Autism detection in High-Functioning Adults with the application of Eye-Tracking technology and Machine Learning

Konstantinos-Filippos Kollias
Laboratory of Robotics, Embedded and Integrated Systems
Department of Electrical and Computer Engineering, University of Western Macedonia
Kozani, Greece
dece00063@uowm.gr

Christine K. Syriopoulou-Delli
Department of Educational and Social Policy, University of Macedonia
Thessaloniki, Greece
csyriop@uowm.edu.gr

Panagiotis Sarigiannidis
Department of Electrical and Computer Engineering, University of Western Macedonia
Kozani, Greece
psarigiannidis@uowm.gr

George F. Fragulis
Laboratory of Robotics, Embedded and Integrated Systems
Department of Electrical and Computer Engineering, University of Western Macedonia
Kozani, Greece
gfragulis@uowm.gr

***Abstract*— High-Functioning Autism Detection in Adults is significantly difficult compared with early Autism Spectrum Disorder (ASD) diagnosis with severe symptoms. ASD diagnosis is usually achieved by behavioural instruments relying on subjective rather on objective criteria, whereas advances in research indicate cutting - edge methods for early assessment, such as eye-tracking technology, machine learning, Internet of Things (IoT), and other assessment tools. This study suggests the detection of ASD in high-functioning adults with the contribution of Transfer Learning. Decision Trees, Logistic Regression and Transfer Learning were applied on a dataset consisting of high-functioning ASD adults and controls, who looked for information within web pages. A high classification accuracy was achieved regarding a Browse (80.50%) and a Search (81%) task showing that our method could be considered a promising tool regarding automatic ASD detection. Limitations and suggestions for future research are also included.**

Keywords—High-Functioning Autism detection, eye-tracking, machine learning, transfer learning, IoT, web.

I. Introduction

Early Autism Spectrum Disorder (ASD) assessment and intervention are thought to have major long-term benefits for ASD children and adults as well as their families. However, the diagnostic process of neurodevelopmental disorders and more specifically ASD assessment is challenging for professionals, as there are no well-established biophysiological diagnostic tests [1], [2]. ASD diagnosis is generally based on behavioural assessment, utilising standardised tools characterised by high validity and reliability, such as the Autism Diagnostic Observation Schedule (ADOS) [3] and the Autism Diagnostic Interview-Revised (ADI-R) [4]. Nevertheless, their time-consuming, costly and difficult administration combined with the need of experienced and trained interviewers can often result in a delayed diagnosis and consequently a retard regarding the onset of early intervention [1], [2], [5].

High-functioning ASD individuals face significant difficulties to get autism diagnosis in adulthood as their symptoms are not that evident compared to early ASD diagnosis when symptoms are severe [6], [7]. More specifically, ASD individuals develop specific strategies throughout their life, which are likely to mask otherwise apparent relevant symptoms. Thus, the development of a screening method for high-functioning ASD identification which does not depend on subjective measures is of essential importance.

ASD is defined as a neurodevelopmental disorder prevalent in 1% of the world's population [8] and characterised by social communication/interaction difficulties and repetitive behaviours/interests [9].

Apart from reduced social interaction and communication, restricted, repetitive, and stereotyped behaviour, people with ASD have a tendency to show a deficit in eye gaze. This characteristic cannot cause autism [9] but constitutes an important item in several diagnostic tests [3]. Eye gaze deficits of people with ASD are associated both with social [10] and non-social stimuli [11].

Unlike conventional assessment approaches to ASD research, eye-tracking technology is considered more beneficial, as it can contribute to early, objective and reliable detection of autism and features of it [10], [12], [13]. Eye-tracking ASD studies have increased steeply during the last decade, either due to easier access to eye-tracking technology [14], or because a great variety of special devices and software playing an important role in easier and less expensive eye-tracking data recording have been developed [12].

Eye-tracking instruments are frequently combined with contemporary artificial intelligence techniques, such as Machine Learning (ML), a data driven technique based on advanced learning of mathematics, theories of information and statistical estimation [15]. ML can be applied in autism research by offering a more objective and reproducible second opinion [16], i.e., diagnosis enhancement [15], early autism screening [17], as well as brain activity [18] and different behaviours observation [19]. Furthermore, ML can be a valid biomarker-based technique contributing to objective ASD diagnosis [20]–[22].

Machine Learning has been applied in Internet of Things (IoT) systems as well, aiming at ASD assessment [23], [24] and early detection [25]. More specifically, an ML method was proposed by [25] with an aim to facilitate doctors detect the type of ASD in children from a preliminary symptom. IoT was utilised for symptoms collection attaining a high accuracy of 83%.

Traditional ML algorithms, such as Random Forests, Logistic Regression and Decision Trees, can be improved by Transfer Learning (TL) which transfers the knowledge acquired in a single or more tasks and utilises it for improving learning in a related target task [26].

A. *Our contribution*

This study aims at high-functioning ASD classification based on eye-tracking data that were acquired from web-related tasks. Decision Trees, Logistic Regression and Transfer-learning are applied. Eye-tracking data were collected by [27] and consisted of high-functioning ASD adults and controls, who looked for information within web pages. The significance of this study lies on the fact that we propose a transfer-learning-based ASD classification framework which can achieve high accuracy. This is a less explored area of research in which a screening method not depending on subjective measures is of essential importance. The utilisation of eye-tracking data obtained from web-related tasks for the classification of ASD and non-ASD people is also prominent. In other words, the acquisition of such kind of data is less-expensive, easier, and less obtrusive than conventional ASD assessment methods such as ADOS, ADI-R and Functional Magnetic Resonance Imaging (fMRI). Therefore, the current study applies Transfer Learning on eye-tracking data collected by [27] devising the hypothesis that a better classification accuracy can be achieved.

B. *Background*

There have been several ASD classification eye-tracking studies in the past which used data collected in previous studies and tried to improve their classification performance. For example, [28] used the eye-tracking data of high-functioning ASD and Typically Developing (TD) participants who passively watched natural scene images in [29]. Specifically, there was a feature selection which was based on the Fischer score method [30] in [28]. This feature selection aimed at finding the images that could best contribute to ASD classification. Deep Neural Networks (DNNs) were used to automatically acquire image features from natural scenes and consequently these features were fed to a linear Support Vector Machine (SVM) that classified ASD and TD participants providing an increased classification accuracy (92%). In another study [31], the authors employed a dataset from a prior study in which ASD and TD children were videotaped while watching their mothers' pictures presented on a computer screen [32]. They added one more dataset of ASD children to balance the amount of ASD and TD participants which increased the validity of the ML model. Additionally, they employed the tracking learning detection algorithm for feature extraction from videos and divided the features into angle and length. They also made accumulative and non-accumulative histograms for single and combined features and fed them to six three-layer Long Short-Term Memory (LSTM) networks for classification. The authors computed Kernel Principal Component Analysis (KPCA) to reduce the data and fed six SVMs. LSTM networks accuracy was 6.2% higher than the SVM one. The best ASD classification performance was attained when LSTM was combined with accumulative histograms with an accuracy of 92.60%.

II. MATERIALS AND METHODS

A. *Dataset*

Eye-tracking data were collected by [27] and comprised high-functioning ASD adults and controls, who looked for information within web pages. The final data included for analysis were attained from 15 high-functioning ASD adults (9 male and 6 female) and 15 controls (8 male and 7 female). The participants were involved in two web-browsing tasks looking for information on some web pages: Browse and Search tasks.

On the browsing task, the participants were free to spend two minutes maximum on each web page while looking for any kind of information that could be interesting to them. During the search task, the participants had 30 seconds to find certain information on each web page which they would exploit to answer two questions verbally asked by the researcher.

A 60Hz Gazepoint GP3 video-based eye tracker was employed with its accuracy ranging from 0.5 to 1 degree of visual angle. Gaze features such as Time to First View, Time Viewed (sec), Time Viewed %, Fixations and Revisits as well as non-gaze features such as Media ID, Area of Interest (AOI) ID, Correct Answer ID, Participant Gender, and Level of Visual Complexity were applied to train the classifiers. There was a definition of Page-specific and Generic AOIs, as well. A Logistic Regression algorithm was implemented. A best classification performance of 0.75 was achieved in Search task and of 0.71 in Browse task when training on selected media took place. The results obtained showed that Generic AOIs were more suitable for tasks such as the Browse task, whereas page specific AOIs were required for tasks like the Search task. Some other non-gaze features did not play a significant role in the classification performance. For more information about the dataset, the tasks, eye-tracking and analysis see [27]. In a more recent study by the same authors [12], containing similar tasks to the earlier one, the data collected in [27] were utilised in addition to some more data.

B. *Classifying Autism based on Transfer-Learning*

In this study, Transfer-learning and various classification algorithms were tested in Matlab to improve the accuracy achieved in [27] by a Logistic Regression algorithm. Decision Trees and Logistic Regression attained the highest accuracy. Both Browse and Search tasks data were used for classification. Gaze as well as non-gaze features were utilised in the training of classifiers.

III. RESULTS AND DISCUSSION

This study aimed at high-functioning ASD classification employing eye-tracking data acquired from web-related tasks [27]. Transfer-learning was applied, and various classification algorithms were tested in Matlab to improve the accuracy achieved by the Logistic Regression algorithm applied in the prior study [27]. Decision Trees and Logistic Regression achieved the highest accuracy concerning Browse and Search task, respectively. According to our results, the classification accuracy of both Browse and Search tasks was higher compared to the results of the prior study [27].

The highest classification accuracy for the Browse task (80.50%) was achieved when all Gaze features, AOI ID, Media ID, Participant Age and Participant Gender were used and Decision trees were applied. As it is depicted in Table I, ASD participants were classified with a higher accuracy (83.3%) than Control ones (77.8%).

TABLE I: CONFUSION MATRIX COMPARING OUR BROWSE TASK BEST RESULT WITH THE BROWSE TASK BEST RESULT OF [27].

	KOLLIAS 2022		**YANEVA 2018**	
	ASD	**CONTROL**	**ASD**	**CONTROL**
ASD	83.3%	16.7%	70.6%	29.4%
CONTROL	22.2%	77.8%	27.8%	72.2%

The best classification accuracy regarding the Search task (81%) was achieved when all Gaze features, AOI ID, Media ID, Participant Age and Participant Gender were used and Logistic Regression was applied. As it is shown in Table II, ASD participants were again classified with a higher accuracy (82.3%) than Control ones (79.5%).

TABLE II: CONFUSION MATRIX COMPARING OUR SEARCH TASK BEST RESULT WITH THE BROWSE TASK BEST RESULT OF [27].

	KOLLIAS 2022		**YANEVA 2018**	
	ASD	**CONTROL**	**ASD**	**CONTROL**
ASD	82.3%	17.7%	80.8%	19.2%
CONTROL	20.5%	79.5%	30.2%	69.8%

Earlier ASD classification eye-tracking studies which employed data collected in previous studies and tried to improve their classification performance dealt with datasets including images as stimuli. For example, [28] employed natural scene images, whereas [31] used images of children's mothers who took part in the study. To our knowledge, our study is the first which included eye-tracking data from web-related tasks collected in a previous study.

IV. LIMITATIONS

Although the results of this study show that Machine Learning and Transfer-Learning can improve the classification accuracy concerning a dataset used in a previous study, there are some limitations that can be addressed in future research. For example, Neural Networks, Principal Component Analysis (PCA) and possibly Random Forests (RF) can be implemented in a future study improving classification accuracy. Another important issue concerns the dataset size, i.e., by employing some additional participants the model's validity could be increased. Additionally, only two web-browsing tasks were analysed in this study, i.e., Browse and Search tasks. Future studies could use datasets from other studies comprising more tasks for instance [12] which contained three web-browsing tasks. Finally, future studies could utilise ML and IoT not only for ASD assessment and early detection, but also for intervention, assistance, monitoring and inclusion in future smart cities [33].

V. CONCLUSION

The current study employed Decision Trees, Logistic Regression and Transfer-Learning aiming at high-functioning ASD classification by eye-tracking data acquired from web-related tasks and collected by [27]. Eye-tracking data consisted of high-functioning ASD adults and controls, who looked for information within web pages. Our proposed method provided increased high-functioning ASD classification accuracy concerning both Browse (80.50%) and Search (81%) task compared to the results attained by [27]. Thus, the accuracy of a screening method not depending on subjective measures is of essential importance, can be improved by transfer-learning and is less-expensive, easier, and less obtrusive than conventional ASD assessment methods such as ADOS, ADI-R and fMRI which are less objective, costly, and time-consuming.

ACKNOWLEDGEMENT

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 957406.

REFERENCES

[1] K. J. Tsuchiya *et al.*, "Diagnosing autism spectrum disorder without expertise: a pilot study of 5-to 17-year-old individuals using Gazefinder," *Frontiers in Neurology*, vol. 11, p. 1963, 2021.

[2] T. Vu *et al.*, "Effective and efficient visual stimuli design for quantitative autism screening: An exploratory study," in *2017 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI)*, Orlando, FL, USA, 16–19 February, 2017, pp. 297–300.

[3] Lord, C., Rutter, M., DiLavore, P. C., and Risi, S., *ADOS. Autism diagnostic observation schedule. Manual*. Los Angeles, CA: Western Psychological Services, 2001.

[4] C. Lord, M. Rutter, and A. Le Couteur, "Autism Diagnostic Interview-Revised: a revised version of a diagnostic interview for caregivers of individuals with possible pervasive developmental disorders," *Journal of autism and developmental disorders*, vol. 24, no. 5, pp. 659–685, 1994.

[5] Q. He, Q. Wang, Y. Wu, L. Yi, and K. Wei, "Automatic classification of children with autism spectrum disorder by using a computerized visual-orienting task," *PsyCh Journal*, vol. 10, no. 4, pp. 550–565, 2021.

[6] L. D. Wiggins, J. Baio, and C. Rice, "Examination of the Time Between First Evaluation and First Autism

Spectrum Diagnosis in a Population-based Sample," *Journal of Developmental & Behavioral Pediatrics*, vol. 27, no. 2, p. S79, Apr. 2006.

[7] C. M. Murphy *et al.*, "Autism spectrum disorder in adults: Diagnosis, management, and health services development," *Neuropsychiatric Disease and Treatment*, vol. 12, 2016, doi: 10.2147/NDT.S65455.

[8] R. Carette, F. Cilia, G. Dequen, J. Bosche, J.-L. Guerin, and L. Vandromme, "Automatic autism spectrum disorder detection thanks to eye-tracking and neural network-based approach," in *International conference on IoT technologies for healthcare*, Angers, France, 24–25 October, 2017, pp. 75–81.

[9] American Psychiatric Association, *Diagnostic and statistical manual of mental disorders*, 5th ed. Washington, DC: Author, 2013.

[10] A. Klin, S. Shultz, and W. Jones, "Social visual engagement in infants and toddlers with autism: early developmental transitions and a model of pathogenesis," *Neuroscience & Biobehavioral Reviews*, vol. 50, pp. 189–203, 2015.

[11] K. Nayar, A. C. Voyles, L. Kiorpes, and A. Di Martino, "Global and local visual processing in autism: An objective assessment approach," *Autism Research*, vol. 10, no. 8, pp. 1392–1404, 2017.

[12] V. Yaneva, S. Eraslan, Y. Yesilada, and R. Mitkov, "Detecting high-functioning autism in adults using eye tracking and machine learning," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 6, pp. 1254–1261, 2020.

[13] M. C. Frank, E. Vul, and R. Saxe, "Measuring the development of social attention using free-viewing," *Infancy*, vol. 17, no. 4, pp. 355–375, 2012.

[14] N. J. Sasson and J. T. Elison, "Eye tracking young children with autism," *Journal of visualized experiments: JoVE*, no. 61, 2012.

[15] D. Bone, M. S. Goodwin, M. P. Black, C.-C. Lee, K. Audhkhasi, and S. Narayanan, "Applying machine learning to facilitate autism diagnostics: pitfalls and promises," *Journal of autism and developmental disorders*, vol. 45, no. 5, pp. 1121–1136, 2015.

[16] R. Carette, M. Elbattah, F. Cilia, G. Dequen, J.-L. Guérin, and J. Bosche, "Learning to Predict Autism Spectrum Disorder based on the Visual Patterns of Eye-tracking Scanpaths.," in *HEALTHINF*, 2019, pp. 103–112.

[17] J. Peral, D. Gil, S. Rotbei, S. Amador, M. Guerrero, and H. Moradi, "A Machine Learning and Integration Based Architecture for Cognitive Disorder Detection Used for Early Autism Screening," *Electronics*, vol. 9, no. 3, Art. no. 3, Mar. 2020, doi: 10.3390/electronics9030516.

[18] Y. Zhou, F. Yu, and T. Duong, "Multiparametric MRI characterization and prediction in autism spectrum disorder using graph theory and machine learning," *PloS one*, vol. 9, no. 6, p. e90405, 2014.

[19] A. Crippa *et al.*, "Use of machine learning to identify children with autism and their motor abnormalities," *Journal of autism and developmental disorders*, vol. 45, no. 7, pp. 2146–2156, 2015.

[20] M. E. Minissi, I. A. C. Giglioli, F. Mantovani, and M. A. Raya, "Assessment of the Autism Spectrum Disorder Based on Machine Learning and Social Visual Attention: A Systematic Review," *Journal of Autism and Developmental Disorders*, pp. 1–16, 2021, doi: https://doi.org/10.1007/s10803-021-05106-5.

[21] K.-F. Kollias, C. K. Syriopoulou-Delli, P. Sarigiannidis, and G. F. Fragulis, "The Contribution of Machine Learning and Eye-Tracking Technology in Autism Spectrum Disorder Research: A Systematic Review," *Electronics*, vol. 10, no. 23, p. 2982, 2021.

[22] K.-F. Kollias, C. K. Syriopoulou-Delli, P. Sarigiannidis, and G. F. Fragulis, "The contribution of Machine Learning and Eye-tracking technology in Autism Spectrum Disorder research: A Review Study," in *2021 10th International Conference on Modern Circuits and Systems Technologies (MOCAST)*, 2021, pp. 1–4.

[23] M. E. Alam, M. S. Kaiser, M. S. Hossain, and K. Andersson, "An IoT-belief rule base smart system to assess autism," in *2018 4th International Conference on Electrical Engineering and Information & Communication Technology (iCEEiCT)*, 2018, pp. 672–676.

[24] M. Hosseinzadeh *et al.*, "A review on diagnostic autism spectrum disorder approaches based on the Internet of Things and Machine Learning," *The Journal of Supercomputing*, vol. 77, pp. 2590–2608, 2020.

[25] S. R. Dutta, M. Roy, S. Datta, and R. Datta, "IoT in Autism Detection in Its Early Stages," in *Internet of Things: Enabling Technologies, Security and Social Implications*, S. Kumar Pani and M. Pandey, Eds. Singapore: Springer, 2021, pp. 47–58. doi: 10.1007/978-981-15-8621-7_5.

[26] L. Torrey and J. Shavlik, "Transfer Learning," *Handbook of Research on Machine Learning Applications and Trends: Algorithms, Methods, and Techniques*, 2010. https://www.igi-global.com/chapter/transfer-learning/www.igi-global.com/chapter/transfer-learning/36988 (accessed Dec. 27, 2021).

[27] V. Yaneva, L. A. Ha, S. Eraslan, Y. Yesilada, and R. Mitkov, "Detecting autism based on eye-tracking data from web searching tasks," in *Proceedings of the 15th International Web for All Conference*, Lyon, France, 23–25 April, 2018, pp. 1–10.

[28] M. Jiang and Q. Zhao, "Learning visual attention to identify people with autism spectrum disorder," in *Proceedings of the ieee international conference on computer vision*, Venice, Italy, 22–29 October, 2017, pp. 3267–3276.

[29] S. Wang *et al.*, "Atypical visual saliency in autism spectrum disorder quantified through model-based eye tracking," *Neuron*, vol. 88, no. 3, pp. 604–616, 2015.

[30] P. E. Hart, D. G. Stork, and R. O. Duda, *Pattern classification*. Wiley Hoboken: Hoboken, NJ, USA, 2000.

[31] J. Li, Y. Zhong, J. Han, G. Ouyang, X. Li, and H. Liu, "Classifying ASD children with LSTM based on raw videos," *Neurocomputing*, vol. 390, pp. 226–238, 2020.

[32] J. Li, Y. Zhong, and G. Ouyang, "Identification of ASD children based on video data," in *2018 24th International conference on pattern recognition (ICPR)*, Beijing, China, 20–24 August, 2018, pp. 367–372.

[33] T. Ghosh *et al.*, "Artificial intelligence and internet of things in screening and management of autism spectrum disorder," *Sustainable Cities and Society*, vol. 74, p. 103189, Nov. 2021, doi: 10.1016/j.scs.2021.103189.