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Sentiment Analysis of Indonesian Tweets on AI Impact: A Comparison between Random Forest and SVM

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Abstract. The rapid development of Artificial Intelligence (AI) has sparked diverse public opinions, making sentiment analysis a crucial tool for understanding public perception. This study conducts a comparative analysis of two machine learning algorithms, Random Forest (RF) and Support Vector Machine (SVM), to determine the most effective model for classifying public sentiment regarding the impact of AI in Indonesia. Research data were collected from the social media platform X/Twitter and processed through a series of stages, including text preprocessing, feature extraction using Term Frequency-Inverse Document Frequency (TF-IDF), and two experimental scenarios: baseline testing and optimization via hyperparameter tuning. The model performance was evaluated based on accuracy, precision, recall, F1-score, and AUC metrics. The results indicate that SVM consistently outperformed RF, with the best model achieving an accuracy of 67.44% and an AUC of 0.73. The optimization process successfully improved the RF's performance to 65.36% with an AUC of 0.71, but did not alter the SVM's performance, whose configuration was already optimal. While SVM achieved higher accuracy, the difference was not found to be statistically significant. Therefore, this study suggests that SVM holds a slight performance advantage, but both models exhibit comparable robustness for this case study. This study contributes by providing a direct, in-depth comparison of these two popular models on Indonesian-language AI sentiment, which includes comprehensive diagnostic analyses to explain the performance differences.

Keywords: AI Public Opinion, Indonesian Tweet Classification, Machine Learning Comparison, Random Forest, Sentiment Analysis, Support Vector Machine

1 Introduction

The advancement of Artificial Intelligence (AI) has become a defining feature of the current technological landscape, pervasively impacting various sectors of society (Pakpahan, 2021). The emergence of a computer program that can learn from data to perform tasks typically requiring human intelligence has generated significant global discourse (Rouhiainen, 2018). This discourse is dual-natured; on one hand, AI is lauded for its potential to enhance efficiency and productivity, while on the other, it raises

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concerns about job displacement and its ethical implications. Social media platforms, particularly X/Twitter, have emerged as the primary arenas for public debate, offering vast amounts of unstructured text data rich in public opinion. Sentiment analysis, a field dedicated to extracting opinions from text (Liu, 2012), is widely employed to analyze these opinions systematically.

The application of machine learning for sentiment analysis is a well-established field, as detailed in several surveys and reviews (Medhat et al., 2014; Salloum et al., 2020). Among the most prominent supervised learning methods are Random Forest (RF) and Support Vector Machine (SVM). RF, an ensemble method introduced by Breiman (2001), is recognized for its robustness to overfitting. SVM, developed by Cortes & Vapnik (1995), is highly effective in high-dimensional spaces, making it a powerful text classification choice.

In the Indonesian context, numerous studies have explored these methods for various topics. Researchers have successfully compared Naive Bayes and SVM for sentiment analysis on diverse social issues, from the COVID-19 pandemic (Hasri & Alita, 2022) to emerging technologies like the Metaverse (Zahra & Yasia, 2022). Direct comparisons between RF and SVM, similar to this study's approach, have been conducted for analyzing trending social issues (Sudianto et al., 2022). Other research has also evaluated RF and SVM alongside different algorithms like Naive Bayes for application review analysis (Fitri et al., 2020). Specifically regarding AI sentiment, studies have utilized a range of approaches, from lexicon-based methods (Putra & Wijaya, 2023) to optimized Naive Bayes (Indrayuni & Nurhadi, 2023). Likewise, Wijanarko et al. (2017) demonstrated that RF could achieve high accuracy, and another study by Saepudin et al. (2024) highlighted the effectiveness of SVM and its potential for optimization. While these studies confirm the individual potential of both algorithms, a direct, in-depth comparative study of RF and SVM on Indonesian language sentiment data regarding the general impact of AI, complete with diagnostic analyses, remains a research gap. Therefore, this study aims to fill this gap by conducting a comprehensive comparative analysis of Random Forest and Support Vector Machine.

2 Methodology

This study implements a systematic methodological framework based on established data mining concepts (Han et al., 2012).

2.1 Data Acquisition and Preprocessing

A dataset of 2,161 Indonesian tweets was collected and manually labeled into three sentiment classes: positive, negative, and neutral. The text then underwent a preprocessing pipeline consisting of case folding, cleaning, tokenization, stopword removal, and stemming.

2.2 Feature Extraction: TF-IDF

The Term Frequency-Inverse Document Frequency (TF-IDF) method was used to convert the processed text into numerical vectors. This technique is standard for weighting terms in text classification tasks.

2.3 Classification Models

The two models compared were Random Forest (RF) and Support Vector Machine (SVM). The experiment was conducted in two scenarios: (1) baseline testing with default parameters and (2) optimization using GridSearchCV with 5-fold cross-validation to determine the optimal hyperparameters for each model.

2.4 Evaluation Metrics

The model performance was evaluated using a confusion matrix and its derivative metrics: accuracy, precision, recall, F1 score, and the area under the ROC curve (AUC).

3 Results and Discussion

This section presents the experimental results and provides an in-depth discussion of them.

3.1 Dataset Characteristics and Lexical Analysis

The dataset consisted of 2,161 tweets, distributed into 986 neutral (45.6%), 590 positive (27.3%), and 585 negative (27.1%) sentiments, as detailed in Table 1.

Table 1. Sentiment Class Distribution In The Dataset

Sentiment Class	Data Count	Percentage (%)
Positive	590	27.3%
Negative	585	27.1%
Neutral	968	45.6%
Total	2,161	100%

3.2 Comparative Model Performance

The quantitative evaluation results are presented in Table 2. SVM exhibited a clear advantage in all metrics.

Table 2. Model Performance Comparison Before and After Tuning

Algorithm	Scenario	Accuracy	F1-Score (Weighted)
Random Forest	Baseline	0.6351	0.62
Random Forest	Tuned	0.6536	0.64
Support Vector Machine	Baseline	0.6744	0.67
Support Vector Machine	Tuned	0.6744	0.67

After optimization, the RF's performance improved, but its final accuracy (65.36%) still could not surpass the SVM's stable accuracy of 67.44%. To statistically validate this performance difference, a McNemar's test was conducted. The resulting p-value was greater than 0.05, indicating that there is no statistically significant difference between the performance of the two models.

3.3 In-depth Diagnostic Analysis

Confusion matrix analysis, Figures 1 and 2 show that the SVM has a lower error rate in distinguishing between opinionated and neutral sentiments.

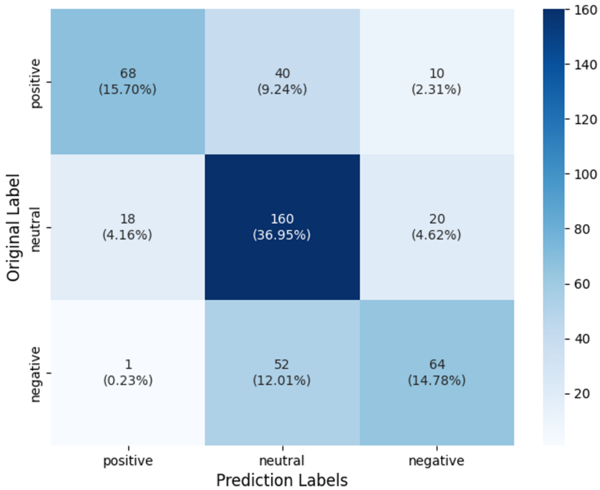

Figure 1. SVM Confusion Matrix

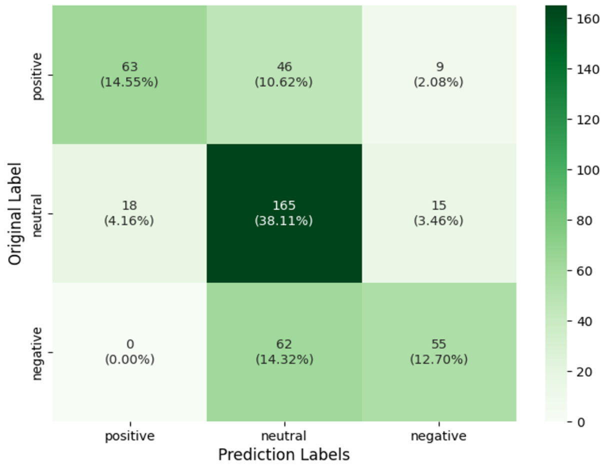

Figure 2. RF Confusion Matrix

Figure 3 presents the feature importance analysis of the RF model validates that the model learns from words that are relevant intuitively. Figure 4 shows that the learning curve for the SVM model indicates a well-fitted model that did not exhibit severe overfitting. Finally, Figure 5 highlights the ROC Curve analysis confirmed SVM's superiority with an AUC of 0.73, compared to RF with an AUC of 0.71.

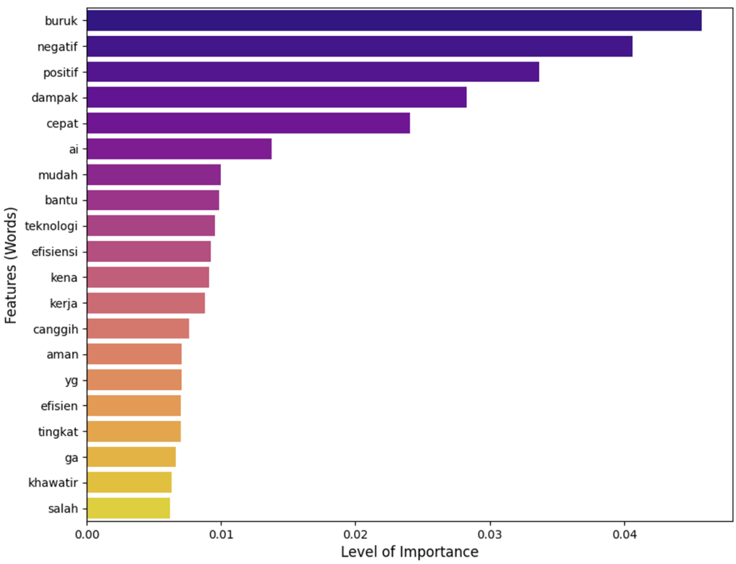

Figure 3. Feature Importance

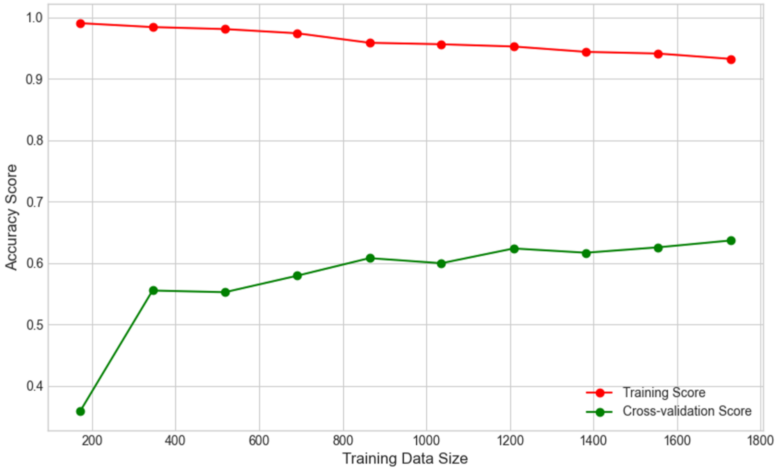

Figure 4. Learning Curve

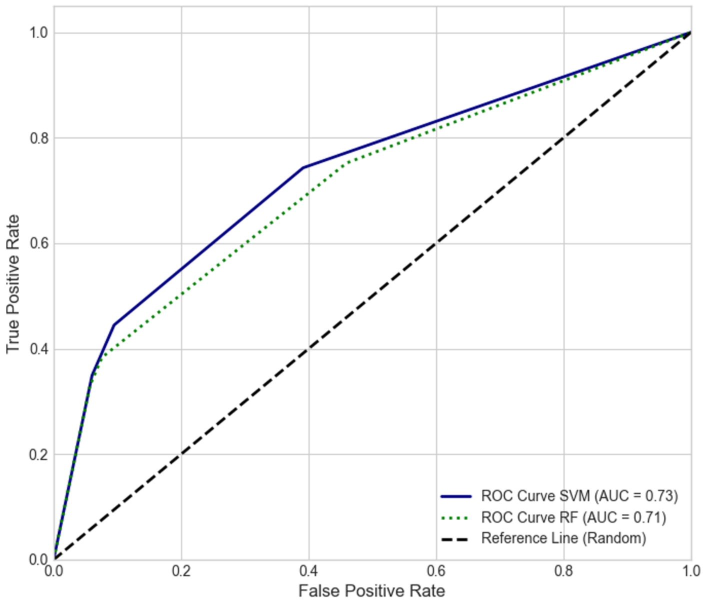

Figure 5. ROC Curve

As shown in Table 3, the accuracy achieved in this study (67.44%) is notably more conservative than the high accuracies reported by Wijanarko et al. (2017) at 94.00% and Saepudin et al. (2024) at 89.50%. This significant difference can be attributed to a key methodological distinction: both of the aforementioned studies conducted a binary classification (positive vs. negative). In contrast, this study addresses a more challenging three-class classification problem, which includes a large and often ambiguous neutral class. As noted in comprehensive reviews, multiclass problems are inherently more complex than binary tasks (Yadav & Vishwakarma, 2020). The inclusion of a large neutral class, which often shares lexical features with both positive and negative sentiments, increases the classification challenge and results in more realistic, albeit lower, accuracy scores.

Table 3. Performance Comparison with Related Studies

Study	Topic	Algorithm	Accuracy
This Study	General AI Impact (3-class)	SVM	67.44%
Wijanarko et al. (2017)	AI Development Impact (2-class)	RF	94.00%
Saepudin et al. (2024)	AI in Education (2-class)	SVM+PSO	89.50%

4 Conclusion

This study concludes that while the Support Vector Machine (SVM) with a linear kernel achieved higher performance metrics, the difference was not statistically significant when compared to the tuned Random Forest model. This suggests that for this specific case study, both algorithms demonstrate a comparable level of robustness. This finding provides a practical recommendation to prefer SVM based on its higher point-estimate accuracy, while acknowledging that its definitive superiority cannot be statistically established. Although hyperparameter tuning improved the RF’s performance, its results still did not surpass the SVM's already optimal baseline performance. For local technology development, this model can serve as a baseline for building more sophisticated public opinion monitoring tools for governmental or commercial entities in Indonesia. Future work should not only explore deep learning models (Yadav & Vishwakarma, 2020) but also focus on developing aspect-based sentiment analysis to provide more granular insights into public concerns regarding AI.

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