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ANALYSIS OF HYBRID LEARNING SENTIMENT AMONG INFORMATION SYSTEMS STUDENTS USING THE NAÏVE BAYES CLASSIFIER

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ABSTRACT

Hybrid learning, which combines online and face-to-face instruction, has gained significant attention. Particularly in the Faculty of Computer Science, student engagement in hybrid learning is a central concern that arises during implementation. Hybrid, or blended learning, integrates various teaching methods, such as face-to-face, computer-based, and mobile learning, and offers advantages by reducing the time required for meetings and information delivery. Sentiment analysis, a branch of text mining, aims to determine public opinion or sentiment on topics, events, or issues. This study surveyed 112 Information Systems students using an online questionnaire to assess their responses to hybrid learning, classified as positive, negative, or neutral using the Naïve Bayes classifier. The research stages included data collection, preprocessing, Naïve Bayes model training, model evaluation, and sentiment analysis. The study aimed to analyze hybrid learning's impact on students' learning experiences and assess the accuracy of the Naïve Bayes method in classifying sentiments regarding this impact. The results indicated that the initial test had an accuracy of 60.87% without using the SMOTE up-sampling operator, while the second test achieved 80.65% accuracy with the operator.

Keywords*: accuracy, hybrid learning, naïve bayes classifier, sentiment analysis, SMOTE up-sampling.*

I. INTRODUCTION

THE Faculty of Computer Science is located at Campus II of Universitas Muslim Indonesia, Jalan. Urip Sumoharjo KM.5, Makassar, South Sulawesi. Established in 1999, it comprises two study programs: Information Systems and Informatics Engineering. Hybrid learning, combining online and in-person instruction, has garnered significant attention, especially in the Faculty of Computer Science, where its implementation may present challenges, notably regarding student interaction and unstable internet connectivity. These issues may hinder participation and create accessibility gaps. Hybrid learning, also known as blended learning, merges various instructional approaches, including in-person, computer-based, and mobile instruction, and provides the advantage of reducing time needed for meetings or content delivery [1].

Sentiment Analysis is a branch of text mining research used to identify emotions in text [2], helping to ascertain public opinions or subjectivity on topics, events, or issues. Text mining involves analyzing information to yield specific insights. Sentiment analysis classifies text into positive, negative, or neutral categories [3]. This study employs the Naïve Bayes Classifier, a classic and straightforward method for probabilistic classification [4], to gauge public and student perceptions through text processing. Sentiment analysis in this context is conducted using natural language processing (NLP) techniques. NLP focuses on developing methods and algorithms to recognize, understand, and manipulate text, transforming human language into a format comprehensible to machines. The primary objective of NLP is to enable computers to communicate with humans naturally and intuitively [5].

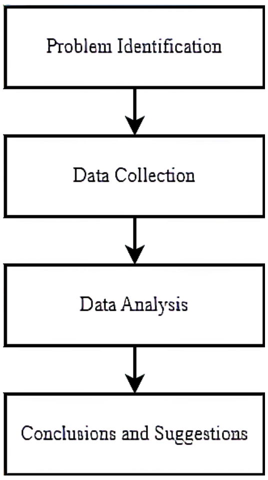

Figure 1. Research stages

This study references several previous studies related to sentiment analysis using the Naïve Bayes classification method. One study examined sentiment analysis of e-commerce on Twitter using the Naïve Bayes method to classify independent variables and social sentiment, labeling each sentence as positive or negative, achieving an accuracy rate of 79% [6]. Another study applied the Naïve Bayes method with RFFS to reduce features and classify sentiments, obtaining an average accuracy of 62.6% with the Naïve Bayes test and 65.3% with the RFFS classification accuracy test [7]. A third study analyzed facial skincare product reviews using the Naïve Bayes classifier with N-gram feature selection and Document Frequency (DF) Thresholding to assess the impact of DF-Thresholding on classification accuracy. The results showed a feature reduction by 16,312, with a combination of unigram and bigram yielding 43 features, achieving a precision of 0.23, recall of 0.26, and F-measure of 0.24 [8]. Additional research on negative comment sentiment analysis on Facebook used Naïve Bayes with a confusion matrix, obtaining an accuracy of 86%, precision of 84.61%, recall of 88%, and F1-score of 86.27% [9]. Another study on public sentiment classification regarding Ganjar Pranowo on Twitter used the Naïve Bayes Classifier with a 10% test sample, achieving an accuracy of 83% [10].

Through this study, the Faculty of Computer Science's Information Systems program aims to understand student sentiments toward hybrid learning, offering deeper insights into student responses and experiences with this learning approach. Based on preliminary observations of several Information Systems students, it is necessary to conduct a "Sentiment Analysis of the Impact of Hybrid Learning on Information Systems Students Using the Naïve Bayes Classifier Method," utilizing Natural Language Processing (NLP) techniques. This sentiment analysis aims to assist the faculty and program in evaluating the success of new learning methods and making improvements based on the analysis results.

Sentiment analysis is a technique for categorizing opinions, feelings, and emotions expressed in text, organizing them into positive, negative, and neutral sentiments [11]. NLP, a subfield of artificial intelligence, focuses on natural language processing to address issues where computers can recognize commonly spoken languages [12]. The Naïve Bayes algorithm is a classification algorithm used for data and text processing, suitable for assessing public opinion through the Naïve Bayes Classifier [13]. This method involves two main stages: a training process, where data is prepared and processed, and a classification process, resulting in a representation [14]. The TF-IDF algorithm identifies significant words in a document by calculating term frequency (TF) and inverse document frequency (IDF). TF measures word frequency, while IDF measures word rarity [15]. The purpose of this study is to analyze the impact of hybrid learning on students' learning experiences and to assess the accuracy of the Naïve Bayes method in classifying sentiments related to hybrid learning.

II. RESEARCH METHOD

A. *Research Stages*

The research stages to be undertaken are illustrated in Figure 1. The research process consists of four stages: Problem Identification, where issues related to the impact of hybrid learning are identified to

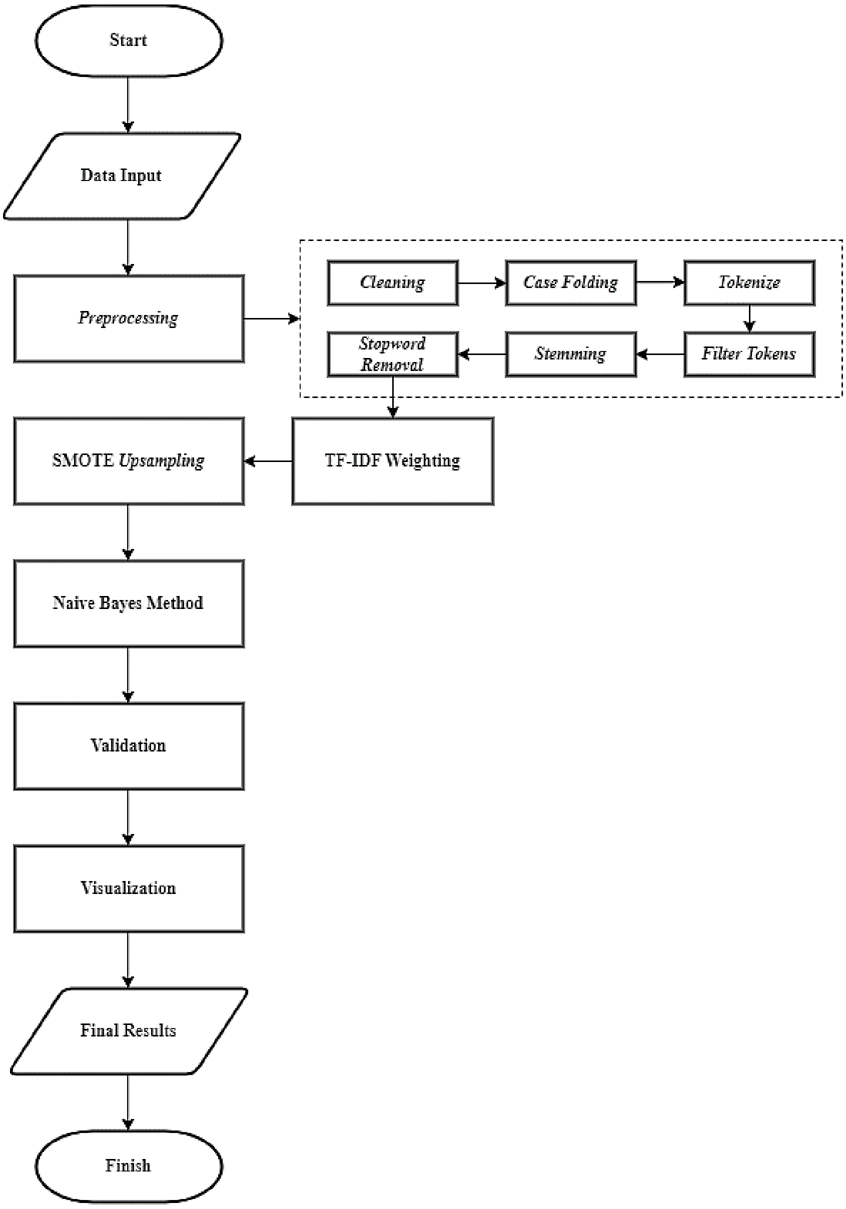

Figure 2. Research design

determine potential positive, negative, or neutral influences within the student environment; Data Collection, conducted in three ways—observation, questionnaires, and literature review; Data Analysis, where researchers used RapidMiner tools to analyze the data through stages that include data input, preprocessing, TF-IDF word weighting, data classification using the Naïve Bayes classifier, validity analysis, and data visualization; and Conclusions and Suggestions, where the findings from the sentiment analysis are summarized, addressing the initial problem statement and offering insights for future improvements.

B. Research Design

The research was conducted through several stages, as shown in Figure 2. Figure 2 illustrates the research design flow: Data Input, where data is collected via an online questionnaire using Google Forms and labeled to distinguish between positive, negative, and neutral sentiments; Preprocessing, which involves cleaning, case folding, tokenizing, filtering tokens, stemming, and removing stopwords; Weighting with TF-IDF to calculate the weight of each word; Balancing through the SMOTE up-sampling operator to adjust class imbalance; Classification using the Naïve Bayes classifier to calculate probability values for each class; Model Evaluation to assess the performance accuracy; and Data Visualization, where sentiment analysis results are displayed with word clouds. The final results are then summarized as conclusions and recommendations.

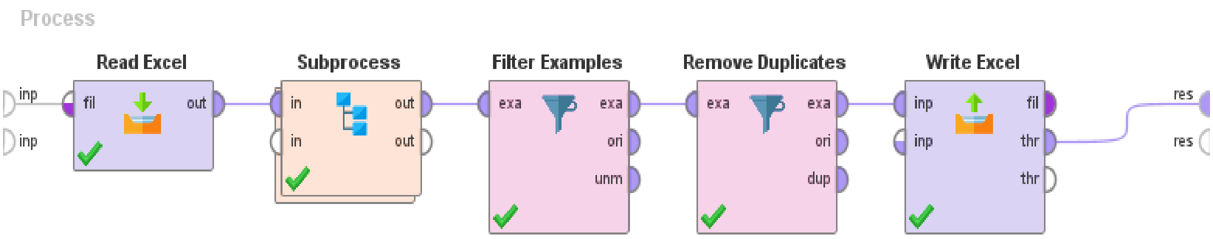

Figure 3. Cleaning process

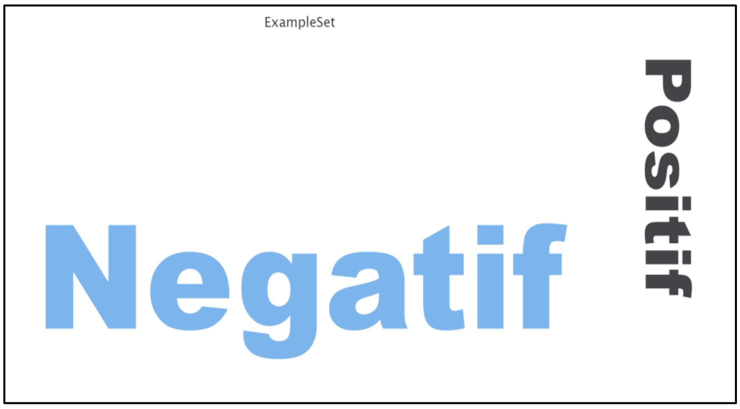

Figure 4. Wordcloud visualization

C. Stages

This study consists of several stages. Time and Location: The research was conducted in the Information Systems Study Program at the Faculty of Computer Science, Universitas Muslim Indonesia, from January to March 2024. Research Instruments: The hardware used included a laptop with an Intel(R) Celeron(R) N4020 processor and 4GB RAM. Software tools included Windows 11 Pro (64-bit), Microsoft Excel, and RapidMiner Studio. Data Collection Techniques: Data was collected from Information Systems students (batch 2020 to 2023) at the Faculty of Computer Science. A total of 112 online questionnaires were distributed via Google Forms. The collected data was manually labeled to classify responses as positive, negative, or neutral. In this study, positive responses include constructive and respectful feedback, negative responses consist of criticism or disrespectful language, and neutral responses are comments without significant positive or negative emotion.

D. Data Testing Techniques

1) Cleaning

The cleaning process (see Figure 3) removes irrelevant characters and unimportant sentences to optimize data for sentiment analysis. This includes eliminating numbers, question marks (?), URLs, hashtags (#), commas (,), and emoticons [17].

2) Case Folding

This step reduces repetitive and inconsistent data by standardizing text to lowercase. For instance, words with uppercase letters are converted to lowercase [18].

3) Tokenizing

Tokenizing breaks down sentences into individual words (tokens) to facilitate text weighting, aiding further analysis [19].

4) Filter Token

At this stage, tokens are cleaned and filtered to retain only relevant words, refining the text for subsequent processing [20].

5) Stemming

Stemming removes affixes to yield the root form of words, reducing variations of the same root into a simplified form [21].

6) Stopword Removal

Stopword removal eliminates meaningless words, leaving only the base words by stripping prefixes, suffixes, greetings, and affixes from the text [22].

After preprocessing, the TF-IDF weighting stage is applied. This step calculates term frequency (TF) and inverse document frequency (IDF) to assess how often each word appears across documents in the dataset.

Naïve Bayes Classification is employed to test accuracy and determine the highest probability value in sentiment classification, categorizing opinions as positive, negative, or neutral. To balance the dataset, the SMOTE (Synthetic Minority Over-sampling Technique) Upsampling operator is used, which generates synthetic data through a linear combination of existing samples, effectively increasing the number of minority class samples. This reduces model bias toward the majority class, enhancing sensitivity to the minority class.

Data Validation Analysis: This stage utilizes K-fold Cross Validation, which involves repeating evaluations based on the chosen K value and randomizing the input data. This approach allows the system to test with randomized inputs, providing robust validation results [23]. Following this, the classification process applies the Naïve Bayes method to measure accuracy, precision, recall, and F1-score.

Data Visualization: Figure 4 illustrates the word cloud used for data visualization, highlighting the most frequently occurring keywords in the dataset. Word cloud visualization offers a visual summary of predominant topics and supports the analysis of emerging sentiments [24]. It displays the most common words in positive, negative, and neutral categories within the analyzed text.

III. Results and Discussion

A. Result

The research results include stages of preprocessing, TF-IDF weighting, Naïve Bayes classification, and calculation of the Naïve Bayes classification. The preprocessing steps are shown in Figure 5, beginning with data cleaning. This stage documents various sub-processes such as case transformation, tokenization, token filtering (by length), stemming, and stopword filtering (dictionary). Prior to these steps, the nominal-to-text process operator converts the selected nominal attribute type to text. Figure 5 illustrates each phase of the preprocessing process and its outcomes.

The TF-IDF weighting stage is shown in Figure 6. In the TF-IDF process using RapidMiner tools (Figure 6), words (terms) are weighted based on the preprocessed data. This process assigns a weight to each frequently appearing word in the document. The Naïve Bayes classification comparison process is divided into two experiments.

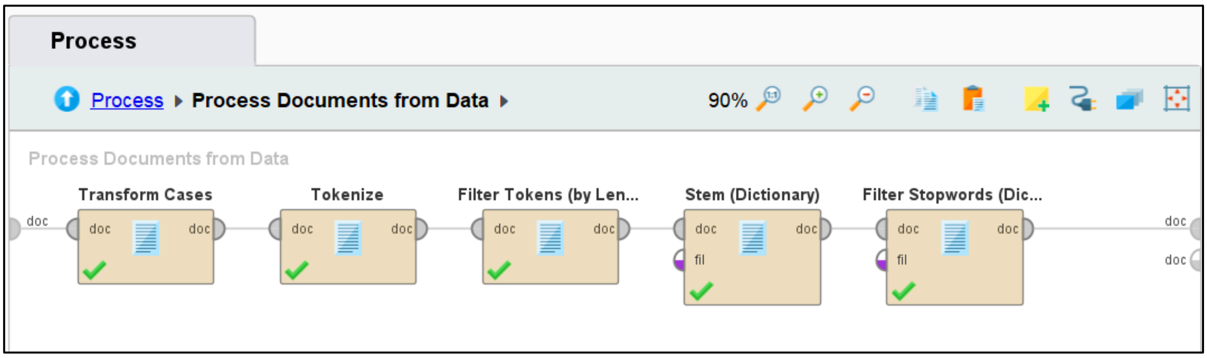

Figure 5. Preprocessing view

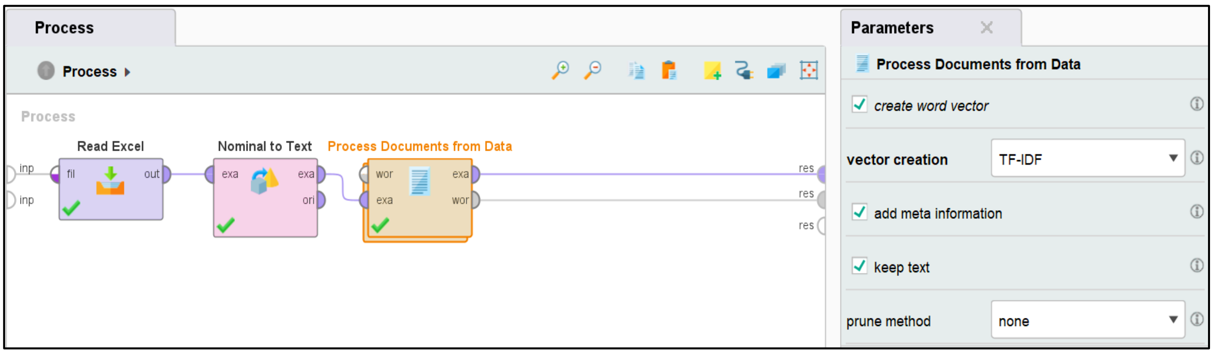

Figure 6. View of TF-IDF process

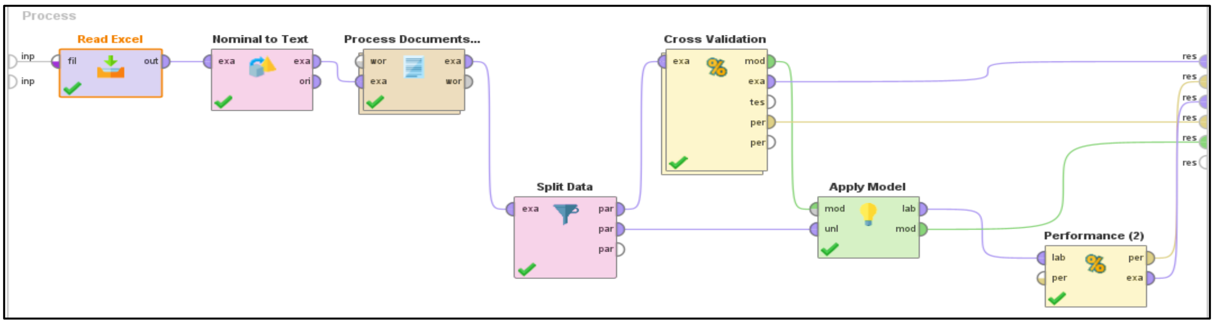

Figure 7. Experiment 1 Naïve Bayes classification

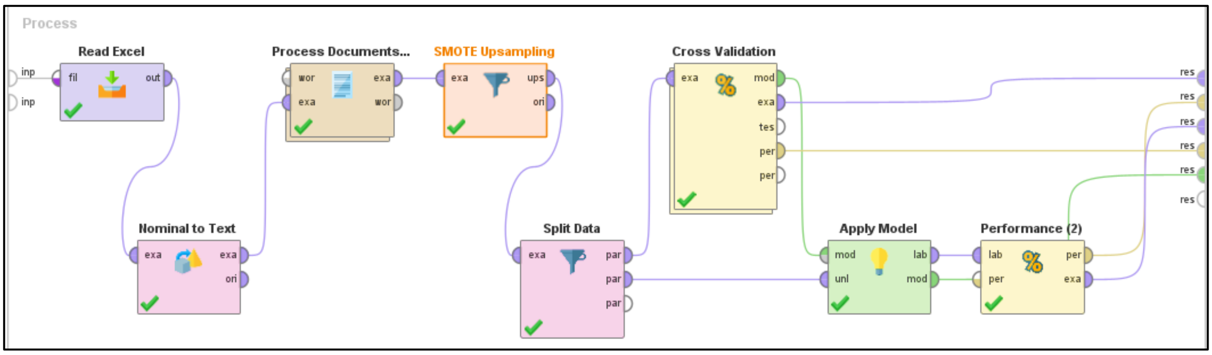

Figure 8. Experiment 2 Naïve Bayes classification

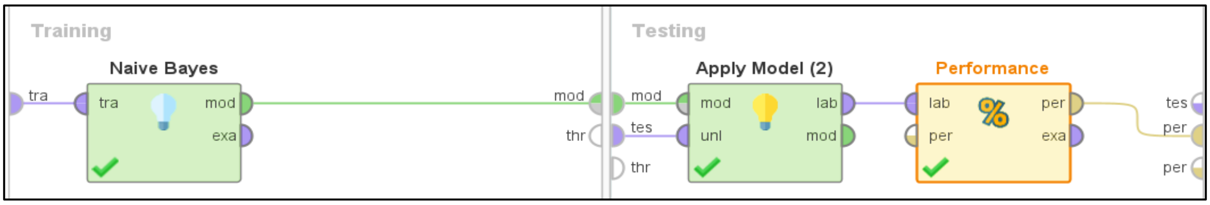

Figure 9. Naïve Bayes method process

1) First Experiment

The setup of Experiment 1 is shown in Figure 7. In this experiment, the Naïve Bayes classification process is applied to research data in Excel files containing cleaned positive, negative, and neutral comments. The data is connected to the nominal-to-text operator to facilitate the preprocessing stage. Next, the split data operator divides the data into training and test sets, with an 80:20 ratio, followed by cross-validation to apply the Naïve Bayes method and assess the performance of the test data.

2) Second Experiment

The setup of Experiment 2 is shown in Figure 8. In Experiment 2, as illustrated in Figure 8, the Naïve Bayes classification process uses research data in cleaned Excel files with labeled positive, negative, and neutral comments. The data is connected to the nominal-to-text operator for preprocessing and then to the SMOTE Upsampling operator. SMOTE balances the dataset by generating synthetic samples for the minority class, improving classification performance. To prevent overfitting and underfitting, SMOTE is applied before splitting the data into training and test sets (80:20 ratio), followed by cross-validation to apply the Naïve Bayes method and calculate performance.

B. Naïve Bayes Classification Calculation

Figure 9 displays the Naïve Bayes classification process. The training section includes the Naïve Bayes algorithm operator, while the testing section incorporates the applied model and performance operators. Cross-validation with 10 folds assesses the accuracy, recall, precision, and F1-score, based on the Naïve Bayes classification results.

1) First Experiment Results: Naïve Bayes Classification

As shown in Table 1, the results of Experiment 1 using the split data operator yielded an accuracy of 70.69%. For the negative class, precision was 75% with a recall of 50.00%; for the positive class, precision was 55.56% with a recall of 27.78%; and for the neutral class, precision was 72.06% with a recall of 92.45%.

TABLE 1
EXPERIMENT 1 RESULTS OF NAÏVE BAYES CLASSIFICATION

	True Negative	True Positive	True Neutral	Class Precision
Pred. Negative	9	1	2	75.00%
Pred. Positive	2	5	2	55.56%
Pred. Neutral	7	12	49	72.06%
Class Recall	50.00%	27.78%	92.45%	

Accuracy: 70.69% +/- 14.26% (micro average: 70.79%)

TABLE 2
EXPERIMENT 2 RESULTS OF NAÏVE BAYES CLASSIFICATION

	True Negative	True Positive	True Neutral	Class Precision
Pred. Negative	51	2	1	94.44%
Pred. Positive	0	4	0	100.00%
Pred. Neutral	2	12	52	78.79%
Class Recall	96.23%	22.22%	98.11%	

Accuracy: 86.35% +/- 7.30% (micro average: 86.29%)

TABLE 3
EXPERIMENT 1 RESULTS OF TESTING DATA CALCULATION

	True Negative	True Positive	True Neutral	Class Precision
Pred. Negative	2	1	1	50.00%
Pred. Positive	0	0	0	0.00%
Pred. Neutral	3	4	12	63.61%
Class Recall	40.00%	0.00%	92.31%	

Accuracy: 60.87%

TABLE 4
EXPERIMENT 2 RESULTS OF TESTING DATA CALCULATION

	True Negative	True Positive	True Neutral	Class Precision
Pred. Negative	13	1	2	81.25%
Pred. Positive	0	1	0	100.00%
Pred. Neutral	0	3	11	78.57%
Class Recall	100.00%	20.00%	84.62%	

Accuracy: 80.65%

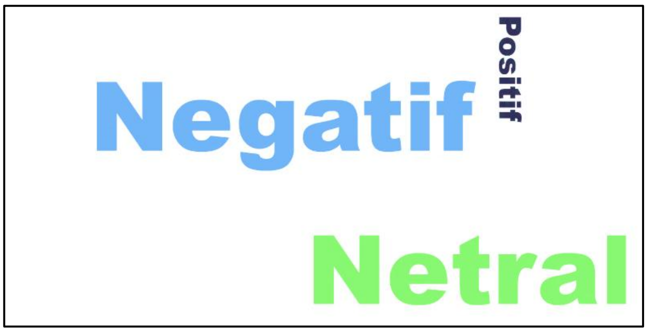

Figure 10. Wordcloud visualization

2) Second Experiment Results: Naïve Bayes Classification

Table 2 presents the results of Experiment 2, which utilized the SMOTE Upsampling and split data operators, resulting in an accuracy of 86.35%. For the negative class, precision was 94.44% with a recall of 96.23%; for the positive class, precision reached 100% with a recall of 22.22%; and for the neutral class, precision was 78.79% with a recall of 98.11%.

C. Discussion

The following discussion covers data validation analysis and data visualization. In the data validation analysis, performance metrics such as accuracy, precision, and recall were calculated for the test data.

In the data validation analysis, performance metrics such as accuracy, precision, and recall were calculated for the test data.

1) Experiment 1 Testing Data Calculation

As shown in Table 3, Experiment 1 testing data using the split data operator achieved an accuracy of 60.87%. For the negative class, precision was 50.00% with a recall of 40.00%; for the positive class, precision and recall were both 0.00%; and for the neutral class, precision was 63.16% with a recall of 92.31%.

2) Experiment 2 Testing Data Calculation

Table 4 shows the results of Experiment 2 testing data using the SMOTE Upsampling and split data operators, achieving an accuracy of 80.65%. precision was 81.25% with a recall of 100.00%; for the positive class, precision was 100.00% with a recall of 20.00%; and for the neutral class, precision was 78.57% with a recall of 84.62%. Figure 10 displays the data visualization results, indicating that negative and neutral sentiments are balanced compared to positive sentiments.

IV. CONCLUSION

This study performed a sentiment analysis using the Naïve Bayes Classifier method to examine the impact of hybrid learning on Information Systems students. Based on the evaluation and comparison results, particularly from Experiment 2 utilizing the SMOTE Upsampling operator, the following conclusions were drawn. First, negative and neutral sentiments are balanced in comparison to positive sentiments. Specifically, 13 sentiments were identified as negative, 13 as neutral, and 5 as positive. Second, in the data performance testing for Experiment 2, the Naïve Bayes classifier achieved an accuracy of 80.65%. For the negative class, precision was 81.25% with a recall of 100.00%; for the positive class, precision was 100.00% with a recall of 20.00%; and for the neutral class, precision was 78.57% with a recall of 84.62%.

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