Deep Learning-Based Classification of Autism Spectrum Disorder Using Short-Duration Postural Sway Data

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Summary

This study aimed to develop a deep learning-based approach for classifying children with ASD using short-duration center of pressure (COP) data. COP data were collected from 49 children (ages 6-14) during 15-second quiet standing trials. A convolutional neural network (CNN) was trained on 5-, 10-, and 15-second data segments, achieving 76.3%, 97.5%, and 98.0% accuracy, respectively. Longer durations slightly improved accuracy but increased training time and chances of fidgeting. These findings suggest CNN models can aid early ASD diagnosis using brief postural sway measurements.

Introduction

Assessing postural stability in children is challenging due to spontaneous fidgeting, making it difficult for them to remain still during quiet standing tasks. This challenge is even more pronounced in children with ASD. Consequently, many studies investigating postural stability in children have used relatively short test durations [1,2]. Previous research has also demonstrated that shorter test durations (<30 s) can maintain construct and concurrent validity [3].

The purpose of this study was to develop a deep learning-based approach to accurately classify children with ASD using COP data obtained from brief test durations.

Methods

The study was approved by the IRB and informed consent was obtained from all participants before data collection.

A total of 49 children (ages 6 -14 yrs) were recruited, including 20 typically developing children (control) and 29 children diagnosed with ASD. Participants were instructed to stand barefoot on a force plate. They were encouraged to remain as still as possible for 15 seconds under eyes-open and eyes-closed conditions. Each condition was tested twice. The COP data were collected at 100 Hz.

COP data from each trial were segmented using a sliding window approach with a window size of 1 second and a stride of 0.25 seconds. Data segments corresponding to total durations of 5, 10, and 15 seconds were used for analysis.

A CNN model was developed to classify participants' groups (ASD or control) based on COP data. The model architecture (Figure 1) consisted of and initial 1D convolutional layer followed by a pooling layer, a second 1D convolutional layer with another pooling layer, and a fully connected dense layer with a sigmoid activation function for binary classification. A dropout rate of 0.5 was used to reduce overfitting. The dataset was randomly split into training (80%) and testing (20%) subsets. Model performance was evaluated using accuracy, precision, recall and F1 score.

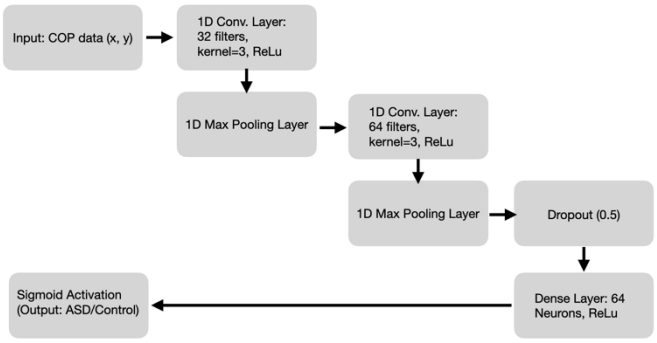

Figure 1: CNN architecture flowchart.

Results and Discussion

Using 5-second COP data, the CNN model achieved a classification accuracy of 76.3%. When the duration was increased to 10 seconds, accuracy improved significantly to 97.5%. Extending the duration to 15 seconds resulted in a slight increase in accuracy to 98.0%; however, this extension also increased both the training time and chances of participant fidgeting. Additional classification performance metrics are presented in Table 1.

Table 1: Classification performance of CNN with different total durations.

	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
5-second	76.3	81.6	75.0	78.2
10-second	97.5	97.4	98.1	97.8
15-second	98.0	97.2	99.4	98.3

Conclusions

The findings demonstrate that a CNN-based approach can accurately classify children with ASD using short-duration (10-second) COP data. This method has significant potential for aiding the early diagnosis of ASD, particularly in young children who may struggle to remain still for extended periods.

References

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