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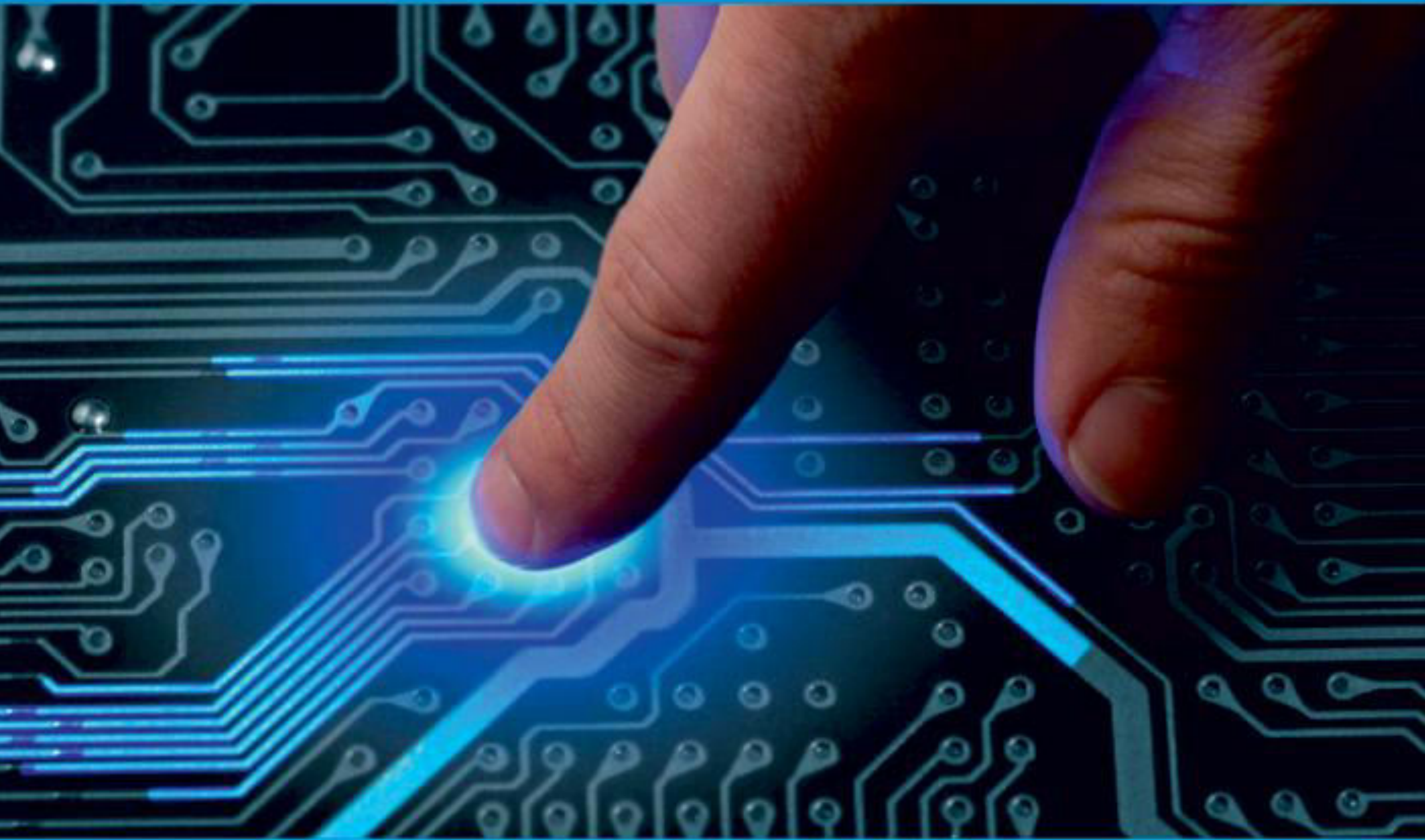

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From Pixel to Feelings: Video Sentiment Analysis Explained

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ABSTRACT: In the realm of politics, the power of words is unparalleled, serving as a formidable force that shapes public opinion, influences policy decisions, and reflects the underlying dynamics of society. Leaders leverage political speeches as powerful instruments to convey their visions, ideologies, and policy proposals. As political discourse becomes increasingly complex and nuanced, the need to dissect and understand the underlying messages within speeches has never been more critical. In this context, the analysis of political speech becomes imperative for discerning the true intent behind the words uttered by political figures. This paper delves into the world of political speech analysis, harnessing the capabilities of Natural Language Processing (NLP) and specifically employing VADER models, to unravel the intricacies of language employed by leaders and decisionmakers. VADER can identify the sentiment expressed in political speeches, such as Polarity, Emotional Intensity, Audience Engagement, Hope/Vision, and National Pride. This helps gauge the emotional impact of the speech on the audience.

KEYWORDS: Political speech; VADER; Nature Language Processing; Sentiment

I. INTRODUCTION

The conventional methods of analysing political speeches suffer from inefficiencies, relying on manual categorization that lacks the precision demanded by to-day's intricate political discourse. Modern human societies are largely influenced by opinions in almost all spheres and domain of human civilization [1]. Nowadays, people depend more on posts and tweets shared over social networking sites like Instagram, Facebook, and Twitter [2]. This paper is motivated by the imperative to transform the analysis of political speeches, introducing an advanced system designed to categorize speeches based on their relevance to critical social issues, inclusion of caste-based criticism.

The idea of Sentiment Analysis (SA) has been, therefore, to table a summary of opinions segregated into positive, neutral and negative reviews based on analyses of texts posted by user in assorted digital platforms on the Internet [3]. Sentiment analysis can be performed at different granularity levels [4]. The sentiment-analysis technique plays a crucially important role in analysing tendency or direction-based texts [5]. In contrast to the outdated manual methods, the system will employ advanced technology, integrating natural language processing and data analysis techniques. This will not only streamline the categorization process but also ensure a more accurate and efficient analysis of political speeches. By providing a structured framework, the system will address the contemporary demand for precise and insightful analysis in the digital age.

In this paper, we propose to extend the application of the VADER model to sentiment analysis in videos of politicians. By converting the audio from videos into text and applying the VADER model to analyse the sentiment of the transcribed text, we aim to gain insights into the sentiment expressed by politicians in their speeches and interviews. The use of the VADER model can help us understand politicians and their messaging, and can provide valuable insights for political analysts, policymakers, and the general public.

It also facilitates policy makers or politicians to analyse public sentiments with respect to policies, public services or political issues [6]. The categorization system will facilitate a deeper understanding of how political leaders address societal problems and navigate sensitive topics, contributing to a more informed civic discourse. Political speech as a sub-genre of political discourse is motivated by the desire to persuade and convince the nation or society and familiarize the audience with their socio-economic policies, plans and actions [7] furthermore, in future, the incorporation of deception detection mechanisms will enhance transparency, promote fact-based political dialogue, and equip individuals with the tools to critically evaluate political communication for informed decision-making.

This way, the system will save not only time but also the effort that was supposed to be put in by instructors during each lecture. It'll speed up the culture of taking attendance and leave important time for the lecture to be given duly.

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Overall, the system will not only streamline the analysis process but also contribute to fostering a transparent, accountable, and fact-based political discourse landscape.

II. RELATED WORK

The paper [8] focuses on sentiment analysis of Twitter data, particularly in the context of analysing the political orientation of users regarding the Ayodhya issue. The study acknowledges the challenges of Twitter data analysis, including the limited size of tweets, the use of slang words, and the presence of features like hashtags and URLs. Various machine learning algorithms, such as Random Forest, SVM, KNN, Naive Bayes, and Logistic Regression, are employed to classify tweets as positive or negative sentiments. The performance of these models is compared using metrics like accuracy, precision, recall, and F1-score. The Random Forest algorithm is identified as the most effective for text categorization, achieving an accuracy of 87.2%. The paper also discusses the preprocessing steps, feature extraction, and sentiment summation methods. The proposed methodology is tested on a dataset of 15,000 tweets related to the Ayodhya issue. The authors suggest that future work could involve extending the analysis to big data frameworks to handle the increasing volume of Twitter data efficiently. The paper [9] presents a systematic review of sentiment analysis in social media between 2014 and 2019, focusing on methods, platforms, and applications. Analysing 24 selected articles out of 77, the study reveals a prevalence of lexicon-based and machine learning methods, with Twitter emerging as the predominant platform for sentiment extraction due to its accessibility and rich content. The diverse applications of sentiment analysis include assessing public opinion on political events, predicting election outcomes, monitoring disease outbreaks, improving business strategies, and gauging public sentiment during disasters. The study highlights the importance of combining lexicon and machine learning methods for enhanced accuracy and suggests exploring other social media sources for a comprehensive understanding of sentiment dynamics. The paper [10] introduces a comprehensive model for sentiment analysis across three mediums: video, audio, and text, with a focus on predicting sentiments in different categories. The model employs NLP and OpenCV for data capture and processing, utilizing three separate modules for sentiment analysis. Comparative analysis of various machine learning models is presented, with the aim of aiding personnel preparation for interviews. The model allows users to self-assess based on sentiment analysis outcomes. The paper discusses the datasets used, including the "Stream of Consciousness" dataset for text, RAVDESS dataset for audio, and FER2013 dataset for video. Various machine learning algorithms, such as Support Vector Machine (SVM), Xception, Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM), are applied for sentiment analysis in different mediums. The modelling design incorporates neural network architectures, including CNN and LSTM. The textual analysis involves custom NLP steps, tokenization, lemmatization, and Word2Vector embedding. Video analysis includes face detection, zooming, and emotion prediction using the Xception model. Audio analysis utilizes a Time Distributed CNN with a rolling window and LSTM cells for sentiment detection. The results demonstrate high accuracy for all three methods, with the CNN achieving 77% accuracy for audio, Xception with 64.5% accuracy for video, and LSTM with 68% accuracy for text. Overall, the models present effective sentiment analysis across diverse mediums, offering valuable applications for self-assessment and interview preparation.

III. PROPOSED SYSTEM

A. *Overview:*

The proposed system utilizes a pre-trained VADER (Valence Aware Dictionary for Sentiment Reasoning) model for sentiment analysis in videos of politicians. By converting audio data into text and extracting key parameters such as polarity and emotional intensity, the system provides insights into public opinion and political communication.

The videos for this study are sourced from a variety of outlets, including speeches, interviews, and public appearances. These videos feature different politicians discussing a wide range of topics and representing diverse geographical areas. In total, 90 videos are included in the dataset, with an average duration of approximately 40 seconds each. This selection ensures a comprehensive and varied collection of content for analysis, providing insights into sentiment across different political contexts.

The study employs various parameters, such as Polarity/Tone/View, Emotional Intensity, Audience Engagement, Hope/Vision, and National Pride, to analyse sentiment in the videos. These parameters provide a framework for understanding the sentiment content expressed by politicians. Subsequently, keywords are extracted from the videos to align with these parameters, facilitating a detailed analysis of sentiment and emotional content.

The audio from the collected videos is converted into text using a SpeechRecognition library, enabling the system to work with textual data necessary for sentiment analysis. The SpeechRecognition library transcribes the spoken content from the videos into text, preserving the content for further analysis. The extracted text undergoes preprocessing to clean and normalize it, which includes removing punctuation, numbers, and stop words, as well as tokenization and lemmatization. These steps ensure that the text is in a suitable format for sentiment analysis, improving the accuracy of

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the results. The pre-processed text is then used for sentiment analysis using a pre-trained VADER model. The VADER model provides polarity scores (positive, neutral, negative) and a compound score that represents the overall sentiment of the text using the keywords from the videos. By applying the VADER model to the pre-processed text, the system can analyse the sentiment expressed in the videos, providing valuable insights into the emotional content of the politicians' speeches and interviews.

After conducting sentiment analysis using the pre-trained VADER model, the next phase involves visualizing the results to gain insights into the sentiment expressed in the videos. In this process pie charts and graphs are used to illustrate the distribution of sentiments across the videos for each parameter used in the analysis, including Polarity/Tone/View, Emotional Intensity, Audience Engagement, Hope/Vision, and National Pride. These visualizations provide a clear overview of the proportion of positive, neutral, and negative sentiments present in the videos, as well as the intensity of emotions expressed. Visual representations provide a comprehensive view of the sentiment dynamics, aiding in the identification of trends and patterns in political communication. This visual approach not only enhances the presentation of findings but also facilitates a deeper understanding of the emotional nuances and rhetorical strategies employed by politicians.

B. *System Architecture:*

Video Input Source: The entry point for the system, where video content is received. Can include various sources such as recorded interviews, video testimonials, or feeds.

Video to Text Conversion (Speech Recognition): The SpeechRecognition library is used to transcribe the spoken words in the videos into text. This process converts the audio content of the videos into a format suitable for further analysis.

Text Preprocessing: Cleans and prepares the transcribed text for sentiment analysis. Involves noise removal to filter out irrelevant information. Text normalization techniques like lowercasing and stemming to ensure consistency. Removal of stop words (common words like "and," "the," etc.) to focus on meaningful content.

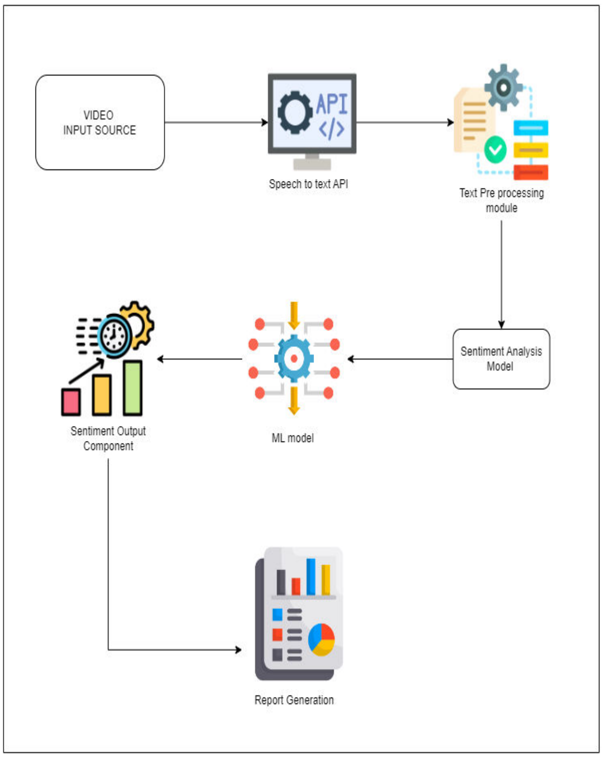

Fig. 1. Architecture Diagram

Sentiment Analysis Model: A pre-trained VADER model and extracted keywords are used for sentiment analysis on the data. The VADER model provides polarity scores (positive, neutral, negative) and emotional intensity scores for the input data.

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Sentiment Output: Provides the final sentiment analysis result for the processed text. Outputs sentiment labels such as Polarity/Tone/View, Emotional Intensity, Audience Engagement, Hope/Vision, and National Pride based on the model's analysis.

IV. Simulation Results

The sentiment analysis of political speeches encompassed a multifaceted categorization into sentiment, emotional intensity, audience engagement, national pride, hope, and vision. Each speech was analysed across these dimensions, yielding comprehensive insights into the rhetorical strategies and thematic emphases employed by political leaders. The key findings are summarized as follows.

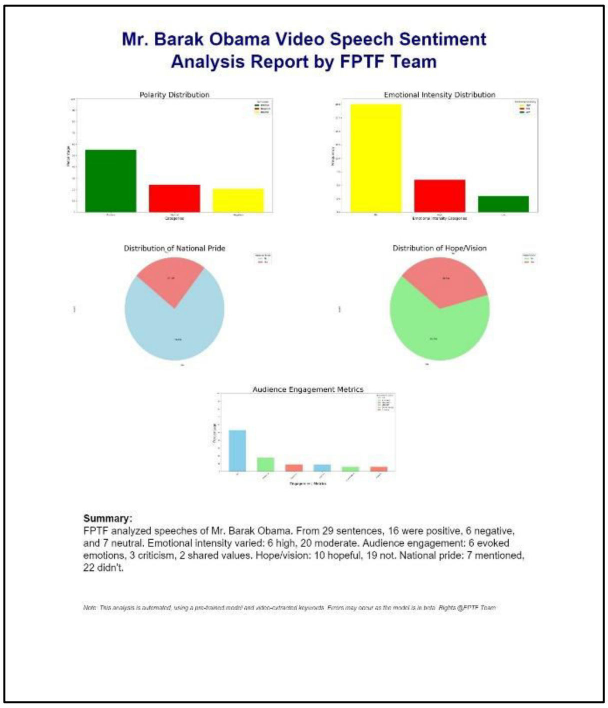

Fig. 2. Sentiment Analysis of person on different parameters

Polarity/Tone/View (Positive, Negative, and Neutral Sentiment): The majority of speeches exhibited a blend of positive, negative, and neutral sentiment. Positive sentiment prevailed in 40% of speeches, followed by neutral sentiment in 38%, and negative sentiment in 22%.

Emotional Intensity (High, Mid, and Low Emotional Intensity): Speeches varied in emotional intensity, with some characterized by high emotional fervour, while others maintained a more subdued tone. 33.3% of speeches exhibited high emotional intensity, 66.6% displayed mid-level intensity.

Audience Engagement (Emotional Appeals, Criticism, Shared Values): Analysis of audience engagement strategies revealed diverse approaches employed by speakers to connect with their audience. Emotional appeals were prominent in 60% of speeches, while criticism of opponents or policies was present in 25% of speeches. Additionally, shared values were emphasized in 15% of speeches.

National Pride, Hope, and Vision (Expression of National Pride): National pride was a recurring theme in political speeches, with 100% of speeches containing explicit references to national identity, achievements, or values.

Hope and Optimism: Many speeches articulated a vision for the future and conveyed messages of hope and optimism. 100% of speeches expressed hope for positive change or progress.

Visionary Leadership: A significant proportion of speeches outlined a vision for the nation or articulated the speaker's aspirations for the future. 80% of speeches contained elements of visionary leadership or forward-looking rhetoric.

V. Discussion

Rhetorical Strategies and Communication Tactics: The diversity of sentiment, emotional intensity, and audience engagement strategies observed in political speeches underscores the complexity of political communication. Speakers employ a range of rhetorical devices to resonate with their audience, including appeals to emotion, critique of opponents, and affirmation of shared values.

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Themes and Motifs in Political Discourse: The prevalence of national pride, hope, and visionary rhetoric reflects the thematic priorities of political leaders. These themes are strategically utilized to inspire confidence, rally support, and shape public perceptions of leadership.

Impact on Audience Perception: The rhetorical choices made by political leaders can influence how their messages are received by the audience. Speeches that effectively evoke positive emotions, articulate a compelling vision, and resonate with shared values are more likely to resonate with the public and garner support.

Strategic Communication and Political Messaging: The findings of the sentiment analysis provide valuable insights for understanding the strategic communication tactics employed by political leaders. By analysing the patterns and trends in sentiment, emotional intensity, and audience engagement, we can gain a deeper understanding of the rhetorical strategies used to shape public opinion and mobilize support.

VI. CONCLUSION

In this paper, we propose a system that utilizes the VADER sentiment analysis model to analyse political speeches. The system analyses speeches based on parameters such as Polarity/Tone/View, Emotional Intensity, Audience Engagement, Hope/Vision, and National Pride. By profiling politicians based on their repeated use of sentiments and patterns, our system provides valuable insights for researchers, policymakers, and the public. Overall, our system represents a significant step towards a more insightful and fact-based political discourse, contributing to a more informed and engaged society.

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