# Understanding Social Media Engagement in Response to Disaster Fundraising Attempts During Australian Bushfires

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**Abstract.** This article studies the impact of social media posts specific to a disaster incident – the Australian bushfires of 2019–2020. We analyse the social media content posted by the Australian Red Cross Organization's Facebook page, and the user generated comments on their posts. We identify user sentiments in response to the natural disaster and towards the organization's fundraising attempts. This study shall enable the stakeholders to understand how the general public reacts to fundraising protocols at the times of unforeseen disasters. It shall also allow policymakers to design sustainable goals to promote healthy donation behaviour through social media platforms. Further, we also analyse how benchmark Natural Language Processing tools, namely, VADER, Afinn, and TextBlob, perform in an unsupervised scenario to perform sentiment classification. Overall VADER results were best among the other algorithms Afinn and TextBlob in the term of accuracy, precision, recall and f1 score performance measure.

**Keywords:** Sentiment analysis · social media engagement · disaster fundraising · Australian bushfires

## 1 Introduction

The innovation of internet technology and communication through social media provides a new strategy for the fundraising process that a Non-Profit Organization (NPO) uses to achieve an organization's mission. Social media such as Facebook, Twitter, and Instagram are omnipresent, and their interactive designs have changed the way people communicate. Through social media platforms, users can connect with people across the Globe, create their content, and interactively share their opinion or thoughts. According to the Global NGO Technology Report, 93% of NPOs in Australia & New Zealand regularly utilize social media to engage their supporters and donors [1]. It is essential for


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NGOs with limited budgets to provide comprehensive communications to various stakeholders quickly and efficiently. The use of social media is an effective tool to connect with supporters and engage with the audience. Regarding fundraising, social networking sites can effectively reach potential donor groups [2]. Social media creates the opportunity to communicate with the potential audience and disseminate information about brands, eventually leading to increased charitable contributions. Researchers have focused on social media usage for building a relationship with the audience in the past decades. [3] developed a conceptual model of driving brand advocacy and reciprocity to improve customer-based brand equity. Brand advocacy refers to positive recommendations from those customers who are strongly connected with brands. Users actively participate on social media platforms that allow advocacy through bidirectional conversations rather than one-way communication. This interactive conversation builds emotional attachment and satisfaction with that brand [4]. The communication conducted on social media also affects the other users and shapes their opinion of the brand. Another critical aspect of the relationship between brands and users is trust. A shared positive brand experience on social media establishes a secure relationship among social media platforms [5]. Social media users are also influenced by each other's experiences, opinions, sentiments, and preferences. Social media engagement is a core factor in mobilizing volunteers, raising awareness, and influencing potential donors.

Reciprocity represents the practice of mutual exchange between people. Many social media users express and share their ideas to find someone who can give them feedback. This reciprocal information sharing facilitates the engagement of social media users. [6] states that reciprocity and brand advocacy are critical mechanisms for effectively improving brand equity. However, the contents of information on social media need to be unique, authentic, and accurate to disseminate the information to a population. As of January 2021, there were 4.66 billion active internet users, 59.5% of the global population in the world [7]. Facebook is one of the biggest social media platforms, with roughly 2.89 billion monthly active users as of April 2021 [8]. There is a tremendous amount of information on the internet, and it would be easy to fail to take advantage of information without any specific strategy. Australian bushfires started in September 2019. The Australian Red Cross organization has solicited bushfire donations from October 2019 to June 2021. The time-series bushfire donation data from the Australian red cross from 2011–2021 was analysed for this study, and we specifically selected the 2019–2021 time period for this research, owing to the massive disastrous bushfires and large donation amounts in its reciprocity. The Guardian reported that Andrew Constance, the Liberal MP for the Bega in New South Wales, criticizes the fundraising decision by the Australian Red Cross [9].

This article provides a brief literature review on the impact of social media, the function of social media as brand advocacy by organizations, and the technological advancements in machine learning and natural language processing for sentiment analysis in Sect. 2. In Sect. 3, we discuss the data collection and annotation strategy, and the unsupervised methods employed for sentiment classification. Section 4 illustrates the results of social media content analysis and sentiment analysis depicting Facebook users' behaviour and emotions in response to the disaster. We also compare the sentiment classification performance of VADER, Afinn, and TextBlob algorithms. Section 5 summarizes the article.

## 2 Literature Review

Using social media and data extracted from the online platform is critical for disaster management, and it faces many challenges in filtering the correct data. The main focus is text analysis for developing a solution for the authorities to get information about the disaster and respond quickly to emergency services. [10] used supervised and unsupervised machine learning and deep learning techniques based on data collected from real-time online sources. One of the biggest challenges is limited information in the data using informal language. Social media contains actionable content related to advice, precautionary measures, and fundraising after disaster hits; thus, it is imperative to filter the correct data from given information.

To minimize this problem, the blockchain framework improves the accuracy and security of sharing wrong information. The system was trained to use block chaining and machine learning (ML) pipeline-based techniques to map the data automatically due to the crisis caused after the disaster. The data gathered is handled utilizing directed learning and data information mining strategies to deliver related knowledge reports that progressively sum up to significant data about continuous occurrences, hence giving a significant choice to help and rescue the teams. In the current environment around the world, many examinations of English social media take place, while very little work on refining the information about Arabic social media content is produced consistently. Their work centered on the characterization of Arabic feeds data and the utilization of unfavourable weather patterns in the UAE as an experiment. Support Vector Machines (SVM) and Polynomial Networks (PN) classifiers were used for analysis and without the help of stemming, and the outcomes showed a high degree of characterization exactness and a quick reaction time [11].

[12] discussed various Machine Learning Techniques used for analysing and classifying data collected from online sources. Multidimensional models of classification and recognition are used for pandemic diagnoses, monitoring, and prediction. Disaster management is one of the top trending issues on social media; therefore, ML algorithms are used for constructing different models, and these models can be merged with other techniques to improve the results of classification and recognition [13]. They also addressed various phases of ML algorithms used to predict and determine the early sign of disaster. This can minimize the disaster risk, unusual social interaction, and suspicious issues. They also highlighted some of the challenges faced during their survey as specific data is required to analyse for ML algorithms due to which data accuracy is affected.

Twitter data in tweets and comments were used for the sentimental analysis of text, and R language was used to retrieve and analyse the data collected from social media. By applying text mining techniques to find the correlation between the negative public opinion about unemployment after a crisis or disaster occurs. This also helps to find the key features that can affect the employment rate when an incident can cause this situation [14]. Social media data was used to detect the early clue about three different brands' products that causes allergies and adverse event from customers' feedback. [15] try to analyse the data gathered from Facebook and Twitter comments. Two approaches were applied to classify the data, lexicon-based sentiment classification and machine learning-based sentiment classification. Regarding classification, they also compared the results from both techniques and showed results with negative scores from both agree closely while there was a sharp change in the result for positive and neutral.

The internet and smart devices have brought a revolutionary change in this world, and media coverage through social media has become very easy for everyone [16]. Thus, public opinion mining through online feedback is beneficial in targeting the correct related information for users. They showed that Bert (bidirectional encoder representation from transformers) model is improved and fine-tuned to classify the data in the form of comments. The results obtained from the pre-trained Bert model are processed using a constructed neural network model. The accuracy and validity were 85.83%. They also compared the obtained results with other models and found that the Bert model results performed best among all three models used for classification. Religion is significant in accordance with extremism, as stated by [17]. Translation of social media data in two local languages, Sinhala, and Tamil, was initially done, and then tried to predict religious extremism in the context of data extracted from social media in Sri Lanka after a bombing incident occurred. The three well-known algorithms, Naive Bayes, SVM, and Random Forest, for evaluation of text data, were used, in which they have shown Naive Bayes algorithm result accuracy was 81% for Sinhala tweets data, and on the other side, random forest algorithm has shown best results of 73% accuracy rate for the Tamil language tweets.

Disaster affecting in the form of bushfires, earthquakes, floods, cyclones, and heat-waves around the world on social media is discussed every day. It is interesting to study the nature of disasters hitting different places on our globe and through social media the opining of users related to disaster can be studied. Location oriented disasters are a very interesting topic to understand the opinion of how people react differently. Thus, disaster situations are of prime importance for experts and decision makers. [18] presented a new automated approach by using natural language processing and artificial intelligence named entity recognition (NER), irregularity detection, regression, and Getis Ord Gi algorithms to do sentiment analysis of data extracted from social media related to disaster. They proposed a system having sufficient knowledge of social media data including 39 different languages and a data set comprising 67515 tweets. The algorithm extracted 9727 locations around the world with more than 70% reliability through live location feeds collected from twitter of specific regions. The algorithm with the accuracy of 97% is achieved after automatic classification. In the regard they also highlighted the research gaps related to inaccuracy of disaster related tweets classification, limited languages used for analysis and classification, and lack of location oriented live feedback of disaster. Limited online information using mobile apps is another issue. With the help of a proposed approach using mobile devices by implementing AL and NPL, organizations would be able to tackle more productively the crises and emergencies caused by disaster. They also suggested that their data set can be Merage with NASA's global landslide inventory for future prospective [19].

Traditional text mining on social media, i.e., Twitter, suffers from many challenges such as limited characters' restrictions and the noisy nature of tweets posted. Event detection from Twitter is badly affected by the nature of the tweet. Thus, it is crucial to evaluate the segmentation and sentiment of the tweet. SegAnalysis framework was used to handle these challenges faced on social media. [20] in their work, the segmentation was performed using POS (Part of speech) tags to fetch data. Naive Bayes classification and online clustering techniques detect the subject. The Naive Bayes and clustering mechanism help identify the event detection and reduce computational overheads. Segmentation is also very beneficial in preserving the semantic meaning of tweets NER (Named Entity Recognition). In this work, the authors highlighted some challenges related to any disaster, i.e., earthquake, flood, hurricane, or human disaster such as terrorist attacks. They try to analyse the data collected from online sources Facebook, Twitter, and Instagram, among these, most of the time, using API, Twitter is given preference by the researcher in analysing the data using different Machine learning and deep learning techniques. This study collects feedback about research articles for disasters or crises regarding early detection and warning, response after the disaster, and damage caused. This helps other researchers work on three aspects of any disaster before, during, and after user reactions to the crisis. It will support response teams in taking quick action on any disaster or crisis. Their studies showed that researchers face several issues and problems during classification and analysis to improve the precision, recall and accuracy of the detected information gathered from online sources. Their work also provides a source for exploring new ways to understand different techniques used to detect disaster through social media data [21].

It is very important to study the aftereffects of a disaster once it occurs. The reaction of people on social media gives feedback and their intentions to react with the situation. This also enables researchers to study the general as well as individual behavior of people. To find the sentiment in the data, based on the opinion in the response of any action plan tried by organizations to be implemented. A very limited work-related bushfire was addressed previously. Thus, in this research we identified user sentiments in response to the natural disaster and towards the organization's fundraising attempts specific to a disaster incident – the Australian bushfires of 2019–2020.

## 3 Data Preparation and Methods

The Australian Red Cross organization published 186 posts on its Facebook page from October 2019 to March 2020. We have collected a corpora of all the text content of the related posts and their comments from the Australian Red Cross organization Facebook page using the Facebook Graph API. The data fields of the corpora include text data of the post which create and update the time of the post, post type, post URL, and the social engagement count such as share, comment, likes, and so forth. Some of the comments are filtered out concerning the privacy filtering settings of Facebook users. We also excluded the replies from the comments data. The posts on the Facebook page were categorized into four types. Figure 1 shows the graphical representation of the post count in each category. Among the 186 posts published on the page, 86 posts are photo (image) type. Link posts are posted with a URL link to a donation site or lifehack articles on Red Cross homepages. Album posts often reports the Australian Red Cross activities with multiple photos. It was founded that only 14 videos were posted in the five-month duration as shown in Fig. 1 below.

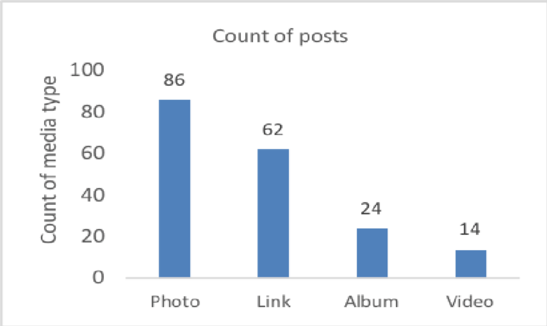


**Fig. 1.** Count of Media Type

### 3.1 Sentiment Annotation

To understand the user behaviour closely, we perform sentiment analysis on the Facebook data to categorize each comment as positive, negative, or neutral. Understanding the users' sentiment through their comments on the Australian Red Cross Facebook posts highlights the necessity of social media engagement for disaster fundraising and related events. Since the comments data collected from Facebook Graph by using API does not contain sentiment values, three human annotators manually labelled all the comments, considering the inter-coder reliability.

The process of manual annotation requires a set of specific rules to produce consistent sentiment labels. Due to the nature of the subjectivity of natural language, the lack of specification leaves the annotator in doubt over how to label certain kinds of instances. [22] proposes two annotation schemes: A simple and semantic-role-based sentiment questionnaire. A simple sentiment questionnaire focuses on the language itself. If a text contains negative words such as bad, sad, violent, etc., then the text is labelled as negative even if the speaker's intention is positive for that expression. This annotation scheme is easy to use and cost- effective. However, the simplicity of this questionnaire may not suit the social media text because there are various expressions used in social media, and it is vital to understand the context of the texts. A semantic role-based sentiment questionnaire focuses on not only a word itself but also the target of opinion and the speaker's emotional state. The important aspect of this questionnaire is that it takes account of the entity in a text. For instance, if the text criticizes the Australian Red Cross, Australian Red Cross is the Primary Target of Opinion (PTO), and if the speaker's expression is negative towards the organization, the sentence is likely to be negative. This questionnaire obtains rich information from the social media context and helps label sentiment values. Given such a practical framework, we employed [22] semantic role-based sentiment questionnaire to label the comment data on the Australia Red Cross Facebook posts. To carry out the sentiment annotation task, each human annotator answers the set of questions to categorize each text item into a sentiment category as positive, negative, or neutral as shown in Table 1.

**Table 1.** Set of questions answered by each annotator during manual sentiment annotation.

| | |
|---|---|
| Q1 | How to read the text, and the speaker's emotional state can best be described as positive, negative or a neutral state? |
| Q2 | How to read the text, and identify the entity towards which opinion is being expressed or the entity towards which the speaker's attitude can be determined? |
| Q3 | What best describes the speaker's attitude, evaluation, or judgment towards the primary target of opinion (PTO)? |
| Q4 | What best describes the sentimental impact of the primary target of opinion (PTO) on most people? |

### 3.2 Methods

Natural language processing (NLP) is a sub-domain of artificial intelligence. It handles human language and assists computer processes, derives, and understands its content and context in the same way human beings can. The information technology industry has accelerated computational performance exponentially in the last couple of decades. Accordingly, researchers are utilizing NLP to deduce more value from a large amount of data. However, the growing amount of social media data is voluminous, complex, and even unmanageable to be processed manually. NLP enables the extraction of useful information from large amounts of textual data and the analysis of content information for collective insight [23]. Sentiment analysis incorporates natural language processing to analyse people's opinions, sentiments, attitudes, and emotions from the text. This technique transforms unstructured text data into structured and qualitative text data labelled with sentiment categories. Conducting sentiment analysis for Facebook comments shall provide an overview of public opinion towards the Australian Red Cross and help them design strategies to communicate with their target audience.

In addition to the human annotation, we utilize Valence Aware Dictionary for Sentiment Reasoning (VADER), Afinn, and Textblob to compute machine-generated sentiments. This additional task for sentiment analysis is performed to measure the capability of unsupervised machine learning techniques. This is helpful in scenarios where user-generated data is in vast volumes and cannot be processed by manual human-based annotations. Evaluation of these machine learning techniques shall aid non-profit and non-government organizations in carrying out independent machine-based tasks for social engagement understanding [23]. Afinn is the simplest, yet popular lexicons used for sentiment analysis. It contains 3300+ words with a polarity score associated with each word. TextBlob is another lexicon-based sentiment analyser which comes with predefined rules (word and weight dictionary), which has scores that help to calculate a sentence's polarity. VADER is a rule-based model for general sentiment analysis and microblog content such as text on Facebook and Twitter [24]. There are several advantages of VADER performing in social media contexts. Firstly, the VADER lexicon performs exceptionally well on social media [25]. Text data in social media contains many punctuation marks and simple words such as emojis, acronyms, and slang that are typically removed in the pre-processing step. However, these algorithms can efficiently produce sentiment analysis scores from those ambiguous words. Computationally, these do not require any training data, i.e., they work in an unsupervised fashion. Training machine learning models can be a time-consuming and complicated process and requires huge volumes of annotated data. The employed algorithms eliminate the necessity of labelled data and makes the opinion analysis process robust.

Text pre-processing is a crucial step for performing data analysis in machine learning. The unstructured or raw data contains noise, which adversely affects the overall performance of a machine learning model [26]. We performed text pre-processing prior to performing the sentiment analysis using VADER, Afinn and Textblob. The implementation is carried out on Google Colab using Python version 3. The raw data was cleaned by removing the hashtags and non-English words from the comments. However, we didn't removed punctuation marks, emojis, or acronyms from the text as they affect the sentiment intensity and score. The 'polarity scores' method in the "Sentiment Intensity Analyzer" object produces a compound score that is the sum of positive, negative, and neutral scores ranging between $-1$ (negative) and $+1$ (positive) from a given text. A text with more than a 0.05 compound score is classified as positive. A text with less than or equal to a $-0.05$ compound score is negative. In other cases, a text is classified as neutral.

# 4 Results

## 4.1 Content Analysis

This subsection discusses the type of content on the Australian Red Cross Facebook page and analyses its constituency. Table 2 shows the shares, comments, and likes on each type of media content, i.e., albums, photos, videos, and links. It is observed that album posts, on average, get a more significant number of likes and shares, followed by photos, videos, and links, in that order. However, posts with videos engage the viewers more towards leaving a comment followed by the album, photos, and links. It can be inferred that users are less likely to engage with a URL post. The presence of high visual media content, such as multiple photos or videos uploaded together as an album in a post, demonstrate the highest engagement. Multiple media uploads can be used to target and trigger a greater audience. Photo and video posts earn their fair share of engagement through likes, shares, and comments. The table also implies that the visual media types tend to attract more viewers and let them comment more quickly.

## 4.2 Sentiment Analysis

Figure 2 shows the sentiment distribution of 4761 comments. Out of 4761 comments, 2507 comments are classified as positive by VADER, 1297 comments are classified as

Negative, and 957 comments are classified as Neutral. The number of positive comments significantly differs from the comment distribution by the human rater. Considering the number of negative comments is quite similar, either one might fail to distinguish between positive and neutral comments. VADER classified half of the comments as positive. Most of the classified neutral comments have a sentiment score of zero. This is partly because of the shortness of the comment. Many common words appear both in positive and negative comments.

There are instances where positive comments are classified as negative or neutral as shown in the Tables 3, 4, and 5. This is attributed to the fact that some positive or neutral sentences containing negation words like 'not,' 'never,' or 'no' are labelled with negative sentiments. The presence of negation words is impacting the sentiment score by reducing it. We can observe the limitation that machine-generated sentiment scores are not context-sensitive but only focus on word sentiment individually. In such a case, human-rated annotations are more trustworthy as it seeks human cognition and context awareness to label a particular comment.

Table 6 provides Accuracy (A), Precision (P), Recall (R) and F1 scores (F1) for VADER, Afinn and TextBlob. It was observed that amongst the three algorithms, VADER has the highest scores, followed by Afinn and TextBlob. Figure 3 illustrates the frequency of occurrence of comments based on their sentiment scores. We can affirm the observation derived from figure, as the positive comments have significantly higher occurrence than the negative ones, along with a massive spike around the neutral score of 0, which explains the presence of roughly a fourth of comments being sentiment neutral.

**Table 2.** Number of social engagement attributes per post

| Media Type | # Shares | # Comments | # Likes |
|---|---|---|---|
| Album | 216 | 44 | 869 |
| Link | 89 | 18 | 186 |
| Photo | 137 | 42 | 337 |
| Video | 97 | 73 | 146 |

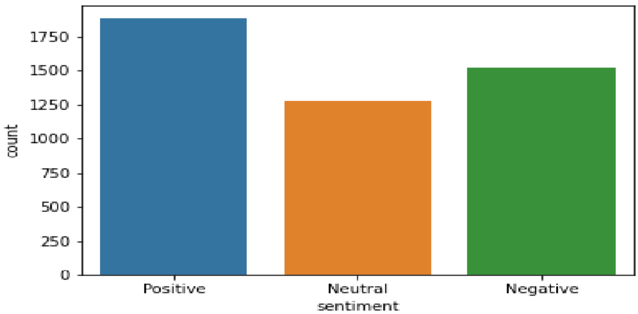


**Fig. 2.** Sentiment distribution of comments.

**Table 3.** Example of comments classified as positive.

| **Row ID** | **Message** | **Sentiment** | **Sentiment Score** |
|---|---|---|---|
| 79 | Done. Happy to help beautiful country that I could hope visit one day❤️ | Positive | 0.9591 |
| 80 | Done ✅ keep up your wonderful work❤️ | Positive | 0.5719 |
| 81 | Donated. Sending love and praying for all victims of tragedy 🖤 🙏 | Positive | 0.6369 |
| 82 | Donated. Keep up your generous work. 👏 | Positive | 0.5106 |
| 83 | Done just now keep up the fantastic work ❤️ | Positive | 0.5574 |

**Table 4.** Example of comments classified as negative.

| Row ID | Message | Sentiment | Sentiment Score |
|---|---|---|---|
| 138 | The people who have been left devastated by the bushfires need that money now dont hold | Negative | −0.7964 |
| 156 | Stop donating through red cross | Negative | −0.2960 |
| 159 | Is it true that you are taking a ridiculous of what australias and others have donated to… | Negative | −0.5062 |
| 166 | Now pass on all the money pffft red cross so disappointed | Negative | −0.6113 |
| 221 | Donors for the tragic bush fires please do not donate to the red cross the red cross intends | Negative | −0.8555 |

**Table 5.** Example of comments classified as neutral.

| Row ID | Message | Sentiment | Sentiment Score |
|---|---|---|---|
| 15 | I have just had the same issue on the 1st attempt but on 2nd it went through | Neutral | 0.0000 |
| 222 | should we register if we have evacuated from our homes but not to one of the eva. | Neutral | 0.0000 |
| 452 | how much per dollar raised will go to the recipients of the bushfires genuine quest… | Neutral | 0.0000 |
| 1271 | who will be independently auditing this financial program | Neutral | 0.0000 |
| 3804 | the money should be distributed now | Neutral | 0.0000 |

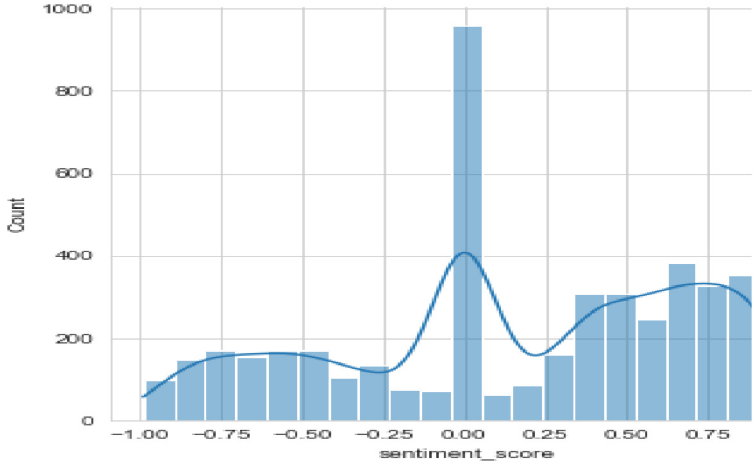


**Fig. 3.** Distribution of sentiment scores

**Table 6.** Sentiment classification results.

| Algorithm | A (%) | P (%) | R (%) | F1 (%) |
|---|---|---|---|---|
| VADER | 62.21 | 61.55 | 62.21 | 61.06 |
| Afinn | 58.16 | 58.11 | 58.16 | 57.26 |
| TextBlob | 51.96 | 55.12 | 51.96 | 52.11 |

## 5 Conclusion

This study identifies that most of the sentiment of the user-generated comments is positive from Oct. 2019 to Mar. 2020. In accordance, the social engagement attributes such as share, likes, and reach are also high in the same period of time. Although there are strong positive correlations between each social engagement attribute, they do not necessarily correlate with the amount of donation. The results suggest the necessity of developing robust unsupervised algorithms for sentiment classification that can handle the challenges of conflicting text, understand contextual meaning, and provide accurate sentiment annotations in the absence of labelled data resources. Such a development is highly demanded for real world use-cases like natural disasters and emergencies. It shall allow the policymakers and various stakeholders to better understand people's opinion, devise social media-based fundraising strategies, and positively influence their donation behaviour.

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