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EXAMINING VIEWER SENTIMENTS AND EMOTIONAL ENGAGEMENT IN KID-CENTRIC YOUTUBE VIDEOS THROUGH SENTIMENT ANALYSIS

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Abstract

To analyze and quantify viewer sentiments and emotional engagement in kid-centric YouTube videosusing sentiment analysis techniques. The goal is to understand the emotional impact and response patterns in these videos to help content creators optimize audience engagement. The title suggests applying sentiment analysis methods to understand viewer emotions and engagement levels in YouTube videos specifically created for children. This study focuses on analyzing the feedback and comments to uncover emotional responses and their impact on the successofkid-centriccontent.Beforemachinelearning,sentimentanalysiswasdonemanually by reading and categorizing viewer comments, which was time- consuming and subjective. Basic keyword-based approaches were used to gauge sentiment without understanding the nuances of human emotions. Content success was often judged by simple metrics like views and likes, without deeper emotional insights. Traditional system like manual review of commentsfor sentiment classification by content creators or marketers, Basic keyword-based sentiment detection without context, Reliance on like/dislike ratios or view counts as engagement indicators, with no analysis of emotional tone. Manual analysis of viewer sentiment in kid-centric YouTube videos is inefficient, subjective, and prone to misinterpretation. Traditional systems lack the ability to deeply analyze emotional engagement on a large scale. The growing influence of digital content on children's emotions and behavior calls for a deeper understanding of their emotional responses. This can help optimize contentto createmore positive and engaging experiences for young audiences. Machine learning- based likeNLP sentimentanalysis canautomatethe processing of large volumes ofcomments, accurately identifying emotions and engagement patterns in kid-centric YouTube videos. AI can detect nuanced emotional cues, enabling contentcreatorstotailortheirvideosfor betteremotionalresonancewiththeiraudience.

Keywords: Sentiment Analysis, YouTube Videos, Emotional Engagement, NLP.

1. INTRODUCTION

Social media entail diverse modes of communication, collaboration, and the interactive expression of ideas. The advent of social media platforms has profoundly transformed the global landscape, progressively supplantin gconventionalmethodsofcommunication, idea dissemination, and even individual learning approaches. Currently, social media is predominantly regarded as a means of communication and information exchange, prompting
both enterprises and individuals to perceive it as a valuable marketing tool. While numerous studies have evaluated the impact of social media on the marketing research domain, this represents just one of its manifold potential applications. A captivating research area relating to social media is its contribution to the educational context and how it can influence the learning process. In their study, Zheng investigated the educational opportunities that arise from social media, particularly in fostering cooperative learning to enrich the learning experience. Notably, platforms like YouTube, which host video content, play a pivot al role in providing learners with easily accessible information devoid of constraints. Numerous researchers support the idea that integrating social media in higher education teaching and learning practices can lead to bridging the gap between students. Research has identified a correlation between the use of YouTube and its role in enhancing the learning process with one condition: the video must be relevant to the subject matter. his study also highlights that incorporating visual elements, such as videos, supports the educational process as students become more engaged in their learning by actively seeking and watching relevant content on YouTube. This, in turn, facilitates a better understanding of the topic. Additionally, YouTube's active engagement fosters nursing students' participation in the learning process, encouraging them to approach problems from aholistic standpoint, discuss, and analyze them, and enhance their critical thinking. Moreover, YouTube plays a significant role in the field of performing arts. Utilizing YouTubeasalearningtoolinperformingartscanadapttocurrenttrendsand encourage social collaboration within the course. This approach can ignite creativity and imagination in both students and professors, thus enhancing the overall learning experience. Overall, it can be suggested that YouTube and the visual stimuli that it offers can be a powerful tool for reshaping the educational process YouTube has become a powerful platform for kid-centric content, with creators in India and worldwide engaging young audiences through various educational, entertaining, and playful videos. According to reports, India ranks as one of the top countries for YouTube viewership, with children making up a significant portion of the audience. Children's digital content consumption rose substantially during the COVID-19 pandemic, leadingto a surge in content specifically tailored to this demographic. Parents and content creators alike are increasingly interested in understanding how this content emotionally impacts young viewers. By analyzing viewer sentiments and engagement, creators can optimize their content to resonate more deeply with children, making the viewing

experience joy able, educational, and emotionally enriching.

2. LITERATURESURVEY

There are several recent studies that explore sentiment analysis methods on social media extracted datasets. However, most of them are not oriented in educational videos. Recently, Anastasiou applied a hybrid approach using lexicon and machine learning approaches to predict sentiment from YouTube extracted datasets. Their comparative findings demonstrated the prevalence of TextBlob over VADER to detect sentiment from YouTube comments on health care-related videos. Suhasini employed supervised learning to detect motions in Twitter data. They compared two algorithms, namely K-nearest neighbor (KNN) and naive Bayes (NB). Their research findings indicate that naive Bayes outperformed K- nearest neighbor in this context. In another study by Jayakody. Twitter data related to product reviews were gathered and subsequently analyzed. They utilized the support vector machine (SVM), logistic regression, and K-nearest neighbor machine learning algorithms. Additionally ,they employed count vectorization and term frequency-inverse document frequency mechanisms to convert text into vectors suitable for input into the machine learning model. The highest accuracy score of 88.26% was achieved by logistic regression in combination with a count vectorizer. Furthermore, Bhagat adopted a hybrid approach, combining naive Bayes and K-nearest neighbor algorithms, to categorize tweets into three classes: positive, negative, and neutral sentiment. Their approach yielded superior accuracy compared to the random forest algorithm. As regards deep learning approaches, several researchers applied BERT on text classification, achieving high performance rates of almost92%.

Topic clustering on social media extracted datasets has been mainly performed through Latent Dirichlet Allocation (LDA) to identify topics of interest and different audiences. For instance, recently, Wahidapplied LDA for the annotation of textual data to detect the most dominant topics on an unstructured social media dataset and then classified them through BERT embeddings. In another study, Zhang appled LDA to identify audiencegroupsfor books in social media.

Althoughnumerousresearchershaveconductedanalysesontheeducationalapplicationsof social media, only afew have focused on YouTube's educational comments, with medicine being the most common domain.

Lee conducted an experiment using 150 videos and gathered 29,386 comment traced from YouTube channels to investigate whether YouTube, as a social media platform, could contribute to Self-Directed Learning(SDL).The aim of their research was to demonstrate that social technologies, such as social media platforms ,could truly enhance autonomous learning by providing appropriate instructions to learners. They employed a combination of sentiment and qualitative analysis, resulting in data triangulation to emphasize the significanceof the results. The sentiment analysis results indicated that out of the 150 videos, only 8 had more negativethan positive comments. The main conclusions of the study were that employing various analytical techniquesto study of online expressions. Additionally, the study shed light on the correlation between comments and SDL traits. Furthermore, it revealed that social learning is enhanced through comments, as learners exhibited behaviors, such as sharing goals, expressing thankfulness, having fun, and displaying a more social and extroverted behavior. The practical aspects of the study were also mentioned by the researchers. Firstly, the collaboration between learners and contributors encourages SDL and participation. Secondly, it provides a powerful tool for institutions, particularly for life long education ,by empowering the educational process.

Dubovi and Tabak in also conducted research on YouTube by analyzing 1560 comments from six post-videosin the fieldof science. The primarygoal of thisstudywas to investigate whethersocialmedia,especiallyYouTube,couldestablishafoundation forcollaborative knowledge through discourse moves. The researchers categorized their work into three segments: discourse moves, knowledge construction, and the combination ofboth,andtheyperformeddifferenttypesofanalysiswithineachcategory.Inthe first category, their analysis of the comments revealed that the dominant interaction was neutral assertions or countering assertions without immediate disagreements. Subsequently, an ANOVA analysis on user tendencies showedthat counter assertions and disagreements were followed by evidence. However, only a small percentage of comments supporting counter assertions or disagreements was accompanied by evidence credibility (21%21% of the comments). For the second category, they applied collaborative knowledge construction analysis. Tolkach and Pratt conducted research that focused on an unexplored aspect of YouTube, namely its potentialfor learningin the tourism sector. The study analyzedvideos from a YouTube channel called "Travel Professors", which featured short videos film various locations and provided a un dant research and learning material related o the tourism domain. The researchers used the YouTube analytics tool to extract data about the channel, and for the comments, they performedcontentanalysis.The findings revealed that videos featuring less popular tourism locations garnered significant attention from viewers. Additionally, the study high lighted that students appreciated the use of videos as study and discussion material in class. Videos served as a bridge between theoretical knowledge and real-world experiences, enhancing the learning process. The true essence of combining YouTube with tourism and hospitality learning lies in approaching this domain from both theoretical and practical perspectives.

Azer focused on evaluating the quality of videos on YouTube related to ileostomy and colostomy. They identified 1816 videos, of which 149 met the inclusion criteria aligned with medical instructions and guidelines from reputable medical organizations. After assessing these 149 videos, only52were found to have an educational purpose and presented accurate information about ileos to my and colons to my. The excluded videos lacked scientific in for mation and often failed to adhere to proper hygiene standards. The study emphasized the importance of videos created by medical experts, organizations,institutions, or patients who had experience with these medical conditions. Such videos could significantly contribute to public education about ileostomy and colostomy.King and McCashin (cite) conducted an exploration of YouTube vlogs centered around Borderline Personality Disorder (BPD) and performed a thematic analysis of the accompanying comments. The vlogs focused on individuals living with BPD and were sourced from YouTube Ireland, utilizing the search term "Living with Borderline Personality Disorder Vlog". Through the application of rigorous inclusion and exclusion criteria, there searchers included only four vlogs for analysis.

3. PROPOSEDMETHODOLOGY

To overcome these limitations, this project proposes a machine learning-based sentiment analysis system specifically designed for kid-centric YouTube videos. This system will leverage advanced Natural Language Processing (NLP) models like BERT (Bi directional Encoder Representations from Transformers) and CNN-LST Marchitectures, which have shown high accuracy in sentiment analyze is tasks. Using NLP techniques to process comment data,

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the proposed model will classify comments in to specific emotional categories, allowing creators to analyze the emotional impact of their content effectively. Research papers on sentiment analysis using BERT and CNN-LSTM in domains like movie and social media reviews can serve as are deference, offering insights in to model training, hyper parameter optimization, and evaluation.

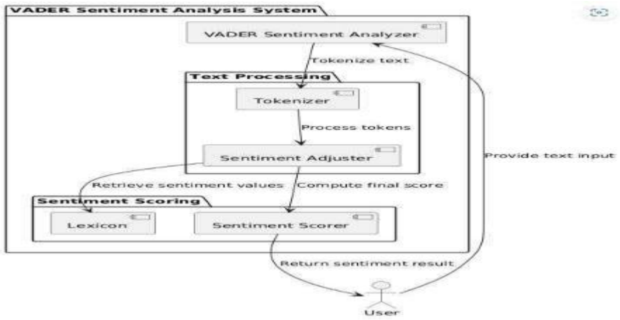

Figure1:Blockdiagram.

KeyComponents:
Models:
User details Model: Stores user details (name, email, password, contact, city, photo, status).
VideoModel:Storesvideodetails(URL,videoID,sentiment,searchauthor).FeedbackModel:Storesuserfeedback(review,rating,sentiment,reviewer).
Views:
MainUserViews:
main_user_login: Handles user login.
main_user_reg: Handles use registration.
main_index,main_about,main_contact:R ender static pages.
UserViews:
user_index:Allows users to search forYouTube videos view sentiment analysis results. user_profile: Allows users to update their profile.user_feedback: Allows users to submit feedback.
AdminViews:
main_admin_login: Handle sad min login.
admin_index: Displays admin dash board with counts of pending users, all users, and feedback.
admin_all_users: Manage user registrations.
admin_searches: Displays video search history.
Applications:
Content Optimization: By identifying trends in view are motions, content creator scan fine-tune their videos to elicit desired emotions, enhancing the overall appeal andengagement of kid-centric content.
Parent Insights: Sentiment analysis provides parents with an understanding of the emotional impact that different videos may have on children, aiding them in crating safer and emotionally enriching content for young audiences.
Platform Recommendations:
Platforms like YouTube can in corporate sentiment analysis results to improve their recommendation algorithms, suggesting more suitable and positively engaging videos for children.
Educational Value Enhancement: For content focused on education, creators can gauge emotional responses to understand how children emotionally connect with learningmaterials, improving educational outcomes.
Advertiser Insights : Advertisers targeting young audiences can analyze sentiment data to tailor ads that align with the positive sentiments expressed

Advantages:
Pre-trained &Fast: No need for training data;VADER is already optimized for sentiment analysis.
Works efficiently in real-time applications.
Handles Social Media Language: Recognizesslang, emojis, punctuation, and capital letters, make ingit ideal for analyzing tweets, reviews, and YouTube comments.
Light weight& Easy to Use: Requires minimal computational resources compared to deep learning models.
Context-Aware: Adjusts sentiment scores using intensifiers, negations, and punctuation.
No Need for Labeled Data : Unlike machine learning models, VADER does not require manually labeled datasets.

4. EXPERIMENTALANALYSIS

Figure1 represents the main interface of sentiment analysis application. It serves as the central hub where users can interact with the system, perform sentiment analysis on YouTube comments, and view visual representations of results.

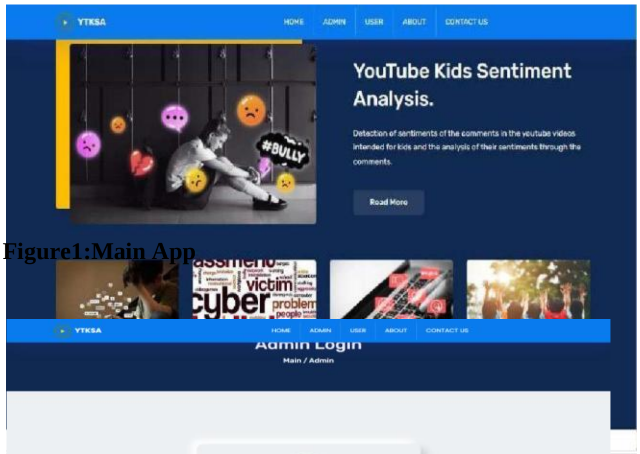

Figure1:Main App

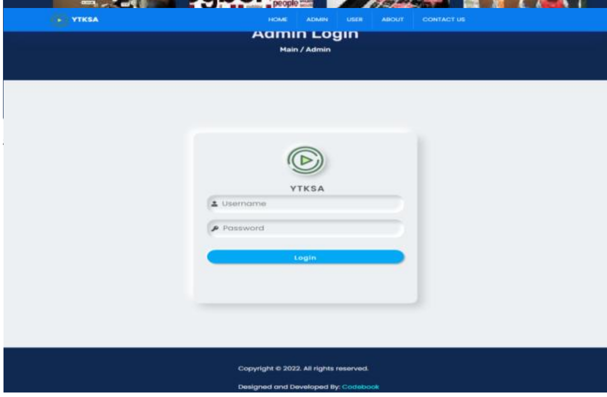

Figure2:Admin Login

Figure 2 shows that the login page for administrators who manage the application. It contains fields for entering an admin username and password, along with a "Login" button.
This interface provides security and restricted access to certain functionalities such as user management, data monitoring, and system configurations.

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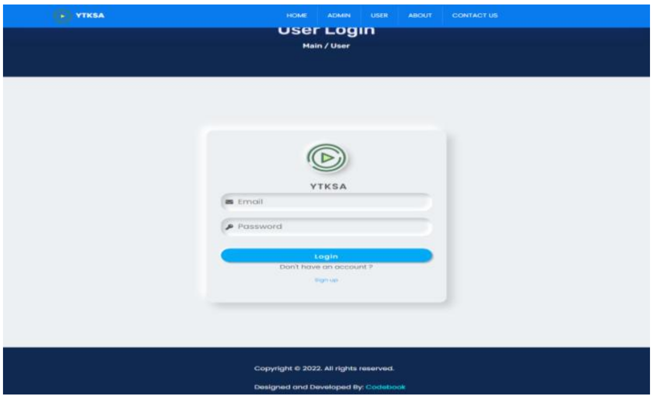

Figure3: User Login

Figure 3 shows the login page for regular users who want to analyze sentiment in YouTube comments. Itinclude fields for entering an email/username and password, along with a "Login" button. Ensures that only registered users can access the application and perform sentiment analysis.

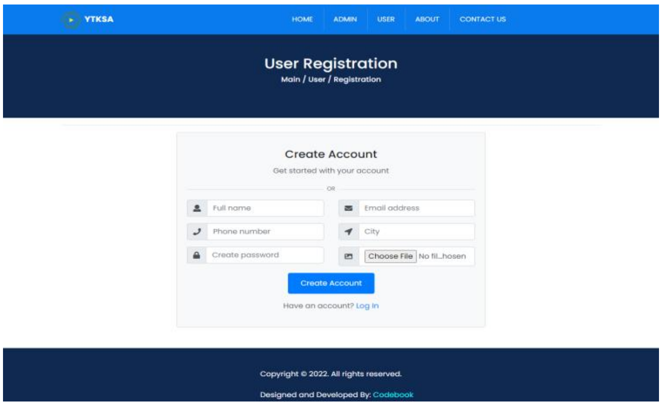

Figure4:User Registration

Figure 4 shows the registration form used for new users to sign up for the application. It includes fields for name, email, password, contact number, and city, along with an option to upload a profile photo. A "Register" button submits the data, allowing users to create an account before using the application.

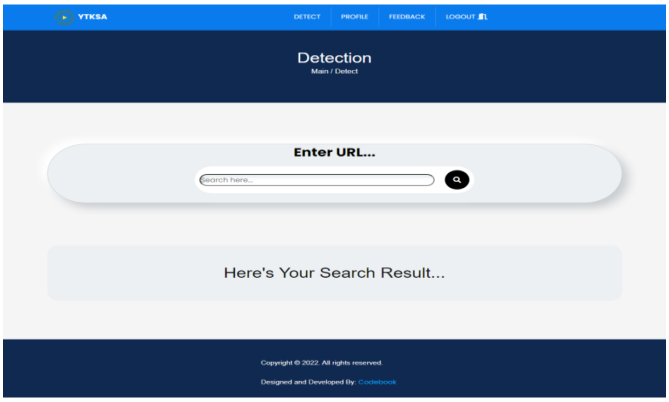

Figure5: User App

Figure 5 This figure represents the user dashboard or the main interface that users interact with after logging in.
It include:
A search bar for entering YouTube video links.Sentiment results (such as positive, negative, neutral classifications).Graphical representations of comment sentiment.A history tab where users can view previous .

5. CONCLUSION

The sentiment analysis of YouTube comments using the VADER (Valence Aware Dictionary and Sentiment Reasoned) algorithm has proven to be an efficient approach for classifyinguser sentiments as Positive, Negative, or Neutral. This study demonstrates how natural language processing techniques can be leveraged to analyze and interpret large volume so fuser-generated content. VADER's ability to handle in formal language, slang, and emojis make sithighly suitable for sentiment analysis on social media platforms. The preprocessing steps, including tokenization, sentiment lexicon lookup, and intensity adjustment, ensure accurate sentiment classification. Compared to traditional machine learning approaches, VADER is computationally efficient and does not require labeled training data, making it a robust and scalable solution. However, the model has certain limitations, such as difficultyin detecting sarcasm and complex contextual sentiments. Overall, this research highlights the effectiveness of VADER for real-time sentiment analysis, offering a foundation for further improvements through hybrid models or deep learning techniques.

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