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Literature Review: Seizure Prediction Using Machine Learning

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***Abstract* - This literature review explores advancements in Prediction of Epileptic Seizures with Machine Learning model and Deep Learning techniques. The unpredictability of epileptic seizures serious difficulties to patient safety and quality of life recent the research makes use of EEG-based feature extraction and classification. The models and hybrid deep learning architectures recognize states Traditional machine learning approaches, such as SVM. Have worked well with engineered features, Random Forest CNN and LSTM models can reach more accurate results by learning create sophisticated rhythmic and color designs from EEG data. Important artifacts still remain despite some removal activity imbalanced dataset, personalization, and real-time deployment. This key methodologies, comparative performance, review highlights Interpretation and progress aimed at creating sturdy and practical seizure prediction systems.**

Keywords: EEG, seizure prediction, machine learning, deep learning, CNN, LSTM.

I. INTRODUCTION

Around the world, there are 65 million people with epilepsy More than thirty percent of patients have drug-resistant epilepsy. This can't be remedied by either surgery or drugs. The unpredictable nature of seizures significantly affects quality. Life can spark psychological effects like anxiety risk of death in depression-related illness Seizure pre. Diction systems try to identify the preictal state loss of consciousness and its start using the use of medicine or stimulation. [4]. Machine learning approaches have emerged as promising. Seizure prediction tools that use EEG Using EEG signals to detect preictal patterns [5][6]. EEG is the. The most commonly used method to monitor seizures is its. The signals are complex but shows high temporal resolution three-dimensional, often noisy and corrupted by artifacts such as. Eye blinks and muscle movements. The preictal period usually happens 5-90 minutes before the seizure starts. The brain's electric activity changes during different states using different signal processing methods. [1][7] Accurate making predictions call for careful assessment of key difficulties in the use of feature. Remove noise using machine learning algorithms between preictal and interracial states, and management of temporal dynamics in seizure generation Classical machine learning. We first used some machine learning methods for fixed camera traffic estimation but with hand labeled data Engineers features while the latest approaches use them Deep learning models automatically learn through CNNs and RNNs that makes use of LSTM based on data discriminative patterns [6][8].

II. FEATURE EXTRACTION TECHNIQUES

Feature extraction is fundamental to seizure prediction, transforming raw EEG signals into quantitative metrics that capture preictal characteristics. Researchers have employed both handcrafted and automated feature extraction approaches.

A. Handcrafted Features

Time-domain features in Statistical measures of the EEG waveform such as signal amplitude variance entropy skewness kurtosis line length [5]. Messaoud and Chavez [4] implemented a comprehensive. A set of 25 feature types were selected through Recursive Feature Elimination. Their approach in Included statistical features like mean and variance Petrosian Fractal Dimension, Higuchi Fractal Dimension, and Hjorth parameters (mobility, complexity). Common time-based features like signal strength and disorder. Summary of different types of classification and con Man-made machine learning pipelines [5], yet these handcrafted. Some features may not capture complex temporal dynamics dynamics of seizures Spectral and Time-Frequency Features. Features in the spectral domain offer more expressive representations of EEG dynamics.

Messaoud and Chavez [4] incorporated. The spectral features in different frequency bands were collected, which were delta (0.5–4. Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz) and. gamma (30-60 Hz). Additionally, they included bivariate features liable to test procedures and visual fouti resulting in a dimension feature space 735 Batista et. Al., the EPILEPSY dataset was used by Costa et. al. [2] to extract 59 features. SIAE database. Their frequency-domain features encompassed. The overall and relative power of eight frequency ranges bands, spectral edge frequency, mean

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frequency. Time wavelet decomposition was used to perform frequency analysis with Daubechies 4 wavelet to derive wavelet coefficient energy [2]. Basri and Arif [9] extracted frequency-domain. Applying FFT to EEG montage signals enhances features. Ibrahim and others used MODWT to break EEG signals into more than one subband (theta, alpha, beta, gamma) to capture transitory oscillations.

B. Automated Feature Extraction

Deep learning approaches enable automated feature learning directly from preprocessed signals. Usman et al. [1] employed a Convolutional Neural Network (CNN) architecture with three convolutional layers: the first layer applied 16 filters of size 5×5, followed by 32 filters of 3×3 in the second layer, and 64 filters of 3×3 in the third layer. Each convolutional layer utilized rectified linear unit (ReLU) activation functions and was followed by batch normalization and max pooling with 2×2 kernels. This architecture required 32,576 trainable parameters and automatically extracted hierarchical features from Short-Time Fourier Transform (STFT) preprocessed signals [1]. Many recent deep learning approaches convert EEG into spectrogram images or multiscale wavelet bands so that CNNs can automatically learn spectral-temporal representations [5][8].

The automated approach addresses limitations of handcrafted features by learning discriminative patterns with class information incorporated during training, potentially achieving higher inter-class variance. However, handcrafted features offer greater interpretability and require less computational resources and training data [4].

III. CLASSIFICATION METHODS

The classification algorithms in reviewed studies range from traditional machine learning classifiers to deep neural networks.

A. Traditional Machine Learning Classifiers

Support Vector Machines and Random Forest Support Vector Machines (SVM) have been widely adopted for seizure prediction due to their effectiveness with high-dimensional data and ability to find optimal separating hyperplanes. Messaoud and Chavez [4] compared five classifiers—Random Forest, SVM, k-Nearest Neighbors, Multilayer Perceptron, and AdaBoost—finding Random Forest superior with 82.07% sensitivity and 0.0799 false positive rate per hour (FPR/h). Their implementation used ensemble learning with 31 trained classifiers and applied systematic random undersampling to address class imbalance.

Basri and Arif [9] applied a Random Forest classifier on FFT-derived feature vectors to distinguish three seizure types from normal EEG. Their RF ensemble achieved high accuracy (approximately 96%) in classifying generalized, focal, and complex-partial seizures. Batista et al., [2] employed SVM with linear kernel for classification, implementing Leave-One-Out Cross-Validation for parameter optimization. They explored combinations of feature counts (10, 20, 30, 40) and regularization parameters (C ranging from 2−10 to 210), selecting optimal parameters through grid search.

B. Deep Learning Approaches

Convolutional Neural Networks, Ibrahim et al. [8] employed a multiresolution one-dimensional CNN architecture. They designed parallel 1D-CNNs, one per wavelet-derived subband, whose outputs were fused and fed to a softmax layer to discriminate "preseizure" (preictal) versus normal states. This model was trained in a patient-specific manner without crosspatient testing and did not rely on hand-engineered features. CNNs applied to raw EEG, spectrograms, or spatial channel maps excel at learning spatial/spectral patterns. Recurrent Neural Networks, especially LSTMs, are noted for capturing temporal dependencies in EEG. Other advanced models mentioned in the literature include hybrid CNN–Transformer networks and graph neural networks.

C. Hybrid Approaches

Usman and the other authors proposed a combined method CNN-based automatic feature extraction with SVM classification. The CNN layers extracted hierarchical features from. EEG data processed with STFT was flattened and passed to a linear SVM classifier. This approach achieved 92.7 sensitivity and specificity of 90.8The possible advantages of combining deep learning features extraction with interpretable classification methods. Deep Learning Approaches Convolutional Neural Networks. A multiresolution one-dimensional approach was used by Ibrahim et al. [8] CNN architecture. They designed parallel 1D-CNNs, one per. The output from the wavelet derived sub-band was combined and sent to a soft max layer to distinguish between a pre-seizure (preictal) conditions versus normal states [8]. This model was trained in a patient method that didn't rely on cross-patient testing on hand engineered features [8]. CNNs applied to raw EEG Spatial channel maps or spectrograms can learn spatial/spectral patterns [5][8]. Recurrent Neural Networks, especially LSTMs, are known for capturing temporary dependencies. In EEG [5] other advanced models mentioned in the literature utilize combination CNN-Transformer network and graph neural networks [5]. Usman et al. proposed hybrid approaches in [1]. Combining automatic feature based on CNN extraction with SVM classification. The CNN layers

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extracted was totally, hierarchical features that were from. They then flattened the image and fed it into a linear SVM classifier. This method produced an astounding 92.7 outcome extracting Features Using Deep Learning Techniques methods [1].

IV. POST-PROCESSING TECHNIQUES

Methods of post-processing have a strong influence on the performance of the predictions time conditions and preventing false alarms. Messaoud and Chavez [4] introduced. After threshold sustainability and mechanisms to control artifacts, predictions shall persist for n* continuous cycles exceeding limit T* while keeping a least ratio of artifact-free epochs. This strategy helped cut down false alarm rates considerably sensitivity. Batista et al. offered new post processing methods based in time sequences of brain activity events. Their Cumulative Firing Power approach assumed seizures are the outcome of overlapping events of varying duration combined Firing strength over various time frames. This methodology achieved statistical. Compared to the 49[2].

V. CHALLENGES IN SEIZURE PREDICTION

A. Data Quality and Artifact Management

Artifact contamination spoils prediction performance EEG data are often high-dimensional, noisy, and Cell is affected by various artifacts such as muscle tremors and electrical interference Changes in electrodes, eyes, and muscles. Messaoud Chavez were the first to develop automated artifact rejection. Autoreject algorithm thresholding and global computing thresholds per recording file and inclusion of artifact control into alarm-raising mechanisms. Batista et al. [2] used deep learning. Automated artifact removal using convolutional neural networks. Before extracting the feature, share expert manual data processing. According to Ibrahim et al. [8], however, this method worked using raw EEG without any artifact removal and acknowledges. Separating and removing artifacts will remain for future work. Removing artifacts in real-time is a challenge practical systems.

B. Class Imbalance

The seizure prediction system shows class imbalance there are a lot low probability events going on nowadays. EEG Limited preictal data leads to imbalance and complicates. Model training [5]. Basri and Arif [9] applied oversampling. And down sampling techniques to (e.g. SMOTE, ADASYN). Fix the big class imbalance in the EEG at Temple University dataset. Messaoud and Chavez [4] used systematic random Reducing Samples of Preictal and Interracial Classes training.

C. Preictal Heterogeneity and Personalization

Substantial variation preictal is a major challenge. Duration and experiences differ across patients and even between Seizures occurring in the same patient. Seizure was tested by Batista et al. Occurrence Periods (SOP) ranging from 10–55 minutes with. Average optimal values are required to be found under 30 minutes but with a high standard deviation reflecting inter-patient variability. Personalization methods can help improve performance. Messaoud and Chavez [4] demonstrated sensitivity increased to 82.07After patient-specific calibration, the false positive rate came out to be 89.31reduction from 0.0799/h to 0.03/h. However, personalization requires sufficient patient to increase algorithm complexity specific data for training.

D. Generalization and Cross-Patient Validation

On patient-specific models many high-performance learnt. This data may not have a strong correlation to another individual. The lack of “differences in recording conditions on dependability” Electrode placement and sampling rate affect model generalization ability [5]. The method by Ibrahim et al. is CNN-based. Each patient’s trial was validated separately, without testing across subjects.

E. Methodological Considerations

Multiple studies have identified key methodological issues Messaoud and Chavez [4] noted that many recent studies. They created a tool that can predict seizures with just a brain scan too much overconfidence due to lacking frameworks performance claims. Proper evaluation requires adherence to framework Characterization of Seizure Prediction Prediction Horizon (SPH) and SOP. Kerr and others put emphasis on challenge while training and validation. Dividing the data and preventing validation data “leakage” Unintended bias in training due to feature selection. hyperparameter tuning. They advocate for explicit separation careful attention to the division of training, testing, and validation sets temporal dependencies in EEG data.

F. Computational and Interpretability Challenges

Deep learning methods, while achieving strong performance are challenging to understand for the clinical acceptance. [1], [4]. Messaoud and Chavez [4] argued that black-box. Medical communities are skeptical of deep learning models. Recommending simpler, more understandable algorithms Performance may be preferable. Deep models like CNNs and Transformers can be computationally expensive and heavy. Clinical use requires models that are reliable and explainable. Nevertheless, Usman et al. [1] proved that hybrid Approaches that combine deep

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learning and inter. It is possible to balance performance and interpretability. The compromises between engineered characteristics and classical measures. End-to-end deep learning techniques and machine learning remain an active area of investigation.

VI. COMPARISON OF REVIEWED STUDIES

Table I Compares several key aspects of the reviewed studies (datasets, feature extraction 11 words) techniques, classifiers, and reported performance measures. The table shows different methods used for various EEG sources (scalp vs intracranial) and prediction targets (seizure types) while traditional Machine learning with engineered features can yield high accuracy on balanced data. Deep learning methods produce individual forecasts of seizures in patients with acceptable degree of sensitiveness on large EEG datasets [8]. Hybrid approaches combining classifier selection and data weighting can benefit from customization Efficient Clinical Performance of Computational Procedure. Want to verify this passes Turnitin?

Table I: Comparison of Reviewed Studies

Study	Dataset	Feature Extraction	Classification Method	Performance	SPH/SOP
Usman et al. [1] (2020)	CHB-MIT (24 subjects)	CNN automated (3 conv layers: 16×5×5, 32×3×3, 64×3×3)	CNN + SVM hybrid	Sensitivity: 92.7%, Specificity: 90.8%, Prediction Time: 21 min	Not specified
Batista et al. [2] (2024)	EPILEPSIAE (37 patients, 209 seizures, 5120 hours)	59 univariate linear (time, frequency, time–frequency)	SVM with Cumulative Firing Power post-processing	Sensitivity: 49%, FPR: 2.12/h (62% above chance)	SPH: 5 min, SOP: 10–55 min
Messaoud & Chavez [4] (2020)	CHB-MIT (20 patients, 103 seizures)	25 univariate features (statistical, fractal, spectral) + Pearson correlation	Random Forest (n = 107 estimators)	Sensitivity: 82.07%, FPR: 0.0799/h (Patient-specific: 89.31%, 0.03/h)	SPH: 5 min, SOP: 30 min
Saadoon et al. [5] (2025)	Multiple public EEG datasets (review)	Temporal (statistical) and spectral (wavelet, STFT)	Various ML/DL (CNN, LSTM, SVM, etc.)	– (review paper)	Varies
Ibrahim et al. [8] (2023)	CHB-MIT (scalp EEG) and AES Kaggle (iEEG)	MODWT wavelet subbands	Multiresolution 1D-CNN	Sensitivity: 82–85%	Not specified
Kerr et al. [7] (2024)	Multiple (review paper)	Various EEG and non-EEG sensors	ML/AI tools including SPaRCNet, RNS	Varies by technology	Varies
Ibrahim et al. [8] (2023)	CHB-MIT (scalp EEG) and AES Kaggle (iEEG)	MODWT wavelet subbands	Multiresolution 1D-CNN	Sensitivity: 82–85%	Not specified
Basri & Arif [9] (2021)	Temple University Hospital EEG (TUH)	FFT-based spectral features	Random Forest	Accuracy: 96%	Not specified
Zhu et al. [10] (2024)	CHB-MIT and Bonn EEG	Time–frequency embedding of EEG	Multidimensional Transformer + RNN hybrid	Accuracy: 94.3%, FPR: 0.06/h	SPH: 15 min, SOP: 30 min
Saemaldahr et al. [11] (2023)	Federated private EEG from multiclinics	Preictal pattern features via CNN encoders	Federated Learning (3-tier) for personalization	Avg. AUC: 0.91, FPR: 0.08/h	SPH: 10 min, SOP: 20 min
Xu et al. [12] (2023)	CHB-MIT (scalp EEG)	Residual shrinkage feature maps	Deep Residual Shrinkage Net + GRU	Sensitivity: 91.5%, Specificity: 89.7%	SPH: 10 min, SOP: 30 min
Costa et al. [13] (2024)	Multiple (prediction vs	Various EEG features	Comparison of forecasting vs	– (methodology study)	Varies

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	forecasting)		prediction models		
Xiang et al. [14] (2025)	Bonn EEG and CHB-MIT	Graph spatio–temporal synchronization features	Graph Spatio–Temporal Attention Network	Accuracy: 95.8%, Sensitivity: 94.1%	SPH: 20 min, SOP: 30 min

VII. CONCLUSION

There are several seizure prediction techniques using machine learning. Depending on the methodology and dataset, sensitivities ranged from 49and task formulation. Random Forest Hybrid CNN-SVM Have Specific Traits. "promise, balancing performance with computational efficiency and interpretability". Appropriate feature extraction or automated feature selection results in good outcome gaining knowledge, strong classification with ensemble strategies, complex post treatment. Including time management and the handling of artifacts still, today, high noise and other artifacts are major issues. Unbalanced Classes in EEG Signals indicates more non-seizure than seizure (12 words) Due to inter-individual variability and the limited generalization across. The tradeoff between performance and interpretability in deep learning models. Future research must. Customized models for preictal heterogeneity help to improve real-time artifacts. Manage and apply strict cross-patient validation protocols and methods diverse long-term ambulatory datasets. The field is progressing toward clinically viable. Prediction tools that can significantly enhance the quality of life for epilepsy patients.
Rephrase
More
Undo By taking action and ensuring safety.

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