Information Technology Journal
Vol. 6 No. 1 July 2024
Homepage: https://jurnal.amikom.ac.id/index.php/intechno
INTECHNO Journal
INFORMATION TECHNOLOGY JOURNAL
e-ISSN: 2655-1438
p-ISSN: 2655-1632

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# EEG Signal Classification Using Low Temporal Information in Virtual Reality Environments

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**Article Info**

***Article history:***

Received July 15, 2024
Revised July 21, 2024
Accepted July 23, 2024
Published July 31, 2024

***Keywords:***

*EEG*
*VR*
*Brain Signal*
*Signal Classification*
*Machine Learning*

**ABSTRACT**

**Purpose:** This research systematically compares the performance of K-Nearest Neighbors (KNN), Random Forest (RF), and Support Vector Machine (SVM) in recognizing emotional and cognitive states from EEG data in a virtual reality (VR) environment. It aims to identify the model with the highest accuracy for each participant.
**Methods:** EEG data were collected from four channels (TP9, AF7, AF8, TP10) with a data range of 0.0 - 1682.815 µV and a sampling rate of 2 Hz. The sampling rate is shallow compared to the standard EEG datasets. Features extracted included statistical measures (mean, standard deviation, skewness, kurtosis) and Hjorth parameters (activity, mobility, complexity), classifier (SVM, RF, KNN). Each classifier's performance was evaluated using accuracy, indicating the proportion of correctly classified instances.
**Result:** RF achieved the highest average accuracy but showed more significant variability. SVM demonstrated a high median accuracy with consistent performance, as indicated by a narrow interquartile range (IQR) and few outliers. KNN exhibited the lowest median accuracy and highest variability, suggesting sensitivity to data characteristics and parameters. These findings highlight RF's potential for consistent performance with careful tuning and SVM's reliability.
**Novelty:** The research's novelty lies in its personalized performance analysis, evaluating each model's accuracy individually for participants. This tailored approach reveals the best-performing model for each person, emphasizing customized machine-learning applications in VR-EEG systems. The study's detailed, participant-specific evaluation enhances emotion and cognitive state recognition precision, advancing individualized VR therapeutic interventions and cognitive research methodologies.



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## 1. INTRODUCTION

Integrating EEG technology with virtual reality (VR) [1] systems has opened new avenues for enhancing therapeutic interventions and understanding cognitive processes. This synergy has been particularly beneficial in mental health treatments, cognitive studies, and the development of immersive environments tailored to individual needs. By analyzing brainwave responses during VR interactions, researchers can gain insights into emotional and mental states, paving the way for more effective and personalized therapeutic approaches.

The VR-EEG [2] system has shown promise as a brief therapy for depressive symptoms, demonstrating comparable efficacy to Zoom online counselling. While roaming a virtual museum [3] did not impact positive emotions, specific interactions, such as doodles and emojis, increased positive emotions. Different game genres elicit varied brainwave responses, suggesting the potential for tailored video game therapies in mental health.

Tetris gameplay has been associated with heightened coherence and entropy values, mainly showing increased coherence between the frontal and temporal brain regions. VRET (Virtual Reality Exposure Therapy) technology [4], when integrated with EEG signals, enhances the precision of patient diagnoses, allowing for nuanced and individualized treatment within the VRET framework [5]. EEG applications in VR driving studies [6] have helped analyze cognitive processes, focusing on driver fatigue, navigation, obstacle avoidance, and monitoring technologies. Different microstates in EEG [7] are linked to emotions within the VR environment, with unique transitions observed between microstates during positive and negative emotions.

Visual distractors [8] were found to reduce theta band activity in EEG signals, whereas auditory distractors enhanced alpha band activity. High classification accuracies were achieved when distinguishing between locomotion and resting states [9], although these accuracies decreased when movement and turning were considered. EEG signals have been used to classify immersion states in VR, with machine learning achieving high accuracy in differentiating difficulty levels. Free-form landscapes [10] induced higher alpha values in more brain regions and revealed subjective cognitive differences compared to regular-form landscapes. These subjective differences were observed consistently.

An evaluation of neural responses [11] recorded using scalp EEG in VR highlighted potential noise interference in high-density EEG measurements. An EEG-based VR system that automatically generates emotion-adaptive scenes [12] was confirmed to be feasible and valuable through experimental studies. Multiple features, particularly theta band features, improved emotion recognition performance, excelling in decoding emotional valence. VR sickness [13] was found to be more significant with head-mounted displays (HMD) than screens, with alpha wave PSD changes observed in specific brain regions. EEG [14] has shown viability for real-time interactions in VR games, where simplified mean EEG values are adequate for non-serious applications. The frontal area of the scalp [15] was significant in classifying fear of heights, with gamma and high-beta bands being the most important in the EEG analysis.

The experiment detailed [16] in the provided Excel data presents a unique and systematic comparison of machine learning models (KNN, RF, and SVM) across multiple participants. The primary contribution of this experiment is its thorough evaluation of these models in a VR-EEG setup, which involves measuring brainwave responses in a virtual reality environment. By identifying which model achieves the highest accuracy for each participant, the study provides valuable insights into how different models recognize emotional and cognitive states from EEG data.

One key novelty of this experiment is its focus on personalized performance analysis. Instead of a one-size-fits-all approach, the study examines model performance on an individual level, revealing which model works best for each participant. This personalized evaluation is crucial because it highlights the potential for tailored machine learning applications in VR-EEG systems, ensuring everyone receives the most accurate and effective analysis possible.

Moreover, the experiment's detailed analysis of accuracy trends helps identify each model's general patterns and specific strengths. For example, despite its variability, the RF model shows the highest average accuracy, suggesting it may be particularly effective with careful tuning. Meanwhile, the SVM model stands out for its consistent performance, making it a reliable choice in many scenarios. This experiment advances the field by providing a clear, data-driven understanding of how different machine-learning models perform in a VR-EEG context. It underscores the importance of personalized model selection, paving the way for more precise and individualized therapeutic and cognitive applications in virtual reality environments.

## 2. METHOD

### 2.1 Dataset

Based on [17], 32 healthy participants, 7 females and 25 males aged between 23 and 45, were initially recruited for the experiment. However, the dataset has only 31 participants. For data collection, the experiment employed the EEG Headset Model "Muse 2016," developed by Interaxon, and the "Mind Monitor" application created by James Clutterbuck. The Muse 2016 electrodes were positioned according to the 10-20 international EEG placement system at TP9, AF7, AF8, and TP10, with a reference at Fpz.

The Mind Monitor application was configured to record data in .csv format with a notch frequency set at 50Hz (to account for the EU/230 Volts power system). The sampling rate was set at 2Hz, which, while providing low temporal resolution, posed challenges as we cannot extract EEG signature waves by using band-pass filtering (for gamma, beta, alpha, delta, and theta waves). The raw EEG signal range recorded was between 0.0 and 1682.815 µV.

The sequence for presenting the VR videos to elicit emotional responses was structured as follows: each quadrant of the VR videos was given for 80 seconds, using four different videos per quadrant. To ensure participants' mental states were reset before transitioning to the next emotional quadrant, a 10-second rest period was included between each video presentation.

**2.2 Feature extraction**

**2.2.1. Statistic Features**

Statistic features [18] are simple and valuable in finding the tendency for the signal to vary with time. Suppose there are $m$ EEG signals simultaneously measured for emotion recognition of one subject. The length of one emotion segment sample is $L_0$. Thus, an emotion EEG signal sample can be described as $S = [s_1, s_i, \dots, s_m]^T$, where $S \in R^{m \times L_0}$, $S = [s_1, s_2, \dots, s_{L_0}]$, and $i = 1, 2, \dots, m$. Suppose there are $N_{stat}$ statistics features extracted from an EEG signal $s_i$, then statistic feature of $s_i$ can be denoted as $F_{stat} = [F_1, F_j, \dots, F_{N_{stat}}]$ where $j = 1, 2, \dots, N_{stat}$. The six statistic features of each $s_i$ commonly used in time domain are the following:

1. Median

$$Median(s_j) = \begin{cases} s'_{\frac{L_0+1}{2}}, L_0 \text{ is odd} \\ (s'_{\frac{L_0}{2}} + s'_{\frac{L_0}{2}+1})/2, L_0 \text{ is even} \end{cases}, \text{where } S'_j \text{ is sorted } s_j \quad (1)$$

2. Mean

$$\bar{s} = \frac{\sum_{j=1}^{L_0} s_j}{L_0} \quad (2)$$

3. Standard deviation

$$SD = \sqrt{\frac{1}{L_0 - 1} \sum_{j=1}^{L_0} (s_j - \bar{s})^2} \quad (3)$$

4. Variance

$$var(s_j) = \frac{1}{L_0 - 1} \sum_{j=1}^{L_0} (s_j - \bar{s})^2 \quad (4)$$

5. Skewness

$$Skewness = \frac{1}{L_0 - 1} \sum_{j=1}^{L_0} (s_j - \bar{s})^3 / SD^3 \quad (5)$$

6. Kurtosis

$$Kurtosis = \frac{1}{L_0 - 1} \sum_{j=1}^{L_0} (s_j - \bar{s})^4 / SD^4 - 3 \quad (6)$$

**2.2.2 Hjorth parameters**

Hjorth parameters [19] are a time domain feature that measures a signal's complexity. It involves three features, i.e., Activity, Mobility, and Complexity. Activity measures the power of the signal. Mobility represents the mean frequency in the signal. Complexity captures the change in frequency. Hjorth parameters are practical EEG features [20], [21].

Activity:

$$a(x) = \frac{1}{n} \sum_{i=1}^{n} (x(i) - \mu_x)^2 \quad (7)$$

Where $\mu_x$ is the mean of x computed as per 2.2.

Mobility:

$$m(x) = \sqrt{\frac{var(\dot{x})}{var(x)}} \quad (8)$$

Where $\dot{x}$ is the time derivative of the time series x. Therefore, var ($\dot{x}$) and var(x) are computed as per 2.6 Complexity:

$$c(x) = \frac{m(\dot{x})}{m(x)} \tag{9}$$

Which is the mobility of the time derivative of x over the mobility of x.

### 2.3 Classification

#### 2.3.1 Support Vector Machine (SVM)

Support Vector Machines (SVM) is a robust set of supervised learning methods for classification, regression, and outlier detection. The primary goal of an SVM in classification is to find the optimal hyperplane that best separates the data into different classes. This hyperplane was chosen to maximize the margin, which is the distance between the hyperplane and the nearest data points from each class, known as support vectors. By maximizing this margin, SVMs aim to improve the model's generalization ability to new, unseen data.

SVMs can handle both linear and non-linear classification tasks. For non-linear data, SVMs use the "kernel trick" technique to transform the data into a higher-dimensional space where it becomes easier to find a separating hyperplane. Standard kernels include the polynomial kernel, radial basis function (RBF) kernel, and sigmoid kernel. This flexibility allows SVMs to tackle complex classification problems by handling various data structures and relationships effectively.

#### 2.3.2 Random Forest (RF)

Random Forest (RF) is an ensemble learning method for classification and regression tasks. It operates by constructing multiple decision trees during training and outputting the class, the mode of the classes (for classification) or the mean prediction (for regression) of the individual trees. Each decision tree in the forest is built from a different sample of the data, created through bootstrapping, which involves randomly sampling the dataset with replacement. It helps create diverse trees, creating a more robust and accurate overall model.

One of the critical advantages of Random Forest is its ability to handle many input features and estimate each feature's importance in the prediction process. It is achieved by randomly selecting a subset of features at each split in the tree-building process, ensuring tree diversity and preventing overfitting. By averaging the results of many decision trees, Random Forest reduces variance and improves the model's ability to generalize to new data, making it a versatile and powerful tool for various predictive tasks.

#### 2.3.3 K-Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN) is a simple yet effective supervised learning algorithm for classification and regression tasks. In KNN, the prediction for a new data point is based on the majority class (for classification) or the average value (for regression) of its nearest neighbours in the feature space. The 'K' in KNN refers to the closest neighbours considered when making predictions.

KNN calculates the distance between the new point and all other points in the training dataset to predict the class or value for a new data point. Typical distance metrics used include Euclidean distance, Manhattan distance, and Minkowski distance. Once distances are computed, KNN identifies the 'K' nearest neighbours to the new data point and assigns the class or value based on the most frequent class (for classification) or the average (for regression) of these neighbours. The choice of 'K' is critical as it affects the bias-variance trade-off: smaller values of 'K' tend to have lower bias but higher variance, while larger values of 'K' have higher bias but lower variance.

KNN is non-parametric and lazy learning because it does not assume any underlying data distribution and does not learn explicit models during training. Instead, it memorizes the entire training dataset, which can be computationally expensive for large datasets but allows for flexibility in handling complex decision boundaries. KNN is straightforward to implement and understand, making it particularly useful for small to medium-sized datasets where it can provide competitive performance compared to more complex algorithms.

### 2.4 EEG Signal Classification Process

The classification of EEG signals is following:

1. EEG Signals
   EEG data with TP9, AF7, AF8, TP10 channels. The data range is between 0.0 - 1682.815 µV. The sampling rate is 2 Hz.
2. Feature Extraction
   Features will be extracted from the EEG signals. It includes statistical features such as mean, standard deviation, skewness, and kurtosis, which provide insights into the distribution and variability of the signals.

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Additionally, Hjorth parameters, including activity, mobility, and complexity, will be computed to capture signal amplitude and frequency characteristics.

3. Classification Methods
   SVM will be utilized to classify the EEG signals based on the extracted features. SVM aims to find an optimal hyperplane that separates different classes with maximum margin. RF will be employed as an ensemble learning method where multiple decision trees are built using bootstrapped data samples. RF averages predictions from these trees to classify EEG signals. KNN will classify EEG signals by calculating distances to the 'K' nearest neighbours in the feature space. The class of the majority of these neighbours will determine the classification.
4. Evaluation
   The performance of each classifier (SVM, RF, KNN) will be evaluated using accuracy, which measures the proportion of correctly classified instances out of the total cases.

Following these steps, we can effectively classify EEG signals and evaluate the performance of SVM, RF, and KNN classifiers based on their accuracy in handling the extracted features, as shown in Figure 1.

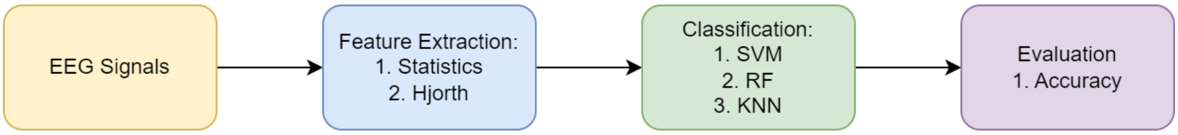


Figure 1. The classification flow chart

## 3. RESULTS AND DISCUSSIONS

Each participant is evaluated using different models, which are KNN (K-Nearest Neighbors), RF (Random Forest), and SVM (Support Vector Machine). There are several reasons for selecting the classification methods. SVM is effective in high-dimensional spaces and suitable for binary classification tasks. It works by finding the optimal hyperplane that separates the classes, making it a powerful tool for datasets with many features. Random Forest is an ensemble method that combines multiple decision trees to improve accuracy and robustness. It is particularly effective in handling large datasets and provides high accuracy by averaging the results of numerous decision trees, thus reducing overfitting and variance. KNN is a simple, instance-based learning algorithm that classifies samples based on the majority class among the k-nearest neighbours. It is particularly effective for smaller datasets and when the decision boundary is irregular, as it relies on the proximity of data points to make classifications. The method parameters for this study is shown in Table 1.

Table 1. Methods parameters

| Feature | Parameter |
|---|---|
| Statistics | n/a |
| Hjorth Parameters | n/a |
| SVM | C=0.01, kernel='linear' |
| RF | n_estimators=100 |
| KNN | n_neighbors=3 |

Figure 2 shows that the RF model frequently yields the highest accuracy across various participants. It might be due to its ability to effectively classify data points by finding the optimal separating hyperplane, especially in high-dimensional feature spaces. Consequently, RF is often the most reliable model for achieving high accuracy in diverse datasets.

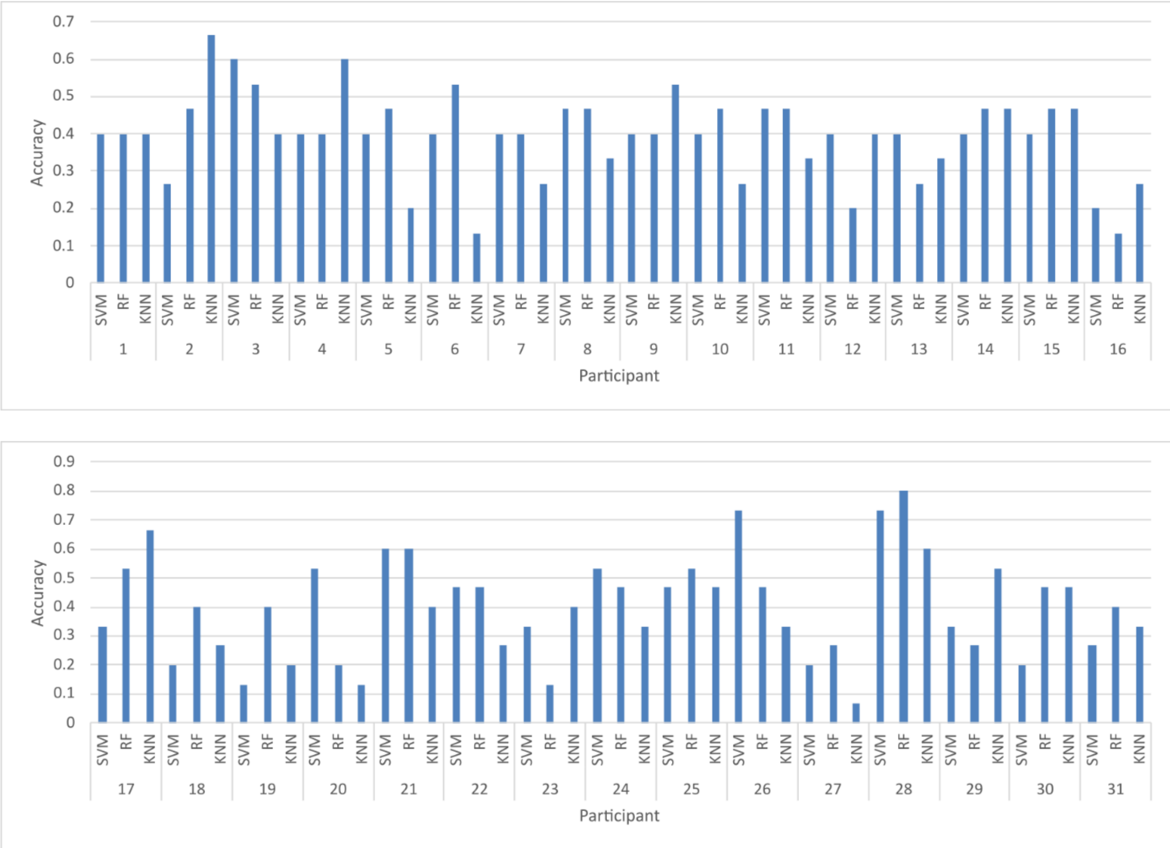


Figure 2. The Accuracy of Each Participant with Different Classifier

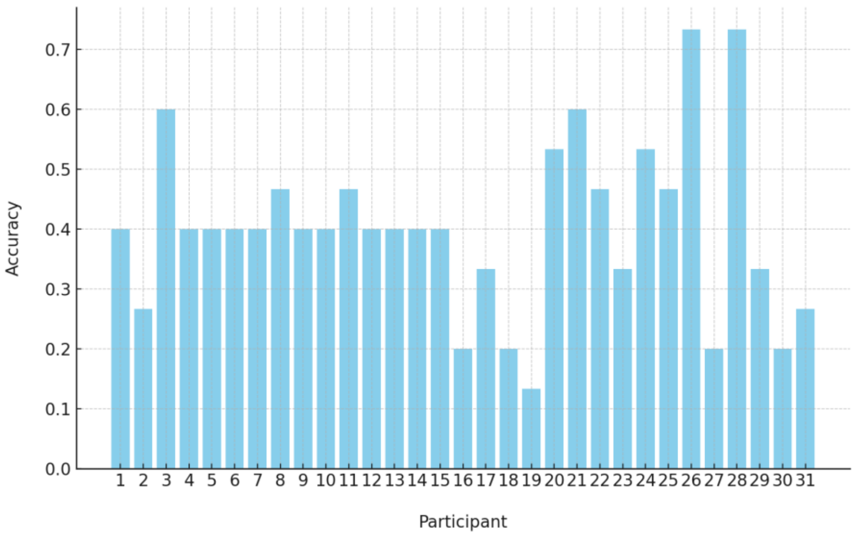


Figure 3. Highest Accuracy Trends Over Participants

Figure 3 illustrates the highest accuracy trends among participants. Here are some observations:

1. **Variability**
   The accuracy varies significantly across participants, indicating differing performance levels for the models used.

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2. **Peaks and Troughs**
   There are notable peaks (e.g., participants 3, 20, 26, 28) where the highest accuracy is relatively high, suggesting that the models worked particularly well for these participants. Conversely, there are troughs where the accuracy is lower, indicating challenges in model performance.
3. **Consistency**
   Some participants have similar accuracy levels, implying consistent performance of the models across those cases.

As shown in Figure 4, the SVM model demonstrates a relatively high median accuracy, indicating good performance across many participants. The interquartile range (IQR), representing the middle 50% of the data, is narrow. It suggests consistent performance, as most accuracy values fall within a close range. The whiskers, which extend to the smallest and largest values within 1.5 times the IQR, are short, indicating few extreme values. Although there are a few outliers, they are not numerous, underscoring the model's reliability and consistency.

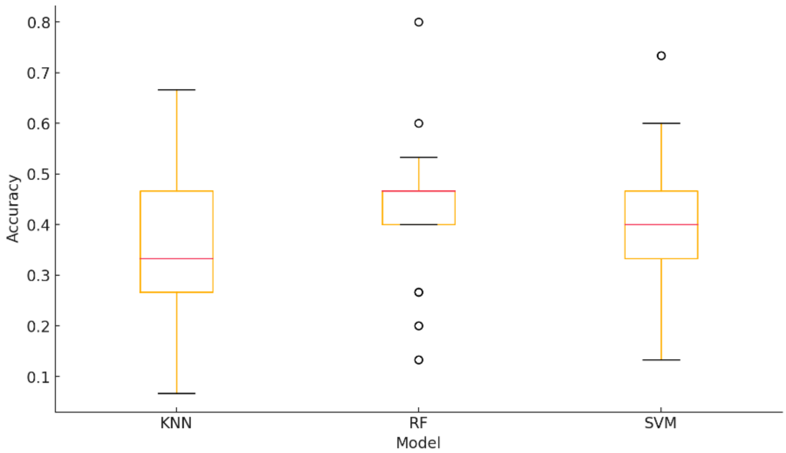


Figure 4. Accuracy Distribution per Model

The RF model shows the highest median accuracy among the three models. The IQR for RF is broader than that of SVM, indicating more variability in the accuracy values. The wider IQR suggests that while the model often performs well, its performance can vary more than SVM. The whiskers are longer, and there are several outliers, reflecting occasional instances of both very high and low performance. This variability can be attributed to the ensemble nature of the RF model, which combines multiple decision trees. Despite the variability, the RF model's high average accuracy makes it a strong contender, especially when adequately tuned ensemble techniques.

The KNN model exhibits the lowest median accuracy among the three models. The IQR for KNN is relatively wide, indicating significant variability in accuracy. The whiskers extend further than those for SVM, and there are several outliers. It highlights KNN's sensitivity to the choice of neighbours and the data structure. The high variability suggests that KNN's performance can fluctuate widely depending on the dataset and the parameters used. Consequently, while KNN can be effective in some scenarios, it often requires careful parameter tuning and may not be as reliable as SVM or RF for consistent performance.

In summary, despite its variability, the RF model stands out for its high average accuracy. With its consistent and generally high performance, SVM remains a reliable choice for many applications. KNN, while effective in some instances, shows the highest variability and lowest median accuracy, indicating it may need careful tuning and may not be as consistently reliable as the other models. These insights can guide the selection and tuning of models for different datasets, optimizing performance based on data characteristics.

## 4. CONCLUSION

In evaluating the accuracy distribution of the SVM, RF, and KNN models, we observe distinct performance characteristics:

1. **Random Forest (RF)** shows the highest average accuracy among the three models. Despite its wider variability, reflected in a broader interquartile range (IQR) and longer whiskers, RF's high accuracy makes it a strong choice for many applications. The presence of outliers suggests that while RF can occasionally perform exceptionally well, it may also require careful tuning to achieve consistent results.

2. **Support Vector Machine (SVM)** demonstrates a high median accuracy with a narrow IQR, indicating consistent performance. Its short whiskers and few outliers highlight its reliability and stable performance across different datasets. SVM stands out as a dependable model, especially in high-dimensional feature spaces.
3. **K-Nearest Neighbors (KNN)** exhibits the lowest median accuracy and the most significant variability among the models. The wide IQR and numerous outliers indicate its sensitivity to parameter choices and data characteristics. While KNN can be effective in specific scenarios, it often requires careful tuning and may not offer the same level of consistent performance as RF or SVM.

In summary, with its high average accuracy, the Random Forest model emerges as the top performer but demands careful tuning due to its variability. The SVM model is notable for its consistent and reliable performance, making it a dependable choice. The KNN model, while potentially effective, shows the highest variability and requires careful parameter tuning to achieve optimal results. These insights can guide model selection and tuning efforts to maximize performance based on specific dataset characteristics.

## ACKNOWLEDGEMENTS

This research has received support from Universitas Amikom Yogyakarta in the form of a fundamental research grant.

## CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

**I Made Artha Agastya:** Conceptualization, Methodology, Code. **Robert Marco**: Writing – original draft. **Mohamad Firdaus**: Writing – review & editing.

## DECLARATION OF COMPETING INTERESTS

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## DATA AVAILABILITY

Data are available on request to Prof. Dr. Jason Teo Tze Wi (jtwteo@ums.edu.my) in accordance with article named "A Dataset for Emotion Recognition Using Virtual Reality and EEG (DER-VREEG): Emotional State Classification Using Low-Cost Wearable VR-EEG Headsets" (https://doi.org/10.3390/bdcc6010016).

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