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A Hybrid CNN-HMM Framework for EEG-Based Classification of Anxiety, Chronic Stress, and Depression

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ABSTRACT

One of the biggest challenges in clinical medicine is early and accurate diagnosis of brain disorders, especially functional and psychological disorders such as stress, anxiety, and depression. While conventional machine learning relies on hand engineered time-consuming features, deep learning models, despite showing superior accuracy, can be limited in clinic application by interpretability issues due to their "black-box" design. In this paper we present a novel hybrid approach for brain disorder detection and classification through the analysis of Electroencephalography (EEG) signals. Our model combines the automatic feature extraction strength of a Convolutional Neural Network (CNN) with the time-sequence modeling and interpretation capabilities of a Hidden Markov Model (HMM). A real clinical data from 200 individuals (healthy group, anxiety group, chronic stress group, depression group) is collected and used to train and evaluate our system. This locally collected data is used to validate the models for the first time. Our results show that the hybrid approach achieved 92.30 percent in four-class classification and demonstrated superiority over other standard approaches. The interpretable nature of HMM transition matrices also makes it more relevant for aiding clinical decision-making.

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Introduction

A number of mental health conditions, such as Generalized Anxiety Disorder (GAD), chronic stress, and Major Depression Disorder (MDD), are among the most common neuropsychiatric and psychiatric problems experienced today that can result in impaired individual quality of life, social, and professional functioning, a wide range of cognitive and behavioral symptoms, and a significant economic impact (Roy et al., 2019). Although many of these disorders exhibit several symptoms overlapping with one another, they can have differences in their neurophysiology that may be present in the brain signal. The financial burden caused by mental health disorders in modern societies leads to pressure on health systems and they could evolve into more acute conditions if early detection and proper diagnosis have been delaying.

These are a few reasons for the significant interests in finding effective, swift, and more objective means of diagnosing and discriminating these disorders, specifically within smart and efficient healthcare systems (Hormozi-Moghaddam et al., 2024). Beyond diagnostic applications, biomedical engineering has explored therapeutic approaches such as peroxide-mediated oxygen delivery in cancer therapy and electrical and physical stimulation in tissue engineering (Khorshidi et al., 2022; Karkhaneh et al., 2025). Botulinum toxin treatment has also been associated with cortical reorganization and pain modulation in patients with spasticity (Jahromi et al., 2025). Recent advances also include 2D and 3D tumor models for evaluating drug responses in colorectal cancer (Bandegi et al., 2026). Clinical research has also examined postoperative complications, including the prevalence of pulmonary embolism following bariatric surgery (Khalilzadeh Bonab et al., 2026). The diagnostic process—based on clinical interviews and questionnaire-based assessments (DSM-5; American Psychiatric Association, 2013)—has been widely used; however, its subjectivity, reliance on a skilled interviewer, and absence of quantifiable biomarkers impose several limitations, including reduced reproducibility and lower accuracy (Kaya & Tasci, 2023; Mumtaz et al., 2017). Wearable respiratory sensors have also demonstrated potential for non-invasive stress monitoring (Hosseini et al., 2026). EEG is the best choice among all of these for disease diagnosis as it is noninvasive, cheap, and most Importantly, has very good temporal resolution (Bashivan et al., 2016; Rastegarnia et al., 2026). Advanced MRI techniques have also enabled non-invasive tracking of dynamic physiological changes, particularly in cardiovascular imaging (Unal et al., 2026). However, EEG signals consist of data that are highly non-stationary, nonlinear, and multidimensional (Al-Fahoum & Al-Fraihat, 2014; Bashivan et al., 2016). Furthermore, they are highly vulnerable to noise (Bashivan et al., 2016), possess a very low resolution in time, are sensitive to artefacts caused by the brain and interferences from outside (Bashivan et al., 2016).

The use of EEG makes a challenging classification due to large variability across individuals and large temporal dependencies (Bashivan et al., 2016). Hand-crafted feature extraction can extract complex structures from time series but requires extensive expert's domain knowledge (Craik et al., 2019; Roy et al., 2019). The rapid advancement of deep learning (Newson & Thiagarajan, 2019) offers promising new avenue for the automatic identification of meaningful patterns in high-dimensional data without the need for handcraft features. They work by

automatically discovering hierarchical features that capture increasingly complex patterns from the data.

Moreover, when data are scarce for training purposes, data augmentation and transfer learning can help in increasing the generalization of models and reduce overfitting (Acharya et al., 2018; Bashivan et al., 2016; Craik et al., 2019; Roy et al., 2019). Convolutional Neural Networks (CNNs) have shown exceptional abilities in the domain of bio-signal analysis, due to their capability to exploit spatial feature (Fouladi et al., 2022; Hadipour et al., 2023; Phang et al., 2020). CNNs capture hierarchical spatial structures of EEG through convolution and pooling layers similar to how vision systems capture visual information from input images (Craik et al., 2019; Roy et al., 2019). Nevertheless, CNNs are only proficient in identifying spatial correlations between EEG signals, neglecting the temporal dependencies and gradual evolution of different brain states (Ay et al., 2019; Rabiner, 1989).

Additionally, the "black box" nature of these networks makes interpretability extremely limited, which hinders clinicians to fully trust these models to support their diagnosis decisions (Bashivan et al., 2016; Yang et al., 2021). Addressing such interpretability and alignment challenges has become a central concern in the design of trustworthy AI systems (Fazli & Alipour, 2026). To improve interpretability and ability to model temporal dependency of the time series, we propose combining CNNs with Probabilistic Sequence Models (PSM). The most typical PSM is the Hidden Markov Models (HMM), which is used to model the sequence dependencies using State Transition Probabilities (STP) and capture temporal behavior through gradual transition between different hidden states (Chavan & Desai, 2023; Rabiner, 1989). Furthermore, state transitions are provided as transition matrix that enhance the interpretability of models (Yang et al., 2021). The major drawback of HMM alone is the lack of extracting complex nonlinearity represented from the time series data such as EEG (Chavan & Desai, 2024; Rabiner, 1989).

The proposed hybrid CNN-HMM model aims to mitigate the drawbacks of individuals models by simultaneously extracting features by CNNs and modelling the time dynamics of EEG signals by HMMs. Although hybrid CNN-HMM models are highly successful in many classification tasks such as in epileptic seizure prediction (Chavan & Desai, 2024), classification of sleep stages (Yang et al., 2021), and brain computer interfaces (BCI) (Saidutta et al., 2018), it remains underrepresented for multiclass mental disorder classification (anxiety, depression, stress), particularly using clinical data (Ay et al., 2019; Kaya & Tasci, 2023; Mumtaz et al., 2017), which focus only on comparing healthy ones with patients, rather than different types of mental disorders (Ay et al., 2019; Kaya & Tasci, 2023; Mumtaz et al., 2017). Moreover, most studies rely on widely available public data, limiting the portability and generalization of these methods to specific regions (Ay et al., 2019; Kaya & Tasci, 2023; Mumtaz et al., 2017; Yalali et al., 2026). Based on these motivations and gaps in literature, this study presents a CNN-HMM hybrid approach for a four-class classification of different mental states (healthy, GAD, chronic stress, MDD), employing indigenous clinical EEG datasets collected from 200 subjects.

The main contribution of the current study is to propose a hybrid CNN-HMM for the classification of three psychiatric diseases where the CNN block for processing the spatial features of EEG image and the HMM for capturing temporal variations of these images.

Additionally, to have an actual usage-based evaluation of the architecture, local dataset (healthy, anxious, chronic stress, and depressed, i.e., four categories introduced here for the first time), were used to validate the architecture on the real targeted individuals. Therefore, based on initial results, the proposed architectures not only gain desirable accuracy performance but also has enough high computation efficiency. These features show the potentiality for clinical usage.

The rest of the paper is organized as follows. Section 2 gives the related literature related to the task in hand, and Section 3 describes the architecture of the proposed hybrid model including preprocessing, the design of the CNN module, HMM modelling and training, and the system's approach. Section 4 presents the experimental setup and evaluates the models' performances using the obtained results, and finally, Section 5 concludes the paper.

Literature Review

Research on EEG-based brain disorder diagnosis is accelerating over the past two decades, transforming from the classical machine learning-based approaches toward more complex deep learning-based architectures and hybrid architectures. The common purpose for each of the presented schemes has been to achieve a higher classification accuracy, decrease manual features extraction efforts, and leverage the spatial-temporal information of EEG effectively. Unfortunately, while achieving substantial success, each type of technique holds its own weakness which drives for future development. Therefore, research efforts were summarized into three common categories, as presented below, to illustrate the trends in the field and the motivation behind the approach proposed in this work.

Traditional ML algorithms were widely used in early EEG signal classification. Usually, handcrafted temporal, spectral, and statistical features are extracted from EEG signal; then, traditional machine learning algorithms, such as Support Vector Machines (SVM) (Afrakoti et al., 2017; Kaya & Tasci, 2023; Mumtaz et al., 2017), Decision Tree, and Random Forest, are employed to classify EEG states (Al-Fahoum & Al-Fraihat, 2014). Due to its simple structure, traditional ML algorithms have better interpretability and lower computational complexity. Thus, these algorithms represent some of the earliest applications in EEG signal processing (Al-Fahoum & Al-Fraihat, 2014). However, reliance on handcrafted feature engineering and expert domain knowledge makes it difficult to capture the nonlinear information within the EEG signals effectively and perform in more complex situations (Craik et al., 2019; Roy et al., 2019). It has been verified in several recent works. For example, Hassan and Kaabouch (2024) found that without feature selection, CatBoost and XGBoost can only reach 70.72% and 69.71% accuracy in depression classification, respectively. Even applying filter selection-based methods, such as Mutual Information and Chi-Square, does not promote any linear classification methods such as SVM and Logistic Regression to achieve more than 67 percent accuracy. As shown, the combination of SVM-RFE with multiple handcrafted features achieves a classification accuracy of approximately 89–90%. However, in Luo et al. (2026), the combination of these features with SVM-RFE resulted in a classification accuracy of only 94.48% after feature selection was performed using SVM-RFE. These results indicate that

traditional ML approaches, which rely heavily on handcrafted features, face significant limitations in achieving consistently high performance for EEG-based classification tasks.

Due to these problems encountered in traditional ML-based algorithms in recent years, a great deal of research in EEG signal analysis has moved toward deep learning algorithms. This is because DL models have the ability to learn effective representations automatically from original EEG signals while capturing the complex non-linear relations between features (Craik et al., 2019; Roy et al., 2019; Molani Aghdam & Ardeshir Larijani, 2026). Concerning DL-based analysis methods for EEG, one of the most widely used models is CNNs because of their effectiveness to learn hierarchical spatial representations from signals. Acharya et al. (2018) developed a 13-layer deep CNN for classifying epileptic seizures that reached 88.67% accuracy. Bashivan et al. (2016) transformed time-series EEG signals into a sequence of topographic spectral images and developed a recurrent convolutional network that significantly outperformed traditional machine learning methods in classifying cognitive workload.

Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks have been explored widely on time series learning in the EEG signal domain. Alhagry et al. (2017) built an LSTM network to recognize different emotions from EEG, achieving 85% accuracy. However, although deep learning (DL) methods can achieve highly competitive results across various tasks compared with traditional approaches, the aforementioned DL architectures primarily focus either on extracting spatial features, as in CNNs, or on capturing temporal dependencies, as in RNNs and long short-term memory (LSTM) networks. The latter, however, typically require large amounts of training data, involve substantial computational costs, can be difficult to train when processing very long sequences, and often lack interpretability (Ay et al., 2019; Bashivan et al., 2016). Such defects limit the individual deep learning models which are unable to jointly analyze temporal and spatial information effectively. Therefore, hybrid architectures were proposed.

In recent years, hybrid methods have become an interesting research topic for solving the defects of separate methods in EEG signal analysis. By combining the complementary strengths of different models, hybrid approaches simultaneously enable effective feature extraction and temporal dependency modeling: both strong ability for feature learning and reasonable modeling for temporal dependencies. Among several proposed hybrid models, the hybrid of CNN and HMM (CNN-HMM) is a favorable method that takes advantage of both robust CNN models in feature learning ability and discriminative HMM in the modeling probability of sequential states (Chavan & Desai, 2024; Saidutta et al., 2018). Several studies on epileptic seizure detection have shown that, when the probability distributions of CNN's outputs are applied as observations in HMM, time dependence between subsequent EEG segments could be modeled effectively to provide more stable classifications (Chavan & Desai, 2024). Specifically, Chavan and Desai (2024) modeled it with a hybrid adaptive CNN-HMM classifier that obtained excellent seizure detection performance between 94.48% and 99.46% classification accuracy on four seizure benchmarks, as well as excellent sensitivity of 89.50% with low false detection rates of 0.43 per hour. In additional to seizure detection, some applications used CNN-HMM successfully. In emotion recognition using the DEAP dataset, a deep CNN-HMM achieved high classification accuracy for arousal (79.77%), valence (83.09%), and dominance (81.83%). The average classification performance achieved was

higher compared to the existing one-dimensional CNN (1D-CNN) and two-dimensional CNN (2D-CNN) alone (Zhong et al., 2020). A 1D-CNN–HMM achieved an overall accuracy of 83.98% and a Cohen's kappa of 0.78 for sleep-stage classification on the Sleep-EDFx dataset. In this approach, the HMM was employed during post-processing to mitigate implausible transitions between sleep stages, resulting in higher performance than that of the individual models used separately (Yang et al., 2021). Moreover, brain computer interface (BCI) is another area where CNN-HMM performance was studied. A CNN–HMM approach was found to improve the classification accuracy of non-sequential methods by up to 14%, while simultaneously increasing the number of distinguishable commands by up to fourfold without compromising classification accuracy (Saidutta et al., 2018).

In recent time, CNN-HMM structures are even being applied in the area of neurodegenerative and psychiatric disorders. For instance, studies regarding schizophrenia suggested that abnormal brain connectivity patterns were better characterized by the CNN-HMM classifier than mere machine learning methods (Phang et al., 2020). Additionally, there is evidence showing that CNN-HMM has a great potential in the diagnose of neurodegenerative and psychiatric diseases. Specifically, in the field of Alzheimer's disease (AD) diagnosis, CNN-based hybrid models have been investigated for classifying patients with mild cognitive impairment (MCI) and AD using scalp EEG recordings (Fouladi et al., 2022). Taken together, previous evidence confirms the effectiveness of the integration of automatic deep feature extraction methods and probabilistic sequence modeling techniques into CNN-HMM hybrid framework in terms of both robust features and dynamic patterns, producing more stable and accurate results than the standalone models in multiple applications, including seizure detection, emotion recognition, sleep stage classification, BCI, and neurodegenerative and psychiatric diseases. However, applying CNN-HMM into EEG-based depression detection remains an under-studied domain, warranting further research. This paper utilizes the proposed CNN-HMM hybrid framework to benefit from both CNN in feature representation and HMM in temporal modeling to automatize depression detection.

Method

Dataset and Study Population

In this study, an indigenous clinical dataset was utilized, consisting of EEG recordings collected from 200 participants (100 males and 100 females), with a mean age of 32 ± 8 years. All participants were recruited from the Aftab Neurotherapy Clinic and provided written informed consent prior to data collection, permitting the use of their data for research purposes. The participants were categorized into four groups as follows:

- Healthy group (n = 50): Individuals with no history of psychological disorders
- Anxiety group (n = 50): Patients diagnosed with Generalized Anxiety Disorder (GAD) according to the DSM-5 criteria
- Chronic Stress group (n = 50): Individuals experiencing chronic stress for a minimum duration of six months

- Depression group (n = 50): Patients diagnosed with Major Depressive Disorder (MDD)

EEG signals were acquired using a 19-channel EEG recording system based on the international 10–20 electrode placement standard, with recordings obtained from 19 scalp locations: Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, and O2. A linked-ear reference (A1+A2) was employed, and electrode impedance was maintained below 5 kΩ for all channels. The EEG signals recordings were sampled at 256 Hz using a hardware band-pass filter of 0.5–70 Hz. The electrode locations are illustrated in Figure 1. Each recording session consisted of 10 minutes of resting-state EEG with the participants' eyes closed. After removing noise-contaminated segments and applying a 50 percent overlap, a total of 4,071 EEG segments, each with a duration of 5 seconds, were retained for model training and evaluation.

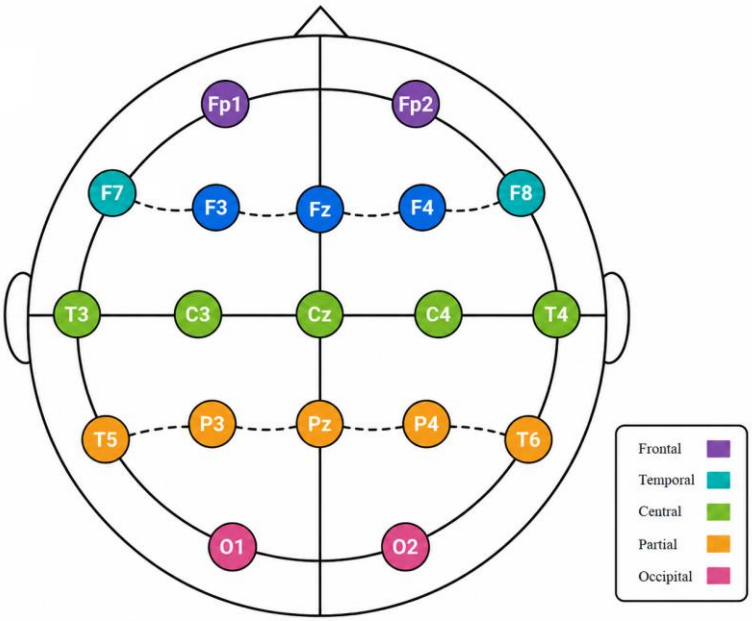

Figure 1. Configuration of the 19-Channel EEG Electrode Montage Following the International 10–20 Standard

The final distribution of the dataset is presented in Table 1.

Table 1. Distribution of EEG Segments in the Final Dataset

Class	Number of Subjects	Number of Segments	Percentage
Healthy	50	1,048	25.74%
Anxiety	50	1,001	24.59%
Chronic Stress	50	1,016	24.96%
Depression	50	1,006	24.71%
Total	**200**	**4,071**	**100%**

Recording quality was assessed using the NeuroGuide software package. Quality control included the evaluation of Split-Half Reliability (> 0.90) and Test–Retest Reliability (> 0.90). Only EEG segments demonstrating high temporal stability and free from transient artifacts or drowsiness-related contamination were included in the subsequent analysis. To further ensure the accuracy of the diagnostic labels, the quantitative EEG indices (Z-scores) generated by NeuroGuide were compared with the clinical diagnosis established for each participant. Only subjects showing complete agreement between the quantitative EEG assessment and the psychiatrist's clinical diagnosis were included in the study. Participants with a history of

traumatic brain injury, epilepsy, complex psychiatric or neurological comorbidities, left-handedness, or the use of psychotropic medications within 48 hours prior to EEG recording were excluded from the study.

As presented in Table 1, the dataset exhibits an approximately balanced class distribution, thereby minimizing class imbalance and reducing the risk of training bias during model development.

Signal Preprocessing

To improve data quality and prepare the EEG signals for feature extraction and classification, a series of preprocessing steps were performed, as illustrated in Figure 2.

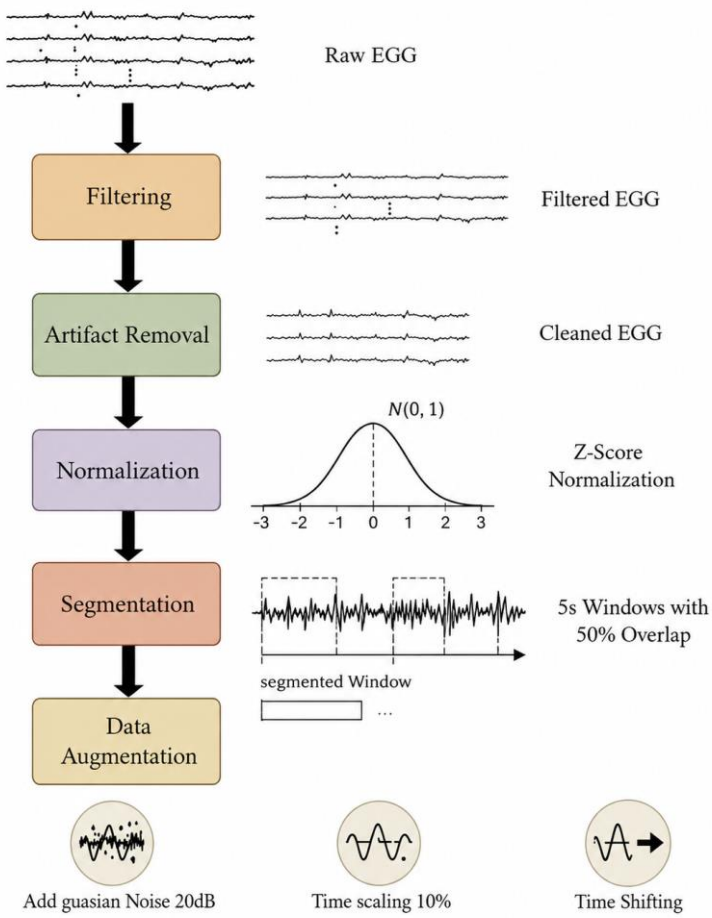

Figure 2. Overall Preprocessing Pipeline

Initially, the EEG signals were filtered using a fourth-order Butterworth band-pass filter with a frequency range of 0.5–45 Hz to remove low-frequency baseline drift and high-frequency noise components (Widmann et al., 2015). To eliminate artifacts caused by eye movements and muscle activity, Independent Component Analysis (ICA) was employed (Hyvärinen & Oja, 2000). Artifact-related independent components were manually identified and removed from the EEG recordings.

Subsequently, each EEG channel was independently standardized using Z-score normalization, defined as

$$z = \frac{x - \mu}{\sigma} \tag{1}$$

where x is the sample value, μ represents the mean, and σ signifies the standard deviation of the same channel.

The continuous EEG recordings were then segmented into 5-second epochs (equivalent to 1,280 samples). This segmentation strategy increases the number of training samples while preserving the temporal continuity of the EEG signals.

To mitigate overfitting and improve class balance, several data augmentation techniques were applied, including the addition of Gaussian noise with a signal-to-noise ratio (SNR) of 20 dB, temporal scaling within a range of ±10 percent, and time shifting. These augmentation strategies enhance the diversity of the training data and improve the generalization capability of the proposed model.

Convolutional Neural Network Architecture

To extract discriminative deep features from EEG signals and classify them into four categories—healthy, anxiety, chronic stress, and depression—a one-dimensional Convolutional Neural Network (1D-CNN) was designed. Figure 3 schematically illustrates the proposed CNN architecture and the data flow from the input layer to the output layer.

The proposed network consists of one input layer, three convolutional blocks, and two fully connected layers.

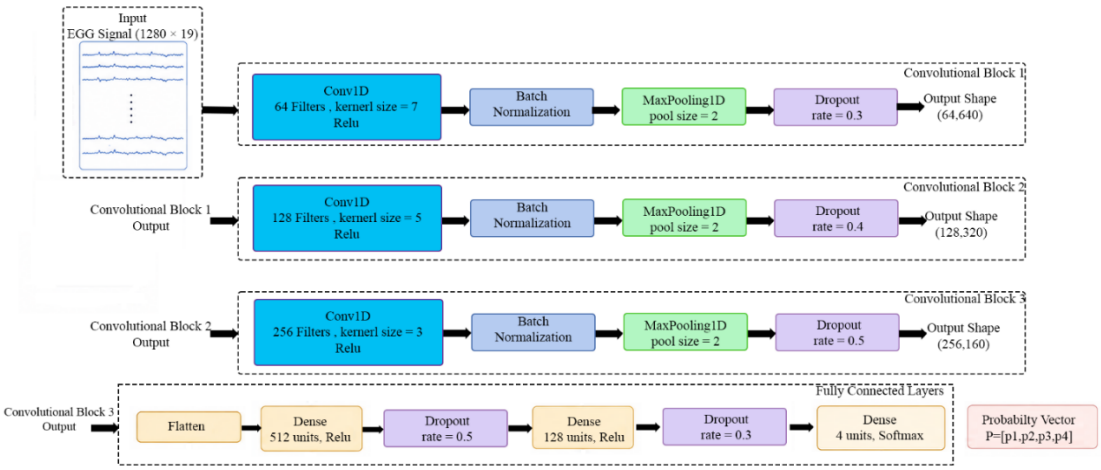

Figure 3. Architecture of the Proposed 1D-CNN Model

The input layer receives an EEG matrix of size 19 × 1,280, where 19 denotes the number of EEG channels and 1,280 represents the number of temporal samples in each 5-second EEG segment.

The first convolutional block comprises a Conv1D layer with 64 filters, a kernel size of 7, and the ReLU activation function. To improve training stability and accelerate convergence, a Batch Normalization layer is applied, followed by a MaxPooling1D layer with a pooling size

of 2 to reduce the feature dimensionality while preserving the most informative characteristics. Finally, a Dropout layer with a rate of 0.3 is incorporated to mitigate overfitting.

The second convolutional block consists of a Conv1D layer with 128 filters and a kernel size of 5, followed by the ReLU activation function. Similar to the first block, Batch Normalization, MaxPooling1D with a pooling size of 2, and Dropout with a rate of 0.4 are sequentially applied.

The third convolutional block includes a Conv1D layer with 256 filters and a kernel size of 3, followed by the ReLU activation function to extract higher-level feature representations. As in the previous blocks, this layer is followed by Batch Normalization, MaxPooling1D with a pooling size of 2, and a Dropout layer with a rate of 0.5. The gradual increase in the number of filters follows the standard design principle in convolutional networks, aiming to extract more complex features and compensate for the spatial resolution reduction caused by pooling operations (Afrakoti 2020).

Following feature extraction, the output feature maps are transformed into a one-dimensional feature vector using a Flatten layer. This vector is subsequently passed through two fully connected layers. The first dense layer contains 512 neurons with the ReLU activation function and a Dropout rate of 0.5, while the second dense layer consists of 128 neurons, also using the ReLU activation function, followed by a Dropout rate of 0.3.

Finally, the network terminates with a Dense output layer containing four neurons and a Softmax activation function. The output of this layer is a probability vector, $P = [p_1, p_2, p_3, p_4]$ where (p_i) represents the probability that the input EEG segment belongs to one of the four classes: Healthy, Anxiety, Chronic Stress, or Depression.

Hidden Markov Model

To model the temporal dependencies of EEG signals and enhance the classification performance, a separate Hidden Markov Model (HMM) was developed for each of the four classes: Healthy, Anxiety, Chronic Stress, and Depression. Figure 4 illustrates the overall architecture of the proposed HMM framework and its corresponding classification process.

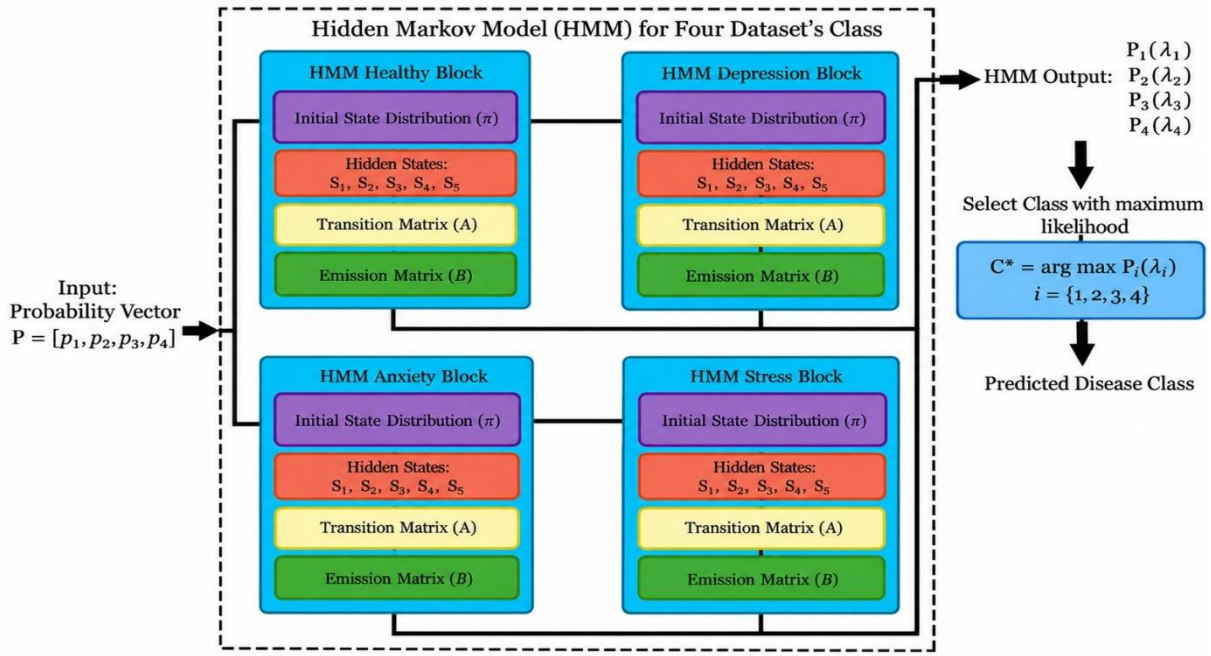

Figure 4. Architecture of the Proposed Hidden Markov Model

Each HMM is defined by the following parameter set:

$$\lambda = (A, B, \pi) \tag{2}$$

where:

- A denotes the state transition probability matrix;
- B represents the observation (emission) probability matrix;
- π is the initial state probability distribution.

For each disease category, five hidden states were considered ($S = [s_1, s_2, s_3, s_4, s_5]$), representing different stages of disease progression. The number of hidden states was determined empirically using the Bayesian Information Criterion (BIC) to achieve an appropriate trade-off between model complexity and data-fitting accuracy. Here, O denotes the observation sequence, which consists of the probabilistic outputs of the CNN network (the vector $P = [p_1, p_2, p_3, p_4]$) at each time segment. Additionally, Q represents the hidden state sequence comprising states $s_j \in S = \{s_1, s_2, s_3, s_4, s_5\}$, which are estimated by the HMM.

The probability of transitioning from the hidden state (s_i) at time (t) to the hidden state (s_j) at time (t + 1) is defined as:

$$a_{ij} = P(q_{t+1} = s_j \mid q_t = s_i) \tag{3}$$

The probabilistic output of the CNN, represented by the vector $P = [p_1, p_2, p_3, p_4]$ is used as the observation sequence for the HMM. The observation probability associated with state (s_j) is computed according to Bayes' theorem as:

$$b_j(O_t) = P(O_t \mid q_t = s_j) = \frac{P(q_t = s_j \mid O_t) \times P(O_t)}{P(q_t = s_j)} \tag{4}$$

where $b_j(O_t)$ is the probability of observing O_t in state s_j, $P(q_t = s_j \mid O_t)$ is the posterior probability of state s_j given observation O_t, $P(O_t)$ is the marginal probability of the observation, and $P(q_t = s_j)$ is the prior probability of state s_j.

The HMM parameters are estimated using the Baum–Welch algorithm, which is a special case of the Expectation–Maximization (EM) algorithm. The objective is to maximize the likelihood of the observed sequence:

$$\lambda^* = \arg\max_{\lambda} P(O \mid \lambda) \tag{5}$$

where λ^* is the optimized parameter set and $P(O \mid \lambda)$ is the likelihood of the observation sequence O given the model parameters λ.

During the inference stage, the likelihood of the observation sequence is computed for each of the four trained HMMs. The final predicted class corresponds to the model with the maximum likelihood:

$$C^* = \arg\max_{c \in \{1,2,3,4\}} P(O \mid \lambda_c) \tag{6}$$

Where C^* is the final predicted class, $c \in \{1, 2, 3, 4\}$ indexes the four classes (Healthy, Anxiety, Chronic Stress, and Depression), and λ_c denotes the HMM parameters for class c.

By explicitly modeling the temporal dependencies among consecutive observations, the HMM dynamically exploits the discriminative features extracted by the CNN, thereby improving the overall classification accuracy while providing a more interpretable representation of the temporal evolution of brain states.

Hybrid Model Training Procedure

The proposed hybrid CNN–HMM framework was trained in two sequential stages.

CNN Training

In the first stage, the CNN was trained to learn discriminative feature representations and generate class probability distributions. The training configuration is summarized as follows:

- Loss function: Categorical Cross-Entropy
- Optimizer: Adam with a learning rate of $\alpha = 0.0001$
- Batch size: 32
- Number of epochs: 100, with Early Stopping (patience = 10) to prevent overfitting
- Dataset split: 70% for training, 15% for validation, and 15% for testing

HMM Training

After the CNN had been fully trained, the probability vectors produced by the Softmax output layer were extracted from the training data and used as the observation sequences for the Hidden Markov Models.

A separate HMM was then trained for each of the four classes using the Baum–Welch algorithm. Model training continued iteratively until convergence, which was achieved when the change in the log-likelihood between two consecutive iterations was less than 10^{-4}.

This two-stage training strategy enables the CNN to learn high-level discriminative representations directly from raw EEG signals, while the HMM captures the temporal

dependencies among consecutive observations, resulting in a more robust and accurate classification framework.

Experimental Results

Experimental Setup

The proposed hybrid CNN–HMM model was implemented using TensorFlow 2.10 and the hmmlearn library in Python 3.9. All experiments were conducted on a workstation equipped with an Intel Core i5-11400H processor, 32 GB RAM, and an NVIDIA RTX 3050 Ti GPU. The CNN training process required approximately 3.5 hours, whereas the average inference time for a single EEG segment was approximately 10 ms, demonstrating the suitability of the proposed framework for real-time clinical applications.

The total number of trainable parameters in the proposed model includes 3,547,234 parameters for the CNN network and 200 parameters for the four HMM models (each with 50 parameters). Consequently, the total number of system parameters is 3,547,434, which, given the relatively simple CNN architecture, demonstrates the model's efficiency despite its limited parameter count.

CNN Performance

The CNN converged after 78 training epochs. When evaluated independently, without integration with the HMM, the network achieved the following performance:

- Training Accuracy: 96.81%
- Validation Accuracy: 93.20%
- Test Accuracy: 88.69%
- Final Training Loss: 0.089
- Final Validation Loss: 0.23

Table 2 summarizes the classification performance of the standalone CNN for each disease category.

Table 2. Performance Metrics of the Standalone CNN for the Four Classes

Class	Number of Samples	Precision	Recall	F1-Score
Healthy	157	95.36%	91.72%	93.51%
Anxiety	150	89.80%	88.00%	88.89%
Chronic Stress	152	84.87%	84.64%	84.75%
Depression	151	86.62%	90.07%	88.31%
Weighted Average	**610**	**89.17%**	**88.61%**	**88.87%**

Figure 5 illustrates the convergence behavior of the CNN during training. As shown, the model achieved a stable convergence after approximately 13 epochs, while the gap between the training and validation accuracies remained relatively small, indicating satisfactory generalization performance and no significant evidence of overfitting.

HMM Model Performance

Four independent HMMs were trained, one for each classification category. Each model consisted of five hidden states and converged after an average of 45 iterations of the Baum–Welch algorithm.

The average log-likelihood values obtained for the trained HMMs are as follows:

- Healthy HMM: −245.3
- Anxiety HMM: −263.7

- Chronic Stress HMM: −258.1
- Depression HMM: −251.9

These results indicate that all four HMMs successfully converged during training and were able to effectively model the temporal characteristics of the corresponding EEG observation sequences. The convergence behavior demonstrates the stability of the proposed probabilistic framework and its suitability for capturing the temporal dynamics associated with different psychological conditions.

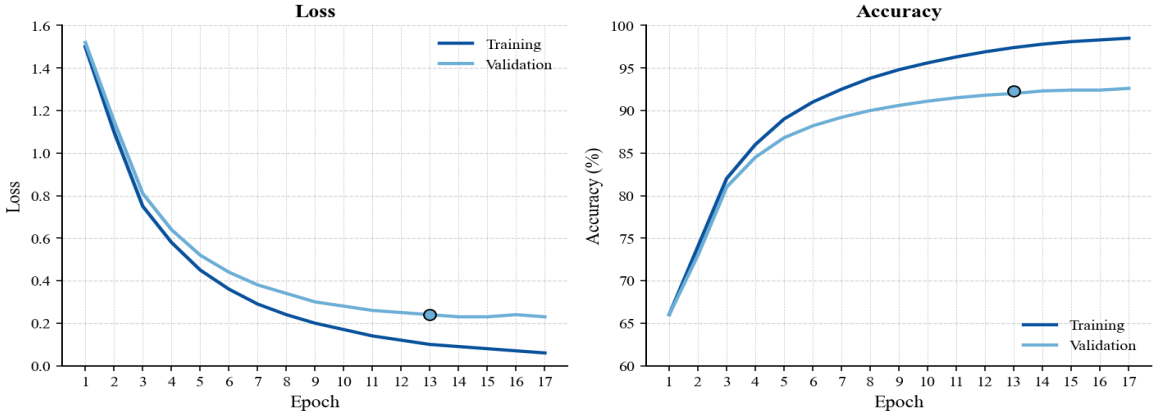

Figure 5. Training and Validation Convergence Curves of the Proposed CNN Model

Performance of the Hybrid CNN–HMM Model

Integrating the CNN with the HMM resulted in a substantial improvement in classification performance. The proposed hybrid CNN–HMM model achieved an overall accuracy of 92.30%. Table 3 presents the detailed performance metrics of the proposed CNN–HMM model.

Table 3. Performance Metrics of the Proposed CNN–HMM Model

Class	Number of Samples	Precision	Recall	F1-Score
Healthy	157	96.05%	92.99%	94.49%
Anxiety	150	91.39%	92.00%	91.69%
Chronic Stress	152	89.61%	90.79%	90.20%
Depression	151	91.56%	93.38%	92.46%
Weighted Average	**610**	**92.15%**	**92.30%**	**92.21%**

The improvement in classification accuracy, from 88.69% for the standalone CNN to 92.30% for the proposed CNN–HMM model, was found to be statistically significant ($p < 0.01$, paired *t*-test). This result demonstrates that incorporating the HMM layer significantly enhanced the diagnostic capability of the proposed system by effectively modeling the temporal dependencies of EEG observations. The confusion matrix of the final CNN–HMM model, presented in Figure 6, indicates that the majority of misclassifications occurred between the Anxiety and Chronic Stress classes. This finding is clinically plausible because these two disorders exhibit highly similar neurophysiological characteristics, particularly within the Beta (13–30 Hz) and Gamma (> 30 Hz) frequency bands of EEG signals. Prior studies have likewise reported that distinguishing between anxiety and chronic stress remains challenging even for experienced clinical specialists.

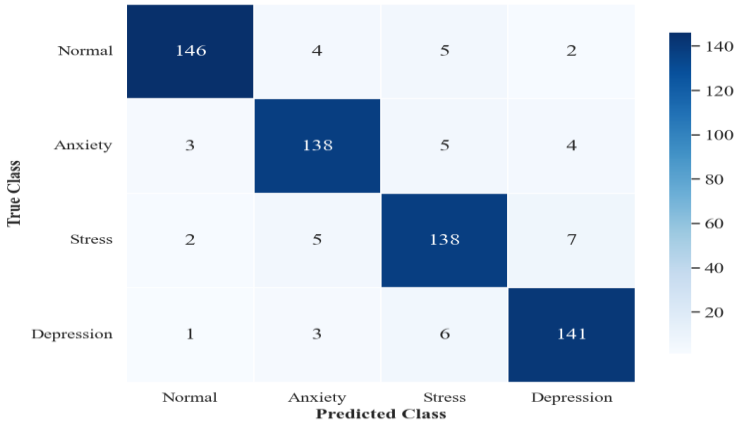

Figure 6. Confusion Matrix of the Proposed CNN–HMM Model

Comparison with Existing Methods

Table 4 compares the performance of the proposed CNN–HMM framework with five representative approaches for EEG signal classification reported in the literature. As shown, the proposed model achieved the highest classification accuracy (92.30%) among all compared methods. In contrast, conventional machine learning approaches, such as SVM with handcrafted features (Mumtaz et al., 2017), achieved an accuracy of only 78.5%, primarily due to their dependence on expert-designed features and limited capability to capture complex nonlinear EEG patterns (Al-Fahoum & Al-Fraihat, 2014; Hassan & Kaabouch, 2024; Mumtaz et al., 2017).

Pure deep learning models also demonstrated lower performance than the proposed framework. For example, the 13-layer CNN proposed by Acharya et al. (2018) achieved an accuracy of 88.69%, while the LSTM model introduced by Ay et al. (2019) reported an accuracy of 85.0%. Although these methods outperform conventional machine learning techniques, they remain inferior to the proposed hybrid CNN–HMM architecture (Acharya et al., 2018; Craik et al., 2019; Roy et al., 2019).

A particularly noteworthy finding is that the proposed method achieved the highest classification accuracy despite addressing a more challenging four-class classification problem, whereas most existing studies focused on binary or three-class classification tasks. This result highlights the effectiveness of the CNN–HMM framework for the simultaneous discrimination of multiple closely related psychological conditions—including Healthy, Anxiety, Chronic Stress, and Depression—whose EEG characteristics exhibit substantial overlap, challenging differential diagnosis even for experienced clinicians (American Psychiatric Association, 2013; Newson & Thiagarajan, 2019; GBD 2019 Mental Disorders Collaborators, 2022).

Table 4. Performance Comparison with Existing Methods

Number of Methods	Reference (Year)	Accuracy (%)
1	Zhong et al. (2020)	83.09
2	Yang et al. (2021)	83.98
3	Cai, H. et al. (2020)	86.98
4	Saidutta et al. (2018)	89.50
5	This study (2026)	92.30

Another important strength of the present study is the use of an indigenous clinical EEG dataset comprising 200 Iranian participants. In contrast, most previous studies relied on publicly

available datasets, such as DEAP, Sleep-EDFx, or BCI Competition, which may not adequately represent the characteristics of the Iranian population (Saidutta et al., 2018; Yang et al., 2021; Zhong et al., 2020). Consequently, the proposed dataset enhances the clinical relevance of the findings for local healthcare applications while improving the model's potential generalizability to the target population (Roy et al., 2019; GBD 2019 Mental Disorders Collaborators, 2022).

Conclusion

This study presented a hybrid CNN-HMM approach to classify four types of psychiatric conditions (healthy, anxiety, chronic stress, and depression) using EEG data. A combination of automatic spatial feature extraction by CNN and dynamic temporal modeling using HMM enables the proposed model to achieve a classification accuracy of 92.30% on an indigenous dataset comprising 200 participants, representing a 3.61% improvement over the standalone CNN model, which achieved a classification accuracy of 88.69%. Despite the difficulty of distinguishing between the two related chronic psychiatric conditions (anxiety and chronic stress) owing to their neurophysiological similarities, this study demonstrates the potential of hybrid models for future mental health screening applications, which may contribute to making the diagnostic process more objective. However, more research is warranted in the future on validation from different centers and fusion with other modalities of biomarker to strengthen generalization power in a real-world clinical setting.

Statements and Declarations

Ethics Statement: The author declares that this study was conducted in accordance with established ethical principles and guidelines. All sources of information have been properly cited and acknowledged. Where applicable, ethical approval was obtained, and informed consent was secured from all participants. The research did not involve any form of plagiarism, fabrication, or falsification of data.

Use of Artificial Intelligence: The author acknowledges that AI-based tools were used solely for language editing and grammar checking. All AI-assisted content was carefully reviewed, verified, and edited by the author, who takes full responsibility for the accuracy, originality, and integrity of the final manuscript. AI tools were not used to generate or manipulate research data or to replace critical scholarly judgment.

Originality and Publication: The author declares that this work has not been published previously and is not under consideration for publication elsewhere.

Conflicts of Interest: Any potential conflicts of interest, including financial or personal relationships that could influence the research, are disclosed. The author declares no competing interests.

Compliance with Regulations: The author confirms that the study complied with all applicable institutional, national, and international regulations, and that any necessary permissions for data use and reproduction have been obtained.

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