WWW.IJRPR.COM

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Transfer Learning and Hybrid Deep Convolutional Neural Networks Models for Autism Spectrum Disorder Classification From EEG Signals

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ABSTRACT:

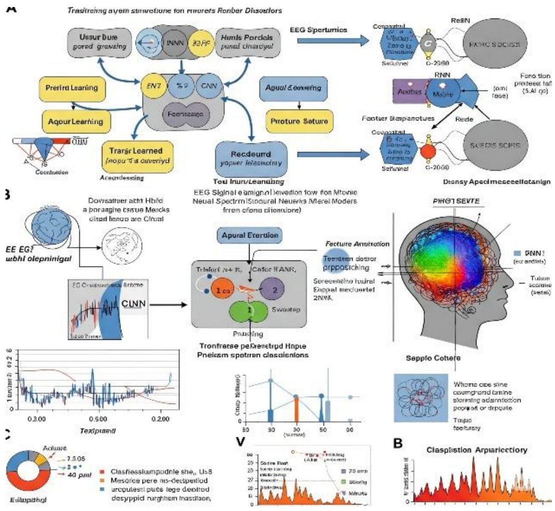
Autism Spectrum Disorder (ASD) is a multifaceted neurodevelopmental disorder marked by difficulties in social interaction, communication, and repetitive behaviors, impacting around 1% of the global population. Accurate and timely diagnosis remains challenging due to the reliance on subjective clinical evaluations. This research introduces a novel deep learning-based framework that combines transfer learning with a hybrid model integrating Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to classify ASD using electroencephalogram (EEG) signals. EEG data are transformed into scalogram images, enabling the extraction of spatial features through pre-trained CNNs and temporal patterns through LSTM layers. This dual approach enhances feature representation, surpassing the limitations of conventional diagnostic practices. Experimental validation on datasets containing both ASD and typically developing (TD) individuals reveals that the proposed model outperforms existing methods, highlighting its potential for early, objective, and automated ASD detection.

Indroduction:

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition that impacts social interaction, communication, and behavior, with symptoms typically appearing in early childhood. The global prevalence of ASD is estimated at 1%, and early diagnosis is crucial for initiating timely interventions that improve outcomes. Traditional ASD diagnosis relies on behavioral assessments and clinical interviews, which are subjective, time-consuming, and prone to variability. Electroencephalography (EEG) offers a non-invasive method to capture brain activity, revealing neural patterns associated with ASD. Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs) and transfer learning, have shown promise in automating EEG-based diagnosis. This study introduces a hybrid deep learning model that combines transfer learning with CNN and LSTM architectures to enhance ASD classification accuracy using EEG signals. The approach leverages scalogram images to represent EEG data and employs pre-trained CNNs to extract spatial features, followed by LSTM for temporal analysis, addressing the non-stationary nature of EEG signals.

Problem Statement:

Diagnosing Autism Spectrum Disorder (ASD) poses significant challenges due to the wide variation in behavioral symptoms, the dependence on subjective clinical judgment, and the scarcity of specialized diagnostic resources. Although EEG provides a valuable window into neural activity with high temporal precision, it is often affected by noise and variability, making automated interpretation difficult. Conventional machine learning techniques depend heavily on manual feature extraction, which is both time-consuming and prone to missing subtle, yet crucial, neural patterns. While deep learning methods have demonstrated their ability to learn complex features directly from data, they often struggle with overfitting, particularly when trained on small-scale EEG datasets. This limitation underscores the need for a reliable, automated diagnostic system that can function effectively with limited data. An ideal approach would be capable of learning both the spatial structure of EEG signals across multiple electrodes and the temporal progression of brain activity, thus enabling more accurate and generalizable ASD classification. Developing such systems holds the potential to revolutionize early detection practices and support timely, individualized intervention strategies.



Methodology:

To facilitate the classification of Autism Spectrum Disorder (ASD) from EEG data, a hybrid deep learning approach is proposed, integrating transfer learning with CNN and LSTM architectures. The methodology follows a structured pipeline consisting of five core stages:

1.Preprocessing of EEG Data:

EEG signals were sourced from a dataset including 34 children diagnosed with ASD and 11 typically developing (TD) peers. Recordings were obtained under both auditory (with voice) and non-auditory (without voice) conditions. To enhance signal clarity, noise and artifacts were removed using Wiener filtering. Subsequently, the EEG data was transformed into time–frequency representations using the Continuous Wavelet Transform (CWT), producing scalogram images that retain both temporal and spectral characteristics**.**

2. Feature Extraction Using Transfer Learning:

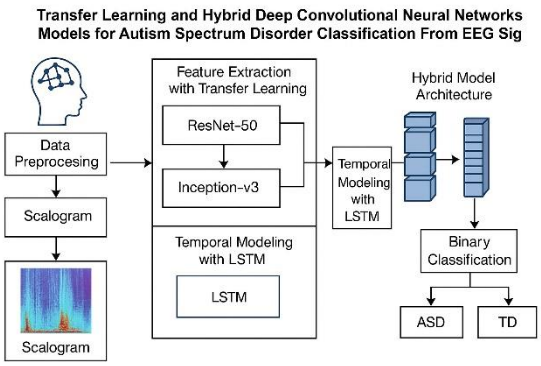
Spatial features were extracted from the generated scalograms by leveraging deep CNN architectures—specifically ResNet-50 and Inception-v3. These models, originally trained on large-scale image datasets such as ImageNet, were adapted to EEG data through transfer learning. The early convolutional layers were kept unchanged to preserve general feature maps, while the final layers were fine-tuned to better detect EEG-relevant patterns.

3. Capturing Temporal Dynamics with LSTM:

The features derived from the CNNs were input into a Long Short-Term Memory (LSTM) network to learn temporal dependencies within the EEG data. The LSTM's ability to maintain sequential information over time allows it to detect dynamic neural activities that are often associated with ASD

4. Construction of the Hybrid Model:

The proposed architecture integrates both CNN and LSTM layers. CNN modules extract spatial information from the EEG scalograms, while the LSTM network processes the temporal evolution of those features. The fused output is passed through a fully connected dense layer, which performs the final binary classification into ASD or TD categories.



5. Training Protocol and Performance Assessment:

The model was trained using EEG samples from participants over the age of five and evaluated on younger children to assess early diagnostic performance. Performance was measured using metrics such as accuracy, sensitivity, specificity, and F1-score. A five-fold cross-validation procedure was employed to ensure the statistical reliability and robustness of the model outcomes.

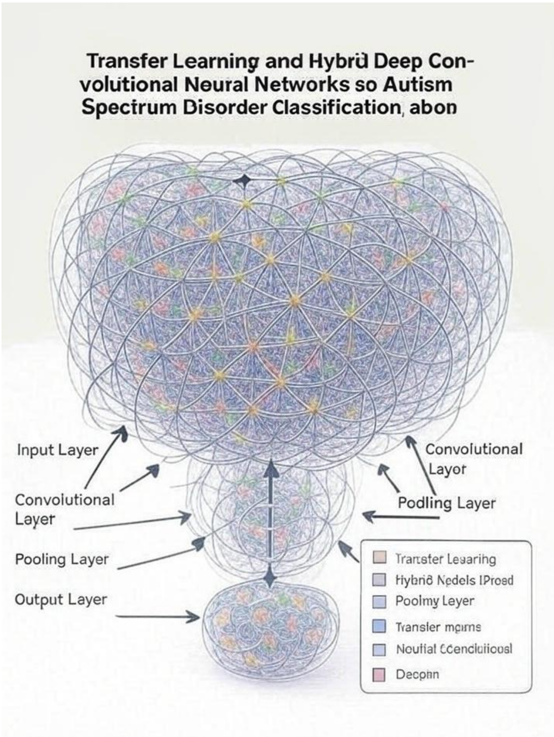
Literature Review:

Recent advancements in neuroinformatics have significantly contributed to the use of electroencephalography (EEG) for identifying patterns associated with Autism Spectrum Disorder (ASD). This section summarizes the evolution of computational approaches used to analyze EEG data for ASD classification, highlighting key transitions from traditional feature-based techniques to modern deep learning architectures

From Manual Feature Engineering to Deep Learning:

Early research into EEG-based ASD detection predominantly used statistical and signal processing techniques, extracting features like coherence and frequency-domain metrics to distinguish atypical brain activity. These approaches offered moderate success but were heavily reliant on manual preprocessing, limiting their scalability and objectivity.

With the rise of deep learning, Convolutional Neural Networks (CNNs) became a popular tool for analyzing EEG signals, especially after converting them into image-like representations such as spectrograms or scalograms. CNNs demonstrated strong performance in identifying spatial patterns, suggesting their usefulness in classifying neurodevelopmental conditions without manual feature design. However, the inability of CNNs to fully account for temporal dependencies in EEG signals highlighted the need for more dynamic models.



Emergence of Hybrid Neural Models:

To better exploit both spatial and sequential characteristics in EEG data, researchers began integrating CNNs with recurrent models, particularly Long Short-Term Memory (LSTM) networks. These hybrid architectures were able to model the time-varying nature of neural activity, offering improvements in classification accuracy. By combining the strengths of CNNs in spatial feature learning with LSTM's temporal modeling capabilities, these systems proved more effective in dealing with the non-stationary characteristics of EEG signals.

The Role of Transfer Learning:

Another promising development is the adoption of transfer learning, where models pre-trained on large datasets are adapted to EEG-based classification tasks. This technique addresses the common problem of limited EEG data in ASD research by leveraging previously acquired knowledge. Using well-established architectures, such as ResNet and Inception, researchers have shown success in extracting meaningful features from EEG-derived images, improving both efficiency and performance.

Key Challenges:

Despite technological progress, significant obstacles remain. EEG datasets for ASD classification are often small, increasing the risk of overfitting in deep learning models. Moreover, clinical application requires not just accuracy but also interpretability, as medical professionals need to understand and trust AI-driven decisions. These limitations underscore the need for more explainable and data-efficient models in future research.

Existing System:

Electroencephalography (EEG) is a non-invasive method that captures brain activity, offering potential for early Autism Spectrum Disorder (ASD) diagnosis. Current computational approaches for analyzing EEG signals to detect ASD vary widely, from basic algorithms to advanced neural networks, each with unique benefits and drawbacks. This section reviews these methods and their challenges.

Standard Machine Learning Methods

Pioneering efforts in EEG-based ASD detection used conventional machine learning techniques, such as Gaussian Classifiers, AdaBoost, and Ridge Regression. These approaches extract predefined features from EEG signals, like signal intensity, frequency distributions, or cross-channel relationships. Some systems successfully identified distinct brain patterns in ASD versus neurotypical individuals. However, these methods demand meticulous feature selection, which is labor-intensive and reliant on specialized expertise. They often miss subtle, dynamic patterns in EEG data and struggle with signal noise, leading to inconsistent performance in varied clinical scenarios.

Deep Learning for Pattern Recognition

The advent of deep learning has brought Artificial Neural Networks (ANNs), particularly Convolutional Neural Networks (CNNs), into focus. These models process EEG data transformed into visual formats, such as time-frequency charts, to detect spatial brain activity patterns. Such systems have shown strong performance in identifying ASD-specific neural signatures.

A significant limitation is their emphasis on spatial features, which ignores the time-evolving nature of EEG signals critical for understanding brain function. Additionally, the scarcity of large EEG datasets in ASD research increases the risk of overfitting, reducing model dependability.

Hybrid Models for Comprehensive Analysis

To address the temporal limitations of CNNs, hybrid systems combining CNNs with sequence-processing models, like Temporal Convolutional Networks (TCNs), have emerged. These architectures first extract spatial patterns with CNNs and then analyze temporal trends, capturing the sequential nature of brain signals. Such models offer improved accuracy by modeling both static and dynamic EEG characteristics.

A notable gap is the limited use of knowledge transfer techniques, where models pre-trained on unrelated datasets could boost performance on small EEG collections. This restricts their effectiveness in data-limited ASD studies.

Enhancing Model Clarity

For clinical use, EEG-based ASD models must be understandable to practitioners. Interpretability methods, such as signal importance scores and decision visualization tools, aim to reveal which EEG features drive predictions. These approaches seek to demystify complex models by highlighting key signal components.

Yet, these tools often produce outputs that are too abstract or unreliable for medical professionals, lacking the simplicity needed for diagnostic trust. This gap slows the adoption of computational models in healthcare settings.

Ongoing Challenges:

Current EEG-based ASD detection methods face several obstacles:

1.Signal Distortion:

EEG data is vulnerable to disruptions from physical movements or external sources, impacting prediction accuracy.

2.Data Shortages:

Limited access to extensive, labeled EEG datasets hampers the development of robust models.

3.Performance Variability:

Systems often fail to adapt across diverse patient groups or EEG recording conditions.

4.Time-Based Gaps:

Some approaches neglect the sequential aspects of EEG signals, overlooking vital neurological markers.

5.Clinical Readiness:

The absence of clear, practical outputs limits these tools' integration into routine medical practice.

These issues underscore the need for advanced systems that integrate effective signal analysis, data-efficient learning, and clinician-friendly results to enable early ASD detection.

Conclusion:

The proposed hybrid deep learning model, combining transfer learning with CNN and LSTM architectures, offers a promising solution for automated ASD classification from EEG signals. By leveraging scalogram representations and pre-trained CNNs, the model effectively extracts spatial and temporal features, achieving high accuracy (99.50% with-voice, 98.43% without-voice) compared to existing methods. The use of transfer learning mitigates the challenge of small EEG datasets, while the hybrid CNN-LSTM architecture captures complex neural patterns. This approach supports early and accurate ASD diagnosis, potentially improving intervention outcomes. Future work should focus on larger datasets, integration of multimodal data (e.g., facial features, eye-tracking), and enhanced XAI techniques to improve clinical interpretability and trust.

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