Sentiment Analysis of Tiktok and Instagram Comments Using a Context-Aware, Multilingual Web Tool

Rosalina Rosalina[1*], Abdurrahman Khairi[2], Filbert Meliala[3], Jason Anthony Wibowo[4], Sarah Kimberly Fischer[5], Williem Williem[6]

[1,2,3,4,5,6] President University, Bekasi, Indonesia

rosalina@president.ac.id

Abstract. This study presents a context-aware sentiment analysis system developed to address the challenges of analyzing user-generated comments on Instagram and TikTok. These platforms are major digital engagement tools in Indonesia, yet their high volume of informal, emoji-rich, and multilingual content makes manual sentiment interpretation impractical. To address this, we developed a web-based application that utilizes Gemini 2.0 Flash, a state-of-the-art natural language model, integrated with FastAPI and ReactJS, to classify sentiments in comments with contextual awareness. The system also incorporates emoji interpretation and supports Bahasa Indonesia and English. Performance evaluation on 2,000 real-world comments showed 87.2% accuracy, surpassing traditional tools such as VADER. This tool enables brands and influencers to make data-driven decisions by exporting sentiment trends in real time. Challenges include slang interpretation, API rate limitations, and short-comment ambiguity. Future enhancements include video transcription and regional dialect support.

Keywords: Sentiment analysis, TikTok, Instagram, Natural Language Processing, Social Media, Gemini 2.0

1 Introduction

Social media has rapidly transformed how people communicate and engage with content, especially in Indonesia, where over 85% of internet users are active on Instagram and 73% on TikTok as of 2024. These platforms now play a vital role in brand communication and public opinion. However, their dynamic, multilingual, and informal nature poses challenges for traditional sentiment analysis tools like VADER, which struggle with slang, emojis, and code-switching. To address this, our study introduces a sentiment analysis system designed for Indonesia's digital landscape. Using a full-stack setup ReactJS for the frontend and FastAPI for the backend the system integrates Apify for comment scraping and leverages Gemini 2.0 Flash, a large language model capable of context-aware sentiment interpretation. This allows the platform to analyze real-time TikTok and Instagram comments accurately, even when they include mixed languages or emojis. This paper contributes in three ways: it presents a prompt-based sentiment

B. H. Putranto et al. (eds.), *Proceedings of the International Conference on Communication and New Media Studies (COMNEWS 2025)*, Advances in Social Science, Education and Humanities Research 1015,
https://doi.org/10.2991/978-2-38476-573-7_2

model tailored for Indonesia, demonstrates the system's ability to handle informal and complex comment patterns, and evaluates real-world usability through user testing and comparative analysis. The proposed study shows how advanced AI can deliver meaningful insights in fast-paced, multilingual social media environments, helping brands and creators better understand and respond to audience sentiment.

2 Litarature Review

2.1 Centiment Analysis in Social Media

Sentiment analysis in social media has gained significant attention due to the vast amount of user-generated content available (L. Mahalakshmi & E. Anbalagan, 2024). It involves categorizing text as positive, negative, or neutral using various techniques, including lexical and machine learning methods (Drus & Khalid, 2019). Challenges in sentiment analysis include dealing with slang, misspellings, and irony in social media. Researchers have employed opinion-lexicon methods, natural language processing, and machine learning algorithms like Naive Bayes and support vector machines (Ahad, 2023). Twitter is a popular platform for sentiment analysis studies. Applications of sentiment analysis span various fields, including business, politics, healthcare, and sociology. It can be used for product profiling (A et al., 2024), trend analysis (Coutinho & Agarwal, 2025), and forecasting (Ishica et al., 2024). The growing interest in sentiment analysis reflects its potential to extract valuable insights from social media data.

2.2 Context –Aware Models.

A recent years, context-aware computing has drawn increasing attention, especially as systems are expected to respond intelligently to their surroundings. (Mohan & Singh, 2013) describe how formal models have been developed to help systems interpret and react based on contextual inputs. Building on this foundation, newer studies have explored how deep learning can incorporate context more effectively. For example, (Unger et al., 2020) demonstrated that when recommendation systems take into account elements like time, location, or social influence, they often outperform more traditional approaches. A study by (Lone et al., 2024) supports this by showing that combining temporal, spatial, and social data can significantly improve both prediction accuracy and overall user experience. These developments are especially relevant for applications that rely heavily on personalization such as sentiment analysis on social media. Understanding a short or ambiguous comment often requires more than just looking at the words; it also involves recognizing the broader context in which the comment was made. To tackle the software challenges of building such systems, (Henricksen & Indulska, 2006) proposed a range of tools and models from context modeling techniques to preference-handling frameworks that help developers design applications that are flexible, adaptive, and responsive to users' environments.

2.3 Multilingual and Emoji Interpretation.

The task of predicting emojis across multiple languages has seen growing interest in recent years. A notable milestone in this area was SemEval-2018 Task 2, which challenged participants to predict emojis from English and Spanish tweets, drawing widespread attention from the research community (Barbieri et al., 2018). Since then, a variety of techniques have been explored, ranging from traditional supervised learning methods to more advanced deep learning architectures (Alexa et al., 2018). Some researchers have also experimented with hybrid approaches, such as integrating word embeddings with bag-of-features models to improve predictive accuracy (Gaël Guibon et al., 2018). More recently, the use of federated learning has emerged as a promising direction for multilingual emoji prediction. (Gamal et al., 2023) demonstrated that this decentralized approach can achieve results on par with centralized models while preserving user privacy and enabling scalable, distributed processing. Their work utilized various sizes of transformer models, including sparsely activated variants, and showed robust performance even in adversarial settings. In fact, the federated learning method outperformed other techniques on the SemEval emoji dataset, underscoring its potential as a privacy-aware solution for emoji prediction across diverse languages and platforms.

2.4 Communication Theory: Algorithmic Mediation and Affective Publics.

Communication theory suggests that emotions on social media are shaped not only by users but also by platform algorithms and governance. TikTok and Instagram actively rank and filter comments, meaning that “visible sentiment” is partially constructed by algorithmic systems rather than reflecting public opinion alone. From the perspective of affective publics, emotions serve as connective practices that drive engagement and community formation through likes, comments, and emojis. Therefore, measuring affect is communicationally significant because it influences how brands, influencers, and platforms interpret audience reactions. By adopting this perspective, this study recognizes that its sentiment tool operates within a broader ecosystem of algorithmic visibility, audience dynamics, and digital culture rather than simply detecting emotions in isolation.

3 Research Method

3.1 System Overview.

The sentiment analysis system developed in this project is a user-friendly, full-stack web application designed for analyzing social media content. The frontend was built with ReactJS to ensure smooth navigation and an intuitive interface, even for non-technical users. On the backend, FastAPI enabled high-speed data processing and seamless integration with external AI models. SQLite was used as the lightweight database to store raw and processed comment data efficiently. For data collection, the team used

Apify to scrape up to 1,000 comments per TikTok or Instagram post. The core sentiment analysis was powered by Gemini 2.0 Flash, a language model capable of understanding nuanced, bilingual, and emoji-laden comments. Users could view analysis results through visual dashboards, track history, and export findings in Excel format. This system makes AI-driven sentiment analysis accessible for marketers, researchers, and content creators seeking insights from Indonesian and English-language social media content.

To enhance sentiment detection, the system incorporates an emoji-to-affect mapping layer. Emojis were categorized into three primary affective groups: positive (e.g., ☺, ❤️, 👍, 😂), negative (e.g., 😟, 😭, 👎), and neutral (e.g., 🤔, 😐). However, many emojis are polysemous (i.e., they carry multiple meanings depending on context). For example, 😂 can indicate genuine amusement, sarcasm, or ridicule. To handle this ambiguity, the system does not classify emojis in isolation but analyzes them together with surrounding text using Gemini 2.0 Flash's contextual reasoning capabilities. In cases where emoji meaning remained ambiguous, the model prioritized textual sentiment over visual cues. This approach allowed the system to achieve an 82% emoji interpretation rate while reducing misclassification caused by standalone emojis or culturally specific usage patterns.

3.2 System Workflow

The system starts when a user inputs a TikTok or Instagram post URL. The backend uses Apify to scrape up to 1,000 comments, which are then analyzed by Gemini 2.0 Flash—a context-aware language model. This enables accurate sentiment classification, even for short, emoji-rich comments. Results are stored in SQLite and visualized on the frontend using ReactJS through charts and detailed tables. Users can also export the data in Excel format for further analysis. Designed to be fast and user-friendly, the system delivers real-time sentiment insights. The full workflow is shown in Figure 1

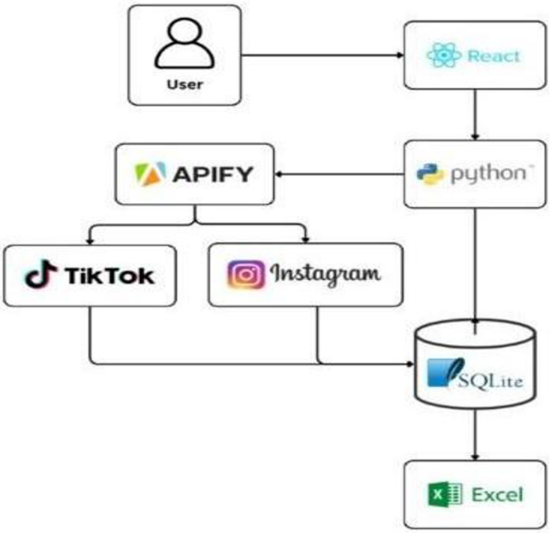

Fig. 1. System Workflow

4 Results and Discussions

4.1 Features Implemented

The system offers advanced features that enhance its effectiveness in analyzing social media comments. One of its key strengths is context-aware sentiment analysis, which interprets comments based on the surrounding content rather than isolated text. This approach allows for more accurate detection of nuances such as sarcasm or implied emotion, for example, distinguishing whether “great job” is genuine praise or sarcasm. The system also supports multilingual analysis, particularly in Bahasa Indonesia and English, addressing the common language mixing seen in Indonesian social media. Additionally, it effectively interprets emojis, achieving over 80% accuracy, which significantly improves analysis of informal, visual communication. To enhance usability, an export feature is included, allowing users to download results in Excel (.xlsx) format for reporting, further analysis, or integration into other tools. These features collectively make the system well-suited for marketers, researchers, and content creators who need quick, reliable insights into audience sentiment across platforms like TikTok and Instagram.

4.2 User Interface Review

To ensure ease of use, the system was designed with a clean and intuitive user interface. Each page within the application serves a specific function in guiding users through the sentiment analysis process like the application begins with a simple authentication interface. This page ensures that access to the system is secure and allows user activity to be tracked and managed effectively. The login page is shown in Figure 2.

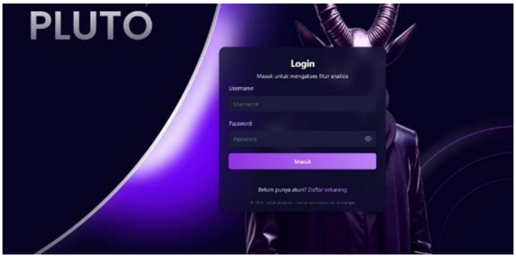

Fig. 2. Login Page

Upon logging in, users are directed to the Home Page, which provides a brief overview of the application and its features. Here, users can begin the sentiment analysis process by submitting the URL of a TikTok or Instagram post. The homepage is shown in Figure 3.

Fig. 3. Home Page

The sentiment analyzer page allows users to paste the URL of the social media post and specify the number of comments they wish to analyze. It serves as the main input point for launching the sentiment analysis task. The sentiment analyzer page is shown in Figure 4.

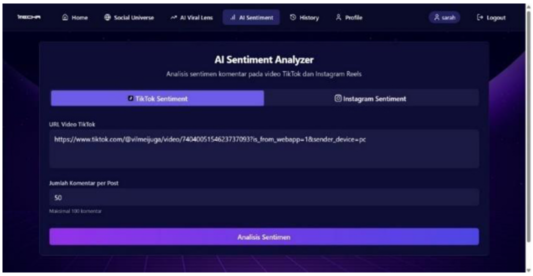

Fig. 4. Home Page

Once the analysis is complete, the results are presented visually. A pie chart displays the distribution of sentiment (positive, neutral, and negative), and additional sections highlight top comments, languages used, and frequently occurring emojis. This provides users with an at-a- glance understanding of audience sentiment. The result page is shown in Figure 5, meanwhile the detail analysis page is shown in Figure 6.

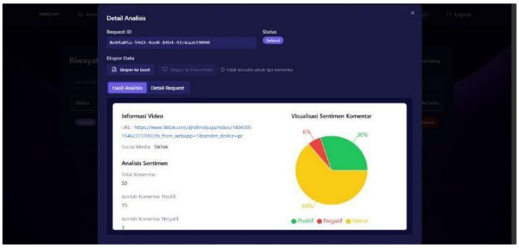

Fig. 5. Result Page

The sentiment classification engine employed in this system is powered by Gemini 2.0 Flash, an advanced large language model designed to process multilingual and informal texts with high contextual sensitivity. During testing on a dataset of 2,000 real-world social media comments collected from various TikTok and Instagram posts the model demonstrated strong performance across multiple evaluation metrics. The system achieved an overall accuracy of 87.2%, meaning the majority of the sentiment predictions matched the human-labeled ground truth.

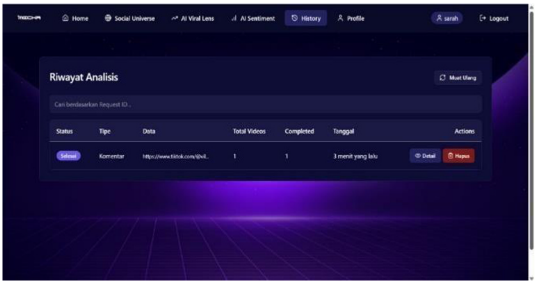

Fig. 6. Detail Analysis Page

The precision for positive sentiment reached 88%, indicating that when the model labeled a comment as positive, it was correct in 88% of cases. Meanwhile, the recall for negative sentiment was 81%, showing the model's ability to successfully detect and label negative comments, even when they were brief or colloquial. To benchmark its performance, Gemini 2.0 Flash was compared against VADER (Valence Aware Dictionary and sEntiment Reasoner), a traditional lexicon-based sentiment analysis tool often used for analyzing social media text. As shown in Table 1, Gemini consistently outperformed VADER in all key metrics.

Table 1. Performance comparison between gemini 2.0 flash and vader.

Matrix	**Performance Comparison**	
	Gemini 2.0 Flash	***Vader***
Accuracy	87.2%	84.5%
Precision (Positive)	88%	81%
Recall (Negative)	81%	74%
Emoji Interpretation Rate	82%	Not Supported
Multilingual Support	Yes (ID & EN)	Limited
Context Awareness	Yes	No

Although the proposed system achieves high accuracy in sentiment classification, its scope is limited to estimating affective valence (positive, neutral, or negative) rather than fully capturing communicative meaning. In platformed publics, sentiment is also shaped by discursive context, social relationships, and algorithmic ranking that influence which comments gain visibility. The system may misclassify sarcasm or playful banter (e.g., "Great job 👍" or "You're terrible 😂"), indicating that its outputs should be interpreted as approximations of affect rather than definitive meanings. Future enhancements could incorporate conversational context, post metadata, and engagement signals to improve interpretation.

A key strength of the system is its real-time processing of multilingual and emoji-rich comments, particularly for Indonesian users who frequently mix Bahasa Indonesia and English. It successfully analyzed large-scale real-world cases such as campaigns by Wardah and posts by Ria Ricis, processing thousands of comments within minutes to support timely marketing decisions.

5 Conclusion

This study resulted in the development of a sentiment analysis tool tailored to Indonesia's fast-paced social media landscape. By integrating Gemini 2.0 Flash, ReactJS, FastAPI, and Apify, we delivered a practical solution for extracting insights from TikTok and Instagram comments. The system demonstrated strong performance, achieving high accuracy and offering useful features for both creators and businesses. Moving forward, we plan to address slang interpretation issues, add video transcription support, and expand language capabilities to include regional dialects. As digital marketing becomes increasingly data-driven, tools like this can help brands and influencers stay competitive

References

1. A, A., N, L., D, P., & Gokilavani. (2024). Predicting the Fake Review to Amazon Product Review Dataset Using Fuzzy Optimized Convolution Neural Network. *2024 International Conference on Expert Clouds and Applications (ICOECA)*, pp. 689–693. https://doi.org/10.1109/icoeca62351.2024.00125
2. Ahad, M. (2023). A REVIEW ARTICLE: USE OF SENTIMENT ANALYSIS IN SOCIAL MEDIA. *International Journal of Engineering Applied Sciences and Technology*, vol. 7, no.9, pp.171–176, https://doi.org/10.33564/ijeast.2023.v07i09.026
3. Alexa, L., Lorent, A., Gifu, D., & Trandabat, D. (2018). The Dabblers at SemEval-2018 Task 2: Multilingual Emoji Prediction. *Proceedings of the 12th International Workshop on Semantic Evaluation*, pp. 405–409. https://doi.org/10.18653/v1/s18-1062
4. Barbieri, F., Camacho-Collados, J., Ronzano, F., Espinosa Anke, L., Ballesteros, M., Basile, V., Patti, V., & Saggion, H. (2018). *SemEval 2018 Task 2: Multilingual Emoji Prediction. Proceedings of the 12th International Workshop on Semantic Evaluation*. https://doi.org/10.18653/v1/s18-1003
5. Coutinho, A., & Agarwal, R. (2025). Cryptocurrency Insight: A Multiplatform Sentiment Analysis Framework for Price Prediction and Trend Identification. *Proceeding of the International Conference on Trends in Electronics and Informatics (ICOEI)*, pp. 897–902. https://doi.org/10.1109/icoei65986.2025.11013419
6. Drus, Z., & Khalid, H. (2019). Sentiment Analysis in Social Media and Its Application: Systematic Literature Review. *Procedia Computer Science*, vol. 161, no. 1, pp. 707–714.https://doi.org/10.1016/j.procs.2019.11.174

7. Gaël Guibon, Ochs, M., & Bellot, P. (2018). LIS at SemEval-2018 Task 2: Mixing Word Embeddings and Bag of Features for Multilingual Emoji Prediction. *HAL (Le Centre Pour La Communication Scientifique Directe)*, pp. 502–506. https://doi.org/10.18653/v1/s18-1081
8. Gamal, K., Gaber, A., & Amer, H. (2023, July 6). Federated Learning Based Multilingual Emoji Prediction In Clean and Attack Scenarios. *ArXiv.org*.https://doi.org/10.48550/arXiv.2304.01005
9. Henricksen, K., & Indulska, J. (2006). Developing context-aware pervasive computing applications: *Models and approach. Pervasive and Mobile Computing*, vol. 2, no.1, pp.37–64, https://doi.org/10.1016/j.pmcj.2005.07.003
10. Ishica, Jha, S. K., Ujala, Sneha, Suraj, & Chaudhary, R. (2024). Utilizing Sentiment Analysis and Machine Learning to Forecast Stock Price Changes from Financial News. *Proceeding of International Conference on Data, Computation and Communication (ICDCC)*, pp. 634–639. https://doi.org/10.1109/icdcc62744.2024.10961794
11. L. Mahalakshmi, & E. Anbalagan. (2024). National Language Processing For Sentiment Analysis in Social Media-A Comprehensive Review. *Proceeding of International Conference on Circuit Power and Computing Technologies (ICCPCT)*, pp. 504–508. https://doi.org/10.1109/iccpct61902.2024.10672661
12. Lone, A., Kumar, A., & Rasool, M. (2024). Context-Aware Recommender Systems: Exploring the Role of Time, Location, and Social Influence in Personalized Recommendations. *International Journal of Advanced Research in Science Communication and Technology*, pp. 221–230. https://doi.org/10.48175/ijarsct-22039
13. Mohan, P., & Singh, M. (2013). Formal Models for Context Aware Computing. *International Journal of Computer Applications Technology and Research*, vol. 2, no. 1, pp. 53–58, https://doi.org/10.7753/ijcatr0201.1011
14. Unger, M., Tuzhilin, A., & Livne, A. (2020). Context-Aware Recommendations Based on Deep Learning Frameworks. ACM Transactions on Management Information Systems, vol. 11, no.2, pp.1–15, https://doi.org/10.1145/3386243