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Application of Gated Recurrent Unit in Electroencephalogram (EEG) - Based Mental State Classification

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ABSTRACT

The classification of mental states based on electroencephalogram (EEG) recordings has recently gained significant interest in cognitive monitoring and human-computer interaction fields. Due to high signal variability and sensitivity to noise, correct classification is still tricky, even with advances in the analysis of EEG signals. Among deep learning models, Gated Recurrent Unit (GRU) models have established great potential for sequential EEG data analysis. The applications of the GRUs are less reviewed in tasks concerning classification cases of mental states compared to hybrid and convolutional models. Based on this paper, we will propose a method for developing a model based on the GRU network trained with raw EEG data in the classification tasks of mental states of concentration and relaxed conditions. We analyzed 400 EEG recordings taken from 10 subjects within a controlled environment and collected using the Muse EEG Headband. The mean, standard deviation, skewness, kurtosis, power spectral density, zero-crossing rate, and root mean square were extracted as statistical features from the raw EEG data. After parameter tuning, the GRU-based model achieved an excellent average accuracy value of 95.94% and also yielded precision, recall, and F1-scores within the range of 0.95 to 0.97 over 5-fold cross-validation. This shows that GRU works well in classifying mental states based on the EEG data.

I. Introduction

The classification of mental states based on electroencephalogram (EEG) technology has become crucial in brain-computer interaction, cognitive state monitoring, and mental health status diagnosis. Non-invasive EEG gives real-time measurement of the brain's activity with high temporal resolution; hence, this technique is efficient for recognizing specific mental states such as concentration and relaxation conditions. Lightweight and portable versions of electroencephalogram devices, such as the Muse Headband, have been used recently. This headband is an inexpensive, non-invasive EEG sensor that uses four electrodes to track activity in the brain: TP9, AF7, AF8, and TP10. This provides an excellent opportunity for research and practical applications related to assessing one's mental state [1]. This technology holds promise for developing adaptive systems in various domains, including such exciting applications as cognitive load estimation and therapy tools for supporting mental health conditions [2], [3]. Subsequently, there came an increase in research relating to the classification of mental states using EEG and convincingly showed that EEG signals could provide good insight into an individual's cognitive and emotional states [1].

Numerous studies have investigated deep learning methodologies to address these challenges and enhance mental state classification. Researchers in [4] introduced a convolutional gated recurrent unit model incorporating an attention mechanism for emotion detection, attaining an accuracy of 96.5% in differentiating emotional states by utilizing both temporal and spatial EEG information. Researchers in [5] employed a hybrid 1D-CNN and GRU model for multi-class emotion identification, achieving accuracy values beyond 94% by integrating the feature extraction capabilities of CNNs with the sequence modeling proficiency of GRUs. Examination of mental and emotional sentiment classification utilizing an EEG-based brain-machine interface through deep learning was found in [6], achieving a classification accuracy of 87% with multi-class SVM. A further study by [7] employed a Bi-GRU architecture to improve emotion recognition, attaining an average F1-score of 0.82, demonstrating that recurrent networks like GRUs can proficiently manage the temporal dependencies of EEG data. [8] shown that recurrent neural networks surpass other deep learning methodologies for EEG neural classification, achieving an average accuracy of 92% on a mental workload dataset.

One of the main challenges in EEG-based mental state classification is that devices must be designed for high accuracy with limited data in real-time, especially in wearable sensors like Muse Headband. Traditional machine learning approaches suffer from the nonlinear and non-stationarity nature of EEG signals [1] characteristics result in varying performance across different subjects and recording conditions. Furthermore, many previous works require complex hybrid models that combine CNNs with recurrent layers. This increases the computational demands and makes such models unsuitable for real-time applications [5] [4]. The researchers in [5] also mentioned that while their proposed hybrid CNN-GRU model provides good accuracy, the computational cost was an issue when deploying the model in real-time applications. [4] also noted the trade-off between model complexity and real-time applicability, where their attention-based GRU model, though highly accurate, demanded heavy processing resources.

This research further develops previous research by applying a GRU network to classify mental states, such as concentration and relaxation, using EEG data acquired from the Muse Headband. GRU is used because it is more computationally efficient than other recurrent methods, like LSTM. Researchers in [9] state that GRU, which has fewer gates than LSTM, streamlines the architecture, resulting in faster training speeds, fewer parameters to update, and lower data requirements. CNN is especially suitable for extracting spatial characteristics, perfect for tasks like image processing when spatial dependencies are visible. Conversely, GRU can more effectively manage temporal patterns, which is usually quite crucial in EEG signal analysis; they are beneficial for processing sequential data [9]. Even though this research does not directly leverage raw sequential dependencies due to statistical features, GRUs are still advantageous over CNNs for EEG-based mental state classification. This is because GRUs can capture patterns across sequences of feature sets, effectively modeling temporal patterns in data where shifts and trends are still relevant, even in aggregated form. This research also used a more straightforward model architecture to provide an effective solution to mental state classification, thus showing the effectiveness of the GRU for EEG-based applications without hybrid designs' computational overhead.

II. Methods

The current study classifies mental states using EEG data and a GRU model. These methodologies are divided into seven subsections: EEG data acquisition, preprocessing, feature extraction, model architecture, hyperparameter optimization, training and validation, and evaluation.

A. EEG Data Acquisition

The experiment used the non-invasive, low-cost EEG sensor Muse Headband equipped with four electrodes, TP9, AF7, AF8, and TP10, recording the brain wave activity from the specific brain regions [1]. The given sensors were put on temporal and frontal lobes, as shown in Figure 1, recording the raw EEG signals which can later be identified with mental states such as relaxation and concentration, represented by previous studies conducted, where [10] used Muse's sensors to recognize "relaxing, neutral, and concentrating" states.

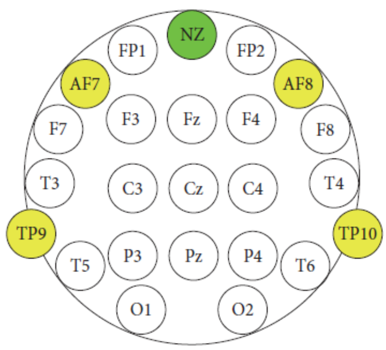


Figure 1. Muse Headband's TP9, AF7, AF8, and TP10 sensors on the international standard EEG layout system [10]

A wireless connection of a Muse device to a computer was done using an open-source application called BlueMuse, which allowed a stable wireless transmission of EEG signals[1]. The EEG data was collected and preprocessed in Python, and various specific libraries were used to help deal with incoming data from the Muse Headband. One of the used libraries is Pylsl which can continuously capture data. Besides, NumPy and Matplotlib were used in fast EEG data calculations.

The data collection process involving ten subjects was held in an empty classroom to minimize external disturbances. Some exercises were selected to induce certain mental states. During the concentration state, participants performed cognitively intensive activities such as reading news articles and attending online classes, which demanded high attention. In line with earlier research that used low-tempo music and sound effects or muscle relaxation [1] to induce relaxation, participants in the relaxation condition in this research were instructed to close their eyes and take deep breaths, a technique frequently used to induce calm and reduce cognitive load. Data was recorded continuously with a sampling rate of 256 Hz, sufficient to capture the spectral features of interest while balancing data processing requirements [4] [11].

B. Data Preprocessing

The preprocessing pipeline for the EEG classification included a few steps: downsampling, filtering of the signal, normalization, segmentation, and windowing. First, downsampling was done to reduce the volume of data from 256 Hz to 200 Hz while retaining important spectral information. The Python library SciPy was used for downsampling and efficiently processing records. Following downsampling, the signal was filtered to remove undesired frequency components and other artifacts, as recommended by [5]. Since frequency bands below 0.5 Hz and above 50 Hz are usually noisy and carry little useful information regarding the classification of a subject's mental state, a bandpass filter was used between 0.5 Hz and 50 Hz to retain the prominent EEG frequency bands. This research also implemented a notch filter at 50 Hz, contributing to rejecting the power line noise [12]. The bandpass and notch filters were designed using the butter and lfilter tools of the SciPy library.

After filtering, the EEG signals were normalized and scaled. Since the amplitude varies and could affect the classification performance, normalization is essential so that every EEG channel participates equally in the model's performance. It brings data consistency and comparability [4]. For every signal, NumPy library in python normalized the mean and variance.

The filtered and standardized EEG data was then split into time periods. Every part, or a window, sets its duration to two seconds with a fifty percent overlap between consecutive frames. This was based on [1], who found that discriminant traits might be revealed from short time lapses of EEG data. This windowing method permits recording transitory EEG signals matching targeted concentration and relaxation changes. As stated in [13], the 50% overlap will provide a continuation of EEG signals in the temporal dimension. Using overlapping windows could boost temporal resolution to detect minor changes in the mental state.

C. Feature Extraction

The current research has only analyzed EEG signals using statistical features instead of focusing on alpha, beta, and theta frequencies. This approach gathers many aspects of signal behavior data without limiting the study to the defined frequency ranges. The feature extraction step includes deriving statistical features from raw EEG data to produce a representative dataset for mental state classification. For every two-second windowed segment, the following statistical characteristics were computed: mean, standard deviation, skewness, kurtosis, power spectral density, zero-crossing rate, and root mean square.

The variability and distribution of the EEG signals could be captured using the statistical selection criteria. In this respect, the mean and the standard deviation represent the central tendency and dispersion of the signal, respectively; thus, it makes the data consistent and comparable. Skewness, by definition, estimates the form and extremities of the EEG signal distribution. Because of this, it would inherently help in finding out data asymmetries and peak aberrations. These properties have been utilized to identify brief temporal intervals in EEG data that signify alterations in mental states [1]

Each EEG channel's frequency domain properties were analyzed using power spectral density (PSD). PSD shows power distribution across frequencies, which helps identify mental processes since various EEG frequency bands connect with concentration or relaxation [5]. As signal energy fluctuates with cognitive load, a zero-crossing rate (ZCR) was introduced to evaluate signal polarity changes within each segment [7]. Zero-crossing rates are relevant to distinguish between concentration and relaxation states, according to [12]. Finally, the RMS of each segment was calculated, which is specifically sensitive to changes in signal intensity, hence distinguishing other states of mental activation [14].

These features were calculated in Python with NumPy for core statistical calculations, SciPy for spectral density analysis using the welch function, and statsmodels for skewness and kurtosis.

D. GRU Model Architecture

GRU is a simple variant of the RNN architecture, comprising only two gates, update and reset, rather than the three gates used in the LSTM, making the GRU architecture lighter and faster [9]. The model in this work was developed with two GRU layers, optimized for speed while being simple—anything more complex may not be practical for real-time applications [5]. The GRU model was trained in Python using two of the most used open-source libraries: TensorFlow and Keras. Keras provides an easy interface to build a GRU layer and configure parameters such as units and dropout rate.

The model, seen in Figure 2, started with a 64-unit GRU layer, followed by a dropout layer with a 0.2 rate to reduce overfitting by randomly removing a subset of the connections during training. After that, a second GRU layer with 32 units that did not return sequences ended the recurrent structure. Another dropout layer with the same rate was added to enhance generalization. It has an output layer with one neuron, where a sigmoid activation function is implemented for binary classification, mapping the output probability between 0 and 1 [8].

The model was constructed using the Adam optimizer with a default learning rate of 0.0001, which can be modified during training to ensure efficient and flexible learning. Binary cross-entropy was chosen as the loss function since it is appropriate for binary classification, and accuracy was used as the significant assessment parameter.

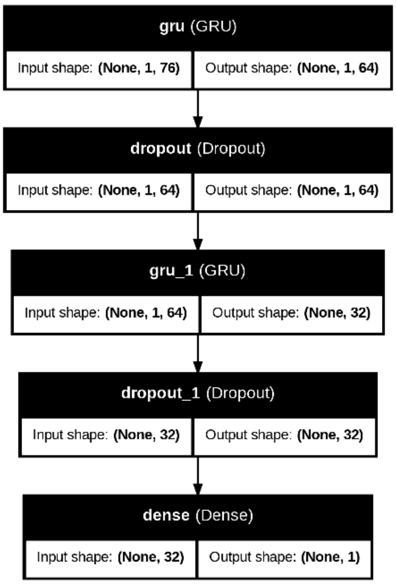


Figure 2. Initial GRU Architecture

E. Hyperparameter Tuning

Tuning the hyperparameter is essential for optimal performance of GRU in EEG data processing. The model's effectiveness relies on these parameters' configurations[11]. The Keras Tuner library tuned the GRU model's hyperparameters to best classify mental states based on EEG data. During this tuning process, key factors were changed to improve the model's performance in the validation set. The number of GRU units varied along with the learning rates to establish an optimum setting for the best classification.

Various values were tried for each parameter to reach the optimum performance. While varying the units of the first GRU layer between 32 and 128, the units of the second layer were tried between 32 and 64. Prevention of overfitting was attempted by varying the dropout rates in steps of 0.1, starting from 0.1 and ending at 0.5. Lastly, the learning rate of the Adam optimizer was spread logarithmically between 0.0001 and 0.01 such that both the accuracy and speed of convergence are excellent. Finally, Random Search tuning from Keras Tuner was used to navigate the hyperparameter space fast. Then, each model configuration was evaluated based on validation accuracy, and the best model was saved instantly to keep the best hyperparameters.

F. Training and Validation

In training and validation, the original data was divided into independent training, validation, and testing data. The data is divided into 80% training and 20% testing to ensure the model does not see the testing data during training. To make the model even better, 20% of the training data was used for validation at the end of each training period.

This research used the K-fold cross-validation technique as part of the experimental setup to validate model performance [15]. This research used 5-fold cross-validation to ensure that such results are more reliable. This method splits the dataset into five segments or folds. The model learns on four folds and verifies the work on the last fold, allowing each smaller segment to be used as a validation set. The GRU model was implemented using TensorFlow and Keras, with scikit-learn for cross-validation.

G. Evaluation

Accuracy, precision, recall, and F1-score were calculated to test the model's performance. The scores were computed using a Keras library. Accuracy shows how many correct predictions out of the total predictions were made. Precision describes the ability of a model to avoid false positives by showing the proportion of accurate positive predictions out of all cases predicted as positive. On the other hand, recall looks at the efficiency of the predictor that finds real positive cases using true positives compared to the total number of actual positive cases. The F1-score, or F1-Measure, seeks the harmonic mean of precision and recall and balances them into a single measure. A high F1-Score means that both accuracy and recall are high, which means the model works well [16]. The final model evaluation was based on averaged cross-validation metrics, which ensured stability over folds and reduced the likelihood of overfitting.

Comparing predicted labels to data labels can assess classifier model performance. Confusion matrix tables summarize this information. The matrices highlighted correct and incorrect classifications, helping us understand common misclassification trends and improve the model [16]. The confusion matrix shows how much data the classifier predicted correctly or falsely using TP, FP, FN, and TN.

III. Results and Discussions

This section presents the research findings by giving an account of the result after each methodological step was carried out and interpreting what that means for EEG-based mental state classification using a GRU model. The results are structured into subsections: data acquisition, data preprocessing, feature extraction, model architecture, hyperparameter tuning, training and validation, and final evaluation.

A. Data Acquisition Results

The Muse Headband is a non-invasive, portable EEG device with four electrodes across the temporal and frontal lobes of the head, which are TP9, AF7, AF8, and TP10. Continuous EEG data were collected from 10 subjects: five males and five females with ages ranging between 20 and 35 years. Data collection was conducted in a controlled and isolated environment to ensure that the amount of known artifacts was as minimal as possible. In the concentration condition, participants read articles or attended online lectures, while in the relaxation condition, they closed their eyes and focused on deep breathing. BlueMuse, an open-source Bluetooth-enabled EEG signal transfer application, recorded EEG signals continuously at 256 Hz. Later, the data were downsampled to 200 Hz.

The FFT plots for frequency analysis states of concentration and relaxation show different peaks at particular frequency ranges. The concentration state has higher peaks around 13–30 Hz, indicating the frontal sensors' active mental engagement in the attention state (AF7 and AF8). On the other hand, the relaxation state shows power distribution in 8-12 Hz. Figure 3 shows the frequency distribution from each sensor's concentration and relaxation state.

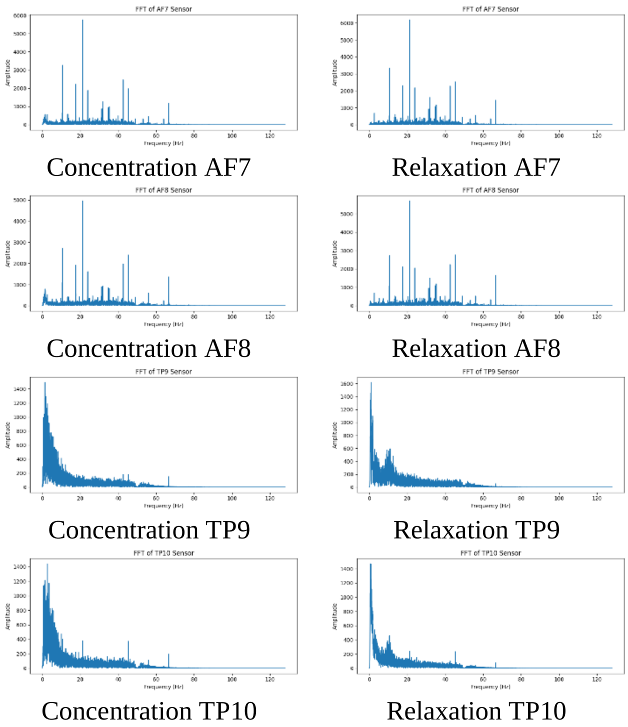
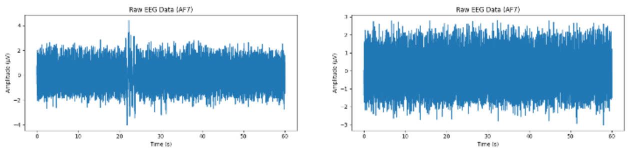


Figure 3. Frequency plots for concentration and relaxation mental state from AF7, AF8, TP9, and TP10 sensors

The visual assessment of the raw EEG data showed differences concerning different mental states. Time-domain plots reflect that the raw EEG graphs, especially in the AF7 and AF8 sensors in the concentration state, have more significant amplitude variations. These reflect the cognitive load of activities like reading or online learning, thus implying more brain activity. In contrast, as shown in Figure 4, the relaxed state manifests much smoother and less erratic signal patterns, especially in the temporal sensors, TP9 and TP10.



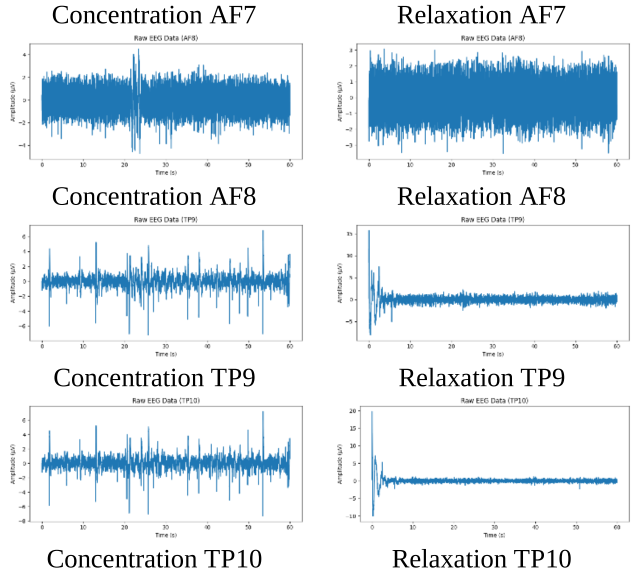


Figure 4. Raw EEG Plots for concentration and relaxation mental state from AF7, AF8, TP9, and TP10 sensors

B. Data Preprocessing Results

This research used structured data preprocessing to prepare the EEG signals for later feature extraction and modeling. Python's SciPy library downsampled 256-Hz EEG data to 200 Hz. This reduced the data volume while preserving critical signal properties related to mental state classification. Noise and other irrelevant features were removed by filtering the signals using the scipy. Signal functions butter and lfilter were used to create a band-pass filter between 0.5 Hz and 50 Hz to isolate the cognitively meaningful frequency bands of the EEG. A notch filter at 50 Hz reduced power line interference, a common noise source in EEG.

After filtering the data, NumPy normalized the signal amplitude across all channels. Normalization was followed by segmentation into 2-second sections with 50% overlap. Windowing captured transient patterns that may signal concentration and relaxation transitions.

C. Feature Extraction Results

From the feature extraction part of this research, statistical measures were computed across segmented EEG data, comprising a complete set of features for both the states of concentration and relaxation. The obtained features were mean, standard deviation, and PTP values showing power spectral properties that present the power distribution across frequency bands. Amplitude-based measures include RMS and ZCR, which estimate the overall signal strength and oscillatory behavior. Skewness and kurtosis are descriptive statistics highlighting the signal distribution and extremes, which may indicate data asymmetries and deviations from normality. Finally, fast Fourier transform statistics features included all statistical aspects.

There are significant differences between the concentration and relaxation states. The mean amplitudes of electrodes such as AF7 and AF8 were lower in the concentration state than during relaxation. Also, the standard deviation and PTP values showed higher variability during relaxation, sometimes indicating more scattered signal activity. Similarly, the kurtosis values, showing the 'tailedness' of the data distribution for the two states, exhibited different peaks in the signal distribution.

D. GRU Model Architecture Results

The GRU model's initial performance was average, with an accuracy of 79.69%, precision, recall, and F1-score values of 79.34%, 80.74%, and 79.84%, respectively, after five-fold cross-validation. These measurements emphasized the model's initial ability to distinguish between concentration and relaxation states but indicated improvement areas. When tested on the test set, the model scored 78% accuracy, with balanced precision and recall between the concentration and relaxation states, around 0.78. The confusion matrix, shown in Figure 5, revealed that the model correctly detected 32 occurrences of concentration class and 30 cases of relaxation class but misclassified 18 samples in total, indicating areas for additional refinement via hyperparameter tunings.

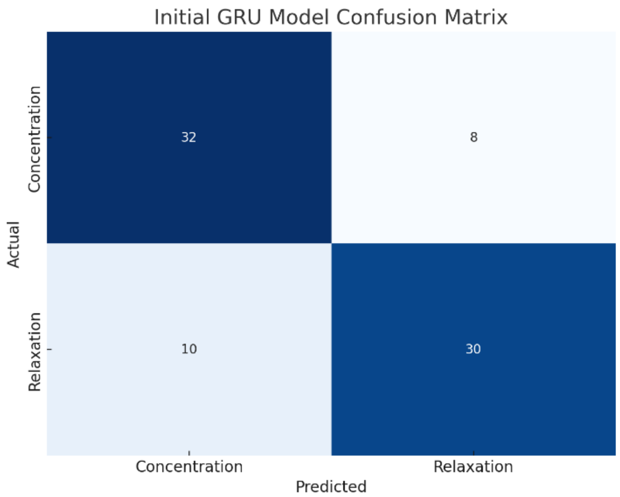


Figure 5. Initial GRU Architecture Confusion Matrix

E. Hyperparameter Tuning Results

The GRU model's initial performance was fair. This underlined its reasonable initial ability to separate the states of concentration versus relaxation but also pointed out some areas for improvement. During hyperparameter tuning, changes to elements such as the number of GRU units, dropout rates, and learning rates were critical in refining the model. Trial 16, with optimized parameters, had the best validation accuracy. Despite this good performance, specific models other than Trial 16 had inconsistent training curves, indicating that some configurations are occasionally unstable.

The configuration of the GRU model can become unstable due to factors like a high learning rate, which can cause large fluctuations in parameter updates, and overly high dropout rates that disrupt the model's learning of consistent features. Additionally, the number of units in each GRU layer must balance complexity and stability; too many units can lead to overfitting, while too few can underfit the data. The model's capacity to detect stable patterns can also be challenged by the inherent variability and noise in EEG data as can the batch size, where lower sizes produce gradient noise and bigger sizes slow down learning. These elements taken together cause instability in model training, especially in sequential models such as GRUs.

The GRU model's configuration was optimized through the hyperparameter tuning process, which involved executing 40 trials to enhance its ability to classify mental states from EEG data. The most optimal model configuration was identified through this search is shown in Figure 6, which featured 128 units in the initial GRU layer and 64 units in the subsequent layer. The dropout rates for both layers were maintained at approximately 0.3. A learning rate of roughly 0.0071 was associated with this configuration.

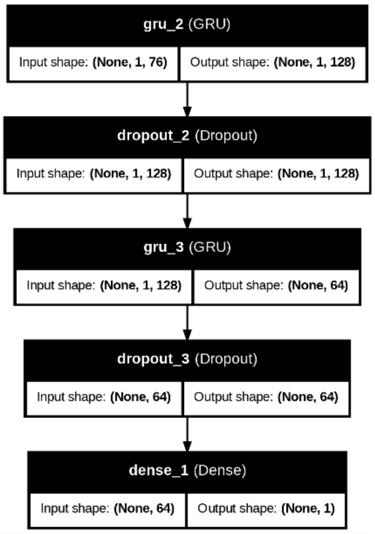


Figure 6. Optimized GRU Architecture

F. Training and Validation

Trained on the given dataset, the model was separated into training and validation subsets during and after development. This experiment consisted of 15 epochs, and the training accuracy grew steadily to almost perfection in the last epoch at a value of 99.61%. Figure 7's steep learning curve suggests that the model is robust in identifying the fundamental trends from the training set. Though with minor changes in some epochs, the validation accuracy is mostly steady at roughly 87.5% in the previous many epochs, indicating the generalizing capability of the model to unseen data.

Starting relatively high, the training loss dropped progressively as the model finally changed its parameters to reach 0.0326. This decline shows how well the model absorbs internal training data attributes. Conversely, in the following epochs, the validation loss first dropped but then plateaued and rose slightly before finally stabilizing at 0.3168, as Figure 8 shows. This trend shows a small overfitting, in which case the model loses more generalism in favor of being tightly tuned to the training data.

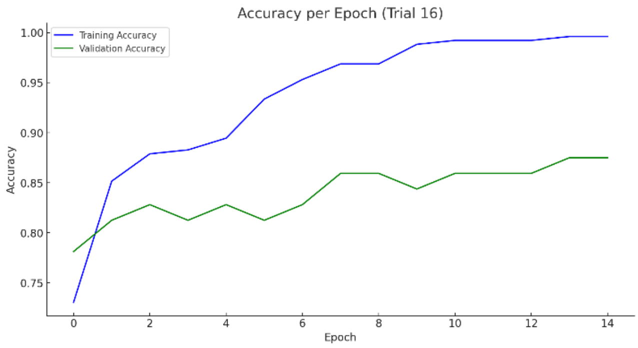


Figure 7. GRU Training and Validation Accuracy

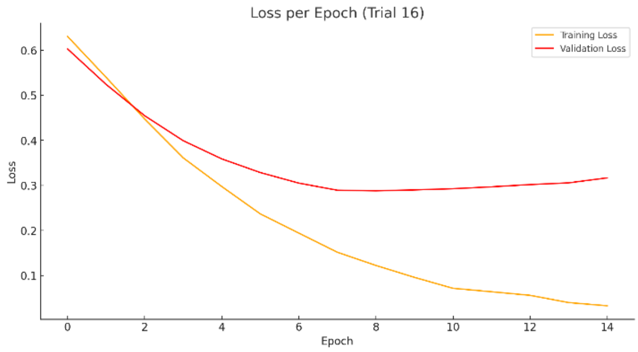


Figure 8. GRU Training and Validation Loss

G. Evaluation Results

The best combination of hyperparameters significantly improved the GRU model's performance. When evaluated on 5-fold cross-validation, the model gave an average accuracy of 95.94%. Precision, recall, and F1-score values varied between 0.95 and 0.97, showing that EEG-based mental state classification performance was outstanding.

A classification report for one of the five-fold validations provides evidence of the model's performance. The precision for the concentration class was 0.96, the recall was 0.93, and the F1-score was 0.95, showing exceptional capabilities of correctly identifying actual attention states while keeping false positives low. Strong measures were also obtained for the relaxation class with a precision of 0.94, recall of 0.97, and an F1-score of 0.96. The total accuracy for this fold was 95%. The accompanying confusion matrix, shown in Figure 9, revealed a high actual positive rate and low misclassifications.

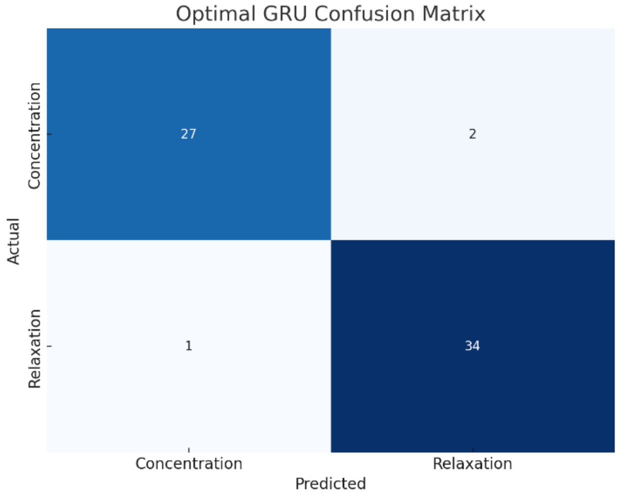


Figure 9. Optimized GRU Confusion Matrix

Comparing the GRU model's performance before hyperparameter adjustment indicates an improvement. The model initially had 79.69% cross-validation accuracy and 79–80% precision, recall, and F1 scores. This showed that the initial model captured common data patterns but needed optimization for efficiency. Testing set accuracy was 78%, and a confusion matrix showed more major misclassifications than the tuned model. Hyperparameter tuning is needed to increase the model's accuracy, as the initial classification report showed reasonable precision and recall.

These results show that hyperparameter tuning, including tweaks to GRU units, dropout rates, and learning rates, can enhance the model's performance. Using EEG data, this optimization produced a more accurate and stable model for mental state classification.

Furthermore, the evaluation of the GRU model demonstrated the extremely competitive results that can arise from even basic model architecture. This emphasizes that, with proper optimization, smaller models can generate outstanding classification performance, hence balancing computational efficiency and great accuracy.

Although it has limitations, the GRU model categorized mental states from EEG data with very great accuracy. The model's sensitivity to noise in EEG readings is a significant limitation, given EEG's sensitivity to environmental distortions and physiological movements. The noise was filtered, but residual noise could compromise model performance, especially in real-world conditions with less controlled EEG data. The model's generalizability across EEG datasets is another drawback. This study used a small sample using specific EEG equipment and controlled settings, which may limit the model's applicability to other EEG devices or participant groups with different demographics. The model's generalizability could be improved by adding noise robustness and testing it on different EEG datasets.

Despite these drawbacks, the GRU model is useful in cognitive monitoring and human-computer interaction. Neurofeedback therapy could help users focus or relax by providing real-time feedback on their mental state using the model's ability to distinguish mental states like concentration and relaxation in cognitive monitoring. This paradigm could enable adaptive systems that adapt to a user's cognitive load in HCI, improving usability and experience.

IV. CONCLUSIONS

A Gated Recurrent Unit (GRU) model identified mental states using EEG data, notably focus and relaxation, according to the current research findings. The performance of the GRU model was improved through hyperparameter adjustment, which led to an average cross-validation accuracy of 95.94%, good precision, recall, and F1-scores ranging from 0.95 to 0.97. This study's results also demonstrated that optimized, simplified structures could perform effectively despite the inherent complexity of EEG data. According to this, GRU-based models have the potential to be utilized in real-time cognitive monitoring and human-computer interaction by utilizing equipment that is both cost-effective and non-invasive, the Muse Headband being one example.

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