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Classification of autism features in electroencephalography recordings using random forest method

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ABSTRACT

Autism Spectrum Disorder (ASD) is a developmental disorder that significantly impacts communication, social interaction, and behavior in children. This study aims to develop a more accurate and objective EEG-based ASD diagnosis method, focusing on improving reliability through advanced preprocessing and precise classification techniques. Specifically, Independent Component Analysis (ICA) and Wavelet Packet Decomposition (WPD) are employed for noise reduction and signal resolution enhancement, respectively. These methods were selected due to their proven ability to effectively isolate brain activity from artifacts and provide detailed signal decomposition for statistical feature extraction. Utilizing a dataset from King Abdulaziz University, comprising 16 children (4 neurotypical and 12 with ASD), Random Forest (RF) classification achieved an accuracy of 76.8%. However, challenges such as data imbalance and high variance were identified, highlighting the need for additional strategies to enhance diagnostic precision. This research contributes to early ASD detection by integrating computational algorithms with EEG signal analysis.

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1. INTRODUCTION

Autism Spectrum Disorder (ASD) is a pervasive developmental disorder characterized by delays and deviations in the development of communication, social interaction, and behavior. Deviations in people with ASD make them show withdrawn behavior, do not want to talk, or repetitive and stereotyped activities, and always look away from others or unable to make eye contact. In previous research, classification accuracy in children with ASD can be improved by integrating Continuous Wavelet Transform (CWT) and Support Vector Machine (SVM) [1].

Research related to ASD has been carried out, previously distinguishing ASD sufferers from normal people was only done by behavioral tests, but the accuracy of these behavioral tests could not be used as a reference, so researchers used Electroencephalography (EEG) to provide objective markers to improve diagnostic accuracy [2]. EEG research involves the use of a Brain Computer Interface (BCI). BCI is a system that connects the brain and computer. BCI can recognize activity patterns by computer algorithms to control external and internal devices [3]. The accuracy of processing autistic and normal EEG signals has been enhanced by Independent Component Analysis (ICA) filtering and Discrete Wavelet Transform (DWT) extraction methods. By generating a smaller frequency, the ICA method has been demonstrated to be effective in eliminating artifacts from normal and autistic EEGs, as well as reducing data storage usage [4].

Research using BCI has been widely applied by other researchers, both in the context of robotics, and in medical needs. EEG-based BCI can incorporate other types such as magnetoencephalogram (MEG), electrocorticogram (ECoG), near infrared spectroscopy (NIRS), and functional magnetic resonance imaging (fMRI). The use of BCI-based EEG is often used because it provides a convenient, inexpensive, and non-invasive solution to use [3],[11].

This research contributes to the RF classification system, which serves to sort out people with ASD from normal people. Before classification, the secondary signal used will be sorted between the source signal and the receiver signal using ICA before transformation using WPD. Transformation using WPD as much as 3 levels, serves to provide clearer details on the signal that has been done ICA. Classification is carried out after the calculation of feature extraction using the RF method, after the classification is carried out, the calculation of classification accuracy will also be carried out by the RF method.

This research addresses the gap in EEG-based ASD classification by integrating advanced preprocessing methods ICA and WPD with Random Forest (RF) to enhance diagnostic accuracy. ICA is utilized for its ability to isolate brain-specific signals by removing artifacts, ensuring cleaner data for analysis, while WPD decomposes signals into detailed time-frequency domains, facilitating the extraction of relevant statistical features [3],[5],[21],[23]. RF method is a method developed from CART by applying bootstrap and random feature selection. The selection stage used in the RF method is a voting system and then the data will be tried on the available filters to get the highest accuracy and was chosen for its robustness in handling high-dimensional and imbalanced datasets, as well as its capability to select the most significant features during training, which improves classification accuracy and interpretability [6],[7],[8],[26]. By combining these methods, the study offers a unified framework that addresses noise reduction, signal resolution, and feature selection, setting it apart from previous works and contributing to more reliable ASD detection.

2. METHODS

MATLAB R2018b is used to perform the steps as shown in Fig. 1. Starting from using secondary data, then preprocessing, using ICA, transforming using WPD, obtaining statistical features, and classification and classification calculations using RF.

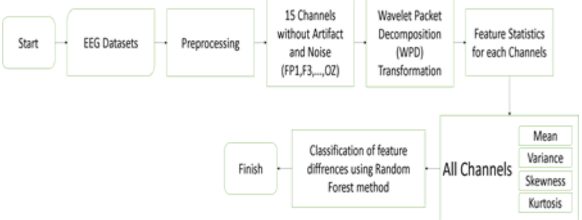

Fig. 1. Research Method

2.1. Research Materials

This is how to start a subsection

The dataset used originates from King Abdulaziz University, featuring EEG recordings of 16 children. Each recording includes a 6x6 matrix representing signals captured from 15 channels positioned across the scalp. These channels cover key regions (e.g., frontal, temporal) relevant to ASD-related neural activity. Filters, including a pass band (0.1–60 Hz) and a notch filter at 60 Hz, were applied to eliminate high-frequency noise and electrical interference. The data still contained motion artifacts, necessitating advanced preprocessing techniques. The dataset can be found from this website https://malhaddad.kau.edu.sa/Pages-BCI-Datasets-En.aspx.

The EEG data is described as having a matrix size of 6x6, which refers to 6 EEG signal channels recorded from 6 different brain locations, with 6 measurement points for each channel. These channels capture signals from various regions, including frontal, temporal, and parietal areas, ensuring comprehensive coverage of brain activity [3]. The dataset contains recordings from 15 EEG channels, but specific electrode placements such as Fp1, Fp2, F3, F4, Cz, and others, are crucial for understanding the spatial localization of the signals. Further technical details, such as the use of a pass band filter between 0.1-60 Hz to isolate frequencies relevant to brain activity and a notch filter at 60 Hz to remove electrical interference, provide clarity on preprocessing strategies. Despite filtering, residual noise from subject movement—such as muscle artifacts or motion-induced disturbances—remains a challenge, emphasizing the importance of ICA in this context [21],[23]. The EEG signals were captured using the BCI2000 system, chosen for its reliability, flexibility in research applications, and non-invasive data acquisition capabilities [6].

2.2. Pre-processing using ICA

ICA was employed to separate independent components of the EEG signals, effectively isolating brain activity from artifacts such as eye movements and muscle contractions. This technique works by maximizing statistical independence among components, ensuring clearer signal representation

In the pre-processing stage, the EEG signal is sampled at 256 Hz. Furthermore, a notch filter is applied, the use of the filter is to minimize noise and artifacts that exist in the EEG dataset, because of this, ICA is applied. ICA serves to eliminate all signals that are not from the brain without reducing the required EEG data. The stages can be seen in detail in Fig 2.

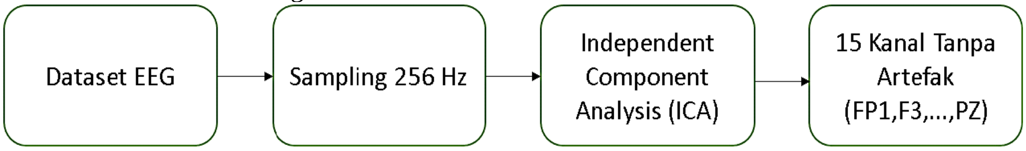

Fig. 2. Preprocessing Diagram

The performance performed by ICA in addition to what has been described above is unmixing signals (separating signals). This is related to the number of nodes used at the time of data collection, because it has more than 1 receiver (node) when data collection takes place, the situations where signals captured by different electrodes are contaminated by common sources, such as external noise or physiological artifacts. By leveraging statistical independence, ICA decomposes the recorded EEG signals into independent components, enabling the removal of non-brain-related activities [21]. For instance, signals originating from brain activity are disentangled from those caused by electrooculography (EOG) or electromyography (EMG), enhancing the clarity of the data used for analysis. This capability makes ICA an effective preprocessing tool for ensuring the quality and reliability of EEG signals in ASD classification. It can be assumed that the signal received at the first node as $\mathbf{x_1}$ and the signal received at the second node as $\mathbf{x_2}$ [30].

$$y_1 = ax_1 + bx_2$$
$$y_2 = cx_1 + dx_2 \tag{1}$$

Formula (1) expresses the mixed signals from two nodes as linear combinations of independent sources.

Where ***a***, ***b***, ***c***, and ***d*** are signal separation coefficients used to convert the mixed signal into the original signal, the modifier is represented as $\mathbf{X \rightarrow Y : Y = W^T X}$

$$\boldsymbol{W} = \begin{bmatrix} \boldsymbol{a} & \boldsymbol{b} \\ \boldsymbol{c} & \boldsymbol{d} \end{bmatrix} \tag{2}$$

Formula (2) introduces the transformation matrix that separates these mixed signals.

Simply the first unmixed source signal $\mathbf{y_1}$ can be extracted using the two mixed signals $\mathbf{x_1}$ and $\mathbf{x_2}$. The signal separation coefficients used can be represented as $\mathbf{w_1}$ and $\mathbf{w_2}$ where $\mathbf{w_1} = (\boldsymbol{ab})^T$, used on $\mathbf{x_1}$, and $\mathbf{w_2} = (\boldsymbol{cd})^T$, used on $\mathbf{x_2}$. Then to get a signal that is close to the original (source) can be assumed as follows:

$$y_1 = ax_1 + bx_2 = w_1^T X$$
$$y_2 = cx_1 + dx_2 = w_2^T X \tag{3}$$

Formula (3) provides the derivation of independent components by iteratively optimizing statistical independence. These formulas are fundamental in isolating brain-specific activity from artifacts, ensuring that the subsequent classification steps receive high-quality data.

2.3. Transformation using WPD

WPD is a method that offers richer or more diverse possibilities for analyzing signals, not only that WPD offers the most suitable possibility analysis in signal analysis. WPD uses the transformation of a signal from the time domain to the frequency domain. It is calculated using a recursion of filter depletion operations that refers to a decrease in time domain resolution and an increase in frequency domain resolution [21]. A simulation of 3 levels of decomposition can be seen in Fig 3.

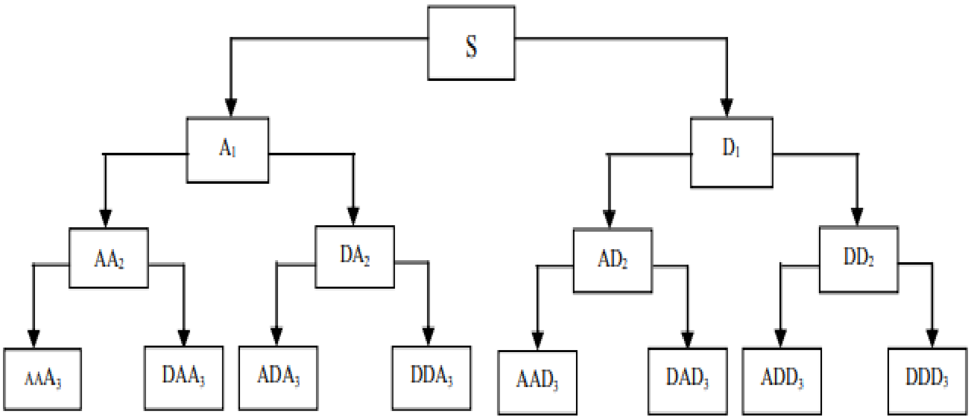

Fig. 3. Wavelet Packet Decomposition Process

Fig. 3 illustrates the WPD process, where "S" represents the original signal, while "A1," "AA2," and subsequent labels indicate progressively decomposed levels of the signal. At the first level, "A1" represents the approximate (low-frequency) component, while the detailed (high-frequency) component is ignored for further decomposition. At the second level, "AA2" denotes the further approximation of the "A1" component, and so forth. This hierarchical decomposition ensures that each level captures distinct frequency bands, preserving both coarse and fine details of the signal [21].

By leveraging this approach, WPD provides a multi-resolution analysis that is crucial for identifying frequency-specific patterns associated with ASD. The hierarchical structure in Figure 3 highlights how each subsequent level refines the time-frequency characteristics of the signal, enabling more accurate feature extraction and classification [23].

$$\int_{-\infty}^{\infty} W_o(t)\mathrm{dt} = 1 \tag{4}$$

2.4. Statistical Features

At this stage, the feature extraction used is statistical data, namely mean, variance, skewness, and kurtosis. The four feature extractions are calculated mathematically. These feature extractions will be used as determining parameters, because the value of these statistical features has a different value for each subject, which will determine whether the subject is a normal subject or a subject with autism.

- Mean

$$\mu_n = \frac{1}{N}\sum_{n=1}^{N-1} x_n \tag{5}$$

- Variance

$$V = \sum_{i=1}^{N} \frac{(x_i - \bar{x})^2}{N-1} \tag{6}$$

- Skewness

$$Skew[X] = E\left[\left(\frac{x-\mu}{\sigma}\right)^3\right]$$
$$Skew\ [X] = \frac{E[x^3] - 3\mu\sigma^2 - \mu^3}{\sigma^3} \tag{7}$$

- Kurtosis

$$Kurt[X] = \frac{E[(x-\mu)^3]}{E[(x-\mu)^2]^2} \tag{8}$$

2.5. Random Forest Classification and Accuracy Calculation

In simulating classification, RF was chosen as the classification method due to its ability to handle high-dimensional data, robustness against overfitting, and effectiveness in working with imbalanced datasets. RF operates by constructing multiple decision trees during training and aggregating their outputs (via majority voting) to determine the final classification, which enhances both accuracy and generalization [6],[7]. RF is particularly advantageous in this study for its feature selection capability, ensuring that only the most relevant statistical features extracted through preprocessing are used. the system will undergo several stages before classifying and measuring the accuracy of the classification. With the input data of the feature extraction parameters, the RF system will remember a data set that will be used as a determining parameter in the classification [25]. For more details, here is the algorithm of RF classification:

- Data is inputted to the RF system to the training phase where subsets of the dataset are used to train the RF model. Specifically, two datasets representing normal (Data A) and ASD (Data B) subjects are used to define the classification boundaries. This step ensures the RF system can learn distinguishing patterns between the two groups.
- Then the RF system will perform training phase, the training phase carried out by the RF system is as follows:

$$\begin{gathered} \mathrm{A1M, A1V, A1S, A1K = A1} \\ \mathrm{A2M, A2V, A2S, A2K = A2} \\ \mathrm{B1M, B1V, B1S, B1K = B1} \\ \mathrm{B2M, B2V, B2S, B2K = B2} \end{gathered} \tag{9}$$

- Formula (9) describes the process of assigning statistical features (mean, variance, skewness, kurtosis) to specific conditions (Cam, Cav, Cas, Cak) for normal subjects and (Cbm, Cbv, Cbs, Cbk) for ASD subjects. These conditions represent thresholds based on feature ranges and are derived by comparing feature values across the two groups.

$$\begin{gathered} \mathrm{A1M \geq A2M = C_{am}} \\ \mathrm{A1V \geq A2V = C_{av}} \\ \mathrm{A1S \geq A2S = C_{as}} \\ \mathrm{A1K \geq A2K = C_{ak}} \end{gathered} \tag{10}$$

- Formula (10) establishes the condition for normal data by ensuring that feature values for normal subjects meet specific thresholds.

$$\begin{gathered} \mathrm{B1M \geq B2M = C_{bm}} \\ \mathrm{B1V \geq B2V = C_{bv}} \\ \mathrm{B1S \geq B2S = C_{bs}} \\ \mathrm{B1K \geq B2K = C_{bk}} \end{gathered} \tag{11}$$

- Formula (11) does the same for ASD data.

$$\{\mathrm{C_{am}, C_{av}, C_{as}, C_{ak}}\} \in \mathrm{A} \tag{12}$$

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$$\{C_{bm}, C_{bv}, C_{bs}, C_{bk}\} \in B$$

- Finally, Formula (12) integrates these conditions into a comprehensive classification rule that evaluates all feature thresholds, enabling the RF model to determine whether a given subject belongs to the normal or ASD group. These formulas collectively define the decision-making process within the RF algorithm and ensure consistency in classification outcomes.

3. RESULTS AND DISCUSSION

The results of this study demonstrate the effectiveness of the proposed framework in classifying ASD and normal subjects based on EEG signals. The preprocessing stage, which utilized ICA and WPD, significantly improved the quality of the EEG data by effectively removing artifacts and enhancing signal resolution. The extracted statistical features—mean, variance, skewness, and kurtosis—exhibited distinct patterns that differentiated ASD from normal subjects, providing strong indicators for classification.

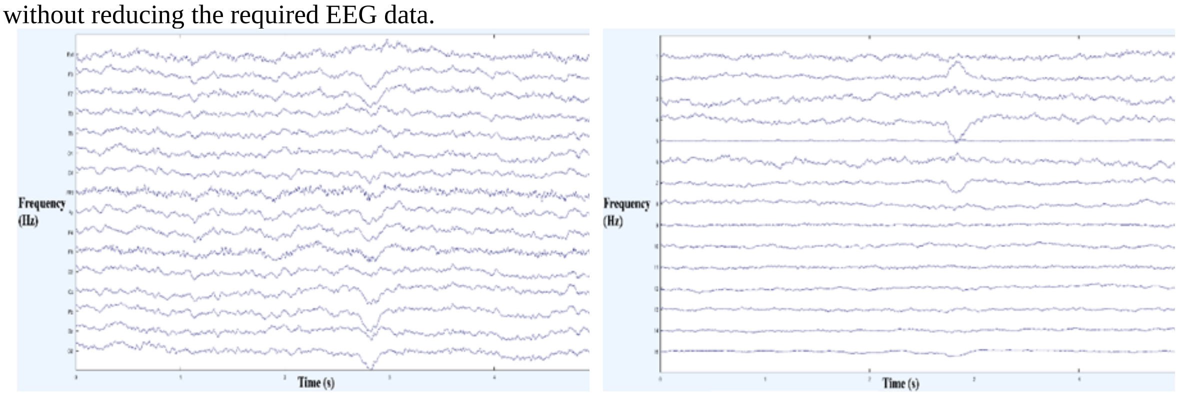
The RF classifier achieved an overall accuracy of 76.8%, indicating its robustness in handling the dataset despite challenges such as data imbalance. Notably, the model's performance was influenced by the limited number of samples, particularly in the normal group, which highlights the importance of balanced datasets in machine learning applications. The analysis revealed that the misclassification errors predominantly occurred in distinguishing normal subjects, likely due to the overlapping feature ranges in certain channels.

Fig. 4 illustrates the preprocessing results, showing the significant reduction in noise and artifact components after applying ICA. Fig. 5 depicts the WPD transformation results, highlighting the decomposition of signals into distinct frequency bands, which facilitated the extraction of meaningful features. The integration of these preprocessing techniques ensured that the RF model received high-quality input data, enhancing its classification performance.

Overall, the findings underscore the potential of combining ICA, WPD, and RF in developing reliable diagnostic tools for ASD. However, future research should explore strategies to address data imbalance, such as augmenting the dataset or employing advanced techniques like synthetic minority oversampling. The incorporation of additional features or alternative classifiers may also further improve diagnostic accuracy and reliability.

3.1. Preprocessing Results

At this stage, the data that has been inputted in the program will be sampled at 256 Hz, the function of sampling is to convert discrete signals into continuous signals without changing the existing data in the 256 Hz frequency range. Next, a notch filter is carried out which functions to minimize and even eliminate noise or artifacts that are still included in the required dataset signal. After that, ICA will eliminate unnecessary signals, without reducing the required EEG data.



(a) (b)

Fig. 4. Preprocessing Data (a) before using ICA (b) after using ICA

Fig. 4 illustrates the impact of applying ICA during preprocessing. In Fig. 4(a), the raw EEG signal is displayed, showing clear contamination from noise and artifacts such as muscle movements or electrical interference. After applying ICA, as shown in Fig. 4(b), the noise components are effectively removed, and the resulting signal highlights the independent brain-specific activity. This visualization underscores how ICA separates mixed signals into independent components, enabling the removal of non-brain-related activities and

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preserving the integrity of the EEG data for subsequent analysis. The process involves iteratively optimizing the statistical independence of the signal components, ensuring that the final output is a cleaner representation of the brain's electrical activity [21],[23].

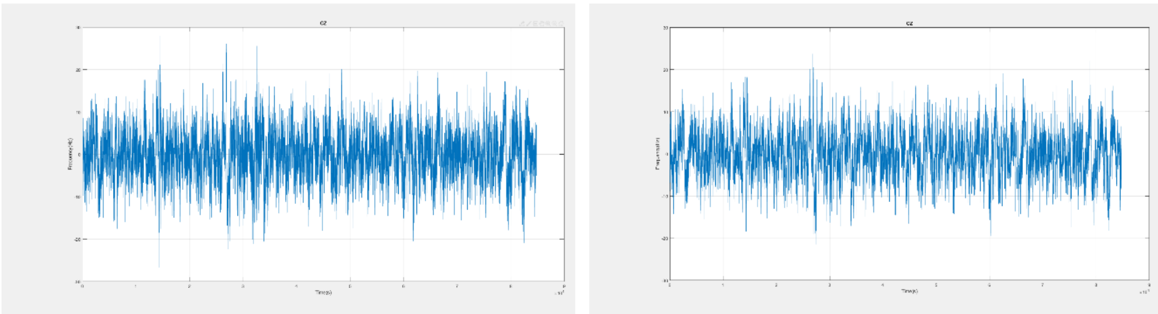
In fig. 4(b) is the signal in fig. 4(a) but has been pre-processed. The signal before pre-processing still has noise, artifacts, and the signal is still mixed between one source and another source, or between one node and another node. Noise and artifacts in fig. 4(a) are found in the amplitude of the signal, which in fig. 4(a) there are several signals that still have a high amplitude that does not match the original source signal. The unneeded signal in fig. 4(a) is the OZ signal, where the MATLAB system reads the entire node inputted in the original signal, but OZ is actually grounding the entire node at the time the data was taken, therefore OZ is an unwanted signal.

3.2. WPD Transformation Results

Fig. 5 illustrates the outcome of WPD applied to the preprocessed EEG signals. This figure highlights how the original signal is decomposed into progressively finer levels of frequency components. Each decomposition level serves to isolate specific frequency bands, which are essential for identifying patterns relevant to ASD classification. For instance, lower frequency bands may correlate with resting states, while higher frequency bands may reflect cognitive activity or artifacts.

Table 1 presents the statistical features (mean, variance, skewness, kurtosis) extracted from specific EEG channels such as AmerFP1, F3, and F7. These channels are strategically located in the frontal and temporal regions of the brain, which are known to be associated with cognitive and behavioral functions often affected in ASD. The calculated statistical features provide quantitative measures that distinguish ASD from normal subjects. For example, the variance indicates the range of signal fluctuation, while skewness and kurtosis capture the asymmetry and sharpness of the signal distribution, respectively. These features are critical for the RF classifier to determine patterns indicative of ASD.

At this stage, the input used in the MATLAB sub-program, Wavelet Analyzer, uses the signal output in the previous stage, the signal that has been pre-processed is transformed using Wavelet Packet Decomposition. The data used in this study is the third approximation data, the third approximation data can also be called the third level Wavelet Packet transformation.



(a) (b)

Fig. 5. Wavelet Packet Decomposition Data (a) before transformation WPD (b) after transformation WPD

3.3. Results of Statistical Features

The data used as classification parameters are the statistical features mean, variance, skewness, and kurtosis. These statistical features each have their own functionality. In the mean statistical feature, it functions to determine the even distribution of positive and negative frequency snapshots, so if the value approaching the mean is close to 0, then the number of snapshots that occur is even. In the variance statistical feature, it functions to determine the range of data used, so the greater the variance value, the more doubtful the results of other statistical features. In the skewness statistical feature, it determines the spread of the data. Finally, the kurtosis statistical feature determines the level of tapering or stability between one data and the next. In this research, here is an example of the statistical features that have been calculated:

Table 1. Statistical Feature Count Results

Channel	Mean	Variance	Skewness	Kurtosis
AmerFP1	0.0016258	2819.3004	0.3885692	12.62257
AmerF3	-0.0001603	1663.3798	-0.10881	14.31750
AmerF7	6.448E-05	1618.8645	-1.4870051	36.34590

3.4. Random Forest Classification Results

The RF algorithm operates by constructing an ensemble of decision trees, where each tree is trained on a random subset of the data and features [4]. This process ensures that the model is robust to overfitting and can effectively handle high-dimensional EEG features extracted from ICA and WPD preprocessing. RF's classification mechanism relies on aggregating the predictions of individual trees to make a final decision based on majority voting or averaging probabilities, which enhances both accuracy and interpretability [4].

In this study, RF was utilized to classify EEG signals into ASD and neurotypical categories [4]. The model achieved an overall accuracy of 76.8%, which is promising given the challenges of working with limited and imbalanced datasets. However, the study identified key challenges, such as variability in signal quality due to differences in recording conditions and the limited size of the dataset. These issues were addressed by employing robust preprocessing methods and careful feature selection, but further improvements are necessary to enhance generalizability.

To overcome the challenges of data imbalance and variance, future efforts could involve increasing the dataset size through additional data collection or employing data augmentation techniques such as synthetic data generation [5]. Techniques like oversampling, undersampling, or class weighting could also be incorporated to balance the dataset. Furthermore, exploring advanced algorithms, such as deep learning models with regularization techniques, may offer better handling of small and imbalanced datasets while improving classification performance [6].

While RF demonstrated effective classification, integrating complementary approaches, such as combining RF with other machine learning models (e.g., boosting algorithms), could further improve the robustness of ASD diagnosis. Addressing these challenges and incorporating these strategies will contribute to more reliable and scalable EEG-based diagnostic frameworks.

4. CONCLUSION

- This study successfully demonstrated the use of ICA and WPD as effective preprocessing methods for EEG-based ASD diagnosis, combined with RF for classification. The research achieved an accuracy of 76.8%, highlighting the potential of this approach for early ASD detection. However, challenges such as data imbalance and variability in signal quality were identified, which require further investigation.
- Future research should focus on addressing these limitations by increasing the size and diversity of the dataset, employing advanced data augmentation techniques, and exploring alternative classification methods such as deep learning models. Additionally, efforts to improve the robustness of the diagnostic framework, such as integrating hybrid machine learning approaches and optimizing feature extraction techniques, are recommended. These developments will enhance the scalability and applicability of EEG-based diagnostic tools for ASD, contributing to more accurate and reliable early detection methods.

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