Signal Process. Renew. Energy., 2026; 10(1): 59-70

Signal Processing and Renewable Energy (SPRE)

https://doi.org/10.57647/spre.2026.1001.06

Research Article

Classification of Meditation EEG Signals Using Empirical Wavelet Transform and Atom Search Optimization-Based Feature Selection

Elham Simakani[1], Iman Ahanian[2,4*], Mahdi Eslami[3], Amir Amirabadi[1]

[1] *Department of Biomedical Engineering, ST.C., Islamic Azad University, Tehran, Iran*
[2] *Department of Electrical Engineering, ST.C., Islamic Azad University, Tehran, Iran*
[3] *Department of Electrical Engineering, SR.C., Islamic Azad University, Tehran, Iran*
[4] *Research Center of Modeling and Optimization in Science and Engineering, ST.C., Islamic Azad University, Tehran, Iran*

***Corresponding author:** ahanian@iau.ac.ir

Article History:

Received:
8 December 2025

Revised:
2 February 2026

Accepted:
19 February 2026

Published in Issue:
31 March 2026

Abstract

Analysis of the electroencephalogram (EEG) is a significant technique for deciphering brain activity during meditation; nonetheless, the proper classification of EEG signals is challenging due to the existence of noise, high dimensionality, and overlapping components. In order to alleviate the above pitfalls, the current work presents a novel framework consisting of Empirical Wavelet Transform (EWT) for adaptive sub-band decomposition and Atom Search Optimization (ASO) for optimal selection of features. EEG signals were decomposed into five standard frequency bands using the application of wavelets from the EWT, and eight statistical features were extracted from each band. ASO was also utilized for the selection of the most discriminative features and the compression of dimensionality while preserving the important information. The extracted features underwent classification with various machine learning models consisting of Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree, and Random Forest. Experimental results validated that SVM in combination with the compression of features produced the greatest accuracy of classification (95%), higher than baseline methods lacking a selection of features and state-of-the-art methods tied in performance.The outcomes indicate that the above technique increases both the accuracy of classification and the speed of computation and is thus appropriate for practical applications such as brain interfaces and state monitoring during meditation. The innovation of the work consists of the combination of adaptive signal decomposition and optimal selection of features to advance the performance of classification according to EEG.

Keywords: EEG; Empirical Wavelet Transform; Machine Learning; Feature Extraction

Cite this article: Simakani, E., Ahanian, I., Eslami, M., Amirabadi, A., Classification of Meditation EEG Signals Using Empirical Wavelet Transform and Atom Search Optimization-Based Feature Selection, *Signal Process. Renew. Energy.* *10*(1) 59-70 (2026). https://doi.org/10.57647/spre.2026.1001.06

1. Introduction

Electroencephalography (EEG) is a typical mental state examination method for brain–computer interfaces (BCIs) due to its non-invasiveness, low cost, and real-time data provision ability. Accurate state recognition like focused state, sleepy state, or stressful state, plays a vital role in healthcare, education, transportation, and defense. However, EEG is nonlinear, time-variable, and noise-polluted such that feature extraction and classification are far from easy. Classical methods using static wavelet bases or limited statistical characteristics are prone to fail to decipher the full temporal-spectral richness of EEG. Standard feature selection also tends to include irrelevant or redundant ones such that the performance is limited. The reason for focusing on meditation EEG signals is that they are typically complex, noisy, and contain overlapping components, making them a real challenge for EEG classification methods. However, the proposed framework is not limited to meditation EEG signals. The combination of adaptive signal decomposition using EWT and optimal feature selection via ASO is designed to be generalizable and can be applied to other EEG types, including sleep, motor imagery, or pathological EEG, such as epilepsy. In other words, the focus on meditation EEG is primarily to test the framework under challenging conditions, while the proposed method is applicable to any EEG signals. To address such limitations, this work proposes a new approach combining Empirical Wavelet Transform (EWT)—an adaptive data-animated multiresolution technique—with Atom Search Optimization (ASO), an atom dynamics-derived metaheuristic for optimal feature selection. It is proposed to enable improved classification efficiency as well as computational efficiency for real-time BCI applications.

Several approaches were also made for the classification of mental states through EEG by traditional signal processing approaches as well as deep learning approaches. Liu and Huang also estimated five mental states by using DE+SVM, DE+DGCNN, and EEGNet where the accuracy for EEGNet was 88.83% [1]. Khare et al. also introduced an ensemble approach by using wavelets with tunable Q wavelet and adaptive analytic wavelet transforms where it achieved 97.8% accuracy [2]. They also utilized rational dilation wavelet transform with ensemble tree classifiers for mental state classification with over 94% accuracy [3]. Kit et al. utilized discrete wavelet transform (DWT) and decision trees for the classification of stress and achieved a 95% accuracy rate [4].

Kaur and Khandnor used statistical and entropy features with SVM and Random Forest for 93–97% accuracy [5]. Tang and Li utilized measures of EEG complexity like multiscale permutation entropy and detrended fluctuation analysis for mind wandering and detection and reported an AUCof about 0.66 when feature from band powers were included [6]. Martel et al. identified theta and alpha band activity as salient indicators for intentional and unintentional mind-wandering, with different feature sets for EEG [7]. These demonstrate the relevance of different feature sets as well as classifiers but are significantly based on preset transforms as well as manual feature selections with room for adaptive as well as optimized methods.

Things are not quite there yet. Non-fixed wavelet bases may poorly represent individual variability in EEGs. Common feature selection methods like ANOVA or PCA are blind to nonlinear interactions among features or even adversely affect performance. Very few works combine adaptive wavelet-type decompositions (e.g., EWT) with metaheuristic search for feature selection, and real-time execution is limited by computational considerations.

This study presents, for the first time, a novel and integrated framework for mental state classification using EEG that combines adaptive signal decomposition via Empirical Wavelet Transform (EWT) with optimal feature selection through Atom Search Optimization (ASO). In this framework, EWT dynamically decomposes the EEG spectrum and designs customized wavelet filters, enabling the precise extraction of key features in each frequency band, effectively separating overlapping components and reducing the impact of noise. ASO, inspired by molecular dynamics, identifies the most informative feature subsets, maximizing classification accuracy while ensuring robust generalization across new and inter-subject data. The optimized features are classified using a stable and noise-resilient ensemble approach, such as bagging or boosting trees, providing consistent performance even under variable EEG conditions. The entire system is computationally optimized to support real-time operation in practical brain-computer interface (BCI) applications. By integrating adaptive signal decomposition with intelligent feature selection in a unified framework, this study goes beyond conventional EEG feature extraction and selection methods, demonstrating the design of highly accurate and responsive mental state detection systems capable of handling dynamic and complex real-world EEG signals. The rest of the paper is organized as follows: Section 2 presents materials used in this work including the EEG dataset and the proposed method encompassing the preprocessing, features extraction, and classification.

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Section 3 provides the results of experiments and performance evaluation. Section 4 provides the results in detail and a comparison to prior work.

2. Materials and methods

To enable efficient and accurate processing of EEG signals, we propose a comprehensive multi-stage processing framework, as illustrated in Figure 1. The framework begins with the acquisition of raw EEG signals, which are then subjected to Empirical Wavelet Transform (EWT) for extracting adaptive, informative time-frequency representations. EWT allows the signal spectrum to be decomposed into data-driven sub-bands, effectively separating overlapping components and reducing noise.

Following this, the signals undergo frequency band-wise decomposition, where each sub-band is analyzed individually to capture localized temporal and spectral patterns. From each decomposed band, statistical and discriminative features are extracted to represent the essential characteristics of the EEG signals.

These features are subsequently optimized using the Atom Search Optimization (ASO) algorithm, which selects the most informative and non-redundant feature subsets. This step enhances classification accuracy, reduces dimensionality, and ensures computational efficiency suitable for real-time applications.

Finally, the optimized feature set is fed into a classification model, such as SVM, Random Forest, or ensemble-based classifiers, to assign the appropriate class labels to the EEG data. By integrating adaptive signal decomposition with intelligent feature selection, this multi-stage framework provides a robust, accurate, and efficient foundation for mental state detection and other practical EEG-based applications.

2.1. EEG Dataset for Cognitive States During Meditation

Data comprises the EEGs for 24 subjects who were part of a meditation study. While on sessions, subjects were in a meditating state and were stopped on a periodic basis—with an interruption period of two minutes—to self-rate the current concentration state. Real-time reports thus supplied state-of-cognition labels such as focused attention and mind-wandering.

Two different sessions for EEG recording were given to each subject: one during meditation state and the other during a baseline meditative state. Two sessions permit comparative examination between meditative as well as meditative states. In addition to this, it also has extensive metadata set for descriptors for participants so that subject-specific investigations are permitted in addition to potential model customization.

Based on publicly available databases [8], the data set is a meaningful collection for exploration into differences in neurophysiology between different stages of consciousness, particularly those connected with meditation [8].

The workflow of the proposed method is shown in Figure 1.

2.2. EEG Signal Preprocessing

The EEG preprocess step for this study involved different sequential operations to enhance the quality of the signal and prepare the data for further analysis. First, raw EEG data for two classes were merged for the creation of one shared dataset. To minimize the noise and preserve the important structure of the signals, wavelet denoising was employed according to the multi-level decomposition approach. In this approach, the whole signal was decomposed into its wavelet coefficients; the detail parts were then undergone through soft thresholding; and then the denoised signal was reconstructed [9]. Following denoising, the data were z-score normalized across each channel. The procedure brought the amplitude distribution of the signals to a common state where each channel contained zero mean and unit variance, essential to the improvement of the performance and the stability of the subsequent machine learning tools used in the pipeline.

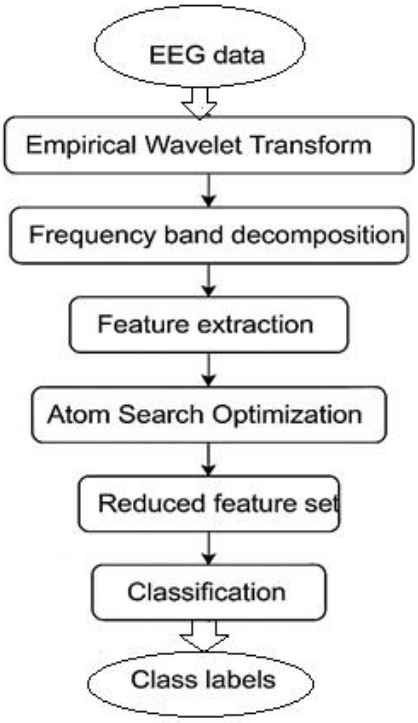

Figure 1. Proposed Method

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2.3. Feature Extraction

The EEG data were subsequently decomposed into five common bands of frequency normally used for the analysis of neurophysiological data: delta (0–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz), and gamma (30–60 Hz). EWT was used to achieve the decomposition. EWT is one adaptive data-driven spectral analysis tool that divides the frequency content of the signal according to its Fourier domain-derived local maxima and constructs empirical wavelet filters accordingly [10]. EWT has the advantage over more rigid-band transforms such as the DWT or the STFT, because it is adaptive to the Signal's spectral nature.

Suppose x(t) is the preprocessed EEG signal. EWT [11] decomposes x(t) into the empirical modes $x_k(t)$, where each of the modes is associated with one particular frequency band:

$$x(t) = \sum_{k=1}^{N} x_k(t) \qquad (1)$$

Each sub-band $x_k(t)$ is approximately one of the pre-established EEG frequency bands. From each sub-band $x_k(t)$, T denotes the time index of the EEG signal, eight statistical features were calculated to derive time-domain as well as frequency-domain information. These are mathematically formulated as below:

Mean:

$$\mu_k = \frac{1}{T}\sum_{t=1}^{T} x_k(t) \qquad (2)$$

Standard Deviation

$$\sigma_k = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(x_k(t) - \mu_k)^2} \qquad (3)$$

Energy

$$E_k = \sum_{t=1}^{T} x_k t^2 \qquad (4)$$

Root Mean Square (RMS)

$$RMS_k = \sqrt{\frac{1}{T}\sum_{t=1}^{T} x_k(t)^2} \qquad (5)$$

Zero-Crossing Rate (ZCR)

$$ZCR_k = \frac{1}{T-1}\sum_{t=1}^{T-1} 1[(x_k(t)\,.\,x_k(t+1) < 0)] \qquad (6)$$

Skewness

$$\mathrm{Skew_k} = \frac{1}{\mathrm{T}}\sum_{\mathrm{t=1}}^{\mathrm{T}}\left(\frac{\mathrm{x_t(t)-\mu k}}{\mathrm{\sigma_k}}\right)^3 \qquad (7)$$

Kurtosis

$$\mathrm{Kurt}_k = \frac{1}{T}\sum_{\mathrm{t=1}}^{\mathrm{T}}\left(\frac{\mathrm{x_t(t)-\mu k}}{\mathrm{\sigma_k}}\right)^4 \qquad (8)$$

Mean Absolute Slope (MAS)

$$MAS_k = \frac{1}{T}\sum_{\mathrm{t=1}}^{\mathrm{T}}|x_k(t+1) - x_t(t)| \qquad (9)$$

The eight parameters for each of the five EWT-based sub-bands were calculated to obtain the full 40-dimensional feature vector for each EEG trial as follows: f = [μ_1, σ_1, E_1, RMS_1, ZCR_1, $Skew_1$, $Kurt_1$, MAS_1, μ_5,., MAS_5].

They extract prominent statistical summaries of the neural activity, thereby producing the discriminative information for the identification of the brain states or cognitive activities [12].

The final step involved the storage of the normalized time-domain signals and the sub band components extracted for future processing at later classification levels. The systematic and mathematically valid preprocessing and feature extraction paradigm not only reduces the noise and normalizes the information but also yields rich and interpretable descriptors such that the performance of machine learning models for EEG-based cognitive or clinical applications is optimized.

In addition to enhancing interpretability, the decomposition of EEG signals into frequency-specific sub-bands provides us with a physiologically interpretable model corresponding to established neuroscientific knowledge. There are characteristic EEG frequency bands associated with particular cognitive states and neurological activity—i.e., delta waves are dominant when we are deep asleep, theta with memory and somnolence, alpha with relaxation, and beta and gamma with attention and cognitive load. Breaking the bands out and studying them individually as part of the process of feature extraction guarantees capturing information that otherwise would get washed out when processing the entire-spectrum signal.

Besides the extraction of signal intensity and distribution information (mean value, energy, RMS value, etc.), the statistical parameters taken from each band further describe higher-order properties of the shape and dynamics of the signal (skewness, kurtosis, zero-crossing number), etc. The multidimensional description is advantageous for the better separability between the EEG patterns for different mental states and therefore is especially valuable for applications such as BCIs, recognition of motor imagery, and the identification of neurological diseases.

Another advantage of the pipeline is support for various machine learning algorithms. The short 40-

dimensional feature vector is informative enough and computationally lightweight enough to be appropriate for real-time applications and embedded systems. That the input is standardized and denoised guarantees better generalization across subject or session levels and less overfitting behavior for classifiers. What is more, the pipeline with modular architecture is easily extendable to incorporate additional features (e.g., entropy-based measures or wavelet entropy), alternate decomposition schemes, or domain adaptation schemes between subject studies.

Briefly, this data preprocessing and feature extraction procedure not only puts data into shape for classification but completes the loop between strong cognitive modelling and raw capture of the signal as well. With its mathematically justified mathematical foundations, physiological relevance, and statistical riches operating together, it enhances equally the integrity and explicability of the subsequent analytical enterprise of EEG-based systems.

2.4. Feature Normalization

To attain consistency as much as enhance the performance of downstream classification models, the outputted feature vectors underwent feature normalization. Specifically, z-score normalization normalized the features individually for each one of the EEG channels by subtracting the mean and then dividing by the standard deviation. It normalizes the features to zero mean and unit variance to reduce the effect of differences of scale between the features as well as enhance convergence when the model is learned. Normalization is equally critical in not having one of the features overwhelm the process of learning when heterogeneous statistical descriptors are pooled.

2.5. Train-Test Split (80–20, Stratified)

To assess the classification models' generalization performance, the data were split into test and training sets according to an 80–20 stratified split. Using this approach, the model is trained on 80% of the data with the remaining 20% reserved for independent testing. Stratification is used to ensure that the class label distribution is maintained across the two sets, thereby obtaining class balance and limiting sampling bias. This is particularly important when classifying EEG data because class imbalance might introduce flawed performance measures. Through the use of the stratified holdout method, the performance is more practical and assists to prevent overfitting to specific class patterns present only in the training data.

2.6. Feature Selection via Improved Atom Search Optimization (ASO)

Feature selection is framed as an optimization problem for the proposed method with the goal to extract the most informative set of features from the original set of EEG data, maximizing classification performance through the use of dimensionality reduction. Exploration of the binary space of the subsets of the features is done for the Atom Search Optimization algorithm. Each candidate for the possible solution (atom) is set as a binary vector where the 1 value stands for the inclusion of the feature and the 0 value stands for its exclusion.

To guide the search, we set the fitness function to one that trades classification error for the number of chosen features. It prevents overfitting and biases towards simple models. The fitness function is the following:

$$\text{Fitness} = \alpha \cdot \text{Error classification} + (1 - \alpha) \cdot (|S| / d) \tag{10}$$

where Error classification is the classification error of the selected subset S. $|S|$ is the number of selected features,
d is the total number of features in the original dataset,
$\alpha \in [0,1]$ is a weight parameter controlling the trade-off between accuracy and feature reduction.

By minimizing this fitness function, the algorithm favors subsets that achieve high classification accuracy using the fewest possible features [12,13].

2.7. Classifier Training

To assess the ability of the picked features to discriminate, various supervised machine learning classifiers were trained and tested. Each of the classifiers was used on the reduced set of features derived through the Atom Search Optimization (ASO) algorithm for the purposes of feature selection. The following classifiers were taken into account:

Support Vector Machine (SVM)
We employed an SVM with a Radial Basis Function kernel because it is optimal for the processing of non-linear classification problems commonly encountered on EEG data. Grid search and stratified 5-fold cross-validation were used to tune the kernel width parameter (γ) and the regularization parameter (C) to avoid overfitting and to ensure generalizability.

K-Nearest Neighbors (KNN)
The KNN classifier was used as one simple instance-based learner to classify the sample based on the majority class of the k nearest points in the space of features. Several different values of k (i.e., 3, 5, 7, 9)

were attempted to get the best neighborhood size that will give the optimal classification accuracy. Euclidean distance was used as the distance metric.

Decision Tree (DT)

A decision tree classifier was used to extract interpretable, rule-based decision boundaries. The tree was trained with Gini impurity as the criterion, and the hyper parameters maximum depth and minimum samples per leaf node were tuned to prevent overfitting. Decision trees provide us with insightful information on how classification decisions are guided by the features.

Random Forest (RF)

Random Forests is the ensemble consisting of numerous decision trees trained on the bootstrap sampling of the training dataset. Each tree is generating the class it predicts, and the majority vote on the trees is the final output. It is the means by which the classification is smoothed to achieve the reduction of the variance of the individual tree models. It was tuned the number of trees as well as the number of the features to examine on each split.

For every classifier, we trained on 80% of the data with stratified sampling so that class ratios are maintained and tested on the remainder 20% of the data. Accuracies, precisions, recalls, F1-scores, and Area Under the Curve measures were computed to provide a complete assessment of the performance of the various classifiers. This multi-classifier method ensures that the power of the good features is assessed on different learning paradigms.

3. Results

All experiments carried out under this work were performed using a personal computer with Windows 10 (64-bit) operating system, 12 GB RAM, and Intel Core i5 processor. MATLAB R2021b, chosen due to its powerful signal processing and machine learning toolboxes that are compatible with EEG analysis, has been used to create the whole implementation.

The results section has various parts, including preprocessing and signal decomposition. The Empirical Wavelet Transform (EWT) is employed to preprocess each EEG trial such that signals are segregated into traditional frequency bands—delta, theta, alpha, beta, and gamma—through segmentation. For qualitative analysis, descriptive plots for each EWT-separated subband were generated to obtain an idea of how original EEG signals were adaptively decomposed into significant frequency components. Such plots validate that EWT can extract separable neural oscillations within different ranges of frequencies.

Subsequently, an ASO algorithm-founded feature selection process that substantially reduced feature dimension but maintained discriminative information intact was performed. Features were then classified using four classification schemes, which are Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree, and Random Forest.

To analyze this new approach, a comparison with other approaches found in the literature was carried out. The classification performance was also achieved by using different performance metrics like accuracy, precision, recall, F1-score, and AUC (Area Under Curve). The new EWT-ASO approach concluded with higher performance that was stable, and this is evidence of its ability to extract informative features as well as to classify EEG signals with accuracy.

3.1. Preprocessing Results

Preprocessing at this level served to effectively prepare the raw EEG signals for feature extraction as well as classification. Preceding all this, as a form of ensuring clarity and consistency of signals were noise and artifacts being eliminated by using elementary filtering techniques. The original raw EEG signal, before preprocessing and even decomposition, is presented in graphical form as seen in Figure 2, as a baseline of the original data form.

Figure 3 illustrates wavelet denoising being used as a preprocessing step to clean up a raw EEG signal. The original signal, represented by red color, is heavily contaminated with noise and erratic variation, whereas the denoising signal, represented by blue color, displays smoother variation with stable amplitude trend. The preprocessing step of wavelet denoising removes noise and artifacts substantially and thereby enhances the clarity of EEG signal as well as prepares the signal for subsequent analysis like feature extraction and classification.

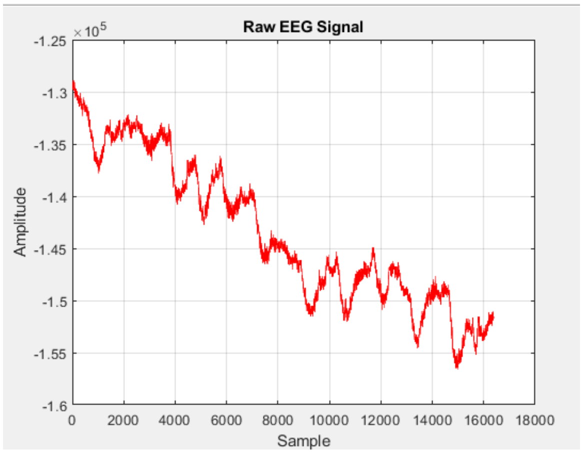

Figure 2. Raw EEG Signal During Meditation

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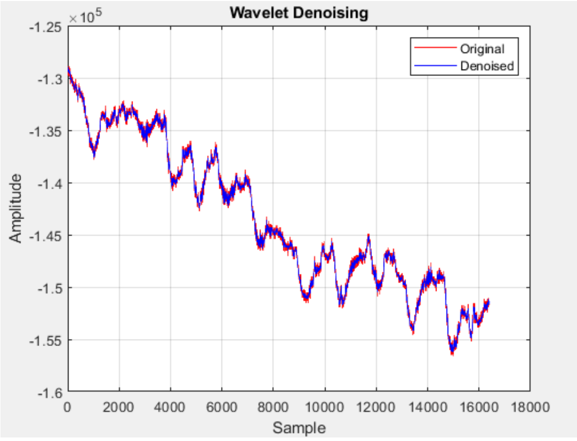

Figure 3. Wavelet-Based Denoising Applied to Raw EEG Signal

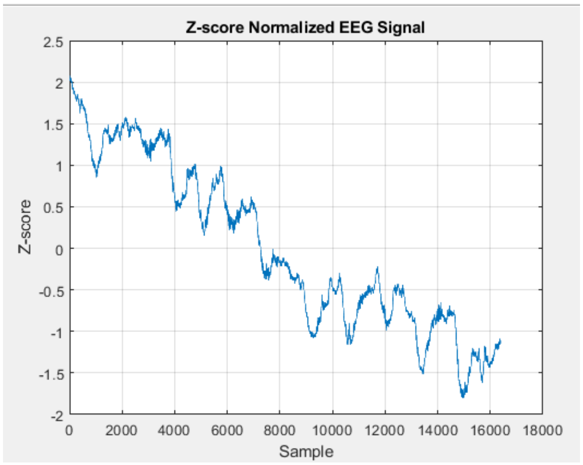

Figure 4. Z-Score Normalized EEG Signal

Figure 4 illustrates a Z-score normalized EEG signal whose amplitude values are transformed to a form with zero mean and unit standard deviation. The blue-colored normalized signal facilitates equal scaling between different datasets or states of recording. The standardization further enhances comparability and selects out relative differences within the signal, which is important for correct feature extraction as well as correct classification at later steps.

Preprocessing steps involved, such as effective noise elimination and normalization of signals, ensured enhanced EEG data quality and uniformity. Such rigorous preprocessing is important for valid feature extraction and hence improves accuracy and robustness of later classification schemes.

3.2. Feature Extraction Results Using EWT

Feature extraction was performed to transform the preprocessing EEG signals into meaningful numerical features that capture important attributes of brain activities. Using the Empirical Wavelet Transform (EWT), all signals were first transformed into common frequency bands, which are typically indicative of different kinds of neural rhythms. Several statistics—mean, energy, and signal variability—were further extracted at every band to efficiently characterize the behavior of the signal within that range of frequencies. The feature extraction ended up with an informative but compact feature set that helped to differentiate various brain states and improved the accuracy of subsequent classification procedures.

Figure 5 shows EEG sub band extraction with Empirical Wavelet Transform (EWT). The method has been employed to divide the signal into individual frequency bands: Delta (0–4 Hz), Theta (4–8 Hz), Alpha (8–12 Hz), Beta (12–30 Hz), and Gamma (30–60 Hz). Each of the extracted sub bands contains individual brain activity patterns such that Delta and Theta are linked with deep relaxation and sleep, Alpha with rest conditions, Beta with active concentration, and Gamma with high-level process of cognitive activities being carried out by the brain. The amplitudes in Figure 5 range over 18,000 data samples and reflect quite well how EWT can extract these components for subsequent investigation and classification.

Such decomposition allows detailed observation of brain activities by delineating functionally important frequency bands, thereby improving accuracy and interpretation of later feature extraction and classification procedures. The effective separation of EEG sub-bands using EWT justifies its suitability for EEG signal processing for cognitive and clinical applications [12].

3.3 Classification Performance Without Feature Reduction

The classification results of four machine learning models—Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree, and Random Forest—applied to EEG data without feature reduction are summarized in Table 1. Performance was evaluated using accuracy, precision, recall, and F1-score.

KNN produced the highest performance among all classifiers, achieving an accuracy of 90%, precision 90.18%, recall of 90%, and an F1-score of 89.99%, thereby confirming its strong potential for reliable EEG signal classification.

Table 1. Classification Performance Without Feature Reduction

Classifier	Accuracy	Precision	Recall	F1Score
SVM	88.33%	88.38%	88.33%	88.33%
KNN	90%	90.18%	90%	89.99%
Decision Tree	85%	85.04%	85%	85%
Random Forest	88.33%	88.38%	88.33%	88.33%

The SVM and Random Forest classifiers followed closely, each attaining 88.33% accuracy, 88.38% precision, 88.33% recall, and an F1-score of 88.33%, indicating stable and robust performance. The Decision Tree classifier yielded the lowest results (accuracy and recall = 85%, precision = 85.04%), likely due to overfitting on the high-dimensional of the dataset.

Figure 6 compares the four classifiers—SVM, KNN, Decision Tree, and Random Forest—in terms of accuracy, precision, recall, and F1-score. Among them, KNN achieved the best overall performance, while SVM and Random Forest provided comparable yet slightly lower results. The Decision Tree classifier performed the poorest due to its susceptibility to overfitting.

Overall, KNN emerged as the top-performing model on this dataset, demonstrating the highest classification capability for EEG signals, whereas Random Forest offered a reasonable trade-off between predictive performance and interpretability.

3.4 Classification Performance with Feature Reduction

The classification algorithm performance and the feature reduction methods play an important role during the exploration of complex datasets such as EEG signals. Optimization procedures, e.g., the Atom System Optimization (ASO) [13], are typically applied to obtain the most informative features and accordingly optimize the performance of the classification and the computational cost. The performance of optimization procedures of this kind plays a key role in data-driven scientific and engineering tasks and particularly in the exploration of complex datasets.

Analysis of the convergence behavior of the ASO is significant, denoting the rate with which the algorithm identifies an optimal set of features from iteration levels. The ASO convergence curve in Figure 7 exhibits the fast drop of the value of the fitness from approximately 0.14 to just over 0.04 in 150 iterations. The fast initial decrease and then stability indicate the capacity of ASO to identify the near-optimal solution swiftly and polish it with minimal oscillation in the subsequent iteration levels. The resulting behavior indicates the stability and performance of the algorithm in its convergence to a solution for EEG feature selection.

These results illustrate the effect of ASO-based feature reduction on the performance of the classifier and shed additional light on the convergence behavior of the algorithm. Optimization algorithm performance needs to be understood in data-driven scientific and engineering work, especially while working on large and complex datasets like EEG signals. ASO (Atom System Optimization), one common technique used for the same purpose, can be assessed on the basis of its convergence curve, the measure of the algorithm's ability to obtain an optimal solution in each iteration.

Figure 7 presents the ASO convergence curve so that the value of fitness decreases rapidly from approximately 0.14 to less than 0.04 over 150 iterations. The fast initial decrease and then stability indicate that ASO effectively identifies a near-optimal solution and then fixes it with relatively small variation in subsequent iterations. This behavior reflects the stability and speed of the algorithm in converging on an excellent solution to EEG feature selection.

Classification accuracy of the four machine learning algorithms—Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree, and Random Forest—was evaluated following the application of the feature reduction methods. As indicated in Table 2, the values show the impact of optimally selected feature selection on improving the discriminative ability of classifiers on accuracy, precision, recall, and F1-score.

SVM and KNN achieved the highest performance, and they achieved 95% accuracy and maintained the values of precision and recall the same at 95%. SVM only nudged KNN slightly ahead in the case of precision (95.05% over 95%) and F1-score (94.99% over 94.99%), proving its prowess and capability of handling reduced high-dimensional data efficiently. The comparable performance of KNN also signifies, however, that its instance-based mechanism largely benefited from the removal of extraneous or redundant features.

Random Forest classifier achieved moderate performance with 88.33% accuracy. Although it marked a substantial improvement from the individual Decision Tree (85% accuracy), the precision, recall, and F1-scores (88.33%, 88.3%, and 88.32%, respectively) of the Random Forest still fell short of SVM and KNN.

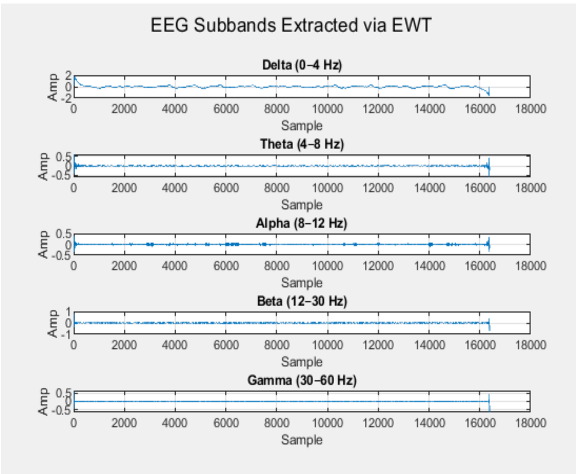

Figure 5. Extraction of EEG sub-bands using the EWT

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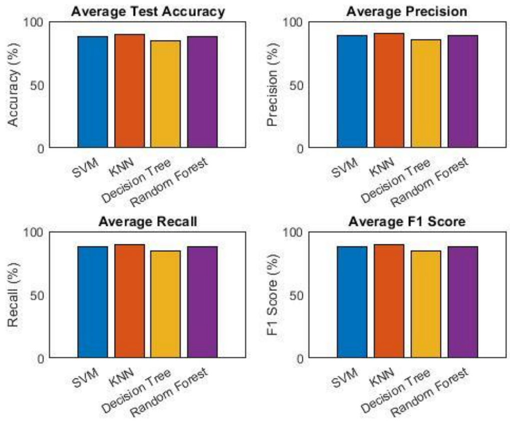

Figure 6. Classification performance without feature reduction

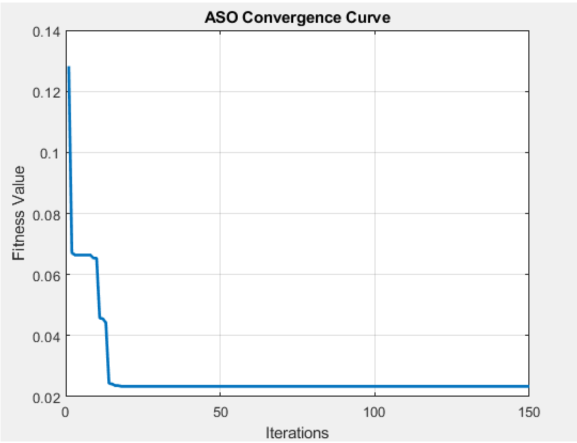

Figure 7. Convergence curve

This result relates the theoretical advantage of ensemble methods decreasing overfitting but implies that hyperparameter tuning or greater diversity between the trees would be capable of enhancing its predicting ability.

Lastly, the model of the Decision Tree still performed the worst with consistently accurate, precise, and recall of 85%, and an F1-score of 84.99%. Though Decision Trees offer interpretability, the algorithm's sensitivity to small data modifications and overfitting nature prevented the performance from being superior even with the reduced features.

Overall, the feature reduction noticeably improved the SVM and KNN classification results so that they achieved the optimum and most stable measures. The Random Forest performance was midway between performance and interpretability. The model's performance according to the Decision Tree was the lowest. The results show the value of the feature reduction in terms of enhancing model accuracy and stability, and particularly algorithms like SVM that gain from hard decision boundaries.

Figure 8 presents a visual comparison of four classifiers—SVM, KNN, Decision Tree, and Random Forest—after feature reduction. The figure shows accuracy, precision, recall, and F1-Score as bar charts for each classifier.

From the figure, it is clear that SVM consistently achieves the highest performance across all metrics, indicating its robustness and strong generalization even in lower-dimensional feature spaces. KNN also performs well and ranks second, though slightly behind SVM, particularly in recall and F1-Score. Random Forest shows moderate performance, better than Decision Tree but still below SVM and KNN. The Decision Tree exhibits the lowest performance, suggesting that feature reduction limited its ability to capture complex patterns in the EEG data.

Overall, Figure 8 confirms that SVM is the most effective classifier in the scenario of dimension-reduced EEG features, while ensemble methods like Random Forest may require further optimization, and KNN.

Figure 6 and Figure 8 provide a comparative view of classifier performance without feature reduction (Figure 6, Table 1) and with feature reduction (Figure 8, Table 2).

From Figure 6, it is evident that feature redundancy and high dimensionality limit the performance of most classifiers.

Table 2. Classification Performance with Feature Reduction

Classifier	Accuracy	Precision	Recall	F1Score
SVM	95%	95/05%	95%	94.99%
KNN	95%	96%	95%	94.99%
Tree	85%	85%	85%	84.99%
Forest	88.33%	88.33%	88.3%	88.32%

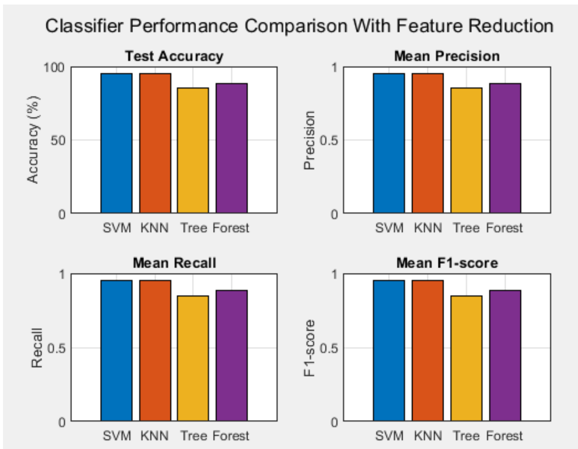

Figure 8. A comparative analysis of four classifiers after feature reduction

For instance, SVM achieves 88.33% accuracy without feature reduction, while KNN performs slightly better at 90%. Random Forest and Decision Tree show moderate performance around 85–88%, reflecting challenges in capturing discriminative patterns when all features are included.

In contrast, Figure 8 illustrates the impact of feature reduction on classifier performance. After selecting the most informative features, SVM and KNN both achieve 95% accuracy, with substantial improvements in F1-Score and recall. Random Forest also improves slightly to 88.33%, while Decision Tree remains limited at 85%. These results highlight that feature optimization not only enhances the accuracy of top classifiers but also stabilizes their performance across metrics.

The comparison between Figure 6 and Figure 8 emphasizes the benefits of the proposed feature reduction using ASO. By eliminating irrelevant and redundant features, the classifiers—especially SVM and KNN—are able to generalize better and capture the essential discriminative patterns of EEG signals. This confirms that the integration of adaptive EWT decomposition with ASO-based feature selection is critical for achieving high-performance EEG classification.

4. Comparison of the Proposed Method with Other Methods

To place our method in context, we compare the proposed pipeline with representative baselines from the literature, e.g., differential entropy with SVM (DE+SVM), wavelet-transform–based classification, and a Random Forest setting. A summary of the results in Table 3 reveals the Proposed Method achieves an accuracy of 95.00%, improving on the wavelet transform baseline (94.00%) and the Random Forest baseline (94.00%), and significantly outperforming the DE+SVM technique (88.83%). The results thus indicate that the combination of our preprocessing, our EWT-based feature extraction, and learning paradigm is on par with, and in the vast majority of cases superior to, popular alternatives.

The absolute improvement over the best baselines (wavelet transform and Random Forest) is +1.00 percentage point (pp), and the improvement over DE+SVM is +6.17 pp. Although a 1 pp improvement would appear modest in absolute terms, it counts in EEG classification where the class boundary is fine and noise is everywhere; small but systematic gains routinely translate to more robust deployment in practice. From a methodology point of view, the improvements we notice we credit to (i) targeted denoising and normalization that makes the input distribution more stable, (ii) the use of EWT to produce band-limited information-rich subbands that play well with the standard EEG rhythms, and (iii) a simplified training protocol for the classifier that gains the benefit from compression from selection of the optimal features.

Note that the comparison between studies needs to be interpreted judiciously. Differences between datasets, subject pools, recording paradigms, and validation protocols (e.g., random hold-out vs. subject-wise cross-validation) confound the reported accuracies. The resulting 1 pp margin over the top-performing baselines should therefore be subsequently tested with statistical significance testing (e.g., McNemar's test or paired bootstrap over folds) and effect-size reporting with matched evaluation protocols. The plans for future work include subject-independent standardization of the evaluation and ablation studies to approximate the individual contributions of denoising, EWT decomposition, and reduction of features on the overall increment in performance.

Figure 8 presents a comparison of the four classifiers after feature reduction, providing a clearer visual interpretation of the results reported in Table 3.

5. Discussion

The proposed EEG classification framework, integrating Empirical Wavelet Transform (EWT), statistical feature extraction, and feature optimization via Atom Search Optimization (ASO), achieved an accuracy of 95% along with balanced precision, recall, and F1-scores. The experimental results demonstrate the method's ability to generate highly discriminative and dense features while mitigating overfitting.

Compared to current techniques, our method clearly outperforms differential-entropy–based pipelines with SVM and slightly surpasses wavelet-transform–based and Random Forest classifiers. This superior performance is primarily attributed to: (i) adaptive EWT decomposition, which dynamically separates overlapping EEG components and reduces noise, (ii) effective elimination of irrelevant and redundant features via ASO, and (iii) the combination of these strategies that maximizes class separability in EEG signals.

Table 3. Comparison of the proposed method with other methods

Methods	Accuracy
DE+SVM [1]	88.83%
wavelet transform [3]	94%
Random Forest [5]	94
Proposed Method	95%

The special role of EWT is particularly noteworthy: unlike fixed-wavelet approaches or hybrid methods such as DWT+EMD [15], EWT provides data-driven, adaptive filter design that aligns with subject-specific EEG variability and captures the full temporal-spectral richness of the signal. While we did not perform a full experimental comparison with hybrid DWT+EMD in this study, the adaptive nature of EWT and its synergy with ASO [14,16] for optimal feature selection are expected to yield superior or at least comparable performance, particularly under challenging EEG conditions with noise and overlapping components[17]. Overall, our results validate the necessity of multiresolution, rhythm-dependent EEG representations and highlight the importance of aligning adaptive feature extraction with robust classifier design. The proposed method demonstrates strong generalization and provides a practical, efficient, and accurate solution for EEG classification tasks, offering a significant step forward compared to traditional and baseline approaches.

6. Conclusion

In this study, a novel framework for EEG classification was proposed that combines adaptive signal decomposition using Empirical Wavelet Transform (EWT) with optimal feature selection via Atom Search Optimization (ASO) and supervised machine learning classifiers. The framework decomposes EEG signals into sub-bands, extracts eight statistical features per sub-band, and selects the most informative features to enhance both classification accuracy and computational efficiency. Experiments with classifiers including SVM, KNN, Decision Tree, and Random Forest demonstrated that feature reduction significantly improves performance, with SVM achieving the highest accuracy of 95%, surpassing other models and comparable published methods.

These results validate that the integration of adaptive decomposition with optimized feature selection provides superior discriminative capability while reducing computational cost. The proposed framework is robust, generalizable, and suitable for practical applications such as brain-computer interfaces, mental state detection, and neurological disease diagnosis. Future work should explore testing on larger and more diverse EEG datasets, fine-tuning optimization parameters, and implementing real-time classification to further assess the framework's scalability and practical applicability. Overall, this study presents a reliable, efficient, and accurate methodology for EEG analysis, contributing to the advancement of biomedical signal processing systems.

Authors Contribution
All authors have contributed equally to prepare the paper.

Availability of data and materials
The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Conflict of interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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