JURTEKSI (Jurnal Teknologi dan Sistem Informasi) ISSN 2407-1811 (Print)
Vol. XII No 1, Desember 2025, hlm. 121 – 128 ISSN 2550-0201 (Online)
DOI: http://dx.doi.org/ 10.33330/jurteksi.v12i1.4170
Available online at http://jurnal.stmikroyal.ac.id/index.php/jurteksi

COMPARISON SVM, RF, BERT PUBLIC SENTIMENT DATA MBG IN X

Gustri Efendi[1*], Rus Yandi[2], Rani Aprilia[1], Irvan Amaroh Bit Taqwa[1]
[1]Information System, Nahdlatul Ulama University West Sumatera
[2]Department Of Law, Nahdlatul Ulama University West Sumatera
email: *gustriefendi@gmail.com

Abstract: MBG is a strategic program of the Prabowo-Gibran administration. This program has become a widely discussed issue in the public. To better understand public perception of this program, sentiment analysis is necessary. This study aims to compare the performance of algorithms *machine learning SVM, RF,* And *BERT* with *preprocessing data* analyzing public sentiment of the MBG program in media X. The total dataset for this study was 39,858 out of 42,465 successfully crawled tweets. The research methods included data collection, *preprocessing data (cleaning, case folding,* word normalization, *stopword removal* and *stemming),* feature extraction, model training (*fine-tuning*), handling *class imbalance* with SMOTE, and evaluation using accuracy, precision, *recall,* and *f1-score.* The research results show that without SMOTE, the best performing models are BERT with 89% accuracy, SVM 87%, and RF 78.4%. After SMOTE, the best algorithms were SVM with 92.94%, BERT with 88.3%, and RF with 86.59%. The results confirmed that SVM is the best algorithm if at least*class imbalance.* BERT is the best algorithm before and after SMOTE, because BERT is more effective in capturing the nuances of language on social media, so BERT is the most recommended in MBG sentiment analysis**.**

Keywords: sentiment analysis; machine learning; SVM, RF, and BERT

Abstrak: MBG merupakan program strategis pemerintahan Prabowo - Gibran. Program ini menjadi isu yang banyak diperbincangkan publik. Untuk mengetahui lebih dalam persepsi masyrakat tentang program ini, perlu dilakukan analisis sentiment. Penelitian ini bertujuan membandingkan kinerja algoritma *machine learning SVM, RF,* dan *BERT* dengan *preprocessing data* menganalisis sentiment public program MBG di media X. Total dataset penelitian ini adalah 39.858 dari 42.465 tweet yang berhasil di crawling. Metode penelitian mencakup pengumpulan data, *preprocessing data (cleaning, case folding,* normalisasi kata, *stopword removal* dan *stemming),* ekstraksi fitur, pelatihan model (*fine-tuning*), penanganan *class imbalance* dengan SMOTE, dan evaluasi menggunakan akurasi, presisi, *recall,* dan *f1-score.* Hasil peneltian menunjukkan, tanpa SMOTE model dengan kinerja terbaik adalah BERT dengan akurasi 89%, SVM 87%, dan RF 78,4%. Setelah SMOTE algoritma terbaik adalah SVM 92,94%, BERT 88,3% dan RF 86,59%. Hasil penelitian menegaskan bahwa SVM adalah algoritma terbaik jika minimal *class imbalance.* BERT adalah algoritma terbaik sebelum dan sesudah SMOTE, karena BERT lebih efektif dalam menangkap nuansa bahasa pada media sosial, sehingga BERT paling di rekomendasikan dalam analisis sentimen MBG.

Kata kunci: analisis sentimen; machine learning; SVM, RF, dan BERT

INTRODUCTION

Developments in artificial intelligence technology, particularly in the field of machine learning, have driven significant progress in large-scale textual data analysis. One widely used application is sentiment analysis, which aims to identify trends in public opinion, attitudes, and emotions toward an issue based on unstructured text data.[1].

Media X generates a large amount of public opinion data characterized by dynamic, informal, and contextual language. This makes sentiment analysis a potential approach for quickly understanding public perceptions of public policy based on data[1][2]. The Free Nutritious Meal Program (MBG) is a national strategic policy directly related to the welfare and quality of human resources. Its implementation has triggered diverse public responses, widely recorded on social media, necessitating analytical methods capable of accurately capturing the complexity of language and the diversity of public opinion[3][4].

Algoritma Support Vector Machine (SVM) dan Random Forest (RF) dikenal memiliki stabilitas kinerja yang baik pada tugas klasifikasi teks[5][6][7], while transformer-based models such as Bidirectional Encoder Representations from Transformers (BERT) show superiority in understanding semantic context through the mechanism of pre-trained language models[3][8]. These different characteristics mean that each algorithm has different data processing requirements and modeling strategies. Furthermore, the data preprocessing stage is also a critical factor influencing sentiment analysis performance[9][10].

Based on a review of previous research, several relevant research gaps remain. First, comparative studies comparing SVM, RF, and BERT algorithms simultaneously within an integrated experimental framework using the same dataset are still limited. Second, the influence of varying data preprocessing methods on the performance of the three algorithms has not been comprehensively evaluated. Third, sentiment analysis of the MBG Program, a relatively new public policy, has not been widely studied using an algorithm-based comparative approach. Based on these issues, this study aims to compare the performance of SVM, Random Forest, and BERT algorithms in analyzing public sentiment toward the MBG Program in Media X.

METHOD

The research stages consist of Crawling data from media X, Initial data analysis, Data preprocessing, Analysis of preprocessed data, Data labeling using Lexicon Based dictionary, Data extraction using TF-IDF feature, Sentiment analysis using SVM, RF, and BERT algorithms, and Model analysis and comparison. The data that was successfully crawled was 42,465 tweets with keywords related to the MBG program using Twitter auth token in the period January 1, 2025 – August 31, 2025.

RESULTS AND DISCUSSION

Data successfully crawled from media X was 42,465 tweets. After removing duplicate data, 39,858 remained.

JURTEKSI (Jurnal Teknologi dan Sistem Informasi) ISSN 2407-1811 (Print)
Vol. XII No 1, Desember 2025, hlm. 121 – 128 ISSN 2550-0201 (Online)
DOI: http://dx.doi.org/ 10.33330/jurteksi.v12i1.4170
Available online at http://jurnal.stmikroyal.ac.id/index.php/jurteksi

```
# FUNGSI HAPUS DATA DUPLIKAT
# ==============================

# FUNGSI HAPUS DATA DUPLIKAT
df.drop_duplicates(subset="full_text", keep='first', inplace=True)

# Tampilkan
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 39858 entries, 0 to 42464
Data columns (total 1 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   full_text  39858 non-null  object
dtypes: object(1)
memory usage: 622.8+ KB
```

Figure 1: Duplicate data removal

Preprocessing Data

The preprocessing stages in this study include Cleaning, Case folding, word normalization, Tokenization, Stopword Removal, and Stemming. Cleaning in this study includes cleaning data from emoticons, symbols and pictographs, transport and maps and symbols. Case folding changes text data to lower case. The word normalization process in this study refers to kamuskatabaku.xlsx downloaded from Kaggle. Tokenization is the process of breaking text (string) into tokens. Stopword Removal is the process of removing or filtering very common words (high frequency words) and does not have significant information value or meaning in a text analysis. Stemming data is one of the techniques in data preprocessing to change or convert words to their basic form / root words[11][12].

Data Labeling

The stage of analyzing text data based on a lexicon-based dictionary. The following are the results of data labeling:

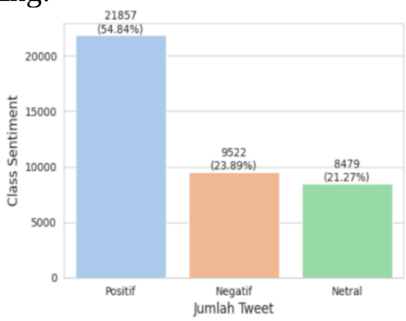


Figure 2: Data labeling results

SVM, RF, and BERT Modeling

TF-IDF is a technique in NLP and information retrieval to measure how important a word is in a document relative to a set of documents [13][14].

$$TF(\mathrm{t},\mathrm{d}) = \frac{f(t,d)}{\sum_k f(k,d)} \qquad (1)$$

Information:

t = term/word

d = document

f (t, d) = number of occurrences of t in d

denominator = total words in d

$$IDF(t) = \log \frac{N}{df(t)} \qquad (2)$$

Information:

N = number of documents

df(t) = number documents containing t

$$TF - IDF(t,d) = TF(t,d)\ x\ IDF(t) \quad (3)$$

```
Feature Extraction Selesai!!!
===== Bentuk Transformasi Feature Extraction ====
(39858, 26496)

===== Top 20 Terms by Total TF-IDF  Score ======
                     term    tfidf_sum
14257                 mbg  2562.858114
7728                 gizi  2044.800427
13623               makan  2043.048686
7944               gratis  1819.362089
19605             program  1732.119187
```

Figure 3 : TF-IDF

Import the components needed for data analysis and train_test_split to divide the data into training data and testing data, Accuracy _score to measure prediction accuracy, confusion matrix for classification evaluation.

```
🔍 Menggunakan DataFrame 'data'...
✅ DataFrame 'data' ditemukan!
📊 Shape: (39858, 3)
📋 Kolom: ['steming_data', 'Score', 'Label']
✅ Jumlah data: 39858
📊 Distribusi label:
Positif    21857
Negatif     9522
Netral      8479
Name: count, dtype: int64
📄 Contoh teks: bijak mbg target luas manfaat rakyat indonesia rasa manfaat.
🔢 X shape (TF-IDF): (39858, 5000)
✅ Data siap untuk training!
📚 Training set: 31886 teks
🧪 Test set: 7972 teks
🔢 Mapping label untuk BERT:
{'Negatif': 0, 'Netral': 1, 'Positif': 2}
```

Figure 4: Preparation for data analysis

Random Forest (RF)

RF is an ensemble learning-based ML algorithm that combines multiple decision trees to generate predictions[15].

$$Accuracy = \frac{\sum Prediksi\ Benar}{Total\ Data} \qquad (4)$$

JURTEKSI (Jurnal Teknologi dan Sistem Informasi) ISSN 2407-1811 (Print)
Vol. XII No 1, Desember 2025, hlm. 121 – 128 ISSN 2550-0201 (Online)
DOI: http://dx.doi.org/ 10.33330/jurteksi.v12i1.4170
Available online at http://jurnal.stmikroyal.ac.id/index.php/jurteksi

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

Information:
TP = True Positive
FP = False Positive
FN = False Negative
TN = True Negative

```
Classifier: Random Forest
Accuracy: 0.7838685398896137
Classification Report:
              precision    recall  f1-score   support

     Negatif       0.74      0.73      0.73      1927
      Netral       0.71      0.48      0.57      1682
     Positif       0.82      0.92      0.87      4363

    accuracy                           0.78      7972
   macro avg       0.76      0.71      0.73      7972
weighted avg       0.78      0.78      0.77      7972

Confusion Matrix:
[[1410  191  326]
 [ 309  807  566]
 [ 198  133 4032]]
```

figure 5: RF Model

The above data RF accuracy is 78.4%

$$Accuracy = \frac{1410+807+4032}{7972} = 0.78$$

Precision is a measure of the accuracy of positive predictions of a class:

$$Precicion = \frac{TP}{TP+FP} \quad (6)$$

Class positive:
TP = 4032
FP = 326 + 566 = 892

$$Precicion\,(positif) = \frac{4032}{4032 + 892} = 0.82$$

Recall is a measure of the model's ability to capture all actual data from a class [13].

$$Recall = \frac{TP}{TP+FN} \quad (7)$$

Class positive :
FN = 198 + 133 = 331

$$Recall(Positive) = \frac{4032}{4032+331} = 0.92$$

F1 – Score merupakan rata-rata harmonik antara precicion dan recall

$$F1 - Score = 2\,x\,\frac{Precicion\ x\ Recall}{Precicion + Recall} \quad (8)$$

Class positive =

$$F1 - Score = 2\,x\,\frac{0.82\ x\ 0.92}{0.82+0.92} = 0.87$$

Positive best class with *Precision*: 82% = of the positive predictions, 82% were correct. *Recall*: 92% = can detect 92% of all true positive data. *F1-score* : 87% = *Recall* And *Precision* balanced. Neutral weakest class with *Precision*: 71% = quite good, *Recall*: 48% = not good, because it only detects 48% of neutral data, *F1-score* : 57% = low performance. Negative = middle class with *Precision*: 74% = quite good, *Recall*: 73% = good, *F1-score* : 73% = good.

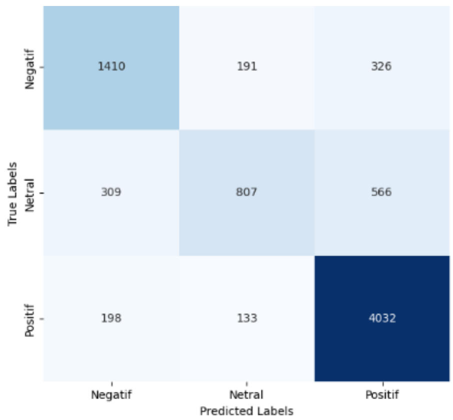


Figure 6: Confusion Matrix RF

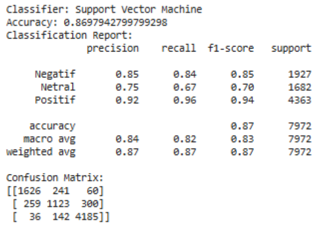
On *Cofusion matrix* There are several error patterns, neutrals are often misclassified as positive (566), negatives are classified as positive (326), and the model is biased towards positive. Then there is *Class Imbalance Effect* that is Model *overfit* to the majority (positive) class, *Recall* neutral is very low (48%), because there is little neutral data. Bias *Toward* Many positive and negative data are misclassified as positive due to an imbalanced data distribution. SMOTE is necessary for imbalanced classes. The model performs well for positive detection but requires significant improvement for the neutral and negative classes.

Support Vector Machine (SVM)

SVM works by finding the best hyperplane that separates the data into classes with the largest margin[14].

JURTEKSI (Jurnal Teknologi dan Sistem Informasi) ISSN 2407-1811 (Print)
Vol. XII No 1, Desember 2025, hlm. 121 – 128 ISSN 2550-0201 (Online)
DOI: http://dx.doi.org/ 10.33330/jurteksi.v12i1.4170
Available online at http://jurnal.stmikroyal.ac.id/index.php/jurteksi

Modeling with SVM yielded an accuracy of 87%.



```
Classifier: Support Vector Machine
Accuracy: 0.8697942799799298
Classification Report:
              precision    recall  f1-score   support

     Negatif       0.85      0.84      0.85      1927
      Netral       0.75      0.67      0.70      1682
     Positif       0.92      0.96      0.94      4363

    accuracy                           0.87      7972
   macro avg       0.84      0.82      0.83      7972
weighted avg       0.87      0.87      0.87      7972

Confusion Matrix:
[[1626  241   60]
 [ 259 1123  300]
 [  36  142 4185]]
```

Figure 7 : SVM Model

Positive class best class with value *Precision*: 0.92% = of all positive predictions, 92% are true positives, *Recall*: 0.96% = the model detects 96% of all true positives, *F1-score* = 0.94% = *Precision* And *Recall* balanced. Negative class = middle class with *Precision*, *Recall*, *F1-score* = 0.85, 0.84, 0.85; solid and balanced performance. Neutral Class = minority class. *Precision*, *Recall*, *F1-score* = 0.75, 0.67, 0.70; performance is quite balanced.

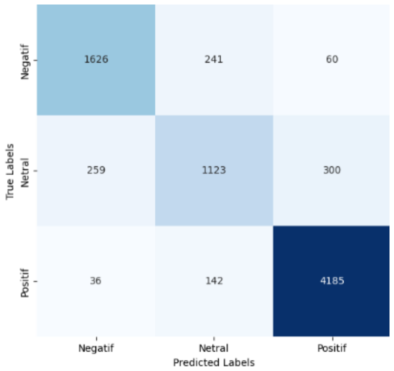
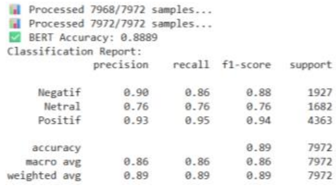


Figure 8: *Confusion matrix* SVM

Misclassification pattern, neutral-positive class: 300 (17.8% of total neutral), neutral-negative class: 259 (15.4% of total neutral), negative-neutral class: 241 (12.5% of total negative). Observed excess, *Margin maximization*: SVM successfully found *hyperplane* optimal. SVM showed statistically significantly better performance compared to RF, with a 9% improvement in global accuracy.

BERT

BERT is a deep learning-based language model for understanding the meaning and context of words in a sentence bidirectionally[16]. This model managed to provide an accuracy of 88.89%.



```
Processed 7968/7972 samples...
Processed 7972/7972 samples...
BERT Accuracy: 0.8889
Classification Report:
              precision    recall  f1-score   support

     Negatif       0.90      0.86      0.88      1927
      Netral       0.76      0.76      0.76      1682
     Positif       0.93      0.95      0.94      4363

    accuracy                           0.89      7972
   macro avg       0.86      0.86      0.86      7972
weighted avg       0.89      0.89      0.89      7972
```

Figure 9 : BERT Model

The positive class is the best class with 93% of positive predictions being correct, 95% of positive data actually being detected, *F1-score* 94% outstanding performance. Negative class = very good with 90% correct negative predictions, 86% negative data detected, 88% f1-score. Neutral class = good with significant improvement from SVM and RF.

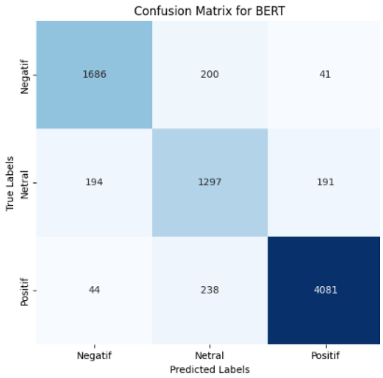


Figure 10: *Confusion matrix* BERT

Support per negative class: 1686 + 200 + 41 = 1,972 *samples*. Neutral: 194 + 1.297 + 191 = 1.682 *samples*. Positive: 44 + 238 + 4.081 = 4.363 *samples*. Best positive class, Data that is actually positive and predicted as positive: True positive : 4081. Data that is actually not positive, but predicted as positive: False positive (FP) : (Negative - Positive) + (Neutral - Positive) : 41 + 191 = 232. Data that is actually positive but

JURTEKSI (Jurnal Teknologi dan Sistem Informasi) ISSN 2407-1811 (Print)
Vol. XII No 1, Desember 2025, hlm. 121 – 128 ISSN 2550-0201 (Online)
DOI: http://dx.doi.org/ 10.33330/jurteksi.v12i1.4170
Available online at http://jurnal.stmikroyal.ac.id/index.php/jurteksi

predicted as not positive: False negative (FN): (Positive-Negative) + (Positive - Neutral) : 44 + 238 = 282. Total actual positive data:

Total positive = TP + FN
= 4081 + 282
= 4363

Total predicted positive:

Predicted positive = TP + FP
= 4081 + 232
= 4313

Accuracy = TP/Total Actual Positive
Accuracy = 4081/4363 = 0.935 = 93.5%

Only 44 were wrongly predicted as negative, 238 were wrongly predicted as neutral.

Negative Class = very good
True Positives = 1686
False Positives = 194 + 44 = 238
False Negatives = 200 + 41 + 241
Accuracy = 1686/1927 = 87.5%

200 were incorrectly predicted as neutral, 41 were incorrectly predicted as positive.

Neutral Class = Good
True Positives = 1297
False Positives = 200 + 238 = 438
False negatives = 194 + 191 = 385
Accuracy = 1297 / 1682 = 385

191 wrongly predicted as negative, 191 wrongly predicted as positive.

SMOTE (Synthetic Minority Oversampling Technique)

A technique to overcome the problem of class imbalance in a dataset, by creating synthetic data for all minority classes, so that the number of samples in the minority class can approach the number of samples in the majority class[5].

Table 1: Distribution Label

Label	**Before**	**After**
Positive	21857	21857
Negative	9522	21857
Neutral	8479	21857

Table 2: Accuracyy SVM, RF, BERT

Algorithm	Accuracy
SVM	92.93%
RF	86.59%
BERT	88,29%

SVM achieved the highest accuracy (92.94%) over BERT and RF. After the SMOTE process, the distribution became balanced, allowing SVM to find a more robust hyperplane. BERT achieved an accuracy of 88.30%, slightly lower than SVM. SMOTE applied to text data does not always produce linguistically contextual synthetic samples. RF achieved 86.59, the lowest compared to SVM and BERT.

Table 3: Clasification Report

	RF	SVM	BERT
Precicion (-)	0.87	0.96	0.88
Recall (-)	0.88	0.90	0.84
F1-score (-)	0.87	0.93	0.86
Precicion (N)	0.85	0.87	0.74
Recall (N)	0.84	0.94	0.76
F1-score (N)	0.85	0.90	0.75
Precicion (+)	0.88	0.97	0.94
Recall (+)	0.87	0.95	0.95
F1-score (+)	0.87	0.96	0.94

Modeling with ML algorithms (SVM, RF, and BERT) after SMOTE, the results of RF have an accuracy of 86.59% Where positive sentiment values precision, recall and f1-score (88%, 87%, and 87%), neutral sentiment (85%, 84%, 85%), and negative sentiment (87%, 88%, 87%). SVM has an accuracy of 92.94%% where positive sentiment values precision, recall, and f1 score (97% 95%, 96%), neutral sentiment (87%, 94%, and 90%), negative sentiment (96%, 90%, 93%). BERT has an accuracy of 88.30% where positive sentiment values precision, recall and f1 score (94%, 95%, 94%), neutral sentiment

(74%, 76%, 75%), and negative sentiment (88%, 84%, 86%).

CONCLUSION

The conclusion of this study is that 21,857 tweets (54.84%) conveyed positive sentiment, only 9,522 (23.89%) expressed negative sentiment, and the rest were neutral. This data indicates that the program was well-received by the public. Modeling with the BERT Machine Learning algorithm was the best algorithm for sentiment analysis without the SMOTE process with an accuracy of 89%. Meanwhile, with SMOTE, the best algorithm for sentiment analysis was SVM with an accuracy of 92.94%.

Further research is sentiment analysis by applying more comprehensive text preprocessing techniques, performing hyperparameter optimization on the SVM, RF, and BERT algorithms, and exploring the use of more advanced transformer models specifically for Indonesian.

BIBLIOGRAPHY

[1] Hidayat EY, Hardiansyah RW, Affandy A. Analisis Sentimen Twitter untuk Menilai Opini Terhadap Perusahaan Publik Menggunakan Algoritma Deep Neural Network. Jurnal Nasional Teknologi Dan Sistem Informasi 2021;7:108–18. https://doi.org/10.25077/teknosi.v7i2.2021.108-118.

[2] Pinza-Jiménez CJ, Garcés-Gómez YA. Assessing the performance of random forest regression for estimating canopy height in tropical dry forests. International Journal of Electrical and Computer Engineering 2023;13:6787–96. https://doi.org/10.11591/ijece.v13i6.pp6787-6796.

[3] Pusung EM, Dewi IN. Optimasi RoBERTa dengan Hyperparameter Tuning untuk Deteksi Emosi berbasis Teks. Jurnal Nasional Teknologi Dan Sistem Informasi 2025;10:240–8. https://doi.org/10.25077/teknosi.v10i3.2024.240-248.

[4] Putra LGR, Prasetya DD, Mayadi M. Student Dropout Prediction Using Random Forest and XGBoost Method. INTENSIF: Jurnal Ilmiah Penelitian Dan Penerapan Teknologi Sistem Informasi 2025;9:147–57. https://doi.org/10.29407/intensif.v9i1.21191.

[5] Anjani AF, Anggraeni D, Tirta IM. Implementasi Random Forest Menggunakan SMOTE untuk Analisis Sentimen Ulasan Aplikasi Sister for Students UNEJ. Jurnal Nasional Teknologi Dan Sistem Informasi 2023;9:163–72. https://doi.org/10.25077/teknosi.v9i2.2023.163-172.

[6] Oktafiani R, Rianto R. Perbandingan Algoritma Support Vector Machine (SVM) dan Decision Tree untuk Sistem Rekomendasi Tempat Wisata. Jurnal Nasional Teknologi Dan Sistem Informasi 2023;9:113–21. https://doi.org/10.25077/teknosi.v9i2.2023.113-121.

[7] Friadi J, Kurniawan DE. Analisis Sentimen Ulasan Wisatawan Terhadap Alun-Alun Kota Batam: Perbandingan Kinerja Metode Naive Bayes dan Support Vector Machine. Jurnal Sistem Informasi Bisnis 2024;14:403–7.

JURTEKSI (Jurnal Teknologi dan Sistem Informasi) ISSN 2407-1811 (Print)
Vol. XII No 1, Desember 2025, hlm. 121 – 128 ISSN 2550-0201 (Online)
DOI: http://dx.doi.org/ 10.33330/jurteksi.v12i1.4170
Available online at http://jurnal.stmikroyal.ac.id/index.php/jurteksi

https://doi.org/10.21456/vol14iss4pp403-407.

[8] Riyadi S, Salsabila LK, Damarjati C, Karim RA. INTENSIF: Jurnal Ilmiah Penelitian dan Penerapan Teknologi Sistem Informasi 233 Sentiment Analysis of YouTube Users on Blackpink Kpop Group Using IndoBERT 1 *. INTENSIF 2024;8:2549–6824. https://doi.org/10.29407/intensif.v8n2.22678.

[9] Furqan M, Kurniawan R, HP KI. Evaluasi Performa Support Vector Machine Classifier Terhadap Penyakit Mental. JURNAL SISTEM INFORMASI BISNIS 2020;10:203–10. https://doi.org/10.21456/vol10iss2pp203-210.

[10] Nissa NK, Yulianti E. Multi-label text classification of Indonesian customer reviews using bidirectional encoder representations from transformers language model. International Journal of Electrical and Computer Engineering 2023;13:5641–52. https://doi.org/10.11591/ijece.v13i5.pp5641-5652.

[11] Hossain MT, Talukder MAR, Jahan N. Depression prognosis using natural language processing and machine learning from social media status. International Journal of Electrical and Computer Engineering 2022;12:2847–55. https://doi.org/10.11591/ijece.v12i3.pp2847-2855.

[12] Tally MT, Amintoosi H. A hybrid method of genetic algorithm and support vector machine for intrusion detection. International Journal of Electrical and Computer Engineering 2021;11:900–8. shttps://doi.org/10.11591/ijece.v11i1.pp900-908.

[13] Sudarma M, Sulaksono J. Implementation of TF-IDF Algorithm to detect Human Eye Factors Affecting the Health Service System. INTENSIF: Jurnal Ilmiah Penelitian Dan Penerapan Teknologi Sistem Informasi 2020;4:123–30. https://doi.org/10.29407/intensif.v4i1.13858.

[14] Yatoo NA, Ali IS, Mirza I. Comparing hyperparameter optimized support vector machine, multilayer perceptron and bagging classifiers for diabetes mellitus prediction. International Journal of Electrical and Computer Engineering 2024;14:5834–47. https://doi.org/10.11591/ijece.v14i5.pp5834-5847.

[15] Thomas B, Chandra J. Random forest application on cognitive level classification of E-learning content. International Journal of Electrical and Computer Engineering 2020;10:4372–80. https://doi.org/10.11591/ijece.v10i4.pp4372-4380.

[16] Nabiilah GZ, Alam IN, Purwanto ES, Hidayat MF. Indonesian multilabel classification using IndoBERT embedding and MBERT classification. International Journal of Electrical and Computer Engineering 2024;14:1071–8. https://doi.org/10.11591/ijece.v14i1.pp1071-1078.