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Sentiment Analysis of Comments on X Regarding Interactive Videos for Children Using Naive Bayes

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ABSTRACT

This study aims to analyze the sentiment of social media comments on interactive videos for children using the Naive Bayes algorithm, which is known to be effective in text classification and sentiment analysis. Data were collected from social media platforms regarding comments on popular interactive videos for children, and then processed through cleaning, tokenization, stopwords removal, and stemming stages. Naive Bayes algorithm was used to classify the comments into three categories: positive, neutral, and negative. The analysis showed that 48.3% of the comments were positive, 47.2% were neutral, and 4.5% were negative. Positive sentiments indicated more support for the educational aspects and interactivity, while negative sentiments focused more on content quality and concerns about screen addiction and age appropriateness. The accuracy of the analysis reached 55.6%, which demonstrates the effectiveness of the Naive Bayes algorithm. This research provides useful insights for content developers and policymakers to understand the public's response to interactive children's videos and improve content quality to better suit children's educational and developmental needs.

Keywords:

Sentiment Analysis,
Naïve Bayes,
Social Media,
Interactive Videos,
Children’s Content

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INTRODUCTION

The development of digital technology has changed the way people communicate and exchange information. Social media such as Facebook, Instagram, X, and Youtube are not only used for personal interaction, but also as a place to share opinions on topics such as interactive videos for children. Interactive videos, which aim to be both educational and entertaining, are growing in popularity as they provide a fun experience while supporting children's creativity. However, along with their popularity comes a range of responses from the public on social media that reflect perceptions and concerns about these videos.

Children in Indonesia need educational and quality videos that can help in their character building. Interactive animation is an effective medium to depict imaginative worlds that match the way children think. Animation balances children's imagination with engaging and relevant visualizations, and provides an immersive interactive experience, making videos an active learning tool.

Interactive videos are designed for digital devices such as gadgets, which have become an important part of children's lives in the digital age. Gadgets allow children to access and replay animations at own pace, and provide a sense of security for parents. With educational content, parents' concerns about exposure to negative content can be minimized.

However, the lack of a thorough understanding of how the public perceived these interactive videos was a major challenge. Comments on social media varied widely, from appreciation of the creativity and educational value to criticism of potential negative impacts, such as developmentally inappropriate content. Negative comments often related to mental health issues, excessive video length, or incompatibility with local cultural values, while positive comments highlighted the educational aspects, technological innovation, and interactive entertainment.

Analyzing large numbers of comments on social media requires a technology-based approach. Sentiment analysis, using the Naive Bayes algorithm, is an effective method for identifying emotional patterns in text, whether they are positive, negative or neutral[1]. addition, child development is also very important in this study. Internal, external, as well as prenatal, perinatal, and postnatal factors affect children's language, moral, and emotional development[2]. In modern families, children often spend more time with technology, which does not always pay attention to their character development. , there is an urgent need for educational videos to guide children in their character building period[3].

This research draws on previous studies related to sentiment analysis, interactive videos for children, and the application of the Naive Bayes algorithm. The aim is to identify research gaps to be addressed in this study, based on previous findings, methods used, and results achieved. In related research, sentiment analysis is used to identify and classify opinions in positive, negative, or neutral categories, by calculating accuracy based on the percentage of training data and test data[4]. The Naive Bayes method is often applied in sentiment analysis to classify text data on social media, which is important for understanding people's perceptions of an issue[5].

One study by Baeningrum Syahfutri analyzed sentiment towards Distance Learning (PJJ) during the pandemic using data from X. This study shows that negative sentiment is dominant with a percentage of 57.88%, related to limited internet access and provider interference, and positive at 42.12%. These results confirm the effectiveness of Naive Bayes in providing accurate and precise predictions[6]. However, this research is limited to the education sector, while sentiment analysis of interactive videos for children is still less explored, so this research focuses on the topic.

Research by Hasanah, Anisa Nur, and Betha Nurina Sari examined public perception of online transportation services through comments on the Google Play Store. With the Naive Bayes method, the results show many positive comments, but some are negative which can be used for application developer evaluation. This study shows the importance of sentiment analysis in understanding consumer needs more deeply[7]. This study is relevant because it highlights the potential of sentiment analysis in understanding public opinion, although the focus is on ride-hailing services and not interactive videos for children.

Another study by Abu Khoir and Aminatuzzuhriah evaluated the impact of interactive animation-based applications on early childhood cognitive development. The results showed an increase in cognitive abilities in the group of children who used interactive animation applications, although it did not explore public opinion on the content. This research opens up opportunities to examine public perceptions of interactive videos for children accessed through social media[8].

Research by Sunandari et al also highlights the importance of children's character education in the digital era. The inevitable flow of the digital era requires appropriate action to prevent moral deviation. The application of character education plays an important role in the moral formation of elementary school children[9]. This shows the relevance of character education in the context of interactive videos that can shape children's morals, although this research does not examine sentiment analysis.

Naive Bayes algorithm, which is probabilistic based, is often used in text classification because of its efficiency in processing large data with a simple structure. Research by Sulindawaty et al analyzed sentiment towards e-commerce products using the Naive Bayes algorithm with an accuracy of 99.5%, precision of 99.49%, recall of 100%. This research shows the superiority of Naive Bayes in sentiment classification [10]. Another study by Saputra et al analyzed the sentiment of public opinion related to the phenomenon of student suicide using the same algorithm, resulting in a majority negative sentiment. This confirms that Naive Bayes is effective in classifying sentiment in the context of social media, although there are still challenges in complex sentiment analysis [10].

While these studies show the success of Naive Bayes in various contexts, its application to sentiment analysis of children's interactive videos is still rare in the literature, so this gap will be filled by this research.

Based on the literature review above, several research gaps can be identified:

1. Specialized Contexts: Previous research tends to focus on sentiment analysis in general contexts such as e-commerce services and education policy, while interactive videos for children are less explored.
2. Public Perception: Previous studies have focused more on the direct impact of interactive videos on child development, while public opinion captured on social media has not been studied.
3. Technology and Methods: While Naive Bayes has proven to be effective, the challenges of handling language variation, social context, and large volumes of data remain issues that need to be resolved.

This research contributes by integrating Naive Bayes algorithm-based sentiment analysis in the context of interactive videos for children, and offers new insights relevant to content developers. As such, this literature review provides a solid foundation for the research conducted and confirms its relevance and contribution in addressing existing gaps.

METHODS

This research follows systematic steps to analyze sentiment from comments on social media related to interactive videos for children. The stages of this research start from planning data collection, data processing, sentiment analysis, to testing the analysis results. In general, the stages of this research can be described as follows:

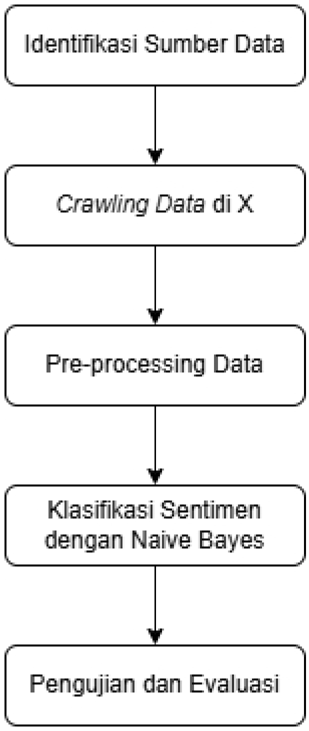

Figure 1. Research Stage

1. Planning and Data Collection
   a. Identify data sources (comments on social media).
   b. Data collection using API X to get comments on interactive videos for children.
   c. Data storage in csv format.
2. Data Pre-processing
   a. Data cleaning (removing irrelevant columns, handling blank data).
   b. Text preprocessing (stopwords removal, stemming, tokenization, and vectorization).
3. Sentiment Analysis
   a. Use of Naive Bayes algorithm to classify sentiment in comments.
   b. Model evaluation uses accuracy, precision, recall, and F1-score metrics.
4. Testing and Evaluation of Results: Testing sentiment analysis results.

Data Collection

This research uses data in the form of comments taken from social media, specifically X, that discuss interactive videos for children. The data was collected through X's API, which allows access to public tweets by using specific queries. In this study, the query focused on topics related to interactive videos for children.

The dataset used consisted of 89 comments relevant to the research topic. The data is organized into several columns that contain important information, namely:

1. Timestamp: The time and date when the comment was created.
2. Likes: The number of likes received by the comment.
3. Retweets: The number of times a comment has been re-shared (retweeted).
4. Username: The name of the user who left the comment.
5. Text: The main content of the comment, which is the main focus in sentiment analysis.

Sentiment Analysis

In this section, a more detailed process of sentiment analysis applied to the comment data is described. This process includes several stages which include:

1. Data Preprocessing: is done to transform the dataset into a more structured format so that the sentiment analysis results become more accurate. The collected data needs to be

cleaned and prepared with methods such as tokenization, stopwords removal, and stemming [11].
2. Tokenization: the process of breaking down text or sentences into smaller words or tokens. This step facilitates analysis as it allows the text to be processed separately based on individual words[12].
3. Stopwords: words that do not have sentiment value or important information, such as conjunctions ('and', 'or', 'but'), personal pronouns, time adverbs, and prepositions. These words are removed as they are considered irrelevant for analysis[13].
4. Stemming: the process of converting a word into its base form. For example, the words 'play', 'bermainan', and 'memainkan' will be converted into 'main'. The purpose of stemming is to simplify words that have similar meanings to be treated as a single entity during analysis[14].
5. Vectorization is the process of converting text into a numerical format that can be processed by machine learning algorithms. One commonly used method is Term Frequency-Inverse Document Frequency (TF-IDF). TF-IDF measures the importance of a word in a particular document compared to the entire document collection[15].
6. TF-IDF is a technique of calculating the weight of a word based on the frequency of its occurrence in a document (Term Frequency) and the number of documents containing that word (Inverse Document Frequency). The TF-IDF formula ensures that common words have a lower weight, while words that rarely appear but are relevant get a higher weight [16].
7. Modeling: Naive Bayes algorithm is applied to classify sentiments in comments.
8. Evaluation: Analysis results are evaluated using performance metrics such as accuracy, precision, recall, and F1-score to assess model performance.

RESULTS AND DISCUSSION

Data Preprocessing

The preprocessing process is done through the following steps:
1. Removing Irrelevant Columns: Columns that have no direct relationship to the analysis, such as conversation_id_str and image_url, are removed. This simplifies the dataset and reduces the complexity of the processed data.
2. Removing Duplication and Blank Values: The dataset was checked to ensure there were no duplicates or blank values. This step helps improve data quality and prevent bias in analysis.
3. Text Cleanup
   a. URLs, mentions, hashtags, and punctuation are removed from the text.
   b. All letters were converted to lowercase to ensure consistency.
   c. This process simplifies the text and makes data processing easier.

Table 1. Example Data Before and After Cleaning

Teks Asli	Teks yang sudah dibersihkan
@dhelsadell Tiap hari anak nonton ini jadi bisa ngomong	tiap anak nonton ngomong inggris dasar
@dhelsadell ini juga favorit anakku dan emang bagus	favorit anak emang bagus

4. Tokenization and Stopwords Removal

   a. The text is broken down into words (tokens).
   b. Stopwords such as "and" and "which" were removed as they did not provide important information in the analysis.
5. Stemming and Slang Word Replacement
   a. Words are converted to their base form using the Literary Stemmer.
   b. Slang words are replaced with standard words to improve data uniformity.

The steps above describe each stage of data preprocessing applied to the dataset. This process includes text cleaning to remove noise, tokenization to break the text into smaller units, as well as stopword removal and stemming to simplify words into their basic form. With this code, the data becomes more structured and ready for further analysis.

Table 2. Comparison of Data Processing Stage

Tahap Preprocessing	**Contoh Sebelum Proses**	**Contoh Sesudah Proses**
Tokenisasi dan Stopwords Removal	tiap hari anak nonton ini	[tiap, hari, anak, nonton]
Stemming dan Penggantian Kata Slang	[tiap, hari, anak, nonton]	[tiap, hari, anak, nonton] (tidak berubah)

Sentiment Analysis Results

The IndoBERT model is used in this research to analyze and classify sentiments from pre-processed comments. The sentiment analysis process starts with giving input in the form of processed text. The text that has gone through preprocessing stages, such as punctuation removal, conversion to lowercase, and removal of irrelevant elements, is processed by the IndoBERT model to identify sentiment patterns in it. The model then generates a sentiment score that describes the strength and direction of the sentiment contained in the text.

1. The model receives input in the form of processed text.
2. Sentiment scores were calculated for each text and categorized as follows:
   a. Score > 0.26: Positive
   b. Score < 0.23: Negative
3. 0.23<= Score <= 0.26: Neutral

Table 3. Example Sentiment Results

Processed_Text	Sentimen	Skor Sentimen
anak nonton ngomong inggris dasar	Positif	0.360301
favorit anak emang bagus	Positif	0.353833
kalo anak suka number blocks sampe kaget...	Netral	0.241698

Model Evaluation and Accuracy

Evaluation was done by dividing the data into training and test data using the 80:20 split method. The Naive Bayes model was used with the following results:

1. Model accuracy: 55,56%
2. The confusion matrix graph shows the dominance of the positive class, while the negative class has a very small number.

Visualization of Results

The sentiment distribution is visualized in the form of a pie chart showing the proportion of positive, neutral and negative sentiments. This diagram shows a predominance of positive sentiments, reflecting the general perception that interactive videos are perceived as useful and enjoyable.

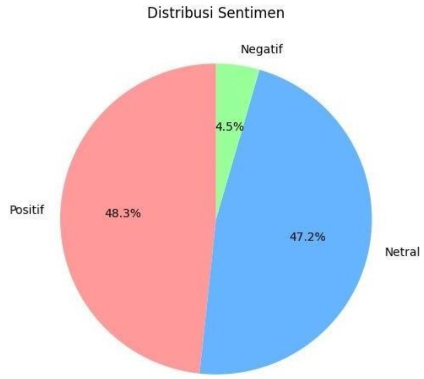

Figure 2. Sentiment Distribution

This pie chart showing the distribution of positive, neutral and negative sentiments illustrates how people respond to interactive videos for kids. From the visualization results, we can see:

1. Positive Sentiment (48.3%): This is the largest section in the diagram, showing that almost half of the respondents found the interactive video useful and fun. This high number indicates a strong positive perception of the video, perhaps due to its educational content or appeal to children.
2. Negative Sentiment (4.5%): This small section shows that only a few respondents have a negative view of interactive videos. This could mean that most people don't feel there are any major issues with the video, although there are still some who may feel that the content is not suitable or effective enough.
3. Neutral Sentiment (47.2%): This figure shows that almost half of the respondents felt neutral or did not have a strong opinion about interactive videos for children. They may feel that the videos don't much impact or are not very engaging, but they also don't object to their use.

The analysis showed that of the comments had positive sentiments, signaling a favorable response to interactive videos for children. However, the accuracy of the model needs to be improved, especially in distinguishing between negative and neutral sentiments.

CONCLUSION

This research analyzes the sentiment of social media comments related to interactive videos for children. The dataset contains 89 comments that were processed through data cleaning, tokenization, stopword removal, and stemming. After preprocessing, sentiment analysis classified the comments into positive, neutral, and negative sentiments, with most of the comments being positive (48.3%), slightly negative (4.5%), and neutral (47.2%). The model evaluation shows an accuracy of 55.56%, with the model being more effective in detecting positive sentiments. Limitations lie in the low precision and recall for negative sentiment, which may be due to the unbalanced data distribution.

Advice

1. Using a larger and more diverse dataset.
2. Trying other machine learning models, such as Support Vector Machine (SVM) or Random Forest, to improve accuracy.

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