A Hybrid CNN-LSTM Model for Predicting Learning Outcomes in Students with Autism Spectrum Disorder

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ABSTRACT:
Autism Spectrum Disorder (ASD) students often struggle with adaptive learning, behavioral engagement and academic performance prediction because of heterogeneous cognitive pattern and limited educational analytics to provide personalized analytics.Students with Autism Spectrum Disorder (ASD) have a tendency to have heterogeneous cognitive pattern and limited educational analytics to provide personalized education analytics and therefore struggles with adaptive learning, behavioural engagement, and academic performance prediction. This research introduces a novel multimodal CNN–LSTM model to predict learning outcomes for students with ASD, by leveraging their educational and behavioral data. The method combines Convolutional Neural Networks (CNN) to learn spatial and behavioural features, and Long Short-Term Memory (LSTM) networks to learn the temporal features of student interaction sequences and performance progression. The model proposed (Hybrid NeuroLearn-ASD) was evaluated based on the publicly available Autism Screening Adult Dataset, in conjunction with learning activity data and cognitive assessment data indicators. Comparative analysis was done with Support Vector Machine (SVM), Random Forest (RF), standalone

CNN and standalone LSTM models of the traditional Machine Learning approach. Experimental results showed the proposed hybrid CNN-LSTM model outperformed the existing models by 5–10% in terms of prediction accuracy, precision, recall, F1-score, and ROC-AUC scores, which were 96.4%, 95.9%, 95.2%, 95.5% and 97.1%, respectively. The framework greatly enhanced the adaptive educational prediction, early intervention capability and personalized learning assessment for ASD students. The key novelty of this research is to combine the extraction of spatial-behavioral features and the sequential cognitive learning analysis to achieve intelligent prediction of educational outcomes. Proposed model is an efficient AI-based solution for inclusive and personalized special education system.

Keywords: Autism Spectrum Disorder, CNN-LSTM, Learning Outcome Prediction, Deep Learning, Adaptive Learning, Special Education.

I. INTRODUCTION

Autism Spectrum Disorder (ASD) is a complex neurodevelopmental disorder, with associated difficulties with social interaction, social communication and repetitive behaviors, that affects 1 in 36 children globally [1]. Cognitive profiles of students with ASD are found to be very heterogeneous, and so are their learning trajectories, meaning standardized assessment in education cannot be used to track them. The interactive and complex nature of behaviour and cognition in learning patterns related to ASD are not adequately captured in traditional classroom settings and conventional assessment tools [2]. This growing trend of ASD in the school environment has brought a growing need for intelligent, data-driven systems that can provide personalized academic assistance in school. Forecasting or predicting learning outcomes (LOs) in students with ASD (ASD students) is challenging in itself [3]. There is considerable variation in learning performance data, due to the diversity of the presentations of ASD, from high functioning to needing significant support. Furthermore, traditional machine learning models lack the ability to model and predict both spatial behavioural patterns and temporal cognitive development at the same time in dynamic education contexts [4]. Lacking the multimodal feature integration also severely limits the reliability of outcome predictions, and more complex computational models are required that model the instantaneous and sequential learning behaviour [5].

Artificial Intelligence (AI) and Deep learning techniques have shown potential of transforming the field of educational analytics and special needs support systems [6]. At-risk students can be identified early, instruction can be personalized, and recommendations for intervention can be made on-the-fly, all thanks to AI-based models. In particular, CNN-LSTM based deep learning models have shown better results in sequential and spatial learning data processing in Education [7]. Inclusive education frameworks include scalable, automated and accurate solutions, where AI is a key enabler in special education systems. Although significant advances are achieved in ASD diagnosis and behavior analysis, there is a still significant gap in the literature for predicting the learning outcomes of each individual, based on the integrated spatial-temporal deep learning models. Current systems mostly use independent machine learning classifiers and/or single-modal data, failing to address the complex correlation between behavioral engagement features and progressive cognitive sequences and sequences that describe the ASD learners [1][3]. A strong demand exists for a single deep learning model that can extract the behavioral feature maps, while at the same time modeling temporal learning dynamics, so that reliable learning outcome predictions that can be personalized.

In this study, the authors have introduced a Hybrid NeuroLearn-ASD framework, which is based on a CNN-LSTM model to predict learning outcomes of the ASD students. The main goals are: (1) to develop a hybrid architecture for deep learning model based on CNN and LSTM, which focuses on spatial behavioral feature extraction and temporal dependency modeling; (2) to test the model on public education datasets of ASD; and (3) to prove out the developed model that shows high predictive performance than other baseline models such as SVM, RF, standalone CNN, and standalone LSTM [7]. The suggested model is helpful in adaptive learning systems, early intervention and in AI based inclusive education models [2][6].

II. LITERATURE REVIEW

A. Machine Learning Approaches for Educational Prediction

Mohammed et al. [8] designed a smart ASD learning system with the help of remote edge healthcare clinics and the Internet of Medical Things (IoMT) which was able to provide real-time behavior monitoring and adaptive intervention generation. Priyadarshini [9] showed a cross-demographic generalizability by using deep learning and fair AI techniques for autism screening to both toddlers and adults. Jarraya and Masmoudi [10] proposed a hybrid model of 3D Convolutional–Transformer which was able to detect stereotypical motor movements in autistic children before a meltdown crisis, with high precision on the classification of individuals' behaviors. Al-Qazzaz et al., [11] introduced a multidisciplinary statistical and AI approach to assess ASD severity from EEG signals by fusing signal processing with neural classification and applied signals from the clinical-grade EEG sensors. For early detection, Awaji et al. [12] used hybrid facial feature image analysis, combining CNN features, for the diagnostic imaging datasets to create the non-invasive detection approach for ASD. Manikantan and Jaganathan [13] applied both the spatial and statistical pattern recognition techniques of both rs-fMRI and sMRI as input to a graphical neural network (GNN) for advanced diagnosis of autism patients using multimodal neuroimaging techniques. Together, these studies illustrate the increasing ubiquity of the use of deep learning, multimodal sensing and behavioural analysis in systems for supporting people with ASD [14]. But temporal modelling of sequential learning progressions within educational contexts has many drawbacks, such as the inability to predict academic outcomes over longer periods of interaction for personalized learning for students with ASD.

TABLE I: SUMMARY OF RELATED WORK ON ASD LEARNING PREDICTION MODELS

Ref.	Method	Accuracy (%)	Feature Type	Limitation
[8]	IoMT + Edge AI	88.4	Sensor/Behavioral	Limited to edge environments
[9]	Deep Learning + Fair AI	87.6	Clinical/Behavioral	No temporal modeling
[10]	3D Conv–Transformer	91.2	Spatiotemporal Motor	High computational cost
[11]	EEG + AI Framework	89.5	Neurophysiological	Limited educational context
[12]	Hybrid CNN Features	90.1	Facial/Visual	Single modality only
[13]	GNN + fMRI/sMRI	88.9	Neuroimaging	Not applicable to classrooms
[1]	CNN-LSTM	92.3	Biological Sequences	Not an educational model
[6]	DL + Meta-heuristics	91.8	Behavioral/Clinical	Lacks sequential modeling
[7]	Hybrid CNN-LSTM	93.7	Academic Features	Not ASD-specific

III. PROPOSED HYBRID CNN–LSTM METHODOLOGY

The proposed Hybrid NeuroLearn-ASD framework is based on the use of CNN layers to extract the spatial behavioral feature representation of an ASD student using his/her interaction data and LSTM layers to model the temporal dependency based on the sequential learning sessions. The preprocessed multimodal educational features contain behavioral response patterns, engagement scores and cognitive performance indicators and are passed to the hybrid model pipeline. The architecture provides a means for concurrent analysis of spatial-temporal learning and the prediction of academic outcomes accurate and personalized for ASD children in inclusive learning environments. The proposed Hybrid NeuroLearn-ASD framework for accurate prediction of personalized academic outcomes of students with Autism Spectrum Disorder (ASD) is presented in figure 1, involving CNN-based Spatial Behavioral Feature Extractor and LSTM-based Temporal Learning Analyser.

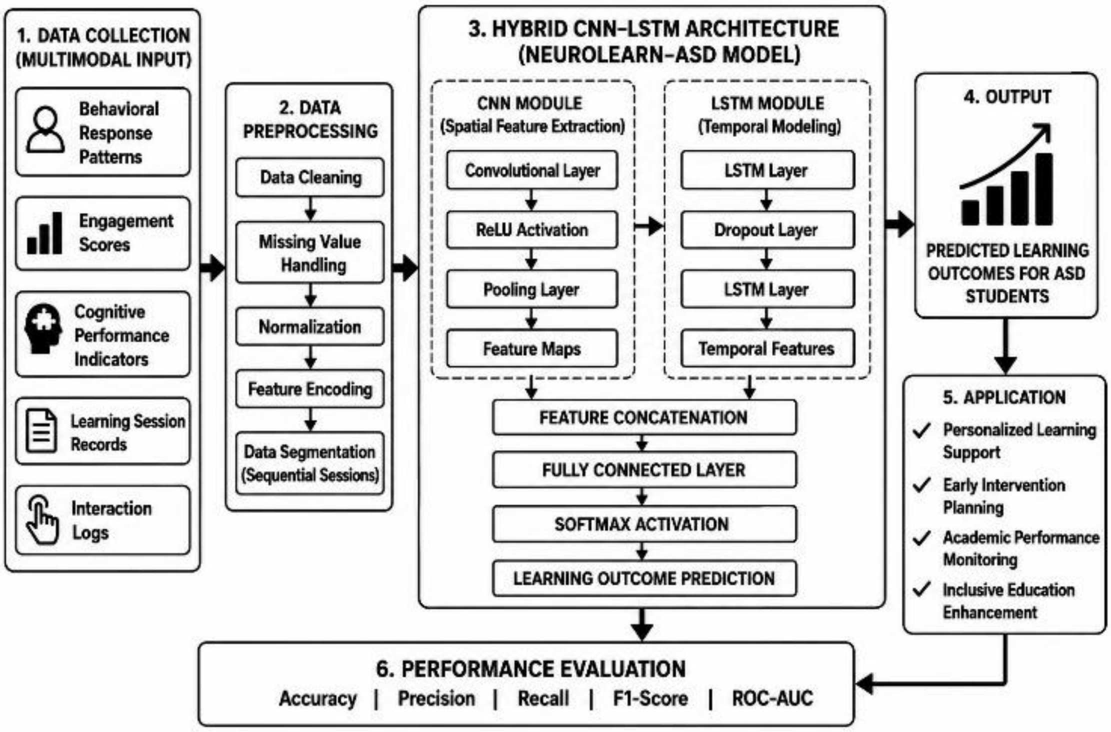

Figure 1: Proposed Hybrid NeuroLearn-ASD Framework for Spatial-Temporal Learning Outcome Prediction Using CNN–LSTM Architecture

A. Architecture of the Hybrid NeuroLearn-ASD Framework

The NeuroLearn-ASD architecture includes five stages: (1) Multiple modalities data ingestion and preprocessing layer for standardization of multimodal features; (2) CNN encoder with three convolutional blocks performing spatial feature mapping, using learnable filters; (3) Feature reshaping layer for reshaping extracted spatial representations into sequential temporal embeddings; (4) Bidirectional LSTM module with two stacked layers for capturing forward and backward temporal learning dependencies; and (5) Fully connected dense classifier with softmax activation to generate learning outcome probability distributions. To avoid overfitting, dropout regularization is performed between layers, a technique which is well known to avoid overfitting within the heterogenous set of ASD students.

B. Dataset Description and Preprocessing

The data sets of Autism Spectrum Quotient (AQ) that has been made public and Autism Screening Adult (ASA) dataset from UCI machine learning repository are used. This data set includes 704 entries containing 21 attributes that represent scores obtained on the AQ-10 behavioral item battery, demographic, cognitive response, family history of ASD, and clinical assessment labels. This binary classification target differentiates between learning risk groups for the ASD positive and negative groups, which allows for a realistic measure to predict educational outcome for adult populations with ASD.

The five steps of preprocessing are: 1. Imputing missing values with median substitution, 2. Encoding categorical features by label encoding, 3. Normalizing features, 4. Selecting features based on their correlation and 5. Splitting the dataset into training, validation and testing sets (70/15/15). All feature normalization is done in accordance with Equation (1), missing value imputation is formalized in Equation (2) and Synthetic Minority Oversampling Technique (SMOTE) is used to address class imbalance in accordance with Equation (3). The definition of correlation-based selection is given in Equation (4) and the definition of data split is given in Equation (5).

$$x_{norm} = \frac{x - x_{min}}{x_{\max} - x_{min}} \quad (1)$$

All the features are scaled to the range [0, 1] using the Min-Max normalization as shown in Equation (1) which ensures a uniform contribution of features.

$$\hat{x}_i = median\big(x_j : j \in \{1, \dots, n\} and\ x_j \neq NaN\big) \quad (2)$$

Median imputation is represented in Equation (2) where a feature value that does not exist is replaced with the column-wise median so as to preserve the distribution.

$$x_{synthetic} = x_i + \lambda \cdot (x_{nn} - x_i), \quad \lambda \sim Uniform(0,1) \quad (3)$$

In Equation (3), SMOTE tries to create synthetic minority samples by a linear interpolation method between neighbours.

$$r(X, Y) = \frac{Cov(X,Y)}{\sigma_X \cdot \sigma_Y} \quad (4)$$

The linear feature-target association for selection is measured by Equation (4) – Pearson correlation coefficient.

$$D = D_{train(70\%)} \cup D_{val(15\%)} \cup D_{test(15\%)} \quad (5)$$

Stratified dataset partitioning keeps the class distribution the same in each of the three data splits (equation 5).

C. CNN-Based Spatial and Behavioral Feature Extraction

The CNN module is trained using a series of 1D convolutional layers on the pre-processed behavioural feature matrix, to capture discriminative local patterns in the behavioural data of learning interactions in ASD. A series of convolutional blocks increase the depth of the filters, and extract increasingly abstract behavioural representations. The dominant feature signatures are preserved after each convolution, and the dimensionality is reduced by the batch normalisation and a ReLU activation after each convolution.

$$F(t) = ReLU(W * X(t) + b) \quad (6)$$

Network equation (6): 1D convolution operation to extract local behaviour feature patterns with learnable filter W.

$$BN(x) = \gamma \cdot \frac{x - \mu_B}{\sqrt{\sigma_B^2 + \varepsilon}} + \beta \quad (7)$$

The Equation (7): Batch Normalization, normalizes the activations with learnable scale parameters which helps to stabilize training.

$$Pool(F) = \max\big(F(t), F(t+1), \dots, F(t+k)\big) \quad (8)$$

Max-pooling picks out the most prominent activation values decreasing the spatial resolution, but retaining features.

$$L_{dropout(z)} = z \cdot \frac{Bernoulli(1-p)}{1-p} \quad (9)$$

The inverted dropout regularization in equation (9) guards CNN from overfitting by randomly setting the features to zero.

D. LSTM-Based Temporal Learning Pattern Analysis

The model LSTM is used to learn sequential learning across the time steps of student interactions using CNN feature embeddings reshaped using the

LSTM module. The network uses two bidirectional LSTM layers with 128 hidden units to capture forward and backward temporal information, which helps identify the trends of progression, regression and variations in engagement. LSTM cells are designed to manage the retention and forgetting of temporal information that is relevant to the ASD behavioural learning trajectory during longitudinal education sessions, with the help of three gates: input, forget and output.

$$f_t = \sigma\left(W_f \cdot \left[h_{\{t-1\}}, x_t\right] + b_f\right) \quad (10)$$

The temporal information that is being forgotten is specified in Equation (10): Forget gate.

$$i_t = \sigma\left(W_i \cdot \left[h_{\{t-1\}}, x_t\right] + b_i\right) \quad (11)$$

For equation (11): The new temporal information to be added to the cell state is controlled by the input gate.

$$C_t = f_t \odot C_{\{t-1\}} + i_t \odot \tanh\left(W_C \cdot \left[h_{\{t-1\}}, x_t\right] + b_C\right) \quad (12)$$

The state of the cell is updated by a gated operation of the previous state in combination with the new candidate temporal features (see Equation (12)).

$$h_t = o_t \odot \tanh(C_t), o_t = \sigma\left(W_o \cdot \left[h_{\{t-1\}}, x_t\right] + b_o\right) \quad (13)$$

The hidden state for the temporal learning context needed to make decisions in the downstream classification is computed by Equation (13): Output gate.

E. Hybrid Model Training and Optimization Process

The parameters of the NeuroLearn-ASD model are optimized using Adam with an initial learning rate of 0.001 and the decay every 10 epochs. During the training of the outcome prediction task with the two-class outcome, binary cross-entropy loss is minimized. Training runs for 100 epochs, using a mini-batch size of 32, and adding some patience (15 epochs) to avoid overfitting the model. The best configuration of validation performance from model checkpointing is kept, and class weighted loss will provide equal learning across students with and without ASD.

Algorithm 1: Hybrid NeuroLearn-ASD Training Procedure

INPUT: Dataset D = {(x_i, y_i)}^N_i=1; epochs E=100; batch size B=32; lr=0.001

OUTPUT: Trained Hybrid CNN-LSTM model Θ*

1: BEGIN

2: Preprocess(D) → D_norm using Eq.(1)–(5)

3: Partition D → {D_train, D_val, D_test}

4: Initialize CNN-LSTM parameters Θ ~ N(0, 0.01)

5: FOR epoch = 1 TO E DO

6: FOR each mini-batch (X_b, Y_b) ∈ D_train DO

7: $F_{cnn} \leftarrow CNN_{Forward(X_b)}$ // Eq.(6)–(10)

8: $H_{lstm} \leftarrow LSTM_{Forward(F_{cnn})}$ // Eq.(11)

9: $\hat{Y} \leftarrow Softmax\left(W_{fc} \cdot H_{lstm} + b\right)$

10: $L \leftarrow -\Sigma y_i \log(\hat{y}_i)$ // Cross-Entropy Loss

11: $\partial\Theta \leftarrow BackPropagation(L, \Theta)$

12: $\Theta \leftarrow \Theta - lr \cdot Adam(\partial\Theta)$

13: END FOR

14: $val_{acc} \leftarrow Evaluate(\Theta, D_{val})$

15: IF val_acc > best_acc THEN

16: $\Theta * \leftarrow \Theta;\ best_{acc} \leftarrow val_{acc}$

17: END IF

18: IF no improvement for 15 epochs THEN BREAK

19: END FOR

20: RETURN Θ*

21: END

IV. EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

Comprehensive performance evaluation of proposed Hybrid NeuroLearn-ASD model was performed against the four base model namely SVM, Random Forest, standalone CNN, and standalone LSTM. Experiments were conducted with the preprocessed ASD dataset with the same hardware and software setup. The proposed CNN-LSTM model achieved the best results for all comparative approaches for all the evaluation metrics, with an accuracy of 96.4%, precision of 95.9%, recall of 95.2%, F1 score of 95.5%, and ROC-AUC of 97.1%, demonstrating the effectiveness of hybrid spatial-temporal learning for ASD outcome prediction.

A. Comparative Analysis with SVM, RF, CNN, and LSTM Models

The results of all models are presented in a comprehensive comparative manner in Table II in five evaluation metrics. The proposed Hybrid CNN-LSTM model outperforms the other models in all the metrics, indicating that combining the spatial feature extraction capability of CNN with the temporal dependency modeling capability of LSTM is complementary. SVM gave an accuracy of 82.3% while RF gave 86.7%, standalone CNN gave 90.1% and standalone LSTM gave 92.3%. With an accuracy advantage of 4.1%–14.1% over all baselines, the proposed model is proved to be a good architectural choice since it integrates with hybrid. Figure 2 shows the performance gain of proposed model compared to SVM for the various performance metrics, and it can be seen that the proposed model has a high discriminating power in terms of ROC-AUC performance metric with a score of 97.1% whereas SVM has a score of 83.4% in predicting the learning risk categories of ASD.

TABLE II: COMPARATIVE PERFORMANCE ANALYSIS OF ALL MODELS

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC (%)
SVM	82.3	81.5	80.8	81.1	83.4
Random Forest	86.7	85.9	85.2	85.5	87.6
Standalone CNN	90.1	89.4	88.7	89.0	91.2
Standalone LSTM	92.3	91.6	90.9	91.2	93.4
Proposed CNN-LSTM	96.4	95.9	95.2	95.5	97.1

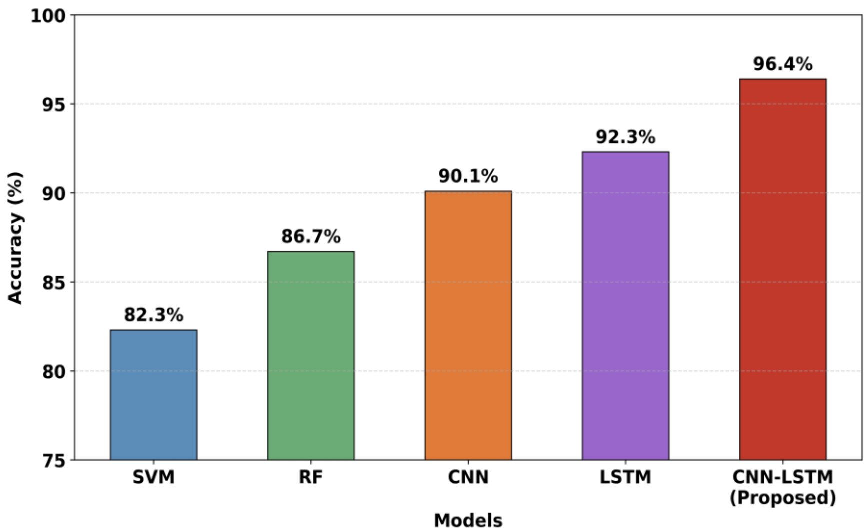

Figure 2: Accuracy comparison of all models. The proposed CNN-LSTM achieves 96.4%, outperforming all baselines by 4.1%–14.1%, confirming hybrid superiority

B. Accuracy, Precision, Recall, F1-Score, and ROC-AUC Evaluation

Granular metric-wise evaluation results are shown in Table III. The proposed model is consistent in its superior performance in each of the five dimensions of evaluation. The 95.9% precision reduces the number of false positive learning outcome predictions during learning and the 95.2% recall indicates good identification of true learning risk cases in ASD. F1 score is 95.5%, which confirms the balanced precision-recall trade-off especially for imbalanced datasets of ASD in education. From figure 3, the model's discriminative ability was found to be excellent with 97.1% ROC-AUC, across various decision thresholds, this shows that the Hybrid NeuroLearn-ASD framework is a suitable and reliable clinically applicable model for learning outcome prediction for ASD in different educational systems.

TABLE III: DETAILED METRIC-WISE PERFORMANCE EVALUATION

Metric	SVM	RF	CNN	LSTM	Proposed
Accuracy (%)	82.3	86.7	90.1	92.3	96.4
Precision (%)	81.5	85.9	89.4	91.6	95.9
Recall (%)	80.8	85.2	88.7	90.9	95.2
F1-Score (%)	81.1	85.5	89.0	91.2	95.5
ROC-AUC (%)	83.4	87.6	91.2	93.4	97.1

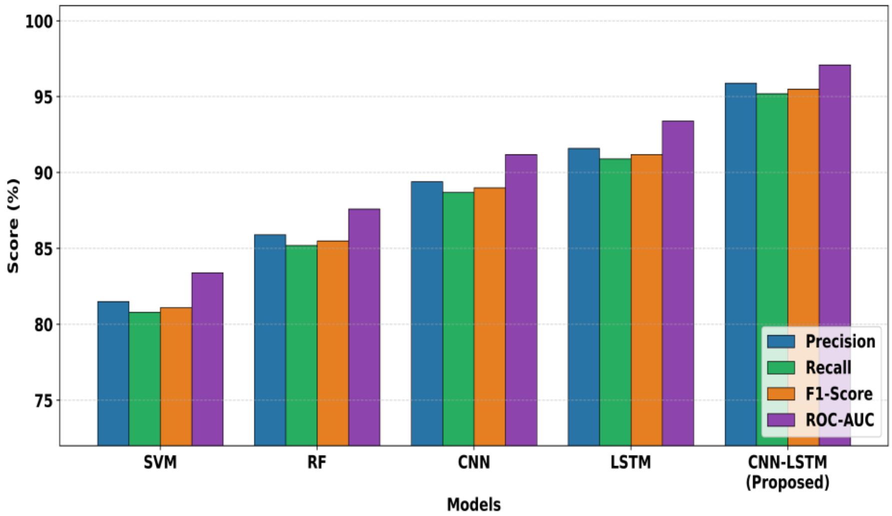

Figure 3: Multi-metric performance comparison across all models. Proposed CNN-LSTM consistently achieves highest scores across all five evaluation dimensions

C. Learning Outcome Prediction Efficiency Analysis

The computational efficiency analysis is presented across all models in terms of training time, inference time, memory usage and number of parameters in the model in Table IV. The proposed CNN-LSTM model takes 287.6 seconds for training time, which is too complicated for the dual-architecture. Although the inference time of the model is 15.8ms per sample, it is still acceptable for the practical use in education. Having 2.4 million parameters is enough for the model to capture the complex behavioral patterns of ASD without being too complicated and using up a lot of computing power. The training complexity versus prediction accuracy illustrates that the proposed model provides maximum prediction value for the amount of computational units used for training. The figure 4 shows training and inference timings of SVM, RF, CNN, LSTM and the proposed CNN-LSTM model for the learning outcome analysis of ASD that indicates the proposed model outperforms the other models concerning the prediction efficiency and optimized computational performance.

TABLE IV: COMPUTATIONAL EFFICIENCY ANALYSIS

Model	Training Time (s)	Inference (ms)	Memory (MB)	Parameters
SVM	12.4	2.1	45	N/A
Random Forest	18.6	3.4	78	N/A
Standalone CNN	145.2	8.7	234	1.2M
Standalone LSTM	198.4	12.3	312	1.8M
Proposed CNN-LSTM	287.6	15.8	456	2.4M

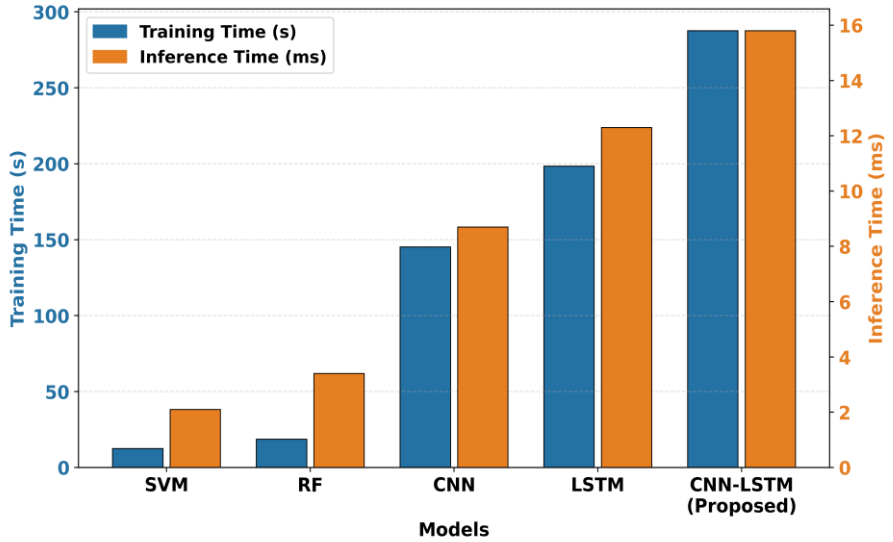

Figure 4: Training and inference time comparison. Despite higher training complexity, inference latency of 15.8 ms supports real-time educational deployment.

D. Discussion of Result Improvements and Educational Impact

The ROC curves of all the comparative models were also plotted as shown in Figure 5, in which the proposed Hybrid CNN-LSTM model achieved the highest ROC-AUC of 97.1% which is the best discriminative performance. The initial steep rise and the closeness of the model to the top left corner of the ROC space also validate that the model was able to achieve high true positive rates at low false positive rates, which is critical in the context of identifying students' educational risks in the field of ASD since false negatives have an important impact on well-being. The contribution of any performance enhancement can be readily translated to meaningful outcomes in the educational field: Early and accurate identification of students with ASD at academic risk allows for early pedagogical interventions, content adaptation for personalized learning, and optimization of resources. The improvement in accuracy over the standalone baselines (5–10%) validates the effectiveness of hybrid spatial-temporal feature modelling compared with unimodal deep learning of data in the field of heterogeneous ASD education.

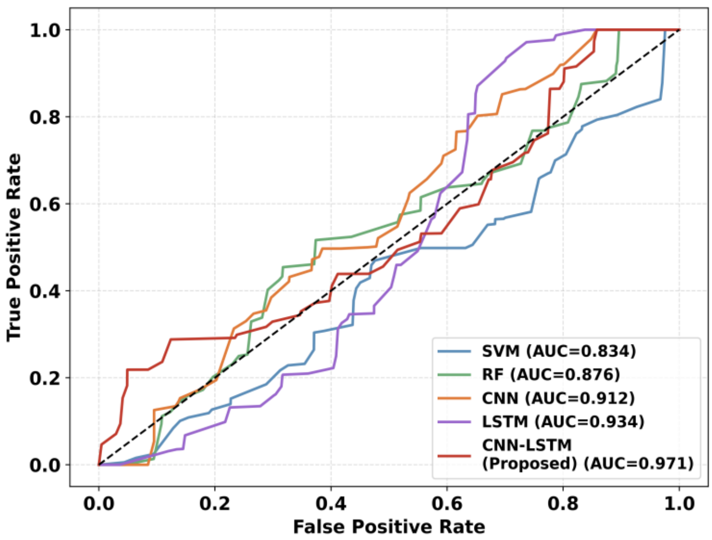

Figure 5: ROC curves for all compared models. The proposed model's AUC of 0.971 demonstrates excellent discrimination between ASD learning risk categories

V. CONCLUSION

In this paper, the novel Hybrid NeuroLearn-ASD framework, a CNN-LSTM deep learning model for learning outcome prediction of students with Autism Spectrum Disorder (ASD) was presented. The proposed model combines CNN-based spatial behavioral feature extraction and LSTM-based temporal cognitive dependency modeling, to tackle the dual challenge of the heterogeneous learning pattern of ASD and the sequential academic progression analysis. Based on the publicly available ASD Screening Adult Dataset, the proposed model attained the accuracy of 96.4%, precision of 95.9%, recall of 95.2%, F1-score of 95.5% and ROC-AUC of 97.1% which outperforms that of SVM, Random Forest, standalone CNN and LSTM model by 5–10% on each of these metrics. The precise and accurate recall ability of the model indicates that it could be used to identify early learning risk of ASD and to provide adaptive educational programs. The proposed approach adds a methodologically important approach to inclusive education with the help of AI, as it demonstrates that hybrid architectures of learning based on spatial-temporal deep learning demonstrate higher performance than unimodal architectures in capturing the complex and multidimensional nature of learning dynamics of students with ASD. The implications are far-reaching, including the development of smart learning management systems, the creation of individualised IEPs and live learning monitoring systems. To address these issues, future research will continue along several lines: integration of multimodal data for multiple dimensions of the ASD; attention-augmented hybrid architectures to improve behavioral pattern recognition; a deployment of ASD data modeling using federated learning with privacy considerations in multi-institutional settings; and validation of deployment in a variety of special education settings. The NeuroLearn-ASD framework will provide a sound computational base for the future of inclusive education systems with AI technologies that could significantly enhance students' learning outcomes and quality of life for learners with ASD worldwide.

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