JIKO (Jurnal Informatika dan Komputer) Accredited KEMDIKTISAINTEK, No.0173/C3/DT.05.00/2025
Vol. 9, No. 1, April 2026, pp. 15-22 p-ISSN: 2614-8897
DOI: 10.33387/jiko.v9i1.11151 e-ISSN: 2656-1948

COMPARATIVE ANALYSIS OF ENSEMBLE CLASSIFICATION MODELS AND SUPPORT VECTOR MACHINES IN MEASURING STRESS LEVELS BASED ON EEG SIGNALS

Seftia Angelina[1*], Saut Dohot Siregar[2], Achmad Ridwan[3], Lewis Francolim[4]

[1,2,3,4]Teknik Informatika, Fakultasi Teknologi dan Ilmu Komputer, Universitas Prima Indonesia, Medan, 20118, Indonesia
*Email: [1]seftiaangelina123@gmail.com, [2]sautdohotsiregar@unprimdn.ac.id, [3]achmadridwan@unprimdn.ac.id, [4]lewis.lim0210@gmail.com

(Received: 17 December 2025, Revised: 30 December 2025, Accepted: 30 January 2026)

Abstract

Stress is a physiological and psychological response that can develop into serious health issues when prolonged. EEG-based stress detection has become an important approach; however, many studies still lack validation for multilevel classification and real-world conditions. This study focuses on inmates at Binjai Correctional Facility and compares the performance of Support Vector Machine (SVM), Random Forest (RF), and a combined ensemble model of Random Forest and AdaBoost for classifying three stress levels: stressed, relaxed, and neutral, using EEG signals. Experimental results show that the SVM model achieved an accuracy of 81% with a Minimum Classification Error (MCE) of 0.16. The Random Forest model significantly improved performance, reaching 96% accuracy and an MCE of 0.04. The best performance was obtained by the ensemble model combining Random Forest and AdaBoost, which achieved an accuracy of 97% and reduced the MCE to 0.03, indicating a 1% improvement over Random Forest alone.

Keywords: *EEG, Stress Classification, Ensemble Model, SVM, Random Forest, AdaBoost*

**Corresponding Author: Seftia Angelina*

---

1. INTRODUCTION

Stress is a physiological, psychological, and behavioral response in humans as they attempt to adapt to and regulate internal and external pressures [1]. Prolonged stress can lead to various disorders such as hypertension, skin problems, and even depression [2]. Several studies indicate a high prevalence of stress; for example, in South Korea, the rate reaches approximately 22–30% among elderly women and 14–20% among elderly men, with women consistently reporting higher stress levels throughout 2009–2019 [3]. According to a meta-analysis on EEG and deep learning, mental stress detection accuracy can reach up to 88%, highlighting the need for more reliable classification models [4].

Various solutions have been proposed using classical machine learning methods such as SVM, Random Forest, and ensemble-based techniques for stress classification from EEG and ECG signals. For instance, Hemakom et al. (2023) combined ECG and EEG using a stacking classifier, achieving accuracy levels of 92.7% for females and 87.6% for males [5]. Another study using an EEG-based ensemble approach (stacking RF + LightGBM + GBC) achieved an accuracy of up to 99.6% in classifying three emotional states (positive, neutral, negative) [6]. In terms of deep learning, LSTM models have also proven effective for stress detection, reaching an accuracy of 93.3% in adolescents with and without ASD [7].

Unlike previous studies, this research provides a direct comparison between ensemble methods and SVM using EEG datasets in real stress settings, with a focus on cross-emotional generalization and robust error analysis. A key distinction of this study is the use of ROC, AUC, and Minimum Classification Error (MCE) analysis, similar to earlier studies that achieved very low MCE values (~0.05%). Furthermore, this study evaluates the performance of both models on multi level stress classification (three categories: stress, relaxed, and neutral), whereas most earlier research relied only on binary classification. This contributes significantly to both methodological development and practical implementation of EEG based stress detection systems.

2. RESEARCH METHOD

In this study, the researcher employs a quantitative research approach, which involves the collection of numerical data and statistical analysis to understand phenomena or answer research questions. This method is commonly used to measure relationships between variables and identify patterns or trends within the data [8]. In this context, the research focuses on comparing the performance of the Support Vector Machine (SVM) model and ensemble models in detecting and classifying multi level stress (stress, relaxed, neutral) based on EEG signals. In this research, the research method that will be carried out can be seen in Figure 1.

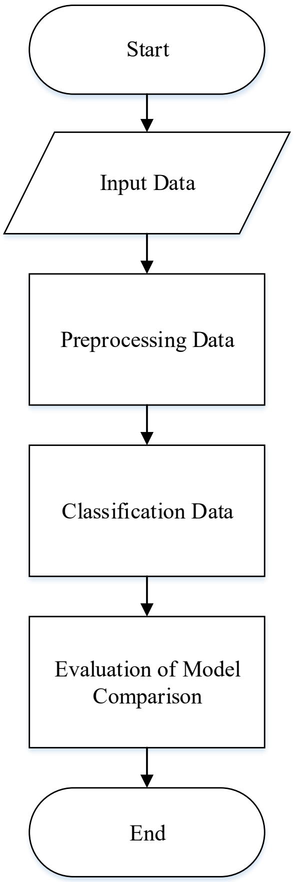


Figure 1. Stages of Research Methods

2.1 Input Data

The EEG data were obtained from 21 subjects from the Binjai Correctional Facility who participated in an experiment conducted with eyes closed using specialized equipment to record brain activity. The tools and materials used in this study included the WinEEG software, an amplifier, gel, and an electrocap, which serve to capture the electrical activity of the brain from the scalp. The amplifier enhances the amplitude of EEG signals measured from electrodes placed on the scalp, while the gel improves the contact between the electrodes and the scalp. The complete set of equipment used in the data-collection process is illustrated in Figure 2.

Figure 2. Tools and Materials for Data Input

2.2 Preprocessing Data

The first stage in this analysis is the preprocessing of the EEG data obtained. Incomplete data or data containing missing values are filled using mean imputation [9].

2.3 Classification Data

The data classification stage is carried out after the preprocessing phase is completed. The main focus of this study is to compare the performance of the combined ensemble methods (Random Forest + AdaBoost) with Support Vector Machine (SVM) in detecting and classifying stress levels based on EEG signals.

1. Combination of Random Forest + AdaBoost
   In this approach, two ensemble algorithms are combined sequentially. First, the Random Forest model is trained to produce initial probability outputs for each class (stress, relaxed, neutral). These outputs are then used as additional inputs or as the basis for the AdaBoost model, which refines the predictions by correcting errors that occurred in the Random Forest stage. This approach leverages the strength of Random Forest in handling complex features and the ability of AdaBoost to iteratively correct classification errors [10]. The combination is expected to improve classification accuracy and produce a more robust model against noise and variations in EEG data collected from real environments such as correctional institutions.
2. Support Vector Machine (SVM)
   SVM is used as the main comparison method because it is a classification algorithm that has proven effective across various domains, including EEG signal analysis. SVM works by finding the optimal hyperplane that separates data based on its classes. The kernel used in this study is the Radial Basis Function (RBF) due to its capability in handling high-dimensional and non-linear data such as EEG signals. SVM is trained using the same feature data and evaluated under identical experimental conditions as the

ensemble model, allowing an objective comparison of their performance [11].

2.3 Evaluation of Model Comparison

Evaluation is conducted to determine how effective the Random Forest + AdaBoost model is compared to SVM in classifying EEG signals into three classes: stress, relaxed, and neutral. This evaluation is essential for identifying which method performs better and is more suitable for use in EEG-based stress detection systems.

1. Confusion Matrix
   A confusion matrix is constructed for each model to observe the distribution of classification errors between classes. From this matrix, accuracy, precision, recall, and misclassification error per class are also calculated as supporting metrics [12][13][14].
2. Area Under Curve (AUC)
   AUC is used to measure the model's ability to distinguish one class from another. Since the classification is multi-class, a One-vs-Rest approach is used to compute the AUC for each class, which is then averaged [15][16].
3. Minimum Classification Error (MCE)
   MCE calculates the minimum number of classification errors. A lower value indicates stable performance and high precision. MCE is highly relevant in real-world applications that require minimal errors [17].

3. RESULTS AND DISCUSSION

The test results obtained in this study were used to analyze and determine the performance comparison between the Support Vector Machine (SVM) model and ensemble models in detecting and classifying multi-level stress (stress, relaxed, neutral) based on EEG signals.

3.1 Data Input Results

The EEG data were obtained from 21 subjects who participated in the experiment with their eyes closed and using specialized equipment to record brain activity. The initial EEG signals contained a high level of noise, as shown in Figure 3.

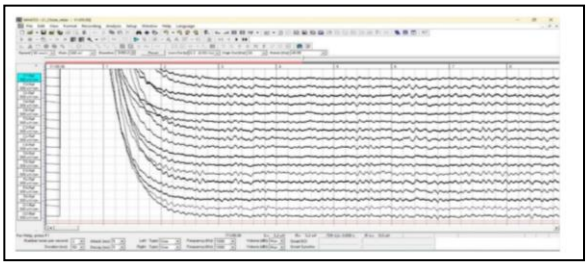


Figure 3. Data Before Filtering

Therefore, filtering was performed using a Band-Pass Filter (BPF) with a frequency range of 0.5 to 50 Hz to remove unwanted noise. Figure 4 shows the data after filtering.

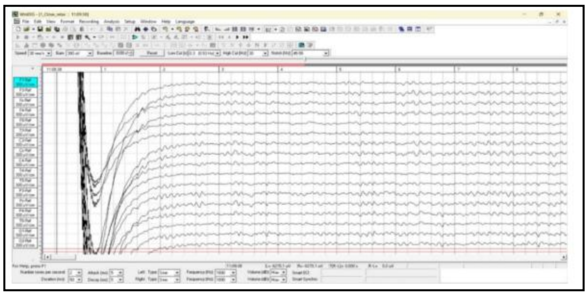


Figure 4. Data After Filtering

After the filtering process, only the relevant brain waves, delta, theta, alpha, and beta, were retained. In addition, the Fp1 and Fp2 electrodes were removed, leaving 18 data points for further analysis. After the preprocessing, filtering, and electrode selection stages, the EEG signals from the 21 subjects were segmented and transformed into a total of 378 EEG data samples, which were used as the final dataset for classification. For classification, the mental state labels were determined based on specific rules: a stress state was assigned if the alpha value was below the median and theta was above the median, a relaxed state was assigned if both beta1 and beta2 values were above the median, and a neutral state was assigned if neither condition was met. The visualization of the EEG dataset, as illustrated in Figure 5, helps in understanding the patterns and signal characteristics observed across these electrodes.

Tabel 1. Research Dataset

	Channels	delta	theta	alpha	beta1	beta2
S1	Fp1-Ref	3.2	3.11	4.92	1.19	1.22
	F7-Ref	2.45	2.38	3.83	1.18	1.21
	F3-Ref	2.75	3.35	5.74	1.39	1.35
	Fz-Ref	2.91	3.41	5.82	1.33	1.31
	F4-Ref	2.79	3.17	5.22	1.36	1.37
	F8-Ref	2.69	2.35	3.4	1.15	1.25
	T3-Ref	2.27	2.22	3.55	1.63	1.65
	C3-Ref	2.61	2.99	5.32	1.41	1.32
	Cz-Ref	3.04	3.44	6.19	1.52	1.49
	C4-Ref	2.95	2.85	4.78	1.44	1.29
	T4-Ref	2.2	2.02	2.93	1.12	0.97
	T5-Ref	2.21	2.16	4.22	1.26	1.16
	P3-Ref	2.95	2.91	5.5	1.53	1.4
	Pz-Ref	2.8	2.9	5.65	1.51	1.38
	P4-Ref	2.93	2.6	5.03	1.42	1.25
	T6-Ref	2.49	2	4.34	1.22	1.11
	O1-Ref	3.06	2.53	5.77	1.58	1.59
	O2-Ref	2.59	2.22	5.15	1.42	1.31

There were 18 electrodes remaining after the filtering process, namely Fp1-Ref, F7-Ref, F3-Ref, Fz-Ref, F4-Ref, F8-Ref, T3-Ref, C3-Ref, Cz-Ref, C4-Ref, T4-Ref, T5-Ref, P3-Ref, Pz-Ref, P4-Ref, T6-Ref, O1-Ref, and O2-Ref. The visualization of the EEG data helps in understanding the patterns and signal characteristics observed, as illustrated in Figure 5.

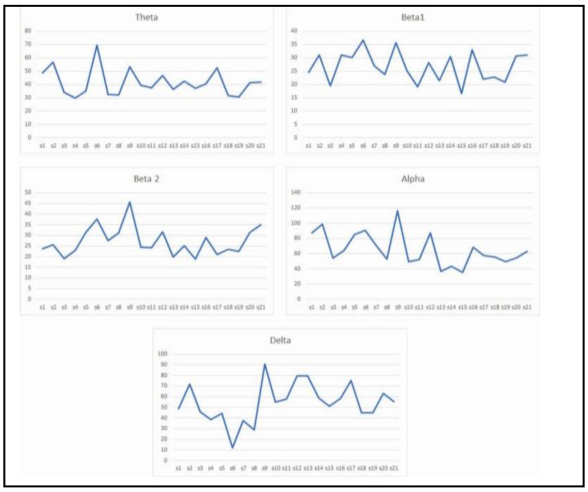
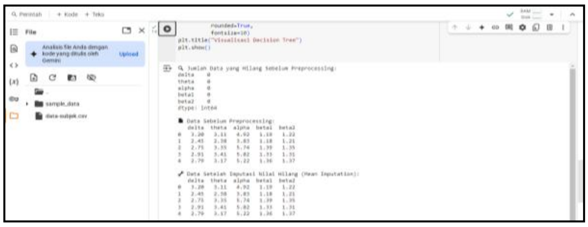


Figure 5. Data Visualization

3.2 Data Preprocessing Results

The data preprocessing stage in this study was carried out using Google Colab, which is based on Python programming. Before proceeding to the next stage, the preprocessing step was performed, starting with handling incomplete data or missing values. Missing values were filled using mean imputation, as shown in Figure 6.



```
            rounded=True,
            fontsize=10)
plt.title("Visualisasi Decision Tree")
plt.show()
```

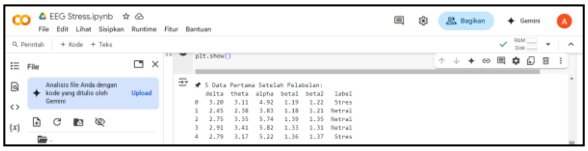
```
🔍 Jumlah Data yang Hilang Sebelum Preprocessing:
delta    0
theta    0
alpha    0
beta1    0
beta2    0
dtype: int64

■ Data Sebelum Preprocessing:
   delta  theta  alpha  beta1  beta2
0   3.20   3.11   4.92   1.19   1.22
1   2.45   2.38   3.83   1.18   1.21
2   2.75   3.35   5.74   1.39   1.35
3   2.91   3.41   5.82   1.33   1.31
4   2.79   3.17   5.22   1.36   1.37

✔ Data Setelah Imputasi Nilai Hilang (Mean Imputation):
   delta  theta  alpha  beta1  beta2
0   3.20   3.11   4.92   1.19   1.22
1   2.45   2.38   3.83   1.18   1.21
2   2.75   3.35   5.74   1.39   1.35
3   2.91   3.41   5.82   1.33   1.31
4   2.79   3.17   5.22   1.36   1.37
```

Figure 6. First Stage Dataset Preprocessing Results

As can be seen in Figure 6, the dataset used did not have any missing values, so the data before and after preprocessing remained the same.

3.3 Data Classification Results

After the preprocessing of the EEG dataset was completed, the data were classified using the Support Vector Machine (SVM) model and ensemble models. The classification labels were determined based on simple logic rules referring to the median values of certain features, as previously described, resulting in the labeling shown in Figure 7.

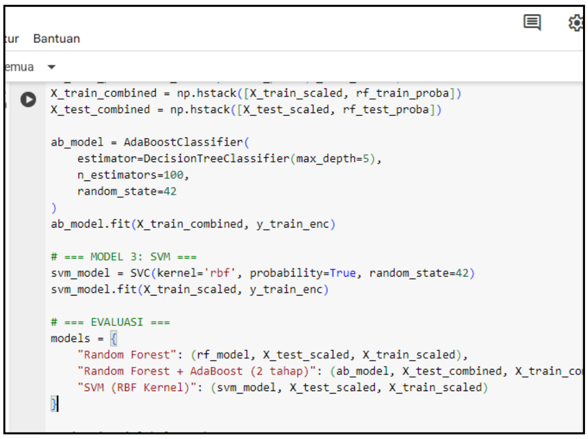


```
plt.show()
```

```
📌 5 Data Pertama Setelah Pelabelan:
   delta  theta  alpha  beta1  beta2   label
0   3.20   3.11   4.92   1.19   1.22   Stres
1   2.45   2.38   3.83   1.18   1.21  Netral
2   2.75   3.35   5.74   1.39   1.35  Netral
3   2.91   3.41   5.82   1.33   1.31  Netral
4   2.79   3.17   5.22   1.36   1.37   Stres
```

Figure 7. EEG Dataset Labeling Results

After labeling, the Support Vector Machine (SVM) and ensemble models were implemented, as shown in Figure 8.



```
X_train_combined = np.hstack([X_train_scaled, rf_train_proba])
X_test_combined = np.hstack([X_test_scaled, rf_test_proba])

ab_model = AdaBoostClassifier(
    estimator=DecisionTreeClassifier(max_depth=5),
    n_estimators=100,
    random_state=42
)
ab_model.fit(X_train_combined, y_train_enc)

# === MODEL 3: SVM ===
svm_model = SVC(kernel='rbf', probability=True, random_state=42)
svm_model.fit(X_train_scaled, y_train_enc)

# === EVALUASI ===
models = {
    "Random Forest": (rf_model, X_test_scaled, X_train_scaled),
    "Random Forest + AdaBoost (2 tahap)": (ab_model, X_test_combined, X_train_co
    "SVM (RBF Kernel)": (svm_model, X_test_scaled, X_train_scaled)
}
```

Figure 8. Data Classification Results

3.4 Modal Comparison Evaluation Results

In the model comparison evaluation stage, the classification results were tested using the Confusion Matrix, ROC curve, and Minimum Classification Error (MCE) to assess the models' ability to classify the data. The dataset was divided into training data (80%) and test data (20%) using the Stratified Sampling method to maintain balanced label proportions. The following is a description of the model comparison evaluation results:

1. Evaluation of the Support Vector Machine (SVM) Model

a. Confusion Matrix Test Results

The results of the Confusion Matrix test using the Support Vector Machine (SVM) model are presented in the form of a Confusion Matrix plot, as shown in Figure 9.

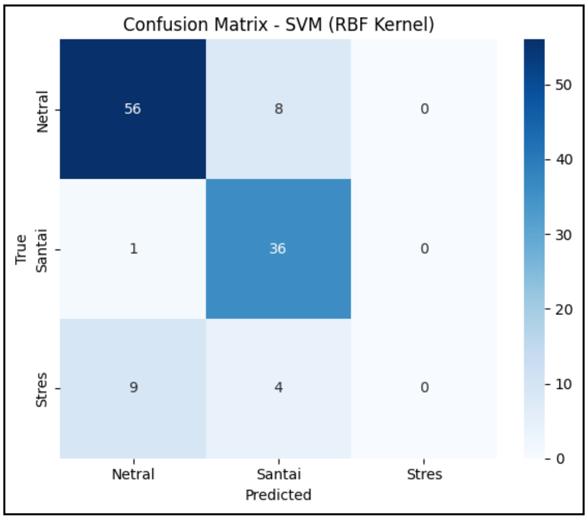


Figure 9. Confusion Matrix Plot Results of a Support Vector Machine Model in EEG Signal Classification to Determine Stress Levels

Based on the Confusion Matrix evaluation results, it can be explained that the performance of the Support Vector Machine model achieved an accuracy of 81.00%, a precision of 72.00%, and a recall of 81.00%.

b. ROC Curve Test Results

Next, an evaluation was carried out using the ROC curve on the Support Vector Machine model which shows the Receiver Operating Characteristics (ROC) graph metrics as shown in Figure 10.

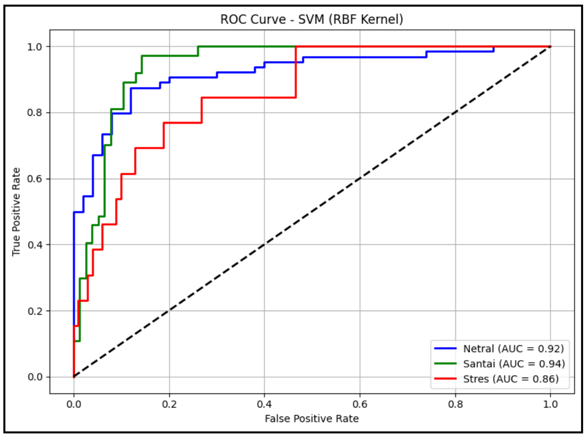


Figure 11. Graphic Results of Receiver Operating Characteristics (ROC) Model Support Vector Machine

Based on the ROC curve shown in Figure 10, the Support Vector Machine model demonstrated excellent performance in distinguishing each class: the neutral class with an AUC of 0.92, the relaxed class with an AUC of 0.94, and the stress class with an AUC of 0.86.

c. Minimum Classification Error (MCE) Test Results

The Support Vector Machine model produced a Minimum Classification Error (MCE) of 0.16, indicating a relatively low classification error rate.

2. Random Forest Model Evaluation

a. Confusion Matrix Test Results

The results of the Confusion Matrix test of the Random Forest model are presented in the form of a Confusion Matrix plot as shown in Figure 11.

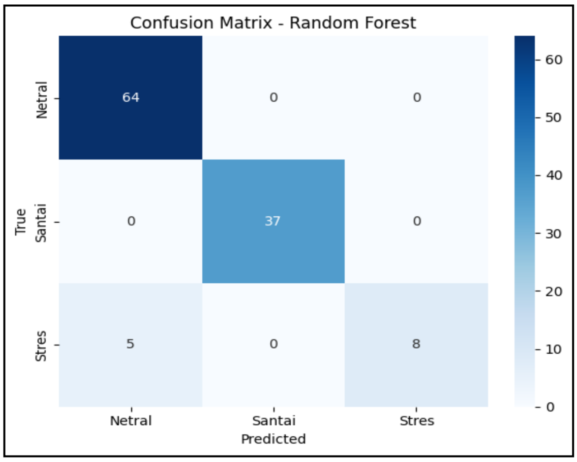


Figure 12. Confusion Matrix Plot Results of Random Forest Model in EEG Signal Classification to Determine Stress Levels

Based on the Confusion Matrix evaluation results, it can be explained that the performance of the Random Forest model achieved an accuracy of 96.00%, a precision of 96.00%, and a recall of 96.00%.

b. ROC Curve Test Results

Next, an evaluation was carried out using the ROC curve on the Random Forest model which shows the Receiver Operating Characteristics (ROC) graph metric as shown in Figure 12.

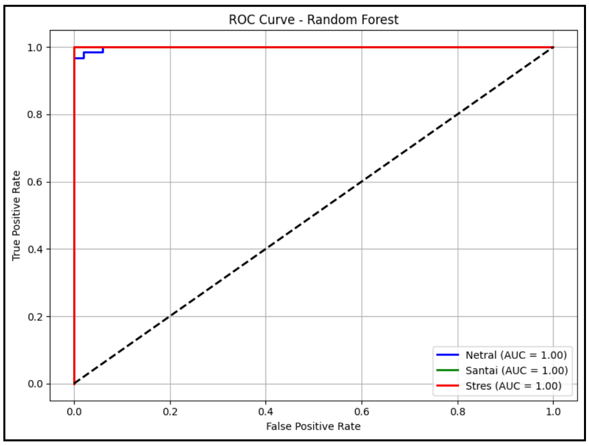


Figure 12. Random Forest Model Receiver Operating Characteristics (ROC) Graphic Results

Based on the ROC curve shown in Figure 12, the Random Forest model demonstrated excellent performance in distinguishing each class: the neutral class with an AUC of 1.00, the relaxed class with an AUC of 1.00, and the stress class with an AUC of 1.00.

c. Minimum Classification Error (MCE) Test Results

The Random Forest model produced a Minimum Classification Error (MCE) of 0.04, indicating a relatively low classification error rate.

3. Evaluation of Ensemble Models (Random Forest + AdaBoost)

a. Confusion Matrix Test Results

The results of the Confusion Matrix test of the ensemble model (Random Forest + AdaBoost) are presented in the form of a Confusion Matrix plot as shown in Figure 13.

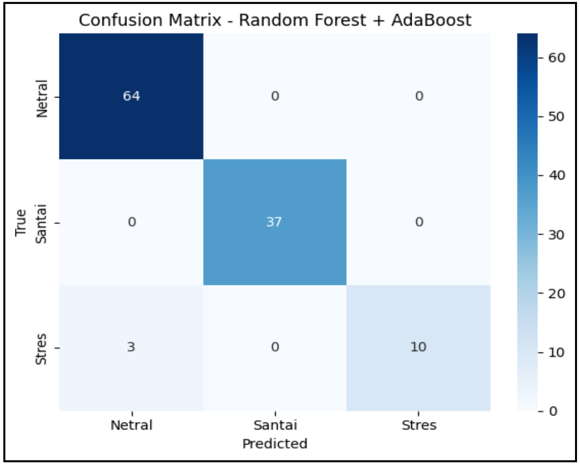


Figure 13. Confusion Matrix Plot Results of Ensemble Model (Random Forest + AdaBoost) in EEG Signal Classification to Determine Stress Levels

Based on the Confusion Matrix evaluation results, it can be explained that the performance of the ensemble model (Random Forest + AdaBoost) achieved an accuracy of 97.00%, a precision of 97.00%, and a recall of 97.00%.

b. ROC Curve Test Results

Next, an evaluation was carried out using the ROC curve on the ensemble model (Random Forest + AdaBoost) which shows the Receiver Operating Characteristics (ROC) graph metrics as shown in Figure 14.

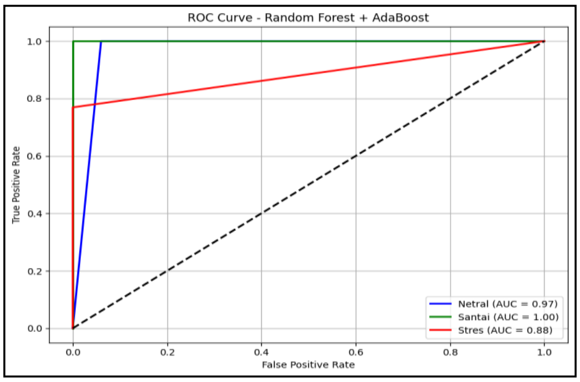


Figure 14. Receiver Operating Characteristics (ROC) Chart Results for Ensemble Model (Random Forest + AdaBoost)

Based on the ROC curve shown in Figure 14, the ensemble model (Random Forest + AdaBoost) demonstrated excellent performance in distinguishing each class: the neutral class with an AUC of 0.97, the relaxed class with an AUC of 1.00, and the stress class with an AUC of 0.88.

c. Minimum Classification Error (MCE) Test Results

The ensemble model (Random Forest + AdaBoost) produces a Minimum Classification Error (MCE) value of 0.03, which means the classification error rate is quite low.

3.5 Discussion

In this subsection, an analysis was conducted on the evaluation results of EEG signal classification models for detecting stress levels. The evaluation was carried out on three models: Support Vector Machine (SVM), Random Forest (RF), and a combination of Random Forest + AdaBoost. The performance comparison of the three models is presented in Table 2, which includes the metrics Accuracy, Precision, Recall, and Minimum Classification Error (MCE).

Tabel 2. Model Performance Comparison Summary (%)

Model	Accuracy	Precision	Recall	MCE
SVM	81,0	72,0	81,0	0,16
RF	96,0	96,0	96,0	0,04
RF + *AdaBoost*	97,0	97,0	97,0	0,03

Based on these results, it can be observed that the Random Forest + AdaBoost combination model demonstrated the best performance with the highest accuracy and the lowest classification error rate (MCE). Meanwhile, the SVM model performed the lowest among the three models tested. To clarify the differences in model performance, a comparison graph has been created as shown in Figure 15.

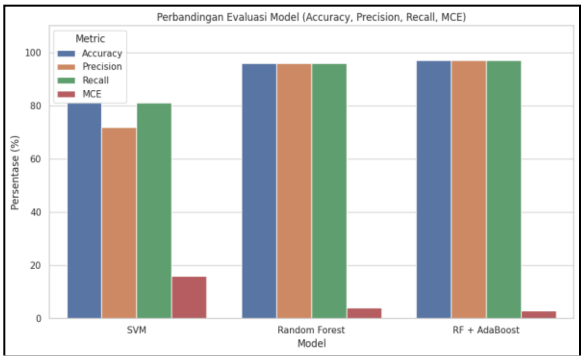


Figure 15. Model Performance Comparison Graph

The evaluation results show that the SVM model achieved an accuracy of 81.0%, a precision of 72.0%, and a recall of 81.0%, with an MCE of 0.16. Although SVM is often used in various signal classification studies, these results indicate that its performance is still not optimal in distinguishing stress levels based on EEG signals. This may be due to the complexity and variability of EEG signals, which are non-linear and non-stationary, meaning that the RBF kernel in SVM cannot fully capture the patterns in the data.

The Random Forest model demonstrated a significant improvement over SVM, achieving an accuracy, precision, and recall of 96.0% each, with the MCE drastically reduced to 0.04. This indicates that the RF model can handle the complex features in EEG data more effectively. Random Forest's ability to perform ensemble decision trees and manage overfitting makes it superior for signal-based classification.

Furthermore, the most optimal results were obtained with the ensemble model combining Random Forest + AdaBoost, which achieved an accuracy of 97.0%, precision of 97.0%, recall of 97.0%, and an MCE of 0.03. This demonstrates that the two-stage ensemble approach, where the probabilistic predictions from Random Forest are used as additional input for AdaBoost, positively contributes to strengthening the classification capability. Compared to using Random Forest alone, this ensemble model increased accuracy by 1%, which, in the context of medical classification such as detecting stress from EEG signals, is a meaningful improvement.

This performance enhancement indicates that the ensemble model not only corrects prediction errors from the base model but is also more robust against noise and variability in EEG data, which are commonly encountered in real-world environments such as correctional facilities. Therefore, it can be concluded that the use of an ensemble model based on Random Forest and AdaBoost is more recommended for EEG signal classification in the context of stress level measurement.

To further validate the results of this study, a comparison with existing EEG-based stress classification research was conducted. Previous studies reported that Support Vector Machine (SVM) achieved accuracy levels ranging from approximately 75% to 90% for mental stress detection, depending on the dataset characteristics and feature extraction methods used [18], [19]. In addition, studies applying Random Forest classifiers for EEG-based stress detection reported average accuracy values of around 85%–90% [20]. Compared to these findings, the proposed Random Forest + AdaBoost ensemble model achieved a higher accuracy of 97%, indicating a significant performance improvement. This result confirms that ensemble learning strategies can provide better robustness and discrimination capability for multilevel stress classification using EEG signals, particularly in real-world environments.

4. CONCLUSION

Based on the results of this study, it can be concluded that the ensemble model outperformed the Support Vector Machine (SVM) in classifying stress levels from EEG signals, achieving 97.00% accuracy, 97.00% precision, 97.00% recall, and an MCE of 0.03, compared to SVM's 81.00% accuracy, 72.00% precision, 81.00% recall, and 0.16 MCE. Compared to Random Forest alone, the ensemble improved accuracy by 1% and reduced MCE from 0.04 to 0.03, demonstrating that the ensemble approach enhances overall classification performance and generalizes better to emotional variations, as reflected by high AUC values of 0.97 (neutral), 1.00 (relaxed), and 0.88 (stress), whereas SVM achieved 0.92, 0.94, and 0.86 for the same classes. For future research, it is recommended to explore other models such as Gradient Boosting, XGBoost, or deep learning architectures (CNN, LSTM) to further improve classification performance, develop real-time stress detection prototypes integrated with wearable EEG devices for field testing, and incorporate feature interpretation analyses using methods like SHAP or LIME to understand the contribution of each feature in classification.

5. REFERENCE

[1] V. Firhana, M. Riliani, R. Arwinda, and S. N. Riani, "Hubungan antara Tingkat Stres dengan Penyakit Gastritis pada Siswa SMA Negeri 2 Tambun Selatan dan Tinjauannya Menurut Pandangan Islam," *Jr. Med. J.*, vol. 2, no. 11, pp. 1295–1302, 2024.

[2] I. Triastuti, W. S. Nurfauziah, and I. Noviyanti, "Tingkat Stres Pada Gen Z Terhadap Pengaruh Media Sosial," vol. 4, no. 1, pp. 264–272, 2025.

[3] E. Choi, H. J. Seo, K. H. Kim, and S. Y. Jung, "Gender-specific secular trends and related factors of high perceived stress level among Korean older adults: a nation-wide serial cross-sectional study," *BMC Public Health*, vol. 25, no. 450, pp. 1–10, 2025, doi: 10.1186/s12889-025-21644-4.

[4] Y. Badr, U. Tariq, F. Al-Shargie, F. Babiloni, F. Al Mughairbi, and H. Al-Nashash, "A review on evaluating mental stress by deep learning using EEG signals," *Neural Comput. Appl.*, vol. 36, no. 21, pp. 12629–12654, 2024, doi: 10.1007/s00521-024-09809-5.

[5] A. Hemakom, D. Atiwiwat, and P. Israsena, "ECG and EEG based detection and multilevel classification of stress using machine learning for specified genders : A preliminary study," *PLoS One*, vol. 18, no. 9, pp. 1–24, 2023, doi: 10.1371/journal.pone.0291070.

[6] S. Chatterjee and Y. C. Byun, "EEG-Based Emotion Classification Using Stacking Ensemble Approach," *Sensors*, vol. 22, no. 21, pp. 1–15, 2022, doi: 10.3390/s22218550.

[7] A. Sundaresan, B. Penchina, S. Cheong, V. Grace, A. Valero-Cabré, and A. Martel, "Evaluating deep learning EEG-based mental stress classification in adolescents with autism for breathing entrainment BCI," *Brain Informatics*, vol. 8, no. 13, pp. 1–12, 2021, doi: 10.1186/s40708-021-00133-5.

[8] H. Ghodang and Hantono, *Metode Penelitian Kuantitatif Konsep Dasar & Aplikasi Analisis Regresi Dengan Jalur SPSS*. Medan: PT. Penerbit Mitra Grup, 2020.

[9] F. Rachmawati, J. Jaenudin, N. B. Ginting, and P. Laksono, "Machine Learning for the Model Prediction of Final Semester Assessment (FSA) using the Multiple Linear Regression Method," *J. Tek. Inform.*, vol. 17, no. 1, pp. 1–9, 2024, doi: 10.15408/jti.v17i1.28652.

[10] T. Hidayat, S. S. Anelia, R. I. Pratiwi, N. Salsabila, and D. S. Prasvita, "Perbandingan Akurasi Klasifikasi Penyakit Diabetes Menggunakan Algoritma Adaboost- Random Forest Dan Adaboost- Decision Tree Dengan Imputasi Median Dan Knn," *Semin. Nas. Mhs. Ilmu Komput. dan Apl.*, no. April, pp. 616–623, 2021.

[11] B. Wijaya, D. Sitanggang, B. Lee, V. Angie, and Eric Simon Giovanni Siahaan, "Application of Support Vector Machine in Measuring Stress Levels Based on EEG Signals," *J. Teknol. dan Ilmu Komput. Prima*, vol. 8, no. 1, pp. 12–25, 2025.

[12] Andi, C. Juliandy, R. Robet, O. Pribadi, and R. Wijaya, "Image Authentication Application with Blockchain to Prevent and Detect Image Plagiarism," *2021 6th Int. Conf. Informatics Comput. ICIC 2021*, no. December, 2021, doi: 10.1109/ICIC54025.2021.9632966.

[13] M. A. Muslim *et al.*, *Data Mining Algoritma C4.5*. 2019.

[14] Andi, R. Purba, and R. Yunis, "Application of

Blockchain Technology to Prevent The Potential Of Plagiarism in Scientific Publication," 2019, doi: 10.1109/ICIC47613.2019.8985920.

[15] A. H. Bik, F. T. Anggraeny, and E. Y. Puspaningrum, "Klasifikasi Penyakit Ginjal Menggunakan Algoritma Hibrida CNN-ELM," *JATI (Jurnal Mhs. Tek. Inform.*, vol. 8, no. 3, pp. 3836–3844, 2024, doi: 10.36040/jati.v8i3.9807.

[16] M. R. F. Nur and S. I. Oktora, "Analisis Kurva Roc Pada Model Logit Dalam Pemodelan Determinan Lansia Bekerja Di Kawasan Timur Indonesia," *Indones. J. Stat. Its Appl.*, vol. 4, no. 1, pp. 116–135, 2020, doi: 10.29244/ijsa.v4i1.524.

[17] Andi, Thamrin, A. Susanto, E. Wijaya, and D. Djohan, "Analysis of the random forest and grid search algorithms in early detection of diabetes mellitus disease," *J. Mantik*, vol. 7, no. 2, pp. 2685–4236, 2023, doi: 10.35335/mantik.v7i2.3981.

[18] R. Katmah, F. Al-shargie, U. Tariq, F. Babiloni, F. Al-mughairbi, and H. Al-nashash, "A Review on Mental Stress Assessment Methods Using EEG Signals," *MDPI Sensors*, vol. 21, no. 15, 2021.

[19] A. Hag, D. Handayani, M. Altalhi, T. Pillai, T. Mantoro, and M. H. Kit, "Enhancing EEG-Based Mental Stress State Recognition Using an Improved Hybrid Feature Selection Algorithm," *MDPI Sensors*, vol. 21, no. 24, 2021.

[20] F. I. S. Ms, F. A. Bachtiar, and B. H. Prasetio, "Analyzing Eeg Signals for Stress Detection Using Random Forest Algorithm," *J. NeutrinoJurnal Fis. dan Apl.*, vol. 17, no. 1, pp. 29–36, 2024, doi: 10.18860/neu.v17i1.28471.