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ECG signal-based classification of physiological states in ASD children using DWT and machine learning

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Abstract

ASD is a neurodevelopmental disorder that affects a child's ability to regulate emotions, interact socially, and respond to environmental stimuli. Monitoring physiological conditions in children with ASD is challenging because it relies on subjective observations. In this study, physiological conditions are defined based on observable behavioral states, namely active and quiet. The active state reflects increased physiological arousal and a higher heart rate, while the quiet state represents a resting state with a more stable heart rate. This study proposes an ECG-based classification system to distinguish between these two states. The dataset consists of 2000 samples for each class. Due to noise in the ECG signal caused by body movements, preprocessing was performed using the DWT to improve signal quality. The processed signals were then classified using three machine learning algorithms: SVM, Random Forest, and AdaBoost. The performance of each model was evaluated using accuracy, precision, recall, and F1-score. The results showed that without DWT, Random Forest achieved the highest accuracy of 91.00%, followed by SVM at 88.87%, and AdaBoost at 87.25%. While using DWT, Random Forest achieved the highest accuracy of 93.75%, followed by SVM at 91.37%, and AdaBoost at 90.25%. This indicates that DWT can produce better signal quality. Furthermore, Random Forest was selected as the optimal model and implemented in a Streamlit-based web application for real-time monitoring. These findings indicate that the combination of DWT and Random Forest is effective for classifying physiological conditions in children with ASD and has potential as an objective monitoring tool.

1. Introduction

Autism Spectrum Disorder (ASD) is a developmental disorder that affects children's ability to communicate, socialize, and manage emotions [1]. In clinical practice, monitoring the emotional and physiological states of children with ASD still relies heavily on subjective observations by caregivers or medical personnel, potentially leading to inaccuracies in monitoring the child's condition [2]. Furthermore, ECG signals recorded from children with ASD are often contaminated by significant noise from body movements during data collection. This makes manual analysis difficult and less reliable [3]. This issue requires objective, reliable, and automated methods to directly monitor the physiological states of children with autism.

With advances in computer technology, many automated diagnostic methods have been proposed to analyze electrocardiogram (ECG) signals [4]. ECG signals represent the heart's electrical activity and can be used to analyze Heart Rate Variability (HRV), which is closely related to physiological conditions and stress levels [5]. Previous research has shown that HRV analysis can differentiate physiological states in children with ASD, such as active and passive states [6].

This study focuses on classifying physiological states, as reflected in behavioral states, namely active and calm, in children with ASD using ECG signals. This classification is not intended to directly infer emotional states, but rather to distinguish observable levels of activity reflected in physiological responses. In the active state, the body is on alert, characterized by increased sensitivity to the environment and an irregular heartbeat with varying amplitude on the ECG. Meanwhile, in the calm state, the body is resting or recovering, with a slow and steady heartbeat [7].

In ECG signal processing, preprocessing is crucial to improve signal quality. Discrete Wavelet Transform (DWT) has been widely used due to its effectiveness in reducing noise while preserving important signal characteristics [8]. In addition, machine learning algorithms have become a popular choice due to their ability to recognize signal patterns with high accuracy [9]. Various machine learning algorithms, such as Support Vector Machines (SVM), Random Forests, and AdaBoost, have been used for ECG signal classification and have shown good performance [10],[11],[12]. Research [10],[11] has shown that the SVM algorithm can achieve high accuracy in classifying ECG signals, which is well-suited for biomedical data and exhibits optimal separation margins between classes. Research [11],[13] also reported high accuracy in classifying ECG signals from autistic children using Random Forest, a machine learning method that uses multiple decision trees to improve model stability and accuracy. Research [11],[12],[13] also shows that AdaBoost achieves high accuracy by sequentially combining multiple weak learners, with each new model focusing on correcting the classification errors of the previous model.

However, several limitations remain in previous research. Most previous studies only evaluated classification performance, without testing live monitoring implementations. Furthermore, the effectiveness of DWT in improving classification performance on ASD-specific ECG datasets has not been thoroughly analyzed. Furthermore, the integration of ECG-based machine learning models into user-friendly, real-time systems, such as web-based applications, remains limited.

Based on these problems, this study proposes an end-to-end system that classifies the physiological conditions of children with ASD based on ECG signals. This system combines DWT-based pre-processing, followed by machine learning classification, and implementation through a web application to assist users in monitoring the condition of autistic children. Unlike previous studies, this study not only evaluates the classification performance but also analyzes the impact of DWT on ASD-specific ECG data and implements the best model in a Streamlit-based system. Streamlit, a Python-based web application development framework, can integrate machine learning models through a simple and informative user interface [14]. Based on the explanation presented in this section, the research problem in this study is formulated as follows: Which machine learning algorithm (SVM, Random Forest, or AdaBoost) provides optimal performance in classifying quiet and active ECG signals in children with autism? And how effective is the Discrete Wavelet Transform (DWT) in improving the quality of noisy ECG signals and enhancing classification performance?

This study proposes a classification system for physiological conditions in children with autism based on ECG signal analysis, incorporating DWT for preprocessing to improve signal quality. The processed signals are then classified using a machine learning algorithm to distinguish between quiet and active states. The model with the best performance will be integrated into the Streamlit web application to provide an interactive and easily accessible platform for real-time monitoring.

The aim of this study is to evaluate the performance of SVM, Random Forest, and AdaBoost in classifying ECG signals and to develop an accurate and objective system for monitoring physiological conditions in children with autism. This system is expected to support practical, real-time decision-making in healthcare settings. The main contributions of this study are

1. Implementation of ECG-based physiological state classification specifically for children with autism spectrum disorder (ASD), a relatively underexplored domain,
2. Comprehensive analysis of the Discrete Wavelet Transform (DWT) for effective noise reduction in ECG signals before classification,
3. Evaluation of several machine learning models, namely SVM, Random Forest, and AdaBoost, to determine the optimal classifier, and
4. Development of an end-to-end web-based system using Streamlit for monitoring and visualization of autistic children, enhancing real-world usability.

2. Research Method

2.1 Dataset

The research materials used in this study are secondary data in the form of a matrix dataset of ECG signals derived from previous research [15], which received ethical approval from the Health Research Ethics Committee in 2023 under No. 028/EA/FK/2023. The data used in this study consist of 10 subjects, including five quiet-class subjects (aged 7-10 years) and five active-class subjects (aged 7-10 years). The extension type of this data is '.txt'. The dataset will be used as input to the ECG signal classification process, which will be divided into quiet and active classes. These two categories represent two different physical conditions, so they can be used as a basis for a classification system for stress conditions in autistic children.

2.2 Data Collection

In this study, the ECG dataset was obtained from an experimental framework described in a previous study [15]. The dataset was obtained from the My Hope Needs Center School in Banda Aceh, Indonesia. Data were collected from children aged 6-10 years with two different testing positions, on the chest and on the hand. Children were informed that they would be tested by attaching three electrodes to their bodies during the test, under parental supervision. Electrocardiogram (ECG) signal data collection was conducted under two main conditions: a calm state and an active state, to obtain different representations of physiological signals from each subject. Data were obtained through a direct acquisition process using the AD8232 sensor to capture the heart signal characteristics optimally [16]. This test obtained

ECG data by comparing the results of testing on the hands and chest of children with ASD in a calm state. Comparison between different electrode installation positions can affect the results of the ECG signal obtained. In a calm state, the subject was in a sitting position with minimal physical activity, and the test was conducted by attaching electrodes to the chest, which yielded a stable ECG signal. The ECG signal recorded under these conditions obtained a signal amplitude of 250-600 mV due to the lack of movement that could disrupt the system during testing. Meanwhile, in the active condition, the electrodes were placed on the subject's hand, which had uncontrolled movement. The results from this test showed unstable signal amplitude. This is due to the electrode's vulnerability to movement that occurs during data collection. The ECG signal recorded under these conditions obtained a signal amplitude of 0-650 mV due to excessive movement. The ECG signal recording under these two conditions aims to observe changes in signal characteristics due to an increase in unstable amplitude. Each piece of data obtained is then stored on a memory card to facilitate the analysis and classification process in the next stage. The recorded data is stored in a digital 'TXT' format containing information on the ECG signal of autistic children. With these two data collection conditions, it is hoped that the developed model will be able to distinguish ECG signal characteristics based on the child's physiological condition more accurately.

2.3 Data Processing

Data preprocessing is carried out in several stages: raw data input, data filtering using the Discrete Wavelet Transform (DWT), signal truncation using a Hanning window, dataset balancing with augmentation, and data division into training and test sets. Figure 1 illustrates the overall system pipeline, which includes ECG signal acquisition, preprocessing using DWT and the Hanning Window, data augmentation, classification, and web-based deployment.

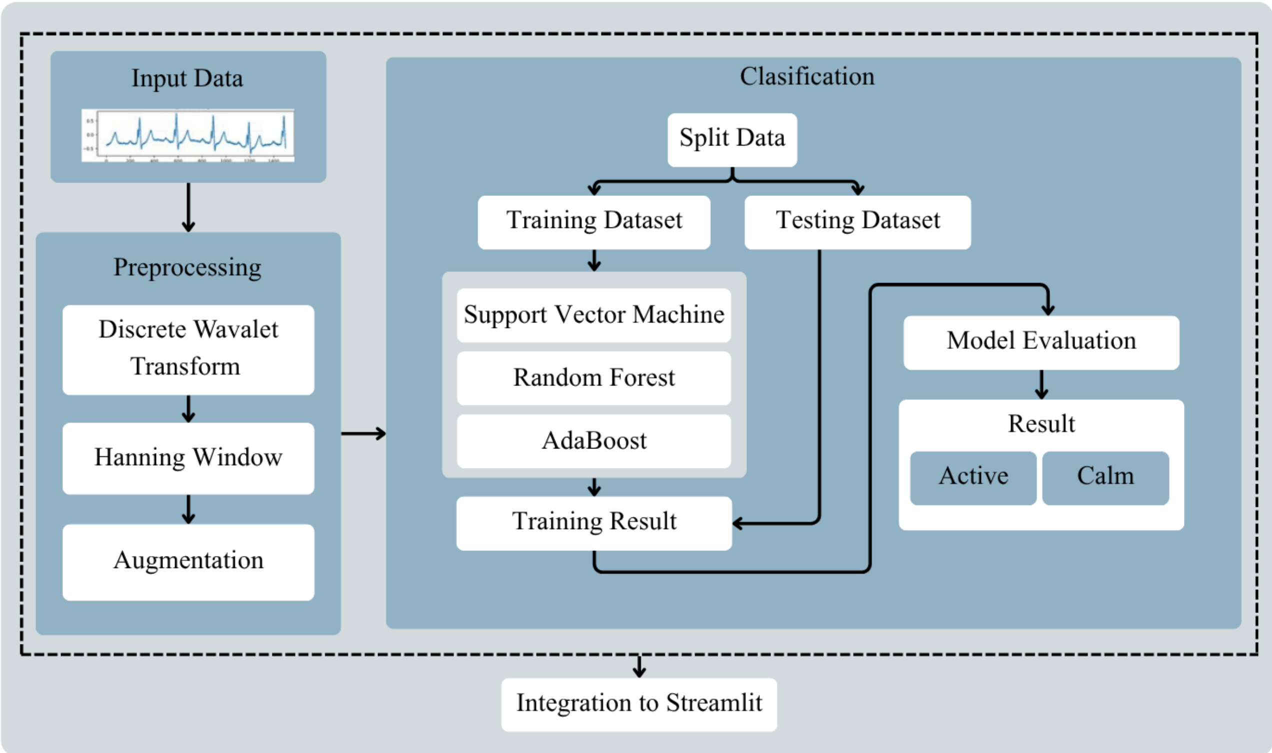


Figure 1. Research Flow in ECG Signal Classification using in this Research

2.3.1 Raw Data Input

Raw ECG signal data stored in matrix (.txt) format is imported into the Google Colab programming environment for analysis. The data is read using the NumPy library's np.loadtxt() function. Once the data is loaded, signal reconstruction is performed by mapping the amplitude values to the time domain using the specified sampling frequency. The converted data is then filtered using the DWT.

2.3.2 Discrete Wavelet Transform

The Discrete Wavelet Transform can comprehensively extract the time- and frequency-domain characteristics of a signal, providing a holistic representation of the original signal [17]. The Discrete Wavelet Transform (DWT) of ECG signals is a signal analysis technique that decomposes signals simultaneously in the time and frequency domains. This is achieved by decomposing the signal into multiple frequency components at different scales, allowing for the extraction of crucial signal characteristics and the isolation of noise components [18]. The DWT works by processing the signal through a cascade of low-pass and high-pass filters, producing low- and high-frequency signatures at each decomposition level. The basic principle of its use in ECG signals is to remove noise, especially noise at the same frequency as the original signal, thereby making conventional filters less effective [8]. DWT is performed on ECG signals using the db6 wavelet up to decomposition level 3. Noise is estimated from the median absolute deviation of the highest-level detail coefficients, and soft thresholding is applied to the high-frequency detail coefficients to suppress noise while preserving important signal information. The effectiveness of the DWT method was further analyzed by comparing the classification performance before and after the application of DWT, so that the effect of the denoising process on improving signal quality and model performance could be determined.

2.3.3 Windowing

The Hanning window is a raised-cosine type weighting function commonly used in time-frequency analysis to reduce spectral leakage when applying the Short-Time Fourier Transform (STFT) or generating spectrograms from non-stationary signals such as electrocardiograms (ECGs) [19]. The use of a Hanning window in signal preprocessing aims to minimize energy leakage between frequency bins, thereby preserving important morphological patterns in the spectrogram, thereby improving the input representation for spectral image-based machine learning models [20]. Several recent studies have reported that Hanning offers better time-frequency resolution than rectangular and is often slightly superior to, or equivalent to, Hamming for spectrogram-based ECG classification tasks. Therefore, many modern classification pipelines use the Hanning window as the default when constructing spectrograms for CNNs/Transformers [21]. The signal is divided into 2-second segments at a sampling frequency of 250 Hz, with each window containing 500 samples and a 50% overlap to maintain temporal continuity between segments. A window size of 500 samples was selected based on empirical evaluation to strike a balance between temporal resolution and computational efficiency. This size is sufficient to capture key ECG waveform characteristics such as QRS complexes [21]. The Hanning window size is adjustable; however, this study employed a fixed window size to ensure consistency across all samples and to minimize variability in feature extraction.

2.3.4 Augmentation

Augmentation is performed to address the limited number of subjects and sample size imbalances between classes that arise during pre-processing, as observed in previous studies [22]. One such augmentation technique is Additive Gaussian Noise Injection, which leverages its ability to introduce variability into the minority class without producing identical values, thereby reducing the risk of overfitting [23]. Furthermore, amplitude scaling, also known as signal magnitude scaling, multiplies all or part of the signal by a random scale factor to simulate gain variations or amplitude variations due to physiological conditions [24]. Meanwhile, time shifting, or time domain augmentation, involves shifting the entire signal to the right or left along the time axis so that the signal remains present but at a different time position [24]. The SMOTE technique is also applied to generate new synthetic samples for the minority class by interpolating between adjacent samples in the feature space [25]. Through this technique, the amount of data can be increased to balance the quiet and active classes. With augmentation, the model is trained on a more diverse signal distribution, making it more robust to real variations and random noise that arise in new data. Data from the active and quiet classes were first combined, and the number of samples per class was standardized to 2000. The augmentation process was performed using four techniques: Gaussian noise addition, amplitude scaling, time shifting, and SMOTE, which aimed to increase data variation and reduce class imbalance without altering the primary physiological characteristics of the ECG signal.

2.3.5 Split Dataset

In the final stage of signal processing, the data generated during the augmentation process is divided into three sets: train and test, with ratios of 80% and 20% respectively. This ratio is chosen for the train-validation-test division because it does not violate the temporal aspect of the data. This method has been successfully applied in previous research [26].

2.3.6 Support Vector Machine

Support Vector Machine (SVM) is one of the most widely used machine learning algorithms for classification and regression tasks. SVMs work by finding the best hyperplane that separates data into two or more classes with the largest margin. This margin is the distance between the hyperplane and the closest data points from each class, known as support vectors [27]. The larger the margin, the better the model's generalization ability to new data. Because it focuses on the most critical points (support vectors), SVM is a robust algorithm for high-dimensional data and complex patterns [11]. In many biomedical signal studies, such as ECG, the RBF kernel is often used because it can capture nonlinear patterns more effectively [28]. With strong generalization and robustness against overfitting, SVM is widely used for physiological condition detection and medical signal classification.

2.3.7 Random Forest

Random Forest is an ensemble learning method that works by building multiple decision trees and combining their predictions to create a new model improve model accuracy and stability. This method was introduced by Breiman and has since become one of the most popular classification and regression algorithms due to its resistance to overfitting, its ability to handle high-dimensional data, and its good performance on non-linear datasets [29]. In the training process, Random Forest uses bootstrap aggregating (bagging), which involves sampling with replacement from the training data to create many decision trees. Each tree is trained with a randomly selected subset of features (random feature selection). The final prediction is determined by majority voting for classification or by averaging for regression [30].

2.3.8 AdaBoost

AdaBoost (Adaptive Boosting) is an ensemble learning algorithm that uses a boosting approach, sequentially integrating many weak models to build a strong model. The core of this method is the flexible adjustment of sample weights at each iteration. Samples misclassified by the previous model are given higher weights so that the next model can focus more on correcting those errors, while correctly classified samples are given lower weights [31]. In this way, weak models that are only slightly better than random guesses can be combined into one strong model with high overall accuracy, because each step focuses on correcting the errors of the previous step [32]. Recent research has shown that this principle underpins the effectiveness of AdaBoost in various application areas, especially when dealing with complex or imbalanced datasets, and it remains a highly relevant technique in ensembles [33].

2.3.9 Model Evaluation

The final evaluation of the model is performed on the test data using a confusion matrix to compare the performance of the SVM, Random Forest, and AdaBoost methods. Equations 1–4 can be used to calculate the accuracy, recall, precision, and F1-Score values to determine the system performance. The parameters used in this study are as follows.

a. Accuracy measures the overall accuracy of the model’s predictions by calculating the proportion of correctly classified examples over the total number of cases [34].

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

b. Precision measures how many of the predicted positives are positive [34].

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

c. Recall measures how many of the actual positives are successfully predicted as positive [34].

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

d. The F1-score is the harmonic mean of precision and recall, used to measure the balance between the two [34].

$$F1 - score = 2x\frac{Precision\ x\ Recall}{Precision + Recall} \tag{4}$$

The confusion matrix is used to evaluate the performance of a classification model by comparing predicted results with actual conditions. The True Positive (TP) value indicates the number of quiet-class data points correctly predicted as quiet. The True Negative (TN) value indicates the number of active class instances correctly predicted as the active class. Meanwhile, the False Positive (FP) value indicates the number of quiet-class data points incorrectly predicted as active-class data. Conversely, the False Negative (FN) value is the number of instances in the active class incorrectly predicted as the quiet class. These four components provide a comprehensive picture of the model's accuracy, error, and ability to distinguish between the two classes.

2.3.10 Statistical Analisis

In evaluating the performance of ECG signal denoising methods, inferential statistical analysis is often used to determine whether the difference in performance between two methods is statistically significant [35]. This test was performed using K-Fold cross-validation, which evaluates a machine learning model by dividing the dataset into K equal parts (folds), then training the model on K-1 parts and testing it on the remaining part [36]. The results of K-Fold cross-validation will be tested using a t-test. Statistical tests using t-tests are used to determine whether there is a significant difference between two groups of data in ECG signals, for example, between active and calm conditions. The t-test works by comparing the average of the two groups and considering data variability and the number of samples [37]. In ECG signal research, classification results using k-fold validation were tested using a t-test to determine whether the differences between classes were significant or simply due to random variation. The results of the t-test are expressed as a p-value, which indicates the level of significance of the difference between the two groups. If the p-value is smaller than a certain threshold (usually 0.05), then the difference is considered statistically significant [38]. In the context of ECG analysis, the use of the t-test helps validate that the features used are capable of distinguishing physiological conditions, thereby increasing the reliability of the classification model and supporting scientific interpretation of the results.

2.3.11 AUC (Area Under the Curve)

Area Under the Curve (AUC) is an evaluation metric used to assess the ability of a classification model to distinguish between two classes. AUC is derived from the ROC (Receiver Operating Characteristic) curve, which describes the relationship between the True Positive Rate (TPR) and False Positive Rate (FPR) at various threshold values. AUC values range from 0 to 1, with values close to 1 indicating excellent classification performance, while values close to 0.5 indicate performance equivalent to random guessing [39]. In ECG signal analysis, AUC is an important metric because it provides a more comprehensive evaluation than a single accuracy value. This is because AUC does not rely on a specific threshold value and is more robust to data imbalance and signal variations that often occur due to noise or differences in individual physiological conditions [40]. Therefore, the use of AUC helps ensure that the model has good discriminatory ability to consistently identify important patterns in ECG signals.

3. Results and Discussion

3.1 Confusion Matrix

Using a confusion matrix, the classification accuracy of the three methods can be measured. The results of the performance accuracy analysis are shown below. Figure 2 shows the confusion matrices of the three models before applying DWT, where (a) shows the SVM confusion matrix, (b) shows the Random Forest confusion matrix, and (c) shows the AdaBoost confusion matrix.

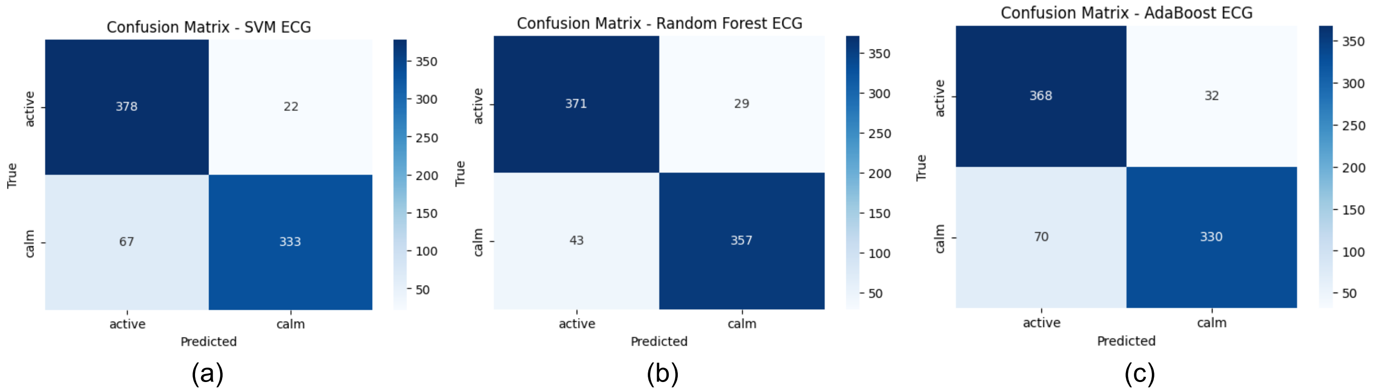
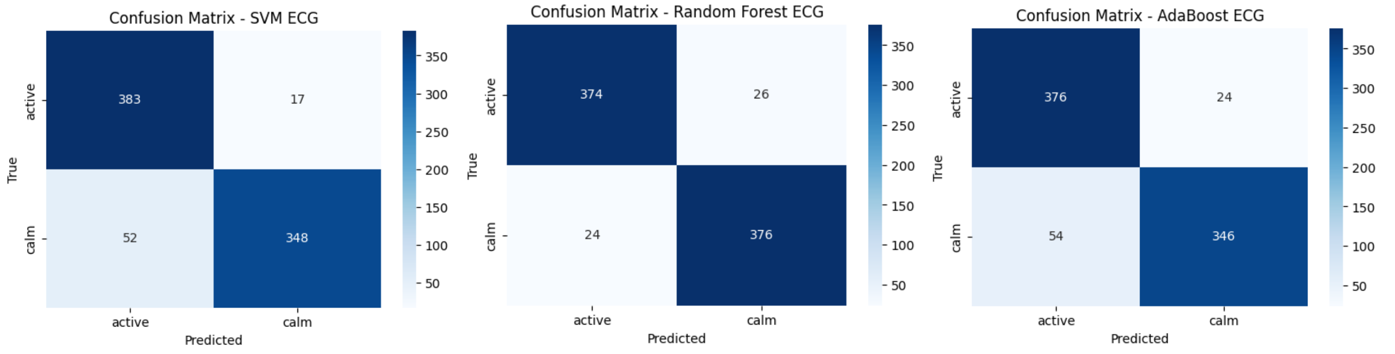


Figure 2. Accuracy Results without DWT using the Confusion Matrix a. SVM, b. Random Forest, c. Adaboost

Meanwhile, we also performed classification by applying the DWT to compare the effectiveness of denoising methods using this technique. The results of the model performance accuracy analysis with DWT are shown below. Figure 3 shows the confusion matrices of the three models with DWT, where (a) shows the SVM confusion matrix, (b) shows the Random Forest confusion matrix, and (c) shows the AdaBoost confusion matrix.



(a) (b) (c)

Figure 3. Accuracy Results with DWT using the Confusion Matrix a. SVM, b. Random Forest, c. Adaboost

In general, before applying DWT, all models were able to correctly classify most of the data, but there were still significant misclassifications, particularly in the calm class. Among the three models, Random Forest showed a more balanced error distribution than SVM and AdaBoost, which tended to have a higher number of false positives. After applying DWT, a decrease in the number of misclassifications was observed across all models. The most obvious improvement was the reduction in errors in the calm class, which was previously more difficult to recognize due to noise in the ECG signal. Furthermore, the prediction distribution became more balanced between the two classes, indicating an improvement in the model's ability to distinguish signal patterns.

Specifically, SVM showed an increase in the number of correct predictions and a decrease in false negatives, although it still had a tendency to overdetect certain classes. Random Forest experienced the most consistent improvement, with a decrease in errors in both classes and the most balanced prediction distribution. AdaBoost also improved, but still showed higher error variance than Random Forest. Among the three models tested, Random Forest showed the most consistent performance improvement with a relatively balanced error distribution, followed by SVM, while AdaBoost still exhibited higher error variability. These findings indicate that the DWT-based denoising process is effective in increasing feature separability, making ECG signal patterns clearer and easier for the model to learn.

Overall, the application of DWT plays a significant role in improving signal quality by reducing noise, which directly impacts accuracy and classification balance across all methods. Compared to models without DWT, the number of errors decreased, especially in the quiet class, indicating that DWT helps the model recognize signal patterns more optimally. Thus, DWT proved effective in improving ECG signal feature quality, enabling all models to perform more accurate and consistent classifications.

3.2 Performance Model

Classification was performed before and after DWT application to evaluate the effect of the denoising process on ECG signal quality and the performance of the classification model. Furthermore, the classification process was performed using three models: Random Forest, SVM, and AdaBoost, with the aim of comparing the performance of each model in classifying ECG signals. This comparison is important to determine the optimal model in distinguishing active and inactive states in children with ASD. Table 1 shows the classification performance before DWT application, which provides an overview of the ability of each model in classifying signals.

Table 1. The Comparison of the Accuracy Achievements of the Three Methods without DWT

Classifier	Accuracy	Precision	Recall	F1-Score
SVM	88.87%	84.94%	94.50%	89.46%
Random Forest	91.00%	89.61%	92.75%	91.15%
AdaBoost	87.25%	87.44%	94.00%	90.60%

To test the effectiveness of DWT, a classification process was also conducted by applying DWT to ECG signals. The goal was to determine the extent to which the denoising process could improve signal quality and impact the performance of the classification model. Table 2 shows the classification performance after applying DWT. This comparison provides an overview of how DWT can improve accuracy, precision, recall, and F1-score for each model, and helps determine the best approach for ECG signal processing.

Table 2. The Comparison of the Accuracy Achievements of the Three Methods with DWT

Classifier	Accuracy	Precision	Recall	F1-Score
SVM	91.37%	88.04%	95.75%	91.73%
Random Forest	93.75%	93.96%	93.50%	93.72%
AdaBoost	90.25%	92.50%	88.09%	90.24%

Table 1 presents a comparison of the performance of three classification models: SVM, Random Forest, and AdaBoost, evaluated using accuracy, precision, recall, and F1-score metrics without DWT implementation. Overall, Random Forest demonstrated the best overall performance, with balanced and stable results across all evaluation metrics, with no bias toward any particular class. The SVM model demonstrated excellent ability to detect positive samples, but on the other hand, it produced more false positive predictions, thus compromising its performance balance compared to Random Forest. Meanwhile, AdaBoost also demonstrated relatively high sensitivity, but its performance tended to be less stable in handling the variability and complexity of ECG signals, resulting in less optimal classification results than Random Forest. Therefore, Random Forest can be considered the superior model in the scenario without DWT because it was able to maintain a more consistent balance between precision and recall.

Table 2 presents the performance of the three models after DWT implementation. The results indicate that DWT positively improved all evaluation metrics for all models. Random Forest again demonstrated the best performance, with very balanced and consistent classification ability, confirming that this model benefited significantly from the improved quality of feature representation resulting from the DWT process. The SVM model also experienced significant improvements, particularly in sensitivity to positive samples, although it still faces challenges in reducing the number of false positive predictions. On the other hand, AdaBoost showed improvements in the accuracy of positive predictions, but was still less optimal in capturing all important patterns in the ECG signal compared to the other two models. Overall, the application of DWT proved effective in reducing noise and improving signal quality, thus directly impacting classification performance. Among the three models, Random Forest remained the most optimal approach, maintaining the most balanced and consistent performance across evaluation metrics.

A paired t-test was performed using the results of 10-fold cross-validation to statistically compare the performance between models. This test aims to determine whether the performance differences obtained are truly significant or simply occur by chance. The test results show that the comparison between Support Vector Machine (SVM) and Random Forest produces a p-value of 0.0251, which means there is a significant difference in performance. Furthermore, the comparison between Random Forest and AdaBoost produces a p-value of 0.0008, which indicates a very significant difference. Meanwhile, the comparison between SVM and AdaBoost produces a p-value of 0.0607, which is greater than the significance threshold (0.05), so there is no significant difference between the two models. These results indicate that Random Forest has statistically superior performance compared to the other models.

To complete the model performance evaluation, an analysis was performed using the Area Under the Curve (AUC) of the ROC curve. Figure 4 illustrates the ROC curves used to analyze the performance of the Random Forest (RF), Support Vector Machine (SVM), and AdaBoost models.

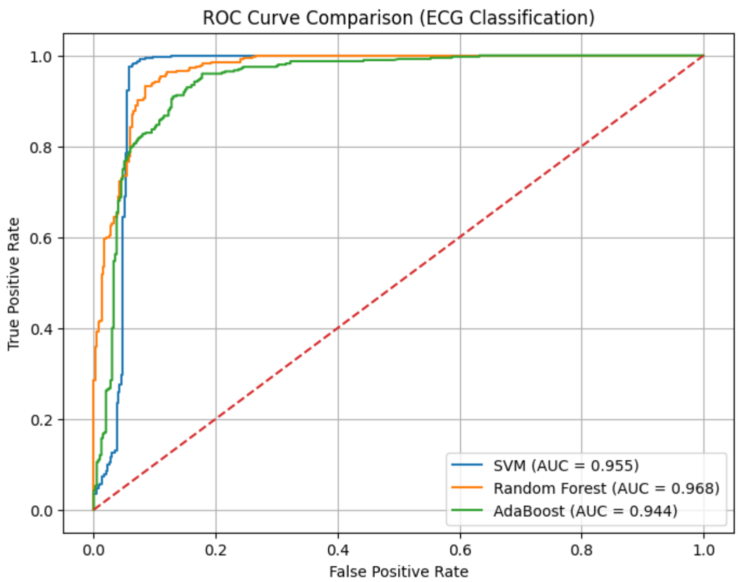


Figure 4. AUC Curve

The results showed that all models had excellent classification ability, with AUC values above 0.9. The Random Forest model obtained the highest AUC value of 0.968, followed by SVM at 0.955, and AdaBoost at 0.944. These values indicate that Random Forest has the best ability to distinguish between active and quiet classes, as indicated by the ROC curve closest to the upper left corner, reflecting a high True Positive Rate (TPR) and a low False Positive Rate (FPR). Furthermore, the shape of the curves indicates that both Random Forest and SVM experience a rapid increase in TPR at low FPR values, making them effective in minimizing classification errors at small thresholds. On the other hand, although AdaBoost still performed well, its resulting ROC curve tended to be flatter, indicating slightly lower discrimination ability compared to the other two models. Overall, these results confirm that Random Forest is the most optimal model for ECG signal classification in this study.

LIME analysis was also performed to demonstrate differences in feature contribution patterns across models. In SVM, feature contribution values were very small and relatively even, indicating that the model does not rely heavily on any particular feature and tends to have a smooth decision boundary but lacks specific pattern capture. Meanwhile, Random Forest showed larger and more consistent feature contributions at certain time points, such as t122, t296, and t356, thus identifying important features more stably. On the other hand, AdaBoost had the highest contribution value, indicating a strong focus on specific features but also indicating high sensitivity to data and potential overfitting. Overall, features that recur across multiple models can be considered key features of the ECG signal, and these results confirm that Random Forest provides the best balance between interpretability and model stability.

3.3 Discussion

This study evaluated the performance of several machine learning models, namely Support Vector Machine (SVM), Random Forest, and AdaBoost, in classifying ECG signals from children with ASD into two states: active and quiet. The results showed that Random Forest outperformed both SVM and AdaBoost in classifying ECG signals from children with ASD. Random Forest achieved the highest accuracy of 93.75%, with balanced precision, recall, and F1-score across both classes. This balanced performance indicates that the model not only excels at recognizing one state but also consistently classifies both states.

Conversely, although SVM performed quite well, it tended to have less balanced sensitivity across classes. SVM was more responsive in detecting the active state but slightly less effective in recognizing the quiet state. Meanwhile, AdaBoost performed the worst among the three models, indicating that the boosting approach, which emphasizes prior classification errors, is not suitable for the ECG signals in this dataset. This suggests that while both methods are capable of high-accuracy classification, they are less optimal in handling the complexity and natural fluctuations of ECG signals compared to Random Forest.

The findings of this study are consistent with recent research evaluating the performance of machine learning models in ECG signal classification. Previous research [11] reported that the Random Forest (RF) method achieved the highest accuracy compared to Support Vector Machine (SVM) and AdaBoost in classifying arrhythmias in ECG signals. This demonstrates RF's superiority in consistently handling ECG signal complexity. Research [12] is also relevant to this study, particularly in the classification of ECG signal quality. SVM and Random Forest demonstrated superior performance compared to AdaBoost. Although other models, such as ExtraTree, were also evaluated, AdaBoost had lower accuracy than RF and SVM for certain metrics.

Overall, these studies show a similar pattern to the results of this study, where decision tree-based ensemble models, such as Random Forest, generally provide more stable performance and often outperform SVM and AdaBoost on complex and variable ECG signals. However, unlike most studies that focus solely on offline evaluation, this study provides additional contributions through analyzing the impact of DWT on ASD datasets and implementing a Streamlit-based system.

Based on model performance and stability considerations, Random Forest was chosen as the primary model for implementation in the Streamlit-based system, as seen in Figure 5. This choice is also supported by the advantages of Random Forest implementation, such as relatively fast inference time, easy integration with web-based applications, and the model's robust ability to handle new data. Therefore, the use of Random Forest in the Streamlit application is expected to provide a reliable, responsive, and easy-to-use ECG signal classification system as a tool for objectively monitoring the condition of children with ASD.

Figure 5. Streamlit View of ECG Signal Classification using Random Forest Model

Figure 5 shows the implementation of a web-based ECG signal classification system using Streamlit, where users can upload ECG signal data in file format (.txt) for automatic classification. After the data is successfully uploaded, the system displays the number of processed samples and the classification results in the form of the number of windows for each class, namely active and calm conditions. This implementation demonstrates that the Random Forest model can be well integrated into a web-based system and is capable of providing fast, stable, and easy-to-use classification results.

The results of this study have important implications for the development of an emotion monitoring system for children with ASD. The selection of Random Forest as the primary model demonstrates that the ensemble method provides consistent and reliable classification results for analyzing ECG signals, particularly on data with high levels of noise caused by the child's movements during recording. The use of this model in a Streamlit-based website allows for the development of an interactive and easy-to-use ECG classification system that can serve as an objective tool for caregivers and healthcare professionals to more accurately monitor children's emotional states. Furthermore, this study can also serve as a basis for further system development, such as integration with live monitoring and exploration of more effective machine learning techniques.

Although the results of this study demonstrate promising performance, several limitations need to be considered. First, the dataset size is still limited to two classes, thus not fully representing the full range of physiological conditions in children with ASD. Second, this study still uses machine learning methods and has not explored deep learning approaches that can capture more complex feature representations. Furthermore, the limitation of Streamlit, which is not designed to handle thousands of simultaneous users, still needs to be addressed.

This study focuses on traditional machine learning models such as SVM, Random Forest, and AdaBoost due to their lower computational complexity and robustness when applied to limited datasets. However, deep learning approaches such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) offer the ability to model more complex temporal and non-linear patterns in ECG signals and will be explored in future research. Furthermore, the addition of other physiological features such as Heart Rate Variability (HRV), RR intervals, and respiration signals has the potential to enhance context information, thereby improving classification accuracy. In terms of signal processing, although DWT has proven effective for denoising, alternative methods such as Empirical Mode Decomposition (EMD) and Variational Mode Decomposition (VMD) can be explored to improve signal quality, especially in conditions with high motion artifacts. From an implementation perspective, the development of web-based systems like Streamlit needs to be upgraded to a scalable architecture, for example, through integration with cloud infrastructure to be able to handle multiple users and large datasets simultaneously. Therefore, further research needs to test the system under real-world conditions using a wearable ECG device for continuous monitoring. This is crucial to ensure that the model remains robust to dynamic noise caused by movement and can be used practically in clinical applications.

4. Conclusion

This study aims to develop and evaluate an ECG signal classification system for children with ASD to distinguish between active and quiet states using machine learning methods. Three models were evaluated in this study: SVM, Random Forest, and AdaBoost. The test results showed that all models achieved good classification performance, with accuracy above 90% based on DWT. Among the three models, Random Forest achieved the best performance, with the highest accuracy and balanced precision, recall, and F1-score values for both classes. This indicates that Random Forest has a better ability to capture complex and nonlinear patterns in ECG signals compared to SVM and AdaBoost. Furthermore, the application of DWT proved effective in improving the performance of all models. DWT is able to extract ECG signal features in both time and frequency domains simultaneously, thus better representing important information in the signal and minimizing noise. This is reflected in the increased accuracy, decreased classification errors in the confusion matrix, and high AUC values in all models after the application of DWT. With its advantages in accuracy, stability, and resistance to overfitting, Random Forest is the most optimal model and is easy to integrate into web-based systems like Streamlit. Going forward, this research can be expanded by increasing the amount and variety of data, exploring deep learning methods, and integrating the system into real-time monitoring to support clinical applications in children with ASD.

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