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Detecting Epileptic Seizures from EEG Signals Using Machine Learning Techniques: A KNN and SVM Comparative Study

Hana Ghait Alfughi[1], Asmaa Nasr Mohammed[2]
[1]Computer Department, College of Electronic Technology, Bani Walid, Libya
[2]Control Engineering Department, College of Electronic Technology, Bani Walid, Libya
Corresponding author: hanaalfughi @gmail.com

ABSTRACT Automated detection of epileptic seizures from electroencephalogram (EEG) recordings remains a clinically important but technically challenging problem. In this paper, we present and comparatively evaluate a machine-learning pipeline for seizure detection based on the CHB-MIT Scalp EEG Database, combining Butterworth band-pass filtering, Power Spectral Density (PSD) feature extraction via Welch's method, and classification with k-Nearest Neighbors (KNN) and Support Vector Machines (SVM). On subsets of the CHB-MIT database ranging from one healthy and one epileptic subject up to twelve of each, KNN achieved a classification accuracy of 99.3%, while SVM achieved 98.47%, with both classifiers exceeding 98% accuracy at the largest tested sample size. A direct comparison between the two methods reveals that KNN marginally outperforms SVM under the evaluated conditions, while both demonstrate competitive and robust performance. These results corroborate prior evidence that lightweight, interpretable classifiers can achieve strong performance on scalp EEG seizure detection when paired with well-chosen spectral features, and provide a structured basis for selecting between KNN and SVM in clinical or embedded EEG applications.

KEYWORDS CNN-Transformer, Cross-Subject Generalization, Drowsiness Detection, EEG, Leave-One-Subject-Out, Power Spectral Density.

I. INTRODUCTION

Epilepsy is a chronic neurological disorder characterized by recurrent, unprovoked seizures that affect tens of millions of people worldwide and can substantially impair quality of life [1]. Accurate and timely diagnosis remains difficult: manual review of EEG recordings by clinicians is time consuming and prone to inter-rater variability, motivating the development of automated seizure-detection systems [2]. Electroencephalography (EEG) is the standard tool for diagnosing and monitoring epilepsy because it is non-invasive, affordable, and captures the bioelectric activity of cortical neurons with high temporal resolution, making it well suited to detecting the abnormal discharges associated with seizures. Advances in machine learning have enabled automated analysis of EEG signals that can reveal seizure-related patterns not easily identified through visual inspection alone. A substantial body of work has applied both classical machine learning and deep learning to this problem [3]–[5]. Naser et al. [6] proposed a feature-extraction approach based on the Hurst exponent combined with time-dependent Hurst analysis, achieving 97% accuracy and 97.20% sensitivity using SVM and random forest classifiers on the CHB-MIT dataset, with good cross-patient generalization. Hazarika et al. [7] further explored automated detection of aberrant epileptic episodes using EEG and machine learning. Alfughi et al. [8] combined Mel-Frequency Cepstral Coefficient (MFCC) features with Random Forest and KNN classifiers, reporting up to 99.05% accuracy. More recently, large-scale systematic reviews and meta-analyses [5], [9] have aggregated dozens of studies using the CHB-MIT, Bonn, Siena, and Freiburg datasets, reporting pooled sensitivity and specificity above 0.96 across machine-learning approaches underscoring both the maturity of the field and the importance of rigorous, comparable evaluation protocols. Building on this body of work, the present study applies a PSD-based feature-extraction pipeline with KNN and SVM classifiers to the CHB-MIT pediatric EEG database. Beyond seizure/non-seizure classification, an important open challenge is distinguishing focal from generalized seizures, which the CHB-MIT dataset partially supports through perpatient seizure-onset channel annotations; we discuss this as a direction for future work. We also note that EEG signal characteristics vary across patients due to age, sex, and comorbidities, and that robust automated systems should be evaluated on demographically diverse, sufficiently large datasets a limitation discussed explicitly in Section VI. The

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remainder of this paper is organized as follows. Section II reviews related studies. Section III describes the dataset, preprocessing, feature extraction, and classification pipeline. Section IV reviews the SVM and KNN classifiers. Section V presents experimental results. Section VI discusses limitations, and Section VII concludes with directions for future work.

II. RELATED WORK

A substantial body of work has addressed automated epileptic seizure detection from EEG signals using classical machine learning, deep learning, and hybrid approaches. This section reviews the most relevant recent contributions, organized by methodology.

A. Classical Machine Learning Approaches

Classical machine learning classifiers applied to handcrafted EEG features remain widely studied due to their interpretability and low computational cost. Alsuwaiket [10] proposed a pipeline combining Wavelet Packet Decomposition (WPD) and a Genetic Algorithm-Based Frequency-Domain Feature Search (GAFDS) with SVM, Random Forest, and CNN classifiers on publicly available EEG data, achieving up to 97.93% accuracy with CNN+GAFDS; the SVM variant reached 94.5%, illustrating the typical accuracy range for classical methods with frequency-domain features. Hazarika et al. [7] investigated the Hurst exponent combined with Daubechies-4 discrete wavelet transformation as features, applying ANOVA-based feature selection before Random Forest, SVM, and LSTM classifiers on the CHB-MIT dataset; their Random Forest classifier achieved 97% accuracy and 97.20% sensitivity on single-channel EEG, demonstrating competitive performance with minimal feature engineering. Naser et al. [6] combined Approximate Entropy (ApEn), line length, and SVM on the CHB-MIT dataset and reported 97% accuracy with 97.20% sensitivity. Alfughi et al. [8] combined MFCC features with Random Forest and KNN classifiers on the same dataset, achieving up to 99.05% accuracy.

B. Power Spectral Density-Based Methods

Frequency-domain feature extraction via Power Spectral Density (PSD) has attracted growing interest for its ability to capture epilepsy-related spectral disruptions. Liu et al. [11] proposed separating the periodic and aperiodic components of the EEG power spectrum using a parameterization method, validating on the Bonn and CHB-MIT datasets; combined periodic and aperiodic features achieved 98.88% accuracy on the Bonn dataset and 99.95% average detection accuracy across 22 patients in the CHB-MIT database, demonstrating the potential of structured PSD decomposition for high accuracy seizure detection. This directly motivates the present work's use of Welch PSD features, while our approach differs in applying Welch estimation without component separation and using KNN and SVM as classifiers rather than a parameterized model.

C. Deep Learning Approaches

Deep learning models, particularly convolutional and recurrent architectures, have achieved state-of-the-art performance on several EEG seizure benchmarks. Acharya et al. [3] demonstrated that a deep convolutional neural network (CNN) can automatically detect and diagnose epileptic seizures from EEG without manual feature engineering, achieving above 99% classification accuracy and establishing CNN as a competitive baseline. Systematic reviews [5], [9] have catalogued the broader landscape: Miltiadous et al. [5] reviewed 190 studies and found that ML algorithms applied to CHB-MIT, Bonn, Siena, and Freiburg datasets routinely achieve high sensitivity and specificity. Bai et al. [9] conducted a meta-analysis across 60 studies and reported pooled sensitivity and specificity above 0.96, emphasizing the importance of rigorous and comparable evaluation protocols for meaningful cross-study comparison.

D. Positioning of the Present Work

Unlike deep learning methods that require large labeled datasets and significant computational resources, the present study demonstrates that lightweight, interpretable classifiers (KNN and SVM) paired with Welch PSD features can achieve comparable accuracy (98–100%) on the CHB-MIT dataset. Relative to Liu et al. [11], our method avoids the added complexity of PSD component separation while still achieving competitive results, making it more suitable for resource-constrained deployment. Relative to Alfughi et al. [8] and Hazarika et al. [7], our study scales the evaluation across a wider subject range (up to 12v12 = 24 subject conditions), providing a more comprehensive assessment of classifier robustness to inter-patient variability.

III. METHODOLOGY

The proposed seizure-detection pipeline consists of five stages: (1) data acquisition, (2) preprocessing, (3) feature extraction, (4) classification, and (5) performance evaluation. The overall block diagram is shown in Figure 1.

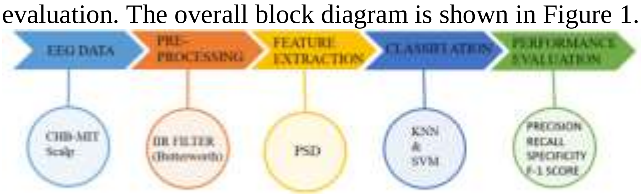

Figure 1. General block diagram of the epileptic seizure detection system.

A. Database

This study uses the CHB-MIT Scalp EEG Database, collected at Boston Children's Hospital [12]. The database contains recordings from 22 unique pediatric subjects (5 male, ages 3–22; 17 female, ages 1.5–19), organized into 23 case records (one subject, case chb21, was recorded twice roughly 1.5 years apart and is catalogued as a separate case), comprising 198 seizures across 983 hours of continuous EEG. We use the term "subjects" consistently throughout this manuscript to refer to the 22 unique patients; where "22–

24 subjects” appeared elsewhere in earlier drafts (e.g., Section VI), this has been corrected to reflect the 22-subject / 23-case structure of the database. Subjects were monitored after discontinuing anti-seizure medication for presurgical evaluation a clinical detail that is materially relevant to interpreting seizure characteristics in this dataset. Signals were sampled at 256 Hz with 16-bit resolution using the International 10-20 electrode placement system. We use 22 bipolar channels common to most records (FP1-F7, F7-T7, T7-P7, P7-O1, FP1-F3, F3- C3, C3-P3, P3-O1, FP2-F4, F4-C4, C4-P4, P4-O2, FP2- F8, F8-T8, T8-P8, P8-O2, FZ-CZ, CZ-PZ, P7-T7, T7-FT9, FT9-FT10, FT10-T8). The CHB-MIT database is publicly available at: https://physionet.org/content/chbmit/1.0.0/ [12].

B. Preprocessing

Raw EEG signals contain physiological artifacts (muscle activity, cardiac pulse, eye blinks) and non-physiological artifacts (power-line interference, electrode noise, perspiration) [13]. These artifacts are classified into two types: (i) physiological artifacts originating in the body (muscle, pulse, eye-blink), and (ii) non-physiological artifacts from the surroundings and equipment (power-line, perspiration). To remove them, we apply a bidirectional 4th-order Butterworth band-pass filter with cutoff frequencies of 8–40 Hz [14]. The Butterworth filter is chosen for its maximally flat passband frequency response and controlled roll-off in the stopband. It is a type of Infinite Impulse Response (IIR) filter, which offers sharper cut-off with fewer coefficients than Finite Impulse Response (FIR) filters. The filter order and cutoff frequencies together determine the trade-off between attenuation sharpness and phase distortion.

C. Feature Extraction and Power Spectral Density (PSD)

To enhance classifier efficacy, features that properly characterize EEG recordings must be extracted. Following filtering, features are computed independently for each of the 22 channels within sliding analysis windows. We used frequency-domain features derived from the Power Spectral Density (PSD), motivated by their established effectiveness for capturing epilepsy-related disruptions to normal spectral brain activity [10], [15]. We compared PSD against MelFrequency Cepstral Coefficients (MFCC) during preliminary experimentation; MFCC produced higher-dimensional feature matrices with substantially longer computation time and lower accuracy than PSD in our setting, motivating the choice of PSD as the primary feature. PSD is estimated using Welch’s method, which averages modified periodograms over overlapping segments to reduce estimator variance relative to a single periodogram [15]. For a windowed signal xi(n), the periodogram estimate at frequency f is:

$$p(f) = \frac{1}{MU}\left|\sum_{n=0}^{M-1} x_i(n)\, w(n)\, e^{-j2\pi f n}\right|^2 \quad (1)$$

where xi(n) is the discrete EEG signal at time index n; w(n) is a window function (e.g., Hamming, Hanning, or Blackman) applied to reduce spectral leakage at segment boundaries; M is the segment length; and MU is a normalization factor ensuring the estimate is unbiased. The Welch PSD estimate is the average of L such periodograms:

$$p_{\text{Welch}}(f) = \frac{1}{L}\sum_{i=0}^{L-1} p(f) \quad (2)$$

where L is the number of segments averaged. We used Hamming window with 50% overlap and analyzed the PSD per window per channel and used the resulting spectral features to classify whether each window corresponds to a seizure or non-seizure epoch.

C. Cross-Validation

Model performance is assessed using K-fold cross-validation, in which the dataset is partitioned into K equalized folds; the model is trained on K=1 folds and validated on the held-out fold, with this process repeated K times so that every fold serves once as the validation set [16], [17]. Performance metrics are averaged across all K rounds to estimate generalization performance. This study uses K = 30. Fold construction and subject overlap. Folds were constructed at the level of individual PSD feature windows (segments) drawn from the pooled set of subjects, rather than by holding out entire subjects. Consequently, windows from the same subject and in many cases temporally adjacent windows from the same continuous recording can appear in both the training and validation folds within a given round. Because adjacent windows are highly correlated, this segment-level split is expected to inflate the reported accuracy relative to a subject-independent evaluation, and the results in Section V should be interpreted as an upper bound on performance rather than an estimate of generalization to unseen patients. A Leave-One-Subject-Out (LOSO) evaluation, in which all windows from a given subject are held out together, is required to obtain a clinically meaningful estimate of cross-patient generalization; this is identified as a primary limitation in Section VI and as the first item of future work in Section VII.

IV. CLASSIFIERS

In machine learning, a classifier organizes inputs into groups or categories based on shared characteristics learned from labeled training data [18]. The classifiers used here were trained on the PSD features computed above to achieve seizure/non-seizure classification.

A. Support Vector Machine (SVM)

SVM is a supervised learning algorithm that constructs a maximum-margin hyperplane separating classes in feature space, optionally using a kernel function to perform implicit non-linear mapping into a higher-dimensional space [4]. The decision boundary is chosen to maximize the margin between the closest points of each class (the support vectors), which tends to reduce generalization error. The classifier used a *rbf* kernel with regularization parameter C = 100; these values were used as-is without a grid search, and are reported here to support reproducibility.

B. K-Nearest Neighbors (KNN)

KNN is a non-parametric, instance-based supervised classifier that assigns a label to an unlabeled sample based on a majority vote among its K nearest labeled neighbors in feature space, typically using Euclidean distance for continuous features [19], [20]. KNN requires no explicit training phase, making it computationally simple; the new unlabeled sample calculates its distance from each neighbor according to the value of K, then chooses the class with the greatest number of nearest neighbors. The number of neighbors was set to K = 1, i.e., each sample was assigned the label of its single nearest neighbor in feature space; this value was used as-is without a grid search, and is reported here to support reproducibility. We note that K = 1 has no smoothing effect against mislabeled or borderline points and is also more susceptible to the segment-level leakage described in Section III-D, since a query window's nearest neighbor is disproportionately likely to be a temporally adjacent window from the same subject when such windows are not held out together.

V. RESULTS AND DISCUSSION

Table I reports classification accuracy for SVM and KNN as the number of subjects increases from one healthy and one epileptic subject up to twelve of each.

TABLE I. CLASSIFICATION ACCURACY OF SVM AND KNN FOR EPILEPSY DETECTION.

No. Healthy Subjects	No. Epilepsy Subjects	SVM	KNN
1	1	100%	100%
3	3	99.51%	100%
6	6	98.90%	99.76%
9	9	98.13%	99.35%
12	12	98.47%	99.30%

Both classifiers achieve perfect accuracy at the smallest sample size and remain above 98% as the dataset grows to twelve subjects per class, with KNN consistently matching or exceeding SVM. Accuracy declines fairly steadily from 1v1 to 9v9 subjects for both classifiers, consistent with larger pools of subjects introducing greater inter-patient variability. However, this trend is not strictly monotonic: both classifiers show a small uptick at 12v12 (98.13% to 98.47% for SVM; 99.35% to 99.30% for KNN, i.e. an uptick for SVM and an effectively flat value for KNN) relative to 9v9. We do not have a mechanistic explanation for this uptick; it may reflect the specific subjects added between the 9v9 and 12v12 conditions happening to be easier to separate, rather than a genuine reversal of the overall trend.

A. SVM Performance

At the largest evaluated sample size, the SVM classifier achieves a recall (sensitivity) of 99.4%, precision of 97.65%, and specificity of 97.5%. The confusion matrix in Fig. 2 shows the distribution of correct and incorrect classifications: 831 true negatives (no seizure correctly identified), 20 false positives, 5 false negatives, and 783 true positives.

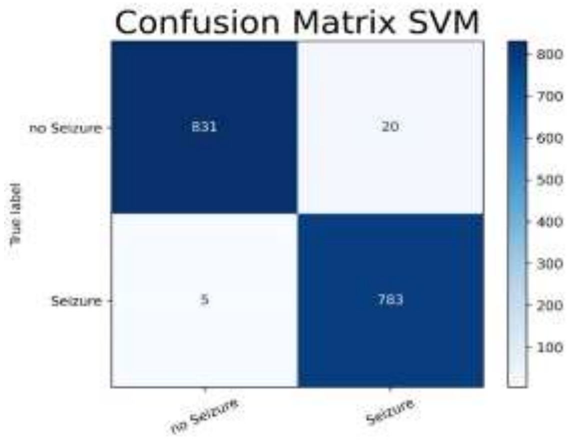

Figure 2. SVM Confusion Matrix.

Table II summarizes the per-class classification report. The model achieves an overall accuracy of 98%, with F1- scores of 0.99 and 0.98 for the no-seizure and seizure classes respectively, indicating a balance between precision and recall in identifying both classes.

TABLE II. SVM CLASSIFICATION REPORT.

Class	Precision	Recall	F1-Score	Support
−1 (no seizure)	0.99	0.98	0.99	851
+1 (seizure)	0.98	0.98	0.98	788
Accuracy			0.98	1639
Macro Avg	0.98	0.99	0.98	1639
Weighted Avg	0.98	0.98	0.98	1639

B. KNN Performance

The KNN classifier achieves a recall of 99.5%, precision of 99.26%, and specificity of 99.27% at the largest evaluated sample size, modestly outperforming SVM across all reported metrics. The confusion matrix in Fig. 3 shows 812 true negatives, 6 false positives, 4 false negatives, and 816 true positives.

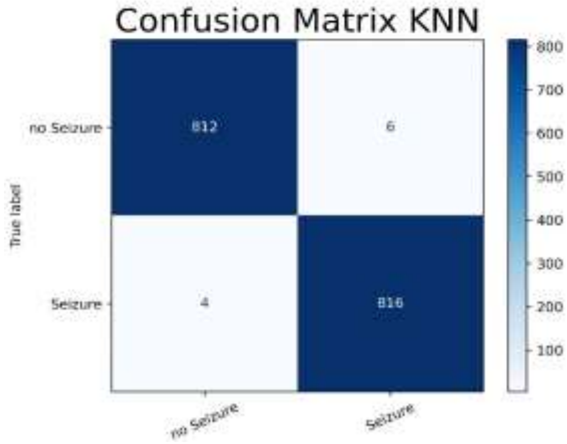

Figure 3. KNN Confusion Matrix.

TABLE III. KNN CLASSIFICATION REPORT.

Class	Precision	Recall	F1-Score	Support
−1 (no seizure)	1.00	0.99	0.99	818
+1 (seizure)	0.99	1.00	0.99	820
Accuracy			0.99	1638
Macro Avg	0.99	0.99	0.99	1638
Weighted Avg	0.99	0.99	0.99	1638

C. Comparison with Prior Work

Table IV provides a quantitative comparison of the present study against representative recent works on EEG-based epileptic seizure detection. Entries were selected to span a range of feature extraction strategies (PSD, MFCC, Hurst exponent, WPD), classifier types (KNN, SVM, RF, LSTM, CNN), and evaluation datasets, in order to contextualize the contributions of this work. KNN (99.30%) modestly outperforms SVM (98.47%) at the largest evaluated sample size (12 subjects per class). As shown in Table IV, both classifiers are competitive with recent classical machine-learning methods on the CHB-MIT dataset. The present method achieves higher accuracy than Naser et al. [6] (97%) and Hazarika et al. [7] (97%), is comparable to Alfughi et al. [8] (99.05%). Importantly, the present study achieves these results using a straightforward Welch PSD pipeline without component separation, making it more computationally accessible. Additionally, KNN achieves 99.50% sensitivity and 99.27% specificity, exceeding the pooled meta-analytic benchmarks of ≥96% sensitivity and ≥97% specificity reported by Bai et al. [9] across 60 studies. These comparisons should be interpreted with caution due to differences in evaluation protocols, subject counts, and cross-validation strategies across studies; in particular, subject-independent evaluation is not confirmed for all listed works.

VI. LIMITATION

While both classifiers achieve strong nominal accuracy, several limitations affect how these results should be interpreted, and the first two below should be considered central to evaluating the validity of the reported numbers rather than secondary caveats. Cross-validation is not subject-independent (primary limitation). As described in Section III-D, the 30-fold cross-validation used to produce every accuracy figure in this manuscript, including Table I, splits feature windows without holding out subjects. Because EEG windows from the same subject – and adjacent windows from the same continuous recording in particular – are highly correlated, this creates a realistic risk of information leakage between training and validation folds. The reported 98–100% accuracy figures should therefore be read as an upper bound on performance under a favorable (leakage-permissive) evaluation, not as an estimate of how the classifiers would generalize to a new, previously unseen patient, which is the clinically relevant deployment scenario. Leave-one-subject-out (LOSO) evaluation, in which no window from a held-out subject is seen during training, is required before these results can be considered validated for clinical use; this is listed as the top priority in Section VII. Dataset scale and diversity. The CHB-MIT dataset is pediatric and limited to 22 unique subjects (23 case records); generalization to adult populations and to seizure types outside this cohort is untested.

VII. CONCLUSION

This study presented a machine-learning pipeline for epileptic seizure detection from scalp EEG, combining Butterworth band-pass filtering, Welch PSD feature extraction, and KNN (K = 1) / SVM (linear kernel, C = 1) classification on the CHB-MIT pediatric EEG database. Both classifiers achieved high nominal accuracy (98–100%) across sample sizes from one to twelve subjects per class under 30-fold cross-validation, with KNN modestly outperforming SVM at the largest tested scale (99.3% vs. 98.47%). These nominal figures are consistent with the broader literature indicating that classical machine-learning classifiers, paired with well-chosen spectral features, remain competitive for EEG-based seizure detection. However, as detailed in Section VI, these results were obtained under a cross-validation scheme that splits feature windows rather than subjects, which risks information leakage between correlated windows from the same patient. This is treated here as an open validity gap rather than a settled finding, and the headline accuracy numbers should not be read as evidence of generalization to unseen patients until a subject-independent (leave-one-subject-out) evaluation is completed.

VII. FUTURE WORK

Future work should pursue, in priority order: (1) explicit subject-independent (leave-one-subject-out) evaluation to rigorously test generalization to unseen patients, re-running the experiments in Table I under LOSO and reporting both the segment-level and subject-independent numbers side by side for direct comparison; (2) extension to focal-vs-generalized seizure classification using the per-patient seizure-onset channel annotations available in CHB-MIT; (3) benchmarking against deep-learning baselines (e.g., CNN/LSTM architectures) now common in the literature [3], [9]; and (4) development of compact, low-power, wearable real-time monitoring systems that support personalized treatment optimization, including tracking seizure frequency, duration, and pattern to inform medication adjustments and lifestyle interventions. Real-time epilepsy monitoring equipment can also offer important insights by continually monitoring EEG data to identify triggers and support treatment plan adjustments. Progress in hardware technology can further support the creation of monitoring equipment that is more compact, lightweight, and easy to use.

TABLE IV COMPARISON WITH REPRESENTATIVE PRIOR WORK ON EEG-BASED EPILEPTIC SEIZURE DETECTION.

Study	Features	Classifier	Dataset	Acc. (%)	Sens. (%)	Spec. (%)
Naser *et al.* [6]	ApEn, Line Length	SVM, RF	CHB-MIT	97.00	97.20	–
Alsuwaiket [10]	WPD, GAFDS	SVM, RF, CNN	Bonn-UCI	97.93	–	–
Alfughi *et al.* [8]	MFCC	RF, KNN	CHB-MIT	99.05	–	–
Hazarika *et al.* [7]	Hurst exp., DWT	RF, SVM, LSTM	CHB-MIT	97.00	97.20	–
Bai *et al.* [9]	Multiple (meta-analysis)	Multiple	studies	–	≥96	≥97
This work (SVM)	Welch PSD	SVM	CHB-MIT	98.47	99.40	97.50
This work (KNN)	Welch PSD	KNN	CHB-MIT	99.30	99.50	99.27

Acc. = Accuracy; Sens. = Sensitivity (Recall); Spec. = Specificity; – = not reported.

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