Intellectual Development Disorder Classification by Machine Learning using EEG

Dung Nguyen Viet, *Fellow, IEEE*, Chuyen Mai Tat, and Khuong Truong Gia, *Member, IEEE*

***Abstract*— This study investigates the classification of EEG signals to differentiate between individuals diagnosed with Intellectual Development Disorder (IDD) and Typically Developing Controls (TDC). The dataset comprises 14 subjects, with seven diagnosed with IDD and seven as TDC. The average age of IDD and TDC subjects is 28.28 ± 2.05 and 21.28 ± 1.60 years, respectively. EEG signals were recorded using the Emotive Epoch+ device at a sampling frequency of 128 Hz from 14 electrodes positioned according to the international 10-20 system. Each subject's EEG data was collected for 2 minutes under resting conditions and 2 minutes during music stimuli. Feature extraction was performed using the Daubechies wavelet family, focusing on energy, standard deviation, and average values. We evaluated the performance of 11 classifiers: K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Nu-Support Vector Machine (NuSVM), Decision Tree, Random Forest, AdaBoost, Gradient Boosting Machine (GBM), Gaussian Naive Bayes, Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), and Logistic Regression. The highest classification accuracy was achieved with QDA and GBM when using all features, while the results when combining features are fluctuating and decreasing. Our findings demonstrate the effectiveness of wavelet-based feature extraction combined with advanced classifiers in distinguishing between IDD and TDC individuals based on EEG signals.**

***Index Terms*— Machine Learning, Feature extraction, EEG, Classification, Wavelet transform**

I. Introduction

Electroencephalography (EEG) is a widely used neuroimaging technique that measures electrical activity in the brain. It provides valuable insights into brain function and is commonly employed in diagnosing and monitoring neurological conditions. In recent years, EEG signal analysis has gained significant attention in the field of machine learning, particularly for classifying different cognitive and developmental disorders. One such disorder is Intellectual Development Disorder (IDD), which affects cognitive functioning and adaptive behavior. Early and accurate diagnosis of IDD is crucial for providing appropriate interventions and support.

Author Dung Viet Nguyen. He is Dean of Electronics Department, School of Electric and Electronic Engineering, Hanoi University of Science and Technology (e-mail: dung.nguyenviet1@hust.edu.vn).

Author Chuyen Mai Tat. He is a student of Advanced Program of Biomedical Engineering, Electronics Department, School of Electric and Electronic Engineering, Hanoi University of Science and Technology (e-mail: chuyen.mt213657@sis.hust.edu.vn).

Author Khuong Truong Gia. He is a student of Advanced Program of Biomedical Engineering, Electronics Department, School of Electric and Electronic Engineering, Hanoi University of Science and Technology (e-mail: khuong.tg213673@sis.hust.edu.vn).

The differentiation between individuals with IDD and Typically Developing Controls (TDC) using EEG signals presents a unique challenge due to the subtle and complex nature of brain activity patterns. Traditional diagnostic methods primarily rely on behavioral assessments and standardized tests, which can be subjective and time-consuming. Therefore, there is a growing interest in developing automated approaches that leverage machine learning techniques to analyze EEG data for more objective and efficient diagnosis.

Wavelet transform is a powerful tool for analyzing non-stationary signals such as EEG. The Daubechies wavelet family, in particular, has been widely used for feature extraction in EEG signal processing due to its ability to capture both time and frequency information. In this study, we employ the Daubechies wavelet family to extract features such as energy, standard deviation, and average from EEG signals collected from individuals with IDD and TDC. These features serve as inputs to various classifiers to distinguish between the two groups.

We evaluate the performance of 11 different classifiers: K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Nu-Support Vector Machine (NuSVM), Decision Tree, Random Forest, AdaBoost, Gradient Boosting Machine (GBM), Gaussian Naive Bayes, Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), and Logistic Regression. The goal is to identify the most effective classifier and feature combination for accurate differentiation between IDD and TDC individuals.

This paper is structured as follows: Section 2 provides an overview of related work in EEG signal classification and the use of machine learning for diagnosing developmental disorders. Section 3 describes the materials and methods used in this study, including data collection, feature extraction, and classification techniques. Section 4 presents the results of the classification experiments. Section 5 discusses the findings and their implications. Finally, Section 6 concludes the study and suggests directions for future research.

By leveraging advanced machine learning techniques and wavelet-based feature extraction, this study aims to contribute to the development of reliable and efficient diagnostic tools for identifying IDD based on EEG signals.

II. Back ground

A. Machine Learning for EEG signal classification

Electroencephalography (EEG) is a widely used technique for capturing the electrical activity of the brain, providing valuable insights into various cognitive and emotional states. The classification of EEG signals using machine learning has become a significant area of research due to its potential applications in brain-computer interfaces (BCIs), neurological disorder diagnosis, and emotion recognition.

Researchers have explored numerous machine learning algorithms for classifying EEG signals. Support Vector Machines (SVM), Neural Networks (NN), K-Nearest Neighbors (K-NN), and Deep Learning Networks (DLN) are some of the commonly used methods. Each algorithm has its strengths and challenges in dealing with the complexity and variability of EEG data.

One of the critical aspects of EEG classification is feature extraction, which involves transforming the raw EEG signals into a set of meaningful and discriminative features. Various methods such as Power Spectral Density (PSD), Principal Component Analysis (PCA), Independent Component Analysis (ICA), and wavelet transforms have been employed for this purpose. Among these, the Discrete Wavelet Transform (DWT) using Daubechies wavelets has gained popularity due to its ability to capture both time and frequency information of the non-stationary EEG signals.

B. Discrete Wavelet Transform (DWT) for feature extraction

The Discrete Wavelet Transform (DWT) is a powerful signal processing technique that has been widely used in various fields, including biomedical engineering, for the analysis of non-stationary signals such as Electroencephalogram (EEG). DWT provides a time-frequency representation of the signal, allowing for the decomposition of the signal into different frequency components with varying resolutions.

a) Wavelet Decomposition: The DWT decomposes a signal into a set of basis functions known as wavelets. This process involves recursively applying high-pass and low-pass filters to the signal, thereby splitting it into approximation (low-frequency) and detail (high-frequency) coefficients. The approximation coefficients capture the general trend of the signal, while the detail coefficients reveal the fine details and rapid changes.

The decomposition is performed in multiple levels, where the approximation coefficients from one level are further decomposed into new approximation and detail coefficients in the subsequent level. This hierarchical process continues until the desired level of decomposition is reached. For EEG signals, this multi-resolution analysis is particularly beneficial as it allows the capture of both transient and stationary characteristics of brain activity.

b) Daubechies Wavelet: In our study, we utilized the Daubechies wavelet, specifically the fourth-order Daubechies wavelet (db4). Daubechies wavelets are a family of orthogonal wavelets characterized by their compact support and smoothness, making them well-suited for signal processing tasks. The db4 wavelet, in particular, strikes a balance between capturing fine details and maintaining computational efficiency.

c) Mathematical Formulation: Mathematically, the DWT of a signal

$$x(t) \tag{1}$$

can be expressed as:

$$x(t) = \sum_{k} a_k \psi_k(t) + \sum_{j\geq 1} \sum_{k} d_j, k\psi_{j,k}(t) \tag{2}$$

where a_k are the approximation coefficients, d_j, k are the detail coefficients, $\psi_{j,k}(t)$ are the scaling functions, and $\psi_{j,k}(t)$ are the wavelet functions at different scales j and positions k.

d) Applications in EEG Analysis: For EEG signal analysis, the DWT is particularly advantageous due to its ability to handle the non-stationary nature of the signals. By decomposing the EEG signals into different frequency bands, DWT enables the extraction of meaningful features that reflect various aspects of brain activity. Features such as energy, standard deviation, and average value of the wavelet coefficients can be derived from the decomposed signals, providing critical inputs for machine learning algorithms used in EEG classification.

For instance, Mangala Gowri S G and Dr. Cyril Prasanna Raj P [**3**] used DWT for decomposing EEG signals into 8 levels using ”db4” wavelet. They extracted features such as Energy Density and Power Spectral Density, which were then classified using Artificial Neural Networks (ANNs) to differentiate between various emotional states of the subjects.

Murugappan et al. implemented DWT for feature extraction and used a neural network ensemble algorithm for classification, achieving highest accuracy of 0.88. Similarly, Abdulhamit Subasi et al. combined DWT with statistical feature extraction methods like PCA, ICA, and LDA, and used SVMs for classification, demonstrating promising results in detecting epileptic patterns from EEG signal

In our study, we recorded EEG signals from subjects under different conditions and applied the DWT to extract features from the signals. The use of the db4 wavelet allowed us to capture the intricate details of the EEG signals across multiple scales, facilitating the effective classification of subjects into Intellectual Development Disorder (IDD) and Typically Developing Controls (TDC) categories.

By leveraging the capabilities of DWT and the Daubechies wavelet, our approach enhances the ability to detect subtle differences in EEG signals, thereby improving the accuracy of machine learning-based classification models.

III. Methodology

A. Dataset description

EEG signals were recorded for fourteen participants (seven TDC and seven IDD) during theexperimental tests using the Emotiv Epoc+ data acquisition system. This is a dry-electrode, wireless, portable device. The device has 16 electrodes (14 data channels and two reference channels), which are positioned according to the international 10–20 system. The channel configuration of the device includes AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4 The raw and pre-processed data includes 14-channel EEG data for two

minutes of restingstate followed by two minutes of music state, recorded at 128 Hz sampling rate. The additional behavioural information such as IQ, SQ, music apprehension and facial expressions (emotion) for IDD participants is provided in the file "QualitativeData.xlsx". The entire dataset is hosted on Mendeley data (DOI) and is presented as follows: The raw EEG data is provided in EEGLAB .fdt and .set file format where .fdt file contains the raw data and .set file contains the metadata information (number of channels, sampling frequency, etc.). The raw data from the acquisition device has been modified to provide only the relevant 14-channel EEG recording and has been segmented into 'Rest' and 'Music' state for easy analysis.
The raw TDC data is arranged as:

`Data/RawData/RawData_TDC/Music and Rest`

The raw IDD data is arranged as:

`Data/RawData/RawData_IDD/Music and Rest`

The pre-processed and filtered EEG data is provided in MATLAB's '.mat' file format for easier post-processing and analysis. The raw EEG data can be processed by using the automated pre-processing pipeline, as proposed and explained later in this paper. The clean TDC data is arranged as:

`Data/CleanData/CleanData_TDC/Music and Rest`

The clean IDD data is arranged as:

`Data/CleanData/CleanData_IDD/Music and Rest`

B. Preprocessing

The Discrete Wavelet Transform (DWT) algorithm decomposes a given signal into approximation and detail coefficients to obtain a first level of decomposition [**1**]. Initially, the signal is divided into two parts: approximation coefficients (cA) and detail coefficients (cD). The approximation coefficients represent the low-frequency components of the signal, capturing the overall trend, while the detail coefficients represent the high-frequency components, capturing the fine details and rapid changes.

At each level of decomposition, the approximation coefficients are further decomposed into the next level of approximation and detail coefficients. This process is repeated iteratively until the desired level of decomposition is reached. Each level of decomposition corresponds to a specific frequency band, allowing the signal to be analyzed at different frequency resolutions.

For example, at the first level of decomposition, the signal S is divided into $cA1$ (approximation coefficients) and $cD1$ (detail coefficients). At the second level, $cA1$ is further decomposed into $cA2$ and $cD2$, and this process continues for subsequent levels. This multi-level decomposition provides a hierarchical framework that efficiently captures both the coarse and fine features of the signal across various frequency bands.

The features extracted from the detail coefficients at various levels can reveal the characteristics of the time series and are instrumental in automated systems such as seizure detection. By analyzing the energy, mean, and standard deviation of these coefficients, significant insights into the underlying patterns of EEG signals can be obtained, enhancing the accuracy and reliability of classification algorithms.

For signal decomposition, we used fourth-order Daubechies wavelet (db4) with maximum level decomposition is used as shown in figure . DWT decomposed the signal into high and low-frequency sub-bands till maximum decomposition level is reached. In our case DWT decomposes signal up to 6 levels as shown in figure . The coefficients of high frequencies are called Detail coefficients (cD) and low frequencies coefficients are called as Approximation coefficients (cA). Table shows the decomposition level and respective frequency bands. Different statistical features such as energy, mean, standard deviation are calculated from the wavelet coefficient.

Coefficients	Frequency Bands (Hz)	Wave Type
D1	32-64	Filtered
D2	16-32	Beta Wave
D3	8-16	Alpha Wave
D4	4-8	Theta Wave
D5	2-4	Delta Wave
D6	1-2	Delta Wave
A6	0.5-1	Filtered

TABLE I
FREQUENCY BANDS AND WAVE TYPES FOR DIFFERENT COEFFICIENTS.

C. Classification

In our EEG classification task using machine learning, we fed the features extracted after preprocessing into various classification algorithms. These models were trained on a training set and evaluated on a test set to assess their performance. Typically, hyperparameter tuning is a critical step in training machine learning models, as it can significantly impact the model's accuracy and generalizability. However, to ensure a fair comparison across different algorithms, we decided to use the default parameters and models provided by the scikit-learn library without any hyperparameter tuning.

This approach was chosen to maintain consistency and objectivity in our evaluations. By using default settings, we avoid any potential biases that could arise from optimizing parameters for specific models, which might inadvertently favor one algorithm over another. Our focus was on evaluating the inherent performance of each classifier with the given feature set, rather than fine-tuning each model to its optimal configuration.

The classifiers used in this study included K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Nu-Support Vector Machine (NuSVM), Decision Tree, Random Forest, AdaBoost, Gradient Boosting Machine (GBM), Gaussian Naive Bayes, Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), and Logistic Regression. Each classifier was implemented using the scikit-learn library's default settings. The training process involved splitting the dataset into training and test sets, training each model on the training set, and then evaluating its performance on the test set. This methodology allowed us to compare the performance of different classifiers on the same footing, providing a clear understanding of how well each algorithm performs with the extracted features from the EEG signals. The results highlight the strengths and weaknesses of each classifier in the context of our specific task and dataset, offering insights into their applicability for EEG signal classification without the influence of hyperparameter optimization.

D. Evaluation metrics

To ensure robustness and generalization capability, cross-validation techniques were employed to evaluate model performance on held-out validation data. Kfold cross-validation was performed to partition the dataset into multiple subsets, with each subset used in turn as the validation set while the remaining data was used for training. This allowed for comprehensive assessment of model performance across diverse subsets of the data, reducing the risk of overfitting and bias in model evaluation.

K-Fold cross-validation is applied in such a way, out of 14 subjects 12 are used for training and 2 for testing. Between the two subjects used in testing, it was made compulsory that one subject from each class is taken. This procedure is repeated until all the subjects experienced the testing stage once. We used Accuracy, Precision, Recall and F1-score to evaluate our models performance

Accuracy measures the proportion of correct predictions made by the model across the entire dataset.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{3}$$

Precision measures the proportion of true positive predictions among all positive predictions made by the model.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{4}$$

Recall measures the proportion of true positive predictions among all actual positive instances

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{5}$$

F1-score calculated as the harmonic mean of precision and recall

$$\text{F1-score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{6}$$

IV. Experiment and Results

A. General experiment

The initial data collection involves recording EEG signals from 14 subjects, each using 14 channels (electrodes), with a total of 15360 data points per channel. This corresponds to a 120-second recording period sampled at a rate of 128 Hz (128 samples per second × 120 seconds = 15360 samples) which has demostrated in the Figure 1. This extensive dataset serves as the foundation for subsequent signal processing and feature extraction steps.

The preprocessing phase begins with segmenting the continuous EEG signals into 4-second windows. Given the sampling rate of 128 Hz, each 4-second segment contains 512 data points (128 Hz × 4 seconds = 512 samples). After segmentation, the data dimensions are reordered to (14, 30, 14, 512), where 14 represents the number of subjects, 30 represents the number of 4-second segments within the 120-second recording, 14 represents the channels, and 512 represents the data points per segment. This reordering facilitates more efficient processing in the following steps.

Wavelet decomposition is then applied to each 512-length segment to extract wavelet coefficients using the Discrete Wavelet Transform (DWT). The DWT decomposition level is set to 6, resulting in six sets of coefficients per segment. Consequently, the data dimensions expand to (14, 30, 14, 6, x), where x varies depending on the length of the wavelet coefficients for each level. This decomposition allows for a detailed analysis of the EEG signals across different frequency bands, which is essential for accurate feature extraction.

Feature extraction focuses on deriving meaningful statistical characteristics from the wavelet coefficients. For each decomposition level and each electrode, three key features are extracted: the average (mean value), the standard deviation, and the energy of the wavelet coefficients. Each feature results in a feature array of length 84 (14 channels × 6 decomposition levels). These features capture the essential dynamics of the EEG signals, providing valuable input for classification.

The classification process is conducted in two stages: separate and combined feature classification. In the separate classification stage, each extracted feature type (average, standard deviation, and energy) is independently fed into classifiers. This involves training separate classifiers for each feature type and evaluating their performance based on accuracy and F1-score. This step helps identify the most discriminative features for EEG signal classification.

In the combined classification stage, the three feature sets are concatenated to form a comprehensive feature vector of length 252 (84 + 84 + 84). This combined feature vector leverages the complementary information from all feature types, enhancing the classifier's ability to distinguish between different classes of EEG signals. The combined feature vector is used to train classifiers, which are subsequently evaluated for their overall performance in terms of accuracy and F1-score. This approach aims to improve classification accuracy by utilizing the synergistic effects of multiple features.

B. Trainging process

The training process for evaluating classifiers on EEG signal data involves several critical steps to ensure robust and accurate performance metrics. This process leverages stratified K-fold cross-validation, data standardization, and shuffling to mitigate overfitting and improve generalization.

1) Stratified K-Fold Cross-Validation: Stratified K-fold cross-validation is employed to partition the dataset into k folds (in this case, k = 7) while preserving the proportion of each class within each fold. This method ensures that each fold is representative of the entire dataset's class distribution, which is crucial for maintaining balance during training and testing phases. For each fold, the classifier is trained on $k-1$ folds and tested on the remaining fold. This process is repeated k times, with each fold serving as the test set once. The advantage of this approach is that it provides a more reliable estimate of

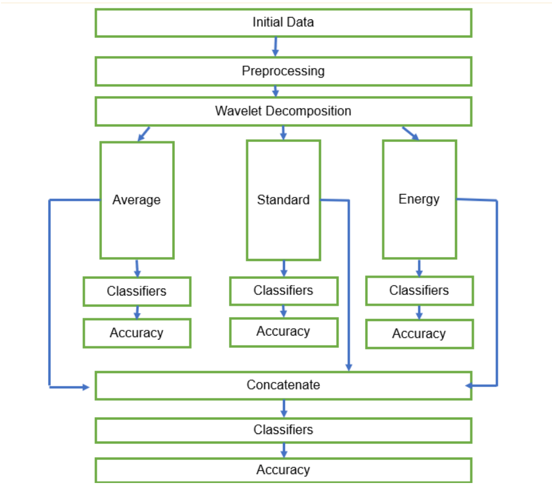

Fig. 1. Algorithm flowchart

the classifier's performance by utilizing the entire dataset for both training and testing.

2) Data Standardization: Standardization is a preprocessing step where the features are scaled to have zero mean and unit variance. This step is critical for many machine learning algorithms, particularly those that rely on distance metrics, such as Support Vector Machines (SVM) and Neural Networks. Standardization ensures that all features contribute equally to the model's performance, preventing features with larger magnitudes from dominating the learning process. In this training process, a StandardScaler is fitted on the training data and applied to both the training and test data, ensuring that the test data is scaled based on the same parameters as the training data.

3) Shuffling: Shuffling the training data before fitting the classifier is an important step to introduce randomness and reduce the chance of the model learning any underlying order in the data. This step helps to improve the generalization of the model, making it more robust to variations in the data.

4) Classifier Training and Evaluation: For each fold, the classifier is trained on the standardized and shuffled training data. The trained model is then used to predict the labels of the test data. The accuracy and F1-scores are calculated for each fold, and their mean and standard deviation are computed across all folds. This provides a comprehensive view of the classifier's performance, indicating not only its average effectiveness but also the variability of its performance across different subsets of the data.

5) Aggregation of Results: The average and standard deviation of accuracy and F1-scores for each classifier are recorded, allowing for a comparison of different classifiers. This aggregated information helps in identifying the most reliable and robust classifier for the given EEG signal classification task.

C. Results and Discussion

In this study, a discrete wavelet-based approach is employed for diagnosing intellectual and developmental disabilities. The Daubechies wavelet of order 4 (db4) is utilized to decompose the signals into their maximum levels. Various features are extracted from the wavelet coefficients, and multiple classifiers are applied to these features both individually and in combination.

Tables IV to XI provide a comprehensive summary of the average accuracy, standard deviation of accuracy, average F1-score, and standard deviation of F1-score for various machine learning algorithms. These evaluations are based on using the mean, standard deviation, and energy coefficients of the Daubechies wavelet (dB4), both individually and in combination, under rest and music conditions. Tables X and XI summarize the overall accuracy and F1-score across different scenarios, providing a clear comparison of the classifiers' performance.

In the rest condition, Quadratic Discriminant Analysis (QDA) and Gradient Boosting (GB) demonstrate superior performance when using the mean feature. QDA achieves an impressive accuracy of 91.90% and an F1-score of 89.86%. Although GB reaches an accuracy of 87.38%, its F1-score is significantly lower at 22.62%. When all three features are combined, the overall performance declines slightly. GB maintains the highest accuracy at 76.67% with an F1-score of 77.29%. However, K-Nearest Neighbors (KNN) surpasses QDA, achieving an accuracy of 73.10% and an F1-score of 79.64%.

Similarly, in the music condition, QDA and GB again lead with the highest accuracy and F1-scores: QDA with 91.90% accuracy and 90.28% F1-score, and GB with 87.86% accuracy and 88.96% F1-score. However, when features are combined, Linear Discriminant Analysis (LDA) emerges as the top performer with an accuracy of 79.29% and an F1-score of 83.29%. Logistic Regression (LR) follows with an accuracy of 76.67% and an F1-score of 79.26%.

These results indicate that machine learning algorithms generally achieve high performance when using the mean feature of the dB4 wavelets. However, the performance is not as high when using the standard deviation and energy features, leading to a slight decline when combining features. Additionally, the experimental results show that the environment (rest vs. music conditions) significantly influences the classification performance of the algorithms. Despite the highest results being returned by the average feature in both conditions, the combination of features changes the ranking of the algorithms, highlighting the environment's impact on classification outcomes.

TABLE II
PERFORMANCE OBTAINED FROM MEAN OF COEFFICIENT OF DB4 WAVELET DURING REST CONDITION

	Acc Avg	Acc Std.	F1 Avg	F1 Std.
KNN	70.24	10.48	77.43	6.34
c-SVM	79.05	**20.95**	79.45	22.10
nu-SVM	81.43	20.77	81.06	**22.36**
DT	66.43	8.84	68.12	6.79
RF	80.24	13.87	80.24	12.94
AB	43.81	12.04	42.91	15.72
GB	**87.38**	8.30	**88.50**	6.90
NB	45.71	8.99	9.19	11.31
LDA	50.95	2.80	53.15	2.35
QDA	**91.90**	9.36	**89.86**	13.11
LR	48.81	3.75	50.56	2.75

TABLE III
PERFORMANCE OBTAINED FROM ENEGY OF COEFFICIENT OF DB4 WAVELET DURING REST CONDITION

	Acc Avg	Acc Std.	F1 Avg	F1 Std.
KNN	**71.90**	22.31	**77.93**	16.07
c-SVM	55.95	9.67	55.41	23.00
nu-SVM	64.29	29.32	66.08	30.08
DT	62.86	24.72	64.69	23.21
RF	55.71	25.66	55.16	25.29
AB	65.24	26.40	63.26	28.19
GB	**71.90**	26.33	**73.96**	22.76
NB	51.19	8.10	11.96	18.05
LDA	64.29	25.15	65.87	29.60
QDA	**69.52**	20.73	44.28	42.33
LR	67.38	24.67	**73.61**	19.23

TABLE IV
PERFORMANCE OBTAINED FROM STANDARD DEVIATION OF COEFFICIENT OF DB4 WAVELET DURING REST CONDITION

	Acc Avg	Acc Std.	F1 Avg	F1 Std.
KNN	69.05	20.76	**75.98**	13.83
c-SVM	64.05	30.90	67.01	29.95
nu-SVM	62.14	29.46	63.17	28.80
DT	68.33	23.60	63.76	29.48
RF	57.38	22.94	56.32	19.62
AB	60.00	26.43	60.52	27.59
GB	**71.43**	21.44	70.87	21.20
NB	51.90	8.66	14.02	20.67
LDA	64.29	25.29	64.75	28.51
QDA	66.90	18.76	39.73	38.98
LR	**71.19**	24.26	**75.20**	18.68

TABLE V
PERFORMANCE OBTAINED FROM COMBINATION OF MEAN, ENERGY, STANDARD DEVIATION OF COEFFICIENT OF DB4 WAVELET DURING REST CONDITION

	Acc Avg	Acc Std.	F1 Avg	F1 Std.
KNN	**73.10**	14.54	**79.64**	9.12
c-SVM	66.90	23.34	70.26	20.23
nu-SVM	68.33	23.03	68.78	23.24
DT	57.38	21.27	47.13	33.67
RF	56.90	23.91	56.38	25.10
AB	63.33	27.02	61.11	30.51
GB	**76.67**	22.36	**77.29**	21.85
NB	51.19	8.58	11.53	19.62
LDA	58.57	20.11	64.16	21.00
QDA	52.62	8.68	63.66	41.02
LR	65.00	26.44	67.16	23.89

TABLE VI
PERFORMANCE OBTAINED FROM MEAN OF COEFFICIENT OF DB4 WAVELET DURING MUSIC CONDITION

	Acc Avg	Acc Std.	F1 Avg	F1 Std.
KNN	70.95	10.91	78.03	6.77
c-SVM	80.00	15.53	80.37	15.48
nu-SVM	81.43	14.18	82.09	13.90
DT	72.62	9.87	71.96	13.45
RF	81.43	12.64	81.58	13.60
AB	57.38	11.12	58.37	12.25
GB	**87.86**	7.54	**88.96**	6.24
NB	55.95	18.25	56.93	20.27
LDA	56.19	4.15	58.48	5.46
QDA	**91.90**	8.14	**90.28**	10.34
LR	54.29	4.53	56.60	6.10

V. CONCLUSION

In this study, we have explored the use of machine learning techniques for the classification of EEG signals to differentiate between individuals with Intellectual Development Disorder (IDD) and Typically Developing Controls (TDC). By employing the Daubechies wavelet transform, we were able to extract meaningful features, specifically energy, standard deviation, and average, from the EEG signals. These features were used as inputs to a variety of classifiers, including K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Nu-Support Vector Machine (NuSVM), Decision Tree, Random Forest, AdaBoost, Gradient Boosting Machine (GBM), Gaussian Naive Bayes, Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), and Logistic Regression.

Our experimental results demonstrate that certain classifiers, particularly Quadratic Discriminant Analysis (QDA) and Gradient Boosting Machine (GBM), perform better when using the full set of features. Additionally, KNN, C-SVM, and NuSVM showed promising results when features were combined. These findings suggest that wavelet-based feature extraction, combined with appropriate machine learning classifiers, can provide a reliable and efficient approach for distinguishing between IDD and TDC individuals.

One of the significant contributions of this study is the comparative analysis of various classifiers in the context of EEG signal classification for developmental disorders. By utilizing default parameters from the scikit-learn library, we ensured a fair comparison across different classifiers, providing valuable insights into their performance without extensive parameter tuning.

While our study presents encouraging results, there are several avenues for future research. Firstly, the use of more advanced feature selection techniques could further enhance the classification accuracy. Secondly, incorporating additional data, such as other neuroimaging modalities or behavioral assessments, may provide a more comprehensive diagnostic approach. Lastly, exploring deep learning methods could potentially yield even better performance due to their ability to automatically learn complex features from raw EEG signals.

In conclusion, this study underscores the potential of wavelet-based feature extraction and machine learning in the diagnosis of IDD. The promising results achieved with various classifiers highlight the importance of selecting appropriate features and models for accurate EEG signal classification. We hope that our findings will contribute to the development of automated diagnostic tools, ultimately improving the early identification and intervention for individuals with developmental disorders.

VI. FUTURE DIRECTIONS AND CHALLENGES

While this study has demonstrated the effectiveness of wavelet-based feature extraction and machine learning classifiers in distinguishing between individuals with Intellectual Development Disorder (IDD) and Typically Developing Controls (TDC), there are several future directions and challenges that need to be addressed to further advance this field.

TABLE VII
PERFORMANCE OBTAINED FROM ENERGY OF COEFFICIENT OF DB4 WAVELET DURING MUSIC CONDITION

	Acc Avg	Acc Std.	F1 Avg	F1 Std.
KNN	68.81	19.77	**75.96**	13.98
c-SVM	65.24	22.03	66.51	24.84
nu-SVM	61.67	22.27	62.56	26.82
DT	56.90	26.06	62.62	28.18
RF	68.57	24.81	71.39	28.27
AB	65.48	25.27	72.12	23.50
GB	65.71	22.87	71.16	21.70
NB	51.43	24.73	43.27	26.85
LDA	65.71	17.16	73.56	10.39
QDA	63.81	24.64	40.53	40.75
LR	**75.95**	15.81	**78.36**	14.63

TABLE VIII
PERFORMANCE OBTAINED FROM STANDARD DEVIATION OF COEFFICIENT OF DB4 WAVELET DURING REST CONDITION

	Acc Avg	Acc Std.	F1 Avg	F1 Std.
KNN	64.76	21.77	**73.73**	14.93
c-SVM	66.90	21.97	69.96	22.46
nu-SVM	64.05	22.95	65.73	25.66
DT	56.43	26.25	64.75	23.80
RF	71.19	24.51	73.04	26.91
AB	62.86	12.17	62.42	24.22
GB	65.95	23.14	71.55	22.00
NB	57.62	23.50	52.78	26.33
LDA	64.52	15.73	69.80	13.91
QDA	55.71	18.06	27.00	31.79
LR	**79.52**	15.32	81.59	12.34

TABLE IX
PERFORMANCE OBTAINED FROM COMBINATION OF MEAN, ENERGY, STANDARD DEVIATION OF COEFFICIENT OF DB4 WAVELET DURING MUSIC CONDITION

	Acc Avg	Acc Std.	F1 Avg	F1 Std.
KNN	67.62	18.06	75.49	12.01
c-SVM	67.86	21.43	67.95	24.10
nu-SVM	65.95	24.18	65.14	28.23
DT	54.76	27.54	64.21	23.69
RF	66.19	24.38	69.60	27.68
AB	67.14	24.92	71.81	26.46
GB	71.19	22.62	74.62	20.96
NB	55.48	23.68	50.01	26.62
LDA	**79.29**	14.80	**83.29**	10.06
QDA	53.33	11.62	43.71	26.32
LR	**76.67**	15.71	**79.26**	12.90

TABLE X
PERFORMANCE OBTAINED FROM COMBINATION OF MEAN, ENERGY, STANDARD DEVIATION OF COEFFICIENT OF DB4 WAVELET DURING MUSIC CONDITION

	Average		Std		Energy		Combined	
	Acc	F1	Acc	F1	Acc	F1	Acc	F1
KNN	70.24	77.43	71.90	77.93	69.05	75.98	**73.10**	**79.64**
c-SVM	79.05	21.43	55.95	55.41	64.05	67.01	66.90	70.26
nu-SVM	81.43	24.18	64.29	66.08	62.14	63.17	68.33	68.78
DT	66.43	27.54	62.86	64.69	68.33	63.76	57.38	47.13
RF	80.24	24.38	55.71	55.16	57.38	56.32	56.90	56.38
AB	43.81	24.92	65.24	63.26	60.00	60.52	63.33	61.11
GB	**87.38**	22.62	71.90	73.96	71.43	70.87	**76.67**	**77.29**
NB	45.71	23.68	51.19	11.96	51.90	14.02	51.19	11.53
LDA	50.95	53.15	64.29	65.87	64.29	64.75	58.57	64.16
QDA	**91.90**	**89.86**	69.52	44.28	66.90	39.73	52.62	63.66
LR	48.81	50.56	67.38	73.61	71.19	75.20	65.00	67.16

A. Future Directions

a) Time-Domain Signal Analysis: In addition to frequency-domain features obtained through wavelet transforms, analyzing the EEG signals in the time domain could provide complementary information. Features such as signal amplitude, phase, and time-based patterns may offer additional insights that can enhance the classification performance. Combining time-domain and frequency-domain features could lead to a more comprehensive understanding of EEG signals.

b) Advanced Feature Selection Techniques: Employing more sophisticated feature selection methods, such as recursive feature elimination (RFE) or genetic algorithms, could help identify the most relevant features and improve classification accuracy. These techniques can reduce the dimensionality of the feature space and mitigate the risk of overfitting.

c) Integration of Multimodal Data: Combining EEG data with other types of neuroimaging data, such as functional MRI or PET scans, and behavioral assessments could provide a holistic view of brain activity. Multimodal approaches have the potential to enhance diagnostic accuracy and offer deeper insights into the neurobiological underpinnings of IDD.

d) Deep Learning Approaches: Exploring deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), could further improve the classification performance. These models have the ability to automatically learn hierarchical features from raw EEG signals, potentially capturing complex patterns that traditional methods might miss.

e) Personalized Models: Developing personalized classification models that account for individual variability in EEG patterns could improve diagnostic accuracy. Personalized models can be tailored to specific subjects, considering factors such as age, gender, and comorbidities, to provide more precise predictions.

B. Challenges

a) Data Variability: EEG data is inherently variable due to factors such as electrode placement, environmental noise, and individual differences in brain activity. Developing robust preprocessing and normalization techniques to handle this variability remains a challenge.

b) Small Sample Sizes: Many studies, including this one, often have limited sample sizes, which can affect the generalizability of the findings. Increasing the sample size through collaborative efforts and data sharing among research institutions could help overcome this limitation.

c) Real-Time Implementation: Translating these machine learning models into real-time diagnostic tools presents significant technical challenges. Ensuring low-latency processing, user-friendly interfaces, and reliable performance in clinical settings are critical steps for practical implementation.

In summary, while the current study has made significant strides in using wavelet-based features and machine learning for EEG classification, addressing these future directions and challenges is essential for advancing the field. By integrating time-domain analysis, employing advanced feature selection, leveraging multimodal data, exploring deep learning approaches, and considering personalized models, we can

TABLE XI
PERFORMANCE OBTAINED FROM COMBINATION OF MEAN, ENERGY, STANDARD DEVIATION OF COEFFICIENT OF DB4 WAVELET DURING MUSIC CONDITION

	Average		Std		Energy		Combined	
	Acc	F1	Acc	F1	Acc	F1	Acc	F1
KNN	70.95	78.03	68.81	75.96	64.76	73.73	67.62	75.49
c-SVM	80.00	80.37	65.24	66.51	66.90	69.96	67.86	67.95
nu-SVM	81.43	82.09	61.67	62.56	64.05	65.73	65.95	65.14
DT	72.62	71.96	56.90	62.62	56.43	64.75	54.76	64.21
RF	81.43	81.58	68.57	71.39	71.19	73.04	66.19	69.60
AB	57.38	58.37	65.48	72.12	62.86	62.42	67.14	71.81
GB	**87.86**	**88.96**	65.71	71.16	65.95	71.55	71.19	74.62
NB	55.95	56.93	51.43	43.27	57.62	52.78	55.48	50.01
LDA	56.19	58.48	65.71	73.56	64.52	69.80	**79.29**	**83.29**
QDA	**91.90**	**90.28**	63.81	40.53	55.71	27.00	53.33	43.71
LR	54.29	56.60	75.95	78.36	79.52	81.59	**76.67**	**79.26**

continue to enhance the accuracy and utility of EEG-based diagnostic tools.

REFERENCES

[1] O. Faust, U. R. Acharya, H. Adeli, and A. Adeli, “Wavelet-based eeg processing for computer-aided seizure detection and epilepsy diagnosis,” Seizure, vol. 26, pp. 56–64, 2015.

[2] G. R. Lee, R. Gommers, F. Waselewski, K. Wohlfahrt, and A. O’Leary, “Pywavelets: A python package for wavelet analysis,” Journal of Open Source Software, vol. 4, no. 36, p. 1237, 2019

[3] Gowri, M., Raj, C. P. (2018). EEG feature extraction using Daubechies wavelet and classification using neural network. In Proceedings of the International Conference on Intelligent Systems and Control (ISCO) (pp. 1-6).

[4] T. Anwar, ”A Machine Learning approach for Recognizing Intellectual Development Disorder using EEG,” 2020 International Conference on Biomedical Innovations and Applications (BIA), Varna, Bulgaria, 2020, pp. 9-12, doi: 10.1109/BIA50171.2020.9244283.