# Power-Efficient Epileptic Seizure Detection Using Linear Predictive Coding for Wearable Applications

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## Abstract

Epilepsy is a critical neurological disorder affecting millions worldwide, requiring accurate and timely detection to prevent life-threatening complications. Clinical devices achieve high accuracy in seizure detection, ensuring reliable medical monitoring. However, the demand for wearable devices necessitates lightweight, low-power, real-time solutions. Wearable EEG-based seizure detection requires efficient signal encoding to optimize power consumption while maintaining classification accuracy and computational efficiency. In this study, we hypothesize that applying Linear Predictive Coding over long EEG segments provides a computationally efficient approach suitable for wearable applications. To evaluate this, EEG signals were analyzed using Linear Predictive Coding, Discrete Wavelet Transform, and Power Spectral Density-based features, and classified using Multilayer Perceptron, Random Forest, and Support Vector Machines. Among the tested combinations, the Linear Predictive Coding and Random Forest model achieved the best energy efficiency with an average consumption of 2.73 microjoules per percent and classification accuracy of 93.18%. One-way analysis of variance showed no significant accuracy difference among feature extraction methods ($p = 0.856$) but revealed a significant difference in energy efficiency ($p = 1.93 \times 10^{-75}$). These findings demonstrate that Linear Predictive Coding is a promising technique for wearable seizure detection, offering a balance between accuracy and energy efficiency for next-generation medical applications.

## Keywords

Epileptic seizure detection, EEG, energy efficiency, linear predictive coding, discrete wavelet transform, random forest, support vector machine, multilayer perceptrons

## 1. Introduction

Epilepsy is a neurological disorder characterized by recurrent seizures caused by abnormal electrical activity in the brain's neurons. Affecting more than 70 million people worldwide, this condition significantly reduces individuals' quality of life. Due to the unpredictable nature of epilepsy, patients experience considerable social, psychological, and physical challenges. Sudden seizures restrict daily activities and may lead to hazardous situations. Therefore, accurate and timely diagnosis of epilepsy is crucial to minimizing its impact [1, 2, 3].

Traditionally, electroencephalography (EEG) recordings are used for the diagnosis of epilepsy. In clinical settings, EEG-based systems are commonly employed for detecting epileptic seizures, and these methods achieve high accuracy rates. However, due to the limitations of clinical environments, continuous monitoring of patients is not feasible [4, 5]. At this point, wearable EEG devices offer a promising alternative for epilepsy patients. These devices can automate seizure detection by collecting EEG data while patients continue their daily activities. However, for wearable devices to continuously record data, they must have low power consumption, minimized computational load, and efficient memory usage. Therefore, the algorithms used for epileptic seizure detection must be energy-efficient and computationally optimized.

Various methods have been employed in literature for automatic epileptic seizure detection. Traditional signal processing techniques, such as Time-Frequency Analysis [6, 7, 8, 9], Discrete Wavelet Transform (DWT) [10, 11, 12], and Principal Component Analysis (PCA) [13, 14, 15], are widely used. Additionally, different machine learning and deep learning models, particularly Autoencoders (AE) [16,17,18] and Convolutional Neural Networks (CNNs) [19, 20], have achieved significant success in analyzing EEG signals. However, these models often require high computational power and consume considerable energy, necessitating substantial optimization for real-time implementation on portable devices. For instance, Sopic et al.'s e-Glass system achieved 93.8% accuracy using the Physionet CHB-MIT dataset but had a limited battery life of only 2,71 days [21].

Yu et al. attempted to enhance epilepsy detection by integrating ECG and BVP with EEG, achieving 83.9% sensitivity [22]. However, their study did not incorporate any energy consumption optimizations.

Widely used seizure detection methods lack sufficient energy efficiency optimization. Traditional methods such as Discrete Wavelet Transform (DWT) and Principal Component Analysis (PCA) may lead to loss of information, while deep learning-based approaches require high energy consumption. Huang and Sun proposed an Autoencoder (AE)-based feature extraction method for EEG signals, achieving an accuracy of 97% compared to PCA [23]. However, AE-based approaches have disadvantages in terms of computational cost and energy consumption.

Linear Predictive Coding (LPC) is rarely studied for epilepsy detection but offers high computational efficiency, making it promising for portable devices. Tran et al. achieved 94% accuracy using LPC-based EEG features [24], while Jeppesen et al. (2021) combined LPC with HRV analysis for seizure detection [25]. However, these studies used small datasets, and LPC's real-time applicability to wearable devices remains underexplored.

In this study, we hypothesize that applying Linear Predictive Coding (LPC) over an extended time window of 2048 samples (~11.8 seconds) instead of short windows (10-25 ms) improves energy efficiency. We anticipate that this approach reduces computational complexity while maintaining high classification accuracy, making it highly suitable for wearable EEG devices.

Also, we propose the most energy-efficient approach for epileptic seizure detection by comparing different feature extraction methods, including Linear Predictive Coding (LPC), Discrete Wavelet Transform (DWT) and Power Spectral Density Features (PSDF) based approach. A review of the literature reveals that most studies focus primarily on deep learning-based methods while failing to adequately address energy efficiency for wearable devices. In this context, our study contributes significantly to the development of energy-efficient and high-accuracy epileptic seizure detection systems for wearable EEG devices.

In this context, we aim to investigate the energy efficiency and classification performance of various feature extraction techniques for epileptic seizure detection, including Linear Predictive Coding (LPC), Discrete Wavelet Transform (DWT), and Power Spectral Density-based Features (PSDF). The study further evaluates the compatibility of these methods with common classifiers such as Multi-Layer Perceptron (MLP), Random Forest (RF), and Support Vector Machines (SVM), emphasizing their suitability for resource-constrained, wearable applications.

The proposed methodology is expected to contribute to the development of energy-efficient and high-performance seizure detection algorithms for wearable EEG systems. By focusing on computational efficiency, memory usage, and accuracy, this research aims to provide a foundation for optimizing portable and real-time neurological monitoring technologies.

## 2. Materials and Methods

### 2.1 EEG datasets

The general information about the EEG datasets from the Epileptology Department of Bonn University used in the study is provided in Table 1, while the statistical information is given in Table 2 [26].

#### 2.1.1 Dataset splitting

In this study, EEG datasets provided by the Epileptology Department of the University of Bonn, whose characteristics are presented in Table 1, were used. The original datasets consist of five different classes (A, B, C, D, E), each containing 100 EEG signals. These signals were recorded at a sampling frequency of 173.61 Hz, with each signal comprising 4096 samples. However, in our study, the signals were split into two equal segments, resulting in 200 signals of 2048 samples each.

The primary motivation for this segmentation process is to expand the dataset and enhance the model's generalization capability. Machine learning models require a sufficient amount of training data to be effectively trained. Since the number of signals in the original dataset is limited to 100, splitting them into two segments increases the dataset to 200 signals, allowing the model to learn from a larger number of examples. This helps the model better capture different variations and improves its generalization ability [27].

Since EEG signals contain time-varying frequency components, analyzing them within shorter time windows can provide valuable insights. In signals with a length of 4096 samples, distinguishing time-dependent frequency components can be challenging. However, by segmenting the signals into 2048-sample segments, temporal variations can be better captured. This, in turn, enables a more accurate analysis of time-dependent features.

**[Table 1 here]**

Large datasets help prevent overfitting, enabling the model to achieve better generalization. A limited number of signals in the existing dataset may cause the model to memorize specific examples rather than learn general patterns. Segmenting the signals increases data diversity, allowing the model to learn a broader range of patterns and make more accurate predictions on new data. The analysis of critical frequency components is essential in epilepsy diagnosis. Shorter signal segments facilitate the examination of transient epileptic activities, enabling a more precise assessment of seizure onset and progression.

**[Table 2 here]**

Additionally, shorter signals enhance computational efficiency for intensive signal processing techniques such as spectral analysis, wavelet transformation, and other time-frequency methods. Performing analysis on 2048 samples instead of 4096 reduces processing time, making it more practical to work with large datasets. Fig. 1 shows the amplitude-sample value representation of the signal obtained by averaging the signals from sets A, B, C, D, and E.

Although the recording modalities of healthy and epileptic subjects differ (extracranial vs. intracranial), this dataset has been widely used in the literature as a benchmark for seizure detection tasks. Therefore, it provides a valuable standardized framework for evaluating classification and energy efficiency performance across heterogeneous conditions.

[Figure 1 here]

### 2.2 Feature vector extraction techniques

In the presented study, various feature extraction methods such as LPC, DWT and PSDF were employed. These techniques were selected with particular consideration given to computational time and memory consumption. Each method is inherently capable of being optimized to achieve higher accuracy. However, they were chosen based on configurations that meet the minimum computational time and memory requirements. Detailed information regarding the employed techniques and the extracted features is provided below.

#### 2.2.1 Linear predictive coding (LPC) based features

LPC is a method based on predicting future samples of a signal as a weighted sum of previous samples. LPC is widely used, particularly in time series analysis and speech processing applications [28]. The residual error represents the difference between the predicted signal and the actual signal, and it is referred to as the modeling error. The LPC coefficients are defined by Eq. 1.

$$X(n)=\sum_{i=1}^{p} a_{i\partial} X(n-i)+e(n) \quad (1)$$

Here; *X(n)*: Existing signal example, $a_i$: LPC coefficients, *p*: Degree of the model (In this study, it was chosen as 10), *e(n)*: Residual error (modeling error), The Residual error average is calculated with Eq. 2.

$$E_{res}=\frac{1}{N}\sum_{n=1}^{N} e(n) \quad (2)$$

In our study, 10th-order LPC coefficients were calculated from 2048-sample EEG signals. The feature vector consists of a total of 11 features, including the 10 LPC coefficients and the average of the modeling error. Unlike conventional applications where LPC is applied to short segments (typically 10-25 ms), we apply LPC to an entire 2048-sample segment (~11.8 s). This allows for reduced computational overhead and energy consumption while still capturing key signal characteristics.

### 2.2.2 Discrete wavelet transform (DWT) based features

DWT allows for time-frequency analysis by decomposing a signal into different frequency bands [29]. In this study, the signal was decomposed into four levels using the Daubechies 4 (db4) wavelet. The signal components separated in the DWT process are expressed by Eq. 3.

$$X(t) = A_4 + D_4 + D_3 + D_2 + D_1 \quad (3)$$

Here; $A_4$: The approximate coefficient at level 4 and $D_4$, $D_3$, $D_2$, $D_1$: The detail coefficients.

In our study, the $D_4$, $D_3$, $D_2$, $D_1$, and $A_4$ coefficients were extracted using DWT. Four statistical features (mean, standard deviation, skewness, and kurtosis) were computed for each component, resulting in a feature vector consisting of a total of 20 features.

### 2.2.3 Power spectral density (PSD) based features

In our study, the Welch method is used to calculate the Power Spectral Density (PSD) [30]. However, to minimize processing time, only the most discriminative spectral features have been extracted. It is possible to add other features, but it should be noted that this would increase memory consumption and processing time [31].

In PSD based feature (PSDF) extraction; $D_1$: Total spectral power (the total power of all frequency bands), $D_2$: Spectral entropy (measurement of the irregularity of frequency components), $D_3$: Spectral bandwidth (distribution of power density), $D_4$: Spectral skewness (shows the change in trend, which may help detect seizure onset), $D_5$: Peak frequency (the frequency component with the highest power), $D_6$: Delta band power (0.5-4 Hz), $D_7$: Theta band power (4-8 Hz), $D_8$: Beta band power (13-30 Hz). The specified features $D_1$, $D_2$, $D_3$, $D_4$, $D_5$, $D_6$, $D_7$ and $D_8$ form the feature vector in the PSDF extraction approach.

## 2.3 Classification methods and classification performance evaluation

In the classification stage, three different classifiers were utilized: RF, SVM and MLP. RF is a tree-based learning method composed of multiple decision trees, which not only achieves high accuracy but also effectively reduces the risk of overfitting [32]. This characteristic enhances the generalizability and stability of the model, thereby improving energy efficiency in the classification process by avoiding unnecessary computations and yielding faster and more efficient results. Additionally, RF has the capability to effectively distinguish between classes, enabling accurate classification of complex signal data while contributing to energy savings.

SVM is a classifier that aims to find the maximum margin between classes, often delivering high accuracy rates. It is particularly effective in nonlinear classification problems, making it well-suited for the classification of high-dimensional and complex signal data [33]. From an energy efficiency perspective, SVM's ability to achieve high accuracy in nonlinear data enables obtaining correct results with a smaller number of samples and shorter computation times. This reduces computational power requirements, thereby enhancing energy efficiency.

MLP is a neural network-based classifier that leverages deep learning methodologies to learn complex relationships [34]. It has the potential to achieve high accuracy when working with large datasets and is particularly effective in tasks such as epileptic seizure detection. Although MLP typically requires substantial computational power during the training process, energy efficiency can be improved through optimized network architectures and low-resolution modeling techniques. This allows for achieving high performance while consuming less energy.

These three classifiers offer different classification strategies, contributing to the overall accuracy and reliability of the model while also providing significant benefits in terms of energy efficiency. The appropriate selection of classifiers helps avoid unnecessary computations, enables faster results, and reduces energy consumption, making them highly beneficial for time-critical applications such as epileptic seizure detection, where both accuracy and energy efficiency are crucial.

To evaluate the epileptic seizure detection performance of the model, we used two typical classification indicators [35]. These indicators are accuracy and F1-score.

## 2.4 Energy efficiency

In our study, feature vectors were extracted using the LPC, DWT, and PSDF methods, and these vectors were tested with 10-fold cross-validation using RF, SVM, and MLP classifiers. The processing time consists of the total duration of the feature extraction and classification steps. Energy efficiency is used to assess the balance between the accuracy of a method and its computation time [36]. Energy efficiency determines the relationship between the energy consumed during processing time and accuracy according to the Eq. 4.

$$E = \frac{P \times T}{\alpha} \tag{4}$$

Here; $E$: Energy efficiency in Joules, $P$: Processor power in Watts, $T$: Total calculation time in seconds, $\alpha$: Accuracy rate in 0-1 or %.

In the presented study, the total time for feature extraction and classification processes was recorded to determine energy efficiency, the accuracy rate ($\alpha$) of each method was established, and energy consumption was calculated based on a processor model operating at 1 GHz and consuming 1 mW of power. The energy efficiency values obtained for all methods were compared to identify the most efficient method. Since energy efficiency is defined as accuracy per unit energy, a lower value means higher efficiency. A lower energy efficiency value demonstrates that higher accuracy is achieved with less energy consumption. In other words, the smaller the energy efficiency of a method, the more efficient and energy-saving it is.

## 3. Results and Discussion

In this study, to evaluate energy efficiency in epileptic seizure detection, feature vectors were separately extracted using LPC, DWT, and PSDF methods from the Bonn University EEG datasets. These feature vectors were then used to train RF, SVM and MLP classifiers, and their performance was assessed using 10-fold cross-validation. The total processing time consisted of three main stages:

Feature extraction, classifier training, and testing. The flow diagram of the proposed study is given in Fig. 2.

The feature extraction stage involved processing EEG signals and converting them into the specific vector formats defined by each method. In the classification computation phase, the Weka software was used to train the classifiers, perform 10-fold cross-validation, and compute accuracy and F1-score metrics. All computations were carried out on a laptop computer equipped with an Intel i5-1235U processor (1.3 GHz, 10 cores) and 16 GB of RAM.

Table 3 presents the accuracy (Acc) and F1-score (F1) values for RF, SVM, and MLP classifiers trained with feature vectors derived from LPC, DWT and PSDF across 14 different classification tasks. Fig. 3 illustrates the graphical representation of these values for both 14-class classification tasks.

Overall, the RF classifier achieved the highest accuracy and F1-score values across all feature groups. Particularly when using PSDF, the RF model obtained the highest success with an average accuracy of 95.70%. The MLP model also produced results close to RF and demonstrated strong performance, especially with LPC and DWT features. SVM, on the other hand, exhibited lower accuracy compared to the other two classifiers. In multi-class classification tasks (e.g., A-B-C-D-E, B-C-D-E), SVM's accuracy dropped below 70%, whereas RF and MLP maintained relatively high accuracy levels. In binary classification tasks (e.g., A-C, B-E, A-E), all classifiers achieved high accuracy and F1-scores. Particularly, RF and MLP achieved over 99% accuracy in classifications involving seizure-containing classes such as A-E and B-E. While SVM also performed well in these tasks, its accuracy fell below 95% in some cases. This indicates that distinguishing seizure-containing classes from healthy individuals or non-seizure patients is relatively easier.

**[Figure 2 here]**

However, classifier performance declined in multi-class classification tasks. In cases where all five classes (A-B-C-D-E) were included, SVM yielded the lowest accuracy (70.60%), whereas RF achieved up to 89.40% accuracy with DWT and PSDF. MLP performed slightly lower than RF in multi-class classifications but still produced successful results. This suggests that RF generalizes better in high-dimensional and complex datasets. When evaluating feature sets, PSDF generally provided the highest accuracy rates. When used with RF, accuracy rates remained above 95% even in multi-class classification tasks. DWT features produced results similar to PSDF in some tasks but were generally slightly lower with RF. LPC features, on the other hand, exhibited the lowest accuracy, particularly in multi-class classification.

In conclusion, the highest success in epileptic seizure detection was achieved with the RF and PSDF combination. However, MLP also performed comparably well in many cases. The SVM model was hindered by lower accuracy, especially in multi-class classification problems. These findings highlight that RF and PSDF methods form one of the best combinations for seizure detection.

**[Table 3 here]**

A one-way analysis of variance (ANOVA) was conducted to determine whether there were significant differences in classification accuracy between the three methods: LPC, DWT, and PSDF. The results showed no statistically significant difference among the methods, $F(2.120)=0.155$, $p=0.856$. Since the p-value is much greater than the conventional threshold of 0.05, we fail to reject the null hypothesis, indicating that the accuracy values obtained from LPC, DWT, and PSDF do not significantly differ from each other.

**[Figure 3 here]**

Table 4 presents the total processing time and energy efficiency values for RF, SVM, and MLP classifiers using feature vectors extracted with LPC, DWT and PSDF across 14 different classification tasks. Fig. 4 illustrates the graphical representation of the results for all 14 classification tasks.

Among the feature extraction methods, LPC demonstrated the lowest energy consumption across all classification tasks. The average energy consumption when using LPC based features was 2.73 µJ/% for RF, 2.63 µJ/% for SVM, and 2.78 µJ/% for MLP. This efficiency is attributed to the lower computational complexity of LPC, as calculating linear predictive coefficients requires fewer operations compared to other methods. DWT based features exhibited moderate energy consumption, with average values of 5.39 µJ/% for RF, 6.00 µJ/% for SVM, and 6.11 µJ/% for MLP. Since DWT involves time-frequency transformations, it requires more computational resources than LPC, leading to an increase in energy consumption. However, its energy consumption remains lower than that of PSDF. PSDF resulted in the highest energy consumption among the three methods, with average values of 12.45 µJ/% for RF, 13.81 µJ/% for SVM, and 13.13 µJ/% for MLP. The high energy requirement of PSDF is due to the additional spectral computations involved in power spectral density estimation, such as Fourier transformations and statistical calculations. This increased computational load makes PSDF less suitable for low-power wearable and portable systems.

In terms of classifiers, RF exhibited the lowest energy consumption, with an average of 12.45 µJ/% across all tasks. The tree-based structure of RF allows it to make quick decisions in the feature space, resulting in efficient computation. On the other hand, SVM had the highest energy consumption, with an average of 13.81 µJ/%. This is particularly evident when using DWT and PSDF. The MLP classifier consumed less energy than SVM but more than RF, with an average of 13.13 µJ/%.

**[Table 4 here]**

Although the SVM classifier exhibited the shortest computation time among the tested classifiers, its overall energy efficiency remained lower due to its relatively poor classification accuracy. Energy efficiency is determined not only by computational cost but also by the effectiveness of the classification process. Since SVM achieved lower accuracy compared to RF and MLP, the energy spent per correctly classified instance was higher, reducing its overall efficiency. This can be attributed to SVM’s sensitivity to feature selection and hyperparameter tuning, which may have led to suboptimal decision boundaries in this study. Additionally, while SVM benefits from a fast training and inference process, its performance tends to decline in complex, high-dimensional classification tasks, particularly when dealing with EEG signals that exhibit non-stationary characteristics. In contrast, RF and MLP, despite requiring slightly longer computation times, achieved higher accuracy, thereby utilizing their energy consumption more effectively. As a result, SVM's lower computational demand did not translate into higher energy efficiency, highlighting the importance of balancing computational cost with classification performance in energy-constrained applications.

The nature of the classification tasks also influences energy consumption. Binary classification tasks (such as A-C, A-E, B-D) required lower energy consumption than multi-class classification tasks. This is because binary classifications involve simpler decision boundaries, reducing computational complexity. In contrast, multi-class classification tasks (such as A-B-C-D-E, B-C-D-E) significantly increased energy consumption, especially when PSDF was used. Multi-class problems require the classifier to process more complex decision boundaries, increasing the computational burden and consequently raising energy consumption.

**[Figure 4 here]**

When considering feature extraction methods, DWT and PSDF significantly increase energy consumption, particularly in multi-class classification tasks. PSDF, in particular, requires extensive spectral computations, making it the most power-intensive feature extraction method. Therefore, LPC or DWT should be preferred in wearable devices where energy efficiency is a priority. In summary, the combination of LPC features with the RF classifier provides the highest energy efficiency. For low-power applications, LPC based features, and RF should be the preferred choice. If PSDF is used to improve classification accuracy, the additional energy cost must be considered, and hardware optimizations should be implemented to mitigate its impact.

The statistical analysis conducted using a one-way ANOVA test reveals a significant difference in energy efficiency among the three methods: LPC, DWT, and PSDF. The results show an F-statistic of 947.13 and a p-value of $1.93 \times 10^{-75}$, indicating that the observed differences are highly statistically significant ($p < 0.05$). Given the extremely low p-value, we reject the null hypothesis and conclude that energy efficiency varies significantly among the three methods.

When evaluating the feature extraction methods LPC, DWT, and PSDF in terms of memory consumption, significant differences arise due to the number of extracted features and computational complexity. Assuming each feature is stored in 64-bit (8-byte) double precision floating-point format, the total memory requirement varies across methods. The LPC method, which includes 11 features, consumes a total of 88 bytes of memory. This is due to the ability of LPC coefficients to summarize the spectral characteristics of the signal with a small number of parameters. In contrast, the DWT method, which includes 20 features obtained through multi-resolution wavelet decomposition, requires 160 bytes of memory. While DWT provides a richer feature set by capturing both time and frequency domain information, this results in higher memory usage. The PSDF method, on the other hand, contains 8 features and has the lowest memory consumption at 64 bytes. However, despite its memory efficiency, PSDF is computationally expensive, making it less suitable for low-latency wearable device applications. In conclusion, LPC is the most memory-efficient method, DWT requires the most memory, and PSDF has the lowest memory consumption but demands the highest computational resources. Therefore, when selecting a feature extraction method for wearable systems, a balance must be struck between memory, computational efficiency, and classification performance.

The EEG dataset from the University of Bonn, used in our study, is a highly suitable and comprehensive dataset for epileptic seizure detection. One of its greatest advantages is that it is divided into five distinct classes: A, B, C, D, and E. These classes cover a wide spectrum ranging from healthy individuals to epilepsy patients and include recordings taken during seizures. Alternative datasets often contain fewer classes or have lower sampling frequencies. Therefore, the use of the University of Bonn EEG dataset provides a significant advantage for seizure detection and comparative analyses.

Among alternative EEG datasets, notable examples include the CHB-MIT EEG dataset, the TUH EEG dataset, and the Epilepsy Ecosystem dataset [37, 38]. The CHB-MIT EEG dataset focuses on pediatric epilepsy patients and provides long-term EEG recordings, making it valuable for real-time analyses. However, due to its high sampling frequency and large data size, processing requires greater computational power, leading to increased energy consumption. The TUH EEG dataset encompasses a broad patient population and includes EEG recordings obtained from various electrode systems. While this diversity is beneficial for model generalization, the heterogeneity of the dataset can complicate the analysis process. The Epilepsy Ecosystem dataset, on the other hand, consists of EEG recordings collected from portable EEG devices, making it advantageous for real-time applications. However, its lower sampling frequency and limited patient population may hinder the model's generalizability on a larger scale.

The superiority of the University of Bonn EEG dataset over these alternatives lies in its clean and well-structured nature. Working with single-channel averaged EEG signals eliminates variations arising from different electrode systems, making model training more consistent. Additionally, since the recordings were obtained in a controlled laboratory environment, the noise levels are low, simplifying the signal processing pipeline. On the other hand, a limitation of the Bonn dataset is that it does not contain long-term EEG recordings like other datasets and represents only a specific patient group. This may make it challenging to generalize models for real-time applications or broader patient populations.

Several factors directly influence the impact of dataset selection on energy efficiency calculations. One key factor is the sampling frequency, which determines the energy efficiency of a dataset. Higher sampling frequencies generate more data points, increasing processing time and consequently energy consumption. However, the University of Bonn EEG dataset has an optimal sampling frequency of 173.61 Hz, which does not impose an excessive computational burden in terms of energy consumption. If an alternative dataset with a higher sampling frequency, such as CHB-MIT (256 Hz. or higher), were used, the increased data volume would lead to a significant rise in processing time and energy consumption. Conversely, if a dataset with a lower sampling frequency, such as the Epilepsy Ecosystem dataset, were chosen, energy consumption might decrease, but accuracy could be compromised. The broad scope of the TUH EEG dataset allows for the development of a more diverse model; however, its large data size could extend processing time and reduce energy efficiency.

Thus, the Bonn University EEG dataset offers a balanced trade-off between energy efficiency and accuracy. While datasets containing long-term EEG recordings provide more information for epilepsy detection, they require higher computational power due to their large data volume. In this context, the Bonn EEG dataset has been one of the most suitable choices for our study, thanks to its optimal sampling frequency, low noise level, and balanced class structure.

The applicability of the methods examined in our study to wearable EEG devices and their impact on power consumption is a critical consideration. In a wearable EEG device, signals from EEG electrodes would need to be transmitted via Bluetooth to a portable device, such as a smartwatch, for analysis. In this context, the computational power and memory requirements of the employed methods directly affect battery life. LPC stands out as the most suitable method due to its low computational cost and energy efficiency, making it the most efficient option for real-time processing in wearable EEG devices. While DWT offers advantages in terms of accuracy, its high computation time and memory requirements may increase power consumption. PSDF, due to its high computational demands, can rapidly drain the device's battery.

Although the selected methods have been generally successful, alternative approaches can also be considered. Techniques such as Wavelet Packet Decomposition (WPD) can enhance the decomposition of EEG signals into different frequency components, potentially improving classification accuracy. Empirical Mode Decomposition (EMD), due to its adaptive nature, may better capture the dynamic characteristics of EEG signals. Deep learning-based models, particularly Convolutional Neural Networks (CNN) and Long Short-Term Memory Networks (LSTM), can be effective for direct processing and classification of EEG data. However, these methods are characterized by high computational costs and low energy efficiency. Additionally, methods such as Autoencoder and Principal Component Analysis (PCA) can also be explored. While Autoencoder is effective for feature extraction, it requires significant computational resources and memory, especially when using deep models, leading to increased processing time and energy consumption. PCA, as a dimensionality reduction technique, can reduce memory usage, but its performance is highly dependent on the dataset size and the number of components retained, which may make it inefficient for large EEG datasets. Therefore, while the methods selected in this study provide the best balance between accuracy and energy efficiency, future research may explore alternative models, such as Autoencoder and PCA, to enhance classification performance, keeping in mind the trade-offs in computational and memory requirements.

In this study, feature vectors extracted using LPC, DWT, and PSDF are utilized with features that can be considered standard. For LPC, 10th-order LPC coefficients and residual error are used, while for DWT, the detail coefficients $D_4$, $D_3$, $D_2$, $D_1$, along with the $A_4$ coefficient, and statistical features (mean, standard deviation, skewness, and kurtosis) are employed. For PSDF, the analysis performed using the Welch method resulted in the extraction of the following features: Total Spectral Power, Spectral Entropy, Spectral Bandwidth, Spectral Skewness, Peak Frequency, Delta band power (0.5-4 Hz), Theta band power (4-8 Hz), and Beta band power (13-30 Hz). Higher-order LPC coefficients, residual error, and statistical features could have been included as additional features for LPC. For DWT, different statistical features and detail coefficients could have been used, and wavelet decompositions with a higher number of decomposition levels could have been considered. For PSDF, a high-resolution power spectrum analysis method could have been applied, incorporating additional spectral features in frequency or time domains, such as Euclidean distance, Manhattan distance, Kullback-Leibler Divergence, Bhattacharyya Distance, and Zero Crossing Rate. All these additions would enhance classification accuracy. However, each addition would increase the computation time, and thus the accuracy improvement is unlikely to have a positive impact on energy efficiency, and it is highly probable that it would have a negative effect instead.

Additionally, the impact of the new feature vectors on memory consumption is unavoidable. In this context, it is essential to consider which types of classification tasks would be critical for wearable devices. If the classification focuses solely on binary tasks, such as the detection of epileptic seizure events, there will be no need for multi-class classification. In such cases, the methods proposed in this study, with the high accuracy values already achieved, would provide sufficient accuracy for wearable devices.

LPC is typically an effective method for modeling signals over short time intervals, such as 25–30 ms [39, 40, 41, 42]. These short durations are particularly suitable for signals with transient characteristics, such as speech signals. However, in our study, LPC was applied to a considerably long EEG signal of 11.8 seconds. This approach introduces both advantages and disadvantages. Applying LPC to a long-duration signal helps capture the overall structure of the signal and identify broad patterns. In dynamic signals like EEG, capturing long-term characteristics can be beneficial. Instead of segmenting the signal into short windows and computing LPC for each, processing a single long segment reduces computation time and memory usage. EEG signals predominantly contain low-frequency components and may exhibit high variability in short-term analyses. Long-term analysis can mitigate this variability, leading to a more stable model. The results obtained from our study support these observations.

However, the limitations of LPC must also be considered. EEG signals exhibit temporal variability, and applying LPC over a long-duration signal may fail to accurately represent these temporal changes, potentially missing dynamic variations within specific time intervals. This can be a drawback, particularly for EEG signals with sudden changes, such as seizure onset. Short-term analyses provide higher temporal resolution, whereas generating a single LPC model for a long signal may lead to loss of detail. This drawback could adversely affect applications requiring high temporal precision, such as epileptic seizure detection.

Performing LPC analysis over shorter time intervals (e.g., 256 or 512 samples) would increase the number of processing windows by 8 and 4 times, respectively, significantly extending the overall computation time. This approach would require generating a separate model for each segment, leading to a substantial increase in computational load and energy consumption. Additionally, since feature vectors must be computed for each window separately, memory usage would also rise considerably. Therefore, in applications requiring low power consumption, such as portable and wearable EEG systems, the computational efficiency and energy savings provided by long-duration LPC analysis offer a significant advantage. Our study suggests that this approach can provide a practical and sustainable solution for applications such as epileptic seizure detection.

On the other hand, studies on epileptic seizure detection for clinical systems have reported near 100% accuracy rates for different classification tasks, using various feature extraction and classification techniques [43, 44, 45, 46, 47, 48]. However, these studies have generally focused solely on accuracy performance, without considering factors such as processing time, computational cost, and energy efficiency. Aghazadeh et al. (2020) conducted a study that is one of the rare works in the literature focusing on energy efficiency [49]. In this study, compressive sensing (CS) and Lomb-Scargle periodogram were used for feature extraction, and an energy-efficient United Dual Linear SVM (UDLSVM) classifier was proposed. The performance and energy consumption trade-off were evaluated for different compression ratios (1–64x) across 24 patients, and hardware optimization was performed. However, with accuracy values of 96–93% and energy efficiency of 18.4μJ, it falls significantly behind the LPC method.

Our experimental results confirm the hypothesis that applying LPC to an extended time window significantly improves energy efficiency. LPC demonstrated the lowest energy consumption across all classification tasks, averaging 2.73 μJ/% for RF, 2.63 μJ/% for SVM, and 2.78 μJ/% for MLP. This efficiency is attributed to the reduced number of computations required compared to short-segment processing. These finding highlights that applying LPC to long-duration EEG signals effectively balance energy efficiency and classification performance, making it an optimal choice for wearable seizure detection applications.

## 4. Conclusions

In this study, three different feature extraction methods, LPC, DWT and PSDF were compared in terms of energy efficiency, memory consumption and processing time for epileptic seizure detection. The Bonn University EEG dataset, with its inclusion of different patient groups and provision of cleaned signals, offers advantages; however, the lack of long-duration EEG recordings presents limitations. The feature extraction, data preprocessing, and classification processes were evaluated separately, and processing time measurements were taken.

The results strongly support our hypothesis that applying LPC to long EEG segments increases energy efficiency while maintaining classification accuracy. Due to its low computational cost, LPC stands out as the most suitable method for portable EEG devices and low-power systems. While DWT produces successful results in terms of accuracy, it is less energy-efficient than LPC due to its high processing time and memory consumption. PSDF, on the other hand, is limited for portable systems due to its high processing time.

This study's contribution to the literature lies in its focus not only on accuracy rates but also on processing time, memory consumption, and energy efficiency in epileptic seizure detection. Considering the battery life and processing capacity of wearable EEG devices, algorithms with low energy consumption are critical. In this context, LPC emerges as the most suitable method, while methods requiring high computational power, such as DWT and PSDF, need to be integrated with cloud-based systems or optimized using hardware acceleration techniques.

Moreover, our findings confirm our hypothesis and demonstrate that LPC is a promising alternative for low-power, real-time epilepsy detection. Future research could focus on developing hybrid feature extraction methods and deep learning-based models that further reduce processing time. For instance, combining LPC with low-computation methods like PCA could optimize energy consumption while increasing accuracy. The selection of the most distinctive features from EEG signals using AI-based optimization techniques could make epilepsy detection in portable EEG devices more efficient.

In conclusion, this study contributes to identifying the most energy-efficient feature extraction method for epileptic seizure detection. LPC is determined to be the most efficient method, while DWT is considered a potential alternative. Future research should focus on methods that further optimize processing time and develop low-energy, real-time EEG analysis systems.



**References**


1. Milligan, T. A. "Epilepsy: A Clinical Overview." *The American Journal of Medicine*, vol. 134, no. 7, pp. 840-847, (2021), https://doi.org/10.1016/j.amjmed.2021.01.038.
2. Asadi-Pooya, A., Brigo, F., Lattanzi, S., et al. "Adult Epilepsy." *The Lancet*, vol. 402, no. 10399, pp. 412-424, (2023), https://doi.org/10.1016/S0140-6736(23)01048-6.

3. Ahmad, I., Yao, C., Li, L., et al. “An Efficient Feature Selection and Explainable Classification Method for EEG-Based Epileptic Seizure Detection.” *Journal of Information Security and Applications*, vol. 80, p. 103654, (2024), https://doi.org/10.1016/j.jisa.2023.103654.
4. Shoeibi, A., Khodatars, M., Ghassemi, N., et al. “Epileptic Seizures Detection Using Deep Learning Techniques: A Review.” *International Journal of Environmental Research and Public Health*, vol. 18, no. 11, pp. 5780, (2021), https://doi.org/10.3390/ijerph18115780.
5. Siddiqui, M. K., Menendez, R., Huang, X., et al. “A Review of Epileptic Seizure Detection Using Machine Learning Classifiers.” *Brain Informatics*, vol. 7, no. 1, p. 5, (2021), https://doi.org/10.1186/s40708-020-00105-1.
6. Sameer, M., and Gupta, B. “Time–Frequency Statistical Features of Delta Band for Detection of Epileptic Seizures.” *Wireless Personal Communications*, vol. 122, pp. 489-499, (2022), https://doi.org/10.1007/s11277-021-08909-y.
7. Amiri, M., Aghaeinia, H. and Amindavar H. “Automatic Epileptic Seizure Detection in EEG Signals Using Sparse Common Spatial Pattern and Adaptive Short-Time Fourier Transform-Based Synchrosqueezing Transform.” *Biomedical Signal Processing and Control*, vol. 79, p. 104022, (2023), https://doi.org/10.1016/j.bspc.2022.104022.
8. Liu, S., Wang, J., Li, S., et al. “Epileptic Seizure Detection and Prediction in EEGs Using Power Spectra Density Parameterization.” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 31, pp. 3884-3894, (2023), https://doi.org/10.1109/TNSRE.2023.3317093.
9. Canyurt, C., and Zengin, R., “Epileptic Activity Detection Using Mean Value, RMS, Sample Entropy, and Permutation Entropy Methods.” *The Journal of Cognitive Systems*, vol. 8, no. 1, pp. 16-27, (2023), https://doi.org/10.52876/jcs.1226579.
10. Fıçıcı, C., Telatar, Z. and O. Eroğul. “Automated Temporal Lobe Epilepsy and Psychogenic Nonepileptic Seizure Patient Discrimination from Multichannel EEG Recordings Using DWT-Based Analysis.” *Biomedical Signal Processing and Control*, vol. 77, p. 103755, (2022), https://doi.org/10.1016/j.bspc.2022.103755.

11. Rizki, I., Subekti, S., Indriyanto S., et al. "Epileptic Seizure Detection Using DWT Based on MRMR Feature Selection Method." *Proceedings of the 2024 International Conference on Electrical and Information Technology (IEIT)*, IEEE, pp. 84-89, (2024), https://doi.org/10.1109/IEIT64341.2024.10763220.
12. Yousefi, M. R., Dehghani, A., Golnejad, S., & Hosseini, M. M. "Comparing EEG-Based Epilepsy Diagnosis Using Neural Networks and Wavelet Transform." *Applied Sciences*, vol. 13, no. 18, p. 10412, (2023), https://doi.org/10.3390/app131810412
13. Zeng, W., Shan, L., Su, B., and Du, S. "Epileptic Seizure Detection with Deep EEG Features by Convolutional Neural Network and Shallow Classifiers." *Frontiers in Neuroscience*, vol. 17, p. 1145526, (2023), https://doi.org/10.3389/fnins.2023.1145526.
14. Bhattacherjee, I. "Real-Time Epileptic Seizure Detection Using Machine Learning Techniques." *Proceedings of the 2022 9th International Conference on Computing for Sustainable Global Development (INDIACom)*, IEEE, pp. 1-7, (2022), https://doi.org/10.23919/INDIACom54597.2022.9763176.
15. Sharma, R. and Meena, H. K. "Enhanced Epileptic Seizure Detection Through Graph Spectral Analysis of EEG Signals." *Circuits, Systems, and Signal Processing*, vol. 43, no. 8, pp. 5288-5308, (2024), https://doi.org/10.1007/s00034-024-02715-0.
16. Hilal, A. M., Albraikan, A. A., Dhahbi, S., et al. "Intelligent Epileptic Seizure Detection and Classification Model Using Optimal Deep Canonical Sparse Autoencoder." *Biology*, vol. 11, no. 8, p. 1220, (2022), https://doi.org/10.3390/biology11081220.
17. Shoeibi, A., Ghassemi, N., Khodatars, M., et al. "Detection of Epileptic Seizures on EEG Signals Using ANFIS Classifier, Autoencoders and Fuzzy Entropies." *Biomedical Signal Processing and Control*, vol. 73, p. 103417, (2022), https://doi.org/10.1016/j.bspc.2021.103417.
18. Wang, Y., Yuan, S., Liu, J. X., et al. "Combining EEG Features and Convolutional Autoencoder for Neonatal Seizure Detection." *International Journal of Neural Systems*, vol. 34, no. 8, p. 2450040, (2024), https://doi.org/10.1142/s0129065724500400.

19. Jiwani, N., Gupta, K., Sharif, M. H. U., et al. "A LSTM-CNN Model for Epileptic Seizures Detection Using EEG Signal." *Proceedings of the 2022 2nd International Conference on Emerging Smart Technologies and Applications (eSmarTA)*, IEEE, pp. 1-5, (2022), https://doi.org/10.1109/eSmarTA56775.2022.9935403.

20. Sameer, M. and Gupta, B. "CNN-Based Framework for Detection of Epileptic Seizures." *Multimedia Tools and Applications*, vol. 81, no. 12, pp. 17057-17070, (2022), https://doi.org/10.1007/s11042-022-12702-9.

21. Sopic, D., Aminifar, A. and Atienza, D. "e-glass: A Wearable System for Real-Time Detection of Epileptic Seizures." *Proceedings of the IEEE International Symposium on Circuits and Systems (ISCAS)*, IEEE, pp. 1-5, (2018), https://doi.org/10.1109/ISCAS.2018.8351728.

22. Yu, S., El Atrache, R., Tang, J., et al. "Artificial Intelligence-Enhanced Epileptic Seizure Detection by Wearables." *Epilepsia*, vol. 64, no. 12, pp. 3213-3226, (2023), https://doi.org/10.1111/epi.17774.

23. Huang, X., Sun, X., Zhang, L., et al. "A Novel Epilepsy Detection Method Based on Feature Extraction by Deep Autoencoder on EEG Signal." *International Journal of Environmental Research and Public Health*, vol. 19, no. 22, p. 15110, (2022), https://doi.org/10.3390/ijerph192215110.

24. Tran, L. V., Tran, H. M., Le, T. M., et al. "Application of Machine Learning in Epileptic Seizure Detection." *Diagnostics*, vol. 12, no. 11, p. 2879, (2022), https://doi.org/10.3390/diagnostics12112879.

25. Jeppesen, J., Fuglsang-Frederiksen, A., Johansen, P., et al. "Seizure Detection Based on Heart Rate Variability Using a Wearable Electrocardiography Device." *Epilepsia*, vol. 60, no. 10, pp. 2105-2113, (2022), https://doi.org/10.1111/epi.16343.

26. Andrzejak, R. G., Lehnertz, K., Mormann, F., et al. "Indications of Nonlinear Deterministic and Finite-Dimensional Structures in Time Series of Brain Electrical Activity: Dependence on Recording Region and Brain State." *Physical Review E*, vol. 64, no. 6, p. 061907, (2001), https://doi.org/10.1103/PhysRevE.64.061907.

27. Ikizler, N. and Ekim, G. “Investigating the Effects of Gaussian Noise on Epileptic Seizure Detection: The Role of Spectral Flatness, Bandwidth, and Entropy.” *Engineering Science and Technology, an International Journal*, vol. 64, p. 102005, (2025), https://doi.org/10.1016/j.jestch.2025.102005.

28. Spratling, M. W. “A Review of Predictive Coding Algorithms.” *Brain and Cognition*, vol. 112, pp. 92-97, (2017), https://doi.org/10.1016/j.bandc.2015.11.003.

29. Shah, S. Y., Larijani, H., Gibson, R. M., et al. “Epileptic Seizure Classification Based on Random Neural Networks Using Discrete Wavelet Transform for Electroencephalogram Signal Decomposition.” *Applied Sciences*, vol. 14, no. 2, p. 599, (2024), https://doi.org/10.3390/app14020599.

30. Abdullayeva, E. and Örnek, H. K. “Diagnosing Epilepsy from EEG Using Machine Learning and Welch Spectral Analysis.” *Traitement Du Signal*, vol. 41, no. 2, pp. 971-977, (2024), https://doi.org/10.18280/ts.410237.

31. Ikizler, N. and Ekim, G. “High-Resolution Power Spectral Density Approaches for Epileptic Seizure Detection.” *Politeknik Dergisi*, vol. 1, no. 1, (2025), https://doi.org/10.2339/politeknik.1605362.

32. Wijayanto, I., Rizal, S. and Hadiyoso, S. “Epileptic Electroencephalogram Signal Classification Using Wavelet Energy and Random Forest.” *AIP Conference Proceedings*, vol. 2654, no. 1, AIP Publishing, (2023), https://doi.org/10.1063/5.0116298.

33. Guido, R., Ferrisi, S., Lofaro D., et al. “An Overview on the Advancements of Support Vector Machine Models in Healthcare Applications: A Review.” *Information*, vol. 15, no. 4, p. 235, (2024), https://doi.org/10.3390/info15040235.

34. Mouleeshuwarapprabu, R. and Kasthuri, N. “Feature Extraction and Classification of EEG Signal Using Multilayer Perceptron.” *Journal of Electrical Engineering & Technology*, vol. 18, no. 4, pp. 3171-3178, (2023), https://doi.org/10.1007/s42835-023-01508-w.

35. Naidu, G., Zuva T. and Sibanda, E. M. “A Review of Evaluation Metrics in Machine Learning Algorithms.” *Computer Science On-Line Conference*, Springer International Publishing, pp. 15-25, (2023), https://doi.org/10.1007/978-3-031-35314-7_2.

36. Tripathy, P., Jena, P. K. and Mishra, B. R. “Systematic Literature Review and Bibliometric Analysis of Energy Efficiency.” *Renewable and Sustainable Energy Reviews*, vol. 200, p. 114583, (2024), https://doi.org/10.1016/j.rser.2024.114583.

37. Handa, P., Mathur, M. and Goel, N. “Open and Free EEG Datasets for Epilepsy Diagnosis.” *arXiv Preprint*, arXiv:2108.01030, (2021), https://doi.org/10.48550/arXiv.2108.01030.

38. Shegog, R., Braverman, L. and Hixson, J. D. “Digital and Technological Opportunities in Epilepsy: Toward a Digital Ecosystem for Enhanced Epilepsy Management.” *Epilepsy & Behavior*, vol. 102, p. 106663, (2020), https://doi.org/10.1016/j.yebeh.2019.106663.

39. Altunay, S., Telatar, Z. and Erogul, O. “Epileptic EEG Detection Using the Linear Prediction Error Energy.” *Expert Systems with Applications*, vol. 37, no. 8, pp. 5661-5665, (2010), https://doi.org/10.1016/j.eswa.2010.02.045.

40. Anjum, M. F., Dasgupta, S., Mudumbai, R., et al. “Linear Predictive Coding Distinguishes Spectral EEG Features of Parkinson's Disease.” *Parkinsonism & Related Disorders*, vol. 79, pp. 79-85, (2020), https://doi.org/10.1016/j.parkreldis.2020.08.001.

41. Xu, J., Davis, M. and Fréin; R. “A Linear Predictive Coding Filtering Method for the Time-Resolved Morphology of EEG Activity.” *32nd Irish Signals and Systems Conference (ISSC)*, pp. 1-6, (2021), https://doi.org/10.1109/ISSC52156.2021.9467851.

42. Spratling, M. W. “A Review of Predictive Coding Algorithms.” *Brain and Cognition*, vol. 112, pp. 92-97, (2017), https://doi.org/10.1016/j.bandc.2015.11.003.

43. Li, M., Sun, X., Chen, W., et al. “Classification of Epileptic Seizures in EEG Using Time-Frequency Image and Block Texture Features.” *IEEE Access*, vol. 8, pp. 9770-9781, (2019), https://doi.org/10.1109/ACCESS.2019.2960848.

44. Zhao, X., Zhang, R., Mei, Z., et al. “Identification of Epileptic Seizures by Characterizing Instantaneous Energy Behavior of EEG.” *IEEE Access*, vol. 7, pp. 70059-70076, (2019), https://doi.org/10.1109/ACCESS.2019.2919158.

45. Sharmila, A. and Mahalakshmi, P. “Wavelet-Based Feature Extraction for Classification of Epileptic Seizure EEG Signal.” *Journal of Medical Engineering & Technology*, vol. 41, no. 8, pp. 670-680, (2017), https://doi.org/10.1080/03091902.2017.1394388.

46. Eltrass, A. S., Tayel, M. B. and EL-qady, A. F. "Automatic Epileptic Seizure Detection Approach Based on Multi-Stage Quantized Kernel Least Mean Square Filters." *Biomedical Signal Processing and Control*, vol.70, p.103031, (2021), https://doi.org/10.1016/j.bspc.2021.103031.

47. Wang, Z., Na, J. and Zheng, B. "An Improved k-NN Classifier for Epilepsy Diagnosis." *IEEE Access*, vol. 8, pp. 100022-100030, (2020), https://doi.org/10.1109/ACCESS.2020.2996946.

48. Harpale, V. and Bairagi, V. "An Adaptive Method for Feature Selection and Extraction for Classification of Epileptic EEG Signal in Significant States." *Journal of King Saud University - Computer and Information Sciences*, vol. 33, no. 6, pp. 668-676, (2021), https://doi.org/10.1016/j.jksuci.2018.04.014.

49. Aghazadeh, R., Frounchi, J. and Montagna, F. "Scalable and Energy-Efficient Seizure Detection Based on Direct Use of Compressively-Sensed EEG Data on an Ultra-Low Power Multi-Core Architecture." *Computational Biology and Medicine*, vol. 125, p. 104004, (2020), https://doi.org/10.1016/j.compbiomed.2020.104004.



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**Figure 1.** The average amplitude-sample value representation of EEG signals [27].

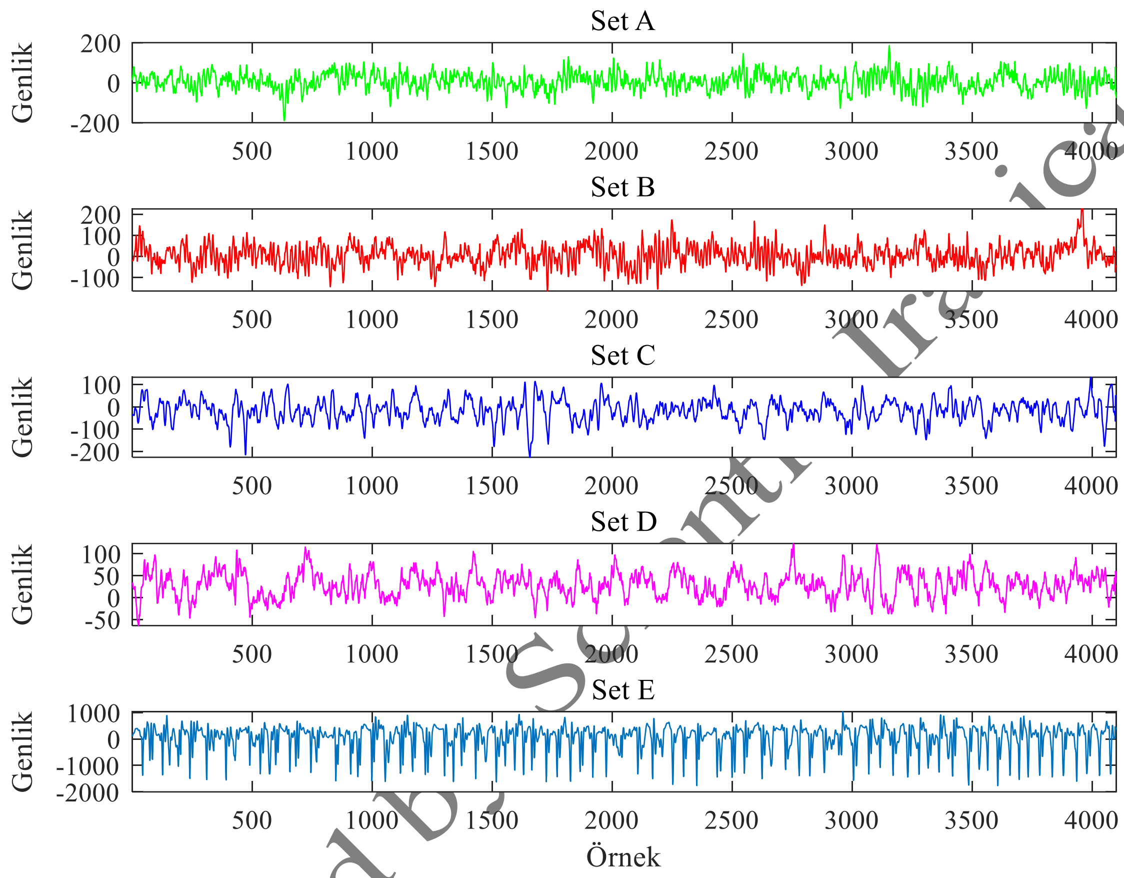


**Figure 2.** Flow diagram of proposed work.

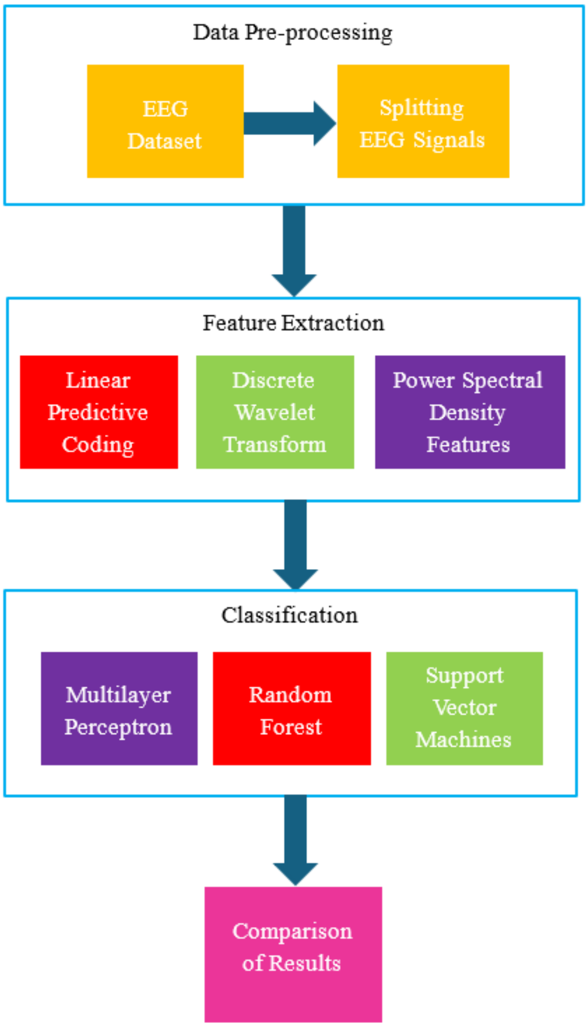


**Figure 3.** Accuracy (Acc) graph for the feature vectors created using LPC, DWT and PSDF evaluated with RF, SVM, and MLP classifiers, for 14 different tasks. Task numbers correspond to the classification cases listed in Table 3.

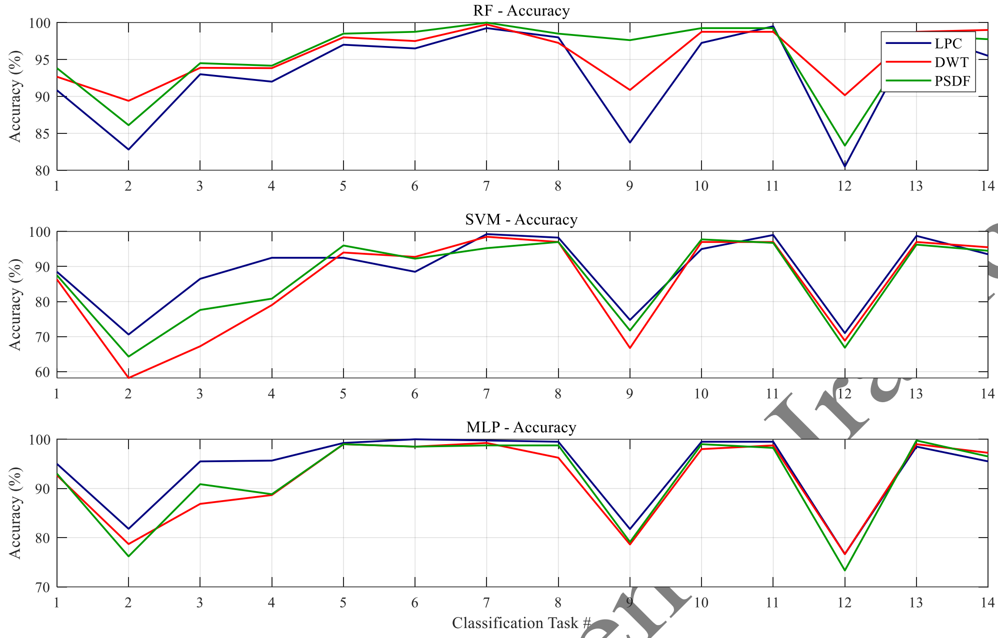
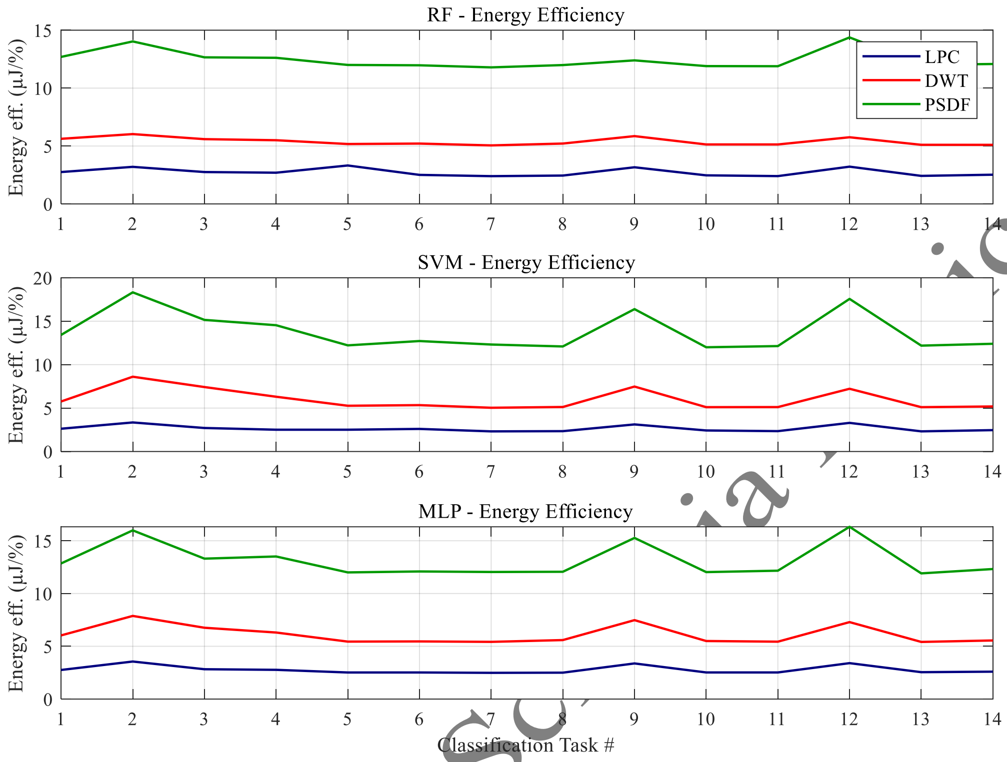


**Figure 4.** Energy efficiency graph for the feature vectors created using LPC, DWT and PSDF evaluated with RF, SVM, and MLP classifiers, for 14 different tasks. Task numbers correspond to the classification cases listed in Table 4



**List of Tables**

**Table 1.** General descriptions of the Bonn University EEG dataset

| Feature | Value |
|---|---|
| Source | University of Bonn, Department of Epileptology |
| Sampling Frequency/Band | 173.61 Hz / 0.53-40Hz |
| Samples/Segments | 4097 samples per segment / 100 segments per set |
| Duration | 23.6 seconds per set |
| Total Channels | 128 → Reduced to a single channel |
| Recording System | 12-bit, recorded using the International 10-20 sys. |
| Artifact Removal | Cleaned from eye and muscle movement artifacts |
| Set A (Healthy-Eyes Open) | 5 healthy volunteers, recorded from the scalp |
| Set B (Healthy-Eyes Closed) | 5 healthy volunteers, recorded from the scalp |
| Set C (Seizure-Free) | 5 epileptic patients, recorded from inside the skull |
| Set D (Seizure-Free) | 5 epileptic patients, recorded from inside the skull |
| Set E (During Seizure) | 5 epileptic patients, recorded from inside the skull |

**Table 2.** Statistical values of Bonn University EEG dataset (presented as mean and standard deviation)

| Feature | Set A | Set B | Set C | Set D | Set E |
|---|---|---|---|---|---|
| Mean Amplitude (µV) | -6.26 ± 24.78 | -12.51 ± 30.6 | -8.88 ± 24.07 | -6.20 ± 23.68 | -4.74 ± 27.18 |
| Median Amplitude | -6.27 ± 24.74 | -13.03 ± 30.7 | -8.41 ± 24.17 | -8.75 ± 30.30 | 6.54 ± 83.18 |
| Min / Max Amplitude | -9.3 ± 42.90 | -6.0 ± 66.00 | -15.1 ± 78.97 | 10.5 ± 214.59 | -24.7 ± 462.1 |
| Skewness | -0.02 ± 0.16 | 0.06 ± 0.15 | -0.15 ± 0.31 | 0.07 ± 0.76 | -0.06 ± 0.77 |
| Kurtosis | 3.21 ± 0.34 | 3.20 ± 0.34 | 3.56 ± 0.77 | 4.25 ± 2.65 | 3.38 ± 1.22 |
| Zero Crossing Rate | 228.5 ± 85.36 | 244.2 ± 77.00 | 138.3 ± 45.79 | 130.0 ± 47.23 | 167.0 ± 48.72 |
| Mean Power (dB/Hz) | -1.24 ± 2.79 | -0.28 ± 3.47 | -3.46 ± 4.21 | -3.27 ± 4.19 | 9.35 ± 5.80 |
| Spectral Entropy | 3.52 ± 0.73 | 3.42 ± 0.64 | 3.05 ± 0.46 | 3.06 ± 0.42 | 3.45 ± 0.47 |
| Delta Band Power (%) | 29.06 ± 12.33 | 15.34 ± 9.50 | 51.18 ± 15.87 | 47.59 ± 18.23 | 23.70 ± 20.92 |
| Theta Band Power (%) | 13.68 ± 6.26 | 10.02 ± 4.73 | 16.58 ± 7.74 | 19.42 ± 10.29 | 39.60 ± 22.60 |
| Alpha Band Power (%) | 17.22 ± 7.63 | 37.10 ± 20.84 | 5.66 ± 3.65 | 8.05 ± 6.67 | 16.80 ± 8.05 |
| Beta Band Power (%) | 14.17 ± 7.74 | 16.30 ± 11.79 | 3.36 ± 3.03 | 3.17 ± 2.16 | 16.57 ± 14.81 |
| Gamma Band Pow (%) | 0.71 ± 0.75 | 0.44 ± 0.40 | 0.20 ± 0.21 | 0.15 ± 0.13 | 0.35 ± 0.43 |
| Wavelet Entropy | 5.82 ± 0.03 | 5.83 ± 0.03 | 5.65 ± 0.08 | 5.59 ± 0.16 | 5.72 ± 0.11 |
| Spectral Roll-off (Hz) | 12.87 ± 4.98 | 13.05 ± 3.31 | 5.95 ± 2.42 | 6.33 ± 2.06 | 12.32 ± 3.41 |

**Table 3.** Accuracy (Acc) and F1-score (F1) values for RF, SVM, and MLP classifiers trained with feature vectors extracted using LPC, DWT and PSDF across 14 different tasks.

| Classification # &Task | Classif. Method | LPC | | DWT | | PSDF | |
|---|---|---|---|---|---|---|---|
| | | Acc (%) | F1 | Acc (%) | F1 | Acc (%) | F1 |
| | RF | 90.83 | 0.908 | 92.66 | 0.927 | 93.83 | 0.939 |
| 1.A-B-C | SVM | 88.50 | 0.886 | 86.33 | 0.864 | 87.50 | 0.875 |
| | MLP | 95.00 | 0.950 | 92.67 | 0.927 | 93.00 | 0.930 |
| | RF | 82.80 | 0.826 | 89.40 | 0.894 | 86.10 | 0.860 |
| 2.A-B-C-D-E | SVM | 70.60 | 0.707 | 58.20 | 0.568 | 64.30 | 0.619 |
| | MLP | 81.80 | 0.818 | 78.70 | 0.787 | 76.20 | 0.760 |
| | RF | 93.00 | 0.930 | 93.87 | 0.939 | 94.50 | 0.945 |
| 3.A-B-C-E | SVM | 86.50 | 0.866 | 67.25 | 0.668 | 77.62 | 0.775 |
| | MLP | 95.50 | 0.955 | 86.87 | 0.870 | 90.87 | 0.910 |
| | RF | 92.00 | 0.920 | 93.83 | 0.938 | 94.16 | 0.942 |
| 4.A-B-E | SVM | 92.50 | 0.925 | 79.00 | 0.783 | 80.83 | 0.808 |
| | MLP | 95.66 | 0.957 | 88.66 | 0.887 | 88.83 | 0.889 |
| | RF | 97.00 | 0.970 | 98.00 | 0.980 | 98.50 | 0.985 |
| 5.A-C | SVM | 92.50 | 0.925 | 94.00 | 0.940 | 96.00 | 0.960 |
| | MLP | 99.25 | 0.992 | 99.00 | 0.990 | 99.00 | 0.990 |
| | RF | 96.50 | 0.965 | 97.50 | 0.975 | 98.75 | 0.987 |
| 6.A-D | SVM | 88.50 | 0.885 | 92.75 | 0.927 | 92.25 | 0.922 |
| | MLP | 100.0 | 1.000 | 98.50 | 0.985 | 98.50 | 0.985 |
| | RF | 99.25 | 0.992 | 99.75 | 0.997 | 100.0 | 1.000 |
| 7.A-E | SVM | 99.25 | 0.992 | 98.50 | 0.985 | 95.25 | 0.952 |
| | MLP | 99.75 | 0.997 | 99.25 | 0.992 | 98.75 | 0.987 |
| | RF | 98.00 | 0.980 | 97.25 | 0.972 | 98.50 | 0.985 |
| 8.B-C | SVM | 98.25 | 0.982 | 97.00 | 0.970 | 97.00 | 0.970 |
| | MLP | 99.50 | 0.995 | 96.25 | 0.962 | 98.75 | 0.987 |
| | RF | 83.75 | 0.836 | 90.87 | 0.909 | 97.62 | 0.875 |
| 9.B-C-D-E | SVM | 74.75 | 0.748 | 66.75 | 0.643 | 71.75 | 0.689 |
| | MLP | 81.75 | 0.816 | 78.62 | 0.786 | 79.12 | 0.785 |
| | RF | 97.25 | 0.972 | 98.75 | 0.987 | 99.25 | 0.992 |
| 10.B-D | SVM | 95.00 | 0.950 | 97.00 | 0.970 | 97.75 | 0.977 |
| | MLP | 99.50 | 0.995 | 98.00 | 0.980 | 99.00 | 0.990 |
| | RF | 99.50 | 0.995 | 98.75 | 0.987 | 99.25 | 0.992 |
| 11.B-E | SVM | 99.00 | 0.990 | 97.00 | 0.970 | 96.75 | 0.967 |
| | MLP | 99.50 | 0.995 | 98.75 | 0.987 | 98.25 | 0.983 |
| | RF | 80.50 | 0.804 | 90.16 | 0.902 | 83.33 | 0.837 |
| 12.C-D-E | SVM | 71.00 | 0.705 | 68.83 | 0.648 | 66.83 | 0.630 |
| | MLP | 76.67 | 0.765 | 76.66 | 0.767 | 73.33 | 0.731 |
| | RF | 98.75 | 0.987 | 98.75 | 0.987 | 98.25 | 0.982 |
| 13.C-E | SVM | 98.75 | 0.987 | 97.00 | 0.970 | 96.25 | 0.962 |
| | MLP | 98.50 | 0.985 | 99.00 | 0.990 | 99.75 | 0.997 |
| | RF | 95.50 | 0.955 | 99.00 | 0.990 | 97.75 | 0.977 |
| 14.D-E | SVM | 93.50 | 0.935 | 95.50 | 0.955 | 94.50 | 0.945 |
| | MLP | 95.50 | 0.955 | 97.25 | 0.972 | 96.50 | 0.965 |
| | RF | 93.18 | 0.931 | 95.61 | 0.956 | 95.70 | 0.949 |
| Average | SVM | 89.18 | 0.891 | 85.36 | 0.847 | 86.75 | 0.860 |
| | MLP | 94.13 | 0.941 | 92.01 | 0.920 | 92.13 | 0.920 |

**Table 4.** Total processing time and energy efficiency values for the feature vectors created using LPC, DWT and PSDF, evaluated with RF, SVM, and MLP, for 14 different tasks.

| | | LPC | | DWT | | PSDF | |
|---|---|---|---|---|---|---|---|
| Classification # &Task | Classifi. Method | Total time (ms) | Energy eff. (µJ/%) | Total time (ms) | Energy eff. (µJ/%) | Total time (ms) | Energy eff. (µJ/%) |
| 1.A-B-C | RF | 2.50 | 2.7523 | 5.21 | 5.6227 | 11.91 | 12.6931 |
| | SVM | 2.32 | 2.6214 | 4.97 | 5.7569 | 11.74 | 13.4171 |
| | MLP | 2.62 | 2.7578 | 5.59 | 6.0321 | 11.95 | 12.8494 |
| 2.A-B-C-D-E | RF | 2.65 | 3.2004 | 5.39 | 6.0290 | 12.08 | 14.0302 |
| | SVM | 2.36 | 3.3427 | 5.01 | 8.6082 | 11.78 | 18.3203 |
| | MLP | 2.91 | 3.5574 | 6.20 | 7.8780 | 12.18 | 15.9842 |
| 3.A-B-C-E | RF | 2.56 | 2.7526 | 5.25 | 5.5928 | 11.96 | 12.6560 |
| | SVM | 2.34 | 2.7052 | 4.99 | 7.4200 | 11.76 | 15.1507 |
| | MLP | 2.70 | 2.8272 | 5.87 | 6.7572 | 12.09 | 13.3047 |
| 4.A-B-E | RF | 2.48 | 2.6956 | 5.16 | 5.4993 | 11.88 | 12.6168 |
| | SVM | 2.32 | 2.5081 | 4.98 | 6.3037 | 11.75 | 14.5366 |
| | MLP | 2.65 | 2.7702 | 5.59 | 6.3049 | 12.00 | 13.5089 |
| 5.A-C | RF | 3.22 | 3.3195 | 5.07 | 5.1734 | 11.82 | 12.0000 |
| | SVM | 2.32 | 2.5081 | 4.95 | 5.2659 | 11.73 | 12.2187 |
| | MLP | 2.50 | 2.5188 | 5.39 | 5.4444 | 11.88 | 12.0000 |
| 6.A-D | RF | 2.42 | 2.5077 | 5.08 | 5.2102 | 11.82 | 11.9696 |
| | SVM | 2.30 | 2.5988 | 4.95 | 5.3369 | 11.73 | 12.7154 |
| | MLP | 2.52 | 2.5200 | 5.38 | 5.4619 | 11.91 | 12.0913 |
| 7.A-E | RF | 2.38 | 2.3979 | 5.04 | 5.0526 | 11.79 | 11.7900 |
| | SVM | 2.30 | 2.3173 | 4.96 | 5.0355 | 11.73 | 12.3149 |
| | MLP | 2.48 | 2.4862 | 5.38 | 5.4206 | 11.89 | 12.0405 |
| 8.B-C | RF | 2.40 | 2.4489 | 5.07 | 5.2133 | 11.81 | 11.9898 |
| | SVM | 2.30 | 2.3409 | 4.97 | 5.1237 | 11.73 | 12.0927 |
| | MLP | 2.49 | 2.5025 | 5.38 | 5.5896 | 11.91 | 12.0607 |
| 9.B-C-D-E | RF | 2.65 | 3.1641 | 5.32 | 5.8545 | 12.10 | 12.3950 |
| | SVM | 2.33 | 3.1170 | 4.99 | 7.4756 | 11.76 | 16.3902 |
| | MLP | 2.76 | 3.3761 | 5.88 | 7.4790 | 12.08 | 15.2679 |
| 10.B-D | RF | 2.40 | 2.4678 | 5.07 | 5.1341 | 11.81 | 11.8992 |
| | SVM | 2.30 | 2.4210 | 4.95 | 5.1030 | 11.73 | 12.0000 |
| | MLP | 2.51 | 2.5226 | 5.39 | 5.5000 | 11.91 | 12.0303 |
| 11.B-E | RF | 2.39 | 2.4020 | 5.07 | 5.1341 | 11.80 | 11.8891 |
| | SVM | 2.32 | 2.3434 | 4.96 | 5.1134 | 11.74 | 12.1343 |
| | MLP | 2.51 | 2.5226 | 5.37 | 5.4379 | 11.95 | 12.1628 |
| 12.C-D-E | RF | 2.59 | 3.2173 | 5.19 | 5.7564 | 11.98 | 14.3765 |
| | SVM | 2.34 | 3.2957 | 4.97 | 7.2206 | 11.74 | 17.5669 |
| | MLP | 2.61 | 3.4041 | 5.59 | 7.2919 | 11.97 | 16.3234 |
| 13.C-E | RF | 2.39 | 2.4202 | 5.04 | 5.1037 | 11.80 | 12.0101 |
| | SVM | 2.29 | 2.3189 | 4.95 | 5.1030 | 11.73 | 12.1870 |
| | MLP | 2.51 | 2.5482 | 5.36 | 5.4141 | 11.88 | 11.9097 |
| 14.D-E | RF | 2.41 | 2.5235 | 5.05 | 5.1010 | 11.81 | 12.0818 |
| | SVM | 2.30 | 2.4598 | 4.95 | 5.1832 | 11.72 | 12.4021 |
| | MLP | 2.48 | 2.5968 | 5.40 | 5.5526 | 11.89 | 12.3212 |
| Average | RF | 2.53 | 2.7335 | 5.14 | 5.3912 | 11.88 | 12.4569 |
| | SVM | 2.31 | 2.6355 | 4.96 | 6.0035 | 11.74 | 13.8176 |
| | MLP | 2.58 | 2.7793 | 5.55 | 6.1117 | 11.96 | 13.1325 |