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Hybrid Deep Learning Framework for EEG-Based Anxiety Detection and Classification in Brain–Computer Interfaces

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ABSTRACT

Anxiety disorders, as depicted with panic disorder, social anxiety disorder (SAD), and generalized anxiety disorder (GAD), are some of the most widespread form of mental health illness, and the challenges of their diagnosis is just as profound as their prevalence. Even though many studies in the field utilize EEG and Deep Learning (DL) to detect anxiety, this work is the first to build a Brain-Computer Interaction (BCI) ecosystem utilizing Electroencephalography (EEG) signals to detect anxiety. The proposed BCI uses a hybrid architecture that integrates CNN, LSTM, and Transformer modules to detect the spatial, the temporal, and the contextual features of the EEG. The data underwent Independent Component Analysis (ICA), outlier removal, normalization, and SMOTE to increase the quality of the outcomes. The best performing individual models were CNN, LSTM, and Transformer, which achieved 85.90%, 91.54%, and 91.12% of accuracy, respectively. The hybrid model, with 97.45% of accuracy, soared ahead of the rest with 7% to 12% presented by the other Deep learning (DL) approaches based on Brain-Computer Interface (BCI). This holds promise and generalizes the model to serve as a highly effective clinical tool that is scalable and non-invasive to conduct clinical anxiety diagnosis. Further work is promised for this to include more physiological signals such as the electrocardiography (ECG) and functional near-infrared spectroscopy (fNIRS), to increase the robustness of the model.

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1. Introduction

Social Anxiety Disorder (SAD), Generalized Anxiety Disorder (GAD), panic attacks, and phobias collectively affect >280 million people suffer from these conditions worldwide [1], according to the World Health Organization (WHO, 2025). These individuals often undergo long-lasting feelings of distress and difficulty with their day-to-day lives [1, 2]. Even when treatment is an option, diagnosis is often extended due to the fact that the interviews and self-reports of patients do not correlate with the brain's activity. One of the best ways to assess anxiety is a Brain-Computer Interface (BCI) [3], which is a safe and non-invasive method. In the beginning, BCIs were used as a treatment alternative for patients with motor impairment [4]. However, they have now shifted to a more complex use of ts for the evaluation of some medical conditions in the field of psycho-neurology. Electroencephalography (EEG) is a method that is safe, relatively inexpensive, and the only one that records the oscillation of the brain's cognitive and emotional activity, like the beta or theta [5, 6]. In fact, the higher the theta and the lower the alpha, the more accurate the diagnosis can be. The more portable the EEG is, as well as the drier the electrodes, the more BCIs can be used. However, some factors, such as noise, variability, and a limited number of samples require good cleaning and strong preprocessing learning methods. This work uses a non-invasive EEG-based BCI with Convolutional Neural Network (CNN), a Long Short-Term Memory network (LSTM), and a Transformer Hybrid architecture, along with preprocessing methods, ICA, percentile-based outlier removal, and SMOTE to enhance class imbalance and signal variability. The model, classifying anxiety from low to severe, was evaluated by assessing accuracy, precision, recall, F1 score, AUC-ROC, and confusion matrix.

1.1. Contribution

- We present an innovative architecture of Deep Learning (DL) that includes CNNs, LSTMs, and Transformers to improve the spatial and temporal as well as the contextual representation of EEG data related to anxiety. The hybrid model is more accurate and generalizable than the standalone models.
- We evaluate the overall system performance accuracy of 97% with precision at all the levels of severity of anxiety above 95%. Such performance rates prove the effectiveness of the hybrid model as it works with real-life data, including noise and artifacts in EEG.
- We analyze the modern preprocessing methods, including ICA to eliminate the artifacts, the percentile clipping to correct outliers, and the SMOTE to handle the imbalance classes, will provide the system with cleaner input data and more robust model learning.
- We investigate whether the model is cross-validated, with well-known metrics (accuracy, precision, recall, F1-score, AUC-ROC) and tested on multiple datasets, which provides its robustness and the possibility of its application to diverse clinical and non- clinical practice.

The paired use of portable EEG devices and DL offers the opportunity to streamline and scale neurofeedback and other cost-effective approaches in the mental health care delivery system. Progress in hybrid BCIs may also improve the diagnosis, tracking, and treatment of anxiety in both clinic and home environments.

2. Related Work

BCIs and Artificial Intelligence (AI) advancements based on EEG data has also allowed for automating the recognition of mental health issues such as anxiety and depression. Shah et al. [7] proposed a hybrid approach to AI, in which historical classifiers are combined with a deep neural network (based on CNN and LSTM) trained using genetic and swarm algorithms. Even though the method was able to match or exceed 90% of the accuracy on the EEG signal, it was influenced by the vagaries of signal quality and by its excessive computational requirements. Nagpal et al. [8] presented a multimodal deep residual CNN model to detect anxiety by combining the features of the voice and behavioral information but it lacked time dynamics and interpretability, which are essential in offering the treatability to a wider range of use. Tsai et al. [9] conducted a systematic review of BCI in the context of elderly that the indicated the applicability of EEG to cognitive and emotional observations. Nonetheless, the rarity of varied samples and intermittent acquisition of signals raised a question regarding the generalization of the model. Husnain et al. [10] established an EEG Acquisition and DL pipeline, where they achieved 94% correctness on the identification of emotional states using a CNN-based classifier. Although this system was powerful enough, it was limited to the binary classification and needed to have a better scale.

Elashmawi et al. [11] evaluated the DL ones, and it was found that CNN-LSTM models had the best effectiveness in classifying EEG signals with an accuracy rate above 95%. Nevertheless, these models failed to focus on anxiety-specific applications. Zhang et al. [12] have also presented a hybrid DL model (EEG is used as input along with Electrocardiography (ECG) and demonstrated 94% accuracy. Biosignal preprocessing and fusion were stressed in the study, but inconsistency and understanding of the models were found to be a problem with populations of diverse backgrounds. Khorev et al. [13] did a meta-review of hybrid systems of BCI in the neurorehabilitation field where they encouraged a combination of imaging modalities. Their findings indicated the necessity of modular and adaptive EEG-based frameworks. Fatima et al. [14] proposed a model (DASentimental) using text-based signals and based on the ideas of emotional remembrance and cognitive networks with 92% of test accuracy to determine stress, depression, and anxiety levels, but without the incorporation of physiological signals into the process.

The Table 1 presents an overview of related work. Lastly, the proposed framework of the work combines CNN, LSTM, and Transformer models in detecting anxiety using EEG. Higher preprocessing, such as artifact elimination and adaptive noise filtering is used to enhance the performance of the classification. This model combines the characteristics of a hybrid model by not only dealing with the issues of EEG variability but with a classification accuracy rate of 97.45% the enhanced interpretability, and cross-population applicability.

Table 1: Comprehensive state-of-the-art literature review snapshot highlighting key findings, emerging trends, focus areas, and the evaluation of existing methods in comparison with the proposed method

Reference	Key Contribution	Research Focus	Methodology	Hybrid	AI/ML	Limitations	Accuracy (%)	Bench-marked
[7]	AI-based depression and anxiety detection using EEG signals	Depression and Anxiety Detection	EEG signal analysis, AI/ML techniques, machine learning classification	✓	✓	Dependent on EEG equipment, quality of training data, computational demands	90%	✓
[8]	Multimodal hybrid DL model integrating behavioral and vocal signals for anxiety/depression detection	Depression and Anxiety Detection	Behavioral data (questionnaires), vocal features (MFCC, pitch, shimmer, etc.), fusion architecture	✓	✓	Static datasets, lack of real-time monitoring, no explainability	81%	✓
[9]	Comprehensive review of BCI applications for elderly cognitive enhancement	Cognitive Aging	Neurofeedback systems, signal processing techniques	✗	✓	Small clinical samples, signal variability	85%	✓
[13]	Systematic review of hybrid BCI rehabilitation technologies	Neurorehabilitation	Literature meta-analysis, technology assessment	✗	✓	High implementation costs, patient variability	90%	✓
[14]	Detecting depression, anxiety, and stress using emotional recall, cognitive networks, and ML	Sentiment Analysis for Mental Health	Emotional recall, Cognitive Networks, Machine Learning, Text Classification	✗	✓	Limited to text-based analysis, may not generalize to speech or non-text data	95%	✓
[10]	Integrated CNN-based EEG system for mood disorder detection	Affective Computing	Hardware-software co-design, binary classification	✗	✓	Only binary classification capability	94%	✓
[11]	Comparative analysis of DL architectures for EEG-BCI	Neural Engineering	CNN-LSTM evaluation	✓	✓	Data quality challenges, clinical validation needed	92%	✓
[12]	A hybrid DL model for multimodal anxiety detection using EEG and ECG signals.	Anxiety Detection	EEG, ECG, CNN, LSTM, Multimodal Data	✓	✓	Variability in sensor data, model interpretability issues	94%	✓
Proposed Method	**Hybrid CNN-LSTM-Transformer model with noise removal for anxiety detection from EEG**	**Anxiety Detection**	**CNN, LSTM, Transformer, hybrid model artifact removal, noise filtering**	✓	✓	**Variability in EEG signals, computational demands**	**97.45%**	✓

3. Material and Methods

This research proposes a hybrid DL model for the early detection of anxiety through EEG signals. The model consists of a CNN, LSTM, and Transformer modules, integrating at once, spatio-temporal and contextual detection of brain signals. The early detection will allow for continuous mental health monitoring and for non-invasive interventions using Brain–Computer Interface (BCI) technologies. As shown in Fig. 1, the BCI system has two steps. The first is the preprocessing of the raw EEG signals, where we address missing data, normalization, outlier removal, Independent Component Analysis (ICA), and class balancing with SMOTE. After this, we extract features, Power Spectral Density (PSD), from the frequency domain and statistical features from the time domain, and feed the MEAN and STDEV of the time domain to the hybrid model. CNN layers model the spatial and LSTM the temporal, and the Transformers model the contextual hierarchies in the model. Model results were evaluated with accuracy, precision, recall, F1, AUC–ROC, confusion matrix, and sensitivity, to diagnose the classes of anxiety.

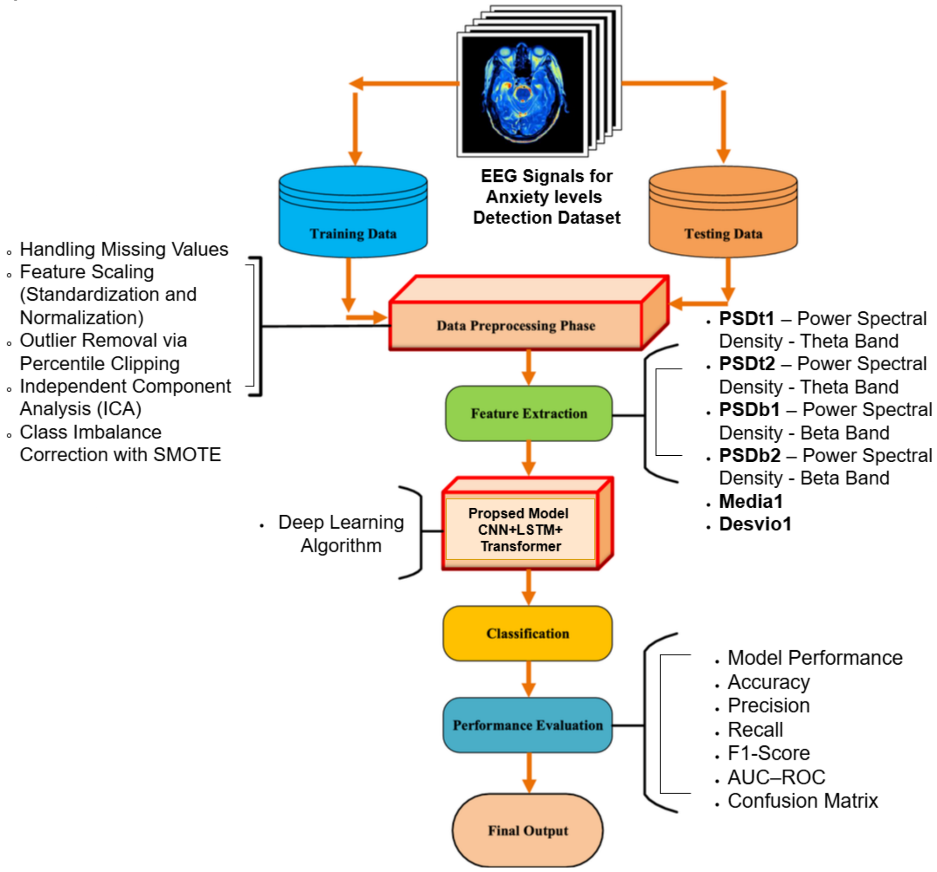
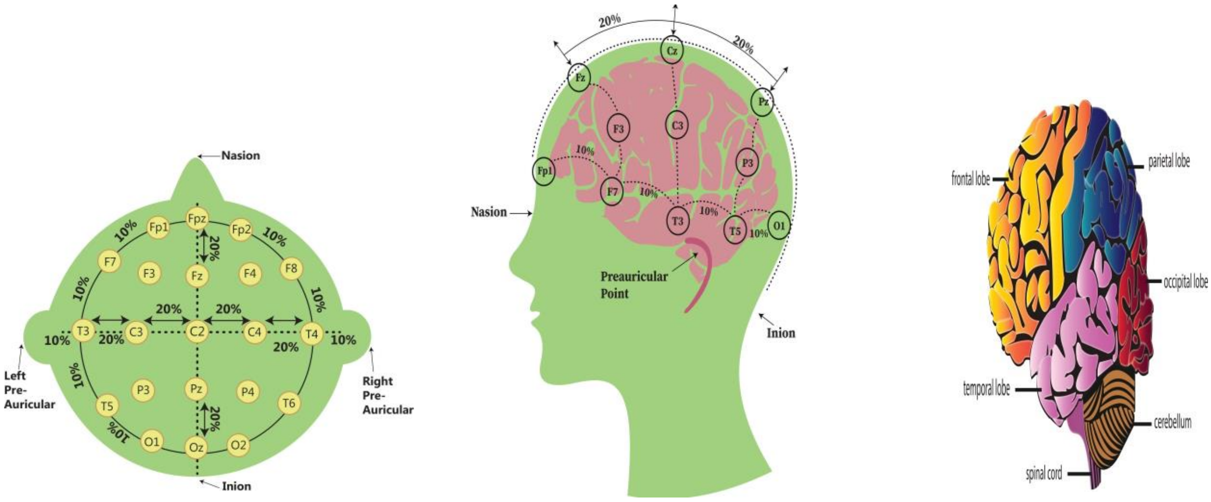


Figure 1: Overview of the proposed BCI framework for anxiety detection.

The EEG data set employed in this paper was freely available on Kaggle and specialized in recognizing the level of anxiety on the basis of brain wave activities. and is categorized into four anxiety levels: Level 0 (Normal), Level 1 (Low), Level 2 (Moderate), and Level 3 (High). The dataset includes statistical parameters (mean, variance, energy), measures derived from the power spectrum density (PSD), and characteristics in the frequency domain. The signals sampled with the 10–20 electrode system (e.g., Fp1, F3, Fz), ensure even cortical coverage and detect activity from areas of the cortex that are pivotal in emotional and cognitive processes. [15]. The ERF (Electrode Region Function) model assigns electrodes to areas of the brain for which they are functionally responsible: frontal (emotion regulation), parietal (sensory integration), occipital (visual), temporal (memory/audio), and cerebellar (motor). This configuration is depicted in Fig 2. EEG WAVE samples often contain missing, inconsistent, or duplicate data due to noise and motion. Large gaps were removed, and for partial gaps, imputation using mean or median values was performed, while for continuous gaps, linear or cubic interpolation was performed. Also, extreme outliers (1st–99th percentile) were substituted with channel medians, . In the case of preprocessing, a 4th-order band-pass filter (0.5–50 Hz), a notch filter at 50 Hz, and spherical-spline interpolation were used for the poor channels, while Fast ICA was used for artifact removal. After feature extraction and label encoding, stratified sampling 70/30 was performed, and to address the class imbalance, SMOTE was used, and window slicing with Gaussian noise was utilized to enhance robustness.



(a) EEG Electrode Layout - View 1
Regions (ERF)

(b) EEG Electrode Layout - View 2

(c) Functional Brain

Figure 2: Overview of EEG acquisition for anxiety detection: (a–b) standard 10–20 electrode layouts; (c) ERF mapping of major brain regions .

A hybrid CNN-LSTM-Transformer model was created to capture and analyze the spatial, temporal, and global patterns of the EEG. In the CNN branch with 64 filters and a dropout of 0.3, spatial feature extraction was performed, while for modeling of temporal sequences, the LSTM branch with 128 units was used, and for capturing long-range dependencies, the transformer branch used four attention heads. The outputs of the three branches were concatenated and trained in an end-to-end manner while using the Adam optimizer with Sparse Categorical Cross-Entropy. The model achieved 97.45% accuracy with a batch processing time of 10 ms and outperformed each of those models individually in CNN, LSTM, and transformer. The execution of the experiments was done in Python 3.9 using TensorFlow 2.12/Keras 2.12 on NVIDIA RTX 3090 (64 GB RAM) with Intel Xeon CPU, GPU.

4. Results and Discussion

This section presents the evaluation of the proposed hybrid CNN–LSTM–Transformer model for anxiety classification using EEG sig- nals. Initially, CNN, LSTM, and Transformer models were trained individually to learn specific features: CNN for spatial patterns, LSTM for temporal dependencies, and Transformer for long-range interdependencies. These models were then integrated into a hy- brid architecture leveraging their complementary strengths. Performance was assessed using accuracy, precision, recall, F1-score, and AUC-ROC, alongside confusion matrices for visual evaluation. The dataset consisted of 12,330 EEG recordings, each with 16 features, partitioned into training, validation, and testing sets in an 80:10:10 ratio. The class distribution was imbalanced, with Class 0 (low anxiety) being overrepresented and Class 3 (severe anxiety) underrepresented. SMOTE was applied to balance the classes, generating synthetic samples for underrepresented categories to improve model stability and performance. This section presents the evaluation of the proposed hybrid CNN–LSTM–Transformer model for anxiety classification using EEG signals. Initially, CNN, LSTM, and Transformer models were trained individually to learn specific features: CNN for spatial patterns, LSTM for temporal dependencies, and Transformer for long-range interdependencies. These models were then integrated into a hybrid architecture leveraging their com- plementary strengths. Performance was assessed using accuracy, precision, recall, F1-score, and AUC-ROC. The dataset consisted of 12,330 EEG recordings, each with 16 features, partitioned into training, validation, and testing sets in an 80:10:10 ratio. Class imbal- ance was observed, with low anxiety overrepresented and severe anxiety underrepresented. SMOTE was applied to generate synthetic samples for underrepresented classes to improve model stability and performance.

Confusion matrices showed that CNN performed well for moderate and severe classes, but sometimes confused adjacent classes. LSTM improved prediction for higher anxiety classes due to its temporal

modeling capabilities. Transformer performed reasonably but struggled with the low anxiety class, likely due to class imbalance. The hybrid model demonstrated minimal misclassification across all classes, effectively combining spatial, temporal, and attention-based features.
Quantitative metrics indicated that CNN performed moderately, especially in higher anxiety classes, while LSTM achieved more bal- anced performance due to temporal sequence learning. Transformer improved prediction for intermediate classes but was less accurate for low anxiety. The hybrid model consistently outperformed all individual models across all classes by integrating spatial, temporal, and attention-based features. Overall classification accuracies were: CNN 85.90%, LSTM 91.54%, Transformer 91.12%, and Hybrid 97.45%. As Fig 3. highlights, this highlights the hybrid model's effectiveness in leveraging complementary strengths of CNN, LSTM, and Transformer for EEG-based anxiety detection.

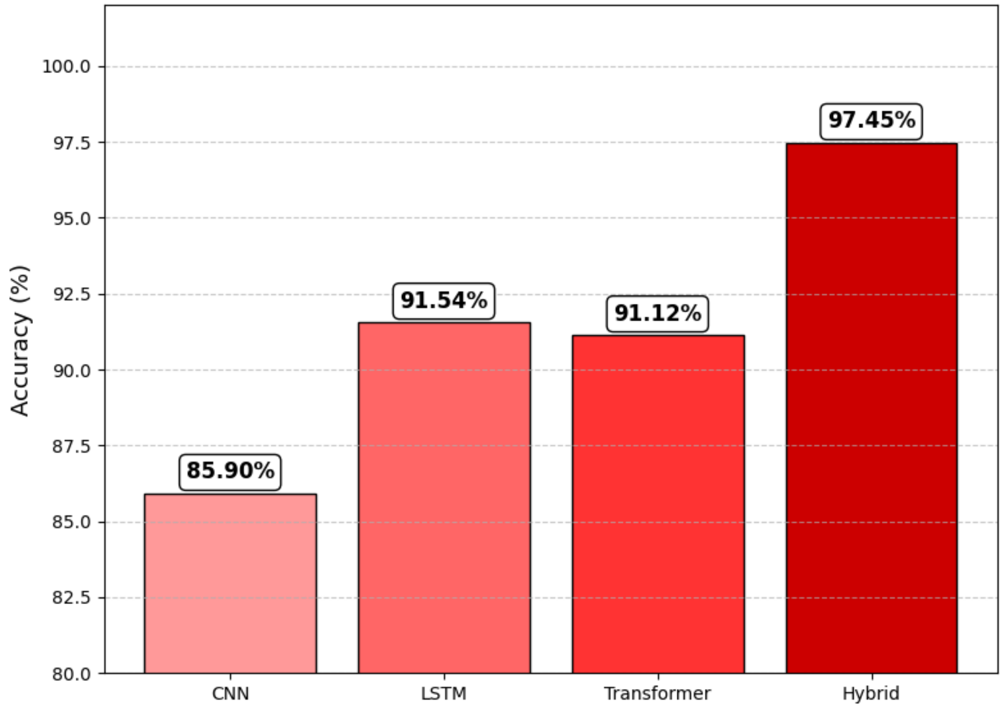


Figure 3: Comparison of model accuracies for anxiety detection.

ROC–AUC analysis further confirmed the hybrid model's superiority. While individual models showed varying True Positive Rates (TPR) and False Positive Rates (FPR) across classes, the hybrid model achieved a perfect TPR for low anxiety and maintained low FPRs across all classes. This demonstrates the efficacy of combining CNN's spatial feature extraction, LSTM's temporal learning, and Transformer's attention mechanisms for accurate classification of anxiety levels.

5. Conclusion

This paper proposes a state-of-the-art BCI system to detect anxiety based on Electroencephalogram (EEG) measures in addition to incorporating DL methodologies. By the application of Independent Component Analysis (ICA) and SMOTE preprocessing methods, the balanced and noise-filtered EEG dataset consisting of 12,330 recordings was used. The individual models CNN, LSTM, and Transformer reached an accuracy of 85.90%, 91.54%, and 91.12%, respectively, proving their viability in extracting the spatial, temporal, and contextual patterns. The model proposed by us, a hybrid CNN, LSTM and Transformer performed considerably better than all the base and competing models and recorded an accuracy of 97.45%. The system has strong convergences, a high level of generalization, and tolerance of a noisy environment. Although these findings are very encouraging, the model must be confirmed in heterogeneous datasets and in clinical practices before the model can be accepted. The incorporation of other biosignals, including fNIRS and ECG will also be incorporated in the future as a way of improving the process of recognizing emotional states. The given work is relevant to the creation of objective, non-invasive, and personified mechanisms of monitoring of mental health and clinical diagnostics.

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