Sentiment Analysis for YouTube Comments and Videos Using AI

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***Abstract*- The YouTube Comments and Videos Sentiment Analysis project is an advanced system that automates the sentiment classification of both comments and video transcripts associated with YouTube videos. Using Natural Language Processing (NLP) and cutting-edge deep learning models, the system determines whether the sentiments expressed are positive, negative, or neutral. The system integrates tools such as the YouTube Data API to extract comments and the YouTube Transcript API to retrieve video transcripts. Advanced pre-processing techniques like tokenization, lemmatization, and stopword removal are applied to prepare the text for sentiment analysis. The project employs pre-trained models, including BERT for comments sentiment analysis and LSTM and GRU for video transcript sentiment analysis, ensuring high accuracy in sentiment classification. Users interact with the system through a web-based interface where they can input a YouTube video URL. The system then retrieves comments and transcripts, performs sentiment analysis, and visualizes the results in an intuitive graphical format. To ensure the system delivers reliable results, various performance indicators are used to evaluate how well it identifies and interprets sentiment. These measures help verify the system's effectiveness and consistency. This project aims to offer real-time analysis of public opinion, providing valuable insights to content creators, marketers, and businesses. As a result, they can make smarter and faster decisions based on current trends and audience reactions.**

Keywords- Sentiment, YouTube Comments, YouTube URL, LSTM, GRU, BERT, NLP.

I. INTRODUCTION

Analysing the sentiments of YouTube comments and video transcripts manually is time-consuming and inefficient, especially with the large volume of content generated daily. Content creators, marketers, and businesses struggle to assess audience reactions quickly and accurately, hindering decision-making and strategy development. Existing solutions often lack precision or scalability and fail to provide a unified analysis of both comments and video content. This project addresses these challenges by automating sentiment analysis using advanced AI models like BERT, LSTM, and GRU, providing real-time insights into audience sentiments for comments and video transcripts through a user-friendly web application.

The system offers two key functionalities:

1. Comment Sentiment Interpretation:

This module gathers user comments via an authorized data interface. The text is cleaned and processed to categorize each comment into positive, negative, or neutral sentiment classes. Automating this task allows for efficient handling of large volumes of viewer input and delivers timely insights into public opinion.

With the rapid expansion of video-sharing platforms as hubs for content consumption and interaction, gaining insight into audience opinions has become increasingly important for creators, marketers, and organizations. Manually reviewing the large volume of user comments and spoken content presents significant challenges in terms of time and efficiency. This project addresses that gap by introducing an AI-powered solution that automates the interpretation of user sentiment. By analyzing both written feedback and spoken dialogue from videos, the system offers a well-rounded perspective on audience responses. These insights can support content refinement, strategic marketing, and improved viewer engagement. The approach aims to make sentiment interpretation accessible and practical for a wide range of users and industries.

To implement the system's primary capabilities, this project utilizes advanced deep learning techniques. For the analysis of user comments, the current model integrates BERT, a language representation framework known for its ability to capture nuanced contextual meanings in text. To enhance transcript analysis, the proposed system incorporates LSTM and GRU architectures, both of which are highly effective in processing sequential information and preserving context across longer text spans. These models enable accurate identification of emotional tone in both written and spoken content.

II. LITERATURE REVIEW

Sentiment analysis is increasingly being used to interpret public opinions expressed on social media platforms. Among these platforms, YouTube stands out as a major source of user-generated content, offering vast amounts of data through comments and video transcripts. This data can provide valuable insights into viewer opinions, emotions, and engagement. Agarwal et al. [1] explored the use of transformer-based architectures like BERT and RoBERTa to interpret sentiments expressed in YouTube comments. Their work achieved impressive accuracy and demonstrated strong contextual understanding, making these models highly effective for emotion classification tasks. Khan et al. [2] investigated traditional classifiers like Naïve Bayes and Support Vector Machines (SVM), but these methods struggled with sarcasm and complex language. To improve accuracy, H. Zhou [3] invented deep learning models that capture spatial and sequential patterns—such as convolutional neural networks and memory-based recurrent networks. However, most of these models focus on English datasets. To address this, Gupta et al. [4] developed a multilingual sentiment analysis approach using the multilingual BERT (mBERT) model, achieving better results on non-English comments. Besides text, sentiment is also expressed through speech tone, facial expressions, and other non-verbal cues in videos, offering additional insights into user emotions and opinions. Similarly, Chen et al. [5] developed a multimodal framework using three-dimensional convolutional networks alongside audio data to assess emotions in YouTube videos, which improved sentiment prediction accuracy. Recent studies also focus on the need for real-time sentiment monitoring and integrating data across different social platforms. Wang and Li [6] presented a comprehensive sentiment analysis system that collects and analyses user emotions from YouTube, Twitter, and Instagram, providing a wider view of audience reactions. Zhang et al. [7] reviewed deep learning methods for sentiment analysis, discussing their benefits over classic approaches and current challenges. Collectively, these studies highlight the evolution of sentiment analysis from basic text processing to complex multimodal, multilingual, and cross-platform AI systems, indicating a strong potential for future research and real-world applications. In conclusion, recent advancements have transformed sentiment analysis into a more accurate and comprehensive tool by integrating deep learning, multilingual support, and multimodal data from platforms like YouTube.

III. METHODOLOGY

a) SYSTEM ARCHITECTURE

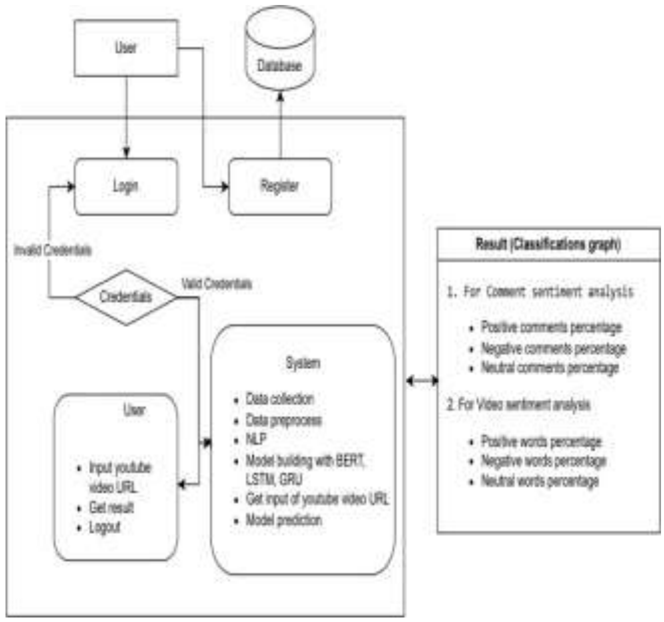

Figure 1 SYSTEM ARCHITECTURE

The architecture illustrates the sentiment of YouTube videos and their associated comments. It provides users with a visual classification of sentiments such as positive, negative, or neutral.

b) MODELS

1. BERT Model

BERT (Bidirectional Encoder Representations from Transformers) is a deep learning model used in this project to classify YouTube comments into positive, negative, or neutral sentiments. It captures the context of each word from both directions, making it highly effective for understanding natural language.

STEP1:Pre-processing:
Comments are tokenized using BERT's tokenizer, which adds special tokens like [CLS] and [SEP]. Padding and truncation are applied to ensure consistent input lengths.

STEP2: Model Training:
A pre-trained Bert for Sequence Classification model is fine-tuned using labelled sentiment data. The AdamW optimizer and a learning rate scheduler are used for efficient training.

STEP3:Evaluation:
The model is tested on unseen data and evaluated using metrics such as accuracy, precision, recall, and F1-score.

STEP4:Prediction:
New comments are processed and passed through the trained model to predict sentiment.

This approach enables accurate and context-aware sentiment classification, improving the reliability of YouTube comment analysis.

2. LSTM-Based Sentiment Analysis Approach

Long Short-Term Memory (LSTM) networks, a specialized form of Recurrent Neural Networks (RNNs), are effective for modelling sequential data and capturing long-range dependencies. In this work, LSTM is applied to sentiment

analysis of user comments. STEP1:Pre-processing:
Text data is first tokenized into sequences using Keras' Tokenizer, followed by padding to ensure all sequences are of equal length.
STEP2:ModelDesign:
The architecture begins with an Embedding layer that transforms words into dense vectors. This is followed by an LSTM layer that learns temporal patterns in the text. Finally, a dense output layer maps the learned features to sentiment categories.
STEP3:Training:
The model is trained using the Adam optimizer and categorical cross-entropy loss. A validation set is used to monitor performance and reduce overfitting.
STEP4:Inference:
New comments are pre-processed and passed through the trained model to generate sentiment predictions.

3. GRU-Based Sentiment Analysis Approach

Gated Recurrent Units (GRUs) are a streamlined variant of LSTM networks, offering similar capabilities with reduced computational complexity. Due to their efficiency, GRUs are well-suited for sentiment analysis tasks in resource-constrained environments.
STEP1:Pre-processing:
The input text is tokenized and padded to ensure consistent sequence lengths, following the same approach as with LSTM.
STEP2:ModelArchitecture:
An Embedding layer first represents words as dense vectors. This is followed by a GRU layer, which captures sequence patterns with fewer parameters than LSTM. A final dense layer classifies the sentiment.
STEP3:Training:
The model is trained using categorical cross-entropy loss and the Adam optimizer. Thanks to its simpler structure, GRU typically converges faster.
STEP4:Inference:
New comments are processed through the trained model to obtain sentiment predictions.

1. Register: Users provide credentials (username, email, password) to create an account.
2. Login: Users log in using their registered credentials.

Input YouTube Video URL: Users input the URL of a YouTube video to analyze the sentiment of its comments and video text.

3. Viewing Results:

Sentiment Analysis for YouTube Comments: Users can view a graph displaying the percentage of positive, negative, and neutral comments.
Sentiment Analysis for YouTube Video: Users can view a graph displaying the percentage of positive, negative, and neutral words from the video.

4. Logout: Users securely log out of the system to protect their session and personal data.

IV. RESULTS and ANALYSIS:

2. Home Page: The Home Page serves as the landing page of your application.

Figure 2: Home Page

3. About Page: The About Page offers detailed information about the project, including its purpose, goals, and the technology used.

Figure 3: About Page

4. Registration Page: The Registration Page allows new users to create an account with the application.

Figure 4 : Registration Page

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5. Login Page: The Login Page enables users to access their existing accounts by entering their credentials. It usually includes fields for entering a username/email and password.

Figure 5 :login page

6. User home Page: After user successfully login this page will be appear

Figure 7 :User Home Page

7. Analyze YouTube comments PAGE: In here user can provide the YouTube video URL and get the sentiments percentages.

Figure 7: Analyse YouTube comments PAGE

8. Result PAGE: In here sentiment's percentages for YouTube comments will be display.

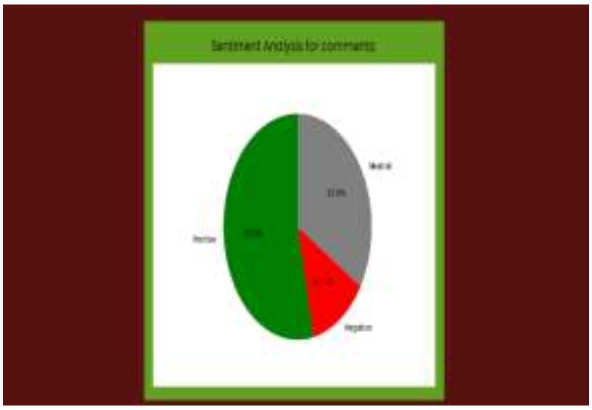

Figure 8 : Result Page

9. Analyze YouTube video PAGE: In here user can provide the youtube video URL and get the sentiments percentages.

Figure 9:Analyze YouTube video page

10. Result PAGE: In here sentiment's percentages for YouTube video will be display.

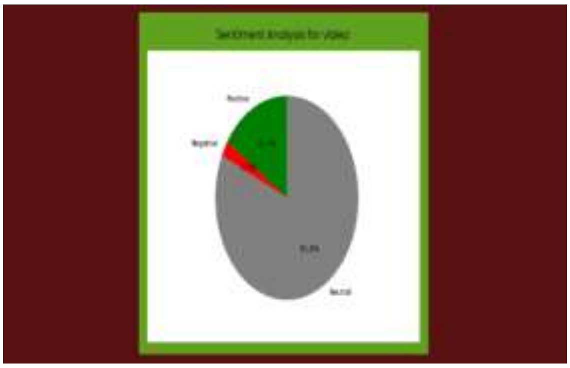

Figure 10: Result Page

V. CONCLUSION

The YouTube Comments and Videos Sentiment Analysis project successfully addresses the need for automated sentiment analysis of YouTube content by combining Natural Language Processing (NLP) techniques with advanced algorithms and libraries. By analyzing both comments and video transcripts, the system provides comprehensive insights into audience sentiment, making it valuable for content creators, marketers, and researchers.

The project integrates state-of-the-art models like BERT for YouTube comments to deliver high accuracy and robust sentiment classification. For video transcripts, lightweight yet effective libraries such as VADER ensure fast and scalable sentiment analysis. The visualization of results through graphs enhances user interpretation, offering a clear understanding of public reactions. This system overcomes the limitations of manual sentiment analysis, providing real-time, scalable, and cost-effective solutions. The modular design allows for future enhancements, such as multilingual support, integration with other platforms, and improved contextual understanding using advanced algorithms. In conclusion, the project serves as a reliable and efficient tool for sentiment analysis, paving the way for better audience engagement, data-driven decisions, and a deeper understanding of public sentiment in the digital content space.

VI. FUTURE SCOPE:

The current YouTube sentiment analysis system works well but has scope for major improvements. First, it only supports English, limiting its global reach. Adding multilingual support would help analyze diverse content more effectively. Second, the system is restricted to YouTube, but expanding it to platforms like Twitter, Instagram, and Facebook would offer broader insights. Third, it only processes text data, missing emotional cues from tone and facial expressions. Introducing multimodal analysis can provide a deeper understanding of audience sentiment. These upgrades would make the system more scalable, versatile, and useful for content creators and marketers.

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