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EEG-Based Cognitive State Classification for Multiple Mental Conditions

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Abstract: Electroencephalography (EEG) has gained importance in the objective study of mental and neurological states due to its high temporal resolution, noninvasiveness, and low cost. The increasing prevalence of neurological and mental health problems calls for reliable, data-driven diagnostic and monitoring techniques that go beyond traditional subjective assessments. This review provides a systematic overview of EEG-based mental state detection techniques, including data collection methods, preprocessing techniques, feature extraction strategies, and classification models. In order to capture discriminative patterns of brain activity across time, frequency, time–frequency, nonlinear, and connection domains, the significance of feature extraction techniques is examined. We cover both sophisticated deep learning architectures like Convolutional Neural Networks, Recurrent Neural Networks, and hybrid models, as well as fundamental machine learning classifiers like Random Forests and Support Vector Machines. According to published performance evaluations, deep learning-based techniques usually provide better resilience and classification accuracy. Despite these advancements, there are still significant issues with noise artifacts, inter-subject variability, the lack of datasets, and overlapping mental state characteristics. This review also outlines future research directions with a focus on improved preprocessing, improved feature learning, scalable model architectures, and therapeutically useful EEG-based systems.

Keywords: Artifact Removal, Convolution Neural Networks, Deep Learning, Feature Extraction, Signal preprocessing, machine learning, and classification of mental states.

I. INTRODUCTION

Electroencephalography or EEG for short is really useful for studying the brain and for interacting with computers. It helps us look at and understand states of the mind like being awake or in different stages of sleep such as non-rapid eye movement sleep and rapid eye movement sleep. EEG also helps us understand conditions like epilepsy, psychosis and schizophrenia levels. These days people are getting more stressed and having mental health issues like anxiety disorders, depression, post-traumatic stress disorder and sleep disorders like insomnia. There are also a lot of problems, including Parkinsons disease, Alzheimers disease and stroke. So it is a time to find new ways to measure and evaluate different states of the mind.[1]

The usual ways of diagnosing problems are not always accurate because they often depend on what someone thinks than, on facts. The Electroencephalography or EEG for short is really good for this. It is not expensive. You can wear it. It measures the electrical activity of the brain. The EEG waveform is based on how something happens how strong it is and where it is in the brain. We can use this to find things that're not normal and to figure out what is going on in the brain. EEG is used for things but it is also very important for brain-computer interface systems. Thee systems or EEG systems take the signals from the brain. Turn them into something useful. They do not need words or actions to do this. When we use an EEG system we have to do a things. First we get the signal from the brain. Then we clean up the signal. After that we find the parts of the signal. Finally we use the signal to do something. EEG systems use techniques, like Machine Learning and Deep Learning to make this work.[5]

Machine learning and deep learning are really important for classifying EEG signals. We use things like Support Vector Machine and K-Nearest Neighbor and Random Forest for this. These are common machine learning techniques. We also use complicated techniques like Convolutional Neural Networks and Recurrent Neural Networks to understand the complex things, about EEG signals.EEG classification has some problems though. For example the data we use can be different. We have to pick the right features. We also have to figure out how to use machine learning and deep learning techniques. The goal of this research is to solve these problems by looking into ways to process and classify EEG signals. This could help create accurate and unbiased treatments for mental and neurological health issues. EEG-based systems can make a big difference in healthcare and also in how humans interact with machines. They can help bridge the gap, between what doctors need and what technology can offer. This could lead to care and new ways for people and machines to work together.

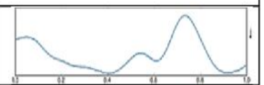
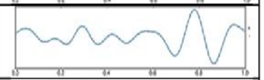
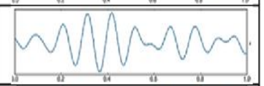
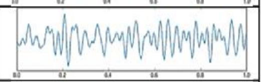
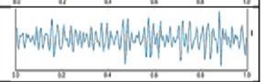
Waves	Frequency bands (Hz)	Behaviour Trait	Signal Waveform
Delta	0.3 – 4	Deep sleep	
Theta	4 – 8	Deep Meditation	
Alpha	8 – 13	Eyes closed, awake	
Beta	13 – 30	Eyes opened, thinking	
Gamma	30 and above	Unifying consciousness	

Figure 1. Frequency band of EEG signals

II. BACKGROUND AND RELATED WORK

The primary aim of this cooperative research work is to enhance Brain-Computer Interfaces (BCIs), which are valuable aids in communication, irrespective of language and behaviour [3, 4]. A significant aspect of this research work is concerned with the detection and comprehension of various mental conditions, such as relaxation and attention, through EEG signals of brain waves. Such conditions can be influenced by certain neurological or psychiatric problems, despite their significance in practical life. [5]The study aims to reveal improved cognitive abilities, including three types of decision-making [(1)]. It will also forecast daily emotions, such as the effects of meditation and work-related stress. [4, 7] Additionally, it will help in diagnosing psychiatric disorders. [6]Recent studies show an increasing tendency to use more efficient methods to reach these goals. Recurrent Neural Networks (RNNs) are particularly good at handling sequential data. Improvements in deep learning have greatly boosted the detection of mental states [2]. However, we can still gain valuable insights from EEG signals using feature-engineering methods like Differential Entropy (DE). [1]

Nonetheless, a major issue in this area is that noisy trials can introduce bias and reduce the quality of signal processing in EEG recordings [2]. This means that more reliable techniques for preparation and processing will be necessary in the future.

A. Data Acquisition

1) Common Problems with EEG Acquisition and Their Fixes

Mental state analysis is based on electroencephalography (EEG) signal acquisition, which is widely favoured due to its non-invasiveness and relative wearability compared to other neuroimaging techniques [2].

However, the lack of a standardized method poses serious problems for the field. In every study that has been reviewed, the EEG signal is essentially utilized as the primary input for prediction and classification models [2, 7]. The primary tactics employed in the literature are as follows:

Diverse Mental States: Research focuses on a wide range of brain activity, from basic Resting States (Eyes-Opened/Closed) [1, 6] to particular, complex Cognitive Tasks (e.g., decision-making during a game [1] or a Baseline/Relaxation Task. [2])

Source Dichotomy: Data is either collected live in highly controlled Primary Experiments with small subject cohorts (e.g., 7 subjects [3]) or used as secondary data from existing databases in order to utilize much larger subject pools (e.g., 945 persons [6]).· Hardware Spectrum: Examples of equipment include low-cost, simplified devices meant for consumer applications [(4)] and standard scalp EEG recording systems. [2]

2) Detailed Protocol Example

To illustrate a rigorous experimental design for mental state identification, the protocol used in paper [1] serves as a comprehensive example: “Fifteen healthy students, all in their early twenties, sat down for EEG recordings. The team used a 64-channel NeuroScan system, snapping up brain signals a thousand times every second.

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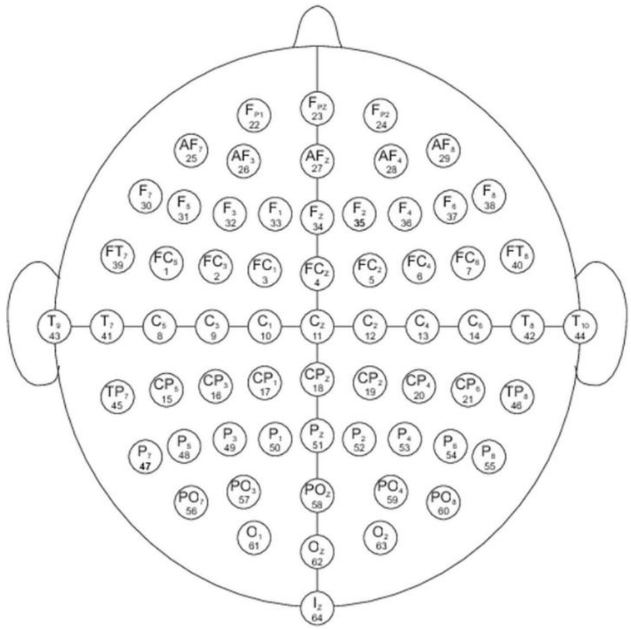

Figure 3. Spatial distribution of the 64-channel EEG electrode configuration

They wanted to see how the brain acts in two situations: just resting (with eyes open or closed), and making tricky decisions in the Ultimatum Game—a classic test where money's on the line. From that game, they got 90 solid decision-making moments to dig into. The researchers didn't mess around with data quality. First, they filtered out noise between 1 and 45 Hz. Then, they ran ICA to strip away stuff like eye blinks or head movements. Any parts of the signal that spiked above 100 microvolts? Gone. In the end, they kept only the cleanest brain signals, so their analysis rested on the clearest possible data.

III. EXTRACTION AND SELECTION OF FEATURES

It is challenging to use EEG signals in their raw form for any classification task because they are intrinsically complex, noisy, and nonstationary.

As a result, the feature extraction stage of EEG processing becomes crucial. The objective is to transform the unprocessed signal into discriminative, structured, and meaningful representations that can emphasize significant aspects of brain activity. Well-established extraction methods that capture temporal, spectral, nonlinear, and connectivity-based information are consistently used in the reviewed studies. underlying brain mechanisms.[1,4,7]

A. Time-Domain

Simple yet powerful statistical insights into the EEG signal are offered by time-domain features. They frequently serve as the foundation for comprehending signal behaviour. Waveform patterns and amplitude variations are summarized by common features like mean, variance, root mean square (RMS), and Hjorth parameters (activity, mobility, and complexity). These features are appropriate for real-time or resource-constrained applications because they are highly interpretable and computationally light. [4,5,7]

B. Frequency-Domain

Because brain rhythms, which range from delta to gamma bands, are directly related to cognitive load, emotional state, and mental processes, frequency-domain analysis is still essential to EEG interpretation. These oscillatory patterns can be extracted using techniques like Power Spectral Density (PSD), absolute/relative band powers, and autoregressive (AR) coefficients. Through their discriminative power, these features have demonstrated strong compatibility with traditional classifiers like SVM and Random Forest, enhancing model performance. [1,5,7]

C. Nonlinearity & Complexity

Nonlinear measures aid in capturing hidden irregularities because EEG signals represent highly nonlinear brain dynamics. Complexity, unpredictability, and structural changes in the signal are commonly measured using metrics such as fractal dimension, approximate entropy, sample entropy, and wavelet entropy. These characteristics are particularly useful for identifying minute changes in mental states that conventional time- or frequency-based metrics might miss. [7,8,12]

D. Time-Frequency

Time-frequency-based representations provide a more comprehensive picture because EEG patterns frequently change quickly over time. Methods such as wavelet entropy, Discrete Wavelet Transform (DWT), and Short-Time Fourier Transform (STFT) record the frequency and timing of specific brain events. Deep learning models, particularly CNNs, can directly use the rich matrices or spectrograms produced by these techniques to extract automated high-level patterns. [1,7]

E. Connectivity

Features of functional connectivity concentrate on the interactions between various brain regions. Synchronized neural activity across channels can be measured using metrics like coherence, phase-locking value (PLV), and correlation coefficients. Deeper modeling of brain networks and inter-regional communication patterns is made possible by numerous studies' conversion of these connectivity matrices into graph structures. [1,2,6]

F. Deep/Learned

Deep learning-based feature learning,in which the model automatically finds the best features from raw or minimally processed EEG data, is becoming more and more important in recent studies. While RNNs/LSTMs effectively learn the temporal progression of brain signals, CNNs capture spatial and spectral patterns. Hybrid CNN–LSTM networks combine both strengths, allowing robust spatial-temporal feature learning without manual hand-crafting. [2,6]

IV. METHODS OF CLASSIFICATION

Following feature extraction, algorithms are used in classification to determine the emotional or mental states connected to the EEG signals. Depending on the complexity and size of the dataset, studies use both sophisticated deep-learning models and conventional machine-learning techniques.

A. Conventional Machine Learning Methods

Due to their stability and efficacy on structured feature sets, traditional classifiers continue to be very successful pertinent. Given the efficacy of Support Vector Machines (SVM) at handling high-dimensional EEG features, they are widely used. Depending on how nonlinear the data is, both RBF and polynomial kernels are used.

By assessing feature importance, Random Forests naturally facilitate feature selection and perform exceptionally well on mixed features (time, frequency, wavelet).

When interpretability and ease of implementation are important, shallow Artificial Neural Networks and simple models like k-Nearest Neighbours (kNN) and Naïve Bayes are utilized. When combined with well-extracted features, these algorithms produce powerful results despite their simplicity.[(4),(5),(7)]

B. Techniques Based on Deep Learning

Deep learning's capacity to automatically recognize intricate patterns has made it an essential part of EEG classification. CNNs are able to identify local correlations, spectral textures, and electrode spatial arrangements from 2D representations such as topographic maps or spectrograms . Long-term dependencies and the sequential nature of EEG signals are well captured by LSTM and RNN architectures. By combining temporal and spatial learning, hybrid CNN–LSTM models generate robust and extremely accurate classifications.

Graph Neural Networks (GNNs), which represent EEG electrodes and their connections as graphs, are used in emerging methods to interpret connectivity features.

Because of their deeper pattern extraction and automatic feature-learning capabilities, deep models consistently outperform traditional methods when paired with appropriate preprocessing and a large amount of training data.[2,6]

V. RESULT

The findings from the experiment show the efficiency of various mental state classification methods using EEG. Among the tests conducted, EEGNet had the highest intra-subject classification accuracy of 88.83% compared to both DE+DGCNN and DE+SVM, with an accuracy of 78.70% and 62.80%, respectively. The highest number of erroneous classifications was made between decision-locked states and between the eyes-open and eyes-closed stages. However, one of the participants had a relatively low classification accuracy since they had too much noise in their EEG signals. The experiment concluded that EEGNet had higher robustness and discriminative power concerning decision-making-related mental states classification compared to various methods in [1].

The model based on RNN performed competitively regarding the complexity of implemented tasks. The accuracy of two-task classification was around 90%, three-task classification was 81%–82%, and with all four cognitive tasks, it was 81%. A linear decrease in mean squared error after 100 epochs during training was observed, implying effective learning Figure 4. Result Outcomes of features relating to EEG-based coherence. These results also affirm that our model based on RNN is comparable with other models for EEG-based classifications described in [2].

Method	Evaluation Metric	Performance Outcome
DE + SVM	Accuracy	62.80%
DE + DGCNN	Accuracy	78.70%
EEGNet	Accuracy	88.83%
RNN Model	Accuracy (2 tasks)	90%
RNN Model	Accuracy (3 tasks)	81–82%
RNN Model	Accuracy (4 tasks)	81%
ICA-Based	Component Similarity	High consistency

For the ICA-based analysis, performance evaluation focused on the reliability of extracting consistent independent components across repeated trials rather than classification accuracy. In fact, there was high similarity in scalp maps and strong correlations between mixing matrices across trials. ICA successfully removed artifacts, and the present task-related EEG pattern proved to be stable, demonstrating that ICA was suitable for reliable feature extraction from EEG prior to classification [3].

VI. DISCUSSION

The results of the literature review demonstrate that deep learning-based techniques outperform conventional machine learning techniques for EEG signal-based mental state classification. When compared to more conventional methods like SVM and Random Forest, models like EEGNet and RNN have attained greater accuracy. This is primarily due to deep learning models' ability to automatically extract significant patterns from EEG data, such as spectral, temporal, and spatial features, without significantly depending on manually created features. It was challenging to identify intricate patterns in EEG signals because previous techniques relied on manually extracting features from time and frequency domains. On the other hand, new developments in deep learning have made it easier to differentiate between overlapping and complex mental states. But there are still difficulties. Misclassification can happen, particularly when mental states like resting and decision-making are extremely similar. These results are crucial for creating brain-computer interface applications and dependable mental health monitoring systems. In addition to increasing accuracy, deep learning aids in automating the process of classifying mental states. To further enhance system performance, problems like poor signal quality and the scarcity of EEG datasets must still be resolved.

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