances as not required), On the basis of this parameter, we can calculate following measurements

- Precision Classifier: Precision measures the exactness of a classifier. A higher precision means

less false positives, while a lower precision means more false positives. This is often at odds with recall, as an easy way to improve precision is to decrease recall.

$$Precision = \frac{T_{Pos}}{T_{Pos} + T_{Neg} + T_{Neu}} \quad (2)$$

- **Recall Classifier:** Recall measures the completeness, or sensitivity, of a classifier. Higher recall means less false negatives, while lower recall means more false negatives. Improving recall can often decrease precision because it gets increasingly harder to be precise as the sample space increases.

$$Recall = \frac{T_{Pos}}{T_{Pos} + F_{Neg} + F_{Neu}} \quad (3)$$

- **Scalability:** As we implemented this system on Hadoop platform its scalability increases.
- **Efficiency:** The task can be divided into multiple node and hence efficiency of system increases
- **Accuracy:** We have used user defined function along with porter stemming algorithm.

$$Accuracy = \frac{(All_{True})}{(All_{Data})} \quad (4)$$

$$F1Measure = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (5)$$

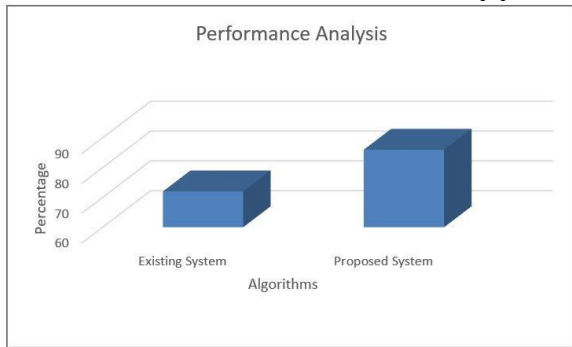


Fig. 4. Performance analysis based on confusion matrix as per algorithms of existing system Vs Proposed system

Table II Top Trends Identified by System With Sample Data Set

Sr. No.	Existing System	Proposed System
Algorithm	Data Mining Algorithms	Naive Baye's Algorithm
Precision	60.2%	65.4 %
Recall	85.5%	89.7%
Accuracy	72%	86%

2. Tweet Analysis Graph

Different Sentiments and their tweet counts are analyzed by sentiment analysis classification using Naive baye's algorithm, where various emotions are captured from tweets shown in Figure 5. and tweet counts with respect to type of sentiments are shown in Table III.

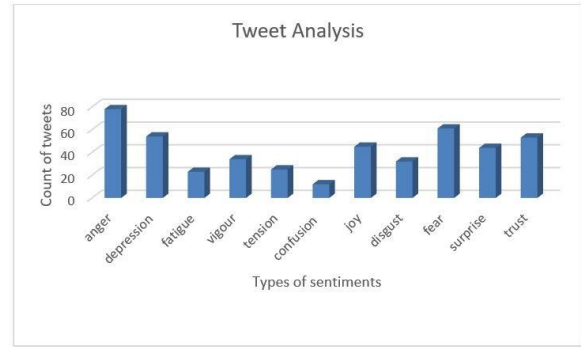


Fig. 5. Analysis of tweets as per various Sentiments

Table III Types of Sentiments With Respect to Tweet Counts

Sr. No.	Types of Sentiments	Tweets Count
1	Anger	78
2	Depression	54
3	Fatigue	23
4	Vigour	34
5	Tension	25
6	Confusion	12
7	Joy	45
8	Disgust	32
9	Fear	61
10	Surprise	44
11	Trust	53

3. Time Complexity

1) Sentiment Analysis

For Sentiment analysis the algorithm first iterate through all tweets to count the positive and negative probability; then it check tweet orientation by calculating score of the individual tweet and identify which party it belongs to. As there are two steps involved for performing sentiment analysis the running complexity of the sentiment analysis is $O(2n)$, where n is the number of tweets. 2) K-means Clustering Algorithm

The running time complexity of K-means clustering algorithm is $O(nkd)$, where n is the number of tweets to be clustered k is the number of clusters d is the number of iterations used

3) Naive Bayes Classifier

Naive Bayes is $O(nd)$, all it needs to do is computing the frequency of every feature value for each class.

Conclusion

With the increased use of social media the current work focused mainly on use of social media as a tool for terrorism. As a way to validate the proposed method, we will add the tweets of terrorism attacks to predict the sentiments using machine learning. Train data sets taken from development account of Tweeter

and Facebook. Our approach use Naive Bayes classifier which is a competitive method for Classification. There is scope for verifying the changed sentiments of the user before and after an attack. This model can be implemented not only to identify the acts of terrorism on social media but also as a safety tool, preventive measures and post-attack examination. The study can also include a machine learning approach to train a system to automatically classify the tweets and do a sentiment analysis on the Tweets/comments. This study has strong social aspect relies on proposed idea where as prediction model could be helpful to the Government and Police to manage the situation after an attack and find the culprit if possible.

Acknowledgment

A moment of gratitude to all those who have been grateful to me, in the making's of this Project. The first deserving gratitude would always be extended to my Project guide Prof. A. S. Vaidya (PG Co-ordinator), who helped me to develop a genuine spirit of research and intellect. Immeasurable appreciation to Prof. Dr. D. V. Patil, (Head of Computer Engineering Department) for his prompt counsel, inspiration and administrative support which helped us to focus on our work with greater enthusiasm.

I am also thankful to all the teaching as well as non-teaching staff of Computer Engineering Department and Librarian, GESCOE, Nashik. It is a proud privilege and a matter of honor to offer my overwhelming gratitude to all the soldiers of our country for sacrificing a lot for our safety.

References

- [1]. H. Chen and C. C. Yang, Special issue on social media analytics: Understanding the pulse of the society, IEEE Transactions on Systems,
- [2]. Man, and Cybernetics-Part A: Systems and Humans, vol. 41(5), pp. 826-827, 2011
- [3]. P. N. Jain, N. V. Alone, Importance of Social Media Analytics during elections: A review, International Journal of Computer Sciences and Engineering, Vol.6(9), Sep 2018, E-ISSN: 2347-2693
- [4]. R. M. Medina, Social network analysis: a case study of the Islamist terrorist network Security Journal, vol. 27(1), pp. 97121, 2014.
- [5]. S. Borau, and S. F. Wamba, Social Media, Evolutionary Psychology, and ISIS: A Literature Review and Future Research Directions, In World
- [6]. Conference on Information Systems and Technologies pp. 143-154, 2019, April
- [7]. A. Fisher, How jihadist networks maintain a persistent online presence, Perspectives on terrorism, vol. 9(3), pp. 3-20, 2015
- [8]. J. Hutchinson, F. Martin and A. Sinpeng, Chasing ISIS: Network power, distributed ethics and responsible social media research, Internet research ethics for the social Age: New challenges, cases, and contexts, pp. 57-73, 2017
- [9]. T. E. Nissen, Terror. com: ISs social media warfare in Syria and Iraq, Contemporary Conflicts, vol. 2(2), pp. 28, 2014
- [10]. H. N. Teodorescu, Using analytics and social media for monitoring and mitigation of social disasters, Procedia Engineering, vol. 107, pp. 325334, 2015
- [11]. D. Pohl, A. Bouchachia, and H. Hellwagner, Online indexing and clustering of social media data for emergency management, Neuro- computing, 172, pp. 168179, 2016
- [12]. T. Simon, A. Goldberg, and B. Adini, Socializing in emergencies A review of the use of social media in emergency situations, International Journal of Information Management, vol. 35(5), pp. 609619, 2015
- [13]. K. K. Kapoor, K. Tamilmani, N. P. Rana, P. Patil, Y. K. Dwivedi, and S. Nerur, Advances in social media research: past, present and future, Information Systems Frontiers, pp. 1-28, 2018
- [14]. R. Pelzer, Policing of terrorism using data from social media, European Journal for Security Research, vol. 3(2), pp. 163179, 2018
- [15]. F. Ali, F. H. Khan, S. Bashir and U. Ahmad, Counter Terrorism on Online Social Networks Using Web Mining Techniques, In International Conference on Intelligent Technologies and Applications, Springer, Singapore. pp. 240250 October 2018
- [16]. Y.K. Dwivedi, G. Kelly, M. Janssen et al., Social Media: The Good, the Bad, and the Ugly, Inf Syst Front vol. 20: 419, 2018
- [17]. M. Mirbabaie, D. Bunker, A. Deubel and S. Stieglitz, Examining Convergence Behaviour During Crisis Situations in Social Media-A Case Study on the Manchester Bombing 2017, In International Working Conference on Transfer and diffusion of IT, Springer, Cham. pp. 6075, June 2018
- [18]. Bunker, D., Mirbabaie, M., and Stieglitz, S. (2017). Convergence behaviour of bystanders: an analysis of 2016 Munich shooting Twitter crisis communication. In Proceedings of the Australasian Conference on Information Systems.
- [19]. M. Mirbabaie, and E. Zapatka, Sensemaking in Social Media Crisis
- [20]. Communication A Case Study on the Brussels Bombings in 2016, 2017
- [21]. A. Gupta, T. zyer, J. Rokne, and R. Alhaji, Social Network Analysis to Combat Terrorism: 2015 Paris Attacks, Social Networks and Surveillance for Society, pp.165-179
- [22]. T. Simon, A. Goldberg, L. Aharonson-Daniel, D. Leykin, and B. Adini, Twitter in the cross fire the use of social media in the Westgate Mall terror attack in Kenya, PLoS one, vol. 9(8), pp. e104136, 2014
- [23]. C. A. Cassa, R. Chunara, K. Mandl, and J. S. Brownstein, Twitter as a sentinel in emergency situations: lessons from the Boston marathon explosions, PLoS currents, vol. 5, 2013
- [24]. J. Lee, M. Agrawal and H. R. Rao, Message diffusion through social network service: The case of rumor and non-rumor related tweets during Boston bombing 2013, Information Systems Frontiers, vol. 17(5), pp. 9971005, 2015
- [25]. P. Burnap, M. L. Williams, L. Sloan, O. Rana, W. Housley, A. Edwards and A. Voss, Tweeting the terror: modelling the social media reaction to the Woolwich terrorist attack, Social Network Analysis and Mining, vol. 4(1):206, June 2014
- [26]. Martin Innes, Colin Roberts, Alun Preece and David Rogers (2018) Ten Rs of Social Reaction: Using Social Media to Analyse the Post-Event
- [27]. Impacts of the Murder of Lee Rigby, Terrorism and Political Violence, 30:3, 454-474, DOI: 10.1080/09546553.2016.1180289
- [28]. O. Oh, M. Agrawal, and H. R. Rao, Information control and terrorism: Tracking the Mumbai terrorist attack through twitter, Information Systems Frontiers, vol. 13(1), pp. 3343, 2011
- [29]. A. Gupta, and P. Kumaraguru, Twitter explodes with activity in mumbai blasts! a lifeline or an unmonitored daemon in the lurking, 2012