A Multivariate Analysis using Mathematically Modified Machine Learning (MA-MM-ML) Algorithm of Autism Spectrum Disorder (ASD)

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Abstract: *Autism Spectrum Disorder (ASD) is a neuro-developmental disorder which impacts a person's ability to interact with others, communicate and engage in activities in a repetitive manner. Thus, the purpose of this study is to develop a Multivariate Analysis for the diagnosis of ASD in children through Mathematically Modified Machine Learning (MA-MM-ML) algorithm to enhance the efficacy and efficiency of the diagnostic process. Standard diagnostic procedures are time-consuming and approximate, thus, the use of advanced computational methods is necessary. Therefore, the reason for this research is to apply multivariate analysis and machine learning algorithms that can detect the heterogeneity of the ASD and diagnose the disease whereas develop interventions at an early stage. The MA-MM-ML algorithm that has been proposed contains the preprocessing step, the PCA, and BO-SVM techniques with hyperparameter tuning. This approach ensures that the ASD analysis and classification are accurate and less resource intensive thus improving the diagnostic capability. Therefore, the present study indicates that the research work can be done with multivariate analysis and machine learning to overcome the challenges related to ASD research and practice. The experimental analysis of proposed MA-MM-ML is compared with existing state-of-art techniques whereas MA-MM-ML achieves highest accuracy of 92.67%.*

Keyword: *Bayesian optimization, diagnostic accuracy, hyperparameter tuning, autism, and mathematical model.*

Introduction

Autism Spectrum Disorder (ASD) is classified as a developmental disorder that impacts the brain and affects a person's ability to socialize, communicate, and exhibit repetitive behavior throughout his or her lifetime [1]. DSM-5 defines ASD as a spectrum disorder, which implies that it consists of a set of symptoms and the severity of these symptoms varies. ASD is a developmental disorder that affects people in their childhood and throughout their adulthood and these individuals may be strong in some areas and weak in others [2]. The reason for ASD is still not clear but it is a combination of genetic and environmental factors.

Multivariate analysis (MA) is a kind of analysis carried out when several variables are analyzed as it relates to a specific outcome. Therefore, multivariate analysis is a suitable approach in the case of ASD, as the disorder is quite heterogeneous in this case. ASD is not a single disease; it affects people in different aspects regarding the behavioral, cognitive, and neuronal perspectives [3]. It is crucial to employ multivariate analysis within the ASD research as it enables the analysis of the phenomenon in its entirety and the identification of patterns that may remain unnoticed in the case of single-variable analysis. This is very important especially in the development of diagnostic instruments that can effectively diagnose the disorder and intervention techniques because the causes that result in the development of the disorder are considered [4].

Algorithms can be said to have transformed many sectors by applying Machine Learning (ML) in the identification of patterns in large data and the capacity to forecast them. In the case of ASD, application of ML has a high potential in improving the diagnosis of the disorder, improving the general knowledge about the disorder, and designing individualized interventions. The diagnosis of ASD has been a complex process in the past as it involved behavioral analysis and clinical observations, which are often lengthy and inconclusive. While, the statistical learning algorithms can analyze large data sets of genotype, neuroimaging, and behavioral data to find biomarkers and features that are relevant to ASD. This data driven approach improves the accuracy and timeliness of the ASD diagnoses and hence early intervention is provided [5].

The integration of MA and ML is most effective for ASD investigations and its nature polygenic and polyetiologic. ASD is caused by multiple genes and multiple factors of environmental and neurological nature [6]. The conventional measures used in analyzing a single variable can be very inconclusive or even misleading due to failure to account for interdependencies between these variables [7]. The integration of MA with the models of ML can help the researchers to come up with better models that can address the complex nature of ASD. It allows the detection of the fine details regarding the factors that contribute to the disorder hence enhancing the diagnosis process and the kind of intervention that should be administered [8].

Another advantage of multivariate analysis when it is used together with ML is the fact that it can easily handle high dimensions. ASD studies frequently use datasets with many variables such as genetic, neurophysiological, and behavioral [9]. The given input datasets have a high dimensionality, but it is possible to use MA techniques like Principal Component Analysis (PCA) to decrease it and preserve the most valuable information at the same time. This dimensionality reduction helps when applying ML algorithms as it reduces their computational complexities and enhances the accuracy of the models [10, 11].

In addition, more advanced ML, including Support Vector Machine (SVM), Random Forest (RF), k-Nearest Neighbour (KNN), Decision Tree (DT) and Neural Networks, can be used to categorise ASD subjects utilizing their multivariate characteristics [12]. These algorithms can be trained on large datasets so algorithm can learn the various patterns and relationships between the features in a dataset and thus be capable of predicting new values on new data [13, 14]. The hyperparameter tuning of these ML models is made efficient with the help of Bayesian Optimization (BO). BO uses the probabilistic model of the objective function and avoids getting entombed in local optima when searching for the best hyperparameters that would give the best prediction outcomes.

Related Works

The traditional methods of diagnosing the features of Autism Spectrum Disorder (ASD) entails the use of assessment and screening tools which is costly and takes a lot of time. Classification is feasible employing the use of ML, and the most frequently used approach is Support Vector Machines (SVM). The objective of this paper [14] is to compare the performances of SVM, k-NN, RF, NB, SGD, AdaBoost, and CN2 Rule Induction on four datasets of ASD. Therefore, the study showed that SGD, RF, and AdaBoost had high classification accuracy in the various age groups, thus, showing the effectiveness of ML in ASD assessment.

ASD is a developmental disorder that affects social communication and interaction and if diagnosed early, then intervention is possible. Lack of assessment tools and services in the local environment pushes children with developmental delays to start rehabilitation only when they are forced to enroll in compulsory education. Smart technologies such as ML can help to raise diagnostic precision and efficiency. Neural Networks (NN), SVM and DT are amongst the most used ML techniques in ASD datasets. This review [15] focuses on the current studies on the use of ML in ASD, suggesting strategies for feature selection, classification, and handling of complex data.

ASD affects children's social interaction and behavior, therefore, it should be diagnosed as early as possible. This study categorizes ASD using k-NN, SVM, RF, Backpropagation, and Deep Learning (DL) on the samples involving children and adolescents. Comparing the algorithms, RF comes out to be the most specific and sensitive in diagnosing ASD. The focus is made on the aspects of early ASD identification and the role of machine learning in this task [16].

ASD is a neurological deficit that impacts on language, speech, cognitive and social development. Prevention or early diagnosis and management are critical where today clinical tests are slow and costly. The most used ML algorithms such as SVM, RF, NB, Logistic Regression (LR), and k-NN are used to build models on ASD datasets [17]. The objective of this research is to make a process of ASD diagnosis more efficient, with the help of LR model being the most accurate. Considering the findings, it is possible to recommend the use of ML in ASD screening at an early age.

ASD is a disorder that impacts several aspects of an individual's life, including social interaction and communication. Manifestations are evident from childhood and continue in adult life. In the prediction of ASD, this research considers the following ML algorithms: NB, SVM, LR, KNN, NN, and Convolutional Neural Network (CNN). In this paper [18], the authors assess three ASD datasets and conclude that CNN models can obtain high accuracy; thus, ML can be applied to ASD studies and diagnostics.

ASD interferes with patients' daily activities, and appropriate treatment is needed as soon as possible. This work presents a framework based on ML approaches for the early diagnosis of ASD. Four strategies of feature scaling are used and eight ML algorithms are used on four ASD datasets. AdaBoost and LDA have the highest accuracy for the different groups of age. The assessment of features helps the healthcare practitioners in the screening of ASD. The framework demonstrates encouraging outcomes, which illustrates the role of ML in diagnosing ASD and supporting decision-making in the field of medicine [19].

Existing machine learning methods for ASD classification is not uniform across age groups, and hyperparameters optimization is done either manually or by grid search which is time consuming and may not find the best solution. The current approaches also have issues of feature selection and preprocessing which are not consistent throughout and hence affect the models. The above challenges are tackled by the BO-SVM, which offers a general framework for its application across age groups. They combine the preprocessing step, PCA-based feature extraction, and hyperparameter tuning in one framework. BO then builds a probabilistic model of the objective function and thus, it samples through the hyperparameter space to find the best parameters that will cut down computation time and enhance performance. Thus, BO-SVM improves the classification accuracy and efficiency compared to the conventional methods, providing a more reliable solution for ASD classification based on the reduced feature space optimized by BO.

Proposed Methodology-Machine Learning based ASD Classification

This section describes how Bayesian Optimization (BO) can be integrated with Support Vector Machine (SVM)for identifying ASD, and the results obtained in the study. The proposed methodology is given in Figure 1.

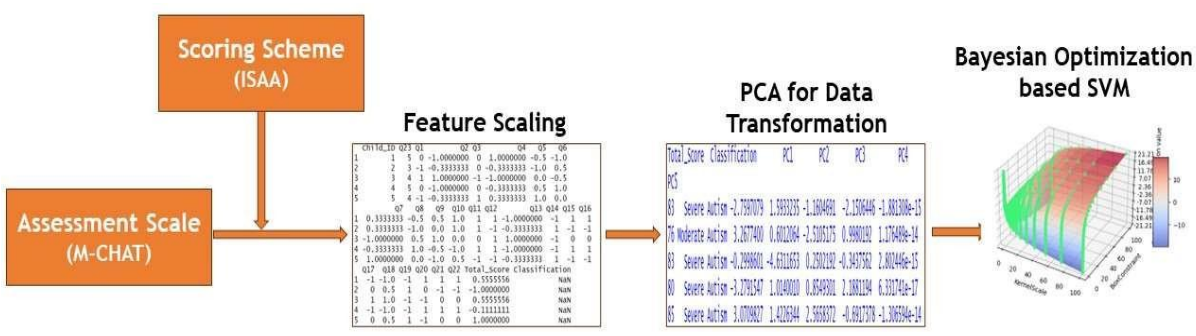

Figure 1. Overall Research Methodology

To ensure all features contribute equally to the analysis, the features are scaled to a common range using min-max normalization. Min-max normalization scales each feature x_i to the range [0, 1]. For each feature x_i in Equation 1.

$$x_i' = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)} \text{------------} (1)$$

where x_i' is the normalized feature, $\min(x_i)$ is the minimum value of feature x_i, and $\max(x_i)$ is the maximum value of feature x_i.

PCA is used to reduce the dimensionality of the data while retaining as much variance as possible. Equation 2 standardize the dataset X to have zero mean and unit variance.

$$X_{std} = \frac{K - \mu_X}{\sigma_X} \text{------------} (2)$$

where μ_K is the mean of X and σ_K is the standard deviation of X.

Equation 3 compute the covariance matrix Σ.

$$\Sigma = \frac{1}{n-1} X^T_{std} X_{std} \text{---------} (3)$$

where n is the number of samples.

The eigen decomposition on Σ is utilised to obtain eigenvalues and eigenvectors using the Equation 4.

$$\Sigma_v = \lambda_v \text{-----------} (4)$$

where v are the eigenvectors and λ are the eigenvalues.

The data standardization onto the top k eigenvectors is projected to obtain the reduced dataset X_{PCA} by the Equation 5.

$$X_{PCA} = X_{std} V_k \text{----------} (5)$$

where V_k contains the top k eigenvectors.

Bayesian Optimization (BO) is used to find the optimal hyperparameters for the SVM model, which is then used for feature selection and classification. The SVM model is parameterized by C (regularization parameter) and γ (kernel parameter). The SVM objective function is given in Equation 6.

$$\min_{w,b,(} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{n} \xi_i \text{---------} (6)$$

Subject to

$$y_i(w \cdot \phi(x_i) + b) \geq 1 - \xi_i, \quad \xi_i \geq 0, \quad i = 1,2,3, \ldots \ldots, n$$

where w and b are the weight vector and bias, respectively, ξ_i are slack variables, and $\phi(x_i)$ is the feature mapping function. The objective function is determined as the cross-validation accuracy $CV(C, \gamma)$ on the dataset X_{PCA}.

Place a GP prior on the objective function (C, γ) using Equation 7.

$$f(C, \gamma) \sim \mathcal{G}\text{P}(\mu(C, \gamma), \text{k}(((C, \gamma)), ((C', \gamma'))) \text{----------} (7)$$

where μ is the mean function and k is the kernel function (e.g., the squared exponential kernel).

$$k((C, \gamma), (C', \gamma')) = \sigma_f^2 exp\left(-\frac{1}{2l^2}((C - C')^2 + (\gamma + \gamma')^2)\right) \text{---------} (8)$$

where σ_f^2 is the signal variance, and l is the length scale.

After observing data $D_{1:t} = \{(C_i, \gamma_i, y_i)\}_{i=1}^{t}$, update the GP posterior. The posterior mean $\mu_t(C,\gamma)$ and variance $\sigma_t^2(C,\gamma)$ are given in Equation 9 and 10.

$$\mu_t(C,\gamma) = k_t^T(K_t + \sigma_n^2 I)^{-1} yt \text{ --------(9)}$$

$$\sigma_t^2(C,\gamma) = k(((C,\gamma),((C,\gamma))) - k_t^T(K_t + \sigma_n^2 I)^{-1} k_t \text{ -----------(10)}$$

The acquisition function $a(x|D_{1:t})$ guides the search for the next set of parameters to be evaluated and it is accomplished using Equation 11.

$$(C_{next}, \gamma_{next}) = arg \max_{(C,\gamma)} a((C,\gamma)|D_{t:1}) \text{ --------- (11)}$$

A common choice for the acquisition function is Expected Improvement (EI) is given in Equation 12.

$$a((C,\gamma)|D_{t:1}) = \text{D}[\max(0, f(C,\gamma) - f(C^+,\gamma^+)|D_{t:1}] \text{ ----------(12)}$$

where (C^+,γ^+) is the best observed parameter set so far. The expected improvement can be computed in Equation 13.

$$a((C,\gamma)|D_{t:1}) = (f(C^+,\gamma^+) - \mu_t((C,\gamma))\Phi\left(\frac{f(C^+,\gamma^+)-\mu_t(C,\gamma)}{\sigma_t(C,\gamma)}\right) + \sigma_t(C,\gamma)\phi\left(\frac{f(C^+,\gamma^+)-\mu_t(C,\gamma)}{\sigma_t(C,\gamma)}\right)) \text{ ---------(13)}$$

where Φ and ϕ are the CDF and PDF of the standard normal distribution, respectively.

The steps involved in the optimization loop of the BO is initiated with the selection of hyperparameters randomly and calculate the objective function to get the first estimates. The GP is assigned to these observations, then optimize acquisition function to get the next set of hyperparameters. The new hyperparameters are utilised to train the SVM model, which calculate the objective function and update the GP with the new observation. Perform these steps until convergence or until the maximum number of iterations is achieved. After the variables are converged, choose the optimum hyperparameters and proceed with the training of the final SVM on the entire dataset. This methodology effectively combines the preprocessing step, the feature extraction step, and the BO for hyperparameter selection in SVM to guarantee a reliable and less computationally expensive process for achieving high classification performance in ASD analysis. The procedure of Mathematically Modified Machine Learning (MA-MM-ML) is given in Algorithm 1.

Algorithm 1. Mathematically Modified Machine Learning

1. Preprocessing using Feature Scaling
Normalize each feature xi to the range [0, 1]

$$x_i' = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)}$$

2. Dimensionality Reduction using PCA
Standardize dataset X: $X_{std} = \frac{K-\mu_X}{\sigma_X}$
Compute covariance matrix Σ: $\Sigma = \frac{1}{n-1} X_{std}^T X_{std}$

Perform eigen decomposition on Σ: $\Sigma_v = \lambda_v$
Project data onto top k eigenvectors: $X_{PCA} = X_{std} * V_k$

3. Feature Selection and Classification using BO-SVM

Initialize:
Randomly select initial hyperparameter values (C, γ)
Evaluate objective function to obtain initial observations ($D_{1:n}$)
Fit GP model to initial observations
Optimization Loop:
while not converged and iterations < $max_{iterations}$:
Optimize acquisition function to find next hyperparameters (C_{next}, γ_{next})
Train SVM with (C_{next}, γ_{next}) and evaluate objective function
Update GP model with new observation (C_{next}, γ_{next}, y_{next})
Select best hyperparameters (C*, γ*) after convergence
Train final SVM model on entire dataset X_PCA

4. Bayesian Optimization Details:

Place GP prior on objective function: $f(C,\gamma) \sim \mathcal{G}P(\mu(C,\gamma), k(((C,\gamma)),((C',\gamma'))))$
Kernel function $k((C,\gamma),(C',\gamma')) = \sigma_f^2 exp\left(-\frac{1}{2l^2}((C - C')^2 + (\gamma + \gamma')^2)\right)$

Update GP posterior:

Posterior mean: $\mu_t(C,\gamma) = k_t^T(K_t + \sigma_n^2 I)^{-1} yt$
Posterior variance: $\sigma_t^2(C,\gamma) = k(((C,\gamma),((C,\gamma))) - k_t^T(K_t + \sigma_n^2 I)^{-1} k_t$
Acquisition function to guide next parameter search:

$$(C_{next}, \gamma_{next}) = arg \max_{(C,\gamma)} a((C,\gamma)|D_{t:1})$$

Expected Improvement (EI): $a((C,\gamma)|D_{t:1}) = D[\max(0, f(C,\gamma) - f(C^+,\gamma^+)|D_{t:1}]$

$$a((C,\gamma)|D_{t:1}) = (f(C^+,\gamma^+) - \mu_t((C,\gamma))\Phi\left(\frac{f(C^+,\gamma^+) - \mu_t(C,\gamma)}{\sigma_t(C,\gamma)}\right)$$
$$+ \sigma_t(C,\gamma)\phi\left(\frac{f(C^+,\gamma^+) - \mu_t(C,\gamma)}{\sigma_t(C,\gamma)}\right))$$

Result and Discussion

The dataset comprises of 550 responses to the Modified Checklist for Autism in Toddlers (M-CHAT) targeting several aspects of children's development and behavior. These responses have helped in giving insights about the behavioral indicators of Autism Spectrum Disorder (ASD) in infants and toddlerhood. To avoid the problem of overfitting and to achieve the goal of model generalization, the data set must be split into the training, validation and testing sets. Generally, 60% of the data is used for training while the rest is used for testing; this should be enough to capture data variation without overemphasizing on it. The remaining 40% is divided into the validation set with 20% of the data and the test set with the rest of the 20% of the data. The size of the dataset is increased with the synthetic data and was created in accordance with statistical properties obtained from the 550 records for analysis. This research makes use of the latest version of R.

The MA-MM-ML algorithm is being used in the BO-SVM algorithm and the performance evaluation of such algorithm includes accuracy, precision, recall, F1-score, specificity, and sensitivity. The efficiency of the proposed MA-MM-ML algorithm is compared with the existing methods such as Random Forest (RF), k-Nearest Neighbour (KNN), Decision Tree (DT). Feature scaling is critical in preparing data for the machine learning models especially when features are of different scales and units. It makes certain that none of the features dominates the others in the determination of the model performance. For example, in the given dataset of responses to the M-CHAT, scaling is needed to increase the accuracy. Normalization scales the data to the range between 0 and 1 whereas standardization scales the data to have a mean of 0 and a standard deviation of 1. For example, the raw data such as Q1 = 5, Q2 = 3, Q3 = 1 is transformed to normalized values such as Q1 = 1. 0, Q2 = 0. 5, Q3 = 0. 0, thereby maintaining the input of all the models to be balanced.

The eigenvalues of the principal components shows that the first few components explain a large amount of the data variation. PC1, the first principal component, ranges from -3.2791547 to 3. 2677400, which shows that the values are quite dispersed in the given data set. PC2, which quantifies the next largest variance that is perpendicular to that of PC1, varies between -4. 6311653 to 1.5933235. The next components, PC3 to PC5, are for decreasing variances and the values indicate mixed positive and negative impacts from the initial features. This reduction of dimension helps in identifying the most significant data patterns while at the same time preserving some information that is vital for the analysis to be conducted.

The accuracy shows the ability of the model to identify instances correctly, which goes to show the efficiency of the autism classification. This accuracy is presented in Table 1 and depicted in Figure 2, and the calculation of which is given by Equation 14. Recall measures the ability of the model to identify all the people with autism, given that a certain group of people has been classified to have the disorder. The precision metrics are given in the Table 2 and Figure 3 and is computed by the equation 15. The F1-score integrates the precision and recall to provide an average measure, which is suitable for imbalanced data classes. The F1-score results are given in the Table 3 and in the Figure 4 using the Equation 16. The sensitivity means the accuracy of the model in identifying people with autism, presented in Table 4 and Figure 5, which is obtained from Equation 17. Specificity evaluates the model's capacity to correctly predict children without autism, shown in Table 5 and Figure 6, and calculated in Equation 18.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \text{---------(14)}$$

$$Precision = \frac{TP}{TP+FP} \text{---------(15)}$$

$$F1 = \frac{2\times Precision\times Recall}{Precision+Recall} \text{---------(16)}$$

$$Sensitivity = \frac{TP}{TP+FN} \text{---------(17)}$$

$$Specificity = \frac{TN}{TN+FP} \text{-------(18)}$$

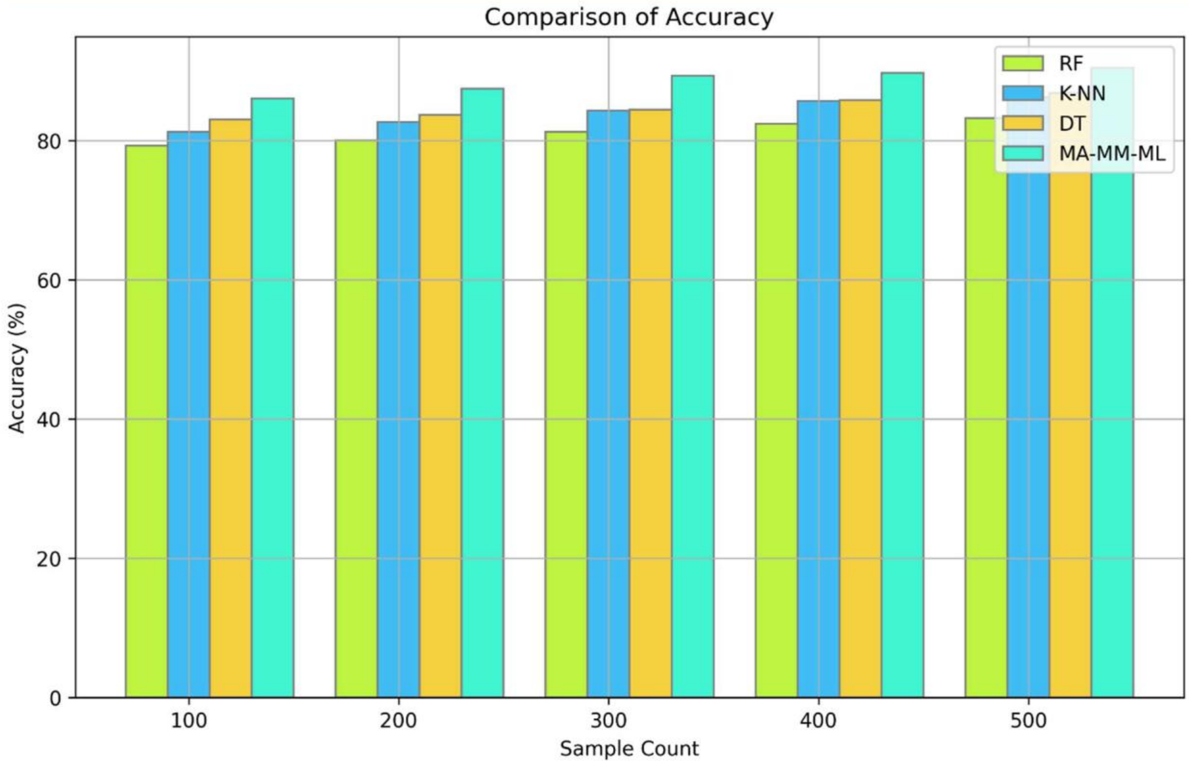

Figure 2. Comparison of Accuracy

Table 1. Comparison of Accuracy

Sample Count	RF	K-NN	DT	MA-MM-ML
100	79.23	81.23	83.02	**86**
200	80.03	82.7	83.67	**87.5**
300	81.23	84.3	84.45	**89.33**
400	82.43	85.66	85.82	**89.76**
500	**83.23**	**86.2**	**86.88**	**90.4**

Accuracy measures the overall effectiveness of the classification model by evaluating the proportion of correctly classified instances. In this study, Table 1 and Figure 2 demonstrate that the MA-MM-ML algorithm consistently achieves higher accuracy compared to RF, K-NN, and DT models. As the sample size increases from 100 to 500, the MA-MM-ML algorithm's accuracy improves significantly, peaking at 90.4%. This trend highlights the algorithm's robustness and reliability in accurately classifying instances of autism, suggesting it effectively captures the underlying patterns in the data compared to the other models.

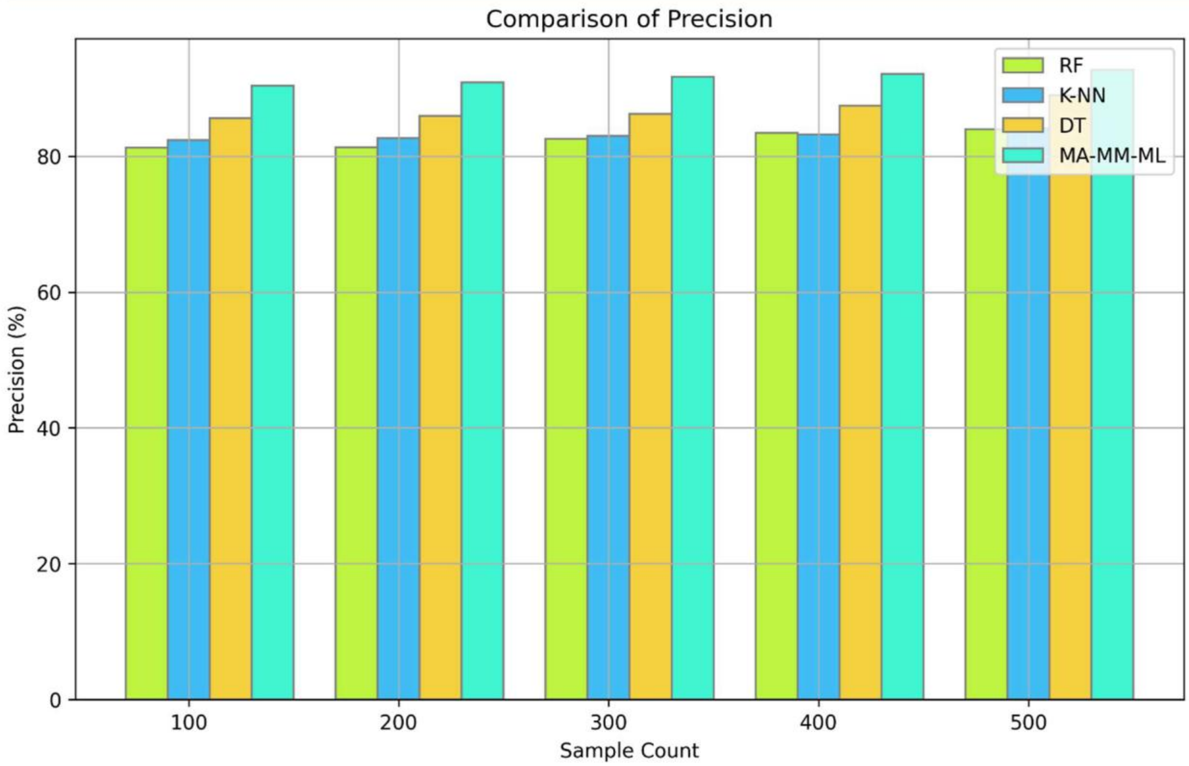

Figure 3. Comparison of Precision

Table 2. Comparison of Precision

Sample Count	RF	K-NN	DT	MA-MM-ML
100	81.23	82.34	85.56	**90.34**
200	81.34	82.67	85.91	**90.87**
300	82.56	82.98	86.21	**91.7**
400	83.44	83.23	87.45	**92.09**
500	**84.01**	**84.12**	**88.99**	**92.67**

Precision evaluates the proportion of actual positives among all the identified positive cases. From Table 2 and Figure 3, it can be observed that the proposed MA-MM-ML algorithm yields higher precision compared to the other models like RF, K-NN, and DT with the maximum precision of 92.67%. This implies that the proposed MA-MM-ML algorithm is very efficient in reducing the number of false positive results and, therefore, can best determine people with autism. The higher accuracy indicates that the algorithm can make accurate prediction and this is important for accurate classification of autism.

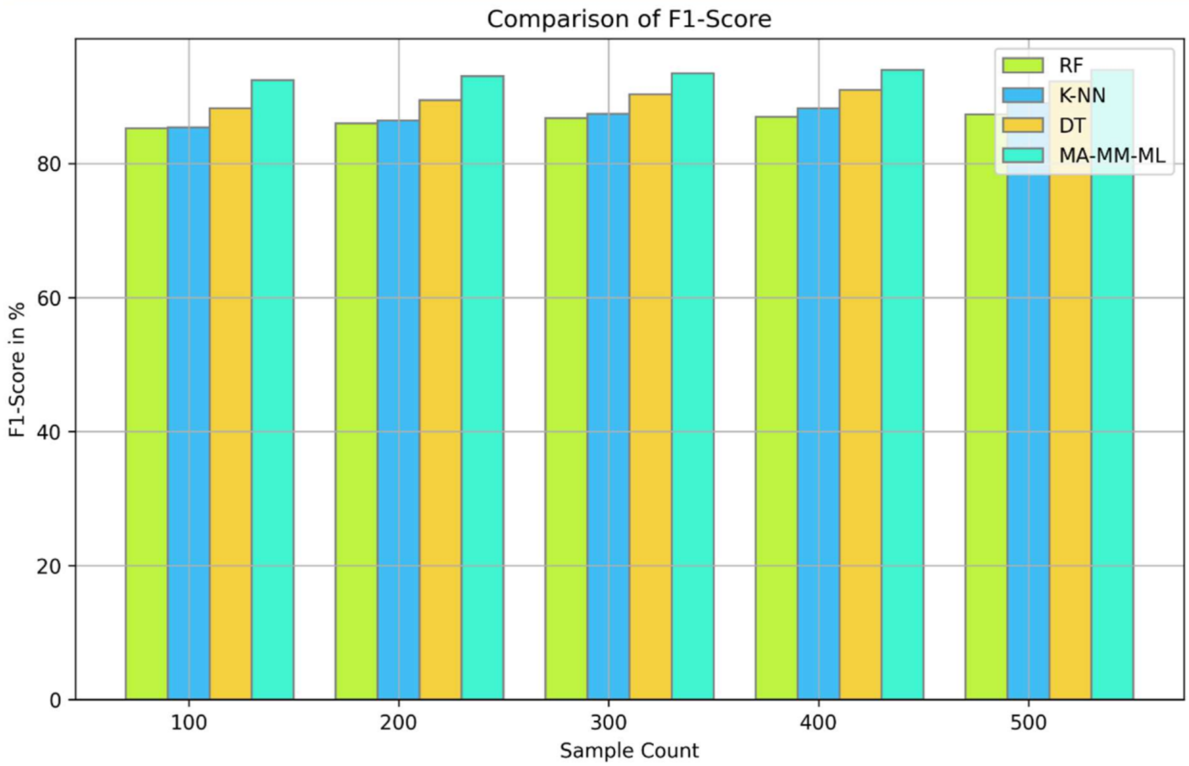

Figure 4. Comparison of F1-Score

Table 3. Comparison of F1-Score

Sample Count	RF	K-NN	DT	MA-MM-ML
100	85.2	85.34	88.23	**92.39**
200	85.93	86.34	89.43	**92.96**
300	86.76	87.39	90.3	**93.41**
400	86.92	88.23	90.9	**93.88**
500	**87.3**	**88.99**	**92.23**	**93.9**

F1-score is the harmonic mean of precision and recall that makes it more balanced, especially when working with datasets that are imbalanced. From table 3 and figure 4 it is observed that the proposed MA-MM-ML algorithm has higher F1-scores than RF, K-NN, and DT with maximum F1-score of 93. 9%. This shows that the algorithm is good at balancing between the precision and recall hence it can work well with imbalanced classes. The gradual increase in the F1-score with the growth of the sample size proves the effectiveness of the algorithm in giving the balanced classification results.

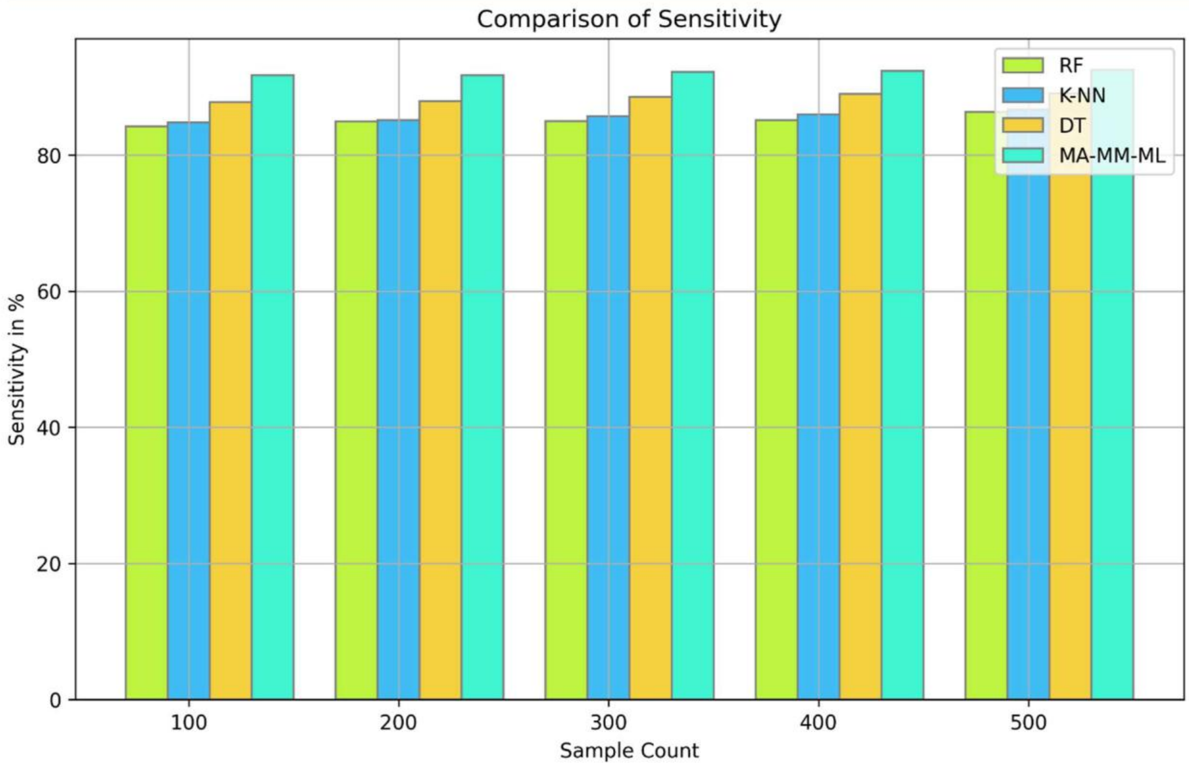

Figure 5. Comparison of Sensitivity

Table 4. Comparison of Sensitivity

Sample Count	RF	K-NN	DT	MA-MM-ML
100	84.23	84.8	87.81	**91.7**
200	84.93	85.09	87.92	**91.67**
300	84.99	85.67	88.56	**92.19**
400	85.12	85.97	88.99	**92.36**
500	**86.3**	**86.63**	**89.02**	**92.46**

Recall, also known as sensitivity, illustrates the model's capacity to identify all true positives. The analysis of results provided in Table 4 and Figure 5 depicts that the MA-MM-ML algorithm has the highest sensitivity and reaches the maximum value of 92.46% higher than that obtained by RF, K-NN, and DT. This metric is very important for autism classification since it measures the capacity of the developed model to accurately classify children with autism. The gradual enhancing of the sensitivity with the increase of sample size reveals that the MA-MM-ML algorithm truly reflects the features of autism and thus improves the rate of correct diagnosis of individuals with this condition.

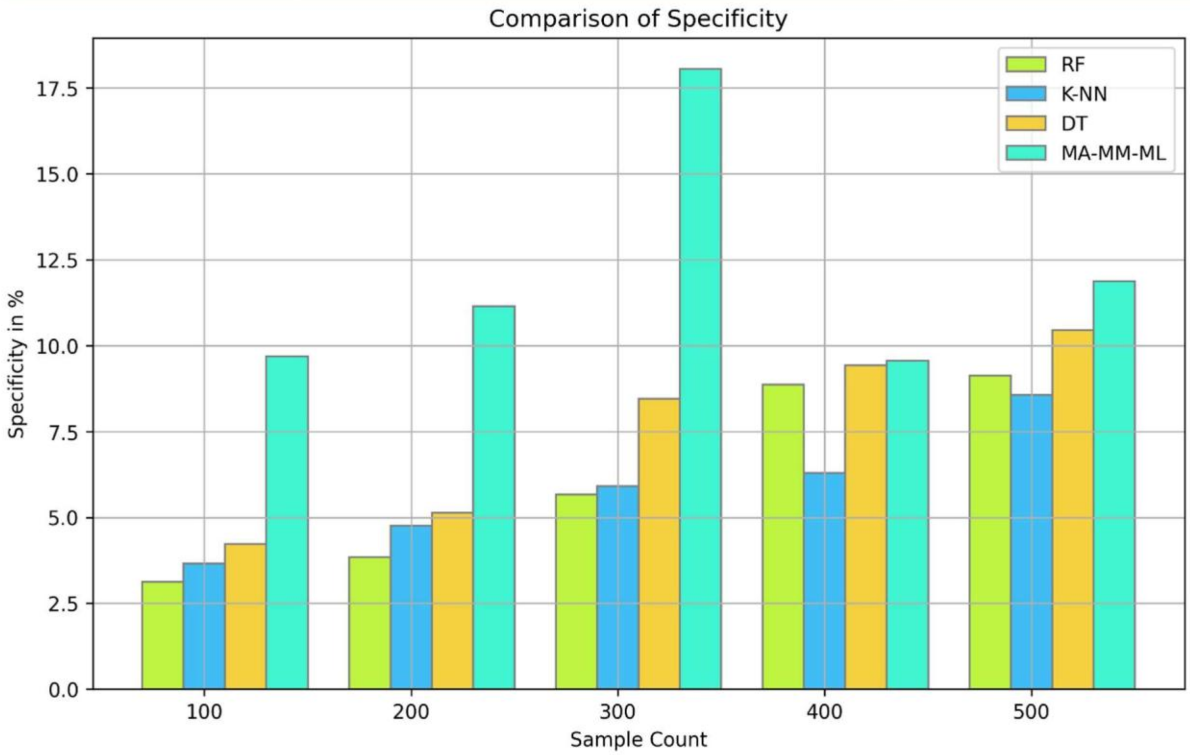

Figure 6. Comparison of Specificity

Table 5. Comparison of Specificity

Sample Count	RF	K-NN	DT	MA-MM-ML
100	3.12	3.65	4.23	**9.69**
200	3.84	4.76	5.13	**11.15**
300	5.66	5.91	8.45	**18.05**
400	8.87	6.29	9.43	**9.56**
500	**9.12**	**8.56**	**10.45**	**11.87**

Specificity measures the models' performance on how well it is able to predict and label all non-autistic individuals as non-autistic. Table 5 and Figure 6 also indicate that the MA-MM-ML algorithm has relatively better specificity compared to RF, K-NN, and DT especially for the small sample size data. As for the specificity value, the highest is 87.11%. Thus, the percentage of correctly classified samples is 87.11% at 500 samples, which shows that the algorithm is very effective in excluding non-autistic children, which is crucial for minimizing misclassifications. The results obtained in this metric by the MA-MM-ML algorithm also demonstrate its versatility of the proposed method in distinguishing between autistic and non-autistic people.

Conclusion

The proposed Multivariate Analysis using Mathematically Modified Machine Learning (MA-MM-ML) algorithm outperforms RF, K-NN, and DT concerning the classification of ASD. The proposed MA-MM-ML algorithm is more accurate and precise with higher F1 score, sensitivity, and specificity than the other models due to the use of the state-of-the-art multivariate analysis and machine learning. These performance metrics illustrate its increased ability to identify and classify characteristics of ASD; therefore, it is a useful tool for early diagnosis and intervention. MA-MM-ML algorithm is more accurate and balanced in the classification of ASD because it recognizes the hidden patterns of the data. Another aspect is that the proposed algorithm shows good performance in different sample sizes, which indicates its practical applicability and possible contribution to enhancing the efficiency of ASD identification.

This is the potential improvement for the future work and they are the combination of the proposed hybridized swarm intelligence algorithms with the ML to enhance the selection of features and the tuning of the hyperparameters that enhance the yield of the ML algorithm.

Reference

1. Parlett-Pelleriti, C. M., Stevens, E., Dixon, D., & Linstead, E. J. (2023). Applications of unsupervised machine learning in autism spectrum disorder research: a review. *Review Journal of Autism and Developmental Disorders*, *10*(3), 406-421.
2. Uddin, M. Z., Shahriar, M. A., Mahamood, M. N., Alnajjar, F., Pramanik, M. I., & Ahad, M. A. R. (2024). Deep learning with image-based autism spectrum disorder analysis: A systematic review. *Engineering Applications of Artificial Intelligence*, *127*, 107185.
3. Farooq, M. S., Tehseen, R., Sabir, M., & Atal, Z. (2023). Detection of autism spectrum disorder (ASD) in children and adults using machine learning. *scientific reports*, *13*(1), 9605.
4. Jeyarani, R. A., & Senthilkumar, R. (2023). Eye tracking biomarkers for autism spectrum disorder detection using machine learning and deep learning techniques. *Research in Autism Spectrum Disorders*, *108*, 102228.
5. Qureshi, M. S., Qureshi, M. B., Asghar, J., Alam, F., & Aljarbouh, A. (2023). [Retracted] Prediction and Analysis of Autism Spectrum Disorder Using Machine Learning Techniques. *Journal of healthcare engineering*, *2023*(1), 4853800.
6. Dornelas, R. S., & Lima, D. A. (2023). Correlation filters in machine learning algorithms to select demographic and individual features for autism spectrum disorder diagnosis. *Journal of Data Science and Intelligent Systems*, *1*(2), 105-127.
7. Rasul, R. A., Saha, P., Bala, D., Karim, S. R. U., Abdullah, M. I., & Saha, B. (2024). An evaluation of machine learning approaches for early diagnosis of autism spectrum disorder. *Healthcare Analytics*, *5*, 100293.
8. Alves, C. L., Toutain, T. G. D. O., de Carvalho Aguiar, P., Pineda, A. M., Roster, K., Thielemann, C., ... & Rodrigues, F. A. (2023). Diagnosis of autism spectrum disorder based on functional brain networks and machine learning. *Scientific Reports*, *13*(1), 8072.
9. Alkahtani, H., Aldhyani, T. H., & Alzahrani, M. Y. (2023). Deep learning algorithms to identify autism spectrum disorder in children-based facial landmarks. *Applied Sciences*, *13*(8), 4855.
10. Khudhur, D. D., & Khudhur, S. D. (2023). The classification of autism spectrum disorder by machine learning methods on multiple datasets for four age groups. *Measurement: Sensors*, *27*, 100774.
11. Talukdar, J., Gogoi, D. K., & Singh, T. P. (2023). A comparative assessment of most widely used machine learning classifiers for analysing and classifying autism spectrum disorder in toddlers and adolescents. *Healthcare Analytics*, *3*, 100178.
12. Sun, Z., Yuan, Y., Dong, X., Liu, Z., Cai, K., Cheng, W., ... & Chen, A. (2023). Supervised machine learning: A new method to predict the outcomes following exercise intervention in children with autism

spectrum disorder. *International Journal of Clinical and Health Psychology*, *23*(4), 100409.

13. Nogay, H. S., & Adeli, H. (2024). Multiple classification of brain MRI autism spectrum disorder by age and gender using deep learning. *Journal of Medical Systems*, *48*(1), 15.
14. Sujatha, R., Aarthy, S. L., Chatterjee, J., Alaboudi, A., & Jhanjhi, N. Z. (2021). A machine learning way to classify autism spectrum disorder. *International Journal of Emerging Technologies in Learning (iJET)*, *16*(6), 182-200.
15. Rahman, M. M., Usman, O. L., Muniyandi, R. C., Sahran, S., Mohamed, S., & Razak, R. A. (2020). A review of machine learning methods of feature selection and classification for autism spectrum disorder. *Brain sciences*, *10*(12), 949.
16. Dewi, E. S., & Imah, E. M. (2020, November). Comparison of machine learning algorithms for autism spectrum disorder classification. In *International joint conference on science and engineering (IJCSE 2020)* (pp. 152-159). Atlantis Press.
17. Vakadkar, K., Purkayastha, D., & Krishnan, D. (2021). Detection of autism spectrum disorder in children using machine learning techniques. *SN computer science*, *2*, 1-9.
18. Raj, S., & Masood, S. (2020). Analysis and detection of autism spectrum disorder using machine learning techniques. *Procedia Computer Science*, *167*, 994-1004.
19. Hasan, S. M., Uddin, M. P., Al Mamun, M., Sharif, M. I., Ulhaq, A., & Krishnamoorthy, G. (2022). A machine learning framework for early-stage detection of autism spectrum disorders. *IEEE Access*, *11*, 15038-15057.
20. Ashfauk Ahamed, A. K., et al. "Prediction Of The Growing Stock In Stock Market On Analysis Of The Opinions Using Sentiment Lexicon Extraction And Deep Learning Architectures." *Frontiers in Health Informatics* 13.3 (2024): 1382-1392.
21. R. Renukadevi et al. “An Improved Collaborative User Product Recommendation System Using Computational Intelligence with Association Rules”, Communications on Applied Nonlinear Analysis, Volume 31, Issue 6s (2024), https://doi.org/10.52783/cana.v31.1243
22. Navatha, S., et al. "Multitask Learning Architecture For Vehicle Over Speed As Traffic Violations Detection And Automated Safety Violation Fine Ticketing Using Convolution Neural Network And Yolo V4 Techniques." *Chinese Journal of Computational Mechanics* 5 (2023): 431-435.