# Machine Learning And Filtering Techniques For Artefact Removal In EDA Signals During Fetal Movement Monitoring

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**Abstract—**Electrodermal Activity (EDA) signals are valuable for monitoring stress and emotional states, but are often corrupted by motion and environmental artefacts. This study compares traditional filtering techniques (Butterworth, wavelet) with machine learning (Isolation Forest, Support Vector Machines (SVM), XGBoost) for artefact removal. Using both real and synthetic noise-contaminated datasets, the models were evaluated using Signal-to-Noise Ratio (SNR), Mean Squared Error (MSE), and correlation with clean reference signals. The results indicate that while conventional filtering techniques are effective for reducing simple noise components, deep learning approaches, particularly DCA, demonstrate superior denoising performance. These findings highlight the potential of AI-based methods for reliable, real-time EDA signal processing in wearable healthcare systems, especially for applications such as fetal movement monitoring.

**Keywords—**Electrodermal Activity (EDA), Artefact Removal, Machine Learning, Deep Learning, Butterworth Filter, Denoising Autoencoder.

## I. INTRODUCTION

EDA is a prominent physiological measurement in stress and emotion recognition studies [3], [4]. The effect represents variation in skin conductance caused by the activation of sweat glands, and these glands are governed by the sympathetic nervous system. Due to the fact that EDA signals are obtained with portable equipment, signals are commonly degraded with motion artifacts, temperature fluctuations, or environmental noise. Artifacts may distort the signal, making proper inter-pretation impossible and reducing the efficacy of monitoring the main systems based on EDA [3], [4].

To ensure the consistency of EDA-based analysis, robust artifact removal methods must be applied. Traditional signal processing techniques, such as low-pass Butterworth filtering and wavelet denoising, are commonly used to suppress high-frequency noise and preserve the morphological structure of EDA signals [8], [21]. However, these approaches often struggle to handle more complex artifacts, including non-linear distortions or overlapping noise patterns that frequently occur in real-world, dynamic environments [20].

With developments in artificial intelligence, machine learn-ing (ML) and deep learning (DL) methods have emerged as powerful alternatives for biosignal processing [2], [7]. ML models such as Support Vector Machines (SVM) and XGBoost can classify clean and noisy signal segments based on engi-neered features, while DL architectures such as Convolutional Neural Networks (CNN) and Autoencoders are capable of learning complex patterns directly from raw inputs [10], [12]. This paper presents a comparative study of filtering-based and ML/DL-based artifact removal approaches for EDA signal processing, evaluating their effectiveness, adaptability, and suitability for real-time health monitoring. .

## II. LITERATURE SURVEY

EDA signals, which are most frequently employed for the detection of stress and monitoring of emotional state, are susceptible to motion, temperature, and environmental artifacts. Such artifacts make the signal unreliable and difficult to analyze in a proper manner [10]. In attempts to overcome this, researchers have employed a variety of methods ranging from simple filtering to sophisticated machine learning (ML) and deep learning (DL) models [4].

Previously, conventional signal processing methods such as low-pass and bandpass Butterworth filters [21], Sav-itzky–Golay filters, and wavelet denoising methods [13] were the most prevalent. The aim of these methods is to eliminate noise components without sacrificing the important features of the signal. Interestingly, wavelet-based methods are at the forefront since they are capable of examining the signal in numerous frequency bands and removing noise without sacrificing the useful part of the data [5]. However, these conventional filters are not sufficient when faced with artifacts that are non-linear, overlapping, or highly dynamic, which is typically experienced in real-world applications of wearable sensors [6].

Consequently, there has been a movement towards solu-tion methods based on ML. Supervised machine learning algorithms such as Support Vector Machine (SVM), Random Forest, Logistic Regression, and XGBoost have been used to classify segments of signals as clean or artifact-contaminated [2]. These models are usually trained using features derived from the signals—for instance, amplitude, frequency, or var-ious statistical features. They often yield high classification accuracy and exhibit strong generalization when trained on sufficiently diverse datasets [7]. However, their performance is highly dependent on the quality of input features and the rep-resentativeness of the training data. In addition, unsupervised models such as Isolation Forest have been investigated for anomaly detection, identifying outlier patterns likely indicative of artifacts [12].

The deep learning revolution has spawned more efficient and mechanized techniques. Specifically, deep learning ar-chitectures like autoencoders, Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) networks have demonstrated strong performance in denoising physio-logical signals [16]. Autoencoders work by learning a com-pressed representation of the input signal and reconstructing it while minimizing the reconstruction error. When trained on clean signals, these models are highly adept at detecting and removing noise during reconstruction. CNNs, known for extracting spatial features, and LSTMs, capable of learning temporal relationships, have been used individually and in hybrid architectures to enhance classification accuracy and en-able artifact rejection [3]. These architectures require minimal hand-crafted feature extraction and are capable of learning directly from raw or lightly preprocessed input, making them excellent candidates for end-to-end real-time applications.

Overall, the literature shows that while simple noise re-moval is straightforward and effective with traditional filtering techniques, they are not capable of dealing with complex signal distortions [4]. Machine learning models improve clas-sification performance through data-driven learning but require carefully engineered features. Deep learning models excel by learning automatically from the data and compensating for signal variability, making them ideal for real-time wearable health monitoring systems. This review therefore justifies conducting a comparative study among filtering-based, ML-based, and DL-based techniques for determining the most efficient approach to artifact removal from EDA signals.

## III. METHODOLOGY

The methodology of this study involves implementing a comprehensive framework for artifact removal in Electroder-mal Activity (EDA) signals, focusing on both classical filtering techniques and modern machine learning (ML) and deep learning (DL) models. The goal is to evaluate and compare the effectiveness of these techniques in enhancing signal quality by reducing noise and artifacts from Galvanic Skin Response (GSR) data, a core component of EDA signals.

### *A.* Dataset and Preprocessing

The dataset used consisted of 2000 labeled GSR signal samples, where each sample was marked either as ”clean” or ”artifact-contaminated.” These labels served as ground truth for supervised learning models. Along with GSR values, the dataset included EEG frequency bands, cognitive state, emotional state, session type, environmental context, and de-mographic details like age and gender. Categorical variables were encoded using Label Encoding, and the GSR values were normalized using MinMax scaling. A column titled ”Preprocessed_Features” containing paired numerical values was split into two distinct features, ensuring a consistent format for model input.

### *B.* Signal Filtering Techniques

To evaluate the effectiveness of traditional signal processing methods, five different filters were applied to the GSR signals. Each method targets noise reduction while preserving the underlying physiological characteristics of the signal.

- **Bandpass Butterworth Filter:** A 4th-order Butterworth bandpass filter with a frequency range of 0.5–50 Hz was applied to remove both low-frequency drift and high-frequency noise. The smooth frequency response of the Butterworth design ensures minimal distortion to the important mid-frequency components of the GSR signal.
- **Savitzky–Golay (SG) Filter:** This polynomial smoothing technique fits a low-degree polynomial to each window of the signal using least-squares optimization. It effec-tively reduces noise while preserving the local shape, peak structures, and morphological features of the GSR waveform, making it suitable for signals requiring feature sensitivity.
- **Wavelet Denoising:** Discrete Wavelet Transform (DWT) using the “db1” (Daubechies-1) wavelet was implemented to decompose the signal into multiple frequency bands. High-frequency wavelet coefficients were thresholded to remove noise, while lower-frequency components were retained to preserve the essential dynamics of the GSR signal. This method is particularly effective for nonstationary and transient noise removal.
- **Moving Average (MA):** A simple moving average fil-ter was used to smooth the signal by averaging data points within a fixed window. This reduces short-term fluctuations and high-frequency variations, providing a smoothed approximation of the underlying trend of the signal.
- **Exponential Moving Average (EMA):** The EMA filter applies exponentially decreasing weights to past samples, allowing more responsiveness to recent values. This dy-namic smoothing method effectively reduces noise while adapting quickly to rapid changes within the GSR signal.

Each filtering method was evaluated using Root Mean Squared Error (RMSE) and Pearson correlation with the original unprocessed signal. These metrics quantify how well each method preserves the true signal characteristics while suppressing noise.

### *C.* Machine Learning models

For the classification of clean versus noisy signal segments, several machine learning (ML) models were trained using the normalized and filtered GSR values as input features. The following models were employed:

- **Random Forest (RF):** Random Forest is an ensemble learning algorithm that constructs multiple decision trees during training. Each tree independently learns patterns that differentiate clean from noisy signal segments, and the final decision is made through majority voting. This makes RF robust to overfitting and capable of capturing nonlinear relationships within the data.

- **Support Vector Machine (SVM):** A linear-kernel SVM was used to find the optimal separating hyperplane be-tween clean and noisy segments. By maximizing the margin between the two classes, SVM performs well when the extracted GSR features are linearly separable or close to linearly separable.
- **Logistic Regression:** Logistic Regression models the probability that a given segment belongs to the clean or noisy class using a sigmoid function. As a simple and in-terpretable baseline model, it helps establish a minimum performance benchmark and performs effectively when feature–label relationships exhibit linearity.
- **XGBoost:** XGBoost is a gradient-boosted decision tree model that builds trees sequentially, with each new tree correcting the errors of the previous ones. In this work, XGBoost effectively captures subtle distinctions between clean and artifact-contaminated segments, handling non-linearities and feature interactions with high accuracy.
- **K-Nearest Neighbors (KNN):** KNN classifies a signal segment based on the labels of the "k" closest training samples in the feature space. The class most common among its neighbors is assigned as the prediction. This makes KNN effective when clean and noisy segments form distinct clusters.
- The dataset was divided into an 80/20 training–testing split. Model performance was evaluated using accuracy, precision, recall, F1-score, and ROC-AUC to provide a comprehensive assessment of the classification effectiveness.
- Deep Learning models: Several deep learning architectures were implemented to automatically classify EDA signal segments as clean or artifact-contaminated by learning directly from the signal features:
- **Autoencoder:** The autoencoder was trained to recon-struct clean GSR signals. During testing, segments with high reconstruction errors were identified as artifact-contaminated, allowing automatic detection of noisy data without manual feature engineering.
- **Convolutional Neural Network (CNN):** The CNN was applied to automatically extract spatial patterns from GSR segments. It learned local signal structures and peak variations that differentiate clean signals from those affected by noise or motion artifacts.
- **Long Short-Term Memory (LSTM):** The LSTM net-work was used to capture temporal dependencies in GSR signals. It modeled the slow-changing trends and temporal correlations, helping to detect arti-facts that occur over multiple consecutive samples.
- **Bidirectional LSTM (Bi-LSTM):** The Bi-LSTM ex-tended the LSTM approach by considering both past and future context within a segment. In our study, this improved detection of transient artifacts that depend on surrounding signal patterns, enhancing classification accuracy.
- **CNN–LSTM Hybrid:** The CNN–LSTM hybrid first extracted spatial features with CNN layers and then modeled temporal dependencies with LSTM layers. This combination allowed the network to capture complex artifact patterns in the GSR signals, resulting in the highest accuracy among all tested architectures.

### *D.* Model Architecture

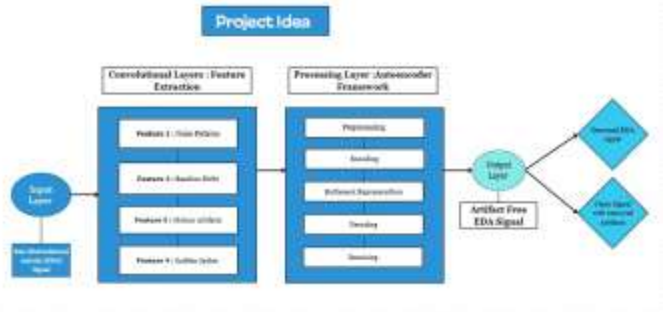


**Fig. 1. Idea**

The figure illustrates the workflow for artifact removal in Electrodermal Activity (EDA) signals using a convolutional autoencoder framework. The raw EDA signal enters the input layer and passes through convolutional layers that extract key features such as noise patterns, baseline shifts, motion artifacts, and sudden spikes. These features are then fed into the autoencoder processing layer, which involves preprocessing, encoding, creating a bottleneck representation, decoding, and denoising stages. The output layer produces an artifact-free EDA signal, resulting in a clean signal with removed artifacts suitable for further analysis.

## IV. RESULTS AND DISCUSSION

### *A.* Filtering Techniques

The performance of each filter was quantified using Root Mean Squared Error (RMSE) and Pearson correlation co-efficient to evaluate how well noise was suppressed while preserving signal integrity. Lower RMSE values indicate less deviation from the original signal, while higher correlation coefficients signify better preservation of the underlying signal features. The results are summarized in Table I.

**TABLE I Performance comparison of different filtering techniques**

| Index | Filter Type | RMSE | Correlation |
|---|---|---|---|
| 1 | Bandpass Butterworth Filter | 1.1753 | 0.2414 |
| 2 | Savitzky-Golay Filter | 0.3929 | 0.5987 |
| 3 | Wavelet Denoising | 0.1881 | 0.9314 |
| 4 | Moving Average (MA) | 0.3796 | 0.6328 |
| 5 | Exponential Moving Average (EMA) | 0.3456 | 0.7151 |

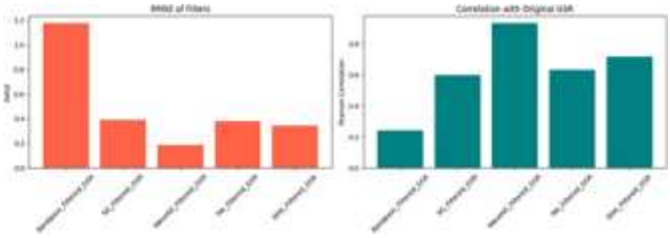


**Fig. 2. RMSE and correlation graphs for the different filters, showing the trade-off between noise reduction and signal preservation.**

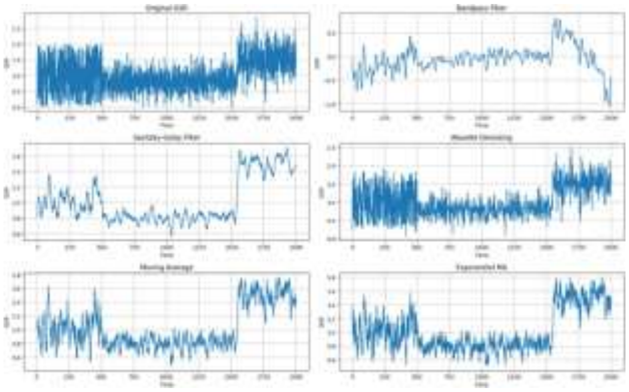


**Fig. 3. Visual comparison of filtered GSR signal outputs demonstrating the effectiveness of each filtering technique.**

*B.* Machine Learning Performance

The machine learning classifiers demonstrated consistent accuracy across models, indicating the effectiveness of feature engineering and classification methods in differentiating clean from artifact-contaminated signals. XGBoost and KNN models slightly outperformed others, likely due to their ability to capture complex patterns and nonlinearities in the feature space. Table II summarizes the classification accuracies.

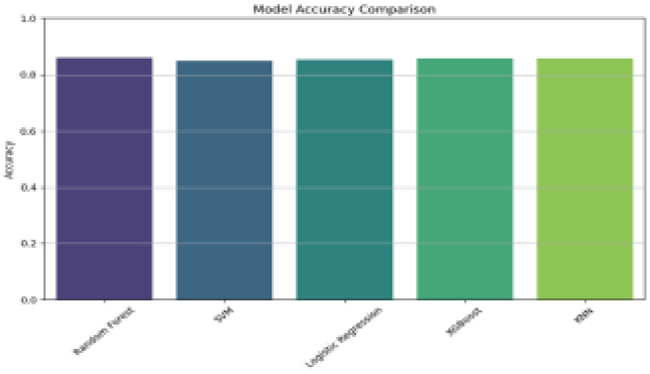


**Fig. 4. Comparative accuracy of machine learning classifiers in artifact detection.**

**TABLE II Accuracy of Machine Learning Classifiers**

| Index | Model | Accuracy (%) |
|---|---|---|
| 1 | Random Forest | 86.00 |
| 2 | Support Vector Machine | 85.00 |
| 3 | Logistic Regression | 85.25 |
| 4 | XGBoost | 85.75 |
| 5 | K-Nearest Neighbors (KNN) | 85.75 |

### *C.* Deep Learning Performance

The accuracies achieved by the implemented deep learn-ing models are summarized in Table III. The LSTM model achieved the highest accuracy among deep learning ap-proaches, followed closely by CNN and the hybrid CNN-LSTM model. Although the autoencoder's accuracy was slightly lower, it remains a promising unsupervised technique for anomaly detection in EDA signals.

**TABLE III Accuracy of Deep Learning Models**

| Index | Model | Accuracy (%) |
|---|---|---|
| 1 | Autoencoder | 81.75 |
| 2 | Convolutional Neural Network (CNN) | 85.25 |
| 3 | Long Short-Term Memory (LSTM) | 85.75 |
| 4 | Bidirectional LSTM (Bi-LSTM) | 85.25 |
| 5 | CNN–LSTM Hybrid | 85.25 |

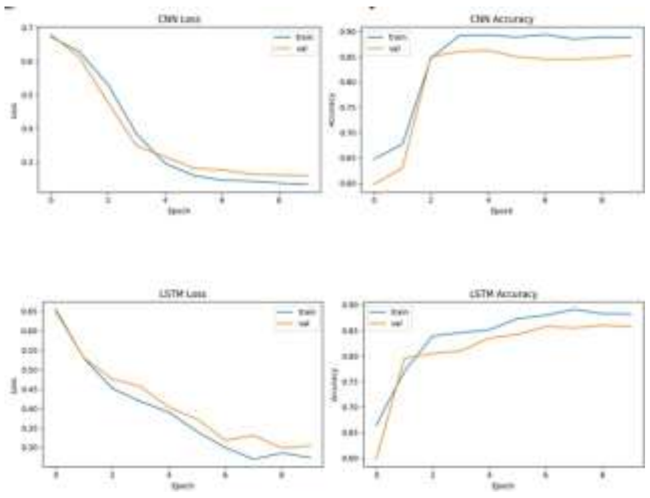


**Fig. 5. CNN and LSTM model accuracy and loss curves illustrating training progress and performance.**

The LSTM model achieved the highest accuracy among deep learning methods, closely followed by CNN and the hybrid CNN-LSTM. These results confirm that deep learning models can effectively capture temporal and spatial depen-dencies in physiological signals. Although the autoencoder's accuracy was slightly lower, it provides a viable unsupervised approach for anomaly detection.

## V. DEPLOYMENT

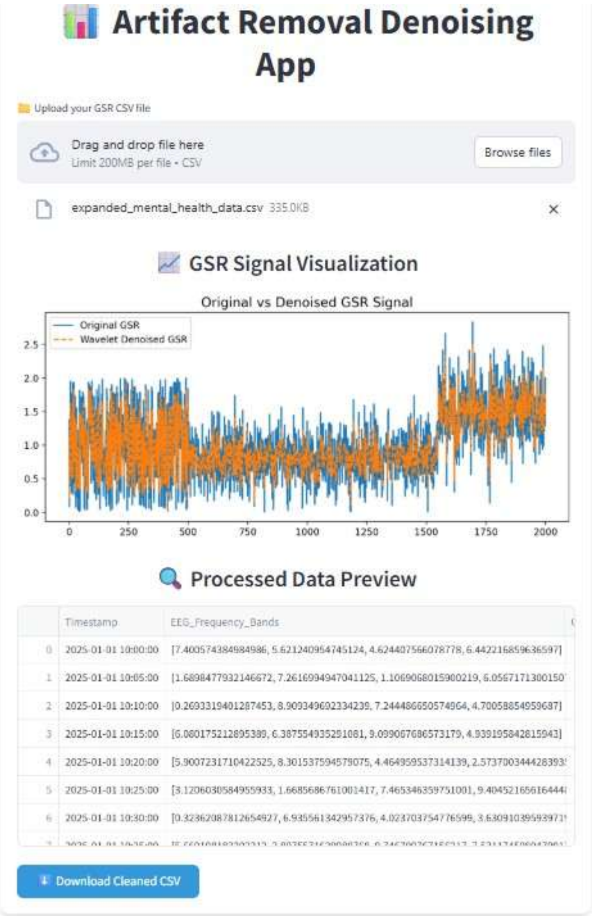
The final system has been deployed as a web-based applica-tion, allowing users to upload or stream EDA signals directly through a user-friendly interface. The platform processes sig-nals in real-time, applies artifact removal, and displays the clean signals along with performance metrics, enabling easy access for researchers and clinicians without requiring local installation of complex software.

complex temporal and spatial patterns of signals from data involving little manual feature extraction.

Deep learning methods emerged as the most effective approach for the elimination of artifacts from EDA signals, demon-strating superior capability in learning complex temporal and spatial patterns with minimal manual feature extraction. These models significantly enhance the robustness and reliability of real-time wearable stress monitoring systems. Furthermore, future work may explore hybrid approaches that integrate the strengths of conventional filtering and deep learning tech-niques, as well as the development of lightweight architectures suitable for mobile and embedded health applications.

## VII. FUTURE WORK

Future work will focus on extending the system to handle multimodal physiological signals, such as heart rate and respi-ration, alongside EDA. Additionally, optimization for mobile and wearable platforms will be explored to enable fully real-time, low-latency monitoring. Incorporating adaptive learning techniques could further improve artifact detection in diverse real-world conditions.



|  | Timestamp | EEG_Frequency_Bands |
|---|---|---|
| 0 | 2025-01-01 10:00:00 | [7.400574384984986, 5.621240954745124, 4.624407566078778, 6.442216859636597] |
| 1 | 2025-01-01 10:05:00 | [1.6898477932146672, 7.2616994947041125, 1.1069068015900219, 6.0567171300150 |
| 2 | 2025-01-01 10:10:00 | [0.2693319401287453, 8.909349692334239, 7.244486650574964, 4.700588549596871] |
| 3 | 2025-01-01 10:15:00 | [6.080175212895389, 6.387554935251081, 9.099067686573179, 4.939195842815943] |
| 4 | 2025-01-01 10:20:00 | [5.9007231710422525, 8.301537594579075, 4.464959537314139, 2.573700344428393 |
| 5 | 2025-01-01 10:25:00 | [3.1206030584955933, 1.6685686761001417, 7.465346359751001, 9.404521656164444 |
| 6 | 2025-01-01 10:30:00 | [0.3236208781265 4927, 6.935561342957376, 4.023703754776599, 3.63091039593971 |

**Fig. 6. Implementation**

## VI. CONCLUSION

This clearly demonstrates a comparative study of conven-tional filtering techniques and contemporary machine learning and deep learning techniques for the removal of artifacts from Electrodermal Activity (EDA) signals. Although conventional filters, like wavelet denoising, are effective in suppressing structured noise while maintaining the integrity of the un-derlying signal, they are ineffective in handling dynamic and intricate artifact patterns present in the real-world data. Machine learning classifiers such as XGBoost and Random Forest demonstrated high classification accuracy based on engineered features derived from GSR signals. Feature quality and interpretability of the model limit their performance. Deep learning models such as LSTM, CNN, and CNN-LSTM per-formed better compared to traditional techniques by learning.

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