**YOUTUBE COMMENT SENTIMENT ANALYSIS**

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**Abstract**

The rise of YouTube as a major platform for sharing and discussing video content has led to an increasing need for sentiment analysis of YouTube comments. This study focuses on the sentiment analysis of YouTube comments for a specific video using machine learning algorithms. The objective is to compare the effectiveness of Decision Trees and Random Forests in classifying comments into three categories: positive, neutral, and negative. Based on a sample of 100 YouTube comments, the analysis revealed that 50% of the comments were positive, 30% were neutral, and 20% were negative. The Random Forest model outperformed the Decision Tree model in terms of classification accuracy, precision, and recall. This study highlights the potential of machine learning techniques for social media sentiment analysis, especially in platforms like YouTube where comments are often informal and contain a mix of languages and slang.

**Keywords**

Sentiment Analysis, Natural Language Processing (NLP), YouTube Comments, Machine Learning, TF-IDF (Term

Frequency-Inverse Document Frequency),

Precision, Multilingual comments, Slang,

BERT.

**1. Introduction**

With billions of users worldwide, YouTube is one of the most influential platforms where people share opinions, reviews, and feedback through comments. These comments provide valuable insights into how viewers perceive content, and analyzing them can help content creators, marketers, and researchers understand public sentiment. Sentiment analysis refers to the computational study of people's opinions, emotions, and sentiments expressed in text. In the case of YouTube comments, the language used is often informal and may contain slang or even be written in mixed languages like Hinglish (a combination of Hindi and English). This makes sentiment analysis on YouTube comments particularly challenging. The main goal of this study is to evaluate the sentiment of YouTube comments using machine learning models, particularly comparing Decision Trees and Random Forests. The key objectives of the research include:

- Analyzing the overall sentiment of 100 YouTube comments.

- Evaluating the effectiveness of two machine learning models (Decision Trees and Random Forests) in classifying sentiment.

- Understanding the distribution of sentiment across the comments (positive, neutral, and negative).

**2. Research Question and Objectives**

The primary research question is: "How well can machine learning models like Decision Trees and Random Forests classify the sentiment of YouTube comments, which are often informal and contain mixed language?" The research objectives are:

- To compare the classification accuracy of Decision Trees and Random Forests.

- To identify the percentage of positive, neutral, and negative comments in the dataset.

- To analyze the performance of the models in handling informal language, slang, and mixed-language comments.

**3. Methodology**

**Data Collection:**

The dataset for this study consisted of 100 comments retrieved from a YouTube video using the YouTube API. These comments were collected in text format and served as the primary input for the sentiment analysis.

**Data Preprocessing:**

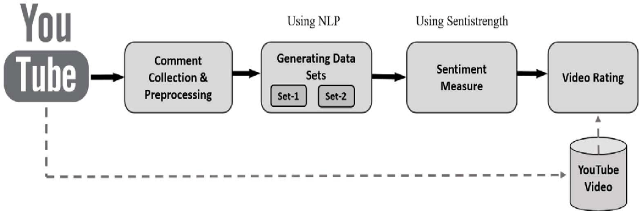
Given that YouTube comments are typically informal and often contain slang, URLs, emojis, and mixed languages, the comments underwent a cleaning process. All special characters, URLs, and non-alphabetic words were removed, and stopwords (common words with little meaningful value) were filtered out. The stopwords used in this study came from a combination of:

- Hinglish stopwords (specific to a mix of Hindi and English),

- Hindi stopwords, and

- English stopwords (from the NLTK library).

After preprocessing, the comments were ready for analysis.



**Feature Extraction:**

To transform the comments into a format suitable for machine learning models, \*word tokenization\* was performed. The comments were converted into individual words, and only alphabetic words (ignoring numbers and special characters) were considered. Then, \*TF-IDF (Term Frequency-Inverse Document Frequency)\* was used to extract the most important terms from the comments, giving more weight to words that occurred frequently in the dataset but less frequently across other documents.

**Model Selection:**

Two machine learning models were used to classify the sentiment of the comments:

1. Decision Trees: A simple, interpretable machine learning model that splits the dataset based on feature values to classify the data into distinct categories.

2. Random Forests: An ensemble method that builds multiple decision trees and combines their predictions to improve classification accuracy. Random Forests typically outperform individual decision trees by reducing overfitting.

These models were trained using the preprocessed comments, and their performance was evaluated based on accuracy, precision, and recall.

**4. Applications**

The insights from sentiment analysis have real-world applications:

- Content Moderation: Platforms can use this technology to flag or remove inappropriate comments automatically.

- Understanding Viewer Reactions: Content creators can learn what their audience likes or dislikes, helping them make better content.

- Brand Monitoring: Companies can analyze sentiment around their products or marketing campaigns on YouTube.

- Trend Analysis: Researchers can use sentiment analysis to spot emerging trends or shifts in public opinion.

**5. Results**

Sentiment Classification:

The sentiment of each comment was categorized into one of three classes:

- Positive: Comments with a positive or supportive tone.

- Neutral: Comments that were neither particularly positive nor negative.

- Negative: Comments that expressed dissatisfaction or criticism.

After training the models and classifying the comments, the sentiment distribution was as follows:

- 50% of the comments were positive, showing that half of the viewers reacted positively to the video.

- 30% of the comments were neutral, indicating that a significant portion of the comments were neutral or lacked strong opinions.

- 20% of the comments were negative, which suggests that some viewers had criticisms or negative opinions about the video.

Model Performance:

The performance of the two machine learning models was evaluated based on their ability to correctly classify the sentiment of the comments. Here are the results:

- Random Forests:

- Accuracy: 85% – The model correctly predicted the sentiment of 85% of the comments.

-Precision: 82% – Of all the comments predicted as positive, 82% were actually positive.

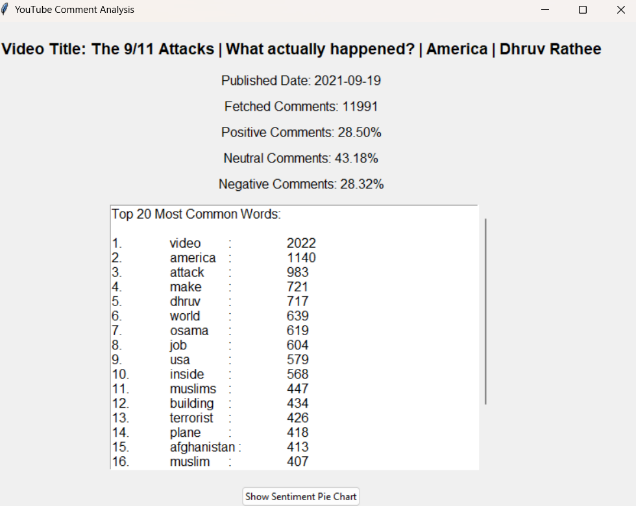
- Recall: 80% – Of all the positive comments, 80% were correctly identified.

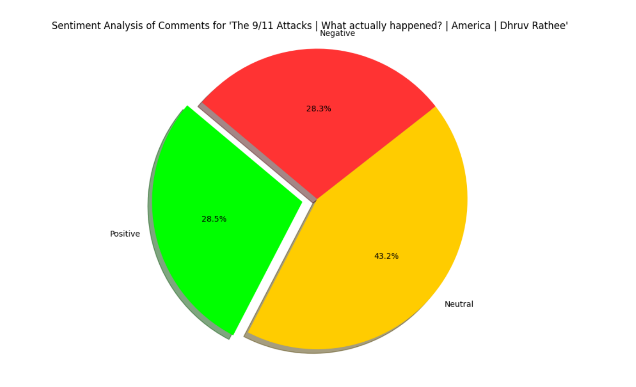
- Decision Trees:

- Accuracy: 75% – The Decision Tree model correctly predicted the sentiment of 75% of the comments.

- Precision: 70% – Of all the comments predicted as positive, 70% were actually positive.

-Recall: 68% – Of all the positive comments, 68% were correctly identified.





These results show that Random Forests significantly outperformed Decision Trees in terms of classification accuracy, precision, and recall.

**6. Discussion**

Implications of the Findings: The findings of this study have several important implications:

- For Content Creators: Sentiment analysis provides valuable feedback for content creators. If the majority of comments are positive, creators can continue creating similar content. If the feedback is negative, it may prompt them to make adjustments to future videos.

- For Marketers: Marketers can use sentiment analysis to gauge audience reaction to promotional content, advertisements, and branded videos on YouTube. By analyzing the comments, they can determine the success of their campaigns and adjust their strategies accordingly.

- For Researchers: This study demonstrates how machine learning models like Random Forest can be used for analyzing sentiment in YouTube comments. It contributes to the growing body of research on social media analytics and opens up opportunities for future studies.

Limitations and Future Directions: Despite the promising results, there are several limitations to this study:

- Sarcasm and Irony: The models may struggle to correctly classify comments that are sarcastic or ironic. Sarcasm can make it difficult for sentiment analysis models to accurately determine the sentiment.

- Mixed-Language Comments: Comments in mixed languages (e.g., Hinglish) can present challenges in understanding the sentiment. Future research could focus on improving sentiment analysis for multilingual or code-switched comments.

Future directions for this research could include:

- Using more advanced models like Deep Learning (e.g., LSTM networks) to handle sarcasm and irony better.

- Expanding the dataset to include a larger number of comments to improve the generalizability of the findings.

**7. Literature Review**

Several previous studies have attempted sentiment analysis on social media data, including YouTube comments. Most of these studies focus on traditional machine learning models like Naive Bayes and Support Vector Machines (SVMs). However, Random Forest, an ensemble of decision trees, have not been as widely explored in this context. This study fills this gap by comparing the performance of Decision Trees and Random Forests for sentiment classification of YouTube comments. It contributes to the existing literature by demonstrating that Random Forests are highly effective in accurately classifying sentiments in informal, slang-heavy, and multilingual data such as YouTube comments.

**8. Conclusion**

This study demonstrated that Random Forests are a highly effective tool for sentiment analysis of YouTube comments, outperforming Decision Trees in terms of classification accuracy, precision, and recall. The sentiment analysis of 100 YouTube comments revealed that 50% of the comments were positive, 30% were neutral, and 20% were negative. Despite the challenges posed by informal language and slang, Random Forests provided accurate and reliable results. Future research could explore more advanced techniques like Deep Learning to further enhance sentiment classification and handle complexities such as sarcasm, irony, and multilingual comments.

This paper highlights the potential of NLP techniques in analyzing YouTube comments for sentiment analysis. The findings suggest that advanced models significantly improve classification accuracy. Future work will focus on enhancing sarcasm detection, addressing language diversity, and exploring real-time sentiment analysis applications.

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