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Software Engineering Department

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Final Project – Phase A (61998)

Identifying patterns of ASD naturalistic behavior using Eye Tracking Technology

Project Code: 26-1-D-1

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Link to GitHub:

https://github.com/GuyZamir12/asd-eye-tracking.git

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Abstract

Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition where early diagnosis is critical for improving developmental outcomes. While traditional diagnosis relies on behavioral observation, eye-tracking (ET) technology has emerged as a powerful, objective tool for identifying the atypical visual attention patterns associated with ASD. By capturing metrics like fixation duration and saccade patterns, ET provides quantifiable data on how individuals process social and non-social information.

Despite its clear potential, the translation of eye-tracking from a laboratory research tool to a practical clinical instrument faces significant challenges. These include variability in experimental protocols, a lack of standardized gaze metrics, and difficulty in applying findings to real-world screening. This project aims to advance the field by developing a practical and data-driven framework for analyzing gaze behavior in children. This document will present the research, the analytical framework developed, and its potential to contribute to the creation of accessible technological tools that can support early diagnosis and intervention planning for ASD.

1 Introduction

Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition characterized by persistent challenges in social communication, social interaction, and restricted, repetitive patterns of behavior [Hirota et al., 2023]. The condition typically manifests in early childhood [Hodis et al,. 2025], and as researchers emphasize, early diagnosis and personalized interventions are critical for improving long-term developmental outcomes [Hirota et al., 2023].

While diagnosis often relies on clinical observation of behavior, there is a growing need for objective, quantifiable biomarkers to support the diagnostic process. Eye-tracking (ET) technology has emerged as a particularly promising solution. It provides a non-invasive means to record and analyze eye movements, offering objective data on the visual attention and cognitive processing patterns that underlie social understanding [Hessels et al.,2024].

The integration of ET into ASD research has confirmed its value. Studies consistently demonstrate that individuals with ASD display atypical visual attention patterns. For instance, children with ASD show reduced attention to social stimuli, such as faces, compared to their typically developing peers and often display a "circumscribed" or narrowly-focused attention on specific non-social elements within a complex scene [Sasson, N et al., 2008]. These findings have been further validated by meta-analyses showing that gaze metrics can reliably distinguish between ASD and non-ASD individuals [Setien-Ramos et al., 2022].

However, despite these clear findings, the translation of ET from a research tool to a widespread clinical diagnostic instrument faces significant hurdles. As noted in recent comprehensive reviews, the field suffers from methodological challenges, including high variability in experimental protocols and a lack of standardized gaze metrics [Eretová, et al., 2024]. Furthermore, while advanced machine learning (ML) and deep learning (DL) algorithms - such as Support Vector Machines (SVM) [Al-Adhaileh et al.,2025A]; Kaloforidis et al., 2025], Long Short-Term Memory (LSTM) networks [Al-Adhaileh 2023, Al-Adhaileh et al., 2025B], and Convolutional Neural Networks (CNNs) [El-Seoud et al., 2022] - have shown high accuracy in classifying gaze data, these models are not yet integrated into unified, accessible frameworks for clinical use. Moreover, many of these models lack interpretability, making it difficult for clinicians to understand *why* a classification was made [Billeci et al., 2024].

Therefore, the main goal of this research project is to address these gaps. This project aims to advance the field by developing a practical and data-driven framework for analyzing gaze behavior in children. This framework is intended to contribute both to the scientific understanding of attention mechanisms in ASD and, critically, to advance the creation of accessible technological tools that can support early diagnosis and intervention planning.

2 Background and Related Work

2.1 Autism Spectrum Disorder (ASD)

ASD typically emerges in early childhood and presents with a wide range of characteristics that vary in intensity and manifestation across individuals [Hodis et al., 2025]. Symptoms may include difficulties in interpreting social cues, challenges in reciprocal communication, and engagement in repetitive behaviors or strong adherence to routines [Hodis et al., 2025]. Hirota et al. (2023) highlight the importance of early identification and tailoring interventions to the specific needs of each child, noting that timely support can significantly improve long-term developmental outcomes [Hirota et al., 2023].
ASD is recognized as a lifelong condition with diverse levels of required support. As emphasized by the Lancet Commission, improving diagnosis, care, and social inclusion requires coordinated, multidisciplinary efforts across the lifespan [Lord et al., 2021]. Epidemiological studies estimate a prevalence of approximately 1–2% globally, with observed increases attributed largely to heightened awareness and enhanced diagnostic practices [Hodis et al., 2025]. Recent advances in neuroscience and clinical research have also expanded the range of diagnostic and therapeutic tools available, including behavioral, digital, and emerging technological

interventions aimed at both core and associated symptoms [Qin et al., 2024]. While no cure currently exists, continuous progress in early detection and evidence-based treatment continues to improve quality of life and functional outcomes for individuals on the spectrum.

2.2 Eye Tracking

Eye tracking is a research technique that records and analyzes eye movements to understand how individuals perceive, attend to, and process visual information. Capturing metrics such as fixation duration, saccade patterns, and gaze trajectories provides objective and quantifiable data on visual attention and cognitive processing. According to Hessels et al, the effective application of eye tracking requires a clear alignment between the theoretical research question and the specific gaze metrics selected, ensuring that the data accurately reflects the underlying cognitive processes being studied [Hessels et al., 2024]. The technology has evolved to include sophisticated hardware and software capable of high-resolution temporal and spatial tracking, making it suitable for a wide range of disciplines from psychology and neuroscience to human–computer interaction and education. In recent years, research in software engineering has also emphasized the importance of rigorous experimental design and analytical precision in eye-tracking studies, highlighting how methodological improvements contribute to the reliability and validity of results across domains [Grabinger et al., 2024]. Building on these developments, introduced a new system of eye-tracking metrics, including the AOI Switch Count (ASC), Favorable AOI Shifts (FAS), and AOI Vacancy Count (AVC) indices, which enhance the precision and interpretability of gaze data. These metrics represent a step forward in transforming raw eye movement data into meaningful indicators of visual attention and cognitive behavior [Wang et al., 2024]. Overall, eye tracking has become an essential tool for understanding visual cognition, enabling researchers to gain deeper insights into how people interact with and interpret their visual environment.

2.3 Integration of ASD and Eye Tracking

The integration of eye tracking technology into ASD research has provided a powerful, objective means of assessing visual attention, social perception, and cognitive processing differences between individuals with and without ASD. Early studies, such as Sasson et al. (2008), demonstrated that children with ASD display circumscribed attention during passive viewing of complex visual scenes, focusing narrowly on specific non-social elements rather than broader social contexts [Sasson et al., 2008]. Subsequent research expanded on these findings using paired-preference paradigms, where children were presented with social and non-social stimuli simultaneously. For instance, Vacas et al. (2021) found that preschool children with ASD showed reduced attention to faces and social images compared to typically developing peers, suggesting fundamental differences in social motivation and gaze behavior [Vacas et al., 2021]. Similarly, Congiu et al. (2024) reported that children with ASD spent less time fixating on facial stimuli and took longer to initiate gaze toward social images, reinforcing the view that atypical visual attention patterns emerge early in development [Congiu et al., 2024].

Recent advancements in eye tracking analysis have strengthened its diagnostic potential. Wang et al. (2024) introduced a novel system of gaze-based metrics (ASC, FAS, and AVC), capable of accurately differentiating between ASD and typically developing children, with the AVC metric showing particularly high sensitivity and specificity [Wang et al., 2024]. A recent meta-analysis further supports these findings, indicating that proportional fixation duration on eyes versus non-social regions reliably distinguishes ASD from non-ASD individuals in both children and adults [Setien-Ramos et al., 2022]. Beyond its diagnostic applications, eye tracking has been recognized as a valuable tool for intervention and treatment monitoring. Studies suggest that gaze-based measures can serve as outcome metrics to personalize therapeutic protocols and track improvements in social attention over time [Hamilton et al., 2021]. Furthermore, comprehensive reviews emphasize its broader role in advancing understanding of the cognitive and perceptual mechanisms underlying ASD, while identifying methodological challenges and directions for future research [Hamilton et al., 2024]. Collectively, these studies underscore the significance of eye tracking as both a research and clinical instrument for uncovering the unique patterns of attention and perception that characterize Autism Spectrum Disorder.

2.4 Algorithmic Approaches for ASD Classification

To translate raw eye-tracking data into a clinical classification, researchers employ a wide range of machine learning (ML) and deep learning (DL) algorithms. Among "classic" ML models, Support Vector Machines (SVM) and K-Nearest Neighbors (KNN) have been successfully applied to features extracted from gaze data, such as fixation duration and saccade counts [Al-Adhaileh et al., 2025A; Kaloforidis et al., 2025].

More recently, deep learning has become prominent due to its ability to automatically learn complex, hierarchical features from the data. As eye-tracking scanpaths are inherently sequential, models designed for time-series data, such as Recurrent Neural Networks (RNNs) and their more advanced variant Long Short-Term Memory (LSTM), have been used to analyze the temporal dynamics of gaze [Al-Adhaileh, 2023; Al-Adhaileh et al., 2025B].

Furthermore, some approaches treat gaze data visually, converting scanpaths or heatmaps into images. This allows for the use of Convolutional Neural Networks (CNNs) to extract predictive spatial features [El-Seoud et al., 2022]. Hybrid models are also increasingly popular, combining, for example, a CNN for feature extraction with an SVM for classification, or merging CNNs with LSTMs to simultaneously capture both the spatial and temporal properties of gaze behavior [El-Seoud at al., 2022]. Beyond classification accuracy, other studies focus on interpretability, using Explainable AI (XAI) models to understand why a classification was made [Billeci et al., 2024]. This focus on a diverse set of algorithms is critical for developing accurate and interpretable diagnostic tools.

2.5 Exploration and Exploitation

Visual attention during scene viewing reflects a continuous trade-off between exploration and exploitation. Exploration refers to shifting gaze toward new, previously unattended regions of a scene, enabling broad spatial sampling, whereas exploitation involves prolonged fixation within a specific region to support deeper visual processing. We constantly have to decide whether to move on to sample another image region or to linger in the currently fixated region for in-depth processing [Gameiro et al., 2017]. These two processes are reflected in distinct gaze metrics: exploration is associated with a higher number of fixations, increased spatial dispersion, higher entropy, and larger saccadic amplitudes, while exploitation is characterized by longer fixation durations and more spatially clustered gaze behavior.

2.6 Tobii Pro Lab

Tobii Pro Lab is a comprehensive eye-tracking software platform designed to support the entire experimental workflow, from stimulus design and calibration to data recording and advanced analysis, without requiring programming experience. It integrates seamlessly with Tobii Pro hardware and enables researchers to present various stimuli (e.g., images, videos, text), capture precise gaze data, and visualize results through metrics such as heatmaps and gaze plots, making it suitable for behavioral, cognitive, and usability studies. The software’s intuitive interface and flexible analytical tools facilitate efficient data processing and interpretation across diverse research paradigms.

3 Engineering Process

3.1 Project Objectives and Future Research Directions

Current research highlights the growing potential of eye tracking as both a diagnostic and therapeutic tool in Autism Spectrum Disorder (ASD). Comprehensive reviews have shown that eye-tracking technology contributes significantly to three major areas: diagnostic screening, intervention monitoring, and the exploration of underlying cognitive-perceptual mechanisms [Eretová et al., 2024]. However, despite these promising advances, several methodological and practical challenges remain. A primary challenge is the reliance on static gaze metrics, such as total fixation duration on an Area of Interest (AOI). While AOIs remain essential for identifying where children look, these metrics alone cannot capture the organization, variability, or strategy of gaze behavior. Recent research shows that incorporating entropy-like measures, such as gaze variability and scanpath dispersion, can reveal important differences in how children explore visual scenes. For example, studies have demonstrated that children with ASD exhibit less organized and more variable scanpaths during social viewing tasks, reflecting differences in attentional strategy [Falck-Ytter et al., 2013], highlighting the value of combining AOI metrics with more dynamic analyses of attention shifts over time. To address these gaps, future research is increasingly focused on establishing unified analytical frameworks that ensure data consistency and reproducibility [Eretová et al., 2024].

To overcome the limitations of static metrics, our project will leverage a more powerful analytical method: gaze transition analysis, often visualized using transition graphs or matrices. This approach moves beyond simply asking "where" a child looked, and instead analyzes the flow and strategy of their gaze. It quantifies the probability of attention shifting from one AOI to another (e.g., from 'Eyes' to 'Mouth' versus 'Eyes' to 'Object'). This sequential analysis provides a richer, more dynamic model of visual exploration, which is crucial for understanding the complex attentional patterns in ASD [Ellis et al., 2021]. This method has proven robust in clinical research, successfully identifying disorganized or atypical gaze transition patterns in other conditions, such as schizophrenia [Ku et al., 2016], demonstrating its value as a powerful analytical tool.

Building on these findings, the current project aims to advance this field by specifically implementing and validating a transition graph-based framework for analyzing gaze behavior in children. By moving beyond static metrics to a dynamic, sequential analysis, we aim to contribute a more robust model to the scientific understanding of attention mechanisms. Ultimately, this will advance the creation of accessible, data-driven, and analytically sophisticated technological tools that can support early diagnosis and intervention planning for ASD.

3.2 Process

This research is conducted in collaboration with researchers from the University of Haifa and focuses on identifying differences in visual attention patterns between children with ASD and TD children. The study combines eye-tracking technology with ML and DL methods to analyze exploration and exploitation behaviors during free-play interaction, as shown in Figure 1.

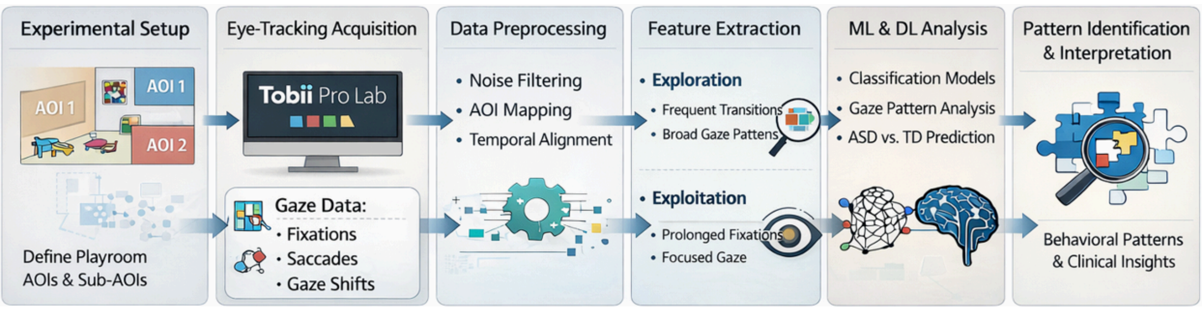

Figure 1: The process

3.2.1 Experimental Setup and Data Collection

The experiment will take place in a dedicated playroom environment. In each experimental session, a single child, either diagnosed with ASD or typically developing, will enter the room individually. Each child will have 10 minutes of free playtime in the room. The playroom will be divided into three main spatial regions, each defined as an Area of Interest (AOI). Within each AOI, multiple sub-AOIs will be defined, representing specific objects or functional elements within the play area. Figures 2–4 illustrate the experimental stimuli included in these areas: games placed on the table (Figure 2), a play cylinder (Figure 3), and a climbing track (Figure 4).

The definition and labeling of AOIs and sub-AOIs will be determined in advance by the researchers from the University of Haifa, based on clinical relevance and experimental design considerations.

During the experiment, the child will wear Tobii eye-tracking glasses, which will continuously record eye movements while the child engages freely with the play environment. The setup allows for naturalistic behavior without direct instructions, enabling the capture of spontaneous visual exploration patterns.

The study was approved, as required, by the Institutional Research Ethics Committee at the University of Haifa. The participants provided informed consent to participate in this study.

Figure 2: Games will be placed on the table during the experiment

Figure 3: Play cylinder

Figure 4: Climbing track

3.2.2 Eye-Tracking Recording and Data Extraction

Eye movement data will be collected using the Tobii eye-tracking system (sampling rate: 120 Hz) and processed through Tobii Pro Lab, which provides high-resolution gaze data aligned with predefined AOIs and sub-AOIs. The recorded data include gaze coordinates, fixation durations, saccadic movements, and temporal sequences of gaze shifts across regions.

The output files generated by the software will serve as the primary data source for subsequent computational analysis.

3.2.3 Data Preprocessing

Prior to analysis, the eye-tracking data will undergo preprocessing to ensure data quality and consistency. This stage includes:

- **Filtering out noise and missing data:** This initial step is performed to ensure the overall quality and consistency of the collected eye-tracking data.
- **Mapping gaze sequences into AOIs and sub-AOIs:** This involves assigning the continuous gaze coordinates to the pre-defined Areas of Interest (AOIs) and sub-AOIs in the playroom environment.
- **Building time-series representations of gaze transitions between regions:** This is the final step, which transforms the raw recordings into structured, sequential data suitable for dynamic feature extraction and computational modeling.

This preprocessing stage transforms raw eye-tracking recordings into structured time-series data suitable for feature extraction and modeling.

3.2.4 Feature Extraction: Exploration and Exploitation

From the processed data, features representing visual exploration and exploitation behaviors will be extracted. Exploration reflects the tendency to scan and sample new regions of the environment and is characterized by frequent transitions between AOIs, broader spatial dispersion of gaze, and higher variability in viewing patterns. Exploitation, in contrast, reflects sustained attention within a specific region and is characterized by longer fixation durations, repeated focus on the same sub-AOI, and spatially clustered gaze behavior. These features enable a dynamic characterization of how children allocate visual attention, capturing not only where they look but also how they navigate the environment visually over time [Gameiro, et al 2017].

To translate these behavioral concepts into clinical classification, we convert the Exploration and Exploitation dynamics into quantitative numerical features (metrics) that will serve as the input for Machine Learning models. The input for the models will not be raw image data, but a structured array of these metrics.

Features (Model Input)

The feature set will include, but not be limited to, the following metrics derived from the eye-tracking time-series:

- Exploration Metrics (Sampling the Environment):
  - AOI Switch Count (ASC): Reflecting the frequency of gaze shifts between major AOIs.
  - Spatial Dispersion & Entropy: Measures of the breadth and variability of the gaze scanpath.

- Exploitation Metrics (Sustained Focus):
    - Average Fixation Duration: Reflecting the amount of time spent processing a single area.
    - Spatially Clustered Gaze Behavior: The degree of repeated focus on specific sub-AOIs.

The goal is to evaluate the ability of these models to distinguish between children with ASD and typically developing children, leveraging the unique contribution of exploration and exploitation patterns to improve diagnostic classification performance.

3.2.5 Machine Learning and Deep Learning Analysis

The extracted exploration and exploitation features will be used as input to Machine Learning and Deep Learning models aimed at distinguishing between ASD and typically developing children. Models suitable for sequential and temporal data will be explored, allowing the analysis of gaze dynamics rather than static summary measures alone.
The performance of different modeling approaches will be evaluated to assess their ability to:

- Accurately classify participants into ASD and non-ASD groups
- Capture meaningful differences in attention strategies
- Reveal the contribution of exploration and exploitation patterns to classification performance

Model Selection

The numerical features from the Feature Extraction stage (3.2.4), which form time-series representing the sequence of gaze events, will be fed into Deep Learning (DL) models that are best suited for sequential data analysis:

- Primary Model: Long Short-Term Memory (LSTM): LSTM models are highly effective for analyzing time-series data, enabling us to capture the temporal dynamics and dependency between successive gaze transitions. This is crucial for analyzing the specific attentional strategy a child employs to shift between exploration and exploitation. As illustrated in Figure 5, the LSTM processes gaze data as a sequence of time steps, where each input represents a gaze event while an internal memory state preserves information from previous transitions. This sequential structure enables the model to capture long-term dependencies in gaze behavior, which are essential for distinguishing between exploration and exploitation patterns.
- Hybrid Models: We will also explore hybrid architectures, such as combining Convolutional Neural Networks (CNNs) to extract local spatial patterns from fixation maps with LSTMs for sequence analysis.

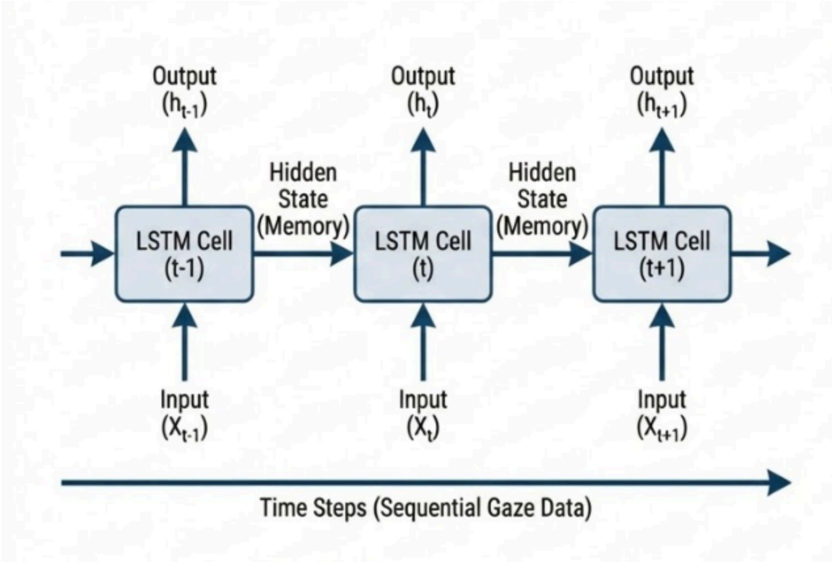

Figure 5: Simplified LSTM-based sequential processing

3.2.6 Pattern Identification and Interpretation

Finally, the results of the models will be analyzed to identify unique attentional patterns characteristic of ASD, such as limited exploration of the environment or repeated focus on certain areas. The interpretation will be done by combining research and clinical knowledge, with the aim of deepening the understanding of the mechanisms of visual attention in ASD and contributing to the development of an applied and unified analytical framework.

3.3 Architecture

The system receives raw eye-tracking data as input, processes it through a unified analytical pipeline for feature extraction, and applies machine learning models to produce classification outputs (ASD vs. TD) and behavioral insights. The architecture represents the complete system responsible for transforming gaze data into interpretable results (Figure 6).

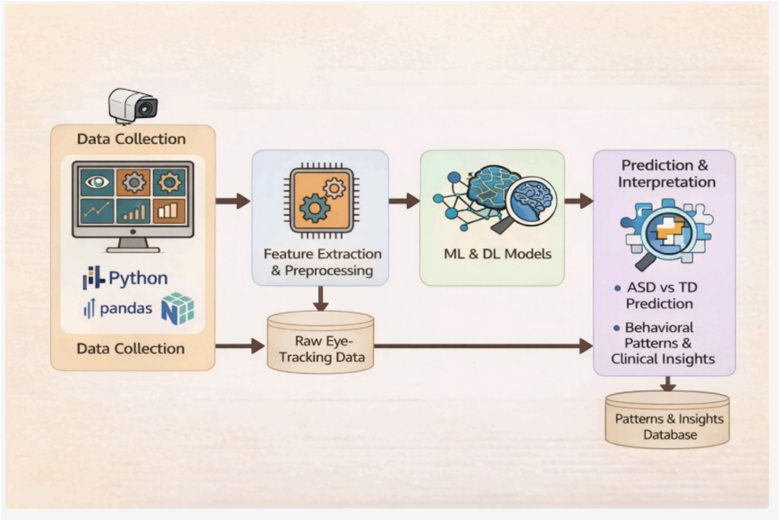

Figure 6: Architecture

3.4 Functional and Non-Functional Requirements

Based on the system's goals to develop a data-driven framework for analyzing gaze behavior in children for ASD diagnosis, the following requirements are identified:

Functional Requirements (FR)

These requirements define the specific capabilities and functions the system will perform:

- **FR1: External Data Ingestion:** The system will support the import and integration of raw eye-tracking data files generated by external systems (e.g., Tobii Pro Lab).
- **FR2: Data Cleaning and Filtering:** The system will enable the automatic filtering of noise and the handling of missing gaze data to ensure data quality and consistency.
- **FR3: AOI Mapping:** The system will perform the mapping of dynamic gaze coordinates to the pre-defined Areas of Interest (AOIs) and Sub-AOIs within the experimental environment.
- **FR4: Time-Series Generation:** The system will transform the raw recordings into structured time-series representations of gaze transitions between regions, suitable for deep learning input.
- **FR5: Exploration & Exploitation Feature Extraction:** The system will calculate and extract specific quantitative metrics representing Exploration behaviors (e.g., ASC, spatial dispersion) and Exploitation behaviors (e.g., Average Fixation Duration).
- **FR6: DL/ML Classification:** The system will perform classification of participants into ASD vs. TD groups using the extracted features, primarily through designated models (LSTM and hybrid architectures).

- **FR7: Reporting and Interpretation:** The system will present the classification results along with reports detailing the contribution of the Exploration and Exploitation metrics to the classification, aiding clinical understanding.

Non-Functional Requirements (NFR)

These requirements define the quality attributes and performance characteristics of the system, based on the project's scope and challenges:

- **NFR1: Accuracy and Performance:** The system should achieve a high level of accuracy in clinical classification, aiming to outperform traditional static measures.
- **NFR2: Scalability:** The analytical framework will be designed to be scalable, capable of efficiently processing and analyzing large datasets and accommodating potential future increases in sample size.
- **NFR3: Data Security and Privacy:** The system will adhere to all relevant data privacy and protection regulations for handling sensitive child behavioral and potential medical data.
- **NFR4: Maintainability:** The feature extraction pipeline and ML models will be modular and well-documented to ensure the ease of updates, debugging, and future extension of the framework.
- **NFR5: Generalizability:** The developed classification models should demonstrate strong generalizability, validated by the ability to perform accurately on public and external datasets (as planned for the backup data source).

3.5 Project Success Metrics: Quantitative Measures for Goal Achievement

The project's success will be quantitatively evaluated by measuring the extent to which the developed framework achieves its stated goals in classification performance and clinical utility. The key metrics are:

1. **Primary Metric: Classification Performance (Accuracy):**
   - **Goal:** The main success indicator will be the classification accuracy (e.g., AUC, Sensitivity, Specificity) of the Deep Learning model (LSTM/Hybrid) in distinguishing ASD from TD participants.
   - **Measure:** Achieve a classification accuracy that **outperforms established baseline models** utilizing only traditional static gaze metrics.
2. **Generalizability (Model Validation):**
   - **Goal:** Ensure the framework is not over-fitted to the collected data and is broadly applicable.

- **Measure:** Achieving a robust and comparable level of classification performance when the model is applied to an **external, publicly available ASD eye-tracking dataset** (as planned for the backup data source).

3.6 Limitations and Expected Challenges

A primary limitation of this study is its reliance on timely data collection by researchers from the University of Haifa; delays or unforeseen constraints may result in insufficient original data. To address this risk, a validated publicly available ASD eye-tracking dataset supported by prior research will be used as a backup. Additional limitations include a potentially small sample size and the inherent noise of eye-tracking data, particularly in studies involving children. These challenges will be mitigated through robust preprocessing, cross-validation techniques, and the use of transition-based gaze features that are less sensitive to noise and AOI definition variability. An additional challenge arises from the fact that this project is being developed in parallel with a complementary project that focuses on image processing and video-based analysis of recordings capturing the experimental room and participant behavior. Future integration of both projects into a unified and larger analytical framework may require the design of an interface or communication mechanism (such as an API) to enable interoperability and data exchange between the two systems.

4. Evaluation Plan

4.1 Testing

The testing phase focuses on validating the correctness, robustness, and performance of the proposed system across all stages of the analytical pipeline. Unit-level testing will be conducted for key components, including data preprocessing, AOI mapping, time-series construction, and feature extraction, to ensure that each module produces consistent and reliable outputs.

At the system level, the complete pipeline will be evaluated using real eye-tracking data collected from children with ASD and typically developing (TD) children. Model performance will be primarily assessed using a confusion matrix, which provides a detailed breakdown of classification outcomes into true positives, true negatives, false positives, and false negatives.

Based on the confusion matrix, standard evaluation metrics will be computed, including accuracy, sensitivity (recall), and specificity. These metrics allow for a clear interpretation of the model's ability to correctly identify children with ASD while minimizing misclassification of typically developing children. This is particularly important in the context of ASD research, where both missed diagnoses and false alarms carry significant implications.

In addition, cross-validation techniques will be applied to assess the stability and generalizability of the results across different data splits. Robustness testing will also be performed to evaluate the system's sensitivity to noisy or incomplete gaze data, reflecting realistic challenges in eye-tracking recordings involving children. The obtained results will be compared against baseline models that rely on traditional static gaze metrics, in order to evaluate the contribution of the proposed exploration–exploitation and transition-based features.

4.2 User Evaluation

User evaluation will be conducted by the collaborating researchers from the University of Haifa. After the completion of the data analysis and model evaluation, the research results will be presented to the expert researchers, including classification outcomes and summaries of the identified exploration and exploitation patterns. The evaluation will focus on assessing the interpretability, relevance, and scientific validity of the results, as well as their consistency with existing clinical and research knowledge in the field of ASD. Qualitative feedback provided by the researchers will be used to identify strengths, limitations, and potential directions for refinement and future development of the proposed framework.

5. GenAI Usage Discloser

During the preparation of this work, the authors used Gemini and ChatGPT to enhance language and grammar. After using this service, the authors reviewed and edited the content as needed and took full responsibility for the content of the published article.

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