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RESEARCH ARTICLE

Identifying ADHD for Children With Coexisting ASD From fNIRs Signals Using Deep Learning Approach

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ABSTRACT Attention deficit hyperactivity disorder (ADHD) for children is one of the most common neurodevelopmental disorders and its prevalence has increased globally. Children with ADHD are faced with various difficulties, including inattention, impulsivity, and hyperactivity. Therefore, it is important to use an early detection system that is simple, non-invasive, and automated. Children with ADHD also suffer from other coexisting one or more disorders, including major depressive disorder (MDD), autism spectrum disorder (ASD), etc and it creates more challenges to detect ADHD children. Very few researchers considered such kinds of these comorbidities in their studies to detect ADHD for children. In this work, we proposed a deep learning (DL)-based algorithm to identify ADHD children with coexisting ASD. Functional near-infrared spectroscopy (fNIRs) signals from thirteen ADHD children who have coexisting ASD and fifteen typically developing (TD) children were recorded during the drawing of handwriting patterns. We asked each child to draw periodic lines (PL) and zigzag lines (ZL) under the predict and trace condition and repeated them three times. Finally, a hybrid approach was designed by combining convolutional neural networks (CNN) and bidirectional long short-time memory (Bi-LSTM) to determine children with ADHD who have ASD. The experimental results showed that our proposed hybrid approach could determine ADHD children with coexisting ASD with a classification accuracy of 94.0%, a sensitivity of 89.7%, specificity of 97.8%, f1-score of 93.3%, and AUC of 0.938, respectively, for the PL predict task.

INDEX TERMS Functional near-infrared spectroscopy, attention deficit hyperactivity disorder, autism spectrum disorder, convolution neural network, long short time memory.

I. INTRODUCTION

Attention-deficit/hyperactivity disorder (ADHD) has recently received great attention as one of the most prevalent neurodevelopmental disorders in children. It is mainly characterized by three symptoms: lack of attention, hyperactivity, and impulsivity. This disorder usually begins in childhood and may persist until adulthood [1]. Around 5% of children worldwide are affected by this disorder [2]. ADHD children often struggle with numerous difficulties such as behavior and emotional problems [3], [4], learning disorders [5], educational, mental health, and social problems [6], and the risk of suicide attempts [7]. Moreover, ADHD children have also been affected by coexisting ASD and other disorders [8],

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[9], [10], which may present an extra burden/challenge for guardians/parents, educators, and healthcare providers. So, it is important to detect or screen ADHD children with coexisting ASD and other disorders at an early stage, which may be helpful for healthcare providers as well as their guardians to take the necessary steps for early treatment.

ADHD is now diagnosed clinically, with questionnaire-based interviews (developed by the Diagnostic and Statistical Manual of Mental Disorders (DSM)) from respondents, their guardians/parents, and teachers [11]. Sometimes, it may also happen due to the guardian's inaccurate report of the symptoms of children with ADHD. As a result, diagnostic criteria give misleading results that discriminate ADHD children from healthy children [12]. So, it is highly valuable and urgent to propose a simple and non-invasive diagnosis method that complements the current diagnostic criteria for ADHD.

Various non-invasive diagnosis methods, like functional near-infrared spectroscopy (fNIRS) [13], [14], electroencephalography (EEG) [15], [16], electrocardiograms (ECG) [17], and functional resonance imaging (fMRI) [18], [19] is widely used for detecting children with developmental disabilities, including ADHD. Among them, fNIRs have a great attraction as a brain imaging technique to measure brain activity. fNIRs has gained considerable attention to be a highly suitable/appropriate technique for the clinical assessment and measurement of brain function characteristics in ADHD children. Various researchers used fNIRs signals to detect ADHD children during various tasks such as n-black tasks [13], Stroop, and go/no go tasks [14], [20], [21], working memory tasks. Moreover, fNIRs signals were also used to show the impact of differences in stimulus array conditions on PFC during cancelation tasks [22]. Moreover, it was also utilized to determine the effect of numerous drugs on ADHD children.

Recently, existing studies strongly suggested that handwriting patterns using pen tablet have also been used to classify adults and children [23], [24]. Moreover, we do not find so much studies to detect ADHD by considering other coexisting disorders including ASD [25]. From these motivations, we have the plan to propose an ADHD with coexisting ASD detection method from fNIRs signals during drawing tasks. In this study, we recorded fNIRs signals from ADHD with coexisting ASD and typically developing (TD) children during two drawing handwriting patterns tasks (Zigzag lines (ZL) vs. Periodic Lines (PL)) under trace and predicted conditions. These recorded signals were analyzed using statistical analysis, machine learning (ML), and deep learning (DL)-based approach. In this study, we employed two DL-based approaches, like convolutional neural network (CNN) and bidirectional long short-time memory (Bi-LSTM), and then proposed a hybrid approach by combining these two approaches to discriminate ADHD with coexisting ASD children from TD children.

The remaining part of this study is organized as follows: Section II represents the related work. Section III introduce materials and methods. This section includes the proposed methodology, device for data collection, data collection procedure, data formation, and classification method. Experimental design and performance metrics are presented in Section IV. Experimental results and discussions are presented in Section V. Finally, the conclusion of this study is presented in Section VI.

II. RELATED WORKS

There are many types of studies about developmental disorder recognition. Recently, some studies were conducted to detect ADHD children based on fNIRs signals. For example, Monden et al. [11] proposed an ADHD detection system based on fNIRs during Go/No GO tasks and obtained a sensitivity of 90.0% and specificity of 70.0%. Gu et al. [26] used multivariate pattern analysis (MVPA) to determine ADHD children from fNIRs signals. These fNIRs signals were recorded from 50 children (ADHD: 25 and healthy: 25) during n-black tasks. They illustrated that about 86.0% of the children could be correctly classified using LOOCV. Xu et al. [27] developed a CNN with a gated recurrent unit (CNN-GRU) model to predict children with ASD based on their fNIRs signals. They recorded fNIRs signals from 25 ASD and 22 TD children. They showed that the CNN-GRU-based model achieved 92.2% accuracy.

Cheng et al. [28] also recorded hemodynamic fluctuations using fNIRs from 25 ASD and 22 TD children. They extracted the power spectrum from each signal and showed that the power of deoxygenated hemoglobin for ASD was higher compared to TD. They adopted SVM for the identification of ASD and TD children and obtained 92.7% accuracy, 90.2% sensitivity, and 95.1% specificity. Yasumura et al. [14] proposed a biomarker for ADHD detection using SVM. The performance index of the Reverse Stroop Task (RST), and fNIRs data measured during the task were used as input features to train SVM model. The SVM model achieved 86.3% accuracy, 88.7% sensitivity, and 83. 8% specificity. Yue et al. [13] also proposed discriminant correlation analysis (DCA) with SVM to identify children with ADHD. They recorded fNIR samples from 50 children (ADHD: 25 and TD: 25) during n-black. They adopted the DCA-based method to determine a joint feature by combining the extracted features for 0-back and 1-back conditions. These joining features were used to train the SVM model for identifying ADHD children, which achieved 88.0% accuracy. Monden et al. [11] used quantitative analysis for ADHD children detection and obtained an accuracy of 85.0% and a sensitivity of 90.0%.

III. MATERIALS AND METHODS

A. PROPOSED METHODOLOGY

This study proposed a DL-based approach to discriminate ADHD with coexisting ASD children from TD children. The overall proposed framework of this study is more clearly explained in Fig. 1. We recorded fNIRs signals from twenty-eight subjects (thirteen ADHD children with coexisting ASD and fifteen TD children while drawing handwriting patterns. In the first stage, we divided the dataset into two sets: training and test sets. We took 1 subject as a test set

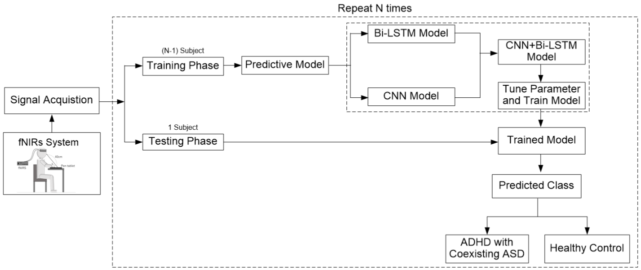

FIGURE 1. Proposed DL-based framework for predicting ADHD children with coexisting ASD using fNIRs data.

and the remaining (N−1) subjects as a training set. Secondly, we implemented two DL-based predictive models separately: Bi-LSTM and CNN. After that, we combined these two models (Bi-LSTM and CNN models) and proposed a novel DL-based architecture for predicting ADHD with coexisting ASD children. In this study, this new architecture is called a "stack CNN-BiLSTM". The next step was to tune the hyperparameters of these two predictive models. Using all of these tuning hyperparameters, we trained the predictive model using a training set. This training model was used on test sets to predict ADHD in children with coexisting ASD. We repeated the whole procedure "N" times and then, performance metrics like accuracy, sensitivity, specificity, f1-score, and AUC were calculated to evaluate our proposed model.

B. DEVICE FOR DATA COLLECTION

This study used a pen tablet for drawing handwriting patterns. During the subjects' performance of drawing tasks on a pen tablet, the neural activity of each subject was recorded using the fNIRS device (OEG-16, Spectratech Inc., Tokyo, Japan), which is presented in Fig. 2a. The device had 16 channels, and each channel recorded the relative changes in oxygenated hemoglobin (oxy-Hb) value, non-oxygenated hemoglobin (deoxy-Hb) value, and total hemoglobin (total-Hb) value. Here, the total-Hb value means the sum of the oxy-Hb value and the deoxy-Hb value. The time resolution of this device is approximately 650 milliseconds. This device records blood flow values in the right prefrontal cortex by Ch1 to Ch6, values in the central prefrontal cortex by Ch7 to Ch10, and values in the left prefrontal cortex by Ch11 to Ch16. Fig. 2b shows the arrangement of each channel.

C. DATA COLLECTION PROCEDURE

The dataset was collected from subjects performing a line-drawing task using a pen tablet device. In this task, the subject drew ZL and PL on the pen tablet. ZL was a line consisting of consecutive baseless triangles, while the PL line consisted of consecutive baseless squares and triangles. We performed the tasks in three ways. First, each subject needs a 20s break for the rest of the brain, followed by 30s drawing trace tasks. Then, the other 20s take a rest, and the next 30s predict drawing tasks. The tracing condition means that the line is formed by tracing the sample line shown on the screen. The predicted condition means that the line is drawn on a blank screen, remembering the line shape. We repeated the procedures three times. Fig. 3 visualizes an example of each line and drawing task flow.

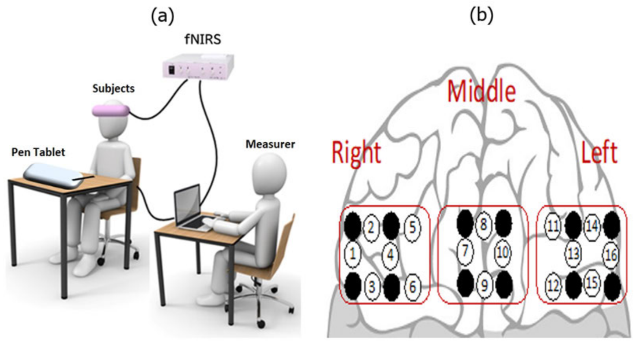

FIGURE 2. (a) Measurement of brain function during drawing handwriting patterns; (b) Arrangement of fNIRs channel.

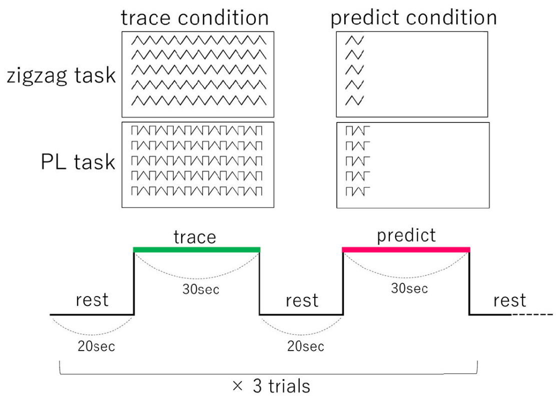

FIGURE 3. Data collection procedure.

TABLE 1. Summary of the utilized fNIRs dataset.

Group	Age (years)	No. of subjects	No. of task	No. of repeat	Total Samples
ADHD with coexisting ASD	5∼14	13	4	3	156
TD	8∼12	15	4	3	180

D. DATA FORMATION

In order to conduct this study, we collected fNIRs signals from thirteen ADHD children with coexisting ASD and fifteen TD children based on their drawing handwriting patterns. The typical fNIRs signals of ADHD children with coexisting ASD and TD children are shown in Fig. 4. Our study included TD children aged 8-12 years and ADHD children with coexisting ASD aged 5-12 years. We asked each child to perform four tasks and repeated them three times. Finally, we got 156 (13×4×3) samples from ADHD children with coexisting ASD and 180 (15×4×3) samples from TD children. The summary of the fNIRS dataset is described in Table 1.

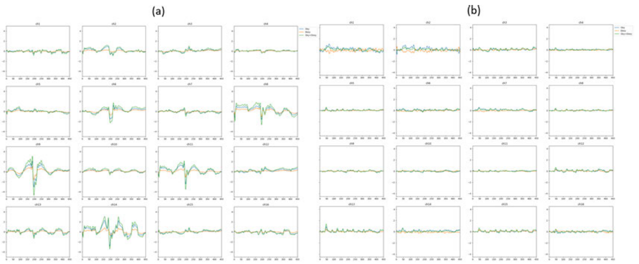

FIGURE 4. Typical fNIRs signal for (a) ADHD children with coexisting ASD, and (b) TD children.

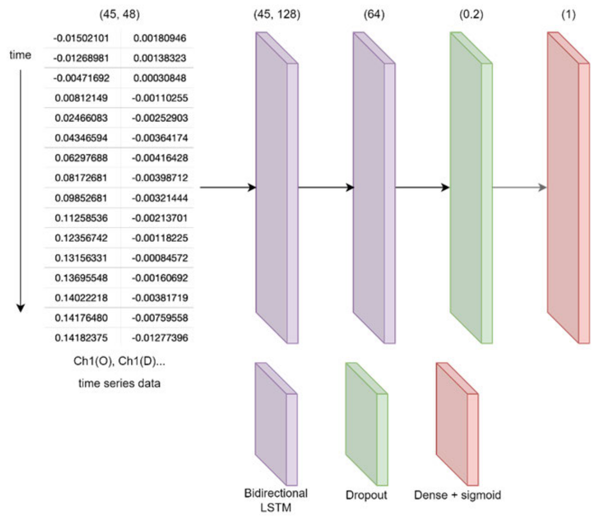

FIGURE 5. The architecture of Bi-LSTM model.

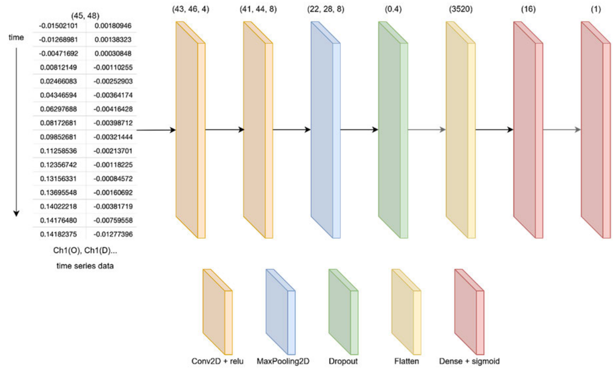

FIGURE 6. The architecture of CNN model.

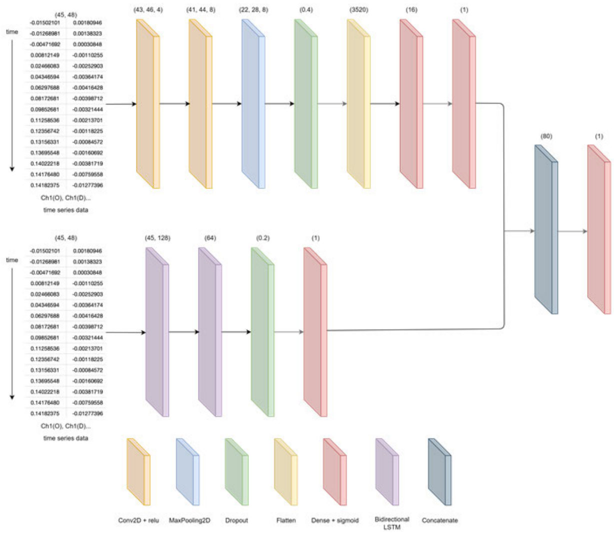

FIGURE 7. The architecture of proposed CNN-BiLSTM model.

E. CLASSIFICATION MODEL

In this work, first, we trained two models (CNN model, BiLSTM) and proposed a new model with a combination of CNN and Bi-LSTM-based models. We complied these models based on the binary cross-entropy function as the loss function and Adam as the optimizer. Moreover, we set 32 epochs, 8 batch sizes, and 0.01 learning rate during training models.

1) BiLSTM

BiLSTM model took an input of 45 $\times$ 48 fNIRS data. A BiLSTM layer with 64 units was added as the first layer, and a BiLSTM layer with 32 units was added as the second layer. The recurrent_dropout for each is 0. Then, a dropout layer of 0.5 was added. Finally, A dense layer was added. The sigmoid function was used for the activation function. The architecture of the BiLSTM model is shown in Fig. 5.

2) CNN

CNN model inputted 45 $\times$ 48 $\times$ 1 fNIRS data. The first convolutional layer consisted of 4 convolutional filters of size 3 $\times$ 3. The second convolutional layer used 8 convolutional filters of size 3 $\times$ 3. Rectified linear units (ReLU) were used as activation functions in the two convolution layers. To prevent overfitting, a maximum pooling layer was used. The pooling size was 2 $\times$ 2. Following these layers, a dropout layer of 0.4 and a flattened layer were added. Subsequently, a dense layer with 16 units and a dense layer with 1 unit was added, respectively. The sigmoid function was used for the activation function of these dense layers. The architecture of the CNN model is shown in Fig. 6.

3) PROPOSED HYBRID APPROACH

Finally, we proposed the CNN-BiLSTM model for classification. This model combined the outputs of the BiLSTM model and the CNN model described in the previous section minus the last dense layer and added a dense layer with 1 unit using the sigmoid function as the activation function. The architecture of the proposed CNN-BiLSTM model is shown in Fig. 7.

IV. EXPERIMENTAL SETUP AND PERFORMANCE METRICS

In this experiment, Python version 3.9.16 was used. We also used Keras version 2.11.0 for building the proposed model and Sklearn version 1.2.2 for cross-validation. We used

TABLE 2. Baseline characteristics of ADHD with coexisting ASD and TD children.

Variable	Overall	ADHD with coexisting ASD	TD Children
Total, n (%)	28	13 (53.6)	15 (46.4)
Gender, Male, n (%)	19 (67.9)	11 (84.6)	8 (53.3)
Age, Ave ± Std (years)	9.4 ± 1.3	8.7 ± 2.2	9.9 ± 1.2

Ave: Average and Std: Standard deviation.

MacbookPro15,4 64-bit with 1.4 GHz Quad-Core Intel Core i5r and 16 GB of RAM. Leave One Out Cross Validation (LOOCV) was used, whereas the "(N−1)" subject was used to train the predictive models, and one subject was used for the test set. These trained models were evaluated on a test set. This process was repeated N (here, N=28*3) times and computed the predicted class of each trial and its probability for all subjects over four tasks. Then, we compared these predicted classes against the actual class and computed the confusion matrix over four tasks. From this confusion matrix, we computed different evaluation metrics such as accuracy, sensitivity, specificity, and f1-score, which were used to evaluate the performance of the proposed system. The formula for calculating these metrics is presented in Equation 1-Equation 4. Moreover, we also calculated the ROC curve with the AUC value to evaluate the performance of the proposed system.

$$\text{Accuracy}\ (\%) = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \times 100 \quad (1)$$

$$\text{Sensitivity}\ (\%) = \frac{T_P}{T_P + F_N} \times 100 \quad (2)$$

$$\text{Specificity}\ (\%) = \frac{T_N}{T_N + F_P} \times 100 \quad (3)$$

$$\text{F1} - \text{Score}\ (\%) = \frac{2T_P}{2T_P + F_P + F_N} \times 100 \quad (4)$$

Here, T_P represents the true positive, T_N represents true negatives; F_P represents false positives; and F_N represents false negatives.

V. RESULTS AND DISCUSSION

A. BASELINE CHARACTERISTICS OF THE SELECTED SUBJECTS

The baseline of characteristics of the selected subjects is illustrated in Table 2. The prevalence of ADHD with coexisting ASD and TD children was 53.6% and 46.6%. In this study, about 84.6% of children who had ADHD with coexisting ASD were male and the rest of the male children were TD. The average ages of children were 8.7 ± 2.2 years for ADHD with coexisting ASD and 9.9 ± 1.2 years for TD children.

B. EXPERIMENTAL RESULTS OF CLASSIFICATION MODEL

In this study, three classification models (CNN, BiLSTM, and CNN-BiLSTM) were trained using (28*3-1=83) subjects, and one subject was used to test the predicted performance of these trained models. Here, 28 is the number of subjects and 3 is the trials. This process was repeated 84 times until each subject was eliminated once. We then compared this predicted class of three models over four tasks against the actual class label. At the same time, we computed the confusion matrix of each classifier over four tasks. The confusion matrix of the proposed CNN-BiLSTM system is presented in Fig. 8, while the confusion matrix of CNN and BiLSTM models are depicted in Fig. 9 and Fig. 10.

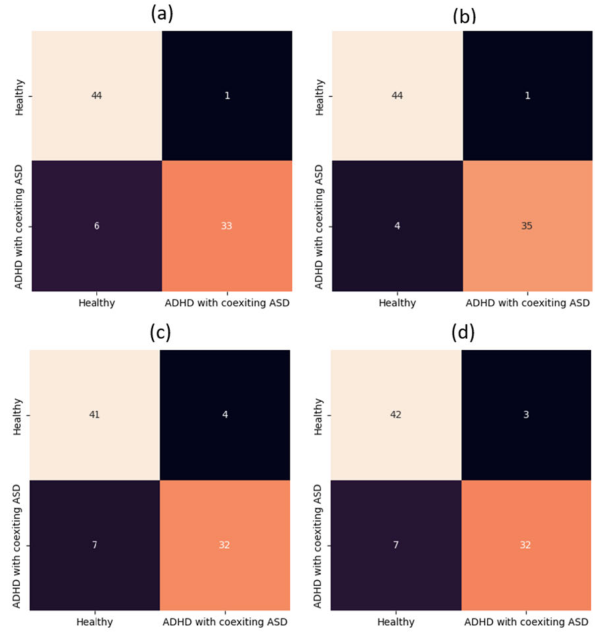

FIGURE 8. Confusion matrix of our proposed CNN-BiLSTM system: (a) PL trace; (b) PL predict; (c) ZL trace; and (d) ZL predict.

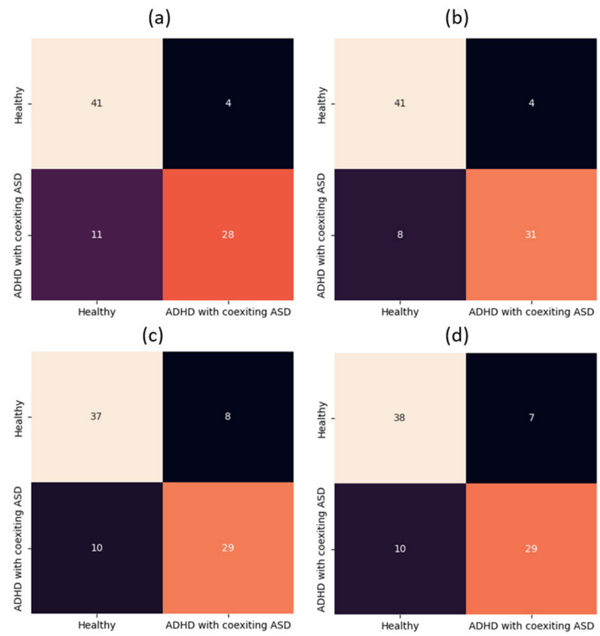

FIGURE 9. Confusion matrix of CNN model: (a) PL trace; (b) PL predict; (c) ZL trace; and (d) ZL predict.

From these confusion metrics, we also computed the different performance metrics (accuracy, sensitivity, specificity,

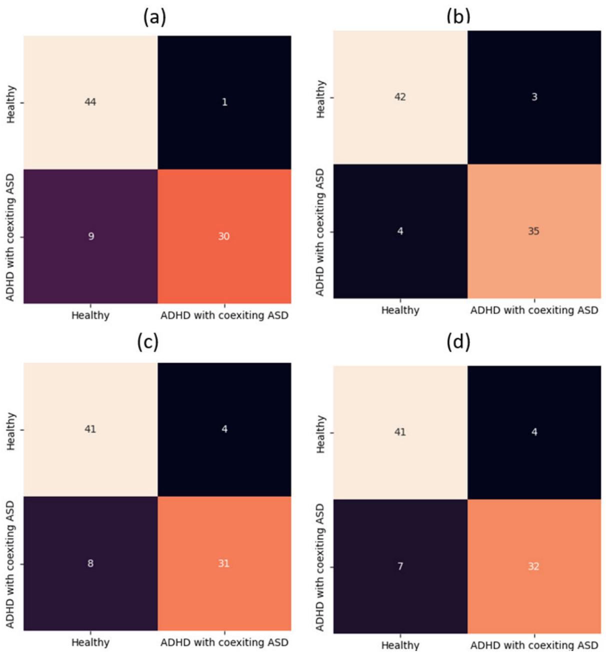

FIGURE 10. Confusion matrix of BiLSTM model: (a) PL trace; (b) PL predict; (c) ZL trace; and (d) ZL predict.

TABLE 3. Classification accuracy (in %) of three different classification models.

Task Types	CNN	BiLSTM	CNN-BiLSTM
PL Trace	82.1	88.1	91.7
PL Predict	85.7	91.7	94.0
ZL Trace	78.6	85.7	86.9
ZL Predict	79.8	86.9	88.1

ZL: Zigzag Line and PL: Periodic Line

TABLE 4. Sensitivity, specificity, f1-score, and AUC of the proposed CNN-BiLSTM-based model.

Task Types	Sensitivity (%)	Specificity (%)	f1-score (%)	AUC
PL Trace	84.6	97.8	90.4	0.912
PL Predict	89.7	97.8	93.3	0.938
ZL Trace	82.1	91.1	85.3	0.866
ZL Predict	82.1	93.3	86.5	0.877

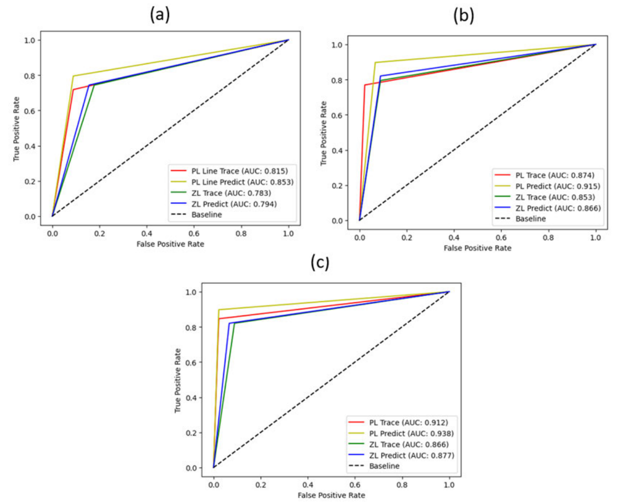

FIGURE 11. ROC curves of three prediction models over four tasks: (a) CNN-based model; (b) Bi-LSTM-based model; and (c) Proposed CNN-BiLSTM model.

TABLE 5. Sensitivity, specificity, F1-score, and AUC of the proposed CNN model.

Task Types	Sensitivity (%)	Specificity (%)	f1-score (%)	AUC
PL Trace	71.8	91.1	78.9	0.815
PL Predict	79.5	91.1	83.9	0.853
ZL Trace	74.4	82.2	76.3	0.783
ZL Predict	74.4	84.4	77.3	0.794

TABLE 6. Sensitivity, specificity, F1-score, and AUC of the proposed BiLSTM model.

Task Types	Sensitivity (%)	Specificity (%)	f1-score (%)	AUC
PL Trace	76.9	97.8	85.7	0.874
PL Predict	89.7	93.3	90.9	0.915
ZL Trace	79.5	91.1	83.7	0.853
ZL Predict	82.1	91.1	85.3	0.866

and f1-score) of each model. The classification accuracy of these classifiers over four tasks is presented in Table 3. We noticed that the proposed CNN-BiLSTM provided better classification accuracy for all tasks than the other models. Especially, the highest accuracy of 94.0% was achieved by the CNN-BiLSTM model for the PL line under predicted conditions compared to other tasks and other models. Whereas, CNN-BiLSTM provided the classification accuracy of 91.7% for PL under trace condition, 86.9% for the ZL task under trace condition, and 88.1% for the ZL task under predicted condition. Moreover, the CNN-based model provided 82.1% accuracy for the PL task under trace conditions, 85.7% for the PL task under predict conditions, and 78.8% and 79.8% accuracy for the ZL task under trace and predict conditions, respectively. On the other hand, BiLSTM achieved 88.1% and 81.7% accuracy for the PL task under trace and predict conditions. In contrast, it achieved 88.5% and 86.9% accuracy for the ZL task under trace and predicted conditions.

Other performance metrics like sensitivity, specificity, f1-score, and AUC of the proposed CNN-BiLSTM model are presented in Table 4. The proposed CNN-BiLSTM model achieved 89.7% sensitivity, 97.8% specificity, and 93.3% f1-score. Moreover, the ROC curves of three models for two lines under two conditions (four tasks) are depicted in Fig. 11, and their correspondence with the value of AUC is presented in the last column of Table 4 for CNN-BiLSTM, Appendix A: Table A1 for CNN and Appendix: Table A2 for BiLSTM. We observed that the highest AUC score of 0.938 was achieved by CNN-BiLSTM for the PL line task under the predicted conditions.

VI. CONCLUSION AND FUTURE WORK DIRECTION

In this paper, we proposed a DL-based approach for discriminating ADHD with coexisting ASD children from TD children using fNIRs signals. We asked each child (both ADHD with coexisting ASD and TD) to draw two lines (PL and ZL) under the trace and predicted conditions. We employed three models (CNN, BiLSTM, and CNN-BiLSTM) to detect ADHD in children with ASD problems. Our experimental results showed that the CNN-BiLSTM model achieved 94.0% accuracy for the PL line under predicted conditions. This result shows that the fNIRs signal is the most effective biomarker for detecting ADHD comorbidity in children with ASD. The outstanding performance was achieved by CNN-BiLSTM while children drew PL tasks under the predicted conditions. This algorithm can help medical professionals improve their diagnoses and can help aid in the development of personalized treatments.

Despite this study obtaining promising results and its had still limitations. For example, this study used a relatively small number of subjects and considered only ASD as a comorbidity. We will extend this study by including more subjects and consider ADHD children with other comorbidities such as MDD, OCD, and so on in order to understand the diagnostic accuracy of our proposed system. Furthermore, we will implement machine learning (ML) and try to develop new DL-based algorithms to detect ADHD with coexisting other comorbidities.

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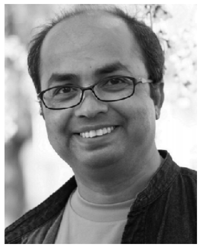

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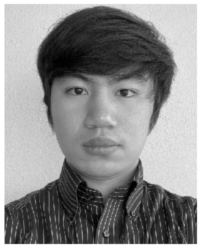

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