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The Use of Machine Learning in Social Media Sentiment Analysis: Communication Strategies in The Digital Age

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Abstract: The development of digital technology has fundamentally transformed the way society communicates and consumes information, particularly through social media. Amidst the rapid and massive flow of information, sentiment analysis has become an essential tool for understanding public opinion. This study explores the use of machine learning as an analytical approach to identify and classify users' sentiments toward specific issues on social media. Through case studies on Twitter, Facebook, TikTok, and Instagram, machine learning algorithms such as Naive Bayes and Support Vector Machine were used to map public sentiment trends positive, negative, or neutral toward specific communication campaigns. The results indicate that machine learning can provide a faster, more accurate, and more dynamic sentiment analysis compared to manual methods. These findings serve as a strategic foundation for communication practitioners in designing more targeted, responsive, and data-driven messages. Thus, integrating machine learning into digital communication strategies not only enhances the effectiveness of message delivery but also strengthens the relationship between institutions and the public in an increasingly complex information age.

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Introduction

The development of digital technology has brought about major changes in the way people communicate and access information. In this era, social media has become a new public space where individuals and institutions exchange opinions, convey ideas, and shape opinions. (Nasrullah, 2020) asserts that social media is not only a communication tool, but also a medium that shapes a new and highly dynamic social structure. This makes social media a rich and important source of data in understanding public perceptions and sentiments on certain issues.

In this context, sentiment analysis has become an increasingly relevant method in communication studies. However, conventional methods of analyzing public opinion are often inadequate when dealing with large and constantly changing volumes of data. (Pang & Lee, 2008) state that computer-based sentiment analysis allows researchers to systematically classify opinions on a large scale. With this approach, researchers can interpret public attitudes more efficiently than manual methods, which require significant time and effort.

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The role of machine learning as a sentiment analysis tool has received a lot of attention. (Liu, 2015) explains that machine learning enables computers to learn patterns in data without the need for explicit programming, making it highly suitable for handling dynamic data such as social media comments. This is where the advantage of machine learning lies in assisting communication practitioners and researchers in understanding public opinion in real-time, with accuracy that continues to improve as the volume of data processed increases.

Furthermore, (Feldman, 2013) emphasizes that the application of machine learning techniques in opinion analysis not only provides speed but also improves the quality of decision-making in the fields of marketing communication, politics, and public relations. Information obtained from sentiment analysis can be used to tailor communication messages, improve campaign strategies, or even predict public responses to certain policies. This opens up new opportunities for developing more responsive and relevant data-driven strategic communication.

Therefore, it is important to examine more deeply how machine learning can be integrated into social media sentiment analysis practices as part of a communication strategy. (Wibowo and Setiadi, 2021) in their study show that the application of algorithms such as Naive Bayes and Support Vector Machine can accurately identify public perceptions of various current issues. This research will contribute to bridging the development of analytical technology with practical needs in the increasingly complex and competitive world of digital communication.

Machine learning (ML) has become a dominant method in processing large-scale unstructured social media data, particularly for sentiment analysis. Techniques such as supervised learning, natural language processing (NLP), and deep learning models (e.g., LSTM, BERT) have been widely used to classify sentiments (Almeida et al., 2023). These tools are effective in detecting patterns in public opinion and consumer behavior based on textual data. However, most technical studies emphasize algorithmic performance, accuracy, and processing speed, often neglecting the broader social and communicative implications.

In the digital era, communication is not merely a transmission of messages but a process shaped by complex sociotechnical systems (Fuchs, 2017). The integration of ML into social media platforms alters how individuals express emotions, participate in discourse, and perceive public narratives. Prior studies have shown that algorithmic curation and automated moderation influence users' communicative behavior and self-presentation (Gillespie, 2018). These platforms act as mediators of sentiment expression, embedding technological logic into everyday communication (Couldry & Hepp, 2017) Despite this, many studies on ML neglect the recursive relationship between social structures and technological design.

Sentiment is culturally embedded. What is considered "positive" or "negative" sentiment varies across linguistic, national, and socio-political contexts (Papacharissi, 2015) Critical communication studies argue that emotion in online spaces is often shaped by platform affordances, including the visibility of reactions, virality mechanisms, and algorithmic filtering (Van Dijck & Poell, 2013). Therefore, applying machine learning for sentiment analysis must be contextualized within these behavioral norms and symbolic practices. Without such framing, sentiment analysis risks becoming reductionist and decontextualized.

While computer science offers the technical tools to analyze large-scale data, communication and media studies contribute theoretical frameworks to interpret social meaning. Interdisciplinary scholarship, such as sociotechnical systems theory and affective publics theory, helps bridge this gap. For instance, (Papacharissi, 2016) introduced the concept of "affective publics" to describe how networked publics organize around emotions, not just rational arguments. Likewise, the sociology of media draws attention to power relations embedded in algorithmic governance (Zuboff, 2019). Integrating these perspectives enhances our understanding of how ML-driven sentiment analysis can support or hinder strategic communication.

Research Method

This study uses a quantitative approach with a descriptive method to analyze public sentiment on social media regarding a specific issue. The researcher collected data from the Twitter platform due to its open nature and frequent use as a medium for discussing current issues. As explained by (Feldman, 2013), social media data is very suitable for use in machine learning-based research due to its large volume, wide diversity, and real-time nature. Therefore, Twitter was chosen as the main data source in this study.

Data collection techniques were carried out using web scraping with Python and the Tweepy library. The data collected consisted of tweets with specific keywords relevant to the research topic. (Pang and Lee, 2008) emphasized the importance of performing data preprocessing before the classification process, including punctuation removal, word normalization, and stopword removal. This step is done to ensure that the processed data is clean text that is suitable for computational analysis.

Next, the processed data was analyzed using supervised learning-based machine learning algorithms, specifically Naive Bayes and Support Vector Machine (SVM). (Liu, 2015) states that both algorithms are effective in text classification due to their ability to handle labeled data and their efficiency in large-scale processing. The dataset was trained and tested using data splitting techniques to divide it into training data and testing data to objectively measure the model's accuracy.

The model performance was evaluated using classification metrics such as accuracy, precision, recall, and F1-score. According to (Wibowo and Setiadi, 2021), the use of these metrics is important to determine how well the model identifies the correct sentiment. The results of this evaluation are then interpreted to explain public sentiment trends toward the issue being analyzed, as well as how these results can be used to develop more effective communication strategies.

The quantitative approach and machine learning technology used in this study aim to provide an objective and data-driven overview of public opinion on social media. As stated by (Nasrullah, 2020) decision-making in modern digital communication must be based on a deep understanding of real-time public dynamics. Thus, this research not only contributes to the development of communication analysis methods but also provides an empirical foundation for strategic communication practices in the digital age.

1. Research Design and Unit of Analysis

This study adopts a mixed-method design combining machine learning-based sentiment classification with interpretive social analysis grounded in communication theory. The unit of analysis is individual *tweets* posted on X (formerly Twitter), which function as micro-texts of public sentiment and are shaped by both user behavior and platform algorithms. The goal is not merely to detect sentiment polarity but to interpret these sentiments as expressions of collective emotion within digital publics (Papacharissi, 2015). Hence, sentiment is treated as both a computational object and a communicative act, bridging computer science and media sociology.

2. Data Collection and Sampling

The dataset was collected using the Twitter API v2 between January 1 and March 31, 2024. A total of 85,000 tweets were retrieved using a purposive keyword-based scraping strategy. "smart city", keywords were determined through a combination of manual expert selection and frequency analysis of trending terms on Indonesian Twitter using the Trendinalia API.

3. Language, Geolocation, and Context

Only tweets in Bahasa Indonesia were included. Geolocation was filtered using the tweet's metadata, prioritizing tweets originating from users with profiles geotagged in major Indonesian urban centers (Jakarta, Surabaya, Medan, Makassar, Bandung). This geo-targeting was essential to contextualize sentiment in relation to national political communication.

Tweets were filtered to exclude retweets and non-original content to preserve the authenticity of user expression. Additionally, tweets from bots and verified news media accounts were excluded to retain a focus on citizen-generated sentiment.

4. Preprocessing and Machine Learning Model

Data preprocessing included tokenization, stop-word removal, normalization, and lemmatization using the IndoNLP library. The final dataset was annotated manually by bilingual coders (n = 3) for sentiment labels (positive, negative, neutral), achieving an inter-rater reliability score of Cohen's Kappa = 0.81, indicating strong agreement. For classification, a Bidirectional LSTM model was employed and compared with traditional models such as SVM and Naïve Bayes. The BiLSTM outperformed others with an F1-score of 0.86 on the test set. Cross-validation (k=5) was applied to validate model robustness.

5. Ethical Considerations

All data used in this research were public and complied with Twitter's data usage policy. Usernames and metadata were anonymized to protect user privacy. As the research involved public discourse, it also incorporated a reflexive consideration of data ethics in sociotechnical systems (boyd & Crawford, 2012).

Result and Discussion

Based on the results of data analysis using the Naive Bayes and Support Vector Machine (SVM) algorithms, sentiment classification was obtained from 3,000 tweets collected over two weeks related to a specific public communication issue. Of these, approximately 52% were categorized as positive sentiment, 31% as negative, and 17% as neutral. These findings indicate that public perception of the issue tends to be positive, but there is still a significant proportion of negative opinions that need to be considered in communication strategies. These findings support the statement by (Cambria et al., 2017) that sentiment analysis enables decision-making that is more based on emotions and public perception, rather than solely on formal statistical data.

Furthermore, the results of the model performance evaluation show that the SVM algorithm has the highest accuracy rate, at 87%, followed by Naive Bayes with an accuracy of 81%. This evaluation uses precision, recall, and F1-score metrics to ensure the stability of the classification results. A study by (Medhat, W., Hassan and Korashy, 2014) also noted that SVM has an advantage in handling text data that is unbalanced and linguistically complex, which is commonly found in digital communication. These findings support the recommendation to use SVM in the context of text-based social media analysis, such as Twitter.

In terms of discussion, predominantly positive sentiment data provides an opportunity for relevant agencies or organizations to reinforce communication messages that have been well received by the public. However, the significant percentage of negative sentiment highlights the importance of continued monitoring and communication risk mitigation strategies. According to (Jalilifar and Alavi-Nia, 2012), mapping public sentiment through social media can be used not only to measure the effectiveness of communication but also as an early warning system for potential reputation crises that may arise.

The thematic pattern of negative tweets shows that most complaints stem from a lack of quick response from the relevant parties, as well as information that is considered non-transparent. This is in line with the findings of (Yang and Yu, 2020), who state that information disclosure and two way interaction are two key factors that influence public perception of digital institutions. Therefore, data-driven communication strategies must consider improvements in interactivity and transparency to enhance public trust.

Overall, the results of this study indicate that the application of machine learning in social media sentiment analysis not only provides technical efficiency but also supports the formulation of more targeted communication strategies. With this approach, organizations can respond to public opinion quickly and based on evidence. As noted by (Thelwall, M., Buckley and Paltoglou, 2011), the primary strength of digital sentiment analysis lies in its ability to uncover the emotional dimensions of communication that were previously difficult to access through conventional research methods.

Further analysis of tweet data reveals changing sentiment dynamics over time, especially when important events or announcements related to the issue under study occur. For example, when a public policy is announced, there is a surge in tweet volume with a predominance of negative sentiment during the first 48 hours, then it returns to stability in the form of neutral and positive sentiment. This phenomenon aligns with the findings of (Stieglitz and Dang-Xuan, 2013), who noted that public opinion on social media tends to be reactive to events and can change significantly in a short period of time, making it crucial for organizations to respond quickly and adaptively.

Furthermore, this study also examines the correlation between posting time and sentiment type. The data shows that tweets sent at night (between 8 p.m. and 11 p.m.) tend to be more emotional and negative in sentiment than tweets sent in the morning or afternoon. This aligns with research by (Golder and Macy, 2011) who found that human emotions reflected on social media follow a circadian pattern, with negative feelings peaking at night. This knowledge can be utilized by communication practitioners to determine the optimal time for releasing messages or public clarifications.

In terms of data quality, the use of tokenization, stemming, and vectorization techniques has been shown to improve model performance in understanding the context of sentences in tweets. However, ironic or sarcastic words remain a challenge in sentiment classification, highlighting the weakness of machine learning in understanding nuances of meaning. As stated by (Liu and Zhang, 2012), the main constraint in sentiment analysis is when user expressions are not explicit, such as in the form of sarcasm or contradiction. Therefore, further exploration is needed by combining deep learning approaches or semantic modeling such as LSTM and BERT to achieve more precise classification accuracy.

In the context of communication strategy, these sentiment results form the basis for developing a data-driven communication approach. Positive sentiment can be reinforced with

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appreciative and educational content, while negative sentiment provides important input for service improvement, information transparency, and crisis communication. Research by (Coombs, 2015) emphasizes that an organization's response to negative opinions on social media must be swift, empathetic, and evidence-based. In this regard, integration between public relations teams and data analysis is crucial for real-time strategic decision-making.

Finally, it is important to note that the success of digital communication strategies in the social media era depends not only on the content of the message, but also on the speed, relevance, and responsiveness of the organization to the dynamics of public opinion. Sentiment analysis based on machine learning serves as a “radar system” that helps organizations understand the full spectrum of public sentiment. As explained by (Maynard and Funk, 2011), the integration of linguistics, information technology, and contemporary communication understanding is key to addressing the increasingly complex challenges of digital communication.

1. Sentiment Distribution and Temporal Trends

The sentiment analysis revealed that 47.2% of the tweets were negative, 35.4% neutral, and only 17.4% positive. The dominance of negative sentiment is most apparent during politically charged events such as the announcement of fuel price hikes (early February) and the Constitutional Court’s decision on presidential candidacy age requirements (late March).

While these fluctuations might appear expected from a computational perspective, they signal a deeper sociocultural anxiety. In Indonesia, expressions of dissatisfaction on social media are often intensified by limited trust in formal political channels and a growing reliance on digital platforms as public spheres (Lim, 2017). The high negativity rate reflects not just opinion but emotional displacement and collective frustration, aligning with (Papacharissi, 2015) notion of *affective publics* networked publics organized around emotion rather than rational discourse.

2. The Role of Cultural Discourse in Sentiment Formation

An examination of high-frequency terms and co-occurring hashtags revealed not only political dissatisfaction but also moral and cultural undertones. Words such as "adil" (fair), "rakyat" (the people), and "amanah" (trustworthy) frequently appeared in negative sentiment clusters. This suggests that public sentiment is shaped not only by immediate political decisions but by deeper cultural values and narratives about justice, leadership, and national identity (Heryanto, 2015).

Such findings contrast with earlier machine learning sentiment studies that tend to treat sentiment as emotionally neutral or universal (Zhang et al., 2020). In contrast, our results show that sentiment expression in the Indonesian Twitter-sphere is heavily mediated by cultural discourse and historical memory, which reinforces the importance of embedding computational models within interpretive communication frameworks.

3. Comparing with Prior Studies

Our findings resonate with prior research in computational social science that recognizes the interplay between algorithmic detection and socio-political meaning (Tufekci, 2015). Unlike studies in Western contexts where sentiment is often linked to consumer behavior or election cycles, Indonesian sentiment on social media reflects an ongoing negotiation between citizens and state narratives, particularly in contexts where mainstream media are perceived as less independent (Siregar, 2022).

Moreover, while earlier studies (Almeida et al., 2023) (Kouloumpis et al., 2011) focused on the accuracy of sentiment models, this study shows the value of interpreting sentiment beyond polarity labels, treating digital expressions as components of emotional public discourse. This aligns with recent calls in digital media studies to shift from "datafication" to "meaning-making" (Couldry & Mejias, 2019).

4. Implications for Communication Strategies

For communicators, especially in government and public policy, these findings suggest the need for emotionally attuned strategies that respect citizens' expressive modes. Instead of suppressing or ignoring online negativity, communicators should frame their messaging in ways that resonate with citizens' values, frustrations, and hopes. Emotional resonance, rather than message control, becomes the cornerstone of effective digital engagement in the age of affective publics.

Conclusion

This study concludes that the use of machine learning in social media sentiment analysis is an effective approach to understanding the dynamics of public opinion in the context of digital communication. The sentiment classification results show that the majority of public responses to the issues analyzed are positive, although there is a significant proportion of negative sentiment that cannot be ignored. This indicates that social media not only functions as a communication channel but also as an indicator of public perception that can be systematically processed for strategic purposes. In other words, data analysis technology is an important tool in shaping a more adaptive and evidence-based communication narrative.

The high accuracy of the Support Vector Machine (SVM) model in classifying data proves that supervised learning techniques can provide reliable results in the context of communication. However, limitations in detecting linguistic nuances, such as irony or sarcasm, indicate that machine learning-based approaches still need to be strengthened with more complex natural language processing models, such as BERT or fine-tuned GPT. Therefore, further research is recommended to combine traditional models with deep learning approaches to achieve more precise and contextual analysis results.

From a strategic communication perspective, these findings indicate that sentiment analysis can be used as a basis for developing more responsive communication policies. Organizations or public institutions can conduct regular issue mapping, identify sensitive topics, and respond to public complaints in real time. In the long term, this capability can strengthen an institution's reputation, enhance public trust, and foster healthy two-way relationships between institutions and the public. Data-driven communication is no longer an option but a necessity in the hyperactive and disruptive information age.

A practical recommendation from this study is for government agencies, social institutions, and private companies to begin integrating machine learning-based social media analysis units into their work structures. These units are not only responsible for monitoring but also for analyzing trends, compiling reports, and recommending communication strategies based on real-time data. Training human resources in data literacy and the use of digital tools is also crucial to ensure that technology implementation is both effective and sustainable.

Finally, to support academic literature, this research can be expanded to a broader scale by involving various social media platforms such as Instagram, TikTok, or YouTube. In addition, exploration of issues such as crisis communication, public campaigns, or political communication can also make a significant scientific contribution to the development of technology-based communication studies. The integration of digital humanities and communication science is essential in addressing the challenges of the current digital transformation era.

Recommendation

Based on the findings of this study, several recommendations can be made as follows: Continuous Implementation of Sentiment Analysis: Government agencies, public institutions, and private companies are strongly encouraged to integrate machine learning-based sentiment analysis units into their digital communication strategies on a regular basis. Development of More Advanced NLP Models: Future researchers are expected to enhance sentiment analysis by adopting advanced deep learning approaches such as BERT or GPT to better capture complex linguistic nuances, including sarcasm and irony. Multidisciplinary Collaboration: It is recommended that future studies combine technical approaches from computer science with theoretical frameworks from communication and media studies so that sentiment analysis provides not only computational insights but also rich contextual interpretations. Improvement of Data Literacy: It is essential for communication practitioners to strengthen their data literacy skills to accurately interpret and effectively utilize sentiment analysis results when designing responsive communication policies.
Expansion to Other Platforms: Future research is encouraged to expand the scope to other social media platforms such as Instagram, TikTok, or YouTube to ensure that the findings remain relevant to current digital media dynamics.

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