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

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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. Around 5% of children worldwide are affected by this disorder [1]. Moreover, ADHD children have also been affected by coexisting ASD and other disorders [2], 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.

PURPOSE

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.

METHODOLOGY

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.

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. At first, the test begins with a 20-seconds break to give the subject a rest. After that, perform the tracing task for 30-seconds. subject will take a 20-seconds break again, the next 30-seconds are spent predicting and drawing the shape drawn in the tracing task. They repeated the procedures three times.

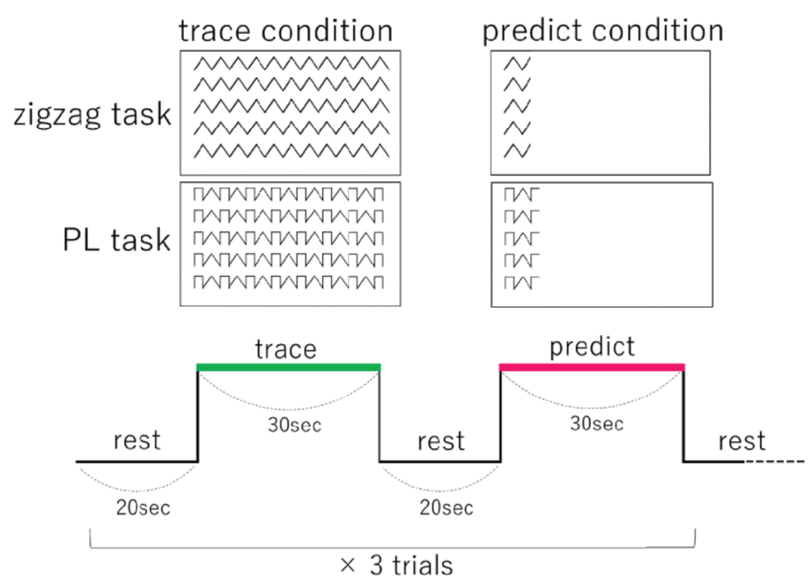

Fig1: Drawing Task and procedures

Data Collection Procedure

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). 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.

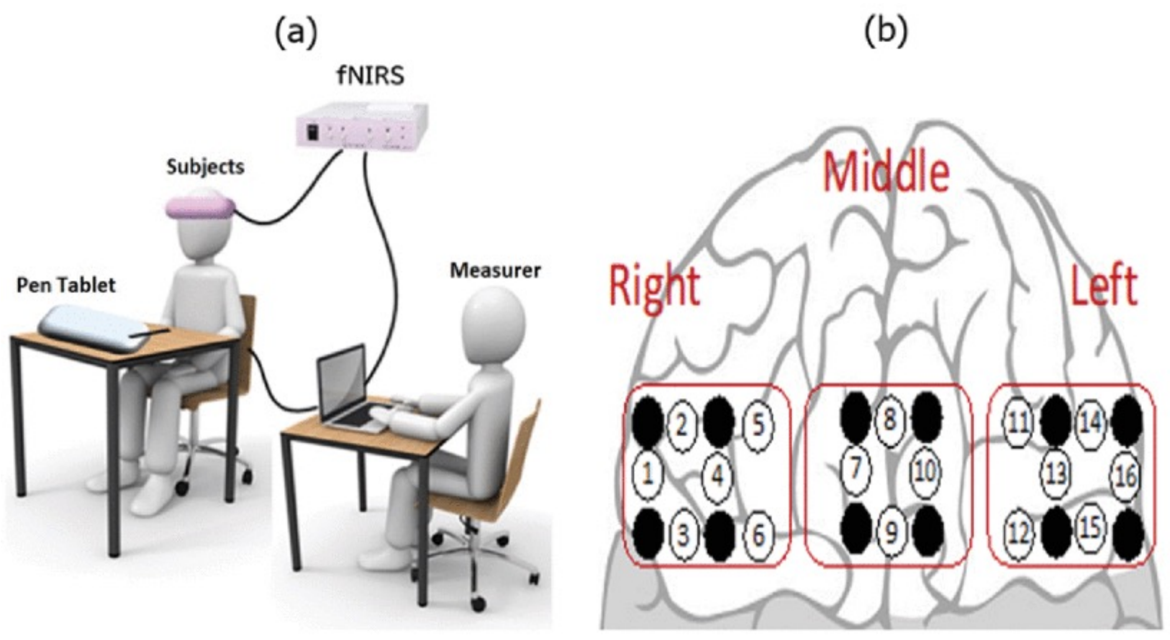

Fig2: (a) Measurement of brain function during drawing handwriting patterns; (b) Arrangement of fNIRs channel.

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.

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. 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.

Classification Model

1) BiLSTM

BiLSTM model took an input of 45×48 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. 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. 3.

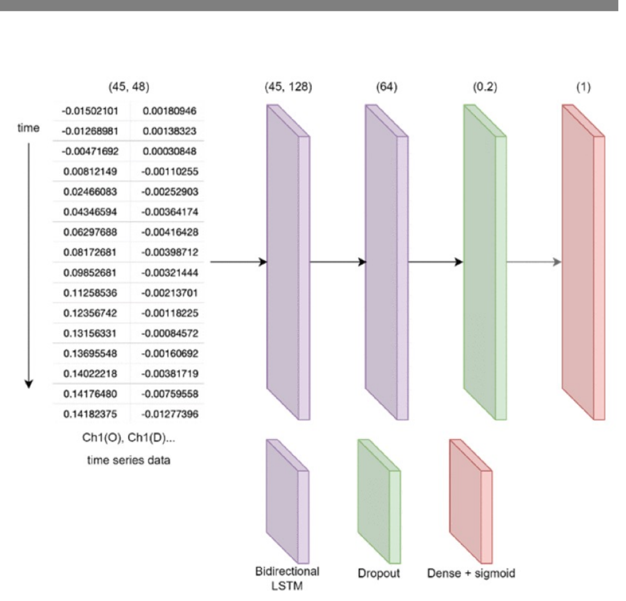

Fig.3: the architecture of BiLSTM

2) CNN

CNN model inputted 45×48×1 fNIRS data. The CNN model consisted of two Conv2D layers with ReLU activation functions, a MaxPool layer, a Dropout layer, and a two Dense layers. The architecture of the CNN model is shown in Fig. 4.

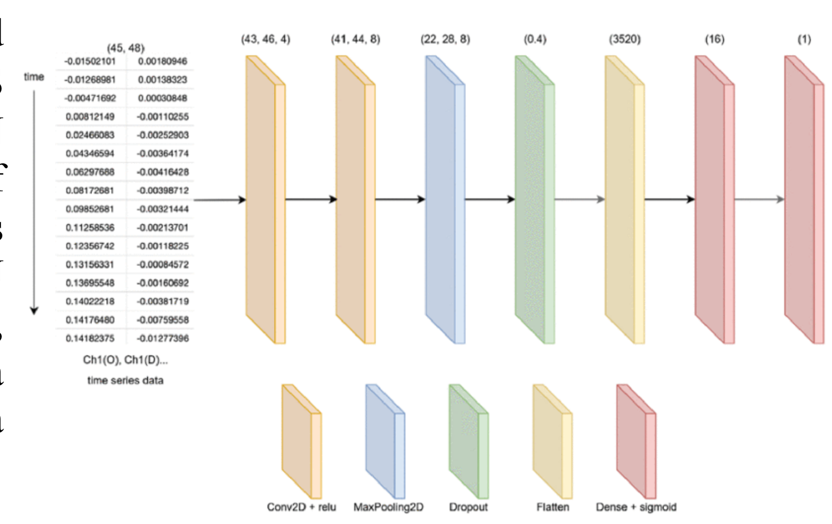

Fig.4: the architecture of CNN

3) BiLSTM+CNN (Ensemble 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.

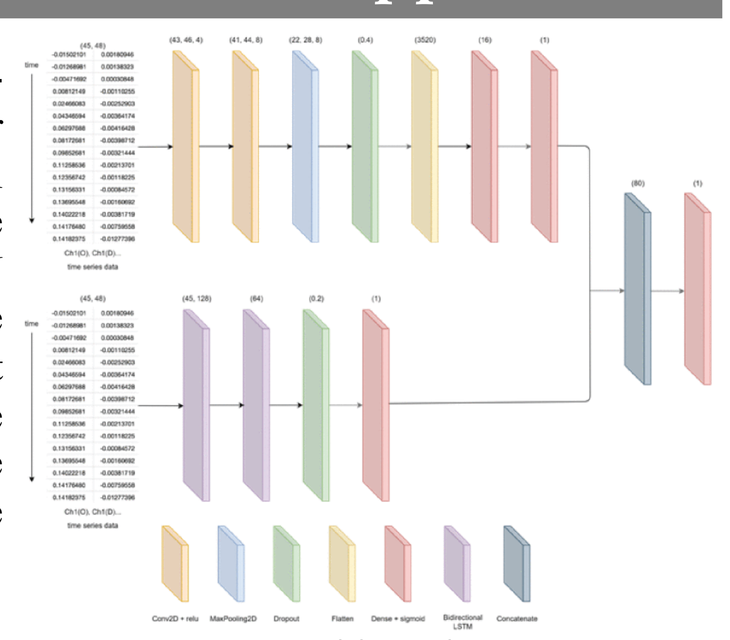

Fig.5: Ensemble architecture

Result

The classification accuracy of these classifiers over four tasks is presented in Table. 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.

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

Conclusion and Future Work Direction

In this experiment, we proposed a DL-based approach for discriminating ADHD with coexisting ASD children from TD children using fNIRs signals. 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. 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 it had still restrictions. For example, this study used a relatively small number of subjects and considered only ASD as a comorbidity. We need to extend this study by including more subjects and considering ADHD children with other comorbidities such as MDD, OCD, and so on. Furthermore, we will analyze handwriting data using machine learning (ML) and try to develop new multi-modal approaches to detect ADHD with coexisting other comorbidities.

References

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[2] L. Reale, B. Bartoli, M. Cartabia, M. Zanetti, M. A. Costantino, M. P. Canevini, et al., "Comorbidity prevalence and treatment outcome in children and adolescents with ADHD", *Eur. Child Adolescent Psychiatry*, vol. 26, no. 12, pp. 1443-1457, Dec. 2017.