

# Machine Learning for EEG-Based Cognitive Response Analysis in the Free Nutritious Meals Program

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## ABSTRACT

Electroencephalography (EEG) signals provide objective information on students' cognitive responses; however, an appropriate classification method is required to effectively process their characteristics. This study aims to compare the performance of six machine learning algorithms in classifying students' cognitive responses based on EEG data collected in the context of the Free Nutritious Meals (MBG) Program. The evaluated algorithms include K-Nearest Neighbors, Random Forest, Logistic Regression, Decision Tree, Naive Bayes, and Support Vector Machine, using delta, theta, alpha, beta, and gamma features. The modeling process involved baseline model development and hyperparameter tuning, followed by performance evaluation using accuracy, precision, recall, and F1-score. The results show that K-Nearest Neighbors achieved the highest baseline accuracy of 88.00%. After hyperparameter tuning, Decision Tree achieved the highest performance among the tuned models, with an accuracy and macro F1-score of 88.00%. However, its accuracy was identical to that of baseline KNN, and no significant difference was observed between their predictions. These findings indicate that hyperparameter tuning affected the evaluated algorithms differently, with Decision Tree showing the largest performance improvement under the experimental configuration used in this study.



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## I. INTRODUCTION

The Free Nutritious Meal (MBG) Program is a national strategic policy aimed at improving the quality of Indonesia's human resources, particularly among school-aged children. As a national strategic initiative, the MBG Program is positioned as a long-term investment in improving the nutritional status of school-aged children while fostering a healthier, more intelligent, and more competitive generation capable of contributing to the nation's future [1][2]. The evaluation of this program has largely focused on physical and administrative indicators and has not yet directly captured changes in brain activity that occur when students perform cognitive tasks [3][4][5]. Electroencephalography (EEG) offers a non-invasive approach for assessing an individual's

cognitive state [6][7]. However, the complex characteristics of EEG signals make these changes difficult to identify through descriptive analysis alone.

The complexity of EEG signals across various domains presents a challenge in accurately characterizing an individual's cognitive state. Several studies have demonstrated that EEG signals can be used to identify patterns of brain activity associated with focus, attention, and cognitive readiness [8][9][10]. On the other hand, the complex, nonlinear, and highly noisy characteristics of EEG data require an appropriate analytical approach [11]. Machine learning is an effective approach for processing and extracting patterns from complex signal data, such as EEG. Various machine learning methods can be implemented using algorithms such as Random Forest, Support Vector Machine

(SVM), Naive Bayes, and other classification algorithms [12][13].

Although various algorithms have demonstrated their capability in EEG-based classification, most studies have focused on patient diagnosis, depression treatment, stress assessment, or authentication systems [14][15][16][17]. Studies specifically evaluating and comparing multiple machine learning algorithms to identify students' cognitive responses based on changes in EEG characteristics before and after consuming the MBG program remain limited. Furthermore, comparisons of model performance before and after hyperparameter optimization in this context have rarely been reported.

Based on these issues, this study aims to compare the performance of six machine learning algorithms, namely K-Nearest Neighbors (KNN), Random Forest, Logistic Regression, Decision Tree, Naive Bayes, and Support Vector Machine (SVM), in classifying students' cognitive responses based on EEG features measured before and after MBG consumption. The modeling process involves developing baseline models and performing hyperparameter optimization to identify the best configuration for each algorithm. Model performance is evaluated using accuracy, precision, recall, and F1-score to compare the classification performance of the evaluated algorithms. The findings are expected to provide an empirical baseline for the ability of various machine learning algorithms to recognize EEG-based patterns of cognitive responses in the context of the MBG program, while also serving as a foundation for the development of EEG-based systems for evaluating students' cognitive responses in future research.

## II. METHODS

This study aims to develop an EEG signal-based model for identifying students' cognitive responses in the MBG Program using machine learning algorithms. The study consists of several interconnected stages, as illustrated in Figure 1, beginning with EEG data analysis, followed by exploratory data analysis (EDA), data preprocessing, hyperparameter tuning, and model evaluation.

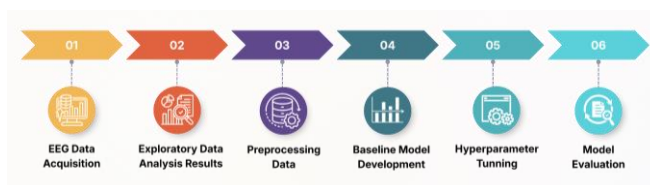


Figure 1. Research Methodology

### A. EEG Data Acquisition

The EEG data used in this study were obtained as electrical signals represented in microvolts ( $\mu V$ ). EEG is a non-invasive method that records changes in electrical potential on the scalp surface through electrodes. Therefore, the raw EEG data are initially represented in the time domain, where each  $\mu V$  value indicates the signal amplitude at a specific measurement time.

The acquired EEG data were then processed to obtain frequency-domain information in Hertz (Hz). This process does not directly convert  $\mu V$  values into Hz; instead, the Fast Fourier Transform (FFT) is used to transform the signal from the time domain into the frequency domain. FFT is an implementation of the Discrete Fourier Transform (DFT) that provides information about the amplitude and phase of oscillations across different frequencies [18]. Subsequently, the spectral information was used to obtain the Power Spectral Density (PSD) characteristics for each EEG frequency band.

Mathematically, the FFT-based transformation of the EEG signal can be expressed as follows [19]:

$$X(k) = \sum_{n=0}^{N-1} x(n)e^{-i2\pi kn/N}$$

where  $x(n)$  represents the EEG signal value in  $\mu V$ ,  $N$  denotes the number of samples, and  $X(k)$  represents the transformed value at the  $k$ -th frequency index. The actual frequency corresponding to each FFT index is determined based on the sampling frequency  $F_s$ , as expressed by the following equation [20]:

$$fk = \frac{kF_s}{N}$$

The equation yields frequency values in Hertz (Hz). Thus,  $\mu V$  represents the amplitude of the input signal, while Hz indicates the frequencies of the signal components obtained through the FFT process.

After the transformation, the spectral values are used to calculate the signal power within each frequency band. In this study, Power Spectral Density (PSD) is used to analyze five EEG frequency bands: Delta (0-4 Hz), Theta (4-8 Hz), Alpha (8-12 Hz), Beta (12-30 Hz), and Gamma (30-45 Hz) [21]. The referenced study also explains that the total magnitude of a frequency band is obtained by summing the spectral components corresponding to the frequencies within that band.

In this study, cognitive response was operationally defined as the students' focus state while performing the cognitive task during EEG recording. Previous EEG studies have associated Beta activity with cognitive processing, attention, and higher mental engagement, whereas Alpha activity is generally associated with lower alertness and attention. The relationship between these frequency bands has also been represented through the Beta-to-Alpha power ratio as an EEG-based index of attention and engagement [22], [23]. Based on this approach, the Focus Score in this study was calculated as:

$$Focus\ score = \frac{P\beta}{P\alpha}$$

where  $P\beta$  and  $P\alpha$  represent the spectral power of the Beta and Alpha frequency bands, respectively. To obtain a binary classification target, an operational threshold was adopted in this study based on the relative dominance of Beta and Alpha power. A Focus Score equal to or greater than 1.0 indicates that Beta power is equal to or greater than Alpha power and was therefore categorized as Focused ( $eeg\_label = 1$ ). Conversely, a Focus Score below 1.0 indicates that Alpha

power is greater than Beta power and was categorized as Not Focused ( $eeg\_label = 0$ ). This threshold was used as an operational criterion for constructing the classification labels in this study rather than as a universal clinical or physiological cut-off.

$$\begin{cases} 1(\text{Focused}), & \text{Focus Score} \geq 1.0 \\ 0(\text{Not Focused}), & \text{Focus Score} < 1.0 \end{cases}$$

In this study, the division of frequency bands is used as the basis for extracting Delta, Theta, Alpha, Beta, and Gamma features from the EEG signals. These features are then used to characterize cognitive responses, including the ratio between Beta and Alpha power. This approach enables the raw EEG data, initially represented as amplitude values in  $\mu V$ , to be transformed into frequency-domain and spectral power features, which are subsequently used as inputs for machine learning analysis and classification.

This study collected data from students participating in the MBG Program at several educational institutions in Pekanbaru City and Kampar Regency, Riau Province, Indonesia. Data collection was conducted from June to August 2026. The data collection process included identifying and selecting students as research participants, conducting measurements before and after participation in the program, and collecting the data required to analyze changes in students' cognitive responses. The collected data were subsequently used as the basis for developing and evaluating EEG signal-based machine learning models to identify changes in the cognitive responses of students participating in the MBG Program.

To examine students' EEG-based cognitive responses within the MBG context, data acquisition was conducted using a paired pre-post measurement design. Each student participated in two EEG recording sessions under different measurement conditions: before consuming the MBG meal (Pre-MBG) and after consuming the MBG meal (Post-MBG). In both sessions, students performed a cognitive task while wearing the Muse 2 EEG headband, and brain activity was recorded for 30 seconds [24]. The same recording procedure and duration were maintained across the two measurement conditions to provide comparable EEG observations for each student. The MBG meal was consumed between the two measurement sessions, making the Pre-MBG and Post-MBG conditions the contextual basis for examining EEG-derived focus states before and after meal consumption. The resulting EEG signals were subsequently processed into spectral features and classified into Focused and Not Focused states using the operational definition described above.

EEG signals were acquired from 123 students using a Muse 2 EEG headband during the cognitive task. The device records EEG activity at a sampling rate of 256 Hz through four EEG channels located at TP9, AF7, AF8, and TP10 [25]. EEG data acquisition was performed through a JavaScript-based interface using the muse2.js library, which enabled the

EEG signals generated by the Muse 2 device to be recorded as time-series amplitude values in microvolts ( $\mu V$ ). During each recording session, the student was seated in front of a laptop in a room at the participating school while completing the cognitive task presented on the laptop. Each EEG recording lasted 30 seconds, and the same recording procedure was applied under both measurement conditions. Each student underwent two recording sessions, corresponding to the Pre-MBG and Post-MBG conditions, resulting in a total of 246 EEG recordings, consisting of 123 Pre-MBG and 123 Post-MBG recordings.

The EEG acquisition system initially stored the recorded signals as time-series amplitude values in microvolts for each recording session. The raw EEG samples collected during approximately 30 seconds of cognitive-task performance were subsequently processed within the muse.js acquisition pipeline. The signals were transformed from the time domain into the frequency domain using the FFT, followed by spectral power estimation for the Delta, Theta, Alpha, Beta, and Gamma frequency bands. The resulting band-power values were used as the EEG features for subsequent machine learning analysis. At the machine learning stage, the numerical EEG features were standardized using StandardScaler within the preprocessing pipeline before model training and evaluation.

### B. Exploratory Data Analysis Results

During the Exploratory Data Analysis (EDA) stage, an initial examination of the dataset was conducted to understand its structure, characteristics, distribution, and patterns before proceeding to the preprocessing stage. EDA can be performed through statistical analysis and data visualization to provide an overview of the dataset and identify potential data quality issues, such as missing values, outliers, and relationships between variables. Previous studies have demonstrated that the systematic application of EDA through univariate and bivariate analyses can help identify data characteristics and quality issues before further analysis is performed [26]. In this study, EDA was used as an initial step to assess the characteristics and quality of the dataset before proceeding to the preprocessing stage.

The Exploratory Data Analysis (EDA) stage in this study was conducted to ensure that the dataset was suitable for the preprocessing stage. At this stage, data distribution was analyzed to examine the distribution of responses across each category in the dataset. In addition, data completeness was assessed by identifying the presence of missing values in each variable. The results showed that no missing values were found in the dataset, with a total of zero missing values. Therefore, all data could be used in the subsequent stage without requiring an imputation process. Checking for missing values is an important part of data quality assessment because missing data need to be identified before a dataset is used for further analysis or modeling [27]. The data completeness assessment conducted during the EDA stage showed that the dataset contained no missing values and therefore required no specific treatment for missing data.

Thus, the EDA results confirmed that the dataset was complete and suitable for further processing in the preprocessing stage.

### C. Preprocessing Data

Data preprocessing is the process of preparing raw data into a suitable format for analysis and machine learning modeling [28]. After EEG feature extraction, the resulting dataset was prepared for machine learning analysis. The preprocessing stage included checking for missing values and ensuring the consistency of the extracted EEG features and target labels. The numerical EEG features, consisting of Delta, Theta, Alpha, Beta, and Gamma band-power values, were standardized using StandardScaler to reduce differences in feature scales. Categorical information used in the modeling process was transformed into a numerical representation where required. To prevent information leakage, preprocessing transformations were incorporated into the machine learning pipeline so that the scaling parameters were learned from the training data and subsequently applied to the test data.

### D. Baseline Model Development

After the data underwent preprocessing, the next stage involved developing the baseline models. Six classification algorithms were implemented, namely K-Nearest Neighbors (KNN), Random Forest, Logistic Regression, Decision Tree, Naive Bayes, and Support Vector Machine (SVM). The selection of these six algorithms aimed to compare the performance of different classification approaches before determining the best-performing model. The algorithms were implemented using the Python programming language and the Scikit-learn library, which provides a range of machine learning algorithms for classification tasks. The use of multiple algorithms as baseline models for performance comparison has also been adopted in previous studies, which implemented SVM, Logistic Regression, Naive Bayes, Random Forest, Decision Tree, and KNN using the Scikit-learn library [29]. Thus, the six models were used as baseline references for evaluating the classification performance of the EEG data before determining the best-performing model.

The models in this stage were developed using the standard parameters (default parameters) provided by each algorithm. Parameters in machine learning models are configuration values used to control the learning process and model construction. Previous studies have evaluated machine learning models using the default hyperparameters provided by the software without manual adjustment or optimization [30]. The use of default parameters also provides an initial assessment of an algorithm's performance before hyperparameter tuning is performed. Previous research has shown that using default parameters without tuning may prevent a model from achieving its optimal performance. In this study, default parameters were used to develop the baseline models, allowing the initial performance of each algorithm to be assessed and compared consistently before proceeding to the model evaluation stage.

### E. Hyperparameter Tuning

Hyperparameter tuning has been applied in several studies involving EEG-based signal analysis. A study on the development of a deep learning model for classifying students' confusion levels using EEG data employed hyperparameter tuning with a Bayesian optimization approach to determine the optimal model configuration. The results showed that the optimized model improved accuracy by 4% to 9% compared with the baseline approaches [7]. Another study developed a protocol for EEG decoding using neural networks by conducting hyperparameter searches across various stages of the pipeline. The results demonstrated that the search strategy and hyperparameter configuration could influence model performance, indicating that hyperparameter optimization is an important step in obtaining more reliable EEG-based models [31].

To avoid subject-level data leakage, the dataset was split using GroupShuffleSplit with student ID as the grouping variable. A fixed random seed of 42 and a test size of 20% were used, resulting in 196 training observations from 98 students and 50 test observations from 25 students. This grouping strategy ensured that the Pre-MBG and Post-MBG recordings from the same student were assigned to the same data partition. Hyperparameter optimization was performed only on the training set using GridSearchCV with 5-fold GroupKFold cross-validation, again using student ID as the grouping variable. Macro F1-score was used as the optimization metric. The final tuned models were subsequently evaluated on the held-out subject-independent test set.

### F. Model Evaluation

The model evaluation stage aims to assess the performance of the developed machine learning models and ensure that the resulting models achieve adequate levels of accuracy, consistency, and reliability for EEG-based modeling in the context of the MBG Program.

Model evaluation in this study was performed using four performance metrics, namely accuracy, precision, recall, and F1-score, supported by a confusion matrix to assess the classification results [28][29]. Accuracy is used to measure the overall correctness of the model in predicting the appropriate and inappropriate categories. Precision indicates the model's ability to correctly identify instances predicted as belonging to each class. Recall measures the model's ability to correctly identify all instances that belong to a particular class. The F1-score provides a balance between precision and recall. The confusion matrix provides a detailed comparison between the predicted results and the actual class labels.

To further examine the comparable performance of the two configurations achieving the highest test accuracy, a 95% Wilson confidence interval was calculated for the accuracy estimate, and an exact McNemar test was used to compare their paired predictions on the same held-out test set [34]. Statistical significance was assessed at  $p < 0.05$ .

## III. RESULTS AND DISCUSSION

### A. EEG Data Acquisition

The results of this study successfully yielded EEG signal data from students participating in the MBG Program. The data were obtained through a structured EEG acquisition process conducted for each research sample. The acquired signals were subsequently used as the primary data for the processing and analysis stages to identify changes in the students' cognitive responses.

The study participants consisted of students from Senior High Schools (SMA) and Vocational High Schools (SMK) who were recipients of the MBG Program. The participating students were between 17 and 18 years of age and were enrolled in Grades 11 and 12. The selection of participants was based on the research requirements for identifying changes in students' cognitive responses following participation in the MBG Program. Each student underwent a series of data collection procedures in accordance with the established research protocol.

During the data collection stage, each student was asked to wear the prepared EEG device to record brainwave activity. Once the device was properly positioned, the students were given questions or cognitive tasks to complete throughout the recording process. The students' brain activity was recorded for 30 seconds during each session. This procedure was carried out systematically to ensure that the EEG signal data obtained had a consistent recording duration across all students.

The data obtained from the EEG device consisted of brainwave activity signals expressed in microvolts ( $\mu\text{V}$ ). Each student generated an EEG recording containing signal amplitude values at each measurement point throughout the recording process. The data were then collected and organized according to each student to facilitate subsequent processing and analysis. The resulting amplitude values served as the initial data for examining the characteristics of the students' brain activity under different measurement conditions.

EEG data were collected during two measurement sessions, namely before and after the students consumed MBG. The first session was conducted before MBG consumption to obtain baseline data on the students' brain electrical activity. Subsequently, the second session was conducted after MBG consumption to obtain data on brain electrical activity under the post-consumption condition. The two recording sessions provided paired EEG observations under Pre-MBG and Post-MBG conditions. These recordings were subsequently processed to extract EEG spectral features and derive the focus-state labels used in the machine learning classification process.

The EEG data transformation process involved transforming the signals originally recorded in microvolts ( $\mu\text{V}$ ) in the time domain into frequency-domain information expressed in Hertz (Hz) using the Fast Fourier Transform (FFT). The  $\mu\text{V}$  values of each sample were used as input to analyze the frequency components contained in the signal. The resulting FFT provided a representation of the signal in terms of its frequency distribution, allowing the frequencies

present in the EEG signal to be identified. Subsequently, the frequency components were categorized into the delta, theta, alpha, beta, and gamma bands based on their respective frequency ranges. This process enabled the EEG data, which initially represented amplitude variations in  $\mu\text{V}$  over time, to be analyzed based on their frequency characteristics in Hz and used to extract EEG features for subsequent data processing.

The results of the EEG data acquisition are presented in Table 1. The dataset contains the students' names, measurement conditions representing the periods before and after MBG consumption, and the delta, theta, alpha, beta, and gamma wave components. The label and response variables are important components of the acquired dataset. The label is assigned a value of 1 (true) when the data meet the criteria based on the PSD calculation and a value of 0 (false) when they do not. Meanwhile, the response variable indicates whether the student answered the instrument correctly or incorrectly while completing the questions.

TABLE 1. RESULTS OF EEG DATA ACQUISITION

| No  | Student   | Condition | Delta | ... | Labelling |
|-----|-----------|-----------|-------|-----|-----------|
| 1   | Student 1 | Pre       | 3.4   | ... | 0         |
| 2   | Student 2 | Post      | 3     | ... | 0         |
| 3   | Student3  | Pre       | 0.67  | ... | 0         |
| ... | ...       | ...       | ...   | ... | ...       |
| 246 | Student n | Post      | 1.3   | ... | 1         |

### B. Exploratory Data Analysis Results

The Exploratory Data Analysis (EDA) stage was conducted to obtain an overview of the characteristics, distribution, and quality of the dataset before proceeding to the preprocessing stage. The analyzed dataset consisted of 246 rows and 9 columns representing measurement information and EEG signal characteristics. Figure 2 illustrates the distribution of responses across the different conditions in the dataset.

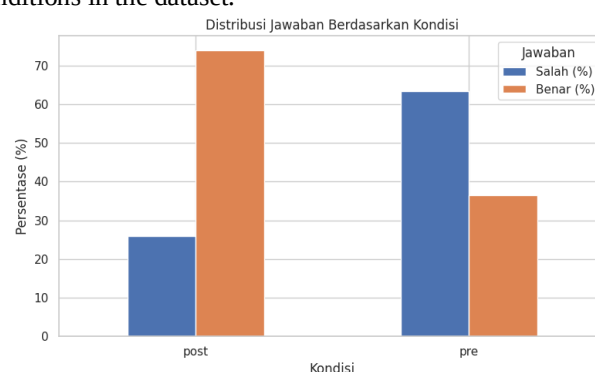


Figure 2. Response Distribution by Condition

The data distribution analysis was conducted based on the pre- and post-measurement conditions to identify the distribution patterns of each EEG feature. In addition, the completeness of the dataset was assessed by identifying missing values in each variable. The results showed that all

variables had zero missing values, indicating that no missing data were found in the dataset, as presented in Table 2.

TABLE 2. MISSING VALUE ANALYSIS

| No  | Data         | Value |
|-----|--------------|-------|
| 1   | delta_pre    | 0     |
| 2   | delta_post   | 0     |
| 3   | delta_change | 0     |
| 4   | theta_pre    | 0     |
| ... | ...          | ...   |
| 16  | gamma_post   | 0     |

Next, the dataset was examined for duplicate records to ensure that no identical data entries were recorded repeatedly. The analysis was also conducted using boxplot visualizations of five EEG wave features, namely Delta, Theta, Alpha, Beta, and Gamma, under the pre- and post-measurement conditions. The visualization results revealed differences in the distributions of several EEG features between the two conditions. Figure 3 presents the code used to identify duplicate records in the dataset.

```
#cek duplikasi
jumlah_duplikat = df.duplicated().sum()

print("Jumlah data duplikat:", jumlah_duplikat)

Jumlah data duplikat: 0
```

Figure 3. Duplicate Data Detection

Based on the visualization results, differences in the distributions of several EEG features were observed between the pre- and post-measurement conditions. The Delta values in the post-measurement condition tended to be higher than those in the pre-measurement condition, whereas the Theta distribution showed a relatively similar pattern. The Alpha feature showed a tendency toward a lower median in the post-measurement condition, while the Beta feature exhibited an increase. For the Gamma feature, the post-measurement condition showed a wider data spread and tended to have higher values than the pre-measurement condition. In addition, several outliers were identified in the Delta, Theta, Alpha, Beta, and Gamma features.

### C. Preprocessing Data

During the data preprocessing stage, the structure and characteristics of each variable in the dataset were identified. This identification was conducted to determine the data types and the roles of each column in the data processing workflow. Information regarding the data types and characteristics of the variables in the dataset is presented in Table 3.

TABLE 3. INFORMATION DATASET

After identifying the structure of the dataset, the next step was to perform data preprocessing to prepare the data for the modeling process. At this stage, the data format was adjusted and labels were assigned based on the conditions of the data used in the analysis. The results of the data preprocessing process are presented in Table 4.

TABLE 4. DATA PREPROCESSING RESULTS

| Column    | Data Type                 | Description                            |
|-----------|---------------------------|----------------------------------------|
| name      | Categorical/Identifier    | Student name, anonymized as student_id |
| condition | Categorical               | pre and post                           |
| delta     | Continuous number         | EEG delta band value                   |
| theta     | Continuous number         | EEG theta band value                   |
| alpha     | Continuous number         | EEG alpha band value                   |
| beta      | Continuous number         | EEG beta band value                    |
| gamma     | Continuous number         | EEG gamma band value                   |
| eeg_label | Binary categorical/target | 0 = Not Focused, 1 = Focused           |
| response  | Binary categorical        | 0 = incorrect, 1 = correct             |
| school    | Categorical               | school_1 to school_4                   |

| No  | Student_id | Condition | ... | Schools  | EEG_label |
|-----|------------|-----------|-----|----------|-----------|
| 1   | S001       | Pre       | ... | school_1 | 0         |
| 2   | S001       | Post      | ... | school_1 | 0         |
| 3   | S002       | Pre       | ... | school_1 | 0         |
| ... | ...        | ...       | ... | ...      | ...       |
| 246 | S123       | Post      | ... | school_4 | 1         |

Following the preprocessing process, the dataset was formatted appropriately for use in the model development stage. At this stage, the students' names were anonymized as student\_id, the measurement conditions were categorized as Pre and Post, and the data were assigned eeg\_label as a binary class. The final preprocessing process resulted in 246 structured records organized according to student identity, measurement condition, school, and data label, as presented in Table 4.

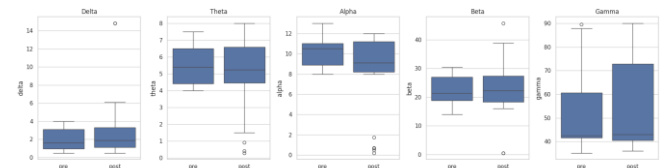


Figure 4. Visualization of Pre and Post Measurement Conditions

### D. Baseline Model Development

The baseline model was established to provide an initial assessment of the performance of each classification algorithm before hyperparameter optimization was performed. This study employed six machine learning algorithms: K-Nearest Neighbors (KNN), Random Forest, Logistic Regression, Decision Tree, Naive Bayes, and Support Vector Machine (SVM). Each algorithm was trained using its default parameters to obtain baseline performance metrics that served as a reference for the subsequent optimization process. Model performance was evaluated

using accuracy, precision, recall, and F1-score. The results of the baseline model development are presented in Table 5.

TABLE 5. BASELINE MODEL DEVELOPMENT

| Model               | Accuracy (%) | Macro Precision (%) | Macro Recall (%) | Macro F1-Score (%) |
|---------------------|--------------|---------------------|------------------|--------------------|
| KNN                 | 88.0         | 87.92               | 87.92            | 87.92              |
| Random Forest       | 84.0         | 83.90               | 83.90            | 83.90              |
| Logistic Regression | 84.0         | 84.24               | 83.57            | 83.77              |
| Decision Tree       | 82.0         | 82.21               | 82.37            | 81.99              |
| Naive Bayes         | 82.0         | 81.98               | 81.72            | 81.82              |
| SVM                 | 82.0         | 82.50               | 81.40            | 81.64              |

The evaluation results showed that the KNN model achieved the highest baseline performance, with an accuracy of 88.00% and macro precision, macro recall, and macro F1-score of 87.92%. Random Forest and Logistic Regression achieved an accuracy of 84.00%, while Decision Tree, Naive Bayes, and SVM each achieved an accuracy of 82.00%. Based on these results, KNN demonstrated the best initial performance among the evaluated models before the hyperparameter tuning process.

### E. Hyperparameter Tuning

Hyperparameter tuning was performed to obtain the optimal parameter configuration for each model, with the aim of improving classification performance. The optimization process was applied to six machine learning algorithms: KNN, Random Forest, Logistic Regression, Decision Tree, Naive Bayes, and SVM. The hyperparameters to be optimized were selected according to the characteristics of each algorithm. For each model, a predefined search space consisting of candidate values for the selected hyperparameters was evaluated using GridSearchCV with 5-fold GroupKFold cross-validation. The optimal parameter configurations obtained for each algorithm through the hyperparameter tuning process are presented in Table 6.

TABLE 6. HYPERPARAMETER SEARCH SPACE AND OPTIMAL CONFIGURATIONS

| Model | Search Space                                                 | Best Parameter                                     |
|-------|--------------------------------------------------------------|----------------------------------------------------|
| KNN   | n_neighbors: 3, 5, 7, 9, 11, 15; weights: uniform, distance; | n_neighbors=15; weights=distance; metric=manhattan |

|                     | metric: euclidean, manhattan                                                                                   |                                                                                                                   |
|---------------------|----------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------|
| Random Forest       | n_estimators: 100, 200, 300; max_depth: 5, 10, None; min_samples_split: 2, 5; min_samples_leaf: 1, 2           | 'model__max_depth': 5, 'model__min_samples_leaf': 1, 'model__min_samples_split': 2, 'model__n_estimators': 200    |
| Logistic Regression | C: 0.01, 0.1, 1, 10, 100                                                                                       | 'model__C': 0.01                                                                                                  |
| Decision Tree       | max_depth: 3, 5, 7, 10, None; min_samples_split: 2, 5, 10; min_samples_leaf: 1, 2, 4; criterion: gini, entropy | 'model__criterion': 'entropy', 'model__max_depth': 7, 'model__min_samples_leaf': 1, 'model__min_samples_split': 5 |
| Naive Bayes         | var_smoothing: 20 logarithmically spaced values from $10^0$ to $10^{-9}$                                       | 'model__var_smoothing': 0.03793                                                                                   |
| SVM                 | C: 0.1, 1, 10, 100; kernel: linear, rbf, poly; gamma: scale, auto                                              | 'model__C': 0.1, 'model__gamma': 'auto', 'model__kernel': 'poly'                                                  |

The hyperparameter tuning results showed that each algorithm had a different optimal parameter configuration. For Random Forest, the optimal configuration consisted of a max\_depth of 5, a min\_samples\_leaf of 1, a min\_samples\_split of 2, and n\_estimators of 200. Logistic Regression used a C value of 0.01, while Decision Tree used the entropy criterion, a max\_depth of 7, a min\_samples\_leaf of 1, and a min\_samples\_split of 5. SVM obtained an optimal configuration with a C value of 0.1, gamma set to auto, and a poly kernel. These configurations were applied to the respective models to achieve optimal classification performance.

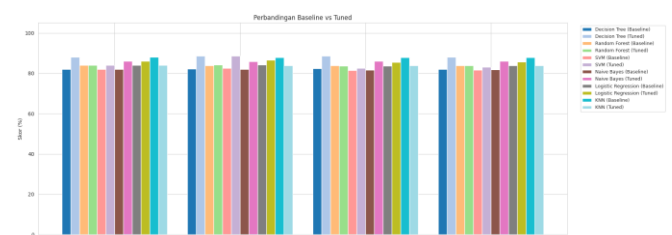


Figure 5. Baseline vs. Tuned Model Comparison

Figure 5 presents a comparison of the performance of the baseline models and the models after hyperparameter tuning based on the accuracy, precision, recall, and F1-score metrics. The comparison results show changes in performance across most models after hyperparameter optimization. These differences in performance indicate the effect of hyperparameter configurations on the classification results of each algorithm. Figure 5 provides a comparative overview of

model performance before and after the hyperparameter tuning process.

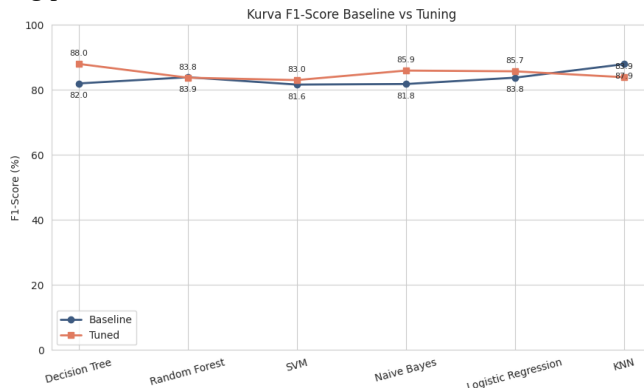


Figure 6. Baseline vs. Tuned F1-Score Curve

Figure 6 presents a comparison of the F1-score values between the baseline models and the models after hyperparameter tuning across the six classification algorithms. The results show that the F1-score values changed for most models following the tuning process. The Decision Tree model improved from 82.0% to 88.0%, while Random Forest remained unchanged at 83.9%. SVM improved from 81.6% to 83.0%, Naive Bayes improved from 81.8% to 85.9%, and Logistic Regression improved from 83.8% to 85.7%. In contrast, the F1-score of KNN decreased from 87.92% to 83.90%. These results indicate that hyperparameter tuning produced different performance changes across the evaluated algorithms.

#### F. Model Evaluation

Model evaluation was conducted to compare the performance of each algorithm before and after hyperparameter tuning based on accuracy, precision, recall, and F1-score. This comparison was performed to identify changes in the performance of each model and to compare the classification performance of the evaluated model configurations. The comparison between the baseline and tuned models is presented in Table 7.

TABLE 7. COMPARISON OF MODEL PERFORMANCE

| Model         | Accuracy (%) | Macro Precision (%) | Macro Recall (%) | Macro F1-Score (%) |
|---------------|--------------|---------------------|------------------|--------------------|
| Decision Tree |              |                     |                  |                    |
| Baseline      | 82.00        | 82.21               | 82.37            | 81.99              |
| Tuned         | 88.00        | 88.57               | 88.57            | 88.00              |
| Random Forest |              |                     |                  |                    |
| Baseline      | 84.00        | 83.90               | 83.90            | 83.90              |
| Tuned         | 84.00        | 84.24               | 83.57            | 83.77              |
| SVM           |              |                     |                  |                    |
| Baseline      | 82.00        | 82.50               | 81.40            | 81.64              |
| Tuned         | 84.00        | 88.57               | 82.61            | 83.02              |

|                     |       |       |       |       |
|---------------------|-------|-------|-------|-------|
| Naive Bayes         |       |       |       |       |
| Baseline            | 82.00 | 81.98 | 81.72 | 81.82 |
| Tuned               | 86.00 | 85.90 | 86.07 | 85.95 |
| Logistic Regression |       |       |       |       |
| Baseline            | 84.00 | 84.24 | 83.57 | 83.77 |
| Tuned               | 86.00 | 86.67 | 85.43 | 85.72 |
| KNN                 |       |       |       |       |
| Baseline            | 88.00 | 87.92 | 87.92 | 87.92 |
| Tuned               | 84.00 | 83.90 | 83.90 | 83.90 |

Table 7 shows that hyperparameter tuning produced different effects across the six classification models. The most notable improvement was observed in the Decision Tree model, whose accuracy increased from 82.00% to 88.00% and macro F1-score from 81.99% to 88.00%. Naive Bayes also showed a clear improvement, with accuracy increasing from 82.00% to 86.00% and macro F1-score from 81.82% to 85.95%, while Logistic Regression improved from 84.00% to 86.00% in accuracy and from 83.77% to 85.72% in macro F1-score. SVM showed a smaller improvement, with accuracy increasing from 82.00% to 84.00% and macro F1-score from 81.64% to 83.02%. In contrast, Random Forest remained relatively stable, with its macro F1-score slightly decreasing from 83.90% to 83.77%, while KNN showed a more noticeable decline from 87.92% to 83.90%. These results indicate that hyperparameter tuning did not consistently improve all classifiers, but affected each model differently according to its parameter configuration and model characteristics.

The precision, recall, and F1-score values reported in Table 7 represent macro-averaged metrics and are presented to two decimal places to provide a more precise comparison across the models. For the tuned Decision Tree, the accuracy was 88.00%, while the macro precision, macro recall, and macro F1-score were 88.57%, 88.57%, and 88.00%, respectively. Thus, the apparently identical values reported previously were due to rounding the evaluation metrics to whole percentages rather than identical values across all evaluation measures.

Among the tuned models, Decision Tree achieved the highest overall performance, representing a clear improvement over its baseline configuration and indicating that the model benefited considerably from hyperparameter optimization. However, its accuracy of 88.00% was comparable to the 88.00% achieved by KNN in the baseline experiment before KNN performance declined after tuning. Therefore, the results should not be interpreted as demonstrating that hyperparameter tuning universally improves model performance or that Decision Tree is absolutely superior to all evaluated configurations. Rather, Decision Tree showed the strongest improvement and the highest performance among the tuned models under the

dataset, feature representation, and experimental configuration used in this study.

The performance of the tuned Decision Tree should also be considered in relation to the validation strategy used in this study. Hyperparameter optimization was performed exclusively on the training data using group-based cross-validation, while the final evaluation was conducted on a held-out subject-independent test set containing students who were not involved in model training or tuning. The Decision Tree maintained an accuracy and macro F1-score of 88.00% on this unseen test set, suggesting that the improvement obtained after tuning was retained when evaluated on independent students. Nevertheless, because the tuned Decision Tree and baseline KNN achieved the same test accuracy, the present results do not provide sufficient evidence to claim that Decision Tree is universally superior to KNN or the other classifiers.

Although the tuned Decision Tree achieved the highest performance among the tuned models, its accuracy of 88.00% was identical to that obtained by the baseline KNN model. The 95% Wilson confidence interval for the accuracy was 76.20% - 94.38%. Furthermore, the exact McNemar test showed no significant difference between the predictions of the two models ( $p = 1.000$ ), with three observations correctly classified only by Decision Tree and three correctly classified only by KNN. These findings indicate that the tuned Decision Tree cannot be considered statistically superior to baseline KNN and should instead be interpreted as the highest-performing model among the tuned configurations evaluated in this study.

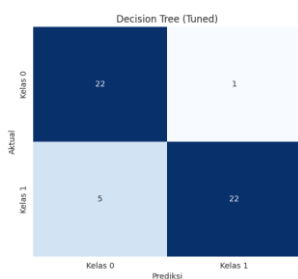


Figure 7. Confusion Matrix Decision Tree (Tuned)

Based on the confusion matrix, the Decision Tree (Tuned) model correctly classified 22 instances of Class 0 and 22 instances of Class 1. Meanwhile, 1 instance of Class 0 was incorrectly predicted as Class 1, and 5 instances of Class 1 were incorrectly predicted as Class 0. These results indicate that the model still produced some misclassifications in both classes. The confusion matrix of the Decision Tree model is presented in Figure 7.

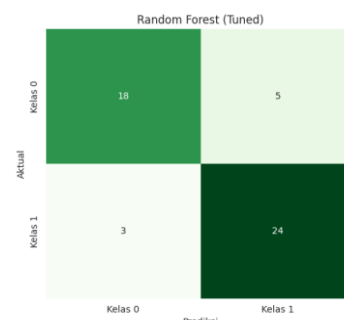


Figure 8. Confusion Matrix Random Forest (Tuned)

The confusion matrix results show that the Random Forest (Tuned) model correctly classified 18 instances of Class 0 and 24 instances of Class 1. In addition, 5 instances of Class 0 were misclassified as Class 1, while 3 instances of Class 1 were incorrectly predicted as Class 0. These results show that the model achieved relatively balanced classification performance across the two classes, although several misclassifications were still observed. The confusion matrix of the Random Forest model is presented in Figure 8.

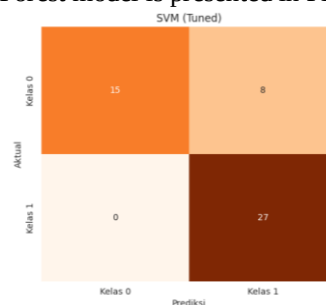


Figure 9. Confusion Matrix SVM (Tuned)

The evaluation results for the SVM (Tuned) model showed that 15 instances of Class 0 and 27 instances of Class 1 were correctly classified. Meanwhile, 8 instances of Class 0 were incorrectly predicted as Class 1, while none of the Class 1 instances were incorrectly predicted as Class 0. These results indicate that the model still produced some misclassifications, particularly for Class 0. The confusion matrix of the SVM model is presented in Figure 9.

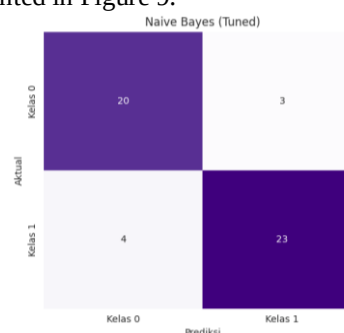


Figure 10. Confusion Matrix Naive Bayes (Tuned)

As shown in the confusion matrix, the Naive Bayes (Tuned) model correctly classified 20 instances of Class 0 and 23 instances of Class 1. Meanwhile, 3 instances of Class 0 were incorrectly predicted as Class 1, and 4 instances of Class

1 were incorrectly predicted as Class 0. These results indicate that the model still produced some misclassifications in both classes. The confusion matrix of the Naive Bayes model is presented in Figure 10.



Figure 11. Confusion Matrix Logistic Regression (Tuned)

The classification results of the Logistic Regression (Tuned) model showed that 18 instances of Class 0 and 25 instances of Class 1 were correctly classified. Meanwhile, 5 instances of Class 0 were incorrectly predicted as Class 1, and 2 instances of Class 1 were incorrectly predicted as Class 0. These results indicate that the model still produced some misclassifications in both classes. The confusion matrix of the Logistic Regression model is presented in Figure 11.

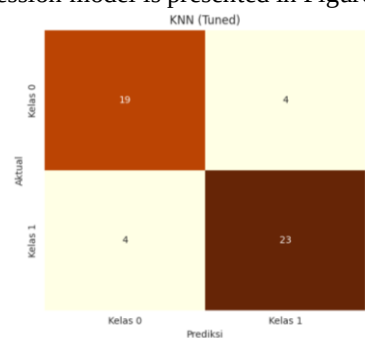


Figure 12. Confusion Matrix KNN (Tuned)

The confusion matrix results show that the KNN (Tuned) model correctly classified 19 instances of Class 0 and 23 instances of Class 1. Meanwhile, 4 instances of Class 0 were incorrectly predicted as Class 1, and 4 instances of Class 1 were incorrectly predicted as Class 0. These results indicate that the model still produced some misclassifications in both classes. The confusion matrix of the KNN model is presented in Figure 12.

### G. EEG Feature Importance Analysis

To further examine the contribution of EEG features to the classification process, feature importance analysis was performed using the Random Forest model. The results showed that Theta had the highest feature importance value (0.2699), followed by Delta (0.2201), Beta (0.1974), Alpha (0.1882), and Gamma (0.1176). In contrast, the Pre-MBG/Post-MBG condition showed a substantially lower importance value of 0.0068. This result indicates that the classification of students' cognitive responses was primarily driven by variations in the EEG spectral features rather than by the measurement condition itself.

The relatively higher contribution of Theta suggests that variations in this frequency band provided useful information for distinguishing the students' EEG-based focus states during the cognitive task. Delta also showed a notable contribution, indicating that the classification was not determined by a single frequency band but by patterns distributed across several EEG features. Beta and Alpha remained important contributors to the model, which is particularly relevant because the operational definition of the focus state in this study was derived from the relative power of these two bands. Overall, the feature importance results suggest that although the Focused and Not Focused labels were operationalized using the Beta-to-Alpha ratio, the Random Forest model also utilized information distributed across the other EEG frequency bands when distinguishing the two cognitive-response classes.

## IV. CONCLUSION

This study shows that the six machine learning algorithms evaluated exhibited different capabilities in classifying students' EEG-based cognitive responses in the context of the Free Nutritious Meals (MBG) Program. The results showed that hyperparameter tuning affected the six models differently. Among the baseline models, KNN achieved the highest accuracy of 88.00%, whereas among the tuned models, Decision Tree achieved the highest classification performance, with an accuracy and macro F1-score of 88.00%. The Decision Tree showed a substantial improvement over its baseline configuration; however, its accuracy was identical to that achieved by baseline KNN, and the statistical comparison did not indicate a significant difference between their predictions. Therefore, the findings should not be interpreted as demonstrating the general superiority of Decision Tree over the other classifiers. Rather, Decision Tree achieved the highest performance among the tuned models under the dataset, EEG feature representation, subject-independent validation design, and experimental conditions employed in this study. These findings can serve as an empirical baseline for developing EEG-based models to evaluate students' cognitive responses in the MBG context. Further evaluation involving larger and independent student populations is needed to assess the generalizability of the observed performance.

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