EEG SIGNAL CLASSIFICATION FOR STRESS LEVEL DETECTION USING THE C4.5 METHOD

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ABSTRACT
Stress is a common response to life's pressures that, if left untreated, can negatively impact physical and mental health. Accurately detecting and classifying stress levels is a significant challenge. Electroencephalography (EEG), as a non-invasive method, is capable of recording brain activity and representing a person's emotional state, including stress levels. However, the complexity of EEG data requires effective classification techniques. This study aims to develop a stress level classification system based on EEG signals using the Decision Tree C4.5 method. The EEG dataset was taken from Binjai Prison, with inputs in the form of brain waves (Delta, Theta, Alpha, Beta1, Beta2) and values from various electrodes. The output is a stress classification into three categories: stressed, relaxed, and neutral. The results show that the C4.5 method is able to classify stress levels with 98.68% accuracy, an average precision of 99.19%, and an average recall of 96.29%. The beta2 feature is the most dominant attribute, followed by theta and beta1. Thus, the C4.5 method shows good performance and provides clear interpretation in classifying stress levels based on EEG signals.

Keywords : Stress, EEG, Decision Tree C4.5, Classification, Brain Waves

INTRODUCTION
Stress is a physiological, psychological, and behavioral response that humans attempt to adapt to and regulate internal and external pressures. Prolonged stress can trigger disorders such as hypertension, skin disorders, and even depression. Research shows a high prevalence of stress; for example, in South Korea, women consistently reported higher stress levels than men during the 2009–2019 period (Choi et al., 2025). A meta-analysis of EEG and deep learning studies found that the accuracy of detecting mental stress reached up to 88%, indicating the need for better validation of classification models (Badr et al., 2024).
According to the World Health Organization (WHO), stress is a natural human response to pressure or changes in life. Stress can be triggered by various factors such as workload, economic crises, adverse events, chronic illnesses, unsafe environments, and other factors (Amelya et al., 2024). Everyone experiences stress, but how they respond to it determines their mental health. If left untreated, stress can have negative health impacts, such as sleep disturbances, high blood pressure, and anxiety and depression. Therefore, effective methods are needed to detect and classify stress levels to support appropriate prevention and management (Larasati et al., 2024).
Electroencephalography (EEG) is a technique used to record the brain's electrical activity through the scalp. Besides its primary role in diagnosing epilepsy, EEG is also used to detect

disorders related to brain function (Fasya & Sari, 2024). This method enables non-invasive research into brain function and can measure spontaneous brain activity in response to stimuli, including those related to aggression and violent tendencies. EEG signals can reflect a person's emotional state and stress levels (Khakim & Kusrohmaniah, 2021). However, EEG data is complex and high-dimensional, making it difficult to analyze without appropriate data processing techniques, requiring more efficient methods (Utari et al., 2023).

One classification method for processing EEG signals is the C4.5 method, a decision tree technique capable of producing interpretive and accurate classification models (Ermillian & Nugroho, 2024). The C4.5 method works by constructing a decision tree based on the attributes most influential in determining stress levels. This method can process EEG data to generate classification rules that can aid in the process of identifying individual stress (Hemakom et al., 2023).

However, there is still a research gap in the use of the C4.5 algorithm for EEG-based stress classification, especially when compared to other algorithms such as Support Vector Machine (SVM) or K-Nearest Neighbors (KNN), which have been widely used and demonstrated high performance in various EEG-related studies. Several studies have shown that SVM can achieve an accuracy above 92.76% in stress classification based on EEG signals (Wijaya et al., 2025). While KNN is often used due to its simplicity, it tends to be less accurate in high-dimensional data. Previous research has shown early stress detection with an accuracy of 84%. Therefore, this study aims to fill this gap by evaluating the performance of the C4.5 method and assessing its potential as an interpretive yet competitive alternative algorithm for EEG-based stress classification.

METHODS

Type of Research

This study employed a quantitative approach, involving the collection of numerical data and statistical analysis to understand a phenomenon or answer a research question. This method is often used to measure the relationship between variables and identify patterns or trends in data (Ghodang & Hantono, 2020). This study focused on classifying EEG signals to determine a person's stress level using the C4.5 method.

Working Procedure

For this research to run smoothly, several research work procedures are required. The following are the work procedures implemented:

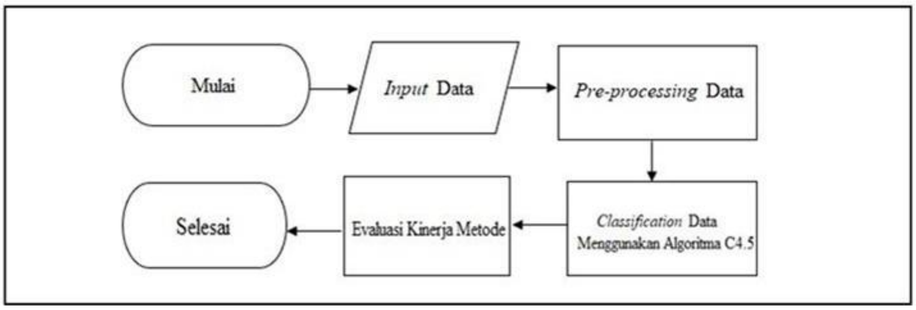

Figure 1. Research Work Procedure

Input Data

EEG data were obtained from 21 subjects from Binjai Prison who participated in the experiment with their eyes closed to minimize visual disturbances and brain activity caused by external stimuli. It also aimed to make the subjects more relaxed and focused, so that the EEG signals obtained reflected a more stable baseline brain activity. Recordings used special equipment to record brain activity. The tools and materials used in this study were Win EEG software, amplifiers, gels, and electrocaps, which are tools and materials used to record brain electrical activity on the scalp. The amplifier increases the amplitude of the EEG signal measured from the electrodes on the scalp, and the gel increases contact between the electrodes and the scalp.

Figure 2. Tools and Materials for Data Input

The EEG signal was then filtered using a bandpass filter with a frequency range of 0.5–50 Hz. This range was chosen to remove low-frequency noise components such as signal drift (below 0.5 Hz), as well as high-frequency interference such as noise from muscle activity (EMG) and 50 Hz alternating current (AC) electrical interference, which are common in laboratory and clinical environments.

Pre-processing Data

The first stage in this analysis is pre-processing the obtained EEG data. Incomplete data or missing values were filled using mean imputation. Then, numerical features from the dataset were selected and normalized using the StandardScaler method to convert the feature values to an equivalent scale, thus simplifying the subsequent analysis process (Rachmawati et al., 2024). In this study, no normality distribution check was performed before the scaling process, considering that StandardScaler can still be used effectively in many cases even if the data is not fully normally distributed, especially as an initial stage in a machine learning-based classification pipeline.

Classification Data

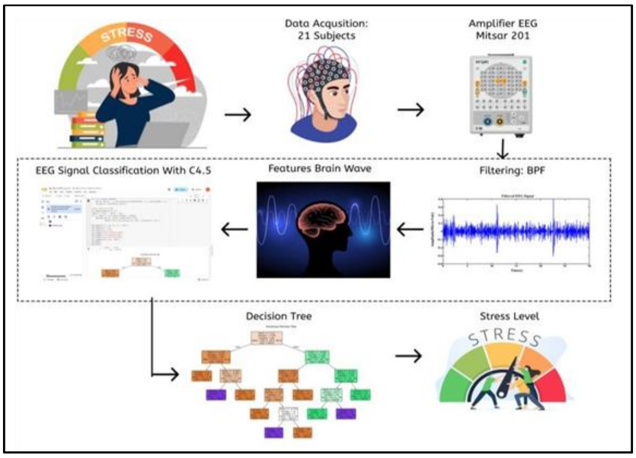

Figure 3. Block Diagram (Brain Computer Interface)

At this stage, the data was classified using the C4.5 algorithm. The data used included five features: delta, theta, alpha, beta1, and beta2, with target labels indicating stress levels: "Stressed," "Relaxed," and "Neutral." The classification process began with data cleaning, removing missing values, and assigning labels based on the following rules (Sani et al., 2014):
• Stressed: If the alpha value is less than the median and theta is greater than the median.
• Relaxed: If both beta1 and beta2 values are greater than the median.
• Neutral: If neither of the above conditions is met.
The class distribution in the data is as follows: Stressed = 80 samples, Relaxed = 72 samples, and Neutral = 69 samples. These values were used as the basis for calculating classification accuracy and to ensure class balance.
The C4.5 model recursively splits the dataset based on the feature that provides the highest gain ratio, thus forming a tree structure that divides the data into relatively homogeneous nodes (close to one class) until it reaches a stopping criterion, such as maximum depth or node purity. In this study, the maximum tree depth is limited to 5 levels to avoid overfitting, a condition where the model is too complex and over-adapts to the training data, thereby reducing its generalization ability to new data. The C4.5 formula (Ardiyansyah et al., 2023):

1. *Entropi (Entropy).*

$$Entropy(S) = -\sum\nolimits^{n}_{i=1} p_i log_2 p_i$$

where pi is the proportion of class i data in set S.

2. *Information Gain.*

$$Gain(S, A) = Entropy(S) - \sum_{v \epsilon Values(A)} \frac{|Sv|}{S} . Entropy(Sv)$$

where Sv is the subset of data for v values of attribute A.

3. *Split Information.*

$$Split\ Information\ (S, A) = -\sum_{v \epsilon Values(A)} \frac{|Sv|}{|S|} log_2 \frac{|Sv|}{|S|}$$

4. *Gain Ratio.*

$$Gain\ Ratio(S, A) = \frac{Gain(S,A)}{Split\ Information\ (S,A)}$$

After the decision tree is formed, the next stage is to describe the rules formed based on the decision tree.

Method Performance Evaluation

The method performance evaluation in this study was conducted using a Confusion Matrix, a cross-tabulation of positive and negative class data grouped into predicted and actual classes (Andi et al., 2021). Before evaluating the model, the dataset was divided into two parts: training data (80%) to train the model to learn data patterns, and testing data (20%) to test the model's performance with previously unseen data. The separation was performed using a stratified sampling method to maintain a balanced class distribution between the training and testing data. The values generated by the Confusion Matrix method are as follows (Muslim et al., 2019):

1. Accuracy, the percentage of data records correctly classified (predicted) by the algorithm.
   Formula: (TP + TN) / Total data = Accuracy
2. Precision, the ratio of positive predictions to positive predicted outcomes.
   Formula: (TP) / (TP + FP) = Precision
3. Recall, the percentage of true positive predictions compared to the total number of true positive data. Formula: (TP) / (TP + FN) = Recall
4. Misclassification (Error) Rate, the percentage of data records classified (incorrectly predicted by the algorithm).
   Formula: 1- Accuracy = Misclassification Rate

In addition to using the Confusion Matrix, the evaluation also includes visualization of the ROC curve for each class. The ROC curve displays the relationship between the True Positive Rate (TPR) and False Positive Rate (FPR), to measure how well the model distinguishes between classes (Bik et al., 2024).

1. The higher the area under the curve (AUC), the better the model's performance.
2. The AUC value is measured by the area under the ROC curve. A value close to 1 indicates excellent class differentiation performance for the model. A value close to 0.5 indicates that the model is no better than random classification.

RESULTS

Data Input Results

EEG data was obtained from 21 subjects who participated in the experiment blindfolded and used special equipment to record brain activity. The initial EEG signals contained high levels of noise, as seen in the image below.

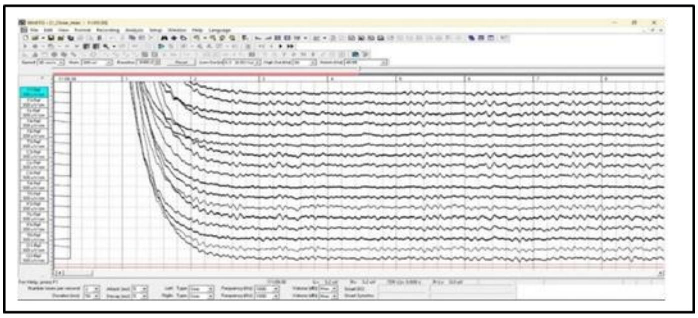

Figure 4. Data Before Filtering

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

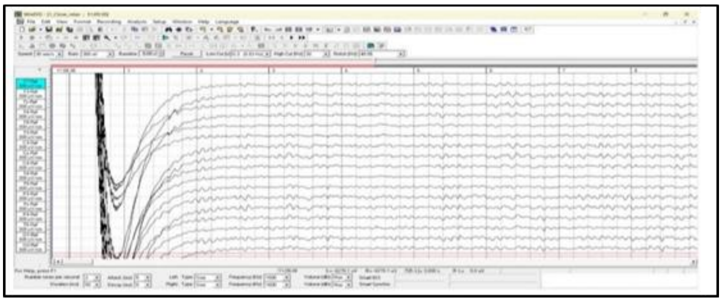

Figure 5. Filtered Data

After the filtering process, only relevant brain waves such as delta, theta, alpha, and beta were retained. Furthermore, electrodes Fp1 and Fp2 were removed, leaving 18 data points for further analysis. The following is an Excel file of the research dataset.

1			delta	theta	alpha	beta1	beta 2
2	S1	Fp1-Ref	3.20	3.11	4.92	1.19	1.22
3		F7-Ref	2.45	2.38	3.83	1.18	1.21
4		F3-Ref	2.75	3.35	5.74	1.39	1.35
5		Fz-Ref	2.91	3.41	5.82	1.33	1.31
6		F4-Ref	2.79	3.17	5.22	1.36	1.37
7		F8-Ref	2.69	2.35	3.40	1.15	1.25
8		T3-Ref	2.27	2.22	3.55	1.63	1.65
9		C3-Ref	2.61	2.99	5.32	1.41	1.32
10		Cz-Ref	3.04	3.44	6.19	1.52	1.49
11		C4-Ref	2.95	2.85	4.78	1.44	1.29
12		T4-Ref	2.20	2.02	2.93	1.12	0.97
13		T5-Ref	2.21	2.16	4.22	1.26	1.16
14		P3-Ref	2.95	2.91	5.50	1.53	1.40
15		Pz-Ref	2.80	2.90	5.65	1.51	1.38
16		P4-Ref	2.93	2.60	5.03	1.42	1.25
17		T6-Ref	2.49	2.00	4.34	1.22	1.11
18		O1-Ref	3.06	2.53	5.77	1.58	1.59
19		O2-Ref	2.59	2.22	5.15	1.42	1.31
20		Fp1-Ref	7.19	5.17	5.22	2.1	1.63
21		F7-Ref	5.05	3.12	3.73	1.48	1.23
22		F3-Ref	3.99	3.13	4.92	1.64	1.55
23		Fz-Ref	3.02	2.62	5.35	1.68	1.47
24		F4-Ref	3.15	2.77	5.38	1.76	1.65
25		F8-Ref	6.73	3.5	4.72	1.91	1.82

- *Stress: If the alpha value is less than the median and theta is greater than the median.*
- *Relaxed: If the beta1 and beta2 values are greater than the median.*
- *Neutral: If neither of the above conditions is met.*

Figure 6. Research Dataset

There are 18 electrodes 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.

Data Pre-Processing Results

The data preprocessing stage in this study was carried out using Google Colab based on Python programming. Afterwards, the preprocessing stage was carried out, which consisted of the first stage, namely having missing values filled in using mean imputation, as shown in the figure below.

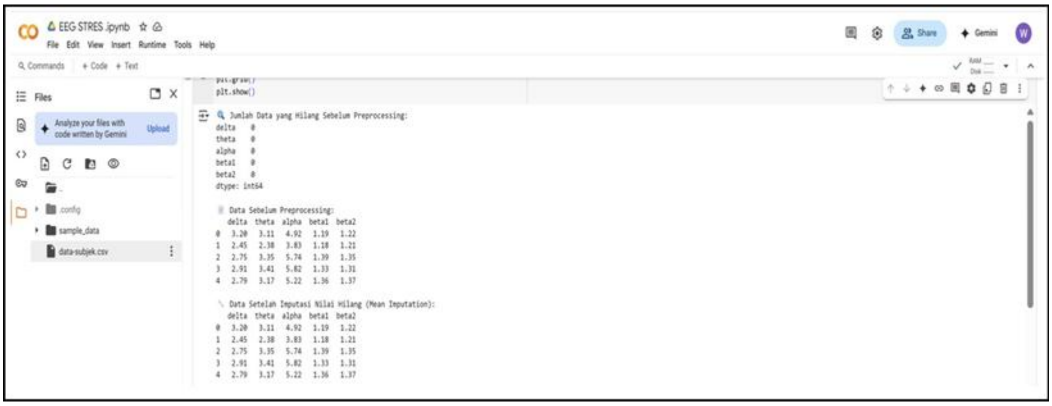

Figure 7. First Stage Dataset Pre-processing Results

As seen in Figure 7, the dataset used had no missing values, so the data before and after preprocessing yielded the same values.

Next, the second preprocessing stage proceeded, where numerical features from the dataset were selected and normalized using the StandardScaler method, as shown in Figure 8.

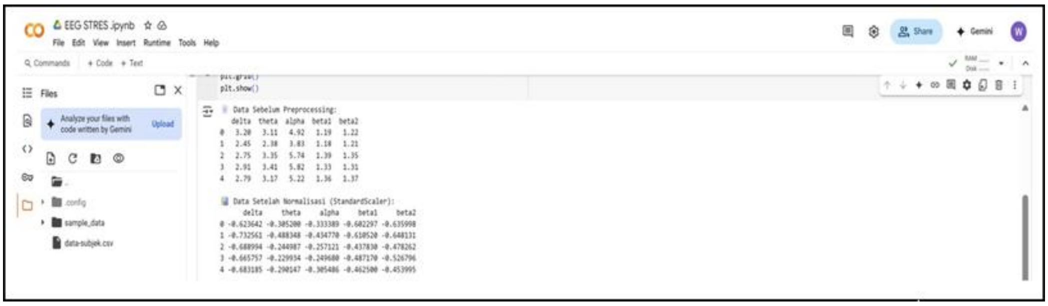

Figure 8. Second Stage Dataset Pre-processing Results

As can be seen in Figure 8, the dataset after normalization has different values from the dataset before normalization, which means that the second stage of pre-processing was successful.

Classification Data Results

After preprocessing the EEG dataset, the data were classified using the Decision Tree C4.5 algorithm. Classification labels were determined based on simple logical rules that refer to the median value of certain features as described previously, resulting in the labeling results shown in Figure 9.

Figure 9. EEG Dataset Labeling Results

After labeling, a C4.5 Decision Tree model was built using feature selection criteria based on entropy (information gain) and gain ratio. This model was trained with a maximum tree depth of 5 to avoid overfitting. Figure 10 shows the resulting Decision Tree.

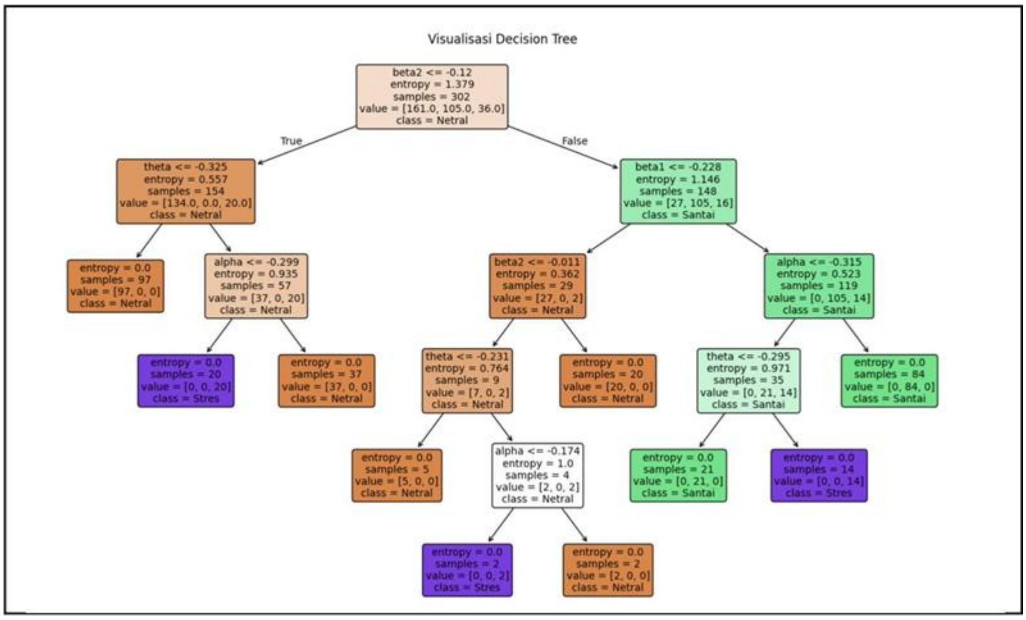

Figure 10 The Results of the Decision Tree Formed

Based on the decision tree visualization results in Figure 10, it can be concluded that the first attribute used as the root node in the decision tree is beta2. In the C4.5 algorithm, the attribute placed at the root node is the one with the highest gain ratio, meaning that beta2 is the most effective in reducing data uncertainty (entropy).

The quantitative results of the gain ratios for each feature shown in Table 1 show that beta2 is followed by beta1, alpha, and theta. The delta attribute is not used because it contributes zero information.

Table 1. Gain Ratio (Feature Importance) for Each Feature

Fitur	Gain Ratio
beta2	0.395617
beta1	0.232683
alpha	0.205200
theta	0.166500
delta	0.000000

After splitting based on beta2 values, the tree divides the data into nodes based on the following attributes: theta and beta1. Theta appears as the next branching node after beta2, indicating that theta also contributes significantly to distinguishing between the "Stressed," "Relaxed," and "Neutral" states. Beta1 is then used for further splitting, primarily to distinguish data that cannot be classified using beta2 and theta alone.

Although the initial dataset includes five features, the decision tree does not always use all attributes. Only attributes that contribute significant information are selected by the algorithm.

In this visualization, the delta and alpha attributes are not used, as their gain ratio contributions are lower than the others.

From the decision tree in Figure 10, rules for classifying EEG signals to determine stress levels are derived. The resulting rules are shown in Figure 11.

```
Rules from Decision Tree (C4.5):

|--- beta2 <= -0.12
|   |--- theta <= -0.33
|   |   |--- class: Netral
|   |--- theta >  -0.33
|   |   |--- alpha <= -0.30
|   |   |   |--- class: Stres
|   |   |--- alpha >  -0.30
|   |   |   |--- class: Netral
|--- beta2 >  -0.12
|   |--- beta1 <= -0.23
|   |   |--- beta2 <= -0.01
|   |   |   |--- theta <= -0.23
|   |   |   |   |--- class: Netral
|   |   |   |--- theta >  -0.23
|   |   |   |   |--- alpha <= -0.17
|   |   |   |   |   |--- class: Stres
|   |   |   |   |--- alpha >  -0.17
|   |   |   |   |   |--- class: Netral
|   |   |--- beta2 >  -0.01
|   |   |   |--- class: Netral
|   |--- beta1 >  -0.23
|   |   |--- alpha <= -0.31
|   |   |   |--- theta <= -0.29
|   |   |   |   |--- class: Santai
|   |   |   |--- theta >  -0.29
|   |   |   |   |--- class: Stres
|   |   |--- alpha >  -0.31
|   |   |   |--- class: Santai
```

Figure 11. Rules Results Formed Based on C4.5 Method

Results of the Method Performance Evaluation

In the model performance evaluation stage, classification results were tested using a Confusion Matrix and ROC curve to assess the model's ability to classify data. The following describes the results of the method performance evaluation:

1. Confusion Matrix Evaluation.

   The dataset was divided into training data (80%) and test data (20%) using the Stratified Sampling method to maintain a balanced proportion of labels. The results of the Confusion Matrix test are presented in the form of a Confusion Matrix plot, as shown in Figure 13, and a numerical Confusion Matrix in Table 2.

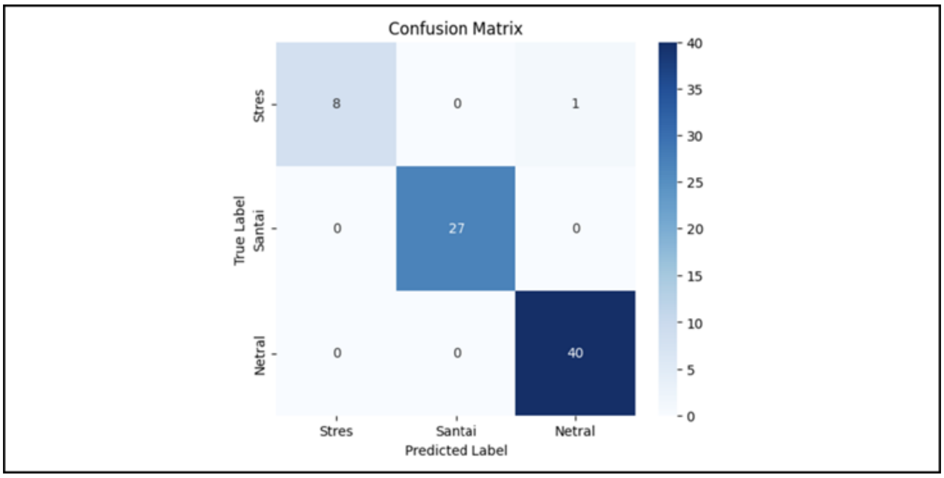

Figure 12. Confusion Matrix Plot Results of C4.5 Method in EEG Signal Classification to Determine Stress Levels

Table 2. Confusion Matrix Numerik

Label	Prediksi: Stres	Prediksi: Santai	Prediksi: Netral
Aktual: Stres	8	0	1
Aktual: Santai	0	27	0
Aktual: Netral	0	0	40

Based on Figure 12 and Table 2, calculations were made for accuracy, precision, recall, and misclassification error, including:

a. *Accuracy/Akurasi*

$$Accuracy = \frac{TP_{Stress} + TP_{Santai} + TP_{Netral}}{Total\ Data}$$

$$Accuracy = \frac{8 + 27 + 40}{8 + 0 + 1 + 0 + 27 + 0 + 0 + 0 + 40}$$

$$Accuracy = \frac{75}{76} = 0{,}9868\ x\ 100 = 98{,}68\%$$

b. *Precision/Presisi*

$$Precision_{Stress} = \frac{8}{8 + 0 + 0} = \frac{8}{8} = 1{,}00$$

$$Precision_{Santai} = \frac{27}{0 + 27 + 0} = \frac{27}{27} = 1{,}00$$

$$Precision_{Netral} = \frac{40}{1 + 0 + 40} = \frac{40}{41} = 0{,}9756$$

Macro Precision = (1,00 + 1,00 + 0,9756) / 3 = 0,9919 x 100 = 99,19%

c. *Recall/Sensitivitas*

$$Recall_{Stress} = \frac{8}{8 + 1} = \frac{8}{9} = 0{,}8889$$

$$Recall_{Santai} = \frac{27}{27 + 0} = \frac{27}{27} = 1{,}00$$

$$Recall_{Netral} = \frac{40}{40 + 0} = \frac{40}{40} = 1{,}00$$

Macro Precision = (0,8889 + 1,00 + 1,00) / 3 = 0,9629 x 100 = 96,29%

d. *Missclassification Error/Kesalahan Klasifikasi*

$$Error = 1 - Accuracy = 1 - 0{,}9868 = 0{,}0132\ x\ 100 = 1{,}32\%$$

Based on the evaluation results above, the performance of the Decision Tree C4.5 algorithm produced an accuracy of 98.68%, a precision of 99.19%, a recall of 96.29%, and a misclassification error of 1.32%.

2. Evaluation with ROC Curve.

Next, an evaluation was performed using the ROC curve, which displays the Receiver Operating Characteristics (ROC) graph metrics, as shown in Figure 13.

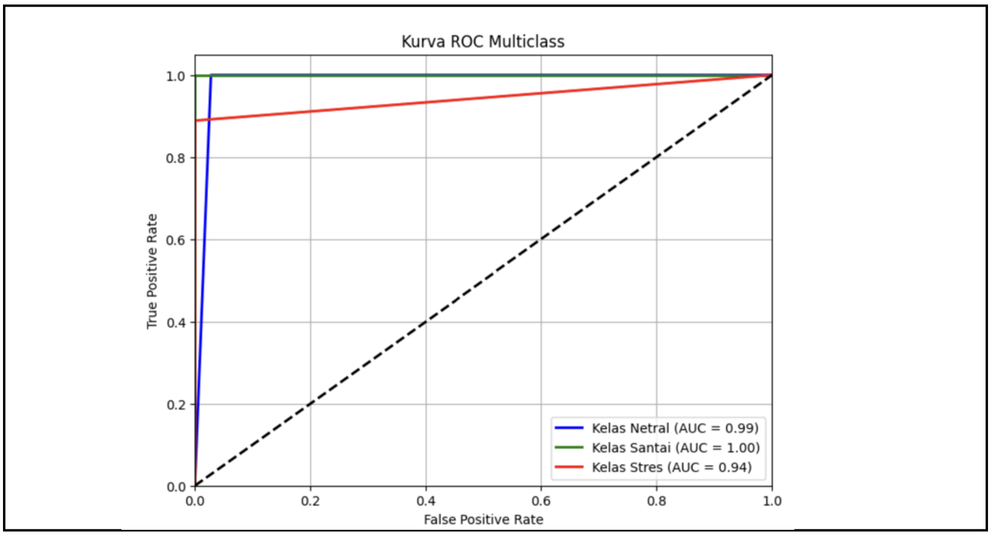

Figure 13. Receiver Operating Characteristics Graphic Results

Based on Figure 13, the C4.5 method shows a neutral class with an AUC value of 0.99, a relaxed class with an AUC value of 1.00, and a stressed class with a value of 0.94.

DISCUSSION

The results of this study demonstrate that the C4.5 Decision Tree method can be used effectively to classify a person's stress level based on EEG signal data, achieving a very high accuracy of 98.68%, along with excellent precision and recall. This achievement indicates that the model has good generalization capabilities in recognizing brain signal patterns associated with stressful, relaxed, and neutral states.

During the classification process, the beta2 attribute was identified as the most dominant feature, as it was selected as the root node in the resulting decision tree. This indicates that beta2 brain waves play a significant role in separating the stress classes studied. Other significant attributes were theta and beta1, which further support separation between classes. Conversely, the delta and alpha attributes were not used in the decision tree due to their lower gain ratios.

Data preprocessing plays a crucial role in ensuring the quality of the input to the model. By removing noise using a Band-Pass Filter and normalizing numerical features using a Standard Scaler, the data becomes cleaner and more representative for the classification process.

The evaluation results using the Confusion Matrix and ROC curve further strengthen the conclusion that the C4.5 method is highly effective. With an average precision of 99.19% and an average recall of 96.29%, the model was proven to correctly identify almost all data. The AUC values approaching 1 for all three classes (neutral, relaxed, and stressed) also indicate that the model has excellent discriminatory ability in distinguishing between classes.

This model is not only capable of classifying data with high accuracy but also provides a logical interpretation that can be traced through the resulting decision tree structure..

To assess the performance of the Decision Tree C4.5 method in this study, the following table presents a comparison of accuracy with several other algorithms commonly used in EEG signal classification as shown in Table 3.

Table 3. Comparison of Research Results with Previous Research

Method	Accuracy (%)	Source	Information
Decision Tree (C4.5)	**98.68**	This research	Interpretive and transparent
SVM (RBF Kernel)	92.76	Wijaya et al. (2025)	Effective for non-linear classification
Random Forest	95.12	Sari et al. (2023)	Robust against overfitting
K-Nearest Neighbors	84.00	Putra & Hidayat (2022)	Simple, but less than optimal on EEG data
CNN	97.45	Anwar et al. (2024)	Excels in EEG spatial feature extraction

CONCLUSION

Based on the results of the study, the following conclusions can be drawn:

1. The C4.5 Decision Tree method demonstrated excellent performance in classifying a person's stress level based on EEG signals. The model achieved an accuracy of 98.68%, with an average precision of 99.19% and an average recall of 96.29%. This indicates that the C4.5 method is highly effective and possesses strong generalization capabilities in recognizing brain-signal patterns that represent stressed, relaxed, and neutral conditions.
2. The C4.5 method is capable of accurately distinguishing whether an individual is in a stressed, relaxed, or neutral state based on EEG signal attributes. The beta2 attribute was identified as the most dominant feature and was selected as the root node in the decision tree, followed by theta and beta1.

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