Sentiment Analysis of Public Opinions about Universitas Royal Using the Support Vector Machine Method

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Abstract
Instagram is one of the communication platforms used by Universitas Royal to interact with the public and serves as a space for users to express opinions, responses, and evaluations of the institution. The large volume of available comments presents challenges in identifying sentiment patterns consistently through manual analysis. This study aims to analyze public sentiment toward Universitas Royal based on Instagram comments using the Support Vector Machine (SVM) method. The dataset consists of 2,457 comments categorized into three sentiment classes: negative, neutral, and positive. The research stages include text preprocessing, feature weighting using Term Frequency–Inverse Document Frequency (TF-IDF), data splitting at an 80:20 ratio, model training, and evaluation using accuracy, precision, recall, and F1-score. The initial evaluation results show that the SVM model achieved 100% across all evaluation metrics on 492 test samples. These results indicate a very high level of agreement between the model predictions and the reference labels in the test dataset. However, the possibility of duplicate comments requires further examination to ensure the reliability of the evaluation and the model's generalization ability. This study has the potential to support the analysis of public opinions toward Universitas Royal as a basis for evaluating the institution's communication through Instagram.

Keywords: *sentiment analysis, Instagram, public opinion, Support Vector Machine, TF-IDF.*
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Introduction

The development of information technology has transformed the way people express opinions and evaluate institutions through social media. Social media provides a platform for users to share opinions through comments, responses, and discussions. These opinions can be used to understand public attitudes toward a particular subject, including higher education institutions. Sentiment analysis is a computational approach that can be used to systematically identify opinions and attitudes expressed in textual data [1], [2]. However, the large volume of unstructured comments makes manual sentiment identification time-consuming and potentially inconsistent.

Universitas Royal uses Instagram as one of its digital communication platforms to disseminate information and interact with the public. Comments on Instagram posts may consist of appreciation, questions, criticism, and complaints that reflect users' responses to various institutional activities. These comments can be classified into three categories: positive, negative, and neutral. However, the use of informal language, abbreviations, spelling variations, and context-dependent expressions presents challenges in the classification process. Hutto and Gilbert [3] explain that social media texts have distinctive linguistic characteristics that need to be considered in sentiment analysis. Therefore, appropriate text processing and classification methods are required to identify sentiment patterns in Instagram comments related to Universitas Royal.

One method that can be used for text classification is the *Support Vector Machine* (SVM). This method works by constructing a decision boundary that separates data based on the characteristics of the learned features. Iqbal [4] explains that SVM is suitable for text categorization involving a large number of relevant features. Before classification, text must be transformed into a numerical representation so that it can be processed by machine learning algorithms. One technique that can be used is *Term Frequency–Inverse Document Frequency* (TF-IDF), a weighting method that considers the frequency of terms within a document and their distribution across the document collection [5]. The combination of text preprocessing, TF-IDF weighting, and SVM enables comments to be represented as numerical features for sentiment classification

Several previous studies have applied SVM to classify opinions expressed on social media. Saputra and Devega [6] applied SVM with TF-IDF weighting to analyze Instagram comments related to *cyberbullying*. Their study reported accuracy values ranging from 95% to 96% under several data-splitting scenarios. Astuti and Andriansyah [7] also investigated sentiment analysis of Instagram comments on educational content by comparing Naïve Bayes and SVM. In addition, Hidayah *et al.* [8] examined public sentiment toward the TikTok application using Naïve Bayes and SVM. These studies demonstrate that sentiment classification can be applied to various types of social media comments, although the results are influenced by data characteristics and evaluation procedures

Related research was also conducted by Rambe and Iqbal [9], who applied TF-IDF in combination with Naïve Bayes and SVM to classify Indonesian-language TikTok comments. Their study used 15,000 comments and reported an SVM accuracy of 92.8%. Furthermore, Simanullang, Sitorus, and Iqbal [10] applied SVM and TF-IDF to analyze public sentiment toward the Free Nutritious Meals Program (*Makan Bergizi Gratis*). Their study achieved an accuracy of 81.51% on the test data. Differences in the results of previous studies indicate that SVM performance needs to be evaluated according to dataset characteristics, preprocessing stages, and the testing procedures employed. The conceptual foundations of sentiment analysis and opinion mining have also been discussed by Mola *et al.* [11] and Tora et al. [12], who highlighted the importance of text-based opinion processing in identifying attitudes toward a particular subject.

Based on previous studies, this research focuses on applying SVM to analyze Instagram comments related to Universitas Royal. Differences in the research subject and comment

characteristics make it necessary to evaluate the method using a Universitas Royal dataset to determine its ability to classify positive, negative, and neutral sentiments. In addition, repeated comments must be considered because identical comments appearing in both the training and testing sets may lead to overly optimistic evaluation results. Therefore, examining dataset quality, label consistency, and appropriate data splitting is essential for obtaining more reliable model evaluation results.

This study aims to apply the *Support Vector Machine* method to analyze public sentiment toward Universitas Royal based on comments collected from Instagram. The research stages include text preprocessing, feature weighting using TF-IDF, classification into positive, negative, and neutral categories, and evaluation using accuracy, precision, recall, F1-score, and a confusion matrix. The findings are expected to provide empirical insights into the performance of SVM in classifying public opinions about Universitas Royal and to support a better understanding of public responses expressed through social media.

Literature Review

Sentiment analysis is a *text mining* approach used to identify opinion tendencies in textual data and classify them into specific sentiment categories. In the context of social media, sentiment analysis can be used to process user comments containing responses, criticism, appreciation, and opinions about a particular subject. Mulyani *et al.* [13] eported that the sentiment distribution was dominated by positive sentiment at 89.60%, while negative sentiment accounted for 10.40%. Evaluation using an 80:20 data-splitting ratio showed that the linear-kernel SVM achieved the highest accuracy of 99.12%, whereas Naïve Bayes achieved 91.62%. Tests across different scenarios indicated that Naïve Bayes was more susceptible to performance degradation, with its lowest accuracy reaching 72.70% under the undersampling scenario with three sentiment classes, while SVM maintained an accuracy above 95%. Word cloud analysis showed that positive sentiment was dominated by optimism toward the government, whereas negative sentiment highlighted concerns about budget corruption risks. The study's limitations included difficulties in understanding sentence context, informal language, and sarcasm. The findings indicated that SVM was more effective and stable for classifying sentiment in imbalanced TikTok text data, demonstrating consistent performance across various testing scenarios.

Saputra and Devega [6] investigated *cyberbullying* sentiment analysis in Instagram comments using SVM with *Term Frequency–Inverse Document Frequency* (TF-IDF) weighting. Their dataset consisted of 1,000 comments collected through a crawling process. The evaluation was conducted using several data-splitting ratios, namely 90:10, 80:20, and 70:30. The results showed an accuracy of 96% with the 90:10 and 80:20 ratios, and 95% with the 70:30 ratio. This study is relevant because it used Instagram comments as the data source and TF-IDF as the feature representation technique before SVM classification.

Arrafiq [14] conducted sentiment analysis of the SeaBank Indonesia application service based on user comments on Instagram. The study used 1,201 comments processed through several stages, including cleaning, normalization, tokenization, stopword removal, and stemming. SVM was then used to classify the comments into positive and negative categories. The evaluation results showed an accuracy of 89%, precision of 93%, recall of 83%, and F1-score of 88%. These findings indicate that applying SVM to Instagram comments can produce good classification performance, although the evaluation results depend on data characteristics and the preprocessing procedures employed.

Astuti and Andriansyah [7] investigated sentiment analysis of comments on educational content on Instagram by comparing the Naïve Bayes and SVM methods. Their study used 4,600

comments categorized into positive, negative, and neutral sentiments. The results showed that Naïve Bayes achieved an accuracy of 84%, while SVM achieved 80%. These findings demonstrate that classification methods need to be evaluated on the specific dataset under investigation, as the performance of one algorithm is not necessarily superior to that of another across all data contexts. This study is also relevant to the present research because it used Instagram comments and three sentiment categories.

Nabila et al. [5] developed a sentiment classification system to analyze public opinion about the Free Nutritious Meals Program (*Makan Bergizi Gratis*, MBG) using the *Support Vector Machine* (SVM) method and the Synthetic Minority Over-sampling Technique (SMOTE) to address class imbalance, which is commonly found in social media data. The dataset consisted of 3,809 tweets divided into three sentiment classes: positive, neutral, and negative. The research stages included data preprocessing, TF-IDF weighting, and SVM classification before and after applying SMOTE. The evaluation results showed that SMOTE increased accuracy from 82.68% to 84.51% and the average F1-score from 81.59% to 83.89%. These findings indicate that SMOTE can improve classification performance and address class imbalance, resulting in a more balanced distribution of predictions. Thus, SVM combined with SMOTE can be applied to sentiment analysis of public opinion about the MBG program on the X platform. Although the research focused on a different subject, its methodological approach provides a relevant reference for analyzing public opinions about Universitas Royal.

Setiawan [15] in a review of sentiment analysis applications in Indonesia during the 2023–2024 period, discussed the use of various methods, including SVM, Naïve Bayes, *k-Nearest Neighbors* (k-NN), and IndoBERT. The review explained that sentiment analysis had been applied to various topics and data sources, particularly social media, and highlighted challenges in processing Indonesian-language text. Based on these previous studies, the present research focuses on applying SVM to analyze public opinions about Universitas Royal using Instagram comments. The study specifically classifies comments into positive, negative, and neutral sentiment categories and evaluates model performance using accuracy, precision, recall, F1-score, and a confusion matrix. Therefore, this research is expected to provide empirical findings on the application of SVM in the context of a higher education institution, while taking into account dataset quality, label consistency, and the possibility of duplicate comments during model evaluation.

Research Methodology

This study employs a quantitative approach with a descriptive-evaluative research design. This approach was selected because the study aims to classify public opinions about Universitas Royal based on comments posted on Instagram and evaluate the performance of the *Support Vector Machine* (SVM) method. The study focuses on classifying comments into three sentiment categories: positive, negative, and neutral. The application of SVM for sentiment classification of Instagram comments has been explored in previous research [6].

The research object is public opinion about Universitas Royal expressed through comments on posts published on the university's Instagram account. The unit of analysis is each comment that meets the data collection criteria. The comments are transformed into numerical representations through text preprocessing and word weighting using *Term Frequency–Inverse Document Frequency* (TF-IDF). These numerical representations are subsequently used as input for the SVM model to learn patterns that distinguish the three sentiment classes. TF-IDF is a weighting technique used to represent documents based on word frequency and the distribution of words across a document collection [16].

The research data consist of primary data in the form of Instagram comments and supporting data in the form of scientific literature related to sentiment analysis, text preprocessing, TF-IDF, SVM, and classification evaluation. Comments are collected from posts relevant to Universitas Royal within the predetermined research period. After collection, the data are examined to identify empty comments, irrelevant comments, and duplicate records. This examination is necessary to ensure that the data used are consistent with the research objectives and to reduce potential bias in the model evaluation results.

The research dataset is then labeled as positive, negative, or neutral according to the established labeling guidelines. These labels serve as the target classes in the supervised learning process. Label assignment must consider the context of each comment because the same word may convey different sentiments depending on how it is used in a sentence. Following the labeling process, the data undergo several preprocessing stages: case folding, cleaning, word normalization, tokenization, stopword removal, and stemming. These stages aim to standardize the text and prepare the comments for feature extraction.

3.1 Word Weighting Using TF-IDF

The next stage transforms the preprocessed text into numerical vectors using TF-IDF. This weighting technique combines the frequency of a word within a document with information about how widely that word occurs across the document collection. TF-IDF is used to generate features that serve as input for the SVM model [2]. The general TF-IDF formula is expressed as follows:

$$TFID_{(t,d)} = TF_{(t,d)}\ x\ IDF_{(t)} \qquad \dots (1)$$

$$IDF_{(t)} = \log\ (\frac{N}{DF_t}) \qquad \dots (2)$$

The formula represents the general formulation of TF-IDF. When the implementation uses *TfidfVectorizer* from the *scikit-learn* library, the actual values may differ depending on the vectorizer configuration and the weighting and normalization procedures applied [17].

3.2 Sentiment Classification Using SVM

The SVM method is used to learn decision boundaries that separate classes based on TF-IDF feature vectors. The main principle of SVM is to construct a hyperplane with an optimal margin between data classes. This method supports multiclass classification and can therefore be applied to distinguish positive, negative, and neutral sentiments [18]. In general, the linear SVM decision function can be expressed as follows:

$$F_{(x)} = w^t x + b(\frac{N}{DF_t}) \qquad \dots (3)$$

Since this study uses three sentiment classes, the SVM model applies a multiclass classification strategy according to the algorithm implementation used. The strategy may vary depending on the selected SVM implementation [18].

3.3 Data Splitting and Testing

The dataset is divided into training data and testing data. The training data are used to build the classification model, while the testing data are used to measure the model's ability to classify comments that were not used during training. The data-splitting ratio is determined according to the experimental configuration used in the study.

To reduce the risk of data leakage, the splitting process must account for the presence of duplicate comments. Identical comments or comments belonging to the same duplicate group should not be distributed across both the training and testing sets. In addition, vocabulary construction and TF-IDF weight learning are performed using the training data, after which the same transformation is applied to the testing data. This procedure helps ensure that information from the testing data is not used during the model training process.

3.4 Model Performance Evaluation

The performance of the SVM model is evaluated using a confusion matrix, accuracy, precision, recall, and F1-score. These metrics are used to assess overall prediction correctness as well as the model's ability to identify each sentiment class. For multiclass classification, these metrics can be calculated for each class and then reported as average values according to the evaluation method employed [18].

Accuracy represents the proportion of correct predictions among all testing data:

$$Accuracy = \left(\frac{\sum TP_i}{N}\right) \quad \ldots(4)$$

$$Percision_i = \frac{TP_i}{(TP_i + FP_i)} \quad \ldots(5)$$

$$Recall_i = \frac{TP_i}{(TP_i + FN_i)} \quad \ldots(6)$$

$$FI_i = 2 \text{ x } \frac{(Precision_i \; x \; Recall_i)}{(Percision_i + Recall_i)} \quad \ldots(7)$$

In Equation (4), (ΣTP_i) represents the total number of correct predictions across all classes. Precision, recall, and F1-score are calculated for each sentiment class: positive, negative, and neutral. Macro-average or weighted-average values may also be included to summarize the model's performance across the three classes. Meanwhile, the confusion matrix is used to examine the number of correct predictions and classification errors for each class.

The evaluation results are subsequently analyzed descriptively to explain the ability of SVM to classify public opinions about Universitas Royal based on Instagram comments. The classification results are also used to describe the sentiment distribution within the analyzed dataset. Conclusions regarding model performance are determined based on the actual testing results, while interpretations of sentiment distribution are limited to the comments included in the dataset.

Results

4.1 Data Processing Results

This study uses 2,457 Instagram comments related to Universitas Royal. The research dataset consists of the comment number, comment ID, date, comment text, and sentiment label. The sentiment labels are grouped into three classes: negative, neutral, and positive. These data are used to analyze public opinions about Universitas Royal on Instagram using the *Support Vector Machine* (SVM) method.

Based on the data processing results, the negative class consists of 825 comments (33.58%), the neutral class contains 824 comments (33.54%), and the positive class comprises 808 comments (32.88%). This distribution indicates that the number of observations across the three classes is relatively balanced, with each class accounting for a nearly equal proportion of the research dataset.

Table 1. Sentiment Data Distribution

Sentiment Class	Number of Data	Percentage
Negative	825	33,58%

Neutral	824	33,54%
Positive	808	32,88%
Total	2.457	100%

4.2 Data Preprocessing Results

Preprocessing is performed to prepare the comment text before the classification stage. The applied procedures include *case folding*, *cleaning*, word normalization, tokenization, stopword removal, and stemming. These procedures aim to simplify the text, reduce variations in writing, and transform words into their root forms so that they can be processed during the feature extraction stage.

For example, the comment "Pelayanannya sangat baik" ("The service is very good") is transformed into "layan sangat baik" after preprocessing. The preprocessed text is then used for word weighting using *Term Frequency–Inverse Document Frequency* (TF-IDF). TF-IDF transforms text into numerical representations based on word occurrence characteristics within individual documents and across the entire document collection. These representations serve as input for the SVM classification model.

4.3 Data Splitting and SVM Modeling Results

The dataset was divided into 80% training data and 20% testing data, resulting in 1,965 training samples and 492 testing samples. The training data were used to build the classification model, while the testing data were used to evaluate the model's ability to predict the sentiment of comments.

The SVM model was trained using text features weighted with TF-IDF. SVM works by identifying an optimal separating boundary, or *hyperplane*, to distinguish data classes based on the available features. In this study, the model was used to classify Instagram comments into three sentiment categories: negative, neutral, and positive.

4.4 SVM Model Evaluation Results

The model was evaluated using accuracy, precision, recall, and F1-score. Accuracy measures the proportion of correct predictions across all testing data. Precision indicates the correctness of predictions for a particular class, while recall measures the model's ability to identify data that actually belong to that class. The F1-score combines precision and recall into a single evaluation measure.

Table 2. Evaluation Results of the Support Vector Machine Model

Evaluation Metric	Results
Accuracy	100,00%
Precision	100,00%
Recall	100,00%
F1-Score	100,00%
Number of Testing Samples	492

Based on the testing results presented in Table 2, the SVM model achieved accuracy, precision, recall, and F1-score values of 100% each. These results indicate that all predictions for the 492 testing samples matched their reference sentiment labels in the evaluation conducted. Therefore, the SVM model demonstrated very high performance on the dataset used in this study.

Nevertheless, the 100% evaluation scores should be interpreted with caution. Potential duplicate comments and similarities between the training and testing data should be examined to ensure that the evaluation results are not affected by data leakage. Therefore, these results

reflect the model's performance in the conducted evaluation and do not automatically demonstrate that the same performance will be achieved on new comments.

4.5 Confusion Matrix Analysis

The confusion matrix is used to examine the agreement between the actual sentiment labels and the predictions generated by the SVM model for each class. This matrix presents the number of correct predictions and classification errors for the negative, neutral, and positive classes. Based on the evaluation results, which indicate that all metrics reached 100%, the model is reported to have made no prediction errors on the testing data. However, this conclusion must be verified by examining the actual confusion matrix generated by the program. If the verified confusion matrix shows that all observations are located along the main diagonal, it can demonstrate that 165 negative comments, 165 neutral comments, and 162 positive comments in the testing dataset were classified in accordance with their reference labels.

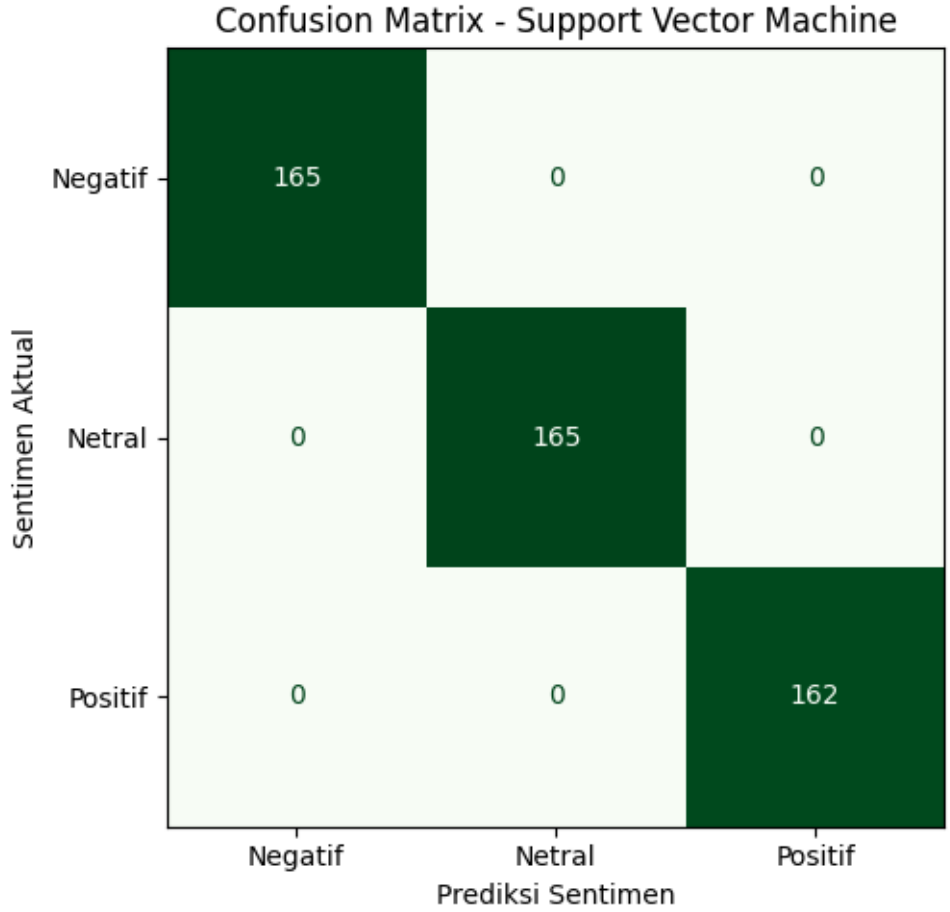


Figure 1. Confusion Matrix of the SVM Model

4.6 Discussion

The results indicate that the SVM method combined with TF-IDF weighting can be used to classify Instagram comments about Universitas Royal into three sentiment categories. The preprocessing stage helps prepare the text in a more structured form, while TF-IDF generates numerical representations that can be used in the classification process.

The initial testing results show that the SVM model achieved evaluation scores of 100% across all reported metrics. These results indicate a very high level of agreement between the model's predictions and the reference labels in the testing data. However, the possibility of repeated comments in the dataset requires attention, as identical texts appearing in both the training and testing sets may lead to overly optimistic evaluation results.

Therefore, duplicate-comment validation, labeling consistency checks, and data-splitting procedures should be verified before these results are used as the basis for final conclusions. Once these validation steps have been completed, the SVM model can be further evaluated as a sentiment analysis approach to help understand public opinion trends about Universitas Royal on Instagram.

Conclusion

This study applies the *Support Vector Machine* (SVM) method to classify public opinions about Universitas Royal expressed through Instagram comments into three sentiment categories: negative, neutral, and positive. The dataset consists of 2,457 comments, divided into 1,965 training samples and 492 testing samples. Based on the initial evaluation, the SVM model achieved accuracy, precision, recall, and F1-score values of 100% each. These results indicate a very high level of agreement between the model's predictions and the reference sentiment labels in the testing dataset. Nevertheless, these results cannot yet be considered definitive evidence of the model's generalization capability, as further examination of duplicate comments and potential data leakage between the training and testing sets is required. In practical terms, SVM has the potential to help Universitas Royal identify public opinion trends on Instagram and support the evaluation of institutional communication and services. Future research should systematically address duplicate comments, implement stricter data-splitting procedures, and test the model on new, independent comments to assess the reliability of the classification results more objectively.

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