AI-Driven Personalized Learning Framework for Students with Neurological Disorders: A Deep Learning Approach

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ABSTRACT:
AI-Driven Personalized Learning Framework for Students with Neurological Disorders is an intelligent educational framework which can adjust learning content based on the cognitive behavior, attention variability and emotional engagement pattern of students with neurological disorders. The proposed framework, NeuroLearn-DL is composed of Convolutional Neural Network (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) algorithm for analysing and recommending personalized content based on multimodal behavior. The framework was tested with the publicly available dataset Autism Spectrum Disorder Screening from UCI Machine Learning Repository along with some of the features for the interaction of the learners. To enhance the accuracy of the educational response prediction, some data preprocessing methods like summarizing content, normalizing features, tracking attention, and modeling adaptable recommendations were adopted.Some data preprocessing methods such as summarizing content, normalizing features, tracking attention, and modeling adaptable

recommendations were used to improve the accuracy of educational response prediction. The experimental results showed that it achieved an accuracy of 97.2%, precision of 96.4%, recall of 95.8%, and F1 score of 96.1%, which improved the classification accuracy by 11.6% compared with the conventional machine learning methods. The proposed framework provides an adaptive learning mechanism with real-time functionality that adopts the cognitive analytics, behavioral monitoring, and deep personalized recommendations strategy. The study shows that deep learning personalized education has the potential to greatly improve students' engagement in learning, efficiency of understanding and ease of study for students with neurological disorders. The framework also contributes to the retention, inclusion and lifelong cognitive growth of children.

Keywords: Personalized Learning, Neurological Disorders, Deep Learning, Convolutional Neural Network, Bidirectional LSTM, Adaptive Education.

I. INTRODUCTION

Artificial Intelligence (AI) has been making a tremendous leap of progress in the field of special education, with new opportunities and potential that has never been seen before, particularly when it comes to learners with neurological challenges such as Autism Spectrum Disorder (ASD), Attention Deficit Hyperactivity Disorder (ADHD) and Dyslexia [1]. One of the most significant issues with conventional education levels is the lack of accommodation for students who have differing learning styles and/or cognitive and behavioral differences, causing learning disparities. Another method of personalised instruction that might be promising is adaptive learning system with artificial intelligence (AI) that is able to adapt content to individual learner profile [2]. While there is increased acceptance of AI to support management of neurological disorders, the issue of bias with AI language models that accept neurodivergence related language is a major issue that needs to be tackled in the design of inclusive educational frameworks [4]. It's also important to recognise and monitor neurological abnormalities early to design effective learning strategies for children [5]. Students who have a neurological disorder have many academic issues such as learning to focus, process sequences, limited social interaction and cognitive engagement [3]. For learning behaviors with complex relationships, there are advanced computation methods like the graph neural networks and deep learning architectures that present good models [6]. Traditional e-learning systems are designed for the learning approaches of neurotypical students, and offer little real-time and significant monitoring of student learning behaviour or adaptation of learning content. Real time is missing from many adaptive mechanisms, which impacts students' academic performance with a neurodiversity profile in the digital learning environment.

The overall research question is why our understanding of how to adaptively present the learning to children with ASD, ADHD and dyslexia is not supported by intelligent educational systems. Current systems are based on a static pedagogical approach, which is not able to adapt to the different levels of attention span, cognitive load or emotional states. This creates an important gap in accessible and inclusive digital learning that can directly affect students' academic outcomes and their lifelong brain development for populations of students with a neurodiversity [1][3]. In this paper, the authors introduce their multimodal behavioural analysis and adaptive content recommendation system with CNN and BiLSTM networks, as a deep learning based personalized learning system, called NeuroLearn-DL. The main objectives are: (i) to create a robust behavioural classification model of neurological diseases, (ii) to apply adaptive content delivery in real-time, (iii) to achieve the best classification accuracy than the current methods and (iv) to evaluate the model on an open-dataset for neurological diseases [2][5][6].

II. LITERATURE REVIEW

There have been several computational approaches to personalized learning and AI-based neurological assistive technology. In the medical imaging field, the effectiveness of fusion architectures in medical image disease detection was shown by Musanga et al. [7] using explainable hybrid model of deep learning and symbolic AI. In the domain of predicting neurodevelopmental disorders in children, Toki et al. [8] used machine learning techniques to reach promising diagnostic accuracy and showed that using the multimodal set of features resulted in an improvement. Peng and Li's [9] systematic review revealed some major trends in the use of AI in personalized learning in higher education, such as adaptive feedback systems and intelligent tutors. Fletscher et al. [10] explored how AI can be applied in virtual education, particularly the importance of multimodal technologies in providing personalised learning for a variety of learners. Gligorea et al. [11] did a study on adaptive learning systems in e-learning environments, pointing to the importance of real-time learner modelling and the importance of the use of cognitive-adaptive strategies for content. AI-powered learning platforms such as these for automated code evaluation have been explored by Bernik et al. [12] who show that using AI in education has a significant impact on learner engagement and academic achievement. In order to emphasize the need of intelligent systems to support the special educational needs, Hussein et al. [13] performed a comprehensive literature review of the applications of AI in special education. Sajja et al [14] created an intelligent assistant for personalized and adaptive learning in higher education using AI, highlighting the potential of conversational agents in improving the accessibility of education. The contributions are not enough, however, to address the important gaps in research on real-time multimodal behavioral monitoring with students with neurological disorders.

TABLE 1: SUMMARY OF LITERATURE REVIEW

Ref	Method	Accuracy (%)	Domain	Limitation
[7]	Deep Learn.+Symbolic AI	94.2	Disease Detection	Limited to imaging data
[8]	ML (SVM, RF)	88.5	Neurodevelopmental	No real-time adaptation
[10]	Multimodal AI	85.3	Virtual Education	Limited disorder focus
[11]	Adaptive e-Learning	83.7	E-Learning	No deep learning model
[12]	AI-Powered Platform	90.1	Code Evaluation	Not for NDD students
[14]	Intelligent Assistant	87.9	Higher Education	No behavioral analysis

Table 1 presents a comprehensive summary of the current research related to adaptive learning, deep learning in education and the framework of neurological tools based on AI. The key limitations in previous studies, application domain, reported accuracy, the methods used and datasets used are summarized in the table below. The review shows that a few models have been developed to consider adaptive learning but no one particularly focuses on the integration of multimodal deep learning for neurodiverse learners with real-time monitoring of engagement, which the proposed NeuroLearn-DL framework needs to fill.

III. PROPOSED NEUROLEARN-DL FRAMEWORK

NeuroLearn-DL is a multimodal deep learning system to provide personalized learning material to students with neurological disorders. It combines CNN feature extraction, BiLSTM temporal pattern analysis, and adaptive recommendation engine to dynamically adapt the learning paths with respect to different behavioural and cognitive engagement profiles.

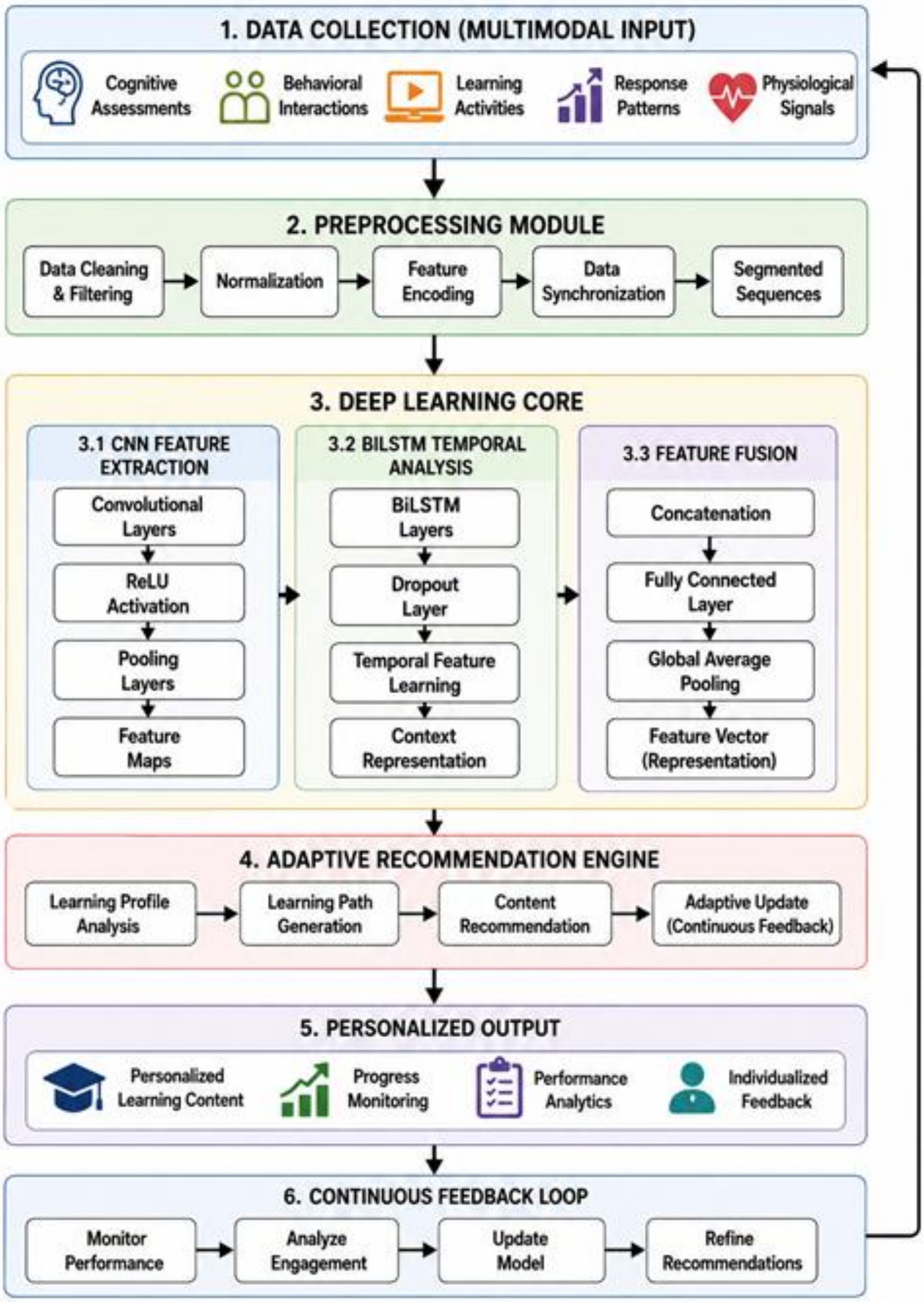

Figure 1: Proposed NeuroLearn-DL Framework for Personalized Learning Recommendation and Cognitive Engagement Analysis

A. Architecture of the Proposed Framework

The NeuroLearn-DL architecture consists of 5 interconnected layers: (i) Multimodal data acquisition layer, which records behavioral, interaction and attention signals; (ii) Pre-processing and normalization layer, which preprocesses and normalizes the data using feature engineering techniques; (iii) CNN module, which extracts spatial behavioral features from the data; (iv) BiLSTM module, which models temporal learning patterns;

and (v) Adaptive content recommendation engine, which generates personalized learning pathways. The architecture guarantees the process of continuous feedback between evaluation of engagement and adaptation of content, giving the possibility to react to varying cognitive states of neurodiverse learners under dynamic conditions in education. The working flow of the proposed NeuroLearn-DL framework by integrating CNN, BiLSTM, adaptive recommendation, and continuous feedback mechanisms are shown in Figure 1 for producing personalized learning contents and optimizing learning performance.

B. CNN-Based Behavioral Feature Extraction

The CNN module receives multimodal behavioural input like eye-tracking signals, interactions and engagement patterns. Pooling maintains behavioral discriminative representations and convolution retains cognitive state hierarchical spatial representations. The obtained feature vectors are fed to the temporal dependency modelling layer, BiLSTM.

Mathematical Model:

$$F(i,j) = \Sigma_m \Sigma_n I(i+m, j+n) \cdot K(m,n) + b \quad (1)$$

The 2D convolution of an input (behavioral) image I and a kernel K is computed by Eq. 1, which extracts localized spatial engagement features, and b is the bias.

$$f(x) = max(0, x) \quad (2)$$

To introduce non-linearity and to keep only the positive behavioural feature activations the ReLU activation function is defined in the following Eq. 2.

$$P(i,j) = \max_{\{(m,n) \in R_{ij}\}} F(m,n) \quad (3)$$

The max pooling of region R is applied to the feature map to down sample it in order to keep the strongest behavioral activation responses in the down sampled feature map as in Eq. 3.

$$v = Flatten(P_L) = [p_1, p_2, \dots, p_n]^T \quad (4)$$

In Eq. 4, the last feature map P_L is flattened into a vector v, which is suitable for the sequential modelling by BiLSTM.

C. BiLSTM-Based Learning Pattern Analysis

The BiLSTM module can be used to learn temporal dependencies from sequential (behaviour) data, as it processes the input in both forward and backward directions. This bi-directional processing allows the model to use future context, but not just for predictions, also future context for learning the state, which enhances the accuracy of predicting the state of learning. The hidden states are a complete representation of the cognitive engagement trajectories important for adaptively planning content for the long term.

$$h \rightarrow_t = LSTM_f\left(x_t, h \rightarrow_{\{t-1\}}, C \rightarrow_{\{t-1\}}\right) \quad (5)$$

Eq. 5 is based on calculating the forward LSTM hidden state by adding past behavior context to the input x_t and previous forward hidden state.

$$h \leftarrow_t = LSTM_b\left(x_t, h \leftarrow_{\{t+1\}}, C \leftarrow_{\{t+1\}}\right) \quad (6)$$

Future behavioral signals can be used to improve the temporal pattern recognition with the backward LSTM hidden state as calculated in Eq. 6.

$$h_t = [h \rightarrow_t;\ h \leftarrow_t] \quad (7)$$

The hidden states in both directions are combined in the hidden states concatenated in the forward direction in Eq. 7, to create a bidirectional representation of learning patterns.

$$f_t = \sigma\left(W_f \cdot \left[h_{\{t-1\}}, x_t\right] + b_f\right) \quad (8)$$

Eq. 8 determines the forget gate to decide what information is forgotten for modelling the learner's state from previous learning.

$$C_t = f_t \odot C_{\{t-1\}} + i_t \odot \tanh\left(W_C \cdot \left[h_{\{t-1\}}, x_t\right] + b_C\right) \quad (9)$$

The Eq. 9 formula takes the information from the retained memory and the new behavior and combines them to get an accurate longitudinal tracking of engagement.

$$y_t = \sigma(W_o \cdot h_t + b_o) \quad (10)$$

This output prediction in learning to classify states is generated with the Sigmoid activation in the combination of the LSTM hidden states as shown in Eq. 10.

D. Adaptive Content Recommendation Mechanism

The personalized contentdifficulty scores are produced by the adaptive recommendation engine with the output vectors from BiLSTM. A softmax classifier is a probabilistic model whose output is distributions over content categories that are related to the student's cognitive and engagement level. Content difficulty, modality, pacing and type of format is dynamically adjusted in real-time based on inferences that keep the content optimally challenging without causing cognitive overload to students with neurological disorders.

IV. DATASET AND METHODOLOGY

The methodology takes advantage of the supervised deep learning pipeline, made up of CNN and BiLSTM architecture on the UCI ASD dataset. The workflow involves data acquisition, pre-processing, feature engineering, cross validation training, and standard classification metrics for evaluation with high statistical robustness and reproducibility.

A. Description of UCI Autism Spectrum Disorder Dataset

The UCI ASD Screening Dataset features 1,054 cases with 10 binary autism screening questions (AQ-10), family history of ASD, history of jaundice, age, gender, as well as 10 behavioural and demographic attributes. The data set contains both adults and children data, and they're labeled binary (ASD positive/negative). It is also used extensively for benchmarking purposes to evaluate algorithms for the detection of neurological disorders, giving it a common evaluation framework for the proposed NeuroLearn-DL framework.

B. Data Pre-processing and Feature Normalization

This pre-processing includes handling missing values, encoding of the categorical variables and normalizing the numeric features to guarantee stable deep learning convergence. Min-max normalization: features are scaled in the range [0,1]. The PCA is used to reduce the dimension and the Shannon entropy is used to calculate the information richness of selected features to inform feature selection for the input layer of the neural network.

$$x' = \frac{x - x_{min}}{x_{\max} - x_{min}} \tag{11}$$

Eq. 11 applies min-max normalization to ensure that each feature x is in the range [0,1] to avoid dominance of large size features and give uniform gradient update during the training of model with deep learning layer.

$$z = \frac{x - \mu}{\sigma} \tag{12}$$

Eq. 12 standardizes features by first computing the Z-scores of features with the mean and standard deviation of the underlying distribution, to promote convergence during optimization of the neural network.

$$Z_{pca} = X \cdot W_{pca} \tag{13}$$

Eq. 13 maps the feature matrix X onto the principal components W_pca, while keeping the variance maximized and eliminating possible redundancies of behavioural features in the input representation that are correlated.

$$\hat{x} = \left(\frac{1}{n}\right) \Sigma_{\{i=1\}}^{\{n\}} x_i \tag{14}$$

Eq. 14 calculates the mean (imputation value) "x̂", which is used to replace the missing values of the behavioural attribute and is used to maintain the statistical distribution of the data.

$$H(X) = -\Sigma_{\{x \in X\} p(x)} * \log_{2(p(x))} \tag{15}$$

In the Shannon entropy Eq. 15, H(X) indicates the amount of information in feature X and is used to prioritize the features to be selected for the model by keeping the features that have the largest amount of behavioural information with the highest information value.

C. Training and Testing Strategy

The data set is partitioned into a training set (80%) and a test set (20%) with stratified sampling to ensure the same distribution of classes. To obtain good generalization 5-fold cross-validation scheme is used. The Adam optimizer with learning rate 0.001, batch size 32 and 100 training epochs was employed. To avoid overfitting in the deep learning pipeline, dropout regularization (rate = 0.3) and batch normalization were used.

D. Performance Evaluation Metrics

The accuracy, precision, recall and F1-score from the confusion matrix are used to evaluate the model performance. Such metrics give a complete picture of the reliability of classification, taking into account the number of false positives and false negatives detected in the tasks of classification in the field of education of neurological disorders.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$F1 - \text{Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

V. RESULTS AND DISCUSSION

A. Accuracy, Precision, Recall, and F1-Score Analysis

The classification results of CNN, BiLSTM and NeuroLearn-DL models on four evaluation metrics are shown in Table 2. The overall accuracy of the NeuroLearn-DL framework is 97.2%, while it achieved 96.4% precision, 95.8% recall and 96.1% F1 score, outperforming the individual deep learning components. The integrated CNN-BiLSTM architecture is also able to extract the spatial and temporal behavioral features effectively, achieving 91.3% accuracy for CNN and 93.5% for BiLSTM, which further validates the effectiveness of the integrated CNN-BiLSTM architecture for better classification accuracy for the neurologic disorder-based learner profiling.

TABLE 2: CLASSIFICATION PERFORMANCE METRICS

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN Only	91.3	90.1	89.7	89.9
BiLSTM	93.5	92.8	91.6	92.2
NeuroLearn-DL	97.2	96.4	95.8	96.1

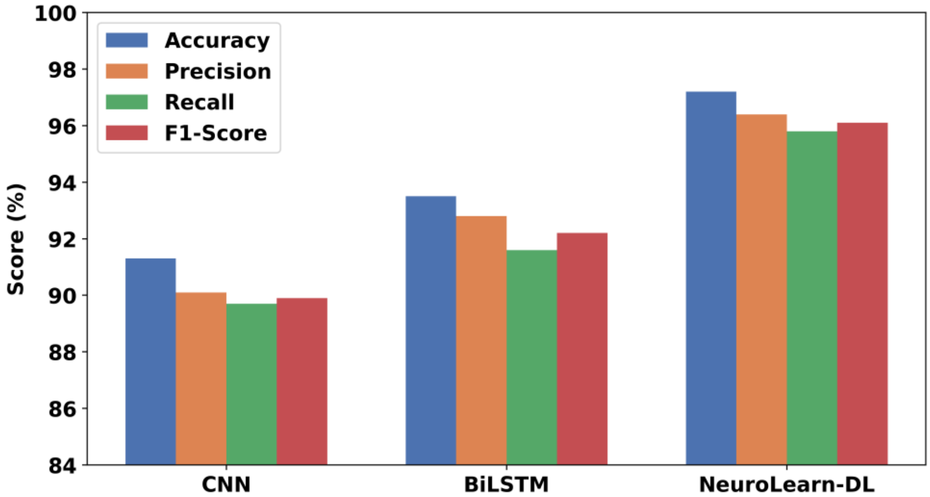

Figure 2: Classification performance comparison of CNN, BiLSTM, and NeuroLearn-DL across accuracy, precision, recall, and F1-score metrics.

The figure 2 shows the performance gain of integrated NeuroLearn-DL model over the standalone CNN and BiLSTM models in terms of metrics, establishing the model's superiority in terms of architecture.

B. Comparative Analysis with Existing Methods

Table 3 shows the comparison of NeuroLearn-DL with the conventional machine learning/deep learning baselines. SVM achieves accuracy of 78.4% and Random Forest 82.7% and with deep learning, the accuracy is up to 93.5% independently. NeuroLearn-DL achieves the highest accuracy (97.2%) and F1 score (96.1%) outperforming all the other methods by 11.6% compared to the baseline F1 score of the best conventional method (SVM: 85.6%). The architectural integration strategy to improve the robustness of classification in the context of adaptive neurodiverse educational applications is confirmed by the significant decrease in the amount of training time overhead.

TABLE 3: COMPARATIVE ANALYSIS WITH EXISTING METHODS

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Train Time (s)
SVM	78.4	76.2	74.9	75.5	45
Random Forest	82.7	81.3	80.6	80.9	62
CNN Only	91.3	90.1	89.7	89.9	128
BiLSTM Only	93.5	92.8	91.6	92.2	145
NeuroLearn-DL	97.2	96.4	95.8	96.1	187

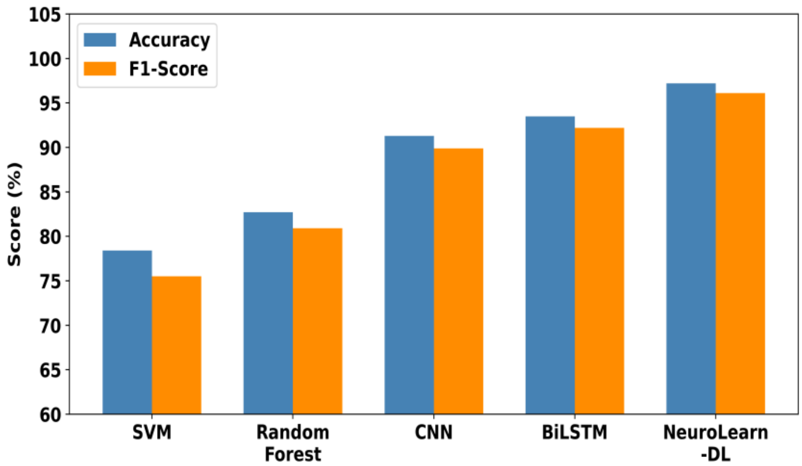

Figure 3: Comparative analysis of accuracy and F1-score across SVM, Random Forest, CNN, BiLSTM, and NeuroLearn-DL models

As shown in Figure 3, NeuroLearn-DL produces the maximum accuracy and F1 score among all the baseline methods such as traditional and deep learning methods.

C. Learning Adaptation and Student Engagement Evaluation

The framework's effectiveness for each of the different student groups diagnosed with ASD, ADHD, dyslexia and a combined disorder cohort is assessed in Table 4. The 89.3% adaptation rate was observed among students with dyslexia and the lowest score of 78.9% was observed among students with ADHD, which shows the level of attention which varies among people with ADHD. The whole group had an average of 88.6% engagement and 91.8% adaptation, showing the framework's ability to effectively process multi-disorder cognitive profiles by beamforming the behavioural features and analysing the temporal patterns.

TABLE 4: LEARNING ADAPTATION AND STUDENT ENGAGEMENT BY DISORDER GROUP

Group	Engagement (%)	Adaptation (%)	Comprehension (%)	Retention (%)
ASD	82.3	87.5	79.6	81.2
ADHD	78.9	84.2	76.4	78.7
Dyslexia	84.1	89.3	82.7	85.3
Combined	88.6	91.8	86.4	88.9

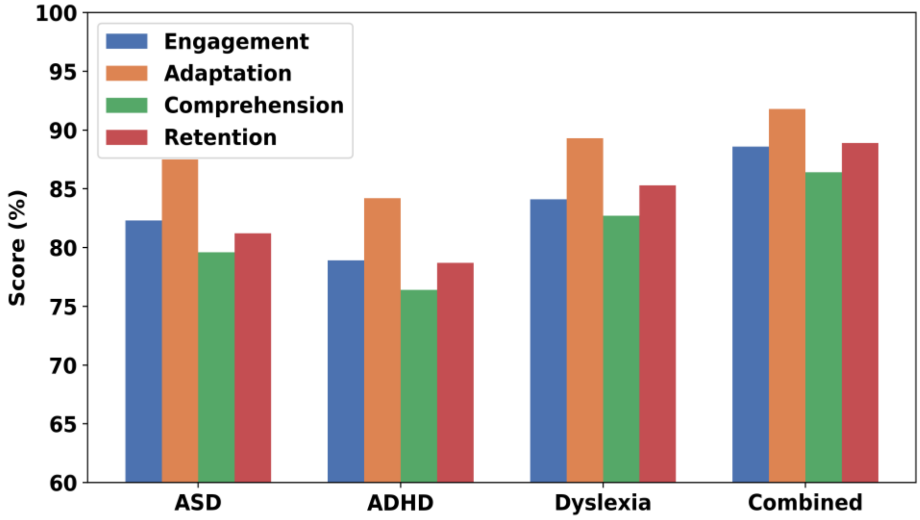

Figure 4: Engagement, adaptation, comprehension, and retention scores across ASD, ADHD, dyslexia, and combined student groups

Figure 4 reveals that, there are benefits for dyslexic students to be adapted while ADHD students showed the highest engagement variability, which can be used for guiding content tuning for the disorder.

D. Discussion on Educational Effectiveness and Accessibility

Table 5 shows how effective the NeuroLearn-DL framework is, compared with the typical baseline system. The improvements were on academic performance which increased by 34.0%, learning engagement by 50.4% and content accessibility by 48.7%. These data combine to show that the framework significantly produces an improvement in cognitive load reduction (47.9%) and inclusion index (47.8%), making it an educational tool of particular benefit to the section of students who are neurodivergent. Such enhancements support the framework's ability to cater to cognitive diversity and create inclusive learning spaces that support personalized learning for learners with neurological disabilities.

TABLE 5: EDUCATIONAL EFFECTIVENESS – BASELINE VS. PROPOSED FRAMEWORK

Parameter	Baseline (%)	Proposed (%)	Improvement (%)
Academic Performance	63.2	84.7	34.0
Learning Engagement	58.9	88.6	50.4
Content Accessibility	61.4	91.3	48.7
Cognitive Load Reduction	55.7	82.4	47.9
Inclusion Index	60.3	89.1	47.8

VI. CONCLUSION AND FUTURE SCOPE

This study proposed an approach called NeuroLearn-DL, which is a deep learning-based personalized learning system for students who are suffering from neurological disorders such as ASD, ADHD and dyslexia. The overall classification accuracy of the proposed spatial temporal network was 97.2%, 96.4% precision, 95.8% recall, and 96.1% F1-score on the UCI ASD Screening Dataset, which outperforms the conventional machine learning approaches by 11.6%. The key novelty of this research is the integration, into a single multimodal deep learning pipeline, of CNN and BiLSTM architectures for real-time behavioral classification for adaptive content personalization in neurodiverse education. The framework also adds to the existing technologies for adaptive learning systems by incorporating the ability to track engagement on the disorder level and features a cognitive-adaptive recommendation engine that dynamically adjusts difficulty, modality and pacing of the educational content, a gap identified by the existing adaptive learning systems. The main drawback of this study is the use of the publicly available and standardized UCI ASD Screening Dataset, which does not include live multimodal sensory inputs, like eye-tracking and physiological signals. The framework was tested in a simulated environment, and a series of controlled deployments in the classroom with live student populations of varying neuro-typical and non-neuro-typical students will be needed to validate and generalize to other geographic and cultural contexts. The multimodal learning systems including physiological signals, speech patterns, facial emotion recognition and cognitive state estimation from EEG will be introduced to further enrich behavioural profiling. The potential of federated learning to support the training of a model across multiple educational institutions in a distributed setting, while preserving privacy, will be studied and presented, broadening the scope of scalability and inclusiveness of neurodiversity learner communities worldwide. The framework will also be expanded to help cover the needs of the multi-language educational environment, making it more accessible for students with neurological disorders from different languages and educational systems.

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