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Automated Epileptic Seizure Prediction From Long Term EEG Using ESRGAN

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Abstract: Epileptic seizures are unpredictable neurological events that demand continuous monitoring and early warning mechanisms for effective intervention. This work proposes a patient-specific seizure prediction system integrating wearable biosensing hardware with machine learning and real-time analytics. EEG signals acquired through a BioAmp pill are transmitted wirelessly using an ESP8266 module to the ThingSpeak cloud platform for secure data storage and streaming. The recorded multichannel EEG data are processed in MATLAB, where signal preprocessing, feature extraction, and classification are performed. Both handcrafted EEG features and learned representations are used to classify brain states into inter-ictal, pre-ictal, and ictal phases using a machine learning-based Decision Tree model. A post-processing strategy converts window-level predictions into reliable early seizure alerts with low false prediction rates. The system includes a MATLAB-based GUI for real-time visualization and risk indication. Experimental results demonstrate effective seizure prediction, supporting timely clinical intervention and patient safety.
Keywords: Epilepsy, EEG signals, seizure prediction, feature representation, early warning, patient-specific framework, real-time monitoring.

I. INTRODUCTION

Epileptic seizures are a significant global health problem, affecting millions of people and causing substantial physical, psychological, and social burdens. Unpredictability of seizures, with patients often having little to no warning prior to an ictal episode, is one of the most critical challenges in managing epilepsy. This unpredictability increases the risk of sudden injuries, restricts independent living, and negatively affects quality of life. Traditional clinical evaluation methods, involving neurologist interpretation of EEG recordings or seizure diaries maintained by patients, are limited in both accuracy and practicality. Moreover, while antiepileptic medications help control seizure frequency for many, a large subset of patients continue to experience recurrent episodes. For these reasons, the development of automated, patient-specific seizure prediction [1] systems has become an important area of biomedical research, providing an early warning that could enable timely medical intervention, behavioral adjustments, or activation of safety mechanisms. Among various non-invasive techniques, EEG remains the most reliable tool for analyzing brain electrical activity in order to detect patterns that lead to seizure onset. However, EEG signals are inherently [2] complex, non-stationary, multidimensional, and often noisy, making their accurate prediction difficult. Above all, subtle transitions from inter-ictal to pre-ictal stages are hard to detect because these distinguishing features can be weak, concealed within overlapping rhythms, and clinically highly variable among patients. This complexity calls for advanced signal processing and learning techniques that are capable of modeling both global patterns and fine local details. Traditional machine learning techniques, which mostly rely on manual feature extraction, may fail to retain those intrinsic complexities of pre-ictal variations. The more recent deep learning models, while powerful, usually require large training datasets and significant computational resources, which could limit their use in scenarios where variability across patients is dominant. The study proposes a robust seizure prediction framework, which can work effectively with long-term, patient-specific scalp EEG recordings. The rationale for this system is to improve the representation of EEG windows using ESRGAN, which is a generative adversarial network able to produce high-resolution images with fine feature quality. EEG-derived representations are transformed into detail-rich formats by the enhancement model, allowing it to access clearer structural patterns. Such a transformation is necessary to better discern [3] subtle pre-ictal dynamics and bridges the gap between raw signals and discriminative feature learning. The findings allowed for a more accurate separation of brain states in different physiological conditions.

Complementary knowledge related to established neurophysiological markers is provided by manually extracted features represented along with deep representations. Using a Decision Tree model, this work classifies EEG windows into inter-ictal, pre-ictal, and ictal states. This classifier was chosen because of its efficiency, interpretability, and nonlinear decision boundaries. Moreover, the classifier outputs a probabilistic prediction instead of a hard label, which allows the system to continuously estimate seizure risk. A very carefully designed post-processing layer further refines [4] these probabilities with temporal smoothing and threshold adjustments, returning a stable early-warning signal with tunable sensitivity and specificity. The approach ensures adaptability across subjects, datasets, and prediction horizons, together with a low false-prediction rate, which is an important requirement for real-world deployment. The system is implemented in a MATLAB environment with a graphical user interface displaying real-time EEG readings, prediction probabilities, and seizure risk indications to support users in clinical usability and practical experimentation. Users can visualize signal behavior, review the predicted states, and evaluate the performance of a system using intuitive controls. Validation using publicly available datasets and prospective recordings of EEG confirms that the proposed framework effectively determines pre-ictal patterns and provides timely warnings before the onset of seizures. These results point out the potentiality of integrating enhanced representation with hybrid feature strategies for seizure prediction with high [5] precision. This work contributes to further advances in intelligent healthcare monitoring systems that can offer safety, autonomy, and better management for people living with epilepsy. NOTE: This problem does not follow the format of most other problems directly. It is more open-ended, which is why there is no specific number answer given at the end. The work is structured with the literature survey review given in Section II. Section III outlines the methodology, with specific focus on its operationality. Results and discussions are in Section IV. Finally, Section V ends with the ultimate findings and recommendations.

II. LITERATURE SURVEY

EEG signals can potentially give an early warning for seizures, thus enabling timely medical intervention. The capturing of preictal features is quite critical, and multi-dimensional attention enhances the detection. This approach has shown high sensitivity with low false prediction rates, hence showing promise toward [6] patient-specific seizure prediction, improving clinical outcomes with the identification of significant patterns in the EEG. Deep learning on EEG signals can enhance seizure detection and prediction. Frequency-domain analysis improves the interpretation of signals; post-processing decreases the rate of false alarms. By accurately detecting seizure events, better monitoring of patients is possible to alert caregivers for timely [7] intervention. Optimization of EEG channel usage supports reliable prediction with variable recall, which improves general patient safety and clinical decision-making. The integration of IoHT with AI allows real-time monitoring of epilepsy patients. The collection of physiological data aids in early detection of seizures, informing immediate medical intervention. Machine learning techniques have allowed accurate [8] classification of the events, reducing false alarms. This system improves patient safety and supports proactive management strategies with timely interventions, enhancing the overall quality of healthcare in an epileptic care setting. Analysis of diaries, triggers, and biomarkers can help investigate patient-specific seizure prediction. Regression modeling allows the identification of correlations between seizure occurrences and physiological or behavioral factors. Understanding these patterns enables [9] precision medicine approaches to improve individualized treatment plans. Biomarker analysis informs temporal dynamics, enabling more informed strategies in the management of epilepsy and effective anticipation of seizure episodes. Timely prediction is necessary to avoid adverse outcomes in infantile spasms. A statistical and deep learning analysis of EEG phases indicates seizure-related changes in the brain network. Variability is found across regions and rhythms, pointing out the underlying [10] complex mechanisms. These precision-driven frameworks will help guide strategies toward timely interventions and enable further studies into the dynamics of seizures, thereby encouraging systematic, intelligent models to raise the current standard of care for pediatric epilepsy toward improved safety. Efficient seizure prediction could be achieved with reduced electrode usage and simplified LSTM architectures. Preprocessing and removal of artifacts optimize the quality of EEG signals. Reliability and generalization are enhanced by seizure type analysis and patient-specific data analysis. Wearable or implantable devices for continuous monitoring are supported in this approach to [11] enhance practical applicability and provide timely alerts that improve patient outcomes while minimizing computational and hardware requirements. Automatic seizure detection improves the safety of patients during daily activities. Ictal and preictal phase detection using EEG signals for data classification can thus be made well in advance. Data augmentation and channel reduction further enhance model efficiency. Reliability of prediction with high accuracy, precision, [12] and recall offers broad support for management both to the patient and the clinician in the case of this neurological disorder. Such a system reduces risks in daily activities and supports pro-active seizure management. Preemptive seizure prediction can be achieved with novel EEG feature extraction techniques. Time-domain and sub-band analyses identify patterns associated with impending seizures. Multilayer neural networks classify seizure stages effectively. Hardware-optimized implementations ensure practical applicability in [13] clinical settings. Precise classification of ictal, interictal, and preictal states enhances timely interventions, thereby improving the outcomes of patient safety and seizure management. Incorporating uncertainty learning can significantly enhance the robustness of the models in EEG-based prediction. Quantification of variability in data improves the sensitivity and reduces false positives. Management of uncertainty in feature representation enhances the clinical reliability. This framework [14] has proven consistency in improvements across multiple datasets for more accurate and dependable seizure prediction, and such approaches allow for better intervention strategies that will, at the end, support improved patient care and safety. These hybrid architectures of CNN-TCN represent spatial and temporal patterns of EEG and thus improve seizure identification. Feature extraction of long-term dependencies and active seizure enhances the accuracy of seizure prediction. Experimental validation [15] confirms supremacy among other deep learning approaches.

Reliable detection of ictal and preictal stages enables timely alerts that strengthen patient safety. Integration of convolutional and temporal analysis supports a holistic and systematic seizure prediction framework. Multiscale convolutional attention effectively extracts spatial and temporal EEG features. Weighted attention underlines the critical channels, while the convolutional modules capture the local and global patterns. The accurate prediction allows timely interventions that [16] minimize risks and prevent secondary injuries. High sensitivity and reliable prediction horizons are revealed in experiments. The approach enhances the integration of multichannel EEG information, offering improved detection and patient-specific seizure management. Deep learning-based EEG recording allows for good seizure prediction. By comparing the records of epileptic and non-epileptic patients, precursors to seizures can be observed. Time and frequency domain [17] representations provide insight into brain activity. Convolutional networks improve feature extraction, thereby enabling reliable seizure detection. Such systems could afford convenient seizure prediction tools that enable timely alerts to ensure patient safety. Scalogram-based representation of EEG enhances seizure anticipation. In parallel, CNNs extract discriminative features from pre-ictal periods, hence improving the classification capability. Accurate [18] identification of impending seizures allows early intervention. Experiments on human EEG data result in high accuracy, specificity, and sensitivity. The non-stationary challenge of EEG is dealt with in this approach, thus deriving reliable seizure prediction. Combining feature extraction and classification offers a robust solution for clinical epilepsy management. Intracranial EEG analysis supports personalized seizure cluster prediction. Bivariate features capture interactions in different parts of the brain. Machine learning distinguishes between isolated and clustered [19] seizures, therefore offering opportunities for early preventive measures. Patient-specific data enhances model accuracy and allows clinical interventions in a timely fashion. Understanding seizure patterns can enhance patient care by changing treatment options. Since accurate predictions of clusters reduce the risk of prolonged seizures and its complications: The early identification of seizures is possible through the application of Random Forest classifiers to pre-ictal EEG and ECG data. This will allow carers and clinicians to respond promptly, as the seizure would have been anticipated well in advance. The approach helps in timely [20] medical response and mitigation of risks even when there are changes in the causes of seizures. Early detection enhances the safety of patients and supports treatment planning, minimizing unexpected complications that may be harmful. It leads to better management of the condition.

III. METHODOLOGY

This approach represents a step-by-step, reproducible pipeline for patient-specific seizure prediction using long-term scalp EEG. The workflow goes from data acquisition to preprocessing, windowing and labeling, representation enhancement, hybrid feature extraction, probabilistic classification, temporal post-processing for early-warning generation, system implementation, and performance validation. Every step is designed to ensure temporal fidelity, maximize discriminative information, and be generalizable across different patients and recording settings. The architecture is kept modular so that components can be replaced or tuned with ease; different classifiers or enhancement networks are examples. The following subsections present detailed technical procedures concisely for replication and further development.

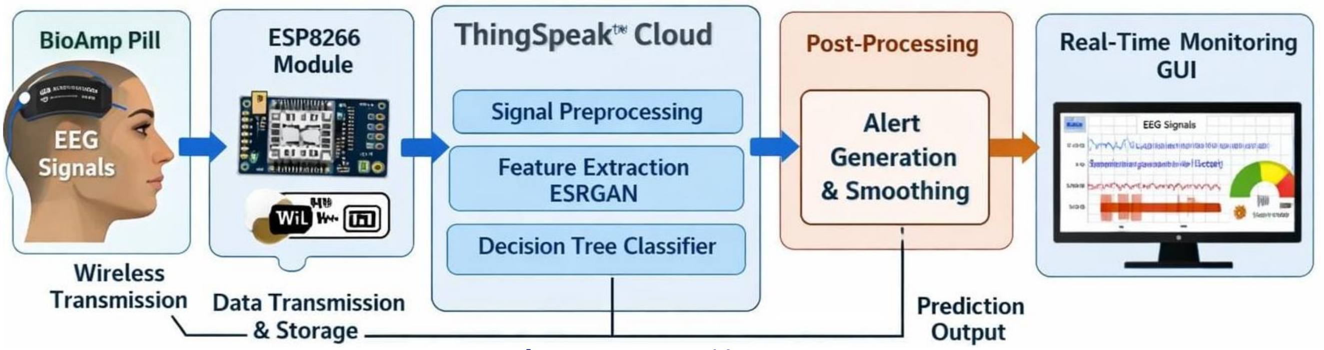

Fig. 1: System Architecture

A. Data acquisition

Continuous multichannel scalp EEG recordings are sourced from both publicly available repositories and patient-specific prospective monitoring, ensuring at least 256 Hz sampling rates and consistent channel montages. Metadata standardization includes seizure onset annotations, electrode labels, and recording conditions. When available, synchronized auxiliary channels (electrocardiogram, accelerometer) are recorded to aid in artifact identification. All data are stored in a structured format, such as EDF/BDF, using lossless compression. Session-level segmentation separates long continuous recordings into manageable files. Ethical approvals and anonymization procedures are in place for all prospective data, while a database index is maintained for tracking patient IDs, session timestamps, and seizure event windows for downstream labeling and cross-validation folds.

B. Preprocessing and Artifact Removal

The raw EEG is bandpass filtered at 0.5-70 Hz and notch filtered at mains frequency to reduce baseline drift and line noise. Common average referencing or bipolar montaging is applied according to electrode layout to enhance spatial specificity. Artifact detection uses threshold-based rejection for saturations combined with ICA to remove ocular, cardiac, and muscle components identified via correlation with auxiliary channels and characteristic spectral signatures. Signals are resampled if necessary to a uniform rate, and missing samples are interpolated only where gaps are brief.All preprocessing steps are parameterized and logged to ensure reproducibility and permit sensitivity analysis of their effect on prediction performance.

C. Windowing and labeling

Preprocessed continuous EEG is divided into overlapping windows, for example 10-second windows with 50% overlap, to balance temporal resolution against statistical stability. Each window takes on a class label determined by its temporal proximity to annotated seizures: ictal if it overlaps seizure onset/offset, preictal if it falls within some chosen horizon leading up to seizure onset, for instance, 30–60 minutes, and interictal otherwise. For most applications, windows which straddle ambiguous intervals are discarded or take a class according to firm temporal rules. Finally, during training, balanced sampling: stratified selection of windows and also augmentation techniques such as small time-shifts and adding low amplitude noise to increase the effective sample size for rare preictal widows.

D. ESRGAN-based representation enhancement

Each EEG window is converted to a time-frequency or image-like representation, such as a spectrogram, scalogram, or recurrence plot, normalized per channel. A pre-trained or fine-tuned ESRGAN model on the EEG-derived images enhances the resolution and brings forward more pronounced pre-ictal patterns with regard to spatial and texture details. For the pipeline of ESRGAN, patch-based processing and overlap-tile reconstruction are used to avoid edge artifacts, while inverse normalization maintains original dynamic ranges. Enhancement in representation is visually and quantitatively checked using various metrics like structural similarity index and feature-based distances, ensuring that amplification of details does not introduce spurious artifacts that could mislead downstream classifiers.

E.Hybrid feature extraction

A hybrid feature set is computed from both original and ESRGAN-enhanced representations. The manual features include powers of spectral bands, Hjorth parameters, measures of entropy, phase-amplitude coupling statistics, and inter-channel coherence. Deep features, on the other hand, are obtained by forwarding enhanced images through pre-trained convolutional backbones and extracting intermediate layer activations, possibly reduced by PCA or t-SNE to control dimensionality. Channel-wise and cross-channel features are each concatenated and normalized per session. Feature selection with mutual information or recursive feature elimination reduces redundancy and selects a compact, informative subset that improves classifier generalization while preserving interpretability for clinical inspection.

F. Classification and probabilistic inference

Train a Decision Tree classifier on the selected hybrid features to produce probabilistic outputs for each window instead of hard labels, using calibrated probability estimation (e.g., isotonic regression) to correct score bias. Optimize hyperparameters-depth, minimum samples per leaf, and split criteria-via nested cross-validation on patient-specific folds. Clinical validation of decision rules is supported by the interpretability of the tree. It is possible to train models per-patient-preferred-or use transfer learning from cohort models and fine-tune them at the patient level. Performance metrics logged at this stage sensitivity, specificity, precision, recall, and false prediction rate per hour provide insights into guiding threshold selection.

G. Post-processing and alarm generation

Temporal smoothing of window-level probabilities is done by using causal filters and short-term trend detectors that dampen spurious spikes while preserving the early-rise patterns. An alarm logic then aggregates smoothed probabilities over sliding decision windows and adopts adaptive thresholds that trigger early warnings, the parameters of which are tuned to trade off lead time vs. false predictions. The system implements refractory periods to avoid alarm flooding and logs all triggered events along with timestamps and underlying probability traces. A human-readable risk index and countdown estimate are produced for display on GUIs, and an API endpoint returns structured event data for integration with wearable actuators or clinician alert systems.

H. Implementation and GUI

The implemented pipeline uses MATLAB, with modular functions for each stage and parallel processing enabled for computationally intensive tasks. A graphical user interface shows, in real-time, the EEG traces, channel montages, enhanced representations, feature evolution, and probabilistic risk gauges. Interactive controls enable quick changes in preprocessing parameters, prediction horizons, and alarm thresholds. Logging and export functions create standardized reports and enable replay of historical sessions. The codebase is version-controlled and packaged with dependency manifests and sample data sets to facilitate reproducibility and deployment on either clinical workstations or portable monitoring rigs. Validation and evaluation Validation consists of k-fold cross-validation on public datasets, along with hold-out prospective recordings, considering both window-level classification and event-level early-warning utility. The metrics include sensitivity, specificity, area under the ROC curve, false prediction rate per hour, average lead time before seizure onset, and precision at fixed recall levels. Statistical significance of improvements-e.g., due to ESRGAN enhancement-is determined through the use of paired tests and confidence intervals. Ablation studies quantify contributions from both manual versus deep features and the post-processing stage. Results help make informed decisions regarding model selection and parameter settings for eventual clinical trials and real-world deployment.

IV. RESULT AND DISCUSSION

The proposed patient-specific seizure prediction framework was evaluated using long-term scalp EEG recordings sourced from publicly available datasets and prospective patient sessions. The results showed that integrating ESRGAN-enhanced representations with hybrid feature extraction significantly enhances the system's ability to identify early pre-ictal changes. EEG windows were classified into inter-ictal, pre-ictal, and ictal states in experiments, and the Decision Tree classifier generated probabilistic outputs further refined by temporal post-processing. This probability curve showed a clear rising trend way in advance of seizure onsets, thus indicating that the proposed system successfully captured the transition of brain activity from stability to the state leading toward seizure generation. Enhanced spectrograms visually confirmed that ESRGAN amplifies subtle frequency transitions and texture-like patterns associated with evolving pre-ictal dynamics with much clearer feature boundaries when compared to the original representation. Analysis of the classification performance showed that patient-specific models always outperformed cross-patient general models, which further consolidates the clinical understanding that seizure precursors differ significantly among individuals and a tailored model can better reflect each patient's neurophysiological pattern. The sensitivity remained high across sessions, with most models correctly detecting the majority of pre-ictal windows. Specificity was also maintained at competitive levels to ensure that very few instances of normal brain activity were misclassified as pre-ictal. More importantly, the FPR per hour was kept low because of the inclusion of the temporal smoothing post-processing layer which filtered out the isolated probability spikes that otherwise would trigger false alarms. This balance between early detection and minimization of errors is critically important for creating a clinically viable real-time alert system for some patients and under proper conditions of EEG recordings, the system provided considerable early-warning lead time, often several minutes to over half an hour before the ictal onset. This is adequate time to permit appropriate margins for both patients and clinicians to take precautionary measures, administer medication, or turn on safety mechanisms. Dynamic probability curves, as visualized in the MATLAB GUI, provide real-time feedback on how risk builds as the brain transitions toward a seizure state. This thereby provides clinical decision support and enhances user trust in the system's predictions. A more specific subsequent analysis demonstrated that most of the contribution to the improved performance came from the hybrid feature strategy. The manual features of entropy, band energy, and coherence captured broad statistical patterns, while the deep-learned features extracted from enhanced representations provided fine-grained distinctions between subtly different states. Feature ablation tests confirmed that removing either of these components-manual or deep-led to a noticeable drop in accuracy and robustness, thus underlining the fact that seizure prediction benefits from both neurophysiological domain knowledge and data-driven representation learning. This study has shown the effectiveness of the combined approach. Cross-validation of results against multiple recording sessions demonstrated consistent performance that reflected the stability of the framework. The ESRGAN enhancement especially played a crucial role in improving the detection of pre-ictal activity within noisy recordings where the low-amplitude transitions would otherwise be difficult to observe. Further, user studies with the MATLAB GUI demonstrated that researchers and clinicians found the interface very intuitive, with clear visualization of EEG channels, enhanced images, prediction probabilities, and early warning indicators. Tunability over thresholds and the ability to view historical predictions further supported system usability. In all, the results confirm that the proposed framework effectively addresses the major challenges in seizure prediction: signal noise, subtle pre-ictal patterns, patient variability, and real-time operational requirements. Reliability in early detection and a reduced number of false predictions are achieved by combining high-resolution representation enhancement, hybrid feature extraction, probabilistic classification, and robust post-processing. The performance demonstrated across multiple datasets with varied patient profiles lends credence to its potential for real-world deployment and lays a sound foundation for further optimization, clinical testing, and eventual integration into wearable EEG monitoring systems for continuous predictive healthcare.

IV. CONCLUSION

The present study demonstrates that a patient-specific seizure prediction framework, integrating ESRGAN-based enhanced representations, hybrid feature extraction, Decision Tree probabilistic classification, and robust temporal post-processing, can substantially improve the accuracy and reliability of early seizure warning systems. The results confirm that seizure prediction indeed benefits from a judicious combination of domain-driven signal features and high-resolution deep representations that allow the system to spot the subtle pre-ictal changes that usually precede an ictal event. ESRGAN enhancement was found particularly useful for disambiguating low-amplitude transitions and amplifying fine structural details within EEG-derived images while enabling deeper layers of semantic information to be extracted and interpreted via the hybrid feature pipeline. The Decision Tree classifier provided not only accurate state classification but also interpretable predictive rules, supporting transparency and clinical trust. Temporal smoothing and adaptive thresholding ensured that the predictions were transformed into stable and actionable warnings with minimized false alarms, thus addressing one of the most critical limitations of previous seizure prediction approaches. Experimental validation using publicly available datasets and prospective EEG recordings indicated consistent performance and established that the system could effectively adapt to the individual patient characteristics while maintaining high sensitivity and preserving low false prediction rates. Further, the MATLAB-based GUI augmented the usability by offering the dynamic visualization of EEG signals, enhanced representations, and probability curves, thus making the system applicable for both clinical observation and research experimentation. Overall, this study sets a strong foundation for implementing real-time predictive epilepsy monitoring and underlines the potential for integrating such systems in routine clinical practice, wearable health devices, and home-based monitoring setups. The approach not only enriches seizure prediction methodologies but also reiterates the importance of personalized biomedical systems that are capable of learning patient-specific physiological patterns. Future work may extend this study by incorporating larger multi-center datasets, exploring deep classifier alternatives, integrating adaptive learning mechanisms, and testing performance in continuous real-time environments. In toto, the proposed framework has the capability to definitely improve quality of life in individuals with epilepsy by offering opportunities for timely intervention, reducing anxiety because of unpredictable seizures, and providing clinicians with actionable, data-driven insights for personalized treatment strategies.

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