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Research paper

Deep Learning Algorithms for The Analysis of Autism Spectrum Disorder

Sneha Sureddy [1] *, Dr. P. L. Lekshmy [2], Dr. Zameer Ahmed Adhoni [3], Aakansha Soy [4], Ashu Nayak [4]

[1] *Assistant Professor, BMS Institute of Technology and Management, Bengaluru, India*
[2] *Assistant Professor, Department of CSE, LBS Institute of Technology for Women, Kerala, India*
[3] *Assistant Professor, Department of CSE, GITAM School of Technology, GITAM (Deemed to Be University, Nagadenahalli, Doddabalapura, Bengaluru, India*
[4] *Assistant Professor, Department of CS & IT, Kalinga University, Raipur, India*
**Corresponding author E-mail: sneha.sureddy@gmail.com*

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Abstract

The neurodevelopmental disorder known as autism spectrum disorder (ASD) is typified by aberrant brain development that is impacted by environmental, biological, and genetic variables. To maximize outcomes and to intervene promptly, it is necessary to identify ASD early. The current methods of screening rely heavily on behavioral assessments, which introduce bias and other limitations. Therefore, objective approaches that mitigate subjectivity should be employed. This study presents using EEG signals and Deep Learning (DL) models to identify ASD via Artificial Intelligence (AI)-based Computer-Aided Diagnostic Systems (CADS. This study examined how well deep learning classifiers (DL classifiers) could classify people with ASD using only their raw EEG data and no manual feature extraction. Several deep learning models, such as FFNN and WST-ASDNet with AlexNet, were employed to categorize people with ASD and controls. As additional signal processing methods for ASD classification, time-frequency representations, Power Spectral Density (PSD) estimates, and Wavelet Scattering Transform (WST) were used. When AleXnet was combined with the other DL model, the suggested Wavelet Scattering Transform-based ASD diagnostic networks (WST-ASDNets) produced accuracies of 98% and 95%, respectively, in separating ASD from standard controls. The AI-based CADS created for ASD diagnosis showed encouraging outcomes and provided a quicker and less labor-intensive method in terms of computation. These techniques have promise as screening instruments for the early identification and classification of ASD. Given the differences in EEG signals among people with ASD, future research may concentrate on expanding these algorithms to categorize ASD subjects into varying severity levels.

Keywords: *Autism Spectrum Disorder; Computer-Aided Diagnostic Systems; Deep Learning; Wavelet Scattering Transform; AleXnet.*

1. Introduction

Autism spectrum disorder (ASD) is a group of complex neurological conditions involving autism, Asperger syndrome, childhood disintegrative disorder, and Pervasive Developmental Disorder-Not Otherwise Specified (PDD-NOS), which includes various developmental disorders affecting communication and social interaction. [1]. Autism Spectrum Disorder (ASD) can have varying degrees of symptoms, which often involve difficulties with communication, social interactions, obsessive interests, reduced facial expressions, and inflexible routines. [23] [25]. ASD typically starts before age five and lasts for a lifetime. The World Health Organization (WHO) states that one out of every hundred children has autism spectrum disorder (ASD). Behavioral assessment forms the foundation for diagnosing autism spectrum disorder. Psychologists and other specialists employ various methods for identifying autism spectrum disorders. These methods often have errors and mainly depend on questionnaires. Even now, there's no way to fix autism, but starting treatment soon helps kids learn how to talk, make friends, and grow their brains. An efficient method for identifying ASD quickly and accurately must be found. Electroencephalography (EEG), which records brain electrical activity, is extensively utilized due to its high temporal resolution, ease of use, lack of invasiveness, availability, and affordability. EEGs are playing a more crucial role in identifying and managing conditions affecting the mind and brain. EEG data analysis and classification are crucial for diagnosing brain diseases [17]. The most common method for distinguishing between various EEG sections helps diagnose someone's well-being or examine their emotional condition during specific tasks. The EEG often produces vast quantities of information, making it difficult to analyze effectively for discriminatory purposes due to high costs, lengthy times required, and frequent errors in processing.

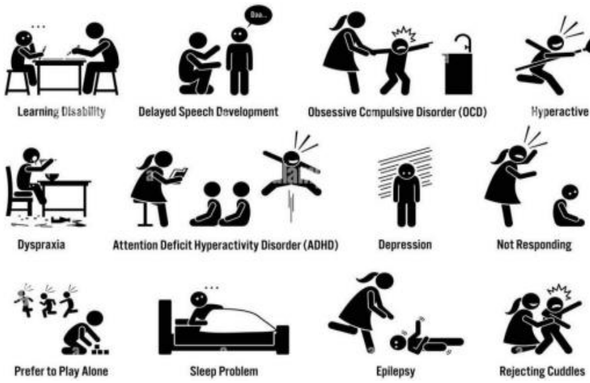

Fig. 1: ASD Symptoms and Co-Morbidities.

For this reason, automatic EEG classification techniques are crucial for facilitating precise neurological disease diagnosis and therapy [4]. In several different brain regions, the excess delta power has been found in both relative and absolute powers. ASD and typically developing individuals have been distinguished in several studies using Machine Learning (ML) methods. This paper aims to determine ASD participants based on EEG signals in conjunction with Deep learning (DL) algorithms. In this work, various methods were applied to classify the ASD and regular participants based on their EEG data. The study suggests new ways of detecting and characterizing ASD by using DL models and EEG data. This work's primary goals are to:

- Use DL classifiers to categorize subjects with ASD and normal people.
- To extract estimates of Power Spectral Density (PSD) from EEG data and use DL algorithms to classify the EEG signals into ASD and standard categories.
- To categorize ASD using the DL and Wavelet Scattering Transform (WST) techniques.
- To assess how well ML and DL models classify ASD cases in comparison.

The following portion of the paper is organized as follows: Section 2 provides an overview of ASD; Section 3 offers a suggested workflow; Section 4 discusses the results and findings; and Section 5 concludes the study.

2. Background Knowledge Related to The ASD Study

The early stages of life for people with autism show significant growth in their brains. Genetic, biological, and environmental factors contribute to abnormal neurodevelopment, which is intensified by changes in how a child interacts with their surroundings during growth. [5], [20]. Before age three, diagnosing autism spectrum disorder can be difficult, and many kids don't get an official diagnosis until preschool or later. Instead of being determined by biology, autism spectrum disorder is identified through behavior. ? If diagnosis or screening relies only on behavioral traits, the critical period for early intervention might be missed due to symptoms of autism spectrum disorder appearing months or even years earlier than abnormal behavior. [6]. Early intervention significantly improves outcomes, resulting in better and more functional results later in life. Earlier recognition of health issues promotes timely treatment. ASD is a tricky condition with many types, which makes it hard to diagnose properly, even when someone is young. The American Psychiatric Association's DSM-5 offers a diagnosis of autism spectrum disorder [7]. The DSM-5 might cause some problems because it could lead to more mistakes when diagnosing autism spectrum disorder. The DSM-5 fails to consider certain behaviors and signs related to autism spectrum disorder when making diagnoses. This oversight can lead to incorrect or missed diagnoses of individuals with ASD. Multiple conditions, such as autism spectrum disorder (ASD), have similar neurological symptoms, making it simpler to retrospectively apply the diagnostic criteria for these individuals who exhibit fewer or more concealed behaviors compared to those with milder forms of ASD. Diagnosing Autism Spectrum Disorder can be challenging due to the lack of diagnostic tools available. Medical professionals consider a patient's actions and development history during their diagnosis process. Age group ASD can also be recorded as 18 months or younger [11]. A person who knows a lot about something says their opinion is good when they're just starting at age two. Clinicians employ various tools for identifying Autism Spectrum Disorder. Tests consist of the Autism Diagnostic Observation Schedule, Second Edition (ADOS-2), the Modified Checklist for Autism in Toddlers (M-CHAT), the Diagnostic Interview for Social and Communication Disorder (DISCO), the Gilliam Autism Rating Scale (GARS), the Developmental, Dimensional, and Diagnostic Interview (3di), the Autism Diagnostic Interview-Revised (ADI-R), the Childhood Autism Rating Scale (CARS), and the Diagnostic Interview for Autism [16] [21]. The ADOS and ADI-R tests identify autism spectrum disorder most accurately. Even though these highly reliable tests are susceptible to errors due to interviewers' memory and understanding of children, unpredictable circumstances may alter interactions between examiners and test-takers, and despite being precise tools for diagnosis, they still exhibit variations in their accuracy. [8]. Due to the numerous restrictions, diagnostic methods that do not rely on behavioral traits and medical knowledge are needed [19]. Numerous studies have been conducted that use neuroimaging data to diagnose ASD (structural and functional). An essential method for analyzing the architecture and anatomical connections between various brain regions in ASD is structural neuroimaging [9]. The primary method for imaging the brain's structure is magnetic resonance imaging (MRI). Many studies have been able to classify ASD based on MRI data and machine learning (ML) techniques, including DL techniques.[8].

On the other hand, MRI-based techniques require comparatively longer scan periods, are noisy, and are highly susceptible to motion artifacts. For people with autism spectrum disorder who may experience sensory sensitivity, anxiety, or difficulty communicating, MRI machines can be stressful places [22] [24]. Artificial Intelligence (AI) based Computer-Aided Diagnostic Systems (CADS) apply ML and DL in the diagnosis of ASD. Stages of a typical AI-based ML CADS include feature extraction, classification, data preprocessing, and data capture. Unlike standard ML approaches, DL-based CADS intelligently performs feature extraction and classification within the model.

In numerous prior works on EEG and ASD, features were handcrafted, and the resulting data were classified, an approach particularly fragile to noise and non-stationarity and highly dependent on the specific choices made in feature engineering [1] [9]. Applying CNNs to spectrograms to facilitate the automation of the approach tends to pose issues, requiring extensive, precisely curated datasets. Limited or heterogeneous data, however, poses a significant risk of overfitting [8] [13]. More recent works using graphs or transformer modules can capture relations of cross-channel and long-range dependencies, although they tend to be more sensitive to montage/graph construction, more computationally costly, and more data-hungry in clinical EEG settings, even though the latter two tendencies are mitigated. Unlike the remainder of the approaches in the literature, the Wavelet Scattering Transform (WST) yields time-shift-invariant and deformation-stable representations that remain stable under noise and continue to perform well in low-data regimes, yielding physics-informed features that possess class-discriminability [18]. Our approach pairs WST with compact deep classifiers (WST-ASDNet and WST-AS-DNet+AlexNet) to fill these gaps: mitigated dependence on manual feature engineering, enhanced resistance to EEG non-stationarities, and high discrimination on brief 30s segments all improved accuracy and AUC in our experiments.

3. Proposed Framework

In this study, the PSD estimates from the EEG signals of participants with ASD and normal subjects were obtained using Welch's periodogram technique. FFNN and WST-ASDNet with AlexNet networks were then employed to identify ASD and healthy controls based on the PSD estimates. Figure 2 displays this study's methodological procedure. The brain impulses are very intricate and unpredictable. Their characteristics are mostly influenced by the person, his or her Age, and his or her mental condition. The onset of the symptoms can potentially occur at any time. The activity and dynamics of billions of connected neurons, as well as their relationship to physiological events, must thus be comprehended using a spectrum of linear and nonlinear signal processing approaches. In this study, we have applied WST ASDNet with AlexNet and FFNN models to ASD categorization based on Power Spectral Density (PSD) estimates based on EEG signals to categorize ASD [10].

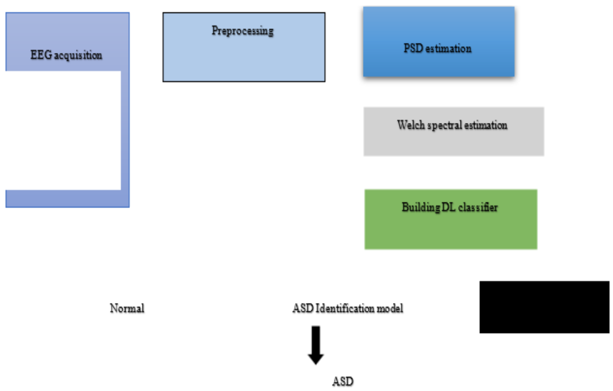

Fig. 2: Overall Architecture.

3.1. Dataset and PSD estimation

As an integral part of this study, the data set containing EEG samples of autism spectrum disorder (ASD) was gathered from freely accessible sources and platforms that are used for ASD research. EEG data were obtained from N=60 (30 ASD and 30 healthy controls) subjects. The ASD group consisted of individuals aged 6 to 18 years (mean 12.1 ± 3.4 years) and comprised 20 males and 10 females. The control group had an almost identical age (mean 11.8 ± 3.6 years) and sex distribution, with 18 males and 12 females. Clinical evaluations of ASD were performed according to the DSM-5 guidelines and graded for severity as mild (n=12), moderate (n=11), and severe (n=7) . The subjects were composed of individuals who had been diagnosed with ASD. Each diagnosed participant was isolated in a recording chamber to capture EEG head scans. 30-second EEG intervals were used in the subsequent analysis.

Table X: Characteristics of the EEG Dataset Used in the Study

Group	No. of Subjects	Age Range (Years)	Mean Age ± SD	Gender (M/F)	ASD Severity Levels
ASD	30	6–18	12.1 ± 3.4	20/10	Mild: 12, Moderate: 11, Severe: 7
Control	30	6–18	11.8 ± 3.6	18/12	Not applicable
Total	60	—	—	38/22	—

The demographic and clinical details of the study subjects are presented in Table 1. The study involved 90 children aged between 6 and 18, half with autism spectrum disorder and half without, both genders equally represented. According to the DSM-5, ASD diagnoses were made, and the severity was categorized into mild, moderate, or severe levels. The details covered here enhance the study's ability to be repeated and support the findings.

The platform provided the data set. From every person in this research, we took short brain wave measurements of just thirty seconds. After all their brain signals were cleaned up first. Welch's periodogram method was used to calculate the PSD of the EEG signals in this study. The time series data is divided into parts, and the fast Fourier transform technique is employed to create the Welch spectral analysis approach. For a standard periodogram to give an accurate spectral estimate, the signal's spectral content must be constant over the considered period. The periodogram often shows too much change and isn't accurate. To smooth out fluctuations over short intervals by averaging periodogram measurements, Welch's method effectively reduces variability. But because of this, the ability to distinguish between closely spaced frequencies decreases. Equation 1 really decides how clearly we can tell sounds apart.

$$f_{res} = {}^{1}/_{t} \tag{1}$$

The zeroth-order coefficients summarize the average energy of the EEG signal over time and act as an average representation of signal magnitude.

where we chose a window of 2/0.5=4 seconds, and t is the signal's duration in seconds. The frequency resolution is lowered to 4 frequency bins per Hertz, or 0.25 Hz every step, by using a 4-second sliding window. Each data segment is given a periodogram, which is followed by the PSD estimates being averaged for each segment of length M and the computation of modified periodograms. The periodogram is computed using a Hamming window, which lowers spectral leakage. The computed periodograms are then averaged to lower variance. The EEG waves were split up into 4-second intervals, with 1024 samples that shared a 50% overlap. Following the acquisition of the PSD values, the EEG signals were classified using DL networks.

3.2. Deep learning algorithms

The Wavelet Scattering Transform (WST) is a method for extracting features that capture stable, time-invariant representations of EEG signals and is robust to noise and small degrees of deformation. This makes WST a good feature extraction method for ASD classification, because it captures discriminative hierarchical representations that are automatically generated and do not require manual feature engineering. WST works by applying a series of wavelet filters and modulus non-linearities, which allow for the decomposition of complex EEG activity into a representation across multiple timescales, with a rich representation of material that will be suitable for the deep learning classifiers.

A recent approach to extracting features is the information-driven Wavelet Scattering Transform (WST) [11]. Wavelet Scattering is the deep CNN counterpart, and it is created by combining several low-pass filters, wavelets, and modulus nonlinearities. It produces representations that are stable against time-warping distortions, resistant to noise, and time-shift invariant. WST has been used with a variety of biological signal types. To classify arrhythmia ECG cardiac signals, 8-time frames were generated from each ECG signal using WST. To distinguish between the EEG signals of normal subjects and those of alcoholic subjects, the WST has also been applied to EEG signals. Seizures have been detected, and preictal and interictal EEG signals have been classified using WST features from surface EEG and intracranial EEG. EEG signals were used, and second-order WST features were extracted from these EEG signals after pre-processing. Following feature reduction via PCA, ASD was classified using CNN-based classification networks and LSTM networks. We introduced two Wavelet Scattering Transform and DL based ASD diagnostic networks (WST-ASDNets) as computer-aided ASD detection techniques [12]. The findings showed that the suggested models outperformed several ML classifiers in terms of performance.

The WST-ASDNets used a bi-layer WST network to extract features from the input. Because it maintains class discriminability and is resilient to deformations, it is great for EEG categorization.

The equation shows how a scaling function "φ" and an input signal "x" convolve at layer 0 (zero order) to produce zero order scattering coefficients.

$$S_{o1} = x * \varphi \tag{2}$$

Local variations in EEG signals are captured by the first-order coefficients, which remain stable under time shifts and noise conditions. WST-ASDNet analyzes the features to distinguish between Autism Spectrum Disorder (ASD) and normal individuals accurately.

Where does convolution stand? After obtaining the zero-order scattering coefficients, the EEG signals are convoluted once more with the mother wavelet 'ω' at a center frequency p1 for the first-order wavelets. The modulus of the CWT coefficients from equation (2) is filtered by the low-pass filter φ, the scaling function, creating layer 1 (first-order) scattering characteristics. Temporal averaging is another term for this procedure. Enforcing time shift invariance through averaging helps maintain stability against time-warping distortions.

To categorize ASD and normal individuals, DL classifiers and WST-ASDNets were used in conjunction with the AleXnet model. FFNN was the DL technique used [13–15]. The likelihood of a class or event occurring (between 0 and 1) is provided by the LR model. In the DT model employed in this study, the split criterion was Gini's diversity index, and 100 splits were accomplished. In this work, we used a Euclidean distance metric and a k-NN with a single neighbor. Using WST-derived features and a Feed Forward Neural Network (FFNN), one WST-ASDNet was able to classify ASDs. Using a WST-ASDNets network and WST characteristics, another WST-ASDNet with AlexNet diagnosed ASDs.

4. Experimental Results and Discussion

This section discusses the classification results that the DL models produced. Fig. 3 shows a typical single-channel EEG signal.

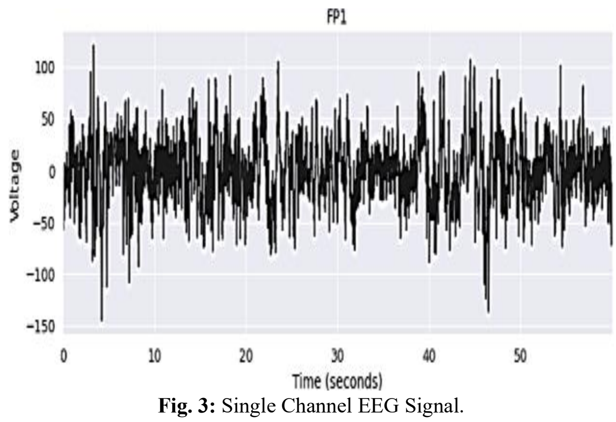

Fig. 3: Single Channel EEG Signal.

Fig. 4 displays the Welch periodogram that was acquired for a single EEG channel (provided in Fig. 3).

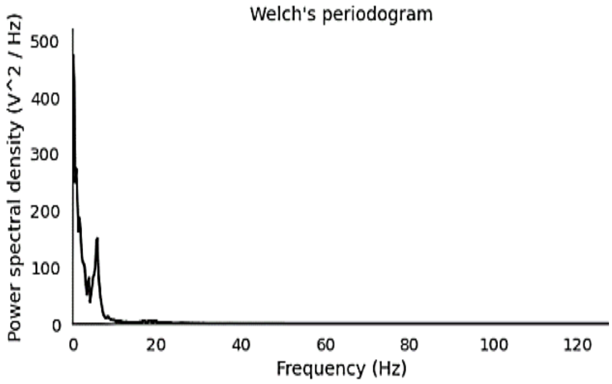

Fig. 4: Welch Periodogram Obtained for Fp1 Channel.

Welch's periodogram was used to calculate the PSD estimations for each EEG channel segment, which consisted of 1024 samples with 50% overlap. The DL models were validated and their accuracy tested using k-fold cross-validation and holdout cross-validation techniques. Using the DL algorithms FFNN and WST-ASDNet with AlexNet, PSD estimates from the Welch's Periodogram method were used to distinguish between the participants with ASD and the healthy controls. The PSD coefficients from the EEG signals were used to construct a 6720x512 dataset. There were 3360 samples from participants with ASD and 3360 samples from subjects without ASD. Following the shuffle, the dataset was divided into training and test subsets. 80% of the samples were used to train the deep learning models, while 20% of the samples were used to test the models. The dimensions of the training and test datasets were 5376 x 512 and 1344 x 512, respectively. The networks were trained using a batch size of 32 and 100 epochs. The suggested models' training procedures are shown in Figures 5(a) and 5(b).

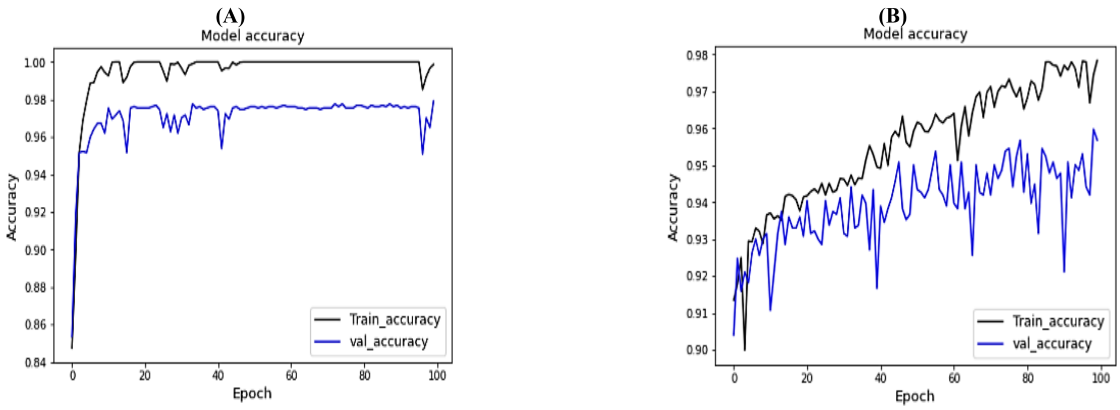

Fig. 5: (A) Training Process of the Proposed FFNN 5 (B) Training Process of the Proposed WST-Asdnet with Alexnet Model.

The Area Under the Curve-Receiver-Receiver Operating Characteristics (AUCROC) curve is a performance metric for categorization difficulties at different threshold levels. A probability curve and the degree of separability are denoted by the words AUC and ROC, respectively. It illustrates the model's cross-class discrimination effectiveness. Figure 6 displays the suggested models' AUC-ROC curves.

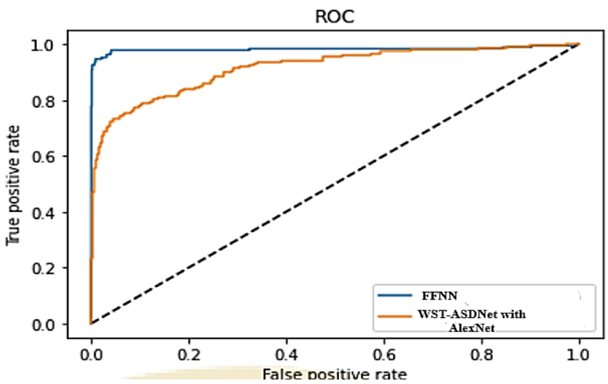

Fig. 6: Predictive ROC Performance of the Classifiers.

AUC values of 0.982 and 0.916, respectively, were obtained by the suggested FFNN model and the WST-ASDNet with the AlexNet model. The high AUC of these two models indicates that they are both effective at differentiating between persons with ASD and healthy individuals. The suggested FFNN model did better in distinguishing between ASD and normal participants, as the AUC-ROC curve illustrates.

Table 1: Overall Evaluation of Performance of the Proposed Models

Performance measures	FFNN	WST-ASDNet with AlexNet
Accuracy	95	98
Sensitivity	95	94
Specificity	96	97
Precision	95	97

Negative predictive value	98.4	98.6
F1_score	97	99
False Positive Rate.	0.18	0.16
False Positive Rate.	0.96	0.97
False Negative Rate	7.85	6.65
Mathews Correlation Coefficient	95.43	96.54

The 5-fold cross-validation technique was employed to assess the DL models' performance. Table 2 presents the acquired results.

Table 2: Comparative Study of Prediction Accuracy Before and After Feature Selection

Model	5-fold cross-validation		Holdout cross-validation	
	Accuracy attained using PSD estimates	Accuracy attained using the raw bandpass filtered EEG	Accuracy attained using PSD estimates	Accuracy attained using the raw bandpass filtered EEG
FFNN	94	79	95	85
WST-ASDNet with AlexNet	96	90	98	87

When PSD estimations were applied to ASD categorization instead of raw band-pass filtered EEG signals, the suggested CNN and LSTM models outperformed one another in terms of performance. Additionally, we saw that when we increased the number of training epochs for the models, the DL models' accuracy rose. However, as the number of epochs exceeded 100, the increase in epochs did not affect the accuracy of DL models.

5. Conclusions

ASD diagnostic indices based on EEG have been the subject of several investigations to develop more precise neuroimaging diagnostic indices. The findings of this investigation imply that the EEG is a valid technique to assist doctors in diagnosing ASD based on the categorization results that were obtained. Two WST-ASDNet with AlexNet based on WST and DL were suggested in this work to classify ASD using EEG data. One hundred and twenty-four-channel data from subjects were used to train and assess the models. ML models sorted out the WST features. The DL-based networks outperformed the traditional ML classifiers across all evaluated metrics for model performance assessment. The effectiveness of WST-ASDNets was assessed through an additional sixteen-channel EEG study, revealing a 98% precision rate for identifying ASD. WST-based deep learning models excel at identifying ASD in EEG data, making them crucial tools for diagnosing ASD in clinics.

Future Directions: While the current study shows high discrimination accuracy between the ASD and healthy control groups, subsequent studies could apply the framework in classifying the severity of ASD (mild, moderate, severe). Multi-classifying approaches may be examined in studies that use WST features combined with methods that are either CNN or LSTM-based. Challenges that remain are inter-subject variability, differences in quality EEG signal, and short duration of recorded signals. In future studies, data augmentation strategies will likely be used as well as transfer learning methods and/or federated learning approaches involving multiple clinics. Severity classifications integrated into clinical workflows can facilitate a more personalized approach for early planning of interventions and decisions about therapy.

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