Plagiarism Detector .net

Plagiarism Report

0% Plagiarism

Unique	100%
Exact Match	0%
Partial Match	0%

Primary Sources

Excluded URL (s)

01 None

Content

Problem Statement and Objectives}

\subsection{\small Problem Statement}
Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition characterized by social and communication challenges. Early diagnosis is critical for effective intervention, yet traditional diagnostic methods are time-consuming, subjective, and require expert evaluation. Eye-tracking technology has shown promise as a non-invasive tool for detecting atypical gaze behavior in individuals with ASD. However, existing studies often suffer from limitations such as small datasets, short-duration tasks, and lack of robust multimodal integration with artificial intelligence. There is a pressing need for scalable, data-driven frameworks that combine eye-tracking features with machine learning to support accurate and objective ASD screening.

\subsection{\small Objectives}
The objectives of this study are as follows:
\begin{enumerate}
\item To review and analyze existing research that integrates eye-tracking data with machine learning models for ASD detection.
\item To identify key gaze-based biomarkers (e.g., fixation duration, scanpath dynamics, areas of interest) that distinguish ASD from typically developing individuals.
\item To design and propose a multimodal predictive framework that leverages eye-tracking data and meta-information for ASD diagnosis.
\item To evaluate the effectiveness of deep learning techniques, such as convolutional neural networks, in classifying ASD based on visual scanpath patterns.
\item To address current limitations (small sample size, short recording duration) by exploring data augmentation and synthetic data generation methods.
\item To contribute towards developing a non-invasive, scalable, and objective screening tool that can complement traditional clinical assessments.
\end{enumerate}

\section{\small Dataset and Preprocessing}

\subsection{\small Description of Metadata}
The metadata associated with the dataset provides important contextual and clinical information about each participant. The dataset includes the following attributes: Participant ID, Gender, Age, Childhood Autism Rating Scale (CARS) score, and diagnostic Class (ASD vs. typically developing). These fields were curated to serve as complementary features alongside visual data from scanpath images.

For computational processing, categorical variables were converted to numerical form. Gender was encoded as binary ($M = 1, F = 0$), while the diagnostic class was mapped as $TS = 1$ for autism cases and $TC = 0$ for control cases. Rows with missing CARS values were removed to maintain data integrity.

To normalize continuous variables, z-score standardization was applied:

\begin{equation}
z = \frac{x - \mu}{\sigma}
\end{equation}

where x is the feature value, μ is the mean, and σ is the standard deviation.

\begin{table}[h]
\centering
\caption{Sample metadata after preprocessing}
\label{tab:metadata}
\begin{tabular}{|c|c|c|c|}
\hline
\textbf{ID} & \textbf{Gender} & \textbf{Age} & \textbf{CARS Score} \\
\hline
001 & 1 & 7 & 32.5 \\
002 & 0 & 8 & 28.0 \\
003 & 1 & 7 & 35.0 \\
\hline
\end{tabular}
\end{table}

\subsection{\small Description of Images}
The image dataset was derived from eye-tracking scanpaths. Each participant's gaze trajectory was transformed into a grayscale image representation encoding spatial and temporal dynamics. Images were resized to 128×128 pixels and normalized to the range $[0,1]$ by dividing pixel intensities by 255.0.

The dataset consisted of two major folders: \texttt{TCImages} (typically developing) and \texttt{TSImages} (ASD). Filenames contained participant IDs, enabling linkage with metadata.

\subsection{\small Preprocessing Techniques}
Several preprocessing steps ensured data quality and robustness:
\begin{itemize}
\item \textbf{Metadata normalization:} Applied z-score scaling using StandardScaler.
\item \textbf{Image normalization:} Pixel values scaled to [0,1].
\item \textbf{Data augmentation:} Random flips, rotations, and zooms introduced synthetic diversity.
\item \textbf{Class balancing:} Weighted loss functions addressed class imbalance.
\item \textbf{Train-validation split:} An 80-20 stratified split preserved label distribution.

\end{itemize}

Mathematically, augmentation transformations can be represented as:

\begin{equation}
I' = T(I), \quad T \in \{\text{flip}, \text{rotation}, \text{zoom}\}
\end{equation}

\subsection{\small Dataset-Preprocessing Pipeline}
Figure~\ref{fig:pipeline} illustrates the end-to-end preprocessing pipeline, showing how metadata and images are aligned, preprocessed, and prepared for multimodal fusion.

References