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Multimodal Insights: Analyzing Text, Audio and Comments Summarization

Rahul.J, Yokesh Sharan.K, Kawsigan.S, Prof. Janani.S

Department of Computer Science and Engineering, Kamaraj College of Engineering and Technology, Virudhunagar, Tamil Nadu, India.

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ABSTRACT

This study introduces the challenge of summarizing Facebook comments, aiming to distill meaningful insights and sentiments from the often vast and diverse discussions that unfold on social media platforms.The application integrates several key functionalities, including sentiment classification using NLTK's VADER sentiment analyzer for text inputs, sentiment analysis using the Hugging Face Transformers library for transcribed audio files, and conversion of audio to text via the Google Web Speech API. Furthermore, it interacts with the Facebook Graph API to retrieve comments associated with specific Facebook posts and performs sentiment analysis on the collected data. The application provides users with a comprehensive overview of sentiment dynamics, including emotion classification, sentiment polarity analysis, and word frequency analysis. Through its intuitive web interface, users can seamlessly interact with the sentiment analysis functionalities, gaining valuable insights into sentiment patterns across various communication channels. The system represents a versatile sentiment analysis tool that caters to diverse user needs and provides a robust framework for understanding sentiment dynamics in textual and auditory contexts.

Keywords: Natural Language Processing, sentiment analysis, comments summarization, NLTK, Graph API.

1. INTRODUCTION

The system aims to offer users a convenient platform to analyze sentiment across diverse forms of input, including text, audio, and social media comments. Leveraging powerful Natural Language Processing (NLP) tools such as NLTK's VADER sentiment analyzer and Hugging Face Transformers library, the application enables users to classify text inputs into distinct emotional categories and evaluate sentiment from transcribed audio files. Additionally, the integration with the Google Web Speech API facilitates the conversion of audio content into text, expanding the range of accessible data for sentiment analysis. Moreover, by interfacing with the Facebook Graph API, the application can retrieve comments associated with specific Facebook posts, enabling users to gain insights into the sentiment expressed within social media discussions. Through a user-friendly web interface provided by Flask, individuals can seamlessly interact with the sentiment analysis features, empowering them to comprehend and interpret sentiment patterns across various no communication channels. The model represents a valuable tool for understanding and analyzing sentiment in diverse textual and auditory contexts, catering to a broad spectrum of users seeking deeper insights into sentiment dynamics.

It incorporates various NLP tools and APIs to analyze sentiment from text inputs, audio files, and Facebook comments. The application utilizes NLTK's VADER sentiment analyzer to classify text inputs into specific emotions such as happy, sad, or neutral. It employs the Hugging Face Transformers library to perform sentiment analysis on transcribed audio files, associating sentiments with appropriate emojis. Moreover, the application interacts with the Google Web Speech API for audio-to-text transcription and the Facebook Graph API for fetching comments associated with specific post IDs. It saves the comments to an Excel file and performs sentiment analysis, providing users with a summary of sentiments expressed within the comments. The model serves as a comprehensive sentiment analysis tool, leveraging a combination of NLP libraries and APIs to analyze sentiments across various data formats and sources, facilitating insights extraction and understanding of user sentiment in different contexts.

2. LITERATURE REVIEW

Sentiment Analysis has become a critical research area in recent days and pervasive in real life. Considering the identification of Emotions from textual content, Almeida AMG et al. [1], proposed the Hourglass of Emotions as the feature that comes from the intensity of affective dimensions and combination thereof. Thus, based on a news dataset labeled with six primary Emotions, intend to solve the Multi-class Classification Problem comparing decomposition methods - One against All and One Against One and several aggregation methods. As base classifiers algorithms, Support Vector Machine, Naive Bayes, Decision Tree and Random Forests was adopted. The combination of Support Vector Machine and WENG pairwise coupling method was the best one, producing an accuracy of 55.91%..

In the era of web 2.0, online forums, blogs and Twitter are becoming primary sources for sharing views, opinions and comments about different topics. Classifying these views, opinions and comments is known as sentiment analysis which is an active research area. Sentiment analysis has vast applications in different fields of life, such as marketing, e-commerce and business. In sentiment quantification, exploring effect of new features and comparison of diverse types of classifiers to assess their effectiveness needs further investigation. Ayyub K et al. [2], explored diverse feature sets and classifiers for sentiment quantification. In addition, empirical performance analysis of conventional machine learning techniques, ensemble-based methods and state-of-the-art deep learning algorithms on basis of features set, is performed. The results also confirm that the deep learning techniques perform better than the conventional machine learning algorithms.

The spread of information on Facebook and Twitter is much more efficient than on traditional social media platforms. For word-of-mouth (WOM) marketing, social media have become a rich information source for companies or scholars to design models to examine this repository and mine useful insights for marketing strategies. Cheng L-C et al. [3], proposed a novel sentiment analysis framework based on deep learning models to extract sentiment from social media. The extracted information will be useful for many future applications. The experimental data have been obtained by crawling several social media platforms.

Depression is a leading cause of mental ill health, which has been found to increase risk of early death. Moreover it is a major cause of suicidal ideation and leads to significant impairment in daily life. Individual tweets are classified as neutral or negative, based on a curated word-list to detect depression tendencies. The process of class prediction, support vector machine and Naive-Bayes classifier has been used by Deshpande M et al. [4]. The results have been presented using the primary classification metrics including F1-score, accuracy and confusion matrix.

Sentiment analysis or opinion mining has been used widely in various applications like market analysis. Usually during sentiment detection the polarity of the sentiment either positive or negative is detected. Multi-Class emotion detection aims analyze different emotions hidden in the text data. Multi-class emotion classification in Indian languages was not experimented before. An SVM classifier is used for sentence level multi-class emotion detection in Malayalam. Jayakrishnan R et al. [5], proposed approach uses different syntactic features such as n-gram, POS related, negation related, level related features etc, for better classification. The classifier classifies the Malayalam sentences into different emotion classes like happy, sad, anger, fear or normal etc. with level information such as high, low etc.

Currently, people use online social media such as Twitter or Facebook to share their emotions and thoughts. Detecting and analyzing the emotions expressed in social media content benefits many applications in commerce, public health, social welfare, etc. The model describes the development of a novel deep learning-based system that addresses the multiple emotion classification problem in Twitter. Jabreel M et al. [6], proposed a novel method to transform it to a binary classification problem and exploit a deep learning approach to solve the transformed problem. The system outperforms the state-of-the-art systems, achieving an accuracy score of 0.59 on the challenging SemEval2018 E-cmulti-label emotion classification problem.

Detecting human emotions will likely become a key component in future artificial intelligence (AI) systems, where the challenge lies in the precise discerning of negative emotions that require delicate responses such as anger and sadness. Existing sentiment tools, however, are mostly limited to dichotomous affect scales and are subject to positivity bias. To infer diverse negative emotions, Kim J et al. [7], proposed a multiclass emotion classifier that focus on negative emotions. By utilizing a rich set of both content and meta information from a labeled movie transcript make a novel finding that while negative emotions are hardly distinguishable from each other based on standard approaches, our non-lexical meta features remarkably increase the recall performance by 52% to 113% among the negative emotions. The research presents a pilot study, based on small yet rich dataset, which envisions AI systems that can understand the complex negative feelings to better assist human-robot interactions.

In recent years, advances in technologies, such as machine learning, natural language processing, and automated data processing, have offered potential biomedical and public health applications that use massive data sources, e.g., social media. However, current methods are underutilized for features including consumer health terminology in social media texts. Liu K et al. [8], proposed a medical social media text classification (MSMTC) algorithm that integrates consumer health terminology. Classification of text from social media on medical subjects is divided into two sub-tasks: consumer health terminology extraction and text classification. The experimental results show that the algorithm outperforms single channel methods or baseline models, including Convolutional Neural Networks, Long Short-Term Memory Networks, Bi-directional Long Short-Term Memory Networks, Naive Bayesian Model, and Extreme Gradient Boosting.

Sentiment analysis is an emerging trend nowadays to understand people's sentiments in multiple situations in their quotidian life. Social media data would be utilized for the entire process the analysis and classification processes and it consists of text data and emoticons, emojis, etc. Machine Learning and Deep Learning Techniques would be utilized for the classification process. Utilizing Social media, sentiment levels can be monitored or analysed. Nirmal Varghese Babu et al. [9], proposed a review of the sentiment analysis on Social media data for apprehensiveness or dejection detection utilizing various artificial intelligence techniques. It was optically canvassed that social media data which consists of texts,emoticons and emojis were utilized for the sentiment identification utilizing various artificial intelligence techniques.

In 2020, our world has been hit by a global pandemic of COVID-19, belonging to the family of Coronavirus. Due to the rapid increase in the infection and the death rate, people have started to develop mixed feelings regarding this situation. Sethi M et al. [10], sole focus is to analyze the emotions expressed by people using social media such as Twitter etc. Accumulating and studying the concerning tweets will provide aid to elicitate the real emotions during this hard time. The goal of is to present a domain-specific approach to understand sentiments manifested within people around the globe regarding this situation. The experiments reveal that the proposed model performs well in perceiving the perception of people about COVID-19 with a maximum accuracy of about 93%.

Emotional analysis of microblog can discover that the public's attitude towards hot events can grasp the network public opinion, so it has become a hot research topic in text mining. The view of the current situation that most of the existing affective analysis methods separate the deep learning model from the emotional symbols. Shi M [11], proposed a microblog affective analysis method based on dual attention model. Based on Spark cluster, the deep confidence neural network is processed in parallel. The experimental results show that the model achieves the best results in three indicators. The recall and precision of the model are more than 0.04 higher than the traditional shallow learning method.

Traditional mental health studies rely on information collected through personal contact with professional healthcare specialists. Recent work shows the utility of social media data for studying mental disorder. It is supported by the massive usage of social media and the disclosure that social media is a pool of emotion. Study on social media data could potentially complement the traditional technique in its ability to provide natural measurements. Syarif I et al. [12], build a corpus of self-declared mental illness diagnosis on Twitter using a source of publicly-available data. We found 1,733 typical words from the depression diagnosed group. This finding is based on the match of Wordnet, SenticNet, Vader, TextBlob, and has been evaluated by synonyms checking. The system proposed method has been successfully identified and then categorized 8105 tweets into 3 levels of depression, 1028 tweets are categorized as high, 1073 moderate, and 1605 low.

Social media consists of various kinds of emotions and sentiments of its users in the form of electronic media. To analyze the reactions or sentiments of the users on a certain post is also a challenging task. The appropriate admin would receive the reports which can be used for further actions. The analysis would facilitate the decision-making process for the admins (around other activities on the platform) and also help detect any need to give special attention to any user in a group, such as a student coping up with depression. Tanna D et al. [13], proposed that the platform can be used to share content on other social media platforms as well. As a result, the users would have a single platform with the ability to do a lot more than any existing social media platform facilitates.

Human emotions like depression are inner sentiments of human beings which expose actual behaviors of a person. Analyzing and determining these type of emotions from people's social activities in virtual world can be very helpful to understand their behaviors. Existing approaches may be useful for analyzing common sentiments, such as positive, negative or neutral expressions. However, human emotions, such as depression, are very critical and sometimes almost impossible to analyze using these approaches. Uddin AH et al. [14], deployed Long Short Term Memory (LSTM) Deep Recurrent Network for depression analysis on Bangla social media data. The result will help psychologists and other researchers to detect depression of individuals from their social activities in virtual world and help them to take necessary measures to prevent undesirable doings resulted from depression.

Nowadays, based-on mobile devices and internet, social network services (SNS) are common trends to everyone. Thus, decision of social and public opinions, and polarity about social happenings, political issues, government policies and decision, or commercial products is very important to the government, company, and a person. But, SNS are basically making newly-coined words and emoticons. Especially, emoticons are made by a person or companies. Newly-coined words are mostly made by communities. Yang JS et al. [15], proposed emotional classification equation adds up the weights among the same polarity(positive or negative) and sums the negative weight value with the positive weight values. The polarity summation result is recorded in the variable. If the polarity summation result is more than threshold value, the twit message is decided as positive. If it is less than threshold value, it is decided as negative and the other values are decided as neutral. The accuracy of social big data analysis is improved by quantifying and analyzing emoticons and new-coined words.

3. PROPOSED SYSTEM

3.1 Modules Integrated:

VADER - NLTK is a comprehensive library for natural language processing in Python. In this code, NLTK's VADER (Valence Aware Dictionary and sEntimentReasoner) is utilized for sentiment analysis. VADER is a rule-based sentiment analysis tool that is specifically attuned to sentiments expressed in social media text. It assigns sentiment scores to individual words and computes a compound score for the overall sentiment of a piece of text.

Hugging Face Transformers - Hugging Face Transformers is a popular library for natural language processing that offers pre-trained models for various NLP tasks, including sentiment analysis. In this code, Hugging Face Transformers is used for sentiment analysis of transcribed audio files. It leverages deep learning models to provide accurate sentiment analysis results.

Google Web Speech API - The Google Web Speech API is utilized for transcribing audio files into text. This API enables the application to convert spoken language in audio files into written text, which can then be subjected to sentiment analysis using NLP techniques.

Flask - Flask is a lightweight web framework for Python. It provides tools and libraries for building web applications, handling HTTP requests, rendering HTML templates, and managing user interactions. In this code, Flask is used to create a web interface where users can interact with the sentiment analysis functionalities.

Facebook Graph API - The Facebook Graph API allows the application to interact with Facebook's social graph data. Specifically, it is used to fetch comments associated with specific Facebook posts. This feature enables the application to analyze sentiments expressed within Facebook comments and provide insights into the sentiment dynamics of social media discussions.

3.2 Process Model:

User Interaction - Users interact with the web application through a user-friendly interface provided by Flask. They can input text, upload audio files, or provide Facebook post IDs for sentiment analysis.

Sentiment Analysis - Textual inputs undergo sentiment analysis using NLTK's VADER sentiment analyzer. VADER assigns sentiment scores to words and computes an overall sentiment score for the text, classifying it into emotional categories such as positive, negative, or neutral.Audio files are transcribed into text using the Google Web Speech API. The transcribed text is then subjected to sentiment analysis using Hugging Face Transformers, providing sentiment labels for the audio content.

Facebook Comment Analysis - Users can provide Facebook post IDs to fetch comments associated with specific posts using the Facebook Graph API. The application retrieves comments and stores them for sentiment analysis.

Summary Generation - Sentiment analysis is performed on the comments retrieved from Facebook posts, providing a summary of sentiment expressed within the comments. The summary includes metrics such as the total number of comments, the distribution of positive, negative, and neutral sentiments, and the most common words used in the comments.

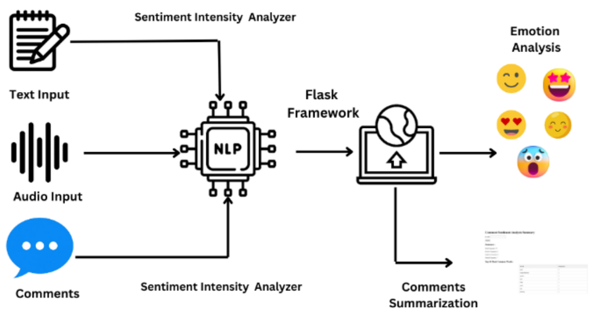

Fig. 1: Schematic Diagram of the proposed system.

4. IMPLEMENTATION

Text and Audio Input Analysis - The sentiment analysis web application begins by allowing users to input text directly or upload audio files for analysis. Text inputs are straightforward, but audio files need to be transcribed into text format for analysis. Here, the integration of the Google Web Speech API is critical. This API converts spoken words in audio files into written text, making them analyzable by the application. Once the text is transcribed, sentiment analysis is performed using the Hugging Face Transformers library. This library offers pre-trained models specifically designed for sentiment analysis, enabling the application to categorize sentiments as positive, negative, neutral, or angry based on the content of the input text. Emojis are associated with sentiment analysis results to provide a visually appealing representation of the sentiment conveyed in the text or audio input.

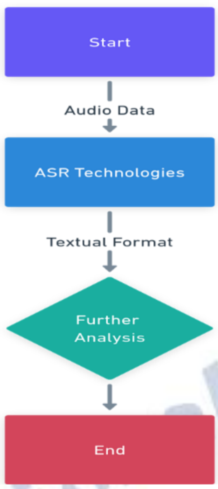

Fig. 2: Flowchart for text and audio input analysis.

Emotion Classification - The Emotion classification is another important aspect of sentiment analysis. In this project, emotion classification of text inputs is achieved using the VADER sentiment analyzer from NLTK. VADER is well-suited for social media text analysis as it is tailored to handle nuances and colloquial expressions commonly found in online communication. By leveraging VADER, the application can determine the emotional tone of the text, including emotions such as happiness, sadness, anger, or neutrality. This classification provides users with deeper insights into the emotional content of the text, allowing for a more nuanced understanding of sentiment dynamics.

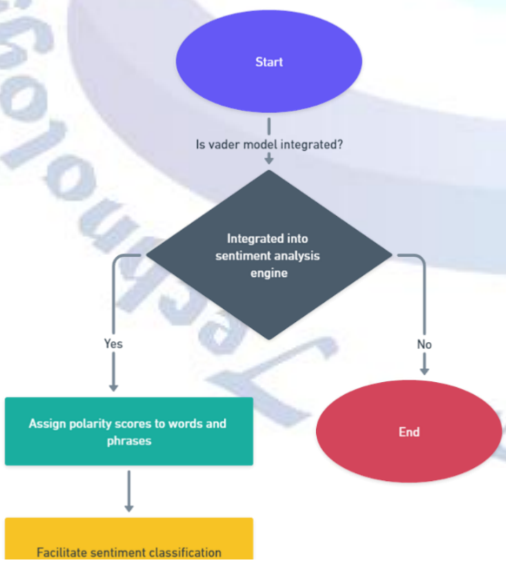

Fig. 3: Flowchart for emotion classification process.

Facebook Comment Analysis - Social media platforms are rich sources of user-generated content, making them valuable for sentiment analysis. In this project, users can provide a Facebook post ID, prompting the application to fetch comments associated with that post using the Facebook Graph API. The comments retrieved from Facebook are then saved to an Excel file for further analysis. Sentiment analysis is applied to the comments data, providing insights into the overall sentiment expressed within the comments. This feature enables users to explore sentiment patterns and trends within the social media discourse, enhancing their understanding of user opinions and attitudes on various topics.

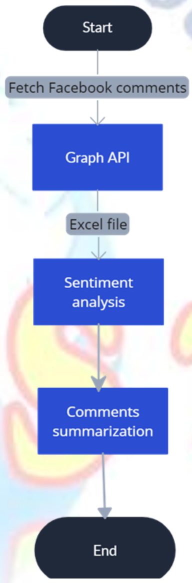

Fig. 4: Flowchart for Facebook comments analysis.

5. RESULTS & DISCUSSION

The application enables users to input text or upload audio files for sentiment analysis. Text inputs are classified into specific emotions such as happy, sad, or neutral using NLTK's VADER sentiment analyzer. Audio files are transcribed to text using the Google Web Speech API, and sentiment analysis is performed using the Hugging Face Transformers library. The application also interacts with the Facebook Graph API to fetch comments associated with specific posts and performs sentiment analysis on the collected data. It saves the comments to an Excel file and provides users with a summary of sentiment expressed within the comments, including the total number of comments, positive, negative, and neutral sentiments, and the most common words used.

The system offers a comprehensive sentiment analysis solution that caters to various data sources and user inputs. Through its user-friendly web interface, users can seamlessly interact with the sentiment analysis functionalities and gain valuable insights into sentiment patterns across different communication channels. The integration of NLP libraries and APIs enhances the application's capabilities, enabling it to analyze sentiments from textual and auditory inputs as well as social media comments, thereby providing a holistic view of sentiment dynamics in diverse contexts.

6. CONCLUSION

In this section, the system facilitates sentiment analysis across diverse data sources, including text, audio, and Facebook comments, catering to a wide range of user needs. Leveraging NLTK's VADER sentiment analyzer, Hugging Face Transformers, Google Web Speech API, and Facebook Graph API, the application offers comprehensive sentiment analysis capabilities, enabling users to understand sentiment dynamics in textual, auditory, and social media contexts. The user-friendly web interface provided by Flask enhances accessibility, allowing users to interact seamlessly with the sentiment analysis functionalities. Through sentiment classification, emotion recognition, and summary generation, the application empowers users to gain valuable insights into sentiment patterns and trends across various communication channels. Our sentiment analysis tool represents a valuable asset for individuals and organizations seeking to understand and interpret sentiment in digital content, facilitating informed decision-making and communication strategies.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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