Exploring Autism Spectrum Disorder Traits and Predictive Modelling using Optimized Feature Engineering in Machine Learning

R.Thiagarajan[1], V.Anithalakshmi[2]

[1]Professor, Department of Information Technology, Prathyusha Engineering College,
Email: rthiyagarajantpt@gmail.com
[2]Assistant Professor, Department of CSE Prathyusha Engineering College,
Email: anithalakshmi83@gmail.com

Received: 22.04.2024 Revised : 25.05.2024 Accepted: 26.05.2024

ABSTRACT
Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder that affects a person's behavior, social interactions, communication, and interests. It typically manifests in early childhood, often before the age of two. ASD is characterized by a wide range of symptoms and severity, which is why it is referred to as a "spectrum" disorder.[1]According to the World Health Organisation, the prevalence of autism spectrum disorder (ASD) has been rising gradually, affecting about one kid out of every 160 worldwide. [2] ASD is a neurodevelopmental disorder that has a major effect on a person's emotional, social, cognitive, and physical well-being. In individuals with autism, neural function in specific regions of the brain is notably affected, particularly in areas such as the cerebral cortex, amygdala, basal ganglia, corpus callosum, and cerebellum. These brain regions play crucial roles in various cognitive and behavioral functions.[3] The obstacles faced by people with autism spectrum disorders (ASD) are numerous and include difficulties focusing, learning disabilities, mental health conditions like anxiety and despair, as well as mobility and sensory abnormalities. The range and severity of ASD symptoms include repetitive behaviours in social settings, obsessive interests, and communication problems.[4] Since autism spectrum disorder (ASD) is thought to be caused by genetic and environmental factors, early detection is essential. Early intervention, however, may help control the effects and possibly prevent further deterioration. The primary method for identification is through observation, involving parents, teachers, and special education teams recognizing potential symptoms. While identifying ASD symptoms in children can be relatively straightforward, the process is more challenging in adults, underscoring the importance of seeking healthcare for comprehensive testing. [5] The aim of this study was to conduct a comprehensive investigation to identify the complex factors contributing to autism spectrum disorder (ASD) in students.The paper unfolds with an exploration of related works, delving into prior studies on Autism Spectrum Disorder (ASD) traits in children and machine learning applications in ASD research. Following this, the paper introduces the comprehensive dataset utilized, curated specifically for investigating ASD development in children. The proposed system is structured into three main components: ASD Trait Analysis, Feature Engineering for machine learning, and Machine Learning Models. ASD Trait Analysis encompasses age distribution, trait prevalence calculation, and co-occurrence condition analysis. The subsequent section focuses on optimizing feature engineering through Recursive Feature Elimination. The final component introduces various machine learning models for predicting ASD, followed by a conclusion summarizing key findings and contributions

Keywords: ASD, autism, callosum, spectrum, cerebellum.

LITERATURE SURVEY

Machine learning methods represent innovative computational approaches that encompass mathematical learning, statistical estimation, and information theories. These methods excel in automatically uncovering valuable patterns within extensive datasets. Their notable advantage lies in their capacity for accurate and reliable predictions, even when dealing with datasets featuring a high number of variables. In psychiatry, recent studies have demonstrated the successful application of machine learning methods in various diagnostic contexts. For instance, they have proven effective in diagnosing Autism Spectrum Disorder (ASD) [6], classifying altered event-related potentials in Attention Deficit Hyperactivity Disorder (ADHD) [7], and distinguishing characteristics through free speech analysis in individuals with

Schizophrenia [8]. A noteworthy study by Bishop et al. [9] utilized machine learning methods to explore the lifetime health problems of adults with ASD. The results were particularly promising, as these methods accurately predicted a range of health issues, including those related to cardiovascular, urinary, and respiratory systems. [10] introduced a Rules-based ML (RML) approach to assess ASD traits. The findings indicated that RML enhances classifier performance, underscoring its potential in improving diagnostic accuracy. In a different study [11] , researchers explored individual significant features distinguishing normal and autistic children in Bangladesh. They employed Tree-based classifiers to discern distinctive patterns. This approach allowed for understanding of the unique characteristics within these groups, contributing to a more refined diagnostic process. Another notable study [12] proposed a computational intelligence (CI) method termed Variable Analysis (VA). This method unveiled feature-to-class and feature-to-feature correlations, employing robust ML techniques such as Support Vector Machine (SVM), Decision Tree (DT), and Logistic Regression (LR) for precise ASD diagnoses and prognoses. By focusing on feature relationships, VA demonstrated its effectiveness in enhancing the accuracy and reliability of ASD assessments. In a different investigation [13], researchers analyzed ASD and typically developing (TD) children, pinpointing 15 preschool ASD cases using only seven features. Interestingly, the study suggested that while these features were informative, cluster analysis might offer a more comprehensive understanding of complex features that predict an ASD phenotype and its heterogeneity. This implies that leveraging cluster analysis could potentially capture intricate patterns within ASD, contributing to a more nuanced and accurate diagnosis [14]. [15] employed various classifiers to discern distinct patterns, ultimately discovering that a mere 5 out of 65 features were adequate for effectively distinguishing ASD from Attention Deficit Hyperactivity Disorder (ADHD). This finding highlighted the potential for a streamlined and efficient diagnostic process, emphasizing the discriminatory power of a select set of features in distinguishing between these neurodevelopmental conditions. The related studies highlights the potential of machine learning not only in diagnostic applications but also in providing valuable insights into the broader health aspects of individuals with ASD. The precision of these predictions underscores the potential for enhancing medical understanding and personalized healthcare for individuals with neurodevelopmental conditions.However, the proposed research encompasses a multifaceted investigation into Autism Spectrum Disorder (ASD) traits, aiming to fill critical gaps in existing researches. By analyzinga detailed Autism Trait Based rofiling of Autism Spectrum Disorder, the study seeks to provide a comprehensive understanding of ASD manifestations. Additionally, investigating the co-occurrence of speech delay, language disorders, learning disorders, depression, and anxiety disorders with ASD traits will contribute to a holistic perspective on associated symptoms. The research's significance lies in its potential to inform tailored interventions and diagnostic criteria. Furthermore, the development of predictive models for ASD traits, incorporating a diverse set of features through Feature Engineering, addressedthe current gap in the literature.

3. Data set

In this research, we employed a comprehensive dataset sourced from AUTISM RESEARCH: UNIVERSITY OF ARKANSAS Computer Science Department, previously available on Kaggle as an open-source dataset. This dataset was specifically curated to investigate factors contributing to the development of Autism Spectrum Disorder (ASD) in children. The dataset comprised a diverse set of features, including but not limited to the Autism Spectrum Quotient, Social Responsiveness Scale, Age in Years, Qchat_10_Score, Speech Delay/Language Disorder, Learning Disorder, Genetic Disorders, Depression, Global Developmental Delay/Intellectual Disability, Social/Behavioral Issues, Childhood Autism Rating Scale, Anxiety Disorder, Sex, Ethnicity, Jaundice, and Family Members with ASD. These variables collectively provided a comprehensive overview of characteristics associated with ASD in children. The inclusion of such varied information aimed to facilitate a nuanced analysis of the disease conditions and advance predictive modeling.

4. Proposed System

The objective of this study was to conduct a thorough inquiry in order to identify the intricate factors that contribute to autism spectrum disorder (ASD) in students.The dataset, meticulously curated from the University of Arkansas Computer Science Department, provided a diverse set of features for in-depth analysis.The age distribution was the first thing the study looked at, and then it thoroughly examined the traits' prevalence and co-occurrence circumstances.The research effort then focused on feature engineering for machine learning, optimising feature selection through the use of Recursive Feature Elimination. Using different machine learning models, including Decision Tree, SVM, Naive Bayes, KNN, K-means, Random Forest, Gradient Boosting, AdaBoosting, Linear Regression, and Logistic Regression, was the main focus of the research. The predictive effectiveness of these models was methodically evaluated, leading to the discovery and assessment of models with high performance using accuracy detection.The suggested system functions as an robust framework with possible applications in early diagnosis and intervention techniques. It is well-suited to provide insightful information about the complex understanding and prediction of ASD.

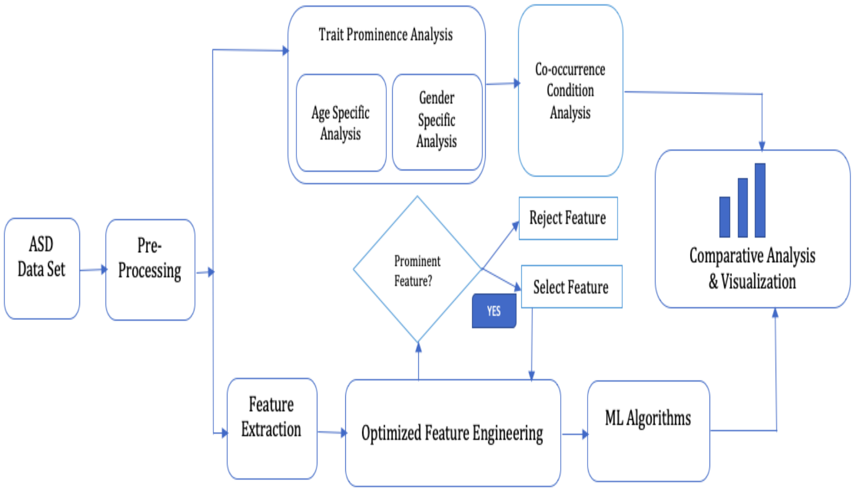

Figure 1. Work Flow Diagram

4.1. ASD Trait Analysis
4.1.1. Age Distribution Analysis
Determining the prevalence of ASD features among various age groups was the main goal of this investigation. In order to accomplish this, the dataset was first filtered to remove people who had ASD traits (ASD_traits = 1). The distribution of these features across different age groups was then visually represented by the construction of a histogram.The histogram that is produced provides a powerful visual representation of the frequency of ASD features in the dataset. Age in years is indicated by the x-axis, while the prevalence of people with ASD features in each age group is shown by the y-axis. By offering a smoothed outline of the distribution, a kernel density estimation (kde) curve enhances the representation even more. Peaks within the histogram pinpoint specific age groups where individuals with ASD traits are more concentrated. These peaks contribute valuable information regarding potential age-related trends.

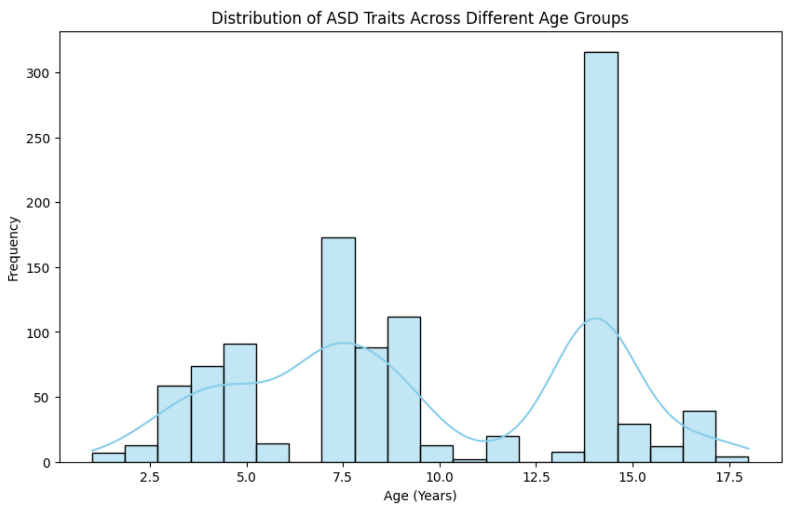

Figure 2. Age Plot – ASD Traits

The exploration of potential associations between demographic variables and Autism Spectrum Disorder (ASD) traits is crucial for gaining insights into the heterogeneous nature of ASD. The bar plot provides an immediate visual insight into how ASD traits are distributed among various ethnic groups. Each bar represents a distinct ethnic background, and the height of the bar corresponds to the count of individuals within that group.

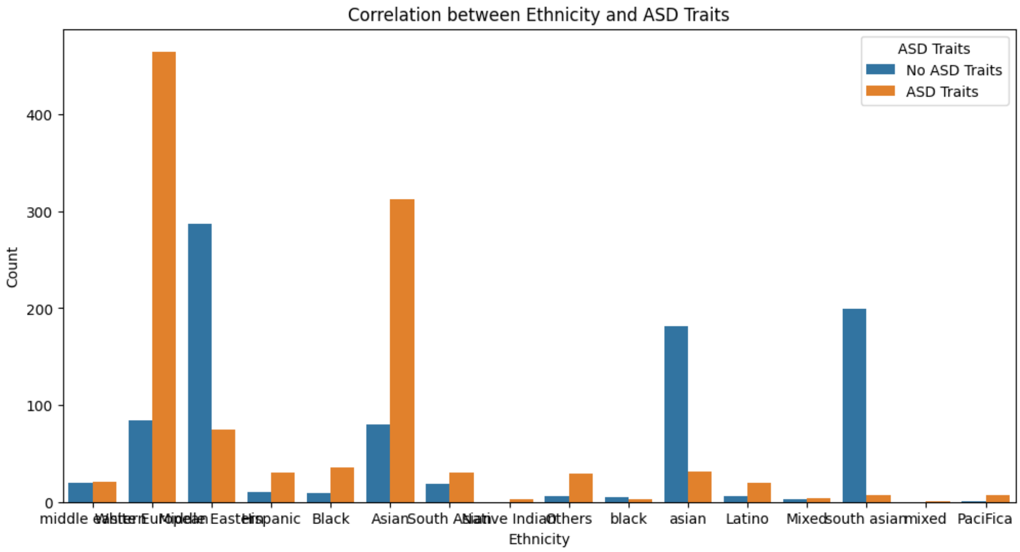

Figure 3. Ethnicity Plot – ASD Traits

Deciphering possible associations between medical illnesses and features associated with Autism Spectrum Disorder (ASD) is essential to understanding the intricate aetiology of ASD. In this study, understanding the relationship between jaundice occurrence and ASD trait manifestation in a particular dataset is one of the essential needs.

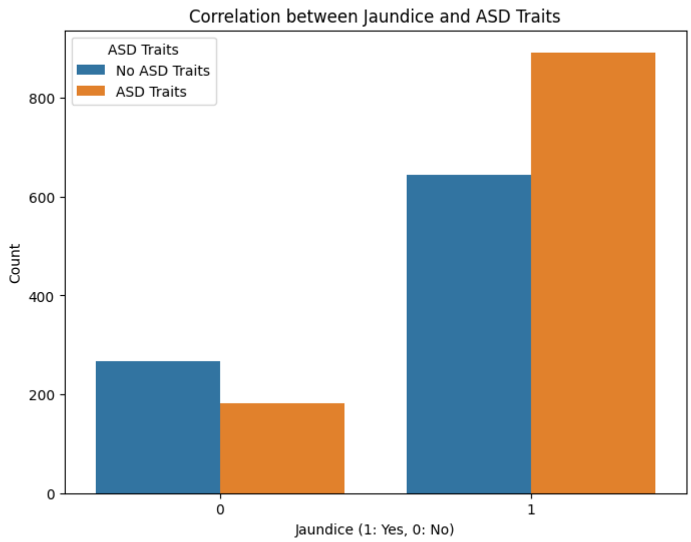

Figure 4. Pre-Condition Jaundice Plot – ASD Traits

It is possible to gain an improved comprehension of autism spectrum disorder (ASD) by examining the prevalence of particular features in people with ASD. Ten major questions (A1 through A10) that cover a range of topics related to perception, attention, and social cognition are the main emphasis of the study.

Data Filtering

Rows are selectively filtered to isolate individuals with ASD traits (ASD_traits = 1), creating a subset for trait-specific analysis.

4.1.2. Trait Prevalence Calculation

The prevalence of each trait is computed by calculating the mean of responses to the ten questions among individuals with ASD traits.

Question Specificity
Each question (A1 to A10) is designed to capture specific aspects of behavior and cognition.

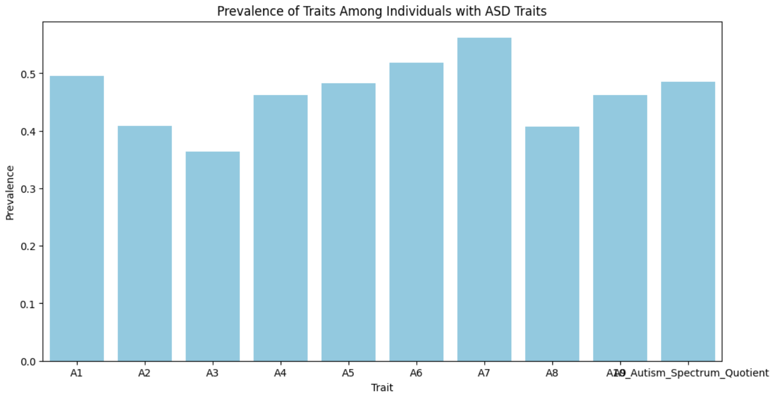

Figure 5. ASD Traits

To compute the prevalence of each specific trait (A1 to A10) among individuals with ASD traits.
Let's denote the following:

- N: Total number of individuals in the dataset
- N_{ASD}: Number of individuals with ASD traits (ASD_traits = 1)
- A_i: The column representing trait i (A1 to A10)

The prevalence Pi of trait i among individuals with ASD traits can be calculated as:

$$Pi = \frac{\text{Number of induviduals with ASD trails exhibiting trait } i}{\text{Total number of induviduals with ASD traits}}$$

$$P_i = \frac{\sum_{j=1}^{N_{\text{ASD}}} A_{ij}}{N_{\text{ASD}}}$$

Table 1. ASD Traits Distribution among Male and Female

Sex	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
F	0.765766	0.63964	0.504505	0.675676	0.603604	0.828829	0.855856	0.594595	0.666667	0.711712
M	0.464174	0.382139	0.346833	0.437175	0.469367	0.482866	0.528557	0.386293	0.439252	0.458982

The dataset unveils distinct trait prevalence values between females (F) and males (M) in the context of Autism Spectrum Disorder (ASD). Notably, traits capture a spectrum of behaviors and cognitive patterns associated with ASD. For instance, A1 reflects heightened sensitivity to small sounds, and A2 indicates a preference for concentrating on the whole picture rather than details. Females consistently exhibit higher prevalence across the assessed traits, with A7, which gauges the ability to interpret others' intentions during story reading, being particularly pronounced.Furthermore, A8, which involves a proclivity for collecting information about categories of things, showcases significant gender differences. Females display a more pronounced interest in this trait compared to males. Understanding these trait-specific nuances is crucial for tailoring interventions, as it provides a granular understanding of gender-specific ASD presentations. The observed disparities emphasize the multidimensionality of ASD traits and highlight the need for personalized support strategies catering to the unique challenges faced by individuals across different genders.
Let's denote the following:

- N_{ASD}: Number of individuals with ASD traits (ASD_traits = 1)
- N_{Male}: Number of males with ASD traits
- N_{Female}: Number of females with ASD traits
- Ai: The column representing trait i (A1 to A10)

The prevalence $P_{i,\text{Male}}$ of trait i among males with ASD traits can be calculated as:

Number of males with ASD traits exhibiting trait *i*

$$P_{i,\text{Male}} = \frac{\text{Number of males with ASD traits exhibiting trait } i}{N_{\text{Male}}}$$

Similarly, the prevalence ,$P_{i,\text{Female}}$ of trait *i* among females with ASD traits can be calculated as:

$$P_{i,\text{Female}} = \frac{\text{Number of females with ASD traits exhibiting trait } i}{N_{\text{Female}}}$$

The proposed system calculated the mean prevalence of each trait separately for males and females with ASD traits. In trait A1, approximately 76.58% of females with ASD traits exhibit heightened sensitivity to small sounds. This interpretation extends to other traits, portraying the prevalence of specific behavioral patterns in females. Conversely, in trait A1 among males with ASD traits, the prevalence is notably lower at approximately 46.42%. This trend persists across various traits, reflecting distinct patterns of trait expression in males. The mean prevalence of particular features varies significantly between males and females with ASD traits. With all factors considered, the mean prevalence of ASD features is higher in females, highlighting gender differences in trait expression. The observed variations in prevalence imply that among persons with ASD features, some symptoms may be more prevalent or express in females differently than in males.

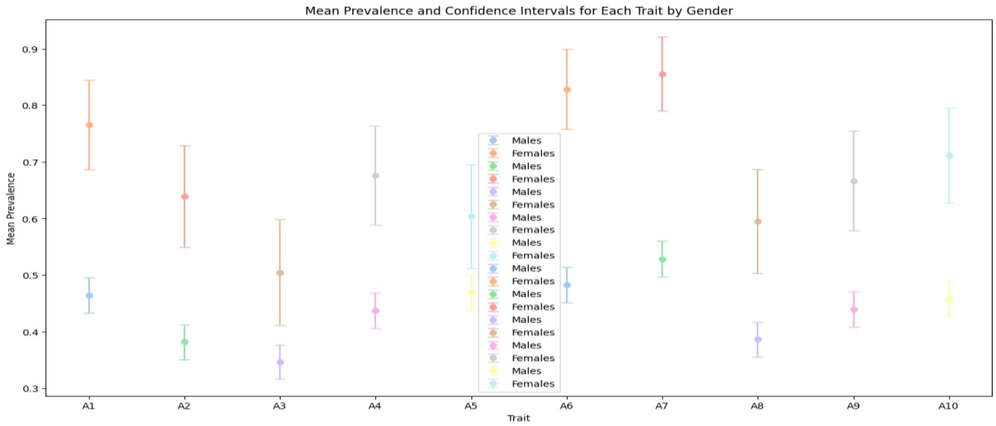

Figure 6. Confidence Intervals – ASD Traits by Gender

The mean prevalence of traits (A1 to A10) among individuals with ASD traits varies significantly between males and females, with females generally exhibiting a higher mean prevalence for each trait compared to males, as evidenced by the non-overlapping confidence intervals.We have examined age-related trends in the prevalence of specific Autism Spectrum Disorder (ASD) features (A1 to A10) in individuals exhibiting ASD traits. People were sorted into different age groups to identify patterns of development and differences in the way traits were expressed. The countplot visualizations contributed to a more sophisticated understanding of age-related trends in the incidence of ASD features by illuminating how these symptoms appeared within particular developmental stages.

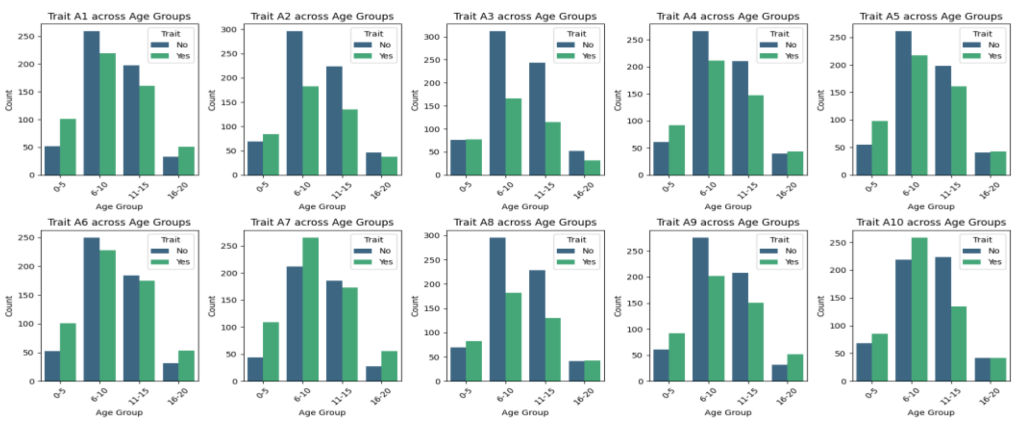

Figure 7. Age Group Plot – ASD Traits

4.1.3. Co-occurance Condition Analysis

It is essential to understand the co-occurrence of autism spectrum disorder (ASD) features with learning disabilities, anxiety disorders, depression, and speech delay/language problems was critical. Examining these interrelated occurrences helped clarify the complex terrain of neurodevelopmental difficulties and mental health disorders in people with ASD. We have analyzed co-occurrence patternsfor people with ASD.The significant correlations found in the research findings presented between autism spectrum disorder (ASD) traits and learning disabilities, depression, anxiety disorders, and speech delay/language disorders highlight the complex interplay between neurodevelopmental disorders and mental health issues. Speech delay/language problems and learning disorders, as well as depression and anxiety disorders, have strong positive correlations that are close to or above 0.98. These correlations point to a large overlap and possible co-occurrence of these conditions.We have conducted a comprehensive analysis of the co-occurrence of conditions, including Speech Delay/Language Disorder, Learning Disorder, Depression, and Anxiety Disorder, among individuals exhibiting Autism Spectrum Disorder (ASD) traits. The analysis involved calculating conditional probabilities to understand the likelihood of each condition given the presence of ASD traits. The proposed system calculated co-occurrence counts by grouping data based on the presence of ASD traits and summing the occurrences of each condition.

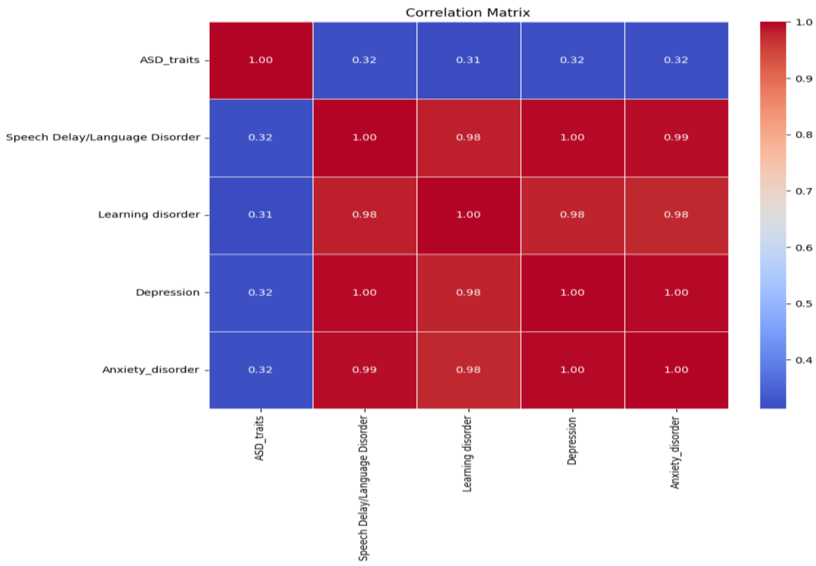

Figure 8. Correlation Analysis of Traits with several conditions

The conditional probabilities were then computed using the formula:

$$P(\text{condition} \mid \text{ASD\_traits}) = \frac{\text{Co-occurrence count of condition and ASD traits}}{\text{Total dataset size}} \times 100$$

These probabilities were visualized through a horizontal bar chart, where each bar represented a specific condition.

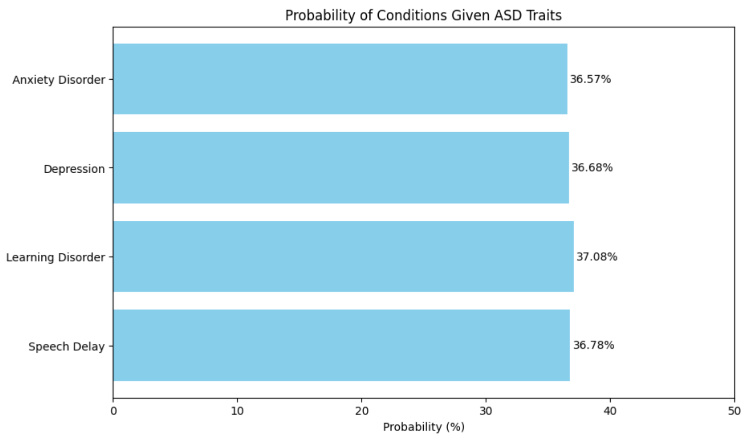

Figure 9. Probability of Conditions - ASD Traits

Our understanding of the intricate interactions between ASD features and related disorders has improved as a result of this analytical method, which has provided insightful information for personalised therapies and improved diagnostic precision.

4.2. Feature Engineering

A significant step in the machine learning process that affects the ability to be interpreted and accuracy of models is feature engineering. The model's capacity to identify patterns linked to ASD traits is improved when pertinent features. The Random Forest algorithm is an ensemble learning method that builds multiple decision trees and merges their predictions. The final prediction is often determined by a majority vote or averaging of individual tree predictions.Random Forest calculates feature importance based on the average impurity decrease or Gini importance across all decision trees. The importance I_f of feature *f* is computed as follows:

$$I_f = \frac{\sum_t I_t(f) \times p_t}{\sum_t p_t}$$

where:

- $I_t(f)$ is the improvement in impurity due to feature *f* in tree *t*,
- p_t is the proportion of samples reaching node *t*.

The initial features extracted were plotted using the graph as depicted in the figure. Recursive Feature Elimination (RFE) is a technique used for feature selection by recursively removing less important features until the desired number of features is reached. When combined with a Random Forest Classifier, RFE becomes a powerful tool for identifying the most relevant features in a dataset related to Autism Spectrum Disorder (ASD) traits. Random Forests are well-suited for this task due to their ability to handle non-linear relationships and capture complex feature interactions.The proposed parameter adjusted RFE algorithm, involved fitting the classifier, evaluating feature importance, and recursively eliminating less important features.

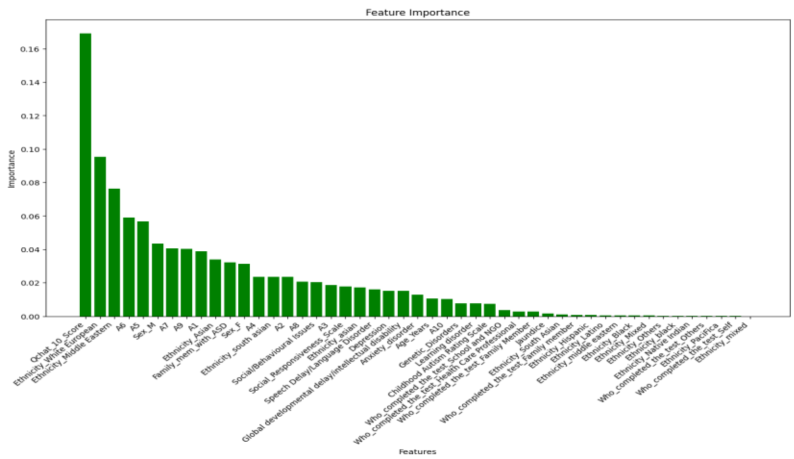

Figure 10. Feature Engineering Plot

In this study, Recursive Feature Elimination (RFE) was applied in conjunction with a Random Forest Classifier to systematically eliminate less important features and enhance model interpretability. The Random Forest Classifier, denoted as *RF*, was initialized with parameters, such as the number of trees *N* and maximum depth *D*, to create a forest of decision trees. The classifier was trained on the entire feature matrix *X* and target variable *y* to derive feature importance scores (FI_i).

$$RF(X, y) \to FI_i, \quad \text{for } i = 1, 2, \ldots, m$$

The features were ranked based on their importance scores, and parameter adjustment was performed to fine-tune the Random Forest Classifier. The process iteratively removed the least important features until the desired number *k* was achieved, resulting in a subset of features (X_{selected}). This optimization aimed to enhance the predictive accuracy of ASD traits by selecting the most informative features and refining model parameters.

$$X_{\text{selected}} = \text{RFE}(RF, X, y, k)$$

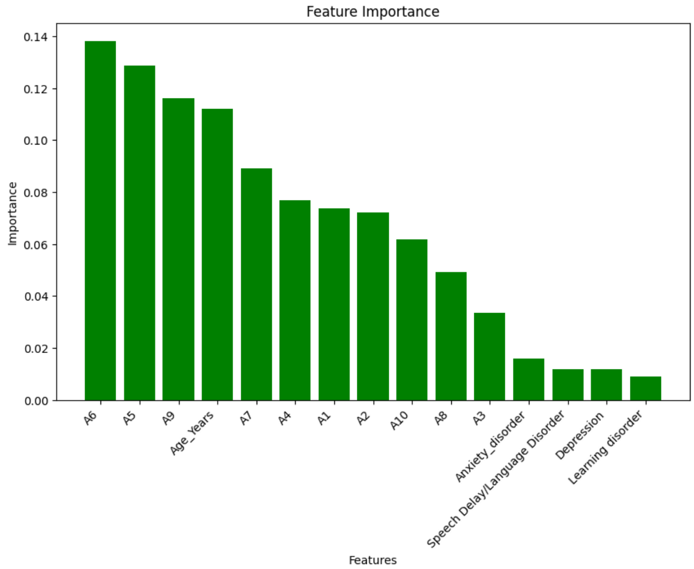

Figure 11. Optimized Feature Extraction

In employing Recursive Feature Elimination (RFE), the objective was to distill the most critical features related to Autism Spectrum Disorder (ASD) traits. The RFE algorithm, coupled with a Random Forest Classifier, systematically identified and eliminated less impactful features. Following the extraction, the selected features were then visualized through a bar plot, highlighting their respective importance scores. This process facilitated a refined understanding of the key contributors to ASD traits, providing valuable insights into the complex interplay of variables within the dataset.

4.3. Machine Learning Models

In the proposed system, various machine learning algorithms were applied to the dataset following feature engineering steps.In the investigation of predicting Autism Spectrum Disorder (ASD) traits within the proposed system, an array of machine learning algorithms was meticulously employed to comprehensively assess their efficacy. Each algorithm serves a unique purpose in modeling and analyzing the intricate relationships present in the dataset. The selected features, including 'Qchat_10_Score', 'A6', 'A5', 'Sex', 'A7', 'A9', and 'A1', underwent preprocessing, such as label encoding for categorical variables and imputation for missing values using SimpleImputer. Multiple classifiers, namely Logistic Regression, Decision Tree, Linear SVC, Naive Bayes, KNN, K-means, Random Forest, Gradient Boosting, and AdaBoost, were employed to predict the target variable 'ASD_traits.'

Linear Regression

Linear regression, a fundamental algorithm, models the relationship between the independent variable x and the dependent variable y. In the ASD trait prediction context, it assesses the linear correlation between specific features and the likelihood of ASD traits.

$y=mx+b$

Logistic Regression

Logistic regression, tailored for binary classification, computes the probability $P(Y=1)$ of an instance having ASD traits. It is crucial for understanding the likelihood of ASD manifestation based on various features.

$$P(Y=1)=\frac{1}{1+e^{-(b_0+b_1X)}}$$

Decision Tree

Decision trees employ recursive splitting to construct a tree-like model. The algorithm facilitates a clear visualization of feature importance, aiding in the identification of key factors contributing to ASD trait prediction.

SVM (Support Vector Machine) Algorithm

SVM seeks an optimal hyperplane for separating instances into different classes. In ASD prediction, SVM aims to delineate the boundary between individuals with and without ASD traits.

Naive Bayes Algorithm
Naive Bayes, grounded in Bayes' theorem, assumes independence between features. In ASD prediction, it calculates the probability of traits based on observed feature patterns, considering the potential influence of each feature independently.

KNN (K-Nearest Neighbors) Algorithm
KNN classifies instances by assessing the majority class among their nearest neighbors. In ASD trait prediction, it gauges the collective influence of neighboring instances to make predictions based on proximity.

K-Means Algorithm
K-Means, an unsupervised clustering algorithm, partitions data into clusters. While not inherently designed for classification, it aids in identifying patterns and grouping similar instances, potentially revealing distinct ASD trait profiles.

Random Forest Algorithm
Random Forest builds multiple decision trees and aggregates their predictions. This ensemble approach enhances predictive accuracy and minimizes overfitting, offering a robust model for ASD trait classification.

Gradient Boosting Algorithm
Gradient Boosting sequentially builds an ensemble of weak learners. It corrects errors from preceding models, emphasizing the significance of features in predicting ASD traits over multiple iterations.

AdaBoost Algorithm
AdaBoost combines multiple weak classifiers to create a robust model. In the ASD trait prediction context, it emphasizes the influence of specific features by assigning higher weights to misclassified instances, ultimately contributing to an accurate prediction.
The accuracy of each classifier was evaluated on the test set, demonstrating their performance in identifying ASD traits. The results, visualized through a bar chart, showcased the comparative accuracies of the classifiers. Notably, the Random Forest classifier exhibited the highest accuracy among the tested algorithms. The systematic approach of applying various machine learning models contributes to a comprehensive understanding of their effectiveness in predicting ASD traits within the proposed system.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

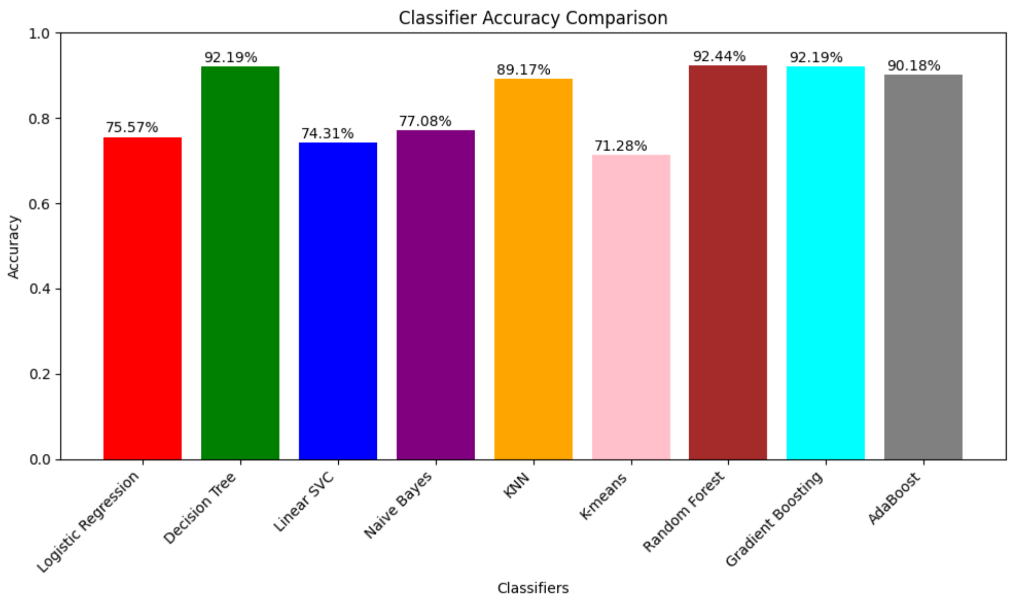

Figure 12. Performance of Machine Learning Algorithms

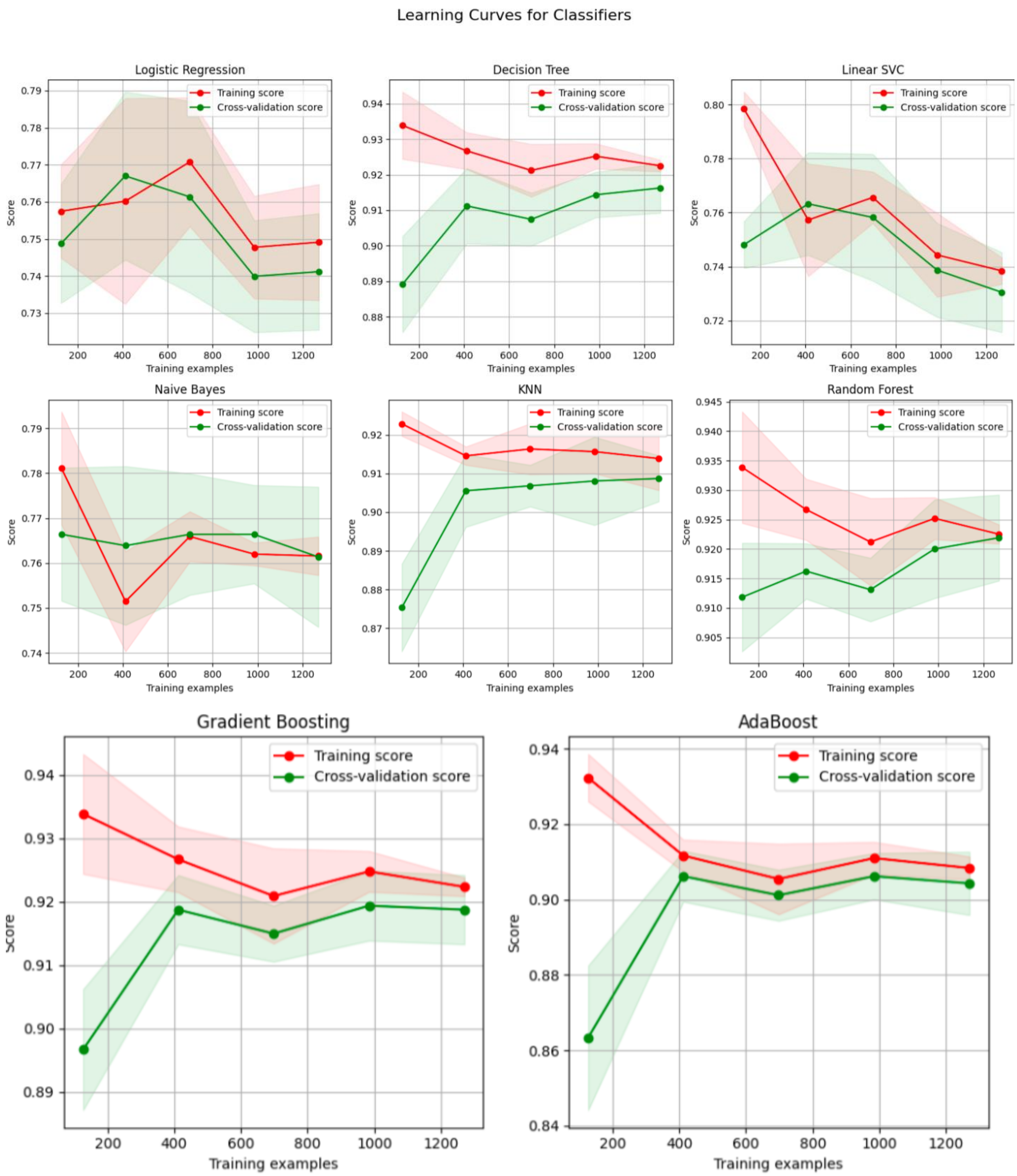

Figure 13. Learning Curves of various Machine Learning Algorithms

In the conducted experiments using various machine learning algorithms for predicting ASD traits in the proposed system, the results revealed varying accuracy scores. Among the classifiers, Random Forest and Gradient Boosting exhibited the highest accuracies, both achieving an accuracy of 92%. These findings underscore the effectiveness of these models in accurately identifying individuals with ASD traits, emphasizing their potential utility within the proposed system for ASD detection.To evaluate the effectiveness of different machine learning classifiers for the prediction of autism spectrum disorder (ASD), a learning curve analysis was conducted. A comprehensive evaluation of model generalisation was made possible by the creation of learning curves that revealed the correlation between the sizes of training datasets and classifier accuracy. In an effort aid in highlight possible overfitting or underfitting problems, the visualisations highlighted patterns in the training and cross-validation scores. The classifiers with the highest accuracies, Random Forest and Gradient Boosting, both reached higher accuracy.

5. CONCLUSION

In conclusion, our research delved into an extensive analysis of Autism Spectrum Disorder (ASD) traits, leveraging a diverse dataset sourced from the University of Arkansas Computer Science Department. The investigation encompassed age distribution, trait prevalence, and co-occurrence conditions, shedding light on patterns associated with ASD development in children. Employing Recursive Feature Elimination for feature engineering and a range of machine learning models, including Linear Regression, Logistic Regression, Decision Tree, SVM, Naive Bayes, KNN, K-means, Random Forest, Gradient Boosting, and AdaBoosting, our study aimed at predicting ASD based on a comprehensive set of features. Notably, Random Forest and Gradient Boosting emerged as the most accurate models, both achieving a remarkable accuracy of 92%. These findings underscore the efficacy of these classifiers in discerning and predicting ASD, contributing valuable insights to the broader understanding of this complex disorder.

REFERENCES

[1] Frith, U., &Happé, F. (2005). Autism spectrum disorder. Current biology, 15(19), R786-R790.

[2] https://www.who.int/news-room/fact-sheets/detail/autism-spectrum-disorders?gclid=Cj0KCQiA5fetBhC9ARIsAP1UMgHdwFHgDqazrhccLcv5fvmP2EBaFweVzwA8MOeIUeyBDEjLBn_X4sEaAqeJEALw_wcB

[3] Karunakaran, P., &Hamdan, Y. B. (2020). Early prediction of autism spectrum disorder by computational approaches to fMRI analysis with early learning technique. Journal of Artificial Intelligence, 2(04), 207-216.

[4] Tripathy, H. K., Mallick, P. K., & Mishra, S. (2021). Application and evaluation of classification model to detect autistic spectrum disorders in children. International Journal of Computer Applications in Technology, 65(4), 368-377.

[5] Abdelwahab, M. M., Al-Karawi, K. A., Hasanin, E. M., &Semary, H. E. (2024). Autism Spectrum Disorder Prediction in Children Using Machine Learning. Journal of Disability Research, 3(1), 20230064.

[6] Wall D, Kosmicki J, Deluca T, et al. Use of machine learning to shorten observation-based screening and diagnosis of autism. Transl Psychiatry. 2012;2:100. doi: 10.1038/tp.2012.10

[7] Mueller A, Candrian G, Kropotov JD, et al. Classification of ADHD patients on the basis of independent ERP components using a machine learning system. Nonlinear Biomed Phys. 2010;4:1. doi: 10.1186/1753-4631-4-S1-S1

[8] Bedi G, Carrillo F, Cecchi GA, et al. Automated analysis of free speech predicts psychosis onset in high-risk youths. NPJ Schizophr. 2015;1:15030. doi: 10.1038/npjschz.2015.30

[9] Bishop- Fitzpatrick et al. Using machine learning to identify patterns of lifetime health problems in decedents with autism spectrum disorder. Autism Res. 2018;11(8):1120–1128. doi: 10.1002/aur.1960

[10] F. Thabtah and D. Peebles, "A new machine learning model based on induction of rules for autism detection", Health Inform. J., 2019.

[11] M. S. Satu, F. F. Sathi, M. S. Arifen, M. H. Ali and M. A. Moni, "Early detection of autism by extracting features: A case study in Bangladesh", Proc. 1st Int. Conf. Robot. Elect. Signal Process. Techn. (ICREST), pp. 87-90, Jan. 2019.

[12] F. Thabtah, F. Kamalov and K. Rajab, "A new computational intelligence approach to detect autistic features for autism screening", Int. J. Med. Inform., vol. 117, pp. 112-124, Sep. 2018.

[13] A. Crippa, C. Salvatore, P. Perego, S. Forti, M. Nobile, M. Molteni, et al., "Use of machine learning to identify children with autism and their motor abnormalities", J. Autism Develop. Disorders, vol. 45, no. 7, pp. 2146-2156, 2015.

[14] F. Thabtah, "Autism spectrum disorder screening: Machine learning adaptation and DSM-5 fulfillment", Proc. 1st Int. Conf. Med. Health Inform., pp. 1-6, 2017.

[15] M. Duda, R. Ma, N. Haber and D. P. Wall, "Use of machine learning for behavioral distinction of autism and ADHD", Transl. Psychiatry, vol. 6, no. 2, pp. e732, 2016.