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AN EXPLAINABLE DATA-DRIVEN MACHINE LEARNING FRAMEWORK FOR AUTOMATED AUTISM SPECTRUM DISORDER SEVERITY CLASSIFICATION

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Abstract
Autism Spectrum Disorder (ASD) comprises diverse neurodevelopmental conditions with symptoms differing based on genetics, development, age, and other factors. Detecting ASD has challenges as symptoms often manifest in early life and can lead to delayed analysis. Because standard diagnostic practices rely heavily on human interpretation, making it prone to bias and inefficiency. To attain objective and effective detection, machine learning (ML) methods have become increasingly valuable. Thus, there is a need for an enhanced and accurate ML method that can successfully handle feature selection (FS) and parameter tuning for ASD severity classification. Therefore, this study presents an Advanced Evolutionary Framework for Automated Autism Detection and Severity Classification (AEF-AADSC). The major aim of this work is to design an intelligent machine learning framework to classify autism spectrum disorder severity grading. Initially, the proposed undergoes preprocessing of the raw dataset to ensure high-quality input for the learning model through missing value handling, encoding, and normalization process. Subsequently, feature selection is carried out using an Improved Genetic Algorithm, which selects the most relevant features and thereby enhances model efficiency. The selected features are then utilized for training a CatBoost classifier for accurate classification of ASD severity levels. In addition, hyperparameter optimization is carried out using Covariance Matrix Adaptation Evolution Strategy to further enhance predictive performance. To improve model transparency and interpretability, Explainable artificial intelligence is incorporated using SHapley Additive exPlanations, enabling analysis of feature contributions and supporting better understanding of the classification decisions. The performance validation of the proposed approach is carried out using the Autism Diagnosis Based on Diagnostic and Statistical Manual of Mental Disorders (DSM)-5 dataset. The AEF-AADSC method achieves improved performance with an accuracy of 96.30% compared to baseline methods in terms of different measures. Therefore, the proposed model is found to be a robust approach for the automated ASD severity grading process.

Keywords: Autism Spectrum Disorder; Severity Classification; Genetic Algorithm; Machine Learning; Hyperparameter Optimization; Explainable Artificial Intelligence

1. Introduction

Autism spectrum disorder (ASD) represents a group of brain-based developmental conditions, which impact how a person communicates and relates to others [1]. Autism symptoms and the severity degree can range highly; some people with this disorder may have trouble in interpreting sensory information, interacting socially, and communicating with others [2]. A study carried out on a large number of populations, nearly 55,266 children, has shown 2.20% projected occurrence of ASD is based on the DSM-5 criterion. It usually occurs due to any genetic linkage or environmental factors, where the nervous system is not only affected, but it also has a total impact on the cognitive and social abilities of adults and children [3]. The intensity and the extent of these disorder symptoms are entirely variable. General signs of this condition include difficulties faced in communication, especially in repeated mannerisms, obsessional interests, and social situations [4]. Detecting ASD in the earlier stage is vitally important as it may help a person with ASD to improve their communication skills in the long term. The proper interaction and training given may help the person with ASD to develop many vital capacities to feel and share the feelings of others. Non-clinical or clinical methods are available to diagnose a case of ASD [5].
As several studies have centered on detecting ASD, most of them rely on time-consuming questionnaires and interviews, which emphasizes the need for earlier diagnosis. In addition, standard techniques such as interviews and observation-based methods are usual nowadays [6]. For example, the childhood autism rating scale (CARS) uses 15 different questions for diagnosing ASD, and it leverages the scores for severity classification. Likewise, in the gilliam autism rating scale (GARS), 56 items are split into four classifications for evaluating the ASD severity [7]. Still, this kind of manual method is not practically feasible for data collection in everyday activities, as it mainly depends on behavioral observations and expert opinion. It needs money and a lot of time as well. Machine learning (ML) is a strong tool used for analyzing large quantities of data and identifying patterns that are used in the detection of ASD [8]. ML is used to create customized treatments using the characteristics of individual patients. Recent developments in ML have made ASD methods more accurate in less time. ML models are important for accurate and quick assessment of risks in ASD and to streamline the whole diagnosis process to assist the families in getting the vital therapies quickly [9]. Different classification methods of ML are used for the earlier prediction of autism disorder and for the prevention of its longer-term impacts in children and adults [10].

1.1. Research Motivations and Contributions

Autism spectrum disorder (ASD) impacts social interaction, behavior, and communication, and its severity differs from person to person, thus making it significant to recognize the precise severity level for offering suitable treatments. Most existing diagnosis techniques depend on interviews, questionnaires, and proficient observations that can be time-consuming, expensive, and not appropriate for large-scale or earlier screening. Timely and precise severity classification must support faster intervention and increase long-term outcomes for individuals with ASD. The ML gives a reasonable outcome to automate this process, decrease human involvement, and increase prediction accuracy by using data-driven techniques. Although there is still a requirement for more effective techniques that must be successfully handled, feature selection (FS) and hyperparameter tuning to increase overall performance. In order to overcome this, this study proposes an Advanced Evolutionary Framework for Automated Autism Detection and Severity Classification (AEF-AADSC) that incorporates an Improved Genetic Algorithm for optimum FS and a CMA-ES enhanced CatBoost classifier to accomplish robust and precise ASD severity grading. The key contributions of this manuscript are as follows:

- Employs an improved genetic algorithm (IGA) for selecting the more relevant features and decreasing redundancy.
- Utilizes the CatBoost classifier for precise and effective severity classification of ASD.
- Applies Covariance Matrix Adaptation Evolution Strategy (CMA-ES) for hyperparameter optimization to improve model performance.
- Incorporates Explainable Artificial Intelligence (XAI) using SHAP to interpret model predictions and analyze feature importance.
- Assesses the model using the DSM-5-based autism dataset and achieves higher performance when compared to baseline techniques across numerous assessment metrics.

2. Literature Review

This section offers a concise review of related studies on ASD detection and severity classification. In [11], an FL approach has been distinctively employed for ASD by training 2 distinct ML classifiers comprising a support vector machine and logistic regression regionally for ASD identification and classification of ASD features in adults and children. The authors [12] designed a model for distinguishing between autistic and normally developing children, examining visual attention behaviors utilizing an eye-tracking model in a virtual atmosphere, as well as an amount of attunement to and mining of socially related data. Liao et al. [13] examined an ML system that unites behavioral data and physiological data, such as EEG, to identify children with ASD. Its performance can enhance identification efficacy and decrease costs. Firstly, the author employed an inventive methodology to extract attributes of facial expression, EEG information, and eye fixation. Moreover, the ML methods are applied to join the complementary data, which can substantially enhance classification accuracy. Assaf et al. [14] designed to evaluate the probability of a confidentiality-enhancing ML approach for ASD recognition utilizing children's speech records. Through completely exploiting structured text-based inputs, our models integrally abstain from the direct usage of recognizable biometric information, like raw video or audio, so as to significantly decrease privacy threats.

Ehsan et al. [15] discussed exploiting (AUTOML) to reorganize the analytic process and improve its precision. Initial recognition of ASD is significant because it permits early intervention, which substantially enhances behavioral, developmental, and communicative results in children. Jabbar et al. [16] proposed an ML technique for inspecting the autism dataset of distinct age categories to classify autism in the earlier stage. The author follows data preprocessing, feature selection strategy, and ML-based classification, and also performs hyperparameter optimization. Sulthana and Kumar [17] addressed ML to identify important ASD traits initially. To verify ASD diagnosis efficiency, the author concentrates on 8 cutting-edge classification approaches. Logistic Regression outshines other classifiers on the United dataset when hyperparameters are appropriately adapted for every system. Khan and Katarya [18] proposed and investigated analyses of several ML algorithms on mining useful information related to distinguishing features of ASD. Recent studies have discovered that the evaluation of biological traits by retaining ML methodologies has supported the process of early ASD identification.

2.1. Research Gaps

- Farooq et al: Utilize the ML methods for ASD identification, but highlight only detection and model comparison. This cannot be considered ASD severity classification or innovative optimization methods.
- Liao et al: Integrates EEG and behavioral data for ASD identification with better accuracy. But it depends on the intricate data and lacks effective FS and lightweight modeling.
- Jabbar et al: Utilize ML for earlier ASD prediction by employing preprocessing and feature representation. Still, it cannot be included as a combination of evolutionary optimization for FS and hyperparameter tuning.

Hence, there is a requirement for an effective and intelligent model that must accurately classify ASD severity levels based on DSM-5 measures by integrating efficient FS and robust hyperparameter optimization methods. Thus, this study develops an innovative evolutionary-based framework that combines an IGA for the feature selection process and a CMA-ES-enhanced CatBoost classifier for increasing the prediction performance.

3. Proposed System

Fig. 1 displays the complete process of ASD severity classification using the DSM-5 dataset. First, the dataset is taken and split into a training dataset. Then, preprocessing is done, like handling missing values, encoding categorical data, and standardizing it to make the data clean and ready. After that, feature selection is carried out using an improved genetic algorithm to pick only important features. These selected features are then fed to the CatBoost model for classification. At the same time, CMA-ES is used to tune the model parameters to get better performance. Finally, the trained model classifies the output classes like no autism, moderate, severe, and autism. Besides, XAI using SHAP is applied for interpreting the model predictions by analyzing feature contributions. The results are then evaluated to check how well the model is working.

3.1. Data Preprocessing

Before training the model, the dataset was preprocessed to enhance data quality, remove unnecessary or repeated data, and make it more useful for better prediction [19]. The dataset is acquired from the openly accessible DSM-5 questionnaire dataset, which comprises behavioral and response-based features relevant to ASD. Such descriptors involve diagnosis-based features, behavioral indicators, and individual questionnaire responses that can contribute to ASD severity stages.

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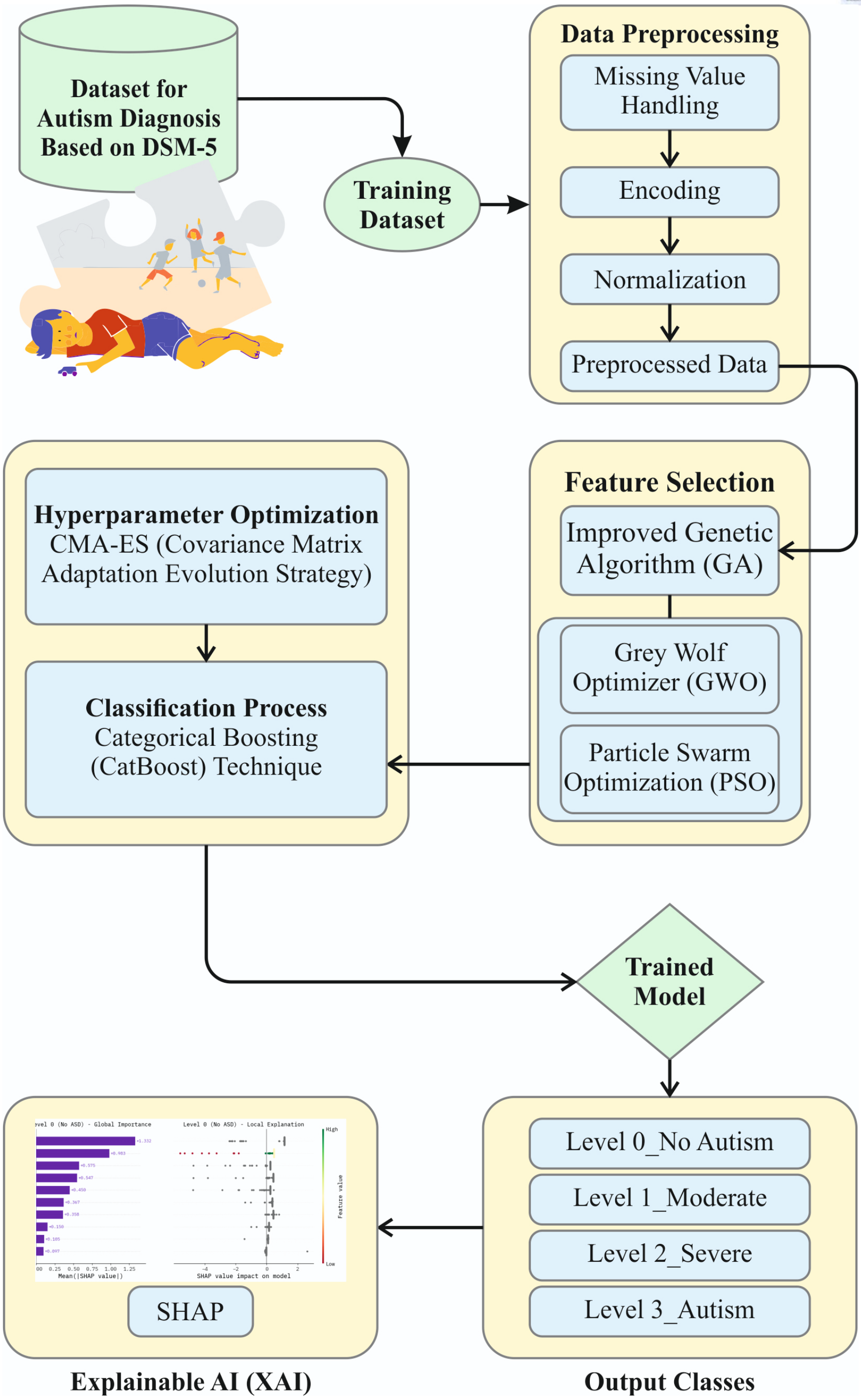

Fig. 1. Overall workflow of the AEF-AADSC approach

Missing Data Handling: Missing values in the dataset have been encountered by employing imputation method to prevent data loss and validate numerical integrity. For numerical features, mean imputation must be utilized in this mathematical form.

$$x_{i,j} = \{x_{i,j}, \, if \, x_{i,j} \neq \emptyset, \frac{1}{n_j}\sum_{k=1}^{n_j} x_{k,j}, otherwise, \tag{1}$$

Here, the parameter n_j refers to the present values in feature j, and the parameter $x_{i,j}$ indicates the values corresponding to the j^{th} feature and the i^{th} sample.

Categorical Feature Encoding: Categorical descriptors contain the behavioral classes and questionnaire response classes, which can be converted into numerical formats by applying one-hot encoding, thus generating the binary indicator vector for all the categories.

$$0_i = [o_{i,1}, o_{i,2}, \dots, o_{i,k}]^T, o_{i,m} = \{1,\ if\ cat\ m\ is\ present, 0,\ otherwise. \quad (2)$$

Normalization: Constant features have been standardized to unit variance and 0 mean to avoid the attributes with higher magnitudes from controlling the model during the training phase, as described in this mathematical form.

$$z_{i,j} = \frac{x_{i,j-\mu_j}}{\sigma_j} \quad (3)$$

Here, the parameter σ_j and μ_j indicate the standard deviation (SD) and mean with respect to the j-th feature.

3.2. Improved Genetic Algorithm-based Feature Selection

Genetic algorithm comes from ideas of natural evolution like selection, mutation and crossover. This can work as a search method formed to determine the optimization intricacy in computational models, thus allowing the recognition of globally optimum outcomes [20]. The feature selection (FS) method is formulated as an optimization problem.

Initialization: Feature subsets must be indicated in GA by applying the binary encoding method. An encoding process of one indicates the feature with respect to the position is chosen, whereas zero represents that it is not chosen. Initialization of n values as the preliminary population, represented by $s_1 - s_n$, thereby demonstrating the DSM-5 questionnaire features for ASD severity classification.

Fitness calculation: First, each individual is converted into a chosen feature subset. Then the fitness is computed using a function that stabilizes predictive performance and subset size, aiming to keep fewer features with better performance.

$$f(s_i) = \alpha \times (1 - accuracy) + \beta \times \frac{n}{N}, 1 \leq i \leq n \quad (4)$$

α and β control how much importance is given to classification error and the count of chosen attributes, while accuracy is calculated using the CatBoost model on the chosen features. Here, n is the chosen feature count, and N is overall features, and a lower fitness value means the solution is better.

Selection: The parameter n individuals must be arbitrarily chosen as parents from the existing population, depending on the fitness. The roulette mechanism is employed for selection. Entities with lesser fitness must be more likely to be chosen, thus providing a higher meaning of feature integrations must be maintained. The selection is completed n times, and every chosen individual is continued to the subsequent stage.

Crossover: Simulation of hybridization in biological evolution exchanges parts of genes among dual individuals, producing new ones with combined features. In feature selection, this helps generate better feature combinations for ASD severity classification.

Mutation: Simulation of the method of genetic mutations in biological development, all the genes must be changed arbitrarily, depending on the probability. It produces new gene data and can direct the search for the globally optimum subsets of features.

Iteration termination: After each step, the fitness is checked again to see if the stopping condition is met. If yes, the best feature set is selected, and the process continues for the next

iteration.
Even though the GA is searched through for the best outcome on a global scale, it generally involves various losses. The functions of mutation and crossover are to present novel genotypes and maintain population diversity, even though the iterative techniques are developed as the population tends to develop into identical individuals, which decreases the capability to produce new outcomes and can lead to convergence to a local optimum.
In order to overcome this complexity, this paper proposes two enhancements for the GA.
Adaptive Mechanism: This idea is about adjusting the crossover and mutation probabilities dynamically instead of keeping them fixed. These values (P_c and P_m) are changed based on fitness and how diverse the population is to improve the search process.
The mathematical form of adaptive modification can be given below,

$$P_c = \{k_1, f' < f_{avg}\ k_2 \frac{(f' - f_{min})(1 + e^{-c_1 f_{std}})}{f_{avg} - f_{min}}, f' \geq f_{avg} \tag{5}$$

$$P_m = \{k_3, f < f_{avg}\ k_4 \frac{(f - f_{min})(1 + e^{-c_2 f_{std}})}{f_{avg} - f_{min}}, f \geq f_{avg} \tag{6}$$

Here, f represents the fitness of individuals used in mutation and the better parent in crossover, while $f_{std}, f_{min},\ and\ f_{avg}$ denote the standard deviation, minimum, and mean of population fitness. Also, c_1 and c_2 are constants greater than zero, $and\ k_1, k_2, k_3, k_4\ \in\ (0,1]$ are parameter values.

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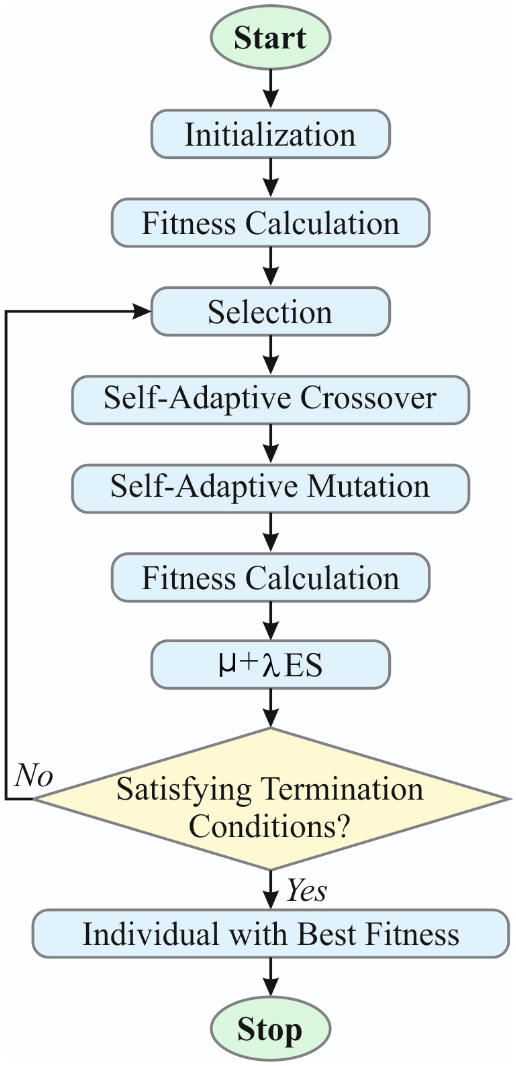

Fig. 2. Process of improved genetic algorithm feature selection

$\mu + 1$ **evolution strategy:** Consider the population size represented by μ, with one offspring produced in all generations. The optimum μ individuals have been selected to create the next generation from the overall of μ+1 individuals. The aforementioned technique retains the maximum individuals in every generation, thus quickens the convergence speed of the population, and improves the search efficiency to pick better features in ASD severity classification. Fig. 2 illustrates the process of improved genetic algorithm feature selection.

3.3. Autism Severity Classification using CatBoost Approach

In this method, an effective ML technique is essential for efficiently classifying ASD severity levels, which depend on DSM-5 questionnaire replies. Because the database covers organized and generally categorical data, a boosting-driven method is more appropriate for taking intricate patterns in the data [21]. Thus, the CatBoost method has been chosen as the classifier method because of its capability to manage categorical characteristics effectively and offer higher predictive precision. This method signifies an improvement of the Gradient Boosting Decision Tree (GBDT) structure. Conventional GBDT methods build every DT depending on the residuals of the recent method, leading to robust correlation among trees and high variance. CatBoost solves this by using ordered boosting and a different weighting idea, where the data is rearranged, and similar feature values are grouped to reduce overfitting. In this model, the mean of class labels is used as the rule for splitting nodes. The particular expression is calculated as follows:

$$\hat{x}_k^i = \frac{\sum_{j=1}^{N} \quad I_{\{x_j^i = x_k^i\}} y_j}{\sum_{j=1}^{N} \quad I_{\{x_j^i = x_k^i\}}} \tag{7}$$

In this Eq. (7), x_k^i represents the i^{th} attribute of the k^{th} training instance; $\hat{x}_k^i$ signifies the value of the mean; $I(\cdot)$ is used as an indicator function to check if a condition is satisfied, while $y_j$denotes the label corresponding to the j^{th} data instance. In contrast to the GBDT method, the CatBoost model combines an adaptive learning rate module. It enables a more accurate adjustment of the effect applied by weaker learning in every iteration, which eventually results in an enhancement in the precision of the method. The computational process for the adaptive learning rate inside the CatBoost method has been summarized below:

$$\{\eta_t = \frac{1}{\sqrt{k+1}} \; \alpha_t = \frac{\sum_{i=1}^{t} \quad \eta_i}{k} \tag{8}$$

Here, t implies the count of iterations, η_t signifies the t^{th} iteration's learning rate, and α_t indicates the learning rate throughout the primary t iterations. Conventional neural network methods require a considerable data quantity for efficient training; techniques trained on restricted databases tend to show lower precision. However, the CatBoost method is a decision tree-driven system that doesn't need a huge instance size as its training set to attain higher prediction accuracy. Moreover, CatBoost is categorized by the higher training efficacy, allowing fast method training and improved prediction speed for the ASD severity classifier, which depends on DSM-5 questionnaire data. Also, CatBoost minimizes the need for heavy pre-processing and intricate feature engineering, making it more practical for real-time medical databases. Because of these benefits, it is considered an appropriate and consistent option for correctly categorizing ASD severity levels into mild, moderate, and severe classes.

3.4. Hyperparameter Optimization

CMA-ES is leveragd to find the best hyperparameters through trying different combinations and selecting the ones that minimize validation error, where CatBoost is trained and tested for each set. It helps handle complex search spaces and improves parameters like iterations, learning rate, depth, and regularization to get better accuracy and performance [22]. The CMA-ES optimizer intends to reduce the classification loss of the CatBoost model, which is typically defined through an error function among the true labels $y(t)$and predicted outputs $\hat{y}(t)$, given as

$$J(\theta) = \frac{1}{N}\sum_{t=1}^{N} \quad \|y(t) - \hat{y}(t)\|^2 \tag{9}$$

Here, the mathematical representation $\theta = \left[depth, learning_{rate}, l2_{leaf_{reg}}, iterations\right]^T$ remains the vector of optimized hyperparameters, thereby indicating the L2 regularization parameter ($l2_{leaf_{reg}}$), the learning rate ($learning_{rate}$), the number of iterations (iterations), and the tree depth ($depth$).

CMA-ES utilizes a multivariate Gaussian distribution for generating candidate solutions, dynamically adapting its covariance matrix to capture the local curvature of the search space $C^{(g)} \in R^{d\times d}$ and mean vector $m^{(g)} \in R^d$, where d refers to the number of hyperparameters. The method can be iteratively updated with such parameters for searching for the optimum solution.

Every generation g, λ offspring solutions are sampled from a multivariate normal distribution.

$$x_k^{(g+1)} \sim \aleph(m^{(g)}, (\sigma^{(g)})^2 C^{(g)}) \tag{10}$$

Here, the mathematical $\sigma^{(g)}$ refers to the global step size that must be controlled to search the radius.

The candidate outcomes have been assessed by applying the objective function $J(\theta)$, and the finest μ' entities can be chosen for updating the mean vector.

$$m^{(g+1)} = \sum_{i=1}^{\mu'} w_i x_{i:\lambda}^{(g+1)} \tag{11}$$

Here, the parameter w_i indicates positive weights that are added to one, and the term $x_{i:\lambda}$ refers to the i-th finest individual amongst the λ candidates. Updating the covariance matrix c refines the search distribution's orientation and scale, directly influencing subsequent sampling steps.

$$C^{(g+1)} = (1 - c_1 - c_{\mu'})C^{(g)} + c_1 p_c^{(g+1)} (p_c^{(g+1)})^T$$
$$+ c_{\mu'} \sum_{i=1}^{\mu'} w_i \left(\frac{m^{(g+1)} - m^{(g)}}{\sigma^{(g)}}\right)\left(\frac{m^{(g+1)} - m^{(g)}}{\sigma^{(g)}}\right)^T \tag{12}$$

Here, the mathematical parameter p_c refers to the evolution path that can combine data about the effective directions for search, and the mathematical terms c_1 and $c_{\mu'}$ indicate experimental parameters that can generally depend on the dimensions of the complexity.

The step size σ must be used to assure effective exploitation and exploration of the search space and has been computed and given below,

$$\sigma^{(g+1)} = \sigma^{(g)} \times exp\left(\frac{c_\sigma}{d_\sigma}\left(\frac{\|p_\sigma^{(g+1)}\|}{E\|\aleph(0, I)\|} - 1\right)\right) \tag{13}$$

Now, the parameter $p_\sigma^{(g+1)}$ refers to the path in the control of the step-size, and the mathematical terms d_σ and c_σ represent adaptation parameters.

CMA-ES uses a fitness function for evaluating candidate solutions and improving classification performance. In this work, the goal is to minimize the classification error rate, which is given as the fitness value. It is computed by dividing the number of incorrect predictions by the overall sample size, as shown below:

$$fitness(x_i) = ClassifierErrorRate(x_i)$$
$$= \frac{no.\ of\ misclassified\ instances}{Total\ no. of\ instances} * 100 \tag{14}$$

3.5. Model Interpretability with SHAP

SHAP is employed to interpret the model architecture and assess feature contributions [23]. As a local explainability tool, It measures the exact impact of every feature on every prediction using Shapley values, offering a clear, feature-by-feature breakdown of the outcome. Additionally, global SHAP values are utilized to analyze general feature trends. The mathematical Eq. (15) represents the fundamental description of the approach and the functional descriptions of the modules.

The SHAP technique describes the involvement of every feature in the output of the ML method depending on cooperative game theory. This method is aimed at properly and reliably measuring the contributions of every feature to the prediction of the model, mainly using the Shapley values. This value for the $i-th$ feature can be calculated as the mathematical form,

$$\phi_i(f,x)=\sum_{S\subseteq F\setminus\{i\}}\frac{|S|!\,(|F|-|S|-1)!}{|P|!}[f_{S\cup\{i\}}(x_{S\cup\{i\})S}-f_S(x_S)] \tag{15}$$

Here, SHAP assigns contribution values to every feature to explain its influence on the model prediction. Additionally, Global SHAP analysis is utilized for measuring the overall importance of features across all samples.

4. Results and Discussions

This section offers the experimental evaluation of the proposed AEF-AADSC approach using the Autism Diagnosis Based on DSM-5 dataset [24]. Autism is a neuro developmental state which affects all the categories of people from children to adults. Autism affected persons have challenges with communication skills, social and cognitive. In accordance with DSM5 criteria, 3 stages of Autism are there: Level 1, Level 2, and Level 3. After diagnosis, by finding a person's level of severity, we can find out the right way of therapy for that particular individual. Most of the research works have focused on the autism diagnosis, as in selective autism affected individuals from non-autism individuals. Few works only have done, classification of autism based on its level of severity using DSM 5 criteria. We have collected the datasets in this study, from persons using DSM5 criteria guidelines by utilising the google forms questionary. The dataset consists of 20 features in total, out of which 14 features were selected after the feature selection process. Table 1 shows that the dataset contains a total of 131 samples across four severity-level classes, namely Level 0 (No Autism), Level 1 (Moderate), Level 2 (Mild), and Level 3 (Severe).

Table 1 Details of datasets

Classes	**Labels**	**No. of Samples**
Level 0 (No Autism))	Level 0_No Autism	50
Level 1 (Mild Autism)	Level 1_Mild	32
Level 2 (Moderate Autism)	Level 2_Moderate	39
Level 3 (Severe Autism)	Level 3_Severe	10
Total Samples		**131**

Table 2 presents the selected attributes and their corresponding attribute numbers for the proposed model.

Table 2 Selected Attributes and Attribute Numbers of the proposed model

S.no	**Selected Attributes**	**Attribute Number**
1	Which age group does your child belong to	4
2	Sex of child	5
3	Which type of disability do he/she have	7
4	Please what is the age of the mother when the child was born	8
5	If Diagnosis is yes, what was his/her diagnosis? (DSM 4 Diagnosis)	10
6	At what age was the child diagnosed	11
7	Where was the diagnosis done?	12

8	Is your child	13
9	How can you rate your child's deficits in social communication and social interaction	15
10	How can you rate your Childs nonverbal communicative behaviors capabilities (i.e abnormalities in eye contact, body language or deficits in understanding, use of gestures, total lack of facial expressions and nonverbal communication)	16
11	Can your Child develop, maintain and understand relationships (as in difficulties in sharing imaginative play or in making friends and absence of interest in peers.)	17
12	Do your Child has Stereotyped or repetitive motor movements and echolalia	18
13	How is his/her Hyporesactivity to sensory aspects of the environment (i.e can he differentiate pain/temperature, respond to specific sounds or textures, do excessive smelling or touching of objects)	19
14	If Diagnosis is yes, what was his/her diagnosis? (DSM 5 Diagnosis)	21

Table 3 and Fig. 3 offer the comparison of feature selection methods, presenting that the proposed IGA performs better than PSO and GWO. The IGA accomplishes the lowest cost value of 0.117, compared to PSO of 0.205 and GWO of 0.261, which indicates more robust feature selection. Among the three methods, GWO demonstrates the highest cost and performs the worst, while PSO provides moderate results. Hence, the IGA offers better feature selection by reducing the cost and identifying more relevant features for the model.

Table 3 Evaluation of feature selection methods based on selected feature subsets and best cost values

Method	**Selected Features**	**Best Cost (0-1)**
Improved Genetic Algorithm (GA)	1,3,4,5,6,7,8,10,12,13,14,17,18,19	0.117
Grey Wolf Optimizer (GWO)	2,3,4,5,6,7,8,11,12,13,15,16,18,20	0.261
Particle Swarm Optimization (PSO)	1,2, 5, 7, 9,10,11,13,14,15,16,17,19,20	0.205

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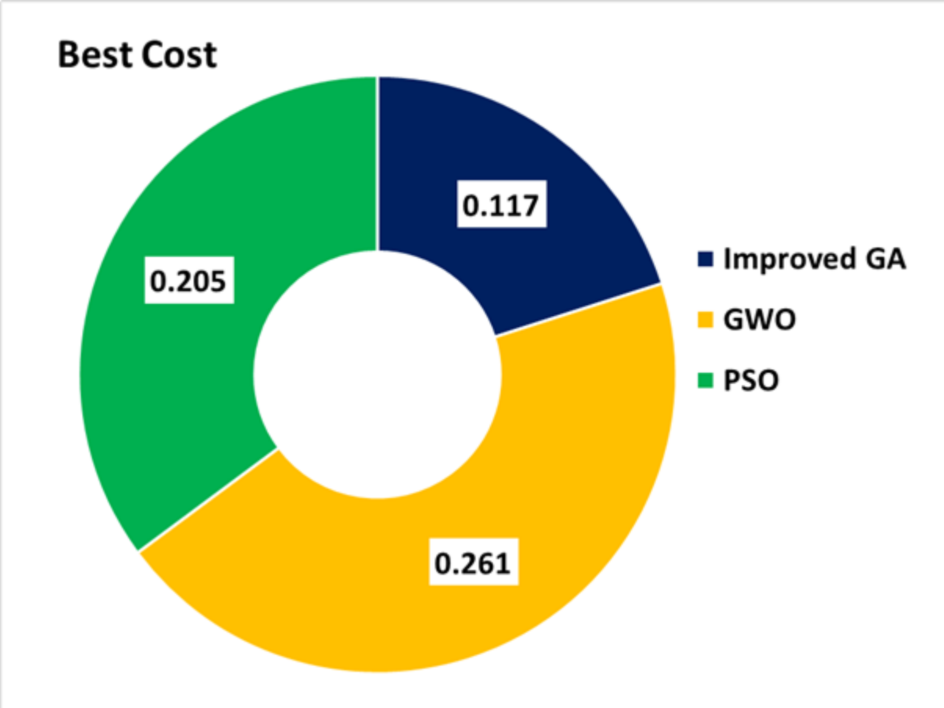
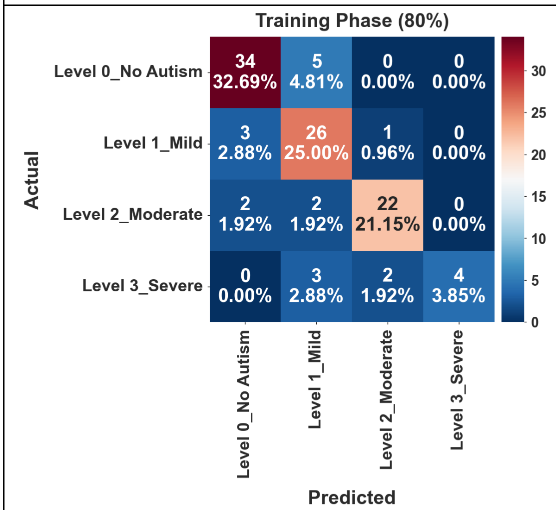


Fig. 3. Feature selection comparison using selected features and cost values

Table 4 and Fig. 4 illustrate the confusion matrices produced by the by AEF-AADSC model under 80:20 of TRAPE/TESPE. The training model produces the better performance with average Accuracy of 91.35 %, Precision of 86.85%, Recall 75.73%, F1-score of 78.45% and MCC of 73.99% and the testing model significantly enhanced classification performance, achieving an Accuracy of 96.30%, Precision of 95.14, Recall of 93.06, F1-score of 93.86% and MCC of 91.31%. The result indicates that the AEF-AADSC model has effectively identify between positive and negative cases across class labels.

Table 4 ASD severity level classifier result of the AEF-AADSC method under 80:20 of TRAPE/TESPE

Confusion Matrix	**Classes**	$Accur_y$	$Preci_n$	$Recal_l$	$F1_{score}$	**MCC**
	Level 0_No Autism	90.38	87.18	87.18	87.18	79.49
	Level 1_Mild	86.54	72.22	86.67	78.79	69.66
	Level 2_Moderate	93.27	88.00	84.62	86.27	81.85
	Level 3_Severe	95.19	100.00	44.44	61.54	64.98
	Average	**91.35**	**86.85**	**75.73**	**78.45**	**73.99**
	Level 0_No Autism	96.30	91.67	100.00	95.65	92.70

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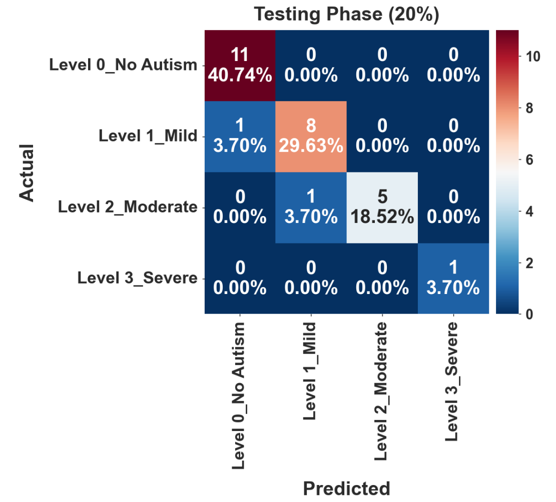	Level 1_Mild	92.59	88.89	88.89	88.89	83.33
	Level 2_Moderate	96.30	100.00	83.33	90.91	89.19
	Level 3_Severe	100.00	100.00	100.00	100.00	100.00
	Average	**96.30**	**95.14**	**93.06**	**93.86**	**91.31**

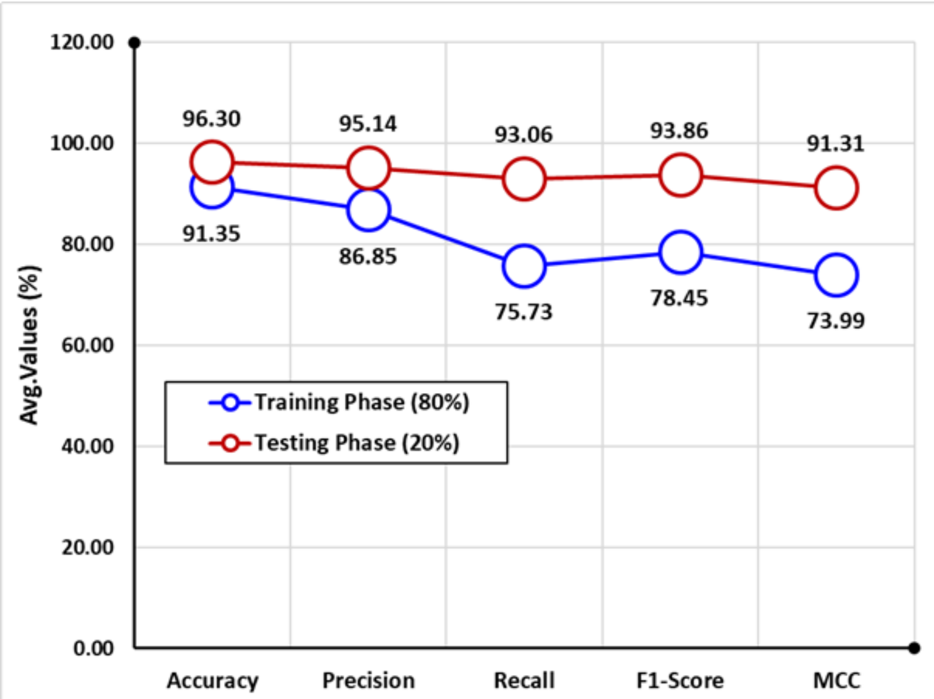

Fig. 4. Average value of the AEF-AADSC method with 80:20

Table 5 and Fig 5 show the confusion matrices produced by the by AEF-AADSC model under 70:30 of TRAPE/TESPE. The training model achieves the better performance with average Accuracy of 91.25 %, Precision of 86.58%, Recall 70.20%, F1-score of 69.66% and MCC of 67.79% and the testing model significantly improved classification performance, attaining an Accuracy of 95.00%, Precision of 90.23, Recall of 80.79, F1-score of 83.16% and MCC of 81.13%. The outcome implied that the AEF-AADSC model has efficiently classify between positive and negative instances across class labels.

Table 5 ASD severity level classifier result of the AEF-AADSC method under 70:30 of TRAPE/TESPE

Confusion Matrix	**Classes**	$Accur_y$	$Preci_n$	$Recal_l$	$F1_{score}$	**MCC**

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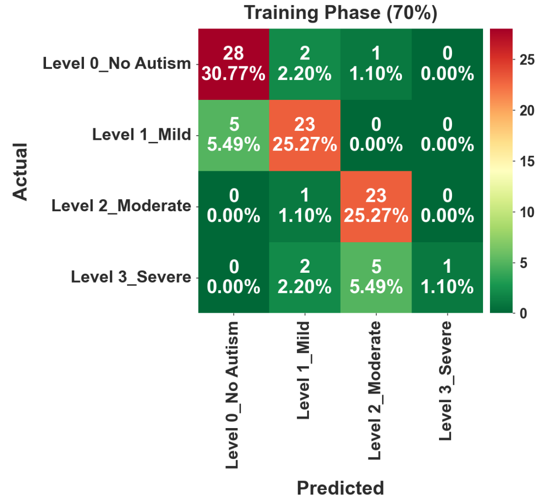
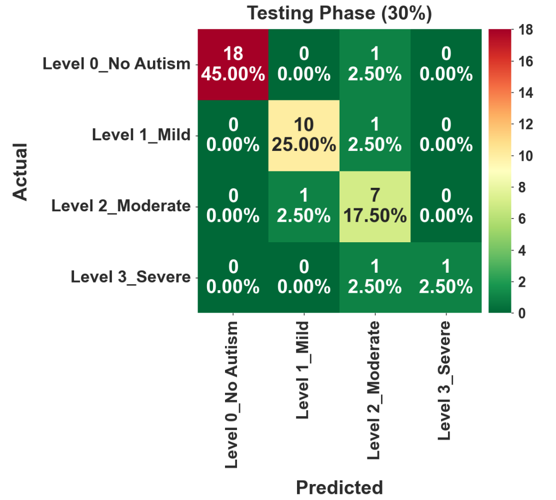
<table>
<tr><td rowspan="5">
</td><td>Level 0_No Autism</td><td>91.21</td><td>84.85</td><td>90.32</td><td>87.50</td><td>80.82</td></tr>
<tr><td>Level 1_Mild</td><td>89.01</td><td>82.14</td><td>82.14</td><td>82.14</td><td>74.21</td></tr>
<tr><td>Level 2_Moderate</td><td>92.31</td><td>79.31</td><td>95.83</td><td>86.79</td><td>82.16</td></tr>
<tr><td>Level 3_Severe</td><td>92.31</td><td>100.00</td><td>12.50</td><td>22.22</td><td>33.95</td></tr>
<tr><td>Average</td><td>91.21</td><td>86.58</td><td>70.20</td><td>69.66</td><td>67.79</td></tr>
<tr><td rowspan="5">
</td><td>Level 0_No Autism</td><td>97.50</td><td>100.00</td><td>94.74</td><td>97.30</td><td>95.10</td></tr>
<tr><td>Level 1_Mild</td><td>95.00</td><td>90.91</td><td>90.91</td><td>90.91</td><td>87.46</td></tr>
<tr><td>Level 2_Moderate</td><td>90.00</td><td>70.00</td><td>87.50</td><td>77.78</td><td>72.17</td></tr>
<tr><td>Level 3_Severe</td><td>97.50</td><td>100.00</td><td>50.00</td><td>66.67</td><td>69.80</td></tr>
<tr><td>Average</td><td>95.00</td><td>90.23</td><td>80.79</td><td>83.16</td><td>81.13</td></tr>
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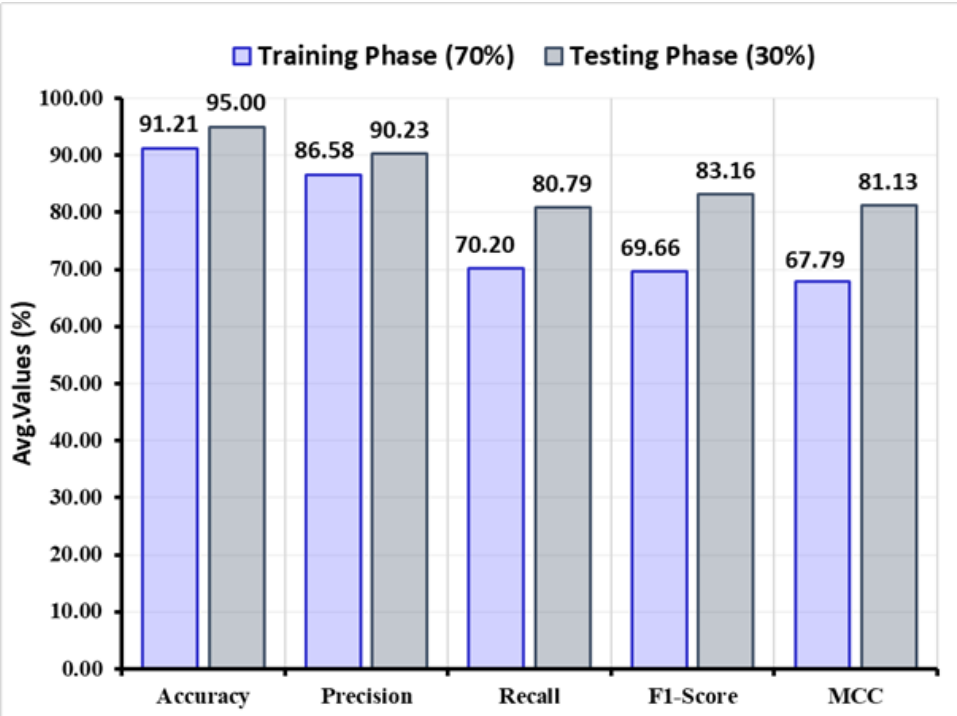

Fig. 5. Average value of the AEF-AADSC method with 70:30 split

Table 6 and Fig. 6 present the comparison performance analysis across various machine learning models for ASD severity classification using key performance metrics including Accuracy, Precision, Recall, F1Score and Computational time [25-27]. The Models like DBN (Deep Belief Network), SAE + SVM models also demonstrated strong performance, achieving accuracies of 94.10% and 94.00%, respectively but the computational time is higher than the proposed model. Similarly, the methods like Naïve Bayes, KNN, and 3D-CNN + GABM demonstrated comparatively low performance, mainly in recall and F1-score, representing weaker classification capability. Among the compared model, our proposed model achieved highest performance with 96.30% of Accuracy, 95.14% of Precision, 93.06%of recall, 93.86% of F1 Score, and less computational time with 1.36 sec.

Table 6 Comparative Performance Analysis of the AEF-AADS approach with other systems

Learning Models	$Accur_y$	$Preci_n$	$Recal_l$	$F1_{score}$	**Computational Time (sec)**
DBN	94.10	93.69	91.94	90.46	2.89
CNN + Spectral	86.90	85.81	85.34	89.14	7.71
DNN	87.11	79.12	78.09	82.81	3.42
Naïve Bayes	80.75	72.78	62.96	70.82	5.29
KNN	81.72	85.66	77.38	85.65	6.55
SAE + SVM	94.00	92.90	90.25	91.86	5.13
3D-CNN + GABM	73.00	79.12	70.70	72.18	4.25
AEF-AADSC	96.30	95.14	93.06	93.86	1.36

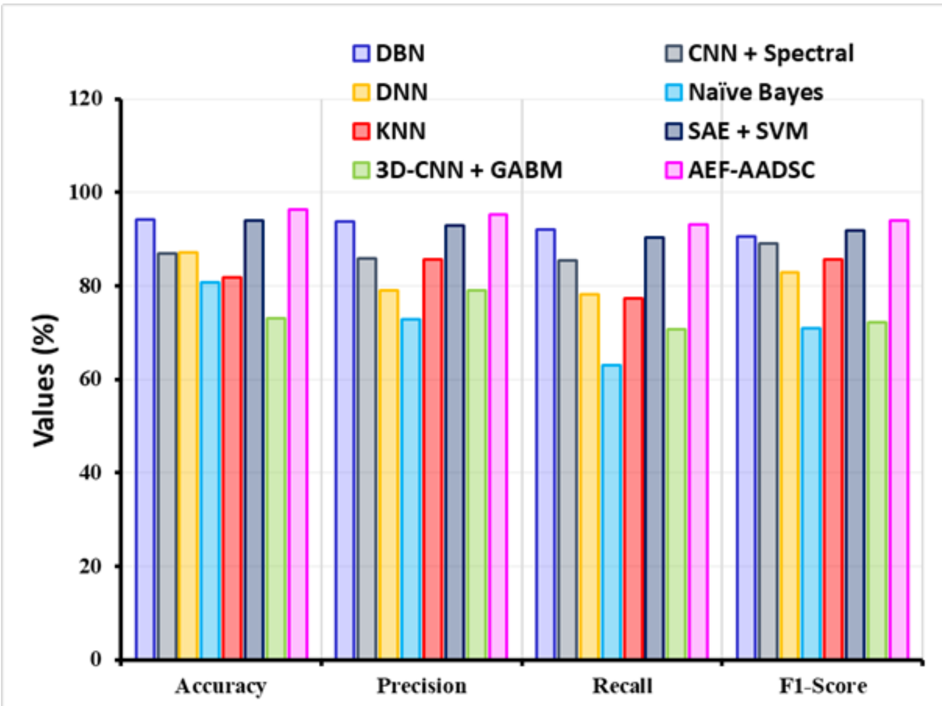

Fig. 6. Comparative Performance Analysis graph of proposed model

Table 7 Ablation study of AEF-AADSC model

Learning Models	$Accur_y$	$Preci_n$	$Recal_l$	$F1_{score}$

CatBoost Baseline model (without feature selection)	95.17	93.98	91.65	92.49
CatBoost + IGA (without hyper parameter tuning)	95.78	94.49	92.43	93.15
AEF-AADSC (CatBoost + IGA + CMA-ES hyperparameter tuning process)	96.30	95.14	93.06	93.86

An ablation study inspects how diverse parts of a model impacts its performance by testing the system with particular components modified or removed. The ablation study of the proposed model represented that the elements are significant and which are impacted with minimum level. With the purpose of comparing the outcomes, the researchers are gained the useful data into the behavior of the model. These findings support higher designs and optimistic outcomes. Table 7 shows the ablation study of AEF-AADSC model. The experimentation outcome values are indicated that CatBoost Baseline model (without feature selection) and CatBoost + IGA (without hyper parameter tuning) techniques are gained lower outcome under diverse aspects. In the meantime, the AEF-AADSC (CatBoost + IGA + CMA-ES hyperparameter tuning process) algorithm has provided greater performance with 96.30% of Accuracy, 95.14% of Precision, 93.06%of recall, 93.86% of F1 Score.
Fig. 7 shows the most influential features contributing to the classification of different ASD severity levels, such as No ASD, Mild, Moderate, and Severe Autism. The global plots present overall feature importance, while the local plots clarify the impact of individual feature values on model predictions.

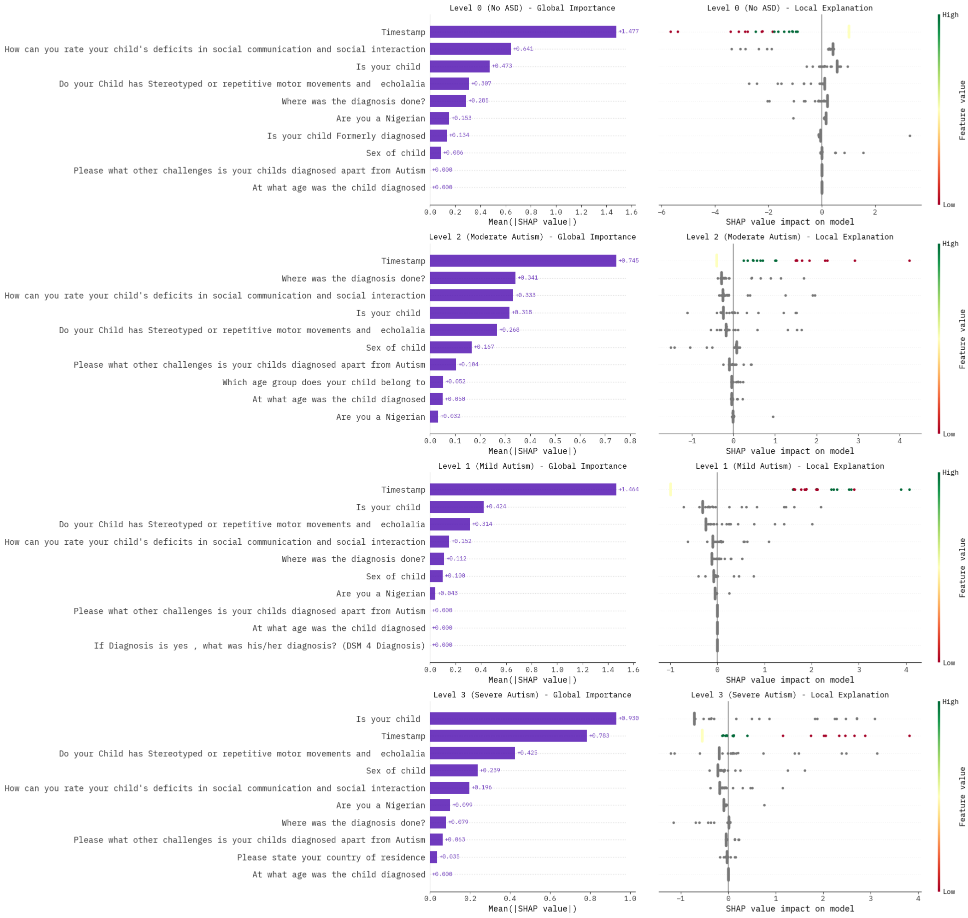

Fig. 7. SHAP-based global and local feature importance analysis for ASD severity classification

The proposed AEF-AADSC methodology achieves higher performance in ASD severity classification, gaining an accuracy of 96.30% with increased precision, recall, and F1-score when compared to existing techniques. The incorporation of IGA and CMA-ES optimization greatly improved FS and model tuning, thus resulting in greater prediction outcomes. The IGA-based feature selection method further refines performance by selecting more optimal feature subsets compared to PSO and GWO. The model also exceeded the baseline CatBoost and alternative ML methods, while preserving less computational time. Such experimental outcomes demonstrate that the proposed model is efficient, dependable, and interpretable for automatic ASD severity grading under DSM-5 measures.

5. Conclusion and Future Work

In this manuscript, the AEF-AADSC model has been presented to classify ASD severity levels using advanced ML methods. Primarily, the proposed method performed preprocessing on the raw dataset to guarantee high-quality input through missing value handling, encoding, and normalization. Subsequently, dimensionality reduction was carried out using an IGA, which selected the most relevant attributes and improved model efficiency. The selected features were then employed for training a CatBoost classifier for precise classification of ASD severity levels, and the hyperparameter optimization was carried out using the CMA-ES algorithm, which enhanced the model predictive ability. By applying SHAP within XAI helps analyze individual feature impacts and gain a clearer understanding of model predictions. The supremacy of the proposed approach was examined using the Autism Diagnosis Based on DSM-5 dataset. The AEF-AADSC model accomplished better performance compared to existing methods across diverse evaluation measures. Thus, the proposed model was found to be an efficient approach for automated ASD severity grading.

Although the model produces higher outcomes, some restrictions still exist. In future work, the model is enhanced by employing greater and more varied datasets and by combining multimodal data, namely behavioral videos, speech, and images, to increase accuracy. The framework can also be expanded with XAI methods and examined in real-world medical settings to boost transparency and practical application. Additional improvements can comprise determining innovative optimization techniques and evolving the user-friendly application for earlier screening and medical decision support.

References

[1] Devi, N.R., Babu, V.V., Samunnisa, K., Srinivasulu, P., Radhika, P., and Swetha, P.B., 2026, February. Deep Learning Framework for Autism Spectrum Disorder Detection: A CNN-Based Comparative Analysis. In 2026, the 5th International Conference on Sentiment Analysis and Deep Learning (ICSADL) (pp. 526-533). IEEE.

[2] Alizadehziri, F. and Khadem, A., 2026. Deep learning for diagnosing autism spectrum disorder using EEG with upright and inverted face processing tasks. Biomedical Signal Processing and Control, 118, p.109655.

[3] Bagchi, P., Ghuge, N., Hiremath, G. and Tiple, A., 2026. Deep Learning-Based Image Analysis for the Prediction of Autism Spectrum Disorder. International Journal of Pattern Recognition and Artificial Intelligence.

[4] Gu, X., Jia, J., Zhang, X., Wei, H., Han, Y., Rong, P., Cui, X. and Tian, H., 2026. Machine Learning Algorithms for Detection of Autism Spectrum Disorders in Early Childhood: A Scoping Review. Journal of Child and Adolescent Psychiatric Nursing, 39(2), p.e70052.

[5] Mishra, M. and Pati, U.C., 2026. sMRI based Hybrid Framework of Light Weight Deep Learning and Ensemble Machine Learning Model for Autism Spectrum Disorder Detection. SN Computer Science, 7(1), p.97.

[6] Martins, S.R.A.L., de Souza, F.A., Teixeira, L.C., Leal, B.R.A., Silva, D.M.P.F. and da Silva, C.M.R., 2026. Towards screening of children students with autism spectrum disorder based on executive functions with serious game and machine learning approaches. Expert Systems with Applications, 295, p.128884.

[7] Irram, S. and Suaib, M., 2025. An early detection of autism spectrum disorder using machine learning. Computers in Biology and Medicine, 198, p.111238.

[8] Prakash, V.G., Kohli, M., Prathosh, A.P., Juneja, M., Gupta, M., Sairam, S., Sitaraman, S., Bangalore, A.S., Kommu, J.V.S., Saini, L. and Utage, P.R., 2025. Video-based real-time assessment and diagnosis of autism spectrum disorder using deep neural networks. Expert Systems, 42(1), p.e13253.

[9] Narayanan, N., KR, R. and Varghese, B.M., 2025. Early detection of autism spectrum disorder via deep-learning application of fMRI and machine learning for ASD children identifications. International Journal of Hybrid Intelligent Systems, 21(2), pp.148-162.

[10] Rai, N., Pradhan, P.C., Saikia, H., Bhutia, R. and Singh, O.P., 2025. ASD-HybridNet: A hybrid deep learning framework for detection of autism spectrum disorder. Magnetic Resonance Imaging, p.110492.

[11] Farooq, M.S., Tehseen, R., Sabir, M. and Atal, Z., 2023. Detection of autism spectrum disorder (ASD) in children and adults using machine learning. scientific reports, 13(1), p.9605.

[12] Alcañiz, M., Chicchi-Giglioli, I.A., Carrasco-Ribelles, L.A., Marín-Morales, J., Minissi, M.E., Teruel-García, G., Sirera, M. and Abad, L., 2022. Eye gaze as a biomarker in the recognition of autism spectrum disorder using virtual reality and machine learning: A proof of concept for diagnosis. Autism Research, 15(1), pp.131-145.

[13] Liao, M., Duan, H. and Wang, G., 2022. Application of machine learning techniques to detect the children with autism spectrum disorder. Journal of Healthcare Engineering, 2022(1), p.9340027.

[14] Assaf, R., Shehabeddine, Z. and Ramesh, V., 2025. Screening autism spectrum disorder in children using machine learning on speech transcripts. Scientific Reports, 15(1), p.34134.

[15] Ehsan, K., Sultan, K., Fatima, A., Sheraz, M. and Chuah, T.C., 2025. Early detection of autism spectrum disorder through automated machine learning. Diagnostics, 15(15), p.1859.

[16] Jabbar, U., Iqbal, M.W., Alourani, A., Shinan, K., Alanazi, F., Sarwar, N. and Ashraf, M.U., 2025. Machine Learning–Based Approach for Early Screening of Autism Spectrum Disorders. Applied Computational Intelligence and Soft Computing, 2025(1), p.9975499.

[17] Sulthana, N. and Kumar, T.A., 2025. Early Detection of Autism Spectrum Disorder Using Machine Learning Techniques. In Harnessing AI and Machine Learning for Precision Wellness (pp. 409-430). IGI Global Scientific Publishing.

[18] Khan, K. and Katarya, R., 2023, February. Machine learning techniques for autism spectrum disorder: current trends and future directions. In 2023 4th international conference on innovative trends in information technology (ICITIIT) (pp. 1-7). IEEE.

[19] Wali, S., Khan, M.I., Zhang, M. and Shakoor, A., 2025. Genetic algorithm-based hybrid deep learning framework for stability prediction of abo3 perovskites in solar cell applications. Energies, 18(19), p.5052.

[20] Ding, J., Du, J., Wang, H. and Xiao, S., 2025. A novel two-stage feature selection method based on random forest and improved genetic algorithm for enhancing classification in machine learning. Scientific reports, 15(1), p.16828.

[21] Qiu, J., Li, J., Xiong, X. and Zhou, K., 2025. Application of a Multi-Algorithm-Optimized CatBoost Model in Predicting the Strength of Multi-Source Solid Waste Backfilling Materials. Big Data and Cognitive Computing, 9(8), p.203.

[22] Peng, S., Guo, Z., Liu, X., Zhang, T. and Yang, Y., 2025. Fuzzy Echo State Network-Based Fault Diagnosis of Remote-Controlled Robotic Arms. Applied Sciences, 15(11), p.5829.

[23] Kişman, Z.A., Kan, A.Ü., Uzun, S., Kan, M.A. and Yıldırım, G., 2026. Analysis of the Effects of World Bank Macroeconomic and Management Indicators on Sustainable Education Quality on PISA Scores Using the SHAP Explainable Artificial Intelligence Method. *Sustainability*, *18*(3), p.1415.

[24] https://data.mendeley.com/datasets/749k3cwbnm/2

[25] Rathod, V.N., Goudar, R.H. and Sangani, S., 2026. An explainable deep learning framework for screening level autism severity using behavioural data. *Discover Applied Sciences*, *8*(4), p.363.

[26] Hanif, M.K., Ashraf, N., Sarwar, M.U., Adinew, D.M. and Yaqoob, R., 2022. Employing Machine Learning-Based Predictive Analytical Approaches to Classify Autism Spectrum Disorder Types. *Complexity*, *2022*(1), p.8134018.

[27] Bahathiq, R.A., Banjar, H., Bamaga, A.K. and Jarraya, S.K., 2022. Machine learning for autism spectrum disorder diagnosis using structural magnetic resonance imaging: Promising but challenging. *Frontiers in Neuroinformatics*, *16*, p.949926.