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SVM and Ensemble Majority Voting Algorithm on Sentiment Analysis of Using ChatGPT in Education

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Abstract

The pros and cons of using ChatGPT in education have caused academic debate as it has influenced current educational praxis. Discussions about the possibility of ChatGPT for writing manuscripts or doing assignments are rife on social media, one of which is Twitter. The purpose of this study is to understand the public perception of the use of ChatGPT in education. The proposed method is sentiment analysis with SVM and Majority Voting algorithms. SVM is one of the superior algorithms in pattern recognition and is suitable for use in classification. The Majority Voting ensemble algorithm combines independent algorithms' prediction results. In this research, majority voting uses three base classifiers, namely Naïve Bayes, Random Forest, and KNN. The results of the study showed that the accuracy of SVM is 83.6% and Majority Voting is 85.4%, with the accuracy of the NB, RF, and KNN base classifiers of 76.82%, 80.91%, and 74.5%, respectively. This proved that the Majority Voting Ensemble is superior to individual algorithms with higher accuracy values. This follows the results of previous research, where the ensemble performs better than the individual algorithm. The accuracy values of SVM and the Ensemble Majority Voting models showed that both models could successfully classify sentiment on tweet data for using ChatGPT in education.

Keywords: Education, Ensemble Majority Voting, Sentiment Analysis, ChatGPT, SVM

1 Introduction

ChatGPT is a natural language model developed by OpenAI to understand and provide natural responses in human conversations [1]. The development of ChatGPT began in 2018, and it was one of the most significant language models at the time. Since then, OpenAI has launched several more prominent versions of ChatGPT, including GPT-2, GPT3, and GPT-4. The general public has widely used ChatGPT to write various education manuscripts. Therefore, it is common for students to use ChatGPT to complete school or university assignments [2].

The advent of ChatGPT has created pros and cons. Teachers revealed that the development of AI seems to have changed the current educational praxis [3], [4]. Nadiem Makarim questioned the impact of ChatGPT, as it makes teachers fearful due to the assessment of quantity and quality in the teaching-learning process. For example, in Texas, students' class certificates were held up due to the use of ChatGPT. However, ChatGPT, which can help improve learning effectiveness by providing access to a broader range of materials, is undeniable [5].

These pros and cons are often discussed on social media, especially Twitter. Twitter is one of the most important social media platforms in social interaction because users for audience management favour it with one of its "#" hashtag features. The hashtag #ChatGPT is always there every day, which indicates that there is high public attention to ChatGPT. This draws attention to sentiment analysis on tweets using ChatGPT [6]. Sentiment analysis is extracting opinions to analyze a person's opinion, sentiment or feelings towards a particular topic [7]. Previous studies have shown that #chatGPT is trending and makes for exciting research. Ananya Sarker et al. [8] conducted sentiment analysis of Twitter data with six different algorithms and found that SVM has the highest accuracy of 84%. Other studies were conducted by Rajani et al. [9]. They did a sentiment analysis of ChatGPT with four different algorithms and found that SVM had the best accuracy of 81.4% compared to NB, RF, and KNN. Abdullah Alsaeedi [10] has also conducted a study on sentiment analysis, which compares several algorithms in sentiment analysis, finding that the ensemble and hybrid algorithms are 85% superior to the SVM and Naïve Bayes algorithms. In the previous research, the use of Ensemble Majority Voting classifiers was also able to improve the model accuracy of single classifier models, especially for Decision Tree and KNN classifier models [11].

The purpose of this study is to analyze public sentiment towards the use of ChatGPT in education using machine learning approaches. Support Vector Machine (SVM) and Ensemble Majority Voting algorithms were used to perform sentiment analysis on tweets with the hashtag #chatGPT. The Ensemble Majority Voting algorithm was built from Random Forest, KNN, and Naïve Bayes to optimize low-accuracy results from the three single algorithms.

2 Material and Methods

The overall work process carried out in this study can be divided into data collection, data preprocessing, data splitting, feature extraction, data modelling and performing metrics, as shown in Fig. 1 below.

2.1 Data

The first process is Data collection. This process consisted of three steps: data crawling, labelling and sampling. The data were crawled from Twitter with the keyword #ChatGPT from 24/03/2023 to 26/07/2023. The number of data is 8517 data tweets. The data were retrieved through the crawling process using Twitter API with the help of the *tweepy library* from Python. Data retrieval was based on #ChatGPT with several search keywords such as academic, school, assignment, exam, thesis, quiz, journal, seminar, and paper. The next is data labelling. Labelling or sentiment on the data was undertaken using *HuggingFace Transformers*, an open-source library that facilitates users to access large-scale models in building and experimenting [12]. The model used is the Indonesian RoBERTa Sentiment Classifier. The RoBERTa model (Robustly optimized BERT Pretraining approach) is a BERT (Bidirectional Encoder Representations from Transformers) pre-train model that has been optimized to exceed the performance of all post_BERT methods [13]. Indonesian RoBERTa Sentiment Classifier is a sentiment classification model based on the enhanced RoBERTa model on the Indonesian dataset with an accuracy of 94.36% [14].

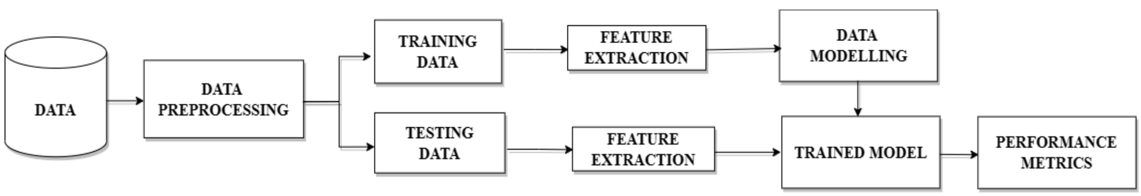

Figure 1. The overall work processes

The dataset that has been obtained is labelled using this model with three sentiment labels, namely positive sentiment, neutral sentiment and negative sentiment.The last step is balancing data. Unbalanced data sets in machine learning can result in incorrect predictions. Machine learning algorithms are designed to work best with balanced data [15]. Undersampling techniques were applied to the number of samples in the majority class to be balanced with the minority class.

2.2 Preprocessing

The data obtained from Twitter is unstructured and still contains noise. It is necessary to do preprocessing with several stages according to Fig. 2, namely Cleaning, to remove characters in tweets except the alphabet and emoticons.

To convert the emoticon in the tweet into a word that represents the emoticon, Emoticon Conversion is used. Next, Case Folding is applied to convert all letters in the tweet to lowercase. Sentences in tweets are truncated based on the words that make up the sentence using the Tokenize process. To convert ambiguous words such as abbreviations and acronyms into the original form of words that are considered to be normal language, Normalisation is used. Stopword Removal is used to eliminate words that have no meaning, for example, “yang”, “dan”, and “di”. The next step is Stemming. In this step, words would be converted into basic words.

2.3 Training and Testing Dataset

After Stemming, the data is ready to be divided into training and testing data with a ratio of 90:10, respectively.

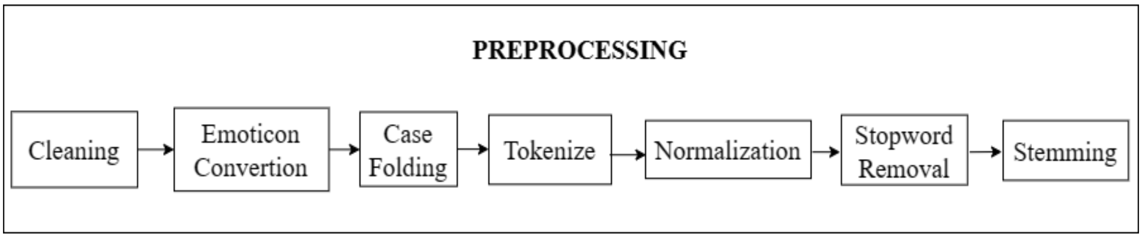

Figure 2. Preprocessing Flowchart

2.4 Feature extraction

Next, in each dataset, the words are weighted using the TF-IDF technique. Term Frequency-Inverse Document Frequency (TF-IDF) is a word weighting method used to measure the significance of features in a document [16]. Term Frequency (TF) determines how important a word is by how often it appears in a document; Inverse Document Frequency (IDF) considers a word critical in a document if it does not seem too often in other documents [17].

2.5 Modelling

Modelling is done using the data from feature extraction. Each model is validated using the K-Fold Cross Validation method on the training data. This method divides the data set into several parts and tests them individually while training is performed on the remaining data [18]. On training each fold, its output error is estimated; finally, the average of all mistakes is the estimated true error [19]. Fig. 3 shows all the various processes that occur in data processing.

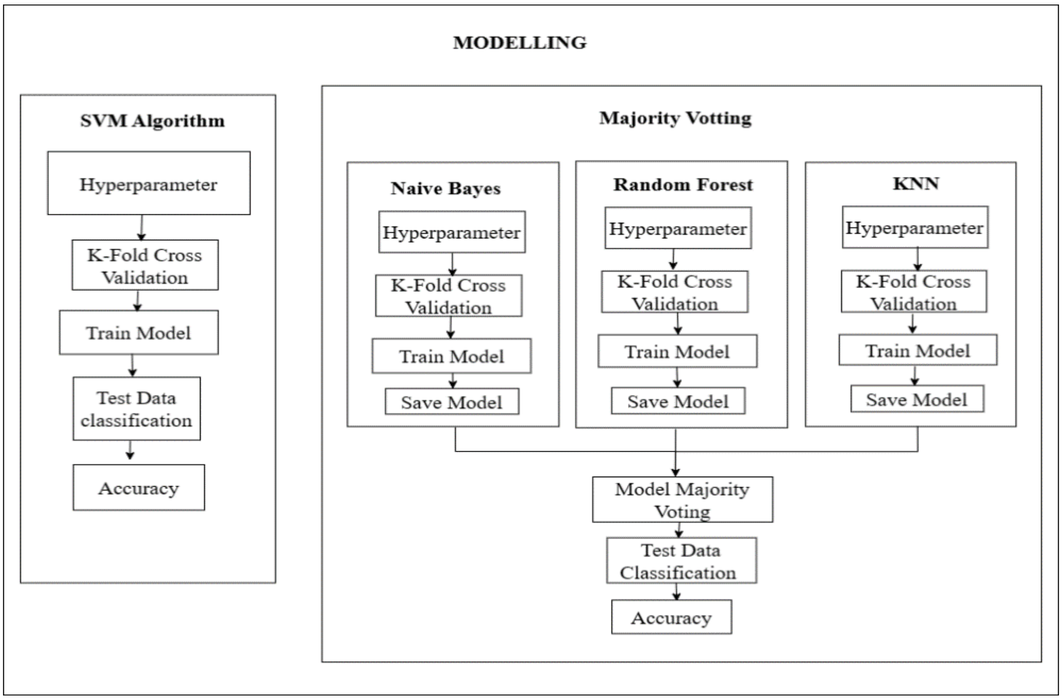

Figure 3. The modelling workflow

2.5.1 Support Vector Machine

SVM is a learning method that works according to the SRM (Structural Risk Minimisation) principle that aims to find the best hyperplane separating two classes in the input space [20]. *A hyperplane* is a dividing line if the number of input features is 2; a 2D hyperplane is needed to separate the number of input features 3 [21]. SVM uses kernels to map data to a higher dimensional space for data classification that cannot be done linearly [22], one of which is by using RBF (Radial Basis Function) kernels, which can be used in Non-linear SVM models [21]. Because of its ability that does not depend on the number of features, SVM is widely applied in classification problems and can produce good performance [20]. This research searches for the best kernel between RBF and Polynomial kernels with supporting parameters. The parameter combinations that will be performed are shown in Table 1.

2.5.2 Ensemble Majority Voting

The majority voting uses one or more classification algorithms, and the output results are given based on selecting predictors (model values from all algorithms) [23]. Each classifier, called the base classifier, chooses one class label, and the final output class label is the class label that receives more than half of the votes [24]. We combined three different algorithms: Naïve Bayes, Random Forest, and KNN. These three algorithms are optimized by finding the best parameters using GridSeacrhCV. The parameter combinations for all three are shown in Table 2.

Table 1. Combination of SVM parameters

Combination	Parameters	Value
1	Kernel C *gamma*	RBF [0.1, 1, 10, 100] [1, 0.1, 0.01, 0.001, 0.0001]
2	Kernel C *degree* *coefficient*	*Polynomial* [0.1, 1, 10, 100] [2, 3, 4] [0.0, 1.0, 2.0]

Table 2. Combination of Base Classifier Parameters

Algorithm	Parameters	Value
Naïve Bayes	nb__alpha fit_prior	[1, 0.1, 0.01, 0.001, 0.0001] [‘True’, ‘False’]
Random Forest	N_estimators Max_dept	[5, 50, 100] [2, 10, 20, None]
KNN	n_neighbors weights algorithm p	[3, 5, 7, 9, 11] [‘uniform’, ‘distance’] [‘auto’, ‘ball_tree’, ‘kd_tree’, ‘brute’] [1, 2]

2.6 Model Evaluation

Measurement of algorithm performance is measured using the Confusion Matrix method. The classification results obtained from each model will form a confusion matrix so that it can be used to calculate accuracy, recall, and precision.

3 Result and Discussions

3.1 Crawling Data

Tweets were crawled 11 times according to the keywords followed after #ChatGPT. For example, the first crawl used "#ChatGPT Academic", the second crawl used "#ChatGPT School", and so on. The data retrieved were tweets, id, dates, and usernames with a total of 8,517 crawled data. An example of crawled Twitter data is shown in Table 3.

Table 3. Example of tweet crawling results

Tweet	Id	Date/Time	Username
baru kali ini gw ngerjain ujian pake chatGPT wkwk.. enak bgt tyt, lovvvv	1553693089512194049	02-05-2023 10:33:54+00:00	kmjeongsgf
@RyomenRogue Ngantri chatgpt dulu agaknya 😂	884334345900630016	02-05-2023 10:12:02+00:00	nakaharaRogue
GW CAPEK BANGET NUGAS SAMA CHATGPT PAKE ACARA NGAMBEK SEGALA NI AI	1380431790410584064	08-04-2023 09:29:35+00:00	ambivalens

3.2 Labelling Data

The Indonesian RoBERTa Sentiment Classifier was used for labelling. Table 4 shows an example of the labelling results. The data distribution for each sentiment on the 8,517 tweets after labelling is shown in Fig. 4.

3.3 Undersampling

The labelled tweet data has an unbalanced amount of data, where the number of negative and neutral tweets is more than the number of positive tweets (Fig. 4). Undersampling technique balances the amount of tweet data in each sentiment classification. The amount of tweet data after undersampling is 5000 data, with the number of positive tweets = 1653, negative = 1705 and neutral = 1642. The sentiment distribution after undersampling is shown in Fig. 5.

Table 4 Example of labelling results

Tweet	**Label**	**Score**
baru kali ini gw ngerjain ujian pake chatGPT wkwk.. enak bgt tyt, lovvvv	POSITIVE	0,993
@RyomenRogue Ngantri chatgpt dulu agaknya 😂	NEUTRAL	0,917
GW CAPEK BANGET NUGAS SAMA CHATGPT PAKE ACARA NGAMBEK SEGALA NI AI	NEGATIVE	0,937

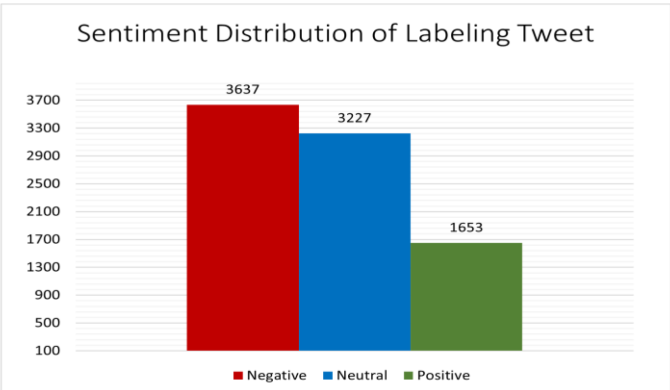

Figure 4. Sentiment Distribution of labelling tweets

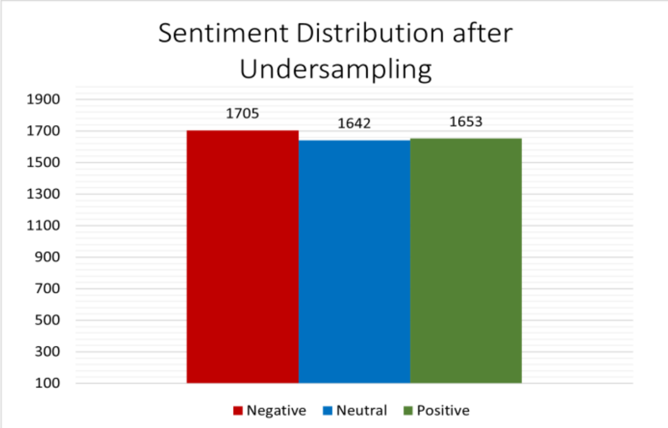

Figure 5. Sentiment Distribution of Tweets After undersampling

3.4 Preprocessing

Preprocessing is done to clean and prepare the tweet data. For example, the tweet data "@RyomenRogue Ngantri chatgpt dulu agaknya 😂" is cleaned through the cleaning stage and produces tweet data as in Table 5. Then, the emoticon conversion stage is applied and produces tweet data, as in Table 6. Next is to shrink all the letters with case folding. The results of case folding are shown in Table 7. The tokenizing stage follows this, and the tokenizing results are shown in Table 8. The next stage is Normalisation. The normalization results are shown in Table 9. The normalization results are then continued with the stopword removal stage. The tweet data after experiencing stopword removal is shown in Table 10. The last stage in preprocessing is stemming. The results of stemming can be seen in Table 11.

Table 5. Cleaning Result

Tweet	Cleaning
@RyomenRogue Ngantri chatgpt dulu agaknya 😂	Ngantri chatgpt dulu agaknya 😂

Table 6. Emoticon Convertion Result

Cleaning	Emoticon Convertion
Ngantri chatgpt dulu agaknya 😂	Ngantri chatgpt dulu agaknya Senang

Table 7. The Case Folding Result

Emoticon Convertion	Case Folding
Ngantri chatgpt dulu agaknya Senang	ngantri chatgpt dulu agaknya senang

Table 8. Tokenize Result

Case Folding	Tokenize
ngantri chatgpt dulu agaknya senang	['ngantri', 'chatgpt', 'dulu', 'agaknya', 'senang']

Table 9. The Normalization Result

Tokenize	Normalization
['ngantri', 'chatgpt', 'dulu', 'agaknya', 'senang']	['mengantri', 'chatgpt', 'dulu', 'agaknya', 'senang']

Table 10. Stopword Removal Result

Normalization	Stopword removal
['mengantri', 'chatgpt', 'dulu', 'agaknya', 'senang']	['mengantri','chatgpt',senang']

Table 11 Stemming Result

Stopword removal	Stemming
['mengantri','chatgpt',senang']	['antri', 'chatgpt', 'senang']

After the Stemming process, 5000 tweet data were divided into two datasets, namely the training and testing dataset, with a ratio of 90:10. So, there are 4500 data tweets in the training dataset and 500 data tweets in the testing data. Furthermore, from 4500 training data, a k-fold cross-validation process is carried out, which divides the training data and validation data according to the k value.

The last process before modelling was feature extraction. Feature extraction is done to convert the data into numerical form and is formed into a matrix for each word. The unigram function in the TF-IDF module calculates the weight of a single word. The results of feature extraction using TF-IDF for the 20 words with the highest weights are shown in Fig. 6.

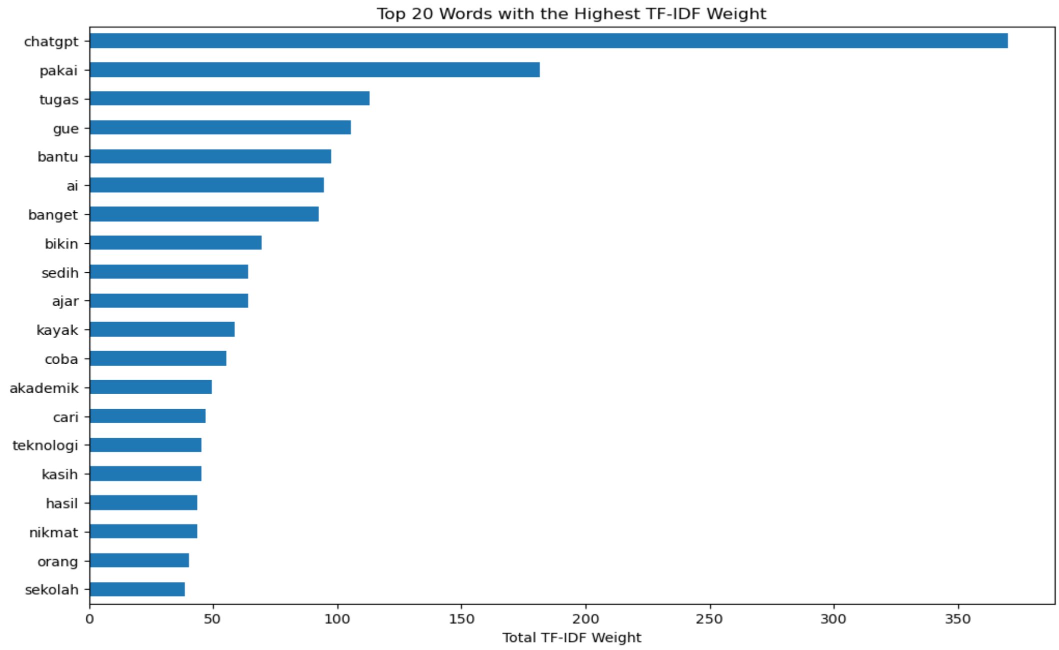

Figure 6. Top 20 Words with Highest TF-IDF Weight

3.5 Modelling Analysis

3.5.1 Support Vector Machine Model (SVM)

The accuracy results of the Support Vector Machine (SVM) on the training dataset were carried out by finding the best parameters between the RBF and Polynomial kernels (see Table 12). The results on the RBF and Polynomial kernels are shown with various Cost values. In contrast, the gamma, coefficient and degree values are fixed because these parameter values are stable and provide good accuracy compared to other parameter values. The best parameters of the SVM model for training data were the 'RBF' kernel with C value = 100 and gamma value = 1. With the K-Fold Cross Validation method K = 10 the SVM model got the best accuracy of 82.94%.

Table 12. The optimal SVM parameter training data results

	C	**Accuracy K=5**	**Accuracy K=7**	**Accuracy K=10**
Combination of RBF *gamma*= 1	0,1 1 10 100	0.4532 0.8161 0.8177 0.8178	0.4612 0.8189 0.8233 0.8245	0.4686 0.8274 0.8284 0.8294

	C	Accuracy K=5	Accuracy K=7	Accuracy K=10
Combination of *Polynomial coefficient* = 1, *degree* = 4	0.1 1 10 100	0.8184 0.8189 0.8199 0.8195	0.8202 0.8225 0.8235 0.8235	0.8283 0.8283 0.8284 0.8284

3.5.2 Ensemble Majority Voting Model

The majority voting model is built with three base classifiers, namely Naïve Bayes, Random Forest and KNN. The three models were optimized by finding the best parameters. The search results for each base classifier are shown in Table 13. The best parameters of the three algorithms are then used in model training with K-Fold cross-validation. It can be seen that the three algorithms get their best accuracy at K = 10, where the accuracy for Naïve Bayes, KNN and Random Forest algorithms are 77.1%, 74.1%, and 80.6%, respectively. The accuracy of the three base classifier compared to SVM (see Fig. 7) showed that these three individual algorithms have a lower accuracy.

Table 13. Base Classifier Parameter Results

Algorithm	**K=5**		**K=7**		**K=10**	
	Parameter	Accuracy	Parameter	Accuracy	Parameter	Accuracy
Naïve Bayes	*alpha:0.5* *fit_prior:False*	0.763	*alpha:0.5* *fit_prior:False*	0.765	*alpha:0.5* *fit_prior:true*	0.771
KNN	*algorithm:auto* *n_neighbors:9* *p:2* *weights:distance*	0.725	*algorithm:auto* *n_neighbors:7* *p:2* *weights:distance*	0.72889	*algorithm:auto* *n_neighbors:11* *p:2* *weights: distance*	0.741
Random Forest	*max_depth: None* *n_estimators:100*	0.789	*max_depth: None* *n_estimators:100*	0.802	*max_depth: None* *n_estimators:100*	0.806

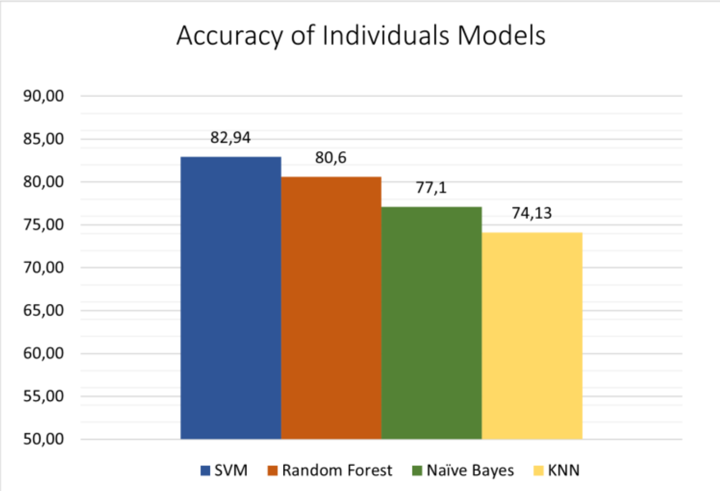

Figure 7. Comparison of individual algorithms

Next, the three base classifier algorithms with lower accuracy than SVM are used as the Majority Voting model builder in testing the test data.

3.5.3 SVM and Majority Voting on Testing Dataset

The SVM and Majority Voting models were tested on 500 testing datasets. The results of both models on the classification of test data are shown in Table 14. From the test results, it can be seen that the Majority Voting results now becoming higher than the Support Vector Machine (SVM) model with precision, recall and accuracy values of 86.04%, 86.09%, and 85.6%, respectively. This proves that the ensemble model works better than the individual classification model. In several previous studies [25]–[27], the ensemble classifiers performed better than the single classifier models. The main reason the ensemble classifier is better than the single model is that it provides a way to reduce the prediction variance, i.e. the amount of error in the prediction made by the single model forming the ensemble. When this occurs, this reduction in variance, in turn, leads to improved prediction performance [28].

Table 14. SVM and Majority Voting Model Results

Performing	SVM	Majority Voting
Precision	0,8392	0,8604
Recall	0,8363	0,8609
Accuracy	0,836	0,856

4 Conclusions

The SVM algorithm provides the best results in performing sentiment classification compared to 3 other algorithms, namely Naïve Bayes, Random Forest, and KNN. The Majority Voting model built with three low-accuracy algorithms (Naïve Bayes, Random Forest and KNN) can produce better accuracy than the SVM model with a difference of 2% where SVM accuracy is 83.6% and Majority voting accuracy is 85.6%. This proved the ensemble model that combines several individual models has successfully improved accuracy in sentiment classification on tweet data using ChatGPT in education.

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