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Public Opinion Toward Viral YouTube Content: Machine Learning–Based Sentiment Analysis of Comments on the MrBeast Channel

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ABSTRACT

Social media, particularly YouTube, has become a primary space for the public to express opinions and respond to various forms of digital content. User comments on viral videos can represent audience perceptions and sentiments; Therefore, analyzing comment data is essential to more systematically understand trends in public opinion. This study aims to examine public opinion toward viral content on the MrBeast YouTube channel through a machine learning–based sentiment analysis approach. The data were obtained from a MrBeast YouTube comments dataset available on Kaggle. The dataset was processed through text preprocessing stages, including data cleaning, text normalization, and the removal of irrelevant words. The text was then transformed into numerical features using Term Frequency–Inverse Document Frequency (TF-IDF), before sentiment classification was performed using machine learning algorithms to categorize comments into three classes: positive, neutral, and negative. The results show that the sentiment distribution consists of 63.09% positive sentiment, 35.50% neutral sentiment, and 1.41% negative sentiment. These findings indicate that the majority of audience comments on MrBeast's content tend to be positive, reflecting strong public acceptance of viral content on the channel. This study is expected to contribute to the development of data-driven public opinion analysis on social media and to serve as a reference for future research in sentiment analysis, digital communication, and viral content studies.

1. Introduction

The development of information and communication technology in recent decades has brought fundamental changes in the way people interact, access information, and shape public opinion. Digital transformation marked by the increasing use of the internet and social media has created a new communication space that is open, interactive, and participatory. In this context, social media no longer only serves as a means of entertainment or the dissemination of information, but also as an arena of public discourse that allows individuals to convey their views, perceptions, and judgments of various social phenomena directly.

One of the social media platforms that has a significant influence on the digital communication ecosystem is YouTube. As the world's largest video-based platform, YouTube not only provides diverse audiovisual content, but also facilitates interaction between creators and audiences through comments, likes, and share features. The comment feature on YouTube is an important space for users to express their opinions on the content they consume. From a communication perspective, these comments can be seen as a form of representation of public opinion that arises spontaneously and organically.

Public opinion in the digital era has undergone a significant shift compared to the era of conventional mass media. If previously public opinion was formed more through one-way media such as television, radio, and newspapers, then in the era of social media, public opinion developed dynamically through multi-directional interaction. Each individual has a role as a producer as well as a consumer of information (prosumer), so that the process of forming opinions becomes more complex, fast, and fragmented. This condition makes social media a digital public space that has a strategic role in understanding the dynamics of public perception.

The phenomenon of viral content is one of the important indicators in understanding how public opinion is formed on social media. Viral content refers to content that spreads quickly and widely through the internet, often driven by emotional factors, uniqueness, and social relevance. Viral content not only attracts a large amount of attention, but it also triggers intense interaction from the audience in the form of comments, discussions, and other emotional responses. This makes viral content a relevant object to be analyzed in the study of public opinion.

One of the creators who is widely known for producing viral content is MrBeast. The channel has unique content characteristics, such as large-scale challenges, social experiments, and philanthropic activities involving humanitarian values. This uniqueness not only attracts the attention of audiences globally, but also encourages a high level of participation in the form of comments. The large number of comments on each MrBeast video creates a very rich data set to analyze in understanding public opinion.

However, the enormous volume of comment data is a challenge in the analysis process. Conventional approaches such as manual analysis are no longer effective for processing large and diverse amounts of data. Therefore, a technology-based approach is needed that is able to process data quickly and systematically. In this case, machine learning is one of the relevant solutions to automatically analyze text data.

Sentiment analysis is one of the methods in machine learning that is used to identify the tendency of opinions in text. This method allows researchers to classify comment data into sentiment categories, such as positive, negative, and neutral. Thus, sentiment analysis can provide a more objective picture of public perception of a content.

Although much research has been done on sentiment analysis, most of the research still focuses on issues such as politics, public policy, and product reviews. Research that examines public opinion on viral entertainment content, especially on the YouTube platform, is still relatively limited. In fact, entertainment content has a significant influence on shaping the experience, emotions, and perception of audiences in the digital era. Therefore, this study has an urgency to fill this void by examining public opinion on viral content in the context of digital entertainment.

In addition, this research also has a novelty value in integrating communication approaches with computational methods. The use of machine learning in public opinion analysis allows for large-scale data processing with a high level of accuracy. This contributes not only to the methodological aspect, but also to the development of data-driven communication research.

Based on this description, the formulation of the problem in this study is how the tendency of public opinion towards viral content on the MrBeast channel on YouTube is based on the sentiment analysis of comments, as well as how effective the machine learning approach is in classifying these sentiments. The purpose of this study is to analyze public opinion on viral content through YouTube comments using a machine learning-based sentiment analysis approach, as well as identify the dominance of sentiment that emerges from the audience.

This research is expected to contribute to the development of communication science, especially in the study of digital communication and public opinion. In addition, this research is also expected to be a reference for future researchers in developing sentiment analysis methods on social media data, as well as providing insight for digital content practitioners in understanding the audience's response to the content they produce.

2. Method

This research uses the type of applied research with a quantitative approach. Applied research was chosen because it aims to solve problems practically, namely analyzing public opinion on social media using technology. The quantitative approach is used because data in the form of comment text will be converted into numbers, then analyzed using machine learning methods to produce a classification of sentiment. The data used in this study is secondary data obtained from the Kaggle platform. The data contains a collection of user comments on videos on MrBeast's YouTube channel.

Data characteristics: (a) In the form of comment text, (b) Unstructured, (c) Contains informal language and (d) Large amounts of data.

Data collection was carried out through a documentation study, namely using datasets that are already available on Kaggle. The researchers did not take the data directly from YouTube but used the previously collected datasets to simplify the research process. This research was carried out through several main stages, namely: (a) Data collection, (b) Data cleansing (preprocessing), (c) Converting text to numbers (TF-IDF), (d) Classification using machine learning and (e) Evaluation of model results.

Before being analyzed, the comment data must be cleaned first to make it neater and easier to process by the system. The stages of preprocessing include:

a. Cleaning

Remove unimportant elements such as:

- Link (URL)
- Symbols
- Numbers
- Excessive punctuation

b. Case Folding

Turns all the letters to lowercase.

- Example:
- "THIS VIDEO IS GOOD" → "this video is good"

c. Tokenizing

Breaking sentences into words.

- Example:
- "this video is amazing" → [this, video, is, amazing]

d. Stopword Removal

Removing words that don't have important meaning.

Example: "is", "the", "and"

e. Normalization

Changing non-standard words to standard.

Example:

- "Luv" → "Love"
- Once the data is cleaned, the text is converted to numbers using the TF-IDF method.
- TF-IDF is used for:
- Defining the word that matters
- Reduce the influence of common words
- Help models understand the content of the text

The more often the word appears in one comment but rarely appears in another, the higher the TF-IDF value.

The machine learning model is used to classify comments into three categories: (a) Positive, (b) Neutral and (c) Negatives.

Stages carried out:

- Data is divided into training data and test data
- The model is trained using training data
- The model is tested using test data

To find out how well the model works, several measurements are used:

- Accuracy → how many predictions are correct
- Precision→ accuracy of prediction results
- Recall → the ability to find the correct data
- F1-score → a combination of precision and recall

A confusion matrix is used to see the results of the classification in more detail. Through the confusion matrix, it can be known which data is predicted to be correct and data that is misclassified. This study has several limitations such as slang language is difficult to recognize models, sarcasm is not always detected, and data is only from one channel.

3. Results and Discussion

Based on the results of data processing using the machine learning method, the classification of user comment sentiment on the MrBeast channel was obtained into three categories, namely positive, neutral, and negative. The results of the analysis showed that the majority of comments fell into the category of positive sentiment, followed by neutral sentiment, and a small percentage of negative sentiment.

The dominance of this positive sentiment indicates that most of the audience responds well to the content presented. This can be seen from the many comments that contain praise, appreciation, and support for content and creators.

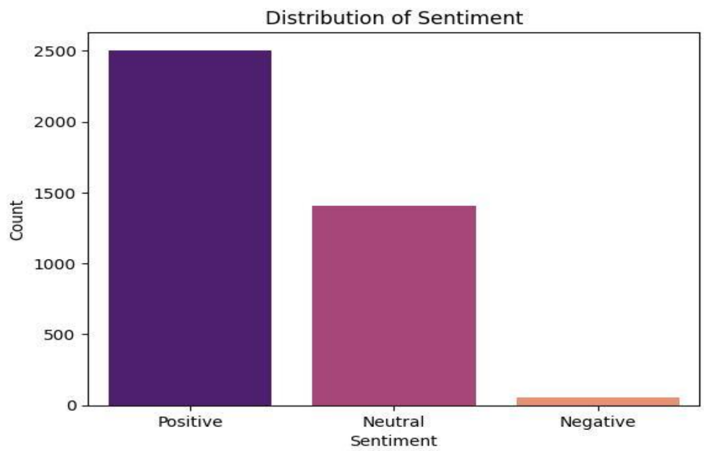

Figure 1. Visualization of Sentiment Distribution

A visualization of the sentiment distribution (Figure 1) shows that the proportion of positive comments is much higher than in other categories. This indicates that the content produced has a strong appeal and is able to meet the audience's expectations.

The performance of the machine learning model in this study was evaluated using several metrics, namely accuracy, precision, recall, and F1-score. The results of the evaluation showed that the model had an accuracy rate of 96%, which indicates that it is able to classify comment sentiment with a very high level of accuracy.

In addition, the high precision and recall values indicate that the model is not only accurate, but also consistent in identifying sentiment categories. A balanced F1-score indicates that the model has a stable performance in handling data.

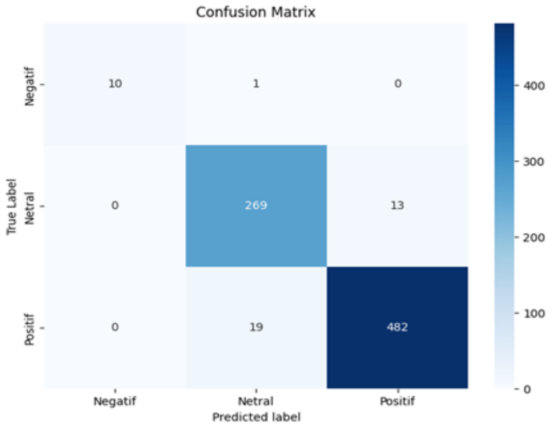

Figure 2. Visualization of the Confusion Matrix

Based on the confusion matrix (Figure 2), it can be seen that most of the data is successfully classified correctly (indicated by the high diagonal value). However, there are still some misclassifications, especially in the neutral and negative categories. This is likely due to ambiguity in the language, such as the use of sarcasm or ambiguous context. The results show that public opinion towards MrBeast's content is dominated by positive sentiment. This indicates that the content presented is able to create an enjoyable experience for the audience. The high level of positive sentiment also reflects a high level of satisfaction with the quality of the content.

This phenomenon can be explained through the characteristics of MrBeast's content tendencies: (a) Entertaining, (b) Contains elements of surprise and (c) Have social value. Content with these characteristics tends to trigger a positive emotional response from the audience, thus increasing the likelihood of positive comments appearing. From the perspective of digital communication, the results of this study show that the audience not only plays the role of the recipient of the message, but also as an active participant in the communication process. Comments left by users become a form of interaction that strengthens the relationship between creators and audiences.

The dominance of positive sentiment also shows that MrBeast's content has managed to build strong engagement with the audience. This engagement is not only reflected in the number of viewers, but also in the quality of the interaction that occurs through comments. In addition, this phenomenon shows that social media functions as a digital public space where public opinion is formed collectively through user interaction.

Although the results show high accuracy of the model, there are several things that need to be critically noted. First, machine learning models still have limitations in understanding complex language contexts, such as sarcasm, irony, or humor. This can lead to errors in the classification of sentiments, especially on comments that have double meaning. Second, the use of datasets that are limited to one channel can affect the generalization of research results. Public opinion on other channels with different types of content may show different sentiment patterns. Third, the dominance of positive sentiment does not necessarily mean that there is no criticism from the audience. There may be bias in the data, where the users who leave comments tend to be those who have had positive experiences.

Thus, the results of this study need to be understood in the context of these limitations. This research has several important implications, both theoretically and practically.

3.1 Theoretical Implications

This study strengthens the study of digital communication by showing that public opinion can be analyzed quantitatively using a machine learning approach.

3.2 Practical Implications

For content creators:

- Be able to understand audience responses
- Can improve content strategy

For researchers:

- Become a reference in sentiment analysis
- Unlocking opportunities for further research

4. Conclusion

Based on the results of the research that has been conducted, it can be concluded that sentiment analysis based on machine learning is able to identify and classify public opinion on viral content on YouTube effectively. Using the comment dataset on MrBeast's channel, the study showed that most of the users' comments were dominated by positive sentiment, which indicated that the content presented received excellent acceptance from the audience.

The high dominance of positive sentiment shows that MrBeast's content has a strong appeal, both in terms of entertainment, emotional value, and social relevance. This strengthens the role of viral content as a medium that is not only entertaining, but also able to build high engagement between creators and audiences.

In terms of methodology, the use of text preprocessing techniques, feature extraction using TF-IDF, and the application of machine learning algorithms have been proven to be able to produce classification models with a high level of accuracy, which is 96%. This shows that computational approaches can be an effective method in analyzing public opinion data on a large scale.

However, the study also has some limitations, such as the model's difficulty in understanding complex language contexts, including sarcasm and irony, and the limitations of datasets that focus on only one YouTube channel. Therefore, the results of this study cannot be generalized widely for any type of content or other social media platforms.

Based on these findings, this research contributes to the development of digital communication studies, especially in data-driven public opinion analysis. In addition, this research also opens up opportunities for future research to develop more complex sentiment analysis methods, such as the use of deep learning, as well as expand the research object to various other social media platforms.

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Finally, the author hopes that this research can provide benefits and contribute to the development of science, especially in the field of digital communication and sentiment analysis.

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