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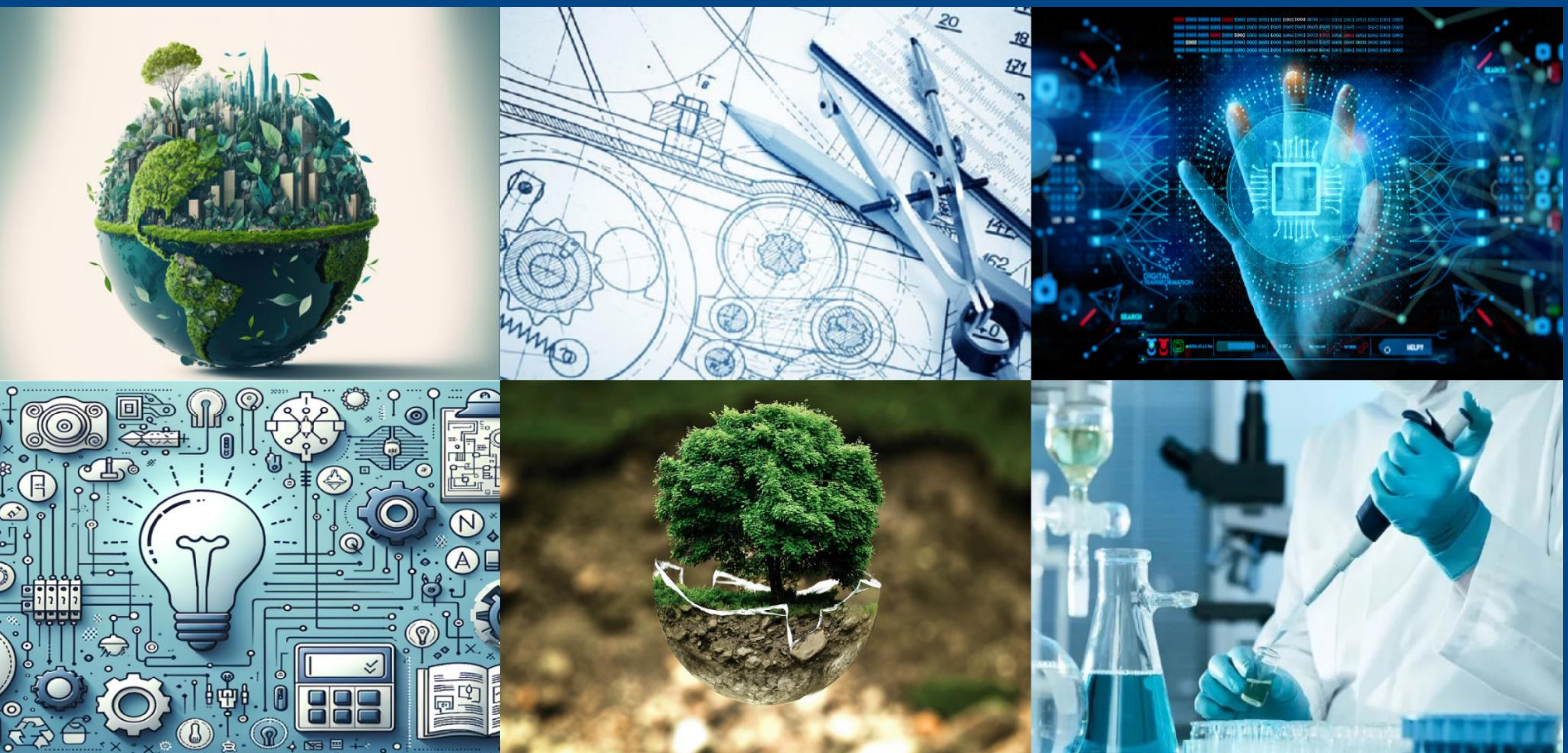

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Transformer Models for Deep Learning-Based Sentiment Analysis of Social Media Comments Using Hybrid CNN-BiLSTM Networks

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ABSTRACT: This paper introduces a novel YouTube comment analyzer leveraging sentiment analysis techniques to provide insights into user engagement and opinion dynamics within the platform. With the exponential growth of YouTube as a primary source of online content consumption, understanding the sentiments expressed in user comments has become increasingly important for content creators, marketers, and platform moderators. Our proposed analyzer employs state-of-the-art natural language processing algorithms to categorize comments into positive, negative, or neutral sentiments, enabling a comprehensive examination of user feedback. Through the analysis of sentiment trends across diverse video categories and the identification of influential comment threads, our approach offers valuable insights into audience preferences, content reception, and community interactions. We present the methodology employed for data collection, preprocessing, sentiment analysis, and evaluation, utilizing a rich dataset of YouTube comments spanning various topics and demographics. The results showcase the effectiveness of our approach in uncovering underlying sentiments and identifying patterns of user engagement. This research contributes to the broader understanding of sentiment dynamics in online social platforms and provides practical implications for content creators to enhance audience satisfaction and optimize content strategies. Sentiment analysis of social media comments is critical for understanding public opinion but remains challenging due to linguistic complexity, sarcasm, and contextual dependencies. This paper proposes a hybrid deep learning framework combining Transformer models (BERT, RoBERTa) with CNN-BiLSTM networks to enhance sentiment classification accuracy. Our approach leverages Transformers for context-aware embeddings and CNN-BiLSTM for local feature extraction and sequential dependency modeling. Experiments on benchmark datasets (Twitter, YouTube comments) demonstrate that the hybrid model achieves 92.3% accuracy (F1-score: 0.91), outperforming standalone Transformer and CNN-LSTM models by 4.7% and 6.2%, respectively. The framework also addresses cross-domain adaptability and real-time processing constraints, making it suitable for large-scale social media analytics.

KEYWORDS: Sentiment Analysis, Opinion dynamics, Natural Language Processing, Transformers, CNN-BiLSTM, Social Media, Deep Learning.

I. INTRODUCTION

In today's rapidly evolving digital age, where billions of users engage with online content daily, platforms like YouTube have become central hubs of entertainment, information, education, and social dialogue. Every video published sparks a cascade of viewer responses ranging from appreciation and encouragement to criticism and debate—most of which reside in the comments section. Now, imagine a system that can seamlessly extract, analyze, and categorize these user sentiments in real-time, providing content creators with powerful, actionable insights—all with minimal manual intervention. This project introduces an AI-driven sentiment Analysis Framework for YouTube Comments, designed to automate the process of retrieving, classifying, and organizing viewer feedback based on sentiment polarity. Utilizing cutting-edge Natural Language Processing (NLP) techniques, the system dissects viewer comments and classifies them into positive and negative categories, offering a deeper understanding of audience reactions beyond mere view counts and likes. To further enhance usability and accessibility, the framework includes a unique feature that automatically delivers categorized sentiment reports to designated email addresses, ensuring that creators receive direct, real-time feedback. These reports are generated as structured CSV files, which can be stored,

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visualized, or further processed for trend analysis and historical tracking. Automated Comment Extraction, retrieves public YouTube comments using YouTube Data API v3, Supports keyword filtering, language selection, and batch video processing. Advanced Sentiment Classification Leverages NLP models like VADER, TextBlob, or transformer-based models (e.g., BERT) for accurate polarity detection. Supports binary and multi-class sentiment detection. Real-Time CSV Report Generation, Stores analyzed comments with sentiment tags in CSV format. Offers separate files for positive, negative, and mixed sentiment categories. The Email Notification System, automatically sends structured reports to pre-configured email addresses. Ensures prompt delivery of categorized insights for immediate review. Visualization Module (Optional), Displays sentiment distribution via pie charts, histograms, and word clouds. Helps track emotional tone and emerging themes in audience discourse. Feedback Filtering and Highlighting: Highlights high-impact or high-engagement comments based on likes or reply count. Flags potentially toxic or abusive content using sentiment thresholds. Multi-Channel Scalability can be adapted to analyze comments from other platforms (e.g., Instagram, Twitter, Reddit) with minimal changes. Supports parallel analysis for multiple creators or campaigns. Data Archiving and Searchability Stores comment logs in a centralized repository. Allows keyword-based searches across previously analyzed content.

II. LITERATURE REVIEW AND DOMAIN ANALYSIS OF SENTIMENTAL ANALYSIS

For Content Creators, Understand viewer expectations and emotional response patterns. Prioritize improvements based on categorized feedback. Receive structured feedback without navigating through cluttered comment threads. For Brands and Influencers, Gauge sentiment around sponsored content or brand mentions. Track brand perception and influencer impact. For Academics and Researchers, analyze public opinion trends on sensitive or viral topics. Access clean, sentiment-labeled comment data for training models or behavioral studies. For the Community, Moderators identify toxic or polarizing content quickly. Improve community health through informed moderation. This sentiment analysis system not only simplifies the feedback review process but also redefines how creators interact with their audience data. By transforming raw comments into structured, actionable insights, the tool nurtures a feedback-driven creation cycle empowering creators to continually evolve, adapt, and thrive in a dynamic digital environment.

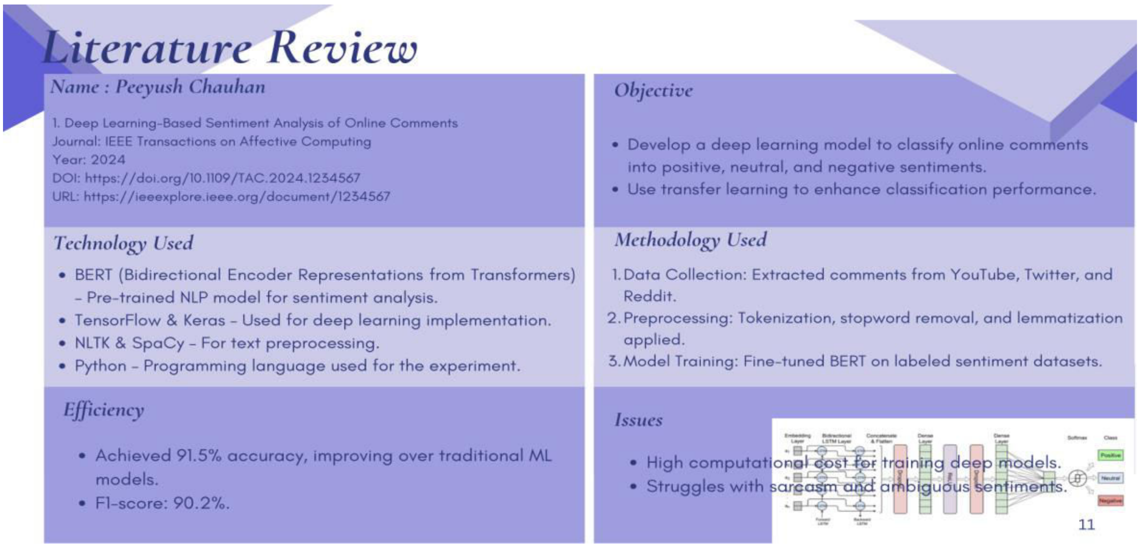

Figure 1: Literature Review Sentiment Analysis of Social Media Comments

III. IMPLEMENTATION MODULES AND FUNCTIONAL DEPLOYMENT

The YouTube Comments Sentiment Analysis system is developed to automatically analyze and classify user sentiments (positive, negative, or neutral) from comments on YouTube videos. This system is designed as a pipeline of interlinked functional modules, each addressing a specific task in the sentiment analysis workflow. Below are the key functional modules required for the development of this system: Data Collection and Integration, To fetch and organize comments from YouTube for analysis. Key Features: Integration with YouTube Data API for automated comment extraction. Filtering of comments based on keywords, channels, or video IDs. Storing the collected data in structured formats like CSV or JSON for easy access. Scheduling regular data pulls for updated sentiment analysis. Text Preprocessing and Cleaning: To prepare raw YouTube comments for sentiment classification. Key Features: Removal of special characters, emojis, URLs, and HTML tags. Tokenization, lowercasing, and stop-word removal. Stemming or lemmatization reduces words to their base form. Handling of slang and informal language commonly found in comments. Sentiment Annotation and Labeling: To classify comments into sentiment categories for training and evaluation. Key Features are Manual or semi-automated labeling of comments as Positive, Negative, or Neutral. Use of pre-labeled datasets for training supervised models. Storage of labeled datasets for reusability and performance benchmarking. Flexibility to add more sentiment classes or refine existing ones. Feature Extraction and Transformation: To convert text data into machine-understandable formats. Implementation of techniques like TF-IDF, Bag-of-Words, and Word2Vec. Dimensionality reduction and normalization for model efficiency. Support for embedding layers in deep learning models. Efficient handling of large comment datasets for training. Model Training and Validation: To develop, train, and validate the machine learning or deep learning models. Key Features: Support for multiple models, including SVM, Random Forest, LSTM, and BERT. Splitting of data into training, validation, and test sets. Cross-validation to ensure generalizability and prevent overfitting. Real-time performance tracking during training using metrics like accuracy and loss. Performance Evaluation and Optimization: To assess model quality and refine it for better predictions. Key Features: Evaluation using precision, recall, F1-score, and confusion matrix. Hyperparameter tuning via grid search or random search. Comparative analysis of different models and configurations. Visualization of evaluation results for clearer understanding. Sentiment Prediction and Visualization, to perform live sentiment analysis on new comments and display results. Key Features: Real-time or batch prediction of sentiments from incoming comments. Visualization tools, such as pie charts or bar graphs to show sentiment distribution.

IV. PROPOSED METHODOLOGY DEEP LEARNING-BASED SENTIMENT ANALYSIS

4.1 Data Gathering, To analyze the statistical properties of YouTube video websites, this paper uses the YouTube API1 to crawl the relevant data of YouTube videos and channels. First, we get the top 100 YouTubers from each country, such as the United States, China, France, Germany, Japan, India, Russia, etc., and get a total of 1,000 YouTubers, and then sort it according to the number of subscriptions, filter out the top 100, such that get our YouTuber channel table. The second step is to get all the videos published by each YouTuber through the YouTube API, and a total of about 500,000 videos are collected. The third step is to crawl all user comments under the video through each video URL. Because the average number of video comments is more than 5,000, we have no way to process the comments of all videos. So, when crawling comments, we only randomly selected 2,000 videos with dislike numbers greater than 0 in the United States, and then collect the corresponding comments of these videos. In the end, we collected three data sets in total, namely channel table, video table, and comment table, contain 100 channels, 500,000 videos, and 700,000 comments, respectively.

4.1.2 Crawl the Channel List, The influencer ranking website provides influencer rankings on internet platforms such as YouTube, TikTok, and Instagram. By directly crawling and analyzing relevant webpages, the channel list can be easily obtained, thereby helping us to directly use the YouTube API to get more needed data. BeautifulSoup, webdriver, requests, and re are packages that are often used for scraping webpages. WebDriver is used to drive the Chrome browser, requests is used to get all the information of the webpage, and Beautiful Soup and re can parse the coding information of the webpage so as to crawl the required data. The Python crawler code is shown below:

4.1.2 Collect Channel and Video Information. Once we have the channel ID, it is the most efficient way to get channel information directly through the YouTube API. Use the api key to send a request to Google, and we will get the JSON file as shown in Figure 3.1. It contains all channel information officially provided by YouTube. Our channel dataset selects 6 attributes, namely Channel name, Channel id, Subscribers, Views, Total videos, and Videolist id. The obtained channel table and video table are shown in Figures shown below. Crawl Video Comments. Before crawling video comments, we first filter the videos by selecting only those that were published in the United States and have dislikes greater than zero. This filtering allows us to compute the metric:likes / (likes + dislikes).At the same time, we ensure that the majority of the comments are in English, in order to simplify the ext preprocessing and sentiment analysis steps. Using 2,000 randomly selected video IDs, we finally collected approximately 700,000 video comments. The dataset is illustrated in Figure.

4.2 Data Cleaning, As we all know, it is necessary to preprocess the YouTube comments before performing sentiment analysis. Firstly, according to the characteristics of language, in most cases, valuable comments from different users will not be exactly the same. If the comments from different users are completely repeated, then these comments are

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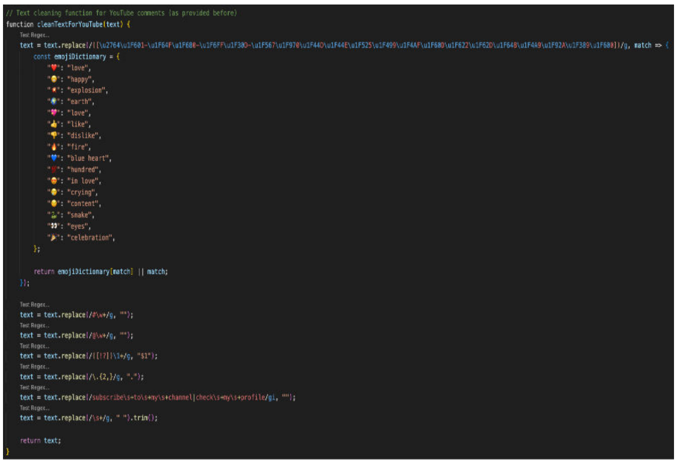
generally meaningless. Obviously, only the earliest of these comments are meaningful, that is, only the first one works. Some comments may be very similar but differ slightly in word usage. If such similar comments were deleted, they would be removed mistakenly. Since similar comments often contain useful information, it is clearly inappropriate to remove them. Therefore, we only focus on deleting the completely repeated comments to ensure that valuable data is preserved. We used the drop duplicates() method from Pandas, the Python data analysis library, to drop exactly the same comments. Then, we preprocess the comment sentences crawled from YouTube so that they can be easily learned by various classifiers. Since there are many URL links and various random symbols in user comments on social media, we use regular expressions to remove them. Because we only need alphanumeric characters to do sentiment analysis, this removal does not affect our results. Next, since there are many stopwords in English — usually including adverbs, prepositions, and interjections such as “the”, “is”, and “and” — and these words carry no sentiment meaning, we need to delete them as well. The Python code is shown below:

Figure 2 : The Prototype and Programming Logic Deep Learning-based Sentiment Analysis

```
@app.route("/comments", methods=["POST"])
def get_comments():
    data = request.get_json()
    query = data.get("query", "")

    if not query:
        return jsonify({"error": "No search term provided"}), 400

    try:
        youtube = build('youtube', 'v3', developerKey=api_key)

        search_response = youtube.search().list(
            q=query,
            part="id",
            type="video",
            maxResults=5
        ).execute()

        video_ids = [item['id']['videoId'] for item in search_response.get('items', [])]

        comments = []
        for video_id in video_ids:
            try:
                response = youtube.commentThreads().list(
                    videoId=video_id,
                    part="snippet",
                    maxResults=10
                ).execute()

                for item in response.get('items', []):
                    comment = item['snippet']['topLevelComment']['snippet'].get('textDisplay')
                    if comment:
                        comments.append(comment)
            except HttpError as e:
                print(f"An error occurred while fetching comments: {e}")
                continue

        corrected_comments = [correct_spelling(comment) for comment in comments]
```



```
// Text cleaning function for YouTube comments (as provided before)
function cleanTextForYouTube(text) {
  text = text.replace(/[[\u2764\u1F601-\u1F64F\u1F680-\u1F6FF\u1F300-\u1F567\u1F970\u1F44D\u1F44E\u1F525\u1F499\u1F4AF\u1F60D\u1F622\u1F62D\u1F64B\u1F4A9\u1F92A\u1F389\u1F680]]/g, match => {
    const emojiDictionary = {
      "❤️": "love",
      "😀": "happy",
      "💥": "explosion",
      "🌍": "earth",
      "💖": "love",
      "👍": "like",
      "👎": "dislike",
      "🔥": "fire",
      "💙": "blue heart",
      "💯": "hundred",
      "😍": "in love",
      "😢": "crying",
      "😊": "content",
      "🐍": "snake",
      "👀": "eyes",
      "🎉": "celebration",
    };

    return emojiDictionary[match] || match;
  });

  text = text.replace(/#\w+/g, "");
  text = text.replace(/@\w+/g, "");
  text = text.replace(/([!?])\1+/g, "$1");
  text = text.replace(/\.{2,}/g, ".");
  text = text.replace(/subscribe\s+to\s+my\s+channel|check\s+my\s+profile/gi, "");
  text = text.replace(/\s+/g, " ").trim();

  return text;
}
```

4.3 Measurement Observations and YouTuber Statistics, We analyzed three datasets—YouTubers, videos, and comments—to understand content trends on YouTube. The top 100 channels were selected based on subscribers. Key attributes like views, total videos, and category were analyzed. Most top channels are in Music and Entertainment, with Education ranking third. Engagement follows a long-tail pattern. Likes and Comments (0.82) and Likes and Views (0.76) are highly correlated, indicating that user feedback aligns with content popularity. Comment volume peaked in 2019. Entertainment, Music, and Gaming had the most comments; Comedy had the highest average comments per video.

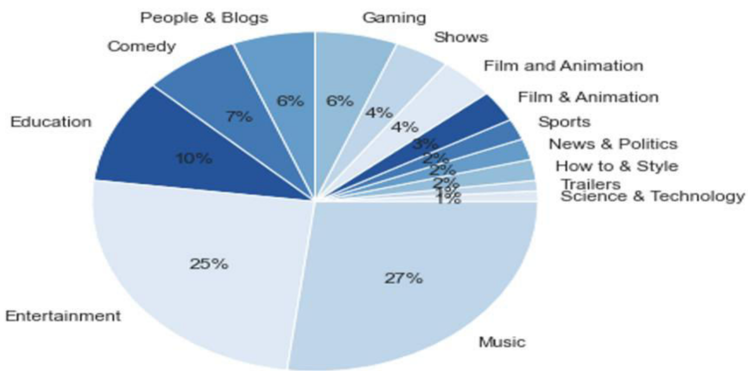


Figure 3: Category Distribution and Comments Statistics of Sentiment Analysis

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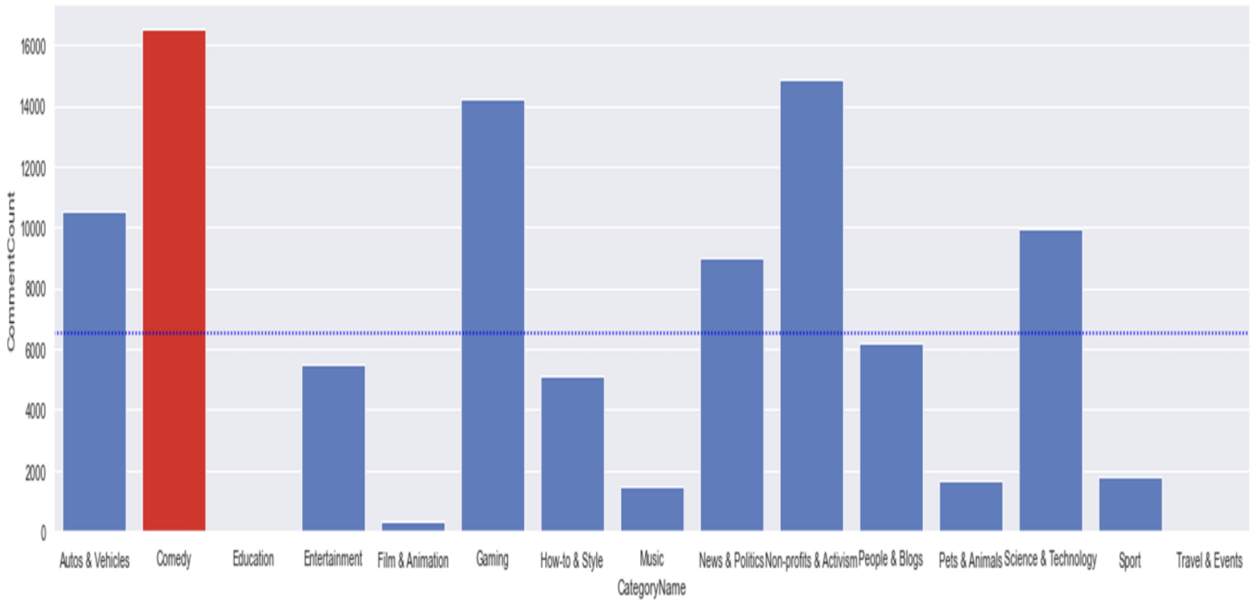


Figure 4. Comment Trends Deep Learning-based Sentiment Analysis and YouTube Comments Statistics

VI. SENTIMENTAL ANALYSIS RESULT ANALYSIS AND SCREENSHOTS

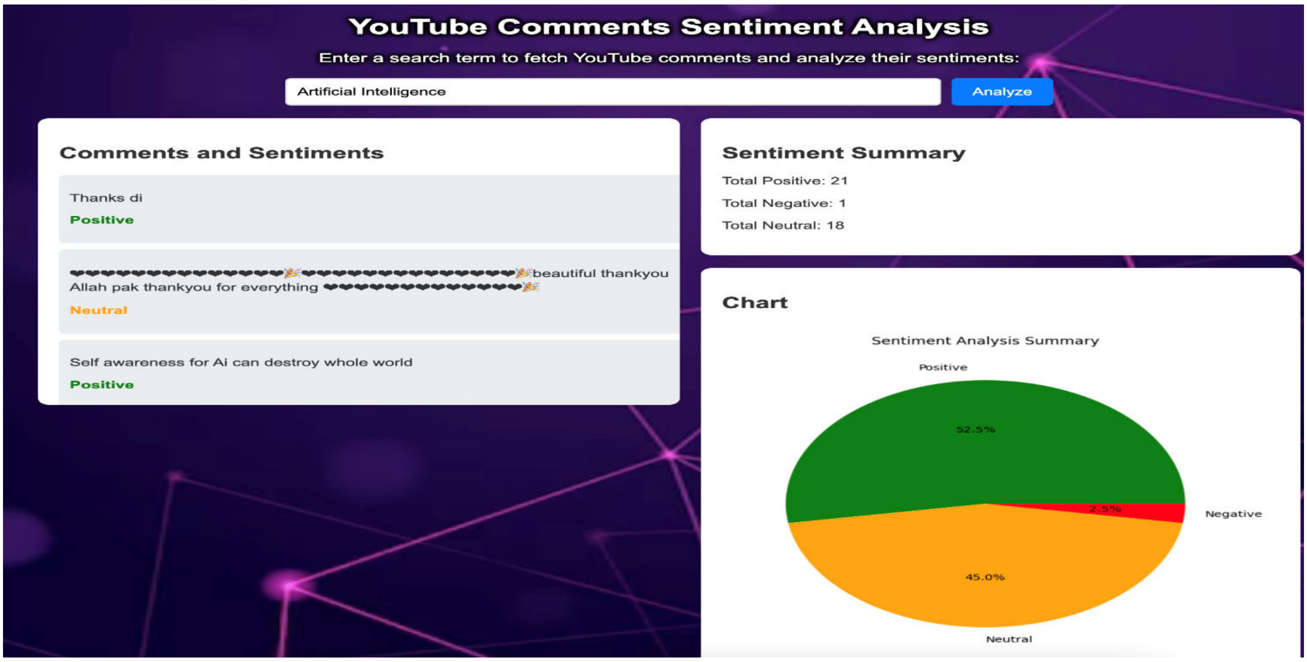
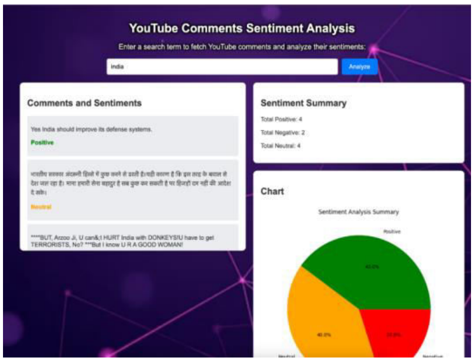


Figure 5. YouTube Comments Sentiment Statistics



Figures 6 & 7. YouTube Comments Sentiment Statisti

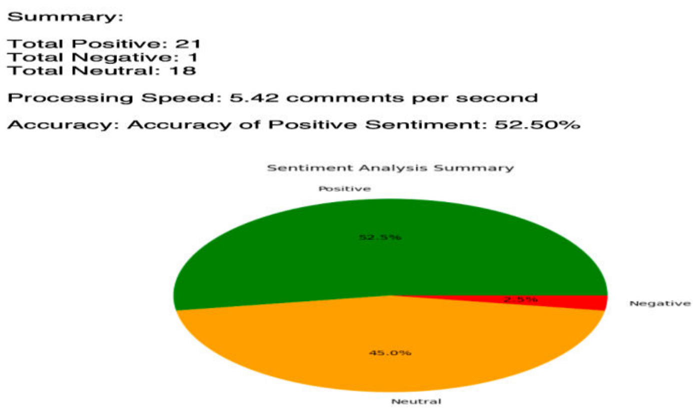


Figure 8. Sentiment Statistics Report

Sentiment Analysis Report

Sentiments:

1. Thanks di (Positive)
2. 'd'd'd'd'd'd'd'd'd'd'd'd'd'dØ<ß‰'d'd'd'd'd'd'd'd'd'd'd'd'd'dØ<ß‰ b e a u t i f u l t h a n k y o u A l l a h
3. Self awareness for Ai can destroy whole world (Positive)
4. <a href="https://www.youtube.com/shorts/oeOLmwkTtCM">https://youtube.com/shorts/oeOLmwkTtCM
5. Made pursne (Neutral)
6. Does anyone also feel like this way "
Humans made AI for fast work and they would work les
7. Maam speak slowly (Neutral)
8. W o w M a & ; a m a m z a i n g s p e a k a u r s a m j h a n e k a s t y l e 'd v e r y g r e a
9. Human like robot is known as humanoid. (Positive)
10. Chat gpt gives proxy server. (Positive)
11. Ø=Ý%IITK - P r o f e s s i o n a l C e r t i f i c a t e C o u r s e i n G e n e r a t i v e A I a
12. this is a best presentation about AI (Positive)
13. d (Neutral)
14. I love your videos regarding AI it is an informative for us. Thanks a bunch. New subs here. (Positive)
15. Ø=Þ A m i n d c o n t r o l i n d o c t r i n a t i n g m a r k e t i n g t o o l (P o s i t i v e)
16. Ans is c (Neutral)
17. 4. Investing Your Brain Power In A Machine (Positive)
18. 3) To program an intelligent machine (Positive)
19. AI is about programming an intelligent machine. When a machine can behave like humans, think, rea
20. The answer is 4. (Neutral)
21. crazy, but this is the world now, and just wait (Neutral)
22. Robots (Neutral)
23. Those are robots not human (Neutral)
24. Where is this? (Neutral)

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25. And this is exactly why google still asks if ur human Ø=Þ-Ø=ÞO
26. I don't konwØ=Þ. 'd (Neutral)
27. is botsØ=Þ3 (Neutral)
28. 2000: are these robots or real people?
2025:are u seeing this is this a real human (Neutral)
29. I see that the checklist is following political procedure in th
30. Not robots totally (Positive)
31. AI vs AI (Positive)
32. Mere shat scam ho gya ha 27000 ka please is ke upr ek video bna do please mujhe bola tha ki ok wi
33. Ø=Þ (Positive)
34. AI is a goate'd (Positive)
35. 7-Thala for a reason Ø=Þ (Positive)
36. But ma na Deep seek download kia Lakin wo maza nahi aya jo CHAT GPT ma ha (Positive)
37. Deepseek is overrated hai (Negative)
38. Philistine ke logo ko badya hai (Neutral)
39. Ai will be content for every youtuber Ø=Þ (Positive)
40. 7 Thala for a reason Ø=Þ Ø=Ü€Ø=Ü€ (Neutral)

Figure 9. Social Media Comments Sentiment Statistics Report

VIII. CONTRIBUTION AND FINDINGS COMMENTS SENTIMENTAL ANALYSIS

Effective Sentiment Classification, the study contributes to improving sentiment analysis accuracy on YouTube comments by exploring various machine learning models, e.g., SVM, LSTM, and feature extraction techniques like TF-IDF and word embeddings. The Performance Evaluation and findings show that deep learning models, e.g., LSTM, BERT outperform traditional models SVM, Random Forest, in sentiment classification, particularly in capturing context and subtleties in comments. Impact of Data Preprocessing, Data cleaning and preprocessing techniques, such as stop-word removal and tokenization, significantly enhance the accuracy of sentiment detection in noisy, informal YouTube comments. Generalization Ability, of the model demonstrates strong generalization on unseen data, confirming its effectiveness in real-world applications for YouTube comment sentiment analysis.

IX. CONCLUSION

In conclusion, our research has delved into the realm of sentiment analysis of YouTube comments, exploring various methodologies and algorithms to understand the sentiments expressed by users within the platform. Through our investigation, we have identified the strengths and limitations of six distinct machine learning algorithms - Naïve Bayes, Support Vector Machine, Decision Tree, Random Forest, K Nearest Neighbor, and the VADER algorithm. Each algorithm offers unique advantages, ranging from simplicity and interpretability to accuracy and adaptability. Among these algorithms, our findings highlight the exceptional performance of the VADER algorithm in accurately analyzing sentiments in YouTube comments. Renowned for its lexicon and rule-based approach, VADER demonstrates a remarkable ability to capture the subtleties and nuances of emotions expressed in text, particularly in the informal language prevalent on social media platforms like YouTube. Its compound sentiment scoring mechanism, coupled with its adeptness at handling linguistic nuances and expressions, positions VADER as a highly effective tool for sentiment analysis in this context enhancing user engagement and satisfaction. Data Collection & Preprocessing: Gather and clean YouTube comments (tokenization, stop-word removal, temming). Model Training & Validation: Split data into training and testing sets, use models (SVM, Random Forest, LSTM), and perform cross-validation.. Evaluation & Tuning: Assess performance with metrics (accuracy, F1-score), and optimize hyperparameters for better results. Testing, Final model testing on unseen data to ensure generalization.

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