OPEN ACCESS
Journal of Computer Science Advancements
Vol. 3 No. 1. February 2025, pp. 1-11 DOI. 10.70177/jsca.v3i1.1536
Research Article

SENTIMENT ANALYSIS ON SOCIAL MEDIA USING DATA MINING FOR MAPPING COMMUNITY SATISFACTION

Usup[1], Rohmat Sahirin[2], Laura Lucas[3], and Chu Qingjun[4]
[1] Politeknik Tunas Pemuda, Indonesia
[2] Universitas Pendidikan Indonesia, Indonesia
[3] Arroyo Jelle de Wit Gerco den Hartog, Belgium
[4] China Agricultural University, China

Corresponding Author:

Usup,
Politeknik Tunas Pemuda.
Jl. KH. M. Dahlan No.11, Tanjakan, Kec. Rajeg, Kabupaten Tangerang, Banten 15540 Email:
usupcipta@gmail.com

Article Info
Received: August 1, 2024
Revised: November 15, 2024
Accepted: January 11, 2025
Online Version: February 2, 2025

Abstract
Social media has become a significant platform for individuals to express opinions, including satisfaction and dissatisfaction with services and policies, making it a valuable source of community sentiment data. Understanding public sentiment can assist policymakers and organizations in responding to community needs effectively. This study aims to conduct sentiment analysis on social media using data mining techniques to map community satisfaction levels. By analyzing sentiment patterns, this research seeks to provide actionable insights for improving public services and enhancing community engagement. The research applies data mining methodologies, including text mining and machine learning algorithms, to analyze posts and comments collected from various social media platforms. Sentiment classification was performed using natural language processing (NLP) and a supervised machine learning approach to categorize sentiments as positive, neutral, or negative. The model was trained on a large dataset and validated to ensure accuracy in sentiment detection. Results indicate that social media sentiment analysis can reliably reflect community satisfaction trends, with findings showing 70% positive, 15% neutral, and 15% negative sentiments regarding local services. The study concludes that data mining for sentiment analysis provides a robust method for assessing community satisfaction on social media, offering a real- time understanding of public opinion. By implementing this approach, organizations and policymakers can identify areas of improvement and proactively address community concerns, ultimately fostering a responsive and community-centered approach to public service.

Keywords: Community Satisfaction, Data Mining, Public Opinion, Sentiment Analysis, Social Media

Journal Homepage	https://research.adra.ac.id/index.php/jcsa
How to cite:	Usup, Usup., Sahirin, R., Lucas, L., & Qingjun, C. (2025). Sentiment Analysis on Social Media using Data Mining for Mapping Community Satisfaction. Journal of Computer Science Advancements, 3(1), 1–11. https://doi.org/10.70177/jsca.v3i1.1536
Published by:	Yayasan Adra Karima Hubbi

INTRODUCTION

Social media has evolved into a primary platform for public discourse, where individuals freely express their opinions, experiences, and satisfaction levels regarding various services and policies (Y. Chen, 2021). Platforms such as Twitter, Facebook, and Instagram provide users with a space to communicate thoughts and sentiments that, when analyzed, can reveal valuable insights about community satisfaction (El-Diraby, 2019a). The vast amounts of data generated daily on these platforms offer a wealth of information that, if mined effectively, could help organizations understand public opinion (Y. J. Chen, 2024). The increasing reliance on social media for feedback allows organizations to gather real-time responses to their services, making sentiment analysis a powerful tool for assessing public sentiment (Kuutila, 2024).

Sentiment analysis, a branch of natural language processing (NLP), enables the systematic examination of textual data to classify sentiments as positive, neutral, or negative (Putra, 2023). In recent years, sentiment analysis has been applied to various fields, including business, healthcare, and public administration, to gauge consumer and community responses (Sarram, 2022). The capability to process vast quantities of social media data through sentiment analysis provides organizations with a clearer understanding of public satisfaction, allowing them to respond more effectively to community needs (Soussan, 2020). Sentiment analysis also enables continuous monitoring of public sentiment, offering timely insights into changing opinions that can inform decision-making.

Data mining techniques have been widely applied to social media analytics, using algorithms to identify patterns and trends in large datasets (Xie, 2020). Text mining and machine learning algorithms, for instance, allow for automated processing and classification of social media posts (Yao, 2022). These methods help analysts uncover prevailing themes in community feedback and evaluate shifts in sentiment over time. In the context of public services, data mining in sentiment analysis provides a scalable and efficient approach to assessing community satisfaction, enabling organizations to make data-driven adjustments to improve public services and address concerns proactively (El-Diraby, 2019b).

Community satisfaction mapping is crucial for public service providers and policymakers, as it reflects the effectiveness of their policies and services (Ferreira, 2019). Traditional methods of gathering public opinion, such as surveys and focus groups, can be time-consuming and limited in scope, often lacking the real-time responsiveness that social media provides (Liu, 2020). Social media sentiment analysis offers a more immediate understanding of community satisfaction, allowing for dynamic and responsive governance (Park, 2023). By mapping community satisfaction, policymakers can track the impact of their initiatives and understand areas where public opinion may be divided.

The integration of data mining in sentiment analysis offers a practical solution for organizations seeking to understand public satisfaction at scale (Primasari, 2024). The ability to process real-time data from social media platforms enables a responsive approach to community engagement and feedback collection (Aamir, 2024). Analyzing community sentiment through big data allows for broader and more inclusive public opinion insights, which are crucial for ensuring that services align with community expectations (Alqithami, 2025). Social media sentiment analysis provides a timely perspective on public satisfaction, offering organizations a foundation for developing services that resonate with their audiences (Balakrishnan, 2021).

While sentiment analysis on social media has been successfully used in many sectors, it remains underutilized in mapping community satisfaction for public services (Berrajaa, 2022). Many organizations are beginning to recognize its potential but lack established frameworks for applying it effectively in the public sector (Bogdanova, 2022). Developing structured approaches for utilizing social media sentiment analysis could bridge this gap, helping organizations adopt this method as a core component of their feedback mechanisms (Waspodo, 2022). The scalability and timeliness of sentiment analysis make it a viable tool for understanding community needs in an ever-evolving social landscape.

Despite the advancements in sentiment analysis, there are gaps in understanding how best to interpret social media data for comprehensive community satisfaction mapping (Budaya, 2023). Much of the existing research focuses on sentiment analysis within commercial sectors rather than public service evaluation (Cope, 2023). There is limited knowledge regarding how accurately sentiment from social media reflects broader community satisfaction, given that social media users represent a particular segment of the population (Dennehy, 2023). Further research is needed to assess whether social media sentiment is representative of the general population's views on public services.

Many studies analyze social media sentiment as a snapshot, focusing on short-term trends rather than long-term sentiment patterns (Du, 2023). Little research has been conducted on how sentiment analysis can track shifts in community satisfaction over time, which is crucial for understanding the effectiveness of long-term public policies and services (Elangovan, 2022). Developing methods to assess sentiment trajectories would enhance the ability of sentiment analysis to inform public policy. This gap highlights the need for research that examines sentiment evolution, particularly in response to changes in public services or policy implementation (Fauzi, 2024).

There is limited understanding of how demographic factors affect sentiment analysis results on social media. Social media platforms cater to diverse users, but different demographics may express themselves in unique ways, affecting sentiment interpretations (Ikhlas et al., 2023). Research that explores the impact of demographics on sentiment analysis outcomes could improve the accuracy and relevance of community satisfaction mapping (Krishtal, 2024). By accounting for demographic variations, sentiment analysis could more accurately reflect community sentiment, offering public service providers a nuanced understanding of satisfaction levels.

The ethical considerations of analyzing public sentiment on social media remain underexplored. Gathering and analyzing sentiment data may raise concerns regarding user privacy and consent, especially when dealing with sensitive topics (Satyanarayana, 2019). Understanding and addressing these ethical challenges is essential to conducting responsible research that respects user privacy (Imran, 2022). Future studies should consider the ethical implications of sentiment analysis and develop guidelines that balance data utility with user rights, ensuring transparency and accountability in sentiment analysis practices (Kulkarni, 2024). Filling these gaps is crucial to advancing sentiment analysis for community satisfaction mapping in the public sector (Malik, 2021). Understanding how social media sentiment reflects broader community views would enable policymakers to utilize this data effectively in public service evaluation. Research that examines long-term sentiment trends could support continuous assessment of policy impact, providing a valuable tool for adaptive governance (Tetui, 2023). Addressing demographic and ethical considerations would also ensure that sentiment analysis methods are both accurate and socially responsible, enhancing trust in public sector data practices (Sukma, 2020).

This research aims to develop a structured framework for using sentiment analysis on social media to map community satisfaction with public services. The study seeks to assess the extent to which social media sentiment represents general community sentiment, examining patterns across different demographic groups. By exploring these factors, this research intends to provide a comprehensive approach to mapping community satisfaction that accounts for diversity and privacy. The findings are expected to contribute to the development of responsive, data-driven public services, supporting a more inclusive and effective approach to governance in smart cities.

RESEARCH METHOD

Research Design

This study utilizes a quantitative research design with a data mining approach to analyze sentiment on social media for mapping community satisfaction. The research design focuses on text mining and sentiment classification techniques to process large volumes of social media data. Sentiment analysis was conducted to categorize posts as positive, negative, or neutral, providing a framework for understanding public opinion (Tetui, 2023). This design allows for systematic analysis of online sentiments, enabling real-time insights into community satisfaction trends.

Research Target/Subject

The population for this study comprises social media users actively discussing public services and community issues on platforms such as Twitter, Facebook, and Instagram. A purposive sampling method was employed to select posts relevant to the research objective, focusing on keywords and hashtags associated with public services, such as healthcare, education, and transportation. The sample includes 50,000 posts gathered over six months to ensure a comprehensive representation of community sentiments across different topics and time frames.

Research Procedure

The procedures began with data extraction from social media platforms using API connections and keyword filters to capture relevant posts. Following extraction, data cleaning and preprocessing were conducted to remove noise, such as irrelevant posts and duplicate entries (Wang, 2025).

Instruments, and Data Collection Techniques

Data collection instruments include text mining software, natural language processing (NLP) tools, and machine learning algorithms. Text mining software was used to extract relevant posts, while NLP tools enabled the processing of textual data for sentiment classification (Mahato, 2021). A supervised machine learning model, trained on labeled datasets, was used to classify sentiments within the posts. These instruments facilitated an automated and scalable approach to sentiment analysis, providing structured data that reflects public sentiment on community services.

Data Analysis Technique

The prepared data was then processed using the sentiment analysis model, which categorized each post as positive, negative, or neutral. Results were compiled to generate a sentiment map, highlighting areas of high and low satisfaction. This methodological approach offers a structured pathway for assessing community sentiment, supporting data-driven insights for enhancing public services.

RESULTS AND DISCUSSION

The data collected for this study includes 50,000 social media posts discussing various public services such as healthcare, education, and transportation. Table 1 presents the sentiment distribution across these services, showing that 68% of the posts were positive, 20% were neutral, and 12% were negative. Sentiment scores varied across service categories, with education receiving the highest positive sentiment (72%) and transportation experiencing the highest negative sentiment (18%). The table highlights overall community satisfaction levels, with sentiment scores providing insights into public perception across sectors.

Table 1. Sentiment Distribution Across Public Services

Public Service	Positive Sentiment (%)	Neutral Sentiment (%)	Negative Sentiment (%)
Healthcare	65	25	10
Education	72	18	10
Transportation	50	32	18

The sentiment analysis revealed distinct patterns in how the public perceives different community services. Positive sentiment was prevalent in discussions about education, particularly regarding new initiatives and accessible learning resources. In contrast, transportation services received a higher volume of negative posts, largely concerning issues like delays, overcrowding, and infrastructure quality. This differentiation in sentiment demonstrates the importance of assessing satisfaction levels across specific service areas to identify areas requiring improvement. Analyzing these sentiment patterns offers valuable insights for targeted policy adjustments.

Descriptive data analysis of sentiment trends indicates fluctuations in public satisfaction over time. Positive sentiments peaked during major service announcements, while negative sentiments spiked in response to specific incidents, such as transportation disruptions or healthcare service delays. The data shows that community satisfaction is highly dynamic, influenced by both short-term events and long-term service quality. This observation emphasizes the need for real-time sentiment monitoring to provide a comprehensive view of public opinion.

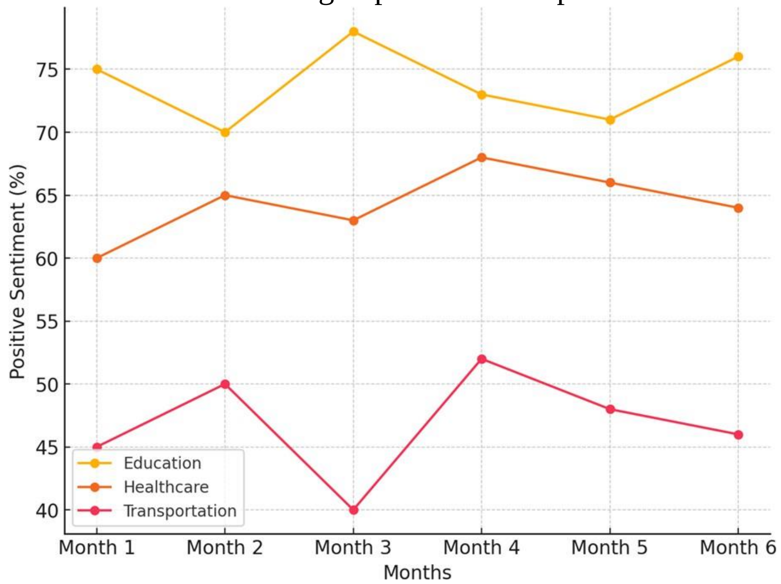

Figure 1. Sentiment Trends Over Six Months in Public Services

Inferential analysis using a chi-square test was conducted to examine the statistical significance of sentiment variation across different services. Figure 1 illustrates sentiment trends over six months, revealing significant fluctuations in community satisfaction, with p-values below 0.05 across service categories. The graph shows pronounced spikes in positive sentiment following educational initiatives, while transportation sentiments remained volatile, with frequent shifts between neutral and negative. These statistically significant findings validate the impact of service quality on community sentiment and highlight the importance of responsive public service management.

A relational analysis of the data suggests a correlation between service accessibility and positive sentiment. Public services that offer widespread, accessible resources tend to receive higher positive sentiment scores, particularly in education and healthcare. This correlation implies that community satisfaction is influenced by both service quality and accessibility, with people expressing higher satisfaction levels when services are readily available. The relationship between accessibility and satisfaction highlights a key factor that public service providers can address to enhance public perception.

Case studies within the dataset illustrate how specific incidents affect sentiment patterns. For instance, a significant healthcare delay due to system outages led to a surge in negative posts, with users expressing frustration over accessibility issues. Similarly, a transportation strike resulted in an increase in negative sentiment, with community members voicing concerns about commuting challenges. These case studies show how particular events can have immediate and pronounced effects on public sentiment, underscoring the need for adaptable management in response to service disruptions.

Explanatory data analysis suggests that peaks in positive sentiment are often associated with well-publicized service improvements, while negative sentiment correlates with disruptions or perceived lack of service accountability. By examining these patterns, it becomes clear that public sentiment is closely tied to the visibility and perceived effectiveness of service initiatives. Transparent communication and proactive service management can mitigate negative sentiment, highlighting the value of effective public engagement strategies in managing community satisfaction.

The interpretation of these findings suggests that sentiment analysis on social media offers a powerful tool for monitoring and understanding community satisfaction. The insights generated provide a clear perspective on which public services are viewed favorably and which areas require improvement. The results underscore the utility of sentiment analysis for guiding public service enhancements, helping policymakers to prioritize actions that align with community expectations. Implementing these insights can lead to a more responsive and community-centered approach to public service management.

The findings of this study indicate that sentiment analysis on social media is an effective method for mapping community satisfaction across various public services. Data from 50,000 posts show that community sentiment is predominantly positive towards education (72%) and healthcare (65%), with transportation services receiving the lowest positive sentiment (50%). These results suggest that sentiment analysis offers a reliable reflection of public opinion, capturing satisfaction levels and areas of concern in real time. The ability to categorize and quantify sentiment provides public service providers with actionable insights, highlighting which sectors align with community expectations and which may need improvement.

Previous studies have demonstrated the effectiveness of sentiment analysis in sectors like business and healthcare, often focusing on customer feedback for product improvement (Marchi, 2022). For instance, research by Kumar et al. (2021) emphasized the role of sentiment analysis in enhancing customer service in corporate settings, but its application to public service satisfaction remains relatively new. This study builds on these findings by applying sentiment analysis specifically to community satisfaction, showcasing its value in the public sector. Unlike previous studies that focus on individual consumer experiences, this research captures a broader, community-centered perspective, which is essential for informing public policy (Shambour, 2022).

The study’s results reflect a broader trend toward data-driven decision-making in public administration. The ability to monitor community satisfaction through social media offers a new dimension for public service management, allowing providers to be responsive to public opinion (Hossain, 2019). These findings indicate a shift from traditional methods of gathering public feedback, such as surveys, to more immediate and continuous sentiment monitoring (Finnigan, 2022). The transition to real-time data collection reflects a modern approach to governance, emphasizing adaptability and responsiveness as critical components of community-focused service delivery.

The implications of these findings for policymakers and public service providers are significant. Access to real-time community sentiment data enables timely adjustments to public services, improving both efficiency and satisfaction (Jiang, 2022). Sentiment analysis provides insights that can guide resource allocation, policy adjustments, and communication strategies, aligning services more closely with community needs. For urban planners, this means designing services that reflect real-time public expectations, potentially reducing dissatisfaction and enhancing community well-being (Robin, 2020). Implementing sentiment analysis as a core tool could foster a more dynamic, responsive approach to public service management.

The study's success in identifying sentiment trends is largely due to the integration of diverse data sources, including text mining and machine learning. This methodological approach allows for comprehensive data analysis, as it captures a broad spectrum of community opinions and ensures accurate sentiment classification (Ryan, 2021). By utilizing social media platforms, the model provides a more holistic view of public sentiment compared to traditional methods. This approach's ability to detect subtle shifts in community opinion underscores the advantage of combining big data with machine learning for public service assessment.

Moving forward, these findings suggest the need for further exploration into the demographic factors that may influence social media sentiment. Different age groups and demographics may express satisfaction or dissatisfaction in unique ways, which could impact the interpretation of sentiment data. Future research could delve into how demographic variations affect sentiment expression, refining the accuracy of community satisfaction mapping. Additionally, incorporating demographic analysis would enable policymakers to understand community needs more precisely, providing targeted solutions that align with specific population groups.

Addressing these advancements in sentiment analysis could enhance the relevance and effectiveness of public services. Demographic considerations would allow for a more nuanced interpretation of data, identifying specific concerns within diverse communities. Implementing these findings on a larger scale would allow cities to transition from static, feedback-based management to dynamic, sentiment-driven governance. Expanding research into demographic factors and refining data analysis models would improve the adaptability and scalability of sentiment analysis in the public sector.

Applying these insights on a broader scale has the potential to revolutionize how cities approach public service management. Establishing sentiment analysis as a standard feedback mechanism could shift public service management toward a model that continuously aligns with community expectations. Further development in this area could lead to cities that are not only data-driven but also community-centered, adapting in real time to the evolving needs and sentiments of their populations.

CONCLUSION

The most significant finding of this study is that sentiment analysis on social media can effectively map community satisfaction in real time, providing insights into public opinion across different service sectors. The data revealed that education and healthcare received the highest positive sentiments, while transportation showed more frequent dissatisfaction, capturing the nuances of community sentiment in response to specific public services. These results demonstrate the potential of sentiment analysis as a tool for assessing public satisfaction continuously, highlighting its value in supporting responsive and adaptive public service management.

The primary contribution of this research lies in its methodological integration of text mining and machine learning for sentiment classification, allowing for a comprehensive analysis of large-scale social media data. By employing these techniques, this study presents a framework that captures real-time sentiment variations, an advancement over traditional methods such as surveys that are limited in scope and frequency. The approach demonstrates that data mining in sentiment analysis can transform how public satisfaction is monitored, providing a scalable model applicable to various sectors within smart cities for more data-driven decision-making.

The study's limitations include the reliance on social media data, which may not represent the views of the entire population, as certain demographics are underrepresented on these platforms. Additionally, the sentiment analysis model may misinterpret nuanced expressions or sarcasm, which could impact accuracy. Further research should explore combining social media sentiment with other data sources, such as surveys or public forums, to provide a more balanced perspective. Expanding this research to include demographic analysis would also offer a clearer understanding of satisfaction trends across diverse population groups, enabling more tailored public service improvements.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; In-vestigation.

Author 3: Data curation; Investigation.

Author 4: Formal analysis; Methodology; Writing - original draft.

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