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Research Article

Emotion Detection in Conflict Discourse: An Unsupervised Approach to Multilingual YouTube Comments

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ABSTRACT

Introduction: Emotion detection from text has become a critical research direction in natural language processing, particularly with the rise of emotionally charged and multilingual content on platforms like YouTube.

Objectives: The main objectives of this study are the automatic annotation of a multilingual corpus and the investigation of the psychological impact of crises on individuals, by analyzing the emotional content embedded in YouTube comments associated with war-related videos.

Methods: This study focuses on unsupervised emotion detection from YouTube comments related to the Gaza war, using data in both English and Arabic. It explores the role of Emojis in enhancing emotional interpretation. Generally, the findings confirm the effectiveness of the clustering techniques in detecting emotional patterns from unstructured and diverse YouTube data. The proposed framework presents a scalable, language-aware solution for unsupervised emotion detection, making it particularly suitable for multilingual and sensitive contexts.

Results: The resulting labeled datasets provide a valuable foundation for training supervised models, thereby contributing to the development of more robust and effective emotion detection systems in the domain of YouTube comment analysis. The results highlights a consistent predominance of negative emotions across both English and Arabic datasets, regardless of emoji inclusion.

Conclusions: Negative emotions exceed 70% in the English data and surpass 80% in the Arabic data, while positive emotions remain notably underrepresented in all cases.

Keywords: Emotion Detection, Unsupervised Learning, Clustering, YouTube Comments, Emojis.

INTRODUCTION

In the digital age, social networks have become vital platforms where people express their opinions, thoughts, and emotions in real time. These platforms generate vast amounts of user-generated content daily, making them an invaluable source of data to understand collective sentiments and psychological trends. Among these platforms, YouTube has a unique position due to its visual content and the discursive density of its comment sections, which often reflect strong emotional and political engagement, particularly in contexts of crisis or armed conflict. A salient example of emotionally driven digital discourse can be observed in the context of the ongoing conflict in Gaza, which has triggered widespread global engagement across social media platforms. YouTube comments on related content often reveal spontaneous affective expressions, providing valuable insight into public sentiment. However, analyzing such short, noisy, and multilingual data remains challenging, particularly in the absence of labeled datasets required

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for supervised emotion detection. Emotion detection, also known as emotion recognition, entails the computational identification and classification of affective states such as joy, surprise, disgust, sadness, anger, and fear within multimodal data including textual data and based on an emotional model (Ekman, 1992). Emotion detection comprises a diverse set of techniques that have evolved significantly with technological advancements, improving the ability of systems to recognize and interpret human emotional states. From the analysis of facial expressions and physiological signals in videos, to speech processing in audio data, and textual content analysis, a wide range of modalities have been explored to detect underlying emotional states.

In this study, we introduce an unsupervised framework for emotion detection in YouTube comments, based on clustering techniques (Aggarwal, 2022). This research contributes to the advancing domain of affective computing (Picard, 2003) and computational social media analysis by proposing a novel unsupervised approach to emotion detection in multilingual and sensitive user-generated content. The findings have potential implications across several high-impact application areas, including digital activism, psychosocial monitoring, computational public opinion analysis, and the automated moderation of emotionally charged or polarizing online discourse.

The paper is structured as follow: the next section is reserved to the background related to the context of this study; the third section explains the detailed methodology of our work followed by the result and discussion section. In the last section, a conclusion and future work is presented.

LITERATURE REVUE

A substantial amount of research, grounded in psychological and computational emotional models, has investigated the application of machine learning techniques for affect recognition (Picard, 2003) across social media platforms. Studies have focused on platforms such as Twitter, Facebook, and YouTube, leveraging user-generated content to automatically detect and classify emotional states like joy, fear, anger, disgust, surprise and sadness. These approaches typically rely on features derived from textual, contextual, and sometimes multimodal data, and have demonstrated the potential of computational methods to model complex emotional responses in dynamic and linguistically diverse environments. Illustrating an amount of recent researches interested in emotion detection from social media, (Gaind et al., 2019; Rahman & Shova, 2023; Zhang, 2023) highlight a wide range of approaches in this context. According to the World Health Organization (World Health Organization, 2001), in contexts of armed conflict, approximately 10% of individuals exposed to traumatic events are likely to develop severe mental health disorders, while an additional 10% may exhibit behavioral issues that impair their daily functioning. The most frequently observed conditions include depression, anxiety, and psychosomatic symptoms such as insomnia and chronic. The study performed in (Aldabbour et al., 2024) highlights the profound psychological impact of the Gaza war on young Palestinians, marked by notably high rates of depression, anxiety, stress, and PTSD. Including social media analysis, the study performed in (Hofmann et al., 2025) indicates a significant presence of hate speech and polarized sentiment in YouTube comments related to the Israel Palestine conflict, with notable differences between public and private content sources. The study in (Liyih et al., 2024) demonstrates that YouTube comments from reputed news channels during the Palestine Israel war are largely neutral in tone, while comments from public sources express significantly stronger sentiments toward Israel or Palestine compared to private sources. They proposed CNN-BiLSTM hybrid model that achieved high classification accuracy, highlighting the effectiveness of deep learning for analyzing emotionally charged social media communications. In the analysis provided by (Ramos & Chang, 2023) of both English and Russian tweets revealed that fear (32%) and anger (15%) were the predominant emotions in English language content, while 86.8% of Russian language tweets presented negative sentiment. These results underscore extensive emotional distress in global digital conversations surrounding the Russia Ukraine conflict. In the same context, (Temel EgiNli̇ & Özmelek Taş, 2023) employs a hybrid sentiment analysis approach, combining AI-based classification with manual validation, to analyze Twitter (X) posts related to the Russia Ukraine war. The reached results show a predominance of negative sentiment, highlighting the emotional impact of conflict related discourse on social media platforms. In the same context of the Russian Ukrainian conflict (Nandurkar et al., 2023), Reddit data was extracted using the PRAW API and annotated using the VADER sentiment tool. Following standard preprocessing procedures, multiple machine learning classifiers were trained and assessed. Among them, the Multinomial Naïve Bayes model demonstrated superior performance, achieving an accuracy of 82.65%. The study performed in (Ng et al., 2024) introduces a novel multi-modal, multi-platform dataset capturing expressions of both love and hate during the 2023 Israel Palestine war, covering text and visual content across social media platforms. The finding is to facilitate advanced analysis of emotionally polarized discourse by enabling cross modal modeling and comparison of affective expressions in conflict related user content. Numerous researches was performed in the text based Emotion detection field (Ramasubba Reddy et al., 2023; Saxena et al., 2020) and particularly in social media text analysis using machine learning techniques (Amangeldi et al., 2024; Marechal et al., 2019; Prajapati et al., 2024; Yasmina et al., 2016). The unsupervised emotion detection approach proposed in (Yasmina et al., 2016) used on a data corpus built from YouTube comments, relying on semantic similarity through measuring the Pointwise Mutual Information parameter (PMI) between each word in the text to classify and representative words of each target emotion. This measurement is based on the co-occurrence between the word to classify and the representative words in the corpus. Their method, aligned with Ekman's six basic emotions, achieved high precision, demonstrating the effectiveness of semantic clustering in multilingual, unstructured contexts. This work remains a key reference for unsupervised techniques in low-resource emotion annotation settings.

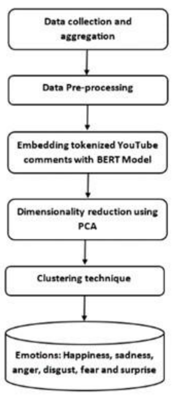
METHODS

The methodological framework of Emotion detection from textual data involves a multi stage pipeline including data collection and preprocessing, and the embedding tokenized YouTube comments with BERT Model as illustrated in Figure1. This schematic serves as a conceptual guide to the overall process; the resulting dataset is annotated with the six emotions based on the Ekman model. Our analysis places particular emphasis on the treatment of Emojis, despite their relatively low frequency compared to textual tokens. While Emojis are relatively scarce in number but possess a high degree of expressive richness, often encapsulating nuanced emotional content that would otherwise require several words to articulate. This highlights the critical importance of integrating Emojis into the emotion detection pipeline. Their capacity to convey affective meaning in a concise and visually salient form makes them essential to a comprehensive and accurate interpretation of emotional signals within the dataset.

1. Data Collection

The multi lingual corpus employed in this study is composed of two complementary Arabic and English datasets collected using YouTube API v3 from videos illustrating war scenes from Gaza originating respectively from Aljazeera Arabic and English public channel. The first Arabic dataset that was collected from user generated text comprises 8970 Arabic comments written in both Modern Standard Arabic and regional dialects. In parallel, the second dataset was sourced using the same API and consisting of 2664 English comments of peoples over the word. The used YouTube Data API provided by Google allows us to programmatically access and manipulate YouTube data. This includes operations such as retrieving video metadata, channel information, playlists, and comments. For each comment, we have the detailed information such as the text of the comment, the publish date, the number of likes on the comment, the author's display name. The table1 presents the mane features of the used corpus.

Figure 1. Methodology steps



Journal of Information Systems Engineering and Management
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Table. 1. Key Features of the corpus

	Arabic Dataset	English Dataset
Total number of comments	**8970**	**2664**
Number of comments with Emojis	3470	527
Number of comments without Emojis	5500	2144
Percentage of comments without Emojis	39%	20%

2. Data preprocessing

Before performing emotion detection, data preprocessing plays a vital role in improving the quality and uniformity of textual input. This process involves a series of tasks carried out over multiple phases, as illustrated in the figure2. Initially, the text is cleaned by removing URLs, user mentions, special characters, HTML tags, stock market tickers,

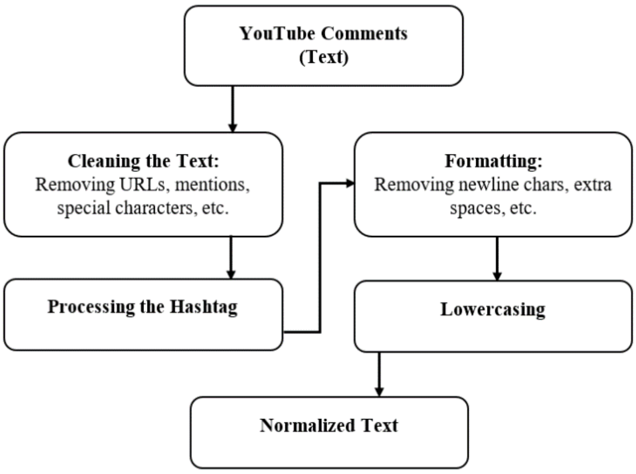

Figure 2. Data pre-processing steps

and other extraneous elements to minimize noise. Then, repeated letters are normalized by limiting the repetition to a maximum of two consecutive characters to standardize word forms. Hashtags are handled by removing the # symbol while retaining the associated words, as they may contain meaningful semantic information. Newline characters are also removed, replacing underscores with spaces, and eliminating extra whitespace to enhance consistency. After that, all text is converted to lowercase to ensure that identical words in different cases are not treated as distinct by the model. Words like articles, prepositions, and conjunctions are commonly removed to reduce noise. Finely, numerical values are preserved during preprocessing, as they can carry significant contextual meaning that may contribute to understanding the intensity or scope of emotional content.

3. Tokenization end generation embedding

After completing the data cleaning stage, text tokenization is performed using BERT's tokenizer. This tokenizer segments the cleaned text into subwords using the WordPiece algorithm, converting them into token identifiers that can be interpreted by the BERT model. These token IDs are then used as input embedding, allowing BERT to capture the contextualized semantic representations of the text in both forward and backward directions. This bidirectional

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Research Article

encoding is essential for tasks such as emotion detection, where understanding the full context of each word is crucial. For English textual data, we utilized the well-established BERT model, In the case of Arabic text; we employed AraBERT v2 is specifically designed to address the linguistic complexities inherent to Arabic, including its rich morphological structure and various dialectal forms.

4. Dimensionality reduction using PCA

The output of the BERT model had a relatively high dimensionality, which posed challenges during the clustering phase due to increased computational complexity and potential noise. To address this issue, we applied Principal Component Analysis (PCA) to reduce the dimensionality of the feature space. PCA allowed us to retain the most significant variance in the data, thereby preserving essential patterns and structures while producing a more compact and manageable representation. This dimensionality reduction step enhanced the efficiency and effectiveness of the subsequent clustering process.

5. Clustering technique

Unsupervised learning techniques offer a promising alternative for labeling textual data with minimal human intervention. This motivates the use of clustering methods in the context of automatic text annotation. Our main contribution lies in the application of clustering algorithms, specifically K-means that is efficient for large datasets offering a well capturing off spherical clusters, to assign appropriate emotional labels to YouTube comments. This process results in a labeled dataset that serves as a foundation for training supervised models aimed at effective emotion detection.

6. Evaluation Metrics

Clustering is an unsupervised learning technique aimed at grouping data points based on their intrinsic similarities in the absence of predefined class labels. It involves partitioning a dataset into distinct clusters such that instances within the same cluster are more similar to each other than to those in other clusters. However, due to the lack of ground truth labels, evaluating the performance of clustering algorithms poses a significant challenge. To address this, several evaluation approaches have been proposed, including internal validation, external validation, and manual inspection. In this study, we focus on internal evaluation measures to assess the quality of the generated clusters. These measures do not require reference labels and instead evaluate clustering performance based on the intrinsic properties of the data. By also measuring intra-cluster cohesion and inter-cluster separation, internal measures provide valuable information about the structural robustness of clustering solutions. The internal evaluation measures adopted in this work are as follows: silhouette coefficient, Davies-Bouldin index, and Calinski-Harabasz index.

RESULTS AND DISCUSSION

In this section, we describe the various results of our work, as well as an evaluation of the effectiveness of the algorithms applied to the two data sets. Emojis are processed using a dedicated Python library designed to facilitate the processing and manipulation of emojis in textual data. It offers a whole range of features, including the insertion, deletion, and conversion of emojis into text, making it particularly useful for tasks involving the analysis of emotion-sensitive texts.

The Table 2 illustrates the results of the application of the K-Means clustering algorithm on the English dataset. It indicate that omitting Emojis provides higher clustering performance across all metrics. Precisely, the Silhouette Score increases from 0.82188326 to 0.86094457, suggesting improved intra cluster similarity and inter cluster separation. Similarly, the Calinski-Harabasz Index shows a substantial rise from 405.51025 to 1879.3656, reflecting better-defined cluster structures. The Davies-Bouldin Index, where lower values indicate better clustering, decreases from 0.1382 to 0.1005, confirming the increased internal compactness and separation of the clusters when emojis are removed from the comments.

Journal of Information Systems Engineering and Management
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Research Article

Table. 2. The silhouette score of the K-Means clustering algorithm for the English dataset

English Dataset	Silhouette Score	Calinski-Harabasz Index	Davies-Bouldin Index
With Emoji	0.82188326	405.51025	0.138194331985677
Without Emoji	0.86094457	1879.3656	0.10046716370294587

The Table3 summarizes the internal clustering evaluation metrics obtained for the Arabic dataset, comparing configurations with and without Emojis. Conversely, to the results observed for the English dataset, the presence of Emojis in the Arabic dataset significantly improves clustering performance across all metrics. The Silhouette Score increases from 0.69637007 to 0.8439086 if emojis are retained, indicating stronger intra cluster cohesion and better separation. Similarly, the Calinski-Harabasz Index shows a marked improvement, rising from 5565.23 to 16072.97, suggesting that the clusters formed with Emojis consideration are more compact and well defined. Additionally, the Davies-Bouldin Index decreases from 0.8035 to 0.1707, confirming that clusters are both more cohesive and better separated when Emojis are preserved in the comments.

Table. 3. The silhouette score of the K-Means clustering algorithm for the Arabic dataset

Arabic Dataset	Silhouette Score	Calinski-Harabasz Index	Davies-Bouldin Index
With Emoji	0.8439086	16072.965	0.17072786876555382
Without Emoji	0.69637007	5565.2344	0.80353033593487773

The Table 4 and the Table 5 present the distribution of emotion labeled YouTube comments in respectively the English and the Arabic datasets, comparing the presence and absence of Emojis. The data reveal notable shifts in emotional composition depending on whether Emojis are retained or excluded.

Table. 4. Results of the English dataset comments labeling based on the Ekman Model

Emotion	Number of comments with Emojis	%	Number of comments without Emojis	%
Angry	98	19%	528	25%
Disgust	63	12%	305	14%
Fear	75	14%	273	13%
Joy	157	30%	450	21%
Sadness	69	13%	280	13%
Surprise	65	12%	308	14%
Positive emotion	370	30%	450	21%
Negative emotion	157	70%	1694	79%

In the English data, when Emojis are preserved, positive emotions, are more frequently represented. Specifically, joy represents 30% of Emojis containing comments, compared to just 21% when Emojis are removed. However, the

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dataset without Emojis shows a significant rise in negative emotional expressions, comprising 79% of all comments, compared to 70% when Emojis are retained.

Table. 5. Results of the Arabic dataset comments labeling based on the Ekman Model

Emotion	Number of comments with Emojis	%	Number of comments without Emojis	%
Angry	568	16%	943	17%
Disgust	569	16%	912	17%
Fear	580	17%	878	16%
Joy	633	18%	992	18%
Sadness	569	16%	931	17%
Surprise	551	16%	844	15%
Positive emotion	360	18%	992	18%
Negative emotion	2837	82%	4508	82%

For the Arabic dataset, the percentages across emotional categories show only minimal variation between the two cases: with and without Emojis extraction. Across both configurations, negative emotions remain dominant, representing 82% of the comments whether Emojis are preserved or not. This category includes angry, disgust, fear, sadness, and surprise showing very similar proportions in both situations. Similarly, positive emotions, particularly joy, remain stable, with joy consistently representing 18% of the total in both cases. The overall proportion of positive emotions remains unchanged at 18%, regardless of emoji presence.Figure 3 illustrates the distribution of positive and negative emotions across English and Arabic datasets, with and without the inclusion of Emojis. The analysis reveals a consistent predominance of negative emotions in all configurations. In the English dataset, the proportion of negative emotions is exceeds 70% of negative emotions in both cases. Similarly, in the Arabic dataset where negative emotions constitute over 80% of the total comments regardless of emoji presence. Positive emotion representation remains low in both cases.

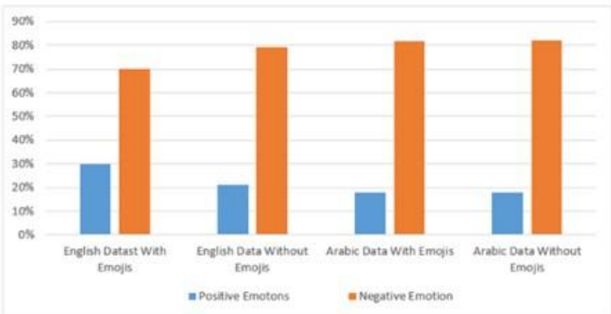

Figure 3. Distribution of the Emotions over the corpus

CONCLUSION

This study presented a comprehensive and innovative framework for unsupervised emotion detection in multilingual YouTube comments related to the Gaza war, focusing on English and Arabic texts. The proposed framework is interested to the integration of unsupervised technique to automatic generate labeled datasets preserving time and effort reserved in the manual annotation process commonly used. The framework leverages the Emojis presence to enhance the clustering results within both datasets composing the used corpus.

In the English data, the results suggest that emojis are more frequently associated with positive affect, and their presence tends to shift the emotional distribution toward a more positive tone. Removing emojis may obscure these affective cues, leading to an unbalanced emphasis on negative emotions during labeling. The presence of Emojis introduces variability that may obscure latent semantic patterns, thus slightly degrading the overall clustering quality. These results highlights the importance of Emoji features in capturing affective nuances within English text, where emojis appear to play a more semantically informative role. By comparison, to the English dataset, the presence of Emojis in the Arabic dataset does not significantly shift the emotional distribution. This suggests that Arabic language comments Shows greater reliance on on textual cues rather than Emoji symbols to convey emotional content, and that Emojis in English are used more consistently across emotional categories.

In conclusion, the findings reveal that the majority of comments conveyed negative emotions across both language groups, English (representing the general population) and Arabic (reflecting a more context-specific population). This consistent pattern highlights the profound and pervasive psychological impact of war on individuals, suggesting that such events imprint emotional traces independently of linguistic or cultural background.

Future directions could involve the development of more sophisticated approaches for emoji processing, enabling their interpretation in ways that enhance emotional expressiveness and nuance. Furthermore, other clustering technique may be used to perform more relevant automatic annotation by creating labeled datasets offering a rich basic data for valuable training for the supervising technique allowing more effective Emotion Detection results in the YouTube comments analysis context in war and peace times.

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