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Sentiment Analysis on Social Media: Investigating Users' Perceptions of MRT and LRTTransportation Services

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Abstract: Providing excellent public transportation in response to the passenger's complaints and recommendations results in long-term improvements to the service. This study investigates public perceptions of the MRT and LRT rail transportation services within the Klang Valley Integrated Transit System, operated by Rapid KL, through sentiment analysis in X. With 4.4 million users in Malaysia as of January 2022, X (previously Twitter) media social serves as a significant platform for public discourse. However, analyzing these perceptions poses challenges due to the limited platforms for analysis, and seeking from X is even more challenging due to the unstructured and noisy nature of the tweets. Therefore,this study aims to develop a sentiment analysis model that organizes tweets into structured data, utilizing machine learning techniques for sentiment classification into positive, neutral, and negative categories. Following the model implementation, the data are collected, translated, cleaned, labeled, analyzed, and classified using a Support Vector Machine before being deployed in a web system for ease of access. Analysis results revealed that user sentiment is predominantly neutral, with a significant focus on MRT services and topic finding related to scheduling. The model scored good accuracy 80% without a kernel and 84% with a Linear kernel, with evaluation metrics demonstrating strong performance on all three sentiment categories. Future enhancements will include label refining and applying more hyperparameter tuning to improve analysis accuracy.

Keywords: *Public transportation, X media social, Sentiment analysis, Machine learning, Support Vector Machine, Evaluation metrics, Label refining, Improved analysis accuracy.*

1. Introduction

Public transportation plays a crucial role in providing ease and convenience for individuals to travel from one location to another. Rail transportation, in particular, offers a viable alternative to mitigate heavy traffic congestion, especially during peak hours, while also being more cost-effective, energy-efficient, and time-saving compared to private vehicles. In the Klang Valley Integrated Transit System, the Mass Rapid Transit (MRT) and Light Rapid Transit (LRT) are one of the services operated by Rapid KL, a subsidiary of Prasarana Berhad. These rail services recorded substantial ridership, serving over 15 million passengers in 2021 (Malaysian Ministry of Transport, 2022). Given this high usage, discussions surrounding these services have become prevalent on social media platforms such as X (previously Twitter). Since its launch in 2006, Twitter has emerged as one of the most widely utilized social media platforms globally, largely due to its accessibility and user-friendly interface (Tiwari et al., 2023). On July 31, 2023, Twitter was renamed to "X" which became the huge conversation amongst Twitter users around that time. However, despite therename, the features inside are still the same. The platform enables users to share feedback, complaints, and suggestions regarding various events, and interactions with businesses, organizations, and even government entities. As of January 2022, Malaysia had approximately 4.4 million X users (Statista, 2023), making it a significant platform for public discourse. X has grown through time to enable users to tweet about events and incidents and express their thoughts, ideas, and sentiments (Quazi & Srivastava, 2023). The nature of tweets, reflecting both satisfaction and dissatisfaction, can significantly influence perceptions of service performance.

However, analyzing perceptions of transportation services presents challenges due to the limited analytical platforms available. Therefore, users often turn to X as a primary medium for expressing their views. WhileX provides a rich source of opinion, manually analyzing sentiments from tweets can be time-consuming, particularly given the unstructured, large volume, and noisy nature of the data. The solution for these problems is to design an automated process of gauging user perceptions called sentiment analysis.Sentiment analysis, in general, is about studying a feeling of people toward an event. It focuses on discovering techniques to unravel the hidden sentiments in reviews or opinion text comments that are being posted online (Khan & Junejo, 2020). By employing sentiment analysis techniques, this study aims to systematically retrieve and classify tweets related to MRT and LRT services into three sentiment categories:

Positive, neutral, and negative, using the Support Vector Machine method and identifying the topic findings in the words. The objectives of this study are to: design a sentiment analysis system on the services' related tweets and classify them into positive, negative and neutral; develop a sentiment analysis system of services' related tweets using a Support Vector Machine and visualize the results; and test the accuracy and functionality of the developed system. Ultimately, this study seeks to provide deep down into user perceptions of the services, enhancing valuable insights into public sentiment toward these vital transportation options.

To address the gaps in understanding user perceptions of MRT and LRT transportation services on social media, existing literature has advised using a variety of viewpoints in sentiment analysis studies concerning rail public transportation services to close these gaps. It emphasizes how critical it is to improvesentiment analysis and machine learning techniques to enhance performance accuracy. The review purpose is to overview the sentiment of public transportation, providing different data collection, cleaning and analysis methods for effectively capturing the complexities of user perceptions on media social platforms from X. The results are based on the accuracy of model performance. By drawing on recent studies related to transportation services, the review aims to highlight inadequately examined areas and provide actionable insights for stakeholders to enhance service quality and user experience in the context of sustainable transportation. The review's significance is to assess the service's performance. Consequently, Rapid KL can monitor the public's opinion of the service to help Prasarana Berhad maintain and improve its performance in response to passenger complaints and recommendations.

2. Literature Review

The emergence of the COVID-19 pandemic significantly impacted commuter behaviors in Indonesia, which compelled many users to stay home because of the lockdown cause leading to significant disruptions in the sector (I. C. Sari & Ruldeviyani, 2020). The review aims to analyze Twitter sentiments regarding commuterline usage at the onset of the pandemic in March 2020, highlighting public concerns and attitudes during this critical period. A total of 340 X tweets were collected using specific keywords, followed by pre-processing and classification through machine learning models of Naïve Bayes and Decision Tree, employing k-fold cross-validation to ensure robust results (I. C. Sari & Ruldeviyani, 2020). The findings revealed that Naïve Bayes outperformed the Decision Tree, achieving an accuracy of 74.37% with 15-fold validation compared to 58.24% with 10-fold validation. Notably, the Naïve Bayes model demonstrated superior sentiment classification across positive, neutral, and negative categories in each validation fold. This effectiveness of Naïve Bayes can be attributed to its foundation in Bayes' theorem, which incorporates the concept of conditional probability and having attributes with a high degree of independence (Nandan et al., 2022). It is one of the most straightforward and effective classification models that helps to build quickmodels with rapid prediction capabilities and higher accuracy than any other models (Mandloi & Patel, 2020). Incontrast, the Decision Tree employs a tree structure as a predictive model, with the leaves of the tree serving asthe conclusions or results and the node serving as the various observations or conditions (Gupta et al., 2019). However, complex tree structures, particularly those with numerous features as nodes make not easy to generalize and visualization (Gupta et al., 2019).

Motorcycle taxi services, which provide motorcycle-based transportation, are a relatively new phenomenon in Indonesia, presenting a unique opportunity to assess public sentiment toward their use, which is crucial for understanding consumer behavior and improving service quality (Jaman & Abdulrohman, 2019). The review aims to analyze customer sentiment regarding online motorcycle taxi services in Indonesia, specifically focusing on Gojek and Grab ID. A total of 1,183 X tweets were collected using specific keywords, followed by pre-processing and feature extraction using Term Frequency-Inverse Document Frequency (TF-IDF) before classifying the sentiment through a machine learning model of Support Vector Machine. To evaluate the effectiveness of sentiment classification, various kernel functions including linear, polynomial, radial basis function, and sigmoid were tested, serving as benchmarks for determining the highest accuracy for each dataset (Jaman & Abdulrohman, 2019). The analysis indicated that negative sentiment predominated, particularly for Gojek, while positive and neutral sentiments were more associated with Grab. Importantly, all kernel functions achieved satisfactory accuracy levels, surpassing 50%. Among these, the linear and sigmoid kernels performed exceptionally well, achieving an accuracy of 80%. This high level of accuracy reflects a strong alignment between the model's predictions and the actual sentiments expressed in the tweets, underscoring the efficacy of the Support Vector Machine model for sentiment classification in this context.

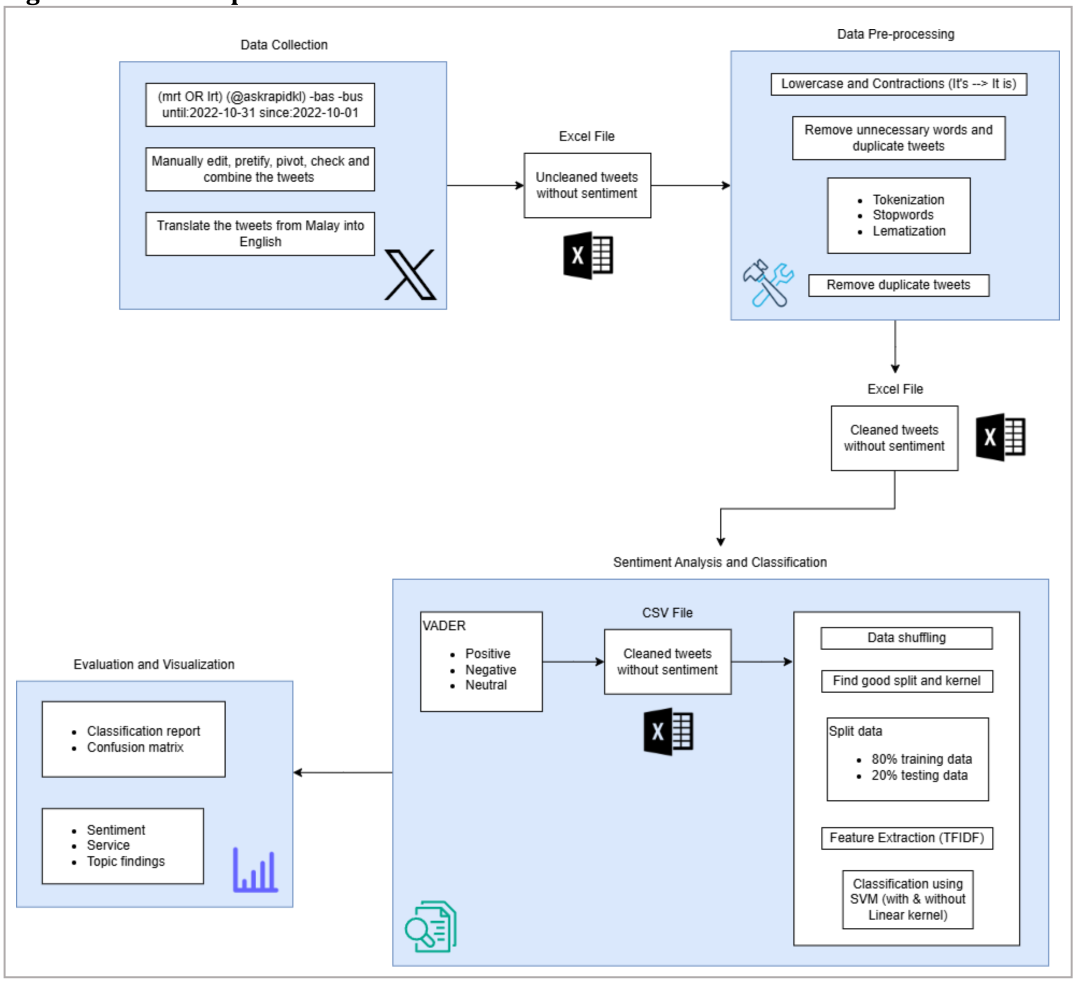
Malaysia's public transportation system, which encompasses the MRT and LRT transit, KL Monorail, and KTM commuter rail, is designed to meet the diverse needs of its users and enhance overall customer satisfaction cause the demand for efficient and reliable public transport services has become important (Wan Fen et al., 2020). This review investigates user perceptions of these transportation modes, analyzing a total of 1,236 tweets collected through the annotation "@". After pre-processing, the sentiment polarity of the tweets was assessed using the Syuzhet, Bing, and Afinn lexicons, implemented through machine learning models such as Support Vector Machine, Random Forest, and Decision Tree. The findings revealed that the Afinn lexicon outperformed the others, achieving accuracy rates of 77%, 75%, and 72% for the respective models. Evaluation metrics, including precision, recall, and F1 score, indicated that the SVM model excelledin precision and F1 score, while the Decision Tree performed best in the recall, with Random Forest showing lower effectiveness. This strong performance of the Support Vector Machine can be attributed to its problem-solving in classification and regression which can identify the hyperplane that differs between the two classes (J. & U., 2022). Overall, the sentiment analysis utilizing the Afinn lexicon indicatedthat positive sentiment was most prevalent, followed by neutral and negative sentiments, highlighting the importance of using various models in conjunction with sentiment lexicons to accurately capture user sentiments toward Malaysia's public transportation system.

The literature review provides essential context and insights for understanding user perceptions of MRT and LRT public transportation services. The examination of the impact of the COVID-19 pandemic on commuter behavior in Indonesia (I. C. Sari & Ruldeviyani, 2020) underscores the critical importance of sentiment analysis in capturing public attitudes during significant disruptions. Moreover, sentiment analysis of motorcycle taxi services of Gojek and Grab ID (Jaman & Abdulrohman, 2019) illustrated the efficacy of feature extraction and machine learning models to classify user sentiments across various kernels. Furthermore, sentiment analysis of Malaysia's public transportation system (Wan Fen et al., 2020) demonstrates that different sentiment lexicons can yield varying results, emphasizing the necessity for robust evaluation metrics to accurately assess user perceptions. By situating this study within the broaderdiscourse of existing research, a deeper understanding of the complexities surrounding user sentiment in the transportation sector was gained. This literature not only serves as a foundational basis for this study but also guides the model implementation, allowing for meaningful and relevantconclusions to be drawn from the findings which may improve public transportation systems.

3. Model Implementation

Figure 1 shows the workflow for implementing the model, which encompasses data collection, data pre-processing, sentiment analysis and classification, and evaluation and visualization using Python in Jupyter Notebook.

Figure 1: Model Implementation



Data Collection: The target population for this study comprises all users who have posted about MRT andLRT services on X media social platform from October 1, 2022, to September 30, 2023. To gather relevant data, tweets were retrieved using a manual scraping technique over one year, specifically targeting posts that included keywords "mrt" and "art." This focused approach ensured that the dataset would consist of content directly related to the services under investigation. Additionally, tweets mentioning the Rapid KL service, denoted by the annotation “@rapidkl,” were also included to enrich the dataset and provide a more comprehensive view of public sentiment towards these transit options. However, given that Rapid KL also operates bus services, the tweets that referred to bus-related content need to be excluded. This meticulous filtering process helped maintain the focus on the services solely. After applying these criteria, a total of 6,035 unique tweets in both Malay and English were compiled. Given thatthe primary focus of this study is on English language content, it was necessary to translate the Malay tweets into English for analysis. This translation process involved careful consideration to maintain the original meaning and context of the tweets. The translation relied on personal observations and a list of Malay shorttext references from Dewan Bahasa dan Pustaka (Bahasa, 2008), ensuring accuracy while unchanged the specific terminology, such as the names of the trains to retain their meaning. This meticulous data collection and translation process not only enhanced the quality of the dataset but also ensured that it accurately reflected users' perceptions of MRT and LRT services over the specified period.

Data Pre-processing: Pre-processing the data is crucial when working with huge text datasets, like those from Twitter (now X), as it helps to streamline the research process (Qi & Shabrina, 2023). Researchers go through several procedures, including cleaning and refining data to make sure the data that will be used is of high quality (Alhari et al., 2023). In this study, the preprocessing begins with converting all tweetsto lowercase, which helps standardize the text. This is followed by the removal of unnecessary words and duplicates, as well as addressing contractions to ensure uniformity. The next step is tokenization, which breaks sentences into individual words, or tokens, facilitating a better understanding of the text by analyzing word sequences (Nandan et al., 2022). Following tokenization, stopwords—common words like "a," "the," and "in" that contribute little or no meaning to the overall sentiment—are removed. The final step is lemmatization, which converts words to their dictionary forms using a lookup table and the context of the terms (Sham & Mohamed, 2022). By reducing words to their base forms, lemmatization ensures consistency in language processing and effectively eliminates redundant text that could skew analysis results. With duplicates removed, the 5,743 tweets are now well-prepared for further analysis and classification, setting the stage for meaningful insights into the data.

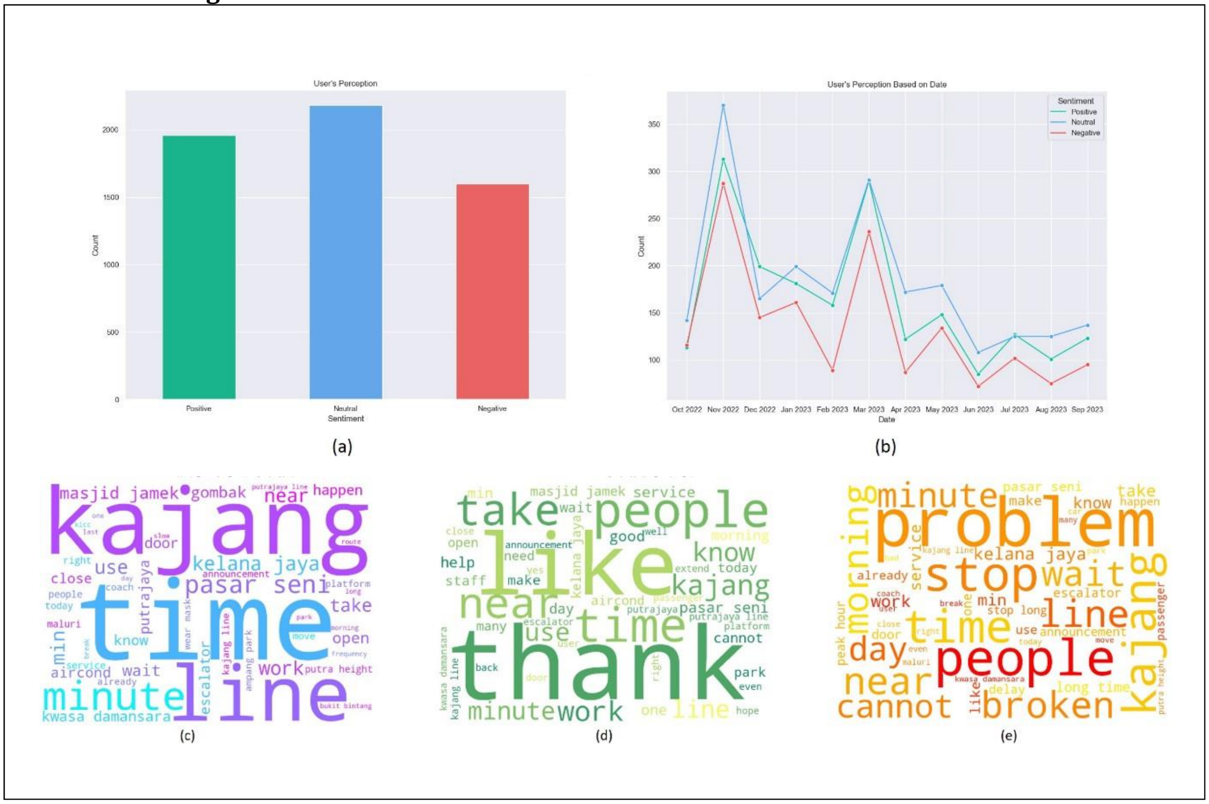
Sentiment Analysis and Classification: In this study, pre-processed tweets undergo sentiment analysis utilizing the VADER lexicon. Developed as a valence-based and generalizable tool, VADER is a human-validated, rule-based sentiment analysis method specifically tailored for social media platforms like Twitter (now X) (Sham & Mohamed, 2022). The analysis classifies tweets into positive, negative, or neutralsentiments based on their polarity scores: scores above 0 indicate positive sentiment, scores below 0 denote negative sentiment, and a score of 0 represents neutrality. To ensure a balanced representation of sentiment, the distribution of polarity scores is visualized. Following this, tweets are categorized into predefined classes using a machine learning model of Support Vector Machine. To enhance the model's performance, data shuffling and splitting are employed, allocating 80% for training and 20% for testing, following Hold-On partitioning. Feature extraction is conducted using Term Frequency-Inverse DocumentFrequency (TF-IDF) to convert tweets into numerical vectors, identifying frequently used terms (TF) while considering their rarity (IDF) within the dataset (Adwan et al., 2020). As computers operate primarily withbinary and numerical data, this transformation is essential for enabling the model to effectively learn fromthe dataset.

Evaluation and Visualization: The model's effectiveness in predicting sentiments for both testing data and new datasets is rigorously evaluated using various metrics. These include a comprehensive classification report that encompasses Accuracy, Precision, Recall, and F1-score, along with a confusion matrix. The confusion matrix serves as a valuable diagnostic tool, providing insights into the model's performance by detailing the rates of true positive predictions, false positives, true negatives, and false negatives (E. Y. Sari et al., 2019). This breakdown enables a nuanced understanding of how well the model distinguishes between different sentiment categories. To complement the numerical evaluations, a varietyof visualizations—such as bar graphs, line charts, and pie charts—are employed to illustrate the distribution of sentiment across the dataset. These visual representations not only highlight trends and patterns but also enhance the interpretability of the findings. The visualizations encompass three key areas: sentiment, service, and topic findings. Sentiment focuses on the count of users' perceptions regarding the service, while service reveals the frequency of mentions related to specific services. Topic findings delve into the keywords and phrases that contribute to users' sentiments, providing a deeper understanding of the factors influencing their opinions.

4. Results and Discussion

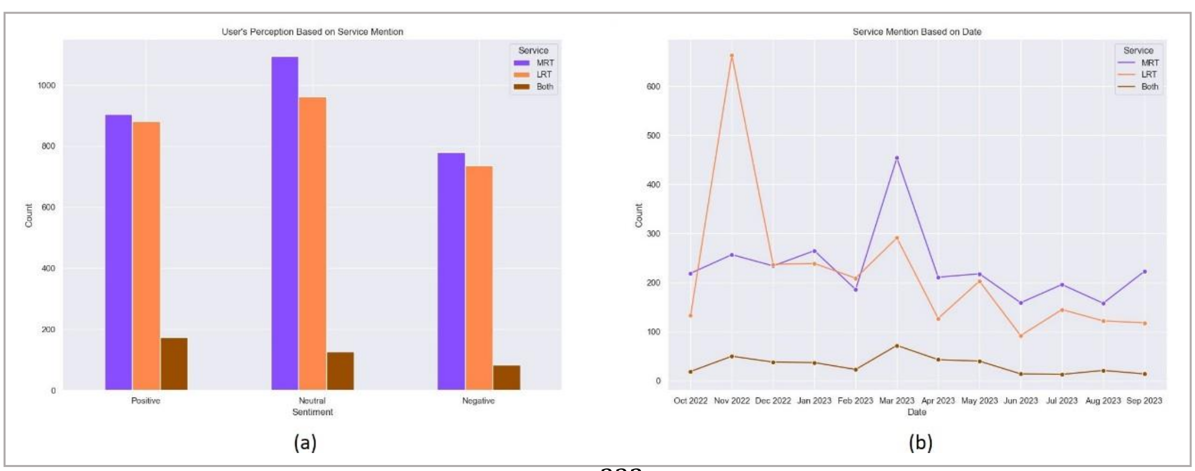
Visualization on Sentiment: The sentiment analysis was conducted on 5,743 cleaned tweets regarding MRT and LRT services. Figure 2 (a) shows that user perceptions are predominantly neutral, with 2,184 tweets (38%) classified as neutral, while positive sentiment accounts for 1,960 tweets (34%), and negativesentiment comprises 1,599 tweets (28%). Figure 2 (b) indicates that positive tweets peaked in December 2022 and July 2023, whereas the majority of tweets in other months were neutral, with negative tweets being infrequent. User engagement reached its highest in November 2022 and March 2023. A word cloud analysis highlighted the 50 most frequently used words in each sentiment category, while station names were kept as single entries. Figure 2 (c) shows that neutral sentiment focused on train timing. Users expressed not much reaction to the timing of the MRT Kajang. Figure 2 (d) reveals that positive sentiment emphasized appreciation for staff and service. Users expressed satisfaction with the service on the MRT Kajang Line, and the staff performed their jobs well. Furthermore, Figure 2 (e) illustrates that negative sentiment addressed service and train issues. Users reported ongoing problems with the MRT Kajang Line and expressed dissatisfaction with broken facilities.

Figure 2: The result shows (a) a bar graph of sentiment count, (b) a multiple-line chart of sentiment count with date, (c) word cloud of neutral sentiment, (d) word cloud of positive sentiment, and (e) word cloud of negative sentiment



Visualization on Service: Figure 3 (a) shows the distribution of sentiment across different services, revealing that neutral sentiment has 1,095 mentions for MRT, 962 for LRT, and 127 for both services. When examining positive sentiment, the figures show 905 mentions for MRT, 881 for LRT, and 174 for both services. Conversely, the data for negative sentiment indicates 780 mentions for MRT, 736 for LRT, and 83 for both services. Overall, these findings imply that users predominantly maintain a neutral stance towards the services, yet the higher frequency of mentions for MRT may point to greater public engagement, not onneutral sentiment but for all sentiment categories. Even so, Figure 3 (b) indicates that tweets about LRT were concentrated in November 2022, December 2022, and February 2023. This spike in mentions during these months could be attributed to specific events, promotions, or changes in service that captured user attention. Interestingly, mentions of both services were relatively rare in other months.

Figure 3: The result shows (a) a multiple bar graph of service mention count, and (b) a multiple line chart of service mention count with the date



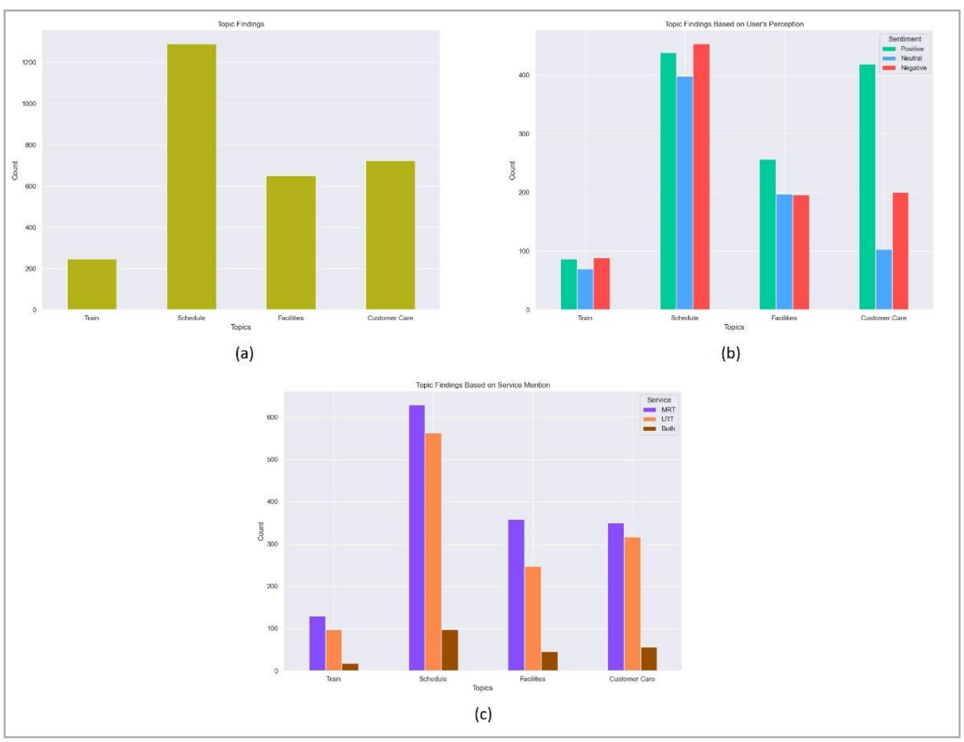
Visualization on Topic Findings: Analyzing the keywords used in tweets provides valuable insights into the specific topics users discuss regarding the services and their corresponding sentiments—positive, negative, or neutral. To identify prevalent topic findings, calculations were performed on the most frequently occurring one- and two-word combinations in the tweets using n-gram. Table 1 shows the four main topics findings emerged, along with their keywords.

Table 1: Topic findings with its keywords

Topic Findings	Keywords
Facilities	"function", "safety", "operating", "maintenance", "woman_coach", "lady_coach", "Coach", "parking_lot", "escalator", "elevator", "lift", "machine", "surau", "CCTV", "staircase", "toilet", "stairs", "kiosk"
Train Schedule	"technical_problem", "service_disruption", "fare", "available", "pack", "crowd" "delay", "peak_hour", "rush_hour", "extend", "time", "minute", "hour", "frequency", "frequent"
Customer Care	"take_action", "response", "answer_question", "feedback", "help", "complaint", "complain", "assistance", "responsible", "listen", "hear", "good_job", "staff", "police", "rapidkl_team", "operator", "admin", "officer", "customer", "management", "prasarana", "worker", "assistant", "rapidly"

Combining the tweets that did not have specific topic findings, the total number of tweets analyzed reached 6,203. While there may be duplicate tweets, each tweet can feature different topic findings. Figure 4 (a) indicates that the Schedule topic received the highest number of mentions, totaling 1,291 tweets, followed by the Customer Care topic with 723 tweets, the Facilities topic with 651 tweets, and the Train topic with 246 tweets.This suggests that users are particularly focused on the schedules of the service. Figure 4 (b) reveals insights from the sentiment analysis, showing negative sentiment associated with the Train and Schedule topics, which had 89 and 454 negative tweets, respectively. In contrast, positive sentiment was recorded for the Facilities and Customer Care topics, with 257 and 419 positive tweets, respectively. Furthermore, Figure 4 (c) highlights that all topics also dominated sentiment discussions related to MRT, featuring 630 positive tweets on the Schedule topic, while the Train topic had the fewest mentions at 130.

Figure 4: The result shows (a) a bar graph of topic findings count, (b) a multiple bar graph of topic findings counts with the sentiment, and (c) a multiple bar graph of topic findings counts with service



A word cloud analysis of the 50 most frequently mentioned keywords for each topic based on sentiment was conducted, omitting train names and irrelevant terms. Figure 5 (a) shows that negative sentiment.

Related to the topic Train topic reflects users' frustrations with various train issues, indicating that users dislike when trains experience problems, leaving them waiting on the platform for extended periods, or when the air conditioning is inadequate inside the train. Figure 5 (b) illustrates that negative sentiment associated with the Schedule topic focuses on train arrival times. These terms suggest that users feel the train schedules are inadequate, resulting in long waits for trains, which many users find frustrating. In contrast, Figure 5 (c) demonstrates positive sentiment related to the Facilities topic, showcasing users' satisfaction with well-functioning amenities, which convey those users appreciate when these facilities are operational and accessible. Finally, Figure 5 (d) highlights positive sentiment regarding Customer Care, emphasizing the helpfulness of staff assistance, suggesting that users feel supported by the staff, indicating that customer care services are effective and beneficial.

Figure 5: The result shows word cloud of (a) Train topic on negative sentiment, (b) Schedule topic on negative sentiment, (c) Facilities topic on positive sentiment, and (d) Customer Care topic on positive sentiment

Classification and Evaluation of Support Vector Machine: The implementation of the Support Vector Machine in this study demonstrated effective classification of user sentiments expressed in tweets about MRT and LRT services. To assess the model's performance, a series of accuracy tests were conducted on both the test dataset and new incoming data. The focus was on the model's ability to accurately predict three distinct sentiment classes: positive, negative, and neutral. This classification is crucial for understanding public opinion and identifying areas for improvement in services. Table 2 compares the optimal configuration for the model concerning data splitting, while Table 3 compares various configurations related to hyperparameters. The analysis indicated that an 80:20 training-to-testing ratio was the most effective, coupled with the use of a Linear kernel to achieve optimal results. The dataset consisted of 5,743 labeled tweets, with 4,594 allocated for training and 1,149 for testing. This division ensured that the model had sufficient data to learn effectively while also being challenged with a representative sample during the testing phase.

Table 2: Model configuration on data splitting

Ratio	**Accuracy**
90:10	80.87%
80:20	**84.68%**
70:30	82.01%
60:40	80.20%
50:50	79.63%

Table 3: Model configuration on hyperparameter

80:20 data splitting	
Kernel	Accuracy
Linear	**83.03%**
Polynomial	67.62%
Radial Basis Function (RBF)	80.24%
Sigmoid	82.94%

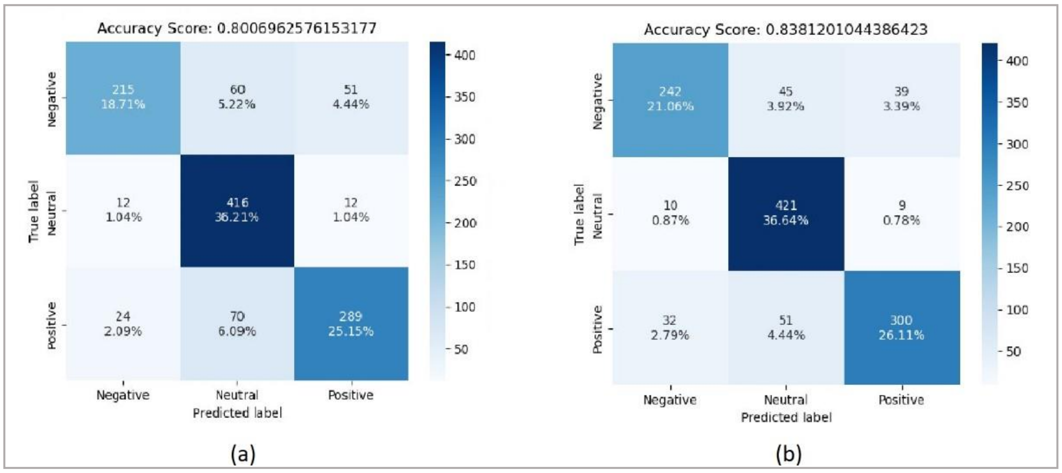
Feature extraction was conducted using Term Frequency-Inverse Document Frequency (TF-IDF) before classification. Table 3 shows the comparison of the classification report of the model with and without the Linear kernel. The model exhibited accuracies of 80% without a kernel and 84% with a Linear kernel. Performance metrics, including precision, recall, and F1-score, were calculated for each sentiment category. The classification report for the model without a kernel indicated scores above 70%, with negative recall being the lowest at 66%. This means the model accurately identified only 66% of actual negative sentiments. In contrast, neutral recall was the highest at 95%, suggesting effective identification of neutral sentiments. Then, a linear kernel was injected to enhance model performance. Following this adjustment, the classification report improved to above 80%, with negative recall increasing to 74% and neutral recall reaching 96%. Nevertheless, the injection of the linear kernel into the model significantly enhanced the model's accuracy, particularly in the correct classification of negative sentiments.

Table 4: Comparison of classification report on the model without and with Linear kernel

		Without Linear kernel			**With Linear kernel**	
	Precision	Recall	F1-Score	Precision	Recall	F1-Score
Negative	0.86	0.66	0.75	0.85	0.74	0.79
Neutral	0.76	0.95	0.84	0.81	0.96	0.88
Positive	0.82	0.75	0.79	0.86	0.78	0.82
Accuracy			0.80			0.84

Figure 6 (a) presents the confusion matrix of the model without Linear kernel. The analysis reveals that thetrue label for negative sentiment exhibits the highest rate of misclassification by the model, followed closely by positive sentiment, while neutral sentiment shows the least amount of misclassification. This pattern suggests that negative and neutral sentiments are challenging for the model; specifically, the negative sentiment has the lowest percentage of Recall, indicating difficulty in accurately predicting true labels. Conversely, the neutral sentiment has the highest percentage in Recall, suggesting that the model is better at identifying neutral cases. Then, a hyperparameter kernel was introduced into the model, aiming to improve the accuracy of the confusion matrix. Figure 6 (b) illustrates the confusion matrix of the model with Linear kernel. The misclassification rate for negative sentiment has been reduced. This improvement indicates that the adjustments made through the kernel have positively impacted the model's ability to correctly identify negative sentiment.

Figure 6: The result shows (a) the confusion matrix of SVM without a Linear kernel, and (b) the confusion matrix of SVM with a Linear kernel.



5. Conclusion and Recommendations

In summary, the sentiment analysis on collected, translated and cleaned X media social tweets has revealed three key dimensions: sentiment, service, and topic findings. Users' perception generally expressed a neutral perception of both MRT and LRT services, followed by positive and negative perceptions. Insightsindicate that factors such as train timing, appreciation for staff and service quality, and service or train-related issues significantly influence user opinions. While MRT was mentioned more favorably overall, the increased discussion about LRT suggests that users have a balanced view of both services. The analysisof topics findings delved into keywords within the tweets, highlighting critical areas of user discourse, including Facilities, Train, Schedule, and Customer Care. Notably, topics about training and Schedule generatedsignificant negative sentiment, while Facilities and Customer Care topics were viewed positively. Utilizing a Support Vector Machine model with an 80% training set and 20% testing set, it was found that employing a linear kernel resulted in higher accuracy compared to a model without a kernel. Evaluation metrics such as Precision, Recall, and F1-Score were reinforcing the model's effectiveness in accurately classifying user sentiment regarding these transportation services. All the results are then deployed in a web interface for easyaccess and visualization.

Engaging actively with users on social media platforms is crucial for collecting valuable feedback and improving service responsiveness. Continuous sentiment analysis will also play a key role in monitoring shifts in public perception and guiding ongoing improvements to MRT and LRT services. This prototype web system represents a significant asset for future research in sentiment analysis and Support Vector Machine classification. To enhance the system's effectiveness, several recommendations can be made. First,to improve the accuracy of the model, it is advisable to explore a wider range of hyperparameters, includinggamma, C, and degree. Optimizing these parameters can lead to better classification performance and more reliable results. Second, for more accurate data labeling, it is suggested to involve qualified individuals proficient in both Malay and English for translation tasks. Engaging experienced English teachers or lecturers can enhance the quality of translations, reducing the presence of untranslated Malay terms in the English text. This approach will facilitate more precise labeling by the Vader sentiment analysis tool, ultimately improving the overall performance of the system.

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