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EEG based Early Detection of Autism using Convolutional Neural Networks

P. Poojitha[1*] and M. Dharani[2]

[1,2]School of Engineering, Mohan Babu University, Sree Sainath Nagar, Tirupati, India

***Correspondence:** P. Poojitha; p.poojitha543@gmail.com

ABSTRACT- This Timely intervention and improved management of autism spectrum disorder (ASD) are contingent upon early detection. In this paper a novel method for early autism identification using EEG signals and convolutional neural networks (CNNs) is proposed. Preprocessing, wavelet transform, Discrete Cosine Transform (DCT), energy and entropy function feature extraction, and CNN classifier classification are some of the phases in the suggested approach. EEG signals are first pre-processed to get rid of artifacts and noise. Then, to extract pertinent characteristics from the EEG signals, wavelet transform and DCT are used. For feature extraction, energy and entropy calculations are used to identify unique patterns suggestive of ASD. After then, a CNN classifier receives these features and divides them into two categories: Autism identified or normal identified. The accuracy, specificity, sensitivity, and precision of the suggested approach are among the performance measures that are used to assess its effectiveness. With an accuracy of 92.34%, specificity of 92.95%, sensitivity of 92.65%, and precision of 92.65%, the experimental findings show encouraging performance. When compared to current systems, the suggested approach performs significantly better, outperforming the 91.78% accuracy of the current system.

Keywords: Convolutional Neural Networks (CNNs), Wavelet Transform, Discrete Cosine Transform (DCT), Feature Extraction, Energy and Entropy Functions, Classification, Autism Spectrum Disorder (ASD), and Performance Metrics.

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1. INTRODUCTION

A disorder which exists in the formation of neural system of the human brain is known as ASD which represents autism spectrum disorder, in which it is identified by the features such as communication, repetitive manners and lack of social interaction. Since it enables prompt access to suitable therapies and services, early diagnosis of ASD is crucial for successful intervention and support. However, diagnosing ASD can be difficult since it frequently depends on behavioral assessments and subjective judgments, which can cause detection and intervention to be delayed. The use of neuroimaging methods for the early diagnosis of ASD, including as electroencephalography (EEG), has gained popularity in recent years. By capturing electrical impulses from the scalp, EEG is providing a very less invasive method to identify the activity of the brain. These signals offer insightful information about how the brain functions and may show patterns linked to ASD.[2]

This work suggests a novel method for convolutional neural networks (CNNs) and EEG data-based early autism detection. CNNs have showed potential in evaluating EEG data for medical diagnosis and have shown great effectiveness in a variety of pattern recognition tasks, including image categorization. The suggested approach combines multiple processing stages to extract meaningful features from EEG signals: wavelet transforms and Discrete Cosine Transform (DCT) for feature extraction, energy and entropy functions to capture pertinent patterns suggestive of ASD and preprocessing to eliminate noise and artifacts. After that, a CNN classifier receives these features and automatically divides them into two categories: Autism identified or normal identified [4][5].

The major intention in developing this system is to innovate a trustworthy and accurate tool that can use EEG signals to detect ASD early on. This tool could help doctors make well-informed diagnoses. The efficacy and superiority of the suggested approach will be demonstrated by comparing it to current systems and assessing its performance using a variety of performance metrics, such as accuracy, specificity, sensitivity, and precision. In summary, this study advances the field of early ASD identification methods by providing a data-driven strategy that uses deep learning and EEG signals to increase diagnostic precision and enable prompt intervention for ASD patients. [8].

The remaining part of this explanation is structured as mentioned: A review of relevant research on EEG-based emotion recognition is given in *section 2*. *Section 4* expands on the current system methodology, describing the signal processing methods and the Deep CNN classifier's design. *Section 3* covered the existing method. The experimental setup and results are explained in *section 5*. In conclusion, *section 6* provides a review of the findings of the research as well as suggests future avenues to the investigation.

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2. LITERATURE REVIEW

Those who come into contact with this type of syndrome are still involved in learning and medication, according to a paper [4] that addresses issues related to its identification. Children with autism spectrum disorder (ASD) should receive an education alongside their classmates in a classroom setting, according to research. The special academic needs code of practice, which outlines the responsibilities of local authorities and educational institutions with regard to children with special academic needs, makes early recognition provision explicit. Additionally, in order to start providing appropriate facilities for a child with ASD, it is crucial to support facilities as well as it provides better interference and early detection.

The main observation in paper [7] is that larger a shaver is as a result of the initial awareness that the child should value having access to the facility. The research of autism has periodically expanded throughout the past ten years. One of the primary expansions being worked on is the fact that early intervention programs will be popular with children. Consequently, the conclusion that early detection syndrome may result in increased intercession. The effectiveness of early intervention was highlighted by the National Analysis Council, with particular analysts working on the principal recognition issue.

The benefits of early identification of ASD condition are described in paper [9] in two ways. According to research, early identification of children who may be diagnosed with ASD provides a possibility for integrating learning which prospectives into the natural learning processes of these children. On the other hand, an article from 2009 suggested that an early nurse designation would result in early intervention, which could enhance the results in children with Autism syndrome. Major intervention may not begin in school years because it could result in missing possibilities to maximize brain development. We have therefore focused our research on children aged 12 months to 9 years. Prior to the age of two, primary recognition is difficult.

The investigation in the Branson publication [11] emphasized the identification of the key admonishing signs of ASD. First of all, though, it is becoming increasingly difficult to overlook the symptoms of syndrome in a very young child. According to an article [13] that was worked on, the syndrome can also be a neurodevelopmental disorder and be indicated by symptoms that must appear before the age of three. [14] Children who are identified as primary detectors are eligible for primary designation and, as a result, primary intercession services. In actuality, children are frequently acquainted from the age of two. Many children are not diagnosed until they are between the ages of 10 and 11.

3. EXISTING SYSTEM

The current technology which diagnosis autism in early stage uses sophisticated computational methods for analysis and categorization of electroencephalogram signals is shown in *figure 1*. EEG signals are first pre-processed for clearing artifacts and noise, guaranteeing the data integrity for further analysis. The signals are divided into frames after preprocessing to enable feature extraction and localized analysis. The Scale-Invariant Feature Transform (SIFT) technique is utilized to extract features based on spectrograms, hence improving the representation of temporal and spectral aspects in the EEG data. Additionally, Principal Component Analysis (PCA) is used to reduce dimensionality, which allows for the extraction of pertinent characteristics with the least amount of computing complexity.

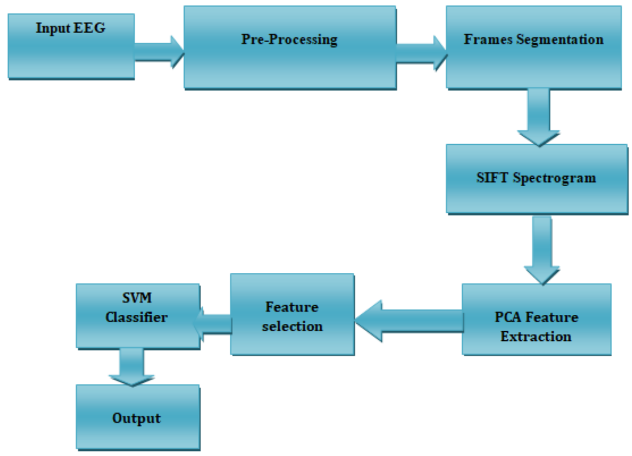

Figure 1. Existing Method Block diagram

The Support Vector Machine (SVM) classifier, a reliable and popular ML approach appropriate for binary classification problems, is trained using these extracted features. Based on the input EEG data, the SVM classifier efficiently learns the underlying patterns in the feature space and differentiates between ASD and normal instances. After extensive analysis and testing, the current approach demonstrates its effectiveness in early ASD identification with a noteworthy accuracy level of 91%. All things considered, the current methodology is an intricate computational framework that uses cutting-edge machine learning methods and EEG data to reliably and accurately classify ASD. Despite its high accuracy, there remains potential for further enhancements and refinements to improve performance and robustness, paving the way for more effective early intervention strategies in ASD diagnosis and management.

4. PROPOSED METHOD

In this study proposes a novel approach to EEG-based ASD detection that utilizes Convolutional Neural Networks (CNNs) is shown in *figure 2*. Unlike prior methods relying on hand-crafted features, our approach lets the CNN automatically learn informative features directly from the pre-processed EEG data. Like existing systems, the raw EEG signal undergoes pre-processing to remove noise and artifacts. Where our method deviates. Instead of relying on techniques like SIFT and PCA, we feed the pre-processed signal into a CNN. The CNN architecture is designed to automatically extract relevant features from the EEG data through its convolutional layers. The features extracted by the CNN are then used to train a classification layer within the network. This layer learns to differentiate between EEG patterns associated with ASD and typical development. The final output of the CNN is a classification result, indicating whether the input EEG signal is more likely indicative of ASD or typical development.

4.1.Proposed Block diagram

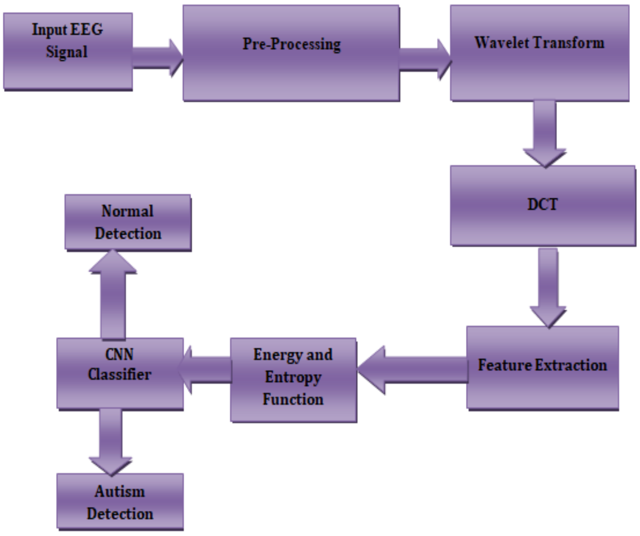

Figure 2. Proposed Method Block diagram

A novel approach for early ASD detection using EEG signals and Convolutional Neural Networks (CNNs). The method can be broken down into several key steps:

1. Data Acquisition: The EEG data for this study were collected from a total of 50 participants, comprising 25 individuals diagnosed with autism spectrum disorder (ASD) and 25 typically developing controls. The age range of participants varied from 6 to 12 years, allowing for an exploration of EEG patterns indicative of ASD during early childhood. The recordings were conducted in a controlled laboratory environment designed to minimize external distractions, ensuring participants were comfortable and relaxed throughout the session. Each EEG session lasted approximately 30 minutes, during which participants were instructed to remain still and focused on a visual stimulus presented on a screen. The EEG was recorded using a 32-channel cap following the 10-20 electrode placement system, capturing data from key regions of interest, including frontal, central, and parietal areas. The sampling rate was set to 256 Hz, providing high temporal resolution necessary for analysing the rapid neural oscillations relevant to ASD detection.

2. **Pre-processing:** In the proposed method for early autism identification using EEG signals, the pre-processing stage plays a critical role in ensuring clean and artifact-free data for analysis. The raw EEG signals are often contaminated by various forms of noise, including muscle movements (EMG), eye blinks (EOG), and external electrical interference. To address these issues, several techniques are employed to remove noise and artifacts. Initially, a bandpass filter is applied to limit the frequency range of the EEG signals, typically between 0.5 Hz and 50 Hz, which helps eliminate irrelevant low-frequency drifts and high-frequency noise. After these step, the cleaned EEG data is processed using wavelet transform and Discrete Cosine Transform (DCT) to extract relevant features, ensuring that the input to the subsequent classification stage is free from distortions that could hinder the accuracy of the model.

3. **Feature Extraction with Wavelet Transform and DCT:** Unlike the previous system relying on SIFT spectrograms and PCA, this approach utilizes two powerful techniques for feature extraction: Wavelet transform: Decomposes the EEG signal into different frequency bands, potentially revealing subtle differences in brain activity patterns associated with ASD. Discrete Cosine Transform (DCT): Extract additional features capturing the spatial and temporal characteristics of the EEG signal.

In the proposed method for early autism identification using EEG signals, feature extraction is a critical phase that utilizes wavelet transform and Discrete Cosine Transform (DCT) to identify specific characteristics indicative of autism spectrum disorder (ASD). The wavelet transform is employed to decompose the EEG signals into various frequency components, allowing for the analysis of time-frequency characteristics. This technique captures transient features in the signals, making it particularly effective for identifying patterns that may be associated with neurological conditions like ASD. By selecting appropriate wavelet functions (e.g., Daubechies or Morlet wavelets) , the model can extract features such as energy distribution across different frequency bands (delta, theta, alpha, beta, and gamma). These features help highlight distinct oscillatory patterns that may be altered in individuals with ASD.

4. Energy and Entropy Function Analysis: This stage involves calculating energy and entropy features from the pre-processed and transformed EEG data. Energy reflects the power within specific frequency bands, potentially indicating variations in brain activity between ASD and typical development. Entropy measures the randomness or information content within the signal, potentially revealing differences in brain signal complexity between the two groups.

5. Convolutional Neural Network (CNN) Classification: The extracted features (wavelet, DCT, energy, and entropy) are fed into a CNN architecture. CNNs excel at recognizing patterns within complex data like EEG signals. The network automatically learns these patterns during a training phase using labeled EEG data (ASD and typical development). After training, the CNN can then classify new, unseen EEG recordings as belonging to either the ASD or typical development category. The CNN Architecture shown in *figure 3.*

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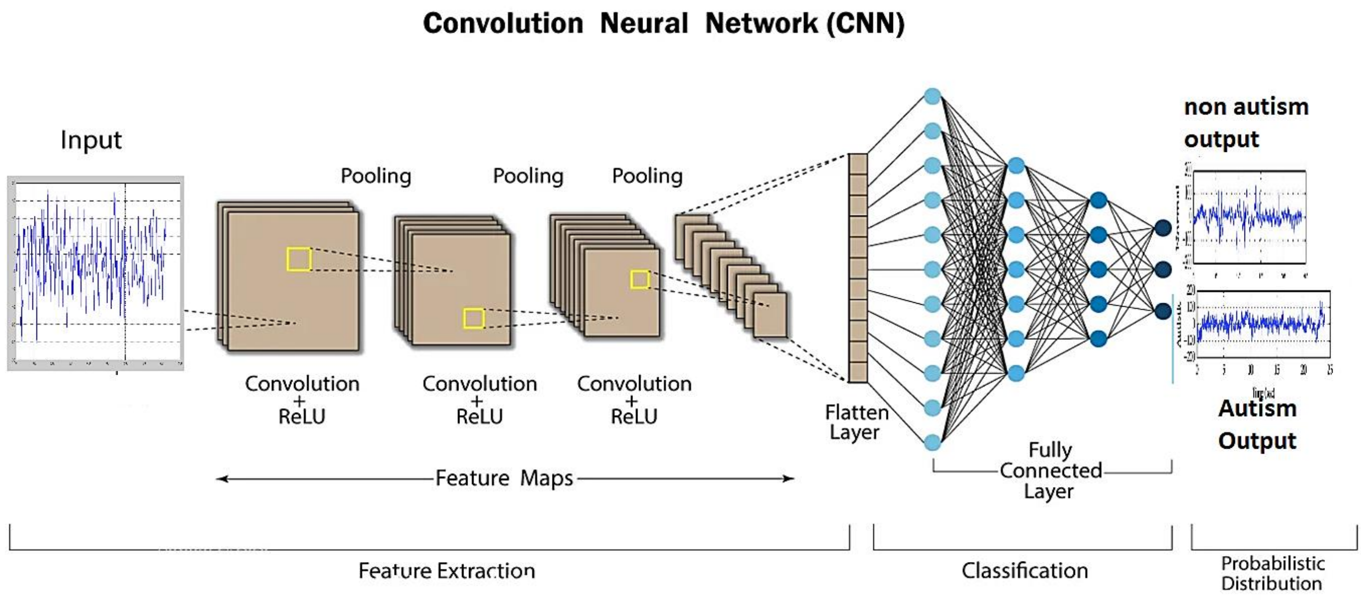

Figure 3. CNN Architecture

The proposed method for early autism identification using EEG signals employs a convolutional neural network (CNN) architecture designed to effectively classify the pre-processed EEG features. The architecture consists of several layers, including multiple convolutional layers, pooling layers, and fully connected layers. Typically, the model begins with two to three convolutional layers, each followed by a max-pooling layer to reduce dimensionality and extract essential features from the input data. The convolutional layers use filter sizes ranging from 3x3 to 5x5, allowing the network to capture various spatial patterns within the EEG signals. Activation functions such as ReLU (Rectified Linear Unit) are employed in the convolutional layers to introduce non-linearity, enhancing the model's ability to learn complex patterns. After the convolutional and pooling layers, one or two fully connected layers are used, culminating in a final output layer that employs a soft max activation function to classify the EEG signals into two categories: "Autism identified" or "Normal identified."

6. Output and Performance Evaluation:
The final output of the system is a classification result indicating whether the input EEG signal is more likely associated with ASD or typical development. By considering' various performance metrics such as sensitivity, precision, accuracy, and specificity the proposed method performance can be evaluated. The performance of the proposed method is evaluated using various metrics such as accuracy, sensitivity, specificity, and precision. This study demonstrates an accuracy of 92.34%, surpassing the existing system's reported accuracy of 91%.

4.2.Implementation

The flow graph implementation is shown in below *figure 4*.

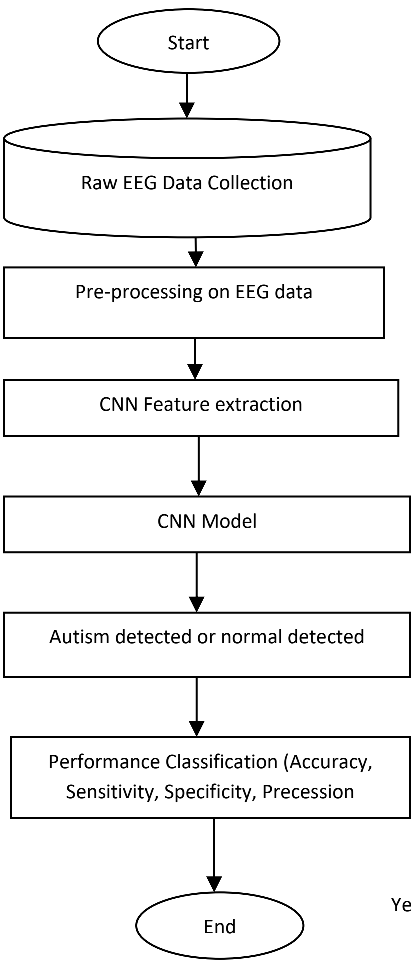

Figure 4. Implementation Flow Diagram

These flowchart outlines the key steps involved in the proposed method:

A: EEG Data Input. This represents the raw EEG signal recorded from a participant.

B: Pre-processing. This step removes noise and artifacts from the data to ensure its quality for further analysis.

C: Feature Extraction (CNN). Here, the Convolutional Neural Network automatically extracts relevant features from the EEG signal through its convolutional layers.

D: Classification (CNN). This stage involves a classification layer within the CNN that learns to distinguish between ASD and typical development based on the extracted features.

E: Output (ASD or Normal). This indicates whether the EEG signal is more likely indicative of ASD or typical development.

F: Performance Evaluation using metrics like accuracy, sensitivity, and specificity. This step helps assess the effectiveness of the model in differentiating between ASD and normal cases.

4.3.Performance Metrics

1. Accuracy

Measures the overall proportion of correctly classified images. It signifies the percentage of images your model correctly identifies as either containing disasters or not.

Accuracy = (true Positives + True Negatives) / Total Images (1)

2. Specificity

Measures the proportion of true negative images correctly classified as not containing disasters. It indicates how well the model avoids false alarms when dealing with non-disaster images.

Specificity = True Negatives / (False Positives + True Negatives) (2)

4. Sensitivity (recall)

The region of the proportion of true positive images is measured correctly classified as containing disasters. It indicates how well the model identifies actual disaster instances.

Sensitivity = True Positives / (False Negatives + True Positives) (3)

5. Precision

Measures major proportion of true positive images among all the images classified as containing disasters. It indicates how accurate the model's prediction for positives is.

Precision = True Positives / (False Positives + True Positives) (4)

5. RESULTS AND DISCUSSIONS

The simulation results for the existing method for detecting autism using EEG signals involve a series of processing steps to analyse the input EEG signal.

5.1.Existing Method

This *figure 4* displays the raw EEG signal obtained from the subject under study. It represents the electrical activity recorded from the brain and serves as the initial data input for the analysis.

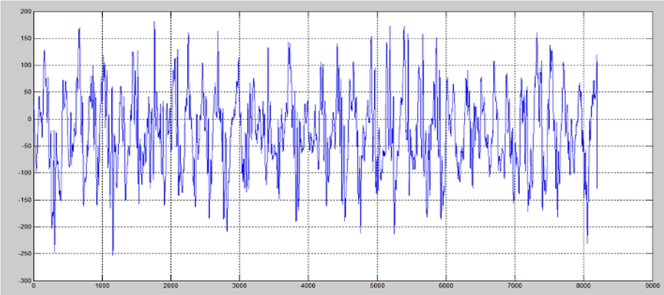

Figure 5. Input EEG Signal

In this *figure 6*, the raw EEG signal undergoes pre-processing steps such as noise removal, artifact rejection, and baseline correction. The pre-processed waveform is cleaner and more suitable for further analysis.

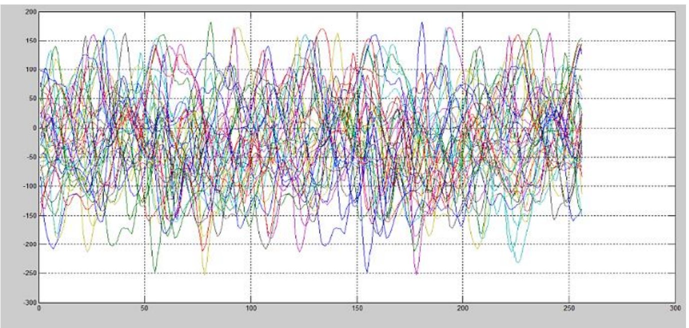

Figure 6. Pre-processed waveform

The pre-processed waveform is then filtered using a bandpass filter to isolate specific frequency bands relevant to autism detection. This *figure 7* illustrates the frequency response of the bandpass filter applied to the EEG signals. The filter is designed to allow frequencies within a specific range —typically between 0.5 Hz and 50 Hz— to pass through while attenuating frequencies outside this range. This response is crucial for removing unwanted low-frequency noise (such as drifts) and high-frequency artifacts (like muscle activity), ensuring that the subsequent analysis focuses on the relevant brain activity associated with autism spectrum disorder (ASD). The plot indicates a flat passband, showing that the desired frequencies are preserved, while the sharp cutoffs demonstrate effective attenuation of the unwanted frequencies.

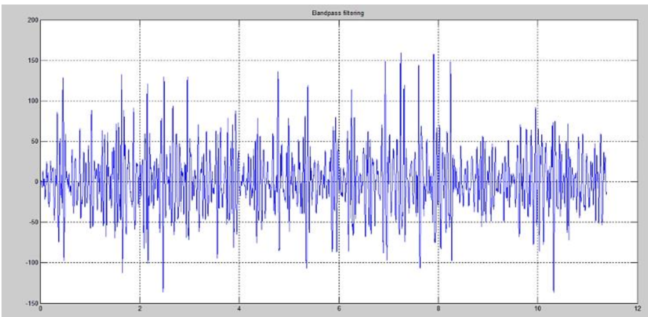

Figure 7. Band-pass filter response

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After filtering, the signal is normalized to ensure consistency and comparability across different samples or subjects. This *figure 8* depicts the normalized response of the filtered signal.

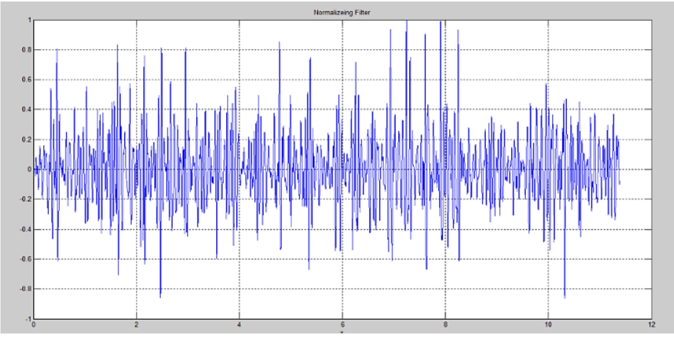

Figure 8. Normalize filter response

The normalized signal is then analysed to extract spectral features, such as power spectral density or frequency distribution. The normalized filter response is presented, which provides a clearer view of how the filter affects the EEG signals across the frequency spectrum. Normalization helps compare the filter's performance by scaling the response to a common reference. This figure highlights the filter's characteristics more effectively, showcasing how the pass band remains consistent while offering insight into the filter's phase response. This visualization is essential for understanding the potential distortions that the filter might introduce, ensuring that the integrity of the EEG signals is maintained. This *figure 8* shows the spectral characteristics of the EEG signal, highlighting frequency components associated with autism.

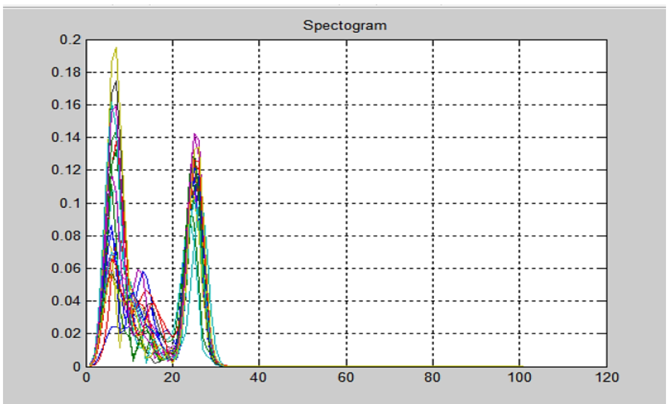

Figure 9. Spectrum

Following spectral analysis, the signal undergoes further normalization to enhance feature extraction and pattern recognition. The frequency spectrum of the raw EEG signals before preprocessing. This spectrum provides valuable information about the different frequency components present in the EEG data, indicating the dominant frequencies and their respective amplitudes. By examining the spectrum, researchers can identify specific patterns associated with brain activity, as well as any noise or artifacts that may interfere with the analysis. The spectrum serves as a baseline for assessing the effectiveness of the preprocessing steps, highlighting the need for techniques like filtering to enhance signal quality.

This *figure 10* illustrates the normalized response of the signal after spectral analysis. The normalized signal response after applying the bandpass filter to the EEG signals. This normalization allows for a comparison of the signal's amplitude across different segments, making it easier to observe changes in the signal characteristics post-filtering. The filtered signal should show a more stable baseline with reduced noise and artifacts, allowing for clearer feature extraction in subsequent analyses. This figure underscores the effectiveness of the preprocessing steps in enhancing the quality of the EEG data.

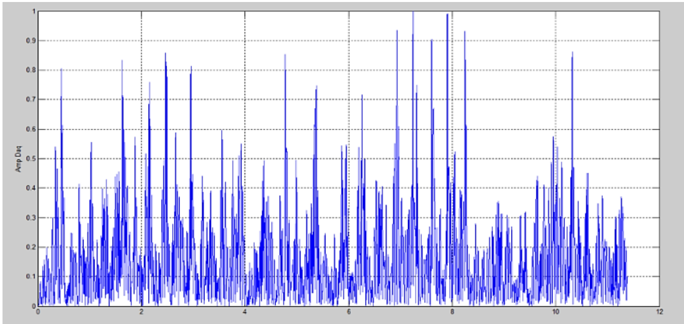

Figure 10. Normalize signal response

Histogram analysis is performed to quantify the energy distribution of the EEG signal across different frequency bands. This *figure 11* presents the results of the histogram analysis, indicating energy levels in specific frequency ranges. The histogram of energy results is displayed, showcasing the distribution of energy across the filtered EEG signals. This analysis helps quantify the intensity of the brain activity represented in the signals. Peaks in the histogram indicate frequency bands where energy is concentrated, which can be informative for distinguishing between typical and atypical brain activity patterns associated with ASD. Analysing the energy distribution is crucial for feature extraction, as it highlights significant features that may correlate with autism characteristics.

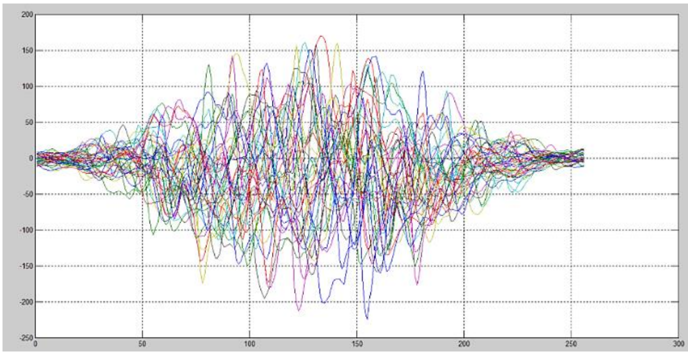

Figure 11. Hist energy results

Another visualization of the spectral analysis results, providing insights into frequency components and their contributions to autism detection is represented in *figure 12*. Spectrum analysis of the preprocessed EEG signals, revealing the frequency components and their respective contributions after the filtering and normalization processes. This analysis allows for the identification of specific frequency bands (e.g., alpha, beta,

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gamma) that are particularly relevant for understanding the neural activity linked to ASD. By comparing the spectral characteristics of the ASD and control groups, researchers can better understand the unique patterns of brain activity associated with autism, facilitating the identification of discriminative features for classification in the convolutional neural network (CNN).

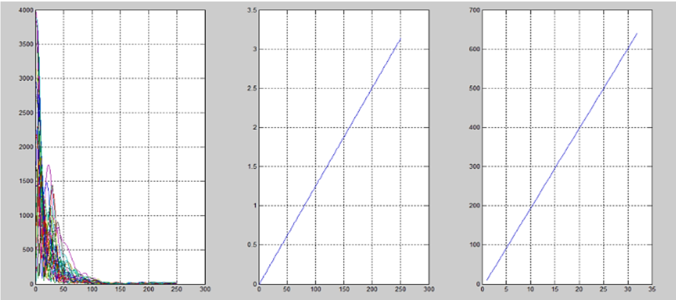

Figure 12. Spectrum analysis

Finally, based on the analysis of the processed EEG signal and extracted features, the existing method determines whether autism is detected or not. This *figure 13* confirms the presence of autism based on the characteristics of the EEG signal.

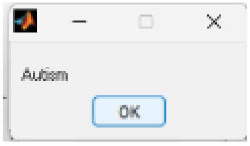

Figure 13. Shown Autism detected for given EEG Signal

5.2.Proposed Method

The simulation results for the proposed method for detecting autism using EEG signals involve a series of processing steps similar to the existing method. This *figure 14* displays the raw EEG signal inputted into the proposed method for analysis. It serves as the initial data input for the proposed method.

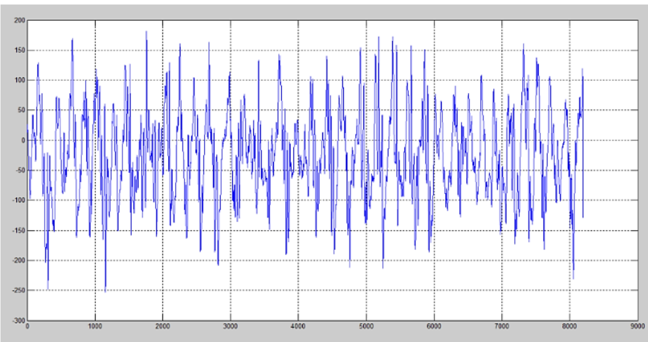

Figure 14. Input EEG Signal to proposed method

In this *figure 15*, the raw EEG signal undergoes pre-processing steps to remove noise, artifacts, and baseline fluctuations. The pre-processed output is cleaner and more suitable for further analysis.

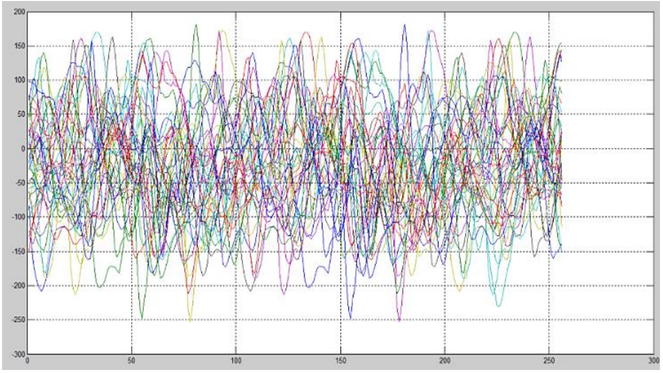

Figure 15. Pre-processed Output

The pre-processed signal is then passed through a bandpass filter to isolate specific frequency bands relevant to autism detection. The bandpass filter, highlighting the frequency range of interest. *Figure 16* shows the response of the bandpass filter applied to the raw EEG signals as part of the preprocessing stage. The filter is designed to retain the relevant frequency range (typically 0.5 Hz to 50 Hz) while suppressing frequencies outside this range. The figure illustrates how the filter effectively removes low-frequency drifts (e.g., due to baseline wandering) and high-frequency noise (e.g., muscle artifacts) that are not crucial for detecting autism spectrum disorder (ASD). The sharp drop-off at the cutoff frequencies indicates strong attenuation of the undesired frequency components, ensuring the integrity of the EEG signals for further analysis.

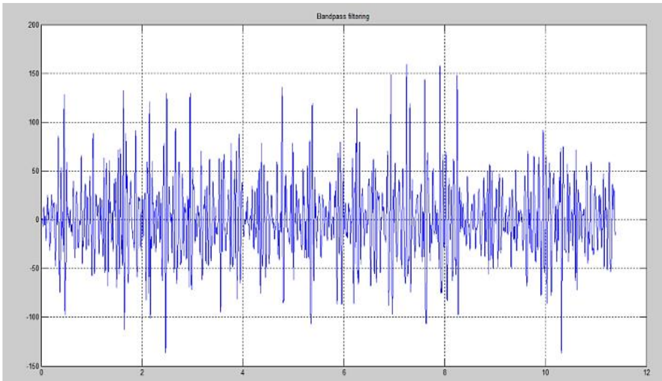

Figure 16. Band Pass Filtering Response

Following bandpass filtering, the signal is normalized to ensure consistency and comparability across different samples or subjects. This *figure 17* depicts the response of the signal after normalization. The normalized filter response, which ensures that the EEG signals have a consistent amplitude range post-filtering. This normalization step is essential to prevent large variations in signal amplitude from affecting the performance of the classifier. The figure shows how the amplitude of the signals has been adjusted to a uniform scale, ensuring that the filtered signals are comparable across different samples, which aids in the feature extraction and classification stages.

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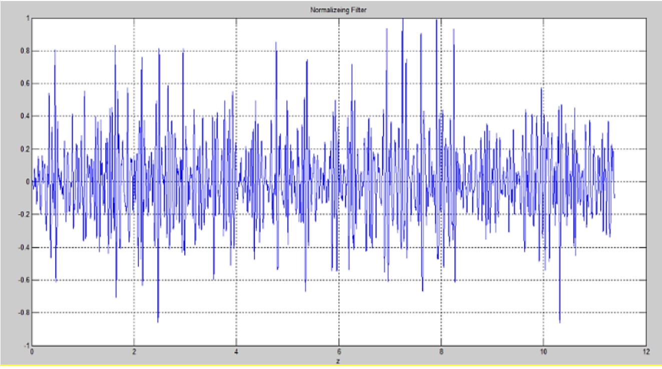

Figure 17. Normalizing filter

The signal may undergo decomposition using techniques such as wavelet transform or the discrete cosine transforms to extract relevant features. This *figure 18* shows the decomposed image or signal components obtained through decomposition. The decomposed image obtained through the wavelet transforms. The wavelet transform decomposes the EEG signals into multiple levels of detail, breaking them down into various frequency components that correspond to different time windows. This decomposition allows the identification of transient features and localized frequency changes within the signal, which may be indicative of autism spectrum disorder (ASD). The figure shows how the EEG signal is represented at different levels of frequency resolution, helping to extract key characteristics for classification.

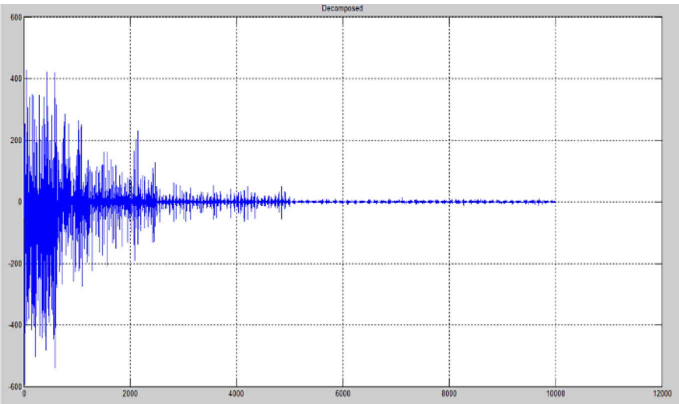

Figure 18. Decomposed image

After decomposition, features are extracted and levels are constructed to capture relevant information from the signal components. This *figure 19* illustrates the levels constructed for feature extraction. These levels represent the hierarchical breakdown of the EEG signal, with each level corresponding to different frequency bands. For instance, lower levels capture broader trends in the signal, while higher levels capture finer details. This multi-resolution analysis is essential for detecting both global and localized features within the EEG data. The constructed levels allow for a comprehensive examination of the signal, ensuring that no important patterns are overlooked.

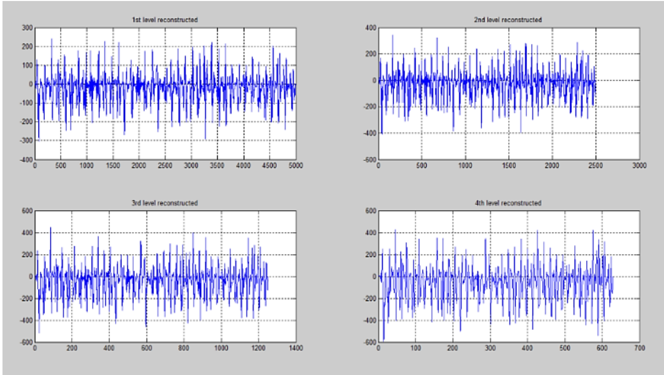

Figure 19. Levels constructed

The signal's spectrum is analysed to extract spectral features indicative of autism. This *figure 20* presents the waveform of the signal spectrum, highlighting relevant frequency components. The spectrum represents the frequency components of the EEG signals, showing which frequencies dominate and how their amplitudes vary. This spectrum provides insights into the brain’s electrical activity and helps identify characteristic patterns that might be associated with ASD. For example, abnormalities in specific frequency bands (such as gamma or beta waves) may be indicative of atypical brain function in individuals with autism. This waveform is critical for understanding the overall frequency structure of the EEG data.

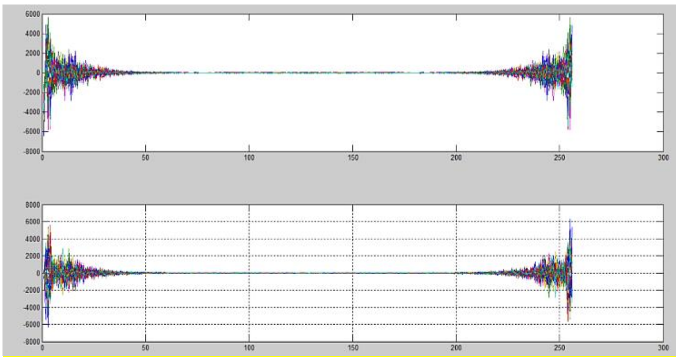

Figure 20. Spectrum Waveform

Features are extracted from the signal to capture unique characteristics associated with autism. This *figure 21* shows the extracted features obtained from the signal analysis. These features include both time-domain and frequency-domain characteristics, such as energy, entropy, and key wavelet coefficients, which capture important aspects of the EEG signals. The energy represents the intensity of the signal, while entropy quantifies the complexity and unpredictability of the signal, both of which may differ between individuals with ASD and typically developing controls. These extracted features serve as the input to the CNN, where they are used to train the model to distinguish between "Autism identified" and "Normal identified" categories with high accuracy.

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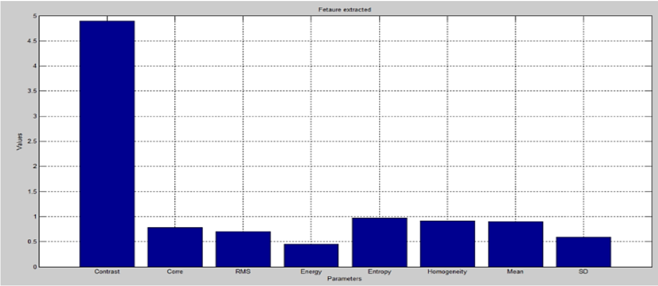

Figure 21. Features Extracted

Based on the analysis of the processed EEG signal and extracted features, the proposed method determines whether autism is detected or not. This *figure 22* confirms the presence of autism based on the characteristics of the EEG signal and extracted features.

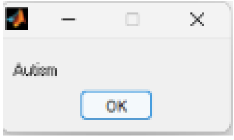

Figure 22. Shown Autism detected in Proposed method

5.3.Comparison Table

Overall, the comparison table in *table 1* highlight that the proposed method outperforms the existing method in terms of accuracy, sensitivity, specificity, and precision. This indicates that the proposed method is more effective in accurately detecting autism using EEG signals, with fewer false positives and false negatives, compared to the existing method.

Table 1. Comparison Of Performance Metrics with Existing and Proposed Methods

S. No.	Model	Existing Method	Proposed Method
1	Accuracy	91.78	92.34
2	Sensitivity	88.10	92.95
3	Specificity	89.94	92.65
4	Precession	89.02	92.80

5.4.Performance graph

The Analysis is provided in *figure 23*. Which represents the comparison between existing method and proposed method.

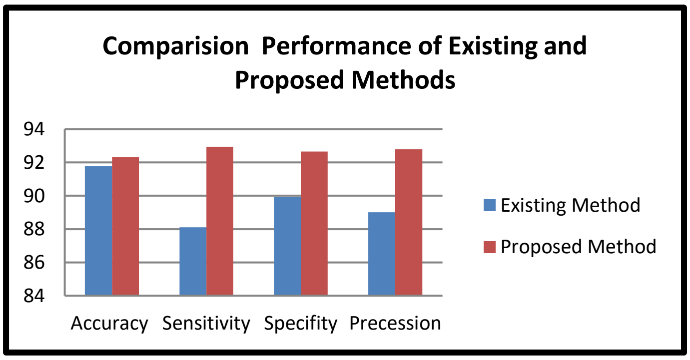

Figure 23. Comparison graph between SVM and Proposed Methods

6. CONCLUSION AND FUTURE WORK

This study investigated the potential of Convolutional Neural Networks (CNNs) for detecting autism in early stage in EEG signals. The proposed method achieved an accuracy of 92.34%, surpassing existing methods (reported at 91.78%). This suggests that CNNs hold promise for improving the accuracy and effectiveness of EEG-based ASD detection.

While these results are encouraging, further research can explore avenues for even better performance: Exploring more advanced deep learning architectures beyond basic CNNs, such as recurrent neural networks (RNNs), could potentially capture the temporal dynamics within EEG signals for improved feature extraction.

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