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EARLY DETECTION OF AUTISM SPECTRUM DISORDER IN TODDLERS: A DATA-DRIVEN APPROACH

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ABSTRACT
Autism Spectrum Disorder (ASD) is a complex neurodevelopmental disorder characterized by difficulty in communication, social interaction, and behaviour that varies among individuals. It is critical to detect ASD early so it can be treated on time but toddlers with ASD are hard to diagnose as the symptoms can differ greatly and overlap with other developmental disorders. This research proposes using machine learning to diagnose ASD at an early stage . This is done through a multimodal dataset that consists of standard screening tool information. Specifically, they will cover Q-CHAT-10, ADOS, and INCLEN in detail. The dataset which is used to either classify someone or not someone to have autism is from the social interaction, communication, sensory and repetitive behaviour domain.

By incorporating various behavioral markers, the data's multimodal aspect improves the model's capability of detecting subtle patterns that indicate ASD. To find out which classifier gives the best results, different machine learning algorithms were evaluated on this dataset. The different algorithms which were evaluated include Logistic Regression, Support Vector Machine, Naive Bayes, Decision Tree, Random Forest, AdaBoost, Gradient Boosting, Bagging, Deep Neural Networks, etc. To measure the performance of the various models, accuracy, precision, recall, F1-score, etc. were used. The findings showed that multiple models especially Naive Bayes, Logistic Regression, Random Forest and Deep Neural Networks have high values of accuracy and recall and therefore have a reliable capacity to distinguish between the ASD-positive and ASD-negative cases.

This study shows how machine learning can accurately diagnose toddlers with ASD through a multimodal model. Combining various diagnostic tools and further evaluating a range of classification algorithms contribute to creating a robust data-driven approach. Therefore, this study offers an intervention to clinicians and parents for early-stage identification of ASD (Autism Spectrum Disorder). This paper analyzes the detection of Autism Spectrum Disorder using classifiers on multimodal data.

Keywords: *Autism Spectrum Disorder, early detection, machine learning, multimodal dataset, classifier comparison, Q-CHAT-10, ADOS, INCLEN.*

I. INTRODUCTION
Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder in which Social and communication behavior is affected and the cognitive functioning takes place which presents various symptoms which varies with the individual. The DSM-5 (Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition) states that the fundamental features of ASD are: deficit in social interaction and communication. Restricted and repetitive behaviours. Cases of ASD are increasing in number. As such, requiring a precedence given to diagnosis and treatment. Finding autism early can improve development as a therapy can help improve cognitive and social skills of children with autism.

Even though there has been great research in this field, diagnosing ASD in toddlers is hard. Often times, traditional diagnostic methods often rely on clinical observations and parent-reported questionnaires, which might not be accurate and objective due to subjectivity in such measures. Moreover, other developmental disorders have symptoms in common with ASD, resulting in diagnostic confusion. The restricted diagnostic process highlights a crucial requirement for more objective, data-driven solutions for early ASD detection.

Diagnostic challenges arise from the varied presentation of autism spectrum disorder (ASD) and overlap conclusions. Right now diagnostic tools tend to be helpful. However, often their assessment can be isolated and not very multifaceted. Tools like the Q-CHAT-10, ADOS and INCLEN evaluate various behavioral domains. Social communication, sensory responses, and repetitive behaviours refer to them. However, their combined use for diagnosis is rare. When we depend only on one single tool or one dimension of a data point to arrive at a diagnostic conclusion, it may lead to incomplete conclusions thus increasing the risk of missed or delayed diagnosis.

This research aims to fill these gaps by creating a multimodal machine learning model that integrates data from several well-validated diagnostic tools. The combination of Q-CHAT-10, ADOS, and INCLEN will provide a more conclusive comprehensive diagnostic profile, facilitating the detection of other critical behavioural and sensory features. This dataset can help the model to determine the relations and patterns of complex symptoms. The model will better be able to segregate ASD-positive from negatives.

The focus of this study is to develop and validate a diagnostic model for ASD using machine learning techniques on a multimodal dataset that spans several behavioural and sensory domains relevant to ASD. This research evaluates a range of machine learning classifiers such as Logistic Regression, Support Vector Machine, Naive Bayes, Decision Tree, Random Forest, AdaBoost, Gradient Boosting, Bagging, Deep Neural Network, to find the best one. The data has answers to a lot of important questions which will help develop a feature set for every individual.

This study hopes to help build a properly researched tool that can be readily available to parents and the doctors so that autism spectrum disorder can be diagnosed at an early age for timely intervention. This study combines behavioral, social, and sensory data using machine learning. It shifts away from current diagnostic practices and takes the field towards more objective and comprehensive detection of ASD. Research shows that using a multiple dataset together can help in making better machine learning supported models to diagnose Autism Spectrum Disorders. By combining several tools and contrasting different classification algorithms, a basis is formed to identify the top-performing model, as well as shedding light on how machine learning can improve early ASD diagnosis. This research can be utilized to develop an accurate and cost-effective diagnostic tool in line with the goal of early detection and intervention of ASD which can impart better developmental outcomes and facilitate support for the beneficiaries and their families.

II. LITERATURE REVIEW

Machine learning and autism spectrum disorder (ASD) diagnosis has made remarkable strides in the past few years, offering new solutions to long-standing challenges in early detection, behavioural analysis and personalized intervention.

A. *Machine Learning Progression for Diagnosis of ASD:*

Bone et al. (2016) study showed how using fusion of information from multiple devices, diagnosis of autism spectrum disorder can be improved using machine learning. By using multiple instruments, the diagnostic accuracy was enhanced and an overall better understanding of the Autism Spectrum Disorder-related symptoms was achieved. In the same way, Wall and colleagues (2012) utilized machine learning algorithms to enhance observation-based screening of ASD that would ultimately shorten diagnostic testing, without losing accuracy. Zhao et al. (2019) built on the concept of multimodal approaches using machine learning methods, integrating behavioral and neurological information for the precise detection of ASD.

B. *Behavioral Distinction and Minimal Feature Sets:*

When a child has both ASD and another developmental disorder like ADHD diagnosis can be difficult. Duda and colleagues (2016) researched the use of machine learning models to differentiate autism spectrum disorder from attention deficit hyperactivity disorder through behavioural patterns.

Kosmicki et al. (2015) focused on a small set of behaviors for diagnosing the ASD. Their work showed that one can get the right diagnosis with a few chosen indicators. Finding out this shows how optimized features are very useful for scalable diagnostic tools.

C. *Applications and Limitations of ML Models:*

Thabtah (2019) tries to opt a study on impact of machine learning in behavioral research in autism spectrum disorder. Research shows several gaps: existing datasets are not diverse (not representative of the populations) and current models cannot be applied to various populations. Thabtah et al. (2020) built a machine learning classification model based on behavior and showed high accuracy. Their work emphasizes the importance of behavioral factors in the diagnosis of ASD.

D. *Prevalence and Predictive Modeling:*

The number of children with developmental disorders, such as ASD, has been steadily rising over the years (Zablotsky et al., 2019). This has raised the urgent need for scalable solutions to diagnose such disorders. Also, Ozonoff et al. (2009) pointed out the importance of early identification of symptoms. They showed that parental concerns reported in infancy predicted future diagnosis of ASD. This shows that early diagnostics could be made by ML models on parent-reported data.

E. *Emerging Applications of ML in ASD:*

Machine learning applications are now predicting behaviors associated with autism spectrum disorder (ASD), besides making diagnoses. In 2021, Tajsic and colleagues developed machine learning models to predict aggressive behaviour in youths with autism spectrum disorder, to aid in behavioural management and care.These developments show how flexible ML is in tackling complex ASD-related problems beyond the initial diagnosis.

F. *Conclusion of Current Research:*

The literature as a whole emphasizes the significant impact that machine learning can have on ASD diagnostics and other areas. Even though there has been notable advancement in creating effective and precise models, obstacles like varying datasets, interpretability, and incorporation of multimodal data continue to exist. These observations serve as a strong basis for additional research on developing comprehensive, data-driven diagnostic instruments for ASD.

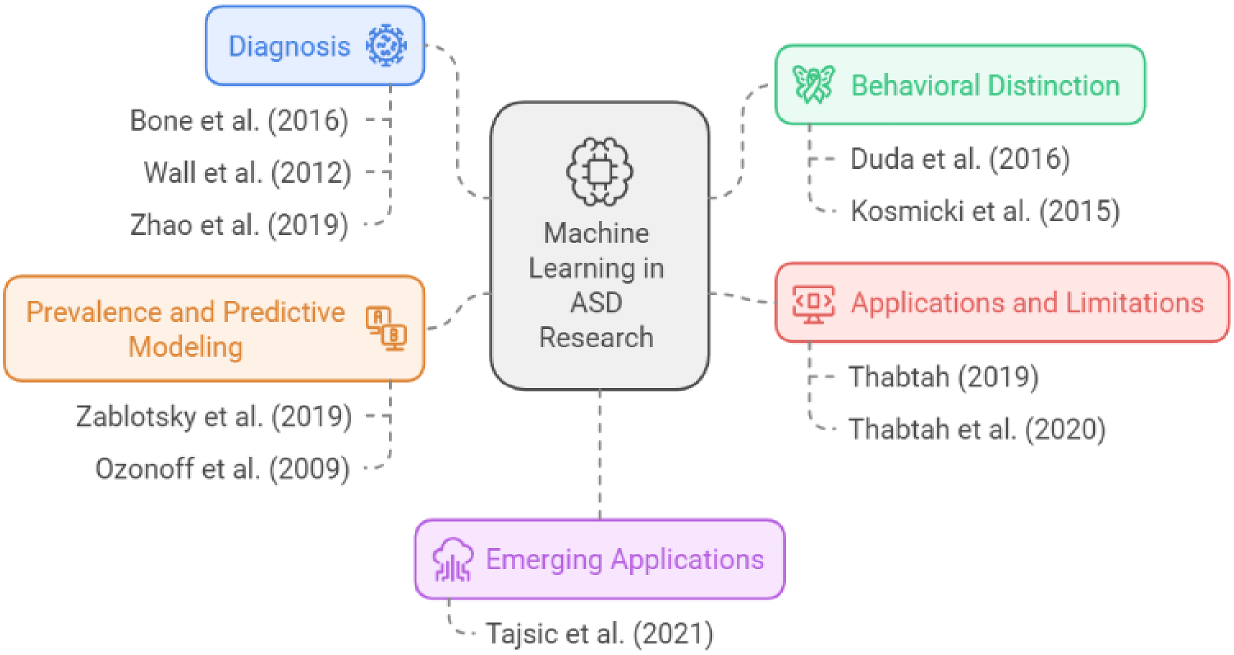

Figure 1: Summary of Literature Review

III. METHODOLOGY

In this study, we use a combination of different methods to make better predictions on ASD diagnosis. The process starts by collecting the data of the system. After which, the data is pre-processed. This approach tells about the information about the system misbehaving.

A. Data Collection

The data for this study combines information from three popular tools for diagnosing ASD, namely, the Q-CHAT-10 (Quantitative Checklist for Autism in Toddlers), ADOS (Autism Diagnostic Observation Schedule), and INCLEN (INDT-ASD) tool. All these tools capture interesting behavioural and social features as well as the sensory features of ASD. There are 750 positive and 750 negative samples in our dataset.

1) ***Q-CHAT-10*:** focuses on parent-reported observations of social interaction and communication in toddlers, providing early indicators of ASD.

2) ***ADOS*:** is a structured observational assessment used to evaluate social communication and play in children, which is often administered by clinicians.

3) ***INCLEN*:** includes a more comprehensive array of ASD markers, encompassing social behaviors, sensory reactivity, and repetitive actions.

This integrated dataset covers a broad spectrum of features, enhancing the model’s ability to recognize diverse symptom patterns.

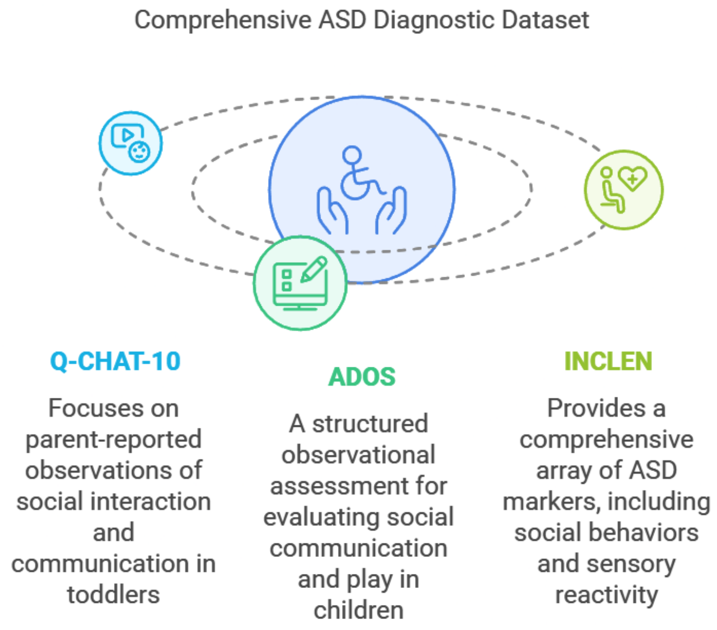

Figure 2: ASD Diagnosing Datasets

B. Data Preprocessing and Feature Engineering

After data collection, preprocessing steps were applied to prepare the dataset for machine learning:

1) ***Data Cleaning*:** Any missing or inconsistent values were handled, with specific attention to maintaining data integrity across the three diagnostic tools.

2) ***Standardization*:** Since each diagnostic tool has its scoring system, feature standardization was applied to scale values into a comparable range, ensuring uniformity across features.

3) ***Feature Engineering*:** New features were engineered by aggregating or combining scores across similar domains (e.g., social interaction and communication scores from ADOS and INCLEN), which allowed for a unified representation of ASD traits in the dataset. This step also involved creating total scores for each tool, which captured overall symptom severity.

C. Model Selection and Implementation

Given the multimodal nature of the dataset, several machine learning algorithms were implemented and compared to identify the most accurate classifier. The selected models include a variety of traditional and advanced classifiers:

1) ***Logistic Regression*:** This linear model was selected for its simplicity and interpretability.

2) ***Support Vector Machine (SVM)*:** SVM was included for its capability to handle high-dimensional data and complex decision boundaries.

3) ***Naive Bayes*:** Known for its effectiveness with structured data, this probabilistic model was tested as a baseline classifier.

4) ***Decision Tree*:** This model was used for its interpretability and ability to capture non-linear patterns.

5) ***Random Forest*:** An ensemble model that combines multiple decision trees, chosen for its robustness and ability to reduce overfitting.

6) ***AdaBoost and Gradient Boosting*:** Both boosting techniques were included to see if iterative refinement could improve accuracy.

7) ***Bagging*:** A method of random sampling with replacement, evaluated for its performance with high variance datasets.

8) ***Deep Neural Network (DNN)*:** A multi-layer neural network was implemented for its capacity to learn complex patterns from large datasets.

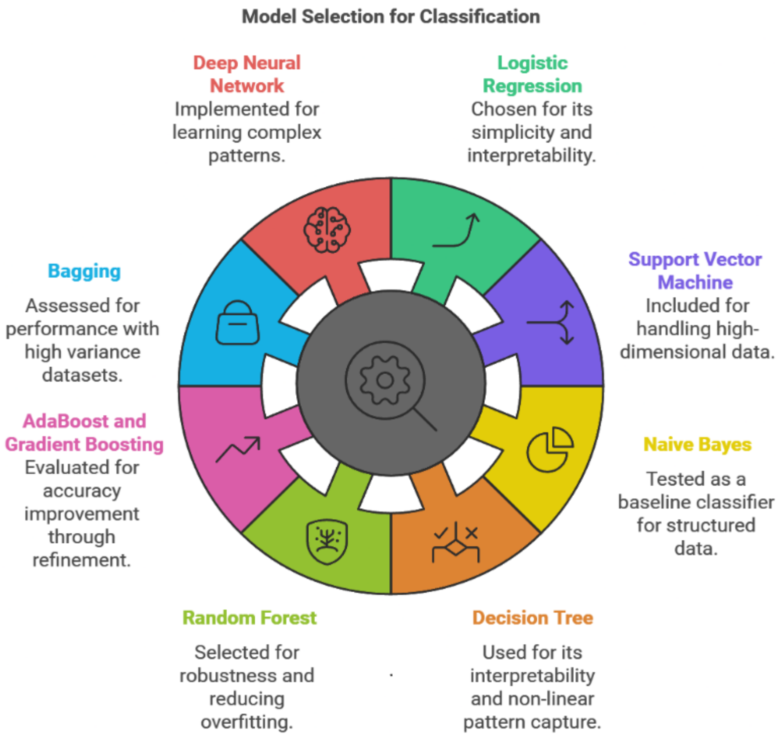

Figure 3: Machine Learning Models used

To guarantee that comparisons between models remained consistent, each model was trained and evaluated on the same split.

D. Model Evaluation and Comparison

The performance of each classifier was assessed through accuracy, precision, recall and F1-score. The selected metrics provide a complete view of the diagnostic ability of each model.

1) ***Accuracy*****:** calculated the ratio of correct predictions.
2) ***Precision*****:** They calculated the ratio of true positive cases to all the predicted positive cases to reduce the number of false positives.
3) ***Recall*****:** It is the ratio of true positive cases to all real positive cases. This is important to reduce false negative cases.
4) ***F1-score*****:** Given the difficulty of diagnosing ASD, this choice presents a balanced measure between precision and recall.

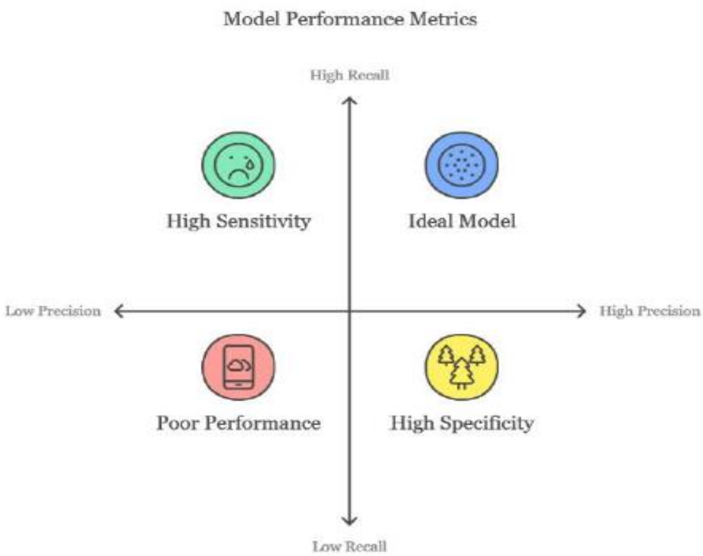

Figure 4: Evaluation Metrics

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Each model's performance was analyzed based on these metrics to identify the best-performing classifier for early ASD detection.

E. Statistical Analysis

We looked at some statistics of the dataset to see which features were most informative. We also studied the relationship between the Q-CHAT-10, ADOS and INCLEN scores. To figure effects that most helped predict autism, they used things like correlation matrices and feature importance. This study improved feature engineering and selection of model by revealing main drivers of ASD symptoms.

IV. RESULTS & DISCUSSION

This part will provide a full analysis of the ML techniques used in this study for ASD early detection. The accuracy, precision, recall, and f1-score are the key parameters used to evaluate the model performance. The metrics offered a deeper insight into the diagnostic potential of each model, especially their abilities to accurately identify ASD-positive and ASD-negative cases, which is vital for clinical reliability in early diagnosis.

A. MODEL COMPARISON AND ANALYSIS

Model Comparison:

	Accuracy	Precision	Recall	F1 Score
Logistic Regression	0.986667	0.974359	1.000000	0.987013
Support Vector Machine	0.980000	0.967949	0.993421	0.980519
Naive Bayes	0.990000	0.980645	1.000000	0.990228
Decision Tree	0.983333	0.974194	0.993421	0.983713
Random Forest	0.986667	0.980519	0.993421	0.986928
AdaBoost	0.970000	0.949686	0.993421	0.971061
Gradient Boosting	0.983333	0.974194	0.993421	0.983713
Bagging	0.980000	0.974026	0.986842	0.980392
Deep Neural Network	0.986667	0.974359	1.000000	0.987013

Figure 5: Results of Each Model

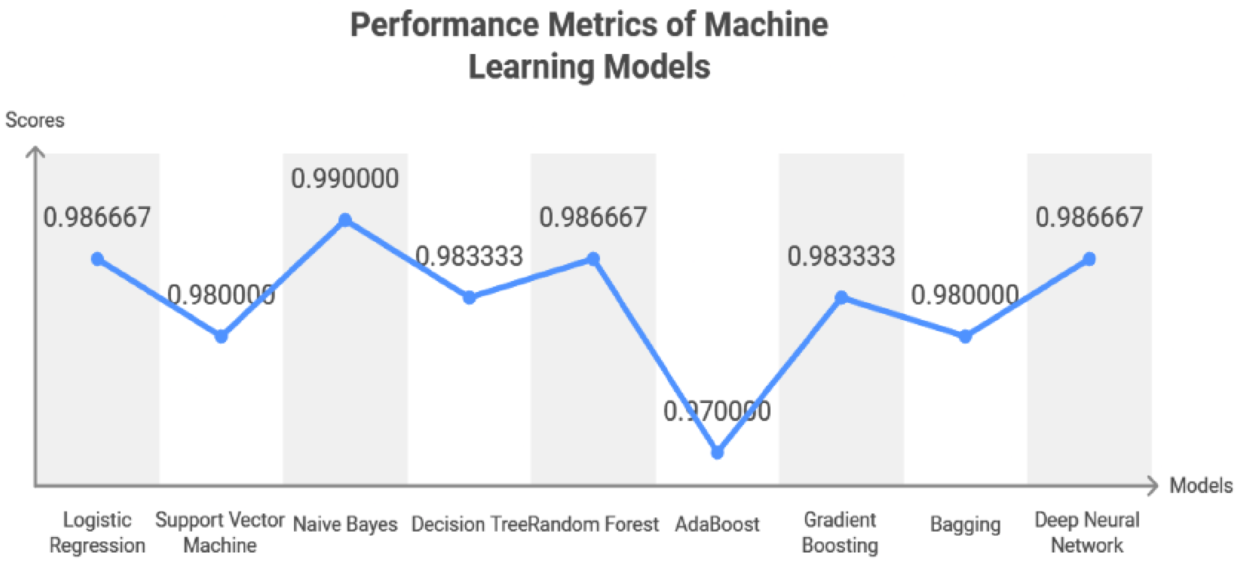

Figure 6: Model comparison wrt accuracy

B. KEY FINDINGS BY MODEL

1) ***Naive Bayes*:**

- **Highest Accuracy and F1-Score:** Naive Bayes obtained accuracy of 99% and F1-score of 0.9902 which suggests the superior diagnostic performance of the model. Naive Bayes captured the patterns well in the multimodal data due to its probabilistic nature with 98% precision and 100% recall.
- **Implications for Clinical Application:** Naive Bayes' high recall benefit helps create a false-negative model for early detection of ASD and thus limits the risk of cases. This strength in catching positive cases makes Naive Bayes a good choice for initial tests where inclusivity is key.

2) Logistic Regression:

- Logistic regression was highly accurate (98.67%) and had high recall (100%) making it a very good predictor of ASD-positive. While logistic regression is no as precise as Naive bayes, it does have the advantage of being easy to interpret.
- **Potential in Clinical Settings:** Logistic Regression's balance of simplicity and accuracy makes it highly suitable for integration into clinical diagnostics. Its ease of interpretability allows clinicians to understand feature contributions to ASD risk, which could enhance transparency and trust in AI-assisted diagnosis.

3) Deep Neural Network (DNN):

- **Comparable Performance to Top Models:** DNN achieved an accuracy of 98.67% and an F1-score of 0.9870, on par with Logistic Regression. DNN's ability to learn complex, non-linear patterns in multimodal data enhanced its performance in distinguishing subtle ASD symptoms.
- **Strength in Complex Patterns:** The DNN's high performance suggests its capability to recognize intricate patterns in toddler behavior and communication, especially when data is comprehensive. However, DNN models can be computationally intensive and less interpretable, which may impact their practical use in resource-limited clinical environments.

4) Random Forest:

- **High Precision and Robustness:** With an accuracy of 98.67% and precision of 98%, Random Forest demonstrated excellent reliability, balancing sensitivity (recall of 99.34%) with specificity. The model's ensemble structure allowed it to capture diverse patterns without overfitting, making it robust against variations in behavior and sensory data.
- **Clinical Application Potential:** Random Forest's ability to handle large datasets and high variance makes it a suitable choice for ASD diagnostics, where diverse symptom presentations require adaptive models. Additionally, the model's interpretability is beneficial for clinicians needing insights into feature importance.

5) Support Vector Machine (SVM):

- **Balanced Accuracy and Recall:** SVM displayed competitive accuracy (98%) and recall (99.34%), performing well in identifying ASD-positive cases with relatively high precision (96.79%).
- **Challenges and Suitability:** While SVM is adept at handling high-dimensional data, it can be computationally demanding, especially when the dataset includes diverse features. Its complexity might limit practicality in some clinical settings, though its decision boundary optimization is valuable for datasets with complex symptom overlap.

6) Decision Tree and Gradient Boosting:

- **Reliable Performers with High Recall:** Both models showed comparable results, with accuracies of 98.33% and F1-scores of 0.9837. Their high recall rates (99.34%) suggest an effectiveness in detecting ASD-positive cases, although they slightly lag behind the top performers in precision.
- **Use Cases in Preliminary Diagnostics:** Decision Tree models are highly interpretable, while Gradient Boosting provides robustness in handling noisy data, making them suitable for early-stage screening tools. However, they may not be as precise as ensemble methods like Random Forest.

7) AdaBoost and Bagging:

- **Moderate Performance:** AdaBoost and Bagging showed accuracy rates of 97% and 98%, respectively. Both methods achieved lower precision than top-performing models but maintained high recall, indicating reliability in identifying ASD-positive cases.
- **Considerations for ASD Screening:** Although these models did not outperform others, their simplicity and high recall rates make them useful in situations where a quick, preliminary assessment is needed.

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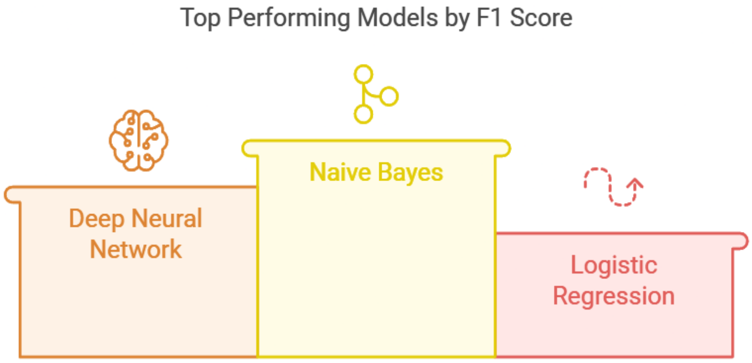

Figure 7: Top Models by F1 Score

C. SUMMARY OF RESULTS

The comparison reveals that Naive Bayes, Logistic Regression, Deep Neural Networks, and Random Forest are particularly effective for early ASD detection. Naive Bayes leads in diagnostic accuracy, while Logistic Regression and Random Forest offer high reliability with the added advantage of interpretability. Deep Neural Networks excel in identifying complex patterns but require more computational resources.

D. IMPLICATIONS AND FUTURE DIRECTIONS

The results demonstrate that a multimodal, machine learning-based approach can significantly enhance ASD diagnosis in toddlers. The integration of multiple diagnostic tools in the dataset allows the model to detect ASD with high accuracy and minimal false negatives. Since early intervention is crucial, it can be seen that models with high recall such as Naive Bayes and Logistic Regression are good candidates for initial screening.

Further research may also involve attempting to collect more behavioral and genetic data to add to the current dataset in order to enhance the robustness of the model. In addition, the use of XAI techniques especially for complex models such as DNNs can help in increasing the transparency of the machine learning models used in diagnosing ASD to enable clinicians to understand the factors that influence the predictions.

E. LIMITATIONS AND FUTURE WORK

1) Dataset Limitations:

One limitation of this study is the range and size of the dataset. We use Q-CHAT-10, ADOS and INCLEN as multiparameter axes which has improved the precision of the diagnosis but the dataset may not be adequate. One way to make this model more robust would be to expand the dataset to include cases from a wider variety of demographic regions, ages and severity of symptoms.

2) Model Enhancements:

Upcoming studies may investigate further model optimization, such as hyperparameter adjustments and sophisticated frameworks like convolutional neural networks (CNNs) or recurrent neural networks (RNNs), especially for analyzing sequential behaviors. Additionally, integrating ensemble techniques with neural networks may enhance diagnostic precision by utilizing the advantages of different classifiers.

3) Potential Use in Clinical Settings:

While the results indicate promising diagnostic performance, more research and clinical validation are needed before implementing this model in medical environments. Collaborating with healthcare providers to conduct real-world testing can ensure the model's reliability and usability, paving the way for it to support clinicians effectively in early ASD diagnosis.

4) Practical Implications:

This research is important for the diagnosis of ASD. By providing a tool that is unbiased and based on data, clinicians and parents can make diagnoses in a timely manner to allow interventions to take place, which benefits cognitive and social development outcomes. If you catch it early, you can make a special plan for your therapy that will match your kid. This has long benefits. Also, allowing a range of diagnostic tools to gather information one the patients and their journeys helps build a wider overview of ASD.

5) Ethical Considerations:

Most ethical issues must be looked into once the machine learning applications in medical diagnostics are made. When managing sensitive health data, it is important that data privacy is ensured—so that patient data is secured and anonymity maintained. Furthermore, informed consent is important if sensitive data is collected from children. The model's model performance may affect diagnostic use. Most importantly, a false positive or false negative would have a profound impact on the child and family. Because of this, it is suggested that a stringent phase of clinical validation should take place to ensure ethical use.

V. CONCLUSION

This study has shown that a machine learning–based multimodal approach has the potential to help detect Autism Spectrum Disorder (ASD) in children efficiently. This study integrates well-established diagnostic tools such as the Q-CHAT-10 and ADOS with the INCLEN to develop a holistic picture of ASD's behavioral, sensory, and social characteristics. A study that uninvolved some classifiers, namely Naive Bayes, Logistic Regression, Random Forest and Deep neural network, suggested the best model that differentiate an Autism Spectrum Disorder-positive cases from Autism Spectrum Disorder-negative cases accurately and effectively.

The results show that using a multimodal dataset is helpful as it makes the model learn complex patterns and subtle symptoms that one-dimensional assessments miss.This method helps with the problems with the traditional diagnosis of this disorder. The cases of subjectivity are decreased and the accuracy of diagnosis is improved. This is very important in cases of early diagnosis. The model delivered strong performance in terms of accuracy, precision and recall, suggesting that the model could be used as an objective diagnostic tool to help clinicians and parents plan timely intervention.

Yet, this study recognizes some limitation, such as the limitation of data set and broad validation. In the future, researchers should collect a bigger dataset and use better machine learning techniques to ensure the model works for everyone. Also, to ensure realistic and effective applications in medicine, the privacy of healthcare data and clinical validation of the lingo of care model required.

Ultimately, this study contributes to the field of ASDs diagnostics through the development of a reliable, data-driven tool that could lead to earlier diagnosis and timely intervention with developmental benefits for children with ASD. This study provides a useful basis for improving machine learning-based applications for other neurodevelopmental disorders to make the diagnosis of autism spectrum disorder more accurate and accessible.

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