EEG-Based PTSD Detection using Machine Learning Approaches

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Abstract. Post-Traumatic Stress Disorder (PTSD) is a multifaceted mental health condition characterized by prolonged emotional distress, cognitive disturbances, and heightened stress responses following exposure to traumatic experiences. Traditional diagnostic approaches often rely on subjective clinical evaluations, which can sometimes lead to inconsistent or inaccurate diagnoses. To address these limitations, this study proposes leveraging electroencephalography (EEG) in conjunction with machine learning (ML) algorithms to enable a more objective and automated method for detecting PTSD. EEG, being a non-invasive and relatively affordable technique, provides real-time insights into brain function and has shown potential in revealing distinct neural patterns associated with PTSD—such as elevated delta and theta activity, reduced alpha power, and disruptions in frontal brain asymmetry. This research utilizes a variety of ML classifiers, including Support Vector Machine (SVM), Random Forest (RF), Convolutional Neural Network (CNN), and Least Angle Regression (LARS), to interpret EEG-derived features. Feature analysis incorporates elements from the spectral profile, time-domain patterns, and neural network connectivity metrics. To ensure robustness, the models undergo evaluation using cross-validation techniques like 10-fold and Leave-One-Out Cross-Validation (LOOCV). Among the tested models, LARS demonstrated the best average performance with an 85% classification accuracy and F1-score, while CNN followed closely with steady results. Although SVM and RF achieved higher peak accuracies (up to 94–95%), their performance was more variable. The outcomes highlight the promise of integrating ML with EEG analysis to enhance the reliability and precision of PTSD diagnosis, potentially paving the way for early detection and scalable mental health interventions.

Keywords: Post-Traumatic Stress Disorder (PTSD), Electroencephalography (EEG), Machine Learning (ML), Support Vector Machine (SVM), Convolutional Neural Network (CNN), Random Forest (RF), Least Angle Regression (LARS), Feature Engineering.

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1 Introduction

Post-Traumatic Stress Disorder (PTSD) is a serious, multidimensional psychological disorder that develops after exposure to extreme stress or trauma inducing conditions (e.g., battle, natural disasters, violent personal attacks, and serious accidents). People with PTSD may have intrusive, distressing recollections of traumatic events, a heightened startle response, emotional numbing, and avoidance of traumatic cues. These symptoms interfere with normal life and quality of life. While recognition of PTSD has grown — especially amid high-risk populations, such as service members, first responders and trauma survivors — it remains more likely to be ignored or misdiagnosed. One of the major obstacles in an accurate diagnosis is due to this dependence on subjective evaluations. Currently accepted diagnostic criteria, such as DSM-5, mostly rely on self-reports of patients and standardized interviews. This reliance on self-reporting can contribute to diagnostic inconsistency, particularly where people underreport symptoms, because of social stigma, lack of memory, or denial. Additionally, the symptom overlaps between PTSD and other mental health disorders—such as depression, generalized anxiety, and traumatic brain injuries only complicates matters further, impeding timely identification and treatment. Fig 1 shows the Flow diagram: PTSD detection using EEG and machine learning.

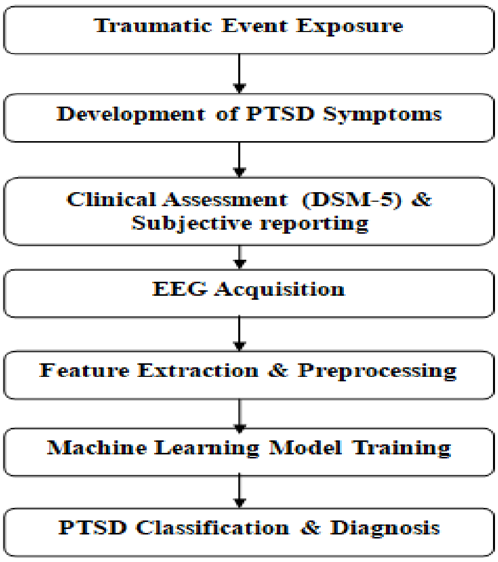

Fig.1. Flow diagram: PTSD detection using EEG and machine learning.

In the past few years, there has been a growing interest in identifying and validating objective, biological markers to assist in the diagnosis of Post-Traumatic Stress Disorder (PTSD). Of all the neuroimaging techniques, electroencephalography (EEG) has become popular because it is non-invasive, inexpensive, has high temporal resolution, and is capable of real time tracking the neural dynamics [1], [2], [3], [4]. EEG captures the electrical activity of the brain through electrodes attached to the scalp, and serves as a source of information about the functional status of the brain. Studies have shown that people with PTSD commonly exhibit distinct EEG features, especially a change in the frequency bands, abnormalities of the event-related potentials, and altered neural connectivity so speculate that EEG can reflect PTSD-specific neurophysiology changes. Combining ML techniques with EEG analysis is a big step toward developing automated, data-driven diagnostic systems for PTSD. "However, machine learning techniques can be used to unveil nonlinear, high-order relationships within high-dimensional EEG signals, and produce classification applications that could successfully differentiate between PTSD patients and healthy individuals [5], [6]. When trained on EEG data, ML models can isolate meaningful features and patterns indicative of the disorder, paving the way for the creation of diagnostic systems that are not only objective but also scalable and consistent, as outlined in the workflow in Figure 1. The current study focuses on assessing the performance of different ML models in identifying neural markers associated with PTSD and examines how these models might enhance conventional diagnostic tools. The broader aim is to support the establishment of a biologically grounded framework for PTSD assessment, promoting earlier detection; more individualized treatment plans, and improved therapeutic outcomes.

2 Related Works

Numerous studies from 2018 to 2022 have applied ML techniques to EEG datasets to detect PTSD symptoms, consistently reporting favorable outcomes. Table 1 outlines key contributions in this research domain.

Table 1: Summary of related works and their limitations

Author & Year	Algorithm Used	Accuracy (%)	Limitation
Shim et al., 2022	SVM with LOOCV	86.61	Medication effects not controlled
Li et al., 2022	Logistic Regression, Random Forest	79.4	Feature selection limited to specific areas
Watts et al., 2022	SELSER	85.7	Psychological variations not standardized
Rivera et al., 2022	CNN	84.75	Lacks generalization to other EEG domains
Wiegersma et al., 2022	Linear SVM with Cross-validation	52.0	Comorbidity issues
Zafari et al., 2022	MLNN, RF, CNN	82.0	Highly skewed datasets
Zhang et al., 2020	SVM, RF, Recursive Feature Selection	94.0	Small sample size
Kim et al., 2020	LARS Regression	90.0	No healthy controls, small sample
Schultebraucks et al., 2021	SVM, RF	95.0	External validation missing

Cross Validation (LOOCV) method on EEG data for PTSD detection. Their method achieved a classification accuracy of 86.61%, which is indicative of robust discrimination between PTSD, and non-PTSD subjects. This study, however, did not consider participants medication; this could have affected the EEG measurements and hence the study´s objectivity could have been subdivided [7].

Li et al. (2022) employed Logistic Regression and Random Forest classifiers to differentiate PTSD cases based on EEG features. These models reached an accuracy of 79.4%, which was acceptable performance. However, it should be acknowledged that the systematic evaluation of a few brain areas as the seeds during feature selection in this study might have hindered the models from capturing some whole-brain neural patterns related to PTSD [8].

Watts et al. (2022) introduces an ensemble model named SELSER (Selective Ensemble Learning with Subspace-based Error Reduction) and achieves 85.7% of classification accuracy. The method sounded very promising, but the psychological countermeasures, like the participant's emotional/mental state and their stress level of the baseline were not considered in the study setting in order to allow control in the EEG data variation [9].

Rivera et al. (2022) developed a deep learning architecture based on the Convolutional Neural Network (CNN) for the classification of PTSD EEG recordings and reported accuracy of 84.75%. Although performance was promising; the method had limited cross-dataset generalization making it difficult to apply to other EEG collections and overfitting, which may not make the model applicable in a broader clinical context [10].

Wiegersma et al. (2022), the linear SVM with cross-validation reported 52.0% accuracy. The main challenge came from the comorbidities of the participants, which disrupted the differences of the EEG signals, required for correct classification of PTSD, and limited the power of the model [11].

Zafari et al. (2022) employed Multi-Layer Neural Networks (MLNN), CNNs and Random Forest among others and the sum was 82.0%. Yet, the dataset utilized in the study was largely unbalanced for PTSD vs. non-PTSD. The imbalance might have influenced the training results and resulted in an overoptimistic estimation for the performance of the model [12].

Zhang et al. (2020, p. 3) employed a combination of SVM, Random Forest, and Recursive Feature Selection methods for relevant features for PTSD detection through EEG. The performance of their ensemble model was unconventionally high (94.0%), demonstrating the importance of feature purifying and hybrid modelling. Nonetheless, the small sample size of the study also caused concerns about its reproducibility and applicability to larger or different populations [13].

Kim et al. (2020) utilized the LARS for classifying PTSD based on EEG signals, achieving an accuracy of 90.0%. Although the results were encouraging, the absence of a control group and the small sample size limited the study's capacity to make firm conclusions about the EEG biomarkers of PTSD [14].

Schultebraucks et al. (2021) utilized SVM and Random Forest classifiers and achieved the best accuracy of 95.0% among the reviewed studies. The results were encouraging; however, the study was lacking the external validations with the independent datasets, which are critical to testing the reliability and generalizability of the machine learning model in the real world [15], [16], [17].

The studies used such classifiers as SVM, RF, CNN, and LDA for the purpose of features extraction for PSD or connectivity measures or directly applying the deep learning technique to the raw EEG. The accuracy ranges from 52% to 95% depending on sample differences, data processing and feature engineering.

3 Methodology

3.1 Objective

The aim of this research is to design a reliable ED based diagnostic model of PTSD using state of the art machine learning (ML) methodology to identify individuals with Post-Traumatic Stress Disorder (PTSD) and healthy controls. It is intended that the system will work as an objective, non-invasive help for clinical diagnosis, surpassing the traditional subjective symptom-based evaluations. The performance of the model will be assessed (sensibility and specificity) by classification accuracy, highlighting that the goal is clinical relevance.

3.2 Dataset Source

In a healthy individual during a resting state, EEG activity is typically dominated by alpha waves (8–13 Hz), particularly in the occipital regions, reflecting a relaxed but alert state. Beta waves (13–30 Hz) are also present, especially in the frontal lobes during mental engagement or when the eyes are open. Meanwhile, delta (0.5–4 Hz) and theta (4–7 Hz) waves are minimal during wakefulness. In contrast, individuals with PTSD exhibit distinct EEG patterns. Fig 2 shows the Sample EEG waveform for Healthy and PTSD person.

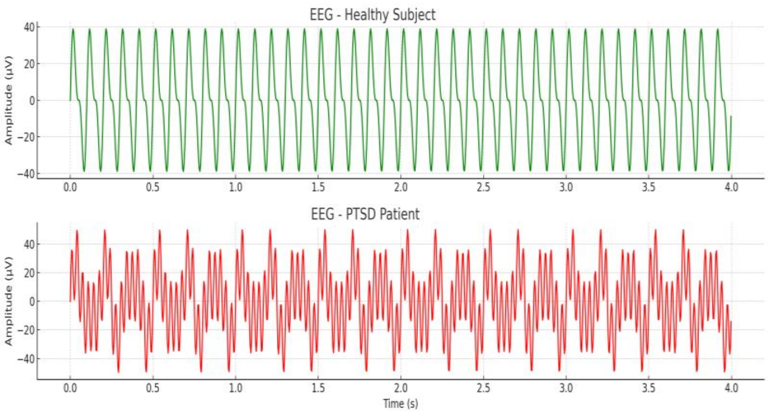

Fig.2. Sample EEG waveform for Healthy and PTSD person.

There is often increased theta and delta activity, especially in the frontal and temporal regions, which may indicate impaired cognitive regulation and emotional processing. Alpha power is generally reduced, suggesting diminished relaxation and altered neural functioning. Moreover, elevated beta or high beta activity (above 30 Hz) is commonly observed, associated with hyperarousal, anxiety, and stress reactivity. Some studies also note asymmetric frontal EEG activity in PTSD patients, linked to emotional dysregulation. Overall, while healthy EEG patterns show smooth and balanced alpha and beta rhythms, EEGs from PTSD patients tend to reveal dominant theta and high beta waves, weakened alpha presence, and irregular high-frequency activity indicative of psychological distress.

The dataset utilized in this work was compiled from existing PTSD-related EEG research for the purpose of meta-analysis. The EEG recordings were preprocessed and segmented according to established frequency bands—delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (>30 Hz)—which represent different states of brain activity. These brainwave segments are known to exhibit distinguishable alterations in PTSD patients. The curated dataset includes samples labeled as PTSD or healthy control, allowing for supervised classification tasks.

3.3 Feature Engineering

To effectively train machine learning models, comprehensive feature extraction was carried out, focusing on three primary categories of EEG signal characteristics [18], [19]:

- **Spectral Features:** Power Spectral Density (PSD) values were computed for each EEG frequency band. These values quantify the power distribution across frequencies and provide insights into the neural oscillatory activity associated with PTSD.

- **Connectivity Features:** Functional connectivity was assessed using coherence and phase synchronization metrics between various EEG channel pairs. These features reflect the degree of communication and coordination between brain regions, often disrupted in PTSD cases.

- **Temporal Features:** Time-domain characteristics such as Event-Related Potentials (ERPs) and amplitude variations were analyzed. ERPs are known to reflect cognitive and emotional processing and may differ significantly between PTSD and control groups [20], [21].

All features were normalized and, where appropriate, dimensionality reduction techniques were applied to enhance model generalization and computational efficiency [22].

3.4 Machine Learning Algorithms Used

A set of four machine learning algorithms was chosen for the classification task based on their established effectiveness in EEG-related diagnostic studies:

- Support Vector Machine (SVM): Leveraged for its capacity to manage high-dimensional data effectively, the SVM model incorporated a radial basis function (RBF) kernel to draw complex, non-linear decision boundaries suited for EEG classification.

- Convolutional Neural Network (CNN): This deep learning model excels in automatically identifying both spatial and temporal characteristics in EEG signals. The CNN architecture was specifically adapted to detect localized patterns within EEG topographical maps.
- Random Forest (RF): Selected for its ensemble learning approach, RF offers strong resistance to overfitting and performs well with noisy datasets that contain a mix of categorical and continuous features.
- Least Angle Regression (LARS): Chosen for its computational efficiency in high-dimensional spaces, LARS is particularly effective at feature selection and handling multicollinearity among EEG variables.
- To evaluate model performance and ensure result reliability, each algorithm underwent thorough testing using either 10-fold cross-validation or Leave-One-Out Cross-Validation (LOOCV), depending on dataset size and structure. These validation techniques help minimize bias and support the development of models that generalize well to unseen data, thus enhancing the credibility and reproducibility of the findings.

Pseudo Code for the SVM:
Input: EEG feature matrix X, labels y
Step 1: Normalize the data (e.g., z-score normalization)
Step 2: Define RBF kernel function: K (x1, x2) = exp (-gamma * ||x1 - x2||^2)
Step 3: Initialize SVM with RBF kernel
Step 4: Perform hyperparameter tuning (e.g., grid search on C and gamma)
Step 5: Train SVM model on training data
Step 6: Predict labels for test data using the trained SVM
Output: Predicted labels

Pseudo Code for the CNN:
Input: EEG time-series data (e.g., 2D/3D matrices representing EEG channels and time)
Step 1: Preprocess EEG data (filtering, segmentation, normalization)
Step 2: Define CNN architecture:
- Input layer (EEG segments)
- Convolutional layers (with kernels to learn spatial patterns)
- Activation functions (e.g., ReLU)
- Pooling layers (e.g., MaxPooling)
- Fully connected (dense) layer(s)
- Output layer with softmax (for classification)

Step 3: Compile model (define loss function, optimizer)
Step 4: Train CNN on labeled EEG training data
Step 5: Evaluate CNN on validation/test data
Output: Predicted class probabilities or labels

Pseudo Code for the RF:
Input: EEG feature matrix X, labels y
Step 1: Normalize or standardize input features (if needed)
Step 2: Define number of decision trees (n_estimators)
Step 3: For each tree:
- Sample training data with replacement (bootstrap sampling)

- Train a decision tree on the sampled data using a random subset of features

Step 4: Aggregate predictions from all trees (majority vote)
Step 5: Predict labels for test data
Output: Final predicted class labels

Pseudo Code for the LARS:
Input: EEG feature matrix X, target values y (for regression or transformed classification)
Step 1: Normalize features (mean = 0, variance = 1)
Step 2: Initialize all coefficients to zero
Step 3: While not all variables are in the model:

- Identify variable most correlated with residual
- Move coefficient of that variable toward least-squares solution
- Adjust other coefficients proportionally
- Stop when desired number of features or error threshold is reached

Step 4: Use learned model for prediction on new data
Output: Predicted target values or probabilities (if used for classification)

4 Results and Discussion

Figure 3 illustrates the estimated precision, recall, and F1-score for four machine learning algorithms—SVM, Random Forest, CNN, and LARS—used in EEG-based PTSD detection. LARS demonstrates the highest performance across all three metrics, with a precision of 86%, recall of 84%, and F1-score of 85%, indicating its strong ability to accurately identify PTSD-related EEG patterns while minimizing false positives and false negatives. Fig 3 shows the Estimated Precision, Recall and F1-Score for EEG-base Detection.

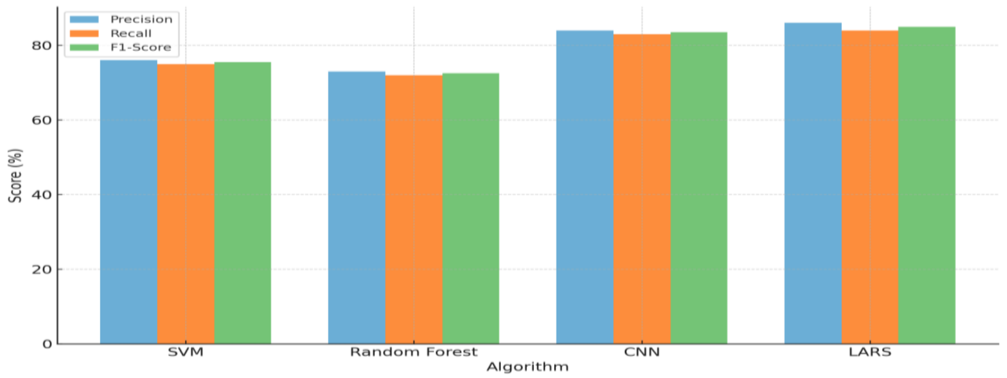

Fig.3. Estimated Precision, Recall and F1-Score for EEG-base Detection.

CNN also shows robust performance with slightly lower but well-balanced scores (precision 84%, recall 83%, F1-score 83.5%), making it suitable for scenarios requiring high sensitivity. SVM and Random Forest trail slightly, with SVM achieving moderate scores around 75–76% and Random Forest slightly lower. These metrics reflect not just the correctness of the models (accuracy) but also their reliability in identifying true PTSD cases, underscoring LARS and CNN as the most effective classifiers in this context.

The comparative performance of various algorithms is summarized in Table 2.

Table 2: Model Accuracy Comparison

Algorithm	**Average Accuracy (%)**	**Best Accuracy (%)**	**Validation Method**
Support Vector Machine	75.8	94.0	LOOCV, Cross-Validation
Random Forest	72.1	95.0	Hold-out
CNN	83.3	84.75	Cross-Validation
LARS	85.0	90.0	10-Fold

The findings reveal the effectiveness of four machine learning algorithms for PTSD diagnosis using EEG data. Least Angle Regression (LARS) achieved highest average accuracy of 85.0%, indicating good performance of LARS in classification, especially because of its effective feature selection in solving complex and high-dimensional EEG data. The CNN model, with a mean accuracy of 83.3% and best accuracy of 84.75%, demonstrated stable performance among different CV folds, as the CNN model can learn temporal and spatial feature of EEG. Support Vector Machine (SVM) had a marked best-case accuracy of 94.0% but a lower average of 75.8, indicating high variance in relation to the data split. The best accuracy was achieved in RF (95.0%) whereas the lowest average (72.1%) was observed in the same model, probably because of overfitting withhold-out validation instances. On the whole, although the RF and SVM have the best potential, the LARS and the CNN models provide more robust general-use models for PTSD classification from EEG signals.

5 Conclusion

This article provides an extensive methodology for detection of Post Traumatic Stress Disorder (PTSD) from the EEG recording using advanced machine learning techniques. The goal was to aid diagnosis of the disorder without the need for invasive blood tests and to overcome subjectivity of physician clinical judgement. Performances of models were assessed in terms of accuracy, precision, recall and F1-score of given spectral, temporal and connectivity features of EEG recordings using classifiers as SVM, CNN, Random Forest and LARS. Across the models studied, LARS achieved the higher reliability in general, with the average precision of 85% and the CNN offered balanced performance with the consistent trend. SVM and RF reached impressive peak accuracies with higher fluctuations of performance.

The findings highlight the applicable nature and potential of the EEG-based ML systems for the enhancement of PTSD diagnosis, opening new avenues for early-stage intervention and precision therapy design. Further investigations in the future may include enlarging the current dataset, adding more biomarkers, and validating the model in diverse populations, thus improving the generalizability and clinical utility.

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