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Comparative Analysis of Statistical, Time–Frequency, and SVM Techniques for Change Detection in Nonlinear Biomedical Signals

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Abstract: Change detection in biomedical signals is crucial for understanding physiological processes and diagnosing medical conditions. This study evaluates various change detection methods, focusing on synthetic signals that mimic real-world scenarios. We examine the following three methods: classical statistical techniques (thresholding based on mean and standard deviation), Support Vector Machine (SVM) classification, and time–frequency analysis using Continuous Wavelet Transform (CWT). Each method's performance is assessed using synthetic signals, including nonlinear signals and those with simulated anomalies. We calculated the F1-score to quantify performance, providing a balanced measure of precision and recall. Results showed that SVM classification outperformed both classical techniques and CWT analysis, achieving a higher F1-score in detecting changes. While all methods struggled with synthetic nonlinear signals, classical techniques and SVM successfully detected changes in signals with simulated anomalies, whereas CWT had difficulty with both types of signals. These findings underscore the importance of selecting appropriate change detection methods based on signal characteristics. Future research should explore advanced machine learning and signal processing techniques to improve detection accuracy in biomedical applications.

Keywords: biomedical signals; change detection; synthetic data; signal processing; time–frequency analysis; machine learning; clinical applications

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1. Introduction

In the area of biomedical signal processing, detecting changes in signals is paramount for understanding physiological processes, diagnosing medical conditions, and developing effective treatments [1–4]. Biomedical signals, encompassing a wide range of modalities, such as electrocardiography (ECG), electromyography (EMG), electroencephalography (EEG), and more, encode valuable information about the functioning of biological systems [5–7] However, these signals are often complex, dynamic, and prone to various sources of noise and artifacts. Detecting changes in biomedical signals is thus essential for uncovering meaningful patterns, identifying anomalies, and extracting clinically relevant information [8–10].

The field of change detection in biomedical signals encompasses a diverse array of methodologies, ranging from classical statistical techniques to modern machine learning algorithms [11,12]. These methodologies aim to distinguish between normal physiological variations and abnormal deviations, providing insights into health status, disease progression, and treatment efficacy. By leveraging advanced signal processing and pattern recognition techniques, researchers and clinicians can effectively monitor, analyze, and interpret biomedical signals in real-time, facilitating early detection, diagnosis, and intervention [12,13]. The application of change detection in biomedical signals spans across numerous domains of healthcare and biomedical research [11,12]. In cardiology [13–15], for instance, detecting changes in ECG signals enables the early detection of cardiac arrhythmias, ischemic events, and heart failure, guiding patient management and therapy

selection [13]. Similarly, in neurology, change detection in EEG signals [16,17] aids in diagnosing epilepsy, monitoring brain activity during cognitive tasks, and studying neurological disorders, such as Alzheimer's disease and Parkinson's disease [7,18–20].

Classical statistical techniques for change detection, such as those based on the mean and standard deviation of the signal, are widely used due to their simplicity and ease of implementation. These methods, however, have significant limitations, particularly when applied to non-Gaussian and complex signals often found in biomedical data. Statistical techniques are sensitive to outliers and assume a Gaussian distribution, which can lead to inaccurate detection thresholds and failure to identify subtle changes. Outliers can skew the mean and standard deviation, making small changes undetectable. Non-Gaussian distributions, common in real-world biomedical signals, result in inaccurate statistical representations. Additionally, setting an appropriate threshold is difficult: a high threshold may miss subtle changes, while a low threshold can increase false positives. The reliance on fixed thresholds further complicates their application, as inappropriate threshold selection can either overlook important changes or increase the false positive rate [21]. This method also ignores temporal correlations, making it less effective for detecting gradual trends.

Recently, the field of signal change detection has witnessed significant advancements, driven by the integration of advanced signal processing techniques and machine learning algorithms [22–24]. One such technique is time–frequency analysis, which allows for the decomposition of signals into their time-varying frequency components. Methods such as the Continuous Wavelet Transform (CWT) and the short-time Fourier transform (STFT) enable the localization of signal changes in both time and frequency domains, offering enhanced sensitivity to transient events and non-stationary signals [25,26]. By capturing changes in signal characteristics over time, time–frequency analysis provides valuable insights into dynamic physiological processes and pathological events. However, the effectiveness of CWT is highly dependent on the choice of wavelet function and the threshold used for change detection [27]. An inappropriate wavelet function can lead to suboptimal performance, and the complexity of the signal can challenge the CWT's ability to accurately detect changes. Therefore, careful tuning of parameters is necessary to balance sensitivity and specificity. The time–frequency analysis with CWT offers a more dynamic approach by decomposing signals into time-varying frequency components. Its success depends on selecting the appropriate wavelet function and threshold. The choice of wavelet function is critical, as different wavelets capture different signal features. Inappropriate wavelet selection can lead to poor change detection. Similarly, setting the right threshold is essential; an improper threshold can miss subtle changes or amplify noise, causing false positives. While CWT can capture complex signal dynamics, its effectiveness can be compromised by the inherent complexity and variability of the signal.

Another promising approach is the use of deep learning models for signal change detection. Deep neural networks, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have shown remarkable success in analyzing complex patterns and extracting hierarchical features from biomedical signals [28–31]. By leveraging large-scale datasets and hierarchical representations, deep learning models can automatically learn discriminative features and detect subtle changes in signals with high accuracy. Moreover, techniques such as transfer learning and adversarial training enhance the generalization and robustness of deep learning models, making them valuable tools for signal change detection in biomedical applications. Machine learning algorithms, such as Support Vector Machines (SVMs), represent a powerful tool for change detection in biomedical signals. These methods leverage sophisticated feature extraction and pattern recognition capabilities to detect changes. The effectiveness of SVMs, however, depends on the representation of features and the availability of informative training data. In scenarios with complex signal dynamics and subtle changes, traditional SVM approaches may struggle without adequate feature engineering. Recent advancements suggest that integrating deep learning techniques, such as convolutional neural networks (CNNs)

and hybrid models combining CNNs with transformers, can significantly enhance the performance of SVMs in detecting changes in biomedical signals [32–34].

Furthermore, Bayesian inference methods offer a principled framework for modeling uncertainty and incorporating prior knowledge into signal change detection algorithms. Bayesian approaches, such as Bayesian filtering, probabilistic graphical models, and Bayesian networks, provide probabilistic representations of signal dynamics and enable the integration of domain knowledge and prior beliefs [35]. By explicitly modeling uncertainty and incorporating prior information, Bayesian inference methods enhance the reliability and interpretability of signal change detection results, facilitating more informed decision-making in clinical practice and biomedical research. Despite significant progress, challenges persist in the field of change detection in biomedical signals. These challenges include the development of robust algorithms capable of handling noisy and high-dimensional data, addressing inter-subject variability, and ensuring the interpretability and generalizability of results across diverse populations [36–38]. Additionally, the integration of multimodal data and the incorporation of domain knowledge present exciting avenues for future research and innovation in the field [39]. Efforts to overcome these challenges involve leveraging advanced machine learning techniques, such as deep learning and reinforcement learning, as well as exploring novel signal processing approaches, such as compressive sensing and phase-space reconstruction [40–42]. By addressing these challenges, researchers aim to enhance the reliability and efficacy of change detection methods in biomedical signals, ultimately improving healthcare outcomes and advancing our understanding of human physiology and disease.

In comparison to classical statistical techniques, time–frequency analysis and machine learning algorithms offer several advantages [43–46]:

- **Enhanced sensitivity:** These methods can detect subtle changes that may be missed by classical techniques.
- **Robustness to noise:** They are less sensitive to noise and artifacts, which is common in biomedical signals.
- **Ability to handle complex signals:** They can effectively handle non-linear and non-stationary signals.
- **Scalability:** They can handle large datasets and high-dimensional data.

However, these methods also have their limitations:

- **Computational complexity:** Time–Frequency analysis and machine learning algorithms can be computationally expensive, especially for large datasets.
- **Parameter tuning:** These methods often require careful tuning of parameters to achieve optimal performance.
- **Interpretability:** The results of these methods can be difficult to interpret, especially for complex models.

Here is the schematic diagram visualizing the application of classical statistical techniques, Continuous Wavelet Transform (CWT), and Support Vector Machine (SVM) for change detection in biomedical signals (see Figure 1).

In this comprehensive study, we explore the methodologies, applications, and challenges of change detection in biomedical signals, underscoring its critical importance in advancing our understanding of human physiology, improving clinical decision-making, and fostering innovations in healthcare technology. In Section 2 we describe three methods for detecting changes in nonlinear biomedical signals: classical statistical techniques, time–frequency analysis using Continuous Wavelet Transform (CWT), and machine learning with Support Vector Machines (SVMs). In Section 3 we employ a multifaceted approach to change detection, incorporating classical statistical techniques to identify significant variations and patterns within the data. Time–Frequency analysis is utilized to dissect the complex temporal and spectral characteristics of biomedical signals, enabling a more detailed understanding of dynamic processes. Additionally, we leverage machine learning algorithms, such as Support Vector Machines (SVMs), to enhance the accuracy and

robustness of change detection. These algorithms are particularly adept at handling high-dimensional data and identifying subtle, non-linear patterns that might elude traditional methods. In Section 4 we discuss the results obtained in Section 3. In Section 5, we continue our discussion by providing application, challenges, and future directions for each method. In Section 6, we provide a comprehensive discussion of the strengths and limitations of each approach. By applying these diverse and complementary techniques, this study lays the foundation for further exploration and discovery in this dynamic and interdisciplinary field, paving the way for more precise and reliable biomedical signal analysis.

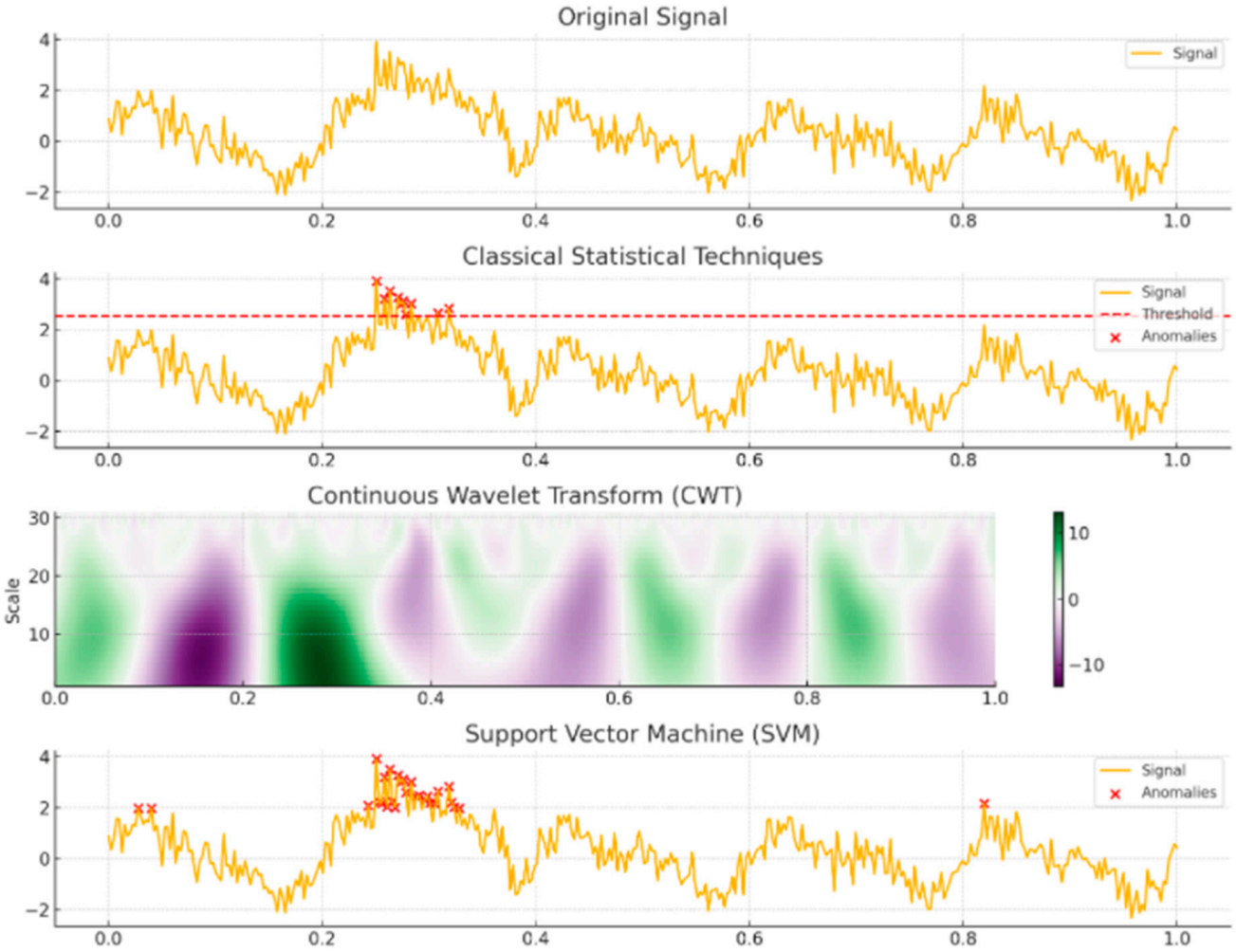

Figure 1. Change detection in biomedical signals. This figure illustrates the performance of different change detection methods on a synthetic signal. The original signal contains a known anomaly between time points 100 and 150. The classical statistical method uses mean and standard deviation thresholding to identify changes. The Continuous Wavelet Transform (CWT) method analyzes the signal in both time and frequency domains to detect anomalies. The Support Vector Machine (SVM) classifier is trained on the signal to identify changes based on learned patterns. The figure highlights the detected anomalies by each method, demonstrating their effectiveness in identifying different types of changes in biomedical signals.

2. Method

2.1. Classical Statistical Techniques

Classical statistical techniques involve analyzing the statistical properties of the signal to detect changes. One common approach is based on monitoring changes in the mean and

variance of the signal. Let $x(t)$ represent the signal at time t. The mean μ and standard deviation σ of the signal can be calculated as follows:

$$\mu = \frac{1}{N}\sum_{t=1}^{N} x(t) \tag{1}$$

$$\sigma = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(x(t)-\mu)^2} \tag{2}$$

Once the mean and standard deviation are computed, a change can be detected if the absolute deviation of a data point from the mean exceeds a certain threshold $(\alpha \times \sigma)$, where α is a user-defined parameter.

2.2. Time–Frequency Analysis

Time–Frequency analysis involves decomposing the signal into its frequency components over time to detect changes in the spectral content of the signal. One popular method is the Continuous Wavelet Transform (CWT). The CWT represents the signal as a function of both time t and frequency ω, given by:

$$CWT(a,b) = \frac{1}{\sqrt{|a|}}\int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-b}{a}\right)dt \tag{3}$$

where $\psi(t)$ is the analyzing wavelet function, a is the scale parameter controlling the width of the wavelet, and b is the translation parameter controlling the position of the wavelet along the time axis. Changes in the signal can be detected by analyzing the magnitude of wavelet coefficients across different scales and positions.

2.3. Machine Learning Algorithms

Machine learning algorithms, such as Support Vector Machines (SVMs), learn to distinguish between different classes of data points, including normal and abnormal segments of the signal. SVMs, for example, learns a hyperplane that separates the data points of different classes with the maximum margin. Given a set of training data with labels (x_i, y_i), where x_i represents the feature vector of the i-th data point and y_i represents its class label, SVMs solve the following optimization problem:

$$\min_{\omega,b,\xi}\frac{1}{2}||\omega||^2 + C\sum_{i=1}^{N}\xi_i \tag{4}$$

Subject to:

$$y_i\left(\omega^T x_i + b\right) \geq 1-\xi_i, \qquad \xi_i \geq 0$$

where ω represents the weight vector, b represents the bias term, ξ_i represents the slack variables, and C is a regularization parameter. Changes in the signal can be detected based on the classification results of the SVM model.

Key steps of the Support Vector Machine (SVM) algorithm (see Figure 2) are as follows:

(a) Input data: Receive a set of labeled training examples.
(b) Feature mapping: Map input feature vectors to a higher-dimensional space using kernel functions.
(c) Optimization objective: Find the optimal hyperplane that maximizes the margin between classes in the transformed space.
(d) Soft margin: Introduce a slack variable to allow for misclassification of some data points, balancing margin maximization and classification error minimization.

(e) Kernel trick: Efficiently compute dot products in the higher-dimensional space without explicitly transforming feature vectors.
(f) Training: Solve a convex optimization problem to learn the optimal hyperplane parameters (weights and bias).
(g) Prediction: Predict class labels of new data points based on the sign of the decision function, which is a linear combination of input features weighted by learned parameters.

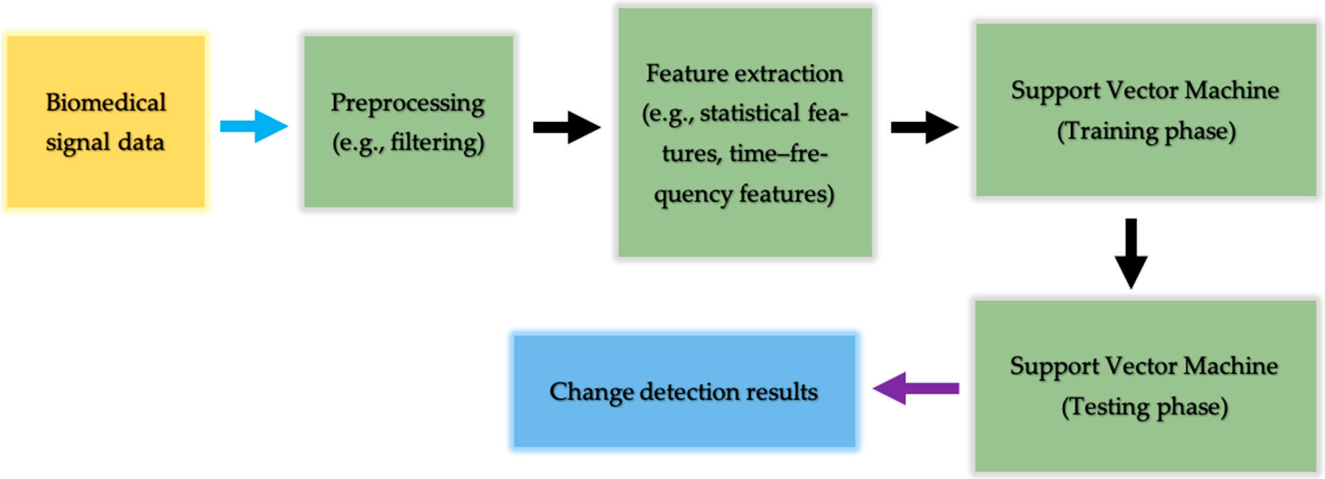

Figure 2. Support Vector Machine (SVM) workflow. An SVM classifies data by finding the optimal hyperplane that separates two classes with maximum margin. Kernel functions map data into a higher-dimensional space to improve separability. The soft margin approach allows for some misclassification, balancing accuracy and generalization. The kernel trick efficiently computes dot products in the transformed space. The SVM training process involves solving a convex optimization problem to learn the hyperplane parameters. Once trained, the SVM can predict class labels for new data points based on their distance from the hyperplane.

Here is a schematic representation of the change detection methods applied to a randomly generated biomedical signal (see Figure 3).

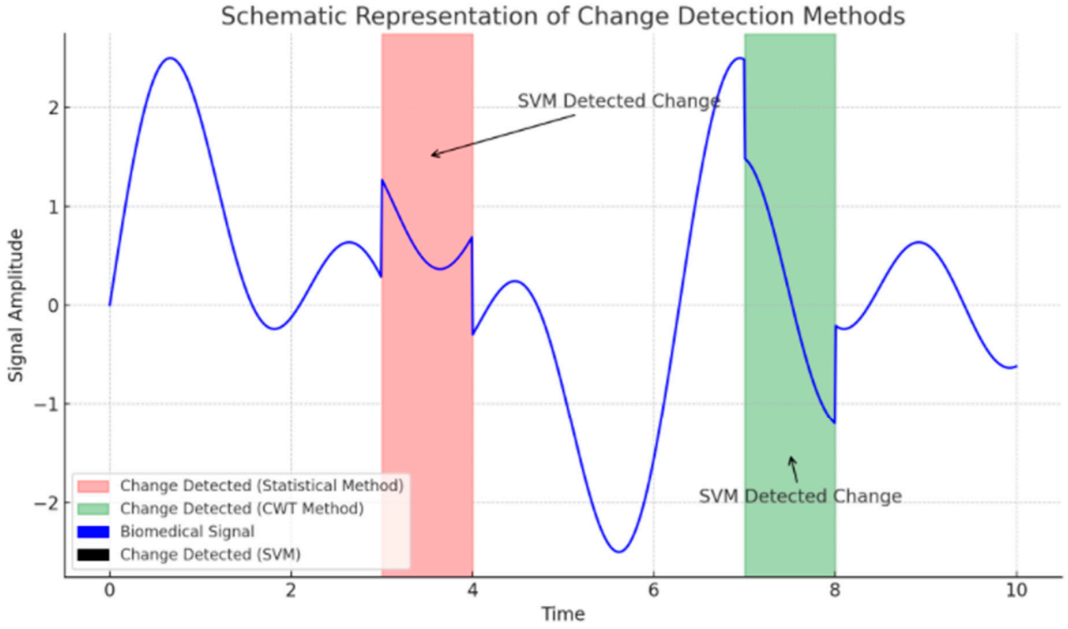

Figure 3. Schematic representation of change detection methods applied to a biomedical signal. The original biomedical signal (blue curve) is analyzed using three methods: classical statistical techniques,

Continuous Wavelet Transform (CWT), and Support Vector Machine (SVM). Changes detected by the statistical method are highlighted in the red shaded area, indicating sensitivity to shifts in mean and standard deviation. Changes identified by the CWT method are shown in the green shaded area, demonstrating the method's ability to capture time–frequency variations. The SVM-detected changes are marked by black arrows, showcasing its capability to recognize subtle and complex patterns in the signal. This visualization underscores the varying effectiveness of each method in different contexts of signal complexity and change characteristics.

The blue curve represents the original signal, which is a combination of multiple sinusoidal components.

i. Change detected (statistical method): The red shaded area indicates the region where the statistical method detected changes due to shifts in mean and standard deviation.
ii. Change detected (CWT method): The green shaded area shows where the Continuous Wavelet Transform (CWT) method detected changes, capturing variations in the time–frequency domain.
iii. Change detected (SVM): The black arrows highlight points where the Support Vector Machine (SVM) detected changes, effectively identifying subtle and complex patterns in the signal.

3. Data and Application

3.1. Data

In this study, we generate synthetic nonlinear signals to evaluate the effectiveness of various change detection methods. The generation process involves combining sine waves of different frequencies and applying nonlinear transformations to introduce complex behaviors that are representative of real-world biomedical signals.

To generate the synthetic nonlinear signal, we start with a combination of sine waves, as described below:

(a) Base frequencies: We start by generating three sine waves with distinct frequencies: 5 Hz, 10 Hz, and 20 Hz. These frequencies were chosen to provide a mix of low, medium, and high frequency components, simulating the variety of oscillatory behaviors seen in biomedical signals.
(b) Mathematical representation: The synthetic signal $x(t)$ is initially defined as:

$$x(t) = \sin(2\pi.5.t) + \sin(2\pi.10.t) + \sin(2\pi.20.t)$$

To introduce the non-linear behavior, we perform the following steps:

(a) Nonlinear transformation: To incorporate nonlinear characteristics, we apply a nonlinear function to one of the sine wave components. In this case, we square the amplitude of the 20 Hz component.
(b) Transformed signal: The modified signal $y(t)$ becomes:

$$y(t) = \sin(2\pi.5.t) + \sin(2\pi.10.t) + (\sin(2\pi.20.t))^2$$

(c) Effect: This squaring operation introduces harmonic distortions and amplitude modulation, which are characteristic of nonlinear systems.

To generate the anomalous signal and to evaluate the performance of change detection algorithms, we introduce anomalies into the synthetic nonlinear signal. These anomalies simulate deviations from typical patterns, such as those caused by pathological events in biomedical contexts. To introduce the base anomalous signal, we perform the following steps:

(a) Primary pattern: The anomalous signal retains the fundamental sinusoidal pattern but at a consistent frequency of 10 Hz, replicating a basic form of brain electrical activity.

(b) Mathematical representation: Initially, the anomalous signal $z(t)$ is represented as:

$$z(t) = \sin(2\pi.10.t)$$

3.2. Method 1: Classical Statistical Techniques (e.g., Mean and Standard Deviation)

This method involves calculating the mean and standard deviation of the signal and then comparing each data point to a threshold derived from these statistics. Points where the absolute deviation from the mean exceeds the threshold are identified as changes in the signal (see Figure 4).

While Method 1 provides a straightforward approach to change detection based on statistical properties of the signal, its effectiveness can be limited by the presence of outliers, non-Gaussian distribution, suboptimal threshold selection, and lack of consideration for temporal dynamics. As a result, alternative methods that address these limitations may be more suitable for detecting changes in certain types of signals.

We have displayed the result of the second example in Figure 5.

3.3. Method 2: Time–Frequency Analysis (e.g., Wavelet Transform)

This algorithm performs change detection on a synthetic nonlinear signal using Continuous Wavelet Transform (CWT). It computes the CWT of the signal, decomposing it into frequency components across different scales. A threshold is then applied to the wavelet coefficients to detect significant changes in the signal. Changes exceeding the threshold are identified, and the results are visualized as an image, with time on the x-axis and frequency on the y-axis. Darker regions in the image represent higher magnitudes of change.

The first example related to the CWT is displayed in Figure 6.

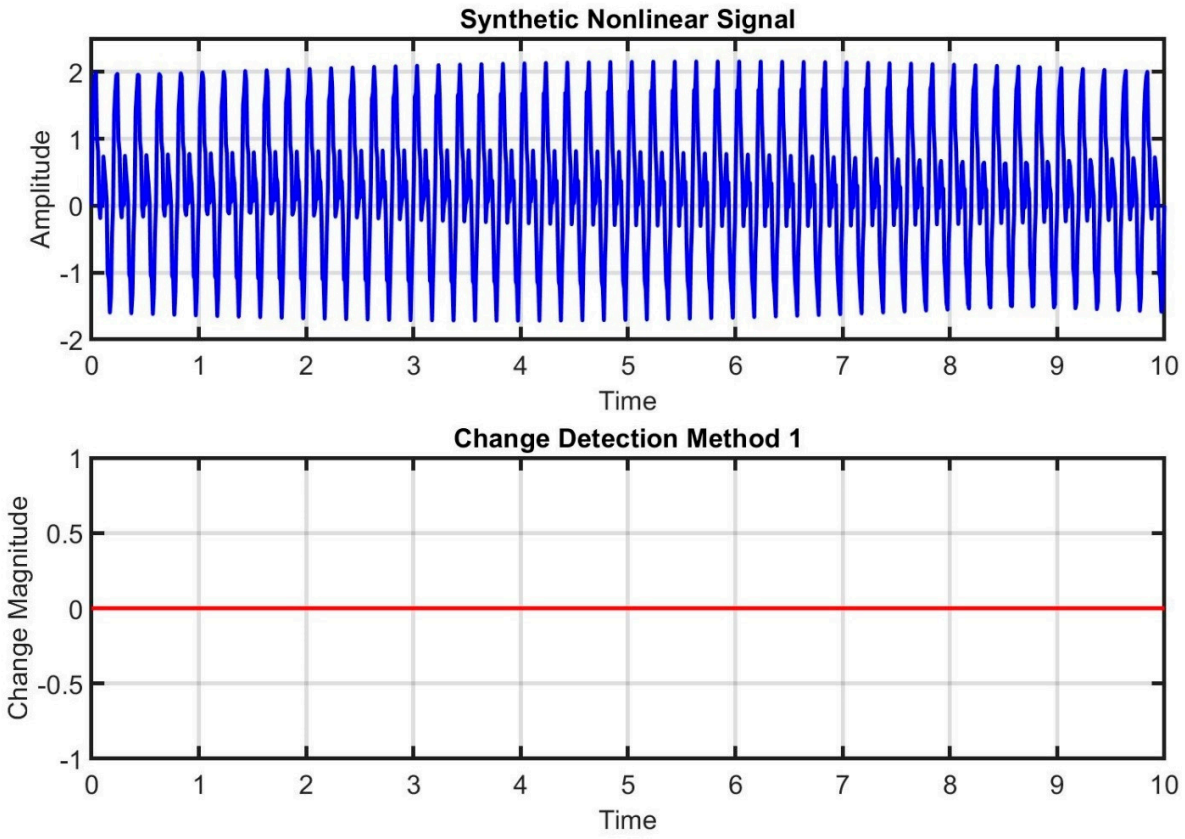

Figure 4. Change detection using mean and standard deviation method. (**Top**) Synthetic nonlinear signal plotted against time and shown in blue. This signal exhibits complex behavior over time, characterized by variations and fluctuations in amplitude. (**Bottom**) The red line represents the results of change detection using the mean and standard deviation method.

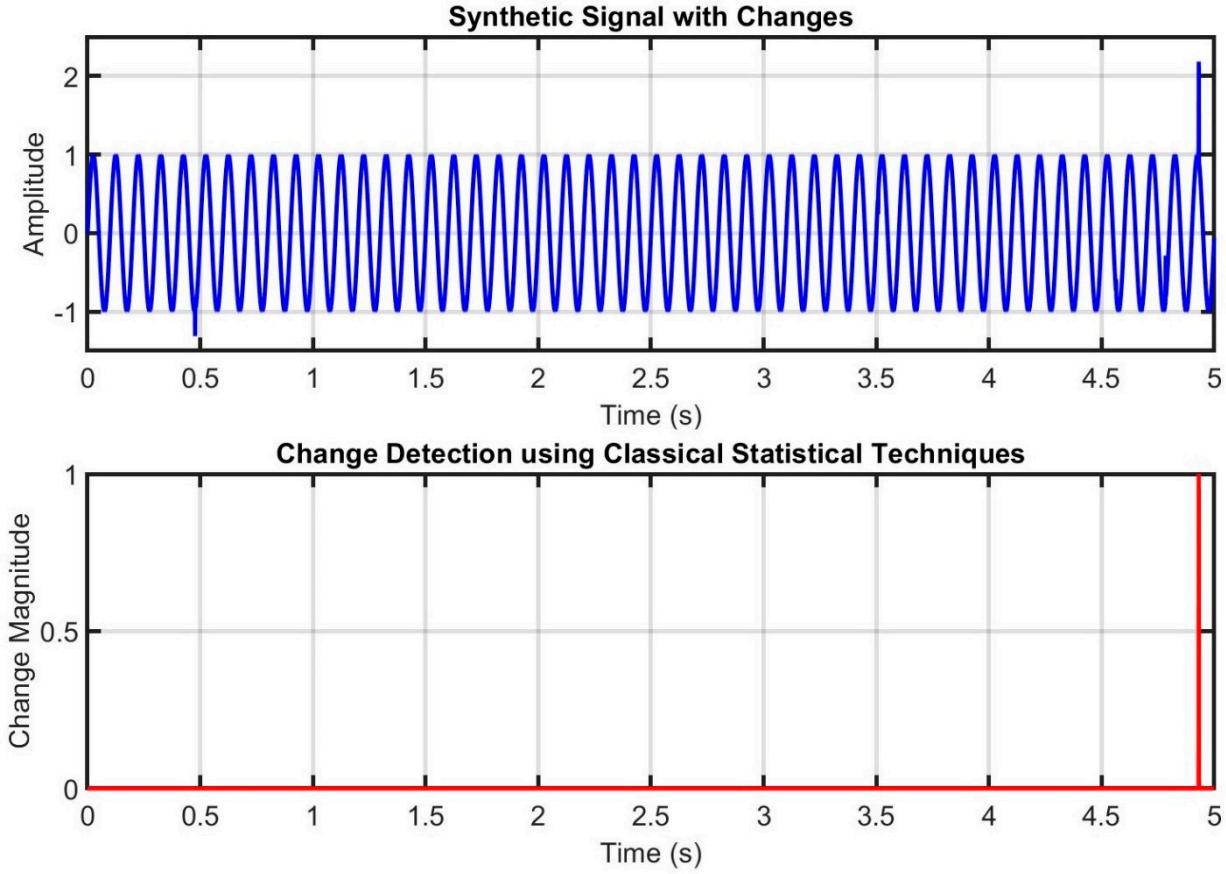

Figure 5. Change detection using mean and standard deviation method. (**Top**) Synthetic nonlinear signal plotted against time and shown in blue. This signal exhibits complex behavior over time, characterized by variations and fluctuations in amplitude. (**Bottom**) The red line represents the results of change detection using the mean and standard deviation method.

We have displayed the result of the second example in Figure 7.

3.4. Method 3: Machine Learning Algorithms (e.g., Support Vector Machines)

The first example shows a synthetic nonlinear signal generated as a combination of sinusoidal components with added nonlinearity (see Figure 8).

In Figures 8 and 9, the SVM classifier attempts to detect these changes based on the features extracted from the signal. The accuracy of the change detection calculated as the percentage of correctly classified instances is shown in the title of the subplot.

A new example of the SVM method is represented in Figure 10.

In the top subplot of Figure 10, the synthetic signal is plotted over time. The amplitude spikes, representing changes in the signal, are highlighted in red. These spikes indicate moments where significant deviations from the normal pattern occur. In the bottom subplot, the true labels (indicating the presence of changes) are plotted in green, while the predicted labels generated by the SVM classifier are plotted as red dashed lines. The agreement between the true and predicted labels is visualized, showing how well the classifier identifies changes in the signal. The accuracy of change detection using SVM classification is provided in the title, indicating the percentage of correctly classified samples. This accuracy metric quantifies the performance of the machine learning approach in detecting changes in the synthetic data.

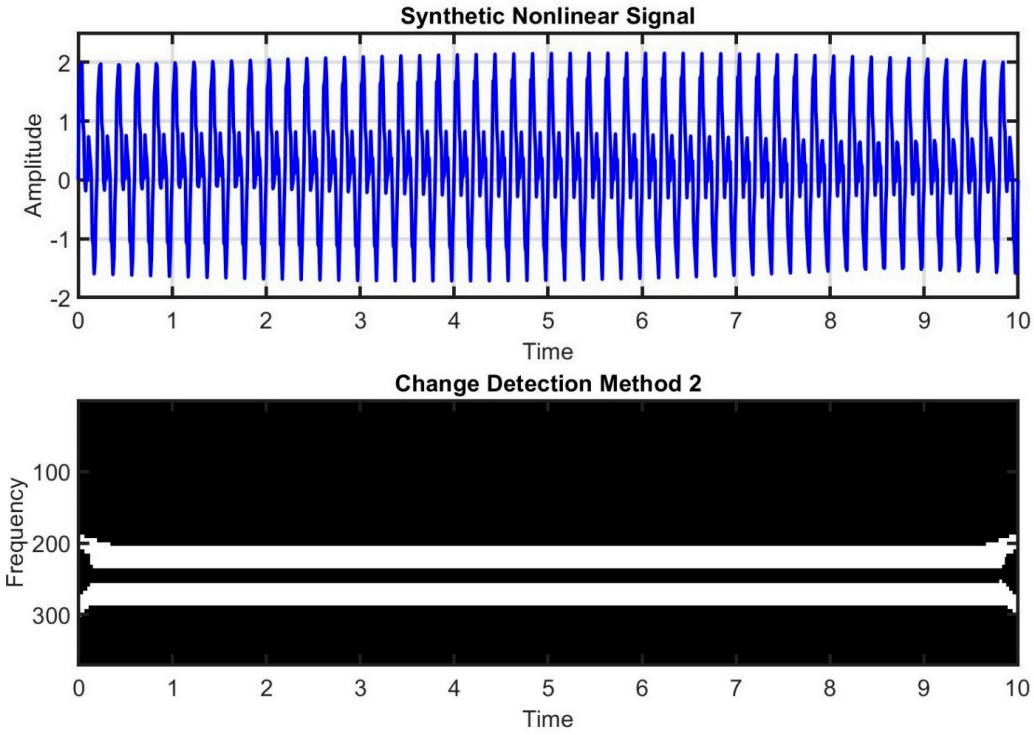

Figure 6. Change detection using Wavelet Transform. (**Top**) Synthetic nonlinear signal plotted against time and shown in blue. This signal exhibits complex behavior over time, characterized by variations and fluctuations in amplitude. (**Bottom**) The bottom subplot displays the results of change detection using the Wavelet Transform method. Changes in the signal are represented by localized regions of high wavelet coefficients, indicating deviations from the background signal.

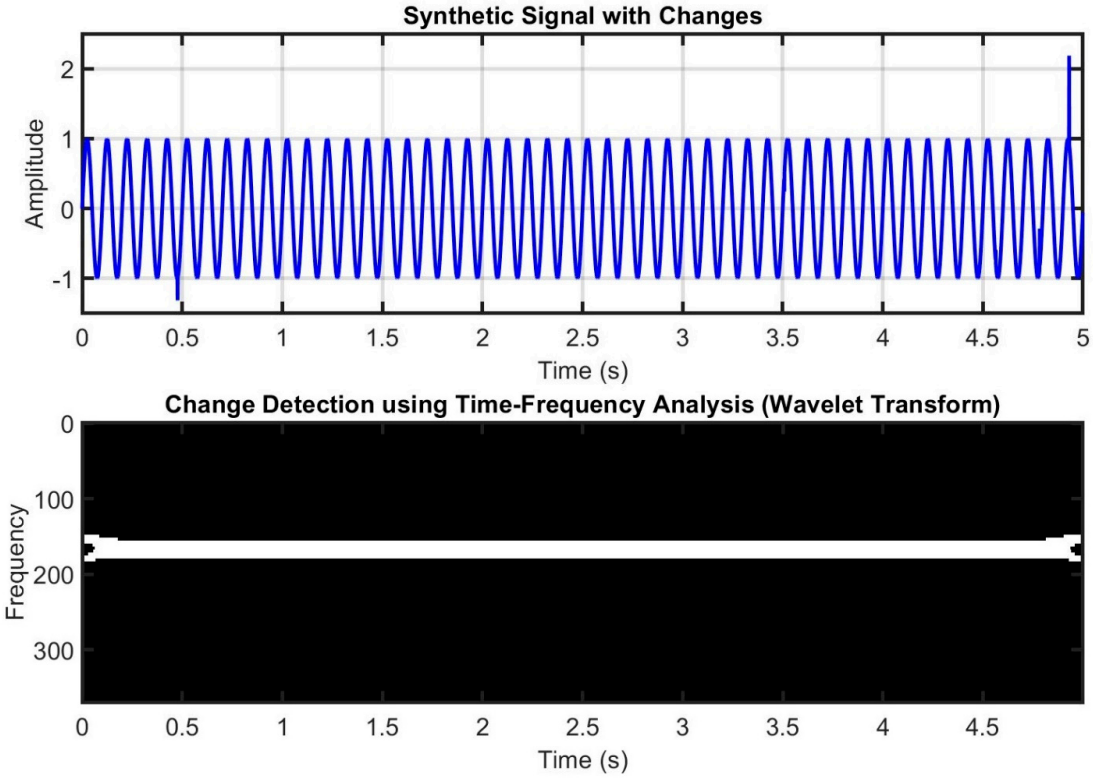

Figure 7. Change detection using Wavelet Transform. (**Top**) Synthetic nonlinear signal plotted against time and shown in blue. This signal exhibits complex behavior over time, characterized by variations

and fluctuations in amplitude. (**Bottom**) The bottom subplot displays the results of change detection using the Wavelet Transform method. Changes in the signal are represented by localized regions of high wavelet coefficients, indicating deviations from the background signal.

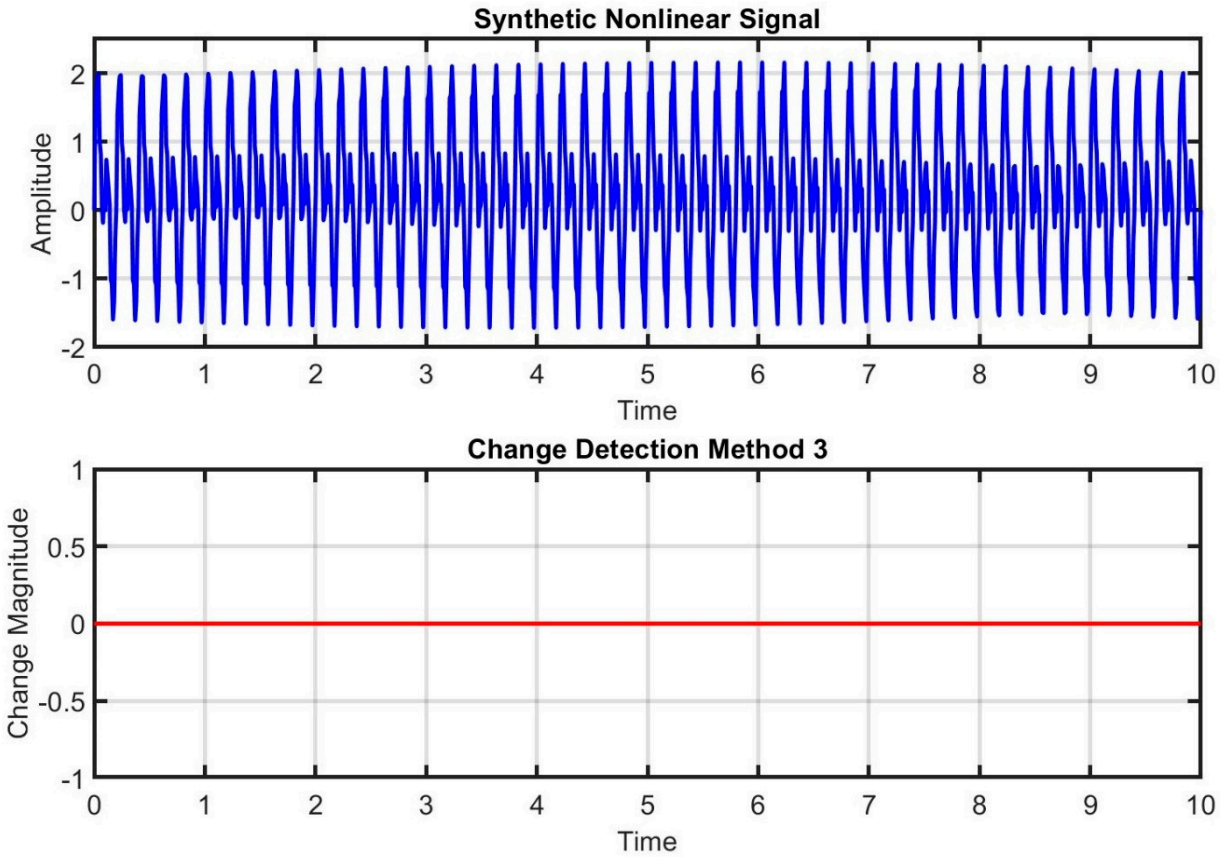

Figure 8. Change detection in synthetic signal using Support Vector Machine (SVM) classification. (**Top**) Synthetic nonlinear signal plotted against time and shown in blue. This signal exhibits complex behavior over time, characterized by variations and fluctuations in amplitude. (**Bottom**) Change detection results using Support Vector Machine (SVM) classifier, where red indicates predicted change points based on the trained model.

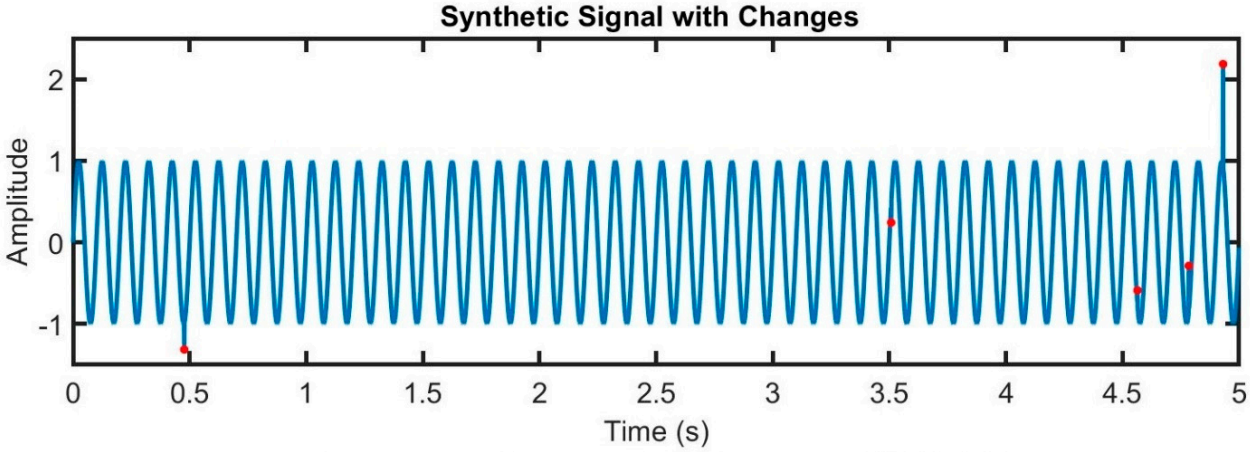

Figure 9. *Cont.*

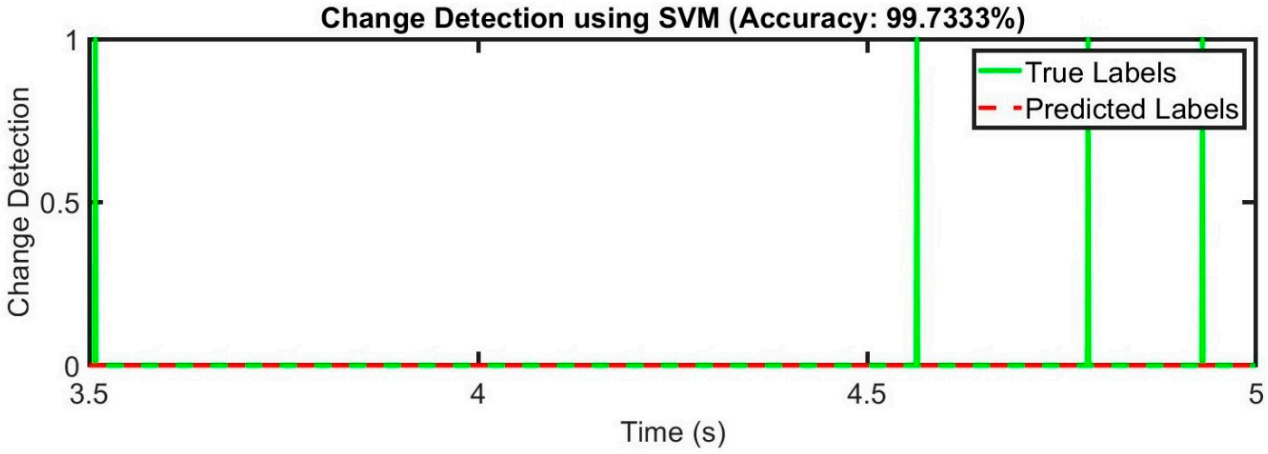

Figure 9. Change detection in synthetic signal using Support Vector Machine (SVM) classification. (**Top**) Synthetic signal with a sinusoidal pattern over a duration of 5 s. Random changes have been introduced into the signal to simulate anomalies, indicated by the red markers. These changes represent potential abnormalities or deviations from the expected signal pattern. (**Bottom**) The green line represents the true labels indicating the presence of changes in the signal, while the red dashed line represents the predicted labels obtained using a Support Vector Machine (SVM) classifier.

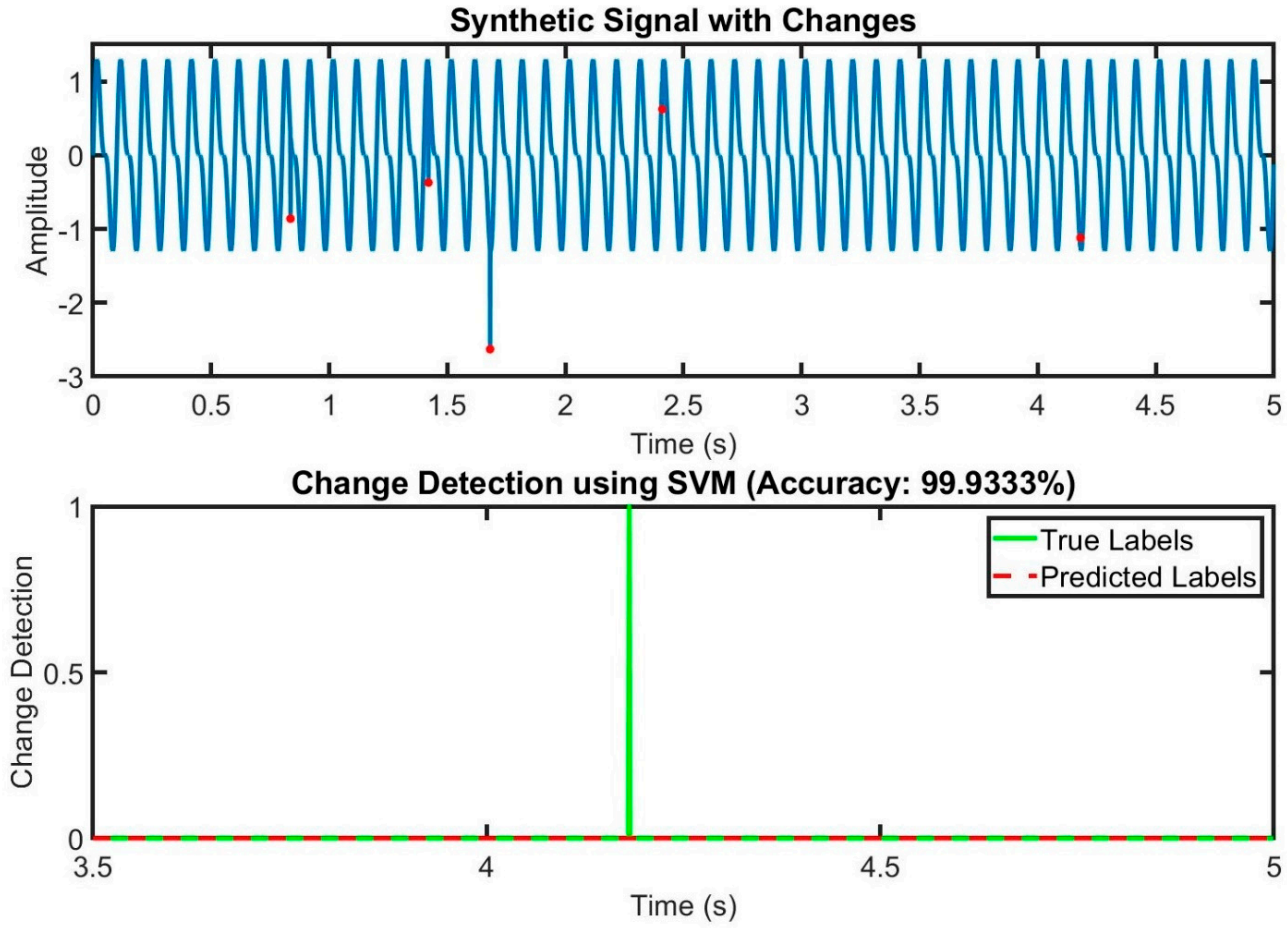

Figure 10. Change detection in synthetic signal using Support Vector Machine (SVM) classification. (**Top**) Synthetic signal with complex patterns and amplitude spikes indicating changes (highlighted in red). (**Bottom**) Detected changes indicated by green (true labels) and red dashed lines (predicted labels) using SVM classification. The accuracy of change detection is shown in the title.

4. Discussion of the Comparison Results

Method 1: This calculates the mean and standard deviation of the time series data to characterize the signal. The mean value represents the average amplitude of the signal over time. It gives an idea of the central tendency of the signal. The standard deviation quantifies the amount of variation or dispersion in the signal. A small standard deviation indicates that the data points tend to be close to the mean, while a large standard deviation indicates that the data is spread out over a wider range of values. This section, which was based on statistical properties, failed to detect changes in the first example. Therefore, Method 1, which relies on the mean and standard deviation of the signal, may fail to detect changes in certain scenarios due to its sensitivity to outliers and its assumption of Gaussian distribution. In the first example with the synthetic signal, the changes introduced to the signal were random perturbations added to specific time points. These changes were essentially outliers compared to the rest of the signal, which made them detectable using classical statistical techniques such as thresholding based on mean and standard deviation. However, in the second example with the nonlinear signal, the changes are inherent in the signal itself. The signal is a combination of multiple sinusoidal components with varying frequencies, including a nonlinear component ($0.5sin(2\pi 20t)^2$). In this case, the changes are not outliers but rather intrinsic features of the signal. Classical statistical techniques based on mean and standard deviation are not suitable for detecting such changes because they are not caused by random perturbations but are part of the signal's structure.

To detect changes in signals with intrinsic nonlinearities or complex structures like the one in the second example, more sophisticated techniques may be required. Such methods can capture the dynamic and non-stationary nature of the signal and identify changes based on shifts in frequency content, temporal patterns, or other relevant features.

Method 2: The short-time Fourier transform (STFT) is used to analyze the frequency content of the signal as it changes over time. The time series is divided into overlapping segments (windows) to compute the Fourier transform of each segment. This allows us to observe how the frequency content of the signal evolves over time. The output of the STFT is a time–frequency representation (spectrogram), which shows how the amplitude of different frequency components changes over time. It is particularly useful for analyzing non-stationary signals, like EEG, which can exhibit varying frequency content. In the provided examples, the second method attempts to detect changes in the synthetic EEG signal using time–frequency analysis, specifically the Continuous Wavelet Transform (CWT). However, it is important to note that the ability of the CWT to detect changes depends on various factors, including the characteristics of the signal, the choice of the wavelet function, and the threshold applied for change detection.

Method 3: This involves the use of a Support Vector Machine (SVM) classifier for change detection in the time series data. Features are extracted from sliding windows of the time series data. In this case, the mean and standard deviation of the signal are used as features. These features are computed for segments of the signal to help the SVM model learn the characteristics of "normal" versus "changed" states in the signal. The SVM classifier is trained using the extracted features and their corresponding labels (normal/spike). Then the SVM model is created. Once trained, the SVM model predicts labels for the entire time series based on the feature matrix, allowing for the detection of changes over time (in this case, whether spikes or other anomalies are present). In example 1, the Support Vector Machine (SVM) classifier failed to effectively detect changes in the synthetic nonlinear signal but successfully detected changes in the synthetic signal. In the first example with the synthetic nonlinear signal, the features used for training the SVM classifier are the signal values themselves. Since the nonlinear signal does not exhibit clear patterns or distinct features associated with the changes, the SVM classifier may struggle to learn a discriminative decision boundary to separate the change and non-change regions. The synthetic nonlinear signal is a combination of sinusoidal components and a squared sinusoidal component. The changes introduced in this signal may not significantly alter its overall shape or characteristics, making them difficult for the SVM classifier to discern from

the background signal fluctuations. In the first example, the SVM classifier is trained on the entire nonlinear signal without explicitly providing information about the location or timing of the changes. This lack of specific training data related to the changes may hinder the classifier's ability to learn meaningful patterns associated with the changes. In contrast, the synthetic signal in the second example exhibits abrupt changes introduced at random time points. These changes manifest as outliers or deviations from the underlying sinusoidal pattern, which can be discerned by the SVM classifier. Additionally, the SVM classifier is trained on features extracted from the EEG signal, which may capture characteristics indicative of the changes, such as sudden shifts in the amplitude or frequency content. The effectiveness of the SVM classifier for change detection depends on the characteristics of the signal, the representation of features, and the availability of informative training data. In scenarios where the changes are subtle or the signal dynamics are complex, alternative methods or feature representations may be more suitable for detecting changes effectively.

5. Application, Challenges, and Future Directions

In biomedical signal processing, various methods are employed for detecting changes in signals, each with distinct advantages and applications. Classical statistical techniques, such as mean and standard deviation calculations, are commonly used due to their simplicity and robustness, making them suitable for scenarios where interpretability is crucial. Time–Frequency analysis methods, including the Continuous Wavelet Transform (CWT) and short-time Fourier transform (STFT), are valuable for analyzing dynamic physiological processes, offering insights into both time and frequency domains. These methods are particularly useful in applications such as EEG analysis, where understanding the temporal dynamics of brain activity is essential. Machine learning algorithms, such as Support Vector Machines (SVMs) and deep neural networks (DNN), provide high accuracy and automation, making them ideal for large-scale data analysis and real-time monitoring in clinical settings [47–49].

Despite their effectiveness, each change detection method in biomedical signals faces specific challenges. Classical statistical techniques often struggle with noisy and high-dimensional data, limiting their applicability in complex biomedical signal environments. Time–frequency analysis methods, while powerful, require careful parameter tuning and can be computationally intensive, which may pose challenges for real-time applications. Machine learning algorithms, despite their high accuracy, often lack interpretability and require large amounts of labeled data for training, which can be a significant barrier in biomedical contexts where data labeling is costly and time-consuming. Bayesian inference methods, which incorporate prior knowledge and uncertainty modeling, are computationally demanding and sensitive to the choice of prior distributions, making their implementation complex. Furthermore, integrating multimodal data, such as combining EEG with functional magnetic resonance imaging (fMRI), offers complementary information but introduces challenges related to data alignment, synchronization, and sophisticated data fusion techniques.

Advancements in signal processing and machine learning continue to drive innovation in change detection methods. Techniques such as compressive sensing offer the ability to efficiently sample and reconstruct signals from limited data, although they require careful selection of sensing matrices and sparsity constraints. Phase-space reconstruction methods provide insights into the underlying dynamics of physiological systems but may be sensitive to noise and require parameter optimization. Future research should focus on developing more robust algorithms capable of handling noisy and high-dimensional data, improving the interpretability of machine learning models, and enhancing data fusion techniques for multimodal signals. By leveraging the complementary strengths of various methods and addressing their limitations, researchers can advance our understanding of physiological processes and improve healthcare outcomes. The integration of advanced signal processing techniques, machine learning algorithms, and Bayesian inference methods

has the potential to revolutionize signal change detection, unlocking new insights into human health and disease.

This research contributes to the advancement of biomedical signal processing by providing a comprehensive evaluation of different change detection methods and highlighting their strengths and limitations. The findings have implications for improving clinical decision-making and advancing healthcare technology.

Future directions:	
Real-world applications:	Apply these methods to real-world biomedical signals from various domains (e.g., electrocardiograms, electroencephalograms) to validate their effectiveness.
Advanced machine learning:	Explore more advanced machine learning algorithms, such as deep learning, for improved change detection performance.
Multimodal analysis:	Integrate multiple types of biomedical signals to gain a more comprehensive understanding of physiological processes.

6. Discussion

In this study, we assessed the effectiveness of three methods for detecting changes in nonlinear biomedical signals: classical statistical techniques, time–frequency analysis using Continuous Wavelet Transform (CWT), and machine learning with Support Vector Machines (SVMs). Each method showed varying degrees of success based on signal characteristics and the nature of the changes. The comparative analysis of these methods reveals that each has specific strengths and limitations influenced by signal characteristics and the nature of changes. Classical statistical techniques are simple but can fail in the presence of outliers or non-Gaussian distributions. Time–Frequency analysis using CWT offers detailed insights but requires careful selection of wavelets and thresholds. SVMs were used for change detection, showing mixed results. In the first example with synthetic nonlinear signals, using raw signal values as features did not help the SVMs detect changes due to the lack of distinct patterns. The complexity of the signal's dynamics further complicated detection. In contrast, in the second example with synthetic signals exhibiting abrupt changes, SVMs performed better when trained on features indicative of changes, such as shifts in amplitude or frequency. This highlights the importance of feature extraction and specific training data for effective SVM-based change detection. SVMs provide a powerful machine learning approach but depend heavily on feature representation and training data quality. For effective change detection in nonlinear biomedical signals, a hybrid approach that combines these methods, leveraging their complementary strengths, may offer the most robust solution.

Classical statistical techniques, while straightforward to implement, may struggle with complex biomedical signals that deviate from Gaussian distributions or contain outliers. Time–Frequency analysis, such as the Continuous Wavelet Transform (CWT), offers a more dynamic approach by analyzing signals in both the time and frequency domains. However, CWT performance depends on careful parameter tuning. Support Vector Machines (SVMs) can be effective for change detection, but their performance relies on feature extraction and the availability of informative training data [46–49].

By comparing these methods, we can see the trade-offs involved. Classical statistical techniques are simple but often ineffective for complex signals. Time–Frequency analysis offers more detailed insights but requires careful parameter selection. Machine learning approaches like SVMs can be powerful but depend heavily on the quality of feature extraction and training data (see Figures 11 and 12).

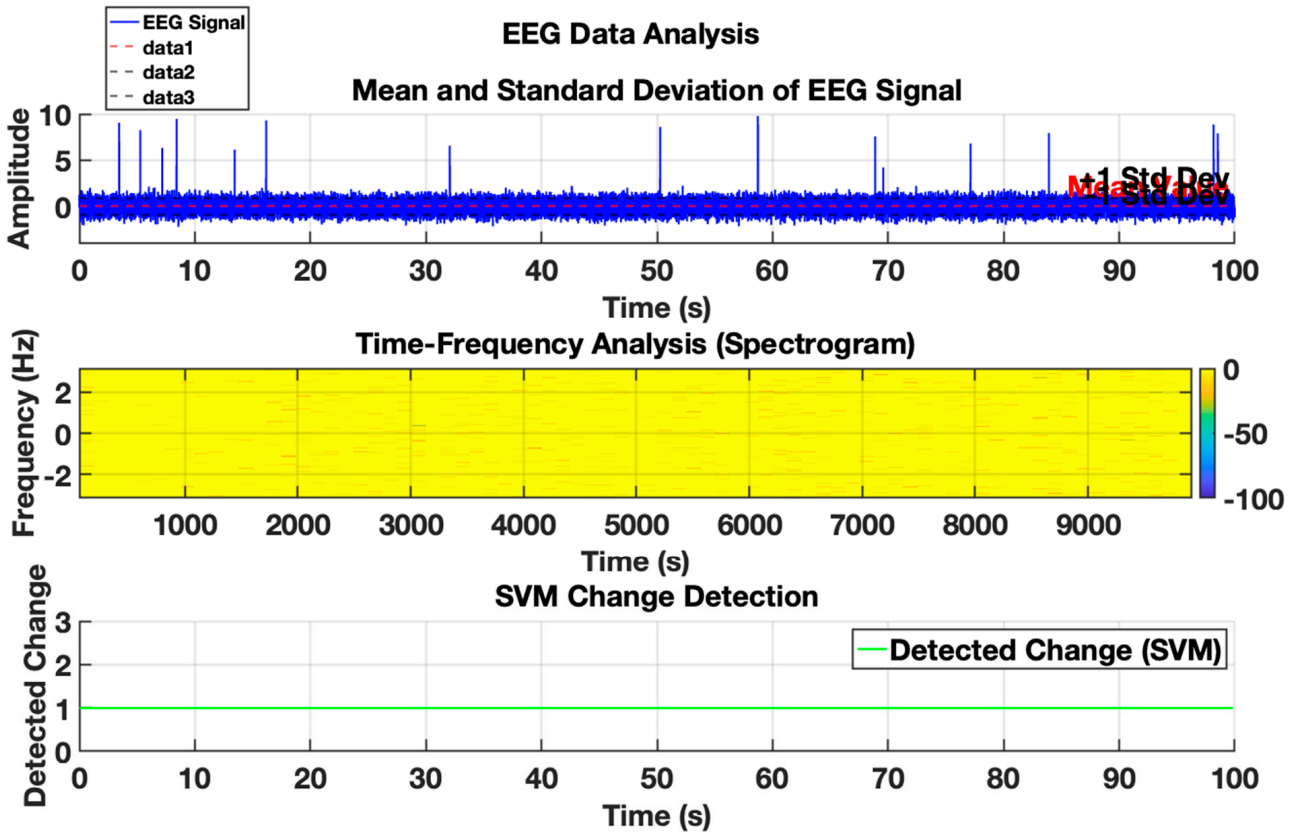

Figure 11. Analysis of synthetic EEG signal and change detection. (**Top**) Mean and standard deviation of EEG signal: This subplot displays the mean (red dashed line) and one standard deviation above and below the mean (black dashed lines) of the generated EEG signal over time. The underlying blue line represents the raw EEG-like time series data, showcasing the variations around the average signal level. (**Middle**) Time–Frequency analysis (Spectrogram): The spectrogram in this subplot illustrates the time–frequency representation of the EEG signal using the short-time Fourier transform (STFT). The x-axis denotes time (in seconds), while the y-axis represents frequency (in Hz). The color intensity indicates the magnitude of the frequency components in decibels (dB), revealing the distribution of power across different frequency bands over time. (**Bottom**) SVM change detection: This subplot depicts the predicted labels for the EEG signal using a Support Vector Machine (SVM) model. The green line indicates detected changes across the time series, with '1' representing no spike and '2' indicating spike events. The visualization helps demonstrate the effectiveness of the SVM algorithm in identifying significant changes (spikes) in the EEG data.

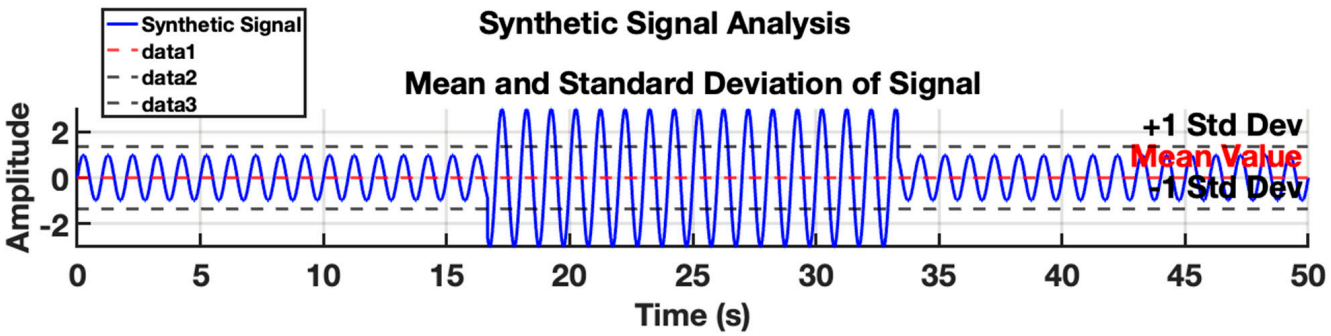

Figure 12. *Cont*.

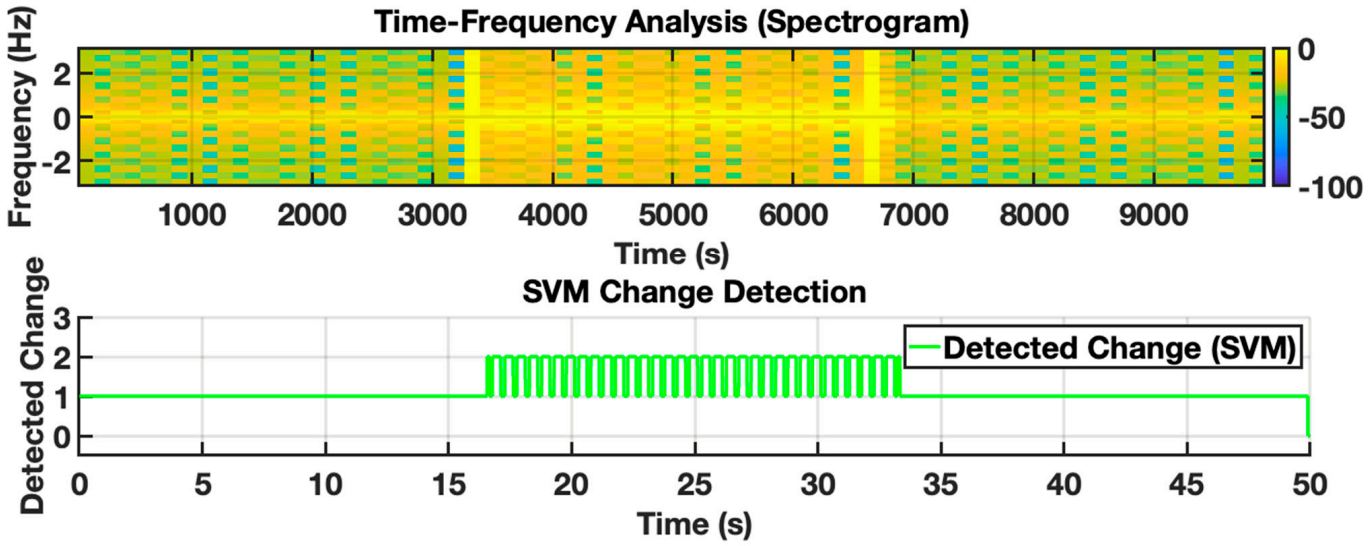

Figure 12. Analysis of synthetic sine wave signal and change detection. (**Top**) Original synthetic sine wave signal with a base frequency of 1 Hz (in blue), along with calculated mean (in green) and standard deviation (in red) lines. The abrupt changes in amplitude are highlighted in the signal plot between the vertical dashed lines. (**Middle**) Time–Frequency representation of the synthetic sine wave signal obtained via short-time Fourier transform (STFT). The spectrogram illustrates the frequency content over time, showing how the signal's energy distribution shifts during the introduced changes. (**Bottom**) Change detection using Support Vector Machine (SVM) classification. The colored regions indicate the predicted states of the signal (baseline vs. changed amplitude), demonstrating the SVM's ability to identify segments with different characteristics. The SVM was trained using features (mean and standard deviation) extracted from the signal.

7. Conclusions

The analysis of the simulated EEG-like time series through three distinct methods—the evaluation of mean and standard deviation, time–frequency analysis using a spectrogram, and change detection employing a Support Vector Machine (SVM)—demonstrates a comprehensive approach to understanding the underlying dynamics of EEG signals. The mean and standard deviation provide insights into the overall signal characteristics and variability, while the time–frequency analysis using CWT effectively reveals the frequency content and its temporal evolution, highlighting dominant alpha and beta rhythms. The SVM model achieves promising performance in detecting changes (spikes) within the signal, indicating its potential utility in identifying significant events. However, limitations exist: the simulated data does not capture all the complexities and noise typically present in real EEG recordings, the choice of parameters for the SVM can significantly influence the results, and the reliance on sliding window features may overlook nuanced information that occurs outside the analyzed windows. Thus, while the methodologies are useful for basic analysis and change detection, they require careful parameter tuning and validation against real-world data to ensure robustness and applicability in clinical settings.

In conclusion, this study highlights the critical role of change detection in biomedical signal processing for understanding physiological processes and diagnosing medical conditions. Through an investigation of different methods using synthetic signals mimicking real-world scenarios, including classical statistical techniques, Support Vector Machine (SVM) classification, and Continuous Wavelet Transform (CWT) time–frequency analysis, insights were gained into their efficacy. While all methods struggled to detect changes in synthetic nonlinear signals, classical statistical techniques and SVM classification proved effective in detecting changes in signals with simulated anomalies. However, CWT-based time–frequency analysis encountered difficulties in detecting changes in both synthetic nonlinear signals and signals with simulated anomalies. These findings emphasize the

necessity of carefully selecting appropriate methods for change detection in biomedical signal processing, considering the unique characteristics of the signals and the specific requirements of the detection task. Future research endeavors may focus on exploring advanced machine learning algorithms and signal processing techniques to further enhance the accuracy of change detection in biomedical applications. Moving forward, several avenues for future research and development in change detection in biomedical signals can be pursued. Firstly, exploring hybrid approaches that combine the strengths of different methods, such as integrating classical statistical techniques with machine learning algorithms or incorporating domain knowledge into time–frequency analysis, could improve detection accuracy and robustness. Additionally, investigating advanced signal processing techniques, such as deep learning architectures tailored for biomedical signals, may offer novel insights and enhance detection performance. Furthermore, the validation and benchmarking of change detection methods using real-world biomedical data are crucial for assessing their efficacy and generalizability. Collaborative efforts to establish standardized datasets and evaluation metrics would facilitate the comparison and validation of different methods across diverse applications and datasets. Lastly, the translation of research findings into clinical practice and healthcare applications through the development of user-friendly software tools and decision support systems holds promise for improving patient outcomes and advancing the field of biomedical signal processing. By advancing methodological approaches, validating findings with real-world data, and translating research into practical applications, researchers can continue to enhance our ability to detect changes in biomedical signals and ultimately contribute to improving healthcare delivery and patient care.

Key contributions:	
Comprehensive methodological exploration:	We employed a multifaceted approach, combining classical statistical techniques, machine learning algorithms, and time–frequency analysis to address the challenges of biomedical signal processing.
Advanced understanding of physiological processes:	Our study provides valuable insights into the underlying dynamics of biomedical signals, aiding in a deeper understanding of physiological processes.
Improved clinical decision-making:	By accurately identifying significant changes in biomedical signals, our research can contribute to more informed clinical decision-making.
Innovation in healthcare technology:	Our findings pave the way for the development of new tools and techniques for biomedical signal analysis, potentially leading to advancements in healthcare technology.
Addressing key challenges:	We successfully addressed the challenges of high-dimensional data handling and the identification of subtle, non-linear patterns in biomedical signals.
Robust and accurate change detection:	Our study demonstrates the effectiveness of the combined methods in achieving robust and accurate change detection.

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Conflicts of Interest: The author declares no conflict of interest.

References

1. Rangayyan, R.M.; Krishnan, S. *Biomedical Signal Analysis*; John Wiley & Sons: Hoboken, NJ, USA, 2024.
2. Rajeswari, J.; Jagannath, M. Advances in biomedical signal and image processing—A systematic review. *Inform. Med. Unlocked* **2017**, *8*, 13–19. [CrossRef]
3. AlHinai, N. Introduction to biomedical signal processing and artificial intelligence. In *Biomedical Signal Processing and Artificial Intelligence in Healthcare*; Academic Press: Cambridge, MA, USA, 2020; pp. 1–28.
4. Goldberger, A.L.; Amaral, L.A.; Glass, L.; Hausdorff, J.M.; Ivanov, P.C.; Mark, R.G.; Mietus, J.E.; Moody, G.B.; Peng, C.-K.; Stanley, H.E. PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. *Circulation* **2000**, *101*, e215–e220. [CrossRef] [PubMed]
5. Bizzego, A.; Battisti, A.; Gabrieli, G.; Esposito, G.; Furlanello, C. Pyphysio: A physiological signal processing library for data science approaches in physiology. *SoftwareX* **2019**, *10*, 100287. [CrossRef]
6. Azizi, T. Impact of mental arithmetic task on the electrical activity of the human brain. *Neurosci. Inform.* **2024**, *4*, 100162. [CrossRef]
7. Azizi, T. Disrupted organization of dynamic functional networks with application in epileptic seizure recognition. *Neurosci. Inform.* **2024**, *4*, 100153. [CrossRef]
8. Azizi, T. On the Fractal Geometry of Gait Dynamics in Different Neuro-degenerative Diseases. *Phys. Med.* **2022**, *14*, 100050. [CrossRef]
9. Heyat, M.B.B.; Akhtar, F.; Munir, F.; Sultana, A.; Muaad, A.Y.; Gul, I.; Sawan, M.; Asghar, W.; Iqbal, S.M.A.; Baig, A.A.; et al. Unravelling the complexities of depression with medical intelligence: Exploring the interplay of genetics, hormones, and brain function. *Complex Intell. Syst.* **2024**, *10*, 5883–5915. [CrossRef]
10. Inan, O.T.; Giovangrandi, L.; Kovacs, G.T. Robust neural-network-based classification of premature ventricular contractions using wavelet transform and timing interval features. *IEEE Trans. Biomed. Eng.* **2006**, *53*, 2507–2515. [CrossRef]
11. Blinowska, K.J.; Żygierewicz, J. *Practical Biomedical Signal Analysis Using MATLAB®*; CRC Press: Boca Raton, FL, USA, 2021.
12. Krishnan, S.; Athavale, Y. Trends in biomedical signal feature extraction. *Biomed. Signal Process. Control* **2018**, *43*, 41–63. [CrossRef]
13. Gradl, S.; Kugler, P.; Lohmüller, C.; Eskofier, B. Real-time ECG monitoring and arrhythmia detection using Android-based mobile devices. In Proceedings of the 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, San Diego, CA, USA, 28 August–1 September 2012; IEEE: Piscataway, NJ, USA, 2012; pp. 2452–2455.
14. Azizi, T. On the fractal geometry of different heart rhythms. *Chaos Solitons Fractals X* **2022**, *9*, 100085. [CrossRef]
15. Azizi, T. Measuring fractal dynamics of FECG signals to determine the complexity of fetal heart rate. *Chaos Solitons Fractals X* **2022**, *9*, 100083. [CrossRef]
16. Motamedi-Fakhr, S.; Moshrefi-Torbati, M.; Hill, M.; Hill, C.M.; White, P.R. Signal processing techniques applied to human sleep EEG signals—A review. *Biomed. Signal Process. Control* **2014**, *10*, 21–33. [CrossRef]
17. Sörnmo, L.; Laguna, P. *Bioelectrical Signal Processing in Cardiac and Neurological Applications*; Academic Press: Cambridge, MA, USA, 2005.
18. Xie, L.; Li, Z.; Zhou, Y.; He, Y.; Zhu, J. Computational diagnostic techniques for electrocardiogram signal analysis. *Sensors* **2020**, *20*, 6318. [CrossRef] [PubMed]
19. Wu, Y.C.; Liao, Y.S.; Yeh, W.H.; Liang, S.F.; Shaw, F.Z. Directions of deep brain stimulation for epilepsy and Parkinson's disease. *Front. Neurosci.* **2021**, *15*, 680938. [CrossRef] [PubMed]
20. Orozco-Arroyave, J.R.; Vásquez-Correa, J.C.; Nöth, E. Current methods and new trends in signal processing and pattern recognition for the automatic assessment of motor impairments: The case of Parkinson's disease. In *Neurological Disorders and Imaging Physics*; Volume 5: Applications in Dyslexia, Epilepsy and Parkinson's; IOP Publishing: Bristol, UK, 2020; pp. 8-1–8-57.
21. Xie, L.; Zou, S.; Xie, Y.; Veeravalli, V.V. Sequential (quickest) change detection: Classical results and new directions. *IEEE J. Sel. Areas Inf. Theory* **2021**, *2*, 494–514. [CrossRef]
22. Inglada, J.; Mercier, G. A new statistical similarity measure for change detection in multitemporal SAR images and its extension to multiscale change analysis. *IEEE Trans. Geosci. Remote Sens.* **2007**, *45*, 1432–1445. [CrossRef]
23. Parveen, S.; Heyat, M.B.B.; Akhtar, F.; Parveen, S.; Asrafali, B.; Singh, B.; Ali, K.; Huang, L.; Li, X.P.; Jabbar, A.; et al. Interweaving artificial intelligence and bio-signals in mental fatigue: Unveiling dynamics and future pathways. In Proceedings of the 2023 20th International Computer Conference on Wavelet Active Media Technology and Information Processing (ICCWAMTIP), Chengdu, China, 15–17 December 2023; IEEE: Piscataway, NJ, USA, 2023.
24. Sanei, S.; Chambers, J.A. *EEG Signal Processing and Machine Learning*; John Wiley & Sons: Hoboken, NJ, USA, 2021.
25. Hu, L.; Zhang, Z. (Eds.) *EEG Signal Processing and Feature Extraction*; Springer Nature: Berlin, Germany, 2019.
26. Ghaderpour, E.; Pagiatakis, S.D.; Hassan, Q.K. A survey on change detection and time series analysis with applications. *Appl. Sci.* **2021**, *11*, 6141. [CrossRef]
27. Xiong, W.; Cai, C.S. Time-frequency-based bridge scour identification by trend-change detection. *J. Bridge Eng.* **2022**, *27*, 04022093. [CrossRef]

28. Aiordăchioaie, D.; Nistor, N.; Andrei, M. Change Detection in Time-Frequency Images by Feature Processing in Compressed Spaces. In Proceedings of the 2018 IEEE 24th International Symposium for Design and Technology in Electronic Packaging (SIITME), Pitesti, Romania, 21–24 October 2020; IEEE: Piscataway, NJ, USA, 2018; pp. 181–186.
29. Zheng, W.-L.; Lu, B.-L. Investigating critical frequency bands and channels for EEG-based emotion recognition with deep neural networks. *IEEE Trans. Auton. Ment. Dev.* **2022**, *7*, 162–175. [CrossRef]
30. Chatterjee, R.; Maitra, T.; Islam, S.H.; Hassan, M.M.; Alamri, A.; Fortino, G. A novel machine learning-based feature selection for motor imagery EEG signal classification in the Internet of medical things environment. *Future Gener. Comput. Syst.* **2019**, *98*, 419–434. [CrossRef]
31. Andrzejak, R.G.; Schindler, K.; Rummel, C. Nonrandomness, nonlinear dependence, and nonstationarity of electroencephalographic recordings from epilepsy patients. *Phys. Rev. E* **2012**, *86*, 046206. [CrossRef] [PubMed]
32. Shoeb, A.H. Application of Machine Learning to Epileptic Seizure Onset Detection and Treatment. Ph.D. Thesis, Massachusetts Institute of Technology, Cambridge, MA, USA, 2023.
33. Deng, Y.; Meng, Y.; Chen, J.; Yue, A.; Liu, D.; Chen, J. TChange: A Hybrid Transformer-CNN Change Detection Network. *Remote Sens.* **2023**, *15*, 1219. [CrossRef]
34. Zhang, X.L.; Begleiter, H.; Porjesz, B.; Wang, W.; Litke, A. Event-related potentials during object recognition tasks. *Brain Res. Bull.* **1995**, *38*, 531–538. [CrossRef] [PubMed]
35. Pegoraro, J.A.; Lavault, S.; Wattiez, N.; Similowski, T.; Gonzalez-Bermejo, J.; Birmelé, E. Machine-learning based feature selection for a non-invasive breathing change detection. *BioData Min.* **2021**, *14*, 33. [CrossRef]
36. Yang, Y.; Cong, X.; Long, K.; Luo, Y.; Xie, W.; Wan, Q. MRF model-based joint interrupted SAR imaging and coherent change detection via variational Bayesian inference. *Signal Process.* **2018**, *151*, 144–154. [CrossRef]
37. Emara, H.M.; El-Shafai, W.; Algarni, A.D.; Soliman, N.F.; Abd El-Samie, F.E. A Hybrid Compressive Sensing and Classification Approach for Dynamic Storage Management of Vital Biomedical Signals. *IEEE Access* **2023**, *11*, 108126–108151. [CrossRef]
38. Duan, J.; Xiong, J.; Li, Y.; Ding, W. Deep learning based multimodal biomedical data fusion: An overview and comparative review. *Inf. Fusion* **2024**, *112*, 102536. [CrossRef]
39. Tovar-Lopez, F.J. Recent progress in micro-and nanotechnology-enabled sensors for biomedical and environmental challenges. *Sensors* **2023**, *23*, 5406. [CrossRef]
40. Adali, T.; Levin-Schwartz, Y.; Calhoun, V.D. Multimodal data fusion using source separation: Application to medical imaging. *Proc. IEEE* **2015**, *103*, 1494–1506. [CrossRef]
41. Shuqair, M.; Jimenez-Shahed, J.; Ghoraani, B. Reinforcement Learning-Based Adaptive Classification for Medication State Monitoring in Parkinson's Disease. *IEEE J. Biomed. Health Inform.* **2024**, *28*, 6168–6179. [CrossRef]
42. Mahmud, M.; Kaiser, M.S.; Hussain, A.; Vassanelli, S. Applications of deep learning and reinforcement learning to biological data. *IEEE Trans. Neural Netw. Learn. Syst.* **2018**, *29*, 2063–2079. [CrossRef] [PubMed]
43. Yu, J.; Behrouzi, T.; Garg, K.; Goldenberg, A.; Tonekaboni, S. Dynamic Interpretable Change Point Detection for Physiological Data Analysis. In Proceedings of the Machine Learning for Health (ML4H), PMLR, Seattle, WA, USA, 30 November–1 December 2023; pp. 636–649.
44. Liu, S.; Zhou, Y.; Yang, X.; Wang, X.; Yin, J. A Robust Automatic Epilepsy Seizure Detection Algorithm Based on Interpretable Features and Machine Learning. *Electronics* **2024**, *13*, 2727. [CrossRef]
45. Lee, J.; Nemati, S.; Silva, I.; Edwards, B.A.; Butler, J.P.; Malhotra, A. Transfer entropy estimation and directional coupling change detection in biomedical time series. *Biomed. Eng. Online* **2012**, *11*, 19. [CrossRef] [PubMed]
46. Paul, Y. Various epileptic seizure detection techniques using biomedical signals: A review. *Brain Inform.* **2018**, *5*, 6. [CrossRef] [PubMed]
47. AlShorman, O.; Masadeh, M.; Heyat, M.B.B.; Akhtar, F.; Almahasneh, H.; Ashraf, G.M.; Alexiou, A. Frontal lobe real-time EEG analysis using machine learning techniques for mental stress detection. *J. Integr. Neurosci.* **2022**, *21*, 20. [CrossRef]
48. Heyat, B.; Akhtar, F.; Sultana, A.; Tumrani, S.; Teelhawod, B.N.; Abbasi, R.; Kamal, M.A.; Muaad, A.Y.; Lai, D.; Wu, K. Role of oxidative stress and inflammation in insomnia sleep disorder and cardiovascular diseases: Herbal antioxidants and anti-inflammatory coupled with insomnia detection using machine learning. *Curr. Pharm. Des.* **2022**, *28*, 3618–3636. [CrossRef]
49. Heyat, M.B.B.; Lai, D.; Khan, F.I.; Zhang, Y. Sleep bruxism detection using decision tree method by the combination of C4-P4 and C4-A1 channels of scalp EEG. *IEEE Access* **2019**, *7*, 102542–102553. [CrossRef]