Enhanced Early Identification of Autism Spectrum Disorder using Deep Learning and Advanced Machine Learning

Dr. M.Vimaladevi	Ms. R. Thangamani	Padmapriya R	Rashmika K R	Rithik Chandrasekar
Associate Professor	Assistant Professor	II Year AIML	II Year AIML	II Year AIML
Department of	Department of	Department of	Department of	Department of
Artificial Intelligence	Artificial Intelligence	Artificial Intelligence	Artificial Intelligence	Artificial Intelligence
vimaladevi.ai@kongu.edu	thangamani.ai@kongu.edu	padmapriyab.22aim@kongu.edu	rashmikakr.22aim@kongu.edu	rithikchandrasekar.22aim@kongu.edu

ABSTRACT

A neurological condition affecting individuals throughout their lives, Autism Spectrum Disorder (ASD) profoundly impacts behavior, activities, cognition, and socio-communication abilities. Timely detection in children between ages two and three is crucial for early intervention. This study employs standard machine learning techniques, and deep learning techniques to predict ASD. Models are rigorously validated using accuracy, precision, and recall measurements. To provide a centralized framework for researchers, comparative analyses consider application types, simulation techniques, comparison approaches, and input data. Additionally, the study includes the best model prediction, highlighting the model that performed most accurately in predicting ASD. Hyperparameter calculation is integral to the study, with optimized hyperparameters determined through meticulous tuning, enhancing the models' predictive capabilities and overall performance. The goal of the entire approach is to offer a solid foundation for early ASD diagnosis and intervention.

Keywords**:** *Autism Spectrum Disorder, Machine Learning Approaches, Comparative Analysis, Random Forest Algorithm, Workflow Representations.*

I. INTRODUCTION

This study delves into the challenging task of early-stage autism spectrum disorder (ASD) detection, which spans different age groups. ASD's intricate nature, affecting behavior and communication, necessitates a meticulous approach. Treatment options for ASD may include behavioral therapy, speech therapy, occupational therapy, and medication to manage symptoms such as anxiety or hyperactivity.The study preprocesses four vital ASD datasets (Toddlers, Children, Adolescents, and Adults) to handle missing values and encoding, ensuring they are primed for analysis. Machine learning and deep learning techniques play a pivotal role in uncovering crucial ASD identification features. Through meticulous feature significance analysis, the study determines the optimal FS technique for each dataset. The evaluation of nine models for prediction, along with a comparison to contemporary publications, underscores the study's rigor and relevance. The research advances a versatile ML framework for early ASD diagnosis, adeptly handling class imbalance with Random Over Sampler. Additionally, the framework identifies key risk factors for ASD prediction through detailed feature importance analysis, offering valuable insights for clinicians and researchers alike.

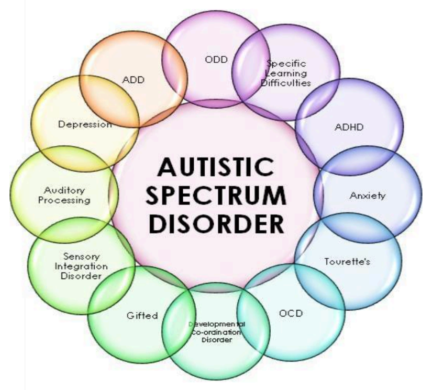

Fig. 1.ASD Features

II. LITERATURE SURVEY

Autism Spectrum Disorder (ASD) is a group of disorders characterized by repetitive behavior, poor language abilities, limited activity repertoire, difficulty interacting with others, and difficulty communicating. Some patients engage in self-destructive behaviors out of anger because they do not understand pain. 0.625 percent of children worldwide suffer from ASD [1]. More than 10% of today's pediatric population suffers from autism spectrum disorder (ASD), yet the diagnosing process is still laborious, subjective, and time-consuming. Since it can take up to a year from the time a suspicion is raised until a diagnosis is made, there is a loss of critical time during which behavioral and treatment interventions could be implemented [3]. Frequent symptoms of the illness include repetitive behaviors, obsessional interests, and trouble communicating, especially in social settings. To identify ASD, a comprehensive assessment involving multiple tests conducted by psychologists and child healthcare specialists is required. Since early diagnosis and treatment of ASD can considerably reduce symptoms, it improves the person's overall quality of life. However, because ASD cannot be accurately identified by displaying merely the behaviors of children or adults in a clinic, a significant amount of crucial time might be lost during the diagnosis process [11]. Machine learning algorithms can be used to evaluate data and obtain the finest biological markers from a hundred biological markers if they have a sufficient amount of data and also have high computation power [13]. A machine-learning framework for ASD detection in people of different ages (Toddlers, Children, Adolescents, and Adults) has been proposed, demonstrating that predictive models based on ML techniques are useful tools for this task [8]. AI has become increasingly widely used in the healthcare sector for diagnosis [2]. Even though there isn't a long-term cure for ASD, early intervention and access to quality healthcare can have a big impact on a child's development by enhancing their behaviors and communication abilities [7]. Thus, giving people with ASD a short, easy-to-use tool that uses items associated with the disorder may make them more likely to seek professional assessment, which is essential for the early diagnosis and treatment of ASD [5].

III. DATASET DESCRIPTION

We gather the four ASD datasets (Toddlers, Children, Adolescents, and Adults) from UCI ML and Kaggle, two publically accessible sources. Every user of the program receives a score ranging from 0 to 10, and a final score of 6 out of 10 denotes a positive ASD. Furthermore, ASD data is sourced from the ASD Tests app, and open-source databases are being created to support this field of study.

Preprocessing :

In the preprocessing phase across all three datasets, a comprehensive approach was adopted to address the challenges posed by outliers and missing values. Outliers were meticulously identified and managed through a data exploratory process employing the box plot technique. Recognizing various missing *values* within the datasets, an iterative imputation method was chosen as the preferred strategy. This method, which treats each feature as a function of others through a regression-like approach, was selected for its capacity to maximize the utilization of available samples in machine learning. This meticulous preprocessing ensures the datasets robustness and establishes a consistent foundation for subsequent analyses, allowing for more accurate and reliable machine learning outcomes.

- A comprehensive approach was used to address issues resulting from outliers and missing values during the tedious preprocessing stage that was carried out on all three datasets. Strict outlier control and identification were carried out via a thorough data exploration procedure that made use of the box plot technique. At the same time, different missing values were found in the datasets, which led to the iterative imputation approach being chosen as the ideal course of action. This strategy was selected because it maximizes sample use in machine learning by considering each characteristic as a function of others in a manner similar to regression.

- It should be noted that the age column in the datasets had null values at first. To guarantee a cohesive and complete dataset, they were methodically fixed by using the backward fill (bfill()) method. Because the missing values are handled with such care, the datasets are more robust and provide a stable basis for further analysis.

- Moreover, an 80:20 ratio was carefully followed when dividing the data into training and testing sets in order to prepare it for machine learning tasks. This partitioning keeps a separate set of data for objective assessment while ensuring that the machine learning models are trained on a significant amount of the data. By implementing these procedures, the preprocessing stage creates a well-balanced and organized framework that is favorable to the production of precise and consistent machine learning results, as well as strengthening the datasets against outliers and missing values.

IV. METHOD OVERVIEW

This research study aims to use different machine learning and deep learning approaches to create a prediction model that can correctly identify autism in people of different ages.The datasets are first gathered, and then oversampling, feature encoding, and missing value imputation are used to complete the preprocessing. The dataset's missing values are imputed using the Mean Value Imputation (MVI) technique. The One Hot Encoding (OHE) method is then used to translate the values of the category features into their corresponding numerical values.

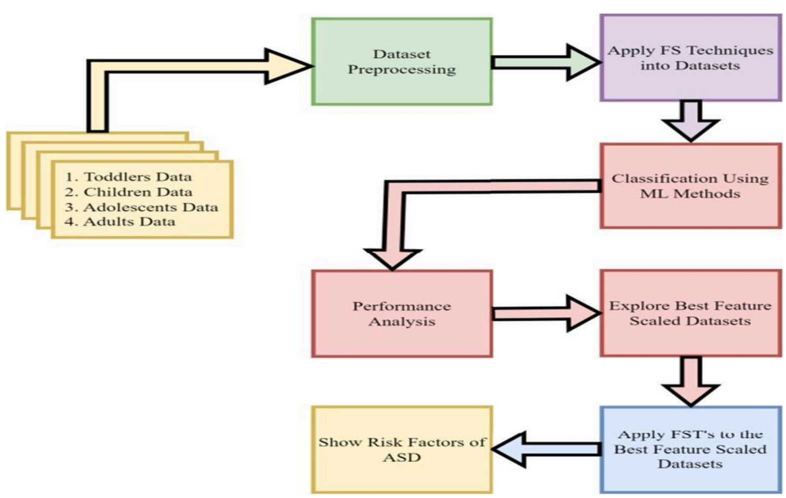

Fig.2. General Overview of Methodology

The analysis involved experimenting with nine algorithms on four datasets segmented by age categories. The objective was to ascertain the top-performing algorithm for each dataset, based on their respective performance metrics. This methodology facilitated a detailed examination of algorithm efficacy across varying age groups, ultimately identifying the most suitable algorithms for each dataset.

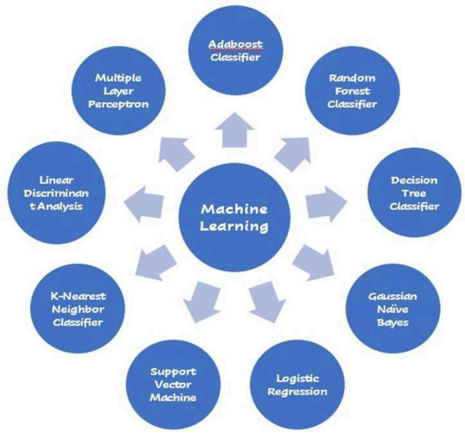

Fig.3. Algorithms Applied

V. EVALUATION BASED ON APPLIED ALGORITHMS

1) AdaBoost Classifier:

AdaBoost is an ensemble learning technique that combines multiple weak classifiers to create a strong classifier. It is especially useful for managing imbalances and complex patterns in the data because of its repetitive nature, which guarantees that instances that are incorrectly classified receive more attention. AdaBoost can dynamically adjust to the changing significance of characteristics in the autism dataset, capturing complex correlations between age, ethnicity, jaundice, and the probability of autism.

Dataset	Accuracy
TODDLER	0.9156
CHILD	0.9753
ADOLESCENT	0.9023
ADULT	0.9672

Table.1. Accuracy for Adaboost

Furthermore, AdaBoost is relatively simple to implement and interpret, making it accessible to users without extensive machine learning expertise. Its iterative approach and focus on misclassified instances make it robust against overfitting, leading to more generalized models. Additionally, AdaBoost's versatility allows it to be applied to various machine learning tasks beyond classification, such as regression and ranking. Overall, these qualities make AdaBoost a valuable tool for analyzing complex datasets like those related to autism, where understanding the relationships between various factors is essential for accurate prediction and diagnosis.

2) Random Forest Classifier:

Random Forest is an ensemble learning technique that works by building several decision trees and merging the predictions from each one. The autism dataset benefits from this ensemble approach since it can handle high-dimensional feature spaces and offer insights into intricate patterns.

One of the key strengths of Random Forest is its ability to identify feature importance. This gives an in-depth knowledge of which factors, such as age or ethnicity, significantly contribute to autism classification. By analyzing the importance of different features, researchers and practitioners can gain valuable insights into the underlying factors driving autism prevalence and diagnosis.

Dataset	Accuracy
TODDLER	0.9810
CHILD	0.9492
ADOLESCENT	0.9243
ADULT	0.9433

Table.2. Accuracy for Random Forest

3) Multilayer Perceptron (MLP):

Multilayer Perceptron (MLP) is a neural network architecture known for its adaptability and proficiency in detecting intricate patterns. Within the autism dataset, MLP demonstrates a strong capability to model complex relationships among variables like age, ethnicity, and jaundice.

MLP's notable strength lies in its ability to identify non-linear correlations. With its multiple layers of neurons, MLP can effectively capture the intricate interplay of various factors affecting autism, particularly in scenarios where relationships are not straightforward.

Dataset	Accuracy
TODDLER	0.9386
CHILD	0.9831
ADOLESCENT	0.9361
ADULT	0.9929

Table.3. Accuracy for MLP

4) K-Nearest Neighbors (KNN):

The strength of KNN lies in its assumption that instances with similar attributes are likely to have similar outcomes. This makes it particularly valuable for uncovering local patterns in the data, providing a context-aware approach to predicting autism.By considering the characteristics of neighboring instances, KNN can make informed predictions about the autism status of individuals based on similarities with other data points. This makes KNN a useful tool for analyzing the autism dataset and understanding the relationships between different factors that contribute to the disorder.

Dataset	Accuracy
TODDLER	0.9384
CHILD	0.8475
ADOLESCENT	0.8571
ADULT	0.9645

Table.4. Accuracy for KNN

5) Decision Tree:

Decision Trees are an efficient way to find important characteristics that affect the existence of autism in the context of the autism dataset. Decision trees can also capture complex relationships in the data since they are adept at handling variable interactions. Moreover, Decision Trees facilitate easy interpretation and explanation of the decision-making process to stakeholders by offering a visual depiction of it. Gaining understanding of the variables impacting autism and fostering confidence in the decision-making process both benefit from this openness.

Dataset	Accuracy
TODDLER	0.9526
CHILD	0.8983
ADOLESCENT	0.9421
ADULT	0.9078

Table.5. Accuracy for Decision Tree

6) Gaussian Naive Bayes (NB):

Gaussian Naive Bayes (NB) is a probabilistic classifier that assumes the features follow a Gaussian distribution. It is particularly well-suited for datasets with continuous features, making it a good option for capturing probabilistic relationships within the autism dataset.One of the key strengths of Gaussian NB is its simplicity and speed. It is computationally efficient, making it suitable for large datasets. Additionally, Gaussian NB is effective in handling continuous data, making it ideal for datasets where features like age are continuous variables.In the context of the autism dataset, Gaussian NB can estimate the likelihood of autism based on the distribution of continuous characteristics such as age.

Dataset	Accuracy
TODDLER	0.9384
CHILD	0.8475
ADOLESCENT	0.8571
ADULT	0.9645

Table.6. Accuracy for Gaussian Naive Bayes

7) Logistic Regression:

Logistic Regression, a statistical approach for binary outcomes, predicts the likelihood of an input belonging to a specific category. In the context of the autism dataset, this method can estimate the probability of an individual having autism based on factors like age, ethnicity, and jaundice.

The ease of use and interpretability of logistic regression is one of its benefits.It provides coefficients for each feature, indicating their impact on the autism likelihood and aiding in understanding the relationships between features and autism probability.

Moreover, Logistic Regression is robust to noise and can handle numerical and categorical features. Its computational efficiency makes it suitable for large datasets.

Dataset	Accuracy
TODDLER	0.9467
CHILD	0.9342
ADOLESCENT	0.9284
ADULT	0.9163

Table.7. Accuracy for Logistic Regression

8) Support Vector Machine (SVM):

Finding the optimum hyperplane to divide instances of distinct classes is the goal of the machine learning algorithm Support Vector Machine (SVM). Even in high-dimensional regions, SVM can find the best decision limits in the context of the autism dataset. One of the key strengths of SVM is its effectiveness in capturing complex relationships. This makes SVM valuable for understanding the intricate interactions between features that influence autism. By finding the hyperplane that maximizes the margin between classes, SVM can effectively classify instances and provide insights into the underlying patterns in the data.

Dataset	Accuracy
TODDLER	0.9905
CHILD	0.9691
ADOLESCENT	0.9524
ADULT	0.9645

Table.7. Accuracy for Support Vector Machine

9) Linear Discriminant Analysis (LDA):

A statistical technique that combines classification and dimensionality reduction is called linear discriminant analysis (LDA). Within the autism dataset, LDA can effectively identify linear combinations of features that optimally discriminate between autism and non-autism case.

Dataset	Accuracy
TODDLER	0.9573
CHILD	0.9476
ADOLESCENT	0.9087
ADULT	0.9574

Table.8. Accuracy for Linear Discriminant Analysis

	DATASETS	TODDLER	CHILD	ADOLESCENT	ADULT
ALGORITHMS	Adaboost Classifier	0.9156	0.9753	0.9023	0.9672
	Random Forest Classifier	0.9810	0.9492	0.9243	0.9433
	Multilayer Perceptron	0.9386	**0.9831**	0.9361	**0.9929**
	K-Nearest Neighbors	0.9716	0.8814	0.9086	0.9504
	Decision Tree	0.9526	0.8983	0.9421	0.9078
	Gaussian Naive Bayes	0.9384	0.8475	0.8571	0.9645
	Logistic Regression	0.9467	0.9342	0.9284	0.9163
	Support Vector Machine	**0.9905**	0.9691	**0.9524**	0.9645

Table.10. Overall Accuracy Report for all Algorithms

VI. BRIEF EXPLANATION OF EACH OF THE METRICS APPLIED IN EACH DATASET

- **Accuracy:** Accuracy is defined as the proportion of correctly identified cases to all instances. On a range from 0 to 1, 1 represents absolute precision.
- **ROC AUC:** The Receiver Operating Characteristic Area Under the Curve, or ROC AUC, measures how well the model can distinguish between classes. Its range is 0–1, where 1 represents perfect performance.
- **F1-Score:** The F1-Score is the harmonic mean of recall and precision. It considers both false positives and false negatives and is useful when there is an imbalance in the classes. The ideal value falls between 0 and 1, with 1 serving as the range.
- **Precision:** A prediction's precision is calculated by dividing its accuracy by the total number of positively predicted observations. It assesses how well the model detects positive cases. The range is 0 to 1, with 1 being the best possible value.
- **Recall:** The percentage of accurately predicted positive observations to all observations made during the actual class is known as the recall ratio. It goes by the names true positive rate and sensitivity as well. It evaluates the model's ability to recognize each and every successful instance. The range is 0 to 1, with 1 being the best possible value.
- **Matthews Correlation Coefficient (MCC):** MCC is a number between -1 and +1. A coefficient of +1

denotes an ideal forecast, 0 is no more accurate than a random guess, and −1 denotes complete discrepancy between the prediction and the observation.

- **Kappa:** Cohen's Kappa accounts for agreement that can arise by accident by measuring the agreement between two raters (in this example, the model and the genuine labels). It has a range of -1 to 1, with 1 denoting full agreement.
- **Log Loss:** When a classification model's prediction input is a probability value between 0 and 1, log loss evaluates the model's performance. The model's predictions get better the lower the log loss.

VII. CLASSIFICATION REPORT

Age description for ASD Detection

- Toddler: 1-3 years old
- Child: 4-12 years old
- Adolescent: 13-18 years old
- Adult: 18+ years old

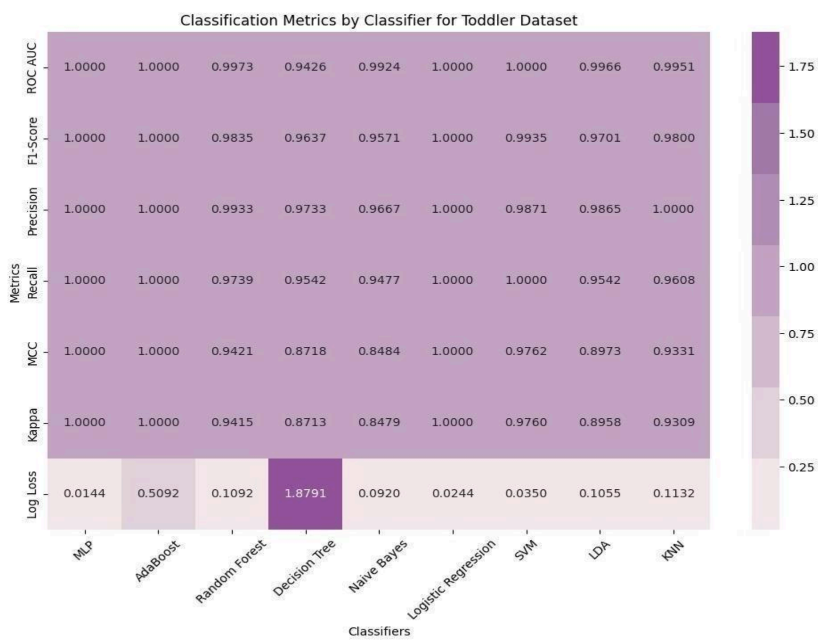

Fig.4. Classification report for TODDLER Dataset

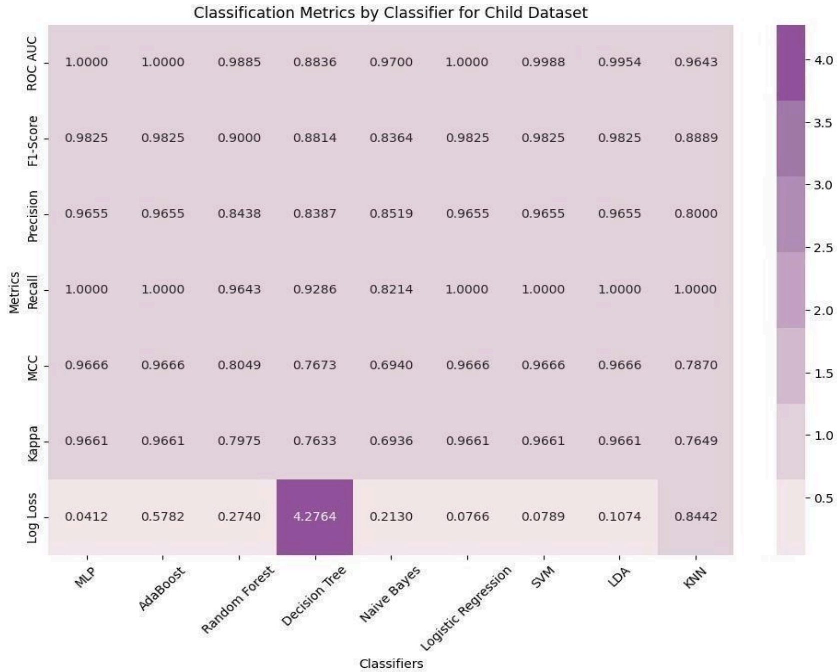

Fig.5. Classification report for CHILD Dataset

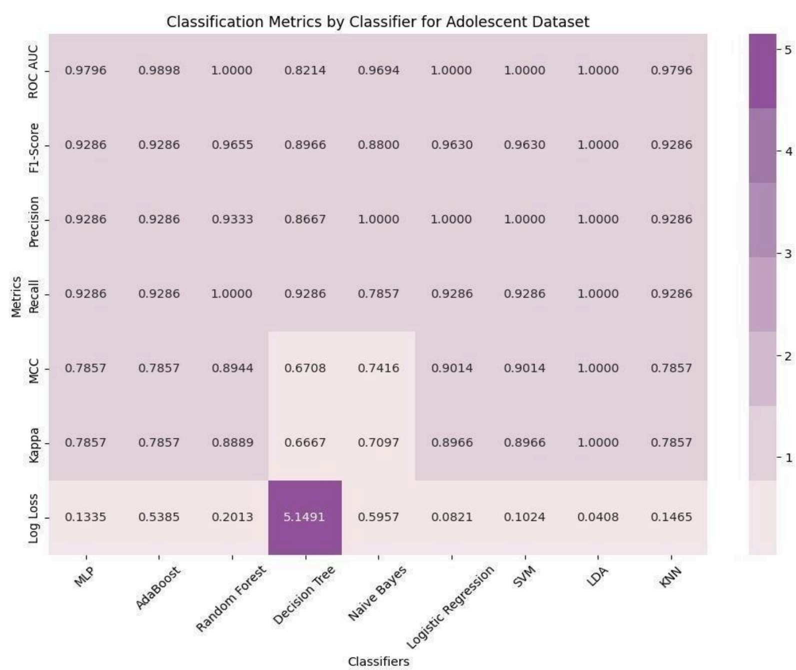

Fig.6. Classification report for ADOLESCENT Dataset

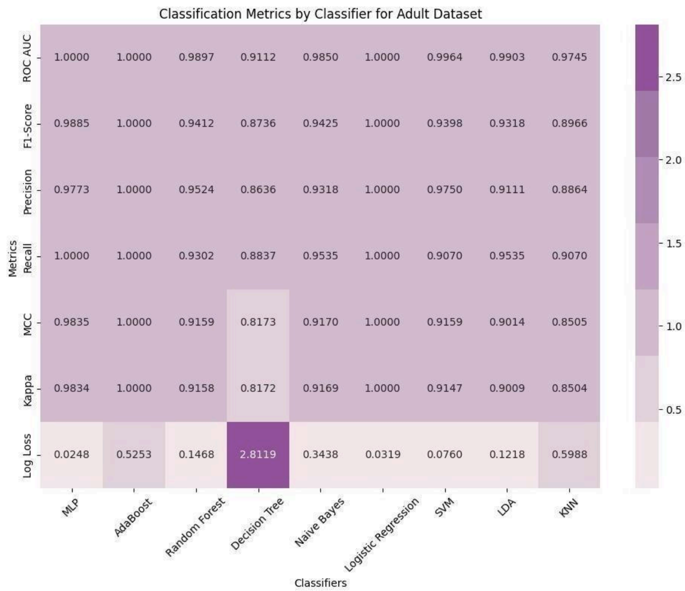

Fig.7. Classification report for ADULT Dataset

VIII. BEST PERFORMING ALGORITHMS WITH THEIR ACCURACY

DATASET	ALGORITHM	ACCURACY
Toddler	SVM	0.9905
Child	MLP	0.9831
Adolescent	SVM	0.9524
Adult	MLP	0.9929

Table.11. Best Performing Algorithms

SVM hyperparameters comprised 'C' (regularization parameter), 'kernel' (kernel type), and 'gamma' (kernel coefficient). The hyperparameters for MLP included 'hidden_layer_sizes' (the structure of hidden layers), 'activation' (the activation function),'solver' (the optimizer), 'alpha' (the L2 penalty), and 'learning_rate'.The optimal hyperparameters for the SVM model on the Toddler dataset were a regularization parameter (C) of 0.1, a'scale' gamma value, and a linear kernel. These parameters suggest that the model should have a soft margin, a low penalty for misclassification, and a linear decision boundary.The ideal hyperparameters for the SVM model on the Adolescent dataset were determined to be a sigmoid kernel, a'scale' gamma value, and a C value of 1. These parameters show a sigmoid kernel function for the decision border, a 'scale' gamma value for non-linear classification, and a greater penalty for misclassification.

MODEL	SVM TODDLER	SVM ADOLESCENT
C	0.1	1
Gamma	scale	Scale
Kernel	linear	Sigmoid

Table.12. Best parameters for SVM

On the Child dataset, on the other hand, the optimal hyperparameters for the MLP model were the 'tanh' activation function, 0.0001 as the regularization parameter, one hidden layer with a size of 100, 'adaptive' learning rate, and the 'adam' solver. These characteristics point to the Adam optimization technique, a medium-sized hidden layer, an adaptive learning rate, a hyperbolic tangent activation function, and a small complexity penalty in a neural network.

Finally, the optimal hyperparameters for the MLP model on the Adult dataset were the 'adam' solver, a 'constant' learning rate, a hidden layer structure of (50, 100, 50), a 'tanh' activation function, and an alpha value of 0.0001

These specifications point to a neural network with the Adam optimization algorithm, a deep hidden layer structure, a small complexity penalty, a hyperbolic tangent activation function, and a constant learning rate.
In summary, hyperparameter adjustment has aided in the SVM and MLP models' optimization for every age group dataset, possibly enhancing their performance and capacity for generalization.

MODEL	MLP CHILD	MLP ADULT
Activation	tanh	Tanh
Alpha	0.0001	0.0001
Hidden Layer Sizes	(100,)	(50,100,50)
Learning Rate	adaptive	Constant
Optimizer	adam	Adam

Table.14. Best Parameters for MLP

IX. CONCLUSION AND FUTURE WORK

This study assesses how well machine learning algorithms identify autism spectrum disorder (ASD) in a range of age groups. In the Adult dataset, the Multilayer Perceptron (MLP) yielded the highest accuracy, however in the Child and Adolescent datasets, the MLP and Support Vector Machine (SVM) demonstrated superior performance. The SVM yielded the best accuracy for the Toddler dataset. These findings suggest that MLP is effective in detecting ASD in adults and children, while SVM is more suitable for adolescents and toddlers. This research represents a comprehensive approach to ASD detection, combining behavioral observations with neurophysiological data to enhance diagnostic outcomes.

An additional prospective development entails crafting a user-friendly interface for ASD prediction utilizing the most effective models for each category. This interface will function as both a prediction platform and a data gathering tool, thereby advancing the accuracy and early identification of ASD.

In future implementations, EEG signals will be incorporated to enhance ASD detection. EEG is a non-invasive technique that provides insights into brain function and connectivity. It is hoped that this analysis of EEG signals in conjunction with behavioral data would increase the precision and consistency of ASD identification. Preprocessing to extract pertinent features from the EEG data will be part of the integration process. These features will subsequently be classified using machine learning methods, including deep learning models.

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