Hyperparameter Tuning in Classification Models for improved Prediction of Autism Spectrum Disorder UsingMachine Learning

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Abstract –Early diagnosis is crucial for addressing a neurological developmental condition characterized by difficulties in social interaction, language proficiency, restricted and repetitive behaviors. Despite the existence of various assessment tools aligned with the Diagnostic and Statistical Manual of Mental illness and disorders(DSM), the diverse range of symptoms makes accurate and timely identification challenging.This difficulty in diagnosis imposes challenges for early intervention and degrades the quality of life for individuals with ASD, as well as for their parents and caregivers.The primary objective is to identify hyperparameter values that optimize generalization to unseen data, laying the groundwork before delving into advanced optimization techniques. We implemented and validated in both Logistic model andNeural Network model, our work seeks to analyze the performance of the model.The significant result of our effort not only showcases the model's ability to detect ASD but also importantly to indicate the influence of various attributes on this disorder.

Keywords–hyperparameter, Artificial Neural Network, intervention,Logistic Regression, assessment tools

I. INTRODUCTION

Autism Spectrum Disorder (ASD) exerts a lifelong impact, profoundly influencing communication, cognition, social interaction, behavior, and communication skills in individuals.In India, the prevalence of autism aligns with global statistics, with approximately one in every hundred children being susceptible to the condition. For every girl affected, there are four boys impacted by autism according to the report given by World Health Organization (WHO). Within India, an estimated 18 million[1] individuals are facing the challenges posed by autism. The Diagnostic Statistical Manual (DSM-5**)[2],**is a standard classification of mental disorders used by mental health professionals and considered as a single diagnosis. The DSM indicates that intellectual disability and atypical conditions coexist. The partially structured assessment tool employed for diagnosing autism spectrum disorder which is Autism Diagnostic Observation Schedule (ADOS) [3].It is designed for individuals of different ages and developmental levels, ranging from toddlers to adults. The assessment is generally monitored by trained professionals and involves direct observation of the individual's behavior in a standardized and interactive arrangement. This is a task-based assessment that allows the examiner to observe and score behaviors related to communication,play, etc. The outcome of the ADOS, along with other clinical information, contributes to the diagnostic process for ASD. While ASD is often identifiable in the initial stage, the subjective nature of follow-ups presents a major barrier, leading to a waiting time of at least 12 months from the initial suspicious. Our work employs Logistic Regression and ANN classifier techniques to disclose the traits in toddlers more predictably. By utilizing a Toddler dataset provided by 'Kaggle' open-source machine learning repository [4], we trained ML and neural network models to indicate the presence of ASD disorder, while also optimizing their concerned hyperparameters to be tuned before we tried to train a model and apply any advanced optimization technique. The ultimate goal is to find the best configuration of the model, before exposing it to the training data. This approach provides no guarantee of consistently accurate outcomes; results may vary across different cases. Choosing different user-defined parameters in the learning model can give the prediction outcome in a shorterspan of duration. It varies depending on the type of model selected for training and the type of dataset. The logistic model [5] is employed as a one-layer neural network, while an artificial neural network (ANN)[6]as a multilayer perceptron, being more susceptible to overfitting, can be considered as an expanded iteration of the logistic regression model.The importance of accuracy in ASD diagnosis is emphasized by research directions, as an incorrect diagnosis (false result) may cause significant stress for families. In this article, mainly we concentrate on studying the performance of models with hyperparameter tuning not only with accuracy alone but also with precision, recall, F1 score, and AUC score based on receiver operating characteristics.

II. LITERATURE SURVEY

The relevantliterature review not only forms thebase work but also highlights the recent findingsin these areas. Singh, A., Farooqui, Z et.al[7]delved into the diagnosis mechanism of autism by extensively monitored various machine learning models. Leveraging the dataset from the University of California, Irvine, they applied machine learning techniques to pinpoint the most crucial indicators of autism in toddlers. Their initial focus involved crafting a neural network classification model, followed by subsequent exploration with the Random Forest classification model by employing the toddler's dataset from University of California, Irvine.Bala, M., Ali, M. et.al [8] useda classifier model based on machine learning designed to scrutinize data across different age groups, aiming for enhanced precision in ASD identification. Their approach involved assembling ASD datasets spanning toddlers, children, adolescents, and adults, coupled with the application of
diverse feature selection techniques. Employing various classifiers, they conducted a comprehensive evaluation of model performance using metrics such as predictive accuracy, kappa statistics, and F1-measure. Alteneiji, M. R., Alqaydi, L. M., et.al [9]delves into the use of machine learning algorithms for predicting individuals with concern ASD notable symptoms. Employing Rstudio, the authors rigorously tested their machine-learning model.The performance metrics such as error rate, accuracy, sensitivity, specificity, and false negative values were scrutinized, delivered best accuracy outcome with the neural network model in the toddler database. DevikaVarshini, G. et.al[10]delves into the diagnosis of early autism traits in toddlers and adults using logistic regression, KNN, and Random Forest classifier models. Leveraging the dataset from Kaggle's open repository, the study assesses the performance of these machine-learning classification techniques. Notably, KNN emerges with a superior accuracy score of 69.2%. Chowdhury, K &Iraj, M. A. [11]employed a dataset that considers datasets for Children, Adolescents, and for adults. This comprehensive dataset comprises ten explorations of various classifiers, SVM with Gaussian Radial Kernel stands out, achieving an impressive accuracy in individual characteristics and ten behavioral features sourced from the publicly available standard ASD dataset. Their findings advocate for the adoption of deep learning methods over traditional classifiers. Baseer, K. K., Nas, S. A., et. al[12]directed their research towards predicting heart disease, employing various classifiers including Logistic Regression (LR), Random Forest (RF), Support Vector Machine (SVM),coupled with hyperparameter tuning. They utilized grid search for optimizing hyperparameters and placed significant emphasis on comparing models with and without hyperparameter tuning based on accuracy. Mohanty et al,[13]employed a deep learning model classifier across different age categories. They incorporated dimensionality reduction and cross-validation techniques to enhance the evaluation parameters, including accuracy, sensitivity, specificity, and F1-score.Jinet al. [14]conducted a study focusing on the production rate in oil and gas field development, employing hyperparameter tuning with a specific implementation of Artificial Neural Networks (ANN). Their methods included considerations for network type, architecture, training, and transfer function settings. Hossain et al[15]conducted a research work focused on the detection of autism in children. The researchers highlighted that Sequential Minimal Optimization (SMO) outperformed other models, especially with a 10-fold cross-validation method, demonstrating higher accuracy, minimal computation time, and lower error rates. The study involved screening datasets from the UCI open-source repository, consisting of 292 instances. They applied 28 classification machine models, evaluating their performance. Omar et al. [16] proposed an article focusing on utilizing machine learning techniques to develop a mobile application and they merged Random Forest-CART (Classification and Regression Trees) with Random Forest-ID3 for predicting Autism Spectrum Disorder (ASD) at any age, excluding children below 3 years. The dataset used for prediction comprised 250 real datasets collected from individuals with or without autism characteristics. Thabtah[17]proposed a machine learning framework for autism screening in adults and adolescents, employing predictive analysis through the LR (Logistic Regression) method. The study's limitation was the unavailability of a large dataset.

III. METHODOLOGY

3.1 Dataset Description and Environment

The well-knownautism spectrum disorder (ASD) screening data for Toddler's dataset that contains 1054 instances with 19 features which is provided by the online repository, compiled by Dr. F. Thabth. Its license has been verified and permitted to be used for research purposes. The attributes include certain information such as age, gender, the identity of the test completers, family membership with ASD, ethnicity, jaundice history, and the target attributes relating to ASD traits[17], behavioral questions regarding assessment from A1-A10 column for the toddler in the age group of 1-3 is summarized in Table.1. The count of "yes" responses is tabulated and recorded in the Q-CHAT-10 column. If there are more than three "yes" responses is categorized as ASD; otherwise, it falls into the non-ASD category. The Responses are of "Sometimes," "Rarely," or "Never" for items A1 through A9 are assigned a value of 1, while the opposite responses are assigned a value of 0. Following analysis of responses provided by testers, we assessed the significance of all features. Among these, Case_no, A2, A3, A4, and jaundice are considered the least significant attributes, as depicted in Fig.1. Each question had five possible answers, with varying degrees of agreement. For instance, if question 4 is "Does your child point to share an interest with you?" Responses of "Sometimes," "Rarely," or "Never" for questions A1-A9 are mapped to a value of 1, while the opposite responses are mapped to a value of 0. It is noteworthy that this mapping of responses was conducted by the dataset creator. For A10, if the response aligns with the three answers representing the highest degree of agreement, it is mapped to a value of 1.

TABLE.1. Feature and description details for the prediction of early autism spectrum disorder of the Toddler dataset.

Feature	Format/ Domain	Description
A1: response to name by calling	*Binary*	Does your child look at you when you call his/her name?
A2: eye contact	*Binary*	How easy is it for you to make eye contact with your child?
A3: Finger pointing to objects	*Binary*	Does your child use point to express desires or needs?
A4: Sharing an interest	*Binary*	*Does your child point to share an interest with you?*
A5: fake	*Binary*	*Does your child pretend?*
A6: able to follow	*Binary*	*Does your child follow you?*
A7: Signs of distress	*Binary*	*Does your child show sign of waving to comfort them?*
A8: first word	*Binary*	*child's first word?*
A9: using simple gestures	*Binary*	*Does your child use simple gestures?*
A10: stare at something with no reason	*Binary*	*Is your child frequently staring into space??*
QCHAT-10	*Numeric*	*Overall score from responses A1-A10*
Age_mon	*Integer*	*Toddler age provided in months*
Gender	*M/F(string)*	*Male or Female details*
Ethnicity	*String*	*ethnicities used for the test*
Who completed the test	*String*	*Parent/caregiver/self*
Born with jaundice	Boolean	*Jaundice while born*
Family member with ASD	*Boolean*	*Whether any family member or siblings have a history of ASD*

The remaining features in the datasets are collected from the "submit" screen in the ASD Tests screening app. It should be noted that the target variable was assigned automatically based on the score obtained by the user while undergoing the screening process using the ASD Tests app[5].Utilizing the Anaconda environment on Microsoft Windows, we effectively harness the capabilities of the Jupyter Notebook. This environment is powered by the versatile Python programming language and further enhanced by utilizing popular Python libraries such as NumPy, Pandas, Matplotlib, Scikit Learn, Seaborn, and TensorFlow.

3.2 Feature Engineering and Importance

To gain a comprehensive understanding, we recognized data visualization as a pivotal tool, initiating a journey to unveil insights through feature distribution imagery. Primarily, the dataset under scrutiny exhibits no missing values. The column 'case_no' is omitted from the dataset as it lacks correlation with the target prediction. Our dataset encompasses records of 1054 subjects, with 728 testers categorized as atypical individuals and 326 as controls. Our dataset lacks complete balance. Referring to Fig.2 for gender distribution, a prevailing dominance of males is observed, constituting 69.7% of affected testers compared to females, possibly influenced by genetic and hormonal factors. This underscores the significance of early ASD diagnosis and intervention. Fig.3 illustrates the gender proportion among patients diagnosed with autism spectrum disorder(ASD). Furthermore, Fig.4 depicts the age distribution of ASDpositive cases within the 1-3year range. Notably, the average age of testers are around 25-28 monthsoffering crucial demographic insights as depicted in Fig.5. Moreover, it unveils the correlation between testers' age and ASD prevalence. The proportion of atypical cases steadily rises with advancing age in months, notably peaking between 25 to 30 months and becoming prominent as children approach 35-36 months old.

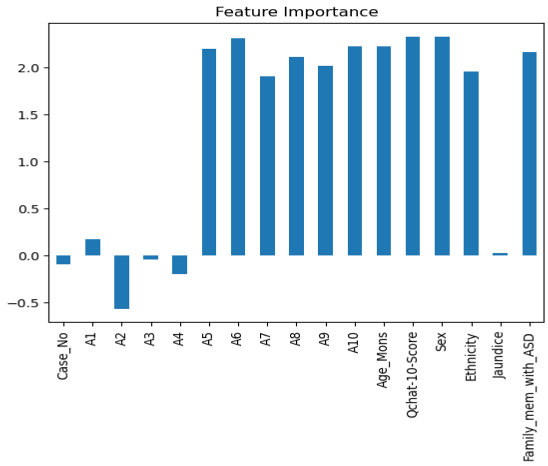


Fig.1 The importance of features within the ASD toddler dataset

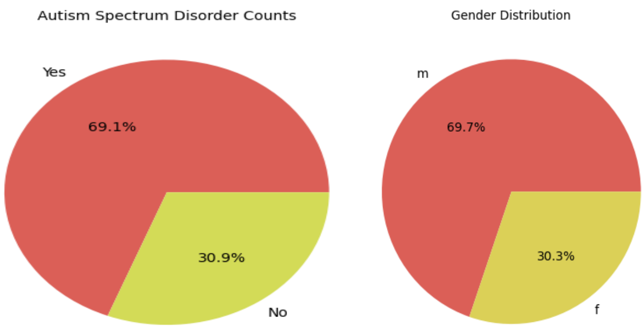


Fig.2 Distribution of Autism Spectrum Disorder cases in overall and gender-specific distributions.

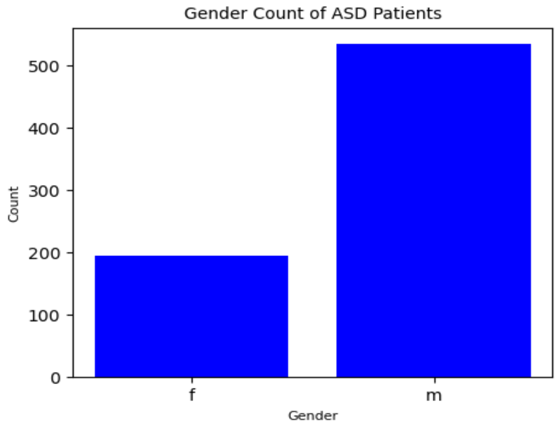


Fig.3 ASD cases in relation to gender distribution

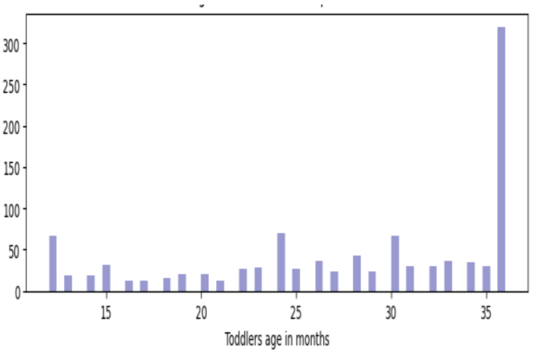


Fig.4 Age distribution of ASD-positive cases in the Toddler dataset

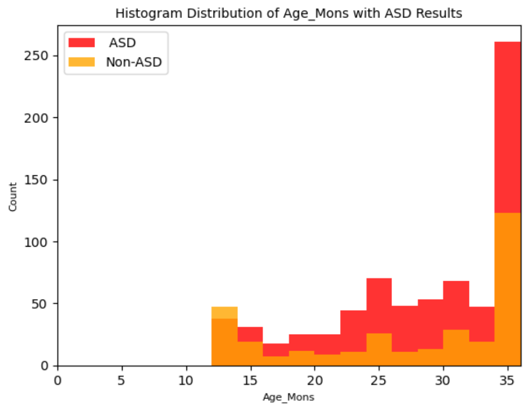


Fig.5 Histogram distribution with Autism prevalence

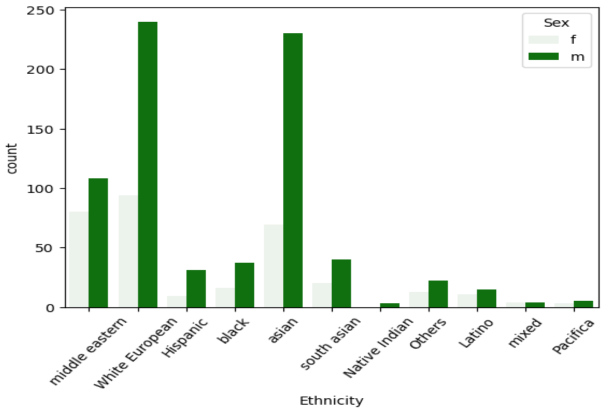


Fig.6. prevalence of autism spectrum disorder cases based on ethnicity Data was collected from individuals representing eleven different ethnicities, with none showing a notable tendency to test positive for ASD compared to others. This highlights the lack of significant ethnic disparities in ASD diagnosis [4]. Here, we note the inclusion of individuals from eleven different ethnic backgrounds in the test. Notably, there is a higher representation of White European testers, followed by Asians, as illustrated in Fig. 6.

3.3. Data Preprocessing

A data preprocessing is nothing but dealing with missing values from the record of data, outlier detection, dealing with different types of variables, dimension reduction etc. Handling of missing values[18]can be done either by imputation. If we have a large dataset, we can drop missing values of the record, but in the other case, we can handle the dataset with an imputation method. Outliers can be promptly identified and eliminated before training the model. The process of identifying prominent features within a dataset is known as Feature selection. It involves evaluating variables in the training set to identify redundant and irrelevant features for elimination. This method reduces input variables in the model to relevant data, effectively removing noise and mitigating the curse of dimensionality.Encoding, which involves transforming categorical variables into numerical ones. One-hot encoding is utilized for ordinal representation, employing N binary variables for N varieties in a variable, while dummy encoding requires N-1 features to represent N labels. Given that our dataset attributes span various scales, normalization [19] becomes necessary to ensure equal contribution of all variables to data analysis. Typically, normalization is performed before model construction, either through min-max normalization for non-Gaussian distributed data or standardization (Z-score normalization) for data following a normal distribution.The generalized workflow for ASD detection mainly based on hyperparameter tuning is illustrated in Fig. 7.

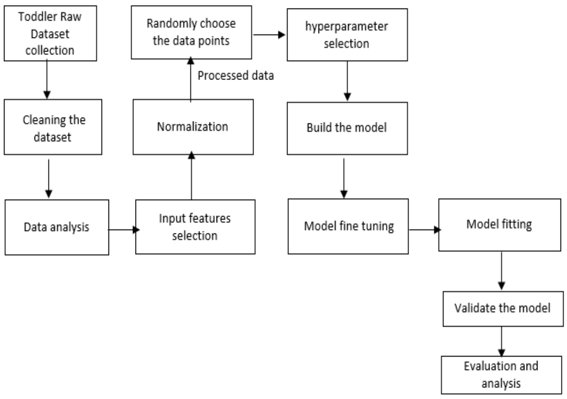


Fig.7. Workflow of Autism Disorder Prediction

After appropriately encoding the data, randomization becomes necessary, involving the random selection of data points for training and testing purposes. The implementation of training and testing for all models begins with the partitioning of the entire dataset into training, testing and validation datasets, with a ratio of 70:30 in our case. Hyperparameter tuning is then conducted to find the optimal set of hyperparameter values for the machine-learning model. A successful machine learning model is capable of accurately estimating the class and generalizing to new test examples. Finally, the model's performance is evaluated using metrics such as accuracy, precision, F1-score, among others.

IV. MODEL IMPLEMENTATION

In this section, we will briefly delve into the Logistic Model classifier and ANN model classifier. In the Machine Learning model, key features are manually extracted and then provided to the algorithm to facilitate classification by incorporating additional information. In contrast, the Deep Learning algorithm is well-suited because it autonomously learns features, eliminating the need for manual feature extraction.

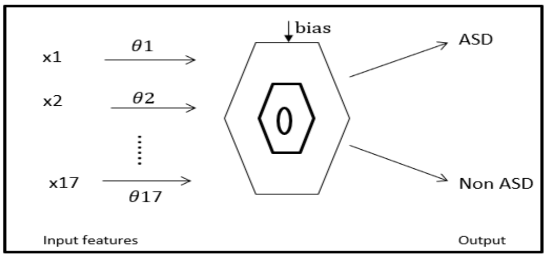


Fig.8. General Structure of Logistic ML classifier for Toddler ASD dataset

This supervised machine learning classifier is primarily utilized for binary classification. The target variable here is binary, either "yes" or "no". The general structure of the Logistic regression machine learning classifier for the Toddler ASD dataset is depicted in Fig.8. It generates a logistic curve with values constrained between 0 and 1. Unlike linear regression, which utilizes probability directly, logistic regression constructs its curve using the natural
logarithm of the target variable's odds. Moreover, the outcomes do not necessarily need to be normally distributed or exhibit the same variance in each group. The probability outcome of the dependent variable varies from -∞ to ∞. However, the resulting probability is constrained between 0 and 1 after applying an activation function,

The logistic model classifier can be expressed as,

$ln\left(\frac{p}{1-p}\right)$= log odds, and p = sigmoid (log odds) **(1)**

Where, $p = 1/(1 + e^{-(bias+x1\theta1+\cdots)})$ (2)

As an outcome, a linear combination of inputs is translated to log (odds), with an output of 1. After the transfer function is utilized as a sigmoid function to translate predictions to probabilities in machine learning. It does not evaluate the 'R squared' or coefficient of determination; instead, its prediction is based on maximum likelihood estimation. The hyperparameter tuning workflow for the logistic regression model proceeds as follows. First, establish a range of hyperparameter values. Next, employ a search space technique, such as grid or random search, to explore this range and assess the model's performance for each hyperparameter set. Finally, select the hyperparameter values that produce the optimal performance. Key hyperparameters to be tuned and tested in the logistic regression model include the solver, penalty, and regularization strength.Within the solver's category, options include: 'lbfgs', 'liblinear', 'sag', 'saga', and 'newton-cg'. 'lbfgs' stands out for its memory efficiency, yet it may encounter convergence issues. 'liblinear' is geared towards large-scale classification problems, 'sag' prioritizes speed, 'saga' is opt for multinomial logistic regression, while 'newton-cg' is computationally intensive due to its reliance on a Hessian matrix.The regularization strength parameter, denoted as "C", varies between 0.1 and 1.0. A lower value indicates stronger regularization, curbing overfitting, whereas a higher value assigns greater weight to the training data.

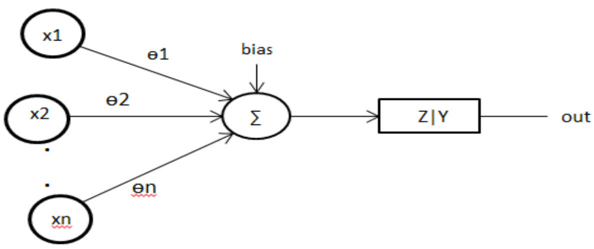


Fig.9. General Structure of ANN model for a Toddler ASD dataset

ANN model mimics the human brain's neuron structure and includes an input layer, one or more hidden layers, and an output layer which is represented in Fig 9. The input data needs to be processed and normalized before it is fed into the input layer. The information contained in the input layer is successively transformed into higher-level features through some non-linear transformations. However, the ANN model allows for the learning of complex, non-linear decision boundaries due to the existence hidden layers. The number of hidden layers and the number of neurons in each layer, is a critical hyperparameter in architecture of the neural network.Too few neurons or layers may result in underfitting, while too many may lead to overfitting**.** The features of the examples from the dataset after being converted into structured format are assigned to the input layer, each neuron denotes one attribute. Then, weights and biases are applied randomly to the inputs. Hyperparameter tuning[12]is a configuration setting externally that is not learned from the data but significantly impacts the training process and the performance of the network. Optimizing an artificial neural network (ANN) entails striking a balance between enhancing its performance on training data and ensuring robust generalization to unseen test data. This endeavor involves meticulous tuning of hyperparameters and the integration of regularization techniques to foster a resilient and high-performing neural network. Essential hyperparameters for tuning in ANN include network topology, learning rate adjustment, per-epoch training duration, and model quality. Early stopping, a regularization technique, involves continuous monitoring of

determination of batch size, and specification of the number of epochs. The choice of batch size impacts overall training time, the model's performance on a validation set. Training ceases upon detecting degradation in validation set performance, thereby mitigating overfitting. The learning rate dictates the

step size at each iteration during the optimization process. Excessively high learning rates may lead to premature convergence and potential overshooting of optimal weights, while excessively low rates can result in slow convergence.

V. RESULT AND ANALYSIS

We establish a baseline model by fitting the classification model with default parameter values, before implementing hyperparameters specific to the Logistic model.Our proposed method's effectiveness is demonstrated through its application to a set of toddler datasets for ASD/Non-ASD detection, with quantitative evaluation performed using performance metrics such as precision, accuracy, F-measure, and AUC score [20]. These performance metrics are derived from True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values [21], and are expressed through mathematical equations ranging from Equation (3) to Equation (6).

$$\text{Accuracy} = \frac{TP+TN}{(TP+FP+TN+FN)} \quad (3)$$

$$\text{P} = \text{Precision} = \frac{TP}{TP+FP} \quad (4)$$

$$\text{R} = \text{Recall} = \frac{TP}{TP+FN} \quad (5)$$

$$\text{F-measure} = 2 \times \frac{(Precison \times Recall)}{(Precision+Recall)} \quad (6)$$

TABLE.II**.**Quantitative findings on the classification of ASD disorder screening among Toddlers

Logistic ML Model	**Precision**	**Recall**	**F-measure**
1	1.00	0.93	0.96
0	0.96	1.00	0.98
Macro avg	0.98	0.96	0.97
Weighted avg	0.98	0.97	0.97

The assessment of the baseline logistic machine learning model, as depicted in Table 2, reveals that the model predicts a precision of 98% for the toddler dataset. This indicates that individuals identified as having ASD by the model are highly likely to indeed have ASD.The F-measure which is the harmonic

measure indicates the balance between precision and recall. Use the metrics achieved from the baseline model as a reference for comparing any improvements obtained during the hyperparameter optimization work. The values of the metrics before applying hyperparameters are as follows:
Accuracy of logistic regression classifier on train set: 0.9848
Accuracy of logistic regression classifier on test set: 0.9748
Precision of logistic regression classifier on test set: 0.9679
This model doesn't require specific hyperparameter tuning. However, variations in performance or convergence may occur with different solvers and regularization strengths. While the model performs well on training data, its performance on test data is less satisfactory. Consequently, we experimented with various solvers excluding regularization strength. Specifically, we tested the solvers 'newton-cg', 'lbfgs', 'liblinear', 'sag', and 'saga' with penalty set to 'none' and max_iterations set to 1000. Initially, 'liblinear' was excluded from consideration as it does not function with a penalty set to 'none'.The resulting outcome, depicted below, includes metrics such as train and test accuracy, precision, recall, and AUC score.

	Train Accuracy	Test Accuracy	Precission	Recall	AUC
0	1.0000	1.0000	0.96789	0.99528	1.00000
2	0.9973	0.9968	0.96789	0.99528	0.99524
3	0.9946	0.9968	0.96789	0.99528	0.99524
1	1.0000	0.9842	0.96789	0.99528	0.98340

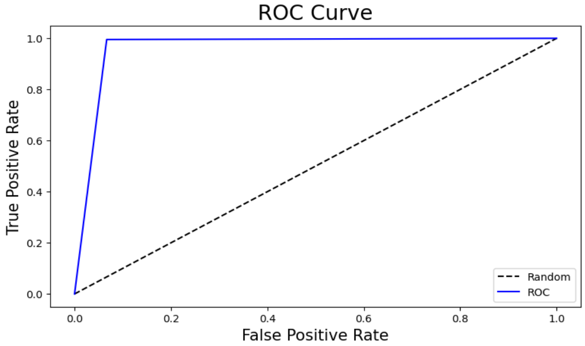
When we observed that regardless of the solver chosen, the model's metrics had improved significantly in terms of both training and testing accuracy, we proceeded with using all solvers with penalty "L2", regularization, and max_iterations set to 1000. The results obtained are as follows:

	Train Accuracy	Test Accuracy	Precission	Recall	AUC
1	1.00000	1.00000	0.96789	0.99528	0.96431
2	1.00000	1.00000	0.96789	0.99528	0.96431
0	0.99322	0.99685	0.96789	0.99528	0.96431
3	0.99864	0.99685	0.96789	0.99528	0.96431
4	0.99457	0.99685	0.96789	0.99528	0.96431

The training and test accuracies improved slightly, while the precision and recall remained unchanged. Additionally, the AUC score remained consistent at 0.96431 across all solver models. Finally, upon examining the logistic regression model with the solver and penalty, considering the regularization strength parameter 'C', the achieved results are as follows. With a 'C' value of 0.2, indicating good regularization strength, the model is less susceptible to overfitting.

	Train Accuracy	Test Accuracy	Precission	Recall	AUC
1	1.00000	1.00000	0.96789	0.99528	0.96431
2	1.00000	1.00000	0.96789	0.99528	0.96431
3	0.99864	1.00000	0.96789	0.99528	0.96431
4	0.99729	0.99685	0.96789	0.99528	0.96431
0	0.98507	0.98738	0.96789	0.99528	0.96431

Given the satisfactory AUC score, the model exhibits commendable performance. The AUC score, derived from the Receiver Operating Characteristics (ROC) curve, is illustrated in Fig. 10. This metric holds significance, particularly considering the somewhat imbalanced nature of the dataset.



Reference	Classifier algorithm	Proposed method	Performance metrics
[12]Toddler dataset with 19 features	Logistic model	Machine learning	Acc: 0.915 Prec: 0.89 Recall: 0.87
[8],Toddler dataset with 19 features	ANN	Machine learning	Acc:1.00 F1-score:1.00
[20]Children dataset with 515 instances with different attributes	ANN	Machine Learning	Acc: 0.9296 Precision:0.90 Recall:0.854 F1 score: 0.87

Fig.10. Receiver Operating Characteristics Curve for Logistic model

An Artificial Neural Network (ANN) is a supervised feed-forward neural network comprising multiple interconnected neurons. Within neural networks, weights and biases serve as parameters, dynamically updated during backpropagation to minimize the cost function. Once the model is appropriately fixed and fine-tuned, the testing phase commences. In our study, we utilized Keras as a foundational model running on top of TensorFlow to construct a neural network. Our dataset comprises 17 input features and aims to classify instances as either ASD or non-ASD.We sequentially designed our model in Keras by specifying Sequential to Keras. We defined fully connected layers with Dense, indicating input and output dimensions along with the activation functions; "relu" for input and hidden layers, and "sigmoid" for the output layer. The optimizer selected was 'Adam' with a learning rate set to 0.001. During training, we set the epoch size to 30 and the batch size to 32, with a validation split of 30%.The performance of our neural network (ANN) was evaluated using accuracy, precision, recall, F-score, and AUC score parameters which is tabulated in Table.3. The AUC score derived from the Receiver Operating Characteristic (ROC) curve, as shown in Fig. 11, which is visually represents the true positive rate (Y-axis) against the false positive rate (X-axis), with an AUC score of 0.966. This score provides insight into the classifier's effectiveness in distinguishing between ASD and non-ASD classes

TABLE.III. Evaluation results for the classification of ASD disorder screening for Toddlers

ANN MODEL	Precision	Recall	F-measure	AUC score
Accuracy0.98	0.9665	0.9758	0.9711	0.9665

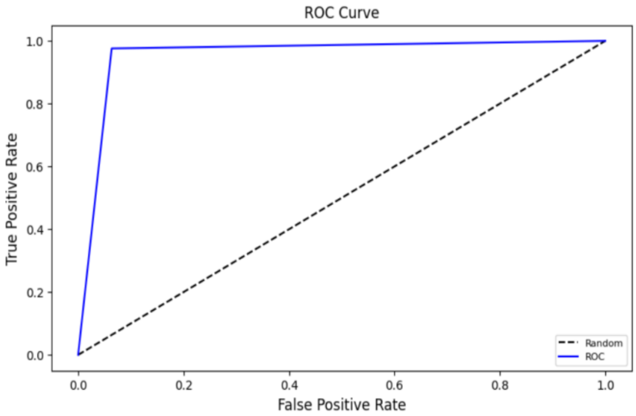


Fig.11. Receiver Operating Characteristics curve for ANN model

The Comparative results with other research studies from the literature focussed on this area are described in Table.4 based on both the Logistic model and artificial neural network model.It is paramount to underscore that the results of this study should be viewed not as definitive conclusions but rather as preliminary exploratory findings.

TABLE.IV Comparison assessment on ASD screening data

It is paramount to underscore that the results of this study should be viewed not as definitive conclusions but rather as preliminary exploratory findings.

VI. CONCLUSION AND DISCUSSION

Hyperparameter tuning is crucial for achieving optimal performance on the data within a reasonable timeframe. However, it is important to note that tuning does not guarantee universally accurate and acceptable results, as its efficacy depends on the type of model selected and data used for training. The early detection of autism spectrum disorder (ASD) significantly reduces disease incidence and enhances the future of not only affected people but parents as well. The primary focus of this study is to assess whether hyperparameter tuning in both Logistic Regression and Artificial Neural Network (ANN) models can effectively aid in identifying the presence of autism spectrum disorder (ASD) in a non-invasive manner. These findings show that, rather than the logistic model the ANN model may be the best to detect autism spectrum disorder based on its evaluation results. The study has demonstrated promising results. There is potential for further refinement by training the model with deep learning algorithms such as Convolutional Neural Networks (CNN) based on hyperparameter tuning to improve the ASD detection process.

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