



## Sentiment Analysis of Twitter User Opinions Data Regarding the Use of ChatGPT in Education

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### ABSTRACT

This article presents a sentiment analysis of Twitter users' opinions regarding the use of ChatGPT in education. ChatGPT, an AI chatbot developed by OpenAI, has gained significant attention for its ability to provide detailed responses across various knowledge domains. However, concerns have been raised about its occasional inclusion of inaccurate information. This study aims to analyze the sentiment of Twitter users' opinions towards ChatGPT in education and evaluate its accuracy. The sentiment analysis process involves data crawling, labelling, preprocessing, sentiment analysis, and evaluation. Data is collected from Twitter using the RapidMiner Studio tool and labelled as positive or negative sentiment based on the presence of positive or negative words. Preprocessing techniques are applied to standardize and reduce the volume of words in the data. The sentiment analysis classification is performed using machine learning algorithms, specifically Naive Bayes and Support Vector Machine (SVM). The accuracy, precision, and recall of the classification models are evaluated. The sentiment analysis results provide insights into Twitter users' overall sentiment towards ChatGPT in education. This study contributes to understanding Twitter users' opinions and sentiments regarding using ChatGPT in education. The findings can be valuable for educators and policymakers in assessing the potential impact of ChatGPT on academic integrity and the educational landscape.

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## 1. INTRODUCTION

A few months back, in December 2022, an Artificial Intelligence (AI) tool called ChatGPT got viral just a month after its release. It is getting recognized by many people because of its ability to solve almost any questions users give. Many people see ChatGPT as a massive breakthrough in the age of AI [1].

ChatGPT is an AI chatbot created by OpenAI and made public in November 2022. The name "Chat" signifies its purpose as a conversational bot, while "GPT" refers to its foundation as a large language model known as a generative pre-trained transformer (LLM). ChatGPT is built upon OpenAI's GPT-3.5 and GPT-4 models and has been fine-tuned for conversational applications using supervised and reinforcement learning methods [2].

ChatGPT was initially introduced as a prototype on November 30<sup>th</sup>, 2022, and gained attention due to its ability to provide detailed and coherent responses across various knowledge domains [3]. However, it has been noted that the chatbot occasionally includes inaccurate information, which is seen as a significant drawback. As a result of the release of ChatGPT, OpenAI's estimated valuation reached US\$29 billion in 2023. This introduction of the chatbot has intensified competition in the field, leading to the development of Google's chatbot Bard (based on LaMDA and PaLM) and Meta's LLaMA foundation model, which is being utilized by others to create their chatbots [4-7].

The initial version of ChatGPT was based on GPT-3.5, but a version utilizing GPT-4, the latest OpenAI model, was made available to limited paid subscribers on March 14<sup>th</sup>, 2023 [8]. The emergence of ChatGPT and GPT-4 has raised concerns among computer scientists such as Geoffrey Hinton and Yoshua Bengio. These concerns include the potential for future AI systems to surpass human intelligence, pursue misaligned goals, and pose existential risks [9].

Regarding ChatGPT, according to a recent survey conducted by Study.com, an online learning platform, 43% of educators express concerns that the program will create additional professional challenges. Conversely, nearly six out of ten teachers anticipate that it will enhance their professional lives [10].

One aspect of concern among educators is the potential threat to academic integrity posed by the program, as it may promote novel methods of cheating and plagiarism. Due to its user-friendly interface, accessibility, and convenience, students have resorted to utilizing the program to generate responses for homework assignments and even complete essays, falsely claiming authorship of the chatbot-generated content as their work [11].

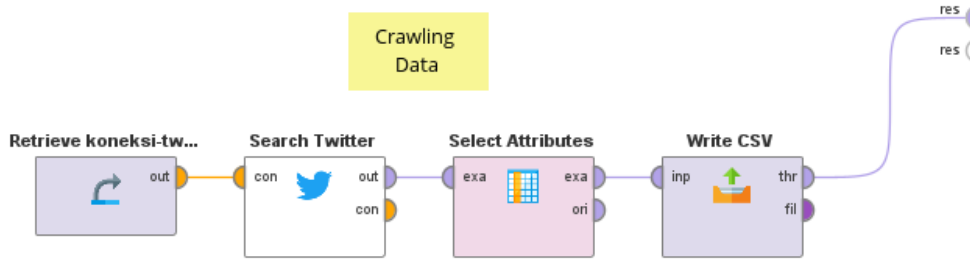
However, on the other hand, some educators find the straightforward design and brainstorming capabilities of ChatGPT appealing, as they recognize its potential to enhance the educational landscape. These teachers argue that, in the long run, the program's impact will not primarily increase academic dishonesty but revitalize lesson plans and classroom instruction [12-16].

## 2. METHODS

To do some sentiment analysis and determine its accuracy, several stages are involved to obtain the best results. The following steps are performed: data crawling, labelling, preprocessing, sentiment analysis, and evaluation to determine accuracy, precision, and recall [17-19].

### 2.1. Data Crawling

The first stage in sentiment analysis is data collection through data crawling. Data is collected from Twitter using the Twitter Application Programming Interface (API) with RapidMiner Studio version 10.1 as the tool. Tweets containing the keyword "chatgpt in education" are retrieved. The crawled data is then manually labelled as either positive or negative sentiment. The model used for crawling Twitter data is illustrated in **Figure 1**.



**Figure 1.** The data crawling process.

**Figure 1.** depicts the Twitter data crawling using the "twitter-v3-connection" operator, which is connected to the Twitter API, and the "Search Twitter" operator. The tweets are retrieved by selecting the "Text" attribute using the "Select Attributes" operator and saved in a .csv file format using the "Write CSV" operator.

### 2.2. Data Labelling

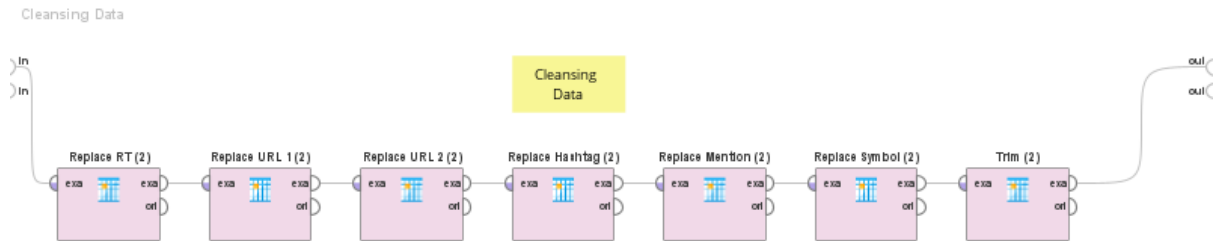
The next stage involves data labelling, where the data is divided into two sentiment classes: positive and negative. The criteria for labelling tweets are based on the presence of positive or negative words. Neutral sentences agreeing that ChatGPT positively impacts education are categorized as positive. In contrast, tweets containing negative words and expressing disagreement regarding the positive impact of ChatGPT on education are classified as negative. **Table 1.** below shows an example of 4 labelled datasets out of the total 804 datasets.

**Table 1.** Data labeling table.

Text	Sentiment
From now on, New York City Public Schools will overturn the ChatGPT ban, embracing the potential benefits of AI in education, and preparing students for the future in this transformative move. <a href="https://t.co/kS4759aOyZ">https://t.co/kS4759aOyZ</a>	Positive
ChatGPT is revolutionizing education! From personalized instruction to assignment assistance, this AI is transforming the way teachers teach and students learn. Link <a href="https://t.co/FzkB2D6QEh">https://t.co/FzkB2D6QEh</a>	Positive
@TRKShady @Xx17965797N AI will not end well for us. ChatGPT has already taken over education. Nearly all high schoolers and college students use it for homework. The workforce is about to get chopped and all I hear are praises and cheers on LinkedIn. <a href="https://t.co/3Z325sTfyj">https://t.co/3Z325sTfyj</a>	Negative
The huge potential problem with chatgpt and other generative ML in vital institutions like medicine, science, education? Law? is as some people have said, there is no clear vetting of information and peer review from a giant dataset already poisoned with misinformation.	Negative

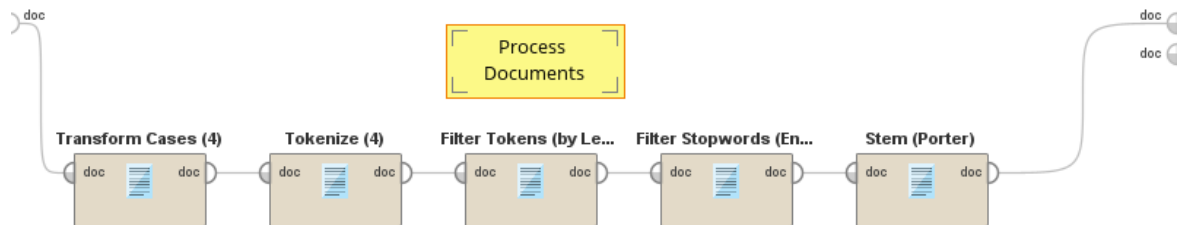
## 2.3. Preprocessing Data

After labelling the data, the next stage is preprocessing. Both the training and testing data need to undergo preprocessing before the classification process to reduce the dimension of the vector space model and make the classification process faster. The goal of preprocessing is to standardize and reduce the volume of words. This stage is performed to prepare the data for analysis. The preprocessing steps are divided into two parts: preprocessing subprocess before splitting the data into training and testing sets and preprocessing in the document process. The cleansing steps in the subprocess include Replace RT, Replace URL 1, Replace URL 2, Replace Hashtag, Replace Mention, Replace Symbol, and Trim. The first preprocessing operator is shown in **Figure 2**. below.



**Figure 2.** The data cleansing process.

The second preprocessing stage in the "Document Process" uses the operators "Transform Case", "Tokenize", "Filter Token by Length", "Filter Stopword (English)", and "Stem (Porter)" as shown in **Figure 3**. below.



**Figure 3.** The preprocessing process in document process.

The following is an explanation of each preprocessing stage:

### 2.3.1. Cleansing

Cleansing is the stage where unnecessary characters and punctuation marks are removed from the text. The purpose of cleansing is to reduce noise or disturbances in the dataset. The cleansing steps include Replace RT, Replace URL 1, Replace URL 2, Replace Hashtag, Replace Mention, Replace Symbol, and Trim. These processes utilize regular expressions (Regrex) as parameters in the RapidMiner operators. Examples of characters removed include URLs, hashtags (#), usernames (@), RT, as well as punctuation marks such as periods (.), and commas (,).

### 2.3.2. Case Folding

The case folding process involves converting all characters in a document to either upper case or lower case. In this study, lowercase is used to standardize the text. Case folding is performed to facilitate search operations as text documents may have inconsistent capitalization. For example, "ChatGPT in Education" is transformed into "chatgpt in education".

### 2.3.3. Tokenization

Tokenization is the process of breaking sentences into meaningful and significant words. It separates each word that forms a sentence. For example, "chatgpt in education" after tokenization becomes "chatgpt", "in", and "education".

### 2.3.4. Filter Tokens by Length

After tokenization, the Filter Tokens by Length stage selects tokens based on a minimum and maximum character requirement. In this study, only tokens with 2-25 characters are included. Thus, only words with 2 to 25 characters are extracted in this process.

### 2.3.5. Stopword Removal

Stopword Removal is the process of eliminating words that do not contribute to the intended meaning. These words are commonly found in a dictionary and are known as stopwords. Examples of stopwords used in this study include "or," "there," "is," "to," "back," "then," "by," and "that."

### 2.3.6. Stemming

Stemming involves transforming inflected or derived words into their base form to capture the underlying meaning and achieve more specific categorization. For example, the word "improper" stems from its base form, "proper".

### 2.3.7. Word Weighting

Word weighting is a mechanism to assign scores to the frequency of word occurrences in a text document.

### 2.3.8. Term Frequency – Inverse Document Frequency (TF-IDF)

Term Frequency – Inverse Document Frequency (TF-IDF) is a powerful and widely used weighted scoring algorithm in the field of information retrieval and natural language processing. It combines the strength of two distinct weighting algorithms, Term Frequency (TF) and Inverse Document Frequency (IDF), to provide a comprehensive measure of word importance within and across a corpus of documents.

TF-IDF operates by calculating the relative frequency of a word in a specific document, considering its inverse proportion across the entire collection of documents. This process helps to discern the relevance and significance of a word within the context of a particular document, as it takes into account not only its occurrence but also its scarcity or prevalence in the overall document collection.

The Term Frequency component of TF-IDF measures the frequency of a word within a given document. It assigns higher weights to words that appear more frequently, assuming that these words are more relevant and informative in conveying the document's content. By

emphasizing frequently occurring words, TF captures the local importance of terms within a document, enabling a more fine-grained analysis of its textual content [20].

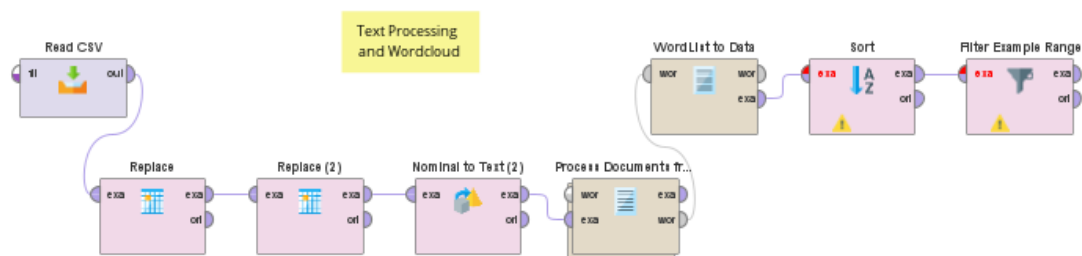
On the other hand, Inverse Document Frequency addresses the global importance of a word across the entire collection of documents. It computes a weight that diminishes the significance of words that are commonly found in many documents, as these words tend to be less discriminative in distinguishing between documents. By inversely scaling the weights of such common words, IDF allows for highlighting words that are more unique and specific to individual documents, thereby enhancing their importance in the ranking and retrieval processes [21].

Integrating TF and IDF in the TF-IDF algorithm facilitates a robust method for identifying essential words in a document and differentiating them from less informative terms. This technique has been widely applied in various applications, including text classification, information retrieval, and document clustering, enabling efficient and accurate analyses of large textual datasets [22].

TF-IDF plays a crucial role in information retrieval and natural language processing tasks by capturing words' relative frequency and significance within individual documents and across a corpus. By combining Term Frequency and Inverse Document Frequency, this algorithm provides a comprehensive and nuanced representation of word importance, contributing to enhanced document understanding and effective text-based analysis.

## 2.4. Wordcloud

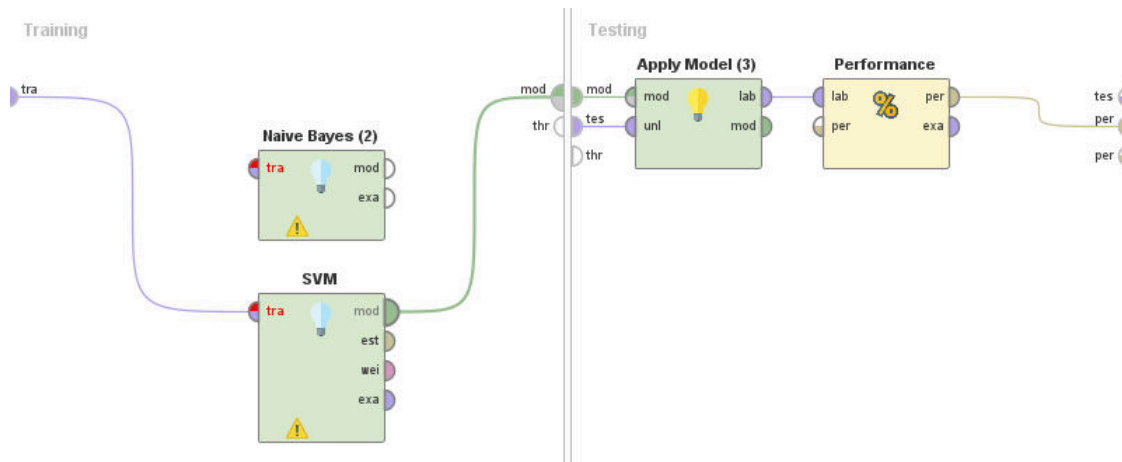
After preprocessing the data, wordcloud generation is performed, which is not crucial to the subsequent processes. Wordclouds are created to visualise frequently occurring words during data crawling on Twitter using the keyword or query "chatgpt in education." The RapidMiner operators used for wordcloud generation are illustrated in **Figure 4**.



**Figure 4.** Wordcloud generation process.

## 2.5. Data Classification Techniques

After data preprocessing, the next stage involves sentiment analysis classification. This stage involves training and implementing various machine learning algorithms. **Figure 5** displays the contents of the "Cross Validation" operator in RapidMiner. Two different classification operators, Naive Bayes and SVM (Support Vector Machine), are used for comparison purposes. After creating the proposed models through experimentation, further experiments are conducted to test the existing models using pre-grouped datasets as training and testing data. The "Performance" operator is used to display accuracy, precision, and recall results.



**Figure 5.** Sentiment analysis classification.

### 2.5.1. Naïve Bayes

Naive Bayes is a machine learning algorithm that utilizes probability calculations based on Bayesian inference. The application of Bayes' theorem in the Naive Bayes algorithm involves combining prior probabilities and conditional probabilities in a formula that can be used to compute the probability of each possible classification. The formula can be seen in Equation [1].

$$P(X) = \frac{P(X|H)P(H)}{P(X)} \quad (1)$$

- X: Data with an unknown class
- H: Hypothesis that data X belongs to a specific class
- P(H|X): Probability of hypothesis H based on condition X
- P(H): Probability of hypothesis H
- P(X|H): Probability of data X based on condition H
- P(X): Probability of X

### 2.5.2. Support Vector Machine (SVM)

Support Vector Machine (SVM) is a powerful and widely used method for analyzing data and identifying intricate patterns that can be effectively employed in classification tasks. In the realm of binary classification, where data is divided into positive and negative classes, SVM stands out as an exceptional approach. This method operates by skillfully constructing hyperplanes in multidimensional input space, and strategically optimizing their positioning to best segregate the different classes. By precisely measuring the boundaries between class memberships, SVM achieves unparalleled accuracy in classification tasks.

Originally, SVM gained prominence for its prowess in classifying numerical data. However, its remarkable capabilities and versatility have transcended beyond numerical domains, making it an invaluable tool for tackling complex text data problems as well. Text data is particularly well-suited for classification using the SVM algorithm due to its inherent high-dimensional nature. Textual information is often characterized by a plethora of features that may not all be relevant, yet tend to exhibit correlations with one another. SVM adeptly handles this challenge by effectively organizing the features into separate linear categories, allowing for efficient and accurate classification of text-based data.



The ability of SVM to excel in classifying text data can be attributed to its unique strengths. By skillfully constructing hyperplanes, SVM can discern subtle linguistic nuances and identify patterns that may not be immediately apparent to human observers. This capability is crucial when dealing with text, as it allows SVM to capture intricate relationships between words, phrases, and concepts, thereby facilitating precise and meaningful classification. Additionally, SVM's robustness to noise and its ability to handle large feature spaces further contribute to its effectiveness in text classification tasks.

Support Vector Machine (SVM) is a sophisticated and versatile method that revolutionizes the field of classification. Its ability to construct hyperplanes in multidimensional spaces enables accurate discrimination between classes, making it an invaluable tool for binary classification problems. Moreover, SVM's exceptional adaptability to text data allows it to efficiently handle the high-dimensional and complex nature of textual information. By effectively organizing features into separate linear categories, SVM unlocks valuable insights hidden within text, paving the way for advanced applications in natural language processing, sentiment analysis, and document classification, among others [23].

## 2.6. Sentiment Analysis Evaluation

After the classification process, evaluation is necessary to determine the quality of the performed process. In this evaluation stage, the performance of the classification process is tested using accuracy, precision, and recall as evaluation parameters. The evaluation in this system analysis is conducted by calculating the accuracy level of a method in analyzing opinions. K-fold cross-validation is chosen to test the accuracy of the Naive Bayes and Support Vector Machine methods. Cross-validation is based on the principle of dividing data into two parts: training data and testing data. In this study, 10-fold cross-validation is used. The data is divided into 10 parts, where Part 1 becomes the training data and Parts 2-10 becomes the testing data. Subsequently, a cross-validation process is performed, where the training data becomes the testing data and vice versa. This process is repeated 10 times.

In the 10-fold cross-validation process, a confusion matrix is created, which consists of True Positives (TP) representing the number of positive class data classified correctly as positive, and True Negatives (TN) representing the number of negative class data classified correctly as negative. False Positives (FP) represents the number of negative class data classified incorrectly as positive, and False Negatives (FN) represents the number of positive class data classified incorrectly as negative. The average accuracy, precision, and recall values can be obtained from the confusion matrix table as shown in **Table 2.** below.

**Table 2.** Confusion matrix table.

	True Yes	True No
Prediction Yes	TP	FP
Prediction No	FN	TN

Accuracy is the number of documents correctly classified when comparing the predicted results of the model with the predetermined sentiment, including both True Positives and True Negatives. The accuracy can be calculated using the formula in Equation [2].

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100\% \quad (2)$$

Precision is the ratio of True Positives to the total number of data predicted as positive. Precision can be calculated using the formula in Equation [3].



$$\text{Precision} = \frac{TP}{TP + FP} \times 100\% \tag{3}$$

Recall represents how many relevant documents are retrieved from the total number of documents that are actually positive, including False Negatives. Recall can be calculated using the formula in Equation [4].

$$\text{Recall} = \frac{TP}{TP + FN} \times 100\% \tag{4}$$

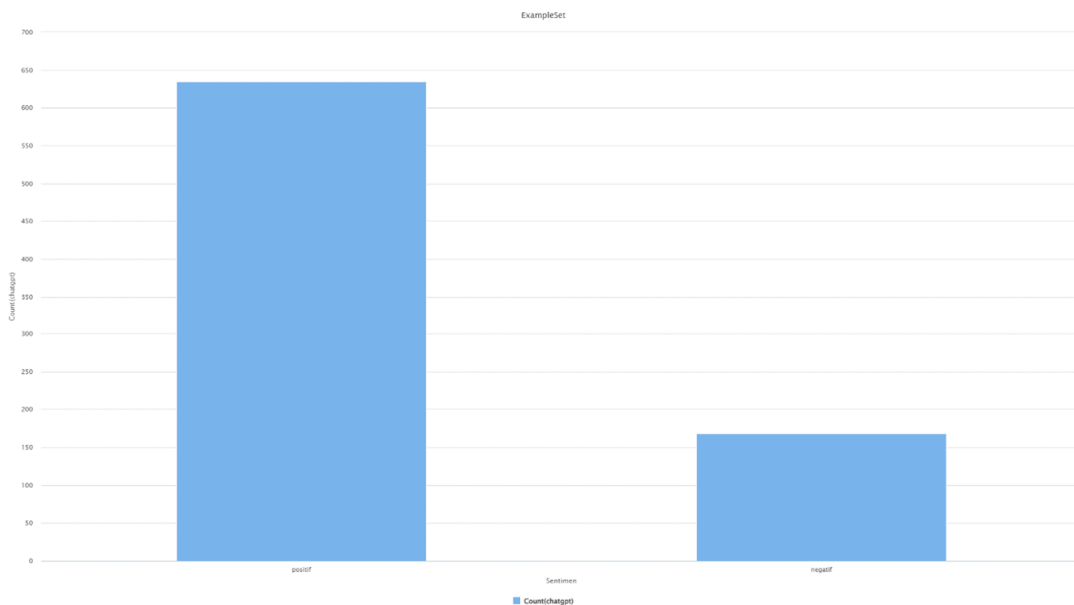
### 3. RESULTS AND DISCUSSION

This section presents the findings of the conducted research. This study aimed to determine the sentiment analysis of Twitter users' opinions regarding the use of ChatGPT in education and compare the classification results between the Naive Bayes and Support Vector Machine (SVM) methods. The research utilized a dataset consisting of 803 tweets, with 300 tweets allocated for training and 503 tweets for testing purposes.

**Table 3.** provides the percentage distribution of sentiment polarity in the obtained tweets. The sentiment analysis of the collected tweets revealed 635 positive tweets and 168 negative tweets. The percentage of positive opinions was 79.07%, while the percentage of negative opinions was 20.93%. Based on these results, it can be concluded that Twitter users' opinions regarding the use of ChatGPT in education were predominantly positive. However, some netizens expressed reservations about the utilization of ChatGPT in the educational context, as it is not their field of expertise. The overall research findings are elaborated in **Table 3.**, **Figure 6.**, and **Figure 7.** below.

**Table 3.** Sentiment polarity of tweets.

	Sum of Tweets	Percentage
<b>Positive Tweets</b>	635	79.07%
<b>Negative Tweets</b>	168	20.93%



**Figure 6.** Histogram of positive and negative tweets.

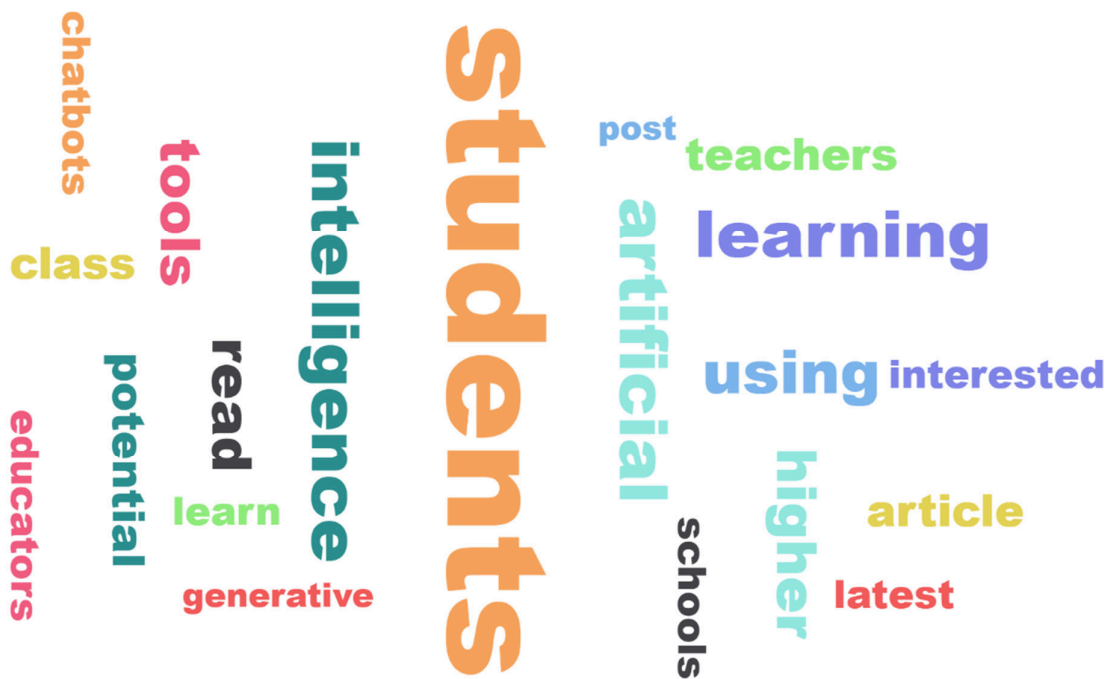


Figure 7. Wordcloud generated based on positive and negative tweets.

Figure 8. illustrates the primary process in the RapidMiner application. The "Dataset" operator represents the "Read Excel" operator used to read the dataset from an Excel file. The "Subprocess" operator signifies the initial stage of preprocessing, where data cleansing takes place. The "Training Process" and "Testing Process" operators denote the "Document Process" operators employed for preprocessing and data weighting. The "Cross Validation" operator is utilized for sentiment analysis classification and evaluation, with the experiment conducted ten times using 10-fold cross-validation.

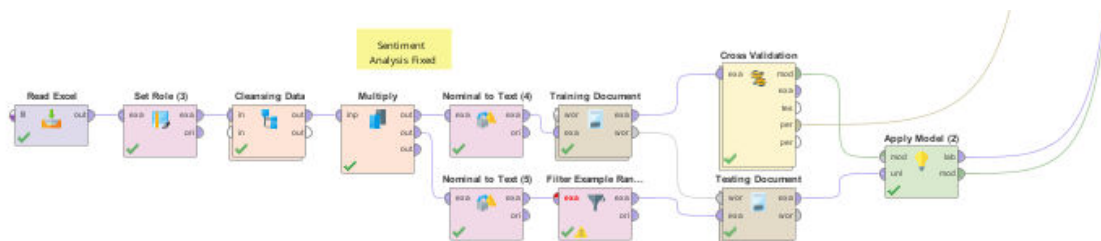
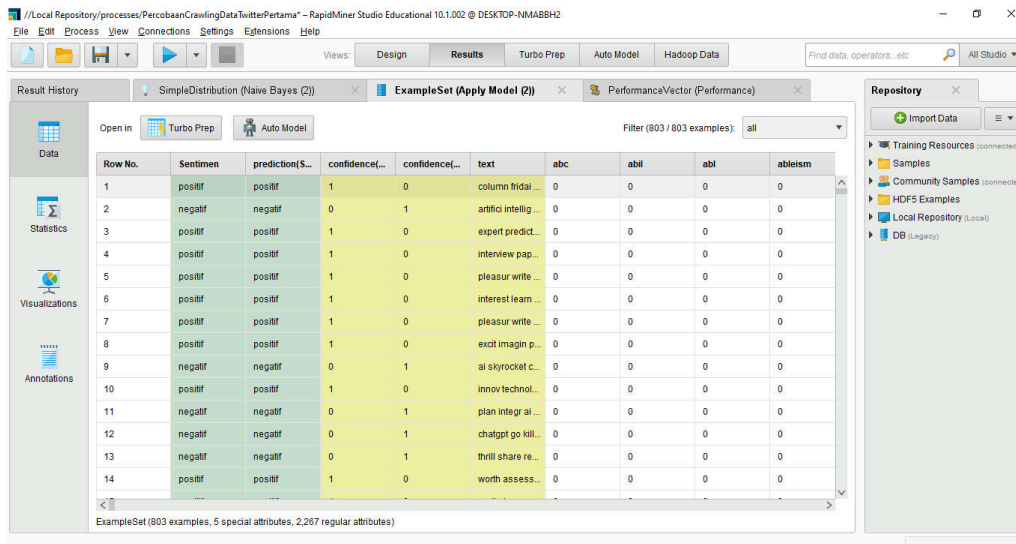


Figure 8. Main Process in RapidMiner

Figure 9. displays the sentiment prediction results obtained from the RapidMiner application. A comparison is made between the predetermined and predicted sentiment labels generated during the process. The following Table 4. presents the confusion matrix results for each algorithm.



**Figure 9.** Prediction Results from RapidMiner

**Table 4.** Confusion matrix for every method.

Metode	True Positive (TP)	False Positive (FP)	True Negative (TN)	False Negative (FN)
Naïve Bayes	614	53	115	21
SVM	628	99	69	7

Based on the confusion matrix table in **Table 4.**, the average values of accuracy, precision, and recall in RapidMiner are shown in **Table 5.**

**Table 5.** Accuracy, precision, and recall results.

Metode	Accuracy	Precision	Recall
Naïve Bayes	90.77%	84.98%	68.42%
SVM	86.79%	90.08%	41.10%

**Table 5.** presents the accuracy results of Naive Bayes as 90.77% and SVM as 86.79%. The precision results for Naive Bayes are 84.98%, while for SVM, they are 90.08%. Furthermore, the recall values for Naive Bayes and SVM are 68.42% and 41.10%, respectively. It can be observed that Naive Bayes performed better as a classifier in sentiment analysis using the Twitter dataset, providing more accurate and precise predictions.

The disparity in results can be attributed to the suitability of dataset characteristics and the different parameters of each algorithm. In this case, Naive Bayes operates on independent variables, specifically text data from tweets.

Due to the compatibility between the data type and variables, Naive Bayes outperforms Support Vector Machine. This difference in polarity results may also stem from SVM separating data based on predetermined linear patterns through word weighting rather than the frequency-based probabilities of the words.

#### 4. CONCLUSION

In this study, a sentiment analysis classification process was conducted on various opinions regarding the use of ChatGPT in the field of education. The conclusion drawn from the sentiment polarity of netizens' opinions indicates a dominant positive sentiment, with positive opinions accounting for 69.72% and negative opinions accounting for 30.28%. Based on these results, this sentiment can be utilized to evaluate the performance of ChatGPT's utilization in education until the completion of this research, as well as to assess and consider future performance.

The research employed two different classifiers, namely Naive Bayes and SVM. These classifiers predicted labels within the dataset based on the data patterns present. The results revealed that the accuracy of Naive Bayes was 90.77%, while SVM achieved an accuracy of 86.79%. The precision results for Naive Bayes were 84.98%, compared to 90.08% for SVM. Moreover, the recall values for Naive Bayes and SVM were 68.42% and 41.10%, respectively. Therefore, it can be concluded that Naive Bayes outperforms SVM by providing more accurate and precise predictions. This difference in performance can be attributed to the suitability of dataset characteristics and the differing parameters of each algorithm. In this study, Naive Bayes operated on independent variables, specifically text data from tweets. Due to the compatibility between the data type and variables, Naive Bayes exhibited superior performance compared to SVM.

Based on the findings of this research, it is recommended to continue exploring the application of ChatGPT in the field of education. The dominant positive sentiment expressed by netizens suggests a favorable perception of its usage. Furthermore, future studies can further focus on refining and enhancing the Naive Bayes classifier to improve accuracy and precision in sentiment analysis tasks. Additionally, it may be beneficial to investigate other machine learning algorithms or hybrid approaches to sentiment analysis to explore their potential to capture the nuances of user opinions more effectively.

#### 5. AUTHORS' NOTE

The authors declare that there is no conflict of interest regarding the publication of this article. Authors confirmed that the paper was free of plagiarism.

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