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Sentiment Analysis on Hate Speech Post 2024 Election for Elected President Using a Hybrid Model

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Abstract. One of the important events in the democratic life of a country is the general election. In addition, the possibility of hate speech appearing on social media increases as political tensions increase. This hate speech can take the form of negative comments, insults, or even threats against the elected president. This research uses the content of tweets as a data source to analyze public opinion and sentiment towards the elected president. This research aims to analyze sentiment towards hate speech held by twitter users towards the elected president after the 2024 election by building a hybrid model using 3 algorithms, namely k-nearest neighbors, long short-term memory and naive bayes. The results of tests carried out with 12,000 tweet data that show the naive bayes method classification results have an accuracy of **72**%, the long short-term memory classification results show an accuracy of 78%, the k-nearest neighbors method accuracy value is 83%, and the hybrid model accuracy value is 78%. Considering the accuracy values of the three algorithm method, by using a hybrid model we can increase the accuracy by combining the three algorithm models. from previously having the lowest accuracy of 72%, by using a hybrid model we can increase the accuracy to 78%.

Keywords: Election, Hybrid Model, K-Nearest Neighbors, Long Short-Term Memory, Naive Bayes

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INTRODUCTION

Elections are a significant event in the democratic life of a country. The 2024 election in Indonesia holds great importance as it will determine national policy direction and leadership for the coming years. This election is predicted to be one of the most heated presidential elections in Indonesia's history[1]. Social media has evolved into one of the primary sources of information and political discussion in recent years. However, with the increased use of social media, there has also been a rise in the spread of hate speech and misinformation. Hate speech is a serious issue in the political context[2].

To facilitate the collection of public opinions post-2024 election, data can be gathered from social media. One social networking site I'll utilize is twitter, which will simplify this research in obtaining the necessary data. Comments made by twitter users will serve as the data source[3].

In a previous study titled "Sentiment Analysis of Public Opinion on Presidential Candidates in Preparation for the 2024 Election Using K-Nearest Neighbor and Particle Swarm Optimization" particle swarm optimization (PSO) and the k-nearest neighbors (KNN) approach were used in the study for optimization. The study's primary goal was to examine popular opinion of presidential contenders. The study's findings indicated that although KNN had an accuracy of 65%, PSO optimization increased that accuracy to 95.19%[4]. A similar study titled "Sentiment Analysis Public Twitter on 2024 Election using the Long Short Term Memory Model" employed the LSTM approach to examine public opinion for the election of 2024. The accuracy of this study was 78%. 52.2% of respondents were positive, 37% were negative, and 10.8% were neutral[5]. In a study titled "Application of naive bayes Algorithm and PSO in Sentiment Analysis of 2024 Presidential Candidates" The three primary 2024 presidential contenders were assessed based on the opinions of the general population using particle swarm optimization and naive bayes methodologies. The dataset of anies baswedan had 63.02% accuracy, 65.13% recall, and 64.61% precision, according to the results. The dataset of ganjar pranowo had 85.43% precision, 87.46% recall, and 87.14% accuracy. The dataset of prabowo subianto had 83.17% accuracy, 83.17% recall, and 84.17% precision[6].

Based on previous studies, opinions on the vice-presidential and presidential contenders for the 2024 election are divided into several positive and negative categories. Since there have already been numerous studies examining sentiment towards presidential candidates in the 2024 election, this study will differ by focusing on the sentiment analysis of hate speech towards the elected president after the 2024 election. As a result, a hybrid machine learning model composed of KNN, LSTM, and naive bayes algorithms will be used for sentiment analysis. This study is titled "Sentiment Analysis on Hate Speech Post-2024 Election for Elected President Using a Hybrid Model." The research aims to achieve high accuracy and precision to provide more accurate information on hate speech towards the elected president after the 2024 election.

METHODS

Sentiment analysis is a technique for identifying and comprehending viewpoints or emotions conveyed in written communication[7]. Sentiment analysis can be used in presidential election contexts to detect hate speech aimed at the chosen president following the 2024 election. Machine learning is a useful technique for sentiment analysis[8]. Through the use of sentiment-labeled text data (positive, negative, or neutral), machine learning models can be taught to identify the traits and patterns of text that convey particular sentiments.[9] A hybrid machine learning model is used in this study, which makes use of long short term memory (LSTM), k nearest neighbors (KNN), and naive bayes. Several algorithms are combined in this hybrid machine learning model to produce more optimal outcomes[10]. After the 2024 election, this study will concentrate on tweets that express neutral, favorable, and negative opinions about how a person or group perceives the president who has been elected. Natural language processing (NLP) techniques will be applied to the research subjects in order to examine public opinions regarding the elected president following the 2024 election[11].

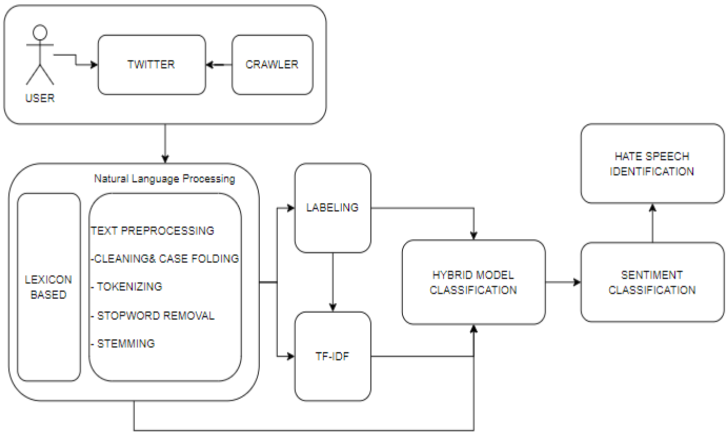

Figure 1. Architecture sentiment analysis

Figure 1. Explain about Architecture sentiment analysis. The first step is crawling, as used in this study, is the practice of autonomously gathering data from webpages. We will utilize the python programming language to collect twitter data[12]. Labeling training and test data, text preprocessing, word weighting, classification using long short term memory (LSTM), k nearest neighbors (KNN), and naive bayes methods, and computing accuracy, precision, and recall are the procedures involved in data processing in this work. The best model will then be evaluated on data without sentiment labels when it has been determined [13]. Tokenizing, remove stopwords, cleaning, case folding, and stemming are some of the phases in the text preparation process. Individual words in their original form are the end product of this process[14]. Thirty percent of the text data from the earlier processing will be used for testing, and seventy percent will be used for training. Raw data without TF-IDF weighting will be utilized for the LSTM model. The model categorization will be carried out by creating and utilizing the proper parameters for each algorithm[15]. After that, the model will be trained to the training set of data so that it can pick up trends throughout the entire set. After obtaining the best model from the long short term memory (LSTM), k nearest neighbors (KNN), and naive bayes algorithms, this model will be implemented to classify text data that still lacks sentiment labels[16]. After these three models have classified the data, we will perform a comparison of

the sentiments provided by each model. Each sentiment output for the given dataset will be compared among the three algorithm models. If the three models choose different sentiments, the algorithm with the highest accuracy during testing will be selected[10].

After obtaining the sentiment analysis predicted as negative by the hybrid model, sentiments labeled as negative will be identified to determine whether these comments constitute hate speech against the elected president post-2024 election or not. The confusion matrix is one of the instruments used to assess a classification model's performance[17]. The hybrid model combines F1-score, recall, and precision. The author can demonstrate how many accurate and inaccurate predictions the hybrid model produced in comparison to the actual known values by using the confusion matrix. We use a three-by-three confusion matrix to classify positive, negative, and neutral sentiments[18].

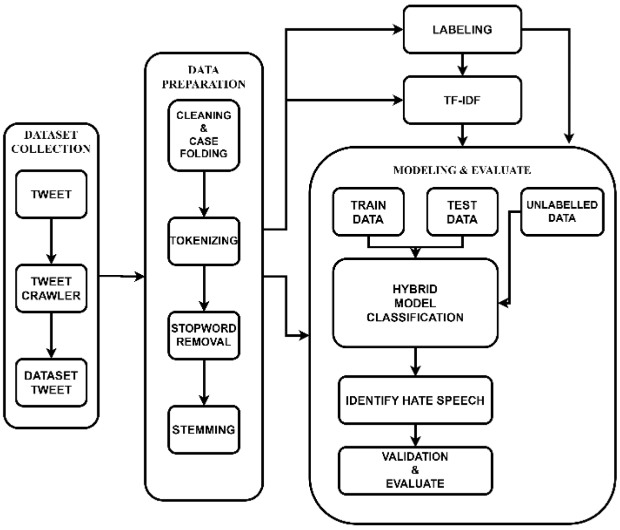

Figure 2. Research stage

Figure 2 is the flow of this research.

1. **Collecting data :**
   The data was obtained from twitter using a crawling technique using the keyword “prabowo curang”, “prabowo pelanggar ham”, “prabowo tempramental”, “prabowo galak”, “prabowo jahat”, “prabowo tidak tahu malu”, “prabowo penipu”, “prabowo pembunuh”, “prabowo pembohong”, “prabowo pendusta”, “prabowo penghianat”, “prabowo penjahat”, “prabowo kejam”, “prabowo pelit”, “prabowo mati”, “prabowo korupsi”, “prabowo suap”, “prabowo licik”, “prabowo pecundang”, “prabowo munafik”, “prabowo pengecut”, “prabowo tukang tipu”, “Prabowo arogan”, “Prabowo manipulatif”, “Prabowo pelanggar hukum”, “prabowo bodoh”, “prabowo sombong”, “prabowo serakah”, “prabowo biadab”, “Prabowo pembual”, “prabowo busuk”, “prabowo kasar”, and “prabowo kalah” within the range of February 15, 2024, to June 30, 2024. The total number of data collected by combining all the keywords above is approximately 12,000 tweets.
2. **Data preperation :**
   In this stage there are several activities carried out, namely cleaning & case folding, tokenization, stopwords removal, stemming, sentiment labeling and TF-IDF.
3. **Modelling & evaluate :**
   The modeling and evaluation stage is the stage of building a hybrid model and evaluating it to get the best results.

RESULT AND DISCUSSION

In this study, data is collected from the social media platform twitter (X). The python programming language is used to retrieve tweets, which are stored in a CSV file format. And from the 12,000 crawled data comments, only the data in the "Full_text" column will be used as the input feature, as this column contains the tweets from twitter users.

```
                                                full_text
Kenapa kemenhan ngutang? Karena Jokowi yang cu...
@IrawanRommi @bengkeldodo @are_inismyname @pra...
```

Figure 3. Data about prabowo

The python programming language will be used to process the previously acquired and combined data. Because the data is more structured, this is done to make classification by the model easier.

Preprocessing text

1. Cleansing and case folding

The data will be cleaned throughout this process to remove different characters like whitespace, emoticons, URLs, digits, mentions, and hashtags. Additionally, the letters will be uniformly converted to lowercase.

```
                                       cleaned_text
0  kenapa kemenhan ngutang karena jokowi yang cur...
1             emang yg ngatur stategi  kalau dia...
```

Figure 4. Cleansing and case folding data

2. Tokenizing

The process of dividing text into manageable chunks in the form of words, phrases, or symbols known as tokens is known as tokenization. The goal of this tokenization is to make the processes of stemming, normalization, and stopword elimination easier.

```
                                     tokenized_text
0  [kenapa, kemenhan, ngutang, karena, jokowi, ya...
1  [emang, yg, ngatur, stategi, kalau, dia, punya...
```

Figure 5. Tokenize data

3. Stopwords removal

The technique of eliminating words or tokens, including as conjunctions, prepositions, and articles, that have no bearing on sentiment is known as stopword removal. In order to improve the model's accuracy in predicting sentiment, stopword reduction aims to reduce the number of characteristics that have no bearing on sentiment.

```
                              Stopwords_removal_text
0  [kemenhan, ngutang, jokowi, curang, dipercaya,...
1  [emang, yg, ngatur, stategi, strategi, kalah, ...
```

Figure 6. Stopwords removal data

4. Stemming

The process of stemming involves deleting inserts, suffixes, and affixes to make words or tokens into fundamental words. In natural language processing (NLP) and text analysis, stemming is mostly used to reduce and harmonize disparate word forms with same underlying meanings. Stemmerfactory from sastrawi is the stemmer that is utilized in this procedure.

```
                                       stemmed_text
0  [kemenhan, ngutang, jokowi, curang, percaya, n...
1  [emang, yg, ngatur, stategi, strategi, kalah, ...
```

Figure 7. Stemming data

5. Sentiment Labeling

The data resulting from the preprocessing process will be labeled to determine the sentiment class of the dataset. In this sentiment analysis, the target sentiment classes are positive, neutral, and negative. Data labeling is done using a lexicon-based method. This method uses a sentiment dictionary from inset

```
                                        stemmed_text sentiment
0  ['kemenhan', 'ngutang', 'jokowi', 'curang', 'p...  negative
1  ['emang', 'yg', 'ngatur', 'stategi', 'strategi...  negative
```

Figure 8. Labeling data

6. feature extraction

The preprocessed data will be weighted based on the number of documents (d), term frequency (tf), which measures how frequently a word appears in each document, and document frequency (df), which counts the number of documents that contain a given phrase. Furthermore taken into account is inverse document frequency (idf), which is the inverse of the quantity of documents that contain a given word. Following the weighting procedure, TF-IDF data with and without sentiment labels will be produced.

```
First 5 rows of tfidf_data_with_sentiment:
   aaaaaa  aaah  aaahmasaaak  aaahyang  aaakh  aah  aahhh  aam  aamiiiiin  \
0     0.0   0.0          0.0       0.0    0.0  0.0    0.0  0.0        0.0
1     0.0   0.0          0.0       0.0    0.0  0.0    0.0  0.0        0.0
2     0.0   0.0          0.0       0.0    0.0  0.0    0.0  0.0        0.0
3     0.0   0.0          0.0       0.0    0.0  0.0    0.0  0.0        0.0
4     0.0   0.0          0.0       0.0    0.0  0.0    0.0  0.0        0.0

   aamiiiin  ...  zonkkk  zonkkkkk  zoyazareen  zulhas  zulkifi  zulkifli  \
0       0.0  ...     0.0       0.0         0.0     0.0      0.0       0.0
1       0.0  ...     0.0       0.0         0.0     0.0      0.0       0.0
2       0.0  ...     0.0       0.0         0.0     0.0      0.0       0.0
3       0.0  ...     0.0       0.0         0.0     0.0      0.0       0.0
4       0.0  ...     0.0       0.0         0.0     0.0      0.0       0.0

   zulkiflihasan  zumanji  zym  sentiment
0            0.0      0.0  0.0   negative
1            0.0      0.0  0.0   negative
2            0.0      0.0  0.0   negative
3            0.0      0.0  0.0   negative
4            0.0      0.0  0.0   negative
```

Figure 9. TF-IDF data with sentiment

```
First 5 rows of tfidf_unlabelled:
   aaaaaa  aaah  aaahmasaaak  aaahyang  aaakh  aah  aahhh  aam  aamiiiiin  \
0     0.0   0.0          0.0       0.0    0.0  0.0    0.0  0.0        0.0
1     0.0   0.0          0.0       0.0    0.0  0.0    0.0  0.0        0.0
2     0.0   0.0          0.0       0.0    0.0  0.0    0.0  0.0        0.0
3     0.0   0.0          0.0       0.0    0.0  0.0    0.0  0.0        0.0
4     0.0   0.0          0.0       0.0    0.0  0.0    0.0  0.0        0.0

   aamiiiin  ...  zonk  zonkkk  zonkkkkk  zoyazareen  zulhas  zulkifi  \
0       0.0  ...   0.0     0.0       0.0         0.0     0.0      0.0
1       0.0  ...   0.0     0.0       0.0         0.0     0.0      0.0
2       0.0  ...   0.0     0.0       0.0         0.0     0.0      0.0
3       0.0  ...   0.0     0.0       0.0         0.0     0.0      0.0
4       0.0  ...   0.0     0.0       0.0         0.0     0.0      0.0

   zulkifli  zulkiflihasan  zumanji  zym
0       0.0            0.0      0.0  0.0
1       0.0            0.0      0.0  0.0
2       0.0            0.0      0.0  0.0
3       0.0            0.0      0.0  0.0
4       0.0            0.0      0.0  0.0
```

Figure 10. TF-IDF data without sentiment

Modelling

Thirty percent of the text data from the earlier processing will be used for testing, and seventy percent will be used for training. This ratio is commonly used to provide enough data for the model to learn while maintaining sufficient data for evaluation. Even in unbalanced datasets, this approach ensures a baseline for model performance comparison. For the LSTM model, the data used will be the raw data from preprocessing, without TF-IDF weighting. To classify the model, appropriate parameters for each algorithm will be created and applied. Then, the model will be fitted to the training data so it can learn patterns from all the data, helping the model capture the nuances even in imbalanced data. After that, the model will attempt to predict the classes on the test data, resulting in evaluation scores in the next stage. this study did not compare the 80% : 20% dataset and 90% : 10% dataset, because the resulting data is not optimal. therefore 70% testing dataset is used: 30% to produce optimal model accuracy.

Once the best model is determined from the LSTM, KNN, and Naive Bayes algorithms, the model will be implemented to classify 12,000 text data points that don’t have sentiment labels. For this stage, a hybrid model with a voting system will be used. The three models (LSTM, KNN, and Naive Bayes) will vote on the sentiment classification for each piece of text. In cases where the votes differ, the model with the highest accuracy during the testing phase (in this case, the LSTM) will make the final decision. This ensures that the most reliable model is used when consensus is not reached.

By using 100% of the data in this final step, the models can leverage all available information to classify the unseen data, maximizing the accuracy and robustness of the predictions, especially in a hybrid voting system.

1. Creating KNN, LSTM, and Naive Bayes algorithm models

30% of the dataset is used for testing, and the remaining 70% is used for training. The accuracy of each model in performing sentiment analysis on the prepared dataset will be determined after training and testing all three model. As the result KNN achieved an accuracy of 87%, naive bayes 82%, and LSTM achieved an accuracy of 92%.

```
KNN Accuracy: 0.8733
Naive Bayes Accuracy: 0.8281
LSTM Accuracy: 0.9200
```

Figure 11. KNN, LSTM and naive bayes accuracy

2. Creating Hybrid Model

In this stage of the research, the author combines various machine learning models' outputs using a hybrid method. Specifically, the LSTM, KNN, and Naive Bayes algorithms are combined to test 12,000 unlabeled sentiment data. The sentiment output for the given dataset is compared among these three models. If the models produce different sentiment predictions, the one with the highest accuracy during testing is selected, with LSTM being prioritized in cases of a tie. Additionally, a voting technique is employed in the hybrid method. For each sentiment prediction, if two or more algorithms agree on the same sentiment, that sentiment will be chosen. This approach ensures a more robust sentiment classification by leveraging the consensus between models.

```
Negative: 10603
Neutral: 528
Positive: 869
```

Figure 12. hybrid model output

After testing using the hybrid model, it was found that out of the 12,000 data points tested, 10,603 were negative, 528 were neutral, and 869 were positive.

```
Accuracy of KNN : 0.83
Accuracy of Naive Bayes : 0.72
Accuracy of LSTM : 0.78
Accuracy of Hybrid Model: 0.78
```

Figure 13. Accuracy of KNN, LSTM, naive bayes and hybrid model

It was found that the accuracy of the KNN algorithm on the new data was 83%, for naive bayes it was 72%, and for LSTM it was 78%. The accuracy of the hybrid model was found to be 78%, Hybrid models in machine learning refer to approaches that combine two or more techniques or models to improve prediction performance or accuracy. This approach typically utilizes the strengths of each model to overcome the weaknesses of the other.

3. Confussion matrix 3 x 3

At this stage, a 3x3 confusion matrix will be used to evaluate the performance of the KNN, LSTM, naive bayes, and hybrid models. This will be demonstrated by comparing the model's number of accurate and inaccurate predictions with the known actual values, yielding an F1 score, accuracy, precision, and recall for the sentiment. Here are the results of the 3x3 confusion matrix for KNN.

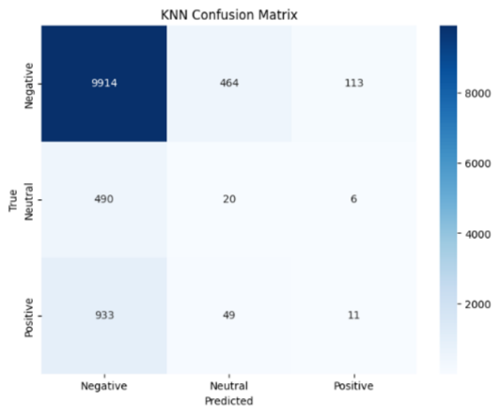

Figure 14. KNN confusion matrix

From figure 14 confusion matrix, the precision, recall and f1-score values of each sentiment class can be calculated as follows.

	negative	netral	positive
Presisi	$\frac{9914}{9914+490+933}=0{,}87$	$\frac{20}{464+2+49}=0{,}03$	$\frac{11}{113+6+11}=0{,}08$
Recall	$\frac{9914}{9914+464+113}=0{,}94$	$\frac{20}{490+20+6}=0{,}03$	$\frac{11}{933+49+11}=0{,}01$
F1-score	$2*\frac{0{,}87\times 0{,}94}{0{,}87+0{,}94}=0{,}90$	$2*\frac{0{,}03\times 0{,}03}{0{,}03+0{,}03}=0{,}03$	$2*\frac{0{,}08\times 0{,}01}{0{,}08+0{,}01}=0{,}01$
Accuracy	$\frac{9914+20+11}{12000}=0{,}83$		

Figure 15. Validate KNN model

Here are the results of the 3x3 confusion matrix for LSTM.

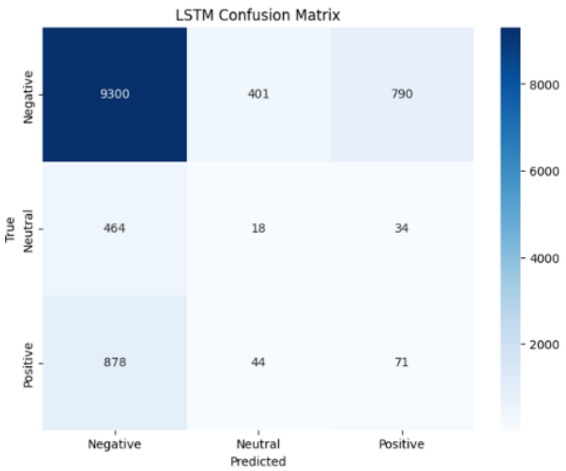

Figure 16. LSTM confusion matrix

From figure 16 confusion matrix, the precision, recall and f1-score values of each sentiment class can be calculated as follows.

	negative	netral	positive
Presisi	$\frac{9300}{9300+464+878}=0{,}87$	$\frac{18}{401+18+44}=0{,}03$	$\frac{71}{790+34+71}=0{,}08$
Recall	$\frac{9300}{9300+401+790}=0{,}88$	$\frac{18}{464+18+34}=0{,}03$	$\frac{71}{878+44+71}=0{,}07$
F1-score	$2*\frac{0{,}87\times 0{,}88}{0{,}87+0{,}88}=0{,}87$	$2*\frac{0{,}03\times 0{,}03}{0{,}03+0{,}03}=0{,}03$	$2*\frac{0{,}08\times 0{,}07}{0{,}08+0{,}07}=0{,}07$
Accuracy	$\frac{9300+18+71}{12000}=0{,}78$		

Figure 17. Validate LSTM model

Here are the results of the 3x3 confusion matrix for naïve bayes.

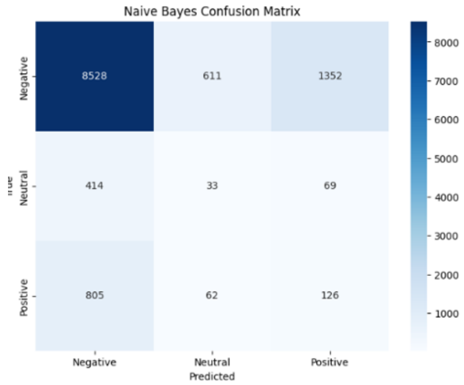

Figure 18. Naive bayes confusion matrix

From figure 18 confusion matrix, the precision, recall and f1-score values of each sentiment class can be calculated as follows.

	negative	netral	positive
Presisi	$\frac{8528}{8528+414+805} = 0{,}87$	$\frac{33}{611+33+62} = 0{,}05$	$\frac{126}{1352+69+126} = 0{,}08$
Recall	$\frac{8528}{8528+611+1352} = 0{,}81$	$\frac{33}{414+33+69} = 0{,}06$	$\frac{126}{805+62+126} = 0{,}13$
F1-score	$2 * \frac{0{,}87 \times 0{,}81}{0{,}87+0{,}81} = 0.83$	$2 * \frac{0{,}05 \times 0{,}06}{0{,}05+0{,}06} = 0{,}05$	$2 * \frac{0{,}08 \times 0{,}13}{0{,}08+0{,}13} = 0{,}09$
Accuracy	$\frac{8528+33+126}{12000} = 0{,}72$		

Figure 19. Validate naive bayes model

Here are the results of the 3x3 confusion matrix for hybrid model.

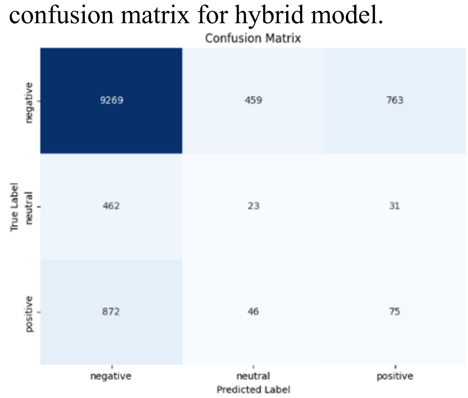

Figure 20. Hybrid model confussion matrix

From figure 20 confusion matrix, the precision, recall and f1-score values of each sentiment class can be calculated as follows.

	negative	netral	positive
Presisi	$\frac{9269}{9269+462+872} = 0{,}87$	$\frac{23}{459+23+46} = 0{,}04$	$\frac{75}{763+31+75} = 0{,}09$
Recall	$\frac{9269}{9269+459+763} = 0{,}88$	$\frac{17}{462+23+31} = 0{,}03$	$\frac{75}{75+46+872} = 0{,}07$
F1-score	$2 * \frac{0{,}87 \times 0{,}88}{0{,}87+0{,}88} = 0.88$	$2 * \frac{0{,}04 \times 0{,}03}{0{,}04+0{,}03} = 0{,}03$	$2 * \frac{0{,}09 \times 0{,}07}{0{,}09+0{,}07} = 0{,}08$
Accuracy	$\frac{9269+23+75}{12000} = 0{,}78$		

Figure 21. Validate hybrid model

In figure 21, The hybrid model's accuracy is 78%, which indicates that 78% of the time it properly classifies the data. Precision is defined as the difference between the actual data and the predicted findings, with 87% of the predictions being negative. By dividing the total number of true negative examples by the number of true negative predictions, recall is computed to represent how well the model retrieves data. The results show a negative recall of 88%. The f1-score is an important metric for measuring classification model performance. A high f1-score indicates good precision and recall, and the f1-score for negative this model is 88%.

Hate speech identification

At this stage, identification will be carried out on the negative sentences predicted as negative by the hybrid model. This identification is used to determine whether the sentences constitute hate speech towards the elected president after the 2024 election or not. The process involves taking the results of the sentiment analysis already classified as negative by the hybrid model, and then checking if the text contains the word "Prabowo". If the word "Prabowo" is found in the sentence, it will be identified as hate speech towards the elected president. If not, it will be treated as general negative sentiment without hate speech implications.

```
Total ujaran kebencian terhadap presiden terpilih: 5063
Ujaran kebencian terhadap presiden terpilih (10 samples):
- ['kemenhan', 'ngutang', 'jokowi', 'curang', 'percaya', 'ngutang', 'legitimate',
- ['menteri', 'ngutang', 'jokowi', 'curang', 'percaya', 'ngutang', 'legitimate',
```

Figure 22. Hate speech identification

Figure 22. Explain after performing hate speech identification, it was found that out of 10,701 data points labeled as negative sentiment by the hybrid model, 5,063 are instances of hate speech towards the elected president after the 2024 election.

Data visualization

At this stage, the results from the hybrid model will be visualized using bar charts, word clouds, time series, and radar charts for each sentiment class. Here is the sentiment visualization using bar chart.

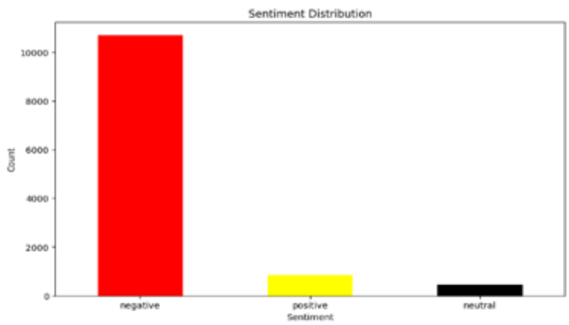

Figure 23. Bar chart

Here is the sentiment visualization using word clouds

Figure 24. Word cloud for negative sentiment

Figure 25. Word cloud for neutral sentiment

Figure 26. Word cloud for positive sentiment

Here is the sentiment visualization using time series

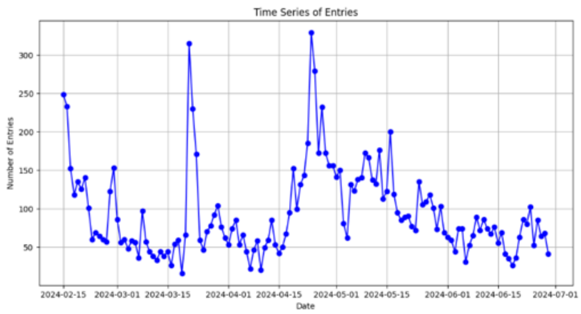

Figure 27. Time series diagram

Here is the sentiment visualization using time series

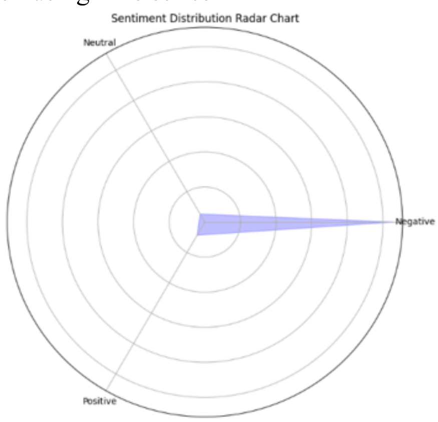

Figure 28. Radar chart

CONCLUSION

An accuracy of 72% was attained by the naive bayes classification approach, 78% by the LSTM classification method, 83% by the KNN classification method, and 78% by the hybrid model classification method. By merging the three methods, the hybrid model can increase accuracy based on the accuracy values of the three algorithms utilized. When employing the hybrid model, accuracy went to 78% from the initial lowest of 72%. As a result, there are more negative sentiment than neutral and positive sentiments, suggesting that a greater proportion of twitter users expressed negative opinions. Based on the sentiment analysis results, it was found that 5,063 opinions are hate speech against the elected president post-2024 election.

REFERENCES

[1] D. Faroek, M. Yusuf, and G. Syatauw, "Sentiment Analysis of the Popularity of Parties Supporting the 2024 Presidential Candidates on Twitter Using the Naive Bayes Classifier Algorithm," *Antivirus J. Ilm. Tek. Inform.*, vol. 17, no. 2, pp. 216–227, 2023, doi: 10.35457/antivirus.v17i2.3261.

[2] R. P. Bastoni, "Analisis Sentimen Opini Publik Terhadap Calon Presiden Indonesia 2024 Menggunakan Metode Naive Bayes Dan Lexicon Based Pada Platform YouTube Skripsi Oleh," 2024.

[3] Z. Febrian, "Perbandingan Algoritma Klasifikasi Naïve Bayes, Logistic Regression, Dan KNN Untuk Analisis Sentimen Peminatan Masyarakat Terhadap Kandidat Bakal Calon …," 2023, [Online]. Available: https://repository.ar-raniry.ac.id/id/eprint/34820/%0Ahttps://repository.ar-raniry.ac.id/id/eprint/34820/1/LAPORAN TUGAS AKHIR %28Zakwan Febrian%29 %281%29 %281%29.pdf

[4] M. S. Hazimi, "Analisis Sentimen Masyarakat terhadap Calon Kandidat Presiden dalam Persiapan Pemilu Tahun 2024 dengan menggunakan Metode K-Nearest Neigjbor dan Optimasi Particle Swarm Optimization," p. 101, 2024, [Online]. Available: https://repository.uinjkt.ac.id/dspace/handle/123456789/76789

[5] D. A. Firdlous, R. Andrian, and S. Widodo, "Sentiment Analysis Public Twitter on 2024 Election using the Long Short Term Memory Model," *Sistemasi*, vol. 12, no. 1, p. 52, 2023, doi: 10.32520/stmsi.v12i1.2145.

[6] Endrik, A. Nugroho, and A. T. Zy, "Penerapan Algoritma Naive Bayes dan PSO pada Analisis Sentimen Kandidat Calon Presiden 2024," *Remik Ris. dan E-Jurnal Manaj. Inform. Komput.*, vol. 7, no. 3, pp. 1367–1380, 2023.

[7] A. Saepudin, "Komparasi Algoritma Support Vector Machine Dan K-Nearest Neighbor Berbasis Particle Swarm Optimization Pada Analisis Sentimen Fenomena Tagar #2019Gantipresiden," *Progr. Stud. Magister Ilmu Komput. Sekol. Tinggi Manaj. Inform. Dan Komput. Nusa Mandirikomputer Nusa Mandiri*, 2018.

[8] A. R. Rivita, Yusra, and M. Fikry, "Klasifikasi Sentimen Masyarakat di Media Sosial Twitter terhadap Calon Presiden 2024 Prabowo Subianto dengan Metode K-NN," *KLIK Kaji. Ilm. Inform. dan Komput.*, vol. 3, no. 6, pp. 786–797, 2023, doi: 10.30865/klik.v3i6.890.

[9] A. Tresnani, I. T. R. Yanto, and R. Hidayat, "Preferensi Pengguna Twitter Terhadap Calon Presiden dan Wakil Presiden Indonesia 2024," *JITSI J. Ilm. Teknol. Sist. Inf.*, vol. 5, no. 1, pp. 9–16, 2024, doi: 10.30630/jitsi.5.1.216.

[10] R. Afrinanda, L. Efrizoni, W. Agustin, and R. Rahmiati, "Hybrid Model for Sentiment Analysis of Bitcoin Prices using Deep Learning Algorithm," *MATRIK J. Manajemen, Tek. Inform. dan Rekayasa Komput.*, vol. 22, no. 2, pp. 309–324, 2023, doi: 10.30812/matrik.v22i2.2640.

[11] M. Alfonso and D. B. Rarasati, "Sentiment Analysis of 2024 Presidential Candidates Election Using SVM Algorithm," *JISA(Jurnal Inform. dan Sains)*, vol. 6, no. 2, pp. 110–115, 2023, doi: 10.31326/jisa.v6i2.1714.

[12] F. A. Wenando, R. Hayami, and A. J. Anggrawan, "Analisis Sentimen Pada Pemerintahan Terpilih Pada Pilpres 2019 Ditwitter Menggunakan Algoritme Naïvebayes," *JURTEKSI (Jurnal Teknol. dan Sist. Informasi)*, vol. 7, no. 1, pp. 101–106, 2020, doi: 10.33330/jurteksi.v7i1.851.

[13] F. T. Industri and U. I. Indonesia, "Analisis Sentimen Calon Presiden Indonesia 2024 Di Facebook Menggunakan Metode Support Vector Machine (Svm) Analisis Sentimen Calon Presiden Indonesia 2024 Di Facebook Menggunakan Metode Support Vector Machine (Svm)," 2024.

[14] Y. Findawati, U. Indahyanti, Y. Rahmawati, and R. Puspitasari, "Sentiment Analysis of Potential Presidential Candidates 2024: A Twitter-Based Study," *Acad. Open*, vol. 8, no. 1, pp. 1–17, 2023, doi: 10.21070/acopen.8.2023.7138.

[15] I. Iin, R. Supriatna, M. Mulyawan, and D. Rohman, "Penerapan Natural Language Processing Dalam Analisis Sentimen Cawapres 2024 Menggunakan Algoritma Naive Bayes," *JATI (Jurnal Mhs. Tek. Inform.*, vol. 8, no. 1, pp. 1109–1115, 2024, doi: 10.36040/jati.v8i1.8572.
[16] Z. C. Dwinnie and R. Novita, "Penerapan Machine Learning Pada Analisis Sentimen Twitter Sebelum dan Sesudah Debat Calon Presiden dan Wakil Presiden Tahun 2024," vol. 8, no. April, pp. 758–767, 2024, doi: 10.30865/mib.v8i2.7504.
[17] C. Prianto, N. H. Harani, and I. Firmansyah, "Analisis Sentimen Terhadap Kandidat Presiden Republik Indonesia Pada Pemilu 2019 di Media Sosial Twitter," *J. Media Inform. Budidarma*, vol. 3, no. 4, p. 405, 2019, doi: 10.30865/mib.v3i4.1549.
[18] H. Permana, Y. Herry Chrisnanto, and H. Ashaury, "Analisis Sentimen Terhadap Bakal Calon Presiden 2024 Dengan Algoritma Multinomial Naïve Bayes Dan Oversampling Smote," *JATI (Jurnal Mhs. Tek. Inform.*, vol. 7, no. 5, pp. 3257–3264, 2024, doi: 10.36040/jati.v7i5.7309.