DOI: 10.14421/ijid.2025.5073 IJID (International Journal on Informatics for Development), *e-ISSN: 2549-7448*
Vol. 14, No. 2, December 2025, Pp. 640-658

Sentiment Analysis on Shopee Xpress Delivery Time Reviews Using Support Vector Machine and Logistic Regression

Sewin Fathurrohman
Department of Information Systems
Universitas Gunadarma
Depok, Indonesia
sewin.fathur@gmail.com

Irfan Ricky Afandi
Department of Informatics Engineering
Universitas Muhammadiyah Prof. Dr. Hamka
Jakarta, Indonesia
richky99@gmail.com

Irma Wahyuningtyas
Department of Mathematics Education
Universitas Muhammadiyah Prof. Dr. Hamka
Jakarta, Indonesia
3melatiputih@gmail.com

Azis Styo Nugroho
Department of Automation Engineering Technology
Universitas Negeri Jakarta
Jakarta, Indonesia
fled0211@gmail.com

Firman Noor Hasan
Department of Informatics Engineering
Universitas Muhammadiyah Prof. Dr. Hamka
Jakarta, Indonesia
firman.noorhasan@uhamka.ac.id

Article History
Received March 12th, 2025
Revised May 17th, 2025
Accepted May 21st, 2025
Published January 2026

***Abstract*—This study examines user sentiment towards Shopee Xpress delivery times using machine learning techniques. We collected 497 reviews from platforms like X and the Google Play Store, leveraging the valuable feedback despite its unstructured and informal nature. After labelling 398 reviews for model training and reserving 99 for sentiment prediction, we implemented two classification algorithms: Support Vector Machine (SVM) and Logistic Regression. These models categorised sentiments into negative, neutral, and positive classes. Despite class imbalance in the training data, SVM outperformed Logistic Regression with an accuracy of 93%, demonstrating a more balanced performance across sentiment categories compared to Logistic Regression's 90% accuracy. Both models showed consistent sentiment prediction on new data. Our findings highlight the potential of sentiment analysis as a valuable tool for Shopee Xpress to understand customer perceptions and improve delivery experiences. By providing actionable insights, this study can inform logistics improvements and enhance customer satisfaction. Future research could benefit from collaborating with Shopee to access internal data and integrating additional data sources for more comprehensive insights, ultimately driving business growth and customer loyalty. This study contributes to the growing body of research on sentiment analysis in logistics and e-commerce.**

***Keywords*—classification algorithms; customer satisfaction; machine learning; sentiment prediction; user sentiment**

1 INTRODUCTION

The growth of e-commerce in Indonesia has accelerated significantly in recent years, driven by the widespread adoption of digital technologies and shifts in consumer shopping behaviour [1]. With increasing competition among e-commerce platforms, logistics performance, particularly the speed and reliability of delivery, has become a key determinant of customer satisfaction and loyalty [2]. As a result, companies continue to innovate to meet user expectations by providing faster and more efficient delivery services [3].

Shopee, one of Indonesia's most prominent e-commerce platforms, has adopted a strategic approach to delivery by establishing its own logistics service: Shopee Xpress (SPX) [4]. This in-house logistics network is designed to enhance operational control and accelerate delivery times, improving the overall customer experience [5]. SPX plays a vital role in ensuring that products are delivered on time, essential for maintaining customer trust and platform competitiveness.

In the digital economy, user-generated reviews on app marketplaces or social media have become an important source of insight into customer satisfaction [6]. Customers often use platforms like the Google Play Store and X (formerly Twitter) to express their opinions about delivery speed, courier behaviour, and overall satisfaction [7]. However, these reviews are typically written in unstructured, informal language, making them difficult to analyse using conventional methods [8]. For logistics providers like Shopee Xpress, analysing such feedback, particularly sentiments related to delivery time, is essential for identifying areas for service improvement and gaining a competitive advantage [9].

One effective approach for analysing unstructured textual data is sentiment analysis, which uses natural language processing (NLP) and machine learning techniques to classify user opinions into sentiment categories such as positive, negative, or neutral [10]. In logistics, sentiment analysis enables companies to track delivery-related complaints or satisfaction trends and translate them into actionable insights for business improvement [11].

Despite the growing interest in sentiment analysis, relatively few studies have focused on evaluating user sentiment related to delivery time. Many existing works assess general service satisfaction without isolating the delivery experience as a separate dimension. Customer reviews often contain sentiments directed toward specific aspects, such as delivery punctuality or courier service, which are critical components of logistics performance but are frequently overlooked in generalised sentiment models.

Previous studies have applied machine learning models such as the Support Vector Machine (SVM) and Logistic Regression to classify sentiments in various domains. For instance, SVM has been used to analyse customer feedback on the MyPertamina application, achieving 85.31% classification accuracy between positive and negative sentiments [12]. Another study employed Logistic Regression to evaluate user reviews of online transportation services, yielding 85% accuracy across three sentiment categories [13]. However, these studies did not specifically examine delivery time sentiments, nor did they utilise multiple data sources for a broader sentiment perspective.

This research adopts both SVM and Logistic Regression as classification models due to their complementary strengths in sentiment analysis tasks. SVM is well-suited for handling high-dimensional and sparse textual data by constructing an optimal separating hyperplane in a transformed feature space [14]. This makes SVM particularly effective for managing noisy user reviews, such as those concerning delivery delays or courier experiences [15]. Nevertheless, SVM can be sensitive to redundant features and may become computationally expensive for large datasets [16]. In contrast, Logistic Regression provides a more interpretable and probabilistic approach, especially with techniques like TF-IDF for feature extraction [17]. Its simplicity allows for efficient sentiment classification even in smaller datasets; however, it may underperform in high-dimensional scenarios without proper regularisation [18]. By leveraging both models, this study aims to conduct a comparative evaluation of their effectiveness in identifying delivery-related sentiments within Shopee Xpress reviews.

The novelty of this research lies in its focused analysis of sentiment toward delivery time, an important but often underexplored dimension in logistics-related sentiment studies. In addition, this study combines data from two distinct platforms, Google Play Store and X, enabling the extraction of structured and spontaneous user feedback. By comparing the performance of two well-established machine learning algorithms, this research identifies the most effective approach for analysing delivery-related sentiment. The findings are expected to provide actionable insights for Shopee Xpress and other logistics service providers to optimise delivery performance and enhance customer satisfaction through data-driven strategies.

2 METHOD

This section provides an overview of the methodology applied in this study. The research used Google Colab and Python as the primary computational tools. Google Colab was chosen due to its accessibility, support for cloud-based GPU acceleration, and compatibility with a wide range of data mining libraries [19]. These features allow efficient data processing and model training without requiring extensive local computational resources [20].

The methodology employed in this study follows a structured workflow to ensure the robustness and reproducibility of sentiment analysis. As illustrated in Fig. 1, the research process contains several key stages. Each stage plays a crucial role in ensuring the accuracy and reliability of the sentiment classification results.

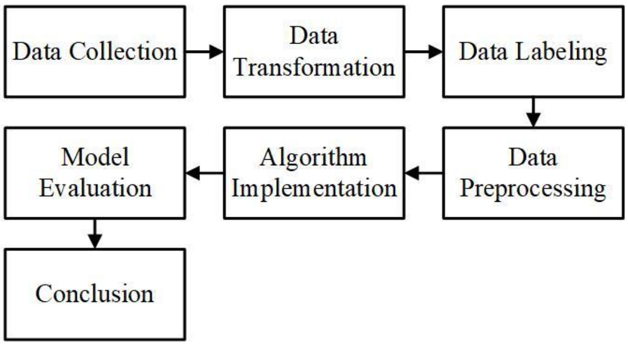

Figure 1. Workflow diagram of the research

The research methodology follows a structured workflow, as illustrated in Fig. 1, which consists of seven main stages:

1. ***Data Collection:*** Customer reviews related to Shopee Xpress were gathered from X and the Google Play Store using web scraping techniques.
2. ***Data Transformation:*** The collected datasets were pre-processed for consistency, including attribute selection and format standardisation.
3. ***Data Labelling:*** The researcher assigned sentiment annotations (positive, negative, neutral) to a subset of the dataset.
4. ***Data Pre-processing:*** Several text pre-processing techniques, such as cleansing, case folding, normalisation, tokenisation, stopword removal, and stemming, were applied to refine the textual data.
5. ***Algorithm Implementation:*** The dataset was transformed into numerical representations using TF-IDF before being processed by machine learning models, namely Support Vector Machine (SVM) and Logistic Regression.
6. ***Model Evaluation:*** The classification performance was assessed using standard evaluation metrics, including accuracy, precision, recall, and F1-score, based on the confusion matrix.
7. ***Conclusion:*** The final analysis interpreted the sentiment distribution and evaluated the model's effectiveness in classifying customer sentiments regarding delivery time from Shopee Xpress.

The following sections provide a comprehensive explanation of each step.

2.1 Data Collection

This research utilises customer reviews from X and the Google Play Store as the primary data sources. The collected reviews specifically mention Shopee Xpress, enabling an in-depth sentiment analysis of customer perceptions of the logistics service, particularly regarding delivery time performance.

2.1.1 *The Search Keywords and Time Frame:* The keywords “Shopee Xpress” and “SPX” were used as search queries to retrieve relevant data. The data collection period spanned from January 1, 2024, to March 31, 2025, capturing a broad range of recent customer opinions.

2.1.2 *Data Acquisition Method:* The data was extracted using web scraping techniques, leveraging the API services provided by both platforms. The scraping process involved retrieving publicly available customer reviews based on predefined search criteria. To maintain data integrity and avoid redundancy, duplicate entries were removed after extraction.

2.1.3 *Dataset Overview:* The final dataset contains 3383 reviews with 621 records from X and 2762 records from the Google Play Store, each containing multiple attributes. X Dataset had attributes include conversation_id_str, created_at, favorite_count, full_text, id_str, image_url, in_reply_to_screen_name, lang, location, quote_count, reply_count, retweet_count, tweet_url, user_id_str, and username. The Google Play Store Dataset had attributes that include reviewId, userName, userImage, content, score, thumbsUpCount, reviewCreatedVersionAt, replyContent, repliedAt, and appVersion.

After collecting data from X and the Google Play Store, the datasets were standardised and merged into a single unified dataset for comprehensive analysis. Since each dataset had different structures and attributes, a transformation process was applied before merging. This involved selecting only the relevant attribute, specifically the review text and the date the review was created, while discarding unnecessary fields. This step ensured the merged dataset maintains a consistent format, making it suitable for further joint processing.

Despite the structural alignment, the two platforms still exhibit notable differences in content characteristics. X limits the number of characters in each post and often includes elements such as mentions, hashtags, and URLs. In contrast, reviews on the Google Play Store are typically longer, unrestricted in length, and may include emojis. A data cleansing stage was applied to harmonise content from both platforms and ensure that only relevant and structured textual data was analysed. Furthermore, data from X frequently contains spam, irony, or sarcasm, which poses challenges for traditional sentiment analysis algorithms like SVM and Logistic Regression; Google Play Store reviews may also be irrelevant, such as those discussing the application itself rather than logistics services. To address these issues, manual filtering was implemented during the labelling stage to ensure that only reviews pertinent to the research topic were included. This filtering process aims to produce a dataset that accurately reflects customer assessments of delivery timeliness by the Shopee Xpress logistics service, thereby enabling more effective and context-specific model training.

2.2 Data Transformation

The X and Google Play Store datasets possess distinct attribute structures, necessitating a transformation process to ensure uniformity and compatibility. This transformation involves attribute selection, data normalisation, and dataset integration to facilitate a coherent sentiment analysis.

2.2.1 Attribute Selection and Standardisation: Given the differences in attribute naming and structure, the following adjustments were applied:

- ***X dataset:*** The selection of attributes used in this research was “created_at” and “full_text”. The “created_at” attribute was originally in a timestamp format and converted into a “date” field. Meanwhile, the “full_text” attribute was extracted and renamed as “review” to align with the dataset from the Google Play Store.

- ***Google Play Store dataset:*** The selection of attributes used in this research was “at” and “content”. The “at” attribute, representing the timestamp of each review, was transformed into a “date” field. Similarly, the “content” attribute was renamed as “review”.

2.2.2 Date Format Normalisation: To maintain consistency in representing temporal data, all dates from X and Google Play Store datasets were standardised to the YYYY-MM-DD format. This normalisation ensures that reviews from both platforms are temporally aligned, enabling chronological sorting and trend analysis.

2.2.3 Dataset Integration and Sorting: After transforming and standardising the attributes, the X and Google Play Store datasets were merged into a single structured dataset. The consolidated dataset was sorted in descending order, with the most recent reviews appearing first. The final dataset consisted of 3383 reviews, ensuring a comprehensive and temporally organised corpus for sentiment analysis.

The transformation process ensures consistency across datasets and facilitates seamless pre-processing for subsequent sentiment analysis [21]. A subset of the transformed dataset is presented in Table 1, illustrating the standardised format after the transformation process.

2.3 Data Labelling

The labelling process was carried out manually by a team of five researchers to ensure that the sentiment classification was done thoroughly and systematically. Each review was categorised into one of the three sentiment classes: positive, negative, or neutral.

Table 1. Sample Transformed Dataset

Date	Review
2024-01-21	Admin @ShopeeCare paket yang saya pesan dengan pengiriman via spx super lama ama lambat ga nyampe pesanan katanya membutuhkan waktu lebih lama kayanya abis ini pesanan tiba2 ilang deh, aduhh. #Kecewa #Lambat
2024-06-16	Sekedar saran buat Shopee, tolong untuk pengiriman SPX (Khusus wilayah Papua) untuk diperhatikan kembali, perlu di perhitungkan dengan baik estimasi waktu pengirimannya, agar tidak melewati batas waktu pengiriman dan akhirnya barang tidak terkirim ke pembeli. Sy perhatikan makin kesini sudah membaik untuk masalah Ongkir, sudah mulai murah, namun harus ditingkatkan kembali terkait jasa pengirimannya 🙏🙏.
2024-10-20	Experience saya Shopee adalah aplikasi terbaik dalam berbelanja, saya lebih suka toko yg mengunakan jasa kirim SPX Express dan saya hanya belanja ditoko yg mengunakan expedisi SPX pengiriman nya mantul selalu tepat waktu kurir nya juga gercep lah buat SPX ★★★★★
2024-12-01	Aplikasi shopie sangat membantu sekali selama ini, masukan saja untuk jasa pengiriman SPX perlu perbaikan dan disiplin waktu jangan sampai barang yang sudah sampai area di kembalikan ke toko.
2025-04-01	pengiriman shopee express berkali kali ga pernah tepat waktu pasti dibawa sma kurirnya dulu. smpe pernah 1 minggu sma sekali ga sampe akhirnya di cancel pake spx 😭 😡
2025-03-28	@ShopeeXpres @ShopeeID semakin kesini semakin bagus pelayanan dn semakin memudahkan buat belanja di shopee,, pengiriman selalu on time dn lebih cepat dgn SPX. pokoknya puas banget belanja lewat shopee. terbaiklah apalagi bnyk discount makin murah #ShopeeXpress #Rekomendasi 👍

2.3.1 Pre-labelling Review Selection: Before the labelling stage, the team filtered the reviews to include only those that explicitly mentioned delivery times by SPX. To identify these, researchers looked for reviews containing keywords like "waktu" (time), "pengiriman" (delivery), and "SPX". Reviews considered spam, overly sarcastic, ironic, or completely unrelated, such as those commenting on the Shopee app, and others were excluded from the dataset. This filtering step narrowed the data to reviews that were relevant to delivery-related sentiment, enabling the labelling process to focus on pertinent content.

2.3.2 Classification and Resolution: Given the subjective nature of sentiment analysis, discrepancies in label assignment among researchers were inevitable [22]. In cases of disagreement, two resolution strategies were employed. The first resolution involves a discussion to reach a mutual agreement on the most suitable sentiment label. The second resolution is majority voting, wherein the sentiment label agreed upon by at least three out of five researchers was assigned as the final label. This approach ensures the reliability and consistency of the labelled dataset, reducing potential biases in the classification process.

2.3.3 Dataset Splitting for Model Training and Testing: After going through the screening process, out of a total of 3383 reviews collected, only 497 reviews specifically discussed the delivery time of the SPX service. These reviews were then selected for use in the next stage of analysis. The dataset was randomly split into training and testing subsets to facilitate machine learning model development. The dataset was split into two parts: 80% (398 reviews) was manually labelled by researchers and used for training to enable the model to learn patterns effectively, while the remaining 20% (99 reviews) was reserved as unlabeled test data to objectively evaluate model performance. This 80:20 split was chosen to balance model generalisation and reliable performance assessment [23], ensuring that the model does not overfit the training data while being adequately tested on unseen samples [24].

The labelled dataset serves as the foundation for training and evaluating machine learning models, ensuring the robustness and validity of the sentiment classification process [25]. A sample of the labelled data is presented in Table 2, showcasing the sentiment classification assigned by the researchers.

Table 2. Sample of Labelled Data

Date	Review	Label
2024-01-21	Admin @ShopeeCare paket yang saya pesan dengan pengiriman via spx super lama ama lambat ga nyampe pesanan katanya membutuhkan waktu lebih lama kayanya abis ini pesanan tiba2 ilang deh, aduhh. #Kecewa #Lambat	negative
2024-06-16	Sekedar saran buat Shopee, tolong untuk pengiriman SPX (Khusus wilayah Papua) untuk diperhatikan kembali, perlu di perhitungkan dengan baik estimasi waktu pengirimannya, agar tidak melewati batas waktu pengiriman dan akhirnya barang tidak terkirim ke pembeli. Sy perhatikan makin kesini sudah membaik untuk masalah Ongkir, sudah mulai murah, namun harus ditingkatkan kembali terkait jasa pengirimannya 🙏🏻🙏🏻.	neutral
2024-10-20	Experience saya Shopee adalah aplikasi terbaik dalam berbelanja, saya lebih suka toko yg mengunakan jasa kirim SPX Express dan saya hanya belanja ditoko yg mengunakan expedisi SPX pengiriman nya mantul selalu tepat waktu kurir nya juga gercep lah buat SPX ★★★★★	positive
2024-12-01	Aplikasi shopie sangat membantu sekali selama ini, masukan saja untuk jasa pengiriman SPX perlu perbaikan dan disiplin waktu jangan sampai barang yang sudah sampai area di kembalikan ke toko.	neutral
2025-04-01	pengiriman shopee express berkali kali ga pernah tepat waktu pasti dibawa sma kurirnya dulu. smpe pernah 1 minggu sma sekali ga sampe akhirnya di cancel pake spx 😭 😡	negative
2025-03-28	@ShopeeXpres @ShopeeID semakin kesini semakin bagus pelayanan dn semakin memudahkan buat belanja di shopee,, pengiriman selalu on time dn lebih cepat dgn SPX. pokoknya puas banget belanja lewat shopee. terbaiklah apalagi bnyk discount makin murah #ShopeeXpress #Rekomendasi 👍	positive

2.4 *Data Pre-processing*

Data pre-processing is a crucial step in text-based machine learning tasks [26], particularly in sentiment analysis, as it enhances data quality and ensures that the input text is well-structured for algorithmic processing [27]. Raw textual data often contains inconsistencies, noise, and unnecessary elements that can negatively impact the performance of classification models [28]. Therefore, pre-processing is essential to improve text uniformity, reduce dimensionality, and optimise feature extraction [29]. This study applied a series of pre-processing steps to refine the dataset before implementing machine learning algorithms. The following steps were conducted: cleansing, case folding, normalisation, stopword removal, and stemming. Each pre-processing technique plays a vital role in refining the dataset for sentiment analysis.

2.4.1 *Cleansing:* It is a fundamental pre-processing step in text mining that removes irrelevant or unnecessary elements from raw textual data. This process is essential in sentiment analysis, as unstructured data often contains noise that can negatively affect model performance [30]. This study draws on data collected from two platforms with notably different content characteristics: X and the Google Play Store. A character limit constrains posts on X and often includes non-textual elements such as user mentions (e.g., "@ShopeeXpress"), hashtags (e.g., "#Kecewa"), URLs, and emojis. The language used is typically informal and concise, reflecting quick, real-time reactions. In contrast, reviews on the Google Play Store tend to be longer and more detailed, with no character restrictions. These reviews are usually more structured, descriptive, and narrative in nature, as users often share their experiences in greater depth. Given these differences, pre-processing the data posed particular challenges. To address this, a thorough data cleansing process was applied to ensure consistency across both sources. This involved removing elements such as mentions, hashtags, and hyperlinks, which are more common on X. Additionally, non-alphabetic characters like emojis and special symbols frequently found in both platforms were also excluded to minimise noise and enhance the clarity of the textual data for further analysis. Table 3 presents an example of the dataset before and after the cleansing process.

Table 3. Sample of Data After the Cleansing Process

Before	After
Admin @ShopeeCare Paket yang saya pesan dengan pengiriman via spx super lama ama lambat ga nyampe pesanan katanya membutuhkan waktu lebih lama kayanya abis ini pesanan tiba2 ilang deh, aduhh. #Kecewa #Lambat	Admin paket yang saya pesan dengan pengiriman via spx super lama ama lambat ga nyampe pesanan katanya membutuhkan waktu lebih lama kayanya abis ini pesanan tiba ilang deh aduhh

Before	After
Sekedar saran buat Shopee, tolong untuk pengiriman SPX (Khusus wilayah Papua) untuk diperhatikan kembali, perlu di perhitungkan dengan baik estimasi waktu pengirimannya, agar tidak melewati batas waktu pengiriman dan akhirnya barang tidak terkirim ke pembeli. Sy perhatikan makin kesini sudah membaik untuk masalah Ongkir, sudah mulai murah, namun harus ditingkatkan kembali terkait jasa pengirimannya 🙏🏻🙏🏻.	Sekedar saran buat Shopee tolong untuk pengiriman SPX Khusus wilayah Papua untuk diperhatikan kembali perlu di perhitungkan dengan baik estimasi waktu pengirimannya agar tidak melewati batas waktu pengiriman dan akhirnya barang tidak terkirim ke pembeli Sy perhatikan makin kesini sudah membaik untuk masalah Ongkir sudah mulai murah namun harus ditingkatkan kembali terkait jasa pengirimannya
Experience saya Shopee adalah aplikasi terbaik dalam berbelanja, saya lebih suka toko yg mengunakan jasa kirim SPX Express dan saya hanya belanja ditoko yg mengunakan expedisi SPX pengiriman nya mantul selalu tepat waktu kurir nya juga gercep lah buat SPX ★★★★★	Experience saya Shopee adalah aplikasi terbaik dalam berbelanja saya lebih suka toko yg mengunakan jasa kirim SPX Express dan saya hanya belanja ditoko yg mengunakan expedisi SPX pengiriman nya mantul selalu tepat waktu kurir nya juga gercep lah buat SPX
Aplikasi shopie sangat membantu sekali selama ini, masukan saja untuk jasa pengiriman SPX perlu perbaikan dan disiplin waktu jangan sampai barang yang sudah sampai area di kembalikan ke toko.	Aplikasi shopie sangat membantu sekali selama ini masukan saja untuk jasa pengiriman SPX perlu perbaikan dan disiplin waktu jangan sampai barang yang sudah sampai area di kembalikan ke toko
pengiriman shopee express berkali kali ga pernah tepat waktu pasti dibawa sma kurirnya dulu. smpe pernah 1 minggu sma sekali ga sampe akhirnya di cancel pake spx 😭😡	pengiriman shopee express berkali kali ga pernah tepat waktu pasti dibawa sma kurirnya dulu smpe pernah minggu sma sekali ga sampe akhirnya di cancel pake spx
@ShopeeXpres @ShopeeID semakin kesini semakin bagus pelayanan dn semakin memudahkan buat belanja di shopee,, pengiriman selalu on time dn lebih cepat dgn SPX. pokoknya puas banget belanja lewat shopee. terbaiklah apalagi bnyk discount makin murah #ShopeeXpress #Rekomendasi 👍	semakin kesini semakin bagus pelayanan dn semakin memudahkan buat belanja di shopee pengiriman selalu on time dn lebih cepat dgn SPX pokoknya puas banget belanja lewat shopee terbaiklah apalagi bnyk discount makin murah

2.4.2 *Case folding:* It is a text pre-processing technique that involves converting all characters in a text to lowercase [31]. This process standardises textual data by eliminating variations in letter casing, ensuring that words with different capitalisations (e.g., "Shopee" and "shopee") are treated as identical. The primary objective of case folding is to minimise lexical discrepancies that may arise due to inconsistencies in capitalisation. Without this step, machine learning models may incorrectly treat words with different letter cases as distinct entities, potentially leading to suboptimal feature extraction and model performance. Table 4 provides examples of text before and after the case-folding process.

Table 4. Sample of Data After the Case Folding Process

Before	After
Admin paket yang saya pesan dengan pengiriman via spx super lama ama lambat ga nyampe pesanan katanya membutuhkan waktu lebih lama kayanya abis ini pesanan tiba ilang deh aduhh	admin paket yang saya pesan dengan pengiriman via spx super lama ama lambat ga nyampe pesanan katanya membutuhkan waktu lebih lama kayanya abis ini pesanan tiba ilang deh aduhh
Sekedar saran buat Shopee tolong untuk pengiriman SPX Khusus wilayah Papua untuk diperhatikan kembali perlu di perhitungkan dengan baik estimasi waktu pengirimannya agar tidak melewati batas waktu pengiriman dan akhirnya barang tidak terkirim ke pembeli Sy perhatikan makin kesini sudah membaik untuk masalah Ongkir sudah mulai murah namun harus ditingkatkan kembali terkait jasa pengirimannya	sekedar saran buat shopee tolong untuk pengiriman spx khusus wilayah papua untuk diperhatikan kembali perlu di perhitungkan dengan baik estimasi waktu pengirimannya agar tidak melewati batas waktu pengiriman dan akhirnya barang tidak terkirim ke pembeli sy perhatikan makin kesini sudah membaik untuk masalah ongkir sudah mulai murah namun harus ditingkatkan kembali terkait jasa pengirimannya
Experience saya Shopee adalah aplikasi terbaik dalam berbelanja saya lebih suka toko yg mengunakan jasa kirim SPX Express dan saya hanya belanja ditoko yg mengunakan expedisi SPX pengiriman nya mantul selalu tepat waktu kurir nya juga gercep lah buat SPX	experience saya shopee adalah aplikasi terbaik dalam berbelanja saya lebih suka toko yg mengunakan jasa kirim spx express dan saya hanya belanja ditoko yg mengunakan expedisi spx pengiriman nya mantul selalu tepat waktu kurir nya juga gercep lah buat spx
Aplikasi shopie sangat membantu sekali selama ini masukan saja untuk jasa pengiriman SPX perlu perbaikan dan disiplin waktu jangan sampai barang yang sudah sampai area di kembalikan ke toko	aplikasi shopie sangat membantu sekali selama ini masukan saja untuk jasa pengiriman spx perlu perbaikan dan disiplin waktu jangan sampai barang yang sudah sampai area di kembalikan ke toko
pengiriman shopee express berkali kali ga pernah tepat waktu pasti dibawa sma kurirnya dulu smpe pernah minggu sma sekali ga sampe akhirnya di cancel pake spx	pengiriman shopee express berkali kali ga pernah tepat waktu pasti dibawa sma kurirnya dulu smpe pernah minggu sma sekali ga sampe akhirnya di cancel pake spx
semakin kesini semakin bagus pelayanan dn semakin memudahkan buat belanja di shopee pengiriman selalu on time dn lebih cepat dgn SPX pokoknya puas banget belanja lewat shopee terbaiklah apalagi bnyk discount makin murah	semakin kesini semakin bagus pelayanan dn semakin memudahkan buat belanja di shopee pengiriman selalu on time dn lebih cepat dgn spx pokoknya puas banget belanja lewat shopee terbaiklah apalagi bnyk discount makin murah

2.4.3 *Normalisation:* It is a text pre-processing technique aimed at standardising words by converting non-standard or informal terms into their proper forms [32]. Normalisation involved several transformations, including the correction of typographical errors such as converting "shopie" to "shopee" and the standardisation of informal terms, where words such as "gak" and "nggak" were mapped to their formal equivalent "tidak." Then unification of synonymous terms such as "ShopeeXpress" and "SPX" was standardised to a single representation to prevent inconsistencies in analysis. In addition, any non-standard or informal words, including those not in proper Indonesian, were converted into their standard forms. For example, the English word "discount" was normalised to the Indonesian equivalent "diskon." Standard abbreviations such as "ongkir" will also be expanded to their complete forms, such as "ongkos kirim." Informal slang terms, including expressions like "mantul," were likewise replaced with more appropriate standard words, such as "bagus." By ensuring that different variations of the same word are unified, the model can focus on analysing sentiment patterns rather than being influenced by lexical inconsistencies. Table 5 illustrates examples of text before and after the normalisation process.

2.4.4 *Tokenising:* is the process of breaking a text sequence into smaller units called tokens, which can be words, phrases, or subwords [33]. Tokenisation plays a vital role in natural language processing (NLP) tasks; it allows the model to analyse text at the word level, improving its ability to detect patterns and relationships within the data. In this research, tokenisation was applied to the normalised text, where each sentence was split into its constituent words based on whitespace and punctuation rules. Table 6 presents examples of data before and after the tokenisation process.

Table 5. Sample of Data After the Normalisation Process

Before	After
admin paket yang saya pesan dengan pengiriman via spx super lama ama lambat ga nyampe pesanan katanya membutuhkan waktu lebih lama kayanya abis ini pesanan tiba ilang deh aduhh	admin paket yang saya pesan dengan pengiriman melalui spx sangat lama dan lambat tidak sampai pesanan katanya membutuhkan waktu lebih lama sepertinya setelah ini pesanan tiba tiba hilang deh aduh
sekedar saran buat shopee tolong untuk pengiriman spx khusus wilayah papua untuk diperhatikan kembali perlu di perhitungkan dengan baik estimasi waktu pengirimannya agar tidak melewati batas waktu pengiriman dan akhirnya barang tidak terkirim ke pembeli sy perhatikan makin kesini sudah membaik untuk masalah ongkir sudah mulai murah namun harus ditingkatkan kembali terkait jasa pengirimannya	sekadar saran untuk shopee tolong pengiriman spx khusus wilayah papua agar diperhatikan kembali perlu dipertimbangkan dengan baik estimasi waktu pengirimannya supaya tidak melewati batas waktu dan akhirnya barang tidak terkirim kepada pembeli saya perhatikan semakin ke sini sudah membaik untuk masalah ongkos kirim sudah mulai murah namun tetap perlu ditingkatkan terkait jasa pengirimannya
experience saya shopee adalah aplikasi terbaik dalam berbelanja saya lebih suka toko yg mengunakan jasa kirim spx express dan saya hanya belanja ditoko yg mengunakan expedisi spx pengiriman nya mantul selalu tepat waktu kurir nya juga gercep lah buat spx	pengalaman saya shopee adalah aplikasi terbaik untuk berbelanja saya lebih suka toko yang menggunakan jasa kirim spx express dan saya hanya berbelanja di toko yang menggunakan ekspedisi spx pengirimannya bagus selalu tepat waktu kurirnya juga cepat untuk spx
aplikasi shopie sangat membantu sekali selama ini masukan saja untuk jasa pengiriman spx perlu perbaikan dan disiplin waktu jangan sampai barang yang sudah sampai area di kembalikan ke toko	aplikasi shopee sangat membantu selama ini masukan saja untuk jasa pengiriman spx perlu perbaikan dan kedisiplinan waktu jangan sampai barang yang sudah sampai di area dikembalikan ke toko
pengiriman shopee express berkali kali ga pernah tepat waktu pasti dibawa sma kurirnya dulu smpe pernah minggu sma sekali ga sampe akhirnya di cancel pake spx	pengiriman spx berkali kali tidak pernah tepat waktu pasti dibawa oleh kurirnya dulu sampai pernah satu minggu sama sekali tidak sampai akhirnya dibatalkan menggunakan spx
semakin kesini semakin bagus pelayanan dn semakin memudahkan buat belanja di shopee pengiriman selalu on time dn lebih cepat dgn spx pokoknya puas banget belanja lewat shopee terbaiklah apalagi bnyk discount makin murah	semakin ke sini semakin baik pelayanannya dan semakin memudahkan untuk berbelanja di shopee pengiriman selalu tepat waktu dan lebih cepat dengan spx pokoknya sangat puas berbelanja di shopee terbaik apalagi banyak diskon semakin murah

Table 6. Sample of Data After the Tokenising Process

Before	After
admin paket yang saya pesan dengan pengiriman melalui spx sangat lama dan lambat tidak sampai pesanan katanya membutuhkan waktu lebih lama sepertinya setelah ini pesanan tiba tiba hilang deh aduh	['admin', 'paket', 'yang', 'saya', 'pesan', 'dengan', 'pengiriman', 'melalui', 'spx', 'sangat', 'lama', 'dan', 'lambat', 'tidak', 'sampai', 'pesanan', 'katanya', 'membutuhkan', 'waktu', 'lebih', 'lama', 'sepertinya', 'setelah', 'ini', 'pesanan', 'tiba', 'tiba', 'hilang', 'deh', 'aduh']
sekadar saran untuk shopee tolong pengiriman spx khusus wilayah papua agar diperhatikan kembali perlu dipertimbangkan dengan baik estimasi waktu pengirimannya supaya tidak melewati batas waktu dan akhirnya barang tidak terkirim kepada pembeli saya perhatikan semakin ke sini sudah membaik untuk masalah ongkos kirim sudah mulai murah namun tetap perlu ditingkatkan terkait jasa pengirimannya	['sekadar', 'saran', 'untuk', 'shopee', 'tolong', 'pengiriman', 'spx', 'khusus', 'wilayah', 'papua', 'agar', 'diperhatikan', 'kembali', 'perlu', 'dipertimbangkan', 'dengan', 'baik', 'estimasi', 'waktu', 'pengirimannya', 'supaya', 'tidak', 'melewati', 'batas', 'waktu', 'dan', 'akhirnya', 'barang', 'tidak', 'terkirim', 'kepada', 'pembeli', 'saya', 'perhatikan', 'semakin', 'ke', 'sini', 'sudah', 'membaik', 'untuk', 'masalah', 'ongkos', 'kirim', 'sudah', 'mulai', 'murah', 'namun', 'tetap', 'perlu', 'ditingkatkan', 'terkait', 'jasa', 'pengirimannya']
pengalaman saya shopee adalah aplikasi terbaik untuk berbelanja saya lebih suka toko yang menggunakan jasa kirim spx express dan saya hanya berbelanja di toko yang menggunakan ekspedisi spx pengirimannya bagus selalu tepat waktu kurirnya juga cepat untuk spx	['pengalaman', 'saya', 'shopee', 'adalah', 'aplikasi', 'terbaik', 'untuk', 'berbelanja', 'saya', 'lebih', 'suka', 'toko', 'yang', 'menggunakan', 'jasa', 'kirim', 'spx', 'express', 'dan', 'saya', 'hanya', 'berbelanja', 'di', 'toko', 'yang', 'menggunakan', 'ekspedisi', 'spx', 'pengirimannya', 'bagus', 'selalu', 'tepat', 'waktu', 'kurirnya', 'juga', 'cepat', 'untuk', 'spx']
aplikasi shopee sangat membantu selama ini masukan saja untuk jasa pengiriman spx perlu perbaikan dan kedisiplinan waktu jangan sampai barang yang sudah sampai di area dikembalikan ke toko	['aplikasi', 'shopee', 'sangat', 'membantu', 'selama', 'ini', 'masukan', 'saja', 'untuk', 'jasa', 'pengiriman', 'spx', 'perlu', 'perbaikan', 'dan', 'kedisiplinan', 'waktu', 'jangan', 'sampai', 'barang', 'yang', 'sudah', 'sampai', 'di', 'area', 'dikembalikan', 'ke', 'toko']
pengiriman spx berkali kali tidak pernah tepat waktu pasti dibawa oleh kurirnya dulu sampai pernah satu minggu sama sekali tidak sampai akhirnya dibatalkan menggunakan spx	['pengiriman', 'spx', 'berkali', 'kali', 'tidak', 'pernah', 'tepat', 'waktu', 'pasti', 'dibawa', 'oleh', 'kurirnya', 'dulu', 'sampai', 'pernah', 'satu', 'minggu', 'sama', 'sekali', 'tidak', 'sampai', 'akhirnya', 'dibatalkan', 'menggunakan', 'spx']
semakin ke sini semakin baik pelayanannya dan semakin memudahkan untuk berbelanja di shopee pengiriman selalu tepat waktu dan lebih cepat dengan spx pokoknya sangat puas berbelanja di shopee terbaik apalagi banyak diskon semakin murah	['semakin', 'ke', 'sini', 'semakin', 'baik', 'pelayanannya', 'dan', 'semakin', 'memudahkan', 'untuk', 'berbelanja', 'di', 'shopee', 'pengiriman', 'selalu', 'tepat', 'waktu', 'dan', 'lebih', 'cepat', 'dengan', 'spx', 'pokoknya', 'sangat', 'puas', 'berbelanja', 'di', 'shopee', 'terbaik', 'apalagi', 'banyak', 'diskon', 'semakin', 'murah']

2.4.5 *Stopword Removal:* It is the process of eliminating common words that do not contribute significantly to the sentiment or meaning of a text [34]. These words, known as stopwords, typically include conjunctions, prepositions, pronouns, and other high-frequency words such as "dan," "di," “ke,” "saya," and "juga." By eliminating these words, sentiment analysis models can concentrate on the most relevant features, thereby enhancing the accuracy of classification. In this research, stopword removal was performed using the Natural Language Toolkit (NLTK) and the Sastrawi library in Python.

The stopword list used was based on predefined Indonesian stopwords, supplemented by custom stopwords relevant to this research. Table 7 provides examples of data before and after the stopword removal process.

2.4.6 *Stemming:* It is the process of reducing words to their root or base form by removing affixes such as prefixes, suffixes, infixes, or confixes [35]. This technique is essential in natural language processing (NLP) to standardise words with similar meanings, ensuring that variations of a word are treated as a single entity. For instance, words like "memudahkan," "berbelanja," and "terbaik" would be transformed into their base forms: "mudah," "belanja," and "baik," respectively. In this research, stemming was conducted using the Sastrawi library in Python, which is specifically designed for stemming the Indonesian language. Sastrawi implements the Nazief-Adriani algorithm, a widely used stemming algorithm for the Bahasa Indonesia. In addition to using the Nazief-Adriani algorithm for the stemming process, researchers also integrated text normalisation techniques to overcome the algorithm's limitations in handling English words, regional languages, slang, and forms such as synonyms, acronyms, and hyponyms. In this stage, researchers compiled a normalisation dictionary containing a collection of non-standard words, slang, and mixed languages found in the dataset. These words were then converted into a more common and easy-to-process standard form. This process also included mapping words that had similar meanings into consistent representations, thereby strengthening the quality of the sentiment analysis performed. Table 8 presents examples of text data before and after the stemming process.

Table 7. Sample of Data After the Stopword Removal Process

Before	After
['admin', 'paket', 'yang', 'saya', 'pesan', 'dengan', 'pengiriman', 'melalui', 'spx', 'sangat', 'lama', 'dan', 'lambat', 'tidak', 'sampai', 'pesanan', 'katanya', 'membutuhkan', 'waktu', 'lebih', 'lama', 'sepertinya', 'setelah', 'ini', 'pesanan', 'tiba', 'tiba', 'hilang', 'deh', 'aduh']	['paket', 'pesan', 'pengiriman', 'spx', 'lama', 'lambat', 'tidak', 'sampai', 'pesanan', 'katanya', 'membutuhkan', 'waktu', 'lama', 'sepertinya', 'pesanan', 'tiba', 'hilang']
['sekadar', 'saran', 'untuk', 'shopee', 'tolong', 'pengiriman', 'spx', 'khusus', 'wilayah', 'papua', 'agar', 'diperhatikan', 'kembali', 'perlu', 'dipertimbangkan', 'dengan', 'baik', 'estimasi', 'waktu', 'pengirimannya', 'supaya', 'tidak', 'melewati', 'batas', 'waktu', 'dan', 'akhirnya', 'barang', 'tidak', 'terkirim', 'kepada', 'pembeli', 'saya', 'perhatikan', 'semakin', 'ke', 'sini', 'sudah', 'membaik', 'untuk', 'masalah', 'ongkos', 'kirim', 'sudah', 'mulai', 'murah', 'namun', 'tetap', 'perlu', 'ditingkatkan', 'terkait', 'jasa', 'pengirimannya']	['saran', 'shopee', 'pengiriman', 'spx', 'khusus', 'wilayah', 'papua', 'diperhatikan', 'dipertimbangkan', 'estimasi', 'waktu', 'pengiriman', 'melewati', 'batas', 'waktu', 'barang', 'tidak', 'terkirim', 'pembeli', 'perhatikan', 'membaik', 'masalah', 'ongkos', 'kirim', 'murah', 'ditingkatkan', 'jasa', 'pengiriman']
['pengalaman', 'saya', 'shopee', 'adalah', 'aplikasi', 'terbaik', 'untuk', 'berbelanja', 'saya', 'lebih', 'suka', 'toko', 'yang', 'menggunakan', 'jasa', 'kirim', 'spx', 'express', 'dan', 'saya', 'hanya', 'berbelanja', 'di', 'toko', 'yang', 'menggunakan', 'ekspedisi', 'spx', 'pengirimannya', 'bagus', 'selalu', 'tepat', 'waktu', 'kurirnya', 'juga', 'cepat', 'untuk', 'spx']	['pengalaman', 'shopee', 'aplikasi', 'terbaik', 'berbelanja', 'suka', 'toko', 'menggunakan', 'jasa', 'kirim', 'spx', 'express', 'berbelanja', 'toko', 'menggunakan', 'ekspedisi', 'spx', 'pengiriman', 'bagus', 'tepat', 'waktu', 'kurir', 'cepat', 'spx']
['aplikasi', 'shopee', 'sangat', 'membantu', 'selama', 'ini', 'masukan', 'saja', 'untuk', 'jasa', 'pengiriman', 'spx', 'perlu', 'perbaikan', 'dan', 'kedisiplinan', 'waktu', 'jangan', 'sampai', 'barang', 'yang', 'sudah', 'sampai', 'di', 'area', 'dikembalikan', 'ke', 'toko']	['aplikasi', 'shopee', 'membantu', 'masukan', 'jasa', 'pengiriman', 'spx', 'perbaikan', 'kedisiplinan', 'waktu', 'barang', 'sampai', 'area', 'dikembalikan', 'toko']
['pengiriman', 'spx', 'berkali', 'kali', 'tidak', 'pernah', 'tepat', 'waktu', 'pasti', 'dibawa', 'oleh', 'kurirnya', 'dulu', 'sampai', 'pernah', 'satu', 'minggu', 'sama', 'sekali', 'tidak', 'sampai', 'akhirnya', 'dibatalkan', 'menggunakan', 'spx']	['pengiriman', 'spx', 'berkali', 'kali', 'tidak', 'tepat', 'waktu', 'dibawa', 'kurir', 'sampai', 'minggu', 'tidak', 'sampai', 'dibatalkan', 'menggunakan', 'spx']
['semakin', 'ke', 'sini', 'semakin', 'baik', 'pelayanannya', 'dan', 'semakin', 'memudahkan', 'untuk', 'berbelanja', 'di', 'shopee', 'pengiriman', 'selalu', 'tepat', 'waktu', 'dan', 'lebih', 'cepat', 'dengan', 'spx', 'pokoknya', 'sangat', 'puas', 'berbelanja', 'di', 'shopee', 'terbaik', 'apalagi', 'banyak', 'diskon', 'semakin', 'murah']	['pelayanan', 'memudahkan', 'berbelanja', 'shopee', 'pengiriman', 'tepat', 'waktu', 'cepat', 'spx', 'puas', 'berbelanja', 'shopee', 'terbaik', 'banyak', 'diskon', 'murah']

Table 8. Sample of Data After the Stemming Process

Before	After
['paket', 'pesan', 'pengiriman', 'spx', 'lama', 'lambat', 'tidak', 'sampai', 'pesanan', 'katanya', 'membutuhkan', 'waktu', 'lama', 'sepertinya', 'pesanan', 'tiba', 'hilang']	['paket', 'pesan', 'pengiriman', 'spx', 'lama', 'lambat', 'tidak', 'sampai', 'pesan', 'kata', 'butuh', 'waktu', 'lama', 'seperti', 'pesan', 'tiba', 'hilang']
['saran', 'shopee', 'pengiriman', 'spx', 'khusus', 'wilayah', 'papua', 'diperhatikan', 'dipertimbangkan', 'estimasi', 'waktu', 'pengiriman', 'melewati', 'batas', 'waktu', 'barang', 'tidak', 'terkirim', 'pembeli', 'perhatikan', 'membaik', 'masalah', 'ongkos', 'kirim', 'murah', 'ditingkatkan', 'jasa', 'pengiriman']	['saran', 'shopee', 'pengiriman', 'spx', 'khusus', 'wilayah', 'papua', 'hati', 'timbang', 'estimasi', 'waktu', 'pengiriman', 'lewat', 'batas', 'waktu', 'barang', 'tidak', 'kirim', 'beli', 'hati', 'baik', 'masalah', 'ongkos', 'kirim', 'murah', 'tingkat', 'jasa', 'pengiriman']
['pengalaman', 'shopee', 'aplikasi', 'terbaik', 'berbelanja', 'suka', 'toko', 'menggunakan', 'jasa', 'kirim', 'spx', 'express', 'berbelanja', 'toko', 'menggunakan', 'ekspedisi', 'spx', 'pengiriman', 'bagus', 'tepat', 'waktu', 'kurir', 'cepat', 'spx']	['pengalaman', 'shopee', 'aplikasi', 'baik', 'belanja', 'suka', 'toko', 'guna', 'jasa', 'kirim', 'spx', 'express', 'belanja', 'toko', 'guna', 'ekspedisi', 'spx', 'pengiriman', 'bagus', 'tepat', 'waktu', 'kurir', 'cepat', 'spx']
['aplikasi', 'shopee', 'membantu', 'masukan', 'jasa', 'pengiriman', 'spx', 'perbaikan', 'kedisiplinan', 'waktu', 'barang', 'sampai', 'area', 'dikembalikan', 'toko']	['aplikasi', 'shopee', 'bantu', 'masuk', 'jasa', 'pengiriman', 'spx', 'baik', 'disiplin', 'waktu', 'barang', 'sampai', 'area', 'kembali', 'toko']
['pengiriman', 'spx', 'berkali', 'kali', 'tidak', 'tepat', 'waktu', 'dibawa', 'kurir', 'sampai', 'minggu', 'tidak', 'sampai', 'dibatalkan', 'menggunakan', 'spx']	['pengiriman', 'spx', 'kali', 'kali', 'tidak', 'tepat', 'waktu', 'bawa', 'kurir', 'sampai', 'minggu', 'tidak', 'sampai', 'batal', 'guna', 'spx']
['pelayanan', 'memudahkan', 'berbelanja', 'shopee', 'pengiriman', 'tepat', 'waktu', 'cepat', 'spx', 'puas', 'berbelanja', 'shopee', 'terbaik', 'banyak', 'diskon', 'murah']	['layanan', 'mudah', 'belanja', 'shopee', 'pengiriman', 'tepat', 'waktu', 'cepat', 'spx', 'puas', 'belanja', 'shopee', 'baik', 'banyak', 'diskon', 'murah']

2.5 Algorithm Implementation

Following the pre-processing stage, the next step in this study involves feature extraction and the implementation of machine learning algorithms. Textual data obtained from X and Google Play Store reviews were merged into a single dataset after being transformed into a uniform structure and undergoing the same pre-processing procedures. This integration aimed to ensure consistency in feature representation and to capture a broader spectrum of user sentiment expressions across different platforms. To convert the textual data into numerical features suitable for machine learning models, the Term Frequency Inverse Document Frequency (TF-IDF) method was employed [36]. This technique was employed to assess the cumulative weight of a word in a document [37]. The TF-IDF formula is shown in (1) [38].

$$TF - IDF_{(t,d,D)} = TF_{(t,d)} \times IDF_{(t,D)} \qquad (1)$$

The resulting TF-IDF vectors were then used as inputs to two classification algorithms: SVM and Logistic Regression. Both were applied to classify sentiment into three categories: positive, neutral, and negative. For SVM, both linear and nonlinear kernels were evaluated. Preliminary analysis, including data visualisation and empirical performance comparison, indicated that the sentiment data were not linearly separable. Consequently, the Radial Basis Function (RBF) kernel was selected, as it is better suited for capturing nonlinear relationships in the feature space. Regarding decision functions, the SVM model utilised the signed distance to the decision boundary (hyperplane) to determine class labels. In contrast, the Logistic Regression model employed the SoftMax function to produce class probabilities. Final sentiment predictions were based on the class with the highest probability in the logistic model, and on the sign of the decision function output in the SVM model.

2.6 Model Evaluation

Evaluating the performance of a classification model is an essential step in sentiment analysis, as it helps ensure that the model can accurately categorise textual data [39]. A well-structured evaluation process not only reveals the strengths and weaknesses of the model but also guides improvements to enhance predictive performance [40].

In this study, the confusion matrix serves as the basis for model evaluation. This matrix compares the predicted sentiment labels with the actual ones [41]. and from it, four key performance metrics are derived and used: accuracy, precision, recall, and F1-score. These four metrics were chosen because they are well-established and widely used in sentiment classification research. Together, they provide a well-rounded picture of model performance.

- ***Accuracy:*** reflects the overall correctness of the model by measuring the proportion of correctly predicted instances out of all predictions made [42]. It gives a general sense of how well the model performs across all sentiment classes [43]. It is defined in (2) [44]:

$$Accuracy = \frac{(TP_{positive} + TP_{negative} + TP_{neutral})}{(Total\ Cases)} \qquad (2)$$

- ***Recall:*** It is sometimes referred to as sensitivity in binary classification, and assesses the model's ability to correctly capture all relevant instances of a particular sentiment, especially negative feedback such as complaints about delayed deliveries [45]. High recall ensures that necessary dissatisfaction signals are not overlooked [46]. It is defined in (3) [47]:

$$Recall = \frac{(TP)}{(TP+FN)} \qquad (3)$$

- ***Precision:*** It measures how many of the instances predicted as positive (e.g., positive delivery experiences) are correct [48]. This is particularly important to avoid overestimating satisfaction when it is not truly present. It is calculated using (4) [49]:

$$Precision = \frac{(TP)}{(TP+FP)} \qquad (4)$$

- ***The F1-score:*** It balances precision and recall into a single metric, making it particularly useful when dealing with imbalanced data, a common scenario in sentiment analysis, where some sentiments may appear more frequently than others [50]. It is calculated using (5) [51]:

$$F1\ score = 2\ x \frac{(Precision\ x\ Recall)}{(Precision + Recall)} \qquad (5)$$

By relying on these four metrics, this study aims to evaluate the predictive performance of the SVM and Logistic Regression models in a way that is both comprehensive and aligned with best practices in sentiment analysis. These metrics are considered sufficient and appropriate for capturing the effectiveness of the models in classifying user opinions related to SPX delivery times.

3 RESULT AND DISCUSSION

This section presents the findings of the sentiment analysis on customer reviews of Shopee Xpress, along with an in-depth discussion of the results. The analysis covers sentiment distribution, word frequency patterns, model performance evaluation, and a comparative assessment of classification models. Furthermore, a quantitative evaluation of the models is conducted to ensure the reliability of the sentiment classification. The insights derived from this study provide valuable implications for improving Shopee Xpress services and understanding customer satisfaction trends.

3.1 Overview of Sentiment Analysis Results

This section provides an overview of the sentiment classification results obtained from the dataset, consisting of 398 customer reviews of Shopee Xpress delivery times. Fig. 2 illustrates the sentiment distribution in the dataset, where the classification process categorises sentiment into three classes: positive, neutral, and negative.

As shown in Fig. 2, customer sentiment regarding the delivery time of Shopee Xpress reveals a noticeable dominance of negative reviews. Out of the 398 total reviews analysed, 156 (39.2%) expressed negative sentiment, followed by 141 (35.4%) with positive sentiment and 101 (25.4%) falling into the neutral category. The distribution of sentiment labels in the dataset shows an imbalance between classes, although it is not extreme. In this study, neither oversampling nor undersampling techniques were applied because they feared that changing the natural characteristics of the data. Instead, the model will be trained using the existing label distribution, and its performance will be thoroughly evaluated using precision, recall, and F1-score metrics for each class. This approach aims to ensure that the model not only excels in the majority class but can also classify the minority class correctly. Validation of the imbalance distribution will be carried out based on the results of these evaluation metrics. Thus, the effectiveness of data distribution in model training can be assessed by the extent to which the model can maintain reasonable and balanced performance across all sentiment categories.

The relatively high percentage of negative sentiment indicates that many customers are dissatisfied with the delivery time of their packages. These complaints often highlight delays beyond the estimated delivery time, repeated late deliveries, or cancellations after prolonged waiting. In several cases, users mentioned that their orders took over a week without clear updates, leading to frustration and mistrust. This suggests that delivery punctuality remains a key weakness for Shopee Xpress, mainly when customers rely on timely shipments. On the other hand, the proportion of positive reviews is not far behind. Many customers expressed satisfaction when their orders arrived on time or earlier than expected. Words like “cepat,” “puas,” and “sesuai” frequently appeared in these comments, showing that Shopee Xpress is capable of providing a pleasant delivery experience when operations go smoothly. This positive feedback highlights the potential of SPX to deliver consistently good service if the supporting logistics are well-managed. Neutral reviews, while smaller in number, also offer helpful insight. Most of these reviews were written in a calm, informative tone and often included constructive suggestions. Some customers acknowledged improvements in shipping costs or general service, but pointed out that delivery time, especially in remote areas, still needs attention. Others noted inconsistent experiences, which may explain their neutral stance.

This sentiment distribution highlights that delivery time is crucial to customer satisfaction. Late deliveries lead to dissatisfaction, while prompt and reliable service generates trust and positive sentiment. For Shopee, this pattern presents both a warning and an opportunity. It suggests the need to improve consistency in delivery times and to address recurring issues, especially in high-risk or remote areas. At the same time, it also shows that there is already a foundation of good practice to build upon. To move forward, Shopee Xpress can focus on reducing delivery time variability, providing clearer tracking updates, and offering proactive solutions when delays happen. Strengthening these areas could reduce negative feedback and encourage positive experiences that build long-term customer loyalty.

3.2 *Sentiment Distribution Over Time*

Understanding how customer sentiment fluctuates is crucial in identifying patterns and potential external factors influencing user experiences. Fig. 3 presents a bar chart showing the monthly sentiment distribution from January 2024 to March 2025, highlighting trends in positive, neutral, and negative sentiment.

The distribution of customer reviews of SPX shipping times from month to month, shown in Fig. 3, shows some interesting patterns. The review volume was still low in early 2024 (January to March), and the sentiment was balanced. The number of negative reviews concerning shipping delays was notably low, with only 2-3 recorded per month, suggesting a relatively quiet period that may be attributed to low order volumes or a lack of motivation among customers to provide detailed reviews.

From April to July 2024, the number of reviews gradually increased across all sentiment categories. Interestingly, positive reviews regarding SPX's shipping time (12 reviews) were more numerous in April than negative or neutral sentiments. This could indicate that customers were starting to feel satisfied with the shipping speed during that period, perhaps because the shipping process was more efficient, or the estimated time was quite accurate.

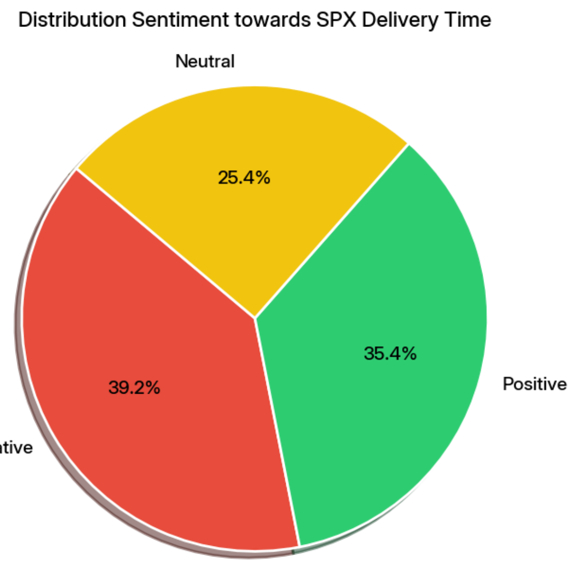

Figure 2. Sentiment distribution in the dataset

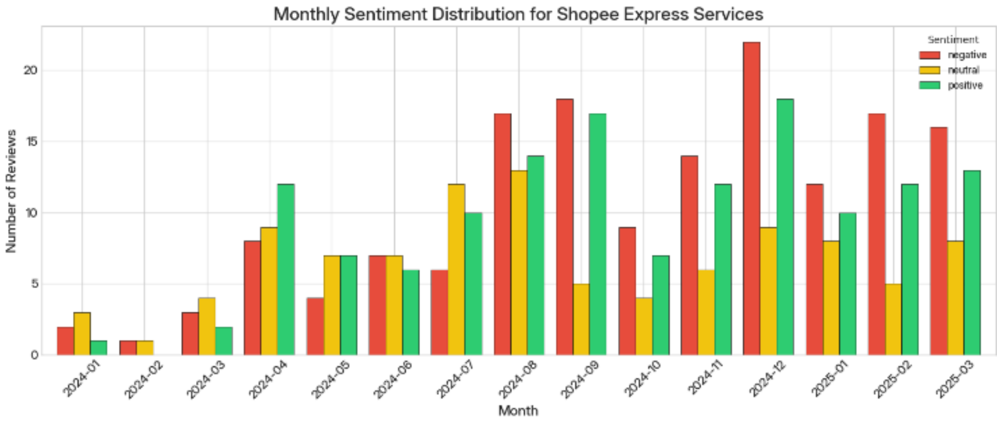

Figure 3. Sentiment distribution by month

From April to July 2024, the number of reviews gradually increased across all sentiment categories. Interestingly, positive reviews regarding SPX's shipping time (12 reviews) were more numerous in April than negative or neutral sentiments. This could indicate that customers were starting to feel satisfied with the shipping speed during that period, perhaps because the shipping process was more efficient, or the estimated time was quite accurate.

However, this trend began to change in August 2024. There was a spike in negative reviews (17) this month, followed by September (18). Although positive reviews also increased (14 and 17), customer experiences are starting to vary, with some receiving their orders quickly while others are beginning to experience delays or inconsistencies in shipping times. This phenomenon could be linked to the increasing number of orders ahead of the considerable promo period, which usually occurs towards the end of the year.

From October to December 2024, negative reviews regarding delivery times increasingly dominate. December recorded the highest number with 22 negative reviews, the highest peak in the overall data. Although the number of positive reviews was also high that month, the dominance of complaints regarding late delivery indicates tremendous pressure in the logistics system during end-of-year promotions, such as the 11.11 and 12.12 shopping campaigns, or approaching the Christmas and New Year holidays. Several reviews even mentioned that orders arrived later than estimated or that there was a discrepancy between the delivery notification and the actual time.

Entering 2025, mainly from January to March, negative sentiment is still relatively high, although not as much as in December. For example, there were 17 negative reviews in February, while only 12 were positive. This shows that some problems with delivery speed have not been fully resolved. This could be a continuation of the spike in deliveries at the end of the previous year, or the system has not yet recovered optimally after that busy period.

Several key insights can be drawn from the sentiment distribution over time:

- ***Anticipate Promo and Holiday Periods:*** The spike in negative reviews from August to December shows that delivery services often experience pressure when the number of orders increases, especially during big promos and the end of the year. Shopee Xpress needs to be more proactive in increasing delivery capacity, strengthening the logistics system, and improving delivery time estimates to avoid delays.
- ***Identify Problem Points:*** Spikes in complaints in certain months can indicate delivery constraints in certain areas, limited couriers, or distribution issues in the warehouse. By analysing the location and content of complaints in more detail, Shopee Xpress can determine which areas need improvement.
- ***Emulate Successful Practices:*** Months like April and September have a good proportion of positive reviews. Shopee Xpress can track what went well during those periods, such as courier speed, accuracy of delivery time estimates, or a more real-time tracking system, and then adapt them to busy months.
- ***Post-Promo Recovery:*** Although there was a slight decrease in complaints in early 2025, it is still apparent that many customers are not fully satisfied. This shows the importance of a recovery period after a big campaign, including system improvements and increased customer communication about delivery estimates and status.

Month-on-month sentiment analysis provides Shopee Xpress with invaluable insights, especially in understanding customer satisfaction with delivery speed. This trend underscores that punctuality is not only a technical logistics issue but also has a profound impact on customer perception and loyalty. By regularly monitoring this pattern, Shopee Xpress can take targeted measures to enhance delivery performance, particularly during peak periods, and ultimately provide a superior shopping experience.

3.3 *Word Frequency Analysis in Customer Reviews*

Analysing word frequency in customer reviews provides valuable insights into users' prevalent themes and recurring concerns. By identifying the most frequently occurring words, it is possible to understand customers' primary topics, reflecting their experiences, expectations, and pain points. This section presents a detailed analysis of word frequency across different sentiment categories, offering a deeper understanding of the language patterns in customer feedback related to Shopee Xpress time delivery.

3.3.1 Overall Word Frequency: Text analysis is a fundamental technique in sentiment analysis, providing insights into the most frequently occurring words within a dataset. One of the most effective visual representations of word frequency is a word cloud, which displays words in varying sizes based on their occurrence rates [52]. The larger the word appears in the visualisation, the more frequently it occurs in customer reviews. Fig. 4 illustrates the word cloud generated from all collected reviews.

The word cloud visualisation results of customer reviews shown in Figure X show the words that appear most often when they share their experiences using the spx delivery service. Some of the most prominent words are “spx,”,= “pengiriman,” and “waktu”. This shows that most customers directly discuss the main topic, namely the delivery process and its punctuality.

Interestingly, the word “lambat” also appears large. This shows that quite a lot of customers have complained about late delivery. Words such as “estimasi,” “kecewa,” and “sampai” also appear and seem to reinforce the picture that one of the main complaints is about the package arrival time, which is not as expected. On the other hand, the words “tepat,” “cepat,” and “sesuai” also appear in the word cloud, although not as large as the word “slow”. This shows that there are also customers who are satisfied because their delivery arrived according to the estimate or even faster than expected.

From a business perspective, these results can be important input for Shopee Xpress. The many words related to time and delivery accuracy can alert customers to pay attention to this. Therefore, improving the accuracy of time estimates, speeding up the delivery process, or clarifying communication when there is a delay can be concrete steps that directly impact customer satisfaction. Overall, this word cloud is a mirror for Shopee Xpress to see what customers feel and care about the most. By hearing user reviews through the words that appear most often, Shopee Xpress can focus more on improving the services that users need.

3.3.2 Frequent Words in Negative Sentiment: Understanding the key terms frequently appearing in negative sentiment reviews provides valuable insights into customer dissatisfaction and recurring service issues. Fig. 5 presents a bar chart visualising the 15 most frequently occurring words in negative sentiment reviews, offering a clearer perspective on the dominant themes of customer complaints.

From the analysis of the most frequently appearing words in negative reviews in Fig. 5, the issue of delivery time is the most dominant complaint. Many users directly mention "spx" in their reviews, indicating that they specifically highlight the performance of this delivery service. Words such as "pengiriman", "waktu", and "lambat" appear repeatedly and reinforce the picture that delays or inaccuracies are the primary source of disappointment. A few also mention "shopie," indicating that some customers see this problem as the responsibility of SPX and the Shopee platform.

In addition, words such as "paket," "kurir," and "kirim" describe technical problems in the field, such as late delivery or lack of clarity in the delivery process. The appearance of the words "hari" and "tepat" shows that many customers expect goods to arrive according to the promised estimated time. Some customers also highlighted that the delivery took longer than it should have, and some were even disappointed because their goods never arrived. Words like “jasa,” “ekspedisi,” and “pakai” signal that there is disappointment with the courier choice used, and some customers may feel as though they have no more reliable alternatives.

Figure 4. Word cloud of customer reviews on Shopee Xpress

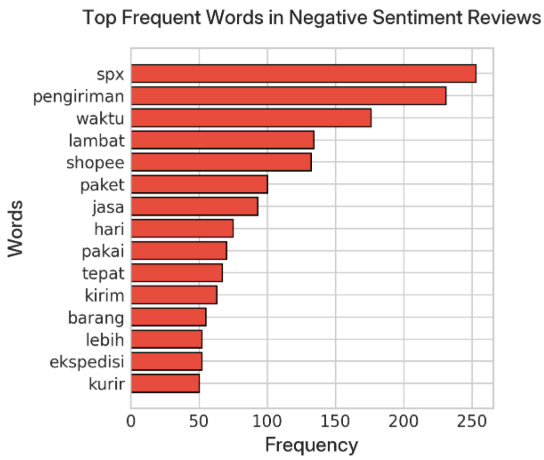

Figure 5. Frequency of words in negative sentiment

The strategic implication for Shopee Xpress is improving the accuracy of estimated delivery times and the punctuality of delivery operations. Shopee Xpress needs to improve the logistics process's efficiency, increase customer service responsiveness to delays, and provide more flexible delivery options. By understanding these complaint patterns, Shopee Xpress can develop concrete steps to improve customer perception and increase confidence in the quality of on-time delivery.

3.3.3 Frequent Words in Neutral Sentiment: Neutral sentiment reviews provide insights into customer experiences that are neither highly positive nor strongly negative, often reflecting transactional or factual statements rather than explicit satisfaction or dissatisfaction. Fig. 6 presents a bar chart illustrating the 15 most frequently occurring words in neutral sentiment reviews, which helps in understanding the nature of these reviews and their implications for Shopee Xpress.

Reviews with neutral sentiment in Fig. 6 generally contain more descriptive or informative comments without showing strong emotions, either satisfaction or disappointment. In these reviews, the words “pengiriman” and “waktu” appear most frequently, indicating that the main topic of discussion remains centred on the duration and accuracy of delivery. Many users mention “spx” explicitly, suggesting that despite the neutral tone of the review, they still want to pay special attention to the performance of the delivery service.

Several other words, such as “sesuai,” “estimasi,” and “informasi” give the impression that customers highlight whether the delivery time is by the estimate promised by the system. The appearance of words such as “paket,” “hari,” “barang,” and “jadwal” strengthens the impression that customers discuss their experiences factually, for example, saying that the delivery arrived on schedule or only slightly later than expected.

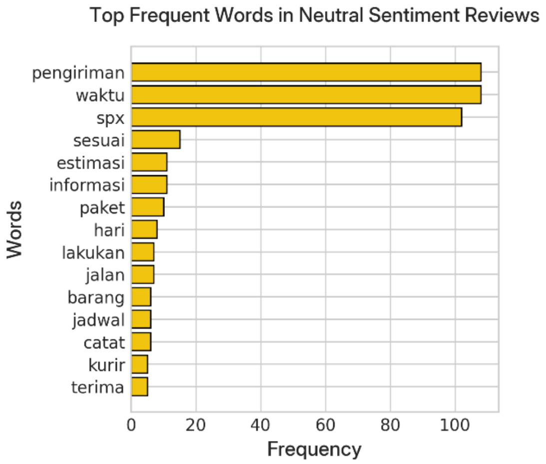

Figure 6. Frequency of words in neutral sentiment

Meanwhile, words such as “catat,” “lakukan,” and “jalan” indicate an explanation of the process or chronology that customers went through, perhaps in the context of tracking the delivery. The words “kurir” and “terima” also appear, indicating that some customers gave neutral reports about the role of the courier or the time the item was received without explicitly stating satisfaction or disappointment.

For Shopee Xpress, these neutral reviews have strategic value because they are open to being directed into positive sentiment. Customers in this category tend not to be emotional but are critical of the accuracy of information, estimates, and the transparency of the process. By providing a consistent and expected delivery experience, Shopee Xpress can turn neutral perceptions into positive ones while strengthening customer loyalty in the future.

3.3.4 Frequent Words in Positive Sentiment: Understanding the most frequently used words in positive sentiment reviews offers valuable insights into the key factors driving customer satisfaction with Shopee Xpress. Fig. 7 presents a bar chart illustrating the 15 most frequently occurring words in positive sentiment reviews, highlighting common themes associated with favourable customer experiences.

As seen in Fig. 7, customers show their appreciation for Shopee Xpress' performance, especially regarding delivery time. The words "spx," "waktu," and "pengiriman" are the most frequently mentioned, indicating that customer satisfaction is closely related to the accuracy and speed of the service provided.

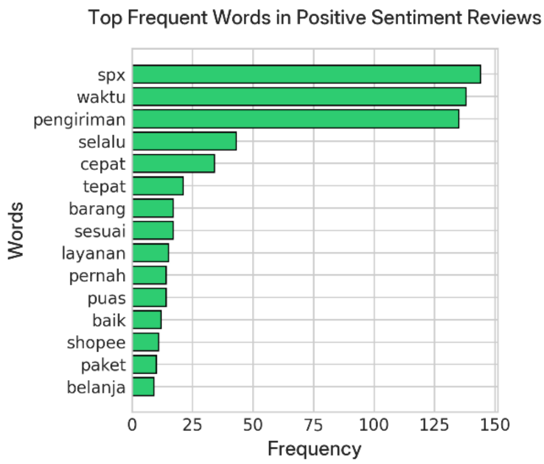

Figure 7. Frequency of words in positive sentiment

Customers not only mention the name of the shipping service directly but also highlight that the delivery time they feel is by or exceeds expectations. The emergence of words such as "selalu," "cepat," and "tepat" indicates a consistently positive experience over time. Customers feel that SPX can regularly and reliably maintain the quality of delivery. The words "barang," "paket," and "sesuai" further strengthen the narrative that their shopping experience went smoothly, from the ordering process to receiving the goods in their hands.

This review also touches on other aspects such as "layanan," "puas," "baik," and "belanja", which shows that satisfaction with delivery time also has an impact on positive perceptions of Shopee's services. Some customers even said that they had never experienced delays or were very satisfied with the speed of delivery provided.

Punctuality is a key factor that drives customer satisfaction towards Shopee Xpress. To maintain and enhance this positive sentiment, Shopee Xpress can continue to maintain fast and accurate delivery performance and ensure a smooth shopping experience from start to finish. By strengthening the aspects of customer value most, the company can maintain user loyalty and expand its overall positive image.

3.4 *Model Performance Evaluation*

Evaluating model performance is crucial in determining the effectiveness of sentiment classification. This section examines the classification capabilities of the models by analysing their confusion matrices, which provide insight into the distribution of correctly and incorrectly classified sentiment labels. The analysis offers a deeper understanding of how well each model distinguishes between negative, neutral, and positive sentiments.

3.4.1 *Confusion Matrix Analysis for SVM:* The confusion matrix provides a detailed evaluation of the Support Vector Machine (SVM) model's classification performance in predicting sentiment categories. Fig. 8 illustrates the confusion matrix, summarising the number of correctly and incorrectly classified sentiment labels across three categories: negative, neutral, and positive.

Each cell in the confusion matrix in Fig. 8 represents a specific classification outcome:

- ***Negative Sentiment Classification:*** The model correctly classified 37 negative reviews, indicating a strong capability to detect negative sentiment. Only one instance was misclassified as neutral, and none was classified as positive. This minimal misclassification suggests that negative expressions in the reviews were clear and distinctive enough for the model to recognise reliably.
- ***Neutral Sentiment Classification:*** 13 neutral reviews were accurately identified, reflecting solid model performance in capturing sentiment without strong polarity. While none of the neutral reviews were misclassified as negative, two instances were incorrectly labelled positive. This may suggest the presence of slightly positive wording in otherwise neutral feedback, potentially confusing the classifier.
- ***Positive Sentiment Classification:*** The model correctly classified 24 reviews as positive. However, two reviews were incorrectly categorised as negative and one as neutral. It indicates that the model had difficulty distinguishing positive sentiment from other classes, possibly due to subtle or mixed expressions where positive sentiment coexists with minor complaints.

3.4.2 *Confusion Matrix Analysis for Logistic Regression:* The confusion matrix provides an in-depth assessment of the Logistic Regression model's classification performance in predicting sentiment categories. Fig. 9 presents the confusion matrix, summarising the number of correctly and incorrectly classified sentiment labels across three categories: negative, neutral, and positive.

Each cell in the confusion matrix in Fig.9 represents a specific classification outcome:

- ***Negative Sentiment Classification:*** The model correctly classified 38 negative reviews without any misclassifications into neutral or positive categories. This result indicates that the model has high accuracy in recognising negative sentiment, possibly because the negative expressions appearing in the reviews are explicit and consistent.

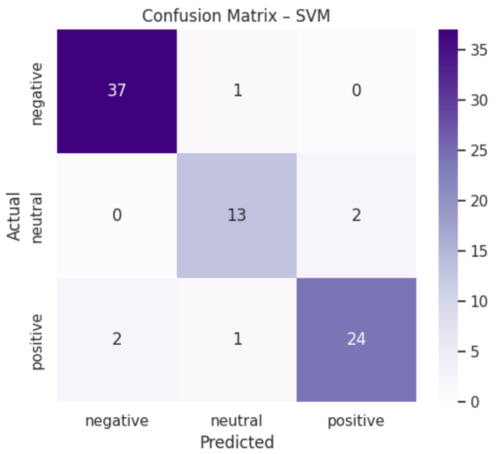

Figure 8. Confusion matrix of the SVM algorithm

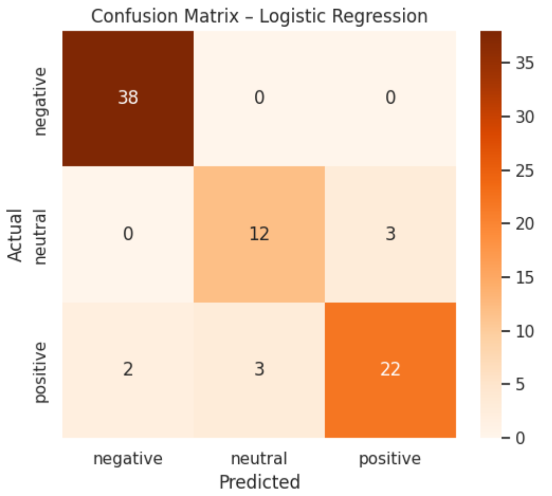

Figure 9. Confusion matrix of the logistic regression algorithm

- ***Neutral Sentiment Classification:*** 12 neutral reviews were correctly classified, while three others were misclassified as positive. No neutral reviews were classified as negative. The model is quite capable of distinguishing neutral from negative sentiment, but still faces challenges when neutral reviews have words that tend to be positive, which can affect the classification results.

- ***Positive Sentiment Classification:*** The model correctly identified 22 positive reviews. However, two positive reviews were misclassified as negative, and three others as neutral. The positive expressions in some reviews may be less intense or mixed with mild complaints, thus confusing the model in determining their polarity.

3.5 *Model Comparison on Unlabeled Data*

To further evaluate the performance and consistency of the SVM and Logistic Regression models, both classifiers were applied to a set of 99 unlabelled reviews. The results of this classification are illustrated in Fig. 10, which presents a bar chart comparing the sentiment distribution predicted by each model.

While both models in Fig. 10 exhibit similar classification patterns, notable differences can be observed in the distribution of sentiment predictions, particularly in the negative and neutral categories. The classification results for SVM and Logistic Regression on the unlabelled dataset are summarised as follows:

- ***Negative Sentiment Predictions:*** Regarding negative sentiment prediction, logistic regression classified slightly more negative reviews than SVM, namely 30 reviews compared to 29. Although the difference is slight, this could indicate that Logistic Regression is more sensitive to reviews with a tone of disappointment or complaint.

- ***Neutral Sentiment Predictions:*** For neutral sentiment, the results of both models are almost identical. SVM classified 45 reviews as neutral, while Logistic Regression classified 46. Both models consistently recognise reviews that tend to be neutral, without too strong emotions towards either the positive or the negative.

- ***Positive Sentiment Predictions:*** Meanwhile, for positive sentiment, SVM predicted slightly more reviews as positive (25 reviews) than Logistic Regression (23 reviews). It could indicate that SVM is slightly more sensitive when capturing expressions of satisfaction or good customer experiences.

Overall, the differences between the models are less striking but still provide an idea of the character of each algorithm in processing the nuances of language in customer reviews.

3.6 *Quantitative Evaluation of Models*

A comprehensive quantitative evaluation is essential to objectively assess the performance of sentiment classification models. This section compares key classification metrics and examines the consistency between manually calculated and programmatically computed evaluation scores. The analysis aims to ensure the accuracy and reliability of the models when classifying sentiment within the given dataset.

3.6.1 Comparison of Classification Metrics: To evaluate the performance of both classification models (SVM and Logistic Regression), a comparison of key classification metrics like True Positive (TP), False Positive (FP), and False Negative (FN) was conducted. These values are summarised in Table 9, derived from the confusion matrices of each model.

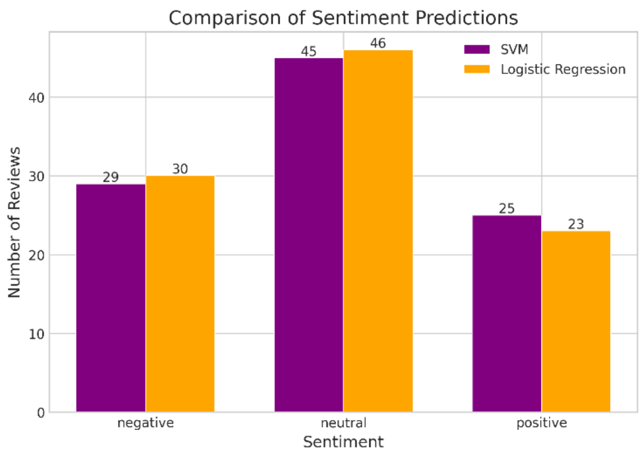

Figure 10. Sentiment distribution across models

3.6.2 Manual vs. Programmatic Calculation of Metrics:

To ensure the reliability of the evaluation metrics, this section compares the manual calculations of classification metrics with programmatically computed values using Python's sklearn.metrics library. Referring to the data presented in Table 9, a manual calculation is performed to obtain the accuracy, recall, precision, and F1-score for both models. This calculation allows for a more precise evaluation of each model's performance in sentiment classification.

- ***Accuracy:*** *using the formula in (2)*
- ***Recall:*** *using the formula in (3), which then can be detailed as follows:*

$$Recall_{negative} = \frac{(TP_{negative})}{(TP_{negative} + FN_{negative})} \quad (3.1)$$

$$Recall_{neutral} = \frac{(TP_{neutral})}{(TP_{neutral} + FN_{neutral})} \quad (3.2)$$

$$Recall_{positive} = \frac{(TP_{positive})}{(TP_{positive} + FN_{positive})} \quad (3.3)$$

- ***Precision:*** *using the formula in (4), which then can be detailed as follows:*

$$Precision_{negative} = \frac{(TP_{negative})}{(TP_{negative} + FP_{negative})} \quad (4.1)$$

Table 9. Comparison of TP, FP, and FN Values for Each Model

Sentiment	Metric	SVM	Logistic Regression
Negative	TP (True Positive)	37	38
	FP (False Positive)	2	2
	FN (False Negative)	1	0
Neutral	TP (True Positive)	13	12
	FP (False Positive)	2	3
	FN (False Negative)	2	3
Positive	TP (True Positive)	24	22
	FP (False Positive)	2	3
	FN (False Negative)	3	5

$$Precision_{neutral} = \frac{(TP_{neutral})}{(TP_{neutral} + FP_{neutral})} \quad (4.2)$$

$$Precision_{positive} = \frac{(TP_{positive})}{(TP_{positive} + FP_{positive})} \quad (4.3)$$

- ***F1-score:*** *using the formula in (5), which then can be detailed as follows:*

$$F1\ score_{negative} = 2\ x \frac{(Precision_{negative}\ x\ Recall_{negative})}{(Precision_{negative} + Recall_{negative})} \quad (5.1)$$

$$F1\ score_{neutral} = 2\ x \frac{(Precision_{neutral}\ x\ Recall_{neutral})}{(Precision_{neutral} + Recall_{neutral})} \quad (5.2)$$

$$F1\ score_{positive} = 2\ x \frac{(Precision_{positive}\ x\ Recall_{positive})}{(Precision_{positive} + Recall_{positive})} \quad (5.3)$$

Fig. 11 illustrates the calculated accuracy, recall, precision, and F1-score for the SVM and Logistic Regression (LR) algorithms. These metrics were obtained using Python and sklearn.metrics library to ensure an accurate and consistent evaluation of model performance. A comparison of the results reveals that manual and programmatic calculations, as illustrated in Fig. 11, produce identical values for all four metrics. This consistency validates the accuracy of the evaluation process, confirming that the implementation is precise and devoid of computational errors.

3.7 Final Model Selection and Business Insights

The final step in this study involves selecting the most suitable sentiment classification model based on key performance metrics. Table 10 presents a comparative analysis of accuracy, recall, precision, and F1-score for both SVM and LR.

Based on the model evaluation results in Table 10, the SVM algorithm showed slightly superior performance compared to LR, especially in overall accuracy (93% vs. 90%). This superiority is also reflected in almost all evaluation metrics, especially in identifying sentiments related to on-time delivery.

Regarding recall, LR is better for identifying negative sentiments with a perfect score (100%), which is very important in detecting customer complaints about late delivery. However, SVM showed a more even performance with higher recall in the neutral (87% vs. 80%) and positive (89% vs. 81%) sentiment categories, indicating its ability to capture the diversity of user expressions more balanced.

```
==== SVM ====
              precision    recall  f1-score   support

    negative       0.95      0.97      0.96        38
     neutral       0.87      0.87      0.87        15
    positive       0.92      0.89      0.91        27

    accuracy                           0.93        80
   macro avg       0.91      0.91      0.91        80
weighted avg       0.92      0.93      0.92        80

==== Logistic Regression ====
              precision    recall  f1-score   support

    negative       0.95      1.00      0.97        38
     neutral       0.80      0.80      0.80        15
    positive       0.88      0.81      0.85        27

    accuracy                           0.90        80
   macro avg       0.88      0.87      0.87        80
weighted avg       0.90      0.90      0.90        80
```

Figure 11. Performance metrics of SVM and LR models

Table 10. Comparison of SVM and LR Model Evaluations

Metric	SVM (%)	Logistic Regression (%)
Accuracy	93	90
Recall (Negative)	97	100
Recall (Neutral)	87	80
Recall (Positive)	89	81
Precision (Negative)	95	95
Precision (Neutral)	87	80
Precision (Positive)	92	88
F1-score (Negative)	96	97
F1-score (Neutral)	87	80
F1-score (Positive)	91	85

In the precision metric, both models showed similarities in negative sentiment (95%), but SVM was again superior in precision for the neutral (87% vs. 80%) and positive (92% vs. 88%) categories. It indicates that predictions by SVM are more accurate and not excessive when labelling sentiments.

The F1-score value as a combined metric of precision and recall shows the consistent superiority of SVM in all three sentiment categories: negative (96% vs. 97%), neutral (87% vs. 80%), and positive (91% vs. 85%). It confirms the stability of SVM performance in handling the variation of sentiments from users.

Although LR performed well in detecting negative sentiment, the overall results suggest that SVM offers a more balanced classification performance. In sentiment analysis, both precision and recall are essential; however, their relative importance depends on the specific goals of the study. In this research, the slightly higher recall values, especially in the minority sentiment classes, are considered beneficial, as they increase the likelihood of capturing a broader range of user opinions, which is crucial when analysing public perception across various sentiment expressions. Accuracy was reported as an overall metric to provide a general overview of model performance. Class-wise accuracy was not calculated, as it tends to be less informative in multi-class classification tasks with imbalanced label distributions. Instead, this study focused on per-class precision, recall, and F1-score to evaluate how well each sentiment class was recognised.

However, it is important to note that the training data used showed an imbalance in the label distribution, with a significant dominance of negative reviews. The evaluation was carried out on separate test data proportionally to overcome potential model bias due to this condition and ensure objective results. In addition, the stable performance of SVM in the minority sentiment category (neutral and positive) indicates that the model can still generalise well.

4 CONCLUSION

This research aims to analyse customer sentiment towards Shopee Xpress delivery time using two machine learning algorithms, namely SVM and Logistic Regression. Of the 497 reviews collected, 398 were used as training data and 99 as testing data. The classification results show that although the data has an unbalanced label distribution, both models can perform well. SVM was chosen as the superior model because it showed an overall accuracy of 93% and a consistently high F1-score value across all sentiment categories (negative, neutral, and positive), reflecting its ability to recognise various user expressions evenly. Meanwhile, logistic regression has a special strength in identifying negative sentiment with perfect recall (100%), which is crucial in detecting customer complaints. However, its performance in other classes is relatively lower, so its classification balance is not as good as that of SVM.

Data imbalance is a challenge that needs to be considered because it can affect the model's tendency to over-recognise the majority class. Performance evaluation uses per-class metrics, such as precision, recall, and F1-score, to reduce the risk of this bias. The results show that SVM has a more stable generalisation ability, including effective classification of minority sentiments, which indicates the model's resilience to uneven label distribution conditions.

These findings indicate that Shopee Xpress can use machine learning-based sentiment analysis to capture customer perceptions systematically. Early identification of negative sentiment can help companies respond more quickly and precisely to delivery issues. In the future, it is recommended that this research be further developed by expanding the scope of review data, applying balancing techniques such as SMOTE to improve representative distribution between classes, and exploring more complex algorithms such as Random Forest or transformer-based models (e.g., BERT) to improve classification accuracy. Collaboration with Shopee Xpress to obtain internal logistics data can also enrich the analysis context and increase the applicability of the research results.

CREDIT AUTHOR STATEMENT

Sewin Fathurrohman: Conceptualisation, Methodology, Investigation, Resources, Software, Project administration, and Supervision. Irfan Ricky Afandi: Data curation, Software, Formal analysis, and Validation. Irma Wahyuningtyas: Investigation, Resources, and Writing: Original Draft, & Formal analysis. Azis Styo Nugroho: Formal analysis, Validation, Visualisation, and Writing: Review & Editing. Firman Noor Hasan: Writing: Review & Editing and Validation. All authors: Investigation and Writing: Review & Editing.

COMPETING INTERESTS

The authors declare that there are no competing interests (CI) or conflicts of interest (COI) related to this research. The study was conducted independently, without any external influence from organisations or entities that could affect the objectivity of the findings and conclusions.

DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this manuscript, AI-assisted tools were used solely for language enhancement, including grammar checking and improving the clarity and readability of the text. The authors confirm that all scientific content, including research ideas, methodology, data analysis, interpretations, and conclusions, was entirely developed by the authors. No generative AI tools were used to create original scientific content, manipulate or analyse data, conduct the literature review, or generate conclusions. The final version of the manuscript was carefully reviewed, verified, and approved by all authors, who take full responsibility for its content in accordance with the publication ethics of this journal.

ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to all individuals who contributed to this research. Special appreciation is extended to those who provided valuable insights, constructive feedback, and support throughout the study. The authors also acknowledge the efforts involved in data collection, pre-processing, and analysis, which were crucial in ensuring the accuracy and reliability of the findings.

REFERENCES

[1] Y. Septiawan, A. Aglasia, and D. A. Muktiawan, "Peningkatan Performa Analisis Sentimen Ulasan Pelanggan terhadap Layanan Pengiriman Menggunakan Model Naïve Bayes yang Dioptimalkan dengan PSO," *ROUTERS: Jurnal Sistem dan Teknologi Informasi*, vol. 3, no. 1, pp. 10–19, 2025, doi: 10.25181/rt.v3i1.4001.

[2] I. R. Afandi, F. Noor Hasan, A. A. Rizki, N. Pratiwi, and Z. Halim, "Analisis Sentimen Opini Masyarakat Terkait Pelayanan Jasa Ekspedisi Anteraja dengan Metode Naive Bayes," *Jurnal Linguistik Komputasional*, vol. 5, no. 2, pp. 63–70, 2022, doi: https://doi.org/10.26418/jlk.v5i2.107.

[3] N. A. Qadri, S. Alam, and M. Taufik, "Analisis Sentimen Brand Barenbliss Menggunakan Machine Learning (Studi Kasus: E-Commerce Shopee)," *INNOVATIVE: Journal of Social Science Research*, vol. 5, no. 1, pp. 1–12, 2025, doi: https://doi.org/10.31004/innovative.v5i1.16163.

[4] T. Widarmanti and A. Munisera, "Analisis Sentimen Mengenai Kualitas Layanan Jasa Ekspedisi Shopee Xpress pada Media Sosial Twitter," *Jurnal Ilmiah Universitas Batanghari Jambi*, vol. 23, no. 3, p. 3370, 2023, doi: 10.33087/jiubj.v23i3.4077.

[5] M. Taufiq, Recky, and Y. P. Sari, "Pengaruh Kompensasi, Motivasi, dan Kepuasan Kerja Terhadap Kinerja Karyawan pada Shopee Express Kabupaten Bandung," *JURNAL ECONOMICA*, vol. 12, no. 2, pp. 226–235, 2024, doi: https://doi.org/10.46750/economica.v12i2.297.

[6] S. Nur Rismanah, R. Astuti, and F. M. Basysyar, "Penerapan Algoritma Support Vector Machine dalam Menganalisis Sentimen Ulasan Pelanggan Shopeefood Berdasarkan Twitter," *JATI (Jurnal Mahasiswa Teknik Informatika)*, vol. 8, no. 1, pp. 406–412, 2024, doi: 10.36040/jati.v8i1.8401.

[7] A. Simanungkalit, J. P. P. Naibaho, and A. De Kweldju, "Analisis Sentimen Berbasis Aspek pada Ulasan Aplikasi Shopee Menggunakan Algoritma Naïve Bayes," *Jutisi: Jurnal Ilmiah Teknik Informatika dan Sistem Informasi*, vol. 13, no. 1, p. 659, 2024, doi: 10.35889/jutisi.v13i1.1826.

[8] A. M. Putri, W. K. Nofa, and D. A. P. Hapsari, "Penerapan Metode Bert untuk Analisis Sentimen Ulasan Pengguna Aplikasi Segari di Google Play Store," *JUIT: Jurnal Ilmiah Teknik*, vol. 4, no. 1, pp. 89–104, 2025, doi: https://doi.org/10.56127/juit.v4i1.1902.

[9] Y. Handika, I. F. Hanif, and F. N. Hasan, "Analysis of Public Sentiment Towards POLRI's Performance using Naive Bayes and K-Nearest Neighbors," *IJID (International Journal on Informatics for Development)*, vol. 13, no. 1, pp. 386–399, 2024, doi: 10.14421/ijid.2024.4500.

[10] S. Heristian, M. Napiah, and W. Erawati, "Analisis Sentimen Ulasan Pelanggan Menggunakan Algoritma Naive Bayes pada Aplikasi Gojek," *Computer Science (CO-SCIENCE)*, vol. 5, no. 1, pp. 35–41, 2025, doi: https://doi.org/10.31294/coscience.v5i1.7775.

[11] Tukino, "Penerapan Algoritma Convolutional Neural Network untuk Klasifikasi Sentimen Pada Layanan e-Commerce," *JURNAL DESAIN DAN ANALISIS TEKNOLOGI (JDDAT)*, vol. 4, no. 1, pp. 44–53, 2025, doi: https://doi.org/10.58520/jddat.v4i1.72.

[12] M. I. Burhan, "Analisis Sentimen Publik Terhadap Aplikasi Mypertamina pada Google Playstore," *Jurnal Manajemen Perbankan Keuangan Nitro*, vol. 8, no. 1, pp. 1–12, 2025, doi: 10.56858/jmpkn.v8i1.390.

[13] B. Kholifah, I. Thoib, N. Sururi, and N. D. Kurnia, "Analisis Sentimen Warganet Terhadap Isu Layanan Transportasi Online Berbasis InSet Lexicon Menggunakan Logistic Regression," *Kumpulan jurnaL Ilmu Komputer (KLIK)*, vol. 11, no. 1, pp. 14–25, 2024, doi: http://dx.doi.org/10.20527/klik.v11i1.655.

[14] N. Sari, M. Jazman, T. K. Ahsyar, Syaifullah, and A. Marsal, "Penerapan Algoritma Klasifikasi Naive Bayes dan Support Vector Machine untuk Analisis Sentimen Cyberbullying Bilingual di Aplikasi X," *Sistemasi: Jurnal Sistem Informasi*, vol. 14, no. 1, pp. 211–224, 2025, doi: https://doi.org/10.32520/stmsi.v14i1.4799.

[15] T. G. W. M. Sidabutar and D. Juardi, "Analisis Sentimen Masyarakat Terhadap Penggunaan Halodoc Sebagai Layanan Telemedicine di Indonesia," *JITET (Jurnal Informatika dan Teknik Elektro Terapan)*, vol. 13, no. 1, pp. 571–575, 2025, doi: http://dx.doi.org/10.23960/jitet.v13i1.5682.

[16] B. Restya and N. Cahyono, "Optimasi Metode Klasifikasi Menggunakan FastText dan Grid Search pada Analisis Sentimen Ulasan Aplikasi SeaBank," *JIKO (Jurnal Informatika dan Komputer)*, vol. 9, no. 1, pp. 226–238, 2025, doi: 10.26798/jiko.v9i1.1523.

[17] E. G. Radjah and A. C. Talakua, "Analisis Sentimen Komentar Terhadap Konten Tenun NTT di Youtube Menggunakan Metode SMOTE dan Logistic Regression," *Jurnal Transformatif*, vol. 13, no. 2, pp. 84–94, 2024, doi: https://doi.org/10.58300/transformatif.v13i2.1005.

[18] N. A. Amalia, I. T. Utami, and Y. Wilandari, "Analisis Sentimen Kebijakan Penyelenggara Sistem Elektronik Lingkup Privat Menggunakan Penalized Logistic Regression dan Support Vector Machine," *Jurnal Gaussian*, vol. 12, no. 4, pp. 560–569, 2024, doi: 10.14710/j.gauss.12.4.560-569.

[19] D. Prasetia, N. Rahaningsih, R. D. Dana, and C. L. Rohmat, "Analisis Sentimen Pengguna Aplikasi Mybluebird dengan Algoritma Naïve Bayes di Playstore," *JITET (Jurnal Informatika dan Teknik Elektro Terapan)*, vol. 13, no. 1, pp. 602–607, 2025, doi: http://dx.doi.org/10.23960/jitet.v13i1.5687.

[20] B. A. Putra *et al.*, "Optimisasi Algoritma K-Means dengan Metode Reduksi Dimensi untuk Pengelompokan Big Data dalam Arsitektur Cloud Computing," *Jurnal Software Engineering and Information System (SEIS)*, vol. 5, no. 1, pp. 1–8, 2025, doi: https://doi.org/10.37859/seis.v5i1.7616.

[21] R. D. R. Apriliansyah, R. AstutI, W. Prihartono, and R. Hamonangan, "Penerapan Algoritma Naive Bayes untuk Analisis Sentimen Pengunjung di Pantai Kejawanan," *JITET (Jurnal Informatika dan Teknik Elektro Terapan)*, vol. 13, no. 1, pp. 917–926, 2025, doi: http://dx.doi.org/10.23960/jitet.v13i1.5774.

[22] S. N. Salombe, S. Alam, and V. Aris, "Analisis Sentimen Ulasan Netizen pada Aplikasi Disney + Hotstar di Aplikasi Google Play Store Menggunakan Machine Learning," *INNOVATIVE: Journal of Social Science Research*, vol. 5, no. 1–9, pp. 5968–5977, 2025, doi: https://doi.org/10.31004/innovative.v5i1.15846.

[23] S. Setyabudi and E. Aryanny, "Sentiment Analysis of Lazada Marketplace User Ratings with Naïve Bayes and Support Vector Machine Methods," *JURNAL INOVTEK POLBENG - SERI*

INFORMATIKA, vol. 10, no. 1, pp. 422–433, 2025, doi: https://doi.org/10.35314/sww8cg21.

[24] R. R. Rismansyah, A. Sudiarjo, and T. Mufizar, "Analisis Sentimen Ulasan Shopee Pada Google Play Store Menggunakan Algoritma Naive Bayes," *Jurnal Elektro & Informatika Swadharma (JEIS)*, vol. 5, no. 1, pp. 109–119, 2025, doi: https://doi.org/10.56486/jeis.vol5no1.661.

[25] S. Fathurrohman, I. R. Afandi, and F. N. Hasan, "Sentiment Analysis of TIMNAS Indonesia's Participation in the Asian Cup U23 2024 on X Using Naive Bayes and SVM," *IJID (International Journal on Informatics for Development)*, vol. 13, no. 1, pp. 434–447, 2024, doi: 10.14421/ijid.2024.4504.

[26] I. D. Yulisa, Gusmelia Testiana, and Imamulhakim Syahid Putra, "Classifying High School Scholarship Recipients Using the K-Nearest Neighbor Algorithm," *IJID (International Journal on Informatics for Development)*, vol. 11, no. 2, pp. 232–241, 2023, doi: 10.14421/ijid.2022.3804.

[27] Y. N. Fernando, A. Y. Rahman, and R. P. Putra, "Analisis Sentimen pada Ulasan Konsumen Ayam Goreng Nelongso di Google Maps Menggunakan Metode Bidirectional Long Short-Term Memory (Bi-LSTM)," *Jurnal Ilmiah Mahasiswa Sains UNISMA Malang (JIMSUM)*, vol. 3, no. 1, pp. 65–85, 2025, doi: http://dx.doi.org/10.33474/jimsum.v3i1.26592.

[28] M. Arsadhana, B. Efendi, and M. Trihudiyatmanto, "Analisis Kepuasan Pelanggan Melalui Sentimen Ulasan Menggunakan Algoritma Naive Bayes," *Jurnal Magisma*, vol. 13, no. 1, pp. 1–8, 2025, doi: https://doi.org/10.35829/magisma.v13i1.471.

[29] S. Wulandari, M. Trihudiyatmanto, and B. Efendi, "Analysis of MSME Customer Perception Through Sentiment Reviews," *Jurnal Magisma*, vol. 13, no. 1, pp. 48–55, 2025, doi: https://doi.org/10.35829/magisma.v13i1.476.

[30] F. Andriansyah and P. Astuti, "Analisis Sentimen Komentar Konten Edukatif di Instagram Dengan Metode Naïve Bayes dan Support Vector Machine," *Jurnal Imtechno*, vol. 6, no. 2, pp. 27–31, 2025, doi: https://doi.org/10.31294/imtechno.v6i1.7262.

[31] M. F. A. Shidiq and D. Alita, "Analisis Sentimen Masyarakat Terhadap Kasus Judi Online Menggunakan Data dari Media Sosial X Pendekatan Naive Bayes dan SVM," *Jurnal Sistem Informasi dan Informatika (Simika)*, vol. 8, no. 1, pp. 24–35, 2025, doi: https://doi.org/10.47080/simika.v8i1.3624.

[32] H. T. Saputra, A. Damanik, M. M. Shaquille, M. A. Rusydi, and M. Habib, "Analisis Modelling pada Reviewes Lazada Indonesia Menggunakan Latent Dirichlet Allocation (LDA) untuk Optimalisasi Strategi Bisnis," *JEKIN: Jurnal Teknik Informatika*, vol. 5, no. 1, pp. 361–370, 2025, doi: https://doi.org/10.58794/jekin.v5i1.1325.

[33] W. Hadi, T. D. Putra, and D. Oktafiani, "Analisis Sentimen Terhadap Review Produk Lazada Indonesia Menggunakan Random Forest Classifier," *INNOVATIVE: Journal Of Social Science Research*, vol. 5, no. 1, pp. 2348–2357, 2025, doi: https://doi.org/10.31004/innovative.v5i1.17934.

[34] K. Khotimah, Martanto, A. R. Dikananda, and A. Rifa'i, "Analisis Sentimen Ulasan Aplikasi Pintu di Google Play Store Menggunakan Algoritma Naïve Bayes," *JITET (Jurnal Informatika dan Teknik Elektro Terapan)*, vol. 13, no. 1, pp. 963–969, 2025, doi: http://dx.doi.org/10.23960/jitet.v13i1.5789.

[35] E. D. K. Wardani, F. F. Yo, and W. N. Meylugita, "Implementasi Algoritma Naïve Bayes untuk Analisis Ulasan Pengguna untuk Aplikasi Seabank di Google Play Store," *Jurnal Kecerdasan Buatan dan Teknologi Informasi*, vol. 4, no. 1, pp. 13–24, 2025, doi: https://doi.org/10.69916/jkbti.v4i1.193.

[36] D. Fadila and M. Ikhsan, "Analisis Sentimen pada Aplikasi Tokopedia Menggunakan Metode Support Vector Machine," *Progresif: Jurnal Ilmiah Komputer*, vol. 21, no. 1, pp. 238–245, 2025, doi: 10.35889/progresif.v21i1.2593.

[37] R. Yusuf, K. Bahumatra, N. Komaria, E. A. Aqma, and L. Cahyani, "Analisis Sentimen Terhadap Aplikasi Google Meet Berdasarkan Komentar Pengguna Menggunakan Metode Logistic Regresion," *Jurnal Ilmiah Edutic: Pendidikan dan Informatika*, vol. 11, no. 1, pp. 53–64, 2024, doi: https://doi.org/10.21107/edutic.v11i1.28113.

[38] R. Maheri, F. N. Salisah, and F. Muttakin, "Analisis Sentimen Ulasan Aplikasi M-Paspor Menggunakan Naive Bayes dan Support Vector Machine," *JIPI (Jurnal Ilmiah Penelitian dan Pembelajaran Informatika)*, vol. 10, no. 1, pp. 448–458, 2025, doi: https://doi.org/10.29100/jipi.v10i1.5826.

[39] I. R. Afandi, I. F. Hanif, F. N. Hasan, E. S. Sinduningrum, Z. Halim, and N. Nunik, "Analisis Sentimen Opini Masyarakat Terkait Penyelenggaraan Sistem Elektronik Menggunakan Metode Logistic Regression," *Jurnal Linguistik Komputasional*, vol. 5, no. 2, p. 77, 2022.

[40] A. R. Hidayati, A. S. Fitrani, and M. A. Rosid, "Analisa Sentimen Pemilu 2019 pada Judul Berita Online Menggunakan Metode Logistic Regression," *Kesatria: Jurnal Penerapan Sistem Informasi (Komputer dan Manajemen)*, vol. 4, no. 2, pp. 298–305, 2023, doi: https://doi.org/10.30645/kesatria.v4i2.164.

[41] A. N. Sativa, A. Rizky, I. Putri, J. A. Putri, A. Irsyad, and Islamiyah, "Analisis Sentimen Twitter Ibu Kota Negara Nusantara Menggunakan Algoritma Naive Bayes, Logistic Regression dan K-Nearest Neighbors," *Adopsi Teknologi dan Sistem Informasi (ATASI)*, vol. 3, no. 2, pp. 34–40, 2024, doi: https://doi.org/10.30872/atasi.v3i2.1371.

[42] T. Prasetyo, A. A. Waskita, and T. Taryo, "Analisis Sentimen Pengguna Seputar Kendaraan Listrik di Twitter Dengan Penerapan Algoritma Naïve Bayes, KNN, dan Decision Tree untuk Klasifikasi," *Jurnal Sistem Komputer dan Kecerdasan Buatan*, vol. 8, no. 2, pp. 108–116, 2025, doi: https://doi.org/10.47970/siskom-kb.v8i1.783.

[43] A. G. Budianto, Rusilawati, A. T. E. Suryo, G. R. Cahyono, A. F. Zulkarnain, and Martunus, "Perbandingan Performa Algoritma Support Vector Machine (SVM) dan Logistic Regression untuk Analisis Sentimen Pengguna Aplikasi Retail di Android," *Jurnal Sains dan Informatika*, vol. 10, no. 2, pp. 1–10, 2024, doi: 10.34128/jsi.v10i2.911.

[44] I. R. Afandi, S. Fathurrohman, and M. W. A. Wibowo, "Sentiment Analysis of Mandatory Halal Certification Policy on Twitter Using the Naive Bayes and K-Nearest Neighbors Algorithm," *Halal Research*, vol. 5, no. 1, pp. 37–58, 2025, doi: https://doi.org/10.12962/j22759970.v5i1.1806.

[45] F. M. Hidayat and H. Sanjaya, "Analisis Sentimen Publik Terhadap Penjualan Iphone 16 dan Kebijakan TKDN di Indonesia," *Infotech Journal*, vol. 11, no. 1, pp. 73–80, 2025, doi: https://doi.org/10.31949/infotech.v11i1.13159.

[46] Z. B. Toyibah, Y. N. Putri, Puandini, Z. M. Widodo, and A. Tsalitsatun, "Perbandingan Kinerja Algoritma Multinomial Naïve Bayes dan Logistic Regression pada Analisis Sentimen Movie Ratings IMDB," *Jurnal Ilmiah Edutic : Pendidikan dan Informatika*, vol. 10, no. 2, pp. 181–189, 2024, doi: https://doi.org/10.21107/edutic.v10i2.28150.

[47] P. W. Hardjita, Nurochman, and R. Hidayat, "Sentiment Analysis of Tweets on Prakerja Card using Convolutional Neural Network and Naive Bayes," *IJID (International Journal on Informatics for Development)*, vol. 10, no. 2, pp. 82–91, 2022, doi: 10.14421/ijid.2021.3007.

[48] A. Septini, Susanto, and Elmayati, "Analisis Sentimen Masyarakat di Twitter Mengenai Open AI CHATGPT Menggunakan Metode Support Vector Machine (SVM)," *Bulletin of Computer Science Research*, vol. 5, no. 2, pp. 138–149, 2025, doi: 10.47065/bulletincsr.v5i2.475.

[49] M. Z. Ramadhan and R. Mubarak, "Analisis Sentimen Masyarakat Terhadap Kenaikan Bahan Bakar Minyak pada Media Sosial Youtube dengan Metode K-Nearest Neighbor dan Support Vector Machine," *JATI (Jurnal Mahasiswa Teknik Informatika)*, vol. 9, no. 1, pp. 984–991, 2025, doi: https://doi.org/10.36040/jati.v9i1.12526.

[50] A. Saninah, W. Prihartono, C. L. Rohmat, and K. Cirebon, "Analisis Sentimen Pengguna Terhadap Aplikasi Duolingo dengan Naïve Bayes Classifier," *JITET (Jurnal Informatika dan Teknik Elektro Terapan)*, vol. 13, no. 1, pp. 619–627, 2025, doi: http://dx.doi.org/10.23960/jitet.v13i1.5691.

[51] Alvinalia, A. Rahim, and T. A. Y. Siswa, "Analisis Sentimen Aplikasi Mysiloam Menggunakan Metode Naive Bayes," *JITET (Jurnal Informatika dan Teknik Elektro Terapan)*, vol. 13, no. 1, pp. 1546–1555, 2025, doi: http://dx.doi.org/10.23960/jitet.v13i1.5997.

[52] Y. R. Z. Mustopo and Afiyati, "Analisis Sentimen Proyek Strategis Nasional Food Estate Menggunakan Algoritma Naïve Bayes, Logistic Regression dan Support Vector Machine," *Jurnal JTIK (Jurnal Teknologi Informasi dan Komunikasi)*, vol. 9, no. 2, pp. 485–494, 2025, doi: https://doi.org/10.35870/jtik.v9i2.3312.