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Sentiment analysis of prospective mathematics teacher on reasoning and proof questions using Naïve-Bayes classification

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Abstract

Reasoning and proof is the ability to arrange patterns, make conjectures, test conjectures, and carry out logical proof, which can be seen as negative or positive for students when solving proof problems requiring reasoning skills. Prospective mathematics teachers in the Mathematics Education Study Program of FKIP Universitas Sriwijaya became the subject of this study. As the research instrument, the questionnaire was designed to explore students' opinions and responses to problems with significant logical difficulty. Sentiment analysis was used to analyze the opinions of prospective mathematics teachers on reasoning and proof questions by grouping positive and negative opinions. The technique used in this study uses the Naïve Bayes algorithm. The classification results in this study were 58.2% positive and 41.86.7% negative, with a total of 70 data. The final result achieved an accuracy value of 53.33%, signifying the reliability of the Naïve Bayes algorithm in understanding and classifying the complex spectrum of sentiments expressed by students. The implications of these findings go beyond sentiment analysis, providing valuable insights for educators, curriculum developers, and policymakers in designing learning strategies and educational policies that can improve mathematics students' reasoning and proof abilities.

Keywords: reasoning and proof, Naïve Bayes, sentiment analysis

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I. Introduction

Writing mathematics at the university level is different from writing mathematics at the school level; prospective mathematics teacher students will encounter many axioms, postulates or definitions that are explained carefully, and each theorem is proven and written in logical and correct words; students also learn to construct logical arguments and construct evidence well. For this reason, prospective teacher students are provided with courses such as Geometry, Algebraic Structure, and Real Analysis as an axiomatic system to practice logical reasoning and reasoning through various mathematical proofs. As expressed by Stefanowiczet al., (2014). There is a big difference between mathematics at school and university. University mathematics students aim to reach mathematical maturity (Kurtz, 1992).

Proof is a logical argument that establishes the truth of a statement. The logic is that each step in the previous steps justifies each step in the argument. This logical sequence requires a person's reasoning skills (Lesseig et al., 2019). Proof and reasoning are mathematical thinking activities from elementary to intermediate levels and are necessary to build a sustainable understanding of mathematics (Hanna, 2000; NCTM, 2000; Stylianides, 2007; and Hanna & de Villiers, 2008). Therefore, prospective mathematics teachers need to be able to construct proofs to facilitate students and help them improve their proof skills (Carrillo et al., 2018; Buchbinder & McCrone, 2022). As a prospective mathematics teacher who is at the final level, the hope is to have a positive attitude when faced with mathematical problems that are not only procedural but also problems that require reasoning and proof as a provision for them to teach mathematics at school, and as one of the elements forming students' reasoning and proof abilities at school later, which are abilities required by the curriculum in Indonesia and also NCTM after students have finished studying mathematics.

Studies measuring positive/negative attitudes and perceptions (Murdiyanto et al., 2021; Puryati et al., 2023) and confidence (Ikrimah, 2023) to explore students' attitudes when dealing with mathematics (Jamiah, 2021) have been done. However, research carried out previously is only limited to agreeing and disagreeing with the statements offered by researchers and has yet to directly listen to students' opinions when faced directly with reasoning and proof questions, which are absolute abilities that a person must possess. Prospective mathematics teacher.

The opinions of prospective mathematics teacher students regarding reasoning and proof questions can be used as evaluation material for lecturers and study programs as producers of prospective mathematics teachers. Evaluation Student opinions are evaluated for each mathematics seminar lecture, and these opinions are made in the form of text messages. The difficulty lecturers have when assessing students' opinions about reasoning and proof questions is whether they like their opinions but cannot solve them or they cannot solve them because they do not like questions that require reasoning to prove them.

In reality, mathematics learning conditions often pose various challenges. Students often find it difficult to face exam questions, especially those related to reasoning and proof skills. Several factors, such as teaching methods, curriculum, and student readiness, may influence their responses to the questions. Therefore, an in-depth study is needed to understand student sentiment towards reasoning and proof questions.

Sentiment analysis offers an innovative approach to measuring student responses. By understanding student sentiment, lecturers can identify thought patterns, barriers and learning preferences that may influence learning outcomes. This analysis can also provide insight into how students respond to questions that test reasoning and proof skills, which can help develop more effective curricula and teaching methods. There is no doubt that sentiment analysis has the potential to revolutionize the way we teach and learn (Shaik et al., 2023, Mite-Baidal et al., 2018).

Sentiment analysis is one part of text analytical studies, namely computational studies to classify a person's opinions, emotions and attitudes towards an entity (Srivastava et al., 2019). Many studies related to sentiment analysis of texts have been carried out using the Naïve Bayes method (Yuniar & Kismiantini, 2023; Taufiqi & Nugroho, 2023 and Burhaein et al., 2023). Naïve Bayes is a data storage system that processes, predicts, and classifies information.

Therefore, to overcome the problem and from several research results on sentiment analysis that have been presented, this research conducted sentiment analysis of student opinions on reasoning and proof questions using the Naïve Bayes method.

This research not only addresses students' sentiments towards reasoning and proof problems but also serves as a stepping-stone in the development of more adaptive mathematics learning and provides an opportunity to explore the extent to which students respond to given mathematical challenges, as well as determine appropriate solutions to improve their reasoning and proof abilities. By analyzing student feedback, teachers can identify areas where students are having difficulty and provide them with the necessary support to overcome these challenges. Sentiment analysis can also help teachers understand the effectiveness of their teaching methods and curriculum. For example, if a particular topic consistently receives negative feedback from students, this can be an indication that the topic needs to be restructured or taught in a different way. Sentiment analysis can also monitor student engagement le vels and identify students at risk of dropping out. This can help teachers provide targeted interventions to help these students succeed (Pooja & Bhalla, 2022; Mite-Baidal et al., 2018; and Shaik et al., 2023).

II. Research Methods

This research uses a quantitative descriptive case study method. The case study in this research is that data was collected by distributing sentiment questionnaires containing reasoning and proof questions to respondents. Researchers chose to use WhatsApp Groups as a tool for data collection. Next, quantitative descriptive is used to analyze and organize the collected data to suit the researcher's needs.

The research variables in this research are divided into two categories, namely: independent and dependent variables. The independent variable includes student opinions, while the dependent variable is the positive and negative labels for these opinions.

This research uses the Naïve Bayes algorithm with the research stages shown in Figure 1 below:

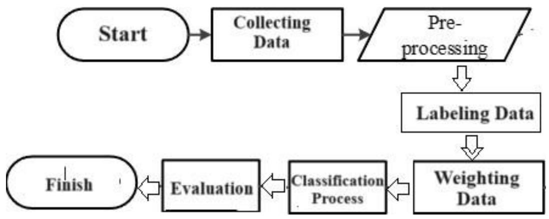


Figure 1. Research stages

Collecting Data

This research uses text-type data from students' opinions when faced with reasoning and proof questions. This data is primarily obtained from respondents who completed the questionnaire as a research instrument. The questionnaire contains questions regarding responses or opinions if they are faced with questions requiring evidentiary skills to prove a mathematical statement logically. Respondents were prospective mathematics teacher students in the mathematics education study program at FKIP Sriwijaya University who had taken courses that required reasoning and proof skills and had taken part in a mathematics colloquium course that required the ability of prospective mathematics teacher students to write logical arguments to prove theorems. Theorems and axiomatically to prove a mathematical statement.

Labeling Data

The researcher chose to label them first before doing preprocessing, namely labelling sentiments, namely positive and negative; this is because the data consisting of 70 student opinions can still be labelled without machine learning, and the information obtained is also very long in 1 opinion so it needs to be read carefully. by researchers because sentiment analysis with an open questionnaire directly filters students' opinions about the questions reasoning and proof it can be said that previous researchers have never done this.

Data Preprocessing

The data preprocessing stage is carried out to select text data so that it becomes more structured and is a very important stage of the sentiment analysis process (Gavilanes et al., 2016) by carrying out several processes, namely

Herlinawati et al., (2020) and Indriyani et al., (2023): (1) Cleansing, (2) Case folding, used to delete unimportant words in a sentence in a document; (2) Tokenization, so that the data can be analyzed, student opinion sentences must be broken down into words or called tokens; (3) Stopwords Removal (dictionary) using Indonesia Stoplist data on Kaggle; and (5) Filtering, the token results are then filtered to get important words. In this study, the (le chosen) filter was chosen with 4 and a maximum of 25.

Weighting Data

Weighting is a method to minimize bias caused by problems with the sample selection method. This weighting function provides a balanced weight to the results of the questionnaire by comparing the sample to the target population. By calculating the weight of each word based on the frequency of occurrence of the word using the method $TF{-}IDF$ (Term et al. Document Frequency of records), TF is a frequency counter for syllables (t). At the same time, DF is the number of occurrences in a collection of documents (N) of syllables with a weighted score. The higher one is considered more significant (Riturajsaha, 2023). This method was chosen because it is more efficient, simple and accurate, with the following formula (Indriyani et al., 2023):

$$W(t,d) = tf(t,d) \times idf(t) = tf(t,d) \times \frac{logN}{df(t)}$$

Information:
$W(t,d)$: TF-IDF Weight
(TFT, d): Number of word frequencies
$idf(t)$: Amountinverse document frequency of each word
$df(t)$: Number of document frequencies for each word
N: Total number of documents

Naïve Bayes Classification

The next process is to carry out Naïve Bayes Classification, which aims to identify the sentiment of student opinions. In data testing, the data will be divided into two, namely training data and testing data. The Naïve Bayes Theorem is used to find out a probability by calculating other related probabilities so that it can be assumed that a feature is independent, equal, and contributes to the result. Naïve Bayes theorem is to calculate the posterior probability with the following formula:

$$P(y|x_1, \dots, x_n) = \frac{P(x_1|y)P(x_2|y) \dots P(x_n|y)P(y)}{P(x_1)P(x_2) \dots P(x_n)}$$

Evalution

Classification is the process of categorizing a certain data set into different categories and producing a model. In machine learning, a Confusion Matrix is used to measure the performance of the classification model obtained. Therefore, the test in this research to evaluate the results of the Naïve Bayes algorithm used a Confusion Matrix. Because the categorical labels in this study are only positive and negative labels, the matrix is in the form of a table. The Confusion Matrix (2×2) is shown in Figure 2 below (Karimi, 2021):

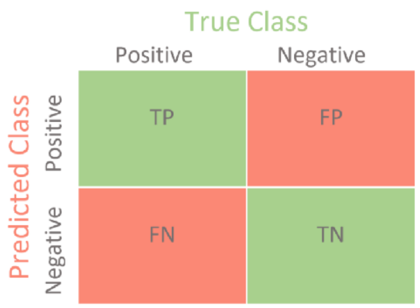


Figure 2. Confusion matrix

Information:
TP: True Positive (Actual value is positive, and the model predicts positive)
FP: False Positive (Actual value is positive, and the model predicts negative)
FN: False Negative (Actual value is negative, and the model predicts negative)
TN: True Negative (Actual value is negative, and the model predicts negative)

The test that will be carried out is by calculating the values of accuracy, recall, precision and F1-Score, which will be displayed in percentage form, with the respective equations as follows:

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

$$Recall = \frac{TP}{TP+FP}$$

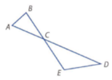
$$Precision = \frac{TP}{TP+FN}$$

$$F1\text{-}Score = \frac{1}{\frac{1}{recall}+\frac{1}{precision}}$$

III. Results and Discussion Collecting Data

Opinion data on questions reasoning and proof. The amount of information collected was 70 pieces. From the opinions expressed by prospective mathematics teachers in the mathematics colloquium class group, there were 82 students, and only 70 students gave their opinions.

Terdapat dua soal berikut, kalian tidak diminta untuk menjawab soalnya, tetapi kalian diminta untuk memberikan pendapat kalian ketika berhadapan dengan soal seperti ini.

1. Buktikan, Jika x bilangan ganjil maka x^2 juga bilangan ganjil.
2. 

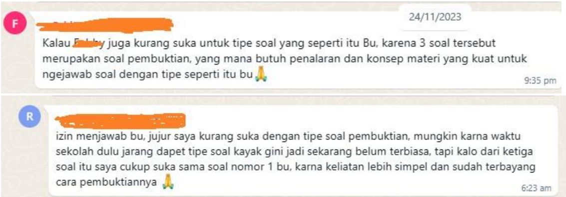
Pada gambar di atas, $\overline{AD}$ dan $\overline{BE}$ berpotongan di titik C dan $m\angle ECD = m\angle D$. Apakah $m\angle A = m\angle D$, jika iya buktikan. Jika tidak, berikan counterexample nya (Fey et al., 2007).

Untuk membuktikan secara deduktif atau secara formal, tidak dibenarkan untuk menggunakan contoh yang memenuhi atau mengambil beberapa angka untuk menjadi bukti yg sesuai.

Dari 2 soal seperti di atas, apa pandangan kalian terhadap soal-soal seperti ini? Bagaimana respon kalian ketika melakukan pembuktian matematika?

Figure 3. Reasoning and proof questions

The dataset obtained is then saved in CSV form and used for the sentiment analysis process.



Labelling

The dataset used in the sentiment analysis process must be labelled first. In this research, researchers still carried out labelling by looking at negative or positive words in students' opinions.

The data used in this research is the opinion data of prospective mathematics teacher students in semester 6, which was taken once at the end of the semester. At the labelling stage, each data will be labelled positive or negative. The data columns that are not needed are deleted, namely the cellphone number and delivery time, and then a label column is added, which contains positive or negative labels for existing opinions. Table 1 presents a sample of data that has been labelled.

Table 1. Data with labels

Opinion	Label
If... you also do not like that type of question, ma'am, because these 3 questions are proof questions, which require strong reasoning and material concepts to answer questions of that type?	Negative
I do not like the type of proof questions, maybe because when I was at school I rarely got this type of question, so now I am not used to it, but of the three questions, I quite like question number 1, because it looks simpler and has Can you imagine how to prove it?	Negative

Data Preprocessing

Several stages of the preprocessing process are carried out, including the case folding process, tokenization, transform cases, stopword filter, and filter tokens (by length).

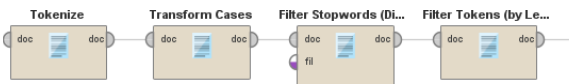


Figure 4. Preprocessing process using Rapidminer

Table 2. Preprocessing results

Stages	Results
Cleansing	**F1:**F also does not like that type of question, ma'am, because these 3 questions are proof questions, which require strong reasoning and material concepts to answer questions of that type, ma'am? **F2:** Permission to answer, ma'am. I do not like the type of proof questions, maybe because when I was at school I rarely got this type of question, so now I am not used to it, but of the three questions, I quite like question number 1, ma'am, because it looks simpler and has Can you imagine how to prove it?
Case Folding	**F1:**I do not like questions like that because these 3 questions are questions of proof, requiring strong reasoning and material concepts to answer the questions. **F2:** To be honest, I do not like proof questions; maybe when I was at school, there were rarely questions like this, so now I am not used to it. Of the three questions, I like question

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Dock.	unders	Like	Thorough	challenged	Prob
Doc.3	0,000	0,000	0,000	0,000	0,000
Doc.28	0,000	0,000	0,000	0,000	0,000
Doc.34	0,000	0.053	0,000	0,000	0.053
Doc.23	0,000	0.033	0,000	0,000	0.033

	number 1, which is simpler, and I can already imagine how to prove it.
Tokenize	**F1:**not enough; Like; For; question; Which; like; That; Because; question; the; constitute; proof; need; reasoning; And; draft; material; Which; strong; For; answer; question **F2:**Honest; I; Like; with; question; proof; Possible; time; school; Formerly; seldom; question; kayak; gini; So; Now; Not yet; used to; from; third; question; That; I; Enough; Like; The same; question; number; more; simple; And; Already; imagined; method; the proof
Transform cases	**F1:** not enough; Like; For; question; Which; like; That; Because; question; the; constitute; proof; need; reasoning; And; draft; material; Which; strong; For; answer; question **F2:** Honest; I; Like; with; question; proof; Possible; time; school; Formerly; seldom; question; kayak; gini; So; Now; Not yet; used to; from; third; question; That; I; Enough; Like; The same; question; number; more; simple; And; Already; imagined; method; the proof
Filtering	**F1:**not enough; Like; For; question; Which; like; Because; question; the; constitute; proof; need; reasoning; draft; material; Which; strong; For; answer; question **F2:**Honest; I; Like; with; question; proof; Possible; time; school; Formerly; seldom; So; Now; Not yet; used to; Like; The same; question; more; simple; Already; imagined; method; the proof.

Weighting Data

After all the training data has been processed, term weighting is carried out for each opinion. Term weighting for each word is carried out using the TF-IDF method. Table 3 and Table 4 below show several words that fall into the positive or category negative category.

Table 3

Negative Category Attributes

Dock.	Confused	foreign	Compli cated	weak	Prob.
Doc.3	0.363	0,000	0,000	0,000	0.363
Doc.28	0,000	0.325	0,000	0,000	0.325
Doc.34	0,000	0,000	0.322	0,000	0.322
Doc.23	0,000	0,000	0,000	0.238	0.238

Table 4. Positive Category Attributes

The probability results of the negative and positive category attributes shown in Table 3 and Table 4 above are then compared to determine the sentiment in the document. If the probability of positive category attributes is higher than negative category attributes, the results indicate that the document has positive sentiment. Conversely, if the probability of negative category attributes is greater than positive category attributes, the document is considered to have negative sentiment. The sentiment results from comparing the probability of positive and negative category attributes in the example documents from Table 3 and Table 4 are shown in Table 5.

Table 5.
Determining the type of student opinion sentiment (document) on reasoning and proof questions

Document	Prob. Negative	Prob. Positive	Sentiment Type
Doc.3	0.363	0,000	Negative
Doc.28	0.325	0,000	Negative
Doc.34	0.322	0.053	Negative
Doc.23	0.238	0.033	Negative

The following is also presented visually as a word cloud of words that appear with the same weight for each word. This visualization is taken from the total weight, not the positive or negative weight.

Figure 5. Wordcloud results on total weigh

The words that appear in the image with the help of rapid miner are taken from the 20 words with the highest number of students using them to convey their opinions when faced with reasoning and proof questions.

Naïve Bayes Classification

At the classification stage using Naïve Bayes, we will classify student opinions as positive or negative opinions based on the arguments submitted by students. Naïve Bayes classifier will learn data patterns and produce a machine learning model in the form of probability values. The dataset that has gone through the labelling and preprocessing stages is divided into 80% training and 20% testing data. Machine Learning will use this training data for classification algorithms on testing data of ten, referred to as training data, using the Naïve Bayes method assisted by Rapidminer software.

Table 6.
Prediction results on training data

Label	prediction(Label)	confidence(pos...	confidence(neg...	Pendapat
negative	negative	0.497	0.503	juga kurang suka u...
positive	negative	0.497	0.503	Mia menyukainya b...
negative	negative	0.497	0.503	mardhotillah soal- s...
negative	negative	0.497	0.503	kalo adisya, lebih s...
negative	negative	0.497	0.503	Kalau menurut Teg...
negative	negative	0.497	0.503	Rima sama seperti t...
negative	negative	0.497	0.503	Kalau menurut want...
positive	negative	0.497	0.503	Kalau nur lebih suk...
positive	negative	0.497	0.503	Kalau menurut habi...
negative	negative	0.497	0.503	Menurut alif untuk s...
positive	negative	0.497	0.503	Ketika bertemu den...
positive	negative	0.497	0.503	Ketika bertemu den...
positive	negative	0.497	0.503	Pandangan saya u...

In the application stage of the table model above, the Label column functions as a supervisor, directing any data labelled positive or negative. The training model produced by Naïve Bayes can be seen from its probability values.

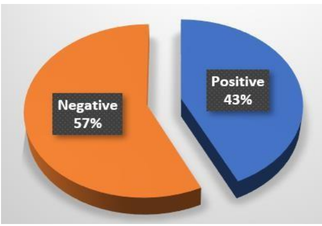

Figure 6. Sentiment classification

The sentiment classification results shown in Figure 6 shows that negative mathematics teacher students give more negative opinions when faced with reasoning and proof questions, with a percentage of 57%. From the comments they conveyed when allowed to express as widely as possible their feelings when they encountered the topic of proof which required axiomatic reasoning, they clearly expressed that they did not like the deductive or axiomatic proof process; from the data, it was also revealed what causes a dislike for reasoning and proof, namely the inability of students to start with proof, what definitions they should use, even the mathematical symbols in the questions also become obstacles for students.

Difficulty using types of reasoning and proof methods is also an obstacle for prospective mathematics teachers; they do not have higher proof schemes that can justify a statement, whether true or not, before being given an intervention by their teachers (Cihan & Akkoç, 2023).

"My view on proof questions like the above is that starting with the initial statement is confusing. I also experienced some confusion because I forgot the mathematical symbols in the questions." (Doc. 55).

This result is because, according to Moralı & Filiz (2023), prospective mathematics teachers have indeed been able to identify that the proof of a theorem is wrong but are unable to explain why the proof of the theorem is wrong. Research results like this have also been found in previous studies by Ko & Knuth (2013) and Selden & Selden (2013), which show that prospective mathematics teachers have difficulty validating whether a deductive argument is true or false. This means that prospective mathematics teachers cannot evaluate mathematical arguments and proofs even though they have been taught mathematics from elementary to college.

The role of proof in mathematics leads us to the need to teach proof in schools (Stylianides et al., 2022). Therefore, the mathematics curriculum in Indonesia and various countries aims to train students' reasoning and proof; NCTM even makes it a standard for the mathematics learning process. The teacher is the person whose role is to bridge mathematics in the classroom, having the authority to justify whether the evidence provided by students is correct or

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just justification without logical reasoning. According to Stylianides (2007), the teacher is tasked with assessing and instructing what arguments are valid or considered as proof.

Teachers' knowledge and beliefs about evidence shape teachers' readiness, willingness, and capacity to support student engagement with evidence (Ellis et al., 2012); (Buchbinder & McCrone, 2022); and (Stylianides, 2007). Therefore, a prospective mathematics teacher needs insight into constructing proofs to facilitate students and help students improve their reasoning and proof abilities in mathematics. This is because recognizing the relationship between mathematical concepts, realizing mathematical thinking, and understanding mathematical concepts depend on proof (Carrillo et al., 2018).

The percentage of positive responses is smaller at 43%, so it can be concluded that the classification results using Naïve Bayes show more negative sentiment opinions than positive sentiment. The results of this research are different from previous studies (Jamiah, 2021; Puryati et al., 2023; and Ikrimah, 2023) who have measured attitudes, self-confidence, and positive or negative perceptions when working with mathematics, which only show agreement or disagreement on a questionnaire containing views on mathematics, but this research is more than that, which shows negative opinions or positive students and explore students' attitudes when faced with questions of the type of reasoning and proof, so that the data obtained is the students' original opinions expressed openly.

Evaluation

After carrying out the classification process stages, the next step is to determine the algorithm's performance; this stage is carried out with a confusion matrix. Confusion matrix is a method for measuring algorithm accuracy at the classification stage. The results of the confusion matrix evaluation stage can be seen in Figure 7.

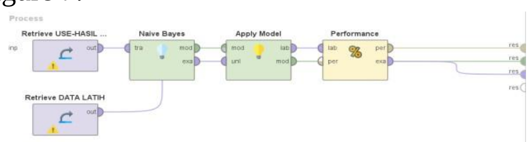

Figure 7. Process of applying model and performance on rapid miner

```
PerformanceVector:
accuracy: 53.33%
ConfusionMatrix:
True:     negative        positive
negative:        8         7
positive:        0         0
```

Figure 8. Sentiment performance results

Accuracy, precision-recall values and F1- Score are obtained using the confusion matrix model. Following are the calculation results.

accuracy: 53.33%

	true negative	true positive	class precision
pred. negative	8	7	53.33%
pred. positive	0	0	0.00%
class recall	100.00%	0.00%	

Figure 9. Confusion matrix results

The results of the testing carried out by Rapidminer on 70 student opinions using the TF-IDF and Term Frequency processes produced the same 48 values. Testing was based on accuracy, class recall and class precision values in sentiment analysis, with an accuracy performance value of 53.33%, with the pra and value at 53.33%. Meanwhile, Class Recall produces a value of 100% (true negative). From testing data analyzed by the rapid miner application, it turns out that negative sentiment was 58.2% greater than positive sentiment, which only got 41.8%.

IV. Conclusion

The results of research using the Naïve Bayes method on student opinions on reasoning and proof questions that have gone through the preprocessing stage are divided into 20% review data and for training data 80% review data. The classification results in this study were 58.2% positive and 41.86.7% negative, with a total of 70 data. Then, the evaluation results at the testing stage of this research used a confusion matrix, and the accuracy obtained was 53.33% using the Naïve Bayes method.

The author tries to analyze the number of words often appearing in the comment data documents in the negative category, the words 'confused' and then 'type'. There are a lot of negative comments on the type of question itself. Because the reasoning and proof type of questions require proof skills, and students are confused about where to start, as stated by Scristia et al., (2021), who studied student proofs in an algebraic structure course, the difficulty students had when compiling proofs was that they could not see the relationship between existing definitions and theorems. In further research, the author suggests adding an information gain selection feature that can reduce the accuracy bias of the Naive Bayes algorithm. This research also has limitations in the amount of data processed. It only relies on the number of students in the final semester; the data can be increased by adding data from other universities.

The implications of these findings go beyond sentiment analysis, providing valuable insights for educators, curriculum developers, and policymakers in designing learning strategies and educational policies that can improve mathematics students' reasoning and proof abilities.

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