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Analysis of student sentiment towards the quality of final project guidance using the Support Vector Machine Algorithm

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ABSTRACT

This research aims to analyze student sentiment towards thesis guidance services at Nurul Jadid University (UNUJA) using sentiment analysis methods with the Support Vector Machine algorithm. Thesis guidance services play a crucial role in shaping high-quality and competitive human resources within the university environment. However, students' sentiment assessments of these services are often complex and may differ from the perspectives of their advisors. The research approach used is quantitative analysis by collecting student feedback data through questionnaires and interviews. The text data from student responses is then processed to clean and format the data before being implemented with the Support Vector Machine algorithm. This algorithm will classify the sentiment into positive, negative, or neutral groups based on the information contained in the text responses. Based on the results of the conducted study, using the Support Vector Machine (SVM) method for sentiment analysis of thesis guidance quality at Nurul Jadid University, this study achieved an accuracy of 87%, precision of 88%, recall of 87%, and an F1 score of 86%.

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Introduction

Final project guidance services are one of the important aspects in the higher education process, especially in universities[1]. Final project guidance aims to provide direction and support to students in completing their research or final projects, which contributes to achieving adequate academic results. As one of the determining factors in the quality of education, the quality of final project guidance services can affect students' ability to complete their final projects well, as well as impact the development of their competence and readiness to enter the professional world (Saputra et al., 2022).

At Nurul Jadid University (UNUJA), the quality of final project guidance is one of the main concerns in improving the quality of competent and competitive human resources. However, students' perceptions and experiences related to the quality of final project guidance services often vary, depending on various factors such as the interaction between students and supervisors, the clarity of the directions given, and the availability of adequate time and resources. This causes the assessment of the quality of final project guidance to often be complex and subjective.

One method that can be used to analyze student assessments or sentiments towards final project guidance services is sentiment analysis (Meiyanti et al., 2023; Sunardi et al., 2018). By using machine learning algorithms, such as Support Vector Machine (SVM), sentiment analysis can provide a clearer picture of student perceptions of the service. SVM is an effective algorithm for classifying text based on the sentiment contained in it, whether it is positive, negative, or neutral (Astuti et al., 2020; Indriyani et al., 2023; Irfani et al., 2020; Sulaeman et al., 2019).

This study aims to analyze student sentiment towards the quality of final project guidance at Nurul Jadid University using the Support Vector Machine algorithm. Through this analysis, it is hoped that deeper insights can be obtained regarding the quality of guidance services received by students, as well as identification of aspects that need to be improved to increase student satisfaction. Thus, this study is expected to contribute to efforts to improve the quality of education at UNUJA, especially in terms of more effective final project guidance services that are in accordance with student needs

Sentiment analysis is a process of determining the attitudes or emotions contained in text. In the context of higher education, sentiment analysis can be used to measure student satisfaction with various academic services, including final project guidance (Meiyanti et al., 2023; Rizal et al., 2021). This technique allows researchers to assess students' feelings or perceptions of their services or experiences without having to rely on more formal survey or interview methods. Sentiment analysis has been widely applied in various fields, such as marketing, social media, and customer service (Isnan et al., 2023; Jeven et al., 2023; Neviarouskaya et al., 2011; Novitasari et al., 2022; Pradhan et al., 2022; Sudhir & Suresh, 2021). In education, the application of sentiment analysis can provide deeper insights into the factors that influence student experiences, which are often subjective and difficult to measure directly.

Support Vector Machine (SVM) is one of the popular machine learning algorithms used in text classification, including sentiment analysis. SVM works by finding a hyperplane that separates data in a feature space that has the largest margin between existing classes (Fide et al., 2021; Jeven et al., 2023; Mahendrajaya et al., 2019; Prayogo et al., 2020). In the context of sentiment analysis, SVM is used to classify text based on the sentiment contained in it, namely whether the text has positive, negative, or neutral sentiment.

Several previous studies have shown that SVM is a very effective algorithm in analyzing sentiment, especially for high-dimensional text data (Jeven et al., 2023). SVM has been shown to have a high level of accuracy compared to other algorithms, such as Naive Bayes or Decision Trees, in many text classification tasks, including sentiment analysis (Neviarouskaya et al., 2011). SVM is also better able to handle imbalanced data problems, which often arise in sentiment analysis where the number of positive and negative texts is unbalanced(Caroline et al., 2024; Kotsiantis, 2007; Teniwut et al., 2022). In education, SVM has been used to analyze student sentiment towards various aspects of academic life, such as teaching quality, campus facilities, and guidance services (Astuti et al., 2020; Sulaeman et al., 2019). The application of SVM in this study can provide a clearer picture of how students feel the quality of the final assignment guidance they receive at Nurul Jadid University.

Several previous studies have shown the great potential of using sentiment analysis in the educational context. For example, a study by Sulaeman et al. (Sulaeman et al., 2019) who used sentiment analysis to assess students' opinions on lecturers' performance evaluation suggestions using TF-IDF and SVM found that the use of the SVM algorithm successfully identified the main factors that influence students' perceptions, such as the availability of guidance facilities and interaction with lecturers. In addition, research by Sunardi (Sunardi et al., 2018) on the use of sentiment analysis to measure the quality of final project guidance at a university in Indonesia found that students tend to give positive assessments to lecturers who are more open and communicative in providing guidance directions. This study confirms that sentiment analysis can provide valuable insights into students' satisfaction with the quality of the final project guidance they receive.

Method

This research was conducted using several main stages which are described in the following method flow diagram:

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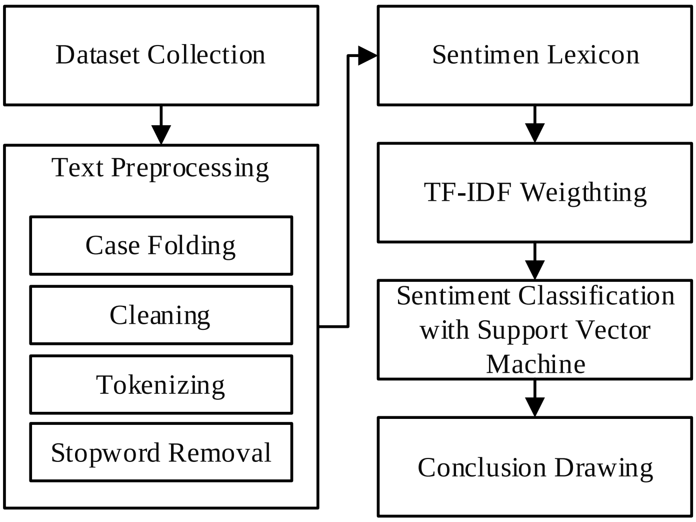

Figure 1. Research Flow

1. Dataset Collection
   The first stage is collecting datasets containing student response data on final assignment guidance services. The datasets were collected through survey methods such as questionnaires and interviews. The data collected is in the form of response texts that will be analyzed further.
2. Text Preprocessing
   The collected text data is then processed through several text preprocessing steps to improve the quality of the data so that it is ready to be used in the analysis. The text preprocessing stages include:
   - Case Folding: Changing all letters in the text to lowercase to match the format.
   - Cleaning: Cleaning the text from irrelevant characters or elements, such as symbols, numbers, or unnecessary punctuation.
   - Tokenizing: Breaking the text into word units or tokens to facilitate analysis.
   - Stopword Removal: Removing common words that do not provide important information, such as "and", "or", and "with".
3. Sentiment Lexicon
   At this stage, a lexicon-based approach is used to analyze the sentiment of the text. The sentiment lexicon contains a list of words with a certain sentiment value (positive, negative, or neutral) which will be used to help identify the initial sentiment in the text data.
4. TF-IDF Weighting
   After the text data is processed, weighting is carried out using the Term Frequency-Inverse Document Frequency (TF-IDF) method. This method assigns weight to each word in the document based on its frequency of occurrence and its importance in the overall dataset(Bafna et al., 2016; Das & Chakraborty, n.d.; Hananto et al., 2018). The result of this stage is a numeric feature representation of the text data that is ready to be used in the classification stage.
5. Sentiment Classification with Support Vector Machine
   Data that has been represented in the form of numeric features is then classified using the Support Vector Machine (SVM) algorithm. The SVM algorithm works by building a hyperplane that separates data into sentiment classes, namely positive, negative, or neutral. This model is trained using training data, then tested to measure classification performance.
6. Conclusion Drawing
   The final stage is drawing conclusions based on the classification results. These results provide an overview of student sentiment towards the final assignment guidance service at Nurul Jadid University. In addition, the results of this analysis can also be used to provide recommendations for improving the quality of guidance services.

Results and Discussions

Based on the stages explained previously, the following are the results obtained and a discussion regarding the implementation and findings of each stage of the research method.

1. **Data Collection**
   The first stage, namely dataset collection, was conducted through a survey involving questionnaires and interviews with students who had used the final assignment guidance service. The data collected consisted of students' text responses which were then used for sentiment analysis. A total of 500 responses obtained were considered representative to provide an overview of students' views on the service. The amount of test data used in this research was 200 test data consisting of positive and negative data.

2. **Text Preprocessing**
   In the text preprocessing stage, various steps are taken to clean and format the text so that it is ready for further analysis.
   - **Case Folding**. At the initial stage in preprocessing in this study is case folding. At the Case folding stage is the initial stage in text processing that changes all letters to lowercase to become a consistent form. Case folding aims to ensure that uppercase and lowercase variations are considered identical, thereby increasing consistency, simplifying searches, and reducing dimensions in text analysis.

Table 1. Case Folding Process

No	Response	Case Folding
1	My supervisor is very responsive and always provides constructive feedback.	My supervisor is very responsive and always provides constructive feedback.
2	His guidance was very helpful, especially when I had difficulty in finding references.	His guidance was very helpful especially when I had difficulty in finding references
3	I feel helped by the lecturer's detailed and clear guidance.	I feel helped by the lecturer's detailed and clear guidance.
4	Although sometimes busy, my supervisor always took the time to discuss with me.	Although sometimes busy, the supervisor always took the time to discuss with me.
5	The advice given greatly enriched my research	The advice given greatly enriched my research
...	…………………………………………………	…………………………………………………
499	Supervisors always provide motivation, but it is often difficult to get a quick response.	Supervisors always provide motivation but it is often difficult to get a quick response.
500	The guidance provided is very useful, but the revisions requested are too many in a short time.	The guidance given is very useful but the revisions requested are too many in a short time.

   - Cleaning. In the cleaning process, it is done to remove all punctuation and remove noise from unnecessary sentences. The text data cleaning process aims to improve data quality by removing unnecessary elements.

Table 2. Cleaning Process

No	Case Folding	Cleaning
1	My supervisor is very responsive and always provides constructive feedback.	My supervisor is very responsive and always provides constructive feedback.
2	His guidance was very helpful especially when I had difficulty in finding references	His guidance was very helpful especially when I had difficulty in finding references
3	I feel helped by the lecturer's detailed and clear guidance.	I feel helped by the lecturer's detailed and clear guidance.
4	Although sometimes busy, the supervisor always took the time to discuss with me.	Although sometimes busy, the supervisor always took the time to discuss with me.
5	The advice given greatly enriched my research	The advice given greatly enriched my research

...	....	....
499	Supervisors always provide motivation but it is often difficult to get a quick response.	Supervisors always provide motivation but it is often difficult to get a quick response.
500	The guidance given is very useful but the revisions requested are too many in a short time.	The guidance given is very useful but the revisions requested are too many in a short time.

- Tokenizing. After going through the Cleaning stage, then move on to the Tokenizing stage, from the Cleaning results then processed at the Tokenizing stage. Tokenizing is a process in text processing where text is broken down into small units called tokens. These tokens are usually individual words, but can also be phrases, sentences, or other elements depending on the purpose of the analysis. Tokenizing is an important step in many natural language processing (NLP) tasks because it allows for more detailed analysis.

Table 3. Tokenizing Process

No	Cleaning	Tokenizing
1	My supervisor is very responsive and always provides constructive feedback.	My supervisor was very responsive and always gave constructive feedback.
2	His guidance was very helpful especially when I had difficulty in finding references	His guidance was very helpful, especially when I was having trouble finding references.
3	I feel helped by the lecturer's detailed and clear guidance.	I, feel, helped, by, the, guidance, of, the, lecturer, which, is, detailed, and, clear
4	Although sometimes busy, the supervisor always took the time to discuss with me.	Although, sometimes, busy, lecturers, supervisors, always, take, time, to, discuss
5	The advice given greatly enriched my research	The advice given was very enriching for my research.
...	....	....
499	Supervisors always provide motivation but it is often difficult to get a quick response.	Lecturers, supervisors, always, provide, motivation, but, often, it, is, difficult, to, get, responses, that, are, quick
500	The guidance given is very useful but the revisions requested are too many in a short time.	Guidance, given, is, very, useful, but, revisions, requested, are, too, many, in, a, short, time

- Stopword Removal. The next process is stopword removal where the data will be processed and processed to remove words that are considered irrelevant such as the prefixes "ny", "di", "yang" and others. The stopword process affects the accuracy value and percentage of word sentiment.

Table 4. Stopword Removal Process

No	Tokenizing	Stopword Removal
1	My supervisor was very responsive and always gave constructive feedback.	Lecturer, guidance, responsive, input, constructive
2	His guidance was very helpful, especially when I was having trouble finding references.	Guidance, help, experience, difficulty, search, reference
3	I, feel, helped, by, the, guidance, of, the, lecturer, which, is, detailed, and, clear	Helped, guidance, lecturer, details
4	Although, sometimes, busy, lecturers, supervisors, always, take, time, to, discuss	Sometimes, busy, lecturer, guidance, take the time, share
5	The advice given was very enriching for my research.	Advice, enrich, research
...	....	....
499	Lecturers, supervisors, always, provide, motivation, but, often, it, is, difficult, to, get, responses, that, are, quick	Lecturer, guidance, motivation, times, difficult, response, fast
500	Guidance, given, is, very, useful, but, revisions, requested, are, too, many, in, a, short, time	Guidance, helpful, revision, short

3. Sentiment Lexicon

After the preprocessing stage is complete, the next process is sentiment classification using a lexicon-based method. In the code used, the processed opinion data will be translated from Indonesian to English using Google Translate. After translation, the translated text is matched with an English lexicon dictionary through the VADER Sentiment Intensity Analyzer to determine the sentiment of the text. VADER uses this lexicon dictionary to provide a sentiment score in the form of a composite value indicating the extent to which the text is positive, negative, or neutral. This process allows for more accurate sentiment classification by considering the intensity and context of the words in the text, resulting in sentiment labels such as "Positive," "Negative," or "Neutral." In this process, data is taken from the stemming results which are then processed in the lexicon process.

Table 4. Examples of stemming and lexicon labeling process

No	Stopword Removal	Stemming	Polarity Text	Lexicon Labeling
1	lecturer, guidance, responsive, input, constructive	lecturers guide responsive constructive entry	3	positif
2	guidance, help, experience, difficulty, search, reference	help guide naturally difficult to find references	-7	negatif
3	helped, guidance, lecturer, details	help guide detailed lecturers	1	positif
4	sometimes, busy, lecturer, guidance, take the time, share	sometimes busy lecturers guide had time to list	0	positif
5	advice, enrich, research	meticulous rich advice	-1	negatif

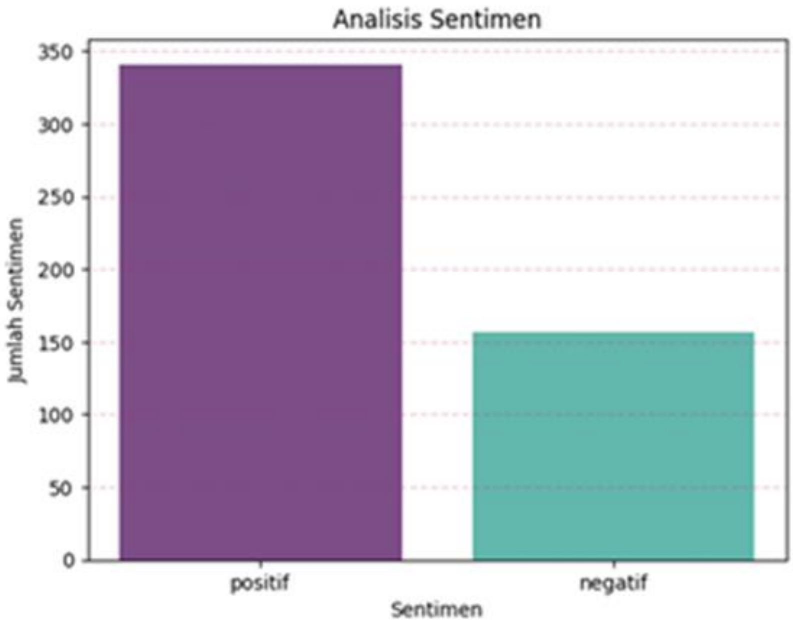

Figure 2. Comparison of Positive and Negative Sentiment Data

4. **TF-IDF Weighting**

The next stage is TF-IDF (Term Frequency-Inverse Document Frequency) weighting. TF-IDF (Term Frequency-Inverse Document Frequency) is a method used to determine the occurrence of a word in a document (Bafna et al., 2016; Cheng et al., 2020; Das & Chakraborty, n.d.). First, Term Frequency (TF) calculates how often a word appears in a document. by dividing the number of occurrences of the word in the document with the aim of giving more weight to words that appear more often in a document because they are likely to have high relevance to a document. Furthermore, document Frequency (DF) calculates the number of documents containing the term in the collection that contains the word. IDF (Inverse Document Frequency) is a value that evaluates how unique a word is by dividing the total number of documents by the number of documents containing the word. TF-

IDF is calculated by multiplying the TF value by the IDF value. The result is a numeric value that indicates the importance of a word in a document. With TF-IDF, we can convert text into a numeric representation that helps in analyzing and understanding documents more deeply. Here is an example of the results of the TF-IDF process.

```
print(data_tf_idf)

                                           stemmed  polarity_text  \
0         dosen bimbing responsif masuk konstruktif              3
1          bimbing bantu alami sulit cari referensi             -7
2                        bantu bimbing dosen detail              1
3      terkadang sibuk dosen bimbing sempat berdiftar            0
4                                saran kaya teliti              -1
..                                             ...            ...
493              dosen bimbing detail revisi bingung             2
494          kritik bantu kali ubah instruksi bingung           -9
495  dukung susun tugas jadwal bimbing kali berubah...           3
496    dosen bimbing motivasi kali sulit tanggap cepet           5
497                    bimbing manfaat revisi singkat            2

    sentimen  agenda  ajar  aju  akademik  aktif     alami  alas  ...  tulis  \
0    positif     0.0   0.0  0.0       0.0    0.0  0.000000   0.0  ...    0.0
1    negatif     0.0   0.0  0.0       0.0    0.0  0.445374   0.0  ...    0.0
2    positif     0.0   0.0  0.0       0.0    0.0  0.000000   0.0  ...    0.0
3    positif     0.0   0.0  0.0       0.0    0.0  0.000000   0.0  ...    0.0
4    negatif     0.0   0.0  0.0       0.0    0.0  0.000000   0.0  ...    0.0
..       ...     ...   ...  ...       ...    ...       ...   ...  ...    ...
493  positif     0.0   0.0  0.0       0.0    0.0  0.000000   0.0  ...    0.0
494  negatif     0.0   0.0  0.0       0.0    0.0  0.000000   0.0  ...    0.0
495  positif     0.0   0.0  0.0       0.0    0.0  0.000000   0.0  ...    0.0
496  positif     0.0   0.0  0.0       0.0    0.0  0.000000   0.0  ...    0.0
497  positif     0.0   0.0  0.0       0.0    0.0  0.000000   0.0  ...    0.0
```

Figure 3. TF-IDF Weighting Process

5. Classification with Support Vector Machine

After the preprocessing stage, lexicon classification, and TF-IDF word weighting are complete, sentiment classification is then carried out using Support Vector Machine to find out the sentiment prediction results from the data. At the Support Vector Machine classification stage assisted by scikit learn support, the Support Vector Machine process is used to obtain SVM classification results. Support Vector Machine algorithm produces 87% accuracy, 88% precision, 87% recall, and 86% F1 score . The results of the classification process on test data can be seen in the confusion matrix and the following table:

Table 5. Classification Results

	Precision	Recall	F1-Score	Support
Negatif	94%	58%	72%	57
Positive	85%	99%	92%	143

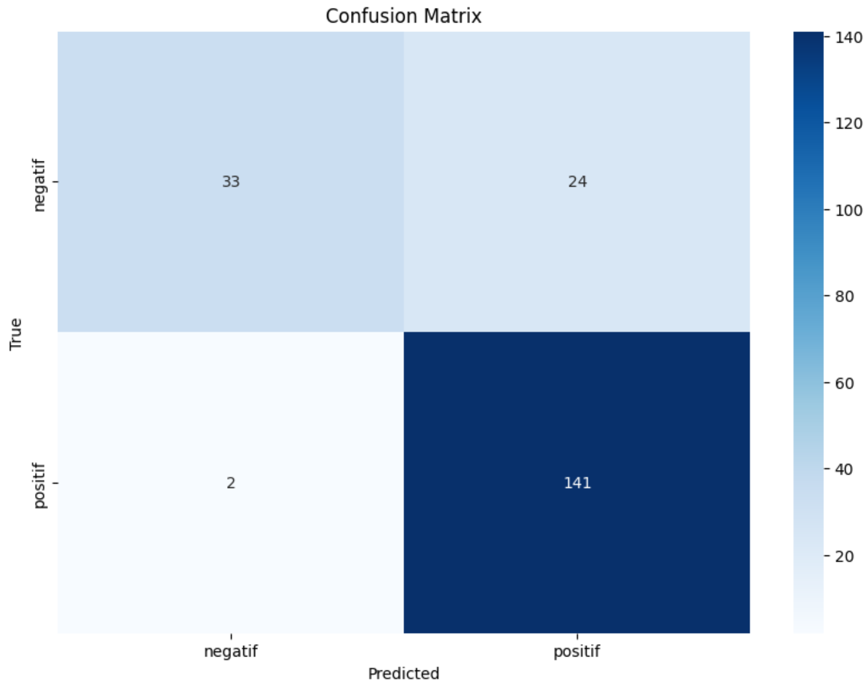

Figure 4. Classification Results Confusion Matrix

6. **Conclusion Drawing**
   Based on the results of experiments that have been conducted using the Support Vector Machine (SVM) method for sentiment analysis on the quality of final project guidance at Nurul Jadid University, the Support Vector Machine algorithm produces 87% accuracy, 88% precision, 87% recall, and 86% F1 score.

Conclusions

Based on the results of sentiment analysis, most students gave positive responses to the final assignment guidance service at Nurul Jadid University. However, there are still complaints about late guidance and lack of communication, indicating the need for improvement. Research using the Support Vector Machine (SVM) method achieved 87% accuracy, 88% precision, 87% recall, and 86% F1 score, proving the effectiveness of the TF-IDF and SVM methods in automatically classifying sentiment. However, the limitations of lexicon-based methods in handling complex or ambiguous contexts are of concern. This study shows the importance of further development, such as the integration of deep learning algorithms (e.g., BERT or Transformer) and the use of larger and more diverse datasets to improve accuracy and generalization. In addition, multidimensional analysis, for example linking sentiment to academic performance or student satisfaction, can provide greater insight. Application-based approaches, such as real-time dashboards, are proposed to help universities design more responsive and data-driven guidance services, so that the results of this study can be the basis for improving the quality of education.

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