An integrated approach to characterize autism spectrum disorder

Ferran Gonzalez Hernandez[1*], Ilias Tachtsidis[2], Paul Burgess[3]
[1] Centre for Computation, Mathematics & Physics in the Life Sciences and Experimental Biology (CoMPLEX), UCL, London, UK.
[2] Department of Medical Physics & Biomedical Engineering, UCL, London, UK.
[3] Institute of Cognitive Neuroscience (ICN), UCL, London, UK.
[*] ferran.hernandez.17@ucl.ac.uk

1. Introduction

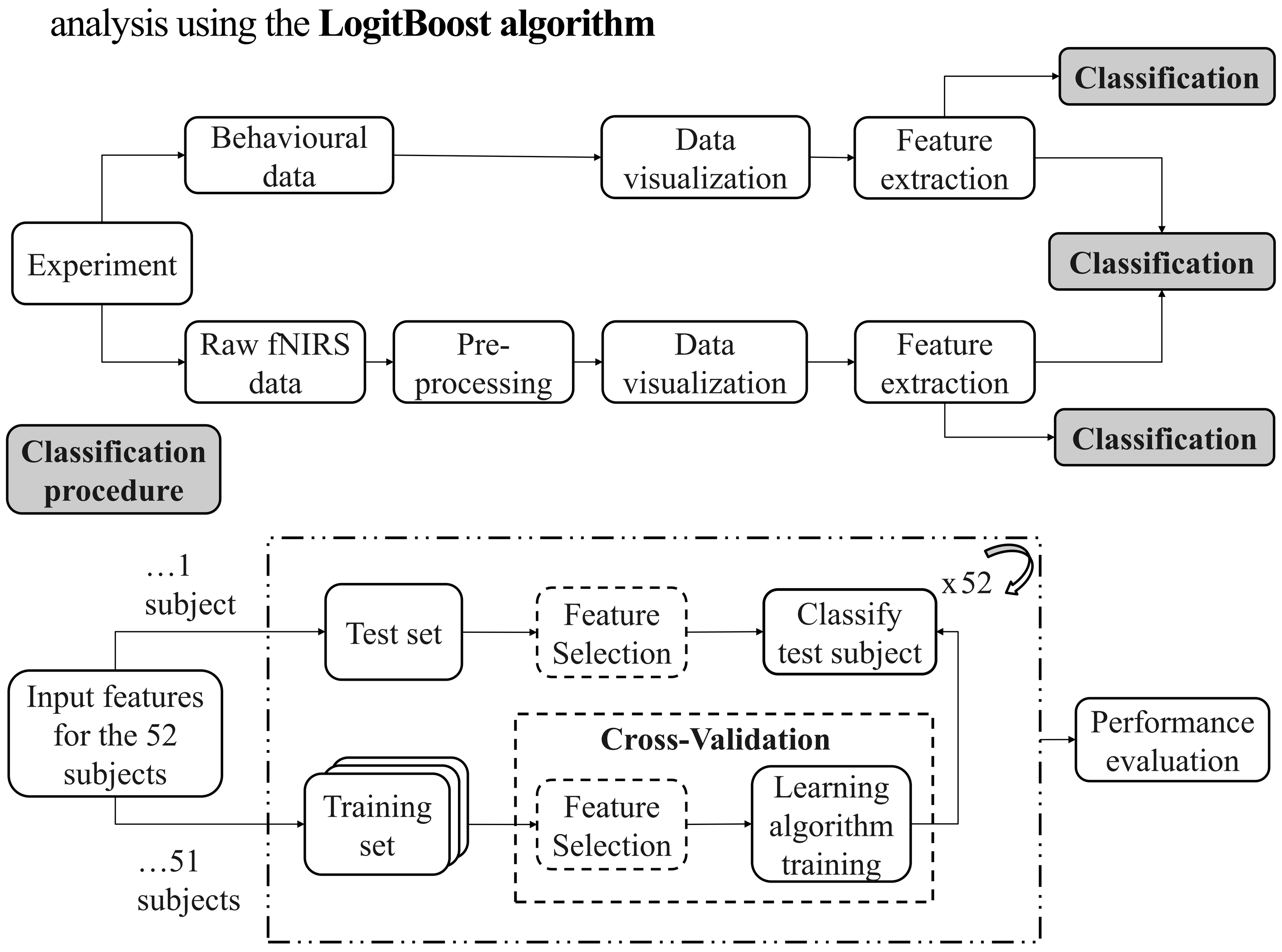
- Autism spectrum disorder (ASD) is a neurodevelopmental condition with a complex pattern of deficits at **multiple levels**
- This pattern is highly **variable** among affected individuals and across the **genetic**, **behavioural** and **neural** domains
- No single measure has been able to explain the whole spectrum, and its **diagnosis** keeps relying on behavioural **observations** and clinical **interviews**, which often results in **misdiagnosed** individuals and **uneffective** treatments

In this study we aimed to answer the following questions:

- Can we **identify** ASD at the subject level?
- Do **multivariate approaches** improve the characterization of ASD?
- Does the information contained in the **behavioural** and **neural** domains provide **complementary** information about ASD deficits?

2. Methods

- Experimental data was obtained from **26 TD** and **26 ASD** subjects
- Neural signal was recorded using Functional Near-Infrared Spectroscopy (**fNIRS**)
- Behavioural and fNIRS features were extracted to perform a classification analysis using the **LogitBoost algorithm**



3. Behavioural analysis

- Participants performed different **tasks** throughout the experiment
- **Nine features** were extracted from their behavioural performance

	Behavioural-based classification	
	All features	Feature selection
Accuracy	**73%**	**65%**
AUC	**0.65**	**0.63**

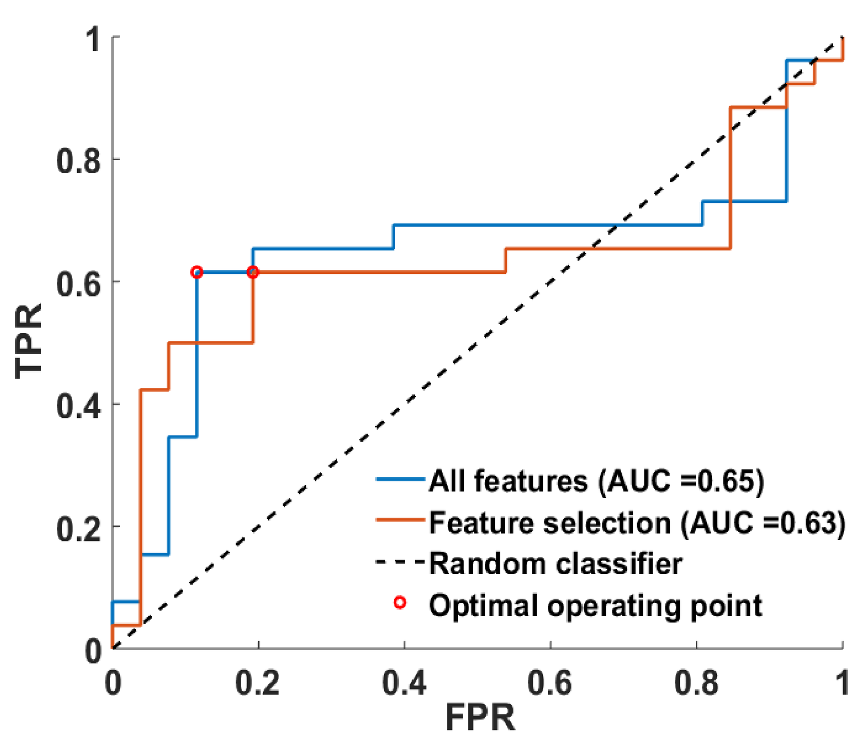


Figure 1. Receiving operating characteristic (ROC) curves from the classification with behavioural features.

Outcomes

- **Four features** appeared as most relevant
- Measures of **variance** were always more discriminant than central tendencies
- High **sensitivity** and low **specificity**
- Feature selection did **not improve** classification

4. Neuroimaging analysis

- Signals were obtained in real time from **16** measurement points (**channels**)
- A total number of **38 features** fNIRS were generated
- Features were extracted from functional events detected with the recently developed Automatic IDentification of functional Events (**AIDE**) algorithm

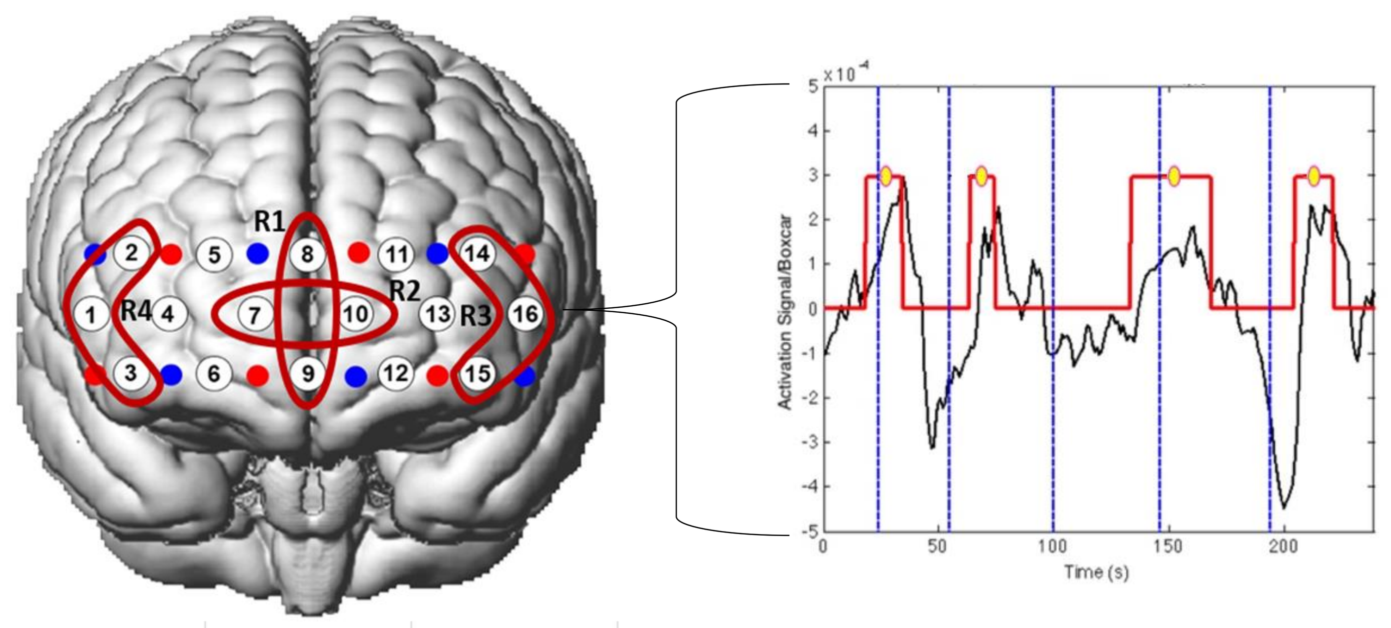


Figure 2. Features from the fNIRS signals were extracted from different channels and averaged across 4 regions. The AIDE algorithm (right panel) was used to detect functional events from the signal and obtain relevant features.

Outcomes

- **Seven features** appeared as the most selected
- Temporal relation **neural event – behavioural task** was the most discriminant
- **Low consistency** on the features selected at each fold was observed

	Classification fNIRS features	
	All features	Feature selection
Accuracy	**69%**	**60%**
AUC	**0.67**	**0.65**

5. Integrated analysis

- The top **4 behavioural** and **7 fNIRS** features were integrated in this analysis
- **Permutation test** was performed to assess **bias** and analyse **significance**

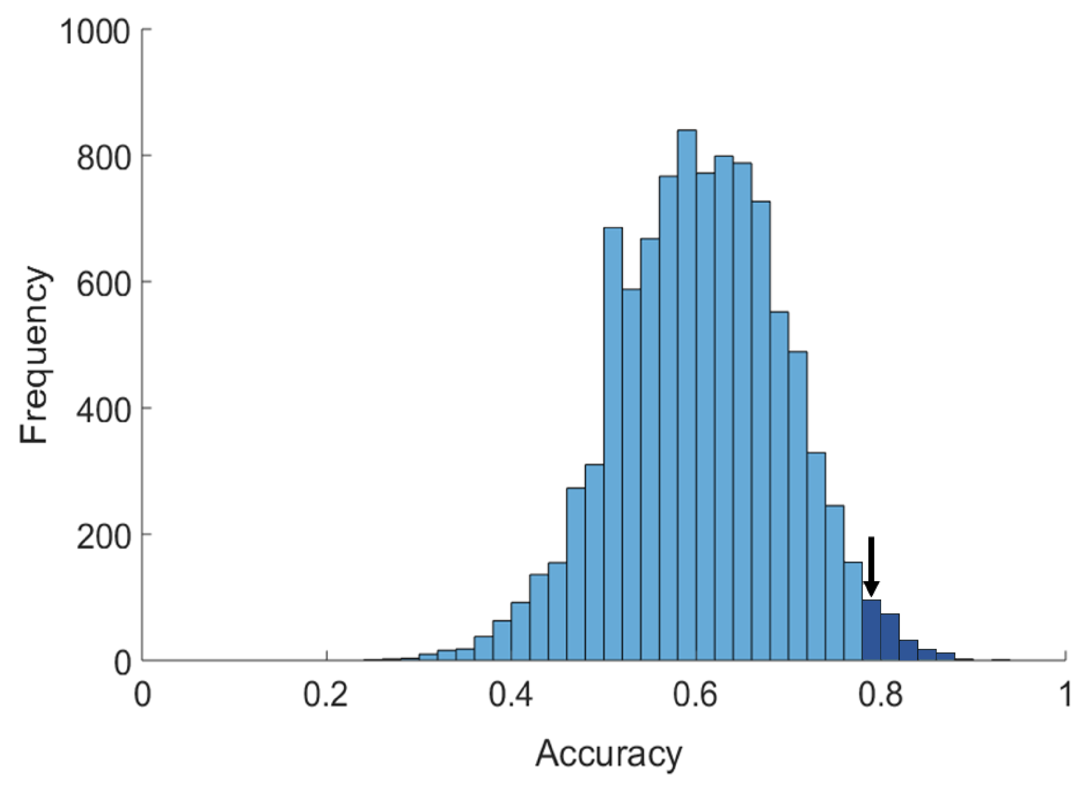


Figure 3. Distribution of accuracies after repeating the procedure 10,000 times permuting the labels each time.

Outcomes

- Results reported **79% accuracy and 0.8 AUC**
- **Procedural bias** was quantified, and significant discriminance (**p-value =0.014**) was detected

6. Conclusions

- ✓ Classification at the single-subject level was **significant**
- ✓ Potential **biomarkers** were detected in both domains
- ✓ Multivariate approaches **outperformed** univariate classification
- ✓ The integration of behavioural and neuroimaging features did **not** show a remarkable **improvement**
- ✓ It is suggested that features extracted in both domains provided **similar information**