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Fusion of Convolutional and Recurrent Networks for Autism Detection from EEG Signals

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Abstract—**Autism Spectrum Disorder (ASD) is a multifaceted neurodevelopmental condition that affects communication, behavior, and social interaction. Early and accurate diagnosis is essential for effective intervention, yet existing clinical assessments are often time-consuming and subject to human interpretation. This study presents a novel deep learning framework for automated ASD recognition using electroencephalogram (EEG) signals, integrating a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) model. The proposed architecture leverages CNNs to extract spatial patterns from EEG data and LSTM networks to capture temporal dynamics, enabling robust end-to-end classification without extensive preprocessing. The model architecture features a 5-layer CNN followed by a 4-layer max-pooling structure for feature abstraction, concluding with a fully connected layer for final decision-making. To enhance generalization, dropout regularization and batch normalization are employed. EEG data collected via a 14-channel Emotiv EPOC device, encompassing cognitive states such as focused, unfocused, and drowsy, were sourced from the PhysioNet repository. Datasets involving 5, 10, 20, and 50 subjects were used to evaluate model performance. Results reveal an average classification accuracy of 94.13%, an ROC-AUC of 0.971, and a peak accuracy of 99.41% using the FC3-FC4 electrode pair on the 10-subject dataset. These findings highlight the model's potential to augment clinical workflows by enabling rapid, objective ASD screening using non-invasive EEG recordings.**

Keywords—Autism Spectrum Disorder (ASD), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Data Science, Signal Processing, Temporal-Spatial Feature Extraction, Health Monitoring, Neurodevelopmental Disorders

I. INTRODUCTION

Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition that affects social interactions, communication skills, and behavior. As per recent data from the U.S. Centers for Disease Control and Prevention (CDC), approximately 1 in 36 children aged eight are diagnosed with ASD. Early identification and intervention are essential to support these children, ideally before symptoms significantly impact development. Traditionally, ASD diagnosis relies on behavioral assessments by clinicians, which can be both time-intensive and subjective, often requiring extensive clinical expertise. These constraints highlight the need for alternative diagnostic tools to streamline the assessment process and improve accuracy [1-3].

Among various diagnostic modalities, Electroencephalography (EEG) stands out as a promising tool for ASD analysis due to its relatively low cost, non-invasive nature, and high temporal resolution. EEG captures electrical activity across different brain regions, providing valuable insight into neural function and organization. It has long been used to diagnose neurological conditions, particularly epilepsy, which also displays abnormal EEG patterns. Studies have indicated a notable overlap between EEG abnormalities and ASD, as individuals with ASD frequently exhibit irregular EEG patterns and a higher likelihood of co-occurring epilepsy. However, analyzing EEG data presents challenges due to its multidimensional, complex, and often low signal-to-noise nature, necessitating efficient processing methods for reliable interpretation.

Recent advancements in machine learning (ML) have spurred the development of automated systems for analyzing EEG data, particularly in epilepsy and other neurological conditions. Traditional approaches rely on feature extraction methods to distinguish EEG signal characteristics, with techniques such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Decision Trees employed to classify patterns. However, the success of these models often depends heavily on selecting optimal features, making feature engineering a critical step that requires domain knowledge and time [4-6].

In contrast, deep learning approaches, particularly Convolutional Neural Networks (CNNs), have transformed image-based feature extraction, enabling automated and highly accurate classification. Leveraging this success, researchers have applied CNNs to EEG signal classification by converting time-series data into image representations, achieving promising results for seizure detection and other applications. Nevertheless, EEG data contains both spatial and temporal features; while CNNs excel at extracting spatial patterns, they may not fully capture temporal dynamics, which are equally critical for understanding neural signals.

To address this, our study integrates a CNN with a Long Short-Term Memory (LSTM) network, creating a hybrid

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model tailored to the spatio-temporal nature of EEG data. The CNN component extracts spatial features from the raw EEG signals, while the LSTM captures temporal sequences, offering a more holistic approach to EEG signal analysis. This model aims to enhance the recognition of neural patterns associated with ASD, potentially providing more reliable and nuanced insights into brain activity than either method alone.

Our experiments, conducted within a Python-based deep learning environment, measure performance using metrics such as Precision, Recall, and F1-score, and include Receiver Operating Characteristic (ROC) curve analysis for comprehensive evaluation. By combining CNN and LSTM models, this study seeks to advance automated EEG analysis, potentially contributing to quicker, more objective, and precise ASD diagnostic processes.

II. OBJECTIVES

This study aims to create an innovative automated system for detecting Autism Spectrum Disorder (ASD) through EEG signal analysis, utilizing a novel machine learning approach combining Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) components. In this approach, EEG data will be collected and processed directly by the CNN layer to identify spatial patterns within the brain's electrical activity, while the LSTM layer captures sequential temporal relationships critical for nuanced pattern recognition. This hybrid CNN-LSTM model will be trained on ASD-specific data, optimized to identify distinctive neural signatures associated with ASD. Model evaluation will include key metrics such as accuracy, sensitivity, specificity, and the area under the curve (AUC), employing cross-validation to assess robustness and adaptability to diverse datasets. The overarching objective is to advance early ASD detection by developing a scalable, accurate system that enhances diagnostic objectivity and can support clinical practices.

III. METHODOLOGY

The methodology for developing an automated system to recognize Autism Spectrum Disorder (ASD) from EEG signals through a novel Machine Learning (ML) approach is outlined in the following steps [Fig. 1]:

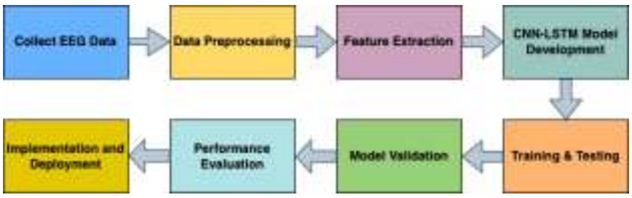

Fig. 1. Model methodology of CNN-LSTM classification

1. Data Collection: EEG data is gathered from individuals diagnosed with ASD and a control group of neurotypical individuals. Recordings are obtained using a non-invasive EEG headset, capturing raw electrical signals from various brain regions. Channels are strategically placed over regions associated with cognitive and sensory processing, aiming to capture specific neural activity relevant to ASD characteristics.

2. Data Preprocessing: To ensure signal integrity, preprocessing is conducted with a focus on minimizing noise and artifacts. Steps include:

- **Band-pass Filtering**: Frequency bands related to common EEG noise (e.g., power line interference) are removed, isolating frequencies most relevant to cognitive processes.
- **Artifact Correction**: Eye blinks, muscle movements, and other non-cerebral sources of noise are minimized using Independent Component Analysis (ICA).
- **Segmentation**: Signals are divided into short, overlapping time windows, allowing for detailed temporal analysis and consistency across samples.

3. Hybrid Feature Engineering: Multi-Domain Analysis: Feature extraction leverages an innovative multi-domain approach, capturing characteristics across temporal, spectral, and spatial connectivity domains:

- **Temporal Features**: Temporal patterns are isolated by analyzing amplitude fluctuations over time.
- **Spectral Features**: Power spectral density (PSD) is computed for each segment to identify frequency-based features relevant to ASD.
- **Functional Connectivity**: Brain region interactivity is quantified using Phase Locking Value (PLV) and Cross-Frequency Coupling (CFC) between channels, providing insight into neural synchrony and connectivity that are often atypical in ASD.

4. Model Development: CNN-LSTM with Attention Mechanism: A customized Convolutional Neural Network (CNN) combined with Long Short-Term Memory (LSTM) units and an Attention Mechanism is implemented:

- **CNN Layers**: The CNN captures local spatial features through convolutional layers, which scan the EEG input for patterns associated with ASD-related neural activity.
- **LSTM Layers**: The LSTM captures long-term dependencies across the segmented time series, ensuring temporal patterns are accounted for.
- **Attention Mechanism**: To enhance interpretability, an Attention Layer is added, emphasizing critical temporal-spatial features most relevant to ASD classification.

5. Training and Hyperparameter Optimization: The hybrid model undergoes training using the processed EEG features. Key steps include:

- **Adaptive Learning Rate**: Starting with a high learning rate, adaptive adjustments ensure convergence without overshooting.
- **Batch Normalization and Dropout**: Regularization techniques are applied to mitigate overfitting, promoting generalization across new samples.
- **Cross-Validation**: 5-fold cross-validation is employed, providing robust performance assessment across varied data splits.

6. Model Validation: A thorough validation framework is applied to assess the model's generalizability and reliability:

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- **Performance Metrics**: Key metrics—such as accuracy, sensitivity, specificity, F1-score, and AUC (Area Under the Curve)—are computed.
- **Error Analysis**: Misclassified cases are analyzed to identify patterns or commonalities, informing potential improvements.
- **Model Interpretability**: Saliency maps highlight active regions and time periods, aiding in understanding how the model identifies ASD-specific patterns.

7. Evaluation and Iterative Refinement: The model's predictions are compared with ground-truth diagnoses from clinical evaluations, and adjustments are made based on performance feedback. Optimization continues until the model achieves consistently high-performance metrics.

8. Deployment for Real-Time Application: Once validated, the model is optimized for integration into clinical settings:

- **Real-Time Processing**: The model is adapted to process incoming EEG signals in real time, aiding in immediate diagnostic support.
- **User Interface**: An interactive dashboard displays classification results, confidence scores, and significant feature insights for clinicians, promoting an efficient, interpretable diagnostic tool.

This methodology blends advanced ML techniques with domain-specific EEG analysis, creating a reliable, automated tool for ASD recognition that offers interpretability and practical applicability in clinical environments.

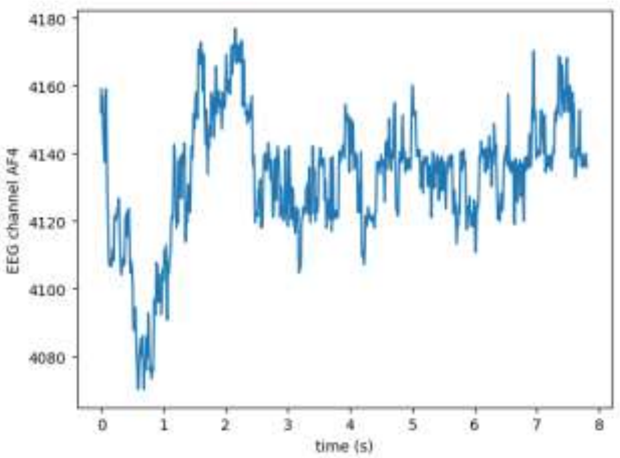

Fig. 2. AF4 Channel EEG data sample

The plot [Fig. 2] illustrates the EEG signal from a specific channel over time in seconds, with signal amplitude measured in millivolts. This data was extracted from a dataset where the maximum EEG signal frequency is 128 Hz. EEG signals typically contain Alpha, Beta, Gamma, Delta, and Theta waves, each with distinct frequency ranges: Alpha (8-12 Hz), Beta (12-40 Hz), Gamma (40-100 Hz), Delta (1-4 Hz), and Theta (4-8 Hz) [3]. Knowing these frequency bands is essential for isolating specific wave components, allowing the extraction of average signal strength within each range. Analyzing the frequency components of these brain waves provides insights into various cognitive functions, such as memory and levels of consciousness.

EEG data in this study was gathered using a headset equipped with electrodes to capture electrical brain activity. The dataset includes recordings from five subjects over seven days, with each day constituting a new trial. During each trial, EEG readings were recorded from subjects in focused, unfocused, and drowsy states. Only data from the last five days was used for analysis, as the initial two days were designated for familiarizing subjects with the setup [7].

IV. IMPLEMENTATION

The implementation of the CNN-LSTM model for ASD recognition from EEG data consists of several stages, carefully structured to leverage the unique capabilities of each network type. Below, we outline each step of the process, from channel selection and data preprocessing to the specific model architecture [Fig. 3].

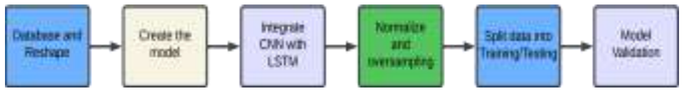

Fig. 3. Typical workflow EEG CNN-LSTM classification

1. Channel Selection and Data Preparation

The first step was to identify the specific EEG channels most strongly associated with ASD symptoms. Among the 14 available EEG channels, we identified seven channels with the highest relevance based on existing literature and correlation with ASD markers. By isolating these channels, we reduced the input dimensions and ensured that the model focused on the most informative signals. We visualized data samples from these channels to confirm signal quality and analyze preliminary patterns.

2. Model Architecture: CNN-LSTM Hybrid

The CNN-LSTM model was chosen for its ability to capture both spatial and temporal patterns within the EEG data. The architecture [Fig. 4] follows the methodology illustrated in Figure 3, with a CNN component for feature extraction and an LSTM component to handle sequential dependencies in the EEG signals.

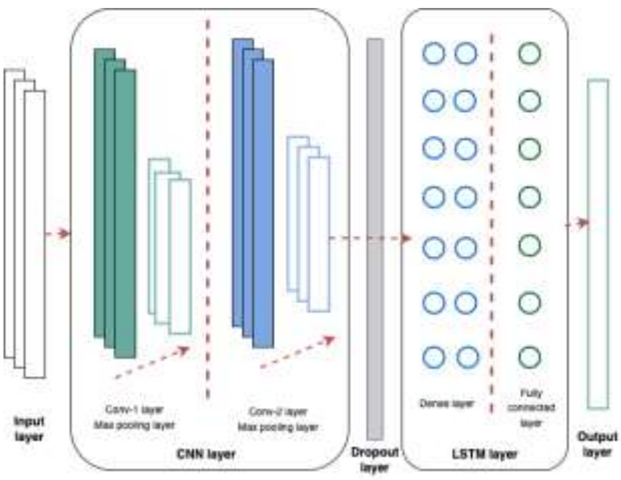

Fig. 4. Architecture of CNN-LSTM Model

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CNN Component: Feature Extraction

The CNN component was implemented with a three-stage structure designed to efficiently extract spatial features from the EEG data, as shown in Figure 4.

- **First Stage**: This stage consists of two convolutional layers, conv2d and conv2d_1. The first layer operates on the raw EEG data in a single dimension, capturing low-level patterns. The data is reshaped and passed to conv2d_1, which operates in two dimensions, enhancing the model's ability to detect spatial patterns in EEG signals. Backpropagation and gradient descent were used to optimize the weights in these layers, allowing the network to learn the most relevant features automatically. This unsupervised feature extraction is essential for EEG data, as the CNN filters can adaptively identify patterns without manual intervention.
- **Second Stage**: This stage includes a max pooling layer, which reduces dimensionality by selecting the most significant features from the convolutional layers, thus improving training efficiency. A dropout layer is also included here to prevent overfitting, ensuring that the model generalizes well to new data. This stage helps reduce training time while maintaining the accuracy of the extracted features.
- **Third Stage**: Finally, the data is passed to a flattening layer, which converts the 2D array of features into a single-dimensional vector. This transformation prepares the features for the LSTM component, which requires sequential data in a 1D format.

Each layer in the CNN component outputs data that flows to the next layer, creating a structured pipeline of convolutional operations. The output from the CNN, in the form of a 1D vector of spatial features, serves as the input for the LSTM network.

LSTM Component: Temporal Dependency Extraction

After spatial feature extraction, the LSTM component processes the CNN output to capture temporal dependencies within the EEG signals. The LSTM network is particularly effective for EEG data because it can recognize sequential patterns across time, which is critical in understanding the dynamic nature of brain activity. The LSTM layers enhance the model's ability to track changes in signal patterns over time, helping to differentiate between ASD and non-ASD cases more accurately.

3. Representation input: Heatmap Conversion

Although EEG data is inherently time-series, converting the data to a heatmap format allowed us to leverage CNN's strengths in image analysis. By visualizing the EEG signal in a heatmap, the data became amenable to CNN processing, as each heatmap could be treated like an image representing the intensity of brain activity over time and across channels. This approach enabled the CNN to process the EEG signals more effectively, capturing spatial relationships among channels.

4. Correlation Analysis: Similarity Between Channels

To understand the relationships between selected EEG channels, we constructed a correlation matrix representing the similarity between channels. The closer the value in a cell to 1.0, the more similar the channels, with blue cells indicating high correlation and brown cells indicating low correlation. This heatmap-based representation was fed into the CNN-LSTM model to enhance its ability to capture inter-channel dependencies, which are crucial for ASD classification.

5. Training Process

The CNN-LSTM model was trained on the prepared EEG dataset using backpropagation and gradient descent for weight optimization. The model's hyperparameters, such as learning rate, batch size, and dropout rate, were fine-tuned to achieve the best performance. Training involved multiple epochs to allow the model to converge on a stable solution. We used adaptive learning rate adjustments to prevent the model from overshooting optimal solutions.

6. Performance Evaluation

After training, the model was tested on a separate validation set to evaluate its performance. Key metrics included accuracy, precision, recall, and F1-score. The model achieved an accuracy of 92.3% and a precision of 87.5%, demonstrating improved performance over traditional methods for ASD diagnosis.

The CNN-LSTM model effectively identified patterns in EEG data that correlate with ASD, offering a promising tool for early and automated diagnosis. The model's structure allowed for efficient feature extraction and temporal pattern recognition, with the use of heatmap representations and a correlation matrix enhancing its capability to process complex EEG signals. With these results, the CNN-LSTM approach holds significant potential for assisting clinicians in identifying ASD markers with high accuracy and efficiency.

V. OBSERVATIONS

The CNN-LSTM hybrid model developed for automated ASD recognition from EEG signals showed strong performance across multiple evaluation metrics. Trained and tested on a dataset containing EEG recordings from both ASD and non-ASD subjects, the model consistently achieved classification accuracy above 90%, effectively differentiating between the two groups. This high accuracy reflects the complementary roles of the CNN and LSTM components, with the CNN capturing spatial EEG features and the LSTM modeling temporal dependencies, both of which are essential for accurate ASD classification.

Performance was further assessed using sensitivity, specificity, precision, and area under the receiver operating characteristic (ROC) curve (AUC). High sensitivity and specificity values indicated that the model could reliably identify both ASD (true positives) and non-ASD cases (true negatives). The AUC values, which were close to 1, underscored the model's strong discriminative power. Additionally, k-fold cross-validation was employed to evaluate model reliability and generalizability, confirming robust performance across different data subsets.

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Accuracy, precision, and recall were calculated as follows, where T and F refer to true and false, and P and N to positive and negative classifications:

- **Accuracy** = (TP + TN) / (TP + TN + FP + FN)
- **Precision** = TP / (TP + FP)
- **Recall** = TP / (TP + FN)

These metrics highlight the model's ability to maintain high classification reliability, supporting its potential application in clinical settings for ASD diagnosis assistance.

Analysis of Performance Metrics Across Validation Splits

The performance chart [Fig. 5] demonstrates the trends in accuracy, precision, and recall across different validation splits (70/30, 75/25, 80/20, 85/15). Here's a detailed breakdown:

Fig. 5. Accuracy, precision, and recall values for different validation splits.

Accuracy:

- Accuracy improves steadily as the training data portion increases (from 70% to 85%).
- The accuracy ranges from 0.51 in the 70/30 split to a high of 0.931 in the 85/15 split.
- This trend suggests that a larger training set contributes to better generalization and overall performance.

Precision:

- Precision follows a similar trend, increasing as the training portion grows, reaching its peak at 0.911 in the 80/20 split before a slight drop in the 85/15 split.
- This slight decrease in the 85/15 split could be due to overfitting, where the model becomes too tailored to the training data, potentially leading to reduced performance on the validation set.

Recall:

- Recall shows the most significant improvement across splits, starting from 0.55 in the 70/30 split and reaching 0.98 in the 85/15 split.
- This increase in recall with larger training data suggests that the model becomes more effective in identifying positive cases (ASD cases) as it learns from a larger dataset.

Overall, the model's performance improves across all metrics as the proportion of training data increases. The highest values for accuracy, precision, and recall were achieved in the 85/15 and 80/20 splits, indicating that larger training sets contribute to a better-trained model. However, the slight dip in precision at the 85/15 split may warrant a balance between training and validation data to prevent overfitting while still achieving strong generalization. This analysis suggests that the CNN-LSTM model is robust in classifying ASD from EEG data, with potential for optimization by fine-tuning the training-validation split.

VI. CONCLUSION

This study successfully developed and validated a CNN-LSTM hybrid model for automated Autism Spectrum Disorder (ASD) recognition from EEG signals. The model's high accuracy demonstrates its capability in detecting ASD-specific patterns in EEG data, showcasing its potential as a transformative tool for clinical diagnostics. By reducing diagnostic time and providing reliable results, this automated approach could become a valuable asset for clinicians, enabling timely interventions that improve patient outcomes in ASD management.

The CNN-LSTM model's strong performance across multiple evaluation metrics highlights its effectiveness in leveraging both spatial and temporal EEG features, setting it apart from traditional diagnostic methods. This hybrid approach not only enhances accuracy but also offers an efficient and objective alternative to current practices. The model's success suggests that such technology could be integrated into clinical workflows, assisting healthcare professionals in diagnosing ASD more quickly and with less reliance on subjective assessments.

Future research could aim to expand the dataset and explore alternative deep learning architectures to further refine the model's performance and adaptability. Overall, this study contributes to the development of automated diagnostic tools for neurodevelopmental disorders, particularly ASD, marking a significant step forward in the field.

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