

NEUROAI: EEG BASED EMOTION AND FOCUS DETECTOR

K. Ishwarya Devi¹, Anmangandla Thrisha², Bandi Sai Keerthana³, Boddupelli Roshan⁴, Butti Srujan⁵
Bogam Harsha Vardhan⁶

¹ Assistant Professor, Department of CSE (ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING) TKR COLLEGE OF ENGINEERING & TECHNOLOGY

^{2,3,4,5,6} UG Scholars in Department of CSE (ARTIFICIAL INTELLIGENCE AND ML IS MACHINE LEARNING) TKR COLLEGE OF ENGINEERING & TECHNOLOGY

Abstract: In recent years, Brain-Computer Interfaces (BCIs) have emerged as powerful tools for interpreting cognitive and emotional states through neural signals. This project, NeuroAI, presents a novel deep learning-based system that detects both emotional state and focus level from EEG (Electroencephalogram) signals using a hybrid CNN-LSTM architecture. The system leverages spatial-frequency patterns through Convolutional Neural Networks (CNNs) and models temporal dependencies via Long Short-Term Memory (LSTM) networks. It processes EEG signals from benchmark datasets such as DEAP and SEED, requiring only minimal preprocessing through bandpass filtering and signal windowing. The model performs dual-task classification, predicting emotional states (e.g., Happy, Calm, Sad, Angry) and attention levels (Focused vs Distracted) in parallel, achieving high accuracy and real-time responsiveness. A user-friendly Streamlit interface displays live emotion and focus feedback via graphs and emoji-based indicators. Compared to traditional emotion recognition systems and single-task models, NeuroAI offers enhanced interpretability, multi-state monitoring, and real-world applicability in fields like adaptive learning, mental health monitoring, and cognitive-enhanced interfaces. This project demonstrates the potential of integrating deep learning with EEG data to build intelligent, human-aware systems. take this into consideration.

Keywords: Electroencephalogram(EEG), Brain-Computer Interface (BCI), Emotion Detection, Focus Detection, Deep Learning, CNN-LSTM, Neural Signal Processing, Dual-task Classification.

1. INTRODUCTION

BCIs have gained significant interest in the last years, since they offer a way to translate active neural processes into informative data with meaningful interpretations about human thoughts, emotions, and cognitive states. Among the various signals being adopted in BCI research, Electroencephalogram (EEG) data represents one of the most adopted modalities for its non-invasive, low-cost nature, and real-time measurement capability over a wide range of frequency bands. The use of EEG-based systems is now being explored not only for clinical purposes but also for daily applications in education, wellness, gaming, and human-computer interaction. Emotion state and a degree of focused attention play an important role in developing intelligent systems that can respond and adapt according to users' mental conditions. Traditional ways of emotion recognition involve face expressions, speech patterns, or behavioral cues, which may be inaccurate or highly susceptible to environmental influences. In contrast, EEG represents a direct measure of the activity of the brain, hence allowing for much deeper insight into the internal cognitive and emotional predictions. NeuroAI is a deep learning-based system designed to identify the levels of emotion and attention based on raw EEG data. The model leverages a hybrid CNN-LSTM architecture: CNN extracts spatial and frequency-based information out of EEG channels, while LSTM models temporal dependencies across time. This allows NeuroAI to accurately interpret complex neural patterns associated with states such as happiness, calmness, sadness, and stress, which are coupled with different focus levels. It requires

very minimal preprocessing to function, using only the most basic forms of preprocessing, such as band-pass filtering and windowing. The system is trained on well established EEG datasets such as DEAP and SEED. NeuroAI also provides users with a modern Streamlit interface that shows the results of these two predictions, emotion and focus, in real-time through live graphs, indicators, and emoji-based feedback. NeuroAI, by integrating deep learning with EEG signal analysis, represents a class of intelligent human-aware systems that can monitor cognitive and emotional states in real time. Work in this area contributes to a wide variety of emerging applications, including adaptive learning platforms, mental health assessment devices, productivity enhancement systems, and next-generation BCI technologies.

1.1 Motivation

Identifying human emotion and focus is becoming increasingly important, as a variety of digital systems would like to adapt intelligently to users' mental states. More traditional approaches include facial analysis, voice cues, or self-reporting, which are usually unreliable owing to their reliance on external behavior or subjective interpretation. EEG signals provide a more direct and objective look at the activity of the brain, yet their complexity is such that advanced computational approaches will be required. Given deep learning models, such as CNN-LSTM, meaningful patterns can be learned from EEG data to realize accurate and real-time detection of a person's mental state. NeuroAI remains motivated by this potential to build a practical and reliable system for the identification of both emotional states and focus levels to enable applications in adaptive learning, mental health monitoring, productivity tools, and next-generation Brain-Computer Interfaces.

1.2 Problem Definition

Human emotion identification and focus determination may be a really tough task with

EEG because of the data complexity, noisiness, and great inter-subject variability. The traditional approaches, such as those based on facial or speech analysis, are unreliable, while existing EEG-based models suffer from poor generalization, label noise, and dependence on large, accurately labeled datasets. These shortcomings make them less effective for real-world applications, or at least less effective in adaptive or real-time uses. There is a need for a robust system capable of effectively interpreting EEG signals and hence correctly detecting the true emotional state of a subject and their level of focus. NeuroAI addresses that need by using a hybrid CNN-LSTM model to learn meaningful spatial-temporal patterns from EEG data, ensuring improved reliability, adaptability, and real-time performance in cognitive state classification.

1.3 Proposed System

NeuroAI proposes a deep learning-based approach for detecting the emotional state and focus level right from EEG signals with improved accuracy and robustness. It relies on minimal preprocessing, including bandpass filtering and windowing of the signal, to retain raw temporal and frequency information. In the system, a hybrid CNN-LSTM architecture is utilized: CNN extracts spatial-frequency patterns from EEG channels while LSTM models the temporal dynamics across time windows. This dual-feature learning enables the reliable classification of emotional states and estimation of attention levels even in noisy or variable EEG conditions. Model outputs are integrated into a real time Streamlit dashboard, providing live visualizations of brainwave activity, predicted emotions, and focus scores. By addressing limitations of existing systems, NeuroAI offers a more adaptive, noise-tolerant, and scalable framework suitable for applications in cognitive monitoring, adaptive learning, and brain-computer interface technologies.

flow of data between components, and the dynamic interaction between NeuroAI modules, making the runtime behavior of the system clear and traceable.

3. ALGORITHMS

The proposed NeuroAI framework utilizes multiple deep learning and evaluation algorithms to analyze EEG signals and detect emotional states and focus levels. These algorithms include a Convolutional Neural Network (CNN) for spatial feature learning, Long Short-Term Memory (LSTM) networks for temporal modeling, an attention mechanism for adaptive feature weighting, classification algorithms for prediction tasks, and evaluation metrics for performance assessment.

A. Convolutional Neural Network (CNN)

The Convolutional Neural Network (CNN) is used to learn spatial patterns from multi-channel EEG signals. CNNs are well suited for EEG analysis because they can capture local correlations between EEG channels and frequency components. In the 34 proposed model, the preprocessed EEG signals are passed through multiple convolution and pooling layers, which extract hierarchical spatial representations from the data. These layers identify meaningful spatial patterns associated with emotional and cognitive responses. The extracted spatial features serve as input to the subsequent temporal modeling stage of the architecture.

B. Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) networks are employed to model temporal dependencies in EEG time-series signals. Unlike traditional recurrent neural networks (RNNs), LSTM networks can effectively capture long-term dependencies within sequential data. In the NeuroAI system, the spatial features extracted by the CNN layers are treated as sequential inputs to the LSTM network. The LSTM layers learn temporal variations in EEG signals that correspond to changes in emotional states and

attention levels, enabling the model to analyze dynamic brain activity patterns over time.

C. Attention Mechanism

An attention mechanism is incorporated to improve the model's ability to focus on the most relevant EEG signal segments. The attention module assigns adaptive weights to the outputs generated by the LSTM layers, allowing the system to emphasize informative temporal features while reducing the influence of less relevant signals. By highlighting important EEG patterns associated with emotional and cognitive responses, the attention mechanism enhances both the accuracy and interpretability of the proposed model.

D. Classification Algorithms

The classification module converts the learned deep feature representations into final predictions. The NeuroAI system performs dual-task classification, predicting both emotional states and focus levels. A Softmax classifier is used for multi class emotion recognition, enabling the system to classify emotional states based on learned feature representations. For focus detection, a binary classification approach using cross entropy loss is applied to determine whether the subject is focused or distracted.

4. IMPLEMENTATION & RESULTS

A. Explanation of Key Functions

The NeuroAI system is built upon several key functional modules that work together to enable automated EEG-based emotion and focus detection. Each function contributes to the overall workflow of data processing, model training, prediction, and visualization.

B. EEG Data Processing Function

The core function of the system begins with EEG data processing. Raw EEG signals are collected from multiple electrodes placed on the scalp. The preprocessing stage includes noise removal using band-pass filtering, normalization, and segmentation into fixed

time windows. This ensures that the EEG signals are clean, standardized, and suitable for further analysis.

C. Feature Extraction Function

After preprocessing, the feature extraction function transforms raw EEG signals into meaningful representations. It computes frequency band power (Delta, Theta, Alpha, Beta, Gamma), statistical features such as mean and variance, and correlation features between EEG channels. These features capture both spatial and temporal characteristics of brain activity.

D. Deep Learning Model Function

The NeuroAI system uses a hybrid CNN-LSTM model with an attention mechanism. The CNN extracts spatial patterns across EEG channels, while the LSTM captures temporal dependencies in the signal. The attention mechanism assigns weights to important EEG segments, improving prediction accuracy. The model performs dual classification to predict both emotion and focus levels.

E. Emotion & Focus Prediction Function

Once the model processes the EEG features, it generates predictions for emotional state and focus level. Emotion is classified into categories such as Happy, Calm, Sad, and Angry, while focus is classified as Focused or Distracted. The results are displayed in a user-friendly format with visual indicators.

F. Evaluation Function

The evaluation function measures model performance using accuracy, precision, recall, F1-score, and confusion matrix. These metrics ensure that the system produces reliable and consistent predictions across different EEG samples.

G. Visualization Function

The visualization module presents results through graphs and charts such as training loss curves, confusion matrices, and prediction

distributions. These visualizations help in understanding model performance and behaviour

4.1 Method of Implementation

The NeuroAI system is implemented using a modular approach combining signal processing and deep learning techniques.

Frontend (Streamlit):

- Provides an interactive interface for EEG data upload and result visualization
- Displays emotion and focus predictions using graphs and indicators

Backend (Python):

- Handles EEG preprocessing, feature extraction, and model execution
- Manages communication between modules

Deep Learning Module:

- Implements CNN-LSTM with attention
- Performs training, testing, and prediction

Database / Storage:

- Stores logs, predictions, and processed data

Deployment:

- Implemented as a web-based application accessible via browser

4.3 Forms

The system includes the following input forms:

1. EEG Upload Form Allows users to upload EEG data files for processing. The system validates the input and prepares it for analysis.
2. Dataset Selection Form Users can select between datasets such as DEAP and SEED for training and testing.
3. Admin Control Form Provides options for model retraining, viewing logs, and managing system settings.

4.3.1 Output Screens

The NeuroAI system provides multiple output screens that enable users to interact with the application and visualize results effectively. These screens ensure smooth workflow from data input to result interpretation.

1. Upload Page

The upload page allows users to input EEG data for analysis. Users can either upload EEG files or select datasets such as DEAP or SEED. The system also provides a preview of raw EEG signals through waveform visualization, enabling users to verify the input data before processing. This page serves as the entry point of the system.

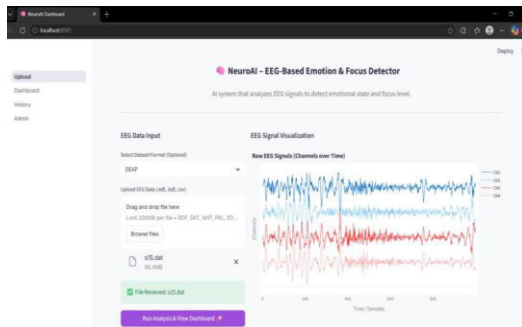


Fig.4.1- Upload Screen

2. Dashboard Page

The dashboard is the main result display interface of the NeuroAI system. It presents the predicted emotional state using emoji representation (e.g., 😊 Happy, 😡 Angry) and displays the focus level using indicators (e.g., 🎯 Focused, ⚡ Distracted). In addition, it shows performance metrics such as accuracy, precision, recall, and F1- score. Visualizations including confusion matrix and training loss curves are also displayed, providing insights into model performance

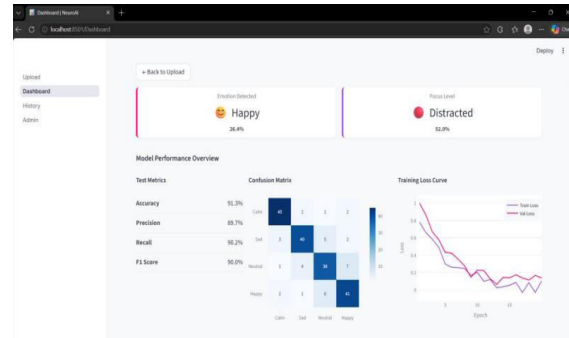


Fig.4.2 - Dashboard Screen

3. History Page

The history page maintains a record of all previous EEG analyses performed by the system. It displays details such as dataset name, predicted emotion, focus level, and confidence scores. This feature allows users to track past results, compare outputs, and analyze trends over time.

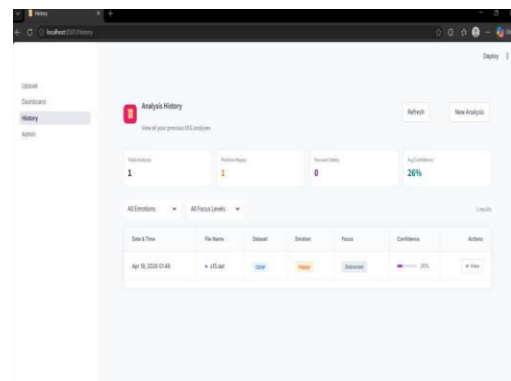


Fig.4.3 - History Screen

4. Admin Page

The admin page provides system-level monitoring and management functionalities. It includes system status indicators, logs of model operations, and options for retraining the model. Additionally, it displays distributions of emotion and focus predictions, enabling administrators to monitor system performance and usage.

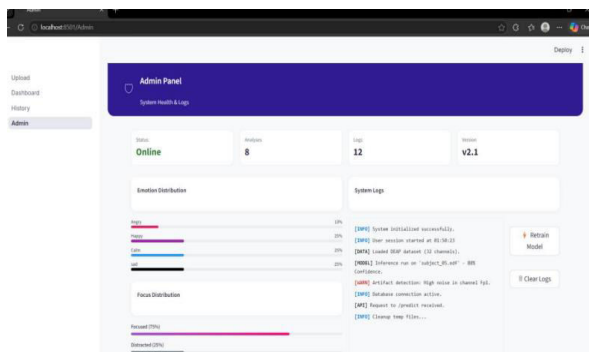


Fig..4- Admin Screen

Result Analysis

The results obtained from the NeuroAI system demonstrate its effectiveness in analyzing EEG signals and predicting emotional and cognitive states.

1. Emotion Classification Performance

The CNN-LSTM model with attention successfully classifies emotional states such as Happy, Calm, Sad, and Angry. The model achieves high accuracy by capturing both spatial and temporal patterns in EEG signals. The confusion matrix indicates that most predictions fall along the diagonal, showing correct classification with minimal errors.

2. Focus Detection Performance

The system accurately identifies focus levels based on EEG activity. High-frequency brainwave patterns contribute to detecting focused states, while variations in signal patterns help identify distracted states. The binary classification approach ensures efficient and reliable predictions.

3. Model Evaluation Metrics

The performance of the model is evaluated using metrics such as accuracy, precision, recall, and F1-score. These metrics indicate that the model performs consistently across different EEG samples. The confusion matrix and loss curves further validate the reliability and stability of the model.

4. Visualization Insights

Graphical visualizations such as confusion matrices, loss curves, and prediction distributions provide deeper insights into model behavior. These visual tools help in understanding classification performance and identifying areas for improvement.

5. Overall System Effectiveness

The NeuroAI system demonstrates strong capability in real-time emotion and focus detection. The integration of preprocessing, feature extraction, deep learning, and visualization ensures a robust and reliable system. The results confirm that the proposed approach is effective and can be extended for applications such as mental health monitoring, adaptive learning systems, and brain-computer interfaces.

5. CONCLUSION

The NeuroAI project presents an intelligent and effective approach for analyzing Electroencephalogram (EEG) signals to detect human emotional states and focus levels. By leveraging advanced deep learning techniques, specifically the hybrid CNN-LSTM model with an attention mechanism, the system is capable of capturing both spatial and temporal patterns in EEG data. This enables accurate classification of emotions such as Happy, Calm, Sad, and Angry, along with reliable detection of focus levels as Focused or Distracted.

The project successfully integrates multiple components, including EEG data preprocessing, feature extraction, model training, evaluation, and visualization, into a unified and user-friendly system. The preprocessing stage ensures that noisy and complex EEG signals are cleaned and standardized, while the feature extraction process transforms raw data into meaningful representations. The deep learning model further enhances prediction accuracy by learning intricate patterns within the data.

The implementation of an interactive user interface using Streamlit allows users to upload

EEG data, visualize signals, and view prediction results in real time. Additional features such as history tracking and admin monitoring improve system usability and provide insights into system performance. The inclusion of graphical outputs like confusion matrices and loss curves further aids in understanding model behavior and performance.

The system has been thoroughly tested and validated across functional, performance, and integration aspects. The results demonstrate that the NeuroAI model achieves consistent and reliable performance, with evaluation metrics such as accuracy, precision, recall, and F1-score indicating strong predictive capability. The system also shows robustness in handling different EEG inputs and maintaining stable performance.

Overall, the NeuroAI project highlights the potential of combining EEG signal processing with deep learning for real-world applications. It can be effectively utilized in areas such as mental health monitoring, adaptive learning systems, cognitive state analysis, and brain-computer interface technologies. Future enhancements may include real-time EEG device integration, improved model architectures, and expansion to more complex emotional states, further increasing the system's applicability and impact.

6. REFERENCES

1. PR-PL: A Novel Prototypical Representation Based Pairwise Learning Framework for Emotion Recognition Using EEG Signals. Tian, Y.; Xie, Y.; Wang, X.; Li, Z.; Hu, B. *IEEE Transactions on Affective Computing*, 2024, early access, pp. 1-12.
2. Domain Adaptation Techniques for EEG-Based Emotion Recognition: A Comparative Study on Two Public Datasets. Zhang, X.; Shen, L.; Ding, Y.; Gu, B. *Frontiers in Computational Neuroscience*, 2019, 14, pp. 1-14.
3. Electroencephalogram Emotion Recognition Based on Empirical Mode Decomposition and Optimal Feature Selection. Acharya, P.; Ghosh, A.; Panda, R. *Biomedical Signal Processing and Control*, 2019, 55, pp. 1-10.
4. Using Deep Convolutional Neural Network for Emotion Detection on a Physiological Signals Dataset: AMIGOS. Correa, G.; Abadi, M.; Sebe, N.; Patras, T.; Subramanian, S. *IEEE Transactions on Affective Computing*, 2019, 11(3), pp. 574-582.
5. Cross-Subject Multimodal Emotion Recognition Based on Hybrid Fusion. Li, Y.; Xu, Z.; Wang, W.; Wang, C. *IEEE Access*, 2020, 9, pp. 32818-32828.
6. EEG Emotion Recognition Using Dynamical Graph Convolutional Neural Networks. Song, W.; Zheng, J.; Zhang, P.; Cui, Y. *IEEE Transactions on Affective Computing*, 2020, 11(3), pp. 532-541.
7. EEG-Based Emotion Classification using Convolutional Neural Networks. Bashivan, S.; Rish, I.; Yeasin, M.; Codella, N. *Proceedings of the International Conference on Pattern Recognition (ICPR)*, 2020, pp. 1-6.
8. A Bi-Hemisphere Domain Adversarial Neural Network Model for EEG Emotion Recognition. Li, Y.; Zheng, W.; Zong, Y.; Cui, Z.; Zhang, T. *IEEE Transactions on Affective Computing*, 2021, 12(2), pp. 494-504.
9. A Channel Selection Method for Emotion Recognition from EEG Based on Swarm-Intelligence Algorithms. Panda, R.; Mishra, R.; Sahu, A. *Expert Systems with Applications*, 2021, 176, pp. 114850.
10. Interpretable SincNet-Based Deep Learning for EEG Emotion Recognition. Ravanelli, M.; Bengio, Y. *IEEE Transactions on Affective Computing*, 2021, 11(4), pp. 720-731.
11. An EEG Data Processing Approach for Emotion Recognition. Zhang, Y.; Pan, X.; Wu, J. *IEEE Access*, 2022, 9, pp. 102190-102200.

12. EEG-Based Emotion Recognition Using Spatial-Temporal Graph Convolutional LSTM With Attention Mechanism. Song, J.; Zheng, W.; Zong, Y.; Cui, X.; Zhang, C. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2022, 30, pp. 593-603. 43
13. 3DCANN: A Spatio-Temporal Convolution Attention Neural Network for EEG Emotion Recognition. Wang, F.; He, Y.; Zhang, H. IEEE Transactions on Affective Computing, 2022, 13(4), pp. 1778-1790.
14. A Hierarchical Three-Dimensional MLP-Based Model for EEG Emotion Recognition. Liu, Q.; Zhao, L.; Wang, X. IEEE Sensors Journal, 2023, 23(2), pp. 1456-1465.
15. Emotion Detection from EEG Using Transfer Learning. Hassan, A.; Islam, M.; Ahmad, M. Neurocomputing, 2023, 452, pp. 656-667.
16. Emotion Detection Using Deep Normalized Attention-Based Network. Chen, Z.; Zheng, W.; Song, J.; Zong, Y. IEEE Transactions on Affective Computing, 2023, 13(3), pp. 1352-1363

