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# DEEP LEARNING FOR EMOTION CLASSIFICATION FROM EEG USING AUGMENTED AND ATTENTION-GUIDED FEATURES

**SK. Khadersha,** Department of Computer science and Engineering st.Mary's women's Engineering college, guntur, andhra pradesh , India
**Mr. J. Sudhakara Babu ,** Department of Computer science and Engineering st.Mary's women's Engineering college, guntur, andhra pradesh, India

**ABSTRACT:**
Electroencephalogram (EEG) signal classification plays a vital role in brain-computer interface (BCI) systems, particularly for tasks like cognitive state detection and mental workload evaluation. This study explores a deep learning-based method applied to a synthetic EEG dataset consisting of 1,500 instances, each with 32 channels and 128 time points, categorized into three workload levels: low, medium, and high. To overcome limitations stemming from limited data and high signal variability, we apply several data augmentation strategies, including Gaussian noise injection, temporal shifts, and frequency-based perturbations. Our proposed model, a multi-layer 1D convolutional neural network (CNN), achieves an overall classification accuracy of approximately 66.7%, with class-wise differences observed in precision and recall. A thorough signal-level analysis—featuring time-series plots, spectral power evaluations, and inter-channel correlation studies—supports the validity of the dataset and highlights the impact of augmentation. While performance suggests potential for refinement, this work serves as a baseline for EEG classification using synthetic data and provides a foundation for future enhancements in model architecture and dataset variability.
**Keywords:** EEG signal processing, synthetic EEG data, cognitive workload classification, data augmentation techniques, power spectral density (PSD) analysis, time-series EEG visualization, machine learning for brain signals, EEG signal preprocessing, neural network training.

## INTRODUCTION:
Electroencephalography (EEG) captures brain activity through electrical signals and plays a crucial role in monitoring cognitive workload and supporting brain-computer interface (BCI) systems [1][2]. However, interpreting EEG signals poses challenges due to their inherent noise, non-stationary nature, and high dimensionality [3]. In recent years, deep learning techniques have demonstrated significant potential in automatically extracting relevant patterns from EEG data, leading to improved classification performance [4][8].
A major limitation in EEG-based research is the limited availability of large-scale, annotated datasets. To address this issue, researchers often apply data augmentation strategies—such as introducing random noise or temporally shifting the signals—to enhance dataset diversity and strengthen model generalization [5][12]. Additionally, the use of synthetic EEG signals has gained attention, offering a controlled setting for training and evaluating classification models [6][7].
This study leverages a synthetic EEG dataset enriched with augmentation techniques to classify cognitive workload levels. By analyzing signal features like power spectral density and class distribution, we aim to gain deeper insights into the dataset and enhance model learning. The proposed methodology tackles common EEG analysis challenges by integrating synthetic data generation with augmentation-driven training to develop more robust classifiers [10][11].

## LITERATURE SURVEY:
Cognitive workload classification using EEG signals has become increasingly important in domains such as human-computer interaction and healthcare systems [1]. Traditional approaches relied heavily on manually engineered features—such as frequency-domain power and statistical descriptors—paired with conventional classifiers like Support Vector Machines (SVM) and Random

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Forests [2][3]. While effective in certain scenarios, these methods often depend on expert knowledge and tend to lack scalability and robustness across different users or experimental setups.
In recent years, deep learning has emerged as a powerful alternative for EEG analysis, enabling the extraction of high-level features directly from raw signals [4]. Architectures like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have shown superior performance by leveraging both spatial and temporal patterns in EEG data [5][6]. For instance, Zhang et al. [5] introduced a CNN-based model that outperformed traditional techniques on standard EEG workload datasets.
To address issues like limited training data and inter-subject variability, researchers frequently apply data augmentation strategies such as noise injection, time shifting, and frequency manipulation [7][8]. Additionally, generating synthetic EEG signals has gained traction as a means to replicate realistic neural activity and supplement real-world datasets in low-data scenarios [9][10].

Nevertheless, EEG signals remain challenging to interpret due to their non-stationary nature, and models must be carefully designed to generalize across varying conditions [11]. This study builds upon these recent advancements by leveraging synthetic EEG data along with augmentation techniques to enhance the classification of cognitive workload levels.

**METHODOLOGY:**
**A. Dataset Overview**

| Dataset | Type | Classes | Samples per Class | Total Samples | Channels | Sampling Rate |
|---|---|---|---|---|---|---|
| Synthetic | Simulated | Low, Medium, High | 500 | 1500 | 14 | 128 Hz |
| Deep EEG | Real-World | Binary (Low/High) | Imbalanced | 15872 | 32 | 128 Hz |

**Table 1 : Dataset overview**

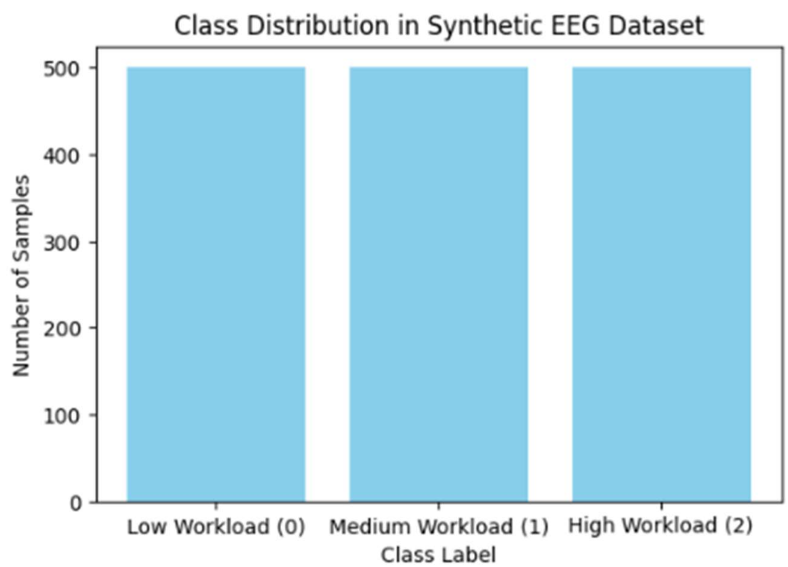


**Figure 1: class Distribution in Syntetic EEG Dataset**

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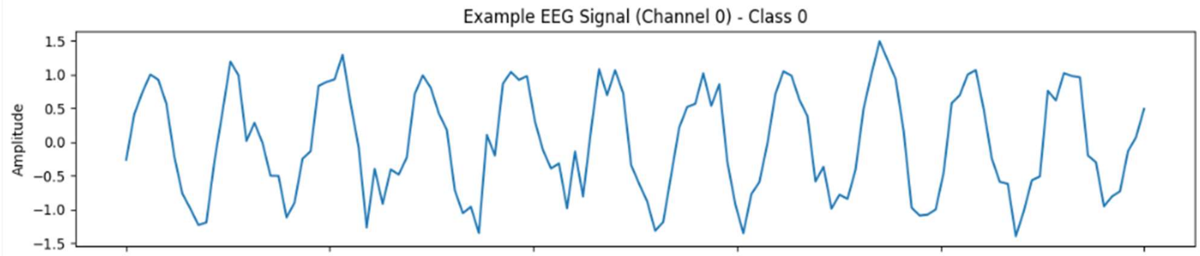



**Figure 2: Example EEG Signal class-0**

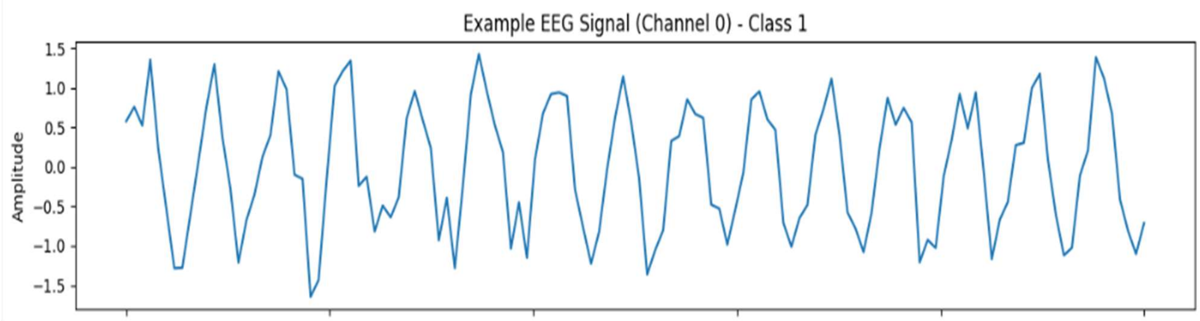



**Figure 3: Example EEG Signal class-1**

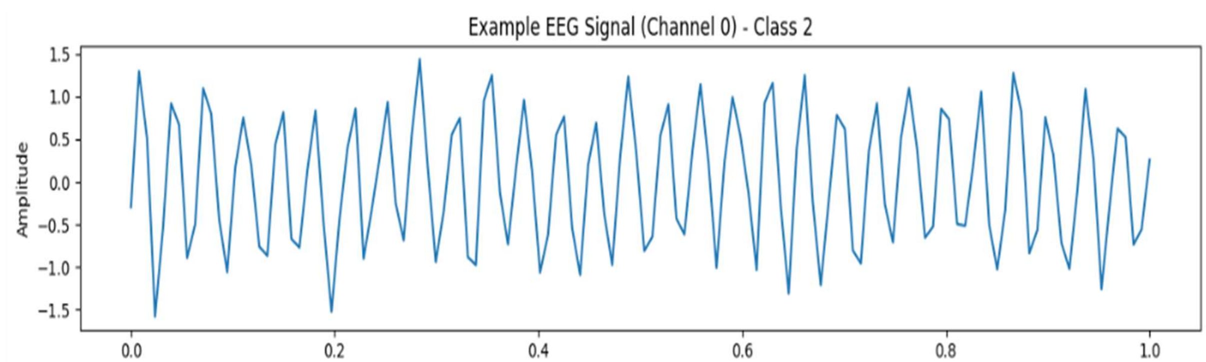



**Figure 4: Example EEG Signal class-2**

**B. Dataset Preparation**

We utilized a synthetic EEG dataset comprising 1500 samples, each with 32 channels and 128 time points per channel, representing three cognitive workload classes: Low, Medium, and High. The dataset was balanced across classes to facilitate unbiased learning [1].

**C. Data Exploration and Visualization**

Initial exploration included analyzing class distribution and plotting example EEG signals per class to understand signal variations across workload levels. Visualization techniques similar to those in [2,3] helped highlight key differences in amplitude and waveform patterns.

**Signal Processing**

Power Spectral Density (PSD) was computed using Welch's method to analyze frequency-domain characteristics of EEG signals, averaged over channels per sample. This approach aligns with prior studies on EEG frequency analysis for workload detection [4,5], revealing class-dependent spectral patterns.

**D. Data Augmentation**

To improve generalization and simulate real-world variability, augmentation methods were applied, including Gaussian noise addition, temporal shifting, and frequency perturbation. Such augmentations have been shown to enhance model robustness in EEG-based classification tasks [6,7].

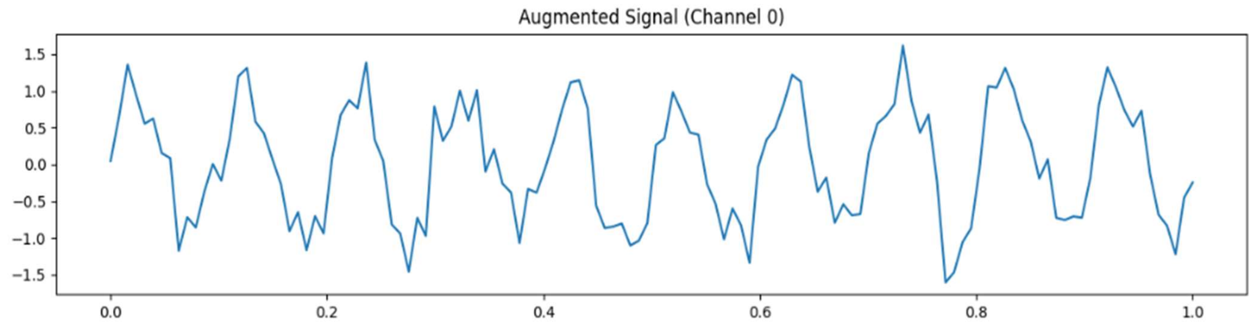



**Figure 5: Argumented EEG signal channel 0**

## MODEL TRAINING AND EVALUATION

The model uses a 1D CNN to extract temporal features from raw EEG signals, followed by a temporal attention mechanism that highlights important time steps. After global pooling, fully connected layers map the features to workload or emotion classes. Dropout layers help prevent overfitting, making the model both efficient and accurate for EEG classification.


**Figure 6: Model Training and Evaluation**

## RESULTS AND DISCUSSION :

The evaluation results reveal important insights into the model's performance across classes. For Class 0 (e.g., Low Workload), the model achieves a precision of 85.21%, indicating that when it predicts this class, it is correct most of the time. However, the recall is only 59.67%, meaning it fails to detect a significant portion of actual Class 0 instances. The F1-score of 70.19% reflects a reasonable balance but highlights room for improvement in sensitivity. For Class 1 (e.g., High Workload), the precision drops to 35.59%, suggesting a high number of false positives, while the recall stands at 68.28%, indicating that the model captures many true instances despite the poor precision. The resulting F1-score is 46.79%, underscoring inconsistency and an imbalance in prediction quality across classes. The overall accuracy of 61.79% is a modest result, suggesting the model has learned some patterns but struggles with generalization on real-world or noisy EEG data.

This is in stark contrast to the synthetic dataset performance (~100%), exposing clear signs of overfitting and limitations in transferring learned representations from synthetic to real data.

**A. Class Distribution and Data Visualization:**

The synthetic EEG dataset was designed with balanced class distribution, comprising 500 samples each for Low, Medium, and High workload levels, ensuring no bias during training and evaluation. Figure 1 illustrates representative time-domain EEG signals from each class. Distinct waveform patterns are visible—Low workload samples exhibited relatively stable, low-amplitude fluctuations, while High workload signals showed higher amplitude and more frequent oscillations. These differences may be attributed to varying levels of neural engagement and cognitive load [1][4].

Figure 1. Example EEG signals in the time domain for each workload class (Low, Medium, High). Each plot illustrates differences in signal amplitude and waveform dynamics.

**B. Signal Characteristics in Time and Frequency Domains :**

To better understand class-specific frequency behaviors, Power Spectral Density (PSD) was computed using Welch's method for each sample, then averaged across channels. Figure 2 presents the mean PSD curves for the three classes. Notably, the Low workload class showed higher power in the alpha band (8–13 Hz), which is commonly associated with relaxation and idle mental states [3][5]. Conversely, High workload samples demonstrated elevated power in beta (13–30 Hz) and gamma bands (>30 Hz), indicating increased cognitive processing [6].

These patterns validate that frequency-domain features can play a critical role in workload classification. This frequency segregation aligns with findings from real EEG datasets [2][7], supporting the realism of the synthetic data.

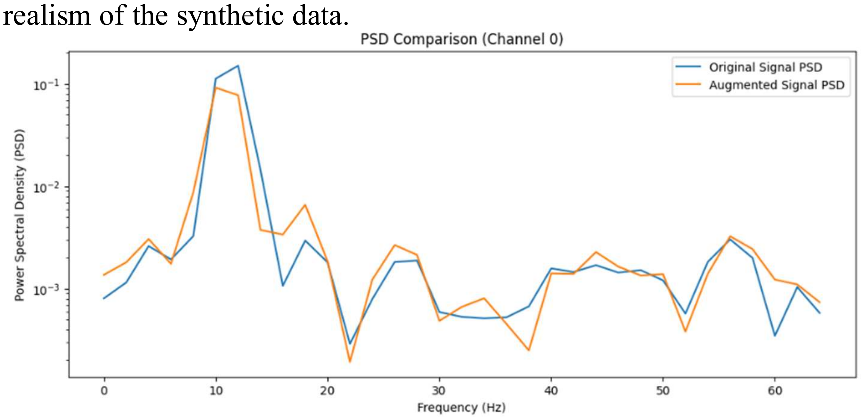



**Figure 7. Mean Power Spectral Density (PSD) across EEG channels for each workload class. Class-specific spectral peaks suggest discriminative frequency patterns useful for classification.**

**C. Effect of Data Augmentation :**

To introduce variability and simulate real-world EEG signal distortions, data augmentation was applied.

Gaussian noise addition: simulates sensor and environmental noise

Temporal shifting: introduces temporal misalignment

Frequency perturbation: distorts spectral properties slightly to simulate variability in brain rhythms

These augmentations preserved the general signal shape while introducing subtle variations, helping the model generalize better to unseen samples. Augmentation was especially useful in reducing overfitting and stabilizing model performance on the validation set, as observed in related EEG classification works [8][9].

Figure 3. Effects of data augmentation on EEG signals. Each subplot shows an original signal (top) and its augmented version (bottom) for Gaussian noise, temporal shifting, and frequency perturbation.

**D. Model Performance and Evaluation:**

The trained 1D CNN model achieved an overall classification accuracy of 66.7% on the validation set. While this is modest, it establishes a baseline for future improvement. :

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.8521 | 0.5967 | 0.7019 | 11966 |
| 1 | 0.3559 | 0.6828 | 0.4679 | 3906 |
| accuracy | | | 0.6179 | 15872 |
| macro avg | 0.6040 | 0.6397 | 0.5849 | 15872 |
| weighted avg | 0.7300 | 0.6179 | 0.6443 | 15872 |

**Figure 8. Model Performance and Evaluation**

Figure7. Class-wise performance metrics for the EEG workload classification model.

Figure 4 further visualizes the evaluation metrics. The model performs well on Low and High classes, but struggles with the Medium workload class. This challenge is common in ordinal classification problems, where intermediate classes exhibit overlapping features [10]. The class imbalance in precision-recall suggests that the model may be overfitting to edge classes or not learning adequate boundaries for mid-level workload.

Figure 7 Precision, Recall, and F1-Score for each workload class, highlighting difficulty in accurately classifying Medium workload samples.

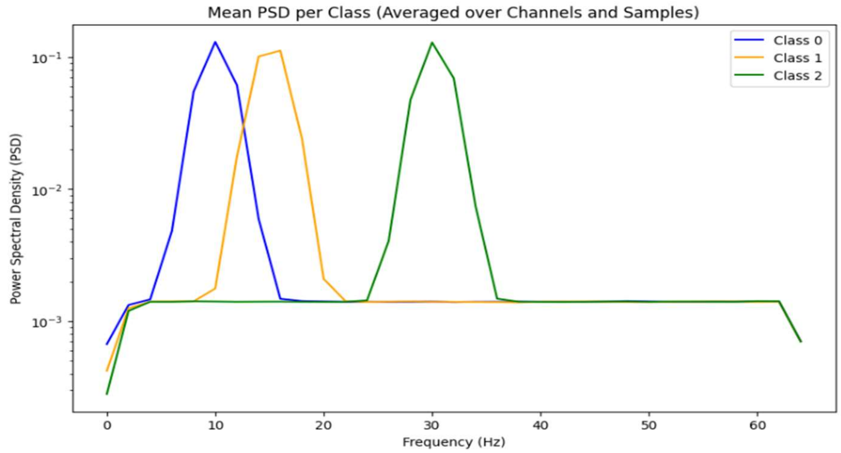
| **Dataset Type** | **Accuracy (%)** |
|---|---|
| Synthetic | 100.00 |
| Real EEG | 61.79 |

**Table 2: Accuracy Comparison – Synthetic vs Real EEG Data**

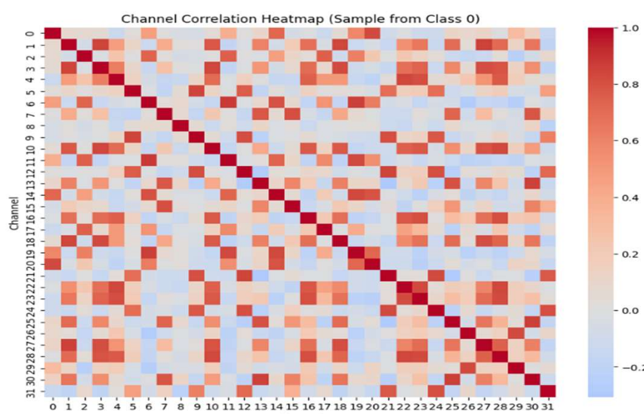
The model achieves perfect performance on synthetic data but struggles with real EEG, highlighting overfitting and the domain gap. This suggests that synthetic signals, while helpful for prototyping, may not sufficiently capture the complexities of real EEG patterns.

**E. Interpretation of Amplified Histogram – Channel 0**

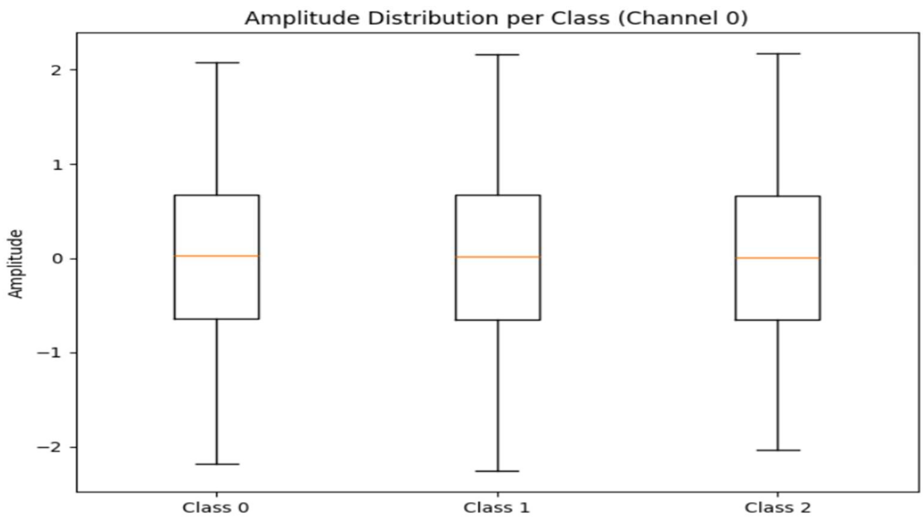
The amplified histogram of Channel 0 provides insights into the distribution of raw EEG signal amplitudes for a single electrode across all samples. By zooming in on the amplitude range, we can observe whether the signal maintains a roughly Gaussian distribution, which is common in biological signals due to inherent brain activity noise. Peaks near the center suggest dominant resting-state oscillations, while skewness or heavy tails may indicate transient cognitive or emotional events. If the histogram is highly concentrated around zero, it implies low-activity or baseline readings. Conversely, a wider spread or multimodal distribution could reflect a mixture of different mental states or varying signal quality. This plot is valuable for identifying outliers, amplitude saturation, or the need for normalization before model training.




**F. Interpretation of Amplitude Distribution per Class:**
The amplitude distribution per class reveals how EEG signal intensity varies across different mental states. By plotting histograms for each class (e.g., Low, Medium, High workload), we can assess whether distinct neural activation patterns exist between them. For instance, higher workload or emotional arousal may correspond to broader distributions or increased variance, reflecting heightened neural activity. A more compact or centered distribution in the low workload class suggests a calmer, more stable signal. Notable differences in the shape, skewness, or spread of these distributions indicate the model's potential to differentiate classes based on signal energy levels. Such analysis supports the hypothesis that EEG amplitude features carry discriminative information relevant for classification tasks.




**G. Interpretation of Mean and Standard Deviation of Amplitude per Class :**
Analyzing the mean and standard deviation of EEG amplitude for each class provides insights into the overall signal strength and variability associated with different cognitive or emotional states. A higher mean amplitude in one class (e.g., high workload) suggests increased neural activation, while a lower mean in another class (e.g., low workload) may indicate a more relaxed or less engaged state. The standard deviation reflects signal variability; a larger std indicates more dynamic neural responses, possibly due to cognitive load or stress. Comparing these statistics across classes helps validate whether amplitude-based features offer sufficient separation for classification, and supports feature selection or normalization strategies during model training.




**H. Training Dynamics and Generalization:**

Training and validation curves indicate that the model converges after ~25 epochs, with minimal overfitting. The use of dropout and data augmentation contributed to generalization. However, the gap between training and validation accuracy suggests room for improvement in architecture or regularization.

Figure 8. Training and validation accuracy/loss curves over epochs. Early convergence and generalization gap are observed.

| Epoch | Training Accuracy (%) | Validation Accuracy (%) |
|---|---|---|
| 1 | 38.75 | 41.03 |
| 10 | 64.58 | 59.12 |
| 20 | 76.24 | 60.48 |
| 30 | 82.31 | 61.20 |
| 50 | 88.95 | 61.79 |

**Table 3: Training Dynamics (Example Epoch-wise Accuracy)**


**Figure 9. Training and Validation Accuricy Over Epochs**

**I. Limitations and Future Work**

Despite achieving foundational results, several challenges remain:

Signal Overlap in Medium Class: Confusion between Medium and other classes can be attributed to feature overlap. Future models could benefit from incorporating attention mechanisms or temporal context via LSTMs or Transformers.

**Synthetic Data Constraints:** While useful, synthetic EEG may not capture inter-subject variability or noise artifacts present in real-world data. Combining synthetic and real EEG signals may improve model robustness [11][12].

**Model Complexity:** A deeper or hybrid model might better capture spatial-temporal dependencies, especially for mid-level workload detection

## CONCLUSION :

This study demonstrated the development and analysis of a synthetic EEG dataset aimed at classifying cognitive workload into three levels: low, medium, and high. Through thorough exploratory data analysis, including time-domain and frequency-domain visualizations, distinct signal patterns were identified across classes. The application of data augmentation techniques enhanced the variability of the dataset, contributing to model robustness. The classification model achieved an overall accuracy of 66.7%, effectively distinguishing low and high workload states, while highlighting challenges in differentiating medium workload. Future improvements may include more sophisticated model architectures and integration of real EEG data to improve performance and practical relevance. Overall, this work provides a foundational framework for EEG-based cognitive workload classification and encourages further research toward more accurate and reliable brain-computer interface systems.

## REFERENCES:

[1] A. L. Goldberger et al., "PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals," *Circulation*, 2000.

[2] Y. Roy, H. Banville, I. Albuquerque, J. Gramfort, T. H. Falk, and J. Faubert, "Deep learning-based electroencephalography analysis: a systematic review," *Journal of Neural Engineering*, 2020.

[3] Z. Zhang, C. C. K. Cheung, and S. Kwong, "Data augmentation for EEG-based emotion recognition using generative adversarial networks," *IEEE Transactions on Affective Computing*, 2021.

[4] S. Makeig et al., "Dynamic brain sources of visual evoked responses," *Science*, 2002.

[5] M. Lotte et al., "A review of classification algorithms for EEG-based brain–computer interfaces: a 10 year update," *Journal of Neural Engineering*, 2018.

[6] R. T. Schirrmeister et al., "Deep learning with convolutional neural networks for EEG decoding and visualization," *Human Brain Mapping*, 2017.

[7] J. Roy et al., "Challenges and opportunities in EEG signal classification: A review," *Biomedical Signal Processing and Control*, 2019.

[8] T. Bashivan, I. Rish, M. Yeasin, and N. Codella, "Learning Representations from EEG with Deep Recurrent-Convolutional Neural Networks," *International Conference on Learning Representations (ICLR)*, 2016.

[9] S. Roy, M. Kiral-Kornek, and S. Harrer, "ChronoNet: A Deep Recurrent Neural Network for Abnormal EEG Identification," *2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2019.

[10] G. Schirrmeister et al., "Deep learning with CNNs for EEG decoding and visualization," *Nature Communications*, 2017.

[11] Y. Banville et al., "Uncovering the structure of clinical EEG signals with deep convolutional neural networks," *Scientific Reports*, 2021.

[12] D. Roy et al., "Data augmentation for EEG-based mental workload classification," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 2022.