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Research Article

Autism Spectrum Disorder Classification in Children Using Eye-tracking Technology and Convolutional Neural Networks

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Abstract:

Autism Spectrum Disorder (ASD) is a highly complex and difficult to treat neural developmental disorder that often manifests with distinct challenges in social abilities such as human interaction and communication, as well as causing children to exhibit behaviors repeatedly. A definitive one-size-fits-all treatment has yet to be developed for ASD, but early diagnosis and detection is critical for implementing effective interventions at an early age which allows children suffering from ASD to achieve greatly better outcomes in their development, pulling them closer to typically developing children. Traditional diagnostic methods are, most of the time, hard to access in undeveloped countries, consume a lot of time and are highly subjective. The most recent breakthroughs and developments in machine learning, particularly deep learning, have allowed for the creation of automated systems for ASD classification. This paper focuses on using a Convolutional Neural Network (CNN) utilizing transfer learning along with the pre-trained VGG16 augmented with further convolutional layers to classify ASD from eye-tracking scanpaths. The proposed method demonstrates high classification accuracy that reaches 98.4%, with precision and recall reaching 96.6% and 100% respectively, supported by robust preprocessing, augmentation and transfer learning techniques, the results emphasize the potential of CNNs as a reliable diagnostic tool, paving the way for integrating AI in clinical settings.

1. Introduction

1.1 Background on Autism Spectrum Disorder

Autism Spectrum Disorder (ASD) affects approximately 1 in 31 children globally, with symptoms manifesting in early childhood and continuing throughout life [1]. The main symptoms of ASD comprise a variety of deficits including performing repetitive behaviors, having highly restricted interests and impaired social communication [2]. These symptoms vary significantly across individuals, making ASD a "spectrum" disorder. The earlier ASD is diagnosed the easier it is to provide timely interventions, which in turn enhances how a child with ASD develops improving long-term outcomes [3, 4].

1.2 Challenges in Traditional Diagnostic Methods

Conventional diagnostic tools, such as the Autism Diagnostic Observation Schedule (ADOS) and Autism Diagnostic Interview-Revised (ADI-R), are widely used. However, they need a lot of time to be carried out, require clinicians with a high degree of training and multiple observation sessions and are vulnerable to misdiagnosis due to various reasons, including untrained clinicians and the presence of the parents, which might induce ASD-like behavior from diagnosed children [4]. This reliance on subjective evaluation leads to inconsistencies, particularly in under-resourced regions [5]. Moreover, cultural and linguistic factors can impact the performance of these tools, further limiting their effectiveness and thus accessibility [6].

1.3 The Role of Eye-Tracking Technology

Eye-tracking technology offers an objective alternative for diagnosing ASD. It measures visual attention patterns, such as fixation duration, gaze trajectory, and saccadic movements, which differ significantly between individuals with ASD and neurotypical individuals [7]. These differences provide valuable biomarkers for early diagnosis. For example, children with ASD are less likely to focus on social stimuli such as faces and more likely to attend to abstract or geometric patterns and repetitive motions [8].

1.4 Advancements in Machine Learning and Deep Learning

Machine learning (ML) has revolutionized pattern recognition and predictive modeling. A subset of ML that is more relevant to the ASD diagnosis task is deep learning, it utilizes the power and flexibility of neural networks to handle the feature engineering task as it performs feature extraction directly from data in its raw form, thus eliminating the necessity of doing feature engineering manually [9, 10]. Convolutional Neural Networks (CNNs) in particular, have shown remarkable success in image-based tasks such as object recognition, medical imaging, and, recently, ASD classification [10, 11, 12]. Transfer learning provides an additional improvement to the performance of pre-developed models incorporating CNNs by exploiting the generalizability of model architectures trained on large datasets such as VGG16 and ResNet50, this allows training to use smaller datasets that are not excessively labeled [13].

1.5 Paper contribution

This paper's most important contributions are:

- Presenting a strong review of the most recent and advanced research on ASD diagnosis using a variety of methodologies utilizing machine learning and deep learning.
- Developing a new model CNN-based by using the VGG16 architecture as it is and adding more layers to it to create a CNN-network that is easily trained, by transfer learning, and adjusted to use eye-tracking data for ASD classification.
- Used data augmentation techniques to improve model training and generalization thus enhancing its robustness.
- Excessive experimental results have been made to achieve the proposed methodology, and the classification accuracy reaches 98.4%.
- Performance is further compared against traditional and existing deep learning approaches.
- Finally, the study shows high potential for clinical usability of the model in real-world settings.

This paper comprises 6 sections: The 2nd section summarizes the most important, recent and relevant research in ASD classification. The 3rd section presents a discussion of this study's problem under focus, highlighting the suggested solution for ASD diagnosis. The 4th section outlines the proposed methodology, including dataset description, preprocessing and data augmentation techniques, and CNN architecture. The 5th section details the obtained experimental results and applies to it a variety of evaluation metrics. Finally, the 6th section concludes with discussions and future recommendations.

2. Literature Review

2.1 Traditional Machine Learning in ASD Detection

Traditional machine learning (ML) methods have demonstrated some success in autism spectrum disorder (ASD) classification. For example, medical claims data for children aged between 18 and 30 months have been used to classify ASD by employing two algorithms, namely Logistic Regression (LR) implemented with the Least Absolute Shrinkage and Selection Operator technique, as well as Random Forests (RF) [14], their main evaluation metric was the (AUROC) curve or area under the receiver operating characteristic curve, they measured the (AUROC) for both algorithms and achieved 0.758 for (LR), and 0.834 for (RF) with 96.4% specificity and 40% sensitivity, but faced challenges due to high data-imbalance and the fact that information availability at these young ages is very scarce, also these techniques typically require heavy manual feature engineering [15].

2.2 Deep Learning for ASD Classification

Deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized ASD detection, deep learning methods automate feature extraction from raw data unlike machine learning methods which complicate models and require heavy manual feature engineering. CNNs excel at identifying hierarchical patterns making them well-suited for tasks like medical imaging. For instance, A deep learning CNN was used to classify ASD based on neuroimaging data achieving a classification accuracy of 97.07% [16], another study has used a self-attention deep learning framework based on the Transformer model on structural magnetic resonance images (sMRI) to classify ASD individuals achieving an accuracy of 72.5% [17]. Lastly, another EEG-data-based study reached an accuracy of 96.9% by extracting brain features from the mu rhythm oscillation and applying a hybrid model, combining feature extraction from spectrogram using deep learning and classification using machine learning [18].

2.3 Eye-Tracking in ASD Research

Gaze direction patterns have emerged as an effective marker for children with ASD making Eye-Tracking a promising technology to employ in ASD research and classification. Often exhibiting atypical gaze directions from an early age, it’s been shown by previous studies that ASD children often have poor eye-contact focusing their gaze on a speaker’s mouth instead of their eyes [19], their difficulty with interpreting human emotions from face expressions [20] is a hindrance to their social communication which negatively impacts their future development. Analyzing eye-tracking scanpaths provided valuable markers for ASD diagnosis. For example, using visual orienting tasks, eye-tracking was used to classify 5-year-old children into 3 groups based on their gaze patterns, with ASD children being split into two distinct groups, the first being children with high functioning ASD (HFA) and the second being children with low functioning ASD (LFA), and lastly typically developing children, by utilizing a K-nearest-neighbor machine learning model, children classification reached 81.1% accuracy with relatively high sensitivity and specificity [21]. Another study utilized eye-tracking scanpaths on 59 school-aged children incorporating a CNN architecture that reached 90% classification accuracy, basically having the same methodology as our study, but suffered from small sample size [22]. Furthermore, it's been also shown by previous studies that children with ASD develop a preference to gaze at geometric or abstract scenes over social ones, a preference non-existent in typically developing children, [23] have used this preference to classify children aged 2-6 years into ASD or typically developing children by incorporating a CNN architecture based on the Caffe framework (a variation of the LeNet architecture) to differentiate gaze directions of children exposed to different scenes achieving a classification accuracy of 95.1%. Finally, another study used a combination of eye gaze fixes map dataset and eye-tracking scanpaths dataset, which is the same dataset we used, to create a hybrid CNN model capable of classifying ASD with an accuracy that reaches 98.1% [24].

Table 1. *Literature Review Comparison.*

Study	Year of Publication	Category	Technique	Accuracy	Disadvantages
[23]	2020	Deep Learning	Caffe framework CNN applied on gaze directions of children watching different scenes	Reached 95.1% accuracy	Subject to overfitting because of using a small sample size and relies on a controlled environment
[21]	2021	Machine Learning	K-nearest-neighbor applied to children’s eye movements	Reached 81.08% accuracy	Small sample size limits training potential and generalizability
[16]	2021	Deep Learning	Convolutional Neural Networks (CNNs) on neuroimaging data	Reached 97.07% accuracy	Relies on complex data, didn’t test the model on different dataset types
[17]	2021	Deep Learning	Self-attention deep learning framework based on the Transformer model used on structural magnetic resonance images (sMRI)	Reached 72.5% accuracy	Low accuracy

[22]	2021	Deep Learning	Capture eye-tracking scanpaths into images and use a CNN architecture for image analysis	Reached 90% accuracy	Small sample size
[14]	2022	Machine Learning	(LASSO) (LR) and (RF) on medical claims data	RF model reached a 96.4% specificity at 40% sensitivity	High data imbalance and scarce availability of information on young-age-children
[18]	2024	Hybrid (Deep Learning + Machine Learning)	Deep learning for feature extraction from spectrogram data in the alpha-beta frequency range followed by a machine learning classifier	Reached 96.9%	Focuses on the alpha-beta band and overlooks other important analysis bands, relies on complex data
[24]	2024	Deep Learning	Feature extraction with Mobile-Net, dimensionality reduction using PCA and then classification using Stacking ensemble	Reached 98.1%	High complexity

2.4 Challenges and Opportunities

Main challenges that faced the recent work in ASD classification, particularly by utilizing eye-tracking scanpaths were:

- Data scarcity, as most studies rely on small datasets which limits their generalizability.
- Data complexity, often dealing with images containing complex data such as brain data or gaze patterns converted into images.
- Furthermore, clinicians demand explainable AI models to be adopted in real world clinical settings as the way their results are obtained can be explained and thus can be verified.

Opportunities lie in multimodal approaches, combining gaze tracking with other modalities, such as EEG or MRI could be crucial for enhancing accuracy and robustness [25].

3. Problem Definition

As discussed previously, autism is an increasingly prevalent neural developmental disorder [1], with its symptoms and effects causing huge difficulties in children development particularly in social aspects such as communication, learning and daily skills, figure 1 shows the increase in ASD prevalence in the recent years upto 2022, according to the center for diseases control and prevention (CDC) [26].

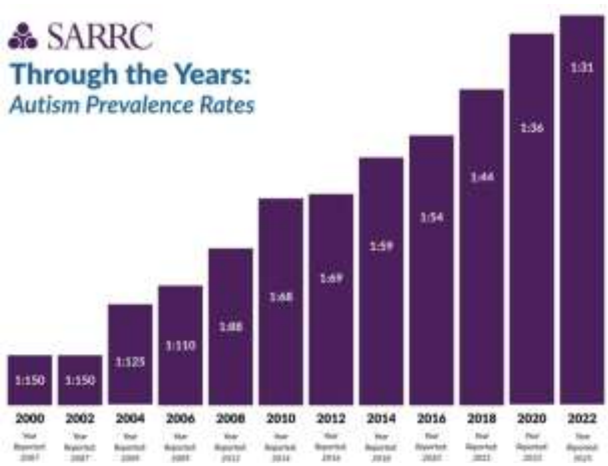


Figure 1. *Autism Prevalence Rates Through The Years.*

Early intervention in childhood provides great chances for controlling and limiting ASD symptoms and enhancing children's development which in turn allows for better long-term outcomes [3, 4], this relies on reliable, accurate and consistent early ASD diagnosis. As illustrated in the literature review, many techniques have been developed and evolved over time for ASD diagnosis, however achieving accurate, reliable and easy to use diagnosis is still complicated and faces a lot of problems both in the scarcity and complexity of available ASD data and in ease of applicability of these techniques in real-world clinical settings, affecting both the accuracy and efficiency of the available techniques.

The suggested strategy named "Intelligent ASD Detector" is presented as a highly reliable and accurate method of diagnosing ASD relying on Eye-Tracking technology as explained in the next section.

4. The proposed "Intelligent ASD Detector"

This study's goal is to provide a reliable and robust solution for ASD diagnosis at an early age by tracking eye/gaze movements while children are exposed to various stimuli, eye tracking data is recorded and visualized and fed to the proposed "Intelligent ASD Detector", a CNN network based on the VGG16 using transfer learning, designed to classify children into two classes: ASD and Non-ASD, images are preprocessed and augmented to improve the model's training speed, convergence and generalization, the following figure shows the proposed methodology.

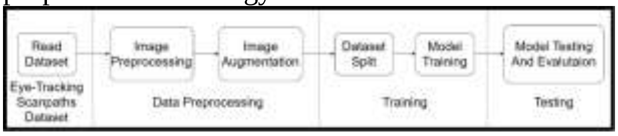


Figure 2. *Proposed Methodology.*

4.1 Input Data

This study uses the ASD Eye-Tracking Scanpaths in Autism Spectrum Disorder dataset found on the Figshare data repository [27], the data comprises 547 RGB images of gaze trajectories recorded for 59 children, samples are split into 328 images for non-ASD participants and 219 for ASD participants, eye-tracking data is recorded using the SMI-RED mobile tracker operating at 60Hz frequency [28, 29] and transformed by the dataset creators into an image format where eye dynamics are constituted using colored lines connecting fixation points, where the change in each color gradient along a given line (red, green and blue) reflects changes in eye movements, a more integrated visual format that is clearer and

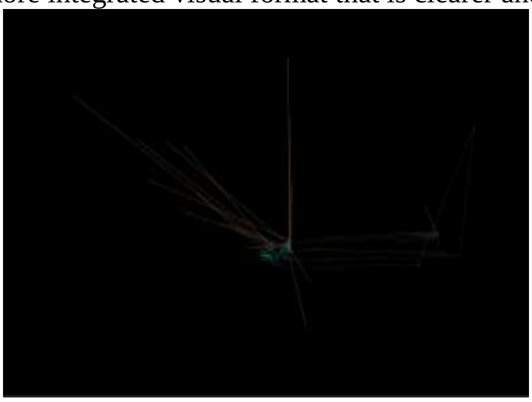


Figure 3. *Eye-tracking scanpath of a normal child.*

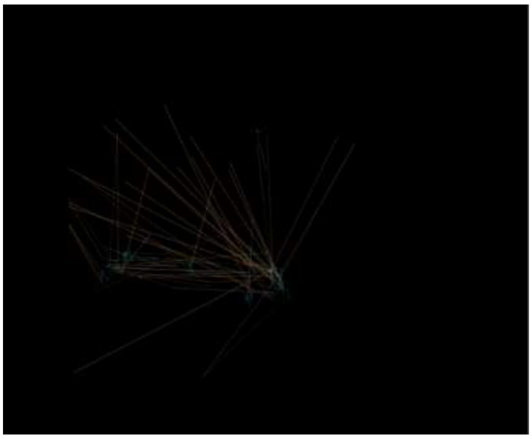


Figure 4. *Eye-tracking scanpath of a child diagnosed with ASD.*

easier to interpret than typical gaze plots [29], Figure 3 shows the eye-tracking scanpaths of a Non-ASD child, while Figure 4 shows a child diagnosed with ASD. In these images, fixation points, colored cyan, and saccade points, colored white or yellow, are connected by lines representing gaze movement, eye motion velocity, acceleration and jerk are captured by RGB gradients, for example, black portions represent low velocities, and the faster the eye moves, the more the lines lean towards deeper degrees of red, the same goes for acceleration, the higher it is the more lines lean towards deeper degrees of green, and lastly, eye jerk values are represented by blue gradients.

4.2 Data Preprocessing

Data preprocessing was necessary for achieving consistent training results and enhancing model robustness, firstly images were resized from 640x480 pixels to 256x256 pixels while maintaining 3 RGB channels, resizing was done using bilinear interpolation, it takes four pixels from the original image, calculates the average of their pixel values and takes the output average as the new pixel value, providing a balance between resulting accuracy and computational complexity [30], ultimately ensuring a uniform input size for our CNN which enhances its efficiency, then pixel intensities were brought to a common scale by using Min-Max scaling normalization by dividing pixel values by 255, disallowing the model from being dominated by large feature values, this increases the model's training speed by avoiding exploding or vanishing gradients which highly improves training convergence [31], while also enabling the model to train on the features of the images not on the effects of varying ranges of pixel intensities, furthermore, a [0 , 1] range unlocks the potential to use the softmax activation function for the classification layer.

Figure 5. *Image before preprocessing.*

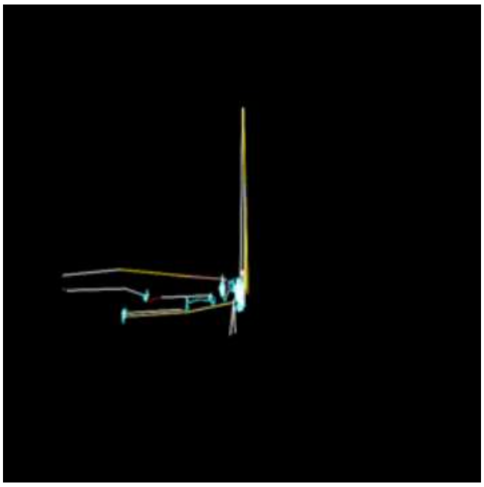


Figure 6. *Image after resizing and normalization.*

4.3 Data Augmentation

In order to compensate for the dataset's size being small, data augmentation was necessary to give the model more room to train, improving its robustness and eliminating overfitting which improves how the model generalizes on new data, three augmentation

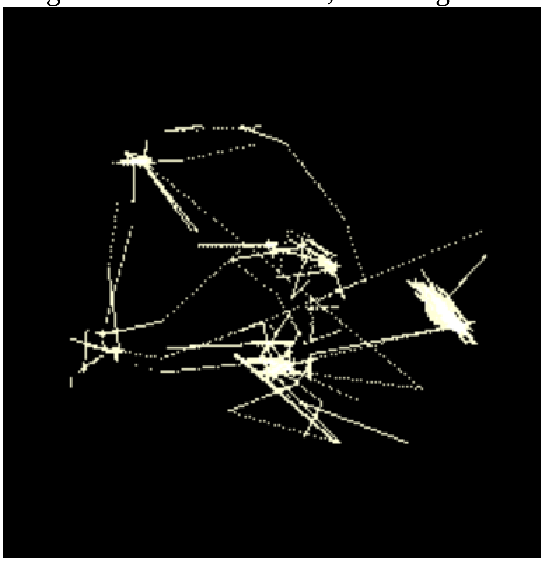


Figure 7. *Normalized image before flipping.*

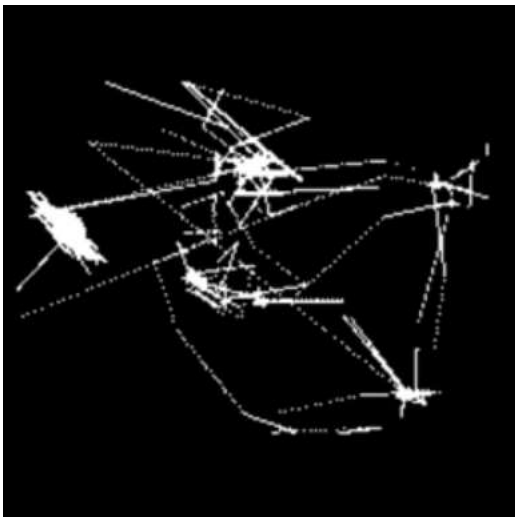


Figure 8. *Normalized image after flipping.*

methods were utilized to expand the dataset, first was random flipping of images both horizontally and vertically, here's an example of an image before and after flipping: The second augmentation method was random rotation of an image either clockwise or counterclockwise up to 20 degrees, here's an example:

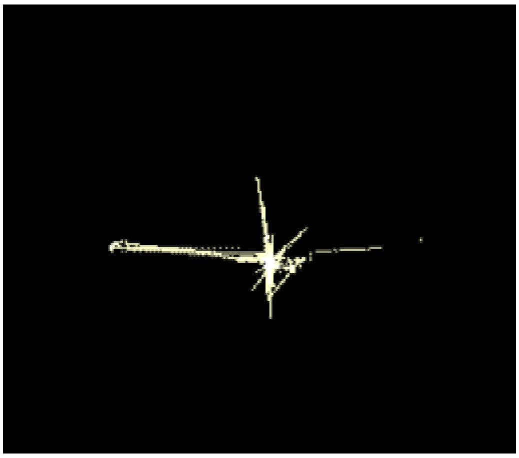


Figure 9. *Normalized image before rotation.*

Figure 10. *Normalized image after rotation.*

And lastly, another augmentation method was random zooming in or out of a picture, zooming in or out was randomly chosen as well as the degree of zooming in a range of up to 20 degrees.

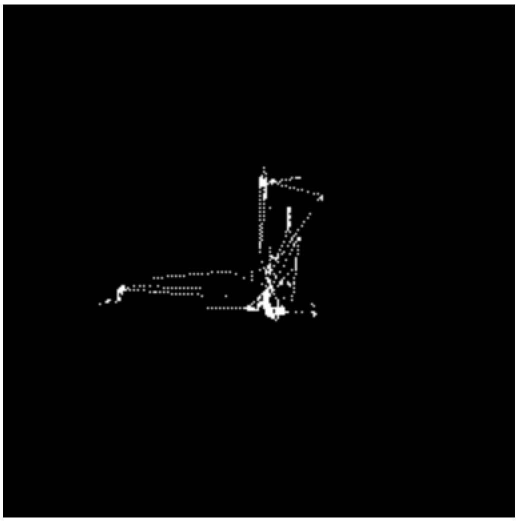


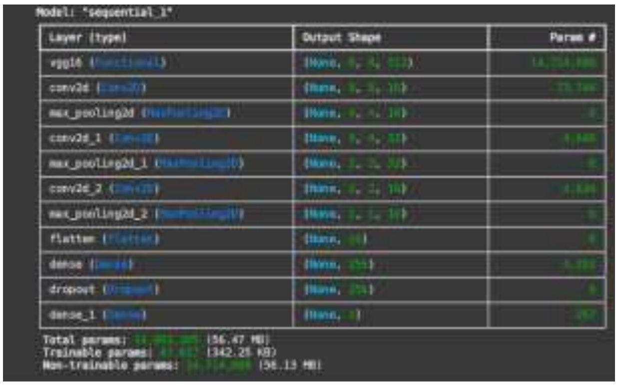
Figure 11. *Normalized image before zooming.*

Figure 12. *Normalized image after zooming.*

4.4 "Intelligent ASD Detector" CNN Architecture

The proposed model is based on the VGG16 architecture [32] with some modifications, the CNN consists firstly of the VGG16 architecture, discarding the final fully connected layers, and is appended by additional convolution and pooling layers to adapt to the dataset, the input layer is modified to accept 256x256 RGB images as input instead of the VGG16's 224x224 RGB, each image is resized and normalized to ensure consistency and facilitate efficient training.
The input layer's output is fed to consecutive convolution and pooling layers, the convolution layers extract hierarchical features from the input images, the early layers focus on detecting basic patterns, such as edges and textures, while deeper layers capture more complex features, such as shapes and regions of interest [33], the VGG16's use of small 3x3 convolutional filters enhances its ability to learn fine-grained details without introducing excessive computational overhead.
The max-pooling layers reduce the spatial dimensions of feature maps while retaining the most salient features, this step helps reduce the model's complexity and prevents overfitting by introducing spatial invariance [33].
The fully connected layers act as classifiers, they take the extracted features and map them to the output classes [33] (ASD or neurotypical), dropout regularization is applied in these layers to mitigate overfitting.
As for the output layer, it uses a softmax activation function to provide probabilities for each class, enabling precise classification.

The model was compiled using the TensorFlow library, figure 13 shows the model architecture table, showing each layer, its output shape and the total number of trainable parameters.



Model: "sequential_1"

Layer (type)	Output Shape	Param #
vgg16 ([illegible])	(None, [illegible])	[illegible]
conv2d ([illegible])	(None, [illegible])	[illegible]
max_pooling2d ([illegible])	(None, [illegible])	[illegible]
conv2d_1 ([illegible])	(None, [illegible])	[illegible]
max_pooling2d_1 ([illegible])	(None, [illegible])	[illegible]
conv2d_2 ([illegible])	(None, [illegible])	[illegible]
max_pooling2d_2 ([illegible])	(None, [illegible])	[illegible]
flatten ([illegible])	(None, [illegible])	[illegible]
dense ([illegible])	(None, [illegible])	[illegible]
dropout ([illegible])	(None, [illegible])	[illegible]
dense_1 ([illegible])	(None, [illegible])	[illegible]

Total params: [illegible] (56.47 MB)
Trainable params: [illegible] (342.25 KB)
Non-trainable params: [illegible] (56.13 MB)

Figure 13. *Model architecture table.*

Figure 14 shows a graph of the model's CNN architecture and layers showing the way our methodology works, a detailed illustration of the "Intelligent ASD Detector" layers is shown below.

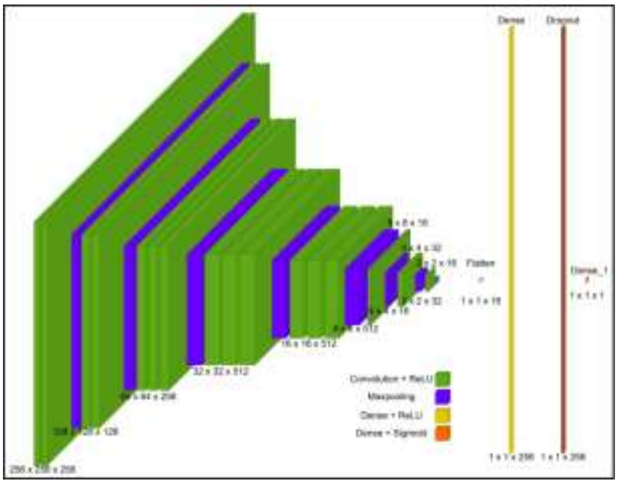


Figure 14. *CNN Architecture for the "Intelligent ASD Detector".*

5. Training and Evaluation Results

5.1 Model Training

Training was done in the online Google Colab environment, the T4 GPU was instrumental for achieving fast training times, the model was trained using the Adam optimizer with a learning rate of 0.001 and a categorical cross-entropy loss function. Multiple models were trained using different combinations of data augmentation methods, the goal was to avoid overfitting and find the best performing model. Evaluation metrics include accuracy, precision, recall and F1-score. The dataset contained 547 images that were split into batches of 32 images each, giving us a total of 17 32-image batches and one 3-image batch, the training-validation-testing split was approximately 70-20-10% yielding 12 batches for training, 3 for validation and 2 for testing, 4 combinations of data augmentation methods were applied to the dataset each giving different results, method 1 was random flipping, method 2 was random rotation and method 3 was random zoom, in the next section we discuss the results of training the model after expanding the training batches using combinations of these methods.

5.2 Model Evaluation and Experimental Results

5.2.1 Model 1

The first model was trained on an augmented dataset consisting of 36 batches of 32 images each for a total of 1152 images, the dataset was extended using random flipping and random rotation, the model achieves an accuracy reaching 92.1%, with precision and recall values reaching 94.4% and 81% respectively.

5.2.2 Model 2

The second model was trained on an augmented dataset consisting of 36 batches of 32 images each for a total of 1152 images, the dataset was extended using random flipping and random zooming, the model overfits the training data reaching a 100% score for all metrics making it unfeasible to use.

5.2.3 Model 3

The third model was trained on an augmented dataset consisting of 36 batches of 32 images each for a total of 1152 images, the dataset was extended using random rotation and random zooming, the model achieves an accuracy reaching 98.4%, with precision and recall values reaching 100% and 95.2% respectively.

5.2.4 Model 4

The fourth model was trained on an augmented dataset consisting of 48 batches of 32 images each for a total of 1536 images, the dataset was extended using all three augmentation methods yielding the best results out of all the models, with an accuracy reaching 98.4% after 70 Epochs of training, with precision and recall values reaching 96.6% and 98.5% respectively.

The following table compares the four models results, clearly indicating that Model 4 is the most effective for the given task.

Table 2. *Experimental results table.*

Model	Precision	Recall	Accuracy
Model 1	94.4%	81%	92.1%
Model 2	-	-	-
Model 3	100%	95.2%	98.4%
Model 4	**96.6%**	**100%**	**98.4%**

5.3 Comparison with Previous Works

Here we present a comparison between our model and previous works focused in eye-tracking technology, higher values of accuracy, precision and recall are highlighted in bold.

Table 3. *Comparison with previous works.*

Model	Precision	Recall	Accuracy
He, Qiao et al. [21]	94.1%	96%	81.1%
Cilia, Federica, et al. [22]	80%	83%	90%
Fernández, Dennis Núñez, et al. [23]	96.7%	92.9%	95.1%
Jaradat, Ameera S et al. [24]	**98.2%**	98%	98.1%
Our Model	96.6%	**100%**	**98.4%**

As shown in the table, the proposed intelligent ASD detector shows a solid advantage in accuracy and recall while maintaining very high and reliable precision compared to the previous works, which emphasizes its potential.

5.4 Loss, Accuracy and Confusion Matrix

As we can see from figures 14, 15 and 16, the intelligent ASD detector exhibits high precision and recall for the ASD class as can be seen from the confusion matrix, a testament to its reliability in classifying ASD children from neurotypicals, in addition, loss curves indicate minimal overfitting and accuracy curves show great reliability in ASD classification.

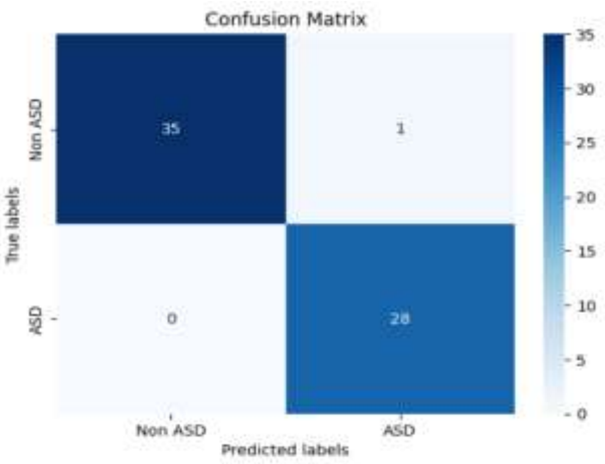


Figure 15. *Confusion matrix.*

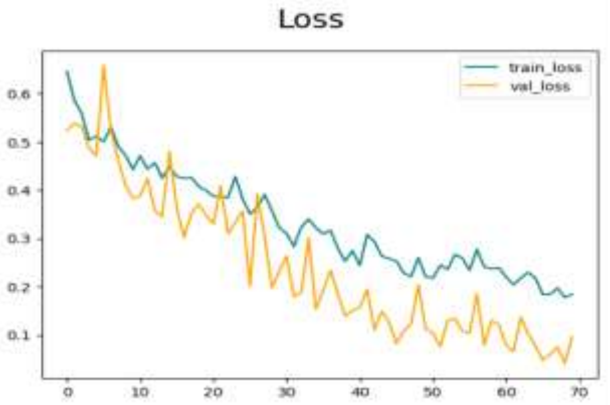


Figure 16. *Loss curves.*

Figure 17. *Accuracy curves.*

6. Conclusions

This paper highlights the potential for eye-tracking technology and CNNs for effective ASD classification at an early age, with early intervention being highly key in positively affecting future development of ASD children, this study offers an effective, reliable non-invasive tool for ASD diagnosis that shows promise for clinical applicability with its high accuracy and simple preprocessing requirements unlike other methods, future work must put an emphasis on developing interpretable AI models for clinical trust, dataset expansion via institutional cooperation and expanding deep learning use creating more robust, effective and multimodal approaches for ASD diagnosis.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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