VISUAL PROCESSING ANALYSIS AND MACHINE LEARNING IN THE EARLY DIAGNOSIS OF ASD USING EYE TRACKING

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ABSTRACT

This non-clinical study explores the effectiveness of holistic processing in facial recognition and the application of eye-tracking systems in the diagnosis of Autism Spectrum Disorder (ASD). Three approaches are adopted: Composite Faces, Part-to-Whole and Flip Effect, highlighting the importance of holistic analytics for efficient facial recognition.

The research utilizes camera-based eye-tracking systems, which are notable for their non-invasive approach and accuracy in detecting specific eye movements. OGAMA® software and data mining tools such as Orange Canvas are used to analyze eye metrics. The methodology includes the identification, storage, and processing of oculometric variables using supervised learning algorithms to predict behavioral patterns in individuals with ASD. The experiments carried out demonstrated the effectiveness of the proposed methodology. Reference data were used to validate the findings, and machine learning techniques were employed to differentiate individuals with ASD, with Neural Networks standing out as the most effective algorithm.

It is concluded that the combination of eye tracking with data mining offers valuable insights for the diagnosis and understanding of ASD, opening up new possibilities for research in holistic processing and contributing significantly to the fields of psychology, medicine and assistive technologies.

Keywords: Eye Tracking Systems. Assistive Technologies. Data Mining. Autism Spectrum Disorder.

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INTRODUCTION

The advancement of computational technologies has had a significant impact on several areas of scientific research, especially in the study of neuropsychiatric disorders such as Autism Spectrum Disorder (ASD). This disorder, which affects millions of people around the world, is characterized by a variety of symptoms related to communication and social behavior. In addition, the significant variability of symptoms between individuals makes diagnosing ASD an ongoing challenge for clinicians and researchers (SMITH and JONES 2018; DOE et al. 2019).

In recent years, there has been a growing interest in the development of computational tools that aid in the early detection and more accurate diagnosis of ASD. Among these tools, the use of Artificial Neural Networks stands out, which, combined with visual programming techniques in software such as Orange Data Mining, allow complex data analysis without the need for advanced programming skills. These tools have the potential to democratize access to technology, facilitating its use by health professionals and researchers from different areas (Tec 2023; Aut 2023; AHMED et al. 2022).

One of the main focuses of this approach is facial image analysis, with the goal of studying the holistic processing of human faces, a skill that is often challenging for individuals with ASD. Holistic processing refers to the ability to interpret the face as a whole, rather than focusing on individual features such as the eyes or mouth. This difference in visual processing can be a valuable indicator for the early diagnosis of ASD (ADAMS and TAYLOR 2022; LEE and HARRIS 2021).

Technologies such as eye-tracking have been widely used in these studies, monitoring the eye movement patterns of individuals while observing visual stimuli. This type of analysis allows us to identify how individuals with ASD process facial information differently from neurotypicals, revealing patterns of attention and visual fixation that may be characteristic of the disorder. These insights are fundamental for understanding the visual behavior of individuals with ASD and, consequently, for the development of more effective diagnostic tools (AHMED et al. 2022; KOLLIAS et al. 2021; DUAN et al. 2019).

The importance of this type of research is amplified by global statistics related to autism. According to the World Health Organization, there are about 76 million autistic people in the world, representing approximately 0.62% of the global population. In Brazil, a recent study estimated that one in every 367 children is diagnosed with ASD. These numbers underscore the urgency of improving the diagnostic and intervention tools currently available (et al. 2011).

With this investigation, it is expected not only to contribute to the advancement of the field of ASD studies, but also to offer a practical and accessible computational tool that helps in the analysis of holistic facial processing. In addition, the use of technologies such as artificial neural networks and eye-tracking can open up new perspectives for early and personalized interventions, improving the quality of life of individuals diagnosed with ASD (ADAMS and TAYLOR 2022; NGUYEN et al. 2021).

The integration between computational methods and behavioral analysis represents a promising advance for a more comprehensive understanding of ASD, in addition to facilitating early diagnosis and more effective interventions, which are fundamental for the healthy development of individuals with autism.

METHODOLOGY

In this section, we detail the methodology used to process the data obtained through eye tracking. The approach is divided into four essential steps to achieve our research objectives.

DESCRIPTION OF THE STEPS

Step 1: Identification of Fixings and Saccades in Response to Visual Stimuli In this step, fixations and saccades on human faces are identified through recognizable visual stimuli, aiming to investigate holistic processing in children with ASD. Areas of Interest (AOI), such as eyes, mouth, and nose, are defined to analyze primary metrics, such as gaze duration and fixation sequences, which are essential factors in understanding participants' visual attention. Previous studies highlight the use of deep learning and machine learning techniques to achieve high accuracy in the early diagnosis of ASD (AHMED et al., 2022).

Step 2: Data Collection and Storage: Crucial variables, such as gaze position, distance, speed, and time of fixations, are collected using the OGAMA® software. The secondary metrics generated, such as the number of fixations per second and the average duration of fixations, are analyzed to understand distinct patterns of eye movement in individuals with ASD. Systematic reviews on the application of eye-tracking technology in combination with machine learning reinforce the importance of this approach (KOLLIAS et al., 2021).

Step 3: Data Processing with Supervised Learning: Supervised learning algorithms, such as Decision Trees and SVM, are used to process the secondary variables. These algorithms are designed to identify patterns and establish significant correlations between variables, which facilitates the detection of diagnostic features of ASD. Related studies highlight the relevance of continuously replicating and improving technology-based diagnostic approaches (DUAN et al., 2019).

Step 4: Prediction of New Data: Trained machine learning models are applied to predict behavioral characteristics of new datasets, being instrumental in identifying telltale signs of ASD. This process allows for more accurate diagnoses and early interventions, as pointed out by research in the area of advanced diagnostic technologies (NGUYEN et al., 2021).

EXPERIMENTO

Eye Tracking Methodology: Setup and Analysis

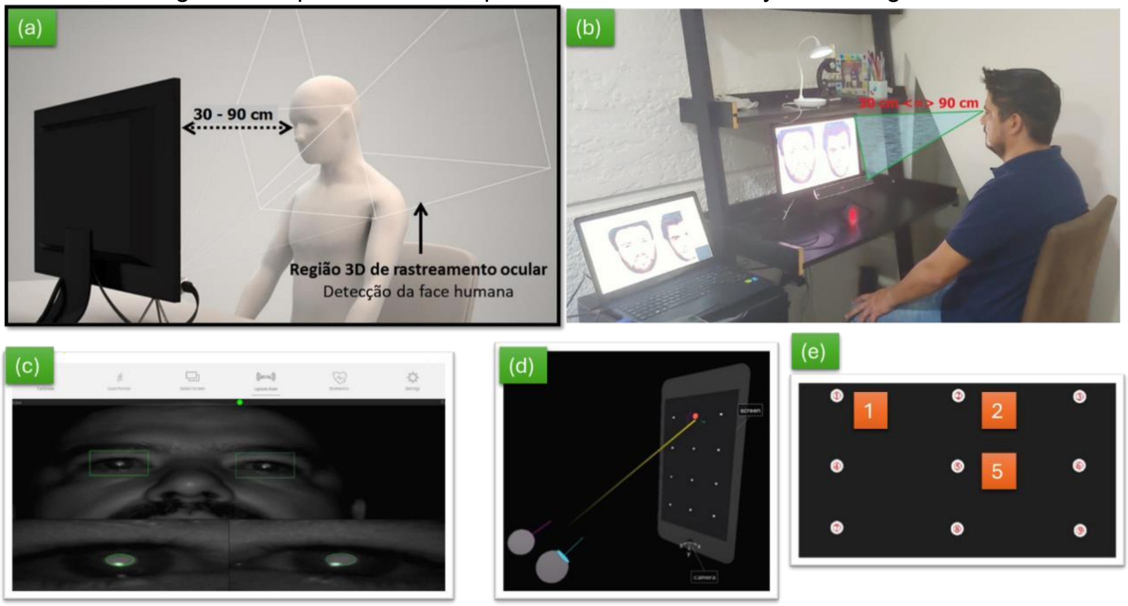
The study used the OGAMA® - Open Gaze and Mouse Analyzer software, developed by the University of Berlin, Germany, together with the Gazepoint GP3 eye tracker, which operates with a frequency of 60 Hz and includes an integrated API/SDK (Gazepoint Research Inc., Vancouver, USA). The recordings were made on a computer equipped with a 2.4GHz Intel® i7-5500U processor, 8 GB of RAM, Windows 10 Home Single Language operating system, 1 TB of hard disk and NVIDIA® GeForce graphics card.

The display device was a 19.5-inch LG-20M37AA-B monitor with a 16:9 aspect ratio, 5,000,000:1 contrast, 5 ms response time (GTG), 200 cd/m² brightness and 1366 x 768 pixel resolution. The monitor's vertical and horizontal refresh rates were 56 to 75 Hz and 30 to 61 kHz, respectively, providing a wide viewing angle of 90° horizontal and 65° vertical.

The experiment environment was set up to simulate normal lighting conditions, with participants accommodated in standard chairs that allowed free movement of the head, trunk and limbs. Due to the variability in the volunteers' biotypes and behaviors, an individual calibration was necessary. To do so, participants were instructed to visually follow nine white dots that appeared sequentially on a black screen, as illustrated in Figure 1, facilitating accuracy in capturing eye-tracking metrics.

This methodology and experimental setup were essential to ensure the accuracy and reproducibility of the eye-tracking data, which were fundamental for the subsequent analysis of the participants' visual behavior.

Figure 1. Experimental Setup and Visualization of Eye-Tracking Data.



(a) Laboratory Configuration Diagram - Illustrates the spatial arrangement between the participant and the monitor within the optimal distance parameters for eye tracking.

(b) Photo of the Real Test Environment - Shows a participant performing the test, providing real context for the application of the eye tracking system.

(c) Tracking Interface Capture – Displays the eye-tracking software interface in action, capturing the participant's eye movements.

(d) Graphical Representation of Eye Movement - Graphical demonstration of eye movements captured during the test.

(e) Calibration Screen - Shows the screen used for eye tracking calibration, with numbered points that the user must follow with the eye.

Data Processing with the Orange Canvas Software for Data Mining

In this study, data mining was performed using the Orange Canvas software. The development of the algorithm is illustrated in Figure 2, showing the complete flow from data loading to final analysis. The process starts with the data stored in the "File" component, where the collected data is in CSV format. To identify the most relevant attributes, the "Rank" component is used to assign scores to the attributes based on various methods, highlighting the most significant ones for the study.

Figure 2: Machine Learning Process Flowchart: Figure 2 illustrates the detailed workflow employed in the machine learning process used in this study. At the beginning of the process, the "Algorithm Training Data" is introduced and proceeds through various processing steps, including the application of algorithms such as SVM (Support Vector Machines), Logistic Regression, and Neural Networks. This flow culminates in the "Decision Test Output Responses", where the results are evaluated through various metrics and visualizations, such as the ROC Curve and the Confusion Matrix. Simultaneously, the "Prediction Data" is processed to generate "Prediction Output Responses", offering a practical view of the model's predictive capabilities.

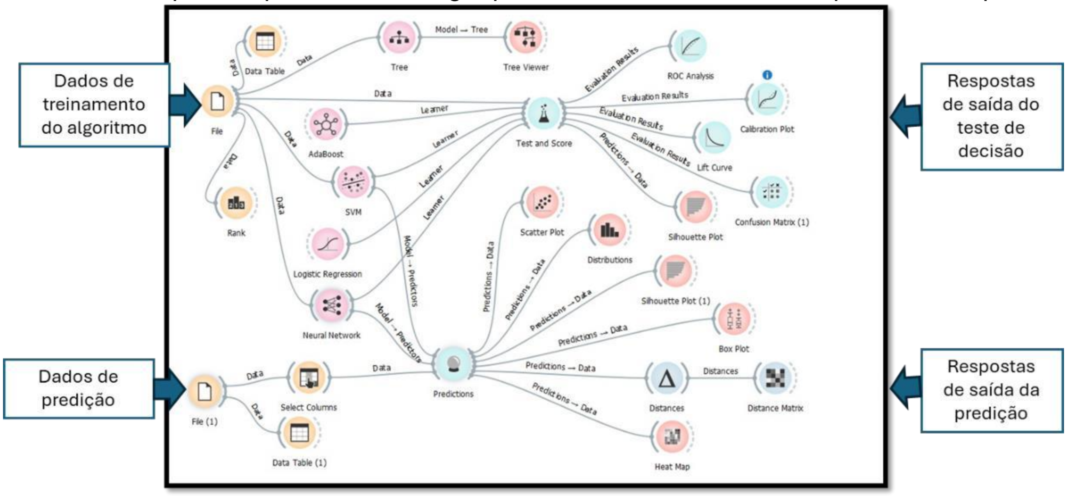
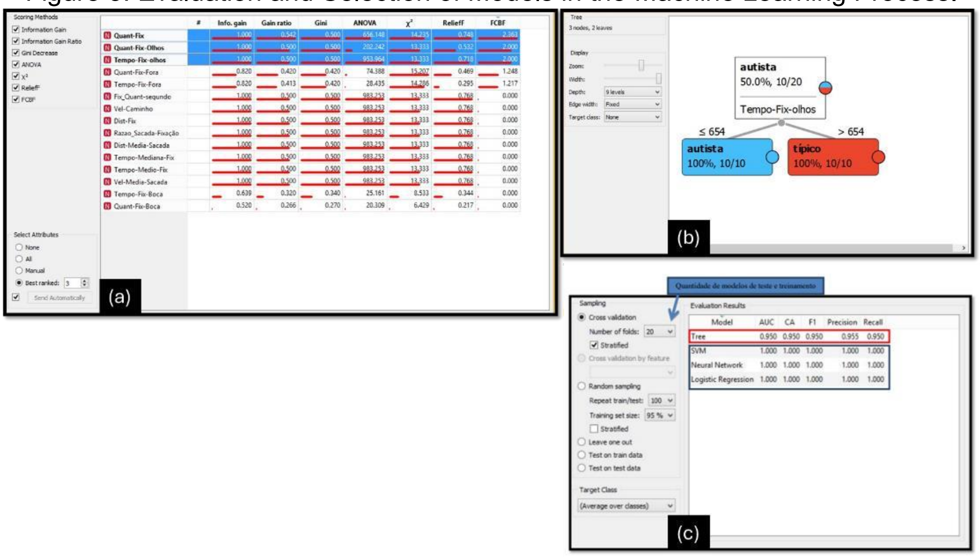


Figure 3a shows the process of classifying the attributes using the FCBF (Fisher Score) method, which evaluates the relevance of each attribute. The validation of these choices is made through the "Tree" component, as shown in Figure 3b, where the attribute 'Eye Fixation Time' was identified as the most relevant, representing the time that the volunteers spent looking at the eyes in the images studied.

Figure 3: Evaluation and Selection of Models in the Machine Learning Process.

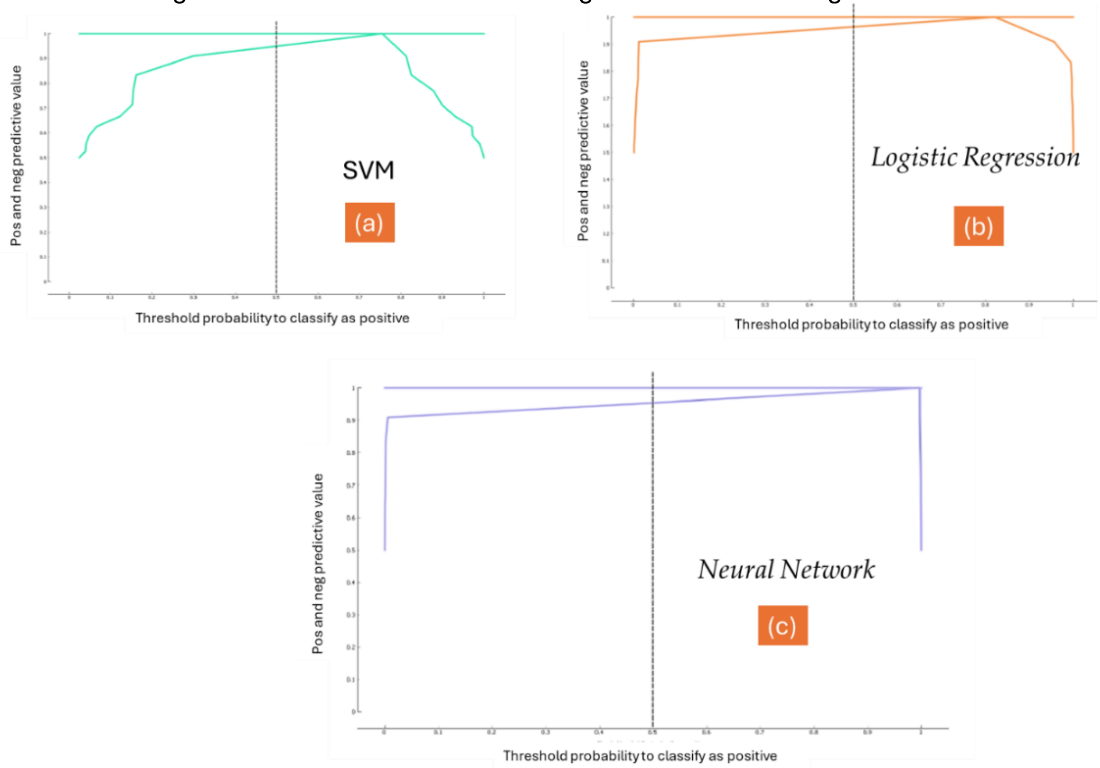


Part (a) of Figure 3 shows a detailed attribute selection table with various scoring methods applied to different variables. Each method, such as Gain Ratio, Gini Index, ANOVA, among others, is used to assess the importance of attributes in the context of the predictive model.
Part (b) of the figure illustrates a decision diagram, where the results of the application of the model are presented in terms of categorization of cases into 'autistic' and 'typical', with details on the count and percentage of cases in each node.

Part (c) displays the evaluation results of various machine learning models, including SVM, Neural Networks, and Logistic Regression. Performance metrics such as AUC, accuracy, and recall are shown, highlighting the effectiveness of each model in the tested dataset.

The "Test and Score" component, seen in Figure 3c, analyzes the performance of classification algorithms, including Tree, SVM, Logistic Regression, and Neural Network. This analysis is performed using the Cross-Validation technique to ensure that the models are robust against unknown data. The analysis revealed that while the "Tree" algorithm performed poorly, the other three algorithms performed comparatively better.

Figure 4: Performance Benchmarking of Machine Learning Models.



Part (a) - SVM (Support Vector Machine): This graph shows the variation of the positive predictive value of the SVM model as a function of the probability threshold for classification as positive. The curve demonstrates how the model classification fits the data when modifying the threshold.
Part (b) - Logistic Regression: This graph displays a characteristically stable curve with a significant jump in positive predictive value as the classification threshold increases, evidencing a clear binary distribution of the model's predictions.
Part (c) - Neural Network: The curve in this graph reflects the rapid response of the neural network in positively rating the data, with an abrupt drop after a specific threshold, highlighting the sensitivity of the model to variations in the classification threshold.
These graphs are essential to understand the effectiveness and operational characteristics of each machine learning model employed in the study, allowing a direct comparative analysis between the methods in relation to the adjustment of thresholds for the positive classification.

Finally, Figure 4 compares the effectiveness of the algorithms based on metrics such as precision, sensitivity, specificity, and accuracy. The areas under the ROC curves of the different models are used to evaluate the predictive effectiveness of each. The Neural Network model proved to be superior, reaching the largest area under the curve, which indicates its superiority as a choice for this study. The detailed results of this comparison are presented in Table 1, which offers a quantitative view of the performance of each algorithm in the tested metrics. The data in the table provide a solid basis for analyzing the strengths and weaknesses of each method evaluated.

Table 1 – Comparison of the Results of the Tested Algorithms

Algorithm	Precision	Sensitivity	Specificity	Accuracy
Tree	95,8 %	89,9 %	79,7%	--
RNA	92,0 %	92,0 %	70,0 %	0,93
SVM	88,5 %	93,1 %	86,2 %	0,89
Logistic regression	73,3 %	97,7 %	97,2 %	0,89

RESULTS AND DISCUSSION

PRESENTATION OF INITIAL RESULTS AND VISUAL ANALYSIS METHODOLOGY

In this section, the data collected during Stage 1 of the proposed methodology are presented, recorded in Table 2 and visualized in Figure 5. These data were obtained through tests carried out by the first author of this article. Each slide corresponds to a test image represented in Figure 5a. However, it was not possible to carry out tests with other individuals due to pending approval by the Health Research and Ethics Committee.

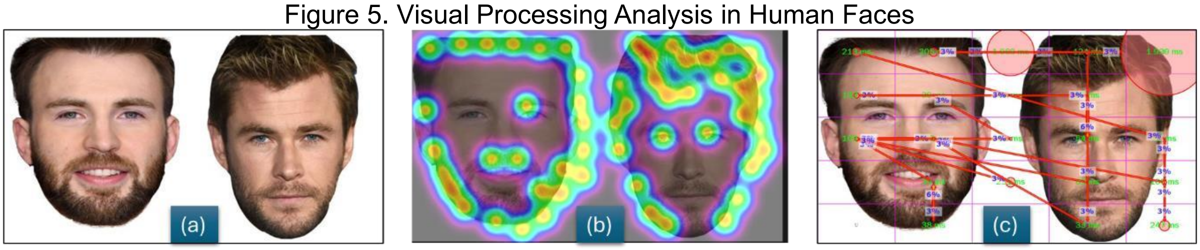
Due to this limitation, a methodology was chosen that can be easily replicated in other contexts. To validate the experimental results, data from previous studies addressing similar techniques were used. Research such as those by DUAN et al. (2019), JIANG AND ZHAO (2017), CARETTE et al. (2018, 2019), YANEVA et al. (2018, 2020), FALCK-YTTER et al. (2013), THAPALIYA, JAYARATHNA AND JAIME (2019), and EMAN AND EMANUEL (2019) provided a solid foundation for the analysis and interpretation of the data.

Table 2 - Data collected from the Experiment: The data includes several metrics such as number of fixations, duration, frequency per second, and balcony movements between points of visual interest. This information is crucial to understanding how individuals visually process information, directly impacting interface design and visual advertising strategies.

	Metric	Slide 01	Slide 02	Slide 03	Slide 04	Slide 05	Slide 06	Slide 07	Slide 08	Slide 09	Slide 10
First	No. of Fixings	54,0	46,0	42,0	38,0	42,0	46,0	34,0	36,0	37,0	50,0
Second	Clamping (Quant/sec)	3,6	3,1	4,2	3,8	4,2	4,6	3,4	3,6	3,7	5,0
Third	Average Fixation Duration (ms)	87,9	86,8	104,3	105,8	67,5	97,6	91,9	125,1	93,4	78,9
4th	Median Fixation Duration (ms)	34,0	35,0	66,0	35,5	34,0	34,0	49,0	34,5	35,0	35,0
5th	Draws/Fixture Ratio	315,9	266,1	437,7	401,9	282,3	449,7	312,1	449,4	344,8	393,7

6th	Average Balcony Length (px)	83,1	111,3	55,4	60,5	66,8	93,0	248,0	90,4	56,3	55,6
7th	Average Balcony Speed (px/s)	0,8	0,8	1,1	1,2	1,0	1,6	5,1	0,9	0,8	0,9
8th	Length of Fastening Connections (px)	4403,7	5006,7	2272,0	2238,1	2738,7	4185,2	8182,7	3164,5	2026,7	2726,3
9th	Path Speed (px/s)	293,2	333,8	227,1	223,7	272,8	419,1	817,7	315,7	202,2	272,1
10th	Time to First Fixation in AOI (ms)	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0
11th	Time to First Fixation on Target AOI (ms)	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0
12th	Time to Second Fixation on AOI 'Target' (ms)	2,0	2,0	2,0	2,0	2,0	2,0	2,0	2,0	2,0	2,0
13th	Analysis Time (ms)	15020,0	15000,0	10006,0	10003,0	10040,0	9986,0	10007,0	10023,0	10021,0	10019,0
14th	Data Loss (quantity)	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
15th	Samples of Off-Monitor Fixings (quantity)	36,0	27,0	19,0	16,0	28,0	20,0	21,0	16,0	62,0	0,0
16th	Data Loss (%)	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
17th	Off-monitor fixtures samples (%)	3,9	3,0	3,3	2,1	4,5	3,2	4,1	2,8	10,2	0,0

Figure 5. Visual Processing Analysis in Human Faces



Part (a): Shows two images of human faces side by side for direct visual comparison. This type of presentation is commonly used to demonstrate variations or similarities between facial features in facial recognition or analysis studies.
Part (b): Displays a heatmap representation of visual attention applied to the same faces. The colors in the heatmap range from blue to red, indicating areas of least to most focus of attention, respectively. This visualization is useful for understanding which facial features capture the most attention and how this can influence visual processing.
Part (c): Presents the same faces with vectors and markers superimposed that detail the points of visual attention and lines of sight. This analysis is crucial for studies investigating how different regions of faces are perceived and what gaze patterns are common among observers.

Figure 5 illustrates visual exploration maps of static images. These maps were generated from the data collected during Stage 2, using the camera and the OGAMA software. In the images, the areas with a redder tone (Figure 5b) indicate regions of greater intensity of attention, while the cooler colors (bluish tones) indicate areas of lower fixation frequency.

Figure 5c shows in detail the path of the fixings and balconies, highlighting the points on which the volunteer focused his attention over time. The numbers in the figures represent the time when each fixation occurred, providing a detailed temporal analysis of the areas of interest (AOI). These AOIs are represented by a purple grid with five columns and five rows, where each rectangle indicates a distinct AOI.

This setup allows for a deep understanding of the visual dynamics and attention patterns of the participants during the experiment. All the data collected are detailed and can be seen in Table 4.

This study advances by proposing new methodologies to analyze eye fixation data, potentially using advanced machine learning techniques or integrating biometric data to deepen the understanding of emotional and cognitive reactions to visual stimuli. Exploring the variation in fixation patterns between different images or in response to varying visual stimuli can reveal valuable insights for the usability of user interfaces and the design of educational content. Correlating these metrics with other behavioral or demographic data can significantly enrich the analysis and accuracy of the results.

DATA PREDICTION ANALYSIS AND RESULTS USING UNSUPERVISED SYSTEM

In this section, the results obtained in STEP 3 and STEP 4 of section 2 are presented, where a prediction of the collected data was made. It is important to note that a clinical study with volunteers was not carried out. Instead, information from a base previously established by Eman and Emanuel (2019) was used for model training. Data from 20 individuals were analyzed, divided equally between the group with Autism Spectrum Disorder (ASD) and the control group (CT). In the prediction phase, data from six more individuals without group identification were included, three from each. The results of this process can be seen in Figure 6.

Detailed analysis of the data was performed using Orange software for data mining, and it was identified that the Neural Network was the most effective algorithm for classifying individuals. More details about the performance of this algorithm can be found in the dissertation by Nogueira Filho (2020), which explores the results through various graphs such as Scatter Plot, Distributions Plot, Silhouette Plot, Box Plot, Distance Matrix, and Heat Map. In addition, the dissertation provides the images used in the tests, offering a complementary visual context to the analysis presented.

Figure 6: Comparison of Prediction Results from Machine Learning Models

	Neural Network	Logistic Regression	SVM	Tree
1	0.01 : 0.99 → típico	0.01 : 0.99 → típico	0.11 : 0.89 → típico	0.00 : 1.00 → típico
2	0.21 : 0.79 → típico	0.01 : 0.99 → típico	0.53 : 0.47 → autista	0.00 : 1.00 → típico
3	0.00 : 1.00 → típico	0.00 : 1.00 → típico	0.00 : 1.00 → típico	0.00 : 1.00 → típico
4	0.99 : 0.01 → autista	1.00 : 0.00 → autista	0.86 : 0.14 → autista	1.00 : 0.00 → autista
5	1.00 : 0.00 → autista	0.99 : 0.01 → autista	1.00 : 0.00 → autista	1.00 : 0.00 → autista
6	0.90 : 0.10 → autista	1.00 : 0.00 → autista	0.56 : 0.44 → autista	0.00 : 1.00 → típico
7	0.01 : 0.99 → típico	0.01 : 0.99 → típico	0.11 : 0.89 → típico	0.00 : 1.00 → típico
8	0.00 : 1.00 → típico	0.01 : 0.99 → típico	0.03 : 0.97 → típico	0.00 : 1.00 → típico
9	0.00 : 1.00 → típico	0.00 : 1.00 → típico	0.07 : 0.93 → típico	0.00 : 1.00 → típico
10	0.01 : 0.99 → típico	0.00 : 1.00 → típico	0.30 : 0.70 → típico	0.00 : 1.00 → típico
11	0.00 : 1.00 → típico	0.00 : 1.00 → típico	0.05 : 0.95 → típico	0.00 : 1.00 → típico
12	0.00 : 1.00 → típico	0.00 : 1.00 → típico	0.05 : 0.95 → típico	0.00 : 1.00 → típico
13	0.01 : 0.99 → típico	0.00 : 1.00 → típico	0.14 : 0.86 → típico	0.00 : 1.00 → típico
14	0.01 : 0.99 → típico	0.01 : 0.99 → típico	0.14 : 0.86 → típico	0.00 : 1.00 → típico
15	0.01 : 0.99 → típico	0.01 : 0.99 → típico	0.14 : 0.86 → típico	0.00 : 1.00 → típico
16	0.00 : 1.00 → típico	0.01 : 0.99 → típico	0.05 : 0.95 → típico	0.00 : 1.00 → típico
17	1.00 : 0.00 → autista	1.00 : 0.00 → autista	0.89 : 0.11 → autista	1.00 : 0.00 → autista
18	0.99 : 0.01 → autista	1.00 : 0.00 → autista	0.81 : 0.19 → autista	1.00 : 0.00 → autista
19	1.00 : 0.00 → autista	1.00 : 0.00 → autista	0.91 : 0.09 → autista	1.00 : 0.00 → autista
20	1.00 : 0.00 → autista	1.00 : 0.00 → autista	0.99 : 0.01 → autista	1.00 : 0.00 → autista
21	1.00 : 0.00 → autista	1.00 : 0.00 → autista	0.96 : 0.04 → autista	1.00 : 0.00 → autista
22	1.00 : 0.00 → autista	1.00 : 0.00 → autista	0.93 : 0.07 → autista	1.00 : 0.00 → autista
23	1.00 : 0.00 → autista	1.00 : 0.00 → autista	0.99 : 0.01 → autista	1.00 : 0.00 → autista
24	0.99 : 0.01 → autista	0.97 : 0.03 → autista	0.86 : 0.14 → autista	1.00 : 0.00 → autista
25	0.99 : 0.01 → autista	1.00 : 0.00 → autista	0.86 : 0.14 → autista	1.00 : 0.00 → autista
26	1.00 : 0.00 → autista	0.98 : 0.02 → autista	0.91 : 0.09 → autista	1.00 : 0.00 → autista

This figure illustrates the detailed prediction results using different machine learning algorithms. The table shows the classification of individuals as 'typical' or 'autistic' based on the probabilities calculated by each model. The results are presented in a matrix that compares the performances between Neural Networks, Logistic Regression, SVM and Decision Trees, highlighting the accuracy and effectiveness in the correct identification of the ASD and CT groups.

CONCLUSION

This study explored the effectiveness of holistic processing and the use of eye tracking in the diagnosis of Autism Spectrum Disorder (ASD), utilizing data mining and machine learning methods. The results indicate that the combination of eye tracking and data analysis can offer valuable insights for the understanding and diagnosis of ASD, opening up new possibilities for more effective interventions and more accurate diagnoses.

The research highlighted the relevance of fixation points and the amount of images used to ensure the robustness of the results and the statistical validity of the inferences. The fixation patterns revealed significant differences in the way individuals with ASD process visual information, which is crucial for developing more accessible interfaces and educational techniques adjusted to their needs.

The study also presented new approaches to the analysis of fixation data, using advanced machine learning techniques to integrate biometric data, which can enrich the understanding of emotional and cognitive responses to visual stimuli.

Figure 6 illustrates the effectiveness of different machine learning algorithms in classifying individuals as 'typical' or 'autistic'. Table 1 highlights the probabilities calculated by each model, demonstrating the superiority of the Neural Network in the precise classification of the ASD and CT groups. This result confirms the potential of using advanced data analysis techniques in the field of ASD diagnosis.

We conclude that the proposed methodology not only contributes to new perspectives for diagnosis and intervention in ASD, but also reinforces the importance of technology in advancing medical and educational research. Thus, this study reiterates the value of integrating computational and analytical technologies in improving the quality of life of individuals with ASD.

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