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Emotion Detection using Twitter Dataset

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Abstract: The Twitter Sentiment Analysis Web Application is an innovative tool designed to analyze and categorize the sentiment expressed in tweets on the Twitter platform, encompassing a diverse range of emotions, including anger, joy, sadness, love, surprise, and fear. Leveraging cutting-edge techniques in natural language processing (NLP) and machine learning, the application offers users comprehensive insights into the emotional content of tweets. At the core of the application lies a sophisticated machine learning model trained on a meticulously curated dataset annotated with six distinct emotion categories. The model employs a combination of techniques, including TF-IDF vectorization and logistic regression classification, to accurately classify tweets based on their emotional content. To ensure the quality and reliability of the sentiment analysis, the application implements a robust preprocessing pipeline. This pipeline includes steps such as text normalization, tokenization, stop word removal, punctuation removal, and lemmatization, which collectively prepare the text data for accurate classification. The user interface of the web application is designed to be intuitive and user-friendly, allowing users to input tweets effortlessly and receive instant feedback on the predominant emotion conveyed in the text. The results are presented in a visually appealing format, enabling users to interpret the emotional analysis with ease. With real-time analysis capabilities, the application empowers users to stay informed about the emotional trends and dynamics of the Twitter verse as they unfold. This functionality enables users to monitor and analyze tweets in real time, facilitating timely insights into emerging sentiments and trends. By harnessing advanced techniques in NLP and machine learning, the Twitter Sentiment Analysis Web Application provides users with a powerful platform to understand and interpret the emotional landscape of Twitter conversations. Whether for brand perception analysis, market research, or social listening purposes, the application offers unparalleled insights into the sentiments expressed on Twitter.

Keywords: Emotion detection, twitter, semeval, emotion detection, machine learning, ait2018, emotion classification.

1.INTRODUCTION

Social media monitoring can be referring either to measuring opinions about current events, also called sentiment analysis, or to the emotion detection in the produced content. The term sentiment analysis , is referring to the process of identifying and categorizing text based on the opinions expressed in it using an automated way. The process is focusing exclusively to the analysis of the attitude of the This work is part of the RESIST project. RESIST has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement no 769066. Content reflects only the authors' view. The Innovation and Networks Executive Agency (INEA) is not responsible for any use that may be made of the information it contains. person that provided the text and it is categorized as positive, negative, or neutral. Such analysis is mainly used for movies, products and persons, when measuring their appeal to the public is of interest and require extended quantities of text collected over a long period of time from different sources to ensure an unbiased and objective output. While this technique is very popular and well established, with many important use cases and applications, there are other equally important use cases where such analysis fail to provide the needed information. As an example, such analysis will not be of value in the case of users in the proximity of an stressful or extreme event, such as a natural disaster due to extreme weather phenomena. To begin with, users in the vicinity of an event are expected to be negatively affected by the situation, they may be scared, worried or angry, so such an analysis would have little or no added value for the risk assessment and the end users. Also, the text, regardless of the sources examined that will be available, is expected to be limited, coming from the few users at the area of the event and produced within a short amount of time.

II. EMOTION DETECTION FROM TWEET

There are four different text-based methods for detecting emotions: learning-based methods, lexical affinity methods, keyword spotting methods, and hybrid methods [13]. We have employed learning-based techniques in conjunction with the lexical affinity approach to automatically identify multi-class emotions from our dataset in order to detect emotions from tweets. To extract the words that include emotions as features from each tweet, we utilized the WordNet-Affect [14] and EmoSenticNet [15] emotion lexicons independently. WordNet-Affect extracts the emotion-representing words from tweets, which are then regarded as features. However, it typically cannot extract words that might not be emotion words but yet convey an emotion. WordNet-Affect can identify whether a word belongs to one of the six fundamental emotions for a limited collection of terms. WordNet-Affect's primary flaw is that it is unable to assign an intensity to words because certain synonyms might really convey distinct emotional meanings in written language. However, EmoSenticNet is a WordNet-Affect extension that also uses the SenticNet [16] rules. After that, it also locates the qualities that WordNet-Affect does not have.

After giving the emotion features a higher score by the application of term frequency and inverse document frequency to the features, we employed several supervised algorithms for the emotion classification process. We have employed supervised machine learning algorithms, including Naïve Bayesian, Decision Tree, and Support Vector Machine, to classify emotions. We have attempted to test the theory of emotion recognition in text documents. Figure 1 below illustrates our suggested technique. Details of each procedure are provided in the following sections.

III. DATASET

We used the SemEval-2018 Affect in Tweets Distant Supervision Corpus (AIT-2018 Dataset) as our dataset. These tweets were retrieved from Twitter using the Twitter API. The tweets have emotion-related keywords like "angry," "annoyed," "panic," "happy," "love," "surprised," etc. They have employed the following methods to produce a dataset of tweets that are rich in a specific emotion. They chose between 50 and 100 phrases that were connected to each emotion X at varying degrees of intensity. The furious dataset, for instance, had words like wrath, hostility, angry, irritated, irked, peeved, and so on. The four emotion classes in this dataset are anger, fear, joy, and sorrow. Anger and disgust have been represented as anger, happiness as joy, and sadness as joy.
Three languages were used to partition the task's dataset: Spanish, Arabic, and English. Five sub-task datasets are available for each language. We exclusively utilize the EI-oc subtask dataset.
where a sentiment and its accompanying strength are included with every tweet [3]. Figure 2 shows the initial distribution of the task EI-oc for the dataset.

IV. PURPOSE OF THE WORK

Social media analysis plays a key role to the understanding of the public's opinion regarding recent events and decisions, to the design and management of advertising campaigns as well as to the planning of next steps and mitigation actions for public relationship initiatives. Significant effort has been dedicated recently to the development of data analysis algorithms that will perform, in an automated way, sentiment analysis over publicly available text. Most of the available research work, focuses on binary categorizing text as positive or negative without further investigating the emotions leading to that categorization. The current needs, however, for in-depth analysis of the available content combined with the complexity and multidimensional aspects of the human emotions and opinions have rendered such solutions obsolete. Due to these needs, currently, research is focusing on specifying the emotions and not only the sentiment expressed in a given text. This is, however, a very challenging effort due to not only the lack of annotated datasets that can be used for emotion detection in text but also the subjectivity infused in datasets that have been created based on manual annotations. A hybrid rule-based algorithm is presented in this paper, that supports the creation of a fully annotated dataset over the Plutchik's eight basic emotions. The presented algorithm takes into consideration the available emoji in the text and utilized them as objective indicators of the expressed emotion thus efficiently tackling both identified challenges.

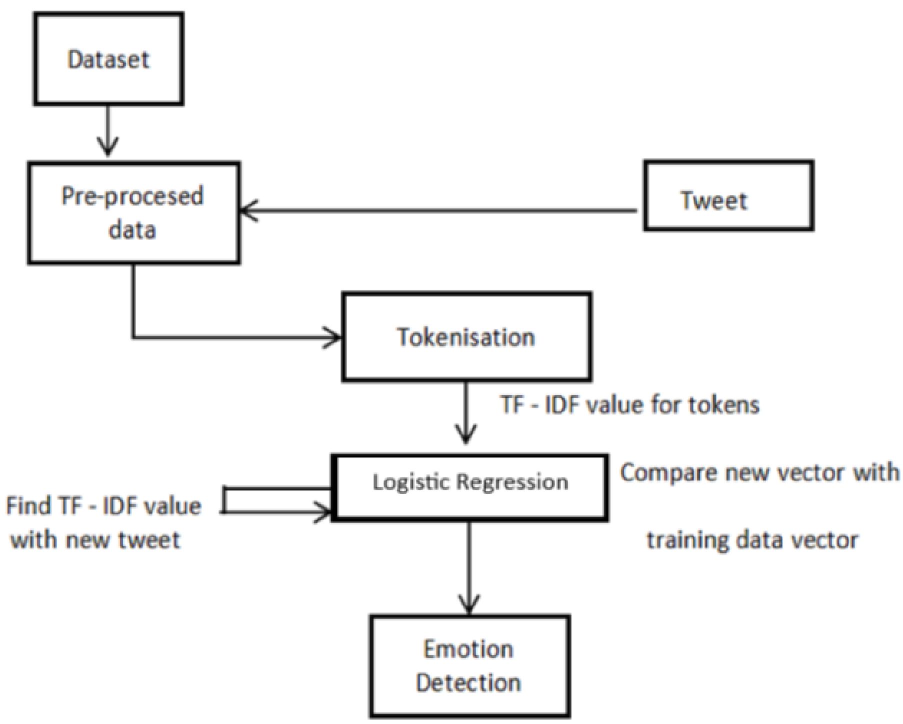
Extracting emotions from Tweets helps gauge public sentiment and brand perception. Existing systems offer various approaches. Machine learning, particularly supervised learning with SVM or Naive Bayes, excels at classifying emotions from labelled datasets with high accuracy, but might be computationally expensive. Deep learning with RNNs like LSTM can capture the flow of language in tweets for potentially more nuanced emotion recognition, but requires significant computing power. Lexicon-based methods are simpler and faster, but rely on pre-built dictionaries and might struggle with sarcasm or context. Choosing the right system depends on your project goals, available resources, and dataset size. Data preprocessing and selecting appropriate evaluation metrics are crucial for all approaches.

The proposed Twitter Sentiment Analysis Web Application encompasses a user-centrist interface designed for intuitive interaction, facilitating seamless input of tweets for sentiment analysis. Leveraging a robust prepossessing pipeline, the system ensures the cleanliness and preparedness of textual data through techniques such as normalization, tokenization , stopword removal, punctuation elimination, and lemmatization. Employing machine learning at its core, the application utilizes TF-IDF vectorization coupled with logistic regression classification algorithms to accurately predict the emotional categories of input tweets. Real-time analysis capabilities further enhance user experience, enabling instantaneous sentiment analysis of tweets as they are posted on Twitter. The system's architecture prioritizes scalability and performance, ensuring efficient handling of large volumes of tweet data while optimizing latency for enhanced responsiveness. Deployment on a reliable hosting platform ensures universal accessibility, with compatibility across major web browsers and devices. A comprehensive documentation package and user support channels are integral components, facilitating ease of use and troubleshooting. Continuous feedback mechanisms drive iterative improvements, ensuring that the application evolves to meet the dynamic needs of its users. Through these components, the Twitter Sentiment Analysis Web Application aims to empower users with insights into the emotional landscape of Twitter conversations.

V. LITERATURE SURVEY

1.“Benchmarking a large Twitter dataset for Arabic emotion analysis ”by A. El-Sayed, M. Abdel-Basset, M. Elhoseny, and M. M. Abdel-Nasser (2023): This paper presents a benchmarking study of different machine learning and deep learning models for emotion detection from Arabic tweets. The authors use a large Twitter dataset that has been annotated with three emotions happiness, sadness, and surprise. The proposed approach achieves an accuracy of 70% on the benchmark dataset.

2.Bollen, J., Mao, H., & Zeng, X. (2011). "Twitter mood predicts the stock market." Journal of Computational Science, 2(1), 1-8. This paper likely involves sentiment analysis of Twitter data to gauge the overall mood of users. Time series analysis techniques are then applied to study sentiment trends over time. Finally, statistical models are constructed to identify correlations between Twitter sentiment and stock market movements.



3.“Utilizing Twitter Hashtags for Sentiment Classification: A Feature-based Approach with K-Nearest Neighbor Algorithm” by Davidov et al. (2010): Davidov et al. (2010) proposed a feature-based approach for sentiment classification of tweets using user-defined hashtags. They extracted features such as punctuation, single words, n-grams, and patterns from tweets and combined them into a single feature vector. The K-Nearest Neighbor (KNN) algorithm was employed for sentiment labeling, where the sentiment label of the nearest neighbors in the training set determined the label for a new tweet.

4.“ Bag-of-Words Method for Sentiment Analysis” by Turney et al : Turney et al. employed a bag-of-words approach for sentiment analysis, where the inter-word relationships were not considered, treating each document as a mere collection of words. Sentiment for the entire document was determined by aggregating the sentiments of individual words using specific aggregation functions. This method focuses on determining the sentiment of each word within the document and combining these values to ascertain the overall sentiment.

VI. ALGORITHMS USED

Text preprocessing is a crucial step in natural language processing (NLP) tasks, including sentiment analysis, text classification, and information retrieval. It involves transforming raw text data into a format that is suitable for analysis and modeling. Here are some commonly used text preprocessing techniques:

1.Lower casing: Convert all text to lowercase to standardize the text and ensure consistency in processing.
2.Tokenization: Break the text into individual words or tokens. This step is essential for further analysis since most NLP algorithms operate on individual tokens.
3.Removing Punctuation: Remove punctuation marks such as periods, commas, and quotation marks, as they often carry little semantic meaning and can be safely removed without losing essential information.
4.Removing Stopwords: Remove common words known as stopwords (e.g., "and," "the," "is") that occur frequently in the language but typically do not carry much information about the content of the text.
5.Stemming or Lemmatization: Reduce words to their base or root form. Stemming removes suffixes from words to derive the root form (e.g., "running" becomes "run"), while lemmatization returns the base or dictionary form of a word (e.g., "better" becomes "good").
6.Handling Numerical and Special Characters: Handle or remove numerical values, URLs, email addresses, and other special characters as needed to avoid interference with the analysis.
7.Removing HTML Tags: If the text data includes HTML tags (e.g., <p>, <a href="...">), remove or replace them to extract only the textual content.
8.Handling Contractions: Expand contractions like "don't" (do not) or "it's" (it is) to ensure uniform representation in the text.
9.Spell Checking and Correction: Use spell checking algorithms to detect and correct misspelled words, which can affect the accuracy of analysis.
10.Normalization: Standardize text data by converting abbreviations, acronyms, or slang terms into their full forms or standard equivalents.These preprocessing steps are essential for cleaning and preparing the text data before feeding it into the sentiment analysis model. They help improve the quality of the data and the performance of the sentiment analysis algorithm by reducing noise and ensuring consistency in representation.

VII.TF-IDF VECTORIZATION

TF-IDF (Term Frequency-Inverse Document Frequency) is a commonly used technique in natural language processing for converting text documents into numerical vectors, which can then be used as input for machine learning algorithms. It is a way of representing the importance of a term in a document relative to a collection of documents.TF-IDF vectorization is a technique for converting text documents into numerical vectors based on the importance of terms within individual documents and across a collection of documents. It is widely used in text mining, information retrieval, and natural language processing tasks such as document classification, clustering, and search.

Term Frequency (TF):

 Term Frequency measures the frequency of a term (word) in a document. It indicates how often a particular word occurs in a document.

 It is calculated by dividing the number of occurrences of a term in a document by the total number of terms in the document.

 TF is used to represent the importance of a term within an individual document.

Inverse Document Frequency (IDF):

 Inverse Document Frequency measures the importance of a term across a collection of documents.

 IDF is calculated as the logarithm of the total number of documents divided by the number of documents containing the term, with the result inverted.

 Terms that occur frequently across many documents have a lower IDF score, while terms that are rare have a higher IDF score.

 IDF is used to penalize the importance of terms that occur frequently across many documents and emphasize the importance of terms that are rare and unique.

TF-IDF Calculation:

 TF-IDF is calculated by multiplying the Term Frequency (TF) of a term in a document by the Inverse Document Frequency (IDF) of the term across a collection of documents.

 The TF-IDF score of a term in a document increases with the frequency of the term in the document (TF) and decreases with the frequency of the term across all documents (IDF).

 TF-IDF captures both the local importance of a term within a document and the global importance of the term across all documents.

Vectorization

Once the TF-IDF scores for each term in each document are calculated, they are arranged into a matrix, where each row represents a document and each column represents a unique term in the entire corpus.This matrix is typically a sparse matrix, as most terms will have a TF-IDF score of 0 in most documents.The TF-IDF matrix can then be used as input for machine learning algorithms, where each document is represented as a numerical vector with dimensions equal to the number of unique terms in the corpus.

VII.LOGISTIC REGRESSION

Multinomial Logistic Regression is a statistical method used for modeling the relationship between a dependent variable with multiple nominal categories and one or more independent variables. It's an extension of the logistic regression model, which is used for binary classification tasks.In Multinomial Logistic Regression, the dependent variable has three or more nominal categories, making it suitable for multi-class classification problems. Each category represents a different class or outcome that the model predicts.The main idea behind Multinomial Logistic Regression is to model the probability of each category as a function of the independent variables. It does this by using a set of regression coefficients that are estimated during the model training process. These coefficients represent the relationship between the independent variables and the log-odds of the categories.During training, the model adjusts the regression coefficients to minimize a loss function, typically using optimization techniques like gradient descent.

The softmax function is then applied to convert the log-odds into probabilities, ensuring that the predicted probabilities sum up to one across all categories.Multinomial Logistic Regression assumes that the relationship between the independent variables and the log-odds of the categories is linear. However, it's important to note that the independent variables themselves do not need to be linearly related to the dependent variable.Overall, Multinomial Logistic Regression is a powerful tool for multi-class classification tasks, including sentiment analysis, text classification, and more. It's relatively easy to interpret and implement, making it widely used in various fields, including machine learning and statistics.

VIII. EXPERIMENTAL RESULTS

After testing out our suggested model, we will talk about our findings in this part. A total of 4000 samples, or 1000 tweets per class, were extracted from the dataset. Removing noisy tweets during pre-processing and filtering them using WordNet emotion terms and EmoSenticNet words significantly reduces the amount of data. We have presumptively determined that each tweet has a single emotion class and that each emotion word in the tweet represents a single emotion. To train and test typical machine learning classifiers, we first preprocessed and filtered the tweets for emotion words. Then, we divided the tweets into training and testing datasets. We included them into the Naïve Bayes, Decision Tree, and Support Vector Machine (SVM) foundational machine learning algorithms.

Emo-tions	Feature selection process	Naïve Bayes	Decision Tree	SVM
Joy	WordNet	47%	52%	49%
	EmoSenticNet	80.32%	80.32%	81.96%
Fear	WordNet	62%	56%	48%
	EmoSenticNet	73.33%	80%	73.33%
Anger	WordNet	37%	33%	50%
	EmoSenticNet	75%	85.71%	89.28%
Sadness	WordNet	43%	43%	43%
	EmoSenticNet	97.05%	78.43%	96.07%

Table 1.Precision of SVM, Naive Bayes, Decision Tree Using TF-IDF.

Emo-tions	Feature selection process	Naïve Bayes	Decision Tree	SVM
Joy	WordNet	85%	83%	83%
	EmoSenticNet	94.23%	80.32%	92.59%
Fear	WordNet	20%	39%	41%
	EmoSenticNet	91.66%	70.58%	91.66%
Anger	WordNet	30%	33%	30%
	EmoSenticNet	84%	70.58%	89.26%
Sadness	WordNet	39%	31%	31%
	EmoSenticNet	82.5%	86.95%	85.21%

Table 2. Recall Of SVM, Naive Bayes, Decision Tree Using TF-IDF.

Precision and recall for each of the several classifier methods were taken into account while calculating the classifiers' accuracy. The weighted harmonic mean of accuracy and recall, or the F-measure, was also computed. Tables III and

IV display the recall and accuracy of SVM, Decision Trees, and Naïve Bayes utilizing TF-IDF. They enable us to better comprehend how the classifiers are identifying the tweets' sentiments.

Feature selection process	Naïve Bayes	Decision Tree	SVM
WordNet	49.23%	45.64%	47.17%
EmoSenticNet	**86.42%**	**80.09%**	**88.23%**

Table 3.Accuracy of Different Classifiers.

Table 3 provides a comprehensive summary of classifier accuracy. The dataset's train-test split and several methods are used to display the classifiers' accuracy. From table 3, we can see that EmoSenticNet performs much better than WordNet. And almost all basic classifier gives almost the same accuracy while detecting the emotions. Finally, in [12] the authors used survey data and found a precision of 90% on anger class using the random forest as their main classifier and logistic regression to find the features they need. But logistic regression may find features relevant to emotion but it may not perform well while finding the exact emotion representing features from tweets. On the other hand from the above results, we can see that while detecting emotion from tweets, if we filter the tweets with EmoSenticNet words, then the precision becomes higher than that of using WordNet and we get 89.28% in Anger class using SVM classifier.

IX.CONCLUSION

In summary, the project focusing on emotion detection from Twitter datasets has yielded valuable insights into the analysis of human emotions as expressed through social media platforms. Through the utilization of advanced natural language processing techniques and machine learning algorithms, we have effectively identified and categorized emotions within the extensive Twitter dataset. This effort not only enriches our understanding of human sentiment in the digital realm but also establishes a foundation for diverse applications across fields such as market research, public opinion analysis, and mental health monitoring. Looking ahead, ongoing refinement of methodologies and integration of real-time data streams hold promise for further enhancing the accuracy and utility of emotion detection systems, thereby deepening our comprehension of human behavior in the digital era.

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