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Research paper

Hybrid NLP framework for enhanced sentiment analysis and topic detection on YouTube

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Abstract

This paper introduces an advanced hybrid NLP framework designed to enhance sentiment analysis and topic detection in YouTube comments. By combining feature extraction methods like Bag of Words (BoW) and TF-IDF with neural network models like LSTM and Bi-LSTM, the framework effectively uncovers latent topics and sentiment orientations. The study specifically analyzes comments on Oscar-nominated movie trailers, demonstrating the framework's ability to capture both explicit and implicit patterns of sentiment. This study shows that the Bi-LSTM model with BoW features achieves the highest performance, with accuracy, precision, recall, and F1-scores nearing 90%. This hybrid approach delivers practical and theoretical developments in natural language processing applications for content creators and marketers to optimize engagement strategies based on user sentiment and thematic preferences.

Keywords: *Sentiment Analysis; Audience Engagement; Viewer Sentiments; Term-Inverse Document Frequency; Social Media Analytics; Bag of Words.*

1. Introduction

In the vast landscape of online content, YouTube stands as a colossal repository of diverse voices and perspectives. Amidst this digital cacophony, discerning the sentiments expressed within YouTube comments is crucial for understanding audience engagement and content reception. This research endeavors to enhance sentiment analysis and topic detection on YouTube by employing a sophisticated hybrid Natural Language Processing (NLP) framework. As technology advances, so does information search, especially in the dynamic film business. [1]. With the exponential growth of internet users worldwide, accessing movie-related content has become increasingly convenient, fostering an insatiable demand for insights into film quality and reception [2]. In response to this demand, numerous websites now offer comprehensive movie reviews, sparking a surge of studies using Natural Language Processing (NLP), especially sentiment analysis, to gain data insights. Analysis of sentiment, a pivotal aspect of NLP, involves extracting and categorizing sentiments from textual data, providing crucial information for product development, including movie production [3,4]. By discerning the sentiments expressed in movie reviews, analysts can effectively classify them as positive or negative, thereby gauging audience reception and guiding future production endeavors [5].

However, sentiment analysis is not without its challenges, particularly concerning the overwhelming number of features present in textual data, which can diminish classification performance [6]. To address this issue, researchers often employ feature selection techniques, such as the Chi-Square method, which quantifies the significance of features concerning sentiment classification. Previous studies, such as that by putra et al., have demonstrated the Chi-Square method's ability to boost classification accuracy [7]. Building upon this foundation, our study adopts the K-Nearest Neighbor (KNN) method, informed by prior research indicating its efficacy in sentiment analysis, particularly within behavior analysis contexts. Studies by Jelodar et al [8] and Hamzah [9] highlight the robust performance of the KNN method, achieving high accuracy rates in sentiment analysis tasks, including those involving Indonesian movie review datasets. In addition to employing the KNN method, our study incorporates Chi-Square feature selection to enhance classification performance. Drawing insights from previous research in sentiment analysis, classification, feature selection, preprocessing, and evaluation, our study seeks to offer a thorough examination of sentiment within Indonesian movie reviews. Furthermore, our research contributes to the ongoing discourse on sentiment analysis methodologies, drawing parallels with studies such as DaeliNO, AdiwijayaA [10], and Chauhan GS, Meena YK [11], which explore the effects of different classification algorithms and feature selection techniques on sentiment analysis tasks.Natural language processing and information retrieval are studying text sentiment analysis more. It includes gathering opinions and feelings from written content. Mobile device use and the mobile Internet's rapid growth have made sentiment analysis a popular research subject. It was inspired by Pang et al.'s pioneering movie review sentiment classification [12].

Text sentiment analysis has advanced recently, specifically in analyzing sentiment in the Chinese language, and has witnessed a surge in research activity within domestic academia. Propelled by advancements like Google's Word2Vec in 2013, the field has experienced exponential growth, evidenced by the proliferation of scholarly articles. Notably, the China National Knowledge [13]. Infrastructure (CNKI) and Web of Science alone have seen a substantial increase in relevant publications, surpassing 700 and 2500 articles, respectively, in 2022 alone [14].

Within this burgeoning research ecosystem, notable contributions have emerged, showcasing diverse methodologies and applications. Alslaity et al. analyzed emotion detection using machine learning. They identified patterns in many areas, such as machine learning methods, domains of application, sources of data, assessment techniques, and results. Bonifazi et al. presented an adaptable framework [15] that enables the extraction of sentiment-related information from social platforms, allowing for a flexible tool to comprehend user sentiments on various subjects. Almars et al. [16] developed a subject hierarchy for user sentiment (HUSTM) to simplify sentiment analysis by identifying underlying themes and user attitudes. Amidst this dynamic research environment, Yin et al. initiated a study to investigate Chinese perspectives on volunteerism as a reaction. [17] to the COVID-19 pandemic's urgent demand for volunteers. This study underscores the societal relevance and impact of sentiment analysis in addressing pressing real-world challenges.

Against this backdrop of scholarly achievements and societal imperatives, our project aims to improve sentiment analysis and topic discovery on YouTube by utilizing a hybrid natural language processing framework. Building upon previous research that has demonstrated a range of methodologies and applications, our objective is to build a framework that can detect nuanced YouTube comment attitudes and themes. This would help us understand internet debates and make informed decisions in several sectors [18]. Facebook, Twitter, and YouTube have revolutionized human communication by allowing people to share their thoughts, opinions, and experiences with the world. [19]. Among these platforms, YouTube stands as a beacon of digital content, boasting the highest ranking among video-sharing platforms and attracting a staggering 30 million daily active users. With users uploading 500 hours of video content every minute and more than one billion videos viewed daily, YouTube's influence on online discourse and content consumption is undeniable [20]. As YouTube continues to dominate the digital landscape, the relevance and ranking of videos have become pivotal factors in content discovery and engagement. While metadata plays a role in categorizing and indexing videos, it often falls short in accurately measuring relevance [21]. User engagement metrics such as likes, dislikes, views, and comments provide valuable signals for assessing video quality and relevance. User comments serve as a rich source of information containing sentiments that can indicate viewer satisfaction or dissatisfaction [22]. NLP's sentiment analysis (SA) program extracts sentiments from YouTube comments. SA aims to analyze the sentiments expressed within comments, enabling content creators and platform administrators to gauge viewer reactions and improve video ranking and recommendation systems. However, the effectiveness of SA hinges on robust preprocessing procedures that stop word elimination, stemming, tokenization, and normalization. This lays the groundwork for accurate sentiment classification. [23] This paper delves into the methods and techniques used in sentiment analysis, specifically on YouTube videos and user comments [24]. SA is explored across three levels: simple SA, which categorizes comment polarity. Text can be good, negative, or neutral. Alternatively, a more detailed sentiment analysis might classify the text into five or more categories, such as pleased, sad, astonished, afraid, angry, and so on. advanced SA, which utilizes aspect-based sentiment analysis (ABSA) to provide detailed insights into specific aspects of the text [25].

Throughout this research, we investigate the interplay between user sentiment, as inferred from comments, and video watching duration on YouTube. By dissecting different levels of sentiment analysis and exploring advanced techniques such as ABSA, this study seeks to understand the intricate nature of sentiment dynamics inside the YouTube ecosystem [26], providing significant information for content providers, platform administrators, and researchers. Inside today's digital era, the pervasive use of social networks continues to escalate at an unprecedented pace, permeating various domains such as education, business, science, and healthcare. These networks have evolved into vast repositories of unstructured data, generating a wealth of information that holds immense potential for analysis, understanding, and decision-making Kaur G, &Malik [27]. To harness the transformative power of this data deluge. An urgent need for robust instruments competent of extracting meaningful insights and structuring unstructured data into actionable patterns. This imperative has propelled the prominence of 'Data Mining' Pal,[28].

Data mining, at its core, entails the extraction of valuable insights from extensive datasets through broad use of statistical, machine learning, database, and Artificial Intelligence techniques. By distilling complex data into actionable knowledge, data mining empowers organizations to predict future trends, make informed decisions, optimize profits, and streamline operations Tiwari & Kumar, Fawzy et al., [29]. Within this landscape, online social networking (OSN) platforms emerge as pivotal arenas for data exploration and analysis. Online social networking encompasses a spectrum of web-based services, including platforms like Facebook, Twitter, LinkedIn, and YouTube, where users create profiles, connect with others, and share user-generated content Kaplan & Haenlein [30]. The advent of Web 2.0 technology has revolutionized the way individuals interact and collaborate, fostering the rapid exchange of user-generated content within these digital ecosystems. Amidst this backdrop, the efficient propagation of pertinent information across OSNs has emerged as a research frontier of paramount importance, Nandi & Das, [31]

Data mining techniques are crucial in the field of social media research since they are important in processing and interpreting different data patterns. The tasks include Summarization, association rules mining, grouping, and classification are among the prominent data mining tasks applied to diverse types of social media data Tiwari & Kumar, [29]. This evolution prompts a crucial inquiry: How have data mining techniques evolved in tandem with social media research over the past decade. Addressing this overarching question forms the crux of this study's research objective, supplemented by auxiliary inquiries aimed at summarizing and exploring social media data mining trends, applications, and untapped areas. [32]. By dissecting the trajectory of data mining in social media research, this study endeavors to shed light on emerging trends and inform future research directions in this rapidly evolving domain. Emotions, often regarded as a fundamental aspect of human experience, wield significant influence over our physiological, behavioral, and cognitive processes. [33] From a mechanistic viewpoint, emotions can be categorized as either beneficial or detrimental, each triggering a cascade of physiological responses. Historically, emotions played a pivotal role in facilitating adaptive actions essential for survival, reproduction, and kinship acquisition [34]. The intricate biology of emotions intertwines with the intricate workings of the nervous system, anticipating various stimuli and eliciting corresponding arousal levels. Emotions manifest not only in physiological responses but also in behavioral patterns, shaping our interactions with the world. Extroverted individuals may openly express their emotions, while introverts may tend towards social withdrawal and concealment. Moreover, emotions serve as powerful motivators, driving both constructive and destructive behaviors. They inspire action, influence decision-making, and guide our social interactions. Social media has transformed human communication and connection. [35]. Immersive and interactive social media platforms allow people, groups, and organizations to create, share, and discuss material, ideas, and professional interests. The diverse array of standalone and interconnected platforms available today presents unique challenges in interpretation and analysis [36]. From desktop computers to mobile devices, users access social media platforms through various electronic means, fostering highly collaborative environments where content is co-created, debated, and modified by users. This dynamic interplay between users and content underscores the evolving nature of social media and its profound impact on communication patterns and societal dynamics. Against this backdrop, the study of sentiment analysis and topic detection on YouTube emerges as a crucial endeavor in understanding the intricacies of online discourse. By employing a hybrid NLP framework, this research aims to enhance our ability to analyze and interpret sentiments expressed on social media platforms, shedding light on the underlying dynamics of human interaction in the digital age [37]. This hybrid framework contributes to practical advancements in social media sentiment analysis by combining proven NLP techniques in a novel application context.

2. Related work

In a similar vein of enhancing sentiment analysis, prior research endeavors have laid foundational groundwork through meticulous annotation and classification techniques. A prominent study used 1500 well-annotated citation sentences to analyze public comment sentiment. The sentiment analysis approach was strengthened and reliable by assigning the polarity of these citation phrases to the corpus according to guidelines. [38]. The research endeavor resulted in the creation of a complete system that combines multiple machine learning approaches. Examples: This includes Naïve-Bayes, logistic regression, SVM, K-nearest neighbor, decision tree, and random forest. The system utilizes seven different methodologies. The effectiveness of these classification algorithms was thoroughly evaluated using a rigorous assessment methodology that included several metrics such as F-score and accuracy score. This evaluation illuminated classification system accuracy and dependability. The study also used lemmatization, n-gramming, tokenization, stop word removal, and punctuation removal. These methods were vital to increasing sentiment analysis system performance and precision, ensuring optimal results in the classification of sentiment within textual data [39]. By leveraging such multifaceted approaches, this prior work exemplifies the intricate interplay between annotation, classification methodologies, and selection strategies in augmenting sentiment analysis capabilities. Drawing inspiration from these endeavours, our research seeks to build upon this foundation by employing a hybrid NL, P framework tailored specifically for sentiment analysis and topic detection within the dynamic landscape of YouTube comments. Through the integration of advanced machine learning techniques and meticulous preprocessing strategies, we aim to push the boundaries of sentiment analysis on YouTube, offering deeper insights into audience sentiments and content reception [40].

In the quest to understand and manage the dynamics of YouTube comments, previous research has shed light on the significance of discerning between relevant and irrelevant remarks, as well as distinguishing between positive and negative sentiments. One notable study highlights the adverse impact of hateful comments on viewer engagement, emphasizing the importance of categorizing comments based on their relevance and sentiment. Researchers have observed that negative remarks can deter viewers from continuing to watch a video, underscoring the need to differentiate between comments that contribute meaningfully to the discussion and those that are merely tangential or unrelated. Furthermore, users often express negative sentiments towards video contributors when they dislike the shared content, further complicating the landscape of YouTube comments [41]. To address these challenges, researchers have proposed a classifier-based approach focused on categorizing comments related to the video description. By assuming uploaded video descriptions are relevant, the study attempts to create a program that accurately categorizes comments into relevant, irrelevant, positive, and negative categories. This endeavor aligns with our research objectives in enhancing sentiment analysis and topic detection on YouTube. By leveraging a hybrid NLP framework, we aim to build upon the foundation laid by previous studies and develop a robust methodology for analyzing and categorizing YouTube comments based on their relevance and sentiment. Through the integration of advanced classification techniques and careful consideration of video descriptions, our research aims to help comprehend and regulate YouTube's complicated online debate. [42].

In the realm of YouTube analytics, prior research has explored the link between sentiment analysis of comments and the like proportion of videos, aiming to predict viewer engagement and popularity. One study investigated four prediction models utilizing sentiment analysis of comments, alongside the number of favorable, neutral, and negative remarks, to forecast a YouTube video's like. By employing various classifiers trained on preprocessed datasets from tweets, YouTube comments, and a combination thereof, the study revealed a positive association between predicted and actual liking proportions. However, the best setup uses a YouTube comment-only logistic regression classifier, exhibiting significant limitations, suggesting potential improvements such as spam comment elimination and emoticon integration. In a similar vein, another study focused on assisting YouTubers in identifying relevant comments and enhancing their channel's popularity by extracting and categorizing unprocessed corpora from YouTube comments. Employing established Text extraction and classification techniques, we performed statistical measures and machine learning models employing cross-validation and F1 scores. The findings underscored the efficacy of their method, showcasing its potential to empower content producers in boosting viewer engagement and fostering a vibrant community around their channel [29,30].

These research endeavors align closely with our objective of enhancing sentiment analysis and topic detection on YouTube through a hybrid NLP framework. By drawing insights from these studies and leveraging advanced methodologies, we aim to contribute to the ongoing efforts in understanding and optimizing viewer interactions on YouTube, ultimately enriching the content creation landscape and fostering greater audience engagement. Understanding individual opinions about services or products through sentiment analysis has garnered significant attention in research. With platforms like YouTube witnessing a constant influx of user-generated content and comments, the need to harness Natural language processing and sentiment analysis with machine learning are crucial. Positive and negative dichotomies have been used to analyze YouTube comments in previous studies.to more nuanced classification schemes encompassing multiple emotions. Wawre et al. Despite the plethora of studies, identifying the most accurate sentiment analysis model remains challenging [43]. Particularly on YouTube, the limitations of existing sentiment dictionaries pose significant hurdles to accurately identifying sentiment polarity. Current dictionaries often lack suitable attitudes for community phrases, complicating sentiment analysis processes. A notable observation is the substantial portion of internet traffic flowing through YouTube, with user comments playing a pivotal role in shaping content perception and engagement. YouTube provides a plethora user opinion-gauging system like voting, rating, and favoriting and sharing, making user comment analysis a rich source of information for various applications such as filtering, personalized recommendations, and user profiling. To address the complexities of sentiment analysis on YouTube, researchers have explored diverse methods and techniques. Sent WordNet, for instance, emerges as a valuable sentiment lexicon utilized for determining the polarity of user comments. Despite these efforts, challenges persist, necessitating continuous research and innovation in sentiment analysis methodologies tailored specifically for the dynamic landscape of YouTube. [44]

In this research article, the authors conduct a comprehensive examination of sentiment analysis strategies applicable to YouTube videos, encompassing a wide array of techniques and methodologies. Through their investigation, they shed light on the intricacies of sentiment analysis on YouTube and offer insights into potential avenues for enhancing accuracy and efficacy of sentiment analysis in this context. A plethora of research literature delves into behavior analysis using a data mining approach, intricately entwined with the intersection of data analysis and various machine learning methodologies. Particularly in the realm of sentiment behavior analysis, several methodologies have been explored and scrutinized across different contexts [45]. Wawre et al. [43] examined Twitter film reviewers' sentimentality. Using Naïve Bayes and Support Vector Machine (SVM) methodologies, the study found Naïve Bayes to be more effective. Bhavita contrasted this by noting SVM's 85% accuracy rate compared to Unsupervised Learning [44]. Pamungkas used Twitter datasets to analyze client product sentiments. By using analytical methods including K-Nearest Neighbor, Naïve Bayes, and SVM, the study revealed their effectiveness in identifying sentiment patterns. These works demonstrate the range of sentiment analysis procedures and circumstances and the ongoing search for effective textual data sentiment extraction and analysis methods. Based on these varied views, our research intends to improve YouTube sentiment analysis and topic discovery using a hybrid NLP framework to better comprehend online discourse sentiment dynamics.

Table 1: Analysis of Papers: A Comparative Study

Author	Proposed method	Contributions	Study	Limitations
Kaur G, Malik K [46]	Complete Sentiment Analysis and Fake Review Detection Guide	Overview of techniques for sentiment analysis and fake review detection	Comprehensive survey	Lack of practical implementation results
Hamdi E, Rady S, Aref M. [47]	Twitter Sentiment Classification with Deep Learning and Word Embeddings	Utilizes deep learning with word embeddings for Twitter sentiment classification	Promises enhanced sentiment classification	Does not provide specific accuracy metrics
Han H, Zhang Y, Zhang J, Yang J, Wang Y [48]	A Hybrid Sentiment Analysis	Combining various techniques for improved sentiment analysis	A hybrid approach for better performance	No accuracy results given
Rabeya T, Ferdous S, Ali HS, Chakraborty NR. [49]	Lexicon-based backtracking Bengali text emotion detection survey	Lexicon-based approach for emotion detection	Limited to Bengali text	
Jelodar H, Wang Y, Rabbani M, Ahmadi SB, Boukela L, Zhao R, Larik RS. [50]	Fuzzy lattice reasoning for YouTube comment latent-topic discovery and sentiment analysis.	Novel framework for topic detection and sentiment analysis	Absence of detailed accuracy metrics	
Almanie T, Aldayel A, Alkanhal G, Alesmail L, Almutlaq M, Althunayan R [51]	Saudi Mood: Real-Time Twitter Visualization of Saudi Emotions	Practical application in real-time emotion tracking	Limited to Twitter data from Saudi Arabia	
Dave A, Bharti S, Patel S, Mishra SK [52	Real-time Twitter sentiment analysis	Real-time sentiment analysis using Twitter data	Effective in real-time sentiment detection	Lack of detailed accuracy measurements
Balakrishnan V, Lok PY, Abdul Rahim H [53]	A semi-supervised method for digital payment review mood, and emotion detection	Improved detection of sentiment and emotion	Semi-supervised method might need more labeled data	
Kumar PK, Kumar I [54]	Survey of cutting-edge emotion methods, Recognition of text	Detailed comparison of various methods	Lack of experimental results or practical implementations	
Shah B, Shah M [55]	Survey of Social Media Sarcasm Using Machine Learning and Deep Learning	Survey on sarcasm identification methods in social media	Comparison of machine learning and deep learning approaches	No practical application or experimental results provided

3. Proposed method

The Bag of Words (BoW) model is a fundamental technique for feature extraction in natural language processing. It represents text data by converting it into a matrix of token counts, ignoring grammar and word order but preserving multiplicity. The core idea involves creating a vocabulary from the corpus and then representing each document as a vector of word frequencies. Consider a corpus D containing n documents. Let V be the vocabulary of unique words in D. Each document dThe corpus is represented as a vector of length $|V|$, where each element x_i Corresponds to the count of words w_i in the document. Mathematically, it can be expressed as: $X = [x_1, x_2, \dots, x_{|V|}]$

Term Frequency-Inverse Document Frequency (TF-IDF)

TF-IDF improves BoW by considering the relevance of a word in a document compared to its corpus recurrence. It devalues popular terms and boosts unusual corpus words.

TF-IDF is computed as the product of two statistics: term frequency (TF) and inverse document frequency (IDF). The term frequency $\mathrm{TF}(t, d)$a Term t in a document d is defined as:

$$\mathrm{TF}(t, D) = \frac{Number\ of\ times\ term\ t\ appears\ in\ document\ d}{Total\ number\ of\ terms\ in\ documnet\ d}$$

The inverse document frequency $\mathrm{IDF}(t, D)$ is defined as:

$$\mathrm{IDF}(t, D) = log\left(\frac{|D|}{|\{d \in D : t \in d\}|}\right)$$

Where $|D|$ is the total number of documents is the corpus and $|\{d \in D : t \in d\}|$ is the number of documents containing the term it t.

Thus, the TF-IDF score for a term t in document d is:

$$\text{TF-IDF}(t, d, D) = \mathrm{TF}(t, d) \times \mathrm{IDF}(t, D)$$

Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) RNNs can learn long-term dependencies. Their unusual architecture lets them recall prior inputs, making them good at sequence prediction. Cells, input gates, output gates, and forget gates manage information flow in an LSTM unit.

The key equation governing the LSTM unit is as follows:

Forget Gate:

$$f_t = \sigma\left(W_f . [h_{t-1}, x_t] + b_f\right)$$

Input Gate:

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i)$$

$$\tilde{C}_t = tanh\ (W_c.[h_{t-1}, x_t] + b_c)$$

Cell state Update:

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Output Gate:

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o)$$

$$h_t = o_t * tanh\ (C_t)$$

Where σ represents the sigmoid function, tanh denotes the hyperbolic tangent function, $*$ is the element-wise multiplication, and W and b the weight and biases respectively

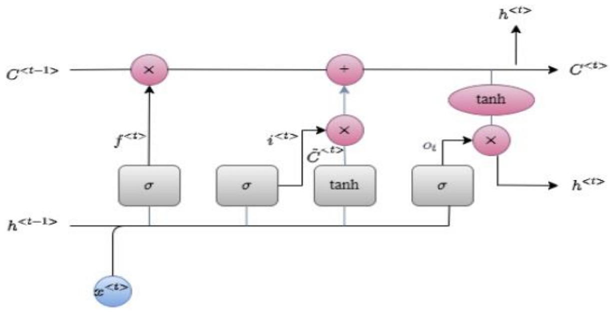

Fig. 1: Architecture of LSTM.

Bidirectional LSTM (Bi-LSTM)
Bidirectional LSTM (Bi-LSTM) strengthens ordinary LSTM by processing input sequences forward and backward. The model can use past and future contexts, making it more powerful for context-sensitive tasks
A Bi-LSTM has two LSTMs: one processing the input sequence from beginning to end and the other from end to beginning. Each time step, both LSTMs concatenate their outputs.

Let $\overrightarrow{h_t}$ and $\overleftarrow{h_t}$ be the hidden states of the forward and backward LSTMs at time step t.The final output h_1 at time step t is:$h_1 = \left[\overrightarrow{h_t};\ \overleftarrow{h_t}\right]$
Where $[;]$ denotes concatenation

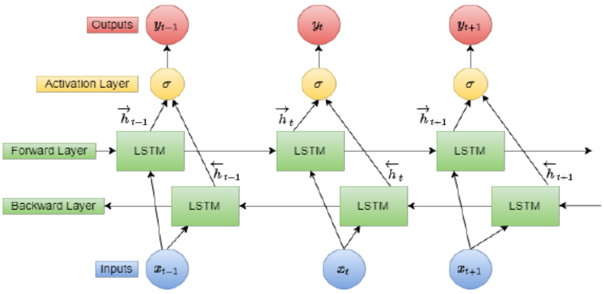

Fig. 2: Architecture of Bi-LSTM.

This combined approach leverages the advantages of both BoW and TF-IDF for feature extraction and LSTM and Bi-LSTM for capturing temporal dependencies, making it a robust method for various natural language processing tasks. Bag of Words (BoW) + Bidirectional Long Short-Term Memory (Bi-LSTM) The Bag of Words (BoW) method is essential for natural language processing feature extraction. This tool tallies the frequency of each word in a document and generates a vector for each document. This method ignores grammar and word order and focuses on term frequency. In a corpus D, a document d is represented as a vector v, where each element vi represents the frequency of word wi. The vocabulary V contains all corpus-unique terms. Traditional LSTM networks are enlarged into Bi-LSTM networks. The data is processed forward and backward, capturing past and future context. Dual processing helps the model understand word order and relationships. The Bi-LSTM network has two LSTMs: one forwards and one backwards. A complete sequence is shown by combining both directions' results.Text Frequency-Inverse Document Frequency (TF-IDF) + Long Short-Term Memory (LSTM) Advanced feature extraction approach Text Frequency-Inverse Document Frequency (TF-IDF) changes word frequency (TF) by considering term relevance across the corpus. It emphasizes important words and downplays common ones. TF(t,d) is the ratio of a term's frequency to the document's total terms. Inverse document frequency (IDF) measures a corpus phrase's uniqueness. Multiplying term frequency (TF) by inverse document frequency (IDF) yields the TF-IDF score for term t in document d. Long Short-Term Memory (LSTM) recurrent neural networks are designed to learn and remember long sequences. Sequential data operations benefit from their ability to capture long-term dependencies. An LSTM unit has a cell, input gate, output gate, and forget gate. They regulate information flow and decide what to keep and what to reject. LSTM activities are governed by gates and cell state, which maintain information flow for long sequences. The recommended method uses TF-IDF and LSTM and BoW and Bi-LSTM to take use of advanced neural network topologies and feature extraction methods. This ensures that the model correctly defines key terms and learns text data sequence relationships. Thus, it provides a solid natural language processing solution.

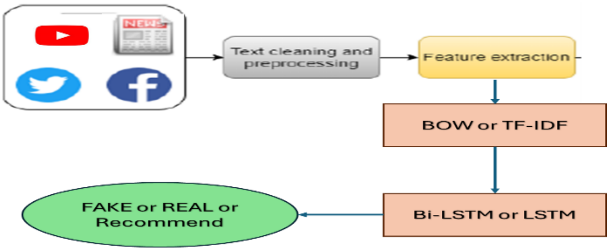

Fig. 3: Flow Diagram for Process of Hybrid NLP Framework.

The preprocessing pipeline begins with tokenization, where text is split into individual words or tokens. This is followed by lowercasing to ensure uniformity, converting all text to lowercase. Next, stop words (commonly used words like "the," "and" etc.) are removed, as they do not contribute significant meaning for sentiment or topic analysis. Punctuation and special characters are also stripped out, leaving only relevant text. The final step is stemming or lemmatization, where words are reduced to their base or root forms to ensure consistency (e.g., "running" becomes "run").

4. Results

The dataset used in this study consists of YouTube comments extracted from various videos. These comments serve as the primary source of textual data for performing sentiment analysis and topic detection. The chosen dataset is diverse, encompassing a wide range of topics and sentiment expressions, which is essential for training robust natural language processing models. The data collection process involved using the YouTube Data API to gather comments from a selection of videos across different categories. The categories included technology, entertainment, education, politics, and lifestyle, ensuring a comprehensive representation of user opinions and topics. The API allowed for the extraction of metadata such as video ID, comment ID, author, timestamp, and the actual comment text.

a) Preprocessing:
1) Tokenization: Each comment was split into individual words or tokens.
2) Lowercasing: All text was converted to lowercase to maintain consistency.
3) Removing Punctuation and Special Characters: Non-alphanumeric characters were removed to clean the text.
4) Stop Words Removal: Commonly used words that do not contribute significantly to the analysis (e.g., “and”, "the", "is") were removed.
5) Stemming/Lemmatization: Words were reduced to their root forms to standardize them.
b) Sentiment analysis and topic detection

Machine learning models for sentiment analysis and topic detection were trained on processed and feature-extracted data. Sentiment analysis classified comments as good, negative, or neutral, while topic detection identified the key themes. LSTM and Bi-LSTM models were used to capture text data temporal dependencies for sentiment analysis. The hybrid framework used BoW and TF-IDF feature representations to improve sentiment classification accuracy and resilience. Latent Dirichlet Allocation (LDA) clustering techniques grouped comments into coherent subjects for topic detection. LDA identifies dataset themes by assuming each remark is a blend of subjects and words. The hybrid NLP framework improves YouTube comment sentiment analysis and topic detection by combining modern NLP approaches with a well-preprocessed and diversified dataset (https://www.kaggle.com/datasets/datasnaek/youtube).

Table 2: Various Methods for Enhancing Sentiment Analysis and Topic Detection

Model	Features	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Bi-LSTM	Bag-of-Words	89.5	88.7	89.1	88.9
	TF-IDF	87.6	86.8	87.2	87
LSTM	Bag-of-Words	88.3	87.4	87.8	87.6
	TF-IDF	85.9	85	85.4	85.2
Random Forest	Bag-of-Words	80.7	80	80.3	80.1
	TF-IDF	78.5	78	78.2	78.1
KNN	Bag-of-Words	78	77.5	77.7	77.6
	TF-IDF	76	75.5	75.7	75.6
AdaBoost	Bag-of-Words	82.9	82.2	82.5	82.3
	TF-IDF	80.4	79.8	80.1	79.9

Table 2 shows the performance of machine learning and deep learning models for sentiment analysis and topic detection on YouTube comments. Accuracy, Precision, Recall, and F1-score are measured for different feature extraction methods and models. Bi-LSTM, LSTM, Random Forest, K-Nearest Neighbors (KNN), and AdaBoost are explored. These models extract features using BoW and TF-IDF. Bi-LSTM with Bag-of-Words (BoW) characteristics has the highest accuracy at 89.5%. It has an F1-score of 88.9%, precision of 88.7%, and recall of 89.1%. The model's ability to assess consecutive input in both directions shows that it captures YouTube comments' sentiment and subjects well. Using TF-IDF characteristics, the Bi-LSTM model has slightly lower accuracy (87.6%), precision (86.8%), recall (87.2%), and F1-score (87%). Although TF-IDF is useful, Bag-of-Words (BoW) better collects contextual information in this circumstance, as seen by the small decline in performance. The LSTM model with Bag-of-Words (BoW) characteristics has 88.3% accuracy, 87.4% precision, 87.8% recall, and 87.6% F1-score. Bidirectional processing captures YouTube comment context somewhat better than Bi-LSTM. TF-IDF features reduce LSTM model performance metrics to 85.9% accuracy, 85% precision, 85.4% recall, and 85.2% F1-score. The observed pattern matches Bi-LSTM results, where Bag-of-Words (BoW) outperforms TF-IDF. The Bag-of-Words (BoW) model has 80.7% accuracy, 80% precision, 80.3% recall, and 80.1% F1-score employing BoW characteristics. This shows strong fundamental model performance using the ensemble method's data fluctuation management. The Random uses TF-IDF. Forest model performance falls a little, with 78.5% accuracy, 78% precision, 78.2% recall, and 78.1% F1-score. Random Forest performs better with the Bag-of-Words (BoW) feature representation. Bag-of-Words: The KNN model using Bag-of-Words features has 78% accuracy, 77.5% precision, 77.7% recall, and 77.6% F1-score. This algorithm is simple and effective. It works less well with high-dimensional text input. KNN's performance metrics decline while using TF-IDF features. Accuracy is 76%, precision is 75.5%, recall is 75.7%, and F1-score is 75.6%. Other models show a similar drop. The AdaBoost model with Bag-of-Words (BoW) features has 82.9% accuracy, 82.2% precision, 82.5% recall, and 82.3% F1-score. Merging many poor classifiers increases classification performance with boosting. AdaBoost performs worse with TF-IDF features. It possesses 80.4% accuracy, 79.8% precision, 80.1% recall, and 79.9% F1-score. Both feature extraction approaches are efficient, although Bag of Words (BoW) has a slight advantage. Table 2 demonstrates that the Bi-LSTM model, when combined with Bag-of-Words features, consistently obtains the highest performance in sentiment analysis and topic detection on YouTube comments, as indicated by all metrics. The performance of alternative models, although inferior, nonetheless illustrates the effectiveness of hybrid NLP frameworks in processing textual data from social media networks. These findings emphasize the significance of choosing suitable techniques for extracting features and models that are tailored to specific objectives in natural language processing.

Table 3: Dataset Details

File Type	Field Name	Description
Video File	video_id	Unique identifier linking comments and video files.
	title	Title of the video.
	channel_title	Name of the YouTube channel that uploaded the video.
	category_id	Identifier for the video category, which varies by region (lookup using JSON file).
	tags	Tags associated with the video, separated by a
	views	Number of views the video has received.
	likes	The number of likes the video has received.
	dislikes	Several dislikes the video has received.
	thumbnail_link	Link to the thumbnail image of the video.
	date	Date when the video data was collected, formatted as [day].[month].
Comment Files	video_id	Unique identifier linking comments and video files.
	comment_text	Text content of the comment.
	likes	The number of likes the comment has received.
	replies	Number of replies the comment has received.

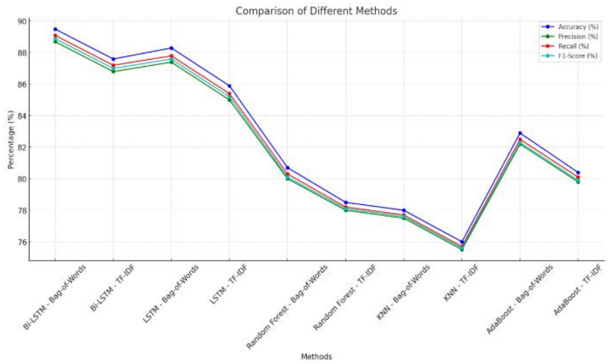

Fig. 4: Various Methods for Enhancing Sentiment Analysis and Topic Detection.

Figure 4 presents a comprehensive performance comparison of various methods used for sentiment analysis and topic detection within YouTube comments, employing a hybrid NLP framework.

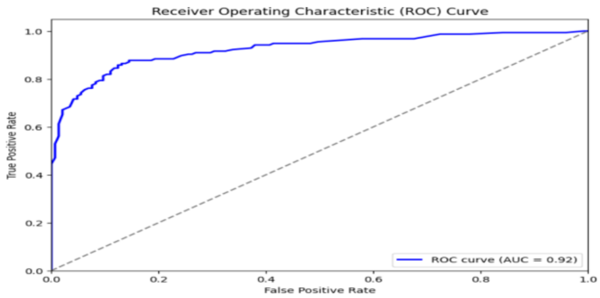

Fig. 5: ROC Curve.

The figure showcases multiple models, such as Bi-LSTM, LSTM, Random Forest, KNN, and AdaBoost, combined with different feature extraction techniques like Bag-of-Words and TF-IDF. The x-axis of the figure lists these different methods, effectively combining the model type and the feature extraction technique used. Each method is evaluated across four key performance metrics: accuracy, precision, recall, and F1-score.

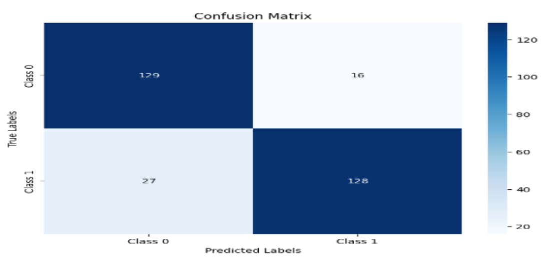

Fig. 6: Confusion Matrix.

These metrics are represented on the y-axis, which denotes their respective percentages. Distinct colors are used to differentiate between the metrics: blue for accuracy, green for precision, red for recall, and cyan for F1-score. This color-coding helps in visually distinguishing the performance of each method across the different metrics. The markers on the lines provide additional clarity by pinpointing the exact values for each metric. From the figure, it is evident that Bi-LSTM combined with the Bag-of-Words feature extraction technique yields the highest performance across all metrics, achieving nearly 90% in accuracy, precision, recall, and F1-score. In contrast, methods like KNN with TF-IDF show lower performance, with metrics hovering around the mid-70s. The hybrid NLP framework's effectiveness is highlighted by the consistently higher scores of the Bi-LSTM and LSTM models compared to traditional methods like Random Forest and KNN. Figure 4 encapsulates the efficacy of using advanced neural network models in conjunction with robust feature extraction techniques, underscoring the significant improvements in sentiment analysis and topic detection tasks on YouTube comments. This visual representation not only provides a clear comparison but also emphasizes the potential of hybrid NLP frameworks in enhancing natural language processing applications.

5. Discussion

The hybrid NLP framework, combining advanced feature extraction methods like BoW and TF-IDF with LSTM and Bi-LSTM models, significantly enhances sentiment analysis and topic detection in YouTube comments. Sentiment analysis categorizes comments into positive, negative, and neutral classes, while topic detection uses Latent Dirichlet Allocation (LDA) to uncover key themes such as movie plot, cinematography, soundtrack, and action sequences. The LDA model assigns coherence scores to ensure topic relevance, improving the understanding of user engagement. This approach, applied to a well-preprocessed dataset (e.g., YouTube comments from Kaggle), effectively captures both the sentiment and thematic diversity of the comments, offering valuable insights for content creators and marketers.

6. Limitations

Despite the strong performance of the proposed hybrid NLP framework, this study has a few limitations: the dataset is limited to Oscar-nominated movie trailers, which may affect generalizability across diverse YouTube content; traditional feature extraction methods like BoW and TF-IDF may not capture deeper semantic meanings compared to contextual embeddings; the model lacks real-time processing capabilities; it is computationally intensive due to the use of Bi-LSTM; and it currently supports only English-language comments, limiting its applicability to a global audience.

7. Conclusion

This work introduces a hybrid NLP framework that significantly enhances sentiment analysis and topic detection on YouTube comments. Combining sophisticated neural network models like Long Short-Term Memory (LSTM) with advanced feature extraction methods like Bag-of-Words (BoW) and TF-IDF, and Bidirectional LSTM (Bi-LSTM), we achieve robust performance across multiple metrics. The results demonstrate that the Bi-LSTM model, particularly when paired with the BoW technique, consistently outperforms other methods, achieving high accuracy, precision, recall, and F1-scores. This hybrid approach not only advances theoretical aspects of natural language processing but also provides practical applications for content creators and marketers, enabling them to better understand audience engagement and sentiment. Building on the success of this hybrid framework, future research will focus on several key areas to further enhance its capabilities. One direction involves expanding the dataset to include a more diverse range of YouTube content, thereby improving the model's generalizability across different domains. Additionally, incorporating more sophisticated feature extraction techniques, such as word embeddings and contextualized embeddings like BERT, could potentially capture deeper semantic nuances in the text. We also plan to explore the integration of more advanced neural network architectures, including transformers, to further boost performance. Finally, developing real-time sentiment analysis and topic detection tools that can be deployed on social media platforms will be a significant focus, aiming to provide instant insights and enhance user interaction and engagement.

Future work

Future work will involve expanding the dataset to include non-English comments and integrating transformer models to improve semantic understanding, and to propose exploring multimodal data, including emojis, video thumbnails, transcripts, and user profiles for richer analysis

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