BAREKENG: Journal of Mathematics and Its Applications
September 2025 Volume 19 Issue 3 Page 1485-1498
P-ISSN: 1978-7227 E-ISSN: 2615-3017
https://doi.org/10.30598/barekengvol19iss3pp1485-1498

# SENTIMENT ANALYSIS OF PRE-SERVICE MATHEMATICS TEACHER THROUGH NAÏVE BAYES CLASSIFIER: THE CASE OF MATHEMATICAL ABSTRACTION PROBLEM

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***Article History:***

*Received: 18th October 2024*
*Revised: 6th January 2025*
*Accepted: 31st January 2025*
*Published: 1st July 2025*

***Keywords:***

*Mathematical Abstraction;*
*Naïve Bayes;*
*Pre-service Mathematics Teacher;*
*Sentiment Analysis.*

*ABSTRACT*

*Mathematical abstraction as part of mathematical thinking process is an important and fundamental process in mathematics and its learning. Pre-service mathematics teachers' experiences and sentiments towards mathematical abstraction can contribute to the way they teach in the future. This study involved 67 Pre-service Mathematics Teachers at one of the Universities in Central Java Province who aimed to analyze their sentiments towards mathematical abstraction problems. The data collection technique used a questionnaire to reveal the Pre-service Mathematics Teacher's response to abstraction problems. Sentiment analysis is used to analyze the responses given which are categorized into positive, negative, or neutral. The technique used in the research is Naïve Bayes Classifier Multinomial. The classification results show 62.9% negative sentiment, 24.2% neutral sentiment, and 12.9% positive sentiment. In addition, the model evaluation results show an accuracy value of 66.7% which indicates the reliability of the model in classifying the sentiments expressed by Pre-service Mathematics Teachers towards mathematical abstraction problems. Pre-service Mathematics Teacher sentiment towards mathematical abstraction problems is dominated by negative sentiment. This shows that the process of mathematical abstraction is still considered a complicated and confusing process.*

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***How to cite this article:***

R. Andriatna and D. Dasari., "SENTIMENT ANALYSIS OF PRE-SERVICE MATHEMATICS TEACHER THROUGH NAÏVE BAYES CLASSIFIER: THE CASE OF MATHEMATICAL ABSTRACTION PROBLEM," *BAREKENG: J. Math. & App.*, vol. 19, no. 3, pp. 1485-1498, September, 2025.

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Journal homepage: *https://ojs3.unpatti.ac.id/index.php/barekeng/*
Journal e-mail: *barekeng.math@yahoo.com; barekeng.journal@mail.unpatti.ac.id*

**Research Article · Open Access**

## 1. INTRODUCTION

In contextual situations, mathematics has a very important role [1]. However, Mitchelmore and White stated that mathematics consists of a system that is independent and separate from the physical or social world which causes mathematics to be unique [2]. This is what causes mathematics as an abstract science that can be obtained through the abstraction process [3]. Due to this abstractness, mathematics provides its own challenges and difficulties in the learning process, including in the process of constructing mathematical concepts.

The process of constructing mathematical concepts is a very important process in learning because through the process of concept construction one will get a way to understand the concept in depth. Dreyfus et al. stated that the concept construction process is expressed as mathematical abstraction [4]. Mathematical abstraction is a process carried out in vertically rearranging mathematical concepts based on previously acquired experience or knowledge [4][5]. In the abstraction process, students must realize the similarity of the characteristics of a mathematical concept that is being built with the knowledge or experience they already have [6], so that it can provide a way to bring up or form new concepts [7]. Thus, through the abstraction process a new concept will be produced for someone. Mathematical abstraction can occur starting with something very simple and maybe something that is not developed and vague [8]. Abstraction is developed through the process of analysis as the initial stage to the synthesis stage which ends with a consistent form [9]. This shows that the process of abstraction can occur not only from a concrete form to something abstract, but also from an undeveloped to a developed form.

Mathematical abstraction is an important and fundamental part of the mathematics learning process, so it has an important role in the success of mathematics learning, when viewed from the cognitive aspect [10]. In addition, the abstraction process is very important because it will be closely related to the knowledge or experience that has been obtained. This has relevance to the nature of mathematics itself, where mathematical concepts are built by linking between new concepts formed through existing concepts. Thus, the learning process that occurs becomes meaningful. But on the other hand, mathematical abstraction is also the main reason for failure in the mathematics learning process [11]. This should certainly be the focus of attention by teachers in the learning process because on the one hand it will be a way for students to get mathematical concepts, but on the other hand it will be a failure if the abstraction process does not run properly.

Mathematical abstraction needs to be one of the concerns in learning mathematics, both at the basic and higher education levels. Mathematical abstraction is very important in the mathematics learning process [7][12][13] so it needs to be introduced in depth to students, including Mathematics Education Study Program Students as Pre-service Mathematics Teachers as part of the mathematical thinking process. Nurhasanah stated that abstraction is not only important in the context of mathematics, but also in teaching mathematics [5]. Mathematics as a composition of a large set of abstract objects needs to be represented by teachers to students so as to provide opportunities for students to connect it with what is already known. Thus, according to [5], it is very important for teachers including pre-service mathematics teachers to be able to know and experience the abstraction process in learning mathematical concepts, including new mathematical concepts in mathematics.

Pre-service Mathematics Teachers have an important role in the future to implement mathematics learning process that involves mathematical abstraction. Pre-service mathematics teachers who facilitate the abstraction process will be able to integrate and guide students towards a deep understanding of mathematical ideas [14]. Therefore, the hope is that having positive attitudes and sentiments towards mathematical abstraction can be a provision in teaching mathematics and become a shaping element of the abstraction process including future abstraction skills.

The disclosure of Pre-service Mathematics teacher sentiments towards mathematics problems, including problems related to mathematical abstraction is important because it can be an evaluation for lecturers or educational institutions as producers of Pre-service Mathematics Teachers [15], including attitudes towards mathematical abstraction problems. Scristia et al. explained that the attitude or opinion can be made in the form of text [15]. Bolshakov and Gelbukh state that text is an overlay of language in oral and written form that has meaning and is practical [16]. Ling et al. stated that one of the information retrievals from text (text mining) can be sentiment analysis [17].

Sentiment analysis is referred to as opinion analysis or opinion mining [18]. Sentiment analysis is the computational study of opinions, sentiments, and emotions expressed through text [19][20]. Sentiment analysis is tasked with classifying text into sentences and then determining the opinions expressed in the analyzed sentences, namely whether they are positive, negative, or neutral, including more nuanced emotions and opinions [21][22][23]. Thus, through sentiment analysis, it can be seen the tendency of response or attitude towards the problem at hand based on the point of view of others. In conducting sentiment analysis, one of the machine learning techniques that can be used is the Naïve Bayes Classifier (NBC) algorithm. The NBC algorithm is a machine learning technique based on the concept of chance, namely the Bayes Theorem, which according to [24] NBC has a simple method with high accuracy and performance in the text classification process. Besides being a simple method, NBC is very suitable for text data analysis such as sentiment. This is because NBC works with bag-of-words or TF-IDF (Term Frequency-Inverse Document Frequency) which are commonly used in text analysis. In addition, it assumes independence between features, which is quite appropriate for text data as each word is considered a separate feature.

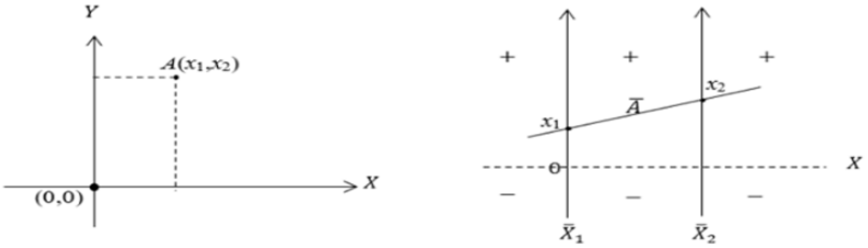
Several studies have been conducted to measure the positive or negative sentiments of pre-service mathematics teachers towards mathematics or towards mathematical problems [25][26][27]. However, the research conducted is limited to only agreeing or disagreeing with the attitude towards learning mathematics through a questionnaire given by the researcher, but has not touched on the student's response or opinion on a given problem. In addition, another study, [15 has revealed the sentiments of pre-service mathematics teachers towards reasoning and proof problems. In contrast to [15, this study aims to look at the sentiments of Pre-service mathematics teachers on mathematical abstraction problems. However, this research not only investigates the sentiments of students as Pre-service mathematics teachers, but is also expected to be a reference for the development of adaptive mathematics learning including providing opportunities for further exploration of students in responding to the mathematical challenges given.

## 2. RESEARCH METHODS

This research is used to reveal the sentiments of Mathematics Education Study Program students as Pre-service Mathematics Teachers on mathematical abstraction problems. The data in this study are in the form of Pre-service Mathematics Teacher opinions or responses collected through questionnaires in Google Form format with instruments in the form of mathematical abstraction problems on non-conventional concepts in the form of Parallel Coordinates quoted from [5]. Data collection was conducted from October 23, 2024 to October 30, 2024. The research instruments used are presented in Figure 1. In this study, the Pre-service Mathematics Teacher's responses were classified into three sentiments, namely positive, negative, and neutral as an extension of two sentiments (Multi-Class Classification). Respondents in this study were Mathematics Education Study Program students from one of the State Universities in Central Java Province as many as 67 respondents.

Here is a mathematics problem, **you are not asked to answer the problem, but only asked for your perception/opinion of what you felt/thought when you first encountered the problem**.

The Parallel Coordinate System is a coordinate system constructed by utilizing the basic components in Cartesian Coordinates. Parallel Coordinate System is a non-coventional material that is not taught in regular lectures. For example, in Two-Dimensional Parallel Coordinates, the first construction process is to create two $Y$ axes labeled $\overline{X_1}$ and $\overline{X_2}$ with a certain distance between them. In dimension two, point $A(x_1, x_2)$ on Cartesian coordinates corresponds to a line segment $\bar{A}$ $(x_1, x_2)$ that lies on the line that intersects the $\overline{X_1}$ axis at point $x_1$ and intersects $\overline{X_2}$ at point $x_2$ on Parallel Coordinates.




Point on Cartesian Coordinates Point on Parallel Coordinate

You are asked to construct the points on Parallel Coordinates i.e. points $A(3,2)$, $B(-1,5)$, and $C(-2,-4)$!

**You are not asked to answer the problem above, but give your response/opinion to the given problem, i.e. what perception comes first when you are faced with the above problem!**

**Figure 1. Research Questionnaire for Mathematical Abstraction**

Data analysis used Naïve Bayes Classifier algorithm for multi-class classification with the help of RapidMiner application. The stages of sentiment analysis in this study are presented in **Figure 2** below.

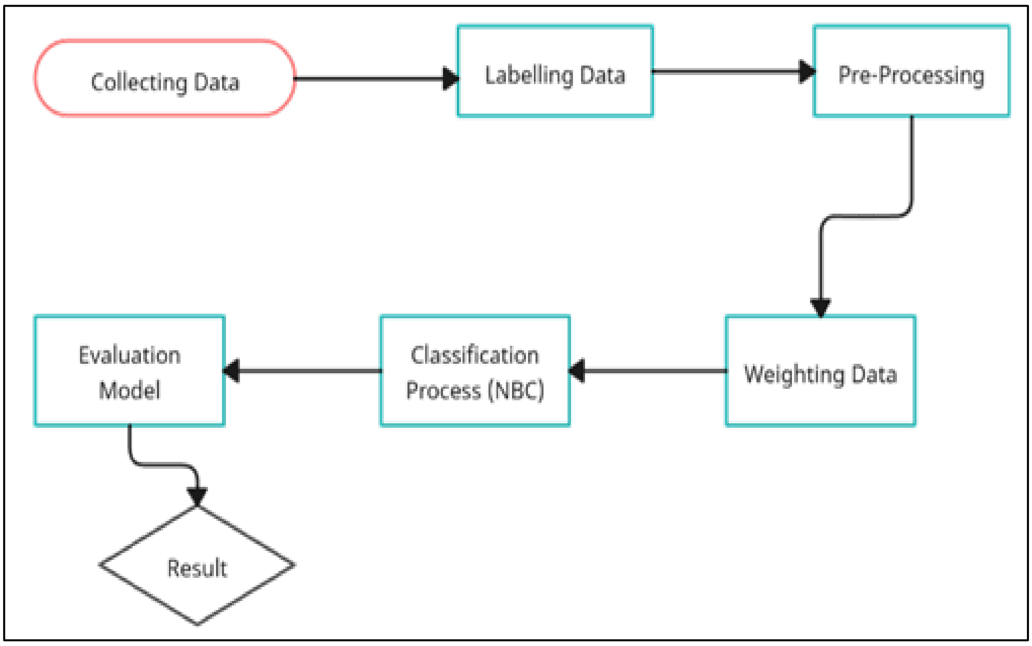



**Figure 2. Flowchart of Sentiment Analysis Stages**

### 2.1 Collecting Data

The data collecting stage is the stage of collecting data in the form of text from Mathematics Education Study Program students in the form of responses in the form of opinions when faced with mathematical abstraction problems. Data was collected through a questionnaire in Google Form format in **Figure 1** as many as 67 responses. The questionnaire used in this study uses test items cited from research **[5]** related to mathematical abstraction.

### 2.2 Labelling Data

At this stage, sentiment labeling is done manually, by researchers namely positive, negative, or neutral. This is done because the data consisting of 67 opinions can still be labeled manually without using machine learning. In this case, the researcher reviews and labels the sentiments given by the respondents based on their responses, including discussing the results of the labeling. This is done because sentiment analysis uses a natural language processing model. Manual labeling is done because it produces accurate data because humans can distinguish sentiments [28] including the possibility of very long information in one opinion. This happens because the sentiment analysis carried out uses an open questionnaire to get student opinions on the questions given.

### 2.3 Pre-Processing

The data that has been collected is then subjected to pre-processing which aims to obtain a more structured text so that the data can be used in the sentiment analysis process [29], including the text cleaning process [30]. In addition, at the word level there may be words in the text that have no impact on the goal, so that they can affect the classification process. The data obtained is subjected to identification and cleaning processes including the removal of irrelevant text, namely punctuation or writing errors, as well as sentences that are duplicated or sent several times. In addition, in pre-processing, several general processes are carried out as stated by [31], namely: (1) Case Folding, which is used to convert the text as a whole into lowercase so that it becomes consistent, including removing numbers; (2) Tokenization, which is to cut sentences into words (tokens); (3) Stopwords Removal (Dictionary) by using Indonesia Stoplist to perform the filtering and elimination stage of words that often appear in the text that have no meaning (in this research used Indonesia stoplist which is accessed through https://www.kaggle.com/datasets/oswinrh/indonesian-stoplist); and (4) Filtering by Length refers to the results of the filtering process of important words, which are selected with a number of 4 and a maximum of 25. Filter token by length is performed which aims to filter words or text based on their length to remove noise and improve the quality of the model.

### 2.4 Weighting Data

Weighting is done to minimize bias caused by errors in sampling [15]. At this stage, a balanced weight is given to the results of the questionnaire through a comparison of the sample with the target population where the weight of each word is based on the frequency of occurrence of the word. Weighting is done using the TF-IDF (Term Frequency-Inverse Document Frequency) method. TF indicates the frequency counter for a syllable (t) in a document (d) show in **Equation (1)**, while IDF or inverse document frequency measures the amount of information provided by a term measured by dividing the total number of documents (N) by the number of documents containing the term show in **Equation (2)** with $D$ is corpus of documents.

$$\mathrm{tf}(t,d) = \frac{f_{t,d}}{\sum_{t' \in d} f_{t',d}} \quad (1)$$

$$\mathrm{idf}(t,D) = \log \frac{N}{|\{d \in D : t \in d\}|} \quad (2)$$

Furthermore, Indriyani et al. (2023) state the weight value used is as follows in **Equation (3)**.

$$W(t,d) = \mathrm{tfidf}\,(t,d,D) = \mathrm{tf}(t,d) \times \mathrm{idf}(t,D) \quad (3)$$

### 2.5 Naïve Bayes Classifier

Furthermore, classification analysis is carried out using the Naïve Bayes Classifier (NBC) algorithm which aims to identify student sentiment. Naïve Bayes is a simple probability classification that is generated from a set of probability values through the summation of frequencies and combinations of values from the data [32]. The NBC algorithm was chosen because it can classify testing data into the right category to determine the highest probability value [33]. In addition, the NBC algorithm is a simple algorithm but has a high accuracy value. In this study, the Multinomial Naïve Bayes Classifier algorithm is used because sentiment is categorized into positive, negative, and neutral. The NBC algorithm refers to Bayes' Theorem with the assumption of naïve independence for each independent variable so that Naïve Bayes is obtained for classification with the following formula in **Equation (4).**

$$P(H|X_1, X_2, \ldots, X_n) = \left(\prod_{i=1}^{n} P(X_i|H)\right) P(H) \quad (4)$$

where $P(H|X_1, X_2, \ldots, X_n)$ with $n$ is the number of independent variable, denotes the posterior probability that the hypothesis of class $H$ is true based on feature $X_i$ (words in the document); $P(X_i | H)$ denotes the probability of word $X_i$ appearing in document class $H$; and $P(H)$ denotes the prior probability i.e. the probability of $H$ occurring before observing the data.

### 2.6 Model Evaluation

Model evaluation is carried out to show the quality of the performance of the classification model created. Model evaluation is done using Confusion Matrix as an important tool in machine learning evaluation [34] which contains actual classification information that will be predicted by the classification system [35]. The confusion matrix for multi-class classification with three sentiments is quoted from [36] as follows in Table 1.

**Table 1. Confusion Matrix**

| | | True Class | | |
|---|---|---|---|---|
| | | **Positive** | **Negative** | **Neutral** |
| **Predictive Class** | Positive | True Positive (TP) | False Positive (FP1) | False Positive (FP2) |
| | Negative | False Negative (FN1) | True Negative (TN) | False Negative (FN2) |
| | Neutral | False Neutral (FNeut1) | False Neutral (FNeut2) | True Neutral (Tneut) |

The test results are obtained through the calculation of the evaluation metrics of Accuracy, Precision, Recall, and F1-Score values expressed in percentage form for Multi-Class Classification, both for each class, and as a whole.

### Accuracy

Accuracy indicates the degree of conformity between the true value and the predicted value [34]. As such, accuracy is a metric that indicates how often a machine learning model correctly predicts an outcome. The formula for accuracy is shown in Equation (5) below.

$$\text{Accuration} = \frac{\text{Correct Prediction}}{\text{All Prediction}} \tag{5}$$

### Precision

Precision indicates how many positive predictions are correct out of the overall positive stated predictions of the entire model. In Multi-Class Classification, the Precision value can be calculated for each class. [36] stated the precision formula for each class as follows in Table 2.

**Table 2. Precision Formula for Class**

| Positive | Negative | Neutral |
|---|---|---|
| $\frac{TP}{TP + FP1 + FP2}$ | $\frac{TN}{TN + FN1 + FN2}$ | $\frac{TNeut}{TNeut + FNeut1 + FNeut2}$ |

### Recall

Recall or sensitivity aims to measure the strength of the model to predict positives [37], also known as model sensitivity. In Multi-Class Classification, Recall value can be calculated for each class. [36] stated the recall formula for each class as follows in Table 3.

**Table 3. Recall Formula for Class**

| Positive | Negative | Neutral |
|---|---|---|
| $\frac{TP}{TP + FN1 + FNeut1}$ | $\frac{TN}{TN + FP1 + FNeut2}$ | $\frac{TNeut}{TNeut + FP2 + FN2}$ |

### F1-Score

F1-Score indicates the overall capability value of the system [34]. In Multi-Class Classification, the F1-Score value can be calculated for each class with formula in Equation (6).

$$F1 - \text{Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{6}$$

In addition to the evaluation metric value of each class, in Multi-Class Classification, the overall metric evaluation can be calculated with the Macro-average value for Precision and Recall [38]. Macro-avergae shows the calculated average of each metric for each positive, negative, and neutral class regardless of the size of the class. The formulas for macro-average precision and recall show in Equation (7) and Equation (8).

$$\text{Precision}_{\text{Macro-average}} = \frac{\sum_{i=1}^{3} \text{Precision Class } i}{3} \tag{7}$$

$$\text{Recall}_{\text{Macro-average}} = \frac{\sum_{i=1}^{3} \text{Recall Class } i}{3} \tag{8}$$

In addition, for data imbalance, namely the acquisition of a class that appears much more often than other classes, the evaluation of multi-class classification can be used weighted average, both for precision and recall for positive, negative, and neutral classes with the formula as presented by [39] as follows in Equation (9) and Equation (10).

$$\text{Weighted Avg. Precision} = \sum_{i=1}^{3} \text{Total Actual Class } i \times \text{Precision Class } i \tag{9}$$

$$\text{Weighted Avg. Recall} = \sum_{i=1}^{3} \text{Total Actual Class } i \times \text{Recall Class } i \tag{10}$$

## 3. RESULTS AND DISCUSSION

### 3.1 Collecting and Labelling Data

The size of data used in this research were 67 in the form of responses obtained from Mathematics Education Students as Pre-service mathematics teachers on mathematical abstraction questions collected through Google Form. Researchers then scrutinized and identified positive, negative, or neutral sentiments manually based on the results of careful reading of opinions, including identifying the completeness of the responses given. The initial identification results obtained five incomplete observations so that the response data that was processed further was 62 observations. The following in Table 4 is an example of a data set that has been done sentiment labeling.

**Table 4. Example Data Set with Label**

| No | Response | Label Sentiment |
|---|---|---|
| 1 | From the given problem, it is easy to solve the problem by skimming the given passage | Positive |
| 2 | The response was a little anxious and thought about whether I could solve a problem like this | Negative |
| 3 | I have learned about parallel coordinates, the perception that arises is that the mathematics I learned is not just counting but also abilities such as analyzing, critical thinking, creativity are needed in this mathematics | Neutral |

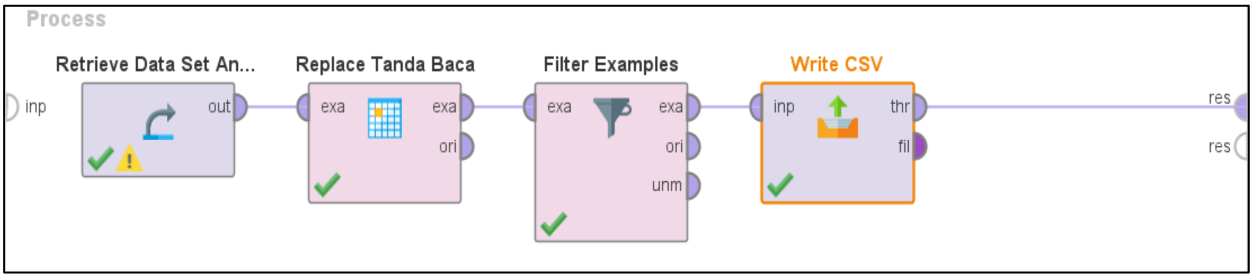



**Figure 3. Data Preparation for Sentiment Analysis through RapidMiner**

In addition, data preparation is also carried out through the process as presented in Figure 3 with the help of RapidMiner to get data that is processed further including data that has been cleaned from various unnecessary signs or symbols as an example of Table 5. In Figure 3, the preparation of data to be analyzed is carried out through several stages, namely Replace Punctuation to remove signs or symbols in the text and Filter Examples, and then the results as presented in Table 5 saved in CSV form.

**Table 5. Example Data Set after Cleaning**

| No | Before Cleaning | After Cleaning |
|---|---|---|
| 1 | What comes to mind: complicated | What comes to mind complicated |
| 2 | Long, story-telling and complicated-looking questions | Long story telling and complicated looking questions |
| 3 | The first thing I felt was confusion, after which came the response in the form of a question 'what are these parallel coordinates used for?' | The first thing I felt was confusion after which came the response in the form of a question 'what are these parallel coordinates used for |

### 3.2 Pre-processing

After the data preparation process is carried out, data pre-processing is then carried out which aims to obtain more structured data [29] including simplifying the data processing process through ignoring some unwanted items [40]. At this stage, several general processes are carried out, namely Case Folding, Tokenization, Stopwords Removal (Dictionary) and Filtering by Length as illustrated in Figure 4.

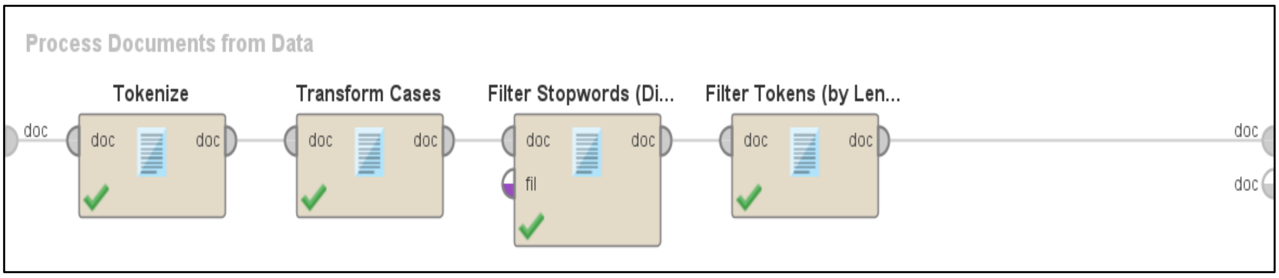



**Figure 4. Stages of data pre-processing in RapidMiner**

In Figure 4, several processes are carried out in the data pre-processing section. Through the process carried out in Figure 4, a data set is produced that has been tokenized, changed letters to lowercase letters, and removed words through stopwords. In addition, filter token by length is performed which aims to filter words or text based on their length to eliminate noise and improve the quality of the model. The results of the pre-processing stage were presented in Table 6.

**Table 6. Example Pre-processing Data Results**

| Pre-processing | Before Pre-processing | After Pre-processing |
|---|---|---|
| Tokenization | The questions are long and look complicated | The questions; are; long; and; look; complicated |
| Transform Cases | The questions are long and look complicated | the questions are long and look complicated |
| Stopword Removal (Dictionary)* | The questions are long and look complicated | look complicated |
| Filter by Length | The questions are long and look complicated | look; complicated |

*Stopword removal (dictionary): The questions (*pertanyaan*); are (*adalah*); long (*panjang*); and (*dan*).

### 3.3 Weighting Data

After all data is processed at the pre-processing stage, the data set is given a term weighting for each response based on the frequency of occurrence. An example of weighting results using TF-IDF with the results presented in Table 7 below.

**Table 7. Example TF-IDF Results**

| Document | Example Term | | | | |
|---|---|---|---|---|---|
| | **Abstract (*Abstrak*)** | **Confused (*Bingung*)** | **Anxiety (*Cemas*)** | **Critical (*Kritis*)** | **Complicated (*Rumit*)** |
| 1 | 0.000 | 0.000 | 0.000 | 0.806 | 0.000 |
| 2 | 0.000 | 0.000 | 0.000 | 0.000 | 0.467 |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |

| Document | Example Term | | | | |
|---|---|---|---|---|---|
| | Abstract (*Abstrak*) | Confused (*Bingung*) | Anxiety (*Cemas*) | Critical (*Kritis*) | Complicated (*Rumit*) |
| 10 | 0.196 | 0.000 | 0.000 | 0.000 | 0.000 |
| 11 | 0.000 | 0.000 | 0.653 | 0.000 | 0.000 |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| 23 | 0.000 | 0.173 | 0.000 | 0.000 | 0.000 |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| 62 | 0.000 | 1.000 | 0.000 | 0.000 | 0.000 |

In **Table 7**, the higher the TF-IDF value of a term indicates that the term often appears in a Document, such as the term "*Kritis*" in Document 1 has a TF-IDF value of 0.806 which is the highest TF-IDF value so it shows that the term often appears in Document 1 compared to other Documents. The value is obtained from the product of Term Frequency (TF) and Inverse Document Frequency (IDF) in document 1. TF value shows how often the critical term appears in document 1, while IDF shows how rarely the critical term appears in the entire corpus. While the term with TF-IDF value equal to 0.000 shows that the term often appears in all documents, but the term is a general term so it does not provide relevant information.


**Figure 5. Wordcloud in Total Weight**

**Figure 5** shows the visualization of the frequency of important words from the text based on weight, where the term "*Bingung*" is the term that appears the most or has a higher weight compared to other terms as presented in **Table 7**.

## 3.4 Model Implementation

The classification process is carried out using NBC as presented in **Figure 6** to classify the sentiments of Pre-Service Teachers of Mathematics into positive, negative, or neutral sentiments towards the given mathematical abstraction problem.

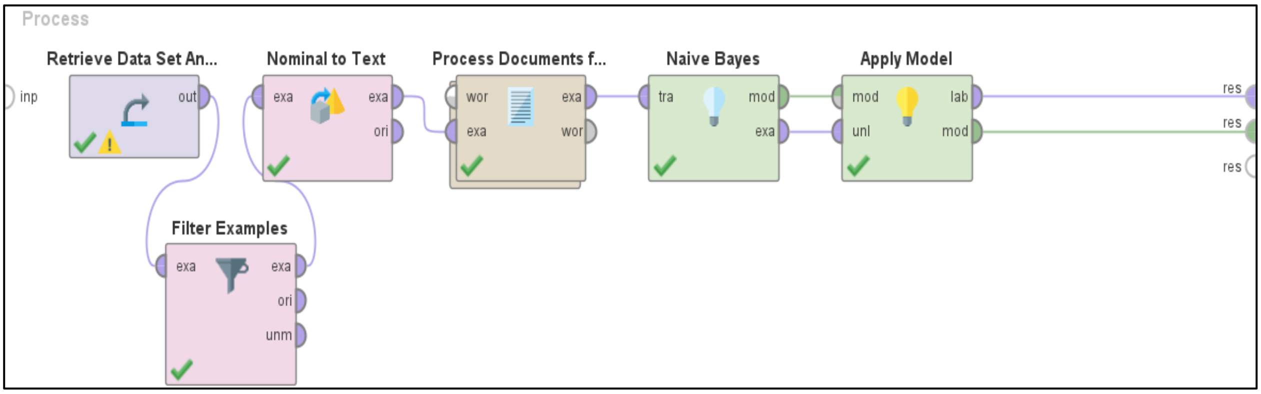



**Figure 6. Naïve Bayes Process in RapidMiner**

In the implementation of the model as presented in **Figure 6**, after the data is processed in the process document from data section, the data is then processed through the NBC algorithm. The results of the application of the NBC model in the form of prediction results on training data are presented in **Table 8** below.

**Table 8. Sentiment Classification Results by Naïve Bayes**

| Nominal Value | Absolute Count | Fraction |
|---|---|---|
| Negative | 39 | 0.629 |
| Neutral | 15 | 0.242 |
| Positive | 8 | 0.129 |

The results of the application of the NBC model in **Table 8** predict that Pre-service Mathematics Teachers are likely to dominantly give negative sentiments when faced with mathematical abstraction problems for non-conventional materials, which is 0.629 or 62.9% compared to neutral (24.2%) and positive (12.9%) sentiments. The results of the analysis show that most Pre-service Mathematics Teachers feel confused and feel complicated about the mathematical abstraction problems presented. These results are in line with the research of [41] which states that the abstraction process provides challenges and obstacles that cause difficulties for students so that it can have an impact on errors in the generalization process. With these challenges and obstacles, the process of mathematical abstraction becomes a complicated thing that has an impact on the emergence of a negative paradigm.

The existence of negative sentiments towards the problem of mathematical abstraction indicates that the abstraction process as a concept construction process is still avoided by Pre-Service Mathematics Teachers. This is supported by Kindt's opinion that the learning process that occurs still avoids the empirical induction process as a concept construction process [42]. In addition, the negative sentiment towards mathematical abstraction problems shows that mathematical abstraction is challenging. Mathematical abstraction as a process of constructing mathematical concepts through experience or knowledge that has been obtained shows a complex process. This is as revealed by [11] that abstraction as a complex process, including can make failure in mathematics during the concept formation process. This shows that the process of mathematical abstraction as a process that requires a high level of thinking (High Order Thinking).

With the negative sentiment towards mathematical abstraction problems given, it does not mean that the learning process should avoid the abstraction process. In mathematics, mathematical abstraction is an important process. This is as expressed by [11] and [43] that mathematical abstraction is a very important process in learning mathematics. Further explained by [7] that through the abstraction process provides an opportunity to bring up new concepts in mathematics.

In addition, pre-service mathematics teachers have a very important future role to teach mathematics through the construction process so that students can build concepts as part of the mathematical thinking process. This is in line with [5] opinion that the experience of mathematical thinking, including the process of mathematical abstraction, is important for pre-service mathematics teachers because the experience makes a positive contribution to the way of teaching mathematics in the future. Nurhasanah further stated that if teachers do not have the knowledge of how to represent abstractions in a form that connects mathematics with their experiences, it will have an impact on students who will not get a deep understanding of what they learn [5]. Thus, it is important for pre-service mathematics teachers to experience the mathematical abstraction process including having a good sentiment towards the mathematical abstraction process.

### 3.5 Model Evaluation

After the classification process is carried out through NBC, model testing is then carried out which aims to see the accuracy or accuracy of the model with the testing algorithm as presented in **Figure 7** with used the ratio of training data and testing data of 80% and 20% in split data. The reason for using this ratio is based on the balance between training data and test data, where the ratio is considered sufficient. In addition, using a large ratio can avoid overfitting or underfitting.

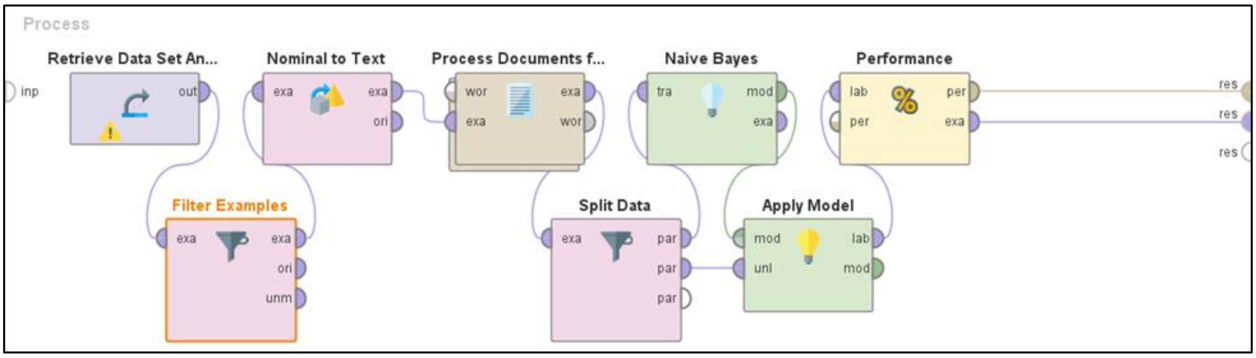



**Figure 7. Naïve Bayes Testing Process for Model Evaluation**

Model evaluation is carried out to show the quality of the performance of the classification model created. Model evaluation as the process presented in **Figure 7** used a ratio of training data and testing data of 80%: 20% or 12 testing data from the entire data. The test results for the evaluation of the Naive Bayes model based were presented in **Table 9**.

**Table 9. Model Evaluation Results Accuracy: 66.67%**

| Class | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|
| Negative | 100.00 | 75.00 | 85.71 |
| Neutral | 100.00 | 33.33 | 50.00 |
| Positive | 20.00 | 100.00 | 33.33 |

Based on **Table 9** above, the model accuracy value is 66.67%, which shows the accuracy of the model in seeing the level of conformity between the actual value and the predicted value as stated by [34]. In other words, the resulting model can correctly classify 66.67% of all test data. Furthermore, the precision value for the Negative and Neutral classes shows a perfect percentage, which is 100% which shows the correct predicted value in accordance with reality (True), while the positive class shows a precision value of 20%. Likewise, for the recall value of each class, the Positive class has a higher recall value of 100% compared to the Negative and Neutral classes, so the model is very good at positive sentiment. In addition to the above values, **Table 9** also shows the F1-Score value which is the value of the overall system capability [34], including a commonly used metric measure [44]. The F1-Score value for the Negative class is higher than the other classes, where the model in the Negative class has a better balance between Precision and Recall so that it can identify a lot of data correctly (True) with few errors (False).

In addition to the metric values presented in **Table 9**, the model evaluation in Multi-Class Classification is carried out through the evaluation of the overall metrics with macro-average values and for Precision and Recall with the results in **Table 10**. However, because the data set processed is not balanced, the weighted-average value is also considered in this case.

**Table 10. Model Evaluation Results based on Macro and Weighted-Average Values**

| Metric | Precision (%) | Recall (%) |
|---|---|---|
| Macro-Average | 73.33 | 69.44 |
| Weight-Average | 93.33 | 66.77 |

Based on **Table 10**, it is found that the macro-average and weighted-average values for precision and recall are the same. The macro-average precision value shows a value of 73.33% which means that all predictions made by the model are correct according to the predicted class, regardless of how much data is in each class or class size. The macro-average value is classified as relatively good although it still provides the possibility for improvement for the accuracy of predictions. Meanwhile, the macro-average recall value obtained is 69.44% which indicates that the average model has correctly detected 69.44% of all data that should be predicted as positive, negative, or neutral. However, the precision value obtained is greater than the Recall value so there is an indication that the model is more careful in providing predictions while still providing room for improvement in increasing recall.

The dataset has unbalanced classes, so the weighted average precision value is found to be 93.33% which indicates that the model has 93.33% precision for the whole, but is influenced by the number of samples, namely the negative class as the largest number of samples so that the precision value has a large impact. In addition, the weighted average recall value shows a value of 66.67%, which means that the model effectively hits about 66.67% of all relevant samples, both positive, negative, and neutral classes by taking into account the distribution of samples between classes. The evaluation results in **Table 9** show that the positive class has the largest recall value which indicates that the model is very good at recognizing positive sentiments.

## 4. CONCLUSIONS

Classification through NBC on multi-class classification shows the dominance of negative sentiments from Pre-service Mathematics Teachers towards the given mathematical abstraction problem, compared to positive and neutral sentiments. By paying attention to the term that appears the most, namely the term "*Bingung*", it shows that Pre-service Mathematics Teachers still feel unsure of the ability of mathematical abstraction and the process of mathematical abstraction in the learning process. The resulting model has an accuracy value of 66.67% with a weight average value for precision of 93.33%, while for recall of 66.67%. However, the resulting model still needs improvement to provide a higher level of accuracy.

The research conducted still has limitations, one of which is the number of respondents involved. For this reason, it is hoped that further research can involve more respondents, including the scope of universities involved. In addition, with the results of the study showing a negative sentiment towards mathematical abstraction from pre-service mathematics teachers, it provides an opportunity for future researchers to be able to design a learning process, especially in the scope of higher education to develop the process of mathematical abstraction.

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