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EEG Emotion Recognition using Deep Neural Network (DNN) in Virtual Reality Environments

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ABSTRACT

Purpose: The purpose of this study is to explore the integration of EEG technology with virtual reality (VR) systems to enhance therapeutic interventions, improve cognitive state recognition, and develop personalized immersive experiences. Specifically, it investigates the classification of EEG signals in a VR environment using machine learning models and identifies the most effective methods for individual-level analysis.
Methods: The study utilized EEG data collected from 31 participants using the Muse 2016 headset, with electrodes positioned according to the 10-20 international system. EEG signals were analyzed for features such as statistical metrics (mean, median, standard deviation, skewness, and kurtosis) and Hjorth parameters (activity, mobility, complexity). Machine learning models, including K-Nearest Neighbors (KNN), Random Forest (RF), and Support Vector Machine (SVM), were evaluated for their performance in classifying emotional and cognitive states in a VR environment.
Result: Integrating EEG with VR technology has transformed therapeutic interventions and cognitive research, providing deeper insights into emotional and mental states for personalized treatments. The VR-EEG system has shown comparable effectiveness to traditional therapies, with specific VR interactions, like emojis, boosting emotional responses. EEG analysis in VR gaming and Virtual Reality Exposure Therapy (VRET) has improved diagnostic precision, achieving 96.93% accuracy with a standard deviation of 0.0214 for emotion recognition tasks. Different game genres and VR environments triggered distinct brainwave reactions, with free-form landscapes enhancing alpha wave activity. Despite some challenges, such as noise interference in high-density EEG, the integration of EEG and VR offers significant potential for advancing mental health care and research.
Novelty: This study is novel in its focus on personalized machine learning model performance in a VR-EEG setup. Instead of a one-size-fits-all approach, it emphasizes individualized analysis, identifying the most effective model for each participant.

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1. INTRODUCTION

The fusion of EEG technology with virtual reality (VR) [1] has revolutionized therapeutic approaches and shattered conventional boundaries in cognitive research. This powerful combination is proving to be a game-changer in mental health treatments, cognitive investigations, and the creation of hyper-targeted immersive environments. By analyzing brainwave responses during VR engagement, researchers are gaining unparalleled insights into emotional and mental states, driving the development of more personalized and highly effective therapeutic strategies.

The VR-EEG [2] system has emerged as a potent short-term therapy for depressive symptoms, demonstrating efficacy that rivals traditional methods like Zoom-based online counseling. While a virtual museum experience had no impact on positive emotions, specific interactive elements, like doodles and emojis, produced a noticeable spike in positive emotional responses. Furthermore, different video game genres provoke distinct brainwave reactions, opening the door to highly customized game-based therapies for mental health.

Tetris, a seemingly simple game, has been shown to generate increased coherence and entropy in brainwave activity, particularly amplifying coherence between the frontal and temporal regions of the brain. When combined with EEG data, Virtual Reality Exposure Therapy (VRET) [3] has enhanced the precision of diagnoses, enabling highly individualized treatments within its framework. EEG applications in VR driving [4] simulations have provided critical insights into cognitive processes like driver fatigue, navigation, obstacle avoidance, and real-time monitoring [5]. Distinct EEG microstates [6] reveal the emotional shifts within VR environments, with sharp transitions between microstates linked to positive or negative emotions.

Visual distractions [7] were found to drastically suppress theta band activity in EEG signals, while auditory distractions had the opposite effect, boosting alpha band activity. High classification accuracies were achieved in distinguishing locomotion [8] from resting states, though these numbers drop when movement and turning are introduced. EEG also proved its worth in classifying immersion states in VR, with machine learning algorithms achieving impressive accuracy in differentiating levels of challenge. Free-form VR [9] landscapes induced stronger alpha activity across a broader range of brain regions, revealing profound cognitive differences compared to structured landscapes and these differences were consistently observed.

EEG studies in VR environments have revealed the potential for significant noise interference, especially with high-density [10] EEG systems. However, experimental studies have proven that EEG-driven VR systems capable of adapting scenes [11] based on emotional responses are not only possible but highly valuable. Specifically, theta band features have proven critical in improving emotion recognition, particularly in decoding emotional valence. VR sickness [12] was found to be far more intense with head-mounted displays (HMDs) than traditional screens, accompanied by notable changes in alpha wave power in certain brain regions. EEG [13] has proven to be a viable tool for real-time interactions in VR games, where even simplified EEG metrics suffice for non-critical applications. The frontal region of the scalp [14] is particularly important for classifying the fear of heights, with gamma and high-beta bands playing dominant roles in these analyses.

In summary, the integration of EEG technology with VR systems offers significant potential for advancing therapeutic, cognitive, and immersive applications. By leveraging EEG's ability to capture real-time neural responses, VR environments can be tailored to enhance emotional well-being, refine therapeutic interventions, and deepen our understanding of cognitive processes. This combination not only enables the creation of adaptive VR experiences but also fosters innovative approaches to mental health treatments, such as emotion-adaptive therapies, precision diagnostics, and real-time neurofeedback systems. As research continues to explore these synergistic technologies, their application is poised to transform fields ranging from psychology and neuroscience to education and entertainment, driving the development of highly personalized and effective solutions for a variety of challenges.

2. METHOD

2.1 Dataset

The dataset was collected by Suhaimi et al. [15]. A total of 32 healthy participants, consisting of 7 females and 25 males aged between 23 and 45, were initially recruited. However, the final dataset included only 31 participants. The data collection process utilized the Muse 2016 EEG Headset, developed by Interaxon, along with the Mind Monitor application, created by James Clutterbuck. The EEG electrodes of the Muse 2016 were positioned according to the 10-20 international EEG system at TP9, AF7, AF8, and TP10, with a reference placed at Fpz. The Mind Monitor app was configured to record data in CSV format, with a notch filter set to 50Hz to accommodate the EU/230V power supply. The sampling rate was set to 2Hz, which, while providing limited temporal resolution, presented challenges in extracting EEG signature waves (such as gamma, beta, alpha, delta, and theta) through band-pass filtering. The raw EEG signal ranged from 0.0 to 1682.815 µV. The sequence of VR video presentations, designed to elicit emotional responses, was structured as follows: each emotional quadrant of the VR videos was shown for 80 seconds, with four different videos for each quadrant. A 10-second rest period was included between each video to help reset participants' mental states before transitioning to the next emotional quadrant.

2.2 Feature extraction

2.2.1. Statistic Features

Statistic features [16] 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 $S = [s_1, s_i, \ldots, s_m]^T$, where $S \in R^{m \times L_0}$, $S = [s_1, s_2, \ldots, s_{L_0}]$, and $i = 1, 2, \ldots, m$. 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

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

2. Mean

$$\bar{s} = \frac{\sum_{j=1}^{L_0} s_j}{L_0} \tag{2}$$

3. Standard deviation

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

4. Variance

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

5. Skewness

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

6. Kurtosis

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

2.2.2 Hjorth parameters

Hjorth parameters [17] 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 [18], [19].

Activity:

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

Where μ_x is the mean of x computed as per 2.2.

Mobility:

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

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.

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2.3 Deep Neural Network

The classification of EEG signals is as follows:

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. Additionally, Hjorth parameters, including activity, mobility, and complexity, will be computed to capture signal amplitude and frequency characteristics.
3. Deep Neural Network (DNN)
   A Deep Neural Network (DNN) will be employed as the classifier for EEG signal data. DNNs are powerful machine learning models capable of capturing complex relationships in data due to their multiple layers of interconnected neurons as simplified in Figure 1. Input Layer: The extracted features from EEG signals, such as statistical metrics (mean, standard deviation, skewness, kurtosis) and Hjorth parameters (activity, mobility, complexity), will serve as input features. Hidden Layers: Several hidden layers will be included, using activation functions like ReLU (Rectified Linear Unit) to introduce non-linearity, enabling the network to learn complex patterns in the data. Output Layer: A softmax or sigmoid activation function will be used, depending on whether the classification problem is binary or multi-class. The output layer will provide class probabilities for each EEG signal instance. Optimization: The model will be trained using optimization algorithms such as Adam or SGD (Stochastic Gradient Descent) with a learning rate chosen through hyperparameter tuning. Loss Function: A suitable loss function like categorical cross-entropy (for multi-class classification) or binary cross-entropy (for binary classification) will be utilized to minimize classification errors during training. The DNN structure will be tailored to the dataset, considering the number of features and expected complexity of the EEG signal classification problem. Regularization techniques such as dropout and batch normalization may be applied to prevent overfitting, ensuring the model generalizes well to unseen data.

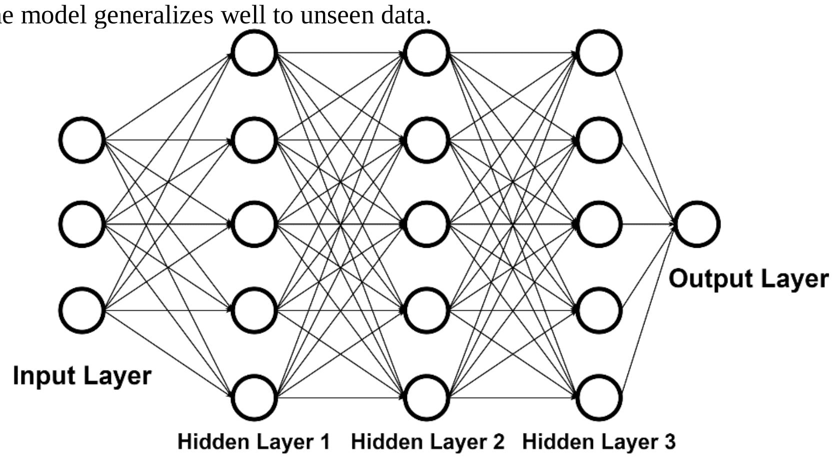

Figure 1. A Four-layer neural network.

4. Evaluation
   The performance 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 LSTM based on their accuracy in handling the extracted features, as shown in Figure 2.

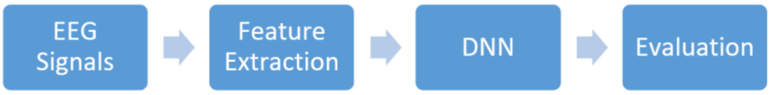

Figure 2. The classification flow chart

3. RESULTS AND DISCUSSIONS

Figure 3 illustrates the performance trends of three machine learning algorithms—SVM, KNN, and DNN—across multiple subjects. The deep neural network (DNN) consistently outperforms the other algorithms, with an average accuracy of 0.9693, highlighting its ability to capture complex patterns in the data. This aligns with the architecture of deep neural networks, which are designed to model intricate, high-dimensional, and non-linear relationships effectively. In comparison, SVM and KNN achieved average accuracies of 0.8008 and 0.8650, respectively, underscoring DNN's superiority in this scenario.

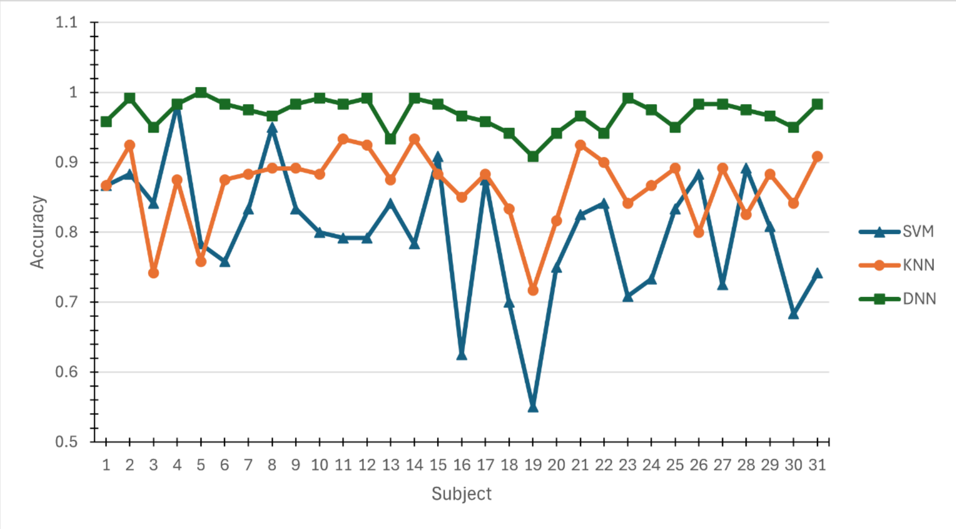

Figure 2. The Performance Comparison

The DNN model used here is specifically tailored for multi-class classification. It consists of two hidden layers with 64 and 32 neurons, respectively, both utilizing ReLU activation functions. These layers progressively learn features from the input data, enhancing the model's ability to differentiate between the four classes. The output layer employs a softmax activation, converting the network's outputs into probabilities for accurate classification. This architecture contributes to DNN's superior performance, as it is well-suited for tasks requiring advanced feature extraction.

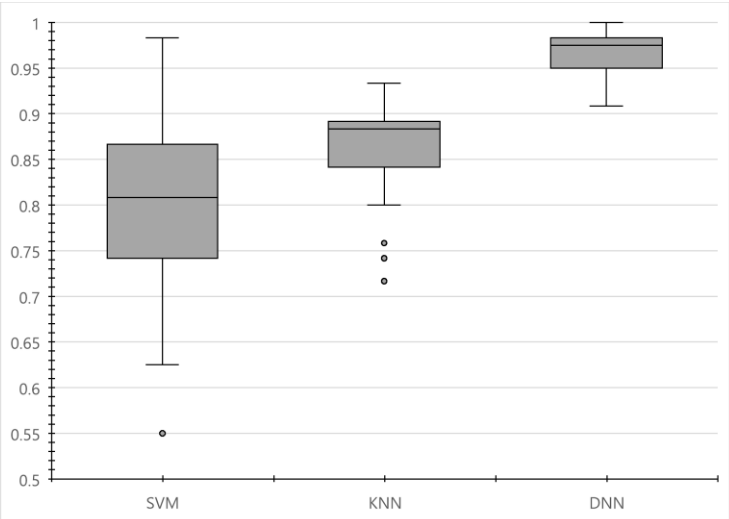

Figure 3. The Box Plot of SVM, KNN, and DNN Accuracy

As Shown in Figure 3, DNN also demonstrates greater stability, with a standard deviation of 0.0214, reflecting its consistent performance across different subjects. In contrast, SVM has a standard deviation of 0.0918, and KNN's standard deviation is 0.0538, indicating that the other algorithms are more prone to fluctuations in their performance. While SVM provides a reliable baseline and KNN offers a simpler, more interpretable approach, DNN's higher performance and lower variance underscore its capacity to handle complex data effectively. However, DNN also comes with trade-offs, such as greater computational demands and the potential for overfitting. Techniques like dropout, batch normalization, and hyperparameter tuning can help mitigate these issues, further enhancing the DNN model's robustness. Overall, the results confirm the advantages of DNN for tasks that require sophisticated feature learning and high classification accuracy, as evidenced by both its higher average accuracy and lower standard deviation.

4. PERFORMANCE COMPARSISON WITH SIMILAR RESEARCH

Table 1 summarizes the performance of various machine learning methods for the task at hand, with a focus on the accuracy achieved by different models. Our deep neural network (DNN) model, which achieved an accuracy of 96.93%, is compared against several other methods from the literature.

Table 1. The Previous Research Performance Comparison

Reference	Year	Method	Accuracy
[15]	2022	SVM	97.66
[20]	2024	XGBoost	95.0
[20]	2024	Random Forest	92.0
[21]	2024	FBSA-Net	96.63
Our	2024	DNN	96.93

The Support Vector Machine (SVM) [15] proposed by Suhaimi et al. achieved an accuracy of 97.66% in the study. SVM is known for its robustness, especially in high-dimensional spaces, and has been widely used for classification tasks. While its accuracy in this case is slightly higher than our DNN, it may come with trade-offs such as longer training times or sensitivity to parameter tuning, especially for complex datasets. Jimenez et al implemented the XGBoost [20], known for its efficiency and strong performance on structured data, achieved an accuracy of 95.0%. XGBoost is an ensemble learning algorithm based on decision trees and has become a popular choice for many machine learning competitions. Its accuracy is slightly lower than DNN, but it often provides competitive results with faster training times and reduced computational requirements. They also experimented with the Random Forest (RF) [20] algorithm, also an ensemble method based on decision trees, and achieved 92.0% accuracy. RF is known for being less prone to overfitting compared to individual decision trees and can handle large datasets well. However, its performance in this study is lower compared to both DNN and XGBoost, possibly due to its less sophisticated ability to model complex, non-linear relationships in the data. The Frequency-Band-Spatial-based Attention Network (FBSA-Net) [21] was proposed by Xie et al. It combines feature selection or attention mechanisms in its architecture, achieved 96.63% accuracy. FBSA-Net shows strong performance, approaching that of our DNN, but slightly lags in terms of accuracy.

Our DNN model achieved an accuracy of 96.93%, which is the highest among the listed methods. The DNN's superior performance highlights its ability to learn complex patterns from high-dimensional data, making it particularly effective for tasks that require deep feature extraction. The DNN architecture employed two hidden layers with 64 and 32 neurons, leveraging ReLU activation functions and a softmax output layer for multi-class classification. While the SVM from [15] offers the highest accuracy of 97.66%, the DNN achieves 96.93%, which is still highly competitive and demonstrates its robustness. The DNN also has the advantage of being well-suited for handling non-linear relationships and high-dimensional data. Compared to other methods like XGBoost (95.0%), Random Forest (92.0%), and FBSA-Net (96.63%), the DNN's performance is highly competitive, with the added benefit of being able to scale effectively to more complex datasets. The slight differences in accuracy between these methods suggest that DNN, while not always outperforming simpler models, remains highly effective for tasks that demand advanced learning capabilities. Moreover, the DNN's flexibility and adaptability make it a strong choice for future applications in complex, multi-class classification problems.

5. CONCLUSION

This study demonstrates the transformative potential of integrating EEG technology with VR systems in therapeutic, cognitive, and immersive applications. The combination of brainwave analysis and VR environments enables personalized therapeutic interventions, advanced cognitive state recognition, and insights into user emotional responses.

Our key findings include:

1. The integration of EEG with VR opens doors for applications like VRET, mental health treatments, and real-time monitoring of cognitive and emotional states. This approach tailors' therapy to individual needs.

2. The comparative analysis of machine learning models (DNN, SVM, KNN) highlights the superiority of DNN in accurately classifying emotional and cognitive states due to its ability to capture complex and high-dimensional patterns.
3. The use of statistical features and Hjorth parameters proves to be an effective way to distil meaningful insights from EEG data.
4. A key contribution of the study is its focus on personalized model selection, emphasizing that different machine learning algorithms suit different participants, paving the way for individualized therapeutic applications.

The VR-EEG synergy holds promise for future research and development, particularly in enhancing mental health treatments, improving cognitive studies, and enabling immersive user experiences. Further studies could refine model performance, incorporate real-time analysis, and explore new applications for this innovative technology.

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CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

I Made Artha Agastya: Conceptualization, Methodology, Code. **Robert Marco**: Writing – original draft. **Dini Oktarina Dwi Handayani**: 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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