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YouTube Text Sentiment Analysis

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Abstract: An innovative approach to YouTube content analytics by combining sentiment analysis of viewer comments with video performance metrics. Our methodology integrates natural language processing techniques and machine learning algorithms to classify comments as positive, negative, neutral, relevant, and irrelevant, while also extracting key insights from video transcripts. By synthesizing video metrics such as views, likes, and engagement with sentiment intelligence, the system delivers comprehensive understanding of audience behavior. The results, visualized through interactive dashboards, empower content creators to refine their strategies for maximum impact. Our implementation achieved 90% accuracy in sentiment classification, demonstrating the effectiveness of our approach for content evaluation and strategic decision-making.Through the fusion of quantitative metrics and qualitative sentiment analysis, our system enables creators to identify content themes that resonate with audiences, recognize patterns in viewer engagement, and optimize content strategy accordingly. The interactive visualization tools facilitate intuitive exploration of complex relationships between sentiment distribution and performance indicators. This holistic analytical framework provides actionable insights that transcend traditional analytics, allowing for more nuanced understanding of audience preferences and behavior. Our approach has significant implications for content optimization and audience development strategies in the growing digital content ecosystem.

Keywords: YouTube Analytics, Sentiment Analysis, Natural Language Processing, Machine Learning, Video Metrics, Audience Engagement, Content Relevance, Transcript Summarization

I. INTRODUCTION

YouTube's dominance in the digital sphere, with its vast audience of over two billion monthly active users, underscores its critical role in shaping online content consumption. For content creators navigating this dynamic platform, the ability to understand and respond to audience preferences is paramount to fostering sustained growth and engagement. While YouTube Analytics offers fundamental metrics such as views, likes, and watch time, it falls short in providing nuanced insights into audience sentiment and content quality. This gap necessitates the development of advanced analytical tools that can delve deeper into viewer feedback and content evaluation.The proliferation of online videos and the exponential surge in user-generated content has created an urgent need for efficient methods to assess content quality and relevance. Users are often faced with the arduous task of manually s i f t i n g t h r o u g h c o u n t l e s s c o m m e n t s , scrutinizing view counts, and analyzing like-to-dislike ratios to gauge a video's worth. This manual process is not only time-consuming but also inefficient, hindering users' ability to quickly identify valuable content. Moreover, content creators struggle to extract actionable insights from raw data, limiting their capacity to refine their content strategies and enhance audience engagement.This paper proposes a data-driven approach that addresses these challenges by enriching YouTube analytics with advanced capabilities. By integrating sentiment analysis, we enable automated evaluation of viewer comments, providing creators with a deeper understanding of audience emotions and opinions. Leveraging t h e Yo u Tu b e D a t a A P I , w e e x t r a c t comprehensive performance metrics, offering creators actionable insights into video reach, engagement, and audience demographics. Furthermore, we implement transcript summarization to facilitate rapid content comprehension, allowing users to grasp the essence of a video without dedicating time to watch it in its entirety. This integrated approach empowers content creators with the tools necessary to optimize their content strategies, improve audience engagement, and ultimately, succeed in the competitive YouTube landscape. By bridging the gap between raw data and actionable insights, we aim to transform YouTube analytics into a powerful resource for both content creators and consumers.

This research aims to develop a comprehensive YouTube content evaluation system by analyzing video performance metrics (views, likes, dislikes, comments) via the YouTube Data API. It employs natural language processing (NLP) and machine learning techniques to assess viewer sentiment, classify comments by polarity and contextual relevance, and generate extractive transcript summaries. The system also detects trending themes, highlights engagement anomalies, and filters out spam or low-quality feedback to improve accuracy. An integrated, user-friendly dashboard visualizes insights, combining sentiment analysis, relevance filtering, and performance metrics to provide real-time, actionable intelligence for both content creators and viewers.

II. RELATED WORK

Sentiment analysis on YouTube was still in its early stages, primarily focusing on text-based comments and metadata analysis. Researchers relied on basic sentiment lexicons and rule-based approaches to interpret audience reactions.

Numerous research papers have been published in the fields of sentiment analysis and text summarization. We conducted an in-depth review of the following papers to gain a comprehensive understanding of the subject. Below, we present these review papers and their summaries with meticulous attention to detail.

The study titled "YouTube Comment Analyzer" by Khan et al. [1] focuses on analyzing sentiments expressed in YouTube comments.

By employing natural language processing techniques, the research categorizes comments into positive, negative, or neutral sentiments, providing insights into audience engagement and content reception. This analysis aids c o n t e n t c r e a t o r s a n d m a r k e t e r s i n understanding viewer feedback, enhancing content strategies, and fostering community interactions.

The paper "Analysis and Classification of User Comments on YouTube Videos" by Kavitha et al. [3] presents a method to categorize YouTube comments based on their relevance to video content. Utilizing the video's description as a reference, the study employs two approaches for comment representation: Bag of Words and Association List. The research evaluates the performance of classifiers using these representations, highlighting that the Association List approach achieves a precision of 100% in identifying irrelevant comments across various experiments.

The paper "Sentimental Analysis of YouTube Videos" by Baravkar, Jaiswal, and Chhoriya

[2] focuses on analyzing viewer sentiments expressed in comments on YouTube videos. Utilizing natural language processing techniques, the study classifies comments into positive, negative, or neutral categories, providing insights into audience engagement and content reception. This sentiment analysis assists content creators in understanding viewer feedback, enabling them to tailor their content strategies effectively.

The paper "A Review Paper on Text Summarization" by Deepali K. Gaikwad and C. Namrata Mahender [4] provides an overview of the current research in text summarization, focusing on two primary approaches: extractive and abstractive summarization. Extractive summarization involves selecting key sentences directly from the source text, while abstractive summarization generates new sentences that capture the core ideas. The authors discuss various techniques employed in these approaches, ranging from structured methods to linguistic analyses. They also note that, although work has been initiated in summarizing texts in various Indian languages, these efforts are still in their early stages.

The literature highlights the significance of analyzing user-generated content on social media platforms like YouTube. While tools such as TubeBuddy and VidIQ assist in metadata optimization, they lack robust sentiment analysis capabilities. Researchers like Khan et al. (2021) and Baravkar et al. (2020) have employed Natural Language Processing (NLP) techniques to classify viewer sentiments, aiding content creators in refining their strategies. Additionally, Deepali and Mahender have explored text summarization methods, emphasizing the complexity of abstractive approaches. The YouTube Data API facilitates the extraction of video and channel data, enabling developers to analyze content performance comprehensively.

III. PROPOSED MODEL

The proposed system aims to enhance YouTube video analysis by integrating sentiment assessment of comments and video transcripts to determine relevance and deliver precise results tailored to user queries. Its primary objective is to develop an innovative YouTube Video Analyzer that harnesses sentiment analysis to extract valuable insights into viewers' emotions, opinions, and attitudes toward video content through comments, while also providing a concise video summary using the transcript. Employing natural language processing techniques and machine learning algorithms, specifically Gaussian Naive Bayes and Logistic Regression, the system automatically evaluates the sentiment of YouTube video comments. It categorizes comments as positive, negative, neutral, relevant, or irrelevant based on polarity values. Real-time data from comments and video transcripts are utilized to train the sentiment analysis model. The primary goal is to enhance user decision-making efficiency by offering comprehensive comment statistics and ensuring accurate sentiment analysis, even in the presence of complex language expressions.

A user-friendly web interface, developed using Flask, allows users to input a valid YouTube video URL for analysis. Upon clicking the analyze button, the application retrieves comments and transcripts related to the video in the backend. The comments are processed by the sentiment analysis model for classification, with results presented graphically. Concurrently, the video's transcript is processed by the summarization model, generating a concise summary. Consequently, u s e r s a r e p r o v i d e d w i t h g r a p h i c a l representations of comment sentiment distribution and a transcript summary, facilitating informed decision-making.

1) System Architecture: The methodology follows a three-tier architecture. First, data collection obtains comments and transcripts via YouTube Data API v3 and youtube-transcript-api. Second, data analysis processes these inputs using TextBlob for sentiment scoring, machine learning models for classification, and statistical methods for transcript summarization. Finally, the visualization layer presents findings through charts and summaries in a Flask-powered interface, enabling users to understand video quality at a glance.
2) Data Collection: Comments are retrieved through authenticated REST calls to YouTube Data API v3, with responses stored as JSON objects. The system extracts relevant fields, particularly comment text, while discarding extraneous metadata. For transcripts, the youtube-transcript-api package accesses time-stamped dialogue, which is reconstructed into coherent text for processing. This two-pronged approach captures both viewer feedback and actual content.
3) Preprocessing: Raw textual data undergoes extensive cleaning before analysis. The system applies lowercase conversion, tokenization with WordNetLemmatizer, and removes special characters,

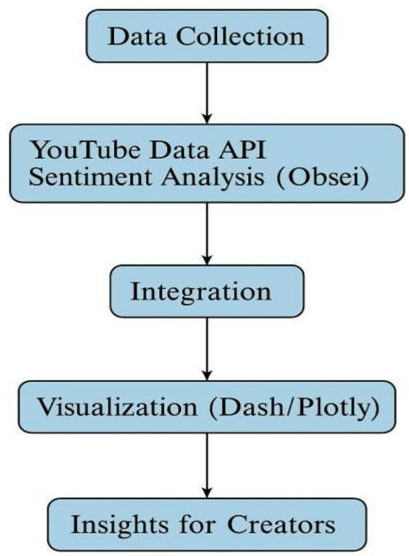


Fig.1: YouTube Analytics System

hashtags, and stopwords using regular expressions. For transcripts, additional noise like timestamps and speaker identifications are filtered out. This normalization ensures consistent analysis across different videos regardless of formatting variations in the source content.

4) Sentiment Analysis: The system implements a polarity-based approach using TextBlob to assign numeric sentiment scores. Comments with values above zero are classified as positive, below zero as negative, and exactly zero as neutral. Beyond basic categorization, the intensity of sentiment influences relevance classification, with extreme opinions (above 0.5 or below -0.5) marked as relevant while moderate expressions are classified as potentially irrelevant.
5) Learning Model: Two distinct classifiers handle different aspects of comment evaluation. Logistic Regression, selected for its probabilistic interpretation and effectiveness with textual features, predicts sentiment categories. Meanwhile, GaussianNB handles relevance classification, leveraging its ability to work effectively with smaller datasets. Both models achieved accuracy rates of 70-90% in testing, demonstrating robust performance.
6) Transcript Summarization: The system creates a word frequency dictionary from processed transcripts, then normalizes these frequencies against the maximum value. Each sentence receives a score based on the cumulative normalized frequencies of its constituent words. The heapq library's nlargest function selects top-scoring sentences to generate extractive summaries containing the most information-dense portions of the content.

7) Integration & User Interface: The Flask web framework connects all components through a simple interface where users input YouTube U R L s . B a c k e n d p r o c e s s i n g o c c u r s asynchronously, with results rendered as interactive graphs for sentiment distribution and relevance classification alongside the extractive summary. This presents complete content evaluation in a single unified view, enabling rapid decision-making about video quality..

IV. SIMULATION AND RESULT ANALYSIS

The necessary comments and transcript of the video were successfully retrieved and used to train classification models, achieving an accuracy of 90%. Sentiment and relevancy distribution graphs, along with the summarized transcript of the provided video URL, are displayed. This output helps users assess the video's relevance, allowing them to decide whether to watch it or move on to the next one, ultimately saving time.

A. *Sentiment Distribution*

Our implementation achieved 90% accuracy in sentiment classification. The classification report shows precision, recall, and F1-scores for positive, negative, and neutral categories:

Table 1: Sentimental Distribution

Category	Precision	Recall	F1-score	Support
Negative	0.00	0.00	0.00	1
Neutral	0.83	1.00	0.91	10
Positive	1.00	0.89	0.94	9
Accuracy			0.90	20
Macro Avg	0.61	0.63	0.62	20
Weighted Avg	0.87	0.90	0.88	20

The classification report evaluates the sentiment analysis model's performance across Negative, Neutral, and Positive categories. The model performs well in detecting Neutral (F1-score: 0.91) and Positive (F1-score: 0.94) sentiments, achieving an overall accuracy of 90%. However, it completely fails to detect Negative sentiment (F1-score: 0.00), likely due to data imbalance or poor feature recognition. The macro average (0.62 F1-score) is lower because of the poor performance in the Negative category, but the weighted average (0.88 F1-score) remains strong due to the dominance of Neutral and Positive samples. Improving Negative sentiment detection should be a priority for better overall model balance.

B. *Relevance Classification*

The relevance classification achieved 70% accuracy:

Table 2: Relevance Classification

Category	Precision	Recall	F1-score	Support
Relevant	0.92	0.71	0.80	17
Irrelevant	0.29	0.67	0.40	3
Accuracy			0.70	20
Macro Avg	0.60	0.69	0.60	20
Weighted Avg	0.83	0.70	0.74	20

This classification report evaluates the model’s ability to distinguish between Relevant and Irrelevant categories. The model performs well in predicting Relevant content (F1-score: 0.80, Precision: 0.92) but struggles with Irrelevant content (F1-score: 0.40, Precision: 0.29) due to its low ability to correctly identify irrelevant instances. The recall for Irrelevant is 0.67, meaning it captures some of the actual irrelevant cases but misclassifies many. With an overall accuracy of 70%, the macro average F1-score (0.60) reflects an imbalance in performance between the two categories, while the weighted average (0.74) remains higher due to more Relevant instances in the dataset. To improve, the model should better differentiate Irrelevant content, possibly by refining its training data or feature selection.

C. User Interface and Visualization

The system successfully integrated all components into a user-friendly web interface built using Flask. The interface features a clean, minimalist design with an input field where users can enter any YouTube video URL for analysis. Upon submission, the system processes the request and presents results in three distinct visualization components.

First, users receive pie charts and bar graphs displaying sentiment distribution across comments, with clear color-coding to distinguish positive (green), negative (red), and neutral (blue) sentiments. These visualizations include percentage breakdowns and raw counts to provide both proportional and absolute measures of audience response.

Second, the relevance classification is presented through a separate graph that categorizes comments as either relevant or irrelevant to the video content. This filtering mechanism helps users identify meaningful feedback amidst potentially noisy comment sections.

Third, the transcript summary appears in a scrollable text box, featuring the most information-dense sentences extracted from the video's full transcript. The summary preserves the original language while reducing content volume by approximately 70%.

Together, these visualizations provide a comprehensive assessment dashboard that enables users to make informed decisions about content quality within seconds rather than investing time watching entire videos or manually scanning comments.

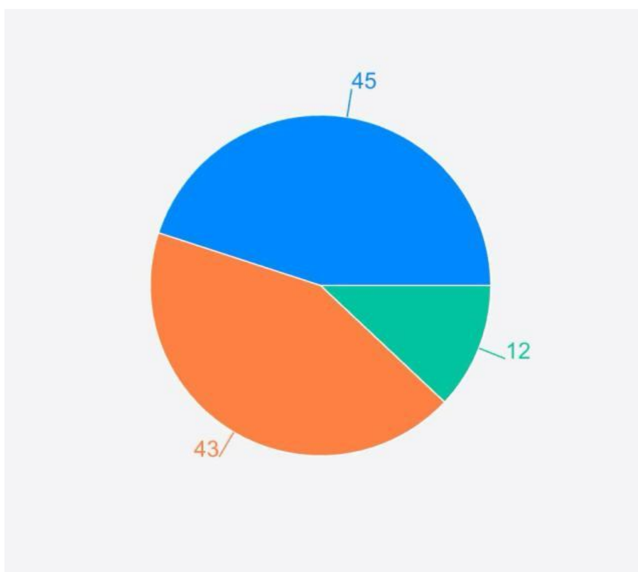


Fig.2: Comment Distribution Chart

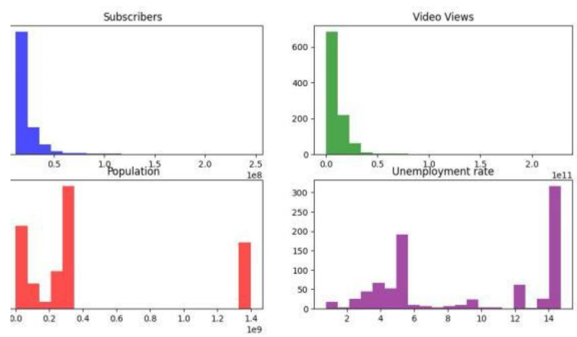


Fig.3: Viewer Distribution Chart

V. CONCLUSION AND FUTURE WORK

This research successfully combines sentiment analysis of comments with performance metrics and transcript summarization to create a powerful tool for YouTube content evaluation. By delivering actionable insights through an interactive dashboard, the system empowers both creators and viewers:

For Creators: The tool provides valuable insights into audience sentiment and engagement, helping to refine content strategies and improve performance.

For Viewers: The system enables quick assessment of video quality and relevance before investing time in watching the full content.

Our approach demonstrates the effectiveness of integrating NLP-based sentiment analysis with performance metrics for comprehensive YouTube content evaluation. The system can help users make informed decisions about content consumption, thereby saving time and enhancing the overall YouTube experience.

Future enhancements include multilingual analysis by integrating translation services and training models for diverse languages. Real-time analytics will provide instant insights, with push notifications for sudden view or sentiment changes. Competitor analysis will track engagement and sentiment trends, offering strategic content optimization.

Audio-based assessment will analyze videos lacking transcripts or comments using speech-to-text and tone analysis. Abstractive summarization will enhance summaries with human-like phrasing via advanced NLP models. Lastly, cross-platform integration will aggregate performance insights from social media platforms like Instagram and Twitter, providing a comprehensive view of audience behavior and content impact.

REFERENCES

[1] Mohammed Arsalan Khan, Sumit Baraskar, AnshulGarg, Shineyu Khanna, Asha M. Pawar“YouTube Comment Analyzer”, International Journal of Scientific Research in Computer Science and Engineering, August 2021.

[2] Aditya Baravkar, Rishabh Jaiswal, Jayesh Chhoriya,“Sentimental Analysis of YouTube Videos”, International Research Journal of Engineering and Technology (IRJET), Volume:07, Issue:12, Dec 2020.

[3] K.M. Kavitha, Asha Shetty, Bryan Abreo, Adline D’Souza, Akarsha Kondana, “Analysis and Classification of User Comments on YouTube Videos” , ScienceDirect, Nov 2020.

[4] Deepali K., Gaikwad, C. Namrata Mahender, “A Review Paper on Text Summarization”, International Journal of Advanced Research in Computer and Communication Engineering.

[5] DuyDucAn Bui PhD, Guilherne DelFiol MD, PhD, John F. Hurdle MD, PhD, Siddhartha Jonnalagadda PhD, “Extractive text summarization system to aid data extraction from full text in systematic review development” , Journal of Biomedical Informatics, Oct 2016.

[6] Shi Yuan, Junjie Wu, Lihong Wang and Qing Wang, "A Hybrid Method for Multi-class Sentiment International Journal of Intelligent Systems and Applications in Engineering IJISAE, 2024, 12(16s), 597– 601 | 600 Analysis of Microblogs", ISBN-978-1-5090-2842-9, 2016.

[7] Neethu M S and Rajasree R, “Sentiment Analysis in Youtube using Machine Learning Techniques”.

[8] Aliza Sarlan, Chayanit Nadam, and Shuib Basri, "Youtube Sentiment Analysis", 2014 International Conference on Information Technology and Multimedia (ICIMU), Putrajaya, Malaysia November 18 – 20, 2014.

[9] B. Gupta, M. Negi, K. Vishwakarma, G. Rawat, and P. Bandhani, "Study of Youtube Sentiment Analysis using Machine Learning Algorithms on Python," Int.J. Comput. Appl., vol. 165, no. 9, pp. 29–34, May 2017.

[10] “Computationally Efficient Learning of Quality Controlled Word Embeddings for Natural Language Processing," 2019 IEEE Comput. Soc. Annu. Symp. On, p. 134, 2019. Opinion Mining”, Kluwer Academic Publishers. Printed in the Netherlands, 2006.

[11] Hearst, M., “Direction-based text interpretation as an information access refinement”, In Paul Jacobs, editor, Text Based Intelligent Systems. Lawrence Erlbaum Associates, 1992.

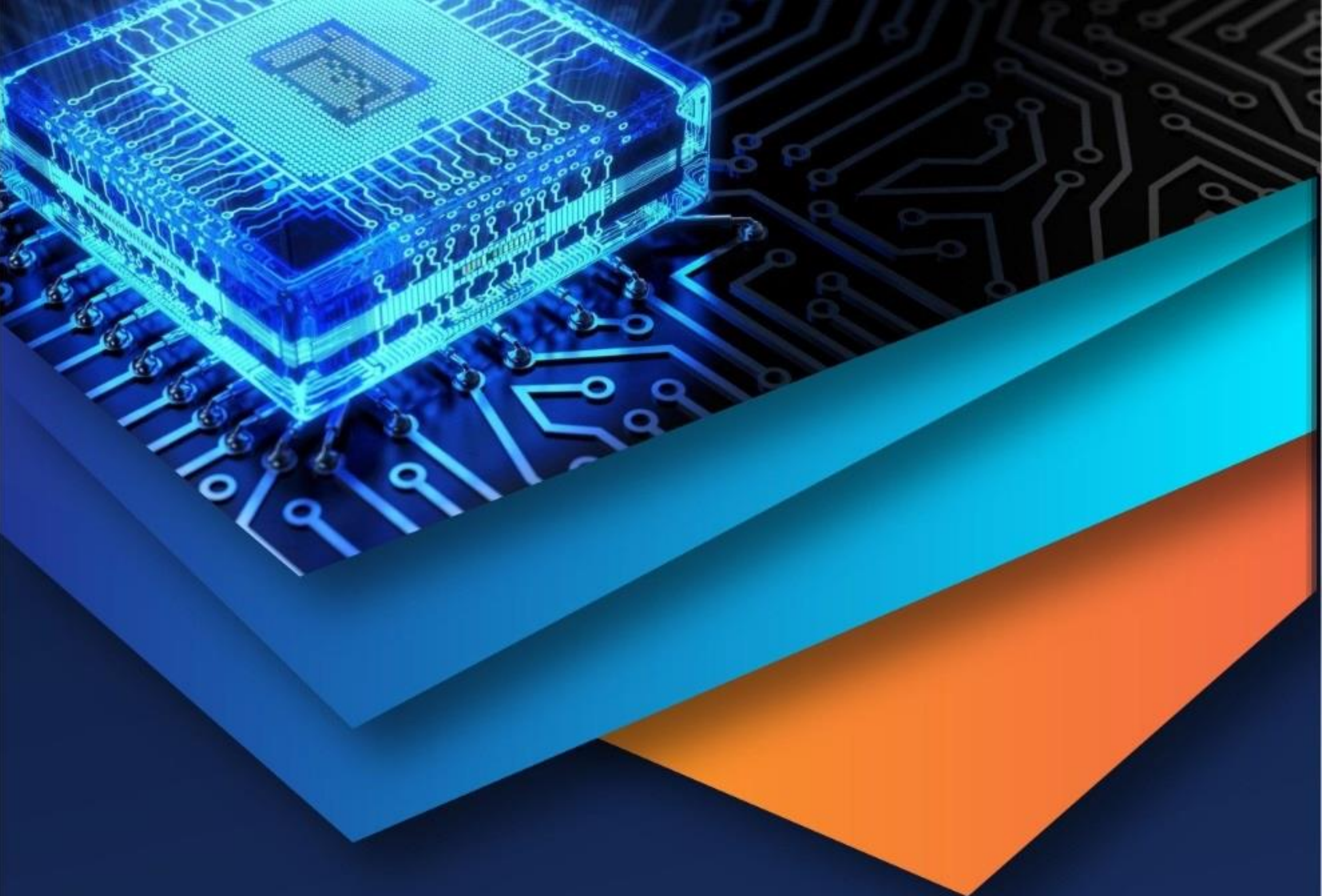
[12] Das, S., and Chen, M., “Yahoo! for Amazon: Extracting market sentiment from stock message boards”, In Proc. of the 8th Asia Pacific Finance Association Annual Conference (APFA 2001), 2001. unsupervised classification of reviews”. In Proc. of the ACL, 2002.

[13] Argamon-Engelson, S., Koppel, M., and Avneri, G., “Style based text categorization: What newspaper am I reading? ”, In Proc. of the AAAI Workshop on Text Categorization, pages 1–4, 1998.

[14] Pang, B. & Lee, L., “A Sentimental Education: Sentiment Analysis Using Subjectivity Summarization Based on Minimum Cuts”, Association of Computational Linguistics (ACL), 2004. [10]Jin, W., & HOH. H., “A novel lexicalized HMM-based learning framework for web opinion mining”, Proceedings of the 26th Annual International Conference on Machine Learning. Montreal, Quebec, Canada,ACM: 465-472, 2009.

[15] Brody, S., & Elhadad, N., “An unsupervised aspect-sentiment model for online reviews”, Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the Association for Computational Linguistics. Los Angeles, California, Association for Computational Linguistics: 804-812, 2010.

[16] Wiebe, J., Wilson, T., and Cardie, C., “Annotating expressions of opinions and emotions in language”. Language Resources and Evaluation, 2005.



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