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A Comparative Sentiment Analysis of Computer Engineering Student Feedback Using Decision Trees and SVM

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ABSTRACT

The University of Borneo Tarakan, like many Indonesian universities, is committed to continuous quality improvement in education services. A crucial aspect of this improvement is gathering and analyzing student feedback to enhance lecturer performance. This research focuses on analyzing student comments using sentiment analysis, a technique that categorizes text into positive, negative, and neutral sentiments. To achieve this, two machine learning algorithms were employed: Decision Trees and Support Vector Machines (SVM). The research involved two approaches: Lexicon-Based Sentiment Analysis and TF-IDF word weighting. The Lexicon-Based approach compared the automated sentiment classification with manual human categorization to assess accuracy. The TF-IDF method, on the other hand, aimed to improve classification accuracy by assigning weights to words based on their frequency and importance. The experimental results demonstrated that Decision Trees outperformed SVM in terms of classification accuracy, achieving 95.454546% compared to 94.805194%. This finding suggests that Decision Trees is a more effective technique for sentiment analysis of student comments in this specific.

I. Introduction

Universities are one of the front lines in educating and producing good educational services for students. In order to increase the quality of universities and teachers (Lecturers), teaching evaluations are carried out.

Teaching evaluation is carried out by analyzing student comments using Google Form, student comment data will be grouped into three clusters, namely neutral, negative and positive. Comment clusters require sentiment analysis. Sentiment analysis is a data mining technique used to analyze emotions or feelings contained in text. Sentiment analysis can be used for various purposes, such as to understand public opinion towards a product or service, to monitor social media, or to detect cyberbullying [1][2][3].

Machine learning, a subset of artificial intelligence, enables computers to learn from data without explicit programming. By analyzing vast datasets, machine learning algorithms uncover patterns and make predictions. Common machine learning algorithms include Support Vector Machines (SVM), Decision Trees, k-Nearest Neighbors, Naive Bayes, and Logistic Regression.[4][5][6]. This research focuses on Decision Trees and SVM. Decision Trees analyze relationships between a dependent variable and multiple independent variables. SVM, a supervised learning technique, is well-suited for classification and regression tasks. SVM's robust mathematical foundation and ability to handle linear and nonlinear problems make it a powerful tool in machine learning.[7]. The Decision tree algorithm is often used because it is easy to understand, especially for people without an analytical background, flexible and efficient so this algorithm is easy to use[8].

Lexicon based is a data analysis method that uses a list of words or phrases that have been labeled with scores or sentiment categories. The sentiment score can be a numeric value [9][10]. Sentiment

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scores can be numeric values, such as positive (1), negative (-1), or neutral (0), or categories, such as “happy,” “sad,” “angry,” or “scared”[9]. This algorithm is efficient and can be used for various types of text, including formal and informal. Following the lexicon-based sentiment analysis, a TF-IDF weighting process was applied to the words. TF-IDF is a technique that transforms textual data into numerical values. Each word or feature is assigned a weight based on its frequency and importance within the text [10].

In a prior study conducted by Rani Puspita, et al [11] entitled " Comparison of KNN, Decision Tree, and Naïve Bayes Methods for Sentiment Analysis of BPJS Service Users ". compare the accuracy of different sentiment analysis techniques, researchers utilized K-Nearest Neighbors (KNN), Decision Trees, and Naïve Bayes algorithms. These experiments were conducted using RapidMiner version 9.7.2. The results indicated that the KNN method achieved a 95.58% accuracy rate in analyzing Twitter sentiment regarding BPJS services. However, its precision for negative and positive predictions was relatively low. The Decision Tree method, on the other hand, demonstrated a slightly higher accuracy of 96.13% with improved precision for negative predictions. The Naïve Bayes method, while achieving a lower overall accuracy of 89.14%, exhibited strong precision for neutral predictions.

Building upon existing research, this study aims to analyze student sentiment towards teachers by comparing the performance of Decision Tree and Support Vector Machine (SVM) algorithms. A key distinction from previous work lies in the inclusion of a preprocessing step before applying lexicon-based sentiment analysis. This approach will be compared with manual sentiment categorization to assess the accuracy of automated methods in classifying comments as positive, negative, or neutral. Additionally, TF-IDF word weighting will be employed to further enhance the accuracy of sentiment classification using both algorithms.

II. Method

To ensure the effective execution of this research, a well-defined process is necessary. A visual representation of the research workflow is provided in Figure 1.

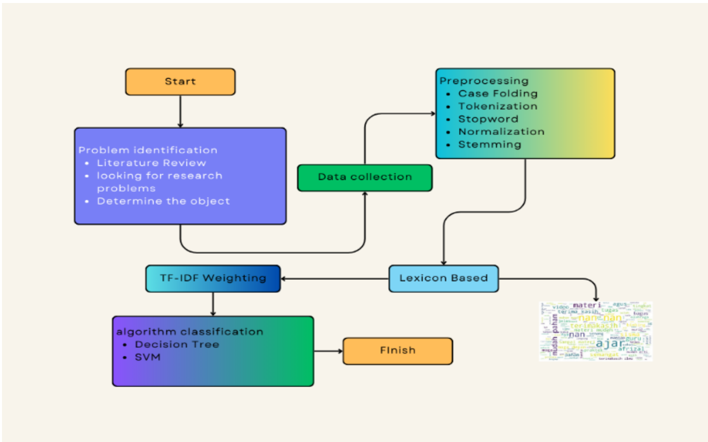

Fig. 1. Research flow

The research process, depicted in Figure 1, involves several key stages:

A. Problem Identification

The initial phase focuses on identifying the research problem. This includes conducting a literature review to explore existing research on sentiment analysis. The specific problem addressed in this study is the sentiment analysis of student comments using lexicon-based techniques. Lexicon-based techniques are computational methods that utilize a lexicon, or a dictionary of words and their associated meanings, to analyze and process natural language text. These techniques often involve assigning semantic or syntactic features to words based on their dictionary definitions, and then using these features to perform tasks such as sentiment analysis, text classification, and information extraction [12]. Decision Trees, and SVM. Student comments, which can be directed towards teachers, are the primary data source. These comments are categorized into three sentiments: positive, negative, and neutral.

B. Data collection

In this stage, student comments are collected and manually labeled with their respective sentiment.

C. Preprocessing

The collected data often contains noise or irrelevant information. To improve the accuracy of sentiment analysis, a preprocessing step is applied to clean and prepare the data. The preprocessing workflow is illustrated in Figure 2.

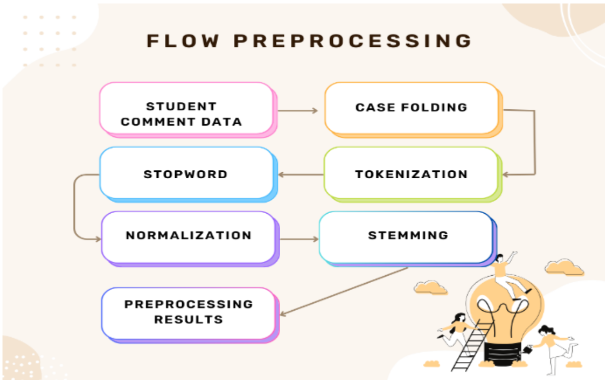

Fig.2. Flow Preprocessing

D. Lexicon-Based Sentiment Analysis:

The preprocessed data is subjected to lexicon-based sentiment analysis. This technique utilizes a lexicon containing sentiment-labeled words to classify comments. The results obtained from lexicon-based analysis are compared with the manually labeled ground truth.

E. TF-IDF weighting

To boost the accuracy of sentiment classification, TF-IDF weighting is utilized. This technique assigns weights to words based on their frequency within a document and their overall rarity. The formula (1) for calculating TF-IDF weights is as follows:

$$W_{t,d} = tf_{t,d} \times idf_t = tf_{t,d} \times \log \frac{N}{Df_t} \quad (1)$$

Where,

$W_{t,d}$ represents the importance of term t in document d as measured by TF-IDF

$tf_{t,d}$ denotes the frequency of term t within document d,

idf_t signifies the rarity of term t across the entire corpus.

Df_t indicates the total number of documents in the collection.

N represents the number of documents containing term t

TF-IDF assigns higher weights to terms that are frequent within a document but rare across the entire corpus, thereby highlighting the most significant terms for sentiment analysis.

F. Algorithm Classification

The classification process involved applying the Decision Tree and SVM algorithms to a lexicon-based dataset with TF-IDF weighting. To evaluate the performance of each algorithm, we employed standard metrics: precision, recall, F1-score, and accuracy

G. Data Sharing

The dataset was partitioned into training and testing subsets, with 70% allocated for training and 30% for testing. This division, illustrated in Figure 3, enabled the development and evaluation of the classification models.

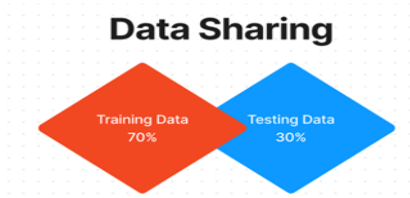

Fig.3. Data Sharing

H. Model Classification

1. Decision Tree

A Decision Tree algorithm leverages a tree-like structure to aid classification. This method requires bagging and boosting to improve its accuracy because it tends to over fit. The structure of this algorithm is like a tree, where there is a root node, child node, and leaf as a place to display the label of a data [13]

A decision tree is a model that helps in understanding what things are like by breaking them down into smaller parts. The root node is where all the information starts and the other nodes are where to learn more about what happens next. There are different types of nodes, such as root and internal, and each tells something different about the data. Classification occurs when looking at the nodes and seeing which one is for the data shown [14].

The decision tree method has several stages, namely training data is prepared and the selection of attributes that will be used as roots using the formulas shown in equations (2) and (3) [15].

$$Entropy\ (S) = \sum_{i=1}^{n} pi * log_2 pi \tag{2}$$

$$Gain(S, A) = Entropy\ (S) - \sum_{i=1}^{n} \frac{|S_i|}{|S|} * Entropy(S_i) \tag{3}$$

where S is the set of cases,

n is the number of partitions,

pi is the proportion S_i of S,

A is a characteristic or property

$|S_i|$ represents the count of instances within the i-th subset,

$|S|$ denotes the total count of instances in the entire set S.

2. Support Vector Machine

SVM is a pattern recognition technique that identifies the optimal hyperplane to differentiate between two groups of data points. This hyperplane maximizes the distance between the closest points of each group. SVM is renowned for its high accuracy in pattern recognition and its efficient learning process. Meanwhile, the disadvantages of SVM are that it is difficult to use in problems with large sample sizes [10][8]. This research will focus on using linear and dividing it into 2 classes, namely positive and negative. The hyperplane search function can be defined in equation (4) and the edge line on the hyperplane to divide the positive and negative classes is defined in equation (5).

$$(w.x) + b = 0 \tag{4}$$

$(w.x) + b \ = +1$ (for positive class) (5)

(w.x) + b = -1 (for negative class)

I. Model Evaluation

Table.1. Confusion Matrix

	Class	
	Positif	**Negatif**
Positif	*True Positive*	*False Positive*
Negatif	*False Negative*	*True Negative*

Based on the performance evaluation matrix in Table 1, Key metrics for evaluating model performance, including precision, recall, and the F1-score, and accuracy, can be employed to assess the effectiveness of algorithms [16].

Following is the formula and explanation:

$$precision = \frac{TP}{TP+FP} \tag{6}$$

$$recall = \frac{TP}{TP+FN} \tag{7}$$

$$F - measure = \frac{2 \times precision \times recall}{precision + recall} \tag{8}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{9}$$

Where is

TP (True Positive): Correctly identified positive cases.

FP (False Positive): Incorrectly identified as positive cases (false alarms).

FN (False Negative): Correctly identified negative cases.

TN (True Negative): Incorrectly identified as negative cases (missed detections)

Equations 6, 7, 8, and 9 present formulas used to evaluate the performance of algorithms. Precision (Equation 6) measures how accurate an algorithm's positive predictions are. Recall (Equation 7) measures how complete an algorithm's positive predictions are. F-measure (Equation 8) balances precision and recall, providing a single metric to evaluate overall performance. A higher F-measure indicates better performance. Accuracy (Equation 9) measures the overall correctness of an algorithm's predictions, considering both correct positive and negative predictions.

III. Results and Discussion

In this discussion, we delve into the results of our research analyzing student sentiment expressed in comments towards lecturers. We utilized SVM and Decision Tree algorithms for this analysis. Student comments were collected as the primary data source and were processed using the Jupyter Notebook environment.

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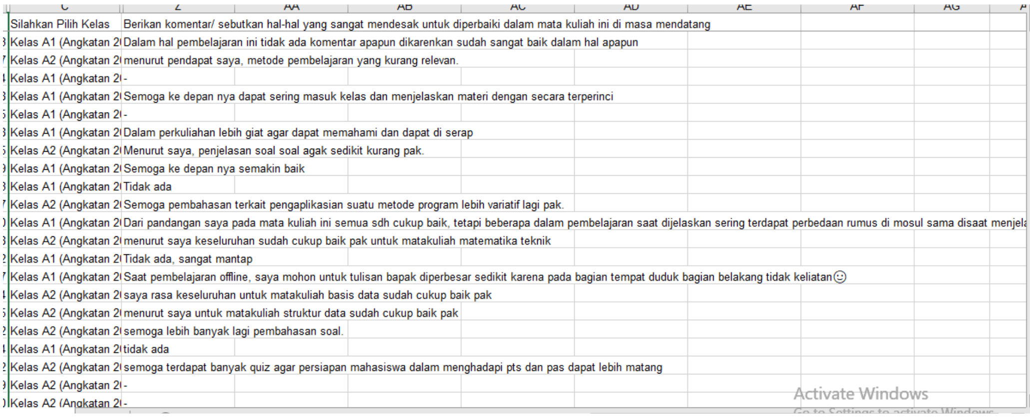
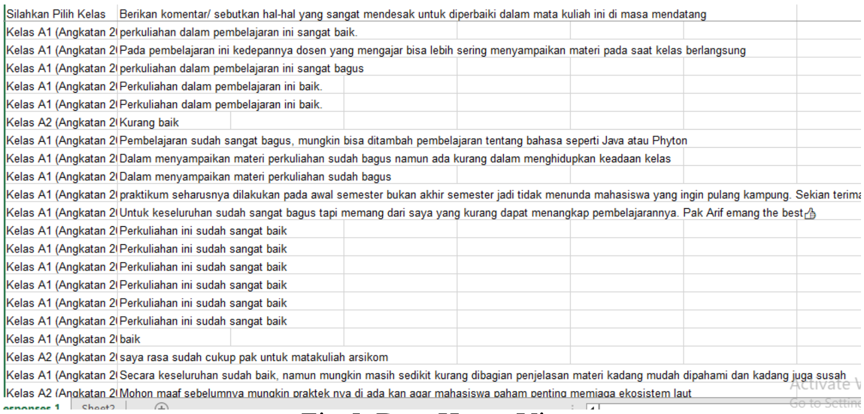
A manual sentiment analysis process was applied to student comment data. The comments were classified into three sentiment categories: positive, negative, and neutral. The resulting sentiment labels were organized into a CSV file, visualized in Figure 4.



Silahkan Pilih Kelas	Berikan komentar/ sebutkan hal-hal yang sangat mendesak untuk diperbaiki dalam mata kuliah ini di masa mendatang
Kelas A1 (Angkatan 2(	Dalam hal pembelajaran ini tidak ada komentar apapun dikarenkan sudah sangat baik dalam hal apapun
Kelas A2 (Angkatan 2(	menurut pendapat saya, metode pembelajaran yang kurang relevan.
Kelas A1 (Angkatan 2(	-
Kelas A1 (Angkatan 2(	Semoga ke depan nya dapat sering masuk kelas dan menjelaskan materi dengan secara terperinci
Kelas A1 (Angkatan 2(	-
Kelas A1 (Angkatan 2(	Dalam perkuliahan lebih giat agar dapat memahami dan dapat di serap
Kelas A2 (Angkatan 2(	Menurut saya, penjelasan soal soal agak sedikit kurang pak.
Kelas A1 (Angkatan 2(	Semoga ke depan nya semakin baik
Kelas A1 (Angkatan 2(	Tidak ada
Kelas A2 (Angkatan 2(	Semoga pembahasan terkait pengaplikasian suatu metode program lebih variatif lagi pak.
Kelas A1 (Angkatan 2(	Dari pandangan saya pada mata kuliah ini semua sdh cukup baik, tetapi beberapa dalam pembelajaran saat dijelaskan sering terdapat perbedaan rumus di mosul sama disaat menjel
Kelas A2 (Angkatan 2(	menurut saya keseluruhan sudah cukup baik pak untuk matakuliah matematika teknik
Kelas A1 (Angkatan 2(	Tidak ada, sangat mantap
Kelas A1 (Angkatan 2(	Saat pembelajaran offline, saya mohon untuk tulisan bapak diperbesar sedikit karena pada bagian tempat duduk bagian belakang tidak keliatan😊
Kelas A2 (Angkatan 2(	saya rasa keseluruhan untuk matakuliah basis data sudah cukup baik pak
Kelas A2 (Angkatan 2(	menurut saya untuk matakuliah struktur data sudah cukup baik pak
Kelas A2 (Angkatan 2(	semoga lebih banyak lagi pembahasan soal.
Kelas A1 (Angkatan 2(	tidak ada
Kelas A2 (Angkatan 2(	semoga terdapat banyak quiz agar persiapan mahasiswa dalam menghadapi pts dan pas dapat lebih matang
Kelas A2 (Angkatan 2(	-
Kelas A2 (Angkatan 2(	-

Fig.4. Manual Labelling Commentary Data

According to Figure 4, our dataset comprises 256 student comments. Each comment is composed of a student ID, the comment itself, and a classification label, as visualized in Figure 5.



Silahkan Pilih Kelas	Berikan komentar/ sebutkan hal-hal yang sangat mendesak untuk diperbaiki dalam mata kuliah ini di masa mendatang
Kelas A1 (Angkatan 2(	perkuliahan dalam pembelajaran ini sangat baik.
Kelas A1 (Angkatan 2(	Pada pembelajaran ini kedepannya dosen yang mengajar bisa lebih sering menyampaikan materi pada saat kelas berlangsung
Kelas A1 (Angkatan 2(	perkuliahan dalam pembelajaran ini sangat bagus
Kelas A1 (Angkatan 2(	Perkuliahan dalam pembelajaran ini baik.
Kelas A1 (Angkatan 2(	Perkuliahan dalam pembelajaran ini baik.
Kelas A2 (Angkatan 2(	Kurang baik
Kelas A1 (Angkatan 2(	Pembelajaran sudah sangat bagus, mungkin bisa ditambah pembelajaran tentang bahasa seperti Java atau Phyton
Kelas A1 (Angkatan 2(	Dalam menyampaikan materi perkuliahan sudah bagus namun ada kurang dalam menghidupkan keadaan kelas
Kelas A1 (Angkatan 2(	Dalam menyampaikan materi perkuliahan sudah bagus
Kelas A1 (Angkatan 2(	praktikum seharusnya dilakukan pada awal semester bukan akhir semester jadi tidak menunda mahasiswa yang ingin pulang kampung. Sekian terim
Kelas A1 (Angkatan 2(	Untuk keseluruhan sudah sangat bagus tapi memang dari saya yang kurang dapat menangkap pembelajarannya. Pak Arif emang the best👍
Kelas A1 (Angkatan 2(	Perkuliahan ini sudah sangat baik
Kelas A1 (Angkatan 2(	Perkuliahan ini sudah sangat baik
Kelas A1 (Angkatan 2(	Perkuliahan ini sudah sangat baik
Kelas A1 (Angkatan 2(	Perkuliahan ini sudah sangat baik
Kelas A1 (Angkatan 2(	Perkuliahan ini sudah sangat baik
Kelas A1 (Angkatan 2(	Perkuliahan ini sudah sangat baik
Kelas A1 (Angkatan 2(	baik
Kelas A2 (Angkatan 2(	saya rasa sudah cukup pak untuk matakuliah arsikom
Kelas A1 (Angkatan 2(	Secara keseluruhan sudah baik, namun mungkin masih sedikit kurang dibagian penjelasan materi kadang mudah dipahami dan kadang juga susah
Kelas A2 (Angkatan 2(	Mohon maaf sebelumnya mungkin praktek nya di ada kan agar mahasiswa paham penting memjaga ekosistem laut

Fig.5. Data Home View

The text preprocessing stage is crucial because the student comments contain a lot of irrelevant information like symbols, punctuation, numbers, and foreign words that can hinder sentiment analysis. This stage involves several techniques: case folding, tokenization, stop word removal, normalization, and stemming, which help to clean and prepare the text data for analysis..

The case folding stage converts uppercase letters to lowercase or vice versa. For instance, "Mungkin" becomes "mungkin." Here's the pseudocode for case folding.

Variable declaration:

Comment = "Mungkin"

Proses lower case

Print Comments

Comment_lower = "mungkin"

The tokenization phase filters out irrelevant characters like have no effect on the sentiment classification process. Characters that are removed include punctuation marks, commas (,), periods (.), symbols, characters such as letters, numbers and separating each student's comments word by word. Here's the tokenization pseudocode.

Variable declaration:

Comment_lower = “mungkin bisa”

Proses tokenization

Print Comment_token

Comment_token = ”[mungkin, bisa]”

The step of removing insignificant words, as determined by a list of common words, is known as stop word removal. Here's a simplified representation of this process.

Variable declaration:

Comment_token = “[materi, mudah, di, pahami] ”

Stopword process

Print Comment_token_stopword

Comment_token_stopword =[materi, mudah, pahami]

The normalization step standardizes non-standard or noisy words, making them suitable for further processing.

Variable declaration:

Comment_token_stopword = “[materi, yg, pahami] ”

Proses normalization

Print Comment_normalization

Comment_normalization =[materi, yang, pahami]

Stemming is a technique that strips words down to their core. For example, 'Tugasnya' is stripped down to 'tugas'. The following pseudocode demonstrates the stemming procedure.

Variable declaration:

Comment_normalization = “[Tugasnya] ”

Process voting

Print Comment_stemming

Comments_stemming =[tugas]

The preprocessing pipeline is complete. As depicted in Figure 6, the text has undergone case folding, tokenization, stop word elimination, normalization, and stemming, resulting in a preprocessed comment.

‹asi	Komentar_lower	Komentar_token	Komentar_token_kemunculan	Komentar_token_Stopword	Komentar_normalized	Komentar_token_stemmed	Komentar_baru
›sitif	okelah tugasnya jgn yg susahsusah ya pak	[okelah, tugasnya, jgn, yg, susahsusah, ya, pak]	{'okelah': 1, 'tugasnya': 1, 'jgn': 1, 'yg': 1...	[okelah, tugasnya, jgn, yg, susahsusah, ya]	[okelah, tugasnya, jgn, yg, susahsusah, ya]	[oke, tugas, jgn, yg, susahsusah, ya]	oke tugas jgn yg susahsusah ya
›sitif	sangat baikterba	[sangat, baikterba]	{'sangat': 1, 'baikterba': 1}	[baikterba]	[baikterba]	[baikterba]	baikterba
›tral	mungkin bisa di beri materi tertulis	[mungkin, bisa, di, beri, materi, tertulis]	{'mungkin': 1, 'bisa': 1, 'di': 1, 'beri': 1, ...	[materi, tertulis]	[materi, tertulis]	[materi, tulis]	materi tulis
›sitif	its ok	[its, ok]	{'its': 1, 'ok': 1}	[its, ok]	[its, ok]	[its, ok]	its ok
›sitif	sudah cukup baik	[sudah, cukup, baik]	{'sudah': 1, 'cukup': 1, 'baik': 1}	[]	[]	[]	
...	...	...	...	...	...	...	...
›sitif	baikk	[baikk]	{'baikk': 1}	[baikk]	[baikk]	[baikk]	baikk
›sitif	materi mudah di pahami	[materi, mudah, di, pahami]	{'materi': 1, 'mudah': 1, 'di': 1, 'pahami': 1}	[materi, mudah, pahami]	[materi, mudah, pahami]	[materi, mudah, paham]	materi mudah paham
›sitif	pembelajaran yang disampaikan oleh pak agus cu...	[pembelajaran, yang, disampaikan, oleh, pak, a...	{'pembelajaran': 1, 'yang': 1, 'disampaikan': ...	[pembelajaran, agus, mudah, dipahami]	[pembelajaran, agus, mudah, dipahami]	[ajar, agus, mudah, paham]	ajar agus mudah paham
›sitif	cukup baik	[cukup, baik]	{'cukup': 1, 'baik': 1}	[]	[]	[]	
›sitif	baik	[baik]	{'baik': 1}	[]	[]	[]	

Fig.6. Preprocessing Result

The classification process leverages preprocessed lexicon-based data. As depicted in Figure 10, this involves utilizing the new comment field. Lexicon-based sentiment analysis identifies words with positive, negative, or neutral sentiment by computing a polarity value. Sentiments are classified as negative if the polarity value is less than 0, neutral if equal to 0, and positive if greater than 0, as illustrated in Figure 7.

Komentar_token_stemmed	Komentar_baru	Compound_Score	Sentiments
[oke, tugas, jgn, yg, susahsusah, ya]	oke tugas jgn yg susahsusah ya	0.000	Netral
[baikterba]	baikterba	0.000	Netral
[materi, tulis]	materi tulis	0.000	Netral
[its, ok]	its ok	0.296	Positif
[]		0.000	Netral

Fig.7. Term-Frequency Based Classification

Lexicon-based classification results indicate a tripartite sentiment distribution among student comments, with the neutral sentiment dominating at 96.67%, while negative sentiment constitutes a mere 0.34%, as visually represented in Figure 8.

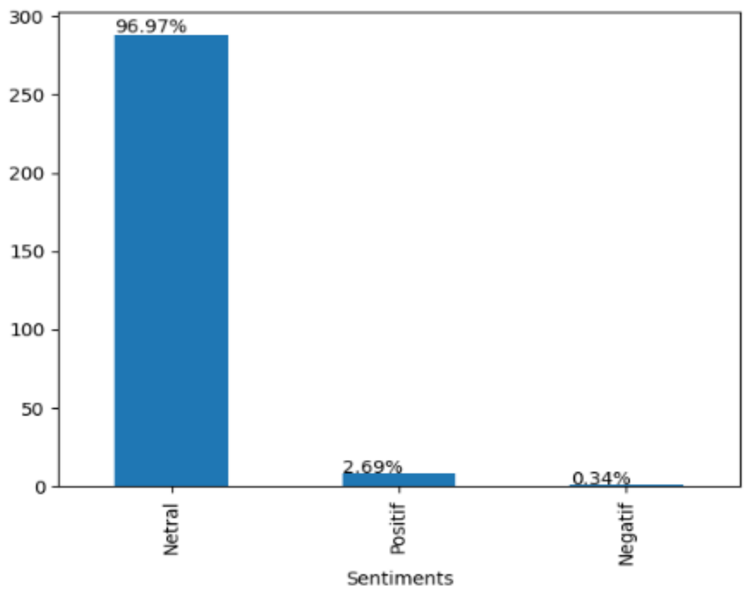


Fig.8. Graphical result Lexicon-based Sentiment

Using lexicon-based sentiment analysis, we created visualizations that categorized words into positive, negative, and neutral sentiments. These visualizations, shown in Figure 9, highlight the words belonging to each sentiment category (a: positive, b: negative, c: neutral).

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Fig.9. Visualized Sentiment Scores from a Lexicon

After initial lexicon-based classification, a TF-IDF weighting scheme is implemented for the newly categorized comments, as depicted in Figure 10.

```
#Menjumlahkan TF-IDF untuk setiap kalimat
result = np.sum(document,axis=1)
result.shape

---------------------------------------------------------------------------
AxisError                                 Traceback (most recent call last)
<ipython-input-84-a0d3eb4ebc1d> in <cell line: 2>()
      1 #Menjumlahkan TF-IDF untuk setiap kalimat
----> 2 result = np.sum(document,axis=1)
      3 result.shape

                                  1 frames
/usr/local/lib/python3.10/dist-packages/numpy/core/fromnumeric.py in _wrapredu
     86                 return reduction(axis=axis, out=out, **passkwargs)
     87
---> 88     return ufunc.reduce(obj, axis, dtype, out, **passkwargs)
     89
     90

AxisError: axis 1 is out of bounds for array of dimension 1

#Ditampilkan TF-IDF setiap kalimat dari kecil ke besar
sorted(result)

[0.0,
 0.0,
 0.0,
 0.0,
```

Fig.10 Outcome of TF-IDF Analysis

Figure 10 displays the outcome of the TF-IDF analysis, revealing 256 comments and 154 unique words or terms after the preceding processing steps. The program output displays the TF-IDF value assigned to each student's comment.

The classification and assessment outcomes of the Decision Tree and SVM algorithms, utilizing a 70-30 training-testing data split, are presented below:

The findings generated by the Decision Tree algorithm are presented graphically in Figure 11.

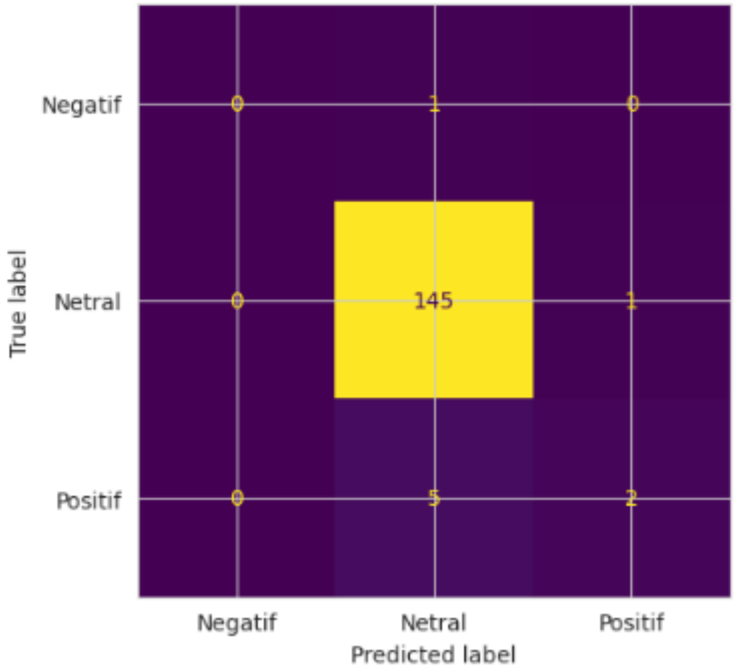

Fig.11 TF-IDF Weighting Results

As depicted in Figure 11, the Decision Tree algorithm demonstrated high accuracy (95.454546%) in analyzing student comments, as evidenced by the confusion matrix.

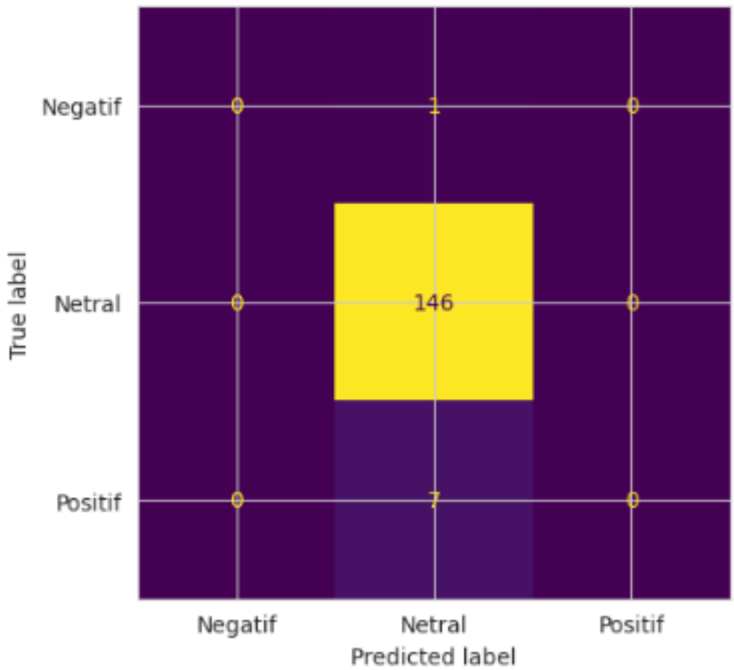

Fig.12 TF-IDF Weighting Results

According to Figure 13, the SVM algorithm's performance in analyzing student comments is demonstrated by a 0.94805194% accuracy rate, further detailed in the confusion matrix.

The Decision Tree and SVM models were evaluated on a 70-30 train-test split. Their performance, measured by precision, recall, F1-score, and accuracy, is presented in the confusion matrix. A comparison of these models is detailed in Table 2.

Table 2. Performance Comparison Results

No.	Algorithm Name	Accuracy Value
1	Decision Tree	95.454546 %
2	SVM	94.805194 %

Table 2 indicates that the Decision Tree algorithm outperforms SVM in terms of accuracy, achieving a 95.454546% success rate. This suggests that the Decision Tree algorithm is the more effective choice for classifying student comment sentiment analysis data. The results of this study are consistent with the research conducted by Jyotsna Singh and friends entitled "Sentiment analysis of Twitter data by making use of SVM, Random Forest and Decision Tree algorithms" where the Decision Tree algorithm is superior to the SVM algorithm [17].

IV. Conclusion

A comparative analysis was conducted between Decision Tree and SVM algorithms, each trained on 70% of the data and tested on the remaining 30%. A Decision Tree method achieved an accuracy of 95.454546 %, precision of 95.026490%, recall of 95.315068%, and F1-score of 94.643097%. The SVM model, on the other hand, yielded an accuracy of 94.805194 %, precision of 98.051948%, recall of 95.556456%, and F1-score of 93.333333%. Overall, the Decision Tree model demonstrated superior performance in classifying the data. To further enhance future research, researchers are encouraged to incorporate data from other popular social media platforms like Threads, Facebook, X, and Instagram to diversify the dataset. Additionally, exploring other classification algorithms could provide more specific and improved classification results.

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