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A Sentiment Analysis about The Acquisition and Policy of X (Twitter) by Elon Musk

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ABSTRACT

Social media platform Twitter (now X) is quite popular because it offers the ability to communicate between users and accelerate the flow of information obtained. During its development, the company's acquisition by Elon Musk led to several changes. Some of the new policies had a direct impact on users and caused mixed reactions. This study applies a comparison between labeling techniques using TextBlob and VADER, a comparison of algorithms using Random Forest and Balanced Random Forest, as well as the use of algorithm parameters by default and Grid Search, to find information on user perceptions related to the acquisition and new policy from X through sentiment analysis. The data used is the result of crawling X's posts in the period from the emergence of the acquisition issue until the rebranding of the Twitter name and logo to X, from April 25, 2022, to July 23, 2023. The results show that visually, these three factors have an accuracy level that shows the use of superior factors, namely TextBlob, Balanced Random Forest, and default parameters, whose combination obtained the highest accuracy value of 87%. The results of sentiment classification using two labeling techniques indicate that positive sentiment is greater than negative sentiment. However, in the negative sentiment, there are several problems based on the highest frequency of words that appear. So in this study, several recommendations are given to meet the expectations of user satisfaction with the X platform.

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1. INTRODUCTION

In this era of rapid technological development, the use of social media is so much needed by every human being to facilitate communication anywhere and anytime. One of the popularly used social media is social media X, previously known as Twitter. Based on We Are Social and Hootsuite reports, Twitter users worldwide have reached 556 million users in January 2023, which is an increase of 27.4% compared to the same period in the previous year, thus placing the Twitter application as the 14th most popular social media platform in the world [1]. This can be caused by the superior features that Twitter continues to develop which make it easier for each user to use the application in terms of communication and information. The trending topic feature on the application is very helpful for users in obtaining information updates related to the most discussed issues by the Twitter community quickly with a wide range of other users without the need to follow user who posted the discussion because of a feature called like, retweet, and comment [2].

In connection with Twitter-related developments, on April 25, 2022, the decision to buy Twitter was made by Elon Musk and successfully completed on October 27, 2022, for a nominal amount of US $44 billion [3]. Elon Musk then took the position of CEO of Twitter and implemented several new policies, including (1) the Twitter Blue subscription feature (now X Premium); (2) extension of the duration of video posts with high quality; (3) longer tweet/post characters (previously 140 characters); (4) verification tags for subscribed users; (5) establishment of a content moderation board; and (6) restrictions and suspensions for fake accounts and bots [4]. On May 11, 2023, through his tweets, Elon Musk stated that he had stepped down from the position of CEO of Twitter and switched to Chairman and Chief Technology Officer (CTO) in the company in charge of overseeing Twitter's products, software, and operating systems [5]. In this position, Elon Musk began implementing other policies, one of which was stated on July 23, 2023, namely the rebranding of the Twitter name and logo which changed to X, which is expected to make the platform not only text-based but everything [6]. With the various changes to the Twitter application until it now becomes X due to new policies implemented after Elon Musk acquired Twitter, there are various opinions from users of the platform.

Users' perceptions of the Twitter/X service policy since its acquisition by Elon Musk can be seen through user tweets, or what is currently referred to as posts. The posts given can be in the form of a response of support or a response of user dislike with the new policy set after the acquisition period occurs. Effective data processing in retrieving information related to posts written by X users can be done through sentiment analysis. The post data obtained will then be labeled according to the sentiment class. Labeling methods commonly used in classification are using TextBlob or VADER. Based on [7] and [8], the difference between TextBlob and VADER labeling methods is in the criteria for determining the type of sentiment, where TextBlob uses polarity scores, while VADER uses compound scores in labeling.

Building a classification model requires selecting the right algorithm to be able to produce maximum and efficient performance in accordance with the observed case [9]. Based on research [10], related to sentiment classification for Ruangguru application user reviews on Google Playstore, the Random Forest algorithm has a higher accuracy value compared to its comparison algorithms. The

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ensemble technique applied to the Random Forest algorithm can provide solutions to complex problems [11]. However, building machine learning classification models often encounters common obstacles, one of which is data imbalance, which can reduce the effectiveness of the model [12]. To overcome this, there is a type of Random Forest algorithm that can specifically handle the problem of data imbalance, called Balanced Random Forest. Research [13] compares the use of several algorithms including Random Forest and Balanced Random Forest, which gives the result that the Balanced Random Forest algorithm is able to provide the best model performance through the confusion matrix. Therefore, compared to the regular Random Forest algorithm model, Balanced Random Forest tends to provide better performance in the case of imbalanced data. In addition, the selection and setting of optimal parameters in an algorithm is also considered to be able to improve the accuracy of the classification model built [14].

This study conducts sentiment analysis on the topic of user perceptions related to the acquisition and Twitter policy by Elon Musk, which has not been widely explored. Likewise, the use of the Balanced Random Forest algorithm is still found in only a few studies. Therefore, the novelty of this study is carried out by applying a comparison of three factors in conducting sentiment analysis, namely the comparison of labeling techniques using TextBlob and VADER, the type of algorithm using Random Forest and Balanced Random Forest, and setting algorithm parameters in the form of default and Grid Search results. The results of data processing are then visualized and analyzed to provide suggestions for improvements according to the negative sentiment results.

2. RESEARCH METHOD

The research design is shown in Figure 1. In processing the data, this study used Jupyter Notebook software with Python 3.0 programming language. The first stage starts with crawling data using the Selenium library, which allows data to be retrieved without requiring API access. The data retrieved is based on the period from April 25, 2022, when Elon Musk began planning to acquire Twitter, to July 23, 2023, when the latest policy issued led to the rebranding of Twitter's name and logo to X. The data criteria are Indonesian-language tweets containing the keywords "*akuisisi* twitter"(twitter acquisition), "*kebijakan* twitter" (twitter policy), and "elon twitter". The first keyword focuses on the acquisition event, revealing the reactions of platform users and its impact. The second keyword captures user reactions to platform transformations resulting from the implementation of new policies. The third keyword relates to opinions that directly mention Elon in the context of policies or actions regarding Twitter, as not all users use formal terms like acquisition or policy. By using these keywords, the data obtained can be representative and focused on the issues in this sentiment analysis study.

The second stage is to perform text preprocessing for post data. At this stage, the process of cleaning unstructured raw text is carried out so that it is ready to be processed further to produce its basic form which is useful for analysis purposes [15]. Text preprocessing starts with cleaning to clean the data and remove unnecessary characters, case folding to convert all alphabetic characters into lowercase, normalization into standard words, stemming to convert into basic words, filtering or stopword removal to remove irrelevant words, and tokenizing to separate words per word [16].

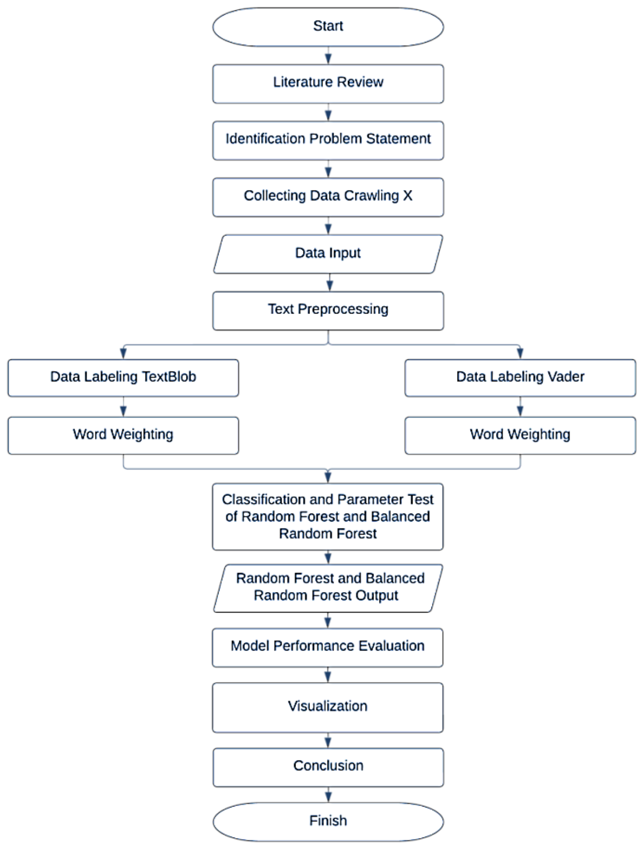

Figure 1. Research Design

The text preprocessing results are then labeled using the TextBlob and VADER libraries. Data labeling is needed to classify posts into positive and negative classes. Both TextBlob and VADER libraries are only capable to process textual data in English. Therefore, the text translation process from Indonesian needs to be converted into English so that lexicon-based labeling can be done. The TextBlob labeling method will categorize the sentiment class based on its polarity scores, where positive sentiment is obtained if the polarity > 0, while the negative is given if the polarity < 0. Meanwhile, the VADER labeling method categorizes sentiment results based on the compound score value. In this study, the determination of the threshold value of the compound score has been adjusted, with the criteria that if the compound score > 0 then the data is positive, while if the compound score < 0 then it is negative [17].

The post data that has been processed will be word-weighted. Word weighting is a stage to evaluate the level of importance of words that can improve the accuracy of the model built. In this case, word weighting will be done with the TF-IDF approach. The approach begins by calculating the number of posts containing a term (DF), calculating the occurrence of a term in a post (TF), calculating the frequency of occurrence of a term in all posts (IDF), and calculating the ratio between TF and IDF values

(TF-IDF) [18].

The next stage is the classification model building involving the Random Forest and Balanced Random Forest algorithms. In this study, the ratio used to divide the amount of data is 90:10, where 90% as training data and 10% as testing data. This is based on research [19] by comparing split data ratios ranging from 90:10, 80:20, 70:30, 60:40, 50:50, and 8 k-folds using the Random Forest algorithm, it was found that the most optimal training and testing data split ratio was to use a 90:10 ratio. The use of a larger training data ratio can provide better model performance results [20]. This is because models trained with a large amount of training data allow the model to recognize examples and patterns better, so as to reduce the error rate on the prediction results [21].

In building a model using an algorithm, it is necessary to set parameters that can improve model performance. The parameters contained in Random Forest are also similar to the parameters of Balanced Random Forest, so the determination of the parameter value settings that will be used to perform Grid Search are also adjusted. Based on research [22], Table 1 shows the types of Random Forest and Balanced Random Forest parameters that are considered important in influencing the prediction results and preventing overfitting, as well as the default parameter values based on [23], [24] and the parameter values that will be used to perform hyperparameter tuning by Grid Search.

Table 1. Parameter Values of Random Forest and Balanced Random Forest

No	Parameter	Description	Default	Grid Search
1.	n_estimators	Number of trees in the tree	100	100, 150, 300
2.	criterion	Measurement for split quality	gini	gini, entropy
3.	max_depth	Maximum depth of the tree	None	5, 10, 15, 25, 30
4.	min_samples_split	Minimum number of nodes required	2	2, 3, 4
5.	max_features	Number of features considered when finding the best split	sqrt	sqrt, log2

Furthermore, visualization will be done using word frequency related to the frequency of words most discussed by X users. The negative class sentiment results from the visualization will then be used to provide suggestions regarding Elon Musk's X service policy.

3. RESULTS AND DISCUSSION

In this study, data collection of posts from X/Twitter users is based on several keywords, namely "elon twitter", "*akuisisi* twitter" (twitter acquisition), and "*kebijakan* twitter" (twitter policy). The results of data collection that have been carried out obtained 848 posts for the keyword "*akuisisi* twitter", 44,582 posts for the keyword "elon twitter", and 6,507 posts for the keyword "*kebijakan* twitter". So the total amount of data obtained is 51,937 posts.

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3.1. Users' Sentiments Towards the Acquisition and Policy of Social Media X (Twitter)

In this study, two comparisons of lexicon-based text labeling methods are conducted by using TextBlob and VADER. The class results focus on only two labels in each method, namely positive and negative, and eliminate neutral sentiments to focus on polarized sentiments and also aim to simplify classification issues. Neutral sentiment is usually assessed as factual information (objective) that does not contain opinions or sentiment expression. Meanwhile, positive sentiment indicates positive statement that can take the form of support, praise, and so on. Then negative sentiment indicates negative statement such as complaint or dissatisfaction that can be useful for continuous improvement.

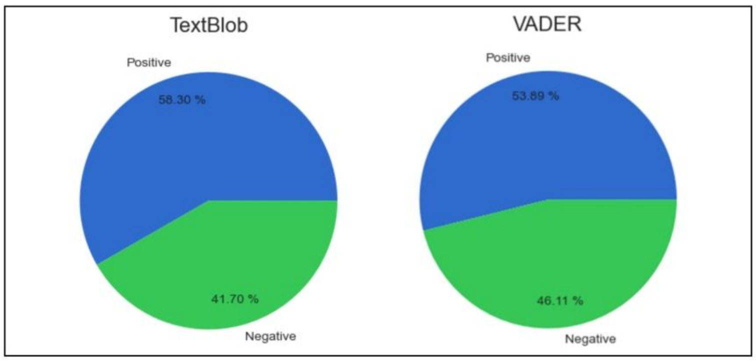

Figure 2. Sentiment Classification

Figure 2 shows the amount of data in the positive and negative sentiment classes based on TextBlob and VADER. In TextBlob labeling, 11,712 data are positive sentiments, and 8,377 data are negative sentiments, so the total data from this labeling result is 20,089 data. In VADER labeling, 12,644 data are positive sentiments, and 10,817 data are negative sentiments, so the total data from the labeling results is 23,461 data. Through both labeling results, it is known that the proportion of positive classes produces a greater number than negative classes.

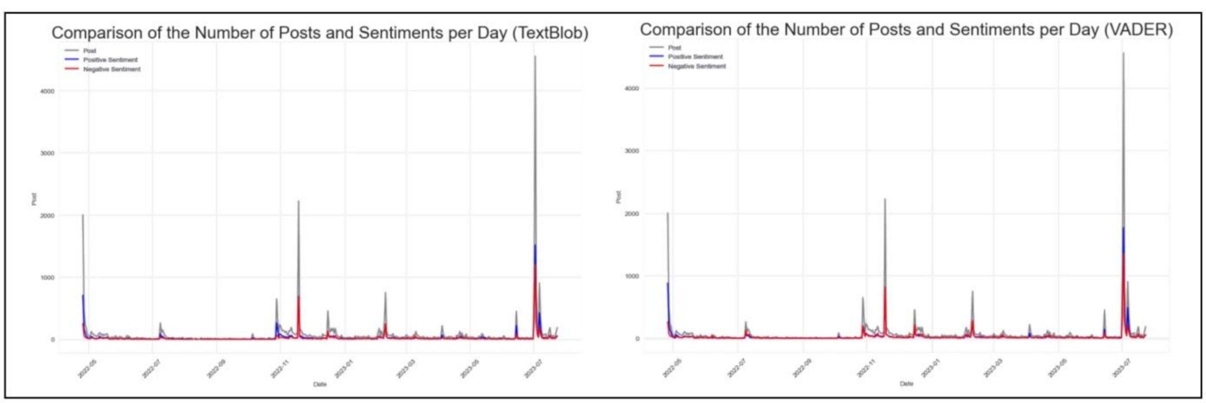

Figure 3. Time Series Sentiment Data Post per Day

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Figure 3 shows the number of positive and negative posts from each labeling result. Positive sentiment has a pattern that is almost the same as the frequency generated by the data as a whole. While the negative sentiment tweets are also almost the same, there are some time differences in the frequency spikes.

Based on research [25], during the period from April to May 2022, Elon Musk expressed his desire to acquire Twitter for a fantastic price as a platform that controls free speech. At that time, Elon Musk also revealed that Twitter would become a private company after its official ownership. This triggered a lot of consideration both positively and negatively from Twitter users regarding the question of what the Twitter platform would be like if the acquisition occurred. In addition, there was a high frequency of this post appearing as a random chat topic related to the ongoing purchase of Twitter.

Furthermore, in November 2022, research [26] stated that the most likely tweets discussed were related to Twitter employee layoffs post-acquisition and Elon Musk's desire to reinstate accounts that were blocked for violating Twitter policies. The topic of layoffs certainly caused a lot of reactions from Twitter users. This is related to the user's question of what the fate of the Twitter application will be with the few remaining employees due to dismissal. At that time, Elon Musk also uploaded a photo or meme on his account depicting a Twitter funeral, so this also caused users to immediately react by raising the hashtag that was trending at the time, namely #RIPTwitter. In addition, the reinstatement of accounts that had previously been blocked by the Twitter team caused opinions to surge and split between positive expressions of joy and negative expressions of dislike. These reinstated accounts, such as those of prominent figures like Donald Trump, Kanye West, as well as ordinary Twitter users.

Last, in July 2023 there was a significant number of posts. According to [27], during this period, it was announced that Twitter had monetized creators through a subscription feature that provided ad revenue to creators by providing content to their followers. This sparked a reaction because any user can register as a creator through the paid feature "Twitter Blue" and get direct revenue from ads published for their posts. The spike in posts this month was also influenced by the previous month, where in June, Twitter began restricting unregistered users from accessing Twitter and continued with restrictions for verified and unverified users to access posts per day. Many users found this policy difficult, but some may have accepted it as it reduced their addiction to the application. Also in July, a Twitter competitor platform called Threads emerged. Threads was introduced as "Instagram's Twitter" under the Meta company that is directly connected to the Instagram platform. Many users weighed in on whether they should switch platforms by using Threads, or stick with Twitter with all its new policies.

3.2. Classification Models

This study provides eight classification model results that contain a combination of applying different labeling techniques, algorithm types, and parameter settings. The optimal parameters of the Grid Search method provide different values depending on the application of the labeling technique factor and the type of algorithm. The different parameter values applied in building the model can be seen in Table 2.

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Table 2. Algorithm Parameters for Classification Model

Parameter	Default	TextBlob_RF	TextBlob_BRF	Vader_RF	Vader_BRF
n_estimators	100	300	300	150	300
criterion	gini	gini	entropy	gini	gini
max_depth	None	30	30	30	30
min_samples_split	2	4	3	2	4
max_features	sqrt	sqrt	sqrt	sqrt	log2

The classification results containing the predicted and actual results are contained in the confusion matrix. Figure 4 shows a comparison between the confusion matrix results generated by the Random Forest and Balanced Random Forest algorithms with the same labeling technique and algorithm parameter values. The numbers 0 and 1 in x and y of the matrix are the result of label encoding which converts the labels into numeric format so that they can be processed in building the model. The number 0 is an annotation of negative sentiment, while the number 1 is a positive sentiment.

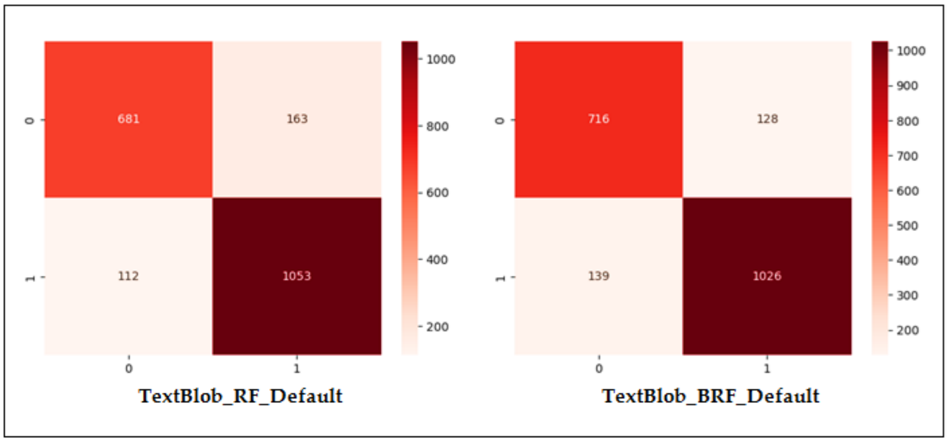

Figure 4. Confusion Matrix

In the matrix, the top left column shows the magnitude of the true negative, the bottom left column is the false negative, the top right column is the false positive, and the bottom right column is the true positive. The Balanced Random Forest algorithm works by reducing bias towards the majority class and giving attention to the minority class [28]. This study produces a greater number of positive sentiments than negative sentiments. So in Figure 4, it can be seen that the Balanced Random Forest (BRF) algorithm tries to reduce the false positive value when compared to the Random Forest (RF) algorithm.

All classification model results are then compared to find out which combination of labeling techniques, algorithm types, and algorithm parameter settings can provide the most optimal performance. There are eight modeling scenarios performed. The overall classification results are presented in Table 3.

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Table 3. Classification Modeling Results

No	Labeling	Scenario Algorithm	Parameter	Accuracy
1.	TextBlob	Random Forest	Default	0.86
2.	TextBlob	Random Forest	Grid Search	0.81
3.	TextBlob	Balanced Random Forest	Default	0.87
4.	TextBlob	Balanced Random Forest	Grid Search	0.85
5.	Vader	Random Forest	Default	0.85
6.	Vader	Random Forest	Grid Search	0.80
7.	Vader	Balanced Random Forest	Default	0.85
8.	Vader	Balanced Random Forest	Grid Search	0.83

Based on the table above, it is obtained that the modeling scenario for the combination of TextBlob, Balanced Random Forest, and default parameters is the one that produces the highest accuracy value, which is 87%. Meanwhile, the lowest accuracy result occurs in the combination of VADER, Random Forest, and Grid Search, which has an accuracy value of 80%. Overall, all models have worked well in classifying data and can be categorized into good classification because they have an accuracy rate in the range of 80% - 89% [29].

On the labeling technique factor, by comparing the performance of the TextBlob and VADER models in the same algorithm and parameter application combination as a whole, it is found that TextBlob labeling is superior to VADER labeling. This can be due to the fact that VADER labeling only considers a word as an individual entity without considering the context in which it is used, whereas TextBlob will consider a word in the form of a phrase so as to capture the nuances of a more complex sentence [30]. In addition, VADER is very suitable for labeling social media texts that are more informal in nature because it is able to take into slang words, emoticons, punctuations, and others [8]. The text preprocessing stage in this study eliminates several things, such as the use of emoticons, punctuations, and equalizing letterforms to become uniform. This allows VADER to be unable to detect the intensity of words that reinforce sentiment and cause classification errors.

On the labeling technique factor, by comparing the performance of the Random Forest and Balanced Random Forest models, it was found that the highest accuracy value for the Balanced Random Forest algorithm was 87% with a combination of the application of TextBlob and default parameters. For the same combination, the Random Forest obtained an accuracy value of 86%, which means that the Balanced Random Forest algorithm is superior to the Random Forest algorithm. The Balanced Random Forest algorithm is able to overcome data imbalance by suppressing bias towards the majority class [28]. Research [13] evaluates the model using confusion matrix performance, where Balanced Random Forest tends to provide better results than the confusion matrix performance of other algorithms. This can occur as a result of data imbalance. To solve the problem of unbalanced data, the performance assessment of a model should be measured from its confusion matrix results, because there is a tendency for the model to predict the majority class.

In the parameter setting factor, by comparing the performance of the default and Grid Search models, it was found that the highest accuracy value for the default parameters type was 87% with a combination of applying TextBlob to the Balanced Random Forest algorithm. For the same combination using the Grid Search result parameters, the accuracy value is 85%. So it can be interpreted that the default parameters are superior compared to the parameters generated through Grid Search. This can be due to the fact that default parameters often provide results that are comparable or not much different from parameter setting efforts [31]. So the use of default parameters plays an important role in efforts to simplify efficiency and effectiveness in optimizing the performance to build a model. Research [32] explains that setting parameters that can affect model performance can be done by conducting sufficient cross-validation. Generally, the use of cross-validation is done 5 or 10 times. This can be one of the factors that cause default parameters to be superior to Grid Search parameter settings, because of the lack of cross-validation determined to perform hyperparameter tuning.

3.3. Visualization Results

This study conducts sentiment analysis to find out the types of sentiments that express the opinions of the users of the X (Twitter) platform regarding the acquisitions made and the policies set after the company changed ownership to Elon Musk. Therefore, visualization needs to be done to extract important information that is widely discussed by users.

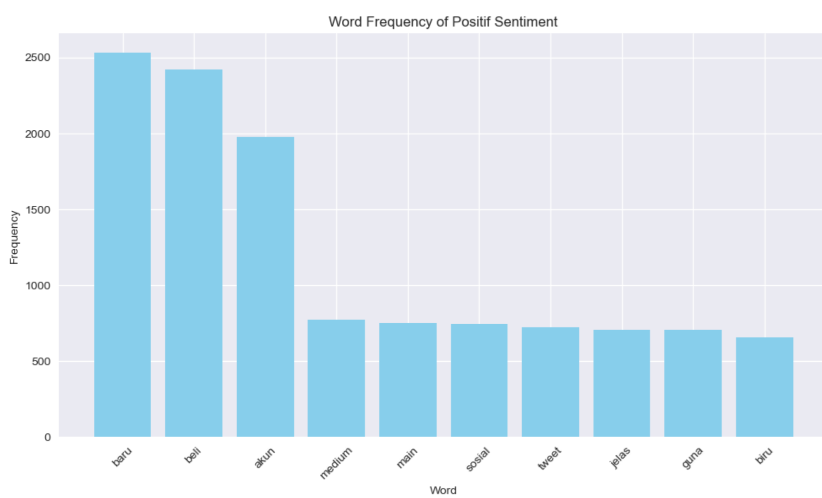

Figure 5. Word Frequency of Positive Sentiment

Figure 5 shows the word frequency results for positive sentiment generated from TextBlob labeling that obtained a total of 11,712 posts. The largest frequency of occurrence are dominated by words, namely "*baru* (new)", "*beli* (buy)", and "*akun* (account)". These words refer to positive statements, such as hopes for the appointment of new CEO Linda Yaccarino, the advantages of the "Tweet Activity" feature, and so on.

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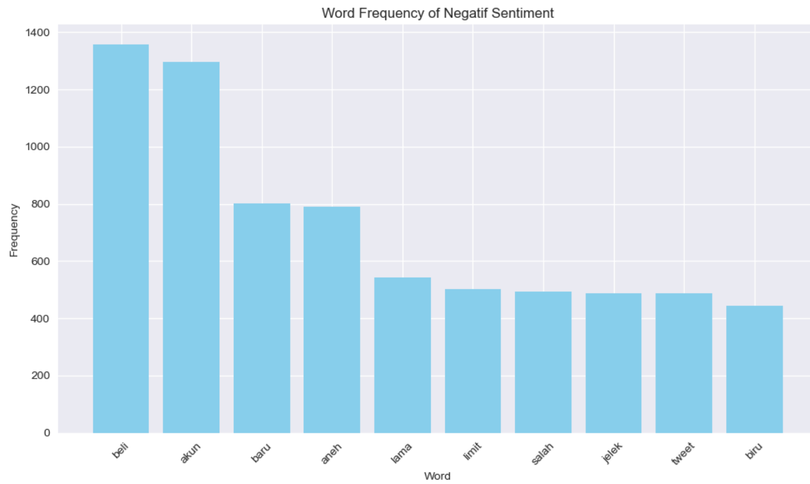

Figure 6. Word Frequency of Negative Sentiment

Figure 6 shows the word frequency results for negative sentiment generated from TextBlob labeling that obtained 8,377 data. Similar to the word frequency for positive sentiment, the three largest occurrence frequencies are dominated by words, namely "*beli* (buy)", "*akun* (account)", and "*baru* (new)". Although they have the same highest word frequency, the context contained within them is different. The difference in context causes the post data to be divided into positive and negative sentiments, with the frequency of word occurrence based on the amount of post data. Negative sentiment results refer to negative statements as well, such as users who dislike Elon Musk's decision to purchase Twitter, complaints about the large number of suspended accounts, and so on.

Negative sentiment provides information about problems that occur related to the acquisition and the new X (Twitter) policies by Elon Musk. Then in providing recommendations, we will focus on negative sentiment. Some problems will be given suggestions that are expected to be able to evaluate a policy or similar problems that may occur in a social media platform as in Table 4.

Table 4. Improvement Recommendations Related to Negative Sentiment Results

No	Factor	Problem Statement	Improvement Recommendation
1	*Akun* (Account)	Frequent mass account suspensions	• Implement identification of average daily usage activity by each account to avoid suspension of accounts that do not violate the policy • Provide specific clarity to users about the reasons for suspension for user evaluation • Publish periodic reports on the number of suspended accounts and their reasons as a form of transparency to users
		Reinstated accounts that violated previous platform policies	• Conduct regular monitoring related to the activities of returned accounts whether they repeat violations of platform policies or not

			• Implement a warning system for accounts that exhibit violative behavior after reinstatement that may be subject to permanent suspension
2	*Aneh* (Strange)	Addition of new features and interface changes that confuse users	• Conduct a pilot test on a group of users to get feedback on the new features and display being launched • Provide an introduction in the form of visualizations and guides that contain information on accessing the new display and features • Provide an option to customize the display according to users' individual preferences
3	*Lama* (Long Time)	Long loading times for applications, either when opening timelines, posts, photos, videos, etc	• Provide a limited view (text, photo, video, audio, appear when switching display) • Provide a lighter size format for the preview display • Provide various resolution settings • Enable cache to speed up subsequent loading time • Create a regular maintenance schedule to improve the application server
4	*Jelek* (Poor)	Quality of application upgrades that do not meet user expectations	• Identify and determine existing features that have a lot of influence on users • Conduct surveys and evaluations regarding what features users expect to be applied
5	Tweet	The emergence of types of post recommendations that do not match interests	• Improve the algorithm that regulates the types of posts that are displayed as recommendations according to the interests chosen and not recommended by the relevant account user
6	*Biru* (Blue)	The emergence of more bot accounts and fake accounts	• Conduct stricter identification and verification of information and data of users who will subscribe to premium features • Monitoring unusual account activity
		The number of affiliate accounts that promote and appear as top posts is very annoying	• Monitoring the activity of verified accounts that spam
		Expensive subscription fee for the premium version of the application	• Provide discounted subscription fees for new users and users who are trying to subscribe for the first time • Provide a free trial of a feature for use within certain limits • Add a subscription method for a frequency of days, for example, 1 week

3.4. Limitations

Limitations include potential bias from excluding neutral sentiments and reliance on keyword-based crawling, which may miss nuanced discussions.

4. CONCLUSION

A study comparing the effect of different labeling techniques, algorithm types, and algorithm parameter settings on post data related to the acquisition and policy of X (Twitter) by Elon Musk provides different accuracy comparison results. There is an increase in each of the factors compared when using the same combination of the other two factors, where the labeling technique shows TextBlob is superior, the Balanced Random Forest algorithm type is superior, and the use of default algorithm parameters is superior. So the highest accuracy result of the 8 model scenarios built is a combination of TextBlob labeling, Balanced Random Forest algorithm, and default parameters, with an accuracy value of 87%. The sentiment classification is done using two labeling techniques, both of which show that the number of positive sentiments is more than the negative sentiments for issues related to acquisitions and new policies on the X/Twitter platform. Based on the visualization results carried out for the negative sentiment class, several problems related to words were obtained, namely "*akun* (account)", "*aneh* (strange)", "*lama* (long time)", "*jelek* (poor)", "tweet", and "*biru* (blue)". Proposed improvement recommendations are given to address some of the problems identified, such as providing resolution setting options for long-loading problems, improving the algorithm that regulates the recommended post types for post recommendations that do not match user interests, and others.

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