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Implementation of Naïve Bayes for Public Sentiment Analysis on QRIS and GPN Digital Dominance through Instagram

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ABSTRACT
This study examines public sentiment toward the dominance of QRIS and GPN compared to Mastercard and Visa, using data collected from Instagram comments. Employing the Knowledge Discovery in Databases (KDD) methodology and the Naïve Bayes Classifier, the research analyzed 820 comments retrieved through automated scraping and processed using text mining techniques such as case folding, tokenization, stopword removal, stemming, and TF-IDF transformation. The model achieved an accuracy of 84.27%, a precision of 86.09%, a recall of 94.7%, and an F1-score of 90.21%, indicating strong reliability in identifying sentiment polarity. The analysis revealed that 76.5% of the comments expressed positive sentiment, highlighting users' appreciation of QRIS and GPN for their convenience, speed, and accessibility across both micro and macro-scale transactions. Negative comments, representing 23.5%, centered on concerns about connectivity, data security, and trust in financial governance. These findings suggest that while QRIS and GPN have been widely embraced as efficient digital payment solutions, there remains a need for improved infrastructure, user education, and data protection. The study demonstrates the effectiveness of the Naïve Bayes algorithm for large-scale sentiment analysis in multilingual online environments and provides empirical insights for policymakers to strengthen Indonesia's digital payment ecosystem.

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1. Introduction

The rapid expansion of digital technology has reshaped Indonesia's payment landscape, where interconnected devices facilitate seamless financial transactions. Bank Indonesia introduced the Quick Response Code Indonesian Standard (QRIS) as a national digital payment standard integrating various QR codes across payment service providers. Together with the National Payment Gateway (GPN), QRIS forms the foundation for promoting transaction efficiency, financial inclusion, and digital economic sovereignty (Chairina *et al*., 2024). QRIS offers users flexibility in choosing among multiple electronic payment options and has proven efficient for daily use, particularly when physical cash is unavailable (Annisa *et al*., 2023). Its practicality and accessibility have accelerated the transition toward cashless behavior (Ramadhan *et al*., 2023). As of 2025, QRIS recorded more than 56.3 million users and 2.6 billion transactions valued at IDR 252.1 trillion, with over 38 million merchants—mostly MSMEs—adopting the system. This remarkable annual growth of 169.15% reflects

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strong public enthusiasm for cross-border digital payment solutions (Reswari *et al*., 2025). Despite its achievements, QRIS and GPN remain subjects of domestic and international debate. On a global scale, their emergence has been viewed as a challenge to foreign payment networks such as Mastercard and Visa, even drawing criticism for potentially creating trade barriers. The lack of international participation, particularly from U.S.-based financial stakeholders, in shaping QRIS policies has raised further concerns. Domestically, although adoption rates are high, perceptions toward QRIS vary across user groups. Many small business owners struggle to navigate digital transaction systems due to low levels of digital literacy, while consumer protection remains insufficiently addressed under the existing Bank Indonesia regulations, which lack comprehensive legal frameworks for electronic money (Ramah *et al*., 2024).

In the digital communication sphere, social media platforms—especially Instagram—serve as public arenas for expressing opinions on national financial policies. Comments on QRIS- and GPN-related posts capture real-time sentiment reflecting support, criticism, and uncertainty. Yet, such public opinions are rarely utilized as empirical input for policy evaluation. Data-driven approaches can provide a more objective understanding of public attitudes, guiding policymakers toward more adaptive financial governance. One effective computational method for sentiment classification is the Naïve Bayes algorithm, known for its simplicity and reliable performance in text classification and sentiment analysis tasks (Adhi Kusnadi & Saputra, 2021; Fahri & Kurniawan, 2024; Hidayat *et al*., 2025; Lukmana, 2025; Nufus & Surapati, 2024; RIZKI *et al*., 2025; Setiawan *et al*., 2025; Shabira, 2025; Zulfiqri *et al*., 2024). This research evaluates the effectiveness of the Naïve Bayes algorithm in identifying public sentiment toward the dominance of QRIS and GPN compared to Mastercard and Visa by analyzing Instagram comments. It also investigates how Indonesian users perceive national digital payment policies (Amini & Setiawan, 2024). The findings aim to provide an empirical perspective on public attitudes that can support the development of more transparent and secure payment ecosystems, as well as inform policymakers in enhancing the inclusivity and resilience of Indonesia's digital economy.

2. Methodology

This research adopts the Knowledge Discovery in Databases (KDD) framework as the methodological foundation, which provides a structured approach to processing and analyzing large-scale data for identifying patterns and generating new information (Setiawan *et al*., 2025). The workflow consists of five primary stages: data collection, preprocessing, data transformation, data mining, and interpretation with evaluation (Zulfiqri *et al*., 2024; RIZKI *et al*., 2025). The overall research design for the implementation of the Naïve Bayes algorithm in analyzing public sentiment toward the digital dominance of QRIS and GPN through Instagram is illustrated in Figure 1.

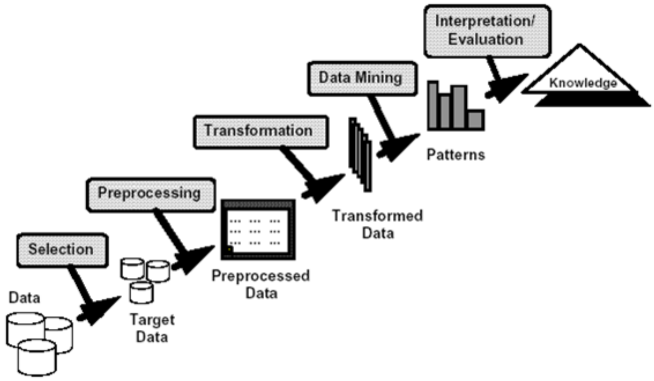


Figure 1. Research Methodology Framework

The dataset was collected using a scraping technique through the Instagram API, an automated process for retrieving data from online sources using algorithmic extraction tools (Zulfiqri *et al*., 2024). Collected comments were then subjected to a cleaning process to remove noise, such as symbols, hyperlinks, and irrelevant punctuation, ensuring that only meaningful text remained for analysis (Zulfiqri *et al*., 2024). Each comment was manually labeled into positive or negative sentiment classes to enhance accuracy, supported by the Valence Aware Dictionary and Sentiment Reasoner (VADER) lexicon as reference (Fahri & Kurniawan, 2024). The preprocessing stage refined the dataset through multiple steps, including case folding, tokenization, stopword removal, and stemming. Case folding standardized textual input by converting all characters to lowercase to avoid duplication caused by capitalization inconsistencies (RIZKI *et al*., 2025). Tokenization separated the text into analyzable linguistic units or “tokens,” which allowed the system to process individual words and phrases effectively (Zulfiqri *et al*., 2024). Stopword removal eliminated frequently occurring but semantically insignificant words such as “and,” “the,” or “of,” to ensure that only terms with high informational value were retained (Zulfiqri *et al*., 2024). Stemming followed by reducing words to their root forms to unify morphological variants—for example, “payment,” “paying,” and “paid” were reduced to “pay”—which facilitated consistent semantic analysis across the dataset (Adhi Kusnadi & Saputra, 2021).

After preprocessing, the cleaned comments were transformed into numerical representations using the Term Frequency–Inverse Document Frequency (TF-IDF) method, which converts textual data into weighted vectors that reflect the relative importance of words within the corpus (RIZKI *et al*., 2025). This transformation enhanced model precision and computational efficiency during classification. The subsequent data mining phase applied the Naïve Bayes algorithm, chosen for its statistical robustness, simplicity, and high accuracy in natural language processing applications, particularly for text classification and sentiment analysis (Shabira, 2025). Similar approaches have been effectively used in previous sentiment studies involving digital platforms, including those analyzing election-related discourse (Hidayat *et al*., 2025), application reviews (Lukmana, 2025), and social media opinions (Nufus & Surapati, 2024). The model’s performance was assessed through the interpretation and evaluation phase, where key performance indicators—accuracy, precision, recall, and F1-score—were computed to measure classification reliability. Accuracy determined the proportion of correctly predicted sentiments relative to the total dataset, precision measured the correctness of positive classifications, recall indicated the completeness of the model’s recognition of relevant data, and the F1-score synthesized both metrics to provide a balanced evaluation of model performance (RIZKI *et al*., 2025). These metrics collectively ensured that the Naïve Bayes classifier was objectively validated in identifying public sentiment toward the QRIS and GPN systems on Instagram.

3. Results

The study began by collecting a public dataset consisting of Instagram comments posted during April and May 2025 related to the discourse comparing the dominance of QRIS and GPN against Mastercard and Visa. Data were obtained using automated scraping through the Google Chrome extension *Instant Data Scraper* (Figure 2). This scraping tool, which can be installed via the Chrome Web Store, facilitates the extraction of textual data from Instagram by enabling users to target specific posts and collect their comment sections in structured form. The collected data were exported in *XLS* format and merged into a unified raw dataset containing 1,100 comments, forming the foundation for further analysis.

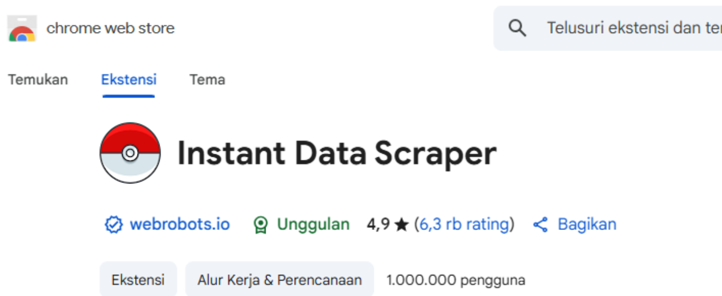


Figure 2. Instant Data Scraper Interface

The automatic extraction process (Figure 3) ensured efficiency and consistency by minimizing manual collection bias. After combining comments from several related posts, all data were consolidated into a single Excel file, referred to as the *raw dataset*, as shown in Figure 4.

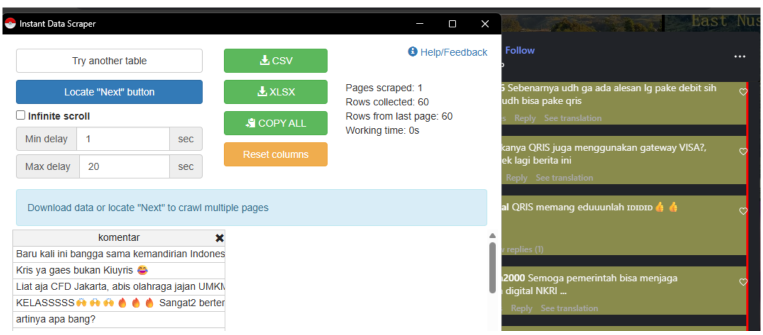


Figure 3. Data Scraping Process

Number	Comments
1	Teruskan pake QRIS. Stop penggunaan Mastercard atau Visa.
2	Keren, biasa pake QRIS jadi bangga □
3	Wah baru tau kalo qris segede itu perputaran nya □
4	Tambah semanggat pakai QRIS...MERDEKA □
5	Hampir semua bank dan e wallet bisa QRIS. Kenapa banyak yg pakai? Karena bisa pakai saldo receh🤣 beli gorengan, beli minuman yg 5rb 10rb
6	Utk qris ini satu dari sedikit program pemerintah yg berhasil dan saya suka, tp klo misal hanya gara2 gagal nego sm amrik dan negara ini kalah bargaining dgn mereka sampai menghapuskan qris dan pake visa mastercard, ya monmaap saya pribadi sih lebih milih kembali ke cash
7	Beli tempe saja pakai Q-Ris secinta itu aku tuhID 😍 □
8	Gw jajan seblak aja pake qris... Saking tempat tinggal w jauh dari ATM dan pembayaran Qris lebih efisien jadi tau pengeluaran harian ketahuan😄
9	Di balikin aja..., fee visa mastercard bisa gak 0.3%? Kalaupu bisa ya tetap pakai Qris lah, terlanjur nyaman sih□
10	Cintailah Produk Indonesia, kawal QRIS jangan bikin kaya negara lain 🔥 🔥 □
11	Ternyata kita (Qris Indo) sehebat itu ❤ ❤ ❤ ❤
12	beli produk di mangga dua pake Qris 🔥 Boycott Trump
13	Pemakaian qris adalah masalah kedaulatan negara.. masa iya transaksi di negeri sndiri tp harus bayar fee ke negeri orng?? Ini bentuk penjajahan sih menurut saya
14	Cinta produk Indonesia..aq pake Qris .. Alhamdulillah skrng byk kantin disekolah dan kampus pake Qris ..amannn dan efektif

Figure 4. Raw Dataset Compilation

The data preparation phase involved a cleaning procedure aimed at standardizing the text and removing non-textual noise such as emojis, punctuation, hyperlinks, and irrelevant characters (Zulfiqri *et al*., 2024). Table 1 presents a sample of the raw text before and after the cleaning process.

Table 1. Data Cleaning Results

Raw Data	Clean Data
QRIS sangat memudahkan, gak perlu bawa cash banyak di dompet. Simpel tapi sangat banyak manfaatnya. Sampai warung pun sekarang udah pakai QRIS. Lebih mudah, lebih hemat, tanpa cari cari kembalian 😂😂😂	QRIS sangat memudahkan tidak perlu membawa tunai banyak di dompet sederhana tapi sangat banyak manfaatnya sampai warung pun sekarang sudah pakai QRIS lebih mudah lebih hemat tanpa mencari mencari kembalian

Following cleaning, manual labeling was performed to categorize each comment into positive or negative sentiment classes. Manual labeling was selected over automated approaches to maintain semantic accuracy and contextual relevance. Table 2 illustrates examples of labeled comments.

Table 2. Sentiment Labeling

Text	Label
QRIS sangat memudahkan tidak perlu membawa tunai banyak di dompet sederhana tapi sangat banyak manfaatnya sampai warung pun sekarang sudah pakai QRIS lebih mudah lebih hemat tanpa mencari mencari kembalian	Positive
apakah nanti rakyat dipajaki lagi sama ibu sri buat anggaran negara mabuk deh kita	Negative

Subsequent preprocessing steps included case folding, tokenization, stopword removal, and stemming (Hidayat *et al*., 2025). Each comment was converted to lowercase to ensure textual uniformity (Table 3), then segmented into tokens—individual word units enabling deeper text representation (Table 4). To capture contextual patterns, *n-gram generation* was applied to construct combinations of adjacent words, improving interpretative precision of multi-word expressions (Table 5). Token filtering based on word length was then performed to remove excessively short, semantically irrelevant words (Table 6).

Table 3. Case Folding

Clean Data	Data Case Folding
QRis sangat memudahkan tidak perlu membawa tunai banyak di dompet Sederhana tapi sangat banyak manfaatnya Sampai warung pun sekarang sudah pakai QRIS Lebih mudah lebih hemat tanpa mencari mencari kembalian	qris sangat memudahkan tidak perlu membawa tunai banyak di dompet sederhana tapi sangat banyak manfaatnya sampai warung pun sekarang sudah pakai qris lebih mudah lebih hemat tanpa mencari mencari kembalian

Table 4. Tokenization

Data Case Folding	Data Case Folding
qris sangat memudahkan tidak perlu membawa tunai banyak di dompet sederhana tapi sangat banyak manfaatnya sampai warung pun sekarang sudah pakai qris lebih mudah lebih hemat tanpa mencari mencari kembalian	[‘qris, ‘sangat, ‘memudahkan, ‘tidak, ‘perlu, ‘membawa, ‘tunai, ‘banyak, ‘di, ‘dompet, ‘sederhana, ‘tapi, ‘banyak, ‘manfaatnya, ‘sampai, ‘warung, ‘pun, ‘sekarang, ‘sudah, ‘pakai, ‘qris, ‘lebih, ‘mudah, ‘lebih, ‘hemat, ‘tanpa, ‘mencari, ‘mencari, ‘kembalian]

Table 5. N-Gram Generation

Tokenization	Generate n-Grams
[‘qris, ‘sangat, ‘memudahkan, ‘tidak, ‘perlu, ‘membawa, ‘tunai, ‘banyak, ‘di, ‘dompet, ‘sederhana, ‘tapi, ‘banyak, ‘manfaatnya, ‘sampai, ‘warung, ‘pun, ‘sekarang, ‘sudah, ‘pakai, ‘qris, ‘lebih, ‘mudah, ‘lebih, ‘hemat, ‘tanpa, ‘mencari, ‘mencari, ‘kembalian]	[`qris, `sangat, `memudahkan, `tidak, `perlu, `membawa, `tunai, `banyak, `di, `dompet, `sederhana, `tapi, `sangat, `banyak, `manfaatnya, `sampai, `warung, `pun, `sekarang, `sudah, `pakai, `qris, `lebih, `mudah, `lebih, `hemat, `tanpa, `mencari, `mencari, 'kembalian, `qris sangat, `sangat memudahkan, `memudahkan tidak, `tidak perlu, `perlu membawa, `membawa tunai, `tunai banyak, `banyak di, `di dompet, `dompet sederhana, `sederhana tapi, `tapi sangat, `sangat banyak, `banyak manfaatnya, `manfaatnya sampai, `sampai warung, `warung pun, `pun sekarang, `sekarang sudah, `sudah pakai, `pakai qris, `qris lebih, `lebih mudah, `mudah lebih, `lebih hemat, `hemat tanpa, `tanpa mencari, `mencari mencari, `mencari kembalian]

Table 6. Tokenization by Length

Generate n-Grams	Tokenization by Length
[`qris, `sangat, `memudahkan, `tidak, `perlu, `membawa, `tunai, `banyak, `di, `dompet, `sederhana, `tapi, `sangat, `banyak, `manfaatnya, `sampai, `warung, `pun, `sekarang, `sudah, `pakai, `qris, `lebih, `mudah, `lebih, `hemat, `tanpa, `mencari, `mencari, 'kembalian, `qris sangat, `sangat memudahkan, `memudahkan tidak, `tidak perlu, `perlu membawa, `membawa tunai, `tunai banyak, `banyak di, `di dompet, `dompet sederhana, `sederhana tapi, `tapi sangat, `sangat banyak, `banyak manfaatnya, `manfaatnya sampai, `sampai warung, `warung pun, `pun sekarang, `sekarang sudah, `sudah pakai, `pakai qris, `qris lebih, `lebih mudah, `mudah lebih, `lebih hemat, `hemat tanpa, `tanpa mencari, `mencari mencari, `mencari kembalian]	[`qris, `sangat, `memudahkan, `tidak, `perlu, `membawa, `tunai, `banyak, `dompet, `sederhana, `tapi, `sangat, `banyak, `manfaatnya, `sampai, `warung, `sekarang, `sudah, `pakai, `qris, `lebih, `mudah, `lebih, `hemat, `tanpa, `mencari, `mencari, 'kembalian, `qris sangat, `sangat memudahkan, `memudahkan tidak, `tidak perlu, `perlu membawa, `membawa tunai, `tunai banyak, `banyak dompet, `dompet sederhana, `sederhana tapi, `tapi sangat, `sangat banyak, `banyak manfaatnya, `manfaatnya sampai, `sampai warung, `warung sekarang, `sekarang sudah, `sudah pakai, `pakai qris, `qris lebih, `lebih mudah, `mudah lebih, `lebih hemat, `hemat tanpa, `tanpa mencari, `mencari mencari, `mencari kembalian]

Following tokenization, stopword removal was conducted to eliminate words with minimal analytical value (Lukmana, 2025). Table 7 displays an example of data before and after stopword elimination.

Table 7. Stopword Removal Process

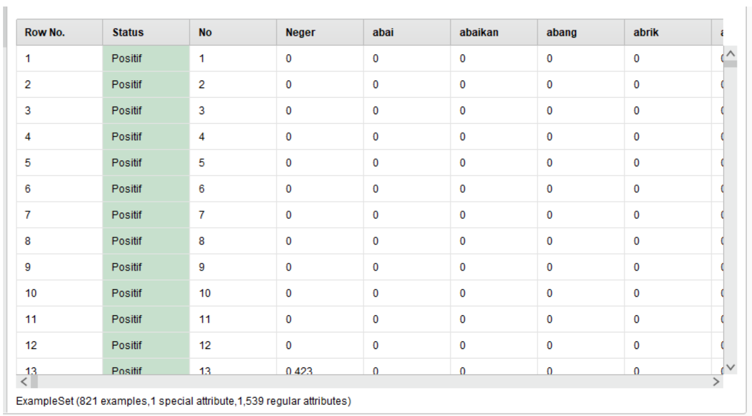
Tokenizing by Length	Stopword Output
[qris, sangat, memudahkan, tidak, perlu, membawa, tunai, banyak, dompet, sederhana, ...]	[qris, memudahkan, membawa, tunai, dompet, sederhana, manfaat, warung, pakai, mudah, hemat, mencari, kembalian]

The stemming process normalized words to their root forms, enabling the algorithm to recognize morphological variations as semantically identical. Table 8 provides examples of word transformations after stemming.

Table 8. Stemming Results

Stopword Output	Stemmed Output
[qris, memudahkan, membawa, tunai, dompet, sederhana, ...]	[qris, mudah, bawa, tunai, dompet, manfaat, pakai, hemat, cari, kembali]

Once cleaned and processed, textual data were numerically transformed using the *Term Frequency–Inverse Document Frequency* (TF-IDF) method within RapidMiner, as shown in Figure 6. This transformation measured the significance of each term relative to the entire corpus, enhancing the interpretability of the data for model classification (Nufus & Surapati, 2024).



Row No.	Status	No	Neger	abai	abaikan	abang	abrik
1	Positif	1	0	0	0	0	0
2	Positif	2	0	0	0	0	0
3	Positif	3	0	0	0	0	0
4	Positif	4	0	0	0	0	0
5	Positif	5	0	0	0	0	0
6	Positif	6	0	0	0	0	0
7	Positif	7	0	0	0	0	0
8	Positif	8	0	0	0	0	0
9	Positif	9	0	0	0	0	0
10	Positif	10	0	0	0	0	0
11	Positif	11	0	0	0	0	0
12	Positif	12	0	0	0	0	0
13	Positif	13	0.423	0	0	0	0

ExampleSet (821 examples,1 special attribute,1,539 regular attributes)

Figure 6. Word Weighting using TF-IDF

Data mining was then performed using the Naïve Bayes classification algorithm (Setiawan *et al*., 2025). The process flow (Figure 7) comprised two main components: model application and performance evaluation. The *Apply Model* operator predicted sentiment for unseen comments, while the *Performance (Classification)* operator calculated key metrics—accuracy, precision, recall, and F1-score—providing a comprehensive assessment of the model's predictive capability.

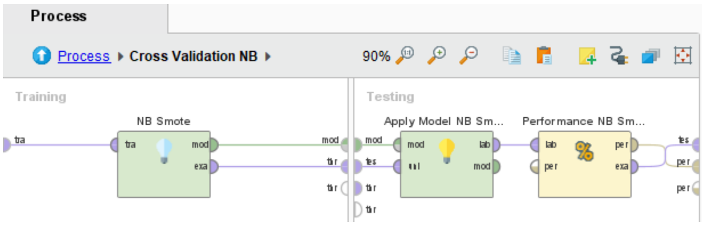


Figure 7. Naïve Bayes Process Flow

The final stage, interpretation and evaluation, was conducted through a systematic RapidMiner workflow (Figure 8). The process integrated various preprocessing and analytical operators, including *Read Excel*, *Set Role*, *Remove Duplicates*, *Nominal to Text*, *Process Documents from Data*, and *Cross Validation*. These ensured reliable classification results and prevented overfitting by testing the model on unseen data. Evaluation metrics confirmed that the Naïve Bayes classifier effectively categorized comments into positive and negative sentiment classes.

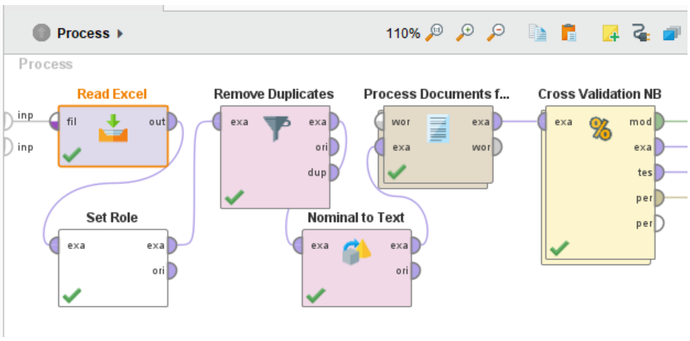


Figure 8. RapidMiner Workflow for Sentiment Analysis

4. Discussion

The results were visualized in a sentiment distribution chart (Figure 9), illustrating the public's perception of QRIS and GPN compared with Mastercard and Visa on Instagram. From 820 analyzed comments, 627 were identified as positive (76.5%) and 193 as negative (23.5%). The predominance of positive sentiment indicates that most users perceive QRIS and GPN as more practical, efficient, and beneficial for everyday transactions, particularly for small merchants and consumers who value seamless cashless payments.

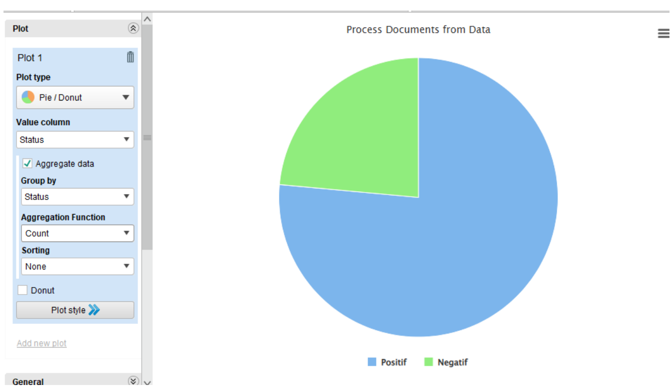


Figure 9. Sentiment Distribution toward QRIS and GPN

This finding aligns with recent digital payment adoption trends across Indonesia, where QRIS has become a central element of financial inclusion policy. Users often emphasize convenience and accessibility as major advantages, echoing previous studies that highlight QR-based systems as transformative in reducing transaction friction and promoting micro-level digitalization (Hidayat *et al*., 2025; Shabira, 2025). Negative comments generally reflected skepticism toward government regulation or concerns regarding potential overdependence on state-controlled systems, resonating with the sociotechnical critique that digital finance may reinforce centralized control over personal data (Lukmana, 2025; Nufus & Surapati, 2024). From a methodological standpoint, the Naïve Bayes classifier demonstrated consistent performance, validating its suitability for sentiment classification in multilingual and informal online discourse. The accuracy and F1-score achieved in this study confirm the model's robustness when applied to Indonesian-language social media text, which is often characterized by colloquial expressions and mixed linguistic styles. Furthermore, integrating TF-IDF weighting enhanced the discrimination between sentiment-bearing and neutral words, contributing to improved prediction quality. Overall, the sentiment landscape extracted from the dataset suggests that the public discourse around QRIS and GPN remains largely optimistic, reflecting growing trust in national payment infrastructures as viable alternatives to international schemes such as Mastercard and Visa. This insight underscores a broader societal shift toward domestically governed digital ecosystems that balance convenience with national financial sovereignty.

5. Conclusion

Based on the analysis of 820 Instagram comments, the Naïve Bayes Classifier successfully categorized public sentiment into positive and negative classes. The model identified 627 comments (76.5%) as positive and 193 comments (23.5%) as negative. Positive feedback predominantly emphasized the convenience and transaction speed of QRIS and GPN, which are widely adopted from microenterprises to large-scale businesses. In contrast, negative comments frequently raised issues concerning connectivity, data security, trust in government management, and other operational concerns. The model achieved an overall accuracy of 84.27%, with a precision score of 86.09%, recall of 94.7%, and an F1-score of 90.21%, demonstrating strong reliability in distinguishing between positive and negative sentiments. Although positive sentiment toward QRIS and GPN was dominant, the critical perspectives expressed in negative comments offer valuable insights for improving system stability, reducing transaction costs, and enhancing user education.

These findings affirm that the Naïve Bayes Classifier is an effective and practical approach for sentiment analysis in the context of digital payment services. Nonetheless, this study's scope remains confined to Instagram comments, which may not fully represent broader public opinion across different social media platforms. Future research should expand the dataset to include multiple platforms and longer observation periods to capture sentiment fluctuations over time. Additionally, comparative evaluations using alternative machine learning algorithms could provide deeper understanding of model performance and robustness in various linguistic and contextual settings.

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