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Association Analysis Between Public Sentiment and Grab Stock Performance Using SVM and Lambda Test

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Abstract

During a period of strong economic performance in Indonesia—marked by a 5.4% growth in the second quarter of 2022—concerns about a potential downturn in the fourth quarter began to surface, as indicated by increased stock market volatility, including fluctuations in Grab's share prices. This study aims to classify public sentiment toward Grab based on comments from the social media platform Twitter, and to analyze its relationship with the direction of the company's stock price movement. Sentiment classification was conducted using the Support Vector Machine (SVM) algorithm through a series of steps including data preprocessing, TF-IDF weighting, imbalance data handling, and model performance evaluation. The dataset was split into 70% training data and 30% testing data. The SVM model achieved an accuracy of 87%, with a precision of 90%, recall of 91%, and F1-score of 91%. Public sentiment for each period was then aggregated using the Net Sentiment Score (NSS), which was subsequently categorized into positive or negative sentiment. These sentiment categories were analyzed in relation to stock price movements using the Goodman-Kruskal Lambda test. The result of λ(stock trend|sentiment)=0.053 indicates that knowing public sentiment reduces prediction error by only 5.3%, while λ(sentiment|stock trend)=0.000 shows no predictive value in the opposite direction. This study contributes a novel approach by integrating machine learning-based sentiment classification with a categorical association test, specifically applied to a regional technology company in Southeast Asia, which remains underexplored in existing literature.

Keywords: Goodman-Kruskal Lambda, Net sentiment score, Sentiment analysis, Stock Price, Support vector machine, Twitter.

I. Introduction

IN the era of digital economy, public opinion plays a crucial role in shaping perceptions of a company. Social media has become an open space for individuals to express their views, which can influence a company's image and reputation in the eyes of investors [1]. One technology company that has experienced such dynamics is Grab, a Southeast Asia-based provider of app-driven transportation and delivery services, including operations in Indonesia. The fluctuation of Grab's stock price, particularly following a major loss reported at the end of 2021, reflects how market expectations and public perception often move in tandem with corporate performance. Within this context, analysing public opinion on social media becomes increasingly important in understanding the relationship between public sentiment and stock price movements [2], [3].

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Indonesia's economic growth reached 5.4% in the second quarter of 2022, supported by a stable rupiah exchange rate and the strengthening of the composite stock index [4]. However, by the fourth quarter of the same year, growth projections declined to 5.03%. One contributing factor was the drop in stock prices of several major companies, including Grab, which experienced a 37% decrease in share value in March 2022 following the announcement of significant quarterly losses.

As a technology company listed on the NASDAQ and a key player in Southeast Asia's digital ecosystem, public perception of Grab plays a crucial role in influencing the company's valuation. Twitter, with millions of active users in Indonesia, serves as a primary platform for the public to express their opinions—both positive and negative. These expressions can shape the company's image and potentially impact stock price movements, given the open and rapidly viral nature of social media.

Grab was selected as the subject of this study not only due to its significant presence in the Southeast Asian digital economy, but also because it represents a regionally relevant case that has received limited academic attention compared to global tech giants. This study aims to contribute to the growing body of literature on sentiment-based financial analysis by focusing on a locally influential company in an emerging market context.

Sentiment analysis serves as an appropriate approach to measure public opinion toward Grab through textual comments on Twitter [5], [6]. However, while many existing studies focus on predicting stock price movement using sentiment-driven machine learning models, few have evaluated the actual association between classified sentiment and stock movement direction using categorical statistical approaches. This presents a gap in understanding whether public sentiment truly correlates with stock trends or merely reflects parallel social dynamics.

To address this gap, this study proposes a two-step approach: first, classifying sentiment using a Support Vector Machine (SVM) model trained on labelled Twitter comments; and second, evaluating the statistical association between sentiment polarity and stock price movement using the Goodman-Kruskal Lambda test. By applying this method to the case of Grab, the study contributes to a deeper understanding of the link between social media sentiment and financial market behaviour, particularly in the context of a Southeast Asian digital enterprise.

II. LITERATURE REVIEW

A. Related Work

Numerous previous studies have demonstrated that the Support Vector Machine (SVM) algorithm performs reliably in text classification tasks, often outperforming alternative methods in terms of accuracy. Building upon this, the present research utilizes social media data to examine whether there is a meaningful association between public sentiment and the movement direction of Grab's stock, employing a non-parametric statistical method for analysis.

Table I presents a summary of related work focusing on the use of social media sentiment for financial prediction. Prior studies have demonstrated the potential of social media sentiment in stock price prediction by integrating sentiment analysis with machine learning models. One study [7] using Twitter and StockTwits data on Microsoft showed that SVM outperformed K-Nearest Neighbors (KNN) and Random Forest (RF) with an F1-score of 76.3%, while also highlighting concerns such as data quality and bot-induced bias. Other research incorporated features like tweet distribution and user influence, finding that models such as MLP offered strong predictive performance for companies like Apple and DJIA [8], [9]. Additionally, sentiment toward political figures was shown to moderately and negatively correlate with stock prices using Long Short-Term Memory (LSTM) and the Spearman test [10].

Research exploring sentiment-based market prediction often emphasizes price forecasting through regression and classification models, without delving into the statistical or categorical association between sentiment and stock direction [11], [12] . An analysis using VADER sentiment and Pearson correlation, for example, identified a strong linear relationship with Microsoft's stock price ($r = 0.78$), though the approach was limited by its short timeframe and lack of causal or categorical depth [13].

TABLE I
SUMMARY OF RELATED WORKS

Reference	Methodology	Key Findings	Limitations	Research Gap
[7]	Twitter/StockTwits + Vader/TextBlob + 7 ML Models include SVM	SVM+Twitter+VADER gave best f1-score (76.3%)	Sarcasm, bots, class imbalance, single stock	No categorical/statistical association tested
[8]	Tweet features + market data with CNN-LSTM, ET	Tweet volume and user profile improved prediction	Limited observation period, Twitter-only	No real-time multi-source sentiment fusion
[9]	SVM for sentiment + MLP for price prediction	MLP outperformed; sentiment helped next-day price	binary sentiment, one year only	No bidirectional or statistical testing
[10]	LSTM + Spearman correlation (Tweet vs stock)	Negative correlation (r=-0.402), LSTM accuracy 90%	Twitter-only, binary sentiment, limited observation period	Few use local context or statistical association
[11]	Technical + sentiment embeddings, RF/SVM/NN	NN + sentiment had best return (85.2%)	Limited observation period, few stocks, no fusion	Few combine deep models + trading simulation
[12]	LSTM + ARIMA + Twitter sentiment	Sentiment boosted LSTM-ARIMA Accuracy	Noisy data, limited interpretability	Few unify ARIMA + DL + sentiment
[13]	VADER + Pearson correlation	Sentiment correlates with stock price (r=0.78)	Short duration, one company, linear only	No causal/statistical testing
This Work	SVM + Goodman Kruskal-Lambda Association	Weak association ($\lambda = 0.053$), high accuracy in classification.	Twitter-only, binary sentiment, limited observation period	Lacks integration of macroeconomic or firm-specific context

Most prior studies have focused on stock price prediction using machine learning models driven by public sentiment. Although the methods employed vary—encompassing models such as SVM, LSTM, MLP, and ARIMA—these approaches are primarily predictive in nature and oriented toward quantitative regression or classification of stock prices. Few studies have explicitly examined the statistical association between classified sentiment and the direction of stock movement using non-parametric methods such as Goodman-Kruskal Lambda, which is suitable for categorical data (e.g., up/down and positive/negative).

Moreover, the majority of existing research centers on large global corporations such as Microsoft and Apple, whereas the present study focuses on Grab—a Southeast Asian technology company that is closely tied to Indonesia's digital economy. This creates a more locally relevant context that remains underexplored in the existing literature. Therefore, this study addresses two key research gaps: the limited exploration of categorical association between sentiment and stock movement, and the lack of studies focusing on regional technology firms within emerging digital economies.

B. *Support Vector Machine Algorithm*

The Support Vector Machine algorithm determines an optimal hyperplane, serving as a decision boundary that efficiently partitions the dataset into two distinct categories based on their feature representations [14]. This boundary is established by maximizing the margin, or the gap between the hyperplane and the closest data points from each class, which are known as support vectors. Determining this hyperplane involves calculating a weight vector $\mathbf{w}$, bias term b, and input vectors $\mathbf{x_i}$ which satisfy (1).

$$\mathbf{w}^T \cdot \mathbf{x_i} + b = 0 \tag{1}$$

To determine the class of a given data point $\mathbf{x_i}$ a decision function as shown in (2) is used. This function evaluates the position of the data point relative to the separating hyperplane and assigns it to a class based on the sign of the resulting value, whether it lies on the positive or negative side of the hyperplane.

$$\mathrm{f(x)} = \begin{cases} 0, & \mathbf{w}^{\mathrm{T}} \cdot \mathbf{x_i} + b \leq -1 \\ 1, & \mathbf{w}^{\mathrm{T}} \cdot \mathbf{x_i} + b \geq 1 \end{cases} \tag{2}$$

C. Goodman-Kruskal Lambda

Goodman-Kruskal Lambda (λ) is a measure of association used to analyse the relationship between two nominal categorical variables, especially from a predictability standpoint. Unlike correlation measures that assess the degree and direction of a relationship, the Lambda statistic quantifies how much knowing one variable can reduce the prediction error of another [15], [16]. Equation (3) defines the formula for calculating the Lambda value.

$$\lambda(\mathrm{Y}|\mathrm{X}) = \frac{\mathrm{E_1} - \mathrm{E_2}}{\mathrm{E_1}} \tag{3}$$

In (10), the value of lambda is obtained by subtracting the number of prediction errors made without knowing the predictor variable (E_1) from the number of errors after knowing the predictor variable (E_2), and then dividing the result by the initial error count (E_1). In other words, the lambda value represents the proportion of error reduction that occurs once information about the predictor variable is taken into account. A lambda value of 0 signifies that knowing the predictor variable does not help in predicting the target variable. Conversely, if lambda approaches 1, it suggests that the predictor variable is highly useful in predicting the target.

III. RESEARCH METHOD

The overall research process in this study follows the Knowledge Discovery in Databases (KDD) framework, which consists of several interconnected stages: data selection, preprocessing, transformation, data mining, and evaluation [17]. Fig. 1 illustrates the workflow of the research, integrating sentiment analysis with financial market analysis in a structured manner.

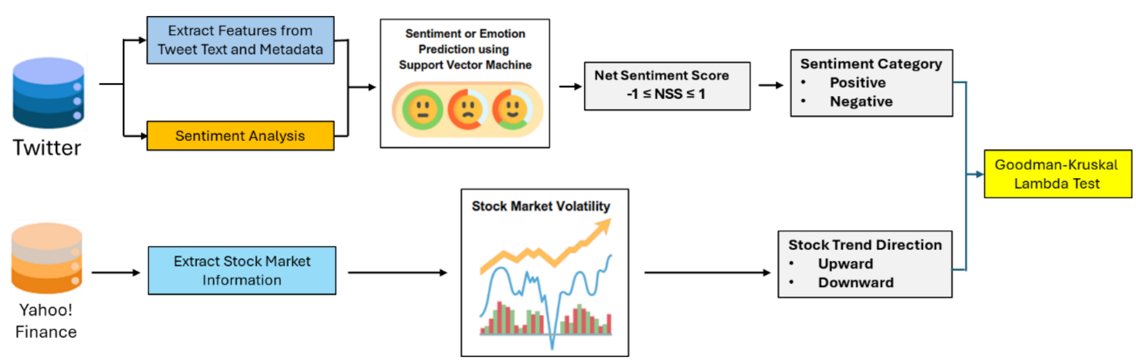

Fig. 1. Research Workflow to Analyze the Relationship Between Twitter Sentiment and Stock Trend Direction (Adapted and modified from [7])

Two main data sources are utilized: (1) Twitter data, containing user-generated text related to Grab, and (2) Stock market data, representing the historical stock price movements of Grab over a defined period. The process begins with the extraction of features from tweet text and metadata, which includes collecting relevant keywords and user comments. This textual data is then processed through a sentiment classification model using Support

Vector Machine (SVM) to identify the polarity of sentiment, positive or negative. The outcome of this process is quantified using the Net Sentiment Score (NSS), which ranges from −1 to +1, and is used to derive the sentiment category for each observation window.

Simultaneously, stock price data is extracted and analyzed to determine the direction of stock price movement, categorized as either upward or downward. These two categorical variables, public sentiment category and stock trend direction, are then statistically tested using the Goodman-Kruskal Lambda method. This final step evaluates the extent to which public sentiment can predict stock movements, or vice versa, based on nominal data associations.

The workflow in Fig. 1 illustrates the implementation of the KDD methodology in this study. The process begins with data selection, where tweet texts and stock market data are collected. In the preprocessing stage, tweet texts are cleaned and labeled, followed by transformation using TF-IDF and SMOTE-Tomek to handle text representation and class imbalance. The data mining stage applies Support Vector Machine (SVM) to classify sentiment into positive or negative. Finally, the evaluation stage involves measuring classification performance and testing the association between sentiment and stock movement using the Goodman-Kruskal Lambda method.

A. *Data Selection*

The data used for sentiment analysis was collected from user comments on the Twitter platform. These comments contained keywords such as *"saham"* (stock), *"saham Grab"*, and *"saham Grab holding"*, and were gathered over the period from December 2022 to March 2023. During this phase, a total of 232,906 raw data entries in the form of Twitter comments were collected. Table II presents an example of the collected Twitter comment data.

TABLE II
SAMPLE OF COLLECTED TWITTER COMMENTS RELATED TO GRAB'S STOCK

Date	Id	Username	Comment
2022-12-06 13:49:18+00:00	1.60013E+18	Abang	*b'Puji tuhan. Hari ini pertama kali saya gabung sebagi mitra grab semoga rezeki saya mengalir terus.. Amiin \xf0\x9f\x99\x8f'*
2022-12-06 13:34:56+00:00	1.60012E+18	Alya	*b'nyampe lah tu di kiara condong hujan ternyata gua coba grab kan DAN LU TAU BERAPA HARGA GRAB.\nsi angka keramat ini\xe2\x80\xa6 https://t.co/3zNrDjggSX'*

Meanwhile, Grab's stock price data was collected for the same period as the Twitter comments, from December 2022 to March 2023. Stock market data were sourced from Yahoo Finance, comprising key indicators such as trading date, opening and closing prices, daily highs and lows, adjusted close values, and overall trading volume.

B. *Data Preprocessing*

Data preprocessing is a stage carried out prior to classification, with the aim of preventing the inclusion of improper or unready data for analysis. This stage has a significant impact on optimizing the results of the subsequent classification process [18]. Before entering the preprocessing phase, a labelling step was conducted, in which Twitter comments were labelled as positive, negative, or neutral. The labelling process resulted in 42,142 comments labelled as positive, 15,076 as negative, and 175,688 as neutral. Since this study only used data with positive and negative labels, all neutral comments were removed, leaving a total of 57,218 entries. Duplicate entries were also removed, resulting in 9,885 unique comments retained for analysis.

The preprocessing then proceeded to the cleansing phase, which involved removing elements such as usernames, URLs, punctuation marks, HTML characters, and numbers. Case folding was performed by converting all letters to lowercase, followed by tokenizing, which splits sentences into individual words. Normalization was conducted to convert informal or non-standard words into their standard forms. During the stopword removal stage, common words that do not carry meaningful information were eliminated. Finally, stemming was applied to reduce words to their root forms by removing affixes such as prefixes and suffixes.

C. Data Transformation

In the transformation phase, text is converted into numerical values using the Term Frequency–Inverse Document Frequency (TF-IDF) technique. This method evaluates the relevance of a term within a document by comparing its frequency in that document to its frequency across the entire corpus. Words that occur more often in a specific document receive higher weights (TF), while words that appear less frequently across many documents are considered more informative (IDF). The resulting TF-IDF values are then used as input features for the classification model, as detailed in Equations (4)–(6) [19].

$$\mathrm{TF} = \frac{\text{number of times the word appears in a document}}{\text{total number of words in the document}} \tag{4}$$

$$\mathrm{IDF} = \ln\frac{(1 + \mathrm{D})}{(1 + \mathrm{df}_{(\mathrm{d,t})})} + 1 \tag{5}$$

$$\mathrm{TF} - \mathrm{IDF} = \mathrm{TF}_{(\mathrm{t})} \times \mathrm{IDF}_{(\mathrm{t,d})} \tag{6}$$

In this context, *t* represents the given term in a document, *d* denotes the collection of all documents, *D* is the total number of documents, and $\mathrm{df}_{(d,t)}$ refers to the number of documents that contain the term t.

D. Data Mining

Prior to the modelling phase, the comment dataset underwent imbalance treatment using the SMOTE-Tomek method. This hybrid technique applies the Synthetic Minority Over-sampling Technique (SMOTE) to generate additional samples for underrepresented classes, while Tomek Links are used to eliminate overlapping data points near class boundaries, enhancing class separation [20], [21]. After achieving a balanced class distribution, the modeling process was carried out using the Support Vector Machine (SVM) algorithm to classify sentiment data into positive and negative categories.

The decision to employ the SVM algorithm in this research was guided by its suitability for the dataset characteristics and the goals of sentiment analysis. SVM is widely recognized for its strong performance in classification tasks, especially when dealing with high-dimensional inputs like text data derived from social media platforms [22].

E. Evaluation

To assess the effectiveness of the classification model, a confusion matrix was utilized. This matrix is a standard evaluation method in classification tasks that compares predicted outcomes with actual class labels in the test dataset [23]. It categorizes predictions into four types: true positives (TP), false negatives (FN), false positives (FP), and true negatives (TN). These components are then used to derive key performance indicators such as accuracy, precision, recall, and F1-score, as outlined in (7) - (10).

$$\text{accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{7}$$

$$\text{precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{8}$$

$$\text{recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{9}$$

$$\text{F1} - \text{score} = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}} \tag{10}$$

Together, these four evaluation metrics offer a thorough assessment of the model's ability to accurately and reliably distinguish between positive and negative sentiment classifications.

IV. RESULTS AND DISCUSSION

This section presents the results of the sentiment classification stage, the calculation of sentiment scores, and the analysis of the relationship between public sentiment and the direction of Grab's stock price movement.

A. *Modeling Result*

For model development purposes, the comment dataset was divided into training and testing subsets with a 70% to 30% proportion, respectively. As a result, 2,966 data points were allocated for testing and 6,919 for training. Since the training data remained imbalanced after splitting, the SMOTE-Tomek method was applied. The number of data instances before and after applying the SMOTE-Tomek technique is presented in Table III.

TABLE III
NUMBER OF DATA SAMPLES

	Number of Comments	
	Positive Class	**Negative Class**
Before SMOTE-Tomek	4,620	2,299
After SMOTE-Tomek	4,608	4,608

After the training data was balanced between the positive and negative classes, the SVM method was implemented using a linear kernel. The training process produced the optimal hyperplane, as shown in (11).

$$\begin{pmatrix} 0.865407 \\ -0.375648 \\ -0.590635 \\ \vdots \\ 0.132920 \end{pmatrix}^{\mathrm{T}} \cdot \begin{pmatrix} 0 \\ \vdots \\ 0.495037 \\ \vdots \\ 0 \end{pmatrix} + (0.277841) = 0 \tag{11}$$

The resulting positive bias value indicates the direction of the hyperplane shift, and together with the weight vector **w**, plays a key role in determining the optimal separating line between the two classes.

B. Performance Evaluation of Sentiment Classification

In the evaluation process, a confusion matrix was used to assess the performance of the model developed in the previous stage. Based on Fig. 2, it can be observed that 1,865 comments were correctly predicted as positive (true positives). In addition, there were 208 comments incorrectly predicted as positive (false positives). Furthermore, 175 comments that were actually positive were incorrectly classified as negative (false negatives). Finally, 718 comments were correctly predicted as negative (true negatives).

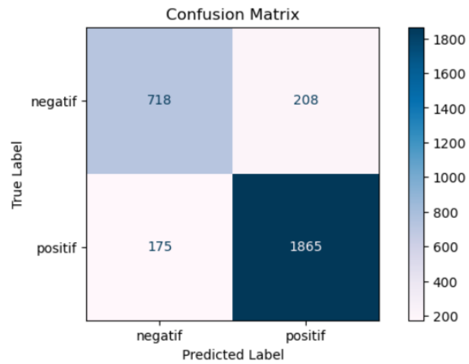

Fig. 2. Confusion Matrix

From the confusion matrix, the resulting values of accuracy, precision, recall, and F1-score are presented in Table IV. The SVM-based sentiment classification model demonstrated very strong performance. With high accuracy and a balanced precision–recall ratio, the model is capable of classifying sentiment accurately and consistently. These results indicate that the SVM model is a suitable approach for performing sentiment analysis on public Twitter comments in the context of Grab's stock.

TABLE IV
PERFORMANCE EVALUATION

Metric	Evaluation
Accuracy	0.87
Precision	0.90
Recall	0.91
F1-Score	0.91

C. Net Sentiment Score Aggregation

After the sentiment classification process was performed on the Twitter comment data using the SVM algorithm, the trained model was applied to the testing data to identify the sentiment category of each tweet. The classification results were then used to construct an aggregated dataset based on stock price movement periods.

All data were compiled and grouped into 40 stock movement periods, with each period representing a distinct time range during which a significant stock price change—either an increase or a decrease—occurred. Within each period, the number of tweets labelled as positive and negative was calculated. To simplify the representation of public sentiment within a given period, the Net Sentiment Score (NSS) was calculated using (12).

$$\text{NSS} = \frac{\text{positive mentions} - \text{negative mentions}}{\text{total mentions}} \tag{12}$$

The NSS value provides a quantitative representation of the overall tendency of public sentiment [24]. If the NSS value is positive, public sentiment during that period is categorized as positive; conversely, if the NSS value is negative, the sentiment is categorized as negative. In this study, there were no cases where NSS equaled zero, which would otherwise indicate neutral sentiment or the absence of a dominant sentiment tendency.

TABLE IV
SUMMARY OF STOCK MOVEMENTS AND AGGREGATE PUBLIC SENTIMENT PER PERIOD

No.	Stock Movement Period	Stock Direction	Positive Tweets	Negative Tweets	NSS	Sentiment Category
1	01/12/2022 – 02/12/2022	Up	35	17	0.3462	Positive
2	05/12/2022 – 07/12/2022	Down	54	25	0.3671	Positive
…	…	…	…	…	…	…
6	21/12/2022	Up	7	9	-0.1250	Negative
…	...	…	…	…	…	…
39	27/03/2023 – 29/03/2023	Up	55	15	0.5713	Positive
40	31-03/2023	Up	1	0	1.0000	Positive

Based on these calculations, Table IV was constructed, containing: the period number, stock movement period, stock movement direction (up/down), the number of positive and negative tweets, the NSS value, and the resulting sentiment category (positive/negative). The data in Table IV were then used as the basis for constructing a contingency table shown in Table V, which represents the distribution between stock price movement direction and public sentiment category.

TABLE V
CONTINGENCY TABLE

		Sentiment		Tot al
		Positive	Negative	
Stock Direction	Up	1	20	21
	Down	2	17	19
Total		3	37	40

D. Association Analysis using Lambda Test

The relationship between the public sentiment category and the direction of Grab's stock price movement was tested using the Goodman-Kruskal Lambda method, which is a measure of association for categorical variables. This test not only assesses the existence of a relationship, but more specifically evaluates the extent to which prediction errors of the target variable can be reduced when the value of the predictor variable is known.

1) Predicting Stock Movement Based on Public Sentiment: In this direction of analysis, the stock movement variable (up/down) is considered the dependent variable, while sentiment (positive/negative) serves as the independent variable or predictor. The resulting lambda value is shown in (13).

$$\lambda(\text{stock trend}|\text{sentiment}) = \frac{19 - (1 + 17)}{19} = 0.053 \tag{13}$$

This means that knowing the public sentiment category reduces the error in predicting stock movement by only 5.3% compared to making predictions without any sentiment information. This value is considered very low and indicates that public sentiment expressed on social media does not provide a significant contribution in forecasting whether Grab's stock price will increase or decrease. In other words, the association between sentiment and stock movement direction is very weak, making the use of sentiment data in this context ineffective as a predictor of stock price fluctuations.

2) Predicting Public Sentiment Based on Stock Price Direction: In the opposite direction, public sentiment is considered the dependent variable. The test yields a lambda value as shown in (14).

$$\lambda(\text{sentiment}|\text{stock trend}) = \frac{3-(1+2)}{3} = 0 \quad (14)$$

A lambda value of zero indicates that knowing the direction of Grab's stock price movement does not reduce prediction error in determining the public sentiment category. In other words, whether the stock price increases or decreases provides no useful information for estimating whether public sentiment is more likely to be positive or negative during that period.

E. Visualization

Further analysis was conducted by presenting n-gram frequency visualizations to reveal recurring word patterns under different data conditions, uncovering thematic links between public sentiment and market dynamics. These high-frequency terms provided contextual cues—such as reactions to services, promotions, or issues—that influenced sentiment. This qualitative layer complements binary classification by offering deeper insight into the topics shaping public opinion during periods of stock movement.

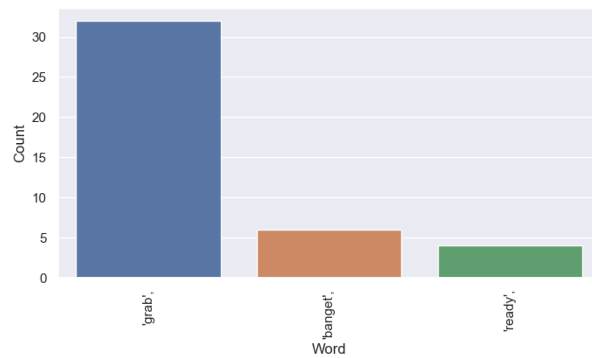

Fig. 3. Top Unigram Frequencies During Periods of Stock Decline and Positive Public Sentiment

Fig. 3 shows the n-gram distribution for Period 5 (15 – 20 December 2022), during which Grab's stock price declined while public sentiment was categorized as positive. The visualization reveals the top three most frequent words during that period: *'grab'*, *'banget'* (very), and *'ready'*. While *'grab'* does not directly carry a sentiment value, its frequent appearance reinforces that Grab remained the central subject of public discussion—even as its stock value was declining.

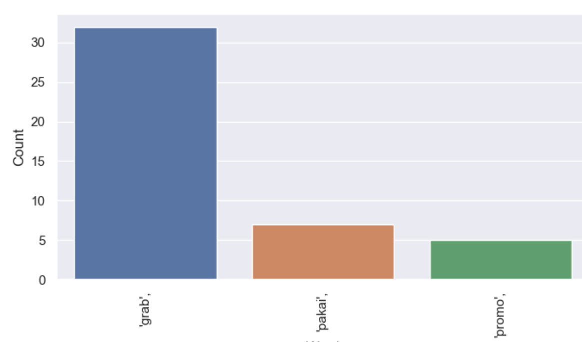

Fig. 4. Top Unigram Frequencies During Periods of Stock Increase and Positive Public Sentiment

The word *'banget'* functions as a positive emotional intensifier, while *'ready'* reflects the availability and responsiveness of the service—both suggesting that public appreciation for Grab's service remained high, even during periods of declining stock performance. This indicates that public perception of service quality is not necessarily influenced by market fluctuations, and that positive sentiment can emerge from functional satisfaction and direct user experience.

In contrast, during periods of rising stock prices accompanied by positive sentiment—such as in Fig. 4, which displays the n-gram distribution for Period 10 (29 December 2022 – 4 January 2023)—the most frequent words were *‘grab’*, *‘pakai’* (use), and *‘promo’*. The word *‘pakai’* reflects active user engagement with the service, while *‘promo’* suggests that the company’s promotional strategies successfully captured user attention and added value to the overall customer experience. This implies that during periods of strong stock performance, positive sentiment is driven not only by service quality but also by effective marketing efforts.

(a) (b)

Figure 5. Wordcloud of Tweets With (a) Positive; (b) Negative Sentiment Toward Grab

Wordcloud visualization is used to provide an overview of language patterns and dominant topics that appear in tweets that have been classified by sentiment. Fig. 5(a) presents a wordcloud of tweets labeled with positive sentiment, showing that words such as *‘grab’*, *‘ready’*, *‘order’*, *‘best’*, and *‘promo’* appear most prominently. The presence of these words indicates that users’ positive sentiment is strongly related to their direct experience with Grab’s services, including service availability (*ready*), ease of ordering (*order*), and responses to promotional strategies (*promo*). Words like *‘best’* and *‘okay’* reflect positive emotional expressions, reinforcing the notion that public perception of the service is both functional and affective in nature.

Conversely, Fig. 5(b) displays the wordcloud of tweets labeled with negative sentiment, which is dominated by words such as *‘cancel’*, *‘order’*, *‘driver’*, *‘stress’*, and *‘error’*. These words directly indicate the primary sources of user dissatisfaction, particularly related to sudden order cancellations, difficulty in obtaining drivers, and technical issues while using the service. In addition, the appearance of the word *‘gojek’* in the negative wordcloud suggests that users may be making comparisons or even shifting their preference toward a competing service. The presence of *‘stress’* and *‘error’* also implies that user discomfort is not solely technical, but also emotional, affecting their day-to-day experience with the platform.

F. Discussion

Sentiment analysis of Twitter data revealed that the majority of public comments about Grab during the observation period fell into the positive category. The SVM model’s performance is presented in Table II, showing an accuracy of 0.87, precision of 0.90, recall of 0.91, and an F1-score of 0.91. These values indicate strong and balanced classification performance, meaning that the model can consistently distinguish between positive and negative sentiments with high accuracy. Therefore, the sentiment classification results can be considered reliable for further analysis.

However, when these classification results were linked to the direction of Grab’s stock price movement, an association test using the Goodman-Kruskal Lambda method produced λ(stock|sentiment)=0.053 and λ(sentiment|stock)=0.000. This indicates that knowing the public sentiment category only reduces prediction error of stock movement by 5.3%, while knowing the direction of stock movement provides no contribution in predicting public sentiment. Both values reflect a very weak level of association between public opinion on social media and the fluctuations in Grab’s stock price.

Further analysis using n-gram and wordcloud visualizations showed that positive sentiment toward Grab under both market conditions was largely driven by users' actual experiences with the service, such as availability, ease of use, and promotional incentives. Despite varying market contexts, the public consistently responded positively to Grab's core service features. This suggests that operational performance has a stronger influence on public sentiment than stock price fluctuations. Nevertheless, as confirmed by the Lambda test, this association is not strong enough to serve as a basis for predicting stock movement, but is more appropriately interpreted as an indicator of customer perception and satisfaction.

The wordcloud visualizations also captured the emotional nuance and focus of public attention for each sentiment category. Although the statistical relationship between sentiment and stock direction is weak, the semantic analysis offers strategic insight into user expectations and critical service issues that matter to customers.

Overall, the results demonstrate that although public sentiment toward Grab is largely positive and the classification model successfully identifies that sentiment with high accuracy, there is no strong or statistically significant correlation between public opinion and the direction of the company's stock movement. This suggests that stock price fluctuations may be more strongly driven by other variables, such as financial disclosures, macroeconomic conditions, or institutional investor actions. Moreover, Twitter-based sentiment—especially from a regional user base—may not fully capture the perceptions of market participants or reflect actual trading behavior, particularly for stocks listed internationally. These considerations offer a plausible explanation for the weak association reflected in the Lambda test.

G. Limitations and Future Work

The findings of this study offer several important implications, both in academic and practical contexts. From an academic perspective, the research reinforces the understanding that while public sentiment analysis from social media can be used to represent public perception of an entity, its predictive power on stock price movements is not necessarily significant, particularly in the case of Grab. This underlines the need for caution when interpreting social media sentiment as a direct indicator of market behavior.

From a practical standpoint, the results show that although companies like Grab may receive a large number of positive reviews from users on social media platforms, such a positive public image does not always align with their stock market performance. This is important for business decision-makers and marketing teams to recognize, as public perception and investor confidence may operate on separate trajectories. Both researchers and investors should remain cautious when relying solely on social media sentiment for stock prediction, as it does not fully capture broader macroeconomic or market-specific factors.

However, this study is subject to several limitations that may affect the generalizability and depth of interpretation. First, the sentiment classification used a binary approach—positive and negative—without including neutral or ambiguous expressions commonly found in social media content. This simplification may overlook subtleties in user opinion. Additionally, the model exclusively used data from Twitter, which, although widely used in Indonesia, may not fully capture the diversity of public sentiment or investor behavior. Future research could improve coverage and nuance by adopting multiclass sentiment models and collecting data from multiple platforms such as Instagram, Facebook, YouTube, and financial discussion forums.

Second, the dataset spanned only four months (December 2022 to March 2023), which limits the temporal scope and may not reflect longer-term sentiment dynamics or changing economic contexts. Although this period was chosen due to significant stock and social media activity, future work should consider longer and more recent timeframes to increase robustness. It is also suggested that future studies should adopt longer observation windows to better capture temporal dynamics and seasonal sentiment patterns. Furthermore, this study employed only the Support Vector Machine (SVM) algorithm for sentiment classification without benchmarking against other methods. Comparative evaluations using models such as Random Forest, Naïve Bayes, or deep learning architectures are recommended to ensure optimal model selection.

Third, stock price movement was modeled using a simple binary label (up/down), without considering macroeconomic indicators, market-wide news, or firm-specific events that typically influence investor behavior. This limited the model's ability to account for real-world complexities. Future frameworks should integrate control variables to enhance contextual accuracy. Finally, while the Goodman-Kruskal Lambda test was suitable for categorical association analysis, it may not detect complex dependencies. More advanced techniques—such as logistic regression, Granger causality, or time-series forecasting—could provide richer insights into the relationship between public sentiment and stock market dynamics, particularly in the context of digital platforms and emerging markets.

V. CONCLUSION

This study aimed to evaluate the relationship between public sentiment on Twitter and the direction of Grab's stock price movement by applying text classification using the SVM algorithm and categorical association analysis through the Goodman-Kruskal Lambda test. The results indicate that while the SVM model successfully classified sentiment with high accuracy, the low lambda values (λ=0.053 for predicting stock direction and λ=0.000 in the reverse direction) suggest that public sentiment does not possess strong predictive power over Grab's stock price fluctuations. Thus, although social media sentiment reflects users' perceptions of service quality, the findings emphasize that public opinion should not be regarded as a primary indicator in stock market prediction This study recommends integrating sentiment analysis with financial variables and adopting more comprehensive predictive approaches to gain deeper insights into the dynamics between public opinion and market behaviour. Furthermore, while this study focused solely on Grab as a case representative of Southeast Asian tech firms, the proposed method is generalizable and may be applied to other companies or sectors in future research to explore broader patterns between public sentiment and stock market performance.

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