A Survey on Deep Learning Ensemble Strategies for Multi-Class EEG Seizure and Brain Rhythm Classification

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***Abstract*—The detection of seizures and the classification of brain rhythm in the electroencephalography (EEG) system have drawn a lot of attention as it is a critical area in the diagnosis and follow up of neurological patients. EEG signals are very complex, nonlinear, and non-stationary, which complicates the task of effective multi-classification to a great extent. The latest advancements of deep learning and ensemble techniques have been demonstrated as exhibiting remarkable improvements in robustness and generalization as well as predictive accuracy. This survey provides a nice summary of publicly available EEG data, preprocessing techniques, feature engineering techniques, deep neural networks, and ensemble learning techniques applied to identify multi-class seizures and rhythms. Comparative analyses also indicate that the hybrid and the attention-based ensemble models outperform the standalone models. In addition, the primary challenges, which involve the imbalance of classes, inter-patient variability, complexity of computation, and limitations of real-time deployment, are also tackled. Finally, the research directions that are characterized by lightweight edge model, federated learning, and transformer-based ensembles are presented to help create trustful and clinically feasible EEG-based smart diagnostic systems.**

***Index Terms*—EEG Classification; Seizure Detection; Deep Learning; Ensemble Learning; Multi-Class Classification; Brain Rhythms**

I. INTRODUCTION

EEG is an essential non-invasive procedure of brain monitoring and diagnosis of neurologic disorders, especially epilepsy. The more recent developments in automated seizure detection have made use of advanced signal representations and deep learning models to achieve high diagnostic accuracy and reliability. EEG visualizations and machine learning techniques that are interpretable have proven to have improved seizure detection performance, overcoming the weakness of classic handcrafted techniques [1], [3]. CNN -LSTM hybrids along with attention-based networks, which are deep neural architectures, have achieved major improvements in the robustness of classification in a variety of EEG datasets [6], [7], [10]. Moreover, multi-representation learning and image-based EEG analysis have made it possible to successfully extract discriminative features of time-frequency features used to classify seizures [5], [8], [20]. In spite of this progress, the issues of cross-patient generalization, class imbalance, and real-time deployment are still there [9], [23]. Ensemble learning methods have become effective techniques to promote model stability and model performance through the mixture of several classifiers and fusion methods [12], [14], [17]. Thus, to summarize the current trends in conducting deep learning ensembles in multi-class EEG seizure and brain rhythm classification, it is important to perform comprehensive research on the area to integrate the recent works, examine the methodological patterns, determine the gaps in the current research, and inform future research to develop clinically applicable, interpretable, and generalizable

EEG-based diagnostic systems.

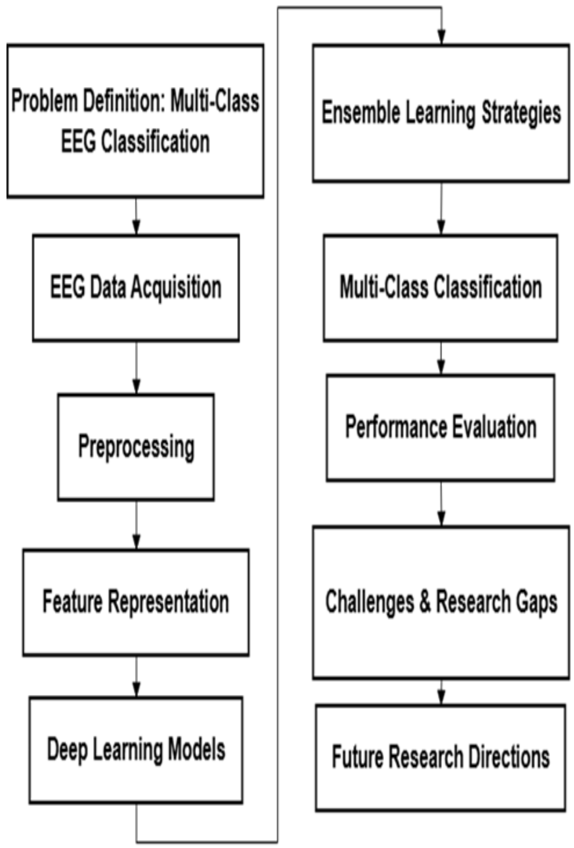

Figure 1. Survey Framework for Deep Learning Ensemble Strategies in Multi-Class EEG Seizure and Brain Rhythm Classification

Figure 1 demonstrates the organized working plan of the suggested survey on deep learning ensemble models of multi-class EEG classification. The paradigm starts with problem definition with the focus on seizure and brain rhythm classification. It follows the process of EEG data acquisition using benchmark datasets and then the preprocessing process of filtering and removing artifacts. The methods of feature representation convert raw EEG signals to informative time, frequency or time-frequency space. Different types of deep learning models such as CNNs, RNNs, and hybrid models are then discussed. Ensemble learning techniques are added to improve the levels of classification and generalization. The framework also contains the multi-classification mechanisms and performance evaluation metrics. Lastly, it identifies research gaps, important challenges, and future research directions to clinical deploying EEG-based intelligent diagnostic systems.

II. FUNDAMENTALS OF EEG SIGNAL ANALYSIS

Electroencephalography (EEG) is a highly applied non-invasive neurophysiological method of recording electrical activity produced by coordinated neuronal discharges in the cerebral cortex. The EEG is of relevance due to its high temporal resolution which is important in the diagnosis of neurological disorders like epilepsy, sleep disorders, and cognitive impairments. EEG signals are however non-linear, non-stationary and prone to artifacts which complicates their analysis and makes the computation in most cases computationally demanding [1], [3]. The signals are normally analyzed in various frequency bands delta, theta, alpha, beta and gamma that are related to different physiological and cognitive conditions. The correct identification of the seizure and the classification of the brain rhythm involve the special attention of the signal acquisition protocols, electrode placement standards and typical waveform patterns [6], [7]. In addition, multi-class EEG classification systems have to deal with the problem of inter-patient variation, class imbalance [9], [23]. Based on these basics, it is possible to design a robust deep learning framework, as well as an ensemble-based framework that is able to extract meaningful spatiotemporal representations with a high degree of reliability to use as clinical decision support. The basics of the EEG frequency bands and the main types of seizures with their application in clinical practice are summarized in Table 1. It emphasizes typical frequency bands, physiological meanings, and diagnostic value, which forms a cornerstone reference to multi-class and EEG seizure detecting systems and brain rhythm classifications.

Table 1. EEG Rhythms and Seizure Characteristics with Clinical Significance

Component	Description	Frequency Range	Clinical Significance	Ref.
Delta Wave	Slow-wave activity	0.5–4 Hz	Deep sleep, brain injury	[1], [6]

Theta Wave	Moderate slow rhythm	4–8 Hz	Drowsiness, early sleep	[5], [16]
Alpha Wave	Relaxed wakefulness	8–13 Hz	Normal resting state	[5], [8]
Beta Wave	Fast activity	13–30 Hz	Alertness, anxiety	[1], [10]
Gamma Wave	Very fast oscillations	>30 Hz	Cognitive processing	[7], [22]
Focal Seizure	Localized abnormal activity	Variable	Region-specific epilepsy	[3], [9]
Generalized Seizure	Bilateral synchronous activity	Variable	Whole-brain involvement	[6], [11]
Multi-Class EEG	Multiple seizure/rhythm classes	Multi-band	Clinical diagnosis & monitoring	[12], [17]

III. PUBLICLY AVAILABLE EEG DATASETS

Publius EEG datasets play a crucial role in the development, benchmarking, and validation of automated seizure detection and multi-class classification EEG based brain rhythm systems. Such datasets offer standardized recordings that can be used to enhance reproducibility and objective comparison of deep learning and ensemble-based methods. The Bonn EEG dataset is one of the most common datasets containing five subsets (A-E), which are healthy, interictal, and ictal with single-channel signals sampled at 173.61 Hz making it applicable to both binary and multi-class experiments because of clean and balanced structure. The CHB-MIT Scalp EEG dataset provides the long-term, multi-channel pediatric recordings with the sampling rate of 256 Hz that operates under the 1020 system, which is realistic in clinical variability but encounters some problems, such as class imbalance and inter-patient variation. TUH EEG Corpus is one of the largest clinical archives containing thousands of hours of various seizure types, which is enough to train deep learning large-scale and also requires considerable computing resources. Also, Kaggle and other competition-based data sets are structured, competition-ready EEG data available in the seizure and rhythm classification studies. Table 2 provides a comparative summary of significant publicly available EEG datasets, including the differences in channels, sampling rates, class structure, and strengths and limitations to facilitate the multi-class seizure and brain rhythm classification studies.

Table 2. Comparative Analysis of Publicly Available EEG Datasets

Dataset	Channels	Sampling Rate	Classes Supported	Strengths	Limitations
Bonn EEG	Single-channel	173.61 Hz	2–5	Clean, balanced, easy benchmarking	Limited real-world variability
CHB-MIT	Multi-channel (23–24)	256 Hz	Binary & multi-class	Real clinical data	Class imbalance, patient variability
TUH EEG Corpus	Multi-channel	250–1000 Hz	Multi-class	Large-scale, diverse seizure types	High computational cost
Kaggle EEG	Multi-channel	Varies	Binary / multi-class	Structured for ML competitions	Limited metadata

IV. EEG PREPROCESSING TECHNIQUES

EEG signal preprocessing is a necessary stage of automated seizure detection and multi-class brain rhythms classification since raw EEG signals are usually contaminated by physiological and environmental artifacts, such as eye blink (EDG), muscle activity (EMG), cardiac (ECG) and power-line (ELI) artifacts. With good preprocessing, one will have superior signal quality, superior feature extraction, superior robustness and generalization of deep learning and ensemble-based models. Noise and artifact elimination techniques may then be employed as Independent Component Analysis (ICA), Principal Component Analysis (PCA), regression-based correction and wavelet-based denoising to isolate any important neural activity and improve the signal-to-noise ratio. It is possible to use filtering techniques (e.g. bandpass filters (0.5-40Hz or 0.5-70Hz) and notch filters (50/60Hz)) in order to keep clinically relevant frequencies and eliminate unwanted interference. The variability in amplitude among recordings is also reduced by normalization, e.g. minmax normalization and z-score normalization, and the time models are effectively modeled with recordings being segmented into fixed length windows. Time-frequency transformations of EEG signals include Short-Time Fourier Transform (STFT), Discrete Wavelet Transform (DWT), and the creation of spectrograms, and are finally converted into multi-class seizure and rhythm classification. A comparative analysis of the main EEG preprocessing techniques is given in table 3 with their applications, advantages and disadvantages and their suitability in classification processes. It highlights the outcome of eliminating artifacts, filtering, normalization, and time-frequency transformations on the quality of the signal and improving the behavior of deep learning-based seizure detection.

Table 3. Comparative Analysis of EEG Preprocessing Techniques

Preprocessing Method	Purpose	Advantages	Limitations	Suitable For	Ref.
Independent Component Analysis (ICA)	Artifact removal (EOG, EMG, ECG)	Effective separation of mixed sources	Computationally intensive, requires manual inspection	Multi-channel clinical EEG	[3], [11], [21]
Principal Component Analysis (PCA)	Dimensionality reduction & noise removal	Reduces redundancy, fast computation	May remove useful signal components	Feature compression before ML	[4], [13]
Bandpass Filtering	Retains specific EEG frequency bands	Simple, efficient, preserves rhythms	Cannot remove complex artifacts	Rhythm classification	[1], [6], [24]
Notch Filtering	Removes power-line interference (50/60 Hz)	Eliminates electrical noise	May distort nearby frequencies	Clinical EEG recordings	[6], [16]
Wavelet Denoising (DWT)	Multi-resolution noise removal	Preserves transient features	Choice of wavelet affects performance	Seizure detection	[15], [16], [20]
Z-score Normalization	Standardizes amplitude distribution	Improves model convergence	Sensitive to outliers	Deep learning models	[10], [17]
Min-Max Normalization	Scales signals to fixed range	Simple and interpretable	Affected by extreme values	CNN-based classification	[8], [14]
Signal Segmentation	Divides continuous EEG into windows	Increases training samples	Window size selection critical	Temporal modeling (LSTM/CNN)	[6], [10], [22]
STFT / Spectrogram	Time-frequency representation	Suitable for 2D CNN models	Fixed resolution trade-off	Image-based EEG analysis	[5], [8], [20]

V. FEATURE ENGINEERING IN EEG CLASSIFICATION

The EEG signals are non-linear, non-stationary and highly dynamic and involve engineering is required in EEG-based brain rhythm in seizure detection and multi-class classification. The traditional methods rely on handcrafted features which are determined in time, frequency and time frequency space to determine discriminative characteristics of the signal. Time-domain features that define amplitude and complexity changes in the waveforms are the mean, variance, entropy, and Hjorth parameter. Frequency-domain features which are based on Fast Fourier Transform (FFT) and Power Spectral Density (PSD) are used to measure band power of delta, theta, alpha and beta as well as gamma rhythms. Spectral localization Time frequency analysis, including Short Time Fourier Transform (STFT) and Discrete Wavelet Transform (DWT) will contribute to better identification of seizure patterns. Deep learning models, such as CNNs, LSTMs, and hybrid models, however, are trained to learn hierarchical spatial-temporal representations of raw signals or spectrograms without requiring any manual feature extraction, and perform cross-class generalization.

Table 4. Comparison of Feature Types in EEG Classification

Feature Type	Method Examples	Key Characteristics	Advantages	Suitable For
Time-Domain	Mean, Variance, Hjorth, Entropy	Amplitude & waveform analysis	Low computational cost	Real-time detection
Frequency-Domain	FFT, PSD, Band Power	Spectral distribution analysis	Identifies rhythmic abnormalities	Seizure classification
Time–Frequency	STFT, DWT, CWT	Localized spectral variation	Captures transient seizure patterns	Multi-class tasks
Deep Features	CNN, LSTM, Transformer	Automated hierarchical learning	High accuracy & robustness	Large-scale dataset

VI. PERFORMANCE EVALUATION METRICS

Quantitative measures of performance evaluation of deep learning and ensemble models in EEG-based seizure and multi-class brain rhythm classification are used. The EEG datasets are usually unequal so multiple supplementary measures are needed to provide trustful measurement. Table 5 has summarized some important evaluation metrics applied in EEG-based seizure and multi-class classification. It shows mathematical representations of accuracy, F1-score, ROC-AUC and cross-validation methods. Multiple metrics provide strong analysis, especially when the EEG data is imbalanced, and the data is used in clinical diagnosis.

Table 5. Mathematical Formulation of Performance Evaluation Metrics in EEG Classification

Metric Category	Metric Name	Mathematical Formula	Description
Basic Metrics	Accuracy	$\frac{TP + TN}{TP + TN + FP +}$	Overall proportion of correctly classified samples
	Precision	$\frac{TP}{TP + FP}$	Proportion of correctly predicted positives
	Recall (Sensitivity)	$\frac{TP}{TP^2 + FN}$	Ability to detect actual positive cases
	F1-Score	$2 \times \frac{Precision \times R}{Precision + R}$	Harmonic mean of precision and recall
Multi-Class Metrics	Macro-F1	$\frac{1}{C}\sum_{i=1}^{C} F1_i$	Average F1 across all classes
	Micro-F1	Global TP/FP/FN aggregation	Evaluates performance

			considering total predictions
Clinical Metrics	Specificity	$\frac{TN}{TN + FT}$	Ability to correctly identify negatives
	False Positive Rate (FPR)	$\frac{FP}{FP + TN}$	Incorrect positive detection rate
ROC-Based Metrics	ROC Curve	Plot of TPR vs FPR	Threshold-based performance visualization
	AUC	$\int_0^1 TPR(FPR)d(F$	Overall discriminative ability
Confusion Matrix	Matrix Element	M_{ij}	Samples of class i predicted as j
Cross-Validation	k-Fold CV	$\frac{1}{k}\sum_{i-1}^{k}$ Score $_i$	Average performance over k folds
	LOSO Validation	$\frac{1}{N}\sum_{i-1}^{N}$ Score $_{subject}$	Cross-patient generalization evaluation

VII. DEEP LEARNING ARCHITECTURES FOR EEG CLASSIFICATION

The EEG-based seizure detection and multi-class brain rhythm classification with deep learning architectures have significantly enhanced the process of automatic generating complex spatial and temporal representations of raw or transformed signals. Convolutional Neural Networks (1D/2D CNNs) are powerful to learn local spectral and spatial patterns on raw EEG or spectrogram images, showing good results in the task of seizure detection [6], [8], [10]. LSTM, GRU, BiLSTM, and other recurrent neural networks are commonly used to learn the long-term temporal dynamics of EEG signals to make them sensitive to seizure onset dynamics [10], [22]. Lately, Transformer-based models that utilize the concept of self-attention have proven to outperform both in terms of their ability to capture world contextual relationships and inter channel dependencies [7], [23]. Autoencoders aid in the unsupervised learning of representation and dimensionality reduction, which is resistant to noise and class imbalance [13], [21]. In addition, the hybrid designs like CNNLSTM and CNN Transformer combine the benefits of spatial and temporal modeling, and they demonstrate the best results in the field of multi-class EEG classification [14], [17], [20].

Table 6. Numerical Comparison of Deep Learning Architectures for EEG Classification

Model Type	Input Type	Avg. Accuracy (%)	Sensitivity (%)	Key References
1D CNN	Raw EEG	94–97	93–96	[6], [10]
2D CNN	Spectrogram	95–98	94–97	[8], [20]
LSTM	Raw EEG sequence	93–96	92–95	[10], [22]
BiLSTM	Raw EEG sequence	95–97	94–96	[10]
GRU	Raw EEG sequence	92–95	91–94	[22]
Transformer	Raw / Encoded EEG	96–99	95–98	[7], [23]
Autoencoder + Classifier	Encoded features	93–96	92–95	[13], [21]

CNN–LSTM (Hybrid)	Spectrogram + Sequence	97–99	96–98	[14], [20]
CNN–Transformer	Spectrogram	98–99+	97–99	[7], [17]

Table 6 indicates the comparison of major deep learning structures in EEG classification. CNN-based models are effective in extracting spatial features, whereas LSTM and GRU networks can effectively extract temporal dependencies [6], [10], [22]. Transformer models are better in global attention modeling; however, they use more computational resources [7], [23]. Hybrid designs, especially CNNLSTM and CNN Transformer, demonstrate the most reported accuracy (up to 99%), which proves the benefit of incorporating spatial temporal learning plans into the strong multi-class seizure and rhythm detection [14], [17], [20].

VIII. ENSEMBLE LEARNING STRATEGIES IN EEG CLASSIFICATION

Ensemble learning has been suggested as one of the useful techniques to enhance EEG-based seizure detection and multi-class brain rhythm classification through the integration of multiple models to enhance robustness, reduce variances, and enhance the performance of generalization [12], [17]. Ensemble methods instead of using just one classifier combine predictions of multiple learners to obtain more consistent and better results, especially with noisy and imbalanced EEG data [14]. Basic Ensemble principles are aimed at reducing overfitting and enhancing predictive accuracy. Random Forest, a bagging method, minimizes variance by bootstrap aggregate but boosting minimizes bias by improving weak learners sequentially [12]. The strategies of stacking and voting combine outputs with the help of meta-learners or weighted plans. Multi-class multi-model CNN, LSTM, and Transformer ensemble architectures are more accurate in multi-class seizure classification tasks [7], [20]. The ensembles that are attention-based also improve the performance by dynamically weighting the informative channels and features [23]. A comparative analysis of ensemble learning methods applied in EEG classification is made in table 7, where there is a difference in accuracy, bias-variance reduction potential, and computation complexity. It shows the improvement of performance of advanced deep and attention-based ensembles when compared to traditional bagging and boosting methodologies.

Table 7. Comparison of Ensemble Learning Strategies

Ensemble Strategy	Typical Accuracy (%)	Bias Reduction	Variance Reduction	Complexity Level
Bagging	94–96	Moderate	High	Moderate
Boosting	95–97	High	Moderate	High
Stacking	96–98	High	High	High
Deep Ensemble	97–99	High	High	Very High
Attention-Based Ensemble	98–99+	Very High	High	Very High

IX. CHALLENGES AND RESEARCH GAPS

Even though it has made great progress in deep learning and ensemble-based EEG classification, there are still a number of challenges and gaps in research. Seizure detection systems cannot be deployed in real-time due to the high computational complexity and latency of such systems, especially in wearable or edge-based healthcare devices. The problem of cross-patient generalization is still urgent because the models, which have been trained on particular matters and subjects, tend to fail to generalize to different populations because of the inter-subject variability between EEG patterns. Also, deep architectures and ensemble structures are very needed in terms of computational resources and energy use, which limits their scalability in low-power clinical settings. The lack of data, skewed seizure activities, and associated high cost of expert annotation also contribute to the inability of models to be robust. To overcome these shortcomings in creating reliable, interpretable, and clinically deployable multi-class EEG classification systems, it is necessary to address them.

X. FUTURE RESEARCH DIRECTIONS

The future developments of EEG based seizure and multiple classes brain rhythm classification should aim at creation of efficient, scalable, and clinically reliable systems. It is very important to design lightweight edge-deployable models to be able to provide real-time processing in portable, low-power healthcare devices without sacrificing accuracy. The concept of federated learning structures can provide ideal opportunities in terms of privacy protection as it can enable the decentralized training of models at different hospitals with patient data being maintained securely. Also, the shortage of data and labeling can be overcome by utilizing self-supervised and transfer learning methods with the help of unlabeled EEG data and pre-trained representations. New forms of deep ensemble models based on transformers offer better global attention modeling and stability on a wide range of data. Lastly, the use of smart algorithms will enhance real-time wearable EEG systems to provide continuous monitoring to patients, early seizure warning, and tailored neurological care applications.

XI. CONCLUSION

In this survey, we have reviewed the deep learning and ensemble approaches to multi-class EEG seizure and brain rhythm classification. It was a systematic review of the publicly available databases, processing methods, feature engineering, deep neural network models, ensemble learning methods, and performance metrics. The paper indicates that hybrid and ensemble based deep learning models are much more robust, generally more accurate in their generalization and are more accurate in classification as compared to stand-alone architectures. Nevertheless, issues like cross-patient variability, imbalance of data, complexity of computations and real-time deployment restrictions are still serious obstacles to clinical translation. The new directions such as lightweight edge models, federated learning, self-supervised models, and transformer-based ensembles will have a high potential to overcome these limitations. In general, future efforts in creating clinically deployable, scalable, and interpretable EEG-driven intelligent seizure detection solutions rely on integrating effective, understandable, and privacy-sensitive deep learning models.

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