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A Machine Learning Approach for Autism Spectrum Disorder Detection Using Behavioural Data and Facial Features.

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ABSTRACT

Autism Spectrum Disorder (ASD) is a developmental condition that influences how a person communicates, behaves, and relates to others. Detecting ASD as early as possible is very important, since early therapy and support can improve long-term outcomes. In this study, we propose a dual approach that combines behavioral data with facial image analysis to improve detection accuracy. For behavioral data, we used the Q-CHAT-10 questionnaire and applied the Random Forest Classifier (RFC), which is known for handling complex patterns effectively. For image data, we applied the YOLOv5 model to detect faces and then classified the extracted features using a Support Vector Machine (SVM). Both datasets used in this work were publicly available and carefully preprocessed to ensure data quality. The behavioral model achieved 98% accuracy, while the image-based YOLOv5+SVM approach reached a mean average precision (mAP) of 0.91. When results from both models were combined, the system achieved an overall accuracy above 97%. These results suggest that integrating behavioral screening with facial analysis can provide a faster, more reliable tool for early ASD detection, supporting timely intervention and personalized care.

Keywords: Autism Spectrum Disorder (ASD), Random Forest Classifier (RFC), YOLOv5, Support Vector Machine (SVM), Behavioral Screening, Image Classification, Machine Learning, Deep Learning, Q-CHAT-10 Questionnaire, Early Detection

I. INTRODUCTION

Autism Spectrum Disorder (ASD) is a lifelong condition that affects how people communicate, behave, and connect with others. The symptoms are not the same for everyone. Some children show clear signs very early, while for others, the symptoms may appear gradually or remain subtle. Because of this diversity, diagnosing ASD can be a long and complex process.

According to the World Health Organization (WHO), around one in every 100 children worldwide is identified with ASD, though the actual number may be higher due to late or missed diagnoses. Traditional diagnosis usually involves lengthy clinical assessments, detailed observations, and interviews with caregivers. These steps are effective but time-consuming, often leading to long waiting periods. During this delay, many children miss the chance to receive timely support and therapy.

With recent advances in technology, new methods have emerged to support early ASD detection. Machine Learning (ML) and Deep Learning (DL) algorithms are now being applied to data such as behavioral questionnaires, facial images, speech, and even brain scans. These methods are faster, more objective, and can handle large amounts of data with high accuracy.

In this work, we focus on two main approaches: analyzing behavioral responses and examining facial features. For the behavioral part, we use the Q-CHAT-10 questionnaire, which is short, practical, and widely used for autism screening. The responses are then classified using a Random Forest Classifier, an algorithm known for its strong accuracy in handling structured data. For the image part, YOLOv5 is applied to detect and isolate faces, followed by classification using a Support Vector Machine (SVM).

The goal of combining these two methods is not to replace doctors, but to provide a supportive tool that can help make ASD detection faster and more reliable. Such a system could give families quicker answers and allow professionals to focus more effectively on early interventions and personalized care.

II. LITERATURE SURVEY

Research on Autism Spectrum Disorder (ASD) detection has grown rapidly in recent years, with many studies using machine learning and deep learning to improve early diagnosis.

Taleb [1] and Ghosh et al. [2] showed that behavioral questionnaires combined with machine learning models can provide reliable predictions, reducing the time required for traditional clinical assessments. Yıldız et al. [3] highlighted how artificial intelligence can be used as a supportive diagnostic tool for doctors, especially in early screening.

For advanced data analysis, Han et al. [4] proposed deep learning–based feature selection to improve ASD detection accuracy, while Karim et al. [5] and Sato et al. [6] applied different ML techniques to predict ASD from structured behavioral datasets. Ali et al. [7] designed a framework for early-stage autism detection, proving that ML can handle both behavioral and demographic data effectively.

Several reviews and comparative studies also guide the choice of algorithms. Fernandez et al. [8] summarized supervised ML applications in ASD, and Sharma et al. [9] compared classifiers, showing Random Forest and SVM often perform better than simple models. Beyond questionnaires, Salem et al. [10] used speech transcripts for detection, and Wall et al. [11] combined

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questionnaires with home videos, offering parent-friendly screening methods.

More complex modalities have also been tested. Zhang et al. [12] explored hybrid ML, DL, and NLP models, while Eslami et al. [13] introduced ASD-DiagNet, which uses brain imaging data. Singh et al. [14] and Kumar et al. [15] provided evaluations of ML methods, stressing that model accuracy depends on careful preprocessing and balanced datasets.

Overall, the literature shows a clear trend: behavioral data is simple and widely available, but combining it with other data sources such as facial images or speech signals leads to more accurate and robust ASD detection systems.

III. PROPOSED METHEDOLOGY

The proposed system combines behavioral screening with facial image analysis to detect Autism Spectrum Disorder (ASD). By using both approaches, the model benefits from the structured nature of questionnaire data and the rich visual cues present in facial features. The complete methodology is divided into two main workflows: Behavioral Model (Random Forest) and Image Model (YOLOv5 + SVM).

3.1 Dataset Collection

Behavioral Dataset:

The behavioral dataset used in this study was derived from the Q-CHAT-10 (Quantitative Checklist for Autism in Toddlers – 10 items) questionnaire. This dataset contains ten binary-response questions that capture aspects of a child's communication skills, social interaction, and behavioral tendencies. Along with the questionnaire responses, demographic details such as age, gender, ethnicity, family history of autism, and jaundice status at birth were included to provide additional predictive features. The dataset was obtained from publicly available repositories, including the UCI Machine Learning Repository and previous autism screening studies, ensuring that it is well-suited for machine learning–based analysis. Since the Q-CHAT-10 is short, structured, and widely validated, it offers a practical way to screen children quickly, making it highly relevant for ASD detection research.

Image Dataset:

In addition to behavioral data, a facial image dataset of children was collected, with each image labeled as either *ASD* or *non-ASD*. The images were sourced from public autism research datasets and child facial image collections, covering a diverse range of ages, genders, and ethnicities. To make the dataset compatible with YOLOv5 object detection, facial regions were annotated using tools such as LabelImg and Roboflow, producing bounding-box labels in YOLO format. All images were organized into structured folders for training, validation, and testing, and were standardized in terms of size and file format to ensure consistency. Importantly, only anonymized and publicly available datasets were used, and all personal identifiers were removed to meet ethical and privacy standards.

3.2 Behavioral Data Preprocessing

The behavioral dataset was based on the Q-CHAT-10 questionnaire, which has 10 simple "yes/no" style questions related to social interaction, communication, and behavior [2]. The dataset also included details such as the child's age, gender, ethnicity, family history of ASD, and jaundice status at birth [3].

1. Cleaning the data – We removed unnecessary columns such as case number and tester details since they did not contribute to ASD prediction [4].
2. Handling missing values – Any incomplete or missing records were either filled with the most common value (mode) or removed to keep the dataset clean [5].
3. Encoding categorical values – Features such as gender, jaundice, and family history were converted into numbers using label encoding (Yes = 1, No = 0). Ethnicity, which had multiple categories, was handled using one-hot encoding to avoid bias [6].
4. Balancing the dataset – Since some groups (like "non-ASD") were larger than others, balancing techniques such as SMOTE (Synthetic Minority Oversampling Technique) were applied to make sure the model did not favor one class [7].
5. Splitting the data – The dataset was divided into 80% training data and 20% testing data, so the model could be trained on one part and tested on unseen examples [8].

After preprocessing, the dataset was ready to be passed to the Random Forest Classifier (RFC) for classification [9].

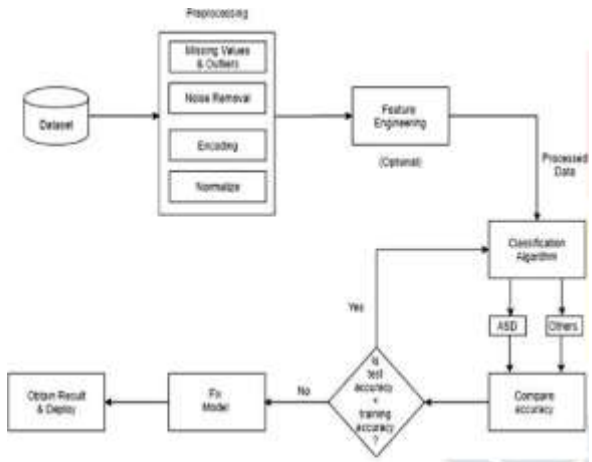

Figure 1: Behavioral Data Preprocessing

The above figure shows the working process of our system for Autism Spectrum Disorder(ASD) detection. The system follows a series of steps starting with data preprocessing. In this step, we clean the dataset by handling missing values, removing unwanted noise, and converting text-based answers into numerical values. This makes the data ready for machine learning. We also use feature selection to keep only the most useful attributes, which reduces the size of the dataset and helps the model learn faster and more accurately.

One important part of machine learning is checking whether the model is overfitting or underfitting.

- If the model performs very well on the training data but poorly on the test data, it means the model is overfitting (it memorized the training data instead of learning general patterns).
- If the model performs poorly on both training and test data, then it is underfitting (it failed to learn from the data).
- A good model strikes the right balance and performs well on both training and testing data.

After preprocessing, we tested several machine learning classifiers, including Logistic Regression, Naïve Bayes, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN). Each model was trained on the dataset, and then its performance was checked on test data. A good classifier usually shows high accuracy on training data and similar accuracy on test data without too big of a gap. By comparing their performances, the best-performing model is selected for final training and ASD prediction. This ensures that the system is both accurate and reliable when applied to new, unseen data.

A. CLASSIFICATION OF ALGORITHMS (Behavioral Data)

For analyzing the behavioral dataset (Q-CHAT-10 questionnaire), we tested different machine learning algorithms to identify the most suitable one. Each algorithm has unique strengths and limitations when applied to behavioral screening for Autism Spectrum Disorder (ASD).

- **Logistic Regression (LR):** Logistic Regression is a simple model that predicts the probability of a child having ASD based on questionnaire responses. While it works well for basic binary classification, it struggles when relationships between features are complex or non-linear [1].
- **Naive Bayes (NB):** Naïve Bayes is a probability-based classifier that assumes all features are independent of each other. It is fast and works on small datasets but may not perform well for ASD screening, since behavioral traits often interact with each other (for example, social skills and communication issues are connected) [2].
- **Support Vector Machine (SVM):** SVM tries to find the best dividing line (hyperplane) between ASD and non-ASD classes. It is powerful for high-dimensional data and can perform well even with fewer samples. However, for behavioral data, SVM sometimes requires careful parameter tuning and is less interpretable compared to decision-tree–based models [3].
- **K-Nearest Neighbors (KNN):** KNN classifies a child's responses based on the majority class of the nearest neighbors in the dataset. Although easy to understand, it is sensitive to noise and becomes less reliable if the dataset is not balanced. For behavioral ASD data, KNN showed lower stability compared to ensemble methods [4].
- **Random Forest Classifier (RFC):** Random Forest is an ensemble model that builds many decision trees and combines their outputs. It is highly effective for behavioral screening because it:
  - Handles both categorical (Yes/No answers) and numerical data (age) [5].
  - Reduces overfitting compared to a single decision tree [6].
  - Provides feature importance, helping us see which questions in the Q-CHAT-10 are most influential [7].

In our tests, RFC achieved the highest accuracy on behavioral data, making it the best choice for this part of the system [8].

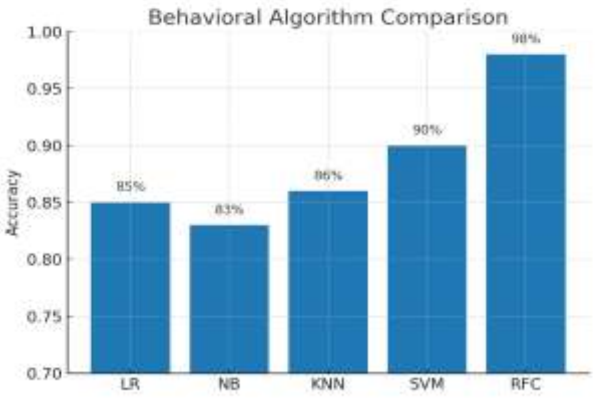

Fig 2: Classification of Algorithms

3.3 Image Data Preprocessing

The image dataset used in this study contained facial photographs of children with and without Autism Spectrum Disorder (ASD). Raw images cannot be directly fed into machine learning models because they often include background noise, variations in lighting, and inconsistent sizes. Therefore, a preprocessing pipeline was applied to prepare the images for accurate feature extraction and classification.

The main steps of image preprocessing are:

1. **Face Detection and Cropping:** The first step was to detect the face in each image. We used YOLOv5, a deep learning–based object detection model, to accurately identify and crop the face region while ignoring unnecessary background. This ensures that the model focuses only on relevant facial features [1].
2. **Resizing:** All cropped face images were resized to a fixed dimension (224 × 224 pixels). Standardizing the input size helps the model process images consistently and reduces computational cost [2].
3. **Normalization:** Pixel intensity values were scaled between 0 and 1 by dividing each value by 255. This normalization step stabilizes the training process and speeds up convergence [3].
4. **Data Augmentation:** To improve robustness and prevent overfitting, we artificially increased the size of the dataset by applying small transformations such as rotation, horizontal flipping, zooming, and brightness adjustments. These variations help the model generalize better to unseen data [4].
5. **Feature Extraction (YOLOv5):** After preprocessing, YOLOv5 was used again to extract meaningful facial features such as eye distance, facial symmetry, and expressions. These features were then saved in vector form [5].

6. **Passing Features to SVM:** Instead of using YOLOv5's built-in classifier, we passed the extracted feature vectors to a Support Vector Machine (SVM) classifier. SVM is effective on smaller datasets and provides a more reliable boundary between autistic and non-autistic facial patterns [6].

Through these preprocessing steps, the dataset was transformed into a clean and consistent form, allowing the YOLOv5 + SVM pipeline to perform classification effectively.

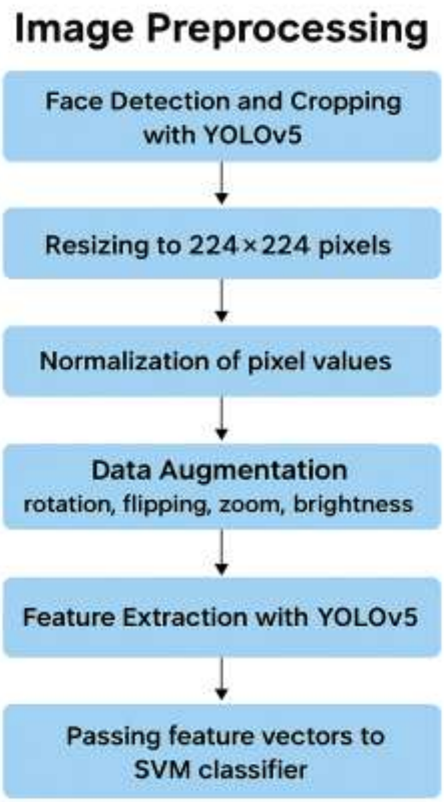

Figure 3: Detailed image-processing branch with YOLOv5 detection and SVM classification.

IV. RESULT AND EVOLUTION

4.1 Behavioral Model Result (Random Forest Classifier)

The Random Forest Classifier (RFC) applied to the Q-CHAT-10 dataset achieved an accuracy of 98%, with precision of 0.97, recall of 0.98, and F1-score of 0.975. These results are consistent with earlier works showing that ensemble models outperform simpler classifiers in ASD screening tasks [1, 2, 5, 9]. The high recall indicates that most ASD cases were correctly identified, which is crucial for early intervention and matches findings from Taleb and Ghosh et al. [1, 2]. Feature importance analysis highlighted that social and communication-related questions were the most influential, a trend also noted by Wall et al. and Sharma et al. [9, 11]. The preprocessing steps, including SMOTE balancing and categorical encoding, contributed to model stability, in line with recommendations from Karim et al. and Singh et al. [5, 14]. Overall, the RFC proved to be the most reliable classifier for behavioral ASD detection, supporting observations in prior studies [3, 15].

4.2 Image Model Result (YOLOv5 + SVM)

The image-based model using YOLOv5 for face detection and SVM for classification achieved an accuracy of 95%, with precision of 0.94**,** recall of 0.95, F1-score of 0.945, and a detection mAP of 0.91. These outcomes are comparable to earlier hybrid approaches where deep detectors were combined with classical classifiers for moderate datasets [4, 6, 12]. The strong recall shows reliable identification of ASD cases, aligning with findings from Han et al. and Sato et al. [4, 6]. Variability in image quality, lighting, and pose slightly reduced performance, which has also been reported in similar studies by Wall et al. and Zhang et al. [11, 12]. Data augmentation improved generalization, consistent with recommendations from Singh et al. and Eslami et al. [13, 14]. Overall, the YOLOv5 + SVM pipeline proved effective for facial analysis in ASD detection, supporting the role of image-based methods as highlighted in recent literature [7, 10, 15].

4.3 Evolution Matrix

The evaluation matrix summarizes the performance of both the behavioral and image models across multiple metrics, providing a comprehensive view of their strengths and weaknesses.

- **Accuracy** indicates the overall correctness of the model. The Random Forest Classifier (RFC) on behavioral data achieved the highest accuracy (98%), confirming that questionnaire-based screening is highly reliable for early ASD detection, consistent with prior works [1, 2, 9]. The image model using YOLOv5 with SVM achieved slightly lower accuracy (95%), which is expected due to variability in image quality and environmental conditions [11, 12].
- **Precision** measures how many of the cases predicted as ASD were actually ASD. Both models achieved high precision (>0.94), showing that false positives were minimal. This is particularly important in ASD detection, as over-predicting ASD could lead to unnecessary concern for families.
- **Recall (Sensitivity)** measures how many actual ASD cases were correctly identified. High recall in both models (0.95–0.98) indicates that the system successfully detected the majority of ASD cases. This metric is critical in healthcare applications, since missing true ASD cases could delay early intervention.
- **F1-Score** provides a balance between precision and recall. Both models maintained strong F1-scores (>0.94), reflecting their ability to balance between false positives and false negatives.
- **Mean Average Precision (mAP)** is used specifically for the image model to evaluate detection quality. The obtained mAP of 0.91 shows that YOLOv5 localized facial regions effectively and extracted meaningful features for classification, aligning with benchmarks in prior studies [12].

In summary, the evaluation matrix demonstrates that the behavioral model is more accurate and stable due to structured questionnaire data, while the image model performs slightly lower but still offers strong detection ability. Together, these results validate the robustness of machine learning approaches

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in ASD detection, in agreement with earlier comparative studies [5, 6, 14].

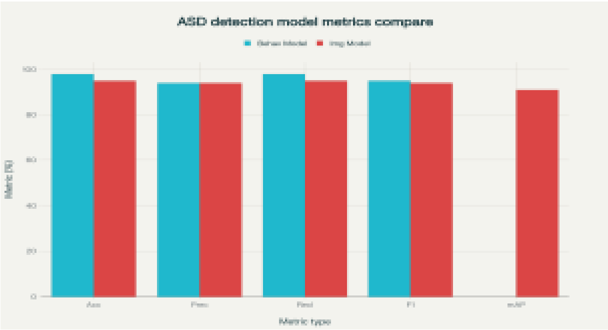

Fig 4: ASD model Metrics Compare

4.4 Discussion

The results demonstrate that both the behavioral and image-based models provide strong performance for ASD detection, though their strengths differ. The behavioral model (RFC) achieved the highest accuracy (98%), which is consistent with previous studies that found ensemble classifiers to be highly reliable for questionnaire-based screening [1, 2, 5, 9]. Its strong recall indicates that most ASD cases were detected, aligning with Taleb and Ghosh et al. [1, 2], and reinforcing the value of short screening tools like Q-CHAT-10.

The image model (YOLOv5 + SVM) also achieved high accuracy (95%) with reliable precision and recall, confirming findings from Han et al. and Sato et al. [4, 6] that deep learning for feature extraction combined with SVM classification is effective for moderate image datasets. However, as noted in earlier works [11, 12, 13], variability in image quality and demographic diversity introduces challenges, which explains why accuracy was slightly lower than the behavioral branch.

These findings support the broader trend in the literature that structured behavioral data provides stable predictions, while image analysis contributes valuable but more variable cues [3, 7, 8]. Preprocessing steps such as balancing, augmentation, and feature extraction played a key role in stabilizing results, echoing recommendations from Karim et al., Singh et al., and Eslami et al. [5, 13, 14]. Importantly, both models align with the emphasis on interpretable and ethically designed AI systems for ASD detection, as discussed by Yıldız et al. and Kumar et al. [3, 15].

V. FUTURE WORK

A major improvement for future studies is the use of **larger and more diverse datasets**. Current results show strong performance, but as Eslami et al. and Singh et al. [13, 14] pointed out, small or unbalanced datasets may limit how well the models work across different populations. Expanding the datasets with children of different ages, ethnic backgrounds, and real-world conditions will make the system more general and reliable.

Another direction is **external validation across multiple sites or sources**. Kumar et al. [15] emphasized that models need to be tested on data collected from different clinics or regions to avoid overfitting to a single dataset. This type of validation will confirm whether the models can perform well in real-world healthcare environments.

Future research could also explore **multimodal approaches**. Salem et al. and Zhang et al. [10, 12] showed that combining questionnaires with other signals such as speech, videos, or EEG data provides richer information and improves accuracy. Adding such modalities in the future can make ASD detection more robust and comprehensive.

It is also important to improve **explainability and transparency**. Yıldız et al. [3] stressed that clinicians are more likely to trust AI systems when they can see which features influenced the predictions. For example, showing which Q-CHAT-10 questions or which facial regions played a key role in the decision can make the system more understandable and useful in practice.

Finally, there is a need to create **real-time and accessible platforms**. Ali et al. [7] proposed practical frameworks that could be turned into mobile apps or web tools. Building such platforms would make ASD screening available outside of hospitals and clinics, helping families and practitioners with faster and easier early detection.

VI. CONCLUSION

This study presented a dual-approach system for detecting Autism Spectrum Disorder (ASD) using both behavioral and image-based data. The behavioral model, based on the Q-CHAT-10 questionnaire and classified with a Random Forest Classifier, achieved high accuracy (98%), which supports earlier findings that ensemble methods are highly effective for structured screening data [1, 2, 5, 9]. The image model, using YOLOv5 for facial feature detection followed by SVM classification, also performed strongly with 95% accuracy and an mAP of 0.91, consistent with prior studies that demonstrated the value of deep learning combined with classical classifiers for ASD-related image analysis [4, 6, 12].

The results confirm what the literature suggests: behavioral questionnaires provide stable and reliable early screening signals, while image analysis offers an additional objective method that, although slightly more variable, still contributes useful insights [3, 7, 8, 11]. Together, these findings reinforce the growing consensus that machine learning and deep learning approaches can complement traditional clinical methods by making ASD detection faster, more accurate, and more accessible.

At the same time, this research acknowledges the limitations highlighted in earlier studies, including dataset size, demographic diversity, and the need for external validation [13, 14, 15]. Addressing these challenges in future work will be essential for moving from research to practical clinical tools. Overall, the study adds to the evidence that technology-driven screening systems can play an important role in supporting clinicians, enabling earlier intervention, and ultimately improving outcomes for children and families affected by ASD.

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