

Transforming Early Autism Screening with Multimodal Machine Learning in Digital Health

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KEY WORDS	ABSTRACT
Autism Spectrum Disorder Deep Learning Image Classification Questionnaire Model Mobile Application Early Detection	Early and accurate detection of Autism Spectrum Disorder (ASD) is the key factor in facilitating early interventions and enhancing development in children with ASD. This paper proposes an innovative, multimodal diagnostic framework that utilizes machine learning methods by combining both behavioral testing through questionnaires and facial image analysis. Each modality was trained independently, and the results were fused in a user-friendly mobile application, increasing accessibility as well as clinical utility. The proposed system demonstrates high performance in identifying ASD-related characteristics, achieving high predictive accuracy through a non-invasive, cost-effective, and scalable method. Our results demonstrate the transformative potential of machine learning to improve early ASD screening (especially in resource-limited contexts) and contribute to the development of intelligent digital health solutions. The integrated model was found to have an overall diagnostic accuracy of 85%, with the questionnaire-based classifier having almost perfect accuracy and the image-based model showing a promising generalizability. These findings show that the proposed system has the potential to become a practical solution for early ASD detection and effectively enable timely, life-changing interventions.

1 Introduction

Autism Spectrum Disorder (ASD) is a neurological condition that affects communication and social interaction abilities. To provide timely interventions that have been shown to significantly improve multiple aspects of cognitive, behavioral, and social outcomes in affected individuals, early detection of ASD is of utmost criticality. The World Health Organization (WHO) states that Autism Spectrum Disorder (ASD) is a varied type of neurodevelopmental disorder that is found in approximately 1 in 100 children worldwide. While characteristics may be observed in early childhood, diagnosis is often delayed, and the needs of individuals with ASD vary widely from those who can

live independently to others who require lifelong care and support [1].

ASD is one of the many neurodevelopmental disorders. It is described as the impaired ability to interact socially as well as engage in communication, with more repetitive and restrictive behavioral patterns. It is the level of expression and understanding that makes the condition complex and a disorder on a spectrum. Due to this, ASD often requires individualized evaluations. Therapeutic interventions can help individuals with ASD if provided as early as possible. The main focus of such interventions is on behavioral, cognitive, and social approaches [2]. Traditional approaches and diagnostic methods are resource-intensive and time-consuming. It needs an expert clinical judgement and resources,

which are not easily available in underprivileged areas. These limitations highlight that there is an urgent need for accessible, efficient, and scalable screening methods for ASD that can support early diagnosis and intervention. [3]

To overcome these challenges, this paper proposes a novel approach by integrating behavioral data and facial images with machine learning algorithms. This approach enhances effectiveness and makes it easier for the clinics to identify ASD. Using this model through mobile application deployment, both caregivers and health professionals can have its accessibility. [4]

2 Literature Review

There has been much interest in recent years regarding the detection of Autism Spectrum Disorder (ASD) since the evolution of machine learning (ML) techniques. Early detection is vital for proper intervention, and many researchers have explored

various methodologies to increase detection accuracy and accessibility.

2.1 Questionnaire-Based Approaches

2.1.1 Behavioral Assessment

Tools: According to Table 1, most conventional diagnostic tools have been based in the past on behavioral assessments conducted by professional personnel. This includes the Autism Diagnostic Observation Schedule (ADOS) and the Autism Diagnostic Interview-Revised (ADI-R). The disadvantage of such an assessment is that it could be subjective and time-consuming. A recent study proposes the use of machine learning algorithms for responses in standardized questionnaires, among which are the Childhood Autism Rating Scale (CARS) and the Social Responsiveness Scale (SRS). Support Vector Machine and KNN applied over questionnaire data by Shrivastava et al in [5] for the assessment of children with ASD classified and have an accuracy rate of 87.52% and 83.53% respectively.

Table 1

Questionnaire Data Collection

		<i>For each item, please circle the response which best applies to your child:</i>				
		A	B	C	D	E
1	Does your child look at you when you call his/her name?	Always	Usually	Sometimes	Rarely	Never
2	How easy is it for you to get eye contact with your child?	Very easy	Quite easy	Quite difficult	Very difficult	Impossible
3	Does your child point to indicate that s/he wants something? (e.g. a toy that is out of reach)	Many times a day	A few times a day	A few times a week	Less than once a week	Never
4	Does your child point to share interest with you? (e.g. pointing at an interesting sight)	Many times a day	A few times a day	A few times a week	Less than once a week	Never
5	Does your child pretend? (e.g. care for dolls, talk on a toy phone)	Many times a day	A few times a day	A few times a week	Less than once a week	Never
6	Does your child follow where you're looking?	Many times a day	A few times a day	A few times a week	Less than once a week	Never
7	If you or someone else in the family is visibly upset, does your child show signs of wanting to comfort them? (e.g. stroking hair, hugging them)	Always	Usually	Sometimes	Rarely	Never
8	Would you describe your child's first words as:	Very typical	Quite typical	Slightly unusual	Very unusual	My child doesn't speak
9	Does your child use simple gestures? (e.g. wave goodbye)	Many times a day	A few times a day	A few times a week	Less than once a week	Never
10	Does your child stare at nothing with no apparent purpose?	Many times a day	A few times a day	A few times a week	Less than once a week	Never

2.1.2 NLP:

Another application that can be used to analyze open-ended questionnaires is in Natural Language Processing (NLP). Themistocleous et al. [6] applied the NLP methods in assessing textual responses of parents concerning their children's behaviors that present prominent patterns leading to ASD. Their feature extraction methods with supervised algorithms significantly improved the accuracy for diagnosis.

2.1.3 Multimodal Data Integration:

Some recent studies have begun to investigate the integration of questionnaire data with other modalities. For example, B. Twala and E. Molloy [7] integrated questionnaire responses with demographic and behavioral data. They used ensemble-learning techniques to improve the predictive performance of their model. Their model showed a strong ability to detect ASD traits, and multimodal data can be used to improve diagnostic tools.

2.2 Image-Based Approaches

2.2.1 Facial Morphology Analysis:

There have been some research findings indicating that children with ASD might have some morphological features on their faces. Some researchers have utilized facial recognition technology and image analysis in finding such features. For example, one of the first studies in this area by S. Wang et al. [8] utilized a CNN on children's facial images, achieving a high classification accuracy of approximately 97.6%. They found some facial features as possible markers of ASD. Fig. 1 illustrates which facial features the image classification model will target.

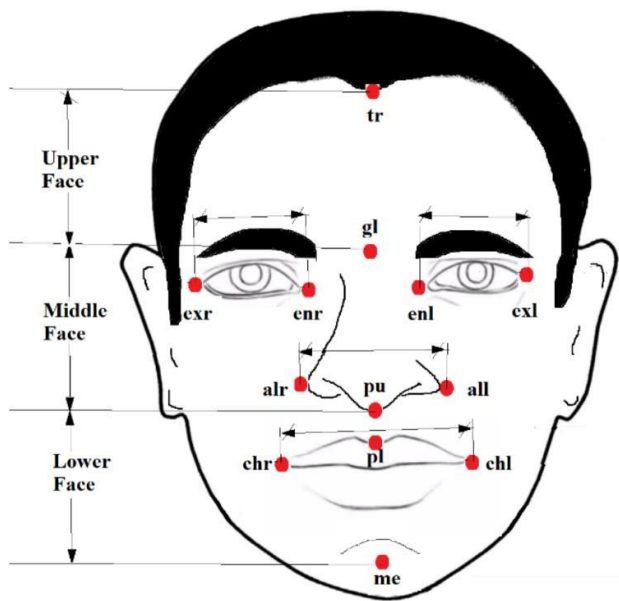


Fig. 1. Which facial features will the image classification model target [19]

2.2.2 Deep learning architecture

Deep learning architectures in image analysis, Patel et al. [9] trained a deep CNN on a large dataset for the classification and analysis of facial images of children diagnosed with ASD and control groups. The high accuracy of the model above 80% has been reported by this model, besides some facial landmarks differences between the two groups being observed, thus providing a deeper understanding of ASD phenotypes.

2.2.3 Behavioural Cues from Video Analysis:

Table 2

Summary of Existing Research

Reference	Techniques	Limitations	Results/Evaluations
Shrivastava, T., Singh, V., & Agrawal, A. (2024). [5]	Random Forest, SVM, KNN, ANN.	Limited/missing data; imbalance; real-world not addressed.	100% (RF), 87.5% (SVM), 83.5% (KNN), 84.4% (ANN)
I. A. Ahmed <i>et al.</i> ,(2022) [8]	NN, CNN, Hybrid ML+DL	Limited evidence for eye-tracking	99.8% (FFNN/ANN), 97.6% (ResNet-18), 93.6% (GoogleNet), 95.5% (GoogleNet+SVM), 94.5% (ResNet-18+SVM)

Recent studies have increasingly turned to video data for extracting real-time behavioural cues linked to Autism Spectrum Disorder (ASD). For instance, H. Kim et al. [10] combined motion capture with convolutional neural networks (CNNs) to identify social engagement behaviors in children during play sessions. Their work suggests that video-based analysis can complement traditional diagnostic methods by offering a richer understanding of how children interact in naturalistic settings.

The authors in [14] researched on data that included eye gaze, body expressions, and facial images. Their approach achieved an accuracy of 96%. Computational cost and the interpretability of their results, however, still posed to be a concern.

Similarly, [15] worked on a dataset of 956 ASD-associated genes. Their study reported diagnostic yields of 17.1% for ASD, 24% for epilepsy, and 28.2% for intellectual disability. Despite these encouraging results, interpretation proved complex due to overlapping psychiatric comorbidities.

In [16], further advances of augmentation techniques with MiAMix, which significantly improved classification accuracy to 96.9% with ResNet-18, albeit needing precise parameter tuning.

Ensemble learning showed promise as well: [17] reported that ensembles achieved better results than single classifiers, but endured interpretability, resource, and range constraints, with performance between 63.8% and 73.5%.

Multimodal approaches have been tested too: [18] integrated EEG with behavioral features and applied a Naïve Bayes hybrid model, obtaining an accuracy of 87.5%, but was constrained by a small sample size and associated overfitting risks.

Most recently, [19] combined Random Forest with XGBoost and feature selection to show that these techniques can together achieve a 98% accuracy, which was constrained due to small datasets and biases on general applicability. A summary of the existing research is given in Table 2.

F. W. Alsaade and M. S. Alzahrani (2022) [9]	Xception, VGG19, NASNET (facial images)	Publication/data issues; peer-review concerns	91% (Xception), 80% (VGG19), 78% (NASNET)
I. Ahmad, J. Rashid, M. Faheem, A. Akram, N. A. Khan, and R. ul Amin (2024) [10]	Facial expression models (ResNet50, Naïve Bayes, AlexNet, PCA)	Limited dataset; privacy concerns	92% (ResNet50), 87.5% (Hybrid NB), 87% (AlexNet), 82.3% (PCA)
M. S. Farooq, R. Tehseen, M. Sabir, and Z. Atal (2023) [11]	Meta-classifier (label encoding, Q-CHART-10)	Device/storage limits; heterogeneous data	98% (child), 81% (adult, LR); 99% (child), 78% (adult, ML)
T. D. Dhamale, S. U. Bhandari, V. K. Harpale, and D. Nandan, (2024) [12]	Structural + functional MRI with CNN	Data scarcity; hyperparameter tuning; small datasets	90.6% (PDCNN+Adam), 88.5% (PDCNN+RMSProp), 70.2% (Parallel CNN)
Mian, T. S. (2023) [13]	Lightweight CNN, transfer learning (EfficientNet, VGG19)	Small datasets; bias in precision/recall; ASD complexity	85% (EfficientNet B0), 84% (VGG19)
B. R. G. Elshoky, E. M. G. Younis, A. A. Ali, and O. A. S. Ibrahim, (2022) [14]	MMDB dataset (behaviour, gaze, asymmetry, AutoML, CNN)	Black-box issue; integration challenges; long training	69% (NB), 57% (LDA), 62% (KNN), 84% (CNN), 89% (VGG16), 96% (AutoML)
A. Genovese and M. G. Butler, (2023) [15]	Gene annotation pipeline (956 genes, X-linked variants)	Behavioral/psychiatric comorbidities	17.1% (ASD yield), 24% (epilepsy), 28.2% (intellectual disability)
W. Liang, Y. Liang, and J. Jia, (2023)[16]	MiAMix augmentation (ResNet-18, CIFAR-10)	Needs parameter tuning; MSDA integration	96.9% (ResNet-18, CIFAR-10)
M. Liao, H. Duan, and G. Wang, (2023) [17]	Ensemble learning (DT, ANN, MSDA, DCS)	Time/resource heavy; interpretability; poor ensemble cases	64.3% (DT), 63.8% (ANN), 73.5% (MSDA), 71.8% (DCS)
F. Hajjej, S. Ayouni, M. A. Alohal, and M. Maddeh, (2022) [18]	EEG + behavioral fusion (Naïve Bayes hybrid)	Small sample (80); overfitting risk; real-world validation needed	87.5% (EEG + behavior fusion)
Mujeeb Rahman, K. K., & Subashini, M. M. (2024) [19]	RF + XGBoost ensemble, feature selection	Small sample; bias; limited generalization	94% (RF-XG), 98% (RF-XG+FS), 85% (LR), 89% (SVM)

3 Methodology

Our methodology, as shown in Fig. 2, illustrates the development and integration of two machine learning models. The models analyze questionnaire data and facial images, respectively, and their outputs are combined using a weighted average approach.

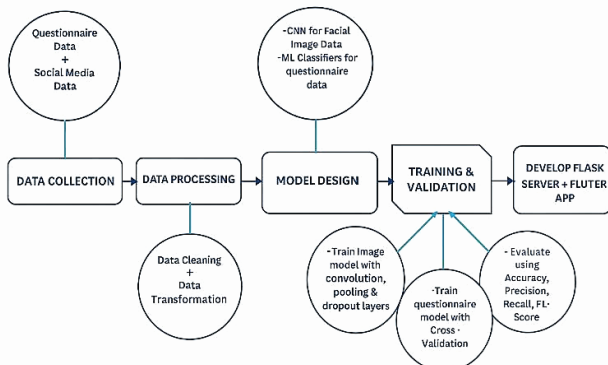


Fig 2: Methodology of Research

3.1 Data Collection

All the data was taken using questionnaires and facial images. Subsequently, the set was further divided into training, validation, and testing sets based on a 70:20:10 ratio following best available practices in machine learning. Sometimes, synthetic data had to be used because true world data is not attainable at times without violating privacy issues or with considerable effort; however, everything is done in accordance with ethical instructions.

3.1.1 Questionnaire Model

The questionnaire model was implemented using a Support Vector Classifier, which is known to work well on a binary classification task. Questionnaire data were pre-processed and encoded before feeding them into the model. The SVC model achieved notable accuracy, making it suitable for our application

3.1.2 Image Classification Model

For the image classification model, we used a CNN model. The CNN was trained on facial images augmented using techniques to address the class imbalance and enhance the generalization of the model. The output of the CNN model was binary: whether the images indicate the presence of ASD traits or not. Figure 3 illustrates the working of the image classification model with the different convolutional layers as its base.

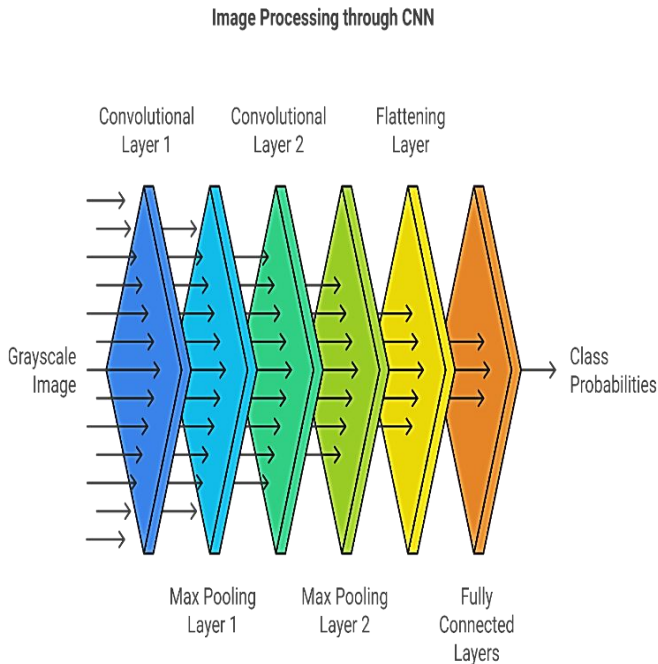


Fig. 3. How a Convolutional Neural Network works.

The configuration of the implemented model and related hyperparameters are given in Table No. 3.

Table 3

Summary of Existing Research

Model Parameter	Configuration/Values
Number of Classes	2 (Autism, Non-Autism)
Model Type	Sequential
Layer Types and configuration	Conv2D layer MaxPooling2D layer Conv2D layer MaxPooling2D layer Conv2D layer MaxPooling2D layer Flatten layer Dense layer Dropout layer
Loss function	Binary Cross-Entropy
Activation Function	Relu and Sigmoid (for Dense Layer)
Dropout Rate	0.5

3.2 Model Integration

The output of the two models was combined by a weighted average, which gave more weight to the questionnaire model because it had more accuracy.

This integration is used to come up with a final decision that depends on both the behavioral and morphological features of ASD.

3.3 Deployment

It had a Flask-based backend service to serve the integrated model. The Flutter application calls the API, makes an inference, and returns the results to the user, hence making it a very responsive and user-friendly system. Fig. 4 shows the overall system from its data preprocessing to complete deployment.

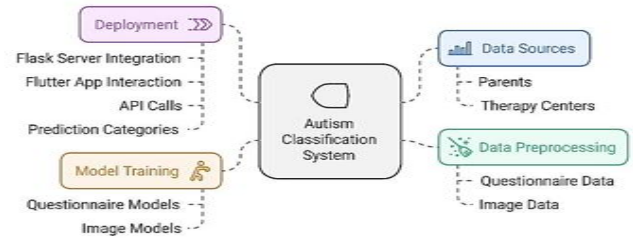


Fig. 4. Overall working of the system

4 Results

4.1 Evaluation Metrics:

In evaluating machine learning models for detecting autism, several performance metrics are essential:

4.1.1 Accuracy

Accuracy measures the proportion of correct predictions (both positive and negative) among all cases. It is calculated as:

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN})$$

Where:

TP = True Positives TN = True Negatives FP = False Positives FN = False Negatives

4.1.2 Precision

Precision (Positive Predictive Value) is the ratio that shows the accuracy of positive predictions. It highlights how many of the predicted positive cases are actually positive and is calculated using the following formula:

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

4.1.3 Recall

Recall reflects how well the model captures actual positive instances by identifying all relevant positive cases. This calculation is done as follows:

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$$

4.1.4 F1 Score

In cases where data is imbalanced, F1 Score provides a harmonic mean between precision and recall, calculated by:

$F1 \text{ Score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$

All these metrics collectively provide an all-inclusive assessment of how well a model performs.

Table 4 shows that our image classification model performs well for all these metrics. It achieved a training accuracy of 77.82% and a validation accuracy of 78.44%, indicating good generalization. Its precision is 70.70% and its recall is 70.25%, reflecting a fair balance between detecting positives and avoiding false positives. The model's overall performance is supported by an F1 score of 70.48. The training loss of 2.49 and validation loss of 1.96 suggest the model is converging, and the lower validation loss indicates overfitting is unlikely. Overall, these results confirm that image classification is a suitable model for further optimization toward higher accuracy.

Table 4

Results of Image Classification Model

Metric	Value
Training Accuracy	0.7781690359115601
Validation Accuracy	0.784375011920929
Precision	0.7070064
Recall	0.70253164
F1 Score	0.704761908386475
Training Loss	2.494826078414917
Validation Loss	1.963855504989624

In Fig. 5, the difference between training and validation in the accuracy graphs is shown. It trained accuracy on a very steep line smoothly, increasing all along from 0.65 to 0.79 with the epoch change in the

8, which clearly shows that it is learning from the data provided in training. The validation accuracy oscillates far more chaotically. It rose to 0.75 in the second epoch, rose to 0.54 in the fourth epoch, and then recovered to 0.76 in the eighth epoch. This might be a symptom of overfitting, as validation accuracy does not keep pace with training accuracy. The gap between training and validation curves continuously widens at the tail end; this is again an indicator of overfitting danger. Possible countermeasures could be some form of regularization that ensures the model is not able to memorize the data in training, or possibly early stopping, which would further enhance its generalization towards unseen data.

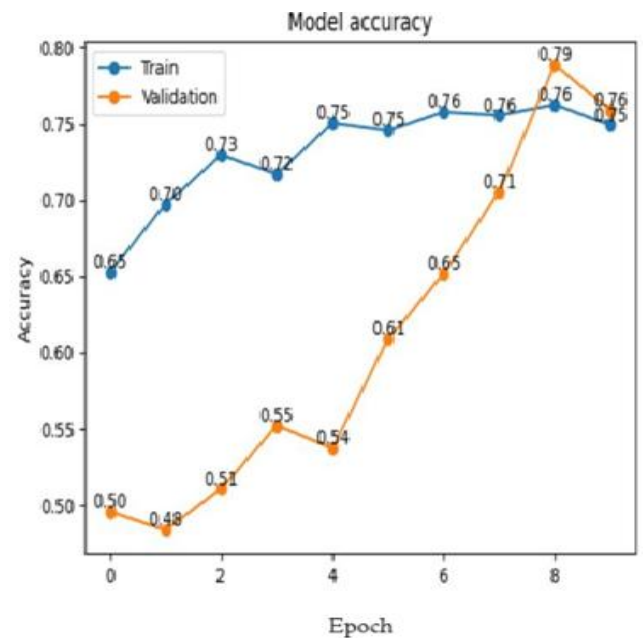


Fig. 5. Accuracy of image classification model

Figure 6 shows the loss graph of how the model is doing throughout the training. In the graph, the blue curve represents the training loss, while the orange curve represents the validation loss. Therefore, both losses are high in the very initial stages and begin to reduce as the training continues to the second epoch, where the minimum value is achieved. Despite this drastic drop in training loss, its validation counterpart also falls until the second epoch and somehow starts rising slightly before falling again. This is a clear divergence of the training loss and validation loss, indicating overfitting.

The model is relying too heavily on the training data and not generalizing well to unseen data. To address this overfitting, early stopping or regularization can be used to prevent the model from memorizing the training data, thereby enhancing its performance on new, unseen data.

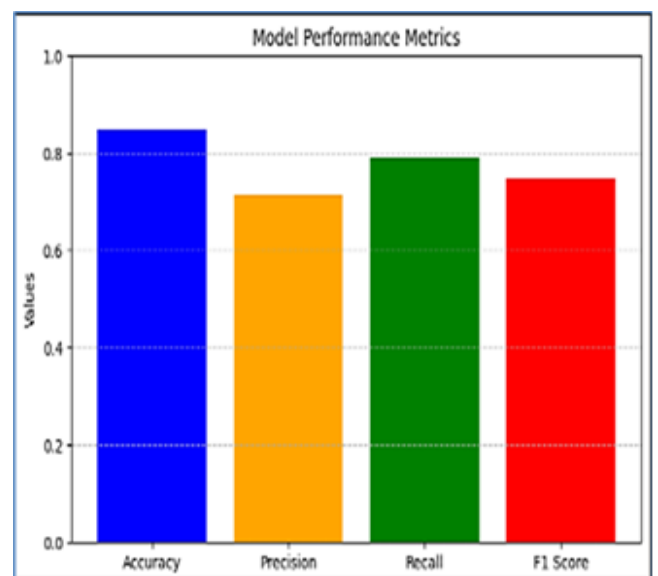


Fig. 6. Comparison of training and validation losses of the image classification model

The questionnaire model is very effective in all the metrics. According to Fig. 7, it has almost perfect accuracy at 0.9988, indicating that it predicts most of the instances in the dataset with correctness. Precision is at 0.9978, recall is 1.0, and the F1 score is at 0.9989, indicating that the model can identify positive cases with a great degree of precision while reducing false positives and false negatives. AUC = 0.9986; Kappa = 0.9975 indicates that the model has made predictions that are almost close to reality, and the Kappa score of 0.9975 indicates almost perfect agreement between the classes obtained by the model and the original classes. The low error rate of 0.00122 confirms the exceptional performance of the model. This makes the model highly accurate and reliable for making predictions on new data.

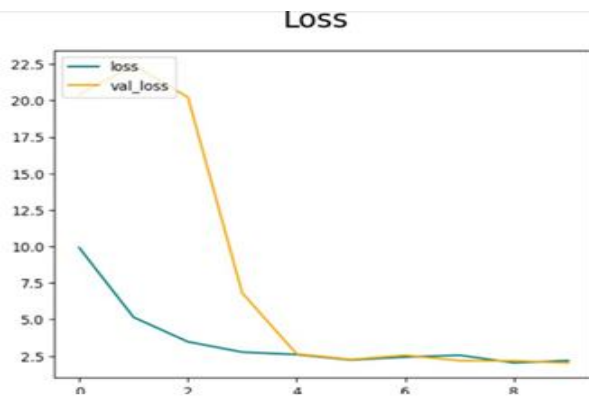


Fig. 7. Results of questionnaire model

The combined model performs well with very good accuracy over multiple measures. As illustrated by Fig. 8, the accuracy attained was 0.85, meaning it classifies 85% of instances in the dataset correctly. It has a precision level of 0.72, meaning 72% of the positive predictions that this model makes are correct. With a recall of 0.80, that is, 80% of the positive instances present in the data set were rightly predicted by the model. A score of 0.76 F1 score provided by the model indicates that the measure is balanced, which is a measure of precision and recall, showing that the overall effectiveness of the model is good. Therefore, the results point to this model as being a good predictive tool for new data, providing good accuracy, precision, and recall.

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Number of features in the training data: 17
10-Fold Cross Validation Score: 1.0
Time Elapsed: 4.381624937057495
Log Loss: 0.004209641654308207
Accuracy = 0.9987775061124694
Precision = 0.9978308026030369
Recall = 1.0
F1 Score = 0.998914223669924
AUC Score = 0.9986033519553073
Kappa score = 0.9975156260440141
Error rate = 0.0012224938875305957

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Fig. 8. Results of the combined hybrid model

5 Application Interface

The results of the combined hybrid model proved that it could classify instances effectively, both based on image data and questionnaire responses, with an overall robust solution for autism detection. Fig. 8 shows the Home Screen, Login Screen, and Profile Screen for the application developed to early identify Autism.

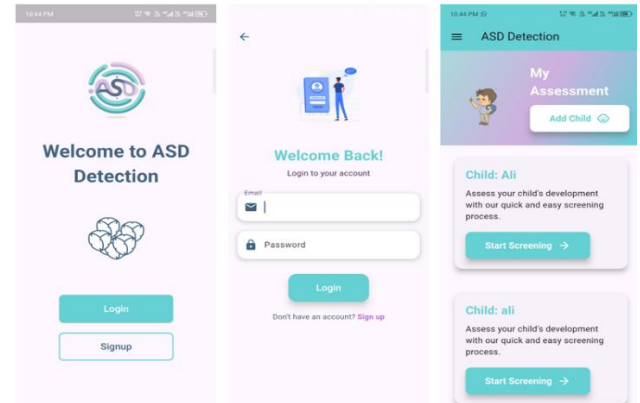


Fig. 9. Home Screen, Login Screen, Profile Screen

Fig. 10 shows the child behavioral questionnaire and image analysis for the detection of ASD.

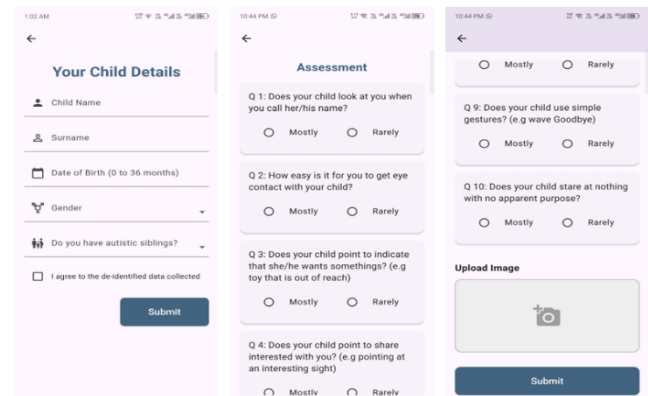


Fig. 10. Child Behavioral and Image Assessment

Fig. 11. clearly depicts the final prediction that the child is at high, low, or very low risk of autism.

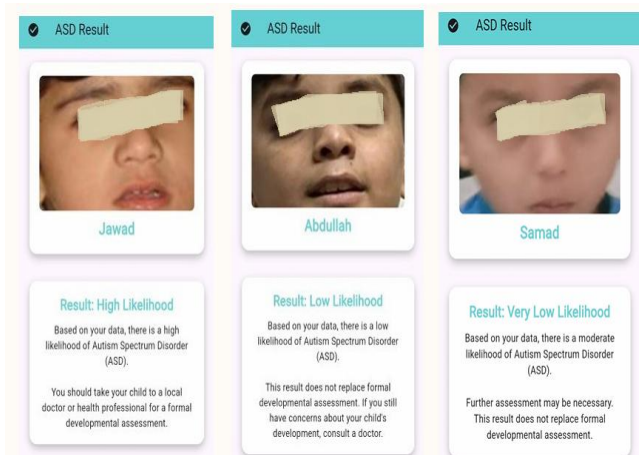


Fig. 11. Final prediction of High, Low, and Very Low likelihood ASD Result

6 Discussion

Results of the image classification model give an encouraging performance with 77.82% training accuracy and a validation accuracy of 78.44%. This would mean it generalizes very well to unseen data, which is important for real-world applications. On the side of precision, 70.70% would give a good balance of recognizing positive cases with minimum false positives, and a recall of 70.25% is reasonable. The F1 score of 70.48% further supports the effectiveness of the model in this regard, thus showing its ability to maintain a trade-off between precision and recall.

The training and validation loss values are at a value of 2.49% for training loss and at 1.96% for validation loss, which indicates convergence during training. Lower validation loss than the training loss, meaning the model is not overfitting to the training data, is good. Still, close inspection of the accuracy graph indicates that the validation accuracy at certain epochs does oscillate or change, and was observed increasing early to 75%, then going down to 54%, and then after several epochs, increasing again to 76%. This would suggest overfitting: the validation accuracy was no longer following a consistent rise corresponding to the steadily improving training accuracy. The wide separation at the end of training of the two curves further supports the intuition for overfitting.

To reduce overfitting in further model iterations, early stopping or regularization techniques might be included. Such techniques aim to enhance generalization as the model is prevented from mere memorization the data given in the training set. In practice, this type of method would cause improvements in validation performance as the model will not be ruined once it comes up with new data.

The loss graph elaborates on the learning dynamics of the model. The graphs indicate that both the losses from training and validation are high even during the very initial stages of learning. With training loss, the decreases are sharp because the effective learning from the data for training is taking place; however, the validation loss first decreases, then shows a nearly constant trend in most cases, and may even increase after the second epoch. This divergence thus signals that the model is specialized on the training set, which disables the generalization ability of the model.

The accuracy in the combined model reaches 85%. It shows an 85% correct prediction on average through the combined model. This, in turn, implies robustness to predictions as the precision comes at 72%, implying a great number of true positives are accurate, while recall suggests that the model identified nearly 80% of

actual positive instances. A high score of 76% for the F1 shows good balance between precision and recall. This means that the combined model not only is reliable but also is able to predict outcomes from integrated data sources.

7 Conclusion And Future Work

This research introduces a multi-modal framework for early diagnosis of ASD utilizing machine learning algorithms. The two modalities used in this work are traditional questionnaires and facial images. Our approach shows nearly flawless accuracy for the questionnaire element and a strong capacity for generalization for facial image classification. Combining all, It performed well and achieved an accuracy of 85% which is a great sign to use this system as a diagnostic tool for caregivers and clinical staff. This model was deployed in a mobile application, making it easy to access for everyone. This system can be extended in many directions and has room for improvement.

7.1 Dataset Extension:

The dataset remains a big challenge in this research, focusing on a very sensitive area due to privacy concerns. It can lead to overfitting in ML models, which affects the performance of the model. Hence, to build a top-notch model, it is essential to gather extensive datasets from multiple varied sources.

7.2 Multimodal Data Integration:

In this model, we only integrated two modalities, questionnaire and facial image; however, it can be further enhanced to add other modalities, making it more accurate by getting behavior clues from audio and video sensors. It would enable a deeper analysis for identifying ASD-associated characteristics and how they appear.

In conclusion, this paper demonstrated a novel approach using various modalities to help in identifying early autism disorders. In continuing this research, larger datasets and incorporating other modalities of data can enhance their effectiveness and applicability, in essence, leading to improved developmental outcomes for children with ASD.

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References

- [1] WHO, "Autism," <https://www.who.int/news-room/fact-sheets/detail/autism-spectrum-disorders>, D.O.A: 05-06-2024
- [2] Aba Discovery, "51 Autism Statistics," <https://www.discoveryaba.com/statistics/how-many-people-have-autism#:~:text=Around%20%25%20of%20the%20worlds,diagnosed%20with%20autism%20spectrum%20disorder>, D.O.A: 30-03-2025
- [3] Clinic Mayo, "Autism Spectrum Disorder - Symptoms and Causes - MayoClinic," <https://www.mayoclinic.org/diseases-conditions/autism-spectrum-disorder/symptoms-causes/syc-20352928>, D.O.A: 28-05-2025
- [4] Radha, S., Abinaya, M. N., Divya Darshini, K., Kamalnath, K. N., & Jayanthi, P. (2023). Ensemble of Behavioral Features for Early Detection of Autism Spectrum Disorder. In International Conference on Soft Computing for Security Applications (pp. 681-694). Singapore: Springer Nature Singapore.
- [5] Shrivastava, T., Singh, V., & Agrawal, A. (2024). Autism spectrum disorder detection with kNN imputer and machine learning classifiers via questionnaire mode of screening. *Health Information Science and Systems*, 12(1), 18.
- [6] Themistocleous, C. K., Andreou, M., & Peristeri, E. (2024). Autism Detection in Children: Integrating Machine Learning and Natural Language Processing in Narrative Analysis. *Behavioral Sciences*, 14(6), 459.
- [7] B. Twala and E. Molloy, "On effectively predicting autism spectrum disorder therapy using an ensemble of classifiers," *Scientific Reports*, vol. 13, no. 1, p. 19957, 2023, doi: 10.1038/s41598-023-46379-3.
- [8] I. A. Ahmed et al., "Eye Tracking-Based Diagnosis and Early Detection of Autism Spectrum Disorder Using Machine Learning and Deep Learning Techniques," *Electronics (Switzerland)*, vol. 11, no. 4, Feb. 2022, doi: 10.3390/electronics11040530.
- [9] F. W. Alsaade and M. S. Alzahrani, "Classification and Detection of Autism Spectrum Disorder Based on Deep Learning Algorithms," *Computational Intelligence and Neuroscience*, vol. 2022, Article ID 8709145, 2022. [Online]. Available: <https://doi.org/10.1155/2022/8709145>. (Retraction published Comput. Intell. Neurosci., Oct. 4, 2023, Article ID 9893015. doi: 10.1155/2023/9893015).
- [10] I. Ahmad, J. Rashid, M. Faheem, A. Akram, N. A. Khan, and R. ul Amin, "Autism spectrum disorder detection using facial images: A performance comparison of pretrained convolutional neural networks," *Healthc Technol Lett*, 2024.
- [11] M. S. Farooq, R. Tehseen, M. Sabir, and Z. Atal, "Detection of autism spectrum disorder (ASD) in children and adults using machine learning," *Scientific Reports*, vol. 13, no. 1, p. 9605, 2023, doi: 10.1038/s41598-023-35910-1.s.
- [12] T. D. Dhamale, S. U. Bhandari, V. K. Harpale, and D. Nandan, "Autism spectrum disorder detection using parallel deep convolution neural network and generative adversarial networks," *Traitement Du Signal*, vol. 41, no. 2, 2024.
- [13] Mian, T. S. (2023). Efficient Net-based Transfer Learning Technique for Facial Autism Detection. *Scalable Computing: Practice and Experience*, 24(3), 551-560.
- [14] B. R. G. Elshoky, E. M. G. Younis, A. A. Ali, and O. A. S. Ibrahim, "Comparing automated and non-automated machine learning for autism spectrum disorders classification using facial images," *ETRI Journal*, vol. 44, no. 4, pp. 613–623, 2022, doi: 10.4218/etrij 2021-0097.
- [15] A. Genovese and M. G. Butler, "The autism spectrum: Behavioral, psychiatric and genetic associations," *Genes*, vol. 14, no. 3, p. 677, 2023, doi: 10.3390/genes14030677.
- [16] W. Liang, Y. Liang, and J. Jia, "MiAMix: Enhancing image classification through a multi-stage augmented mixed sample data augmentation method," *Processes*, vol. 11, no. 12, 2023, doi: 10.3390/pr11123284.
- [17] M. Liao, H. Duan, and G. Wang, "Application of machine learning techniques to detect children with autism spectrum disorder," *Journal of Healthcare Engineering*, vol. 2022, 2022, doi: 10.1155/2022/9340027
- [18] F. Hajjej, S. Ayouni, M. A. Alohal, and M. Maddeh, "Novel framework for autism spectrum disorder identification and tailored education with effective data mining and ensemble learning techniques," *IEEE Access*,

- vol. 12, pp. 35448–35461, 2024, doi: 10.1109/ACCESS.2024.3349988.
- [19] Mujeeb Rahman, K. K., & Subashini, M. M. (2022). Identification of autism in children using static facial features and deep neural networks. *Brain Sciences*, 12(1), 94.
- [20] Centers for Disease Control and Prevention (CDC). (n.d). Data and Statistics on Autism Spectrum Disorder, <https://www.cdc.gov/ncbddd/autism/data.html> 1 (2024, July 2024)
- [21] Milling, M., Baird, A., Bartl-Pokorny, K. D., Liu, S., Alcorn, A. M., Shen, J., ... & Schuller, B. W. (2022). Evaluating the impact of voice activity detection on speech emotion recognition for autistic children. *Frontiers in Computer Science*, 4, 837269
- [22] Shrivastava, T., Singh, V., & Agrawal, A. (2024). Autism spectrum disorder detection with kNN imputer and machine learning classifiers via questionnaire mode of screening. *Health Information Science and Systems*, 12(1), 18.
- [23] Hu, C., Thrasher, J., Li, W., Ruan, M., Yu, X., Paul, L. K., ... & Li, X. (2024). Exploring Speech Pattern Disorders in Autism using Machine Learning. *arXiv preprint arXiv:2405.05126*.
- [24] Siddiqui, M. A., Haider, N. G., & Mustafa, S. M. N. (2024). Hybrid model for speech emotion recognition of normal and autistic children (SERNAC). *Mehran University Research Journal of Engineering & Technology*, 43(2), 20-33
- [25] Lee, S., Mun, J., Kim, S., & Chung, M. (2024). Speech Corpus for Korean Children with Autism Spectrum Disorder: Towards Automatic Assessment Systems. *arXiv preprint arXiv:2402.15539*.
- [26] Ahmed, I. A., Senan, E. M., Rassem, T. H., Ali, M. A., Shatnawi, H. S. A., Alwazer, S. M., & Alshahrani, M. (2022). Eye tracking-based diagnosis and early detection of autism spectrum disorder using machine learning and deep learning techniques. *Electronics*, 11(4), 530.
- [27] Themistocleous, C. K., Andreou, M., & Peristeri, E. (2024). Autism Detection in Children: Integrating Machine Learning and Natural Language Processing in Narrative Analysis. *Behavioral Sciences*, 14(6), 459.
- [28] Trayvick, J., Barkley, S. B., McGowan, A., Srivastava, A., Peters, A. W., Cecchi, G. A., ... & Corcoran, C. M. (2024). Speech and language patterns in autism: towards natural language processing as a research and clinical tool. *Psychiatry Research*, 116109.
- [29] Grande-Ramírez, J. R., Roldán-Reyes, E., Delgado-Maciel, J., Cortes-Robles, G., & Meza-Palacios, R. (2024, October). Model to Early Detection of Autism Spectrum Disorder Through Opinion Mining Approach. In *International Conference on Hybrid Artificial Intelligence Systems* (pp. 61-72). Cham: Springer Nature Switzerland.
- [30] Ahmed, M., Hussain, S., Ali, F., Gárate-Escamilla, A. K., Amaya, I., Ochoa-Ruiz, G., & Ortiz-Bayliss, J. C. (2025). Summarizing recent developments on autism spectrum disorder detection and classification through machine learning and deep learning techniques. *Applied Sciences*, 15(14), 8056.
- [31] Ahmad, I., Rashid, J., Faheem, M., Akram, A., Khan, N. A., & Amin, R. U. (2024). Autism spectrum disorder detection using facial images: A performance comparison of pretrained convolutional neural networks. *Healthcare Technology Letters*.
- [32] Vakadkar, K., Purkayastha, D., & Krishnan, D. (2021). Detection of autism spectrum disorder in children using machine learning techniques. *SN Computer Science*, 2, 1-9.