# A Study of Sentiment Analysis and Polarity Detection on Tweets Regarding Natural Disaster

MUNMI BHATTACHARYYA
Student
*Faculty of Engineering and Technology*
Assam Down Town University
Guwahati, India
Email:
munmibhattacharyya060218@gmail.com

PRASTUTI THAKURIA MALI
Student
*Faculty of Engineering and Technology*
Assam Down Town University
Guwahati, India
Email: prastutitm@gmail.com

NITUMANI SARMAH
Assistant Professor
*Faculty of Engineering and Technology*
Assam Down Town University
Guwahati, India
Email: nitumani.s@inurture.co.in

***Abstract*---The achievement of anything directly depends upon its client's perspectives. So how should we know whether the thing is successful. By utilizing sentiment analysis, we know regardless of whether the thing is compelling. With the assistance of sentiment analysis, we can examine people's perspectives, assessments regarding any matter, organizations, etc. Assessment of virtual entertainment gives basic information to specialists on call in a really long time of natural disasters. The Sentiment analysis is connected to recognizing the opinions, assumptions, mindsets. With the assistance of sentiment analysis individuals additionally can distinguish the positive and negative sentiments towards the disasters. In this paper, we examine the impressions of individuals who are influenced by a natural disaster event that is let out of Twitter data from different re-energize papers. We have taken absolute 25 papers in regards to this subject. By concentrate on that multitude of papers we have perceived that the extra judgments of the feeling values, fuzzy rationale could be introduced. Thus, it is seen that the sentiment analysis with the help of fuzzy rationale will help us for taking strong results here. We have likewise introduced a similar investigation of that large number of papers.**

***Keywords—Sentimental Analysis, Twitter, Natural Disaster***

## 1. INTRODUCTION

Social media have drawn in a huge number of clients to impart sentiments about their routines. The developing act of online media administrations helps following sentiment changes less complex and speedier [1][2]. With the rapid expansion of online media somewhat recently, the web has most certainly changed to enlarge that these days billions of individuals all around the world are uninhibitedly permitted to coordinate various proceedings like sharing, posting, collaborating. Social media can be utilized to redesign an area and preparation for disaster. Nowadays in times of any natural disaster, individuals will generally utilize social media for many reasons like watching out for family and friends, searching for help, assemble news about the disaster.

A natural disaster is a devastating event that occurs suddenly and makes the fear of injury, loss of property, and separation of home [52]. Numerous disasters are there like earthquakes, landslides, volcanic eruptions, Tsunami, cyclones, avalanches and floods that harm the environment as well as individuals [11]. Inside the period between 2000 to 2019, EM-DAT recorded 7,348 disasters [1], which asserted a total of approximately 1.2 million lives. It was affected more than 4.30 billion individuals. Natural disasters kill an average of 60,000 individuals each year all around the world. For the duration of several natural disasters in recent years, Twitter has been found to assume a significant part as an extra mode for lots-to-many emergencies correspondence.

Twitter has become a significant tool for dispersing data during natural disasters, due to the continuous idea of updates and the way that are publicly accessible. One of the most famous interpersonal organization locales is Twitter. Twitter messages were likewise utilized in numerous different fields, for example, financial exchange forecast, disaster management [53], and understudies' opportunity for growth [7]. Various investigations have been from an assortment of viewpoints to understand how Twitter is important in natural disaster's connected correspondence. Some have argued that it becomes an opportunity for the individuals who are engaged as content creators during news or any social media platform rather than simply serving as consumers (Freeman,2011) [8]. One investigation discovered that Twitter become additionally being used as a way to determine what resources were needed in disaster locations (Gao, et al., 2011) [8]. Twitter Alerts highlight the disaster's situation and offers more advantageous visibility from government and emergency responder. Nowadays thousands and thousands of users are on Twitter and they express their feelings like happiness, sadness, angry as well as celebrations [59][49]. Microblogging website Twitter is extending quickly among all different online social networking websites with about 400 million users. Currently, 500 million tweets are sent out per day and 350,000 tweets per minute[2] [25].

Twitter has been utilized for sentiment analysis in numerous examinations [47] for different reasons. The Sentiment

[1] Human cost of disasters.
[2] https://www.dsayce.com/social-media/tweets-day/

© 2022, IJSREM

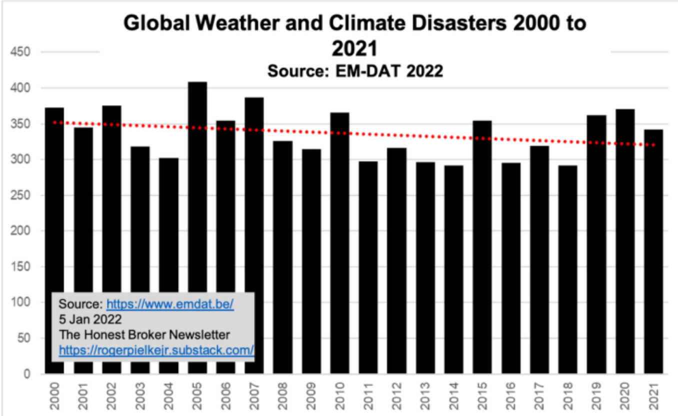
analysis is about identifying the feelings, assessment, opinions, attitudes, and thought about this as a way peoples think or detection of positive and negative sentiment towards a topic, person, or entity. Sentiment analysis works by separating a message into topics and then assigning a sentiment score to every topic. Twitter users use to put up their thoughts, emotions, and messages on their profiles called tweets [45][52]. Sentiment analysis of Twitter is based on NLP (natural language processing) fields. Through Sentiment analysis, we can know the trends of individuals on specific topics with their tweets.

## 2. SENTIMENTAL ANALYSIS

Humans express their feelings regularly, which are called emotions. Researchers are utilizing various strategies including Machine Learning to prepare machines on the best way to comprehend human emotions. This is called Sentiment Analysis. Sentiment Analysis is the field that attempts to enable machines to comprehend the emotions of the users. It's deciding if a piece of text is positive, negative, or neutral [49][45]. It also focuses on feelings and emotions like anger, happiness, sadness, and intentions like interested or not interested [52].

Many disasters like floods, earthquakes, etc that people get a fear injury, loss of property, and separation of home. Also, natural disaster regularly leaves a few financial harms afterward, the seriousness of which relies upon the impacted populace's flexibility and the framework accessible [11]. Emotional state about disaster victims in the disaster occasion and their activities [61]. Every year natural disasters affected many people. Natural disasters influence 218 million individuals and guarantee 68,000 lives each year. Over the most recent 25 years, there have been very nearly 7,000 natural disasters that have killed over 1.35 million individuals[3].

The following diagram depends on information kept by EM-DAT in Belgium, which is generally seen as a legitimate hotspot for information on worldwide calamities[4].




Sentiment analysis is a grouping of the extremity of a given message in the archive, sentence, or stages. The opinion of individuals can be examined utilizing Sentiment Analysis (SA) [15]. The Sentiment investigation is tied in with recognizing the sentiments, appraisals, suppositions, mentalities, and considered this a way people groups think or location of positive and negative opinions towards a topic, individual, or element. As indicated by , Sentiment Analysis is a course of separating the client's feelings, sentiments, or assessment and group them into positive, negative or neutral [18]. The people those who get affected during natural, through sentimental analysis we can know their opinion, feelings and emotion. During the situation of disaster, the people who get affected, through sentiment analysis we can know their opinion, feelings and emotion [48].

Various examinations disclosed that because of the accessibility of web indexes and online media sites [20][21] like Google, Twitter and Facebook, individuals approach a monstrous measure of information than ever before [18]. Twitter has turned into the main device for scattering information during natural disasters, because of the persistent thought of update this is the way that is freely open. It's also significant in natural disaster-related correspondence. Twitter Alerts feature what is happening as well as what to do or what not to do. It offers additional invaluable permeability from government and crisis responder [50]. There are three level of sentimental analysis [57]:

- **Document level:** The point here is to decide the general opinion of a whole record [57]. The Document Level Sentiment Analysis utilizing assessment digging is utilized for extraction of the client opinion on the record. For instance, given an item survey, the undertaking is to decide if it offers positive or negative viewpoints about the item. This level views at the record as a solitary element, hence it isn't extensible to various reports.

- **Sentence level:** This degree of investigation is extremely near emotional arrangement. The assignment at this level is restricted to the sentences and their offered viewpoints [57]. Particularly, this level decides if each sentence conveys a

[3] Center for Research on the Epidemiology of Disasters
[4] Global Weather and Climate Disasters 2000 to 2021. **Graph of the Week #1**

positive, negative, or neutral opinion. This type is utilized for surveys and remarks that contain one sentence and composed by the client

• **Entity and aspect level:** Rather than exclusively examining language develops for example archive, section, sentences; this level gives better grained examination to every perspective. It straightforwardly checks out the assessments for various angles themselves. The point of view level is more troublesome than both document and sentence. It comprises a few sub-issues. It tracks down various accessible opinions [57].

Sentimental Analysis can be classified into two categories [24]:

- **Machine Learning Approach**
- **Lexicon-based Approach**

Machine learning is a method of data analysis. With machine learning, clients input a lot of information into an algorithm, which empowers the PC to settle on suggestions and choices in light of that information [41].

The lexicon-based approach makes use of the sentiment lexicon with data regarding which words [51] and expressions are positive and which are negative. It counts the number of positive and negative words of any text. Assuming the number of positive is more than negative, it will return as a positive opinion. If each is the same then it will return as a neutral opinion. It consists of two classifications such as corpus-based approach and dictionary-based approach [24]. For the corpus-based approach, it collects the dictionary from a basic set by the use of statistical technique and it does not depend on a predefined dictionary. There is a huge number of texts that might have a positive or negative set of words [62]. As for the dictionary-based approach, it creates a dataset of positive and negative words from a basic set of words along with synonyms and antonyms.

## 3. RELATED WORK

Public had started using twitter in order to share their opinion or emotions specifically about disaster event through their post. Many articles have been written about sentiment analysis.

Bello et. al. [4] in their paper, they focused on the examination of how their procedures can understand these feelings inside the Social Network. Their work had shown the utilization of Data Mining techniques to remove Collective Trends from Twitter.

Bollen et. al. [5] in their paper, they explored whether the public mindset as estimated from the enormous scope assortment of tweets posted on twitter.com was related. They also had broken down the text content of everyday Twitter channels by two mind-set following devices, to be specific OpinionFinder and Google-Profile of Mood States (GPOMS).

Xiao et. al. [6] in their paper, they inspected the spatial heterogeneity in the age of tweets after a significant disaster. They proposed the MMAM model to make sense of the number of tweets by mass, material, access, and motivation. They also found that the number of tweets was fundamentally associated with populace size.

Bhadane et. al. [17] in their paper, they focused on the different techniques utilized for grouping a given piece of natural language text as per the suppositions communicated in it for example whether the overall mentality was negative or positive. They additionally examined the two-step strategy that they tracked with the trial arrangement.

Sun et. al. in their paper, [19] they had introduced some agent work of deep learning for NLP and the advancement of deep learning for opinion mining. They likewise researched different ways to deal with opinion mining for various levels and circumstances.

Öztürk et. al. [22] in their paper, they examined the general suppositions and opinions towards the Syrian displaced person emergency, which had impacted a great many individuals and had turned into a broadly examined, polarizing subject on social media all over the planet. They gathered pertinent tweets in two dialects: Turkish and English. Upon sentiment analysis of recovered tweets for every language, they saw that Turkish tweets were conveying more certain feelings about Syrians and exiles when contrasted with English tweets with the proportion of 35% of all tweets versus just 12%, individually.

Güngör et. al. [25] in their paper, they introduced a strategy for spam identification on Twitter. Their datasets were gotten by utilizing spam words and 758 tweets from Twitter were physically named and accuracy rates were acquired by AI strategies was finished on this dataset.

Zhang et. al. [42] in their paper, they previously gave an outline of deep learning and afterward gave an extensive review of its ongoing applications in sentiment analysis. They presented different deep learning models and their applications in sentiment analysis.

Kazemzadeh et. al. [44] in their paper, they introduced two models to address the importance of feeling words. They gave an express portrayal of the importance of their models. Afterward, they observed that the subsequent model was important to catch all the more exceptionally nuanced meanings when the vocabulary of feeling words was enormous.

Pak et. al. [46] in their paper, they focused on utilizing Twitter which was the most well-known microblogging stage, for the undertaking of sentiment analysis. They likewise told the best way to consequently gather a corpus for sentiment analysis and opinion mining purposes. They performed an etymological investigation of the gathered corpus and make sense of found peculiarities.

Tang et. al. [54] in their paper, they introduced a technique that learns word implanting for Twitter opinion characterization in their paper. The proposed learning nonstop word portrayals as highlights for Twitter opinion order under a supervised learning system. They had shown that the word implanting advanced by traditional neural networks was not powerful enough for Twitter feeling arrangement.

Devika et. al. [35] in their paper, different sentiment analysis techniques and their various degrees of examining feelings had been considered. Their definitive point was to concoct Sentiment Analysis which will proficiently arrange different audits. AI techniques like SVM, NB, and Maximum Entropy strategies were examined there in a nutshell, alongside a few other fascinating strategies that can further develop the examination cycle in either way. They had additionally run over a few different strategies like rule-based and lexicon-based techniques.

Ravi et. al. [41] in their paper, they introduced an extensive, state-of-the-art review on the examination work done in different parts of SA from 2002-to 2014. Their paper was checked in six expansive aspects viz. subjectivity arrangement, feeling characterization, audit handiness estimation, lexicon creation, opinion word, and item viewpoint extraction, and different uses of opinion mining.

Liu et. al. [3] in their paper, they introduced an original strategy in view of the sentiment analysis method and the intuitionistic fuzzy set hypothesis to rank the elective items through web-based surveys. In that strategy, online audits of the elective items concerning the highlights were slithered utilizing the crawler programming.

Phan et. al. [13] in their paper, they proposed a technique for working on the presentation of sentiment analysis in tweets containing fuzzy sentiment given the element troupe and CNN models. The component gathering model was connected with tweets containing fuzzy opinions by considering components, for example, lexical, word-type, semantic, position, and feeling extremity of words. Their proposed technique had been probed with genuine information, and the outcome demonstrates success in working on the presentation of tweet sentiment analysis as far as the F1 score.

Suresh et. al. [14] in their paper, they introduced a clever fuzzy bunching model to investigate Twitter channels concerning the opinions of a specific brand utilizing the genuine dataset gathered over a time of one year. The Partition-based bunching strategies would give exact outcomes without manual handling, linguistic information, or preparation. According to their exploratory examination, the proposed approach was shown to help perform top-notch brings about the space of Twitter sentiment analysis.

Vashishtha et. al. [12] in their paper, they processed the opinion of web-based entertainment posts utilizing an original arrangement of fuzzy standards including numerous lexicons and datasets. Their proposed fuzzy framework incorporates Natural Language Processing methods and Word Sense Disambiguation utilizing a clever unsupervised nine fuzzy rule-based framework to group the post into: positive, negative, or neutral opinion classes.

Jefferson et. al. [29] in their paper, a fuzzy methodology was proposed for sentiment analysis, with an emphasis on extremity order. They additionally looked at the precision of the proposed approach with the exactness of two other AI calculations, in particular Naïve Bayes and Decision Trees which were known to be among the best-performing methods for sentiment analysis.

Alamoodi et. al. [23] in their paper, they learned about sentiment analysis within the sight of irresistible illnesses, episodes, scourges, and pandemics for more than 10 years (1 January 2010 to 30 June 2020) were efficiently inspected. Their examination inspiration for that work was the gigantic spread of COVID19. They also referenced that their further examination should focus on the job of social media and sentiment analysis when a comparable incident repeats.

Souma et. al. [28] in their paper, they investigated another heading of sentiment analysis utilizing deep learning. They also characterized an extremity i.e., the positive or negative feeling of the news by noticing the log return of the proportion between normal entity cost briefly before the news relating to the important entity was distributed and one moment after the news had been delivered. They showed that the model predicts the positive news as positive and the negative news as negative, on average.

Qaiser et. al. [9] in their paper, plan to dissect individuals' perspectives about the impact of development on employment and movements in headways and build a machine learning classifier to orchestrate the sentiments. In their review, they saw that 65% of individuals hold pessimistic sentiments concerning that impact.

Yao et. al. [10] paper proposed an area explicit sentiment analysis approach explicitly for tweets posted during hurricanes (DSSA-H). They also found that every classifier i.e., RE and DANN outperform baseline classifiers and that DSSA-H outperforms high-acting general sentiment class tactics when classifying sentiments of tweets posted at some point of hurricanes.

Beigi et. al. [16] examined in their paper the relationship between web-based media, disaster relief, and situational mindfulness. And also clarified how web-based media was utilized in these settings with the focus on sentiment analysis.

Shalunts et. al. [26] had introduced in their paper the fundamental usage of the resulting advancement and models to sentiment analysis of online media data in German, covering information gathered during the Central European surges of 2013.

In Younis's [56] work, an open-source approach, all through which, Twitter Microblogs information had been gathered, pre-handled, dissected also pictured utilizing open-source apparatuses to perform text mining also sentiment analysis.

## 4. METHODOLOGY

Machine Learning allows the computer to examine new tasks without being programmed to perform them. Machine learning automatically detects sentiment without human help. Machine learning gives maximum accuracy and its capacity is verified in solving the tasks of sentimental analysis. They can be classified into three groups: supervised technique, unsupervised technique and semi-supervised [5] . With the supervised technique, we get every textual data along with their polarity, objectivity, and subjectivity. The supervised technique needs two sets of data for testing and training [27]. The unsupervised techniques find out the hidden collection of data without the need for human help and suggested if it is not able to have an advanced set of labeled documents to categorize the rest of the things [58]. Semi-supervised learning works by information researchers taking care of a limited quantity of marked preparing information to an algorithm.

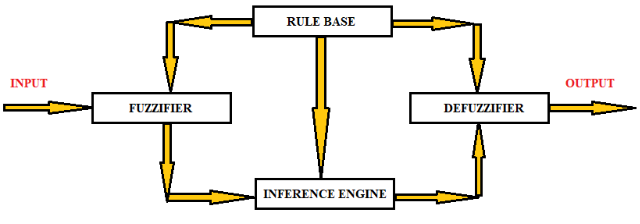
Deep learning is a type of machine learning algorithm that trains computers to do what comes easily to human beings. In deep learning algorithm computers learn to execute any task from any images, audios and texts. Deep learning uses multiple algorithms in a progressive chain of activities to work out complicated problems and allows to tackle huge number of information, accurately and with less human interaction. Sometimes deep learning and machine learning utilized interchangeably. Deep learning is undoubtedly machine learning but deep learning is more advanced than machine learning. Machine learning sometime makes mistake and they need human input to correct it or to change the output and force the model to learn it [33]. However, in deep learning [32], the neural network learns by itself to correct through its advanced algorithm chain [34]. Deep Learning algorithms have been utilized for a few Big Data areas like PC vision [30][31] and discourse acknowledgment [36] [38] it is as yet flawless with regards to Big Data examination [39].

In the past 10 years the deep learning made development and make new results in many application domains [37], beginning from computer vision, then the voice recognition and recently NLP. Deep learning algorithms try to make comparable conclusions as human could by constantly analyzing data with a given logical structure [40][60]. To accomplished this deep learning utilizes a multilayer structure of algorithms called neural networks.

Fuzzy logic is a way to deal with variable handling that considers various conceivable truth esteems to be handled through a similar variable. Fuzzy logic attempts to tackle issues with an open, uncertain range of information and heuristics that makes it conceivable to get a variety of precise ends. Fuzzy logic is intended to take care of issues by thinking about all suitable data and settling on the most ideal choice given the information. Fuzzy logic frameworks can deal with these intrinsic vulnerabilities [43] and have been utilized as a way to address and display influence relations [55]. The development of Fuzzy Logic Systems is simple and justifiable. This framework can work with a data source, whether loose or twisted input data.

Its Architecture contains four parts:

- **Rule Base:** Ongoing improvements in fuzzy theory offer a few successful techniques for planning and tuning fuzzy regulators. The vast majority of these advancements reduce the number of fuzzy rules.
- **Fuzzification:** It is utilized to change over inputs.
- **Inference Engine:** It decides the coordinating level of the current fuzzy contribution for each standard.
- **Defuzzification:** The most fitting one is utilized with a particular master framework to lessen the error.[6]




FUZZY LOGIC ARCHITECTURE

Fuzzy logic works on the idea of choosing the output based on assumptions. It works based on sets and each set show some linguistic variables defining achievable condition of the output. Each possible condition of the input and the stages of change of the state are a part of the set, based upon which the output is predicted. Fuzzy logic requires some mathematical parameters to figure out what is to be considered as unusual error and rate of change of that error [62]. But specific qualities are normally not required until extremely responsive execution is required, where case experimental turning would decide them [62].

---

[5] https://www.techtarget.com/searchenterpriseai/definition/machine-learning-ML

[6] https://www.geeksforgeeks.org/fuzzy-logic-introduction/

## 5. RESULT ANALYSIS

The table shown below depicts the comparative study of all the paper related to sentiment fields-----

| SL NO | Topic name | Author name | Datasets used | Algorithms used | Accuracy percentage |
|---|---|---|---|---|---|
| **1** | Extracting Collective Trends from Twitter Using Social-Based Data Mining | Gema Bello, Hector Menendez, Shintaro Okazaki, David Camacho | Human Labelled, Clustering Techniques. | C4.5 trees, Naive Bayes, K-Nearest Neighbours, Support Vector Machine | N/A |
| **2** | Twitter mood predicts the stock market. | Johan Bollen, Huina Mao, Xiao-Jun Zeng | OpinionFinder, Google-Profileof Mood States (GPOMS) | DJIA | 87.6 % |
| **3** | Understanding social media data for disaster management | Yu Xiao, Qunying Huang, Kai Wu | Mass-material-access-motivation | N/A | N/A |
| **4** | Sentiment analysis: Measuring opinions | Chetashri Bhadane, Hardi Dalal, Heenal Doshi | Lexical Metho, Machine Learning | Baseline Approach, Stemming, Part of Speech Tagging, WordNet, N-grams, Conjunction Rules, Stop Words, Negation method, Support Vector Machines (SVM, Naïve Bayes | 78.05%, 78 % |
| **5** | A Review of Natural Language Processing Techniques for Opinion Mining Systems | Shiliang Sun, Chen Luo, Junyu Chen | Lexicon, Machine Learning, | N/A | N/A |

| | | | | | |
|---|---|---|---|---|---|
| **6** | Sentiment Analysis on Twitter: A Text Mining Approach to the Syrian Refugee Crisis | Nazan Öztürk, Serkan Ayvaz | N/A | N/A | N/A |
| **7** | Tweet and Account Based Spam Detection on Twitter | Kubra Nur Gungor, Ibrahim Alper Dogru, Ayhan Erdem | Spam Detection Method, Machine Learning | Naïve Bayes, Logistic, J48 | 75.5%, 85.3%, 97.2% |
| **8** | Deep Learning for Sentiment Analysis: A Survey | Lei Zhang, Shuai Wang, Bing Liu | Neural Network, Deep Learning | N/A | N/A |
| **9** | Fuzzy Logic Models for the Meaning of Emotion Words | Abe Kazemzadeh, Sungbok Lee, Shrikanth Narayan | Fuzzy | IT2 FSs, EMO20Q | N/A |
| **10** | Twitter as a Corpus for Sentiment Analysis and Opinion Mining | Alexander Pak, Patrick Paroubek | Twitter API | Naïve Bayes, N-gram | N/A |
| **11** | Learning Sentiment-Specific Word Embedding for Twitter Sentiment Classification | Duyu Tang, Furu Wei, Nan Yang, Ming Zhou, Ting Liu, Bing Qin | Baseline | DistSuper, SVM, NBSVM, RAE, NRC | 50% |
| **12** | Sentiment Analysis: A Comparative Study on Different Approaches | Devika M D, Sunitha C, Amal Ganesh | Machine Learning, Rule Based, Lexical Based | SVM, N-gram, Naïve Bayes, ME, K-NN, Multilingual SA, Feature Driven SA | N/A |

| | | | | | |
|---|---|---|---|---|---|
| **13** | A survey on opinion mining and sentimental analysis: Tasks, approaches and application | Kumar Ravi | Machine learning, Lexicon based, Hybrid approaches | N/A | N/A |
| **14** | Ranking products through online reviews: A method based on sentiment analysis technique and intuitionistic fuzzy set theory | Yang Liu, Jian-Wu Bi, Zhi-Ping Fan | Fuzzy | HowNet, IFWA, PROMETHEE II | N/A |
| **15** | Improving the Performance of Sentiment Analysis of Tweets Containing Fuzzy Sentiment Using the Feature Ensemble Model | Huyen Trang Phan, Van Cuong Tran, Ngoc Thanh Nguyen, (Senior Member, Ieee), And Dosam Hwang | Fuzzy | CNN | 9% |
| **16** | An Unsupervised Fuzzy Clustering Method for Twitter Sentiment Analysis | Hima Suresh, Dr. Gladston Raj. S | Twitter API | K Means, EM, Proposed Method | 75.5 %, 63.4 %, 76.4 % |
| **17** | Fuzzy Rule based Unsupervised Sentiment Analysis from Social Media Posts | Srishti Vashishtha, Seba Susan | Fuzzy Rule, Lexicon | SVM | N/A |
| **18** | Fuzzy Approach for Sentiment Analysis | Chris Jefferson, Han Liu, IEEE and Mihaela Cocea, IEEE | Fuzzy | Naïve Bayes, Decision Trees | 0.9 % |

| | | | | | |
|---|---|---|---|---|---|
| **19** | Sentiment analysis and its applications in fighting COVID-19 and infectious diseases: A systematic review | A.H. Alamoodi, B.B. Zaidan, A.A. Zaidan, O.S. Albahri, K.I. Mohammed, R.Q. Malik, E.M. Almahdi, M.A. Chyad, Z. Tareq, A.S. Albahr, Hamsa Hameed, Musaab Alaa | Lexicon based, Machine Learning based, Hybrid-based | Decision trees, K-nearest neighbour, Support Vector Machines, Naive bayes | 89.06%, 86.43% |
| **20** | Enhanced news sentiment analysis using deep learning methods | Wataru Souma, Irena Vodenska, Hideaki Aoyama | Deep Learning | Forecasting | 0.76 % |
| **21** | Sentiment Analysis of Impact of Technology on Employment from Text on Twitter | Shahzad Qaiser, Noorai ni Yusoff, Farzana Kabir Ahmad, Ramsha Ali | Machine Learning, Rule Based, Lexicon Based | SVM, Decision Tree, Naive Bayes | 79.08%, 75.16%, 76.47% |
| **22** | Domain-Specific Sentiment Analysis for Tweets during Hurricanes | FANG YAO, YAN WANG | N/A | Machine Learning, | N/A |
| **23** | An Overview of Sentiment Analysis in social media and its Applications in Disaster Relief | Ghazaleh Beigi, Xia Hu, Ross Maciejewski and Huan Liu | N/A | SentiStrength | 20 % |
| **24** | Sentiment Analysis of German Social Media Data for Natural Disasters | Gayane Shalunts, Gerhard Backfried, Katja Prinz | N/A | N/A | N/A |

| | | | | | |
|---|---|---|---|---|---|
| **25** | Sentiment Analysis and Text Mining for Social Media Microblogs using Open-Source Tools: An Empirical Study | Eman M.G. Younis | Text Mining | Data Mining | N/A |

## 6. CONCLUSION & FUTURE WORK

After a natural disaster, many individuals posted on Twitter. Hashtags permit assembling every one of the tweets about the particular point and make it simpler to find what the client looking for. Using fuzzy rationale, the feeling upsides of tweets not entirely set in stone. We can ascertain the tweets by having the upsides of the tweets. This would give us the degree of positive opinion, negative feelings, and neutral opinions. The main purpose of our work was to break down the sentiments and assessments of people who are influenced by a natural disaster that is removed from Twitter and other virtual entertainment. We had concentrated on fuzzy rationale to break down sentiments on people of this theme.

By involving fuzzy rationale in this point, we imagine that we will come by additional strong results. The investigation has discovered that tiny work has been finished on fuzzy in sentiment analysis to date. We wish that we could see substantially more work on this subject in the future so we can acquire information and data.

Trust this work would be valuable for anyone in any way to get together their inclinations on this point. This was our huge goal of this venture and clutching give considerably more commendable works in our future work.

## References

[1] A. Olteanu, S. Vieweg, and C. Castillo, "What to Expect When the Unexpected Happens: Social Media Communications Across Crises," in Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing, 2015.

[2] H. Bai, G. Yu, and X. Tian, "A Weibo-based approach to disaster informatics: incidents monitor in post-disaster situation via Weibo text negative sentiment analysis," Nat. Hazards, vol. 83, no. 2, pp. 1177–1196, Sep. 2016.

[3] Yang Liu, Jian-Wu Bi and Zhi-Ping Fan, "Ranking products through online reviews: A method based on sentiment analysis technique and intuitionistic fuzzy set theory."

[4] G. Bello, H. Menéndez, S. Okazaki, and D. Camacho, ''Extracting collective trends from twitter using social-based data mining,'' in Proc. Int. Conf. Comput. Collective Intell. Berlin, Germany: Springer, 2013, pp. 622–630.

[5] J. Bollen, H. Mao, and X. Zeng, "Twitter mood predicts the stock market," J. Comput. Sci., vol. 2, no. 1, pp. 1–8, 2011.

[6] Y. Xiao, Q. Huang, and K. Wu, "Understanding social media data for disaster management," Nat. Hazards, vol. 79, no. 3, pp. 1663–1679, 2015.

[7] X. Chen, M. Vorvoreanu, and K. P. C. Madhavan, "Mining social media data for understanding students' learning experiences," IEEE Trans. Learn. Technol., vol. 7, no. 3, pp. 246–259, 2014.

[8] Julia Skinner, "Natural Disasters and Twitter: Thinking from both side of the tweet"- https://journals.uic.edu/ojs/index.php/fm/article/view/4650/3741.

[9] Shahzad Qaiser, Nooraini Yusoff, Farzana Kabir Ahmad and Ramsha Ali, "Sentiment Analysis of Impact of Technology on Employment from Text on Twitter".

[10] FANG YAO and YAN WANG, "Domain-Specific Sentiment Analysis for Tweets during Hurricanes".

[11] G. Bankoff, G. Frerks, D. Hillfort (eds.) (2003). Mapping Vulnerability: Disasters, Development and People. ISBN 1-85383-964-7.

[12] Srishti Vashishtha and Seba Susan, "Fuzzy Rule based Unsupervised Sentiment Analysis from Social Media Posts."

[13] Huyen Trang Phan, Van Cuong Tran, Ngoc Thanh Nguyen, (Senior Member, Ieee), And Dosam Hwang, "Improving the Performance of Sentiment Analysis of Tweets Containing Fuzzy Sentiment Using the Feature Ensemble Model."

[14] Hima Suresh and Dr. Gladston Raj. S, "An Unsupervised Fuzzy Clustering Method for Twitter Sentiment Analysis."

[15] F. Colace, M. de Santo, and L. Greco, "Safe: A sentiment analysis framework for e-learning," Int. J. Emerg. Technol. Learn., vol. 9, no. 6, pp. 37–41, 2014. https://doi.org/10.3991/ ijet. v9i6.4110.

[16] Ghazaleh Beigi, Xia Hu, Ross Maciejewski and Huan Liu, "An Overview of Sentiment Analysis in Social Media and its Applications in Disaster Relief".

[17] C. Bhadane, H. Dalal, and H. Doshi, "Sentiment analysis: Measuring opinions," Procedia Comput. Sci., vol. 45, no. C, pp. 808–814, 2015. https://doi.org/10.1016/j.procs.2015.03.159.

[18] D. M. E. D. M. Hussein, "A survey on sentiment analysis challenges," J. King Saud Univ. - Eng. Sci., vol. 30, no. 4, pp. 330–338, 2018.

[19] S. Sun, C. Luo, and J. Chen, A review of natural language processing techniques for opinion mining systems, vol. 36. Elsevier B.V., 2017.

[20] V. Vyas and V. Uma, "An Extensive study of Sentiment Analysis tools and Binary Classification of tweets using Rapid Miner," Procedia Comput. Sci., vol. 125, pp. 329–335, 2018. https://doi.org/10.1016/j.procs.2017.12.044.

[21] K. Ravi and V. Ravi, A survey on opinion mining and sentiment analysis: Tasks, approaches and applications, vol. 89, no. June. Elsevier B.V., 2015. https://doi.org/10.1016/j. knosys.2015.06.015.

[22] N. Öztürk and S. Ayvaz, "Sentiment analysis on Twitter: A text mining approach to the Syrian refugee crisis," Telemat. Informatics, vol. 35, no. 1, pp. 136–147, 2018. https://doi. org/10.1016/j.tele.2017.10.006.

[23] A.H. Alamoodi, B.B. Zaidan, A.A. Zaidan , O.S. Albahri , K.I. Mohammed , R.Q. Malik , E.M. Almahdi, M.A. Chyad , Z. Tareq , A.S. Albahr, Hamsa Hameed and Musaab Alaa, "Sentiment analysis and its applications in fighting COVID-19 and infectious diseases: A systematic review."

[24] Ummu Hani' HAIR ZAKI, Roliana IBRAHIM a,1, Shahliza ABD HALIMa and Takeru YOKOIb "A Review on Service Oriented Architecture Approach in Flood Disaster Management Framework for Sentiment Analysis".

[25] Kubra Nur Gungor, Ayhan Erdem, and Ibrahim Alper Dogru, "Tweet and Account Based Spam Detection on Twitter".

[26] Gayane Shalunts, Gerhard Backfried and Katja Prinz, "Sentiment Analysis of German Social Media Data for Natural Disasters".

[27] J. Serrano-Guerrero, J. A. Olivas, F. P. Romero, and E. Herrera-Viedma, "Sentiment analysis: A review and comparative analysis of web services," Inf. Sci. (Ny)., vol. 311, pp. 18–38, 2015.

[28] Wataru Souma, Irena Vodenska and Hideaki Aoyama, "Enhanced news sentiment analysis using deep learning methods."

[29] Chris Jefferson, Han Liu, IEEE and Mihaela Cocea, IEEE, "Fuzzy Approach for Sentiment Analysis."

[30] Freedman DA. Statistical models: theory and practice. Cambridge: Cambridge University Press; 2009.

[31] Krizhevsky A, Sutskever I, Hinton GE. Imagenet classifcation with deep convolutional neural networks. In: Advances in neural information processing systems; 2012. p. 1097–105.

[32] Socher R, Huang EH, Pennin J, Manning CD, Ng AY. Dynamic pooling and unfolding recursive autoencoders for paraphrase detection. Adv Neural Inf Process Syst. 2011; 24:801–9.

[33] Gao J, Deng L, Gamon M, He X, Pantel P. Modeling interestingness with deep neural networks. 2014. US Patent App. 14/304,863.

[34] Kalchbrenner N, Grefenstette E, Blunsom P. A convolutional neural network for modelling sentences. arXiv preprint arXiv:1404.2188. 2014.

[35] M. D. Devika, C. Sunitha, and A. Ganesh, "Sentiment Analysis: A Comparative Study on Different Approaches," Procedia Comput. Sci., vol. 87, pp. 44–49, 2016. https://doi.org/ 10.1016/j.procs.2016.05.124.

[36] Pearson K. Notes on regression and inheritance in the case of two parents. Proc R Soc Lond. 1895; 58:240–2.

[37] Graves A, Mohamed AR, Hinton G. Speech recognition with deep recurrent neural networks. In: 2013 IEEE international conference on acoustics, speech and signal processing (ICASSP); 2013.

[38] Dahl G, Mohamed AR, Hinton GE. Phone recognition with the mean–covariance restricted Boltzmann machine. Adv Neural Inf Process Sytst. 2010; 23:469–77.

[39] George E, Yu D, Deng L, Acero A. Context-dependent pre-trained deep neural networks for large-vocabulary speech recognition. IEEE Trans Audio Speech Lang Process. 2012;20(1):30–42.

[40] Seide F, Li G, Yu D. Conversational speech transcription using context-dependent deep neural networks. In: Twelfth annual conference of the international speech communication association; 2011.

[41] K. Ravi and V. Ravi, "A survey on opinion mining and sentiment analysis: Tasks, approaches and applications," Knowledge-Based Syst., vol. 89, pp. 14–46, 2015.

[42] LeiZhang, Shuai Wang, Bing Liu, "Deep Learning for Sentiment analysis: A Survey".

[43] D. Wu, (2012) Fuzzy sets and systems in building closed-loop affective computing systems for human-computer interaction: Advances and new directions, IEEE World Congress on Computational Intelligence, Brisbane, Australia.

[44] A. Kazemzadeh, S. Lee and S. Narayanan, "Fuzzy Logic Models for the Meaning of Emotion Words," IEEE Computational Intelligence Magazine vol.8, issue 2, May 2013, p.34-49.

[45] Taboada, M., Brooke, J., Tofiloski, M., Voll, K., & Stede, M. (2011). Lexicon-based methods for sentiment analysis. Computational linguistics, 37(2), 267-307.

[46] Pak, A., & Paroubek, P. (2010, May). Twitter as a Corpus for Sentiment Analysis and Opinion Mining. In LREC (Vol. 10, pp. 1320-1326).

[47] Zhou, X., Tao, X., Yong, J., & Yang, Z. (2013, June). Sentiment analysis on tweets for social events. In Computer Supported Cooperative Work in Design (CSCWD), 2013 IEEE 17th International Conference on (pp. 557-562). IEEE.

[48] Md. Ansarul Haque and Tamjid Rahman, "SENTIMENT ANALYSIS BY USING FUZZY LOGIC".

[49] Asur, S., & Huberman, B. A. (2010, August). Predicting the future with social media. In Web Intelligence and Intelligent Agent Technology (WI-IAT), 2010 IEEE/WIC/ACM International Conference on (Vol. 1, pp. 492-499). IEEE.

[50] Tumasjan, A., Sprenger, T. O., Sandner, P. G., & Welpe, I. M. (2010). Predicting Elections with Twitter: What 140 Characters Reveal about Political Sentiment. ICWSM, 10, 178-185.

[51] Abdullah Alfarrarjeh, Sumeet Agrawal, Seon Ho Kim and Cyrus Shahabi, "Geo-spatial Multimedia Sentiment Analysis in Disasters".

[52] Mostafa, M. M. (2013). More than words: Social networks' text mining for consumer brand sentiments. Expert Systems with Applications, 40(10), 4241-4251.

[53] J. Rexiline Ragini, P.M. Rubesh Anand and Vidhyacharan Bhaskar, "Big data analytics for disaster response and recovery through sentiment analysis".

[54] Tang Duyu, Wei Furu, Yang Nan, Zhou Ming, Liu Ting, Qin Bing. Learning sentiment-specifc word embedding for twitter sentiment classification. ACL. 2014; 1:1555–65.

[55] C. Karyotis, F. Doctor, R. Iqbal, and A. James, (2015) An Intelligent Framework for Monitoring Students Affective Trajectories Using Adaptive Fuzzy Systems, Proceedings, IEEE International Conference on Fuzzy Systems, 2-5 August 2015, Istanbul, Turkey.

[56] Eman M.G. Younis, "Sentiment Analysis and Text Mining for Social Media Microblogs using Open-Source Tools: An Empirical Study".

[57] Bing Liu, "Sentimental analysis and opinion mining", University of Illinois at chicago).

[58] Chaitanyasuma Jain, "Lexicon Based Sentimental Analysis".

[59] Milstein, S., Lorica, B., Magoulas, R., Hochmuth, G., Chowdhury, A., & O'Reilly, T. (2008). Twitter and the micro-messaging revolution: Communication, connections, and immediacy--140 characters at a time. O'Reilly Media, Incorporated.

[60] Mohamed A, Dahl GE, Hinton G. Acoustic modeling using deep belief networks. IEEE Trans Audio Speech Lang Process. 2012;20(1):14–22.

[61] S. Andrews, S. Yates, B. Akhgar, and D. Fortune, "The ATHENA project: using formal concept analysis to facilitate the actions of responders in a crisis situation," Strategic Intelligence Management. 2013.

[62] Tanuja Bahirat, "Fuzzy Logic Tutorial History, Implementation, Advantages and how it's used" Feb 20,2020.