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# Tweet Summarization using Clustering Mechanism

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**Abstract:**

Among the most popular social networking platforms allowing people to communicate current facts and opinions on any situation is Twitter. Twitter provides more information and opinions about an event than any other medium and reports on events more rapidly. As a result, one of the most practical ways to quickly learn the main points of any event is through Twitter subject summaries. However, the data received on Twitter is frequently loaded with unusual acronyms, grammatical errors, making it difficult to get accurate and helpful information about any situation. Beyond, summarizing a event is a difficult work because, typical text summary techniques lag. Throughout the past decade, numerous research studies have proposed various techniques for automatically summarizing Twitter topics.

This survey work's main objective is to create a thorough review of effective summarizing strategies for a Twitter topic. By looking at current assessment strategies, we also concentrate on automatic summarizing evaluation techniques. Through a thorough study of the most recent summarizing techniques, we emphasize both the existing and upcoming research difficulties in this area towards the conclusion of the survey.

**Keywords**: social media; disaster response; emergency management; Deep learning model

## 1.1 Introduction:

According to extensive study, individuals utilize social media to understand real-time information during disasters[1,2]. Because of the increased usage of portable devices, the growth of Twitter has expanded at an unprecedented rate in recent days. On Twitter, anyone can immediately post or respond to anything.

As of 2022, there are about 450 million active users on Twitter every month[3].

On Twitter, various users tweet a variety of tweets on the disaster under various categories like spam tweets[4], emotional tweets[5], mass emergencies etc. Another user group on Twitter,

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often those who are search users, also looks for these real-time updates [6]. The conventional approach is to use hashtags and phrases related to the event to search the social stream.

Anyway, the number of search results that reply to Boolean query is staggering. For instance, President Obama's win in the 2012 election resulted in nearly 20 million tweets being generated on election night and about 237,000 tweets every minute. Typically, a search user won't read any tweets that don't fit their query beyond the first couple of tweets. Today's social search engines, unfortunately, display tweets that fit the Boolean query in chronological reverse order using retrieval techniques based on relevance. Because of the enormous volume of returned search results[7], Twitter users commonly encounter diversion in order to receive tweets with non-repetitive content of interest[8]. Sometimes, Information may be hard to get by, especially right after rapid incidents, when it is most needed. Because of the developing Information technology and social network sites, there are many opportunities to share and access time-sensitive information during emergencies and natural disasters[9]. Social network media posts are helpful for a variety of response activities, including understanding the situation, recognizing community immediate needs, and determining the extent of uncertainty[10].

Therefore, the tweets are categorized into non-situational and situational tweets[11], the tweets related to network damage etc., comes under situational. Public opinions, communal based tweets comes under non-situational tweets. machine learning classifiers were utilized by the authors[12] to find situational details during the disaster.

In text processing applications including text categorization and natural language processing, deep learning models has achieved tremendous success [13]. It is a difficult challenge to categorize tweets that are written generated during a crisis based on how informative they are. Tweet classification is made possible with exceptional performance accuracy by combining deep learning models[14]. To create a model for categorizing tweets, informative information from the tweets generated during the crisis can be extracted.

This paper presents the findings and study of social media data processing disaster and management responses. Research problems, difficulties for data implementation in disasters are addressed as well.

The contributions of following article is:

- This study gives a structured view about summarization techniques and evaluations.
- This study focuses on existing summarization approaches, algorithms and their performance, challenges etc.

- This study identifies the current issues and problems along with potential future research areas.

**1.2 Overview of Tweet/Text summarization**

Summarization is a technique to present a document in the desired text while retaining the key ideas from the original text. To summarize a topic on Twitter with the desired quantity of tweets, perform the task of topic summarization[15]. Lets say, *T* represents a set of stream tweets of a topic and S represents summary of a topic. On Twitter, it is quite difficult to keep track of a single incident because of the enormous amount of messages. However, Twitter.com has features to help you locate the most crucial subjects and associated tweets for a specific time or instant. Using search terms linked to the topic, any user can find tweets about a specific event. The tool retrieves all tweets that are relevant to the query in posting time order. Many unrelated or tweets in other languages present in the list was also retrieved. It takes a precise manual filtration method to obtain the necessary tweets. In order to create a thorough summary, researchers eventually suggest a variety of summarizing methods to extract the crucial data from relevant tweets.

**2. Existing tweet summarization literature survey:**

The existing text summarizations surveys were investigated and most of them are based on former methods. The recent applications, limitations nor challenges were not discussed.

[31] discussed various ML approaches, fuzzy logic etc, and their limitations include more research is required on abstractive techniques. [32] implemented hybrid text summarization techniques but it requires more contemporary techniques which is a drawback. [33] investigated various ML techniques, frequency driven method etc, but this study used on strategies that are more frequently used. [34] comparison of various studies to handle massive data and multiple documents were conducted in this study but studies details were not mentioned. Table 1 discusses various existing surveys done so far.

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Table 1: Existing tweet summarization literature survey:

| **Ref.no** | **Year** | **Scope** | **Limitations** |
|---|---|---|---|
| 31 | 2020 | discussed various ML approaches, fuzzy logic etc., | more research is required on abstractive techniques |
| 32 | 2021 | implemented hybrid text summarization techniques | it requires more contemporary techniques |
| 33 | 2021 | investigated various ML techniques, frequency driven method etc, | this study used on strategies that are more frequently used |
| 34 | 2020 | comparison of various studies to handle massive data and multiple documents were conducted in this study | studies details were not mentioned |

**3. Motivation of text summarization:**

This study seeks to accelerate knowledge of Text Summarization and current NLP research by providing an overview. Furthermore, it enables the development of new methodologies to the research and industry sectors' needs. Automatic text summarizing and sentiment analysis became possible with the development of NLPs for normal text document summaries. Text summarization enables a broad approach in research fields like NLP, machine learning etc., Text Summarization presents the most recent research and projected directions in various fields by using various information sources.

**4. Summarization Approaches:**

The majority of summarizing methods uses traditional summarizing tools that were previously used on conventional text documents. To address the difficulties posed by informal text, such as tweets, these algorithms were adjusted accordingly[15]. There are two ways to summarize topics on Twitter and it is shown in fig 1.

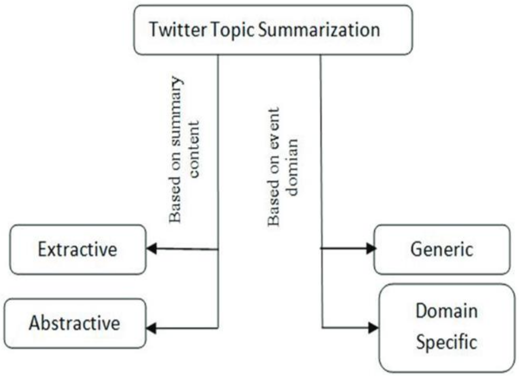


Fig 1: Tweet Summarization Approaches structure.

### 4.1 Extractive summarization

An event's extractive summary is a collection of the most relevant and useful tweets from the event. According to selected length, the summary includes the most significant and relevant tweets[16]. It has following tasks:

a. **Splitting:** The aim is to split the original text to sentences and produce an abstract model of the content. Indicator representation and subject representation are two of the basic categories of intermediate representation [35,36].
b. **Assigning:** Giving each sentence a score based on how well it performs after the formation of the representation to indicate its value.
c. **Selecting:** it selects high score sentences.

In extractive summarization, the Supervised and unsupervised ML approaches are applied and it is shown in fig 2.

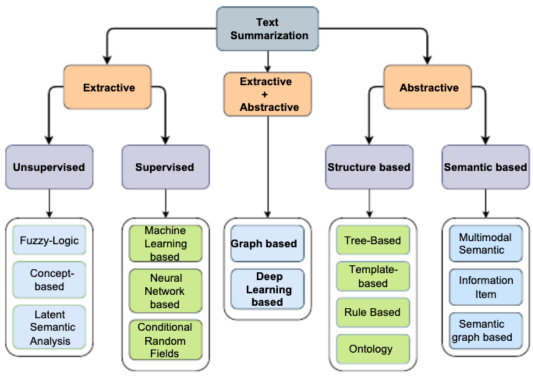


Fig 2: Text summarization classification and its approaches.

- **Supervised learning:** To recognise and learn how to classify documents. These methods utilizes categorized data for training[37].

### 4.2 Abstractive summarization

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An abstractive summary, rather than identifying source tweets, describes an event with crucial information. It uses fewer words than the extractive summary, provides more details about an event. The 2 Methods of abstractive summarization are:

a. **Structure-based:** this method filters the crucial data by applying abstract algorithms. These approaches rely on reasoning schemas like tree-based, templates, rule-based structures and ontologies.
b. **Semantic-based:** this method refines the sentences in a document by implementing NLP[38]. These methods makes less grammatical errors which is advantage but it ignores information sometimes which is a drawback. These methods includes semantic graph-based, multimodal method and information item method.

**4.3 domain specific event:**

Although social networking platforms like Twitter gives real-time information for disaster response, retrieving meaningful information and effectively analysing data for disaster response remains difficult.

At unusual scales, sentiment analysis of social media data enables the detection of impacted people's concern and the analysis of local responses from individuals. However, the technique is domain-dependent. In various contexts, the same phrases or sentences might convey opposing sentiments[17].

**4.4 generic specific event:**

For emergency responders, it's crucial to continuously monitor an incident after it is discovered to gain real-time insights. It handles real-time data, in order to be useful in crises. A live stream of information that is pertinent to an event is typically delivered in real-time. Algorithms use architectures, that play a crucial role when time is a factor because of how urgently the output of an analysis is needed in these circumstances[18].

**4.5 Classification, Summarization and Clustering :**

These days, social network media conversations during any event is very frequent and takes sifting through millions of datasets to identify the pertinent information. Several multimedia and text processing techniques are developed to process voluminous information.

**4.5.1 Data classification:**

Keeping relevant and helpful information separate from irrelevant content is a crucial endeavour. Supervised classification method is used to handle this problem, however it uses labelled data. The social media data available during disasters and the users information needs are key factors behind the choice of the list of categories to be used [19].

**4.5.2 segmentation and summarization:**

A number of tweets are posted on twitter. These tweets are analysed using sentiment analysis to create summaries of the users thoughts and to categorize them in order to understand the user's perspective on a topic. Millions of twitter users with different opinions exist, which presents a challenge for sentiment analysis [20]. Sentiment analysis has practical tests as well. Someone may occasionally tweet something which is not pertinent to other people. In this scenario, summarization plays an important role[21].

The purpose of segmentation and summarization is to obtain a summary for posted users tweets based on their opinions. Segmentation mainly divides the tweets which draws and gains into meaningful sentences[22], and summarization clusters a set of related tweets from these groups and determines their semantics. The clustering algorithms for summarization includes K-means etc.

**4.2.3 Data Clustering:**

A series of techniques known as clustering, which is a machine learning method that is unsupervised, aims to find and explain significant underlying patterns in unlabelled data. Clustering can assist in gathering semantically related messages that need to be evaluated by humans when processing social media data[23, 24]. To enhance the quality of the supervised classification process, clustering methods can be utilized to identify abnormalities in crisis and to identify human interpretation errors [25, 26].

**5. Monitoring systems for social media:**

Numerous systems are developed to process social media during disasters. For semantic enrichment performance of tweets automatic classification[27] provided “Twitris”. To extract and filter tweets from thematic, geographical information [28]”SensePlace2” is used. For event detection, geotagging, text classification [29] Emergency Situation Awareness is used. To categorize humanitarian to real-time events AIDR[30].

**5. Summarization algorithms:**

**A. Supervised methods:**

These are sentence level classification method. These methods cannot make context summaries by their own, it requires more training samples.

1) **Machine learning:** These techniques are used to divide the sentences into classes using training data. Machine learning techniques are mostly used on a training data that

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contain documents to be trained [39]. During training phase, input documents are fed with manual data and categorization is done according to each sentence.

2) **Neural network:** During model training, a neural network technique [41] employs a 3-layered network to learn the phrases features. The RankNet methodology[40], uses neural networks to classify the sentences. When extraction summaries are required for several document copies, these strategies are used.

**B. Unsupervised methods:**

1) **Fuzzy-logic:** The approach based on fuzzy logic is also used to choose the crucial passage from source text. A redundancy elimination methodology is necessary for the fuzzy logic-based method, though, in order to get better outcomes.

**C. Extractive + Abstractive:**

1) **Graph-based:** The necessary phrases or terms are ranked using a graph in this method of unsupervised learning. The graphical method is employed to identify the most important sentences inside a single text [42].
2) **Deep learning algorithm:** Deep learning models can help Text Summarization become more efficient, available, and user-friendly. These models replicate how the human brain works. Deep NN's are frequently used in NLP problems because the structure fits the complex structure of the language; for instance, each layer can tackle a specific task before sending the output to the next[35].

**5. Analysis table:**

The following section describes various summarization learning methods.

Table 2: survey of various summarization learning methods.

| Ref.no | Year | Methods | Advantages | Limitations and future work |
|---|---|---|---|---|
| 43 | 2020 | word2vec | • Sentence similarity measure was done. | • Abstractive summarization for Arabic language was not possible.<br>• Auto or attention encoders can be used in future. |
| 44 | 2020 | Highlighting information | Two stages framework for abstractive-extractive was proposed. | • Required performance improvement for proposed framework. |

| | | | | |
|---|---|---|---|---|
| | | | | • Further work includes improving performance. |
| 45 | 2020 | JECS, HiBert etc | • To decrease summarization redundancy. | • Proposed DISCOBERT but not applied for large document encoding.<br>• Can explore more encoding methods as future work. |
| 46 | 2020 | NN model | • Implemented JECS | • NA |
| 47 | 2020 | LSTM-CNN model | • Developed a asemantic model. | • NA |
| 48 | 2019 | Generative model | • For abstractive summarization authors Proposed adversial technique | • NA |
| 49 | 2021 | Abstractive neural model | • Proposed a model to identify and verify conflicts and real consistency. | • Did not applied on multiple sentence spans.<br>• Proposed model can be improvised with data augmentation model. |
| 50 | 2021 | ROUGE-N, RUOGE-W ETC | • The work focused on summary of unigram measure against a human generated summary. | • N-gram Algorithm compares only system summaries. |
| 51 | 2021 | Extractive methods | • Discussed methods, measurements ofvtext summarization techniques. | • description about Feature extraction classification was missing |
| 52 | 2022 | NA | • discussed former research work and their comparison . | • more discussion is required to specific topic. |

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| | | | | |
|---|---|---|---|---|
| 53 | 2022 | Q-network | • the trained models applied on huge volume of data.<br>• Used NLP model for sentiment analysis. | • The pre-trained model leads to comprehension issues. Fine tuning of parameters can be done further. |

**6. Limitations and challenges:**

The objective of Text summarization is to let users compile information which has to be summarized. As we've covered in earlier sections, there are a variety of summarization approaches that may be used to produce summaries, but these approaches are restricted to abstracting from or broadly paraphrasing the original content. Any ATS system must be capable to yield text summaries similar to human-generated texts. Existing Text Summarization systems still face major difficulties in achieving this goal, nevertheless. Anaphora problem, cataphora problem, etc. are a few typical difficulties. The common challenges include evaluation, interpretability, sentence selection, ambiguity.

In addition to above challenges, there are few limitations which includes:

a. In extractive models, to improve summarization quality, redundancy removal technique is required. To improve summary quality, More similarity measures need to be utilized. while using neural network, human interpretation is required to train a data especially while dealing with large amount of data.
b. In abstractive models, tree based algorithms ignores context phrases, failing to identify relationship between sentences and main drawback is it focuses only on syntax ignoring semantics.in deep learning model, human effort is needed to train data manually.

**7. Conclusion:**

Despite the fact that text summarizing is an old issue, researchers still find it interesting. However, overall text summarizing performance is only average, and the summaries produced are not always accurate. Researchers are therefore working to enhance current text-summarizing techniques. It's also a top priority to create summaries that are resilient and of higher quality using unique summarising techniques. A systematic survey of various text summarization phases was done. This paper gives the current challenges and limitations of summarization techniques which encourages to find new challenges in future work.

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