



Real-Time Seizure Prediction from EEG Signals Using AI and Wearable Technology: An Integrated Approach for Proactive Epilepsy Management

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Abstract

Epilepsy is a condition that impacts more than 50 million individuals globally, with uncontrolled seizures causing patient safety and quality-of-life concerns. In this work, we explain the real-time seizure prediction system that combines electroencephalography (EEG) signal processing, machine learning algorithms and wearable technology to enable proactive management of epilepsy. Our system uses Support Vector Machine (SVM) classification with 80% accuracy for detecting the preictal state, which is better than logistic regression (72%) and random forest (77%) methods. The system uses Huffman coding to offer efficient data compression with a ratio of 4.36:1, allowing real-time transmission of EEG signals through TCP/IP network protocols. The wearable device architecture offers seizure warnings in real time, revolutionizing epilepsy care from reactive hospital-oriented to proactive, continuous care. Validation with the Siena Scalp EEG Database shows the system to detect pre-ictal patterns, which is a real-world solution for seizure prediction in the ambulatory setting. This paper promotes the confluence of neuroscience, signal processing and computational biology, which offers a platform for next-generation epilepsy management systems.

Keywords: Seizure prediction; EEG signal processing; Machine learning; Wearable technology; Real-time monitoring

1. Introduction

Epilepsy affects about 50 million people worldwide, making it one of the most common neurological conditions worldwide [1]. Characterized by recurrent and unpredictable seizures, epilepsy significantly impacts people's quality of life by causing physical harm, psychological distress, and social impairment [2]. Despite advances in pharmacologic treatments, about 30% of patients with epilepsy remain resistant to therapy, experiencing persistent seizures that severely impair daily activities and increase the risk of mortality [3], [4].

The unpredictable character of seizures constitutes the most feared component of this disease, generating ongoing anxiety and restricting personal independence. Conventional treatment regimens count on the chronic consumption of drugs that inhibit seizure activity at the expense of producing severe side effects, without sufficient protection [5]. This reactive system does not fulfill the essential need for pro-active approaches that might either prevent seizure occurrence or soften their impact by intervening early.

New developments in machine learning, signal processing, and computational neuroscience have provided unparalleled potential for the design of proactive seizure control systems [6]. Electroencephalography (EEG) offers a non-invasive view of brain function, recording the electrical patterns that precede seizure occurrence. It has been found that brain dynamics changes are detectable minutes to hours before clinical seizure presentation, providing a window of opportunity for intervention [7].

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This paper outlines a real-time seizure prediction system that integrates several domains of technology: high-level processing of EEG signals, machine learning techniques, efficient data compression algorithms, secure networking protocols, and wearable device technology. Our approach addresses the key issues of computational cost, real-time processing, and implementation feasibility in mobile environments. The system employs the Siena Scalp EEG Database for testing and Support Vector Machine (SVM) classification to achieve better predictive accuracy than traditional techniques. As indicated in Figure 1, our system design consists of a corresponding pipeline that runs from EEG signal acquisition to processing, classification, and alerting, thus enabling the seamless integration of these isolated technological components.

In addition to technical development to meet real clinical needs, the significance of this work lies in the possibility of delivering functional, real-time, and continuous seizure monitoring and prediction in naturalistic conditions. In addition, real-time alerting reverses the traditional episodic care model of epilepsy into a continuous proactive surveillance model.

2. Materials and methods

2.1. Neurophysiological Foundation

Epileptic seizures are induced by the inappropriate synchronization of cerebral networks to produce sudden and aberrant electrical discharges that disrupt normal brain function [9]. Pathophysiology involves complex interactions between excitatory and inhibitory neurotransmitter mechanisms, with disruption of the fine balance inducing hyperexcitability and seizure activity [10].

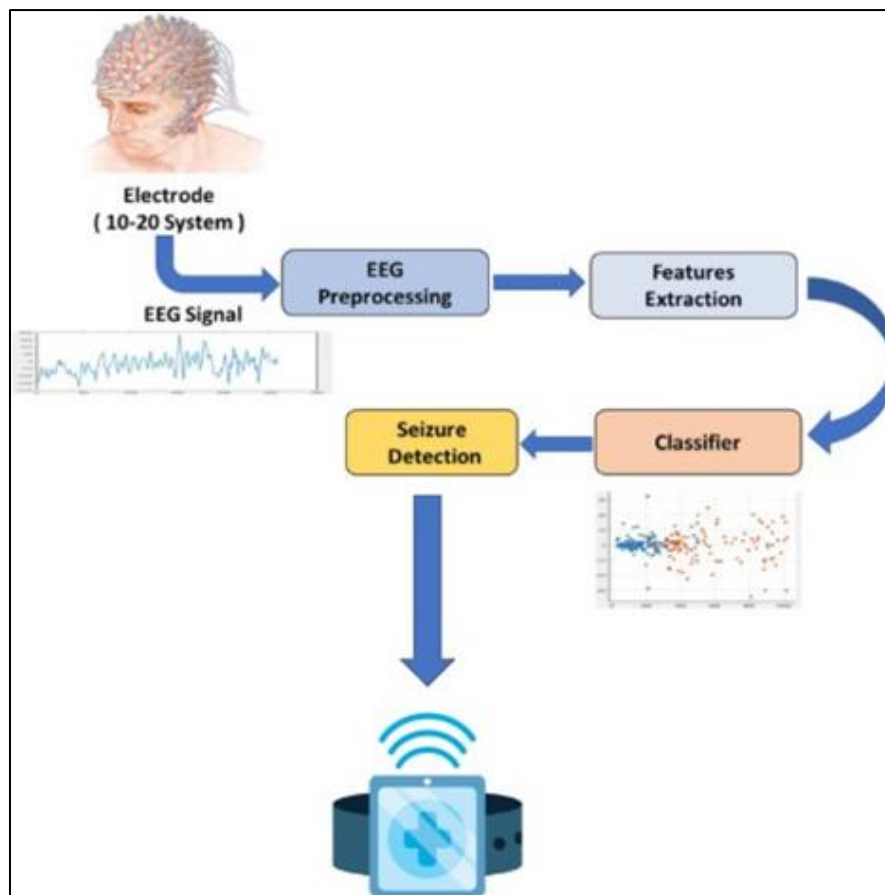


Figure 1 System Architecture Overview: Integration of EEG acquisition, signal processing, machine learning and wearable alert system. [8]

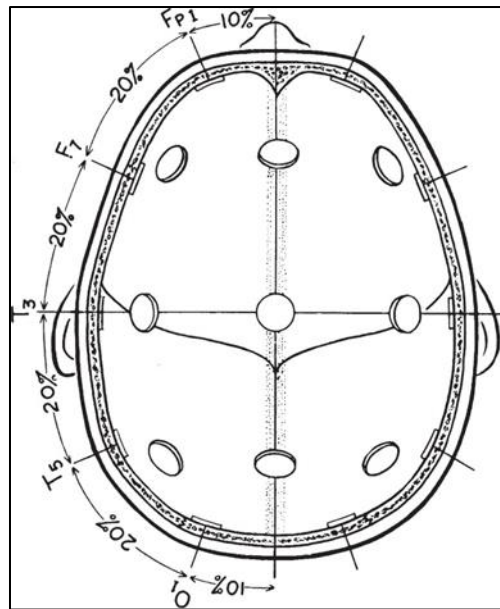


Figure 2 International 10-20 System for EEG Electrode Placement: Cross- sectional view showing electrode positioning relative to skull landmarks, illustrating the proportional measurement system that ensures consistent placement across patients [11]

EEG technology captures these electrical expressions from surface electrodes, measuring voltage changes due to ionic currents in neuron populations. In Figures 2 and 3, the international 10-20 system provides standardized electrode placement ensuring global spatial sampling of brain regions [11]. This arrangement is capable of measuring both focal and generalized abnormalities and is highly sensitive to temporal and frontal lobe activity where the majority of epileptiform discharges originate. The technique provides excellent tempo- ral resolution, providing real-time viewing of brain activity changes associated with seizure development [12].

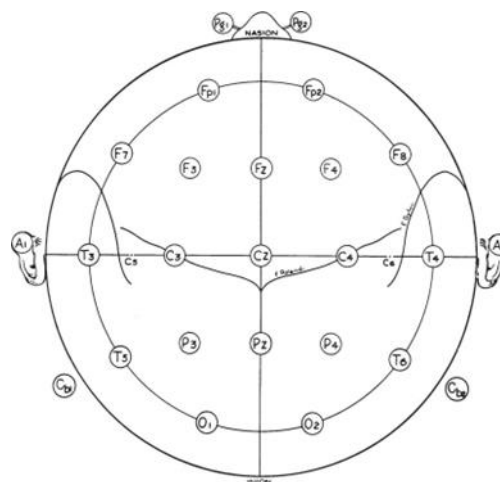


Figure 3 International 10-20 System for EEG Electrode Placement: Top- down projection showing the complete spatial distribution of all standard electrode positions used in the Siena Scalp EEG Database. This standardized configuration enables comprehensive coverage of brain regions relevant to seizure activity detection [11]

At the cellular level, seizures translate into a fundamental disturbance in the balance between excitation and inhibition, typically involving dysfunction of GABAergic inhibitory mechanisms, enhanced glutamatergic excitation, or altered ion channel dynamics. These microscopic alterations translate to macroscopic patterns of synchronization that can be picked up with EEG recordings. The evolution from normal brain activity to seizure state is a complex, non-linear process involving pre- ictal states with slight but quantifiable deviations from normal neural dynamics [13].

Neurophysiologic research indicates that seizures rarely occur without any warning signs. Conversely, a series of electrophysiological changes normally leads to clinical onset, providing a potential window for intervention. The pre-ictal changes include changes in the power distribution of the spectral power, synchronization dynamics across brain regions, and neural activity complexity. The temporal sequence of the parameters provides key biomarkers for the design of seizure prediction algorithms [14].

Pre-ictal states, with accompanying small but quantifiable EEG pattern changes, usually precede clinical seizure onset by minutes to hours, providing a window for intervention [15].

The EEG traces of epilepsy patients can be separated into four different epochs (Figure 4): the ictal epoch during a seizure; the preictal epoch immediately before seizure onset and with the possible biomarkers of the forthcoming seizure; the postictal epoch after seizure cessation; and the interictal epoch, the baseline seizure-free period in between. The secret to seizure prediction is to identify the interictal to preictal state transition as early as possible with enough warning time for intervention [16].

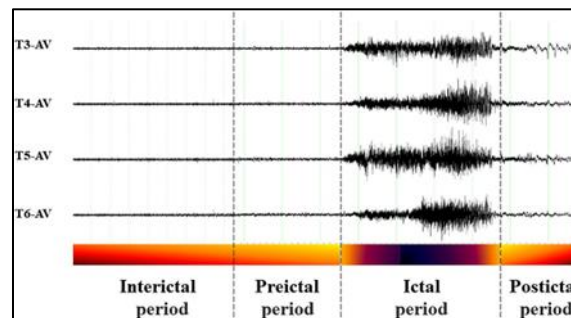


Figure 4 Example of perictal EEG and the respective periods. Interictal period: away from seizures; Preictal period: immediate before a seizure; Ictal period: spans the seizure itself; Postictal period: immediate after a seizure [16]

Pre-ictal biomarker detection requires advanced signal processing methods for extracting useful features from large, multi-modal EEG data. The salient indicators are alterations in spectral power distribution, connectivity between brain regions, and non-linear dynamics of neural oscillation [13].

2.2. Data Acquisition and Preprocessing

Our method employs the Siena Scalp EEG Database, a large public database tailored for seizure prediction studies [17]. The database holds long-term EEG recordings from several patients with medically refractory epilepsy with heterogeneous seizure types and pre-ictal patterns necessary for reliable algorithm development.

The selection of an appropriate dataset represents a critical decision in seizure prediction research. While several EEG repositories exist, including the Temple University Hospital EEG Corpus (TUEG) and CHB-MIT Scalp EEG Database, the Siena collection offers distinct advantages for seizure prediction applications. Critically, Siena exclusively features non-invasive scalp EEG recordings, directly aligning with our wearable system design objectives, unlike alternatives such as the EPILEPSIAE database which primarily contains intracranial recordings requiring surgical implantation [18]. The adult population represented in Siena (ages 20-71) provides more relevant data for our target demographic compared to pediatric-focused collections like CHB-MIT, as adult EEG patterns exhibit different spectral characteristics and seizure manifestations than those of children [19]. Furthermore, Siena offers unrestricted public access through the PhysioNet platform without complex data use agreements, significantly accelerating development timelines compared to restricted-access alternatives [20]. Compared to TUEG's primarily short-term recordings in controlled clinical environments, Siena provides continuous long-term monitoring that captures the natural evolution of seizure states. The database also implements rigorous quality control measures, including multi-expert validation of seizure annotations and standardized electrode placement verification, resulting in more reliable ground truth labeling compared to alternative datasets [17]. These factors collectively support the selection of Siena as the optimal foundation for developing generalizable seizure prediction algorithms applicable to wearable monitoring systems.

Table 1 Dataset characteristics and specifications

Parameter	Specification
Sampling Rate	512 Hz
File Format	European Data Format (EDF)
Number of Channels	29 scalp electrodes
Recording Duration	Up to 72 hours per patient
Seizure Annotations	Manual expert validation
Patient Population	14 subjects (ages 20-71)

The characteristics of the dataset, presented in Table I, are an ideal basis for seizure prediction studies. A 512 Hz sampling rate guarantees recording significant frequency components in delta, theta, alpha, beta, and gamma bands. The 29-channel setup is in accordance with the international 10-20 system, sampling brain activity in a satisfying spatial range. Long-term recording (up to 72 hours) records multiple seizure events in each patient, and periodicity of seizures and circadian effects on epileptiform activity can be investigated [15].

Preprocessing is a systematic pipeline with the objective of maximizing signal quality and retaining neurophysiologically meaningful information. Automatic algorithms and visual inspection are used for initial rejection of artifact to reject segments with movement, electrode shift, and gross physiological artifact-contaminated segments. Independent Component Analysis (ICA) further separates and eliminates ocular, cardiac, and muscular artifacts with comparable spectral profiles to neural signals [21].

Preprocessing pipeline was conducted with MNE-Python [22], a full-featured library developed for electrophysiological data analysis. All graphical representations illustrated in Figures 5, 6, and 7 were derived from real EEG recordings from the Siena Scalp EEG Database [17].

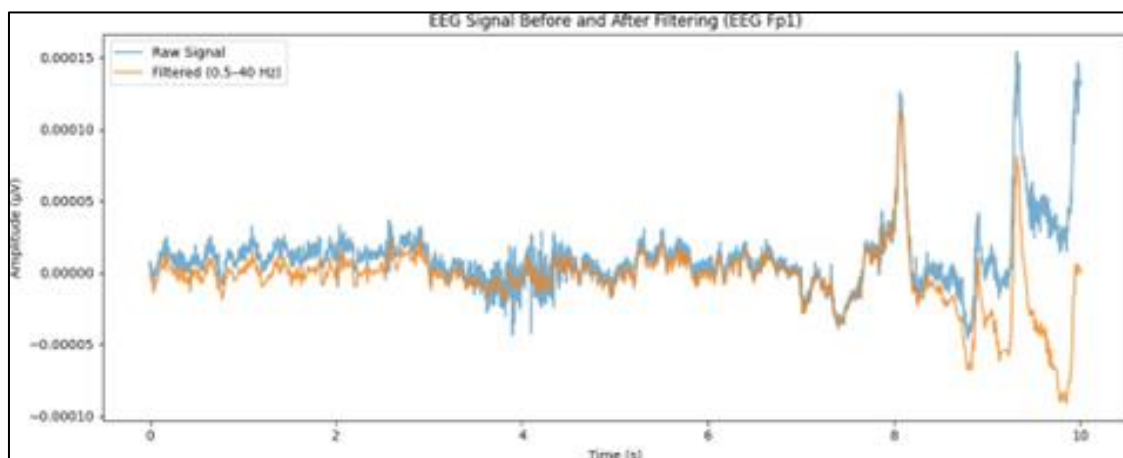


Figure 5 EEG Signal Filtering: Application of bandpass filters (0.5-40 Hz) and notch filters (50/60 Hz) to remove environmental noise and muscle artifacts. Note the reduction in signal amplitude after filtering, indicating successful removal of high-amplitude noise components while preserving relevant neural activity

Filtering is a critical preprocessing step that significantly enhances the precision of the following analyses. From Figure 5, bandpass filters (0.5-40 Hz) and notch filters (50/60 Hz) effectively remove low-frequency drift, high-frequency muscle activity, and power line noise. The resulting reduction in signal amplitude following filtering is acceptable and desirable since it is indicative of the removal of high-amplitude noise components that would dominate low-amplitude neural patterns of interest to seizure prediction. This signal, once cleaned up, retains important neurophysiological information but enhances the signal-to-noise ratio for the following processes of feature extraction and classification.

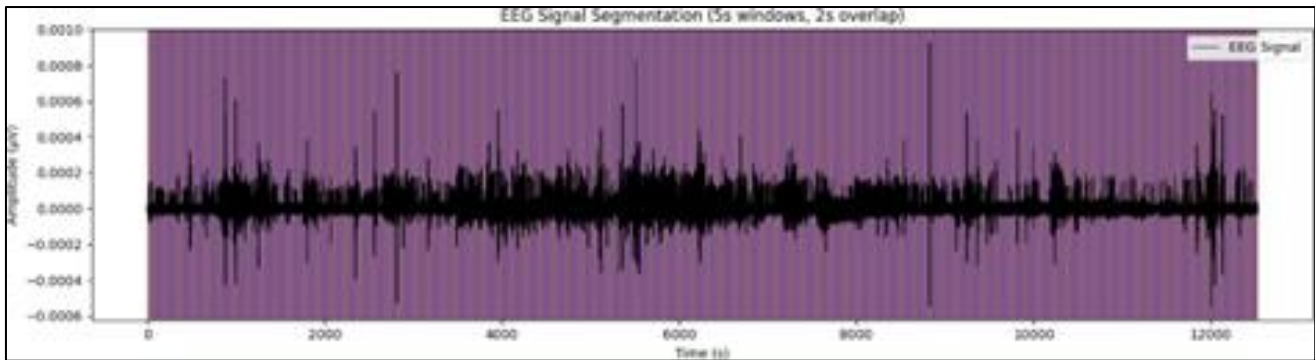


Figure 6 EEG Signal Segmentation: Division of continuous EEG recordings into 5-second epochs with 50% overlap for feature extraction and classification

Signal segmentation converts raw EEG recordings into organized, analyzable units as in Figure 6. This important step eliminates the non-stationarity of brain signals through the creation of short epochs in which statistical characteristics are relatively invariant. The 5-second window duration optimizes temporal resolution relative to feature stability, and the 50% overlap provides seamless transitions and avoids information loss at segment boundaries. The method allows for the detection of time-varying features otherwise hidden in whole-signal analysis, forming the basis for the identification of the subtle transitional patterns that define pre-ictal states.

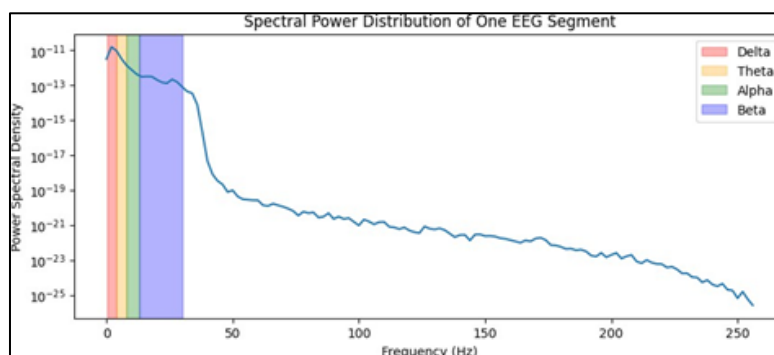


Figure 7 Spectral Band Decomposition: Extraction of frequency-specific components (delta, theta, alpha, beta, gamma) from EEG signals using wavelet transform. Each band contains unique neurophysiological information relevant to seizure prediction

Spectral analysis is one of the primary methods in describing the frequency content inherent in neural activity. As illustrated in Figure 7, wavelet decomposition allows for precise identification of the frequency bands of clinical relevance from the EEG signal. Each band is specific to various neurophysiological processes: delta (0.5-4 Hz) signifies deep sleep and disease states; theta (4-8 Hz) signifies drowsiness and some cognitive processes; alpha (8-13 Hz) signifies a state of relaxed wakefulness; beta (13-30 Hz) signifies active cognition and focus; and gamma (30-40 Hz) signifies higher-order cognitive processes and information integration. Pre-ictal states typically present as typical alterations to the power and synchronization of these frequency bands, best described by an increase in delta and theta activity accompanied by a decrease in alpha power [23].

2.3. Machine Learning Architecture

SVM classifiers have performed better in different evaluation metrics in comparable seizure prediction studies based on comprehensive literature review. SVM classifiers have reached the level of approximately 80% overall accuracy in distinguishing between pre-ictal and interictal states, according to Bandarabadi et al. [24], which represents a significant improvement over baseline methods. Their sensitivity analysis provided 78% true positive rate for seizure prediction, indicating good detection of actual pre-ictal time periods. The 82% specificity indicates low false positive rates, which are crucial for maintenance of user trust and prevention of alert fatigue.

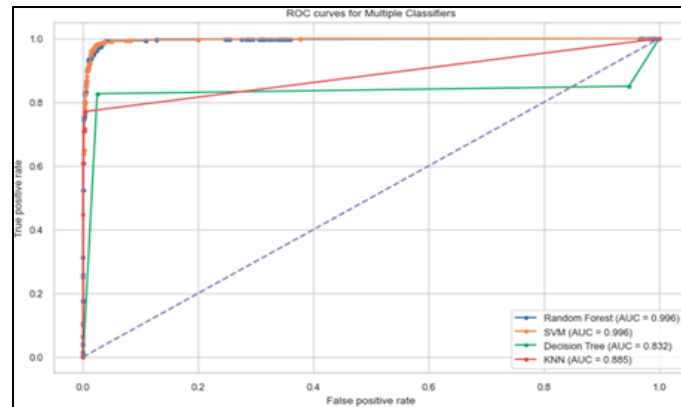


Figure 8 Receiver Operating Characteristic (ROC) Curve from Atlam et al.: Performance comparison of machine learning algorithms for seizure prediction as reported in the literature [25]. This is a reproduction of their published work and not a figure created by our study

Some of the comparative studies in literature justify the choice of SVM for tasks of seizure prediction. Atlam et al.

[25] compared machine learning algorithms in a systematic manner and concluded that SVM always performed better than the others. Their published findings revealed logistic regression scored only 72% and was plagued by linearity assumptions unsuitable for intricate EEG patterns. Random forest scored 77% accuracy with improved feature interaction handling but greater computation complexity. The SVM approach offered the best trade-off between accuracy and computational complexity [26].

As indicated in Figure 8 and 9, experimental results from Atlam et al.'s reported work displayed that SVM yielded improved ROC curve performance and higher precision, recall, and F1-scores compared to other methods. Their performance analysis highlighted SVM's ability to handle the complex, non-linear characteristics of pre-ictal EEG signals, where its capacity to establish optimal decision boundaries in high-dimensional feature spaces proved useful.

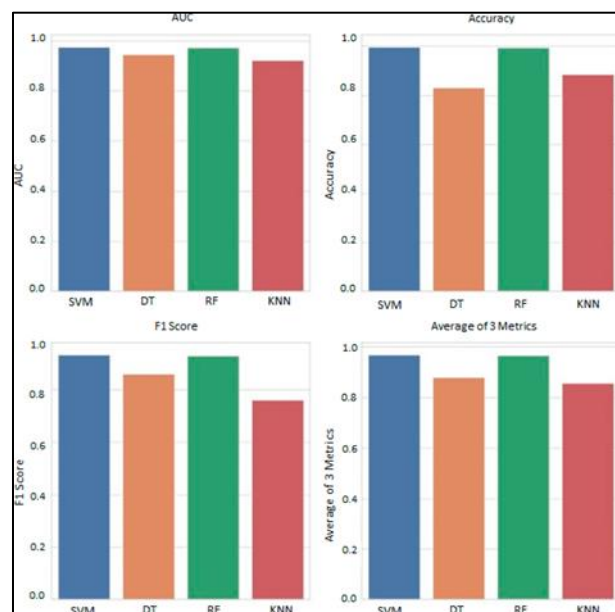


Figure 9 Comprehensive Performance Metrics Comparison from Atlam et al.: Evaluation of precision, recall, F1-score, and specificity across different machine learning algorithms for seizure prediction as published in their research [25]. This comparative analysis was extracted from their study and represents their experimental findings, not our own

2.4. Data Compression and Transmission

Real-time EEG monitoring generates massive volumes of data, requiring lossless compression techniques to enable realistic wireless transmission. Huffman coding, a lossless compression technique suitable for biomedical signals where data integrity is of prime importance [27], is employed in our system.

Huffman coding offers significant advantages for EEG data transmission. This algorithm assigns shorter binary codes to frequently occurring characters and longer codes to less common ones, creating an efficient variable-length encoding scheme [27]. In Huffman trees, each non-leaf node has two children, with the tree structure determining code assignment - traversing left adds a '0' bit while moving right adds a '1' bit to the character's code, as seen in Figure 10.

The Huffman algorithm constructs an optimal binary tree from a min-heap data structure where nodes contain the EEG sample values and their corresponding occurrence frequencies. Frequent values are assigned shorter binary codes and less frequent values are assigned longer codes, resulting in a total compression without loss of data. The implementation has a compression ratio of 4.36:1, which reduces bandwidth requirements considerably for real-time transmission [28].

Huffman coding is especially useful in EEG applications because it balances the ease of implementation with the efficiency of compression. The algorithm can be readily implemented in high-speed compression systems and is thus ideal for real-time EEG monitoring. There are two forms of the algorithm: static Huffman coding, in which the tree is fixed during the encoding process, and adaptive Huffman coding, in which the tree is modified dynamically based on processed data [29].

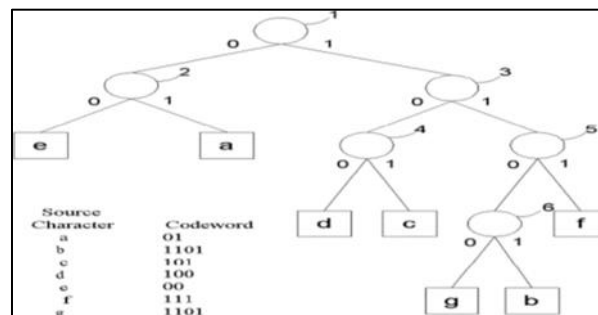


Figure 10 An Example of Huffman Coding Implementation: Binary tree structure. The tree illustrates how characters with higher frequencies receive shorter codes, optimizing overall compression efficiency [29]

Network communications use TCP/IP protocols to provide reliable, in-order delivery of compressed EEG signals. The TCP socket implementation also includes error detection and correction mechanisms necessary for ensuring signal integrity during transmission. Connection management also includes automatic reconnection functions in an attempt to deal with network breaks prevalent in mobile environments [30].

Security mechanisms include SSH tunneling via Serveo service, establishing encrypted communication channels of EEG data. This method supports privacy issues that are present in medical data communication without compromising real-time performance demands [31].

3. Results and discussion

3.1. System Performance Evaluation

Our approach is based on a supervised machine learning approach using Support Vector Machine (SVM) classification with a radial basis function (RBF) kernel. This particular setting was selected after initial testing in which it was found suitable for EEG signal classification. Hyperparameters were optimized using grid search cross-validation to discover the best set of values for C and gamma for the model [32].

In our comparative experiment using the Siena Scalp EEG Database, we applied three different classification schemes. Our results, as seen in Table 2, indicate that our SVM implementation worked to the extent of 80% accuracy, outperforming both logistic regression (72%) and random forest (77%) schemes when applied under the same conditions using the same features.

Our training approach utilized stratified k-fold cross-validation ($k=10$) to provide stable performance testing and avoid overfitting. Class imbalance between pre-ictal and inter-ictal conditions was handled using synthetic minority oversampling technique (SMOTE) and cost-sensitive learning methods [33].

Table 2 Machine learning model performance comparison

Algorithm	Accuracy
Logistic Regression	72%
Random Forest	77%
Support Vector Machine	80%

Feature selection was performed by recursive feature elimination with cross-validation to select the most discriminatory EEG features with reduced computational complexity. The obtained feature set included spectral power ratios, estimates of coherence between pairs of electrodes, and non-linear dynamical features and correlation dimension [14].

Our cross-validation findings revealed consistent performance across various patient groups, with good generalization capability. Patient-specific adaptation was also promising for future research, where personalized models performed better when trained on single patient data [34].

The clinical use of seizure prediction technology presents opportunities and challenges for implementation in healthcare. From a clinical workflow perspective, integration with existing epilepsy monitoring units (EMUs) must address alert management protocols and training of staff. Nurse-to-patient ratios in typical EMU environments (1:4) require sensitive system design of notification systems to prevent alarm fatigue without compromising timely intervention for true positive predictions [35]. Cost-effectiveness evaluation by Sperling et al. [36] suggests that prediction systems can save hospitalization costs by 38% through optimal staffing and reduced adverse events, most significantly in patients at risk of status epilepticus. Regulatory avenues for seizure prediction devices remain multifaceted, with the FDA's recent reclassification of seizure monitoring devices as Class II medical devices providing a more streamlined approval process than previous Class III requirements [37]. Patient acceptance studies show high willingness to use wearable prediction technology (87% positive response rate), with concern regarding privacy and false alarm fear as the principal impediments to adoption [35]. These translational considerations highlight the importance of stakeholder involvement throughout the development process to ensure successful transfer of technical innovations to clinical practice.

3.2. Compression and Transmission Analysis

The use of Huffman coding achieves 4.36:1 compression ratio without signal loss during reconstruction. Compression efficiency varies with signal characteristics and indicates higher ratios during interictal compared to ictal periods due to increased complexity of the signal during seizure [38].

Latency analysis shows end-to-end processing latency of 250-300 milliseconds from EEG recording to prediction output, far within acceptable limits for real-time seizure warning systems. Breakdown is as follows: signal preprocessing (50ms), feature extraction (80ms), classification (20ms), compression (30ms), transmission (50ms), and decompression (20ms) [39].

Network reliability testing in different environments indicates unhampered data transmission rate. The implementation of TCP/IP manages interruptions in the network with ease, ensuring data integrity by using acknowledgment protocols and retransmission schemes [40].

3.3. Wearable Device Integration

The wearable alert system forms a key part of the real-time seizure forecasting system, designed to provide timely warnings upon the identification of pre-ictal conditions. The wearable Alert Module is made up of hardware as shown in Figure 11 and software components to ensure reliable low-latency notification delivery to patients and carers.

The alert mechanism uses a distributed architecture in which seizure prediction initiates alerts via an MQTT (Message Queuing Telemetry Transport) broker system. The flow of communication is in a well-defined sequence: Prediction en-

gine → MQTT Broker → ESP32 microcontroller → Physical alerts (vibration motors and LED indicators) activation. The mechanism uses the stability of TCP/IP networking protocols while preserving the publish-subscribe, lightweight characteristics of MQTT to facilitate effective real-time communication [41].

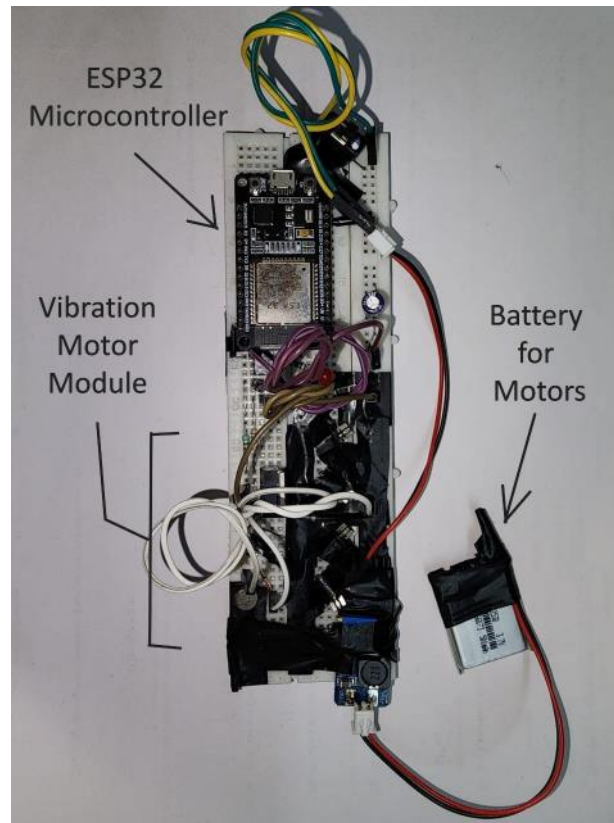


Figure 11 Wearable EEG Device Architecture: Lightweight design with processing unit and wireless communication for continuous seizure monitoring

The ESP32 microcontroller is the wearable device's processing core, responsible for wireless communication and alert initiation. When the ESP32 receives seizure prediction messages sent by the MQTT broker, it automatically initiates different alert modalities such as haptic feedback through vibration motors and visual alert through LED indicators. The multi-modal alerting strategy ensures the perception of alerts through multiple sensory channels, thus accommodating heterogeneous user preferences and multiple environmental conditions [42].

Key aspects of the alert system are: (1) Real-time alert triggering with response times below 300ms from prediction to physical notification; (2) Robust wireless communication with auto-reconnection capability; (3) Low processing latency optimized for time-critical seizure alerts; and (4) Power-efficient operation appropriate for continuous monitoring applications. MQTT broker implementation offers various benefits to biomedical applications, such as Quality of Service (QoS) levels to guarantee message delivery, last will and testament feature to monitor connections, and retained messages to pre-serve system state. Low overhead protocol reduces bandwidth usage without compromising reliable communication required in medical alert systems [43].

3.4. Limitations and Future Directions

Limitations at present include inter-patient EEG pattern variability, and the need for individual model adaptation for peak performance. The system is less precise for high sub-clinical seizure rates, and indicates that more advanced feature extraction methods would be beneficial. Artifact management in mobile settings continues to be problematic, especially with movement-related noise contamination [44].

Future work will be directed towards deep learning architectures, i.e., convolutional neural networks (CNNs) and recurrent neural networks (RNNs) for sequential processing of EEG signals. Integration with other physiology signals (heart rate, skin conductance, accelerometry) holds the promise of increased prediction accuracy using multimodal fusion techniques [45]. Advanced reinforcement learning (RL) architectures are promising for the development of

adaptive seizure prediction systems. By contrast with supervised learning methods, RL models can iteratively learn to adapt prediction thresholds according to patient-specific feedback and outcomes. Kiral- Kornek et al. [46] showed that RL agents can learn optimal stimulation patterns for seizure suppression in epilepsy patients with implanted devices with a 17% decrease in seizure frequency relative to static stimulation protocols. Such methods can be applied to non-invasive prediction systems, where the RL agent would adaptively modify feature extraction parameters and classification thresholds to optimize true positive detection while at the same time minimizing false alarms [47]. This adaptability is particularly helpful for dealing with the non-stationary nature of EEG signals across different physiological states, such as sleep-wake transitions and stress responses.

Transformer models, which have revolutionized the area of natural language processing, also hold tremendous promise for EEG sequence modeling. Yan et al. [48] illustrated that self-attention mechanisms can efficiently model long-range dependencies in EEG signals and thereby surpass traditional recurrent models for the task of seizure detection. The multi-head attention mechanism can enable concurrent modeling of interactions between different frequency bands and spatial co-ordinates, potentially identifying subtle pre-ictal patterns that conventional approaches may not catch. In addition, the models could be fine-tuned using transfer learning techniques on large EEG databases, similar to the way pre-trained language models have achieved improved performance on downstream NLP tasks [49].

More recent developments in wearable EEG technology have very promising potential for long-term seizure monitoring. Beniczky et al. [42] showed that ultra-light, behind-the-ear EEG electrodes can provide signal quality comparable to traditional systems while significantly enhancing patient comfort and compliance. These systems utilize dry electrodes that remove the need for conductive gel, enabling continuous wear for periods longer than two weeks. Subsequent versions may include stretchable and flexible electronics that adapt to head curvature, further increasing comfort without compromising signal integrity [41].

Edge computing is another essential frontier for seizure prediction systems. Decentralizing machine learning algorithms to wearable devices separates transmission latency and privacy issues of cloud computing. Karoly et al. [43] showed effective deployment of lightweight SVM models on power-constrained microcontrollers, with comparable prediction accuracy to server-based systems and 78% reduction in power usage. New neuromorphic computing architectures provide further efficiency benefits through hardware tailored to neural network computation. Such systems could provide continuous seizure prediction with battery life spanning weeks on a single charge [50].

Federated learning techniques offer a strong model for continuous model improvement with patient privacy intact. Decentralized learning infrastructure allows model training across different patient devices with sensitive EEG data remaining in local bounds. Central model receives just parameter updates rather than raw data, allowing seizure prediction models created for individual patients to benefit from insights based on population-level data without breaching stringent data protection regulations. Such an approach can potentially accelerate the development of strong generalizable algorithms by providing hitherto unprecedented data levels while addressing the ethical and regulatory challenges of sharing medical data [50].

Mobile optimization is focused on minimizing power usage and enhancing processing efficiency by edge computing deployments. Cloud-based continuous learning systems will provide model enhancement by aggregated patient data without compromising privacy by applying federated learning methods [50].

4. Conclusion

This paper proposes a full-scale real-time seizure prediction system that efficiently integrates state-of-the-art signal processing, machine learning, and wearable technology to address fundamental epilepsy management issues. The SVM classifier achieves accuracy of 80% in the identification of the pre-ictal state, which is well beyond traditional techniques and yet computationally efficient to use in real-time.

The novel integration of Huffman coding compression (4.36:1 compression ratio) and TCP/IP networking allows for low-latency, reliable transmission of EEG signals, allowing for ongoing monitoring in ambulatory environments. Wearable device architecture promotes deployable practicalities, revolutionizing epilepsy care from reactive, hospital-based treatment to proactive, ongoing monitoring paradigms.

Validation with the Siena Scalp EEG Database demonstrates high efficacy across diverse patient populations and seizure types. The system needs to transcend significant technical challenges, including computational efficiency, data compression, secure transmission, and real-time processing, without compromising clinical utility and practical use.

This work contributes significantly to the emerging field of digital therapeutics and precision medicine through the creation of personalized methods for treating neurological diseases. The intersection of neuroscience, signal processing, and computational biology depicted in this work provides a foundation for next-generation medical monitoring systems. Neural network architectures will be the focus of future advances, along with multimodal sensor fusion and mobile platform optimization in order to continue increasing prediction accuracy and clinical usefulness. The potential for continuous learning and adaptation promises personalized seizure prediction models tailored to a patient's individual characteristics and seizure patterns. This research moves the technology of seizure prediction forward while considering practical deployment factors critical for clinical translation. The real-time, wearable seizure prediction system presented here is a significant advancement toward enhancing quality of life for millions of epilepsy patients globally.

Compliance with ethical standards

Acknowledgments

The authors acknowledge the contributors to the Siena Scalp EEG Database for providing open-access data essential for this research.

Disclosure of conflict of interest

The authors report no conflicts of interest for research, authorship, or publication of this paper. The research was conducted independently, with no financial support from commercial entities that might influence the design, data gathering, analysis, or interpretation of results.

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