CONVOLUTIONAL NEURAL NETWORKS FOR AUTISM SPECTRUM DISORDER DETECTION USING ELECTROENCEPHALOGRAPHY

Hisham Mohamed Mahmoud Ismail[a], Mohd Syahril Ramadhan Mohd Saufi[a], Hanim Mohd Yatim[a]

[a]Faculty of Mechanical Engineering, Universiti Teknologi Malaysia, 81310 UTM Johor Bahru, Johor Darul Takzim, Malaysia

[*]Corresponding email: mmhisham@graduate.utm.my

Article history
Received
27th February 2025
Revised
19th June 2025
Accepted
16th July 2025
Published
1st December 2025

ABSTRACT

Dealing with children with Autism Spectrum Disorder (ASD) is challenging due to their sensory reactions, leading to behavioral issues, self-injury, and safety concerns. Many individuals with ASD also exhibit atypical sensory processing, increasing anxiety and difficulty in daily life. Existing diagnostic tools like the Autism Diagnostic Observation Schedule (ADOS) are subjective, time-consuming, and heavily dependent on trained professionals. This work is presented as a pilot feasibility study, based on EEG spectrograms, to establish a baseline for future large-scale investigations. The EEG data obtained from King Abdulaziz University Hospital, from 16 participants (12 ASD, 4 neurotypical) were preprocessed to remove noise, segmented into 3.5-second windows, and transformed into time-frequency spectrogram images using the Short-Time Fourier Transform (STFT). These spectrograms were classified using both machine learning (ML) models, including Support Vector Machines (SVM), Decision Trees, and Ensemble Methods, and deep learning (DL) Convolutional Neural Networks (CNNs). While ML models achieved moderate accuracy, with Subspace KNN performing best at 90.27%, CNN architectures significantly outperformed them, Model 4 achieving accuracy of 99.89%, demonstrating stability. Smaller batch sizes (32–64) optimized performance, whereas larger batches (128) degraded accuracy by up to 22%. The results highlight the transformative potential of deep learning in automating ASD diagnosis, offering a rapid, and clinically alternative to traditional methods.

Keywords: *Autism Spectrum Disorder, EEG, Machine Learning, Convolutional Neural Network, Deep Learning*

1.0 INTRODUCTION

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition that affects how individuals communicate, interact socially, and process sensory information. It is called a spectrum disorder because it presents differently in each person, some individuals may have mild social difficulties, while others may experience significant challenges in communication and daily functioning [1]. Key characteristics of ASD include difficulty in social interactions, repetitive behaviors, and atypical sensory responses, such as heightened sensitivity to sounds, lights, or textures [2]. Over the years, ASD has become more widely recognized. The World Health Organization (WHO) estimates that ASD affects around 0.76% of the global population [3], though this data represents only 16% of the world's child population, suggesting that the actual prevalence may be higher. Meanwhile, the Centers for Disease Control and Prevention (CDC) reports that approximately 1.68% of 8-year-old children in the United States (equivalent to 1 in 59) are diagnosed with ASD [4].

Similarly, in Malaysia, the number of children diagnosed with autism has surged by 663% between 2013 and 2023. According to data from the Department of Social Welfare (JKM) [5], the number of registered children with ASD increased from 6,991 in 2013 to 53,323 in 2023. This trend was highlighted by Nancy Shukri, Minister of Women, Family and Community Development, in a written response to parliament on July 3, 2023 as shown in Table 1. The steady rise in ASD cases highlights the need for more efficient and objective diagnostic tools to support early intervention and treatment. In response to that, the state government and private sector are exploring ways to expand autism centers and improve ASD-related services.

Table 1: Annual statistics of children diagnosed with ASD in Malaysia [5].

Year	No Of Children Diagnosed With Autism
2013	6,991
2014	8,789
2015	10,708
2016	12,976
2017	15,838
2018	18,754
2019	23,634
2020	27,732
2021	32,471
2022	40,963
2023	53,323

Researchers have found differences in brain function and structure among individuals with ASD, particularly in areas responsible for social skills, communication, and sensory processing [6]. Diagnosing ASD remains a complex and time-consuming process, often relying on behavioral assessments like the Autism Diagnostic Observation Schedule (ADOS) and the Autism Diagnostic Interview-Revised (ADI-R) [7]. These evaluations require trained specialists, making them expensive and less accessible, especially in regions with limited healthcare resources.

Because of these challenges, researchers are exploring new ways to make ASD diagnosis more efficient and objective. Different approaches have been explored to enhance the accuracy and efficiency of ASD diagnosis, ranging from neurophysiological monitoring to artificial intelligence (AI) driven behavioral analysis. Techniques such as functional Magnetic Resonance Imaging (fMRI), and functional near-infrared spectroscopy (FNIRS) have been used to assess brain connectivity in individuals with ASD. However, these methods are limited by high costs, restricted accessibility, and the need for specialized equipment [8,9]. In contrast, Electroencephalography (EEG) has been a suitable tool due to its high temporal resolution, ease of use, non-invasiveness, affordability, and widespread clinical availability [10]. EEG captures brain activity through scalp-attached electrodes, recording electrical impulses across different frequency bands. These signals, often complex and multi-channel, are traditionally interpreted by neurologists through visual inspection, a process that is prone to human error due to the lack of standardized assessment criteria [11,12]. However, EEG signals are complex and typically require expert interpretation. This is where artificial intelligence can play a transformative role. Several types of machine learning models have been applied in this field, each with its own strengths.

Tree-based models, such as Fine Tree, Boosted Trees, and Bagged Trees, are commonly used because they can handle complex data while remaining easy to interpret. Boosted Trees, in particular, have shown high accuracy in classifying ASD, especially when combined with techniques that scale and refine features for better results [13,14]. One challenge in ASD diagnosis is class imbalance, where the number of ASD cases in a dataset may be much smaller than non-ASD cases. RUSBoosted Trees, which combine random under-sampling with boosting, help address this issue by balancing the data and improving classification performance[15]. Subspace Discriminant and Subspace KNN make it easier to analyze complex EEG data, improving efficiency [16]. Meanwhile, Support Vector Machines (SVMs), including Quadratic, Cubic, and Gaussian versions, are great at handling non-linear patterns, making them reliable for detecting ASD from EEG and behavioral data[17].

One of the biggest advantages of deep learning (DL) models is that they can automatically learn patterns from raw data [18] without needing experts to manually extract features. Unlike traditional machine learning (ML) methods, which rely on predefined features selected by specialists, DL models can analyze complex EEG signals on their own, often leading to higher accuracy. However, a major challenge with DL is its "black-box" nature, meaning that it is difficult to understand exactly how the model makes its decisions.

In one study [19], researchers used a Convolutional Neural Network (CNN) to analyze the power spectrum of EEG signals and detect ASD-related brain activity. Their three-layer CNN model achieved an accuracy of 90%, showing the potential of deep learning in ASD classification.While DL models can work directly with raw EEG data, some researchers choose to first extract key features before training. This helps reduce computation time and improves the model's ability to focus on the most important aspects of EEG signals, leading to more efficient and reliable results.

EEG signals constantly change over time, making it difficult to extract stable features for diagnosing ASD. Traditional methods, like Multiscale Entropy (MSE), have struggled to distinguish ASD-related brain activity from typical EEG patterns due to inconsistencies in scale extraction and sensitivity to frequency changes [20]. Researchers have started using time-frequency (T-F) spectrogram images to better capture the changing nature of EEG signals. These images visually represent EEG activity in the T-F domain, where different colors indicate energy variations across different frequencies over time [21]. This approach helps highlight key patterns in EEG data that traditional methods might miss, improving classification accuracy.

T-F spectrogram images have already been successfully used to classify neurological disorders like Epilepsy and Sleep Stages [22], Alzheimer's Dementia [23], Seizure Classification [24], and ASD [25].

2.0 METHODS

This study presents a machine learning, and deep learning-based framework for detecting ASD using EEG data. The methodology follows a structured approach shown in the following flowchart as Figure 1 illustrates the methodology for predicting ASD using EEG data, machine learning, and deep learning. The process begins with raw EEG Data, followed by Pre-Processing to remove noise and artifacts. The cleaned data undergoes Feature Extraction to identify discriminative patterns, which are then fed into multiple machine learning, and deep learning classifiers.

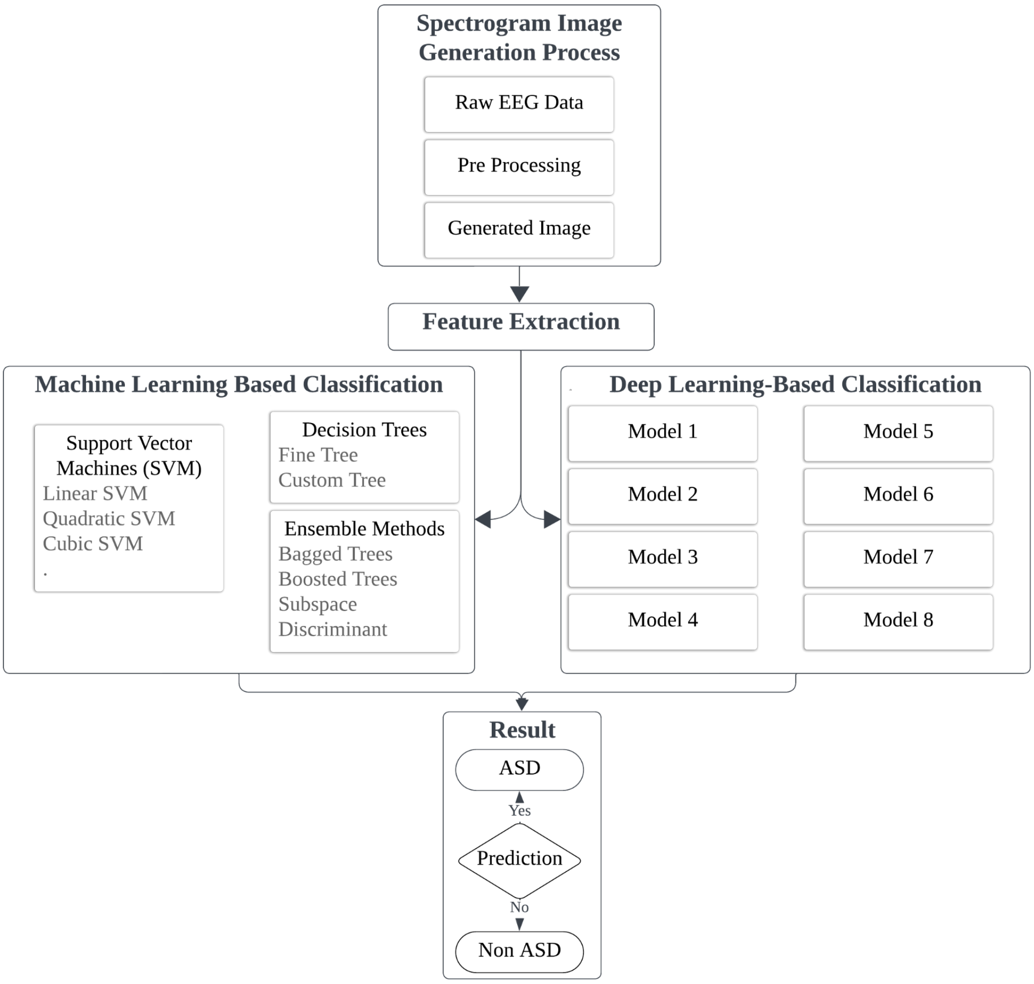

Figure 1: Workflow for ASD prediction using EEG data, ML,and DL.

2.1 Experimental Framework

This study consists of several key stages, beginning with data collection and preprocessing to remove noise and artifacts from raw EEG signals. The signals are then transformed into spectrogram images, which are subsequently used for classification using both machine learning (ML) and deep learning (DL) techniques. This process ensures that the EEG data is optimized for pattern recognition and classification, for ASD detection.

To achieve this, the framework integrates both ML classifiers and Convolutional Neural Networks (CNNs) for automatic feature extraction and classification. The analysis of these two approaches provides insights into the most effective methodology for EEG-based ASD detection.

2.2 Data Collection and Preprocessing

The EEG dataset used in this study was obtained from King Abdulaziz University Hospital. The dataset contained EEG recordings from a total of sixteen participants, including twelve individuals diagnosed with ASD and four neurotypical control participants. This small dataset frames the present work as a pilot feasibility study. EEG recordings were conducted under controlled conditions to ensure the reliability of the data.

The EEG signals were captured using a 16-channel EEG system as shown in Figure 2 with electrodes placed according to the 10-20 international system. A sampling frequency of 256 Hz was used to ensure high-resolution recordings. The EEG data was collected under resting-state EEG condition, where participants were asked to keep their eyes open and closed.

Preprocessing was performed to clean the EEG signals and remove unwanted noise and artifacts. Initially, the raw EEG signals were extracted, and converted into numerical arrays for computational processing. A common average referencing technique was applied to reduce background noise by averaging signals across all electrodes. Subsequently, a bandpass filter (0.1–60 Hz) was used to retain only the frequency range relevant to brainwave activity, while a notch filter at 60 Hz eliminated powerline interference. To facilitate efficient analysis, the EEG signals were segmented into 3.5-second windows at a sampling rate of 256 Hz. Following segmentation,

The dataset was split into training (6,796 spectrograms), validation (1,198), and test sets (7,994) containing (5,009 ASD) and (2,985 neurotypical) spectrograms (class ratio 1.68: 1). The training set concluded 85% of the data, while the remaining 15% was allocated for validation. To avoid the appearance of leakage, all spectrogram windows originating from the same EEG recording session were placed entirely within a single data partition (training, validation, and test). Because each participant contributed only one session, participant-level leakage cannot be fully excluded and is addressed in the future work section. All images were normalized to a pixel range of [0,1] by applying rescaling.

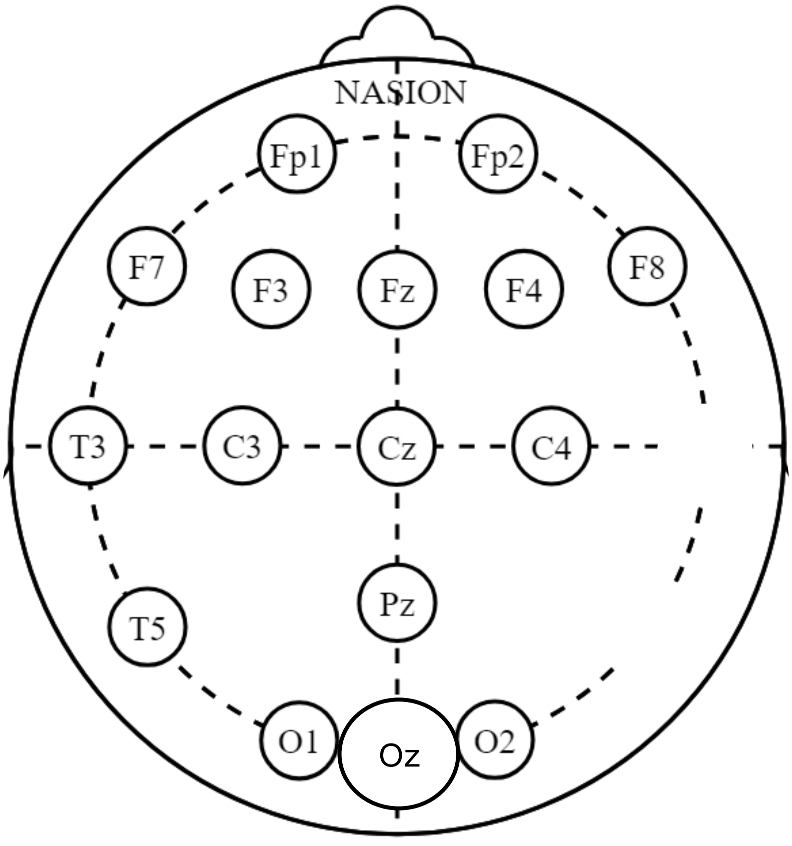

Figure 2: Electrodes placement of autism data acquisition system

To assess the impact of batch size on training efficiency and model performance, experiments were conducted with batch sizes of 32, 64, and 128 for the deep learning models.

The CNN models were trained with validation accuracy monitored throughout the training process. After training, performance was evaluated on the test set using accuracy, precision, recall, F1-score, AUC, and training time. Confusion matrices and ROC curves were generated to further analyze model predictions.

2.3 Spectrogram Generation

To transform EEG signals into a format suitable for deep learning, the Short-Time Fourier Transform (STFT) was applied to generate spectrogram images. Spectrograms provide a time-frequency representation of EEG signals, across standard brain wave bands—delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (>30 Hz). This transformation from raw time-domain EEG to spectrogram format enables the model to visualize and learn patterns in power fluctuations across frequency bands over time, allowing the detection of patterns associated with ASD. The process of spectrogram generation involved several steps. First, a Hamming window function was applied to ensure smooth transitions between overlapping signal segments. The STFT was then computed to extract time-frequency features from the EEG signals. Finally, resulting spectrograms as illustrated in Figure 3 where Figure 3a shows images from ASD group and Figure 3b shows images from normal subjects., with a resolution of 128×128 pixels, which are suitable for CNN-based classification. These spectrogram images serve as the primary input for the machine learning, and deep learning models for automated feature extraction and classification.

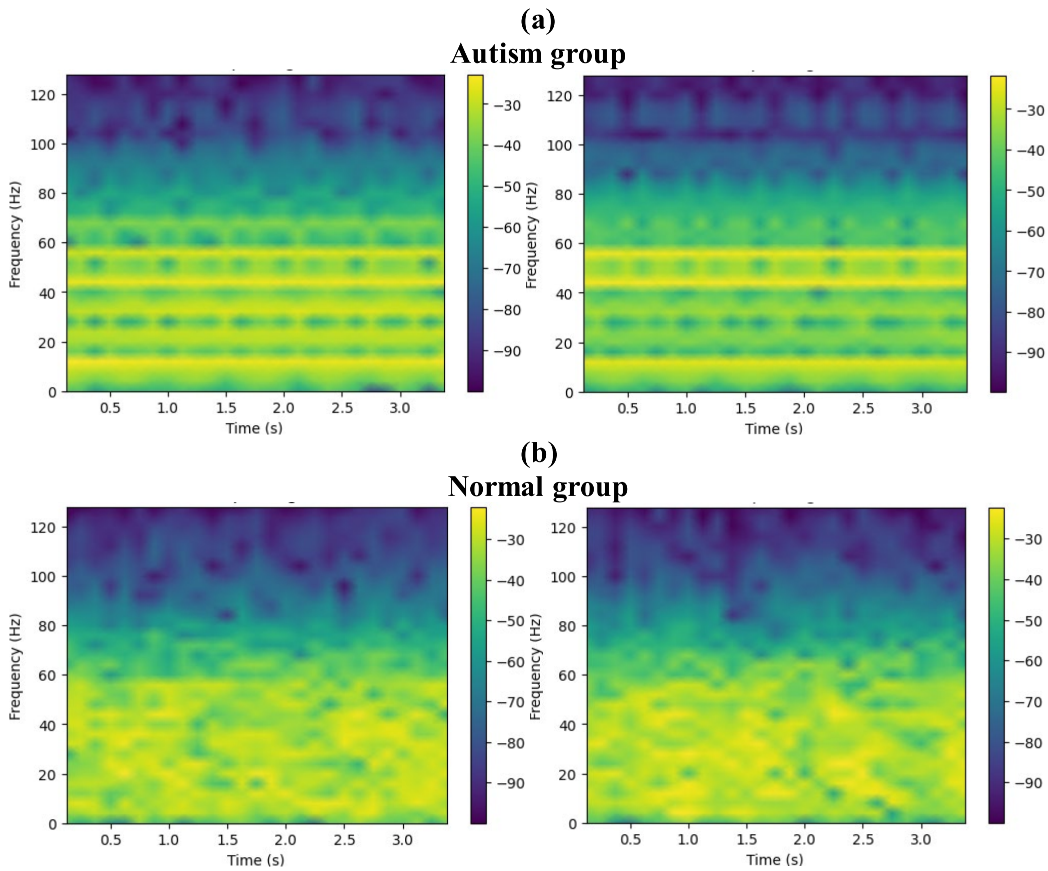

Figure 3: EEG spectrograms. (a) autism group. (b) normal group.

2.4 Feature Extraction for Machine Learning

For the machine learning approach, spectrogram images were transformed into structured feature representations. Feature extraction was carried out using two primary techniques: Local Ternary Patterns (LTP) and Spatial Pyramid Matching (SPM).

LTP was applied to spectrogram images to capture the textural properties of EEG signals. This technique encodes spatial relationships between pixel intensities, enabling the identification of patterns associated with ASD. To further enhance feature extraction, the spectrogram images were divided into multiple subregions using SPM. Histograms of the LTP-transformed images were computed for each subregion, ensuring that both global and localized features were captured.

Following feature extraction, Principal Component Analysis (PCA) was applied to reduce the dimensionality of feature vectors. PCA retained only the most informative components, minimizing the risk of overfitting. These extracted feature vectors were then used as inputs for machine learning classifiers.

2.5 Classification Approaches

Two classification approaches were used: machine learning models and deep learning models. The machine learning approach involved training various classifiers using the extracted feature vectors, while the deep learning approach utilized CNNs for automatic feature extraction and classification.

For the machine learning approach, several supervised learning algorithms were tested, shown in Table 2 including Support Vector Machines (SVM), Decision Trees (DT), K-Nearest Neighbors (k-NN), and ensemble learning techniques such as Bagged and Boosted Trees. These models were trained in MATLAB, and their performance was evaluated based on accuracy, error rate, and computational efficiency.

Table 2: Machine learning models

Model	Hyperparameters
Fine Tree	Max splits: 300, Split criterion: Gini's diversity index, Surrogate decision splits: Off
Boosted Trees	Ensemble method: Boosting, Max learners: 30, Learning rate: 0.1
Bagged Trees	Ensemble method: Bagging, Max splits: 25597, Learner type: Decision tree, Max learners: 30
Subspace Discriminant	Ensemble method: Subspace, Learner type: Discriminant, Max learners: 30, Subspace dimension: 640
Subspace KNN	Ensemble method: Subspace, Learner type: Nearest neighbors, Max learners: 30, Subspace dimension: 640
RUSBoosted Trees	Ensemble method: RUSBoost, Learner type: Decision tree, Max learners: 30, Learning rate: 0.1, Max splits: 20
Custom Tree	Max splits: 300, Split criterion: Gini's diversity index, Surrogate decision splits: Off
Quadratic SVM	Kernel function: Quadratic, Kernel scale: Automatic, Box constraint: 1, Multiclass coding: One-vs-One
Cubic SVM	Kernel function: Cubic, Kernel scale: Automatic, Box constraint: 1
Fine Gaussian SVM	Kernel function: Gaussian, Kernel scale: 8.9, Box constraint: 1
Medium Gaussian SVM	Kernel function: Gaussian, Kernel scale: 36, Box constraint: 1
Coarse Gaussian SVM	Kernel function: Gaussian, Kernel scale: 140, Box constraint: 1

For the deep learning approach, Convolutional Neural Networks (CNNs) were implemented to identify ASD directly from spectrogram images. As shown in Table 3, eight CNN architectures were developed to evaluate model complexity, regularization techniques, and feature extraction capabilities.

Table 3: Deep learning models

Model	Architecture
Model 1	Three convolutional layers (32→64→128 filters, 3 × 3 kernels) with ReLU activation and max-pooling (2×2)
Model 2	Basic CNN + Dropout (50%) after pooling layers to reduce overfitting
Model 3	Six convolutional layers (32→256 filters) for hierarchical feature learning
Model 4	Basic CNN + Batch Normalization after each convolution to stabilize training
Model 5	ReLU replaced with LeakyReLU (α=0.3) to prevent silent neurons
Model 6	Expanded filters (64→256) to enhance feature representation
Model 7	Basic CNN + real-time augmentation (rotation ±15°, horizontal flip)
Model 8	Conv2D layers (32→64 filters) → Reshape → LSTM (64 units) → Dense

The CNN models were trained using the Adam optimizer with a learning rate of 0.001. A binary cross-entropy loss function was used, as it is well-suited for binary classification tasks. To assess the impact of batch size on model performance, experiments were conducted with batch sizes of 32, 64, and 128 over five epochs. Model evaluation was based on accuracy, precision, recall, F1-score, AUC, and training time. The training process was implemented using pycharm.

3.0 RESULTS AND DISCUSSION

This section presents the performance evaluation of both ML and DL models in classifying ASD based on EEG spectrogram images. The results are analyzed in terms of accuracy, training time, and computational efficiency, highlighting the strengths and weaknesses of different models.

3.1 Machine Learning Results.

The classification performance of various machine learning models was evaluated to determine the most effective approach. Table 4 summarizes the validation accuracy, error rate, and training time for different ML models.

Table 4: Machine learning performance metrics.

Model	Accuracy (Validation)	Error Rate (Validation)	Training Time (sec)
Fine Tree	86.47%	13.53%	281.53
Boosted Trees	87.80%	12.20%	5032.2
Bagged Trees	88.85%	11.15%	34479.0
Subspace Discriminant	85.21%	14.79%	**2506.5**
Subspace KNN	**90.27%**	**9.73%**	31454.0

RUSBoosted Trees	83.39%	16.61%	6071.8
Custom Tree	87.21%	12.79%	**9883.7**
Quadratic SVM	86.02%	13.98%	28818.0
Cubic SVM	85.99%	14.01%	45243.0
Fine Gaussian SVM	**50.63%**	**49.37%**	42252.0
Medium Gaussian SVM	85.69%	14.31%	33063.0
Coarse Gaussian SVM	84.66%	15.34%	37472.0

The Subspace KNN model achieved the highest validation accuracy of 90.27% with a low error rate of 9.73%. However, its training time of 31,454 seconds (8.73 hours) was relatively high, making it computationally expensive.

Bagged Trees provided a strong balance between accuracy (88.85%) and training time (9.58 hours, 34,479 seconds), making it an excellent choice for applications that demand both high accuracy and reasonable computational efficiency.

The Fine Gaussian SVM performed the worst, with an accuracy of only 50.63%, making it unsuitable for practical use. Despite this poor performance, it had a long training time of 11.73 hours (42,252 seconds), indicating inefficiency in both accuracy and computational requirements.

On the other hand, RUSBoosted Trees offered moderate accuracy at 83.39%, but its training time of 16.87 hours (60,718 seconds) made it one of the least efficient models in terms of both accuracy and computational performance.

The relationship between training time and validation accuracy for the tested ML models is illustrated in Figure 4. The dual-axis chart presents validation accuracy as blue bars (left y-axis) and training time in hours as a red line (right y-axis), allowing a direct visual comparison of model performance. Models like Subspace KNN and Bagged Trees stand out with high accuracy bars, while RUSBoosted Trees and Fine Gaussian SVM are notable for their long training time spikes in the red line. Conversely, Subspace Discriminant shows a very low training time but also suffers from low accuracy.

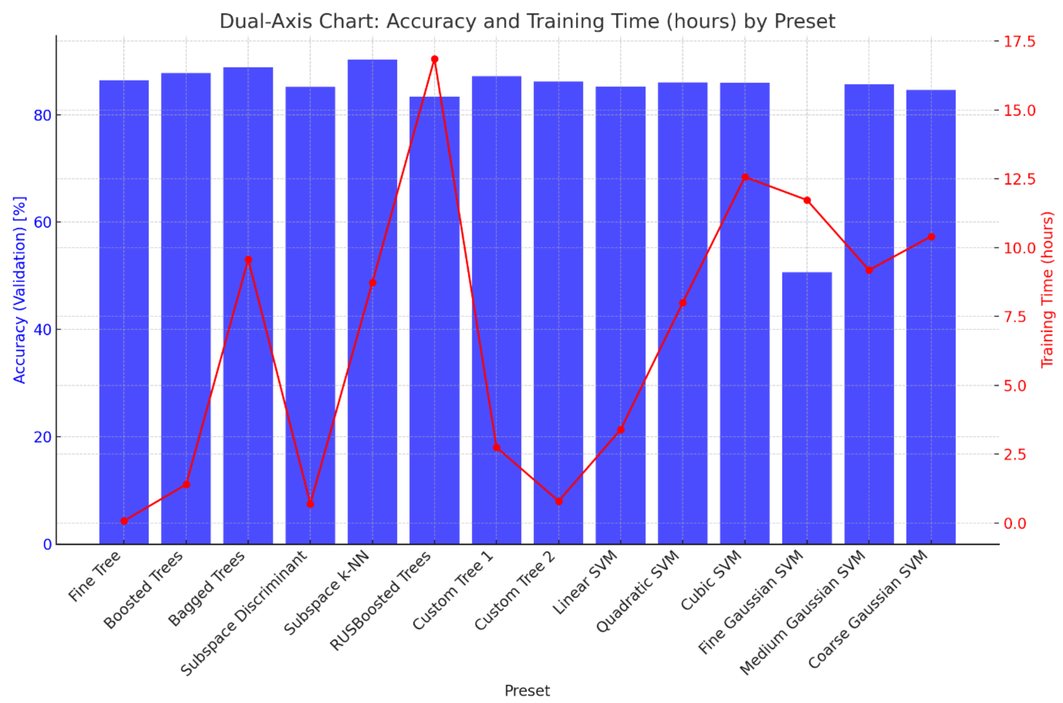

Figure 4: Machine learning accuracy and training time.

3.2 Deep Learning Results.

CNN models were evaluated using different architectures and batch sizes to determine the optimal configuration. Their performance was assessed based on accuracy, precision, recall, F1-score, AUC, and training time. To ensure statistical presentation, 95% Wilson confidence intervals (CIs) were computed for each model [26]. The Wilson interval is preferred over the standard Wald method, especially for high or low proportions, due to its improved coverage properties and reduced bias near the boundaries [26]. The interval is defined as shown in equation 1:

$$\hat{p} = \frac{k}{n}, \qquad CIs = \frac{\hat{p} + \frac{z^2}{2n} \pm z \cdot \sqrt{\frac{\hat{p}(1-\hat{p})}{n} + \frac{z^2}{4n^2}}}{1 + \frac{z^2}{n}} \tag{1}$$

where $\hat{p}$ is the observed proportion (accuracy), n is the total number of test samples, k is the correct predictions, and z is the z-score for the 95% confidence level (z = 1.96). This interval provides a more reliable estimation of the model's true accuracy, by correcting for potential sampling variability.

As presented in Table 5, the best-performing model was Model 4 with a batch size of 32, achieving the highest accuracy (99.89%) and a Wilson interval [99.80, 99.95], Although Model 4 (batch 32) achieved an apparent accuracy of 99.89 %, these values are preliminary and likely optimistic given the sample size and the class ratio of 1.68 : 1 described in Methods.

Table 5: Deep learning performance Metrics.

Model Name	Batch Size	Accuracy (%)	95% CI (Wilson)	Precision	Recall	F1-Score	AUC	Training Time (s)
Model 1	32	99.83	[99.72, 99.90]	0.998	0.999	0.998	0.998	447
Model 1	64	99.36	[99.16, 99.51]	0.998	0.991	0.994	0.994	380
Model 1	128	99.48	[99.30, 99.62]	0.996	0.996	0.995	0.995	567
Model 2	32	99.79	[99.68, 99.88]	0.998	0.998	0.998	0.999	414
Model 2	64	99.69	[99.54, 99.79]	0.998	0.997	0.997	0.997	**357**
Model 2	128	98.53	[98.25, 98.78]	0.989	0.987	0.988	0.986	641
Model 3	32	88.61	[87.90, 89.29]	0.998	0.819	0.900	0.983	428
Model 3	64	81.84	[81.00, 82.68]	0.998	0.712	0.830	0.817	400
Model 3	128	77.19	[76.26, 78.10]	0.998	0.637	0.777	0.772	584
Model 4	32	**99.89**	**[99.80, 99.95]**	0.998	0.999	0.998	0.999	822
Model 4	64	99.82	[99.71, 99.90]	0.998	0.997	0.997	0.997	800
Model 4	128	99.62	[99.45, 99.75]	0.996	0.995	0.996	0.995	1001
Model 5	32	99.78	[99.66, 99.87]	0.997	0.994	0.995	0.998	525
Model 5	64	99.42	[99.23, 99.57]	0.992	0.988	0.969	0.997	464
Model 5	128	97.66	[97.31, 97.97]	0.993	0.986	0.982	0.987	690
Model 6	32	99.84	[99.72, 99.90]	0.998	0.999	0.998	0.999	1200
Model 6	64	99.37	[99.16, 99.51]	0.998	0.997	0.998	0.998	970
Model 6	128	98.71	[98.44, 98.94]	0.995	0.987	0.986	0.987	2496
Model 7	32	98.22	[97.97, 98.40]	0.996	0.998	0.993	0.997	1100
Model 7	64	84.15	[83.33, 84.93]	0.850	0.747	0.763	0.747	1034
Model 7	128	80.49	[79.61, 81.35]	0.773	0.976	0.862	0.975	2925
Model 8	32	99.54	[99.38, 99.67]	0.996	0.996	0.996	0.997	1919
Model 8	64	80.17	[79.28, 81.03]	0.998	0.685	0.812	0.801	2813
Model 8	128	77.21	[58.77, 60.91]	0.998	0.637	0.778	0.771	**4089**

Figure 5 presents the corresponding test-set confusion matrix (TN = 2,977, FP = 8, FN = 0, TP = 5,009), demonstrating that only eight neurotypical samples were misclassified, where ASD represents autism spectrum disorder samples, and N represents the neurotypical samples.

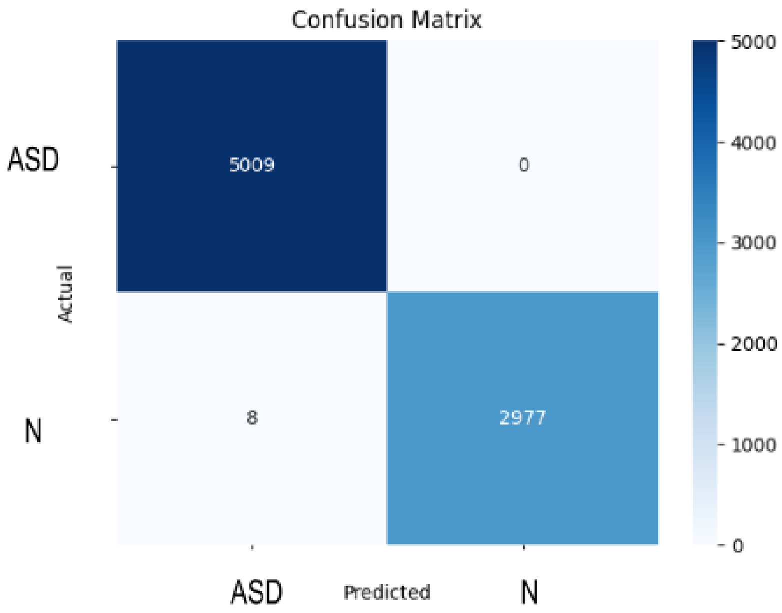

Figure 5: Confusion matrix for Model 4 (batch 32).

Both Model 6 (Batch Size 32) and Model 2 (Batch Size 64) also performed well, with accuracies of 99.84% and 99.69%, respectively. Model 2 (Batch Size 64) was the fastest model (357s training time) while maintaining high accuracy, making it the most computationally efficient choice. Figure 6 highlights that smaller batch sizes (32, 64) generally resulted in better accuracy, reinforcing the importance of batch size selection for optimizing CNN performance.

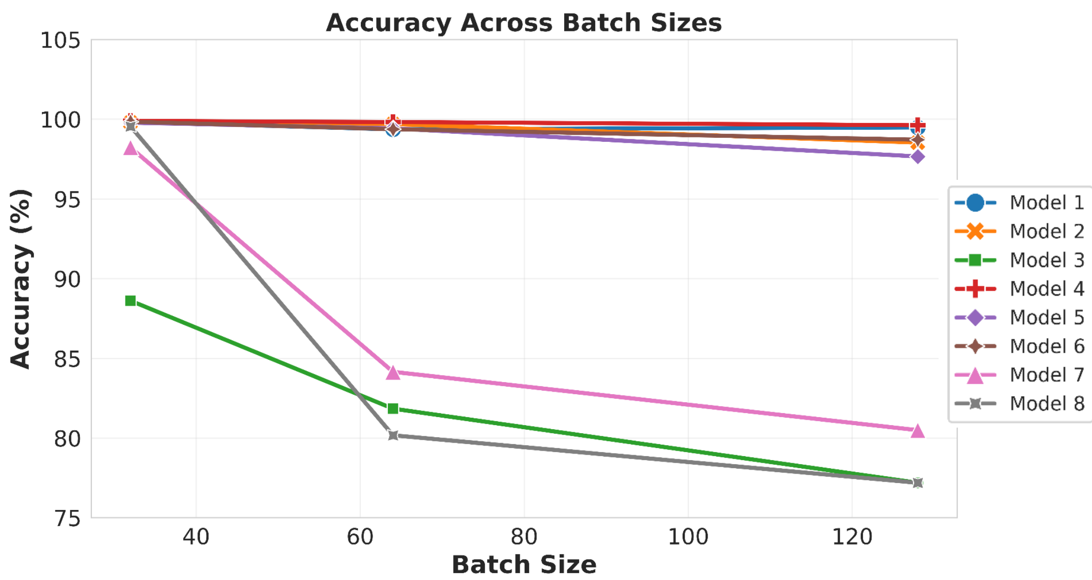

Figure 6: Accuracy across batch sizes

When the batch size increased to 128, a significant drop in accuracy was observed in several models. Model 3 (Batch Size 128) and Model 8 (Batch Size 128) showed the worst performance, with accuracies of 77.19%, highlighting poor generalization at higher batch sizes. Figure 7 illustrates the trade-off between training time and accuracy, where Model 4 (Batch Size 32), achieving the highest accuracy, required training time (822s). While model 8 (Batch Size 128) required the longest training time (4089s) and performed the worst, making it the least efficient configuration.

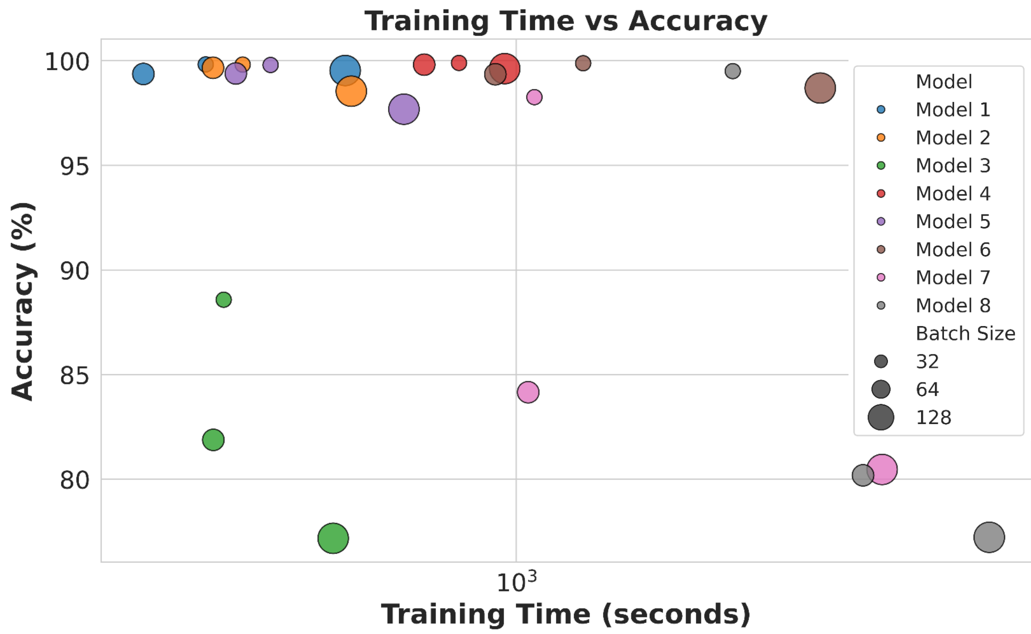

Figure 7: Training time vs accuracy

Figure 8 provides a comparison of training time across models and batch sizes, showing that training time increases disproportionately with batch size. Model 7 (Batch Size 128) and Model 8 (Batch Size 128) exhibited the highest computational cost, suggesting that larger batch sizes lead to inefficient training with diminishing returns in accuracy.

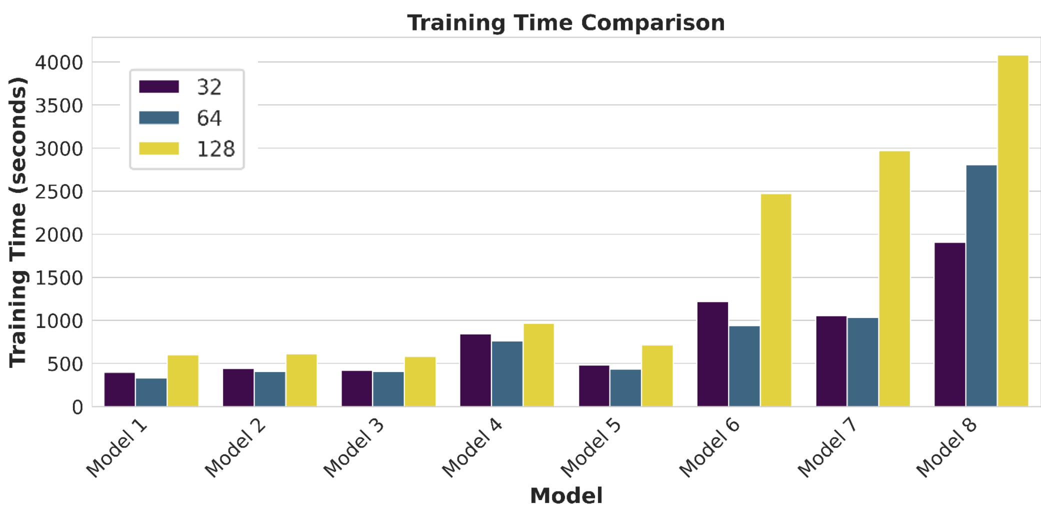

Figure 8: Training time comparison

These results indicate that smaller batch sizes (32, 64) are optimal for achieving high accuracy and stable learning, while batch size 128 significantly degrades model performance. Model 4 (Batch Size 32) emerges as the best overall choice, balancing accuracy, precision, and computational efficiency.

Table 6 summarises reported accuracies for studies that analysed this exact dataset using a variety of feature-extraction pipelines and classifiers. Although the CNN-based spectrogram approach achieves high accuracy (99.89 %), given the initial nature of our work. Nonetheless, the comparison highlights the effectiveness of time-frequency representations.

Table 6: Comparison with existing methods that used the same dataset.

Authors	Feature Extraction	Classifier	Accuracy (%)
Alsaggaf et al. [27]	FFT	FLDA	80.27
Tawhid et al. [25]	Spectrograms	CNN	99.15
Djemal et al. [28]	DWT, SE	ANN	98.60
Alhaddad et al. [29]	FFT	FLDA	90.00
Alturki et al. [30]	DWT, SE	ANN	98.20
Kamel et al. [31]	FFT	RFLD	92.06
Nur et al. [32]	MLPN	MLPN	80.00
This initial study	Spectrograms	CNN	99.89

ANN – artificial neural network; DWT – discrete-wavelet transform; FFT – fast Fourier transform; FLDA – Fisher's linear discriminant analysis; MLPN – multilayer perceptron network; RFLD – regularised Fisher's linear discriminant; SE – Shannon entropy.

4.0 CONCLUSION

The comparison between machine learning (ML) and deep learning (DL) models highlights the advantages of deep learning in EEG-based ASD classification. Among the ML models, Subspace KNN emerged as the most accurate, achieving 90.27% validation accuracy. However, it required an extensive training time of 8.73 hours, making it less practical for large-scale applications. In contrast, the CNN models significantly outperformed ML models, with Model 4 (Batch Size 32) achieving the highest accuracy (99.89%) while maintaining a strong balance across precision, recall, and AUC. This suggests that deep learning is more effective for EEG-based ASD classification, offering higher accuracy and computational efficiency. The smaller batch sizes (32, 64) consistently lead to superior model performance, while larger batch sizes (128) result in a decline in accuracy.

5.0 FUTURE WORK

Future work will ensure a class-balanced dataset; conduct independent testing as soon as additional data become available; collect multi-session recordings for each participant and apply rigorous data-splitting; and implement model-interpretation tools to identify the frequency-time patterns that contribute most to the model's decisions.

ACKNOWLEDGEMENT

The authors acknowledge funding support from Universiti Teknologi Malaysia under UTM digital infused grant (Q.J130000.5124.00L83) and UTM Fundamental Research Grant (Q.J130000.3824.23H70).

REFERENCES

1. H. Hodges, C. Fealko, and N. Soares, "Autism spectrum disorder: definition, epidemiology, causes, and clinical evaluation," *Translational Pediatrics*, vol. 9, no. S1, pp. S55–S65, Feb. 2020 https://doi: 10.21037/tp.2019.09.09.
2. O. Patil and M. Kaple, "Sensory Processing Differences in Individuals with Autism Spectrum Disorder: A Narrative Review of Underlying Mechanisms and Sensory-Based Interventions," *Cureus*, Oct. 2023, https://doi: 10.7759/cureus.48020.
3. World Health Organization: WHO, "Autism," Nov. 15, 2023. https://www.who.int/news-room/fact-sheets/detail/autism-spectrum-disorders
4. "Data and statistics on autism spectrum disorder," *Autism Spectrum Disorder (ASD)*, May 16, 2024. https://www.cdc.gov/autism/data-research/index.html
5. Ova, "Number of children diagnosed with autism in Malaysia increased by 663% from 2013 to 2023," *Ova*, Jul. 11, 2024. https://ova.galencentre.org/number-of-children-diagnosed-with-autism-in-malaysia-increased-by-663-from-2013-to-2023/
6. M. Patil, N. Iftikhar, and L. Ganti, "Neuroimaging Insights into Autism Spectrum Disorder: Structural and Functional Brain," *Health Psychology Research*, vol. 12, Sep. 2024 https://doi: 10.52965/001c.123439.
7. C. Okoye *et al.*, "Early diagnosis of Autism Spectrum Disorder: A review and analysis of the risks and benefits," *Cureus*, Aug. 2023 https://doi: 10.7759/cureus.43226.
8. G. S. Dichter, "Functional magnetic resonance imaging of autism spectrum disorders," *Dialogues in Clinical Neuroscience*, vol. 14, no. 3, pp. 319–351, Sep. 2012 https://doi: 10.31887/dcns.2012.14.3/gdichter.
9. E. Conti *et al.*, "Looking for 'FNIRS signature' in autism spectrum: A systematic review starting from preschoolers," *Frontiers in Neuroscience*, vol. 16, Mar. 2022 https://doi: 10.3389/fnins.2022.785993.
10. P. V. N. N. Ranasinghe and M. S. T. Mapa, "Functional connectivity and cognitive decline: a review of rs-fMRI, EEG, MEG, and graph theory approaches in aging and dementia," *Exploration of Medicine*, pp. 797–821, Nov. 2024 https://doi: 10.37349/emed.2024.00256.
11. P. V. N. N. Ranasinghe and M. S. T. Mapa, "Functional connectivity and cognitive decline: a review of rs-fMRI, EEG, MEG, and graph theory approaches in aging and dementia," *Exploration of Medicine*, pp. 797–821, Nov. 2024 https://doi: 10.37349/emed.2024.00256.
12. B. Frauscher *et al.*, "Learn how to interpret and use intracranial EEG findings," *Epileptic Disorders*, vol. 26, no. 1, pp. 1–59, Dec. 2023, doi: 10.1002/epd2.20190.
13. S. M. M. Hasan, M. P. Uddin, M. A. Mamun, M. I. Sharif, A. Ulhaq, and G. Krishnamoorthy, "A Machine Learning Framework for Early-Stage Detection of Autism Spectrum Disorders," *IEEE Access*, vol. 11, pp. 15038–15057, Dec. 2022 https://doi: 10.1109/access.2022.3232490.

14. T. Akter *et al.*, "Machine Learning-Based Models for Early Stage Detection of autism Spectrum Disorders," *IEEE Access*, vol. 7, pp. 166509–166527, Jan. 2019
https://doi: 10.1109/access.2019.2952609.
15. J. Carrasco, F. Lisón, and A. Weintraub, "RUSBoost: A suitable species distribution method for imbalanced records of presence and absence. A case study of twenty-five species of Iberian bats," *bioRxiv (Cold Spring Harbor Laboratory)*, Oct. 2021
https://doi: 10.1101/2021.10.06.463434.
16. S. Mostafa, W. Yin, and F.-X. Wu, "Autoencoder based methods for diagnosis of autism spectrum Disorder," in *Lecture notes in computer science*, 2020, pp. 39–51
https://doi: 10.1007/978-3-030-46165-2_4.
17. X.-A. Bi, Y. Wang, Q. Shu, Q. Sun, and Q. Xu, "Classification of autism spectrum disorder using random support Vector Machine Cluster," *Frontiers in Genetics*, vol. 9, Feb. 2018
https://doi: 10.3389/fgene.2018.00018.
18. M. Li, Y. Jiang, Y. Zhang, and H. Zhu, "Medical image analysis using deep learning algorithms," *Frontiers in Public Health*, vol. 11, Nov. 2023
https://doi: 10.3389/fpubh.2023.1273253.
19. S. Jayarathna, Y. Jayawardana, M. Jaime, and S. Thapaliya, "Electroencephalogram (EEG) for delineating objective measure of autism spectrum disorder," in *Advances in bioinformatics and biomedical engineering book series*, 2019, pp. 34–65
https://doi: 10.4018/978-1-5225-7467-5.ch002.
20. E. Abdulhay, M. Alafeef, H. Hadoush, V. Venkataraman, and N. Arunkumar, "EMD-based analysis of complexity with dissociated EEG amplitude and frequency information: a data-driven robust tool -for Autism diagnosis- compared to multi-scale entropy approach," *Mathematical Biosciences & Engineering*, vol. 19, no. 5, pp. 5031–5054, Jan. 2022
https://doi: 10.3934/mbe.2022235.
21. L. Yuan and J. Cao, "Patients' EEG Data Analysis via Spectrogram Image with a Convolution Neural Network," in *Smart innovation, systems and technologies*, 2017, pp. 13–21
https://doi: 10.1007/978-3-319-59421-7_2.
22. Ö. F. Alçin, S. Siuly, V. Bajaj, Y. Guo, A. Şengu¨R, and Y. Zhang, "Multi-category EEG signal classification developing time-frequency texture features based Fisher Vector encoding method," *Neurocomputing*, vol. 218, pp. 251–258, Sep. 2016
https://doi: 10.1016/j.neucom.2016.08.050.
23. S. Y. Sen, O. K. Cura, and A. Akan, "Classification of dementia EEG signals by using Time-Frequency images for deep learning," *2022 Innovations in Intelligent Systems and Applications Conference (ASYU)*, pp. 1–6, Oct. 2023
https://doi: 10.1109/asyu58738.2023.10296777.
24. S. Raghu, N. Sriraam, Y. Temel, S. V. Rao, and P. L. Kubben, "EEG based multi-class seizure type classification using convolutional neural network and transfer learning," *Neural Networks*, vol. 124, pp. 202–212, Jan. 2020
https://doi: 10.1016/j.neunet.2020.01.017.
25. Md. N. A. Tawhid, S. Siuly, H. Wang, F. Whittaker, K. Wang, and Y. Zhang, "A spectrogram image based intelligent technique for automatic detection of autism spectrum disorder from EEG," *PLoS ONE*, vol. 16, no. 6, p. e0253094, Jun. 2021
https://doi: 10.1371/journal.pone.0253094.
26. L. A. Orawo, "Confidence intervals for the binomial proportion: A comparison of four methods," Open Journal of Statistics, vol. 11, no. 05, pp. 806–816, Jan. 2021
https://doi: 10.4236/ojs.2021.115047.
27. Alsaggaf EA, Kamel MI. Using EEGs to diagnose autism disorder by classification algorithm. Life Science Journal. 2014; 11(6):305–308
https://doi.org/10.7537/marslsj110614.40
28. Djemal R, AlSharabi K, Ibrahim S, Alsuwailem A. EEG-based computer aided diagnosis of autism spectrum disorder using wavelet, entropy, and ANN. BioMed Research International. 2017; 2017:1–9. https://doi.org/10.1155/2017/9816591 PMID:28484720
29. Alhaddad MJ, Kamel MI, Malibary HM, Alsaggaf EA, Thabit K, Dahlwi F, et al. Diagnosis autism by fisher linear discriminant analysis FLDA via EEG. International Joumal of Bio-Science and Bio-Technology. 2012; 4(2):45–54
30. Alturki FA, AlSharabi K, Abdurraqeeb AM, Aljalal M. EEG Signal Analysis for Diagnosing Neurological Disorders Using Discrete Wavelet Transform and Intelligent Techniques. Sensors. 2020; 20(9):1–17.
https://doi.org/10.3390/s20092505 PMID: 32354161
31. Kamel MI, Alhaddad MJ, Malibary HM, Thabit K, Dahlwi F, Alsaggaf EA, et al. EEG based autism diagnosis using regularized Fisher Linear Discriminant Analysis. International Journal of Image, Graphics and Signal Processing. 2012; 4(3):35–41.
https://doi.org/10.5815/ijigsp.2012.03.06 50

32. Nur AA. Autism spectrum disorder classification on electroencephalogram signal using deep learning algorithm. IAES International Journal of Artificial Intelligence. 2020; 9(1):91–99