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| RESEARCH ARTICLE

Autism Spectrum Disorder (ASD) Detection Using Multiple Deep Learning Models and Comparison of Model Performances

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| ABSTRACT
Autism Spectrum Disorder (ASD) impairs speech, social interaction, and behavior. Machine learning is a field of artificial intelligence that focuses on creating algorithms that can learn patterns and make ASD classification based on input data. The results of using machine learning algorithms to categorize ASD have been inconsistent. More research is needed to improve the accuracy of the classification of ASD. To address this, deep learning techniques such as 1D CNN, DNN, LSTM etc. have been proposed as an alternative for the classification of ASD detection. The proposed techniques are evaluated on publicly available three different ASD datasets (children, Adults, and adolescents). The conventional method for diagnosing ASD involves clinical evaluations which are often time-consuming and subjective. With the rising prevalence of ASD, the demand for automated, scalable, and accurate detection systems has increased. Deep Learning (DL) models, including 1-Dimensional Convolutional Neural Network (1D CNN), Deep Neural Network (DNN), LSTM, BiLSTM, CNN-LSTM have shown remarkable results in this domain. This paper compares multiple deep learning techniques using publicly available ASD datasets for Children, Adolescents, and Adults. Experimental results demonstrate that the DNN achieves the highest accuracy of 93.65% for adolescents, 99.90% for adults and 99% for children, while 1D CNN, LSTM, BiLSTM and CNN-LSTM also offer competitive results.

| KEYWORDS
Autism Spectrum Disorder, Classification, Deep Learning, 1D CNN, DNN, LSTM, BiLSTM

| ARTICLE INFORMATION
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1. Introduction
Autism Spectrum Disorder (ASD) is a neurodevelop mental condition affecting speech, social interaction, and behavior (Voinsky et al., 2023). Current diagnostic methods rely on subjective behavioral assessments from expert interviews, leading to inconsistencies in diagnosis due to differences in training and expertise (Song et al., 2021), (Minissi et al., 2022). As ASD cases continue to rise globally e.g., from 1.47% in 2010 to 3.72% in 2017 among 8 year olds in the U.S. (Lai et al., 2020), the demand for faster, more objective diagnostic tools has grown.

Healthcare, particularly ASD diagnosis, faces delays due to lengthy processes involving multiple specialists (Mellema et al., 2022). Traditional methods may take over six months. Machine learning (ML) offers a promising alternative by enabling rapid and automated analysis of complex datasets (Devika Varshini G & Chinnaiyan R, 2020). ML techniques such as LDA, RF, KNN, NB, DT, and SVM have shown potential in ASD prediction, although their effectiveness varies across datasets (Nafea et al., 2021), (Li et al., 2020).

Deep learning (DL), a subset of ML, has gained attention for its autonomous feature extraction capabilities. While traditional Artificial Neural Networks (ANNs) have limitations, Deep Neural Networks (DNNs) and Convolutional Neural Networks (CNNs) can model more complex data (Li et al., 2020), (Ma et al., 2021). CNNs, in particular, are effective in analyzing spatial data like brain images, while 1D CNNs process time-series signals such as EEG. Recurrent models like LSTM and BiLSTM handle temporal dependencies, and hybrid models (e.g., CNN-LSTM) enhance multi-modal ASD detection.

The motivation behind using these DL models is to enable early ASD diagnosis, especially in children, improving treatment outcomes and reducing healthcare costs. This study explores various DL approaches including 1D CNN on child, adolescent, and adult datasets for accurate ASD classification (Alsaade & Alzahrani, 2022).

2. Literature Review

Past research has extensively employed ML algorithms such as SVM, Decision Trees, KNN, and Random Forests to classify ASD. More recent approaches rely on deep learning models to enhance accuracy and learn complex patterns from data. Studies using 1D CNNs, 2D CNNs for imaging data (Heinsfeld et al., 2020), and DNNs for structured data have all demonstrated promising outcomes.

Baranwal and Vanitha (2020) utilized ASD screening datasets for children, adolescents, and adults to identify potential autism-related issues. They employed several ML models: Logistic Regression (LR), Artificial Neural Networks (ANN), Decision Tree (DT), Support Vector Machines (SVM), and Random Forest (RF) to predict ASD across different age groups and successfully extracted meaningful patterns from the datasets.

Sun et al. (2021) investigated functional differences in resting-state networks (RSNs) using data from 103 ASD patients and 192 healthy controls. They applied independent component analysis and image-based meta analysis to extract spatial features, which were then used as input to an SVM classifier. Their approach effectively distinguished ASD individuals based on functional con nectivity patterns.

Raj and Masood (2020) evaluated several classifiers, including NB, SVM, LR, KNN, CNN, and ANN on three public ASD datasets (adults, adolescents, and children). After addressing missing data, their CNN-based models achieved the highest accuracy, confirming the potential of deep learning methods in ASD classification. Raj and Masood (2020) evaluated several classifiers, including NB, SVM, LR, KNN, CNN, and ANN on three public ASD datasets (adults, adolescents, and children). After addressing missing data, their CNN-based models achieved the highest accuracy, confirming the potential of deep learning methods in ASD classification.

Hossain et al. (2021) focused on automating ASD diagnosis by applying advanced classification and feature selection techniques across four datasets: toddlers, children, adolescents, and adults. Among all the models tested, the multilayer perceptron (MLP) consistently outperformed others, achieving the best accuracy across different age groups.

Kumar and Das (2022) studied ASD prediction using a dataset of 701 samples based on the AQ-10 Adult ques tionnaire. In the first scenario, where no missing values were present, models like SVM, RF, and ANN were used. In the second scenario, they applied Recursive Feature Elimination (RFE) to handle missing data and reduce complexity, followed by classification using LR, RF, DT, and SVM. Both cases yielded promising results.

Mashudi et al. (2021) conducted experiments using various ML models, including SVM, KNN, J48, stacking, bagging, AdaBoost, and NB. Simulations were per formed in the WEKA platform, and evaluation was based on specificity, accuracy, and sensitivity. SVM, J48, and stacking achieved the best performance with minimal error.

Alwidian et al. (2020) explored the Association Classification (AC) technique for early ASD prediction. Seven different algorithms were used to assess the effectiveness of AC in identifying correlations between features. Per formance was evaluated using standard metrics: Accuracy, Recall, Precision, and F-measure with results show ing strong classification performance and high accuracy.

However, the accuracy of detection can still be improved. This study proposed several deep learning techniques to improve the detection of ASD. Applying five of the deep learning techniques could improve the performance of ASD detection accuracy.

3. Methodology

As shown in Fig 1, the design of this study consists of five phases. The first phase is the preparation of datasets where the autism dataset used is from three datasets (Child, Adolescent, and Adult). The second phase will contain preprocessing tasks such as categorical encoding and standardization. The third phase aims to split the dataset into 20% testing and 80% as training. The fourth phase contains the proposed models (1D CNN, DNN, LSTM, BiLSTM, CNN-LSTM) structure. The fifth phase will address the evaluation (accuracy, precision, recall, and f1 score).

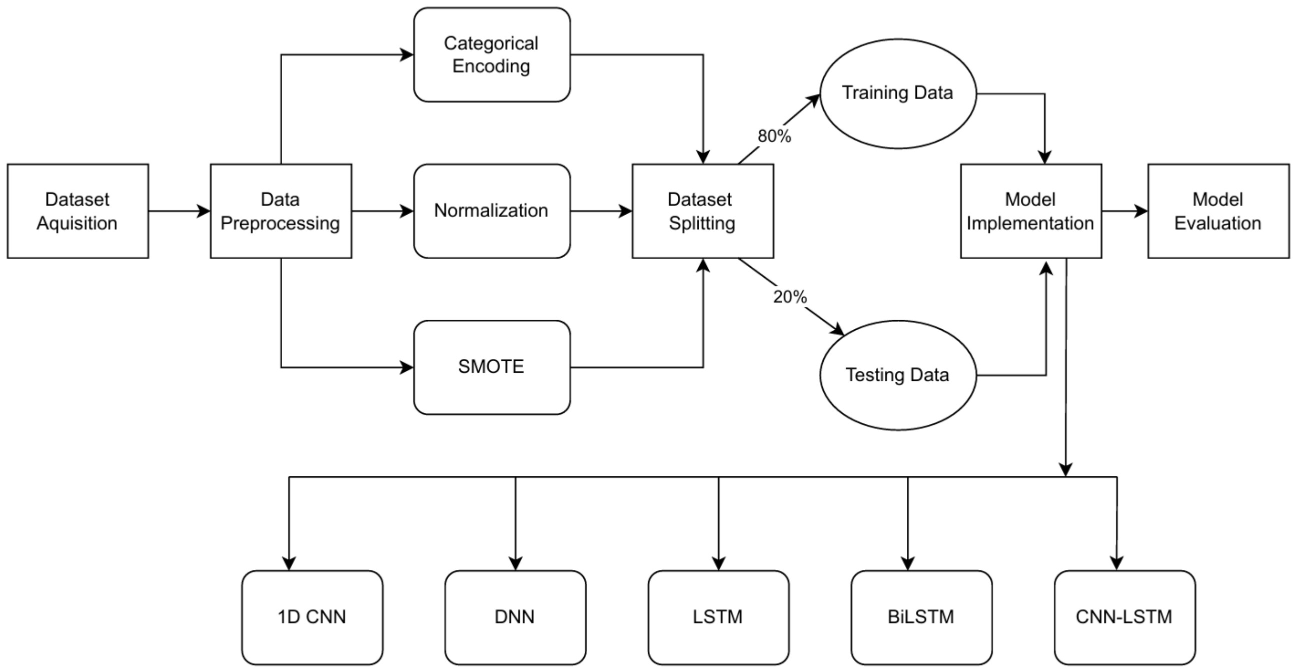

Fig 1 : Proposed Methodology

Recent advances in medical deep learning highlight the need to model contextual relationships rather than treating inputs in isolation. This principle informs the methodological design of our study. Specifically, insights from Intakhab et al. (2025) demonstrate how robust architectural choices can enhance model sensitivity. From their framework, we addressed class imbalance using the Synthetic Minority Over-sampling Technique (SMOTE).

3.1 Dataset Description

In this study, the research utilizes specialized autism screening datasets stratified by key age groups of toddlers/children, adolescents (M. AL-Ani et al., 2021). These datasets, commonly derived from mobile screening tools like ASDTests and publicly accessible via repositories such as Kaggle and UCI Machine Learning Repository, are structured to support machine learning-based detection of Autism Spectrum Disorder (ASD) traits across developmental stages. At the core of each dataset are ten standardized behavioral screening questions (labeled A1 through A10), answered in binary format (YES/NO or 1/0), which are adapted from validated instruments such as the AQ-10 or age-specific variants (e.g., Q-CHAT for younger children). These questions assess observable or self-reported behaviors related to social communication, repetitive interests, sensory sensitivities, and attention patterns, with minor wording adjustments tailored to each age group for developmental relevance. The cumulative score from these ten questions, known as the result numeric or screening score (ranging typically from 0 to 10), serves as a primary indicator of ASD likelihood, where higher scores suggest the need for further clinical assessment. Complementing the behavioral responses, the datasets incorporate a rich set of demographic and contextual features that influence ASD evaluation and enhance predictive accuracy. These include age (numeric, in years or months), gender (Male/Female), ethnicity (text-based categories such as White-European, Asian, or others), jaundice at birth (yes/no, a recognized perinatal risk factor), family history of autism or pervasive developmental disorder (yes/no), relation of the respondent to the individual (e.g., parent, self, caregiver, clinician), country of residence (text format), prior use of a screening app (yes/no), and an age description string categorizing the group (e.g., toddler, child, adolescent, adult). Together, these features enable comprehensive, multi-faceted analysis, allowing machine learning models to account for biological, environmental, and socio-cultural variables while identifying patterns and improving the robustness of ASD prediction across diverse populations.

3.2 Preprocessing

This stage used three-step for preprocessing data as follows:

i. **Categorical Encoding:** Encoding categorical data involves converting non-numeric variables (like gender, ethnicity, or country) into numerical values so they can be used in machine learning models. In this study, columns such as "Gender," "Ethnicity," "Country," "Used," "Desc," and "Relation" were en coded using the LabelEncoder method. This method assigns a unique integer to each category. Encoding is essential for deep learning models like 1D CNN, as they require numerical input and cannot process categorical data directly.

ii. **Normalization:** StandardScaler is a preprocessing technique used to normalise numerical data in deep learning. The purpose of normalisation is to scale the data to have zero mean and unit variance.The StandardScaler calculates the mean and standard deviation of the data and transforms it such that the mean is 0 and the standard deviation is 1. This is achieved by subtracting the mean from each data point and dividing it by the standard deviation. This helps minimize the impact of outliers, thus improving the performance of algorithms.

iii. **Using SMOTE:** Synthetic Minority Over-sampling Technique (SMOTE) is employed in the prepro cessing stage to address class imbalance in the dataset, which is common in medical diagnosis problems like Autism Spectrum Disorder detection. SMOTE generates synthetic samples for the minor ity class by interpolating between existing minority instances, effectively increasing its representation without simply duplicating data. This balancing helps machine learning models avoid bias toward the majority class, leading to improved classifica tion performance, especially in recall and F1-score metrics, by enabling the model to better recognize minority class patterns. Class imbalance of the three datasets is solved using SMOTE.

3.3 Models Compared

The 1D Convolutional Neural Network (1D CNN) is a specialized deep learning architecture designed to process one-dimensional sequential data, such as behavioral questionnaire responses treated as time-series inputs in Autism Spectrum Disorder (ASD) classification. It excels at extracting local spatial features through convolutional layers that scan for patterns, followed by batch normalization to stabilize training, max pooling to reduce dimensionality and focus on prominent features, and dropout layers to prevent overfitting by randomly deactivating neurons during training. In this study, the model uses 128 filters in the first Conv1D layer (kernel size 3, ReLU activation) and 64 in the second, leading to a flattened output fed into dense layers for binary classification via a sigmoid-activated output neuron. With approximately 50,000 trainable parameters, it is particularly effective for capturing hierarchical patterns in ASD datasets, achieving high precision (e.g., 100% on Adolescents with SMOTE) by handling subtle correlations in features like social interaction scores, making it suitable for early screening where data has sequential dependencies.

The Deep Neural Network (DNN) is a fully connected feedforward model optimized for structured tabular data, such as the demographic and behavioral attributes in ASD datasets across age groups. It learns complex non-linear relationships through multiple dense layers with ReLU activation for introducing non-linearity, interspersed with dropout regularization (rate 0.5) to mitigate overfitting and improve generalization. The architecture progressively reduces dimensionality with layers of 128, 64, and 32 units before a final sigmoid output for binary ASD prediction, totaling around 13,000 trainable parameters. In the experiments, the DNN consistently outperformed others, achieving top accuracies like 99.90% on Adults, 99% on Children, and 93.65% on Adolescents with SMOTE, due to its robustness in integrating features like age, gender, and family history, making it ideal for ASD classification where inter-feature relationships are key without requiring sequential processing.

The Long Short-Term Memory (LSTM) network is a recurrent neural network variant tailored for sequential data, capturing long-term dependencies in ASD behavioral patterns through specialized memory cells and gates (input, forget, output) that selectively retain or discard information, addressing the vanishing gradient problem common in standard RNNs. In this implementation, it features a single LSTM layer with 64 units, followed by dropout (rate 0.5) and a dense sigmoid output for binary classification, with about 17,000 trainable parameters. The model processes inputs as sequences, making it suitable for detecting escalating ASD traits in questionnaire responses (e.g., A1–A10), and performed well on balanced data post-SMOTE, such as 93.38% accuracy on Children, though it showed sensitivity to class imbalance without oversampling, highlighting its strength in temporal pattern recognition for developmental disorders like ASD.

The Bidirectional LSTM (BiLSTM) extends the standard LSTM by processing input sequences in both forward and backward directions, enabling the model to capture contextual dependencies from past and future data points, which enhances understanding of inter-related ASD features like behavioral scores influenced by demographics. It includes an input layer, a bidirectional wrapper around an LSTM with 128 units (combining forward and backward states), dropout for regularization, and a sigmoid output, resulting in approximately 34,000 trainable parameters. This bidirectional approach proved effective for ASD detection, achieving high recall (e.g., 100% on Adults with SMOTE) by leveraging full context in datasets, making it reliable for identifying positive cases across age groups where feature relationships may span the entire input sequence.

The CNN-LSTM hybrid model integrates the strengths of convolutional layers for spatial feature extraction with LSTM's temporal processing, making it particularly effective for ASD data that exhibits both local patterns (e.g., in behavioral clusters) and sequential dependencies (e.g., across questionnaire items). The architecture begins with a Conv1D layer (64 filters, kernel size 3, ReLU), batch normalization, max pooling, and dropout, then feeds the output to an LSTM layer (64 units) followed by another dropout and sigmoid dense output, totaling around 34,000 trainable parameters. In the study, it delivered balanced performance, such as 97.09% accuracy on Adults with SMOTE, by first convolving inputs to create feature maps and then modeling sequences, proving useful for multi-modal ASD patterns though slightly trailing DNN in overall metrics.

3.2 Evaluation

The performance of the proposed model for classifying Autism Spectrum Disorder (ASD) was evaluated using four standard performance metrics: Recall, Precision, F1-Score, and Accuracy. These metrics collectively provide a balanced and comprehensive view of the model's effectiveness, particularly in the context of medical classification tasks where datasets may be imbalanced and correctly identifying positive cases (individuals with ASD traits) is of high importance. Recall measures the model's ability to detect actual ASD cases without missing many true positives. Precision assesses how reliable the positive predictions are by minimizing false positives. The F-Score combines precision and recall into a single harmonic mean, offering a balanced indicator that is especially useful when both false negatives and false positives need to be controlled. Accuracy reflects the overall proportion of correct predictions across the entire dataset. Together, these four metrics ensure a thorough and realistic evaluation of the 1D CNN model's performance in ASD classification, capturing its strengths in sensitivity, specificity, balance, and general correctness.

4. Result

The experimental analysis was conducted on three distinct ASD datasets: Adolescents, Adults, and Children. Each dataset was used to train and evaluate five deep learning models: Deep Neural Network (DNN), Bidirectional Long Short-Term Memory (BiLSTM), Long Short-Term Memory (LSTM), CNN-LSTM, and 1D Convolutional Neural Network (1D CNN). Two separate experiments were performed, one using the original datasets and another using SMOTE (Synthetic Minority Over-sampling Technique) to balance class distributions. The DNN outperformed other models in all datasets, especially in the adult set. 1D CNN, LSTM, BiLSTM, and CNN-LSTM still achieved competitive metrics.

Table 1. Performance Comparison of Models on ASD Datasets without Using SMOTE

Dataset	Model	Accuracy	Precision	Recall	F1 Score
Adolescents	DNN	0.8846	0.8493	0.9841	0.9118
Adolescents	BiLSTM	0.8654	0.8267	0.9841	0.8986
Adolescents	LSTM	0.8654	0.8356	0.9683	0.8971
Adolescents	CNN-LSTM	0.8462	0.7975	1.0000	0.8873
Adolescents	1D CNN	0.7885	0.7412	1.0000	0.8514
Adults	DNN	0.9915	0.9841	0.9841	0.9841
Adults	BiLSTM	0.9730	0.9670	0.9312	0.9488
Adults	LSTM	0.9673	0.9415	0.9365	0.9390
Adults	CNN-LSTM	0.9673	0.9462	0.9312	0.9387
Adults	1D CNN	0.2699	0.2688	1.0000	0.4238
Children	DNN	0.9897	0.9792	1.0000	0.9895
Children	BiLSTM	0.9555	0.9638	0.9433	0.9534
Children	CNN-LSTM	0.9384	0.9489	0.9220	0.9353
Children	LSTM	0.9349	0.9178	0.9504	0.9338
Children	1D CNN	0.7534	0.6620	1.0000	0.7966

Table 2. Performance Comparison of Models on ASD Datasets Using SMOTE

Dataset	Model	Accuracy	Precision	Recall	F1 Score
Adolescents	DNN	0.9444	0.9000	1.0000	0.9474
Adolescents	1D CNN	0.9206	1.0000	0.8413	0.9138
Adolescents	LSTM	0.8492	0.7973	0.9365	0.8613
Adolescents	BiLSTM	0.8571	0.8000	0.9524	0.8696
Adolescents	CNN-LSTM	0.7619	0.6854	0.9683	0.8026
Adults	DNN	0.9971	0.9961	0.9981	0.9971
Adults	1D CNN	0.9738	0.9502	1.0000	0.9745
Adults	LSTM	0.9650	0.9724	0.9573	0.9648
Adults	BiLSTM	0.9922	0.9847	1.0000	0.9923
Adults	CNN-LSTM	0.9709	0.9746	0.9670	0.9708
Children	DNN	0.9901	0.9933	0.9868	0.9900
Children	1D CNN	0.8444	0.7626	1.0000	0.8653
Children	LSTM	0.9338	0.9338	0.9338	0.9338
Children	BiLSTM	0.9603	0.9793	0.9404	0.9595
Children	CNN-LSTM	0.9503	0.9416	0.9603	0.9508

The performance comparison tables clearly demon strate that applying SMOTE (Synthetic Minority Over sampling Technique) significantly enhances the effec tiveness of deep learning models for ASD classification across all age groups: Adolescents, Adults, and Children. Models like DNN and BiLSTM consistently achieve higher Accuracy, Precision, Recall, and F1 Scores with SMOTE. For instance, the DNN model in the Adoles cents group improves from 88.46% Accuracy without SMOTE to 94.44% with it, alongside a notable increase in F1 Score (0.9474). Similarly, BiLSTM and CNN LSTM also show marked performance gains, particularly in Recall, indicating their strong sensitivity in detecting ASD, a crucial factor in medical diagnosis.

Without SMOTE, performance declines are evident, especially for 1D CNN, which drops to an Accuracy of 26.99% and an F1 Score of 0.4238 in the Adults dataset, highlighting the detrimental effect of class im balance. Even relatively robust models like DNN and BiLSTM experience reductions in performance without oversampling. This trend is also observed in the Children dataset, where models like LSTM and 1D CNN perform poorly under imbalanced conditions. These findings emphasize the importance of incorporating data-level balancing techniques like SMOTE to improve model learning and generalization, particularly when dataset sizes are limited. Among all models, DNN emerges as the most stable and high-performing across datasets, and its performance is further amplified with SMOTE. Overall, the results affirm that pairing deep learning models with preprocessing strategies like SMOTE leads to more accurate and reliable ASD predictions.

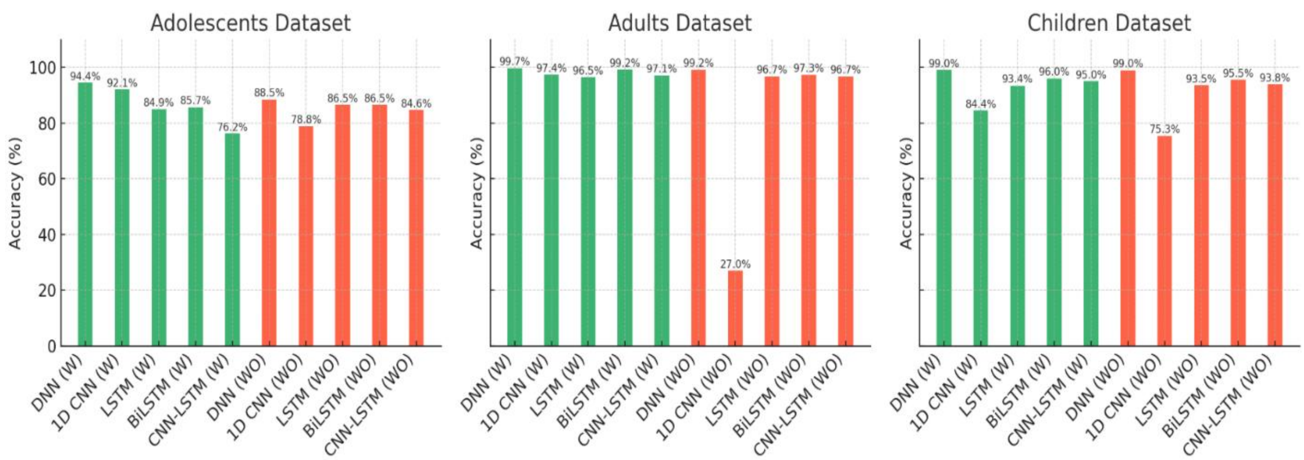

Chart 1 : Accuracy Comparison for All Models (with vs. without SMOTE)

To further evaluate model behavior, we present training and validation accuracy and loss graphs across all datasets. These plots illustrate each model's learning progression, convergence speed, and potential overfitting.

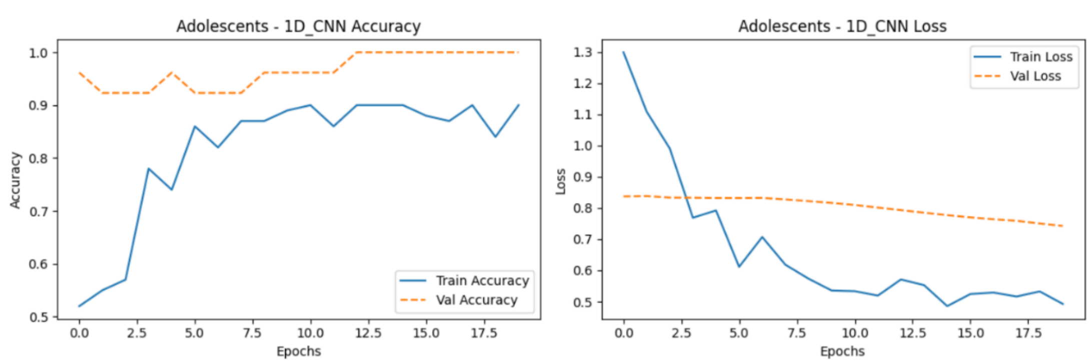

Fig 2 : Training and Validation Accuracy and Loss for 1D CNN on Adolescents Dataset

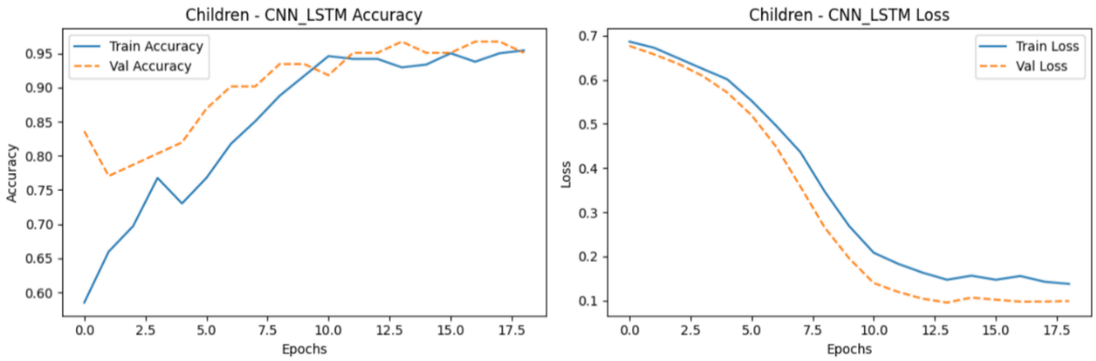

Fig 3 : Training and Validation Accuracy and Loss for CNN-LSTM on Children Dataset

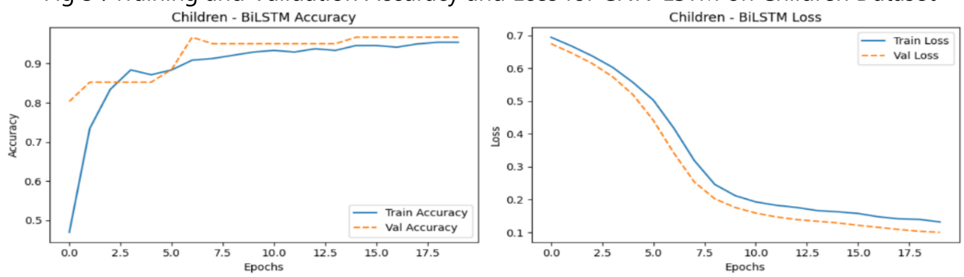

Fig 4 : Training and Validation Accuracy and Loss for BiLSTM on Children Dataset

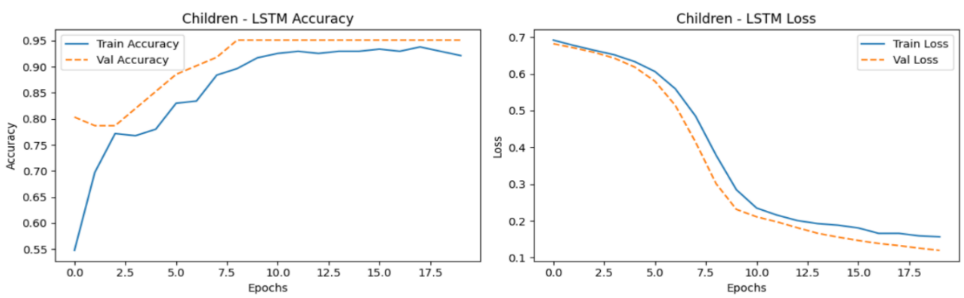

Fig 5 : Training and Validation Accuracy and Loss for LSTM on Children Dataset

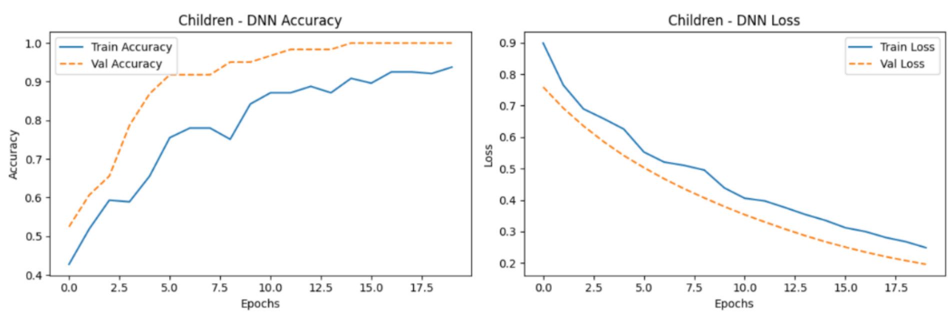

Fig 6 : Training and Validation Accuracy and Loss for DNN on Children Dataset

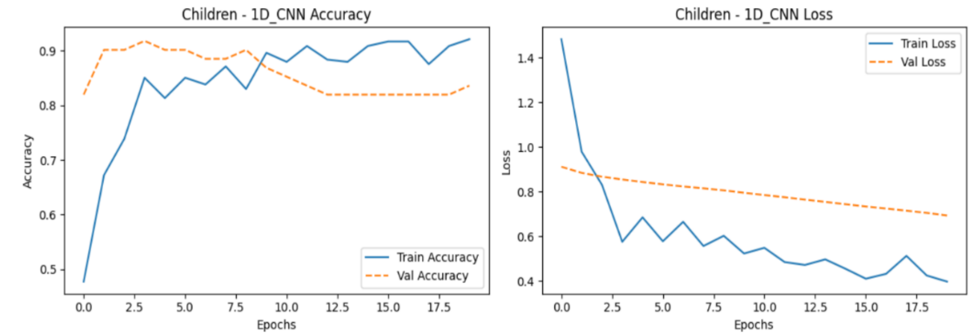

Fig 7 : Training and Validation Accuracy and Loss for 1D CNN on Children Dataset

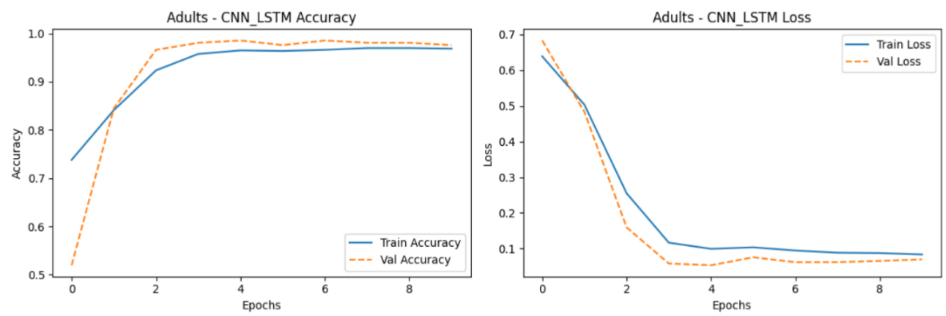

Fig 8 : Training and Validation Accuracy and Loss for CNN-LSTM on Adults Dataset

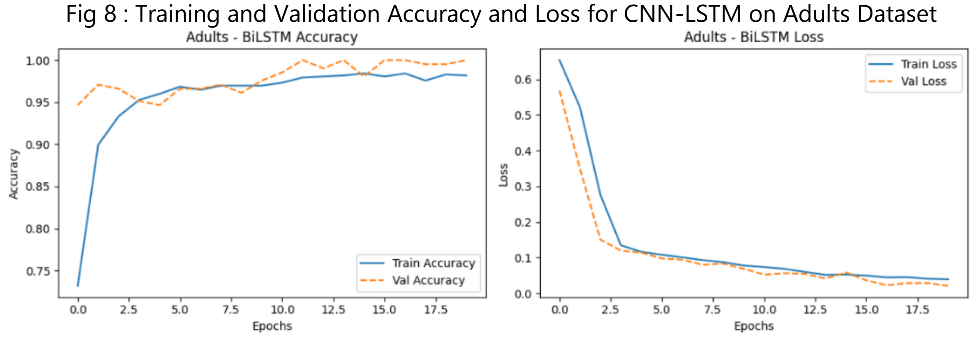

Fig 9 : Training and Validation Accuracy and Loss for BiLSTM on Adults Dataset

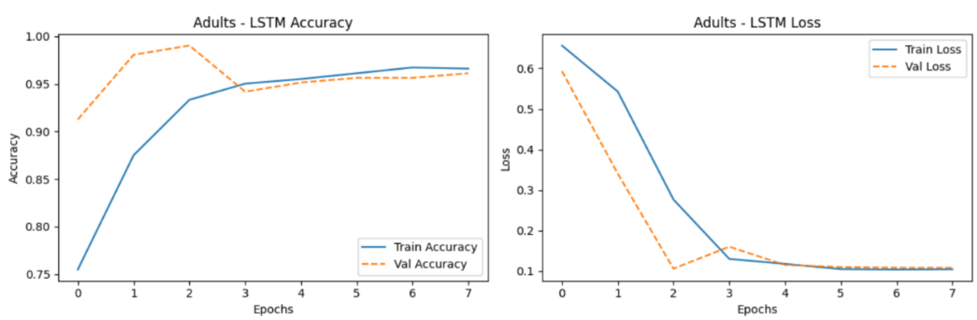

Fig 10 : Training and Validation Accuracy and Loss for LSTM on Adults Dataset

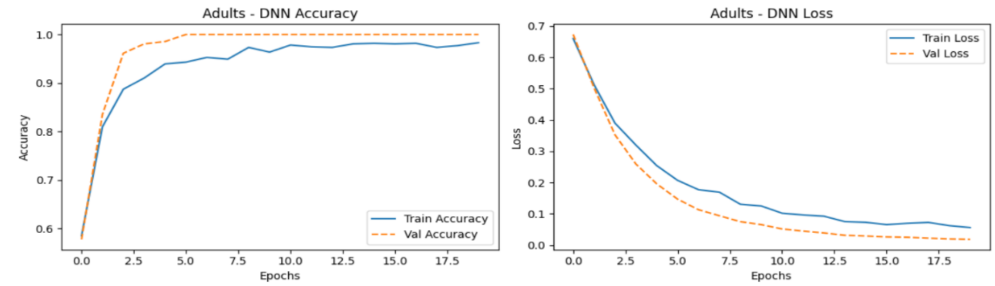

Fig 11 : Training and Validation Accuracy and Loss for DNN on Adults Dataset

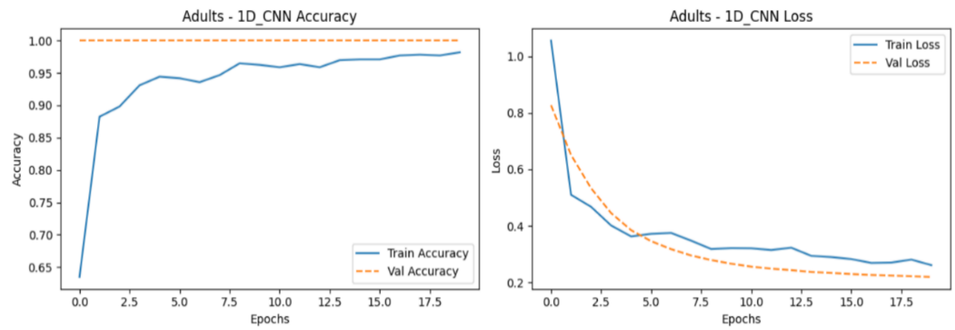

Fig 12 : Training and Validation Accuracy and Loss for 1D CNN on Adults Dataset

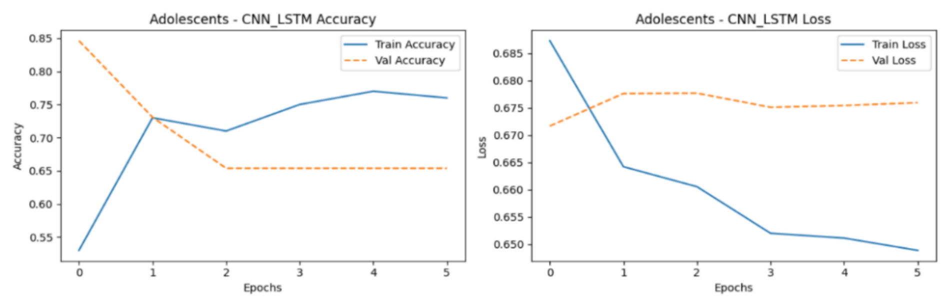

Fig 13 : Training and Validation Accuracy and Loss for CNN-LSTM on Adolescents Dataset

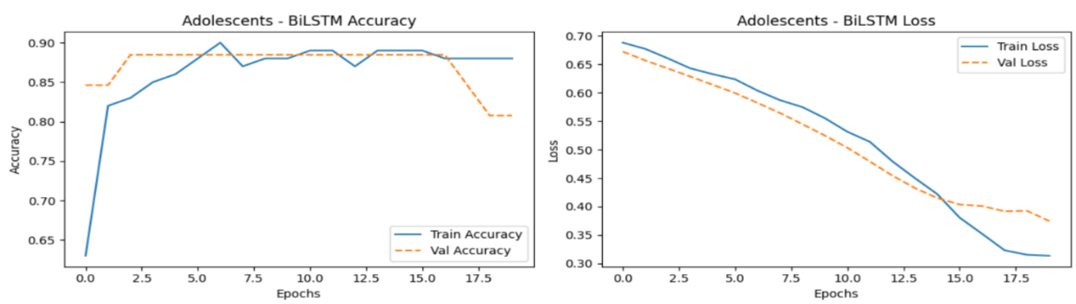

Fig 14 : Training and Validation Accuracy and Loss for BiLSTM on Adolescents Dataset

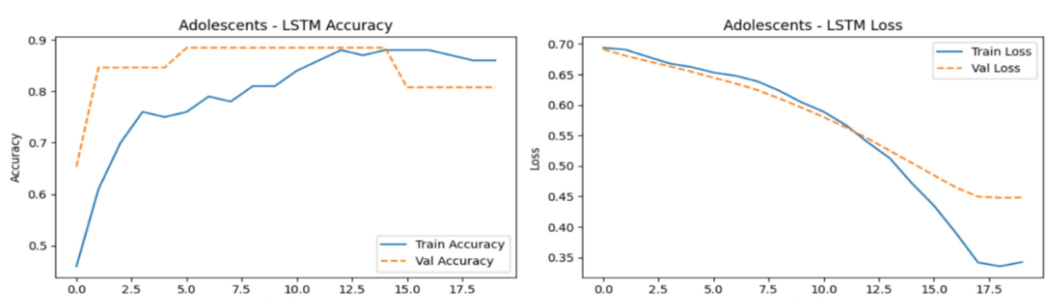

Fig 15 : Training and Validation Accuracy and Loss for LSTM on Adolescents Dataset

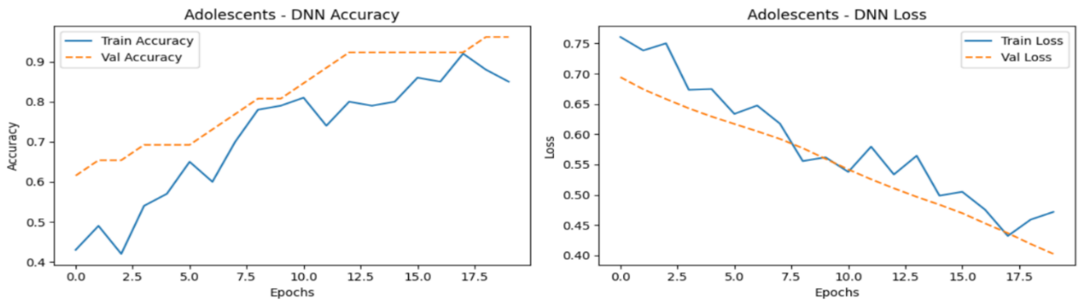

Fig 16 : Training and Validation Accuracy and Loss for DNN on Adolescents Dataset

5. Conclusion and Discussion

The theoretical implications of this research are centered around the use of deep learning models for detecting Autism Spectrum Disorder (ASD). The study demon strates the potential of using such models in improving the accuracy of ASD diagnosis, which could ultimately lead to earlier interventions and improved outcomes for individuals on the autism spectrum. Additionally, the study contributes to the field of deep learning by exploring the use of a novel method for detecting ASD and providing insights into the performance of deep learning models. On the practical side, the findings of this study have significant implications for healthcare providers, researchers, and individuals with ASD and their families. The proposed deep learning models has the potential to provide a non-invasive and cost-effective method for detecting ASD, which can lead to earlier interventions and improved outcomes. This model can be used by healthcare providers to screen individuals for ASD and potentially reduce the wait times for diagnosis. Furthermore, the study provides a valuable resource for researchers in the field of ASD, as it highlights the potential of deep learning models for this application and provides a benchmark for future studies.

This study compared five deep learning models for detecting Autism Spectrum Disorder: 1D CNN, DNN, LSTM, BiLSTM, CNN-LSTM. The DNN achieved the highest overall performance, particularly in structured behavioral datasets. These results indicate that deep learning models can aid in early and accurate detection of autism, potentially leading to earlier interventions and better outcomes for individuals on the autism spectrum. The main contribution of this research is the development of a new methods for detecting ASD using multiple deep learning techniques, improving the accuracy of ASD diagnosis with a non-invasive and cost-effective approach. However, there are several limitations such as the potential impact of cultural and socioeconomic factors on the reliability and generalizability of the model. Future research should address this limitation by including more diverse and representative samples in the dataset and exploring the impact of cultural and socioeconomic factors on the model's performance. Furthermore, future work could include examination of the generalization of the proposed models on larger and more diverse datasets, including data from different geographical locations, ethnicities, and age groups. Additionally, a multi-task learning framework could be developed for jointly detecting ASD and comorbidities. Overall, this study provides valuable insights into the use of deep learning for autism detection and opens up avenues for further exploration in this field.

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