Autism Spectrum Disorder Identification Using Polynomial Distribution based Convolutional Neural Network

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Abstract

One main psychiatric disorder found in humans is ASD (Autistic Spectrum Disorder). The disease manifests in a mental disorder that restricts humans from communications, language, speech in terms of their individual abilities. Even though its cure is complex and literally impossible, its early detection is required for mitigating its intensity. ASD does not have a pre-defined age for affecting humans. A system for effectively predicting ASD based on MLTs (Machine Learning Techniques) is proposed in this work. Hybrid APMs (Autism Prediction Models) combining multiple techniques like RF (Random Forest), CART (Classification and Regression Trees), RF-ID3 (RF-Iterative Dichotomiser 3) perform well, but face issues in memory usage, execution times and inadequate feature selections. Taking these issues into account, this work overcomes these hurdles in this proposed work with a hybrid technique that combines MCSO (Modified Chicken Swarm Optimization) and PDCNN (Polynomial Distribution based Convolution Neural Network) algorithms for its objective. The proposed scheme's experimental results prove its higher levels of accuracy, precision, sensitivity, specificity, FPRs (False Positive Rates) and lowered time complexity when compared to other methods.

Key Words: Autistic Spectrum Disorder (ASD), Modified Chicken Swarm Optimization (MCSO) Algorithm, Polynomial Distribution based Convolutional Neural Network (PDCNN).

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Introduction

ASD development in the human body reflects in behavioral changes. Though termed as a "developmental disorder", it can be diagnosed within two years of its first occurrence. Current diagnostic practices are not standard procedures that are followed and may consume more than a year for even primary screenings [1]. The time gets extended in case the patients are economically weak. These delays gets transformed into delivery delays in patient's speech or behavioral therapies where early deliveries of such therapies have significant impacts on children [2] [3]. The opinions of clinicians also vary for this phenotype creating imbalances in treatments and making therapies ineffective on the patients. Their quality of life is also hindered due to these factors.

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Rapid screening examination designs have gained importance including ASQs (Autism Screening Questionnaires) which differentiate diagnostics between PDD (Pervasive Developmental Disorder), non-PDD, SCQs (Social Communication Questionnaires) and MCHATs (Modified Checklist for Autism in Toddlers) [4]. However, all the aforesaid are more of screening procedures which end with ADOS (Autism Diagnostic Observation) Schedules. Clinicians checking on autism during regular child health screenings are yet to become a universal practice [5]. Most parents do not act until directed by physicians which burdens both the child and parents alike.

ASD is being exploited by MLTs (Machine Learning Techniques) in behavioral sciences domain for hastening screening and improving accuracy in ASD diagnostics. MLTs consider ASD diagnosis as an issue of classification and build predictive models based on previous historical data which are then made a part of the screening process. Data Pre-processing, a standard procedure for obtaining clean data helps in removing errors, accounts for missing values for producing consistency in real-world data that is processed. These prelude processes also eliminates noises or duplicates or errors in data. Pre-processing improves the quality of input data to DMTs (Data Mining Techniques) which enables accurate decision making by the use of feature selections, a subsequent process [6]. Feature selections play a significant role in improved MLT classifier performances by avoiding over fitting. Moreover, feature selection techniques reduce computational intensiveness, help in understandability of data by MLTs for improved classifications [7] [8]. The study in [9] acknowledged many ASD features for predictions: abnormal conversations or speech flows; changes in regular life routines; issues in relating to peers; inconsistency in eye contacts and being excluded as 'odd' by other children.

Classifying data in an important part for MLT models [10] as it creates classes from the data that is processed. These classifications result in accurate predictions. Early recognition of ASD from any form of diagnostics would definitely help in treating ASD prone children better as optimality of predictions helps in formulating specific treatment sequences and thus improving healing probabilities.

Recently, MLTs have been applied in research using autism data sets where schemes using SVMs, KNN (k-Nearest Neighbor) and RF (Random Forest) have classified ASD with behavioral disorder information [11].

Gaps exist in methodologies identifying ASD and existing approaches have drawbacks in terms of increased execution times or accuracy of classifications. Hence, this work in an attempt to cover these gaps proposes a scheme combining MCSO and PDCNN for improving overall performance of systems classifying or predicting ASD. The main contribution of this research is can be summed up as efficient preprocessing, MCSO based feature selection and PDCNN based classification where Autism dataset is exploited for the study.

Related Work

NLP (National Language Processing) was used in [12] to develop a robust MLT for automatic autism detection. The study used medical form information of potential ASD patients as inputs which were then converted digital format, preprocessed and learnt before being classified. The scheme's results were evaluated against clinician's opinion where it achieved 83.4% in accuracy and 91.1% recall values. The scheme reduced ASD diagnosis time periods.

The study in [13] focused on ASD predictions irrespective of age using MLTs. The study used RF, CART AND RF-Id3 in its ASD predictions using the AQ-10 dataset and 250 samples collected from people with/without autistic traces. Their experimental evaluations on both the datasets showed better performances when evaluated in terms of FPRs, accuracy, sensitivity, specificity and precision.

CSO (Chicken Swarm Optimization) was used in [14] where the searching ability of CSO was improved by logistic and tend chaotic maps. The study's proposed CCSO (Chaotic CSO) feature selections were benchmarked with 4 other feature selection algorithms on 5 data sets. The proposed scheme's was also evaluated with other classifiers in terms of sensitivity using its selected features and the dimensionality reductions. The results were satisfactory.

SVM and geometric binary particles were used by [15] in their proposed GBPSO-SVM (Geometric Binary Particle Swarm Optimization-SVM). Their scheme focused on selecting attributed genes suitable for ASD classifications. The study utilized statistical filters and wrapper-based algorithm for its objectives. Similar genes were eliminated by statistical mean and median ratios. Their algorithm

merged selected gene subsets for improving classification accuracy. Their experimentations repetitively discriminated CAPS2 genes and thus identified this gene correlated with risks of ASD.
ECG (electrocardiogram) of heartbeats was exploited in [16]. The novel feature selection method categorized using Fisher ratio and BAT optimization algorithm to select the best feature set for their ECG based classification. They initially extracted features on which higher-order statistics was used to compute symbolic features and decompose the for getting feature vectors. Feature selections utilized Fisher ratio optimized by BA (BAT Algorithm) for maximum discriminations between classes. kNN classified heartbeats in the final step. Their evaluations in terms of accuracy, specificity and sensitivity showed better performances in comparison to other feature selection methods.
Deep learning was used by [17] for automating ASD prediction from a brain imaging dataset. The ASD dataset had fMRI (functional Magnetic Resonance Imaging) images acquired from a multi-site dataset called ABIDE (Autism Brain Imaging Exchange). The proposed DLT classified ASD based functional connectivity patterns. The experimental results scored 70.22% accuracy in ASD detections on the ABIDE I dataset and CC400 functional parcellation atlas of the brain. The DLT, a CNN (Convolution Neural Network) used very few parameters and hence was less computationally intensive, making it a suitable technique FRO pre-screening of ASD in patients.
CNN was also used by [18] for deriving discriminative and meaningful spatial pattern overlaps in the brain. Their proposed 3D-CNN detected ASD from healthy controls. Their experimentations identified and differentiated ASD patterns from spatially distributed patterns in connectome-scale functional network maps. Spatial overlaps are difficult to discriminate amongst connectome-scale networks, but CNN learning could differentiate ASD from controls. This work also implied that CNNs could be used to trace brain disorders like ASD from functional connectomics.

Proposed Methodology

The proposed has three main modules. The first module, preprocessing, transforms raw data into an understandable form. The next module, feature selection, selects most relevant features while these features are classified in the final module.

Data Pre-Processing

Data pre-processing is a preliminary step in data mining and used for transforming data into information that can be processed further. It is in this process that incompleteness and inconsistency in data are nullified. Null values and observations with more than one missing values were identified and a list wise deletion technique was applied to eliminate them. Irrelevant features were also eliminated in this step like for example ID, age, relation etc. DTs (Decision Trees) were used to extract relevant features.

Feature Selection Using MCSO Algorithm

This module of the proposed work enhances classification accuracy by choosing optimal features that help classify instances better. Feature selection not only selects relevant features, but also reduces the dimensionality while working with voluminous datasets. It also reduces computations while improving predictor's performance [19]. The proposed system's overall flow is depicted in Figure 1.

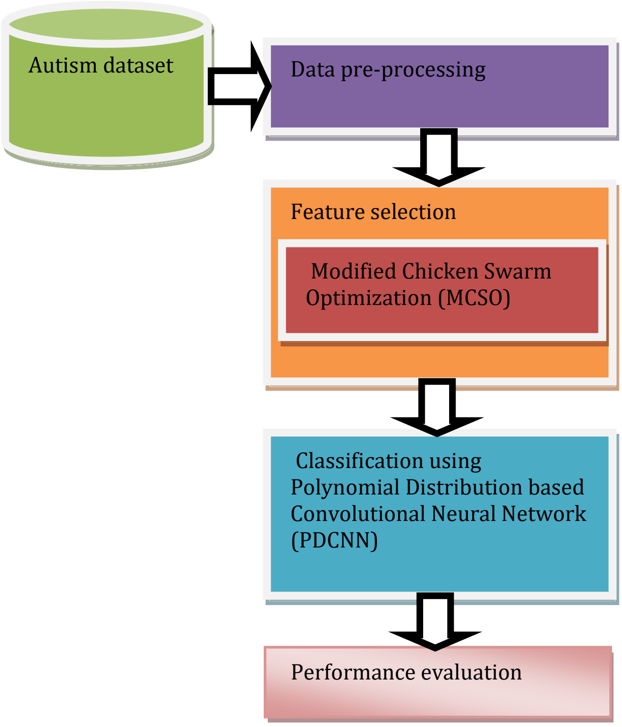

Figure 1. Proposed System's work Flow

This work uses CSO for selecting features in the feature space. CSO algorithm mimics the behavior of chicken swarms. The algorithm can efficiently optimize solutions to problems intelligently. The algorithm follows a hierarchal order with behaviors of individual chickens. The hierarchal order can be divided into groups. Each group has a rooster, hens and chickens where each member follows different laws of motion. A group's hierarchy is maintained by superiors which dominate weak ones in the group. Dominant hens are controlled by roosters who stand at the periphery of the group. Figure 2 depicts CSO algorithm's nature.

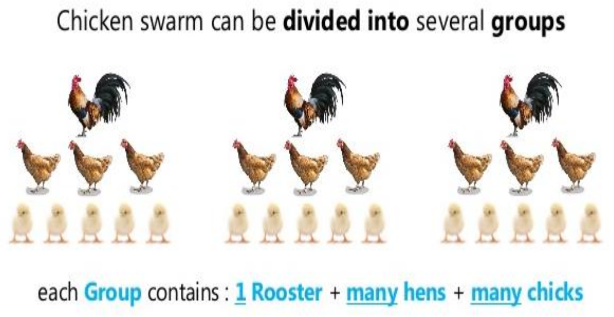

Figure 2. Nature of a CSO algorithm

- *Chicken Movements*

Rooster: Roosters search in wide ranges based on their fitness.

Hens: Hens go behind their group roosters in food searches. They are also capable of stealing good food from others randomly. Thus, dominant hens are in an advantageous position while competing for food.

Chickens: Chickens go behind their mothers for food searches.

CSO formulated mathematically in [20] summarized chicken behaviors as detailed in the following steps:

1. Chicken swarm is separated into groups, each with a leading rooster followed by hens and chickens.
2. The swarm's hierarchy is defined by fitness value of the chickens as the best fitness rooster becomes the group leader while worst fitness values are considered as chickens. Middle level fitness values are hens.
3. Hierarchical order, relationship dominance s or mother-child relationships do not change within a group and are updated for every (G) time steps.
4. Swarms with N virtual chickens have roosters (RN), Hens (HN), Chickens (CN) and Mother Hens (MN). Their positions in an D-dimensional space can be represented as Equation (1)

$$x_{i,j}(i \in [1,\ldots,N], j \in [1,\ldots,D]). \quad (1)$$

In this proposed MCSO, a global search operator based on BA, a weighing factor and a local search operator are introduced for enhancing conventional CSO searches. The introduction of these additional factors are aimed at improved explorations, exploitations and avoiding premature convergences.

Assuming autism dataset features form a chicken swarm, PDCNN is used for classifications classification accuracy, the main objective. Position updates are best objective values relevant to autism data samples.

1. Modified rooster updates for global searches: Rooster positions near optimality due to their best fitness values. CSO uses a Gaussian distribution for its exploitations and easily gets caught in a local optimum. MCSO's introduced global search operator for rooster updates results in an improved search performance. BA parameters Ai (loudness) and r_i (rate of pulse emission) are used in position updates based on Equation (2) and Equation (3)

$$A_i^{t+1} = \alpha A_i^t \quad (2)$$

$$r_i^{t+1} = r_i^0(1 - \exp(-\lambda_{BA} t)) \quad (3)$$

Where, Ai is loudness, r_i is rate of pulse emission, and $0 < \alpha < 1$ and $\lambda BA > 0$ are constants. When $t \to \infty, A_i^t \to 0$ and $r_i^t \to r_i^0$. Preliminary values considered are $A_0 \in [1,2]$ and $r_0 \in [0,1]$, respectively.

BA update method is represented inn Equation (4)

$$x_{i,j}^{t+1} = \begin{cases} x_{best} + \varepsilon \times A^t \; Rand \le r_i^t \\ x_{i,j}^t \times Randn(0,\sigma^2 \; Rand > r_i^t \end{cases} \quad (4)$$

Where, Rand - random number in the interval [0, 1], x_{best} - present best global best location in N chickens. $\varepsilon \in [-1,1]$ - random number, $A^t =< A_i^t >$ - average loudness of all the bats in the time step.

2. Modified updates for hens: Hens unlike roosters are far from optimality for solutions and hence a weighing parameter w for dynamically adjusting step sizes is given in Equation (5)

$$w = \exp(R/K)^P \quad (5)$$

Where, R – count of hens with same fitness values, K – constant. The newly introduced w is related to the iteration count of same fitness values multiple iterations. When w is small it implies solution is in near vicinity while actually w has larger values. Hen positional updates based on w is depicted as Equation (6)

$$x_{i,j}^{t+1} = w \times x_{i,j}^t + exp\frac{f_i - f_{ri}}{|f_i|+\epsilon} \times Rand \times \left(x_{r1,j}^t - x_{i,j}^t\right) + \exp(f_{r2} - f_{r1}) \times Rand \times (x_{r2,j}^t - x_{i,j}^t) \; (6)$$

3. Modified updates for local searches: CSO updates on chickens is based on mother hens which get deviated easily. In this proposed work, the introduced local search factor establishes a contact between chicks and roosters for worst fitness value movements towards roosters and represented in Equation (7)

$$x_{i,j}^{t+1} = x_{i,j}^{t} + FL * (x_{m,j}^{t} - x_{i,j}^{t}) + Rand * (x_{r,j}^{t} - x_{i,j}^{t}) \quad (7)$$

Where, $x_{r,j}^{t}$ – rooster's position in a group

MCSO feature selection algorithm chooses top ranked features for diagnosing ASD diagnosis. Some questions from ADI-R may be more useful for diagnosis than controls. The proposed algorithm Identifies redundant autism features and explores linearity of features in ASD diagnostic feature space.

Algorithm 1: MCSO

Input: Chickens population N (autism data)

Output: Best solution x_{best} (enhanced accuracy)

1. Initialize rooster, hens, chickens and mother hen parameters
2. Find objective function $f(x), x = (x_1, \dots, x_n)^T$
3. Evaluate values of N chickens with $f(x)$ (accuracy)
4. While $t < Max$ iterations do
5. If t%G==0 then
6. Rank chicken values from $f(x)$for establishing the swarm's hierarchy
7. Split the swarm into groups for determining relationship between chickens and mother hens
8. End
9. For i=1 to N features do
10. If i==rooster then
11. Find r_i^t
12. Update the solution using (4)
13. End
14. If i==hen then
15. Calculate w according to (5)
16. Update the solution using (6)
17. End
18. If i==chick then
19. Update the solution using (7)
20. End
21. Evaluate the new solution
22. If the new generated solution is better than its previous one, update it
23. End
24. End
25. Return x_{best} (better accuracy)

In this work, chicken's (autism feature) assignments are executed using random positioning of autism feature data. Chicken's best fitness value is updated for improving feature relevance and computed using best hens global searches as represented in equation (7). The proposed MCSO algorithm finds combination of features that maximize classification accuracy with reduced feature counts. The feature space is created from features whose value is between 0 and 1. The fitness function maximizes classifier performances over a validation set from training data.

Classification Using Polynomial Distribution based Convolutional Neural Network (PDCNN)

In this proposed work, PDCNN classifies test data into two classes namely yes or no. CNNs have input, output and multiple hidden (Convolution, Pooling, Fully connected) layers. CNNs are similar to multi-layer perceptron neural network in principle [21]. Convolution layers convolute inputs and transfer them to the next layer. CNNs may include local/global pooling layers that combine neuron cluster outputs into a single neuron output for the next layer. Average cluster values of neurons in the previous layer are used in mean pooling. Fully connected layers connect every neuron in one layer to every neuron in another layer. The proposed PDCNN uses an input layer, convolution layer, sub-sampling layer and a classification layer. The proposed scheme employs a parameter sharing scheme for handling high dimensional data and reduces the number of parameters in its convolution layer. PDCNN is diagrammatically represented in Figure 3.

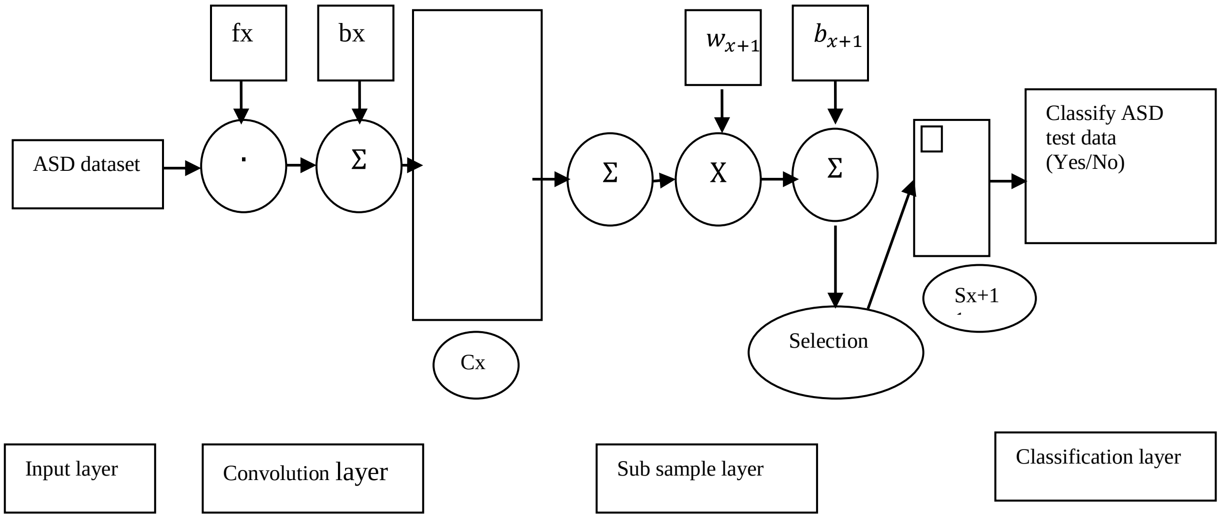

Figure 3. PDCNN Architecture

Autism training samples features are fed as inputs which is the transformed inside the network. Initial parameters like local receptive field scales and filters are also defined in this layer.

Convolution layer (Cx) processes inputs to produce several feature maps which are computed results of prior layers. This layer extracts key features while reducing computational complexity. An activation function in this layer maps output to a set of inputs converting the network to a non-linear structure. Weights are added to all features for obtaining these outputs using the following equations

$$y(n) = f(\sum_{i=1}^{i=N} w_i(n)x_i(n) \quad (8)$$

$$\text{Where } f(x) = \begin{cases} +1 \; if \; x \geq 0 \\ -1 \; if \; x < 0 \end{cases} \quad (9)$$

Where, n – iteration count

Feature weights are updated based on (10)

$$w_i(n+1) = w_i(n) + \eta(d(n) - y(n)x_i(n), i = 1,2,..N \quad (10)$$

Where η - gain factor

Applying SD (Standard Deviation) using (11)

$$\sigma = \sqrt{\frac{1}{n} f_i (x_i - \overline{x})^2} \quad (11)$$

The weight added autism features are fed into PDCNN for obtaining accurate classifications. The polynomial distribution function confirms that the main findings of analysis is performed on the same set of data. Every feature map from the convolution layer is sub-sampled in this layer. In Figure 3, $Sx + 1$, is summary of informative features.

Algorithm 2: Steps in PDCNN

1. Procedure ASD dataset
2. For all input feature, describe autism feature ∈ ASD dataset do
3. Translate input layer to sub layers
4. Find relevant autism features
5. Select feature with more information and gain
6. Train and test dataset samples
7. Copy autism feature labels of features based on the input dataset
8. Classify for ASD results

Experimental Result

Initially, Autism Spectrum Disorder (ASD) datasets such as adult, child, and adolescent is taken as an input. The adult dataset contains 704 instances and 21attributes [22]. The child dataset contains 292 instances and 21attributes [23]. The adolescent dataset contains 104 instances and 21attributes [24]. The performance metrics are considered such as precision, accuracy, sensitivity, specificity, False Positive Rate (FPR) and time complexity. The existing algorithms of RF-CART, Random Forest-CART and the proposed MCSO+PDCNN algorithm is evaluated to perform the above mentioned metrics on the autism dataset.

Precision

Precision is a parameter of accuracy or quality while recall measures completeness. High precision values indicate algorithms return more relevant results. Precision is calculated as follows:

$$\text{Precision} = \frac{\text{True positive}}{\text{True positive+False positive}} \quad (12)$$

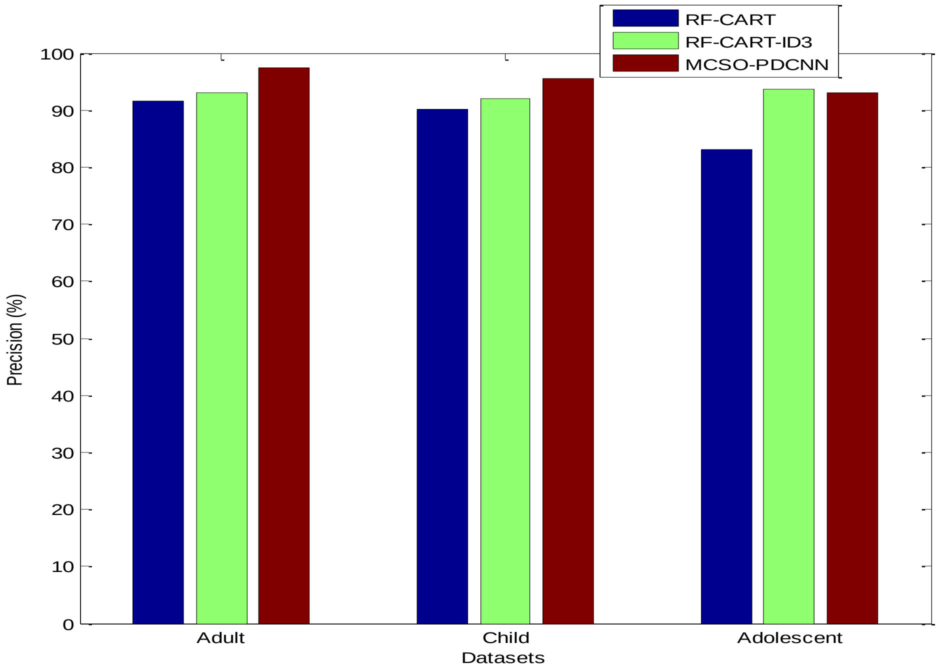

Figure 4. Precision

Figure 4 depicts evaluation comparisons in terms of precision where methods are in x-axis and y-axis represents their precision values. Methods compared are RF-CART, RF-CART-ID3 and proposed MCSO+PDCNN algorithm which provides higher precision for the given adult, child, and adolescent datasets. Thus the result concludes that the proposed MCSO+PDCNN increase the ASD classification accuracy through its optimal selection of features.

Sensitivity

Sensitivity or true positive rate implies the proportion of actual positives that are correctly identified like the percentage of sick people who

$$\text{Sensitivity} = \frac{TP}{TP+FN} \qquad (13)$$

Where TP is True Positive, FN is False Negative.

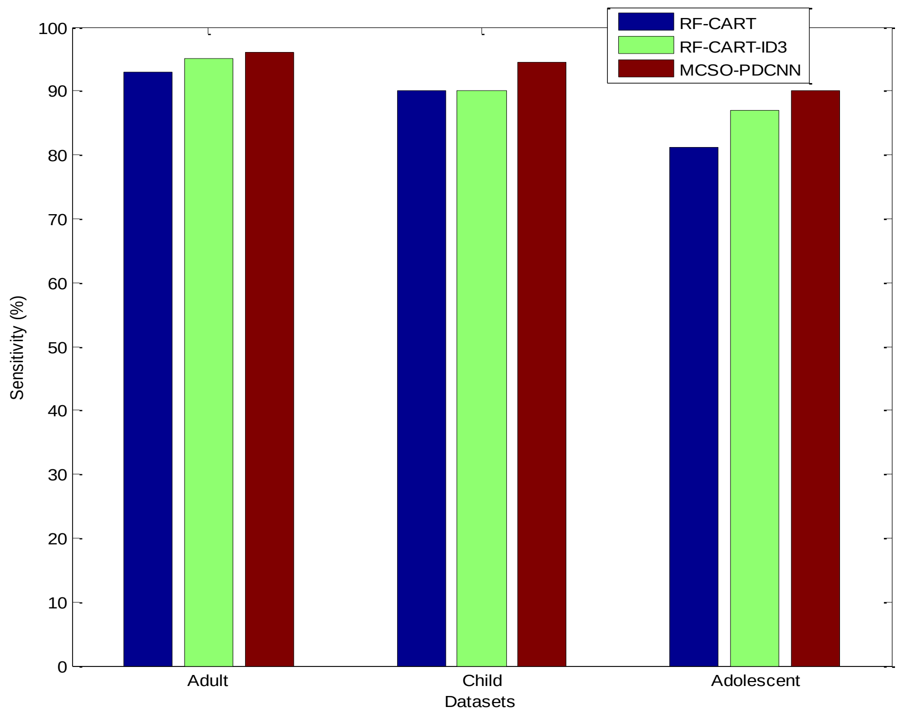

Figure 5. Sensitivity Comparison

Figure 5 depicts evaluation comparisons in terms of sensitivity where methods are in x-axis and y-axis represents their sensitivity values. Methods compared are RF-CART, RF-CART-ID3 and proposed MCSO+PDCNN algorithm which provides higher sensitivity for the given adult, child, and adolescent datasets. Thus the result concludes that the proposed MCSO+PDCNN increases the classification performance by classifying accurate results in ASD dataset.

Specificity

Specificity or the true negative rate, measures the proportion of actual negatives that are correctly identified like the percentage of healthy people.

$$\text{Specificity} = \frac{TN}{TN+FP} \qquad (14)$$

Where TN is True Negative and FP is False Positive.

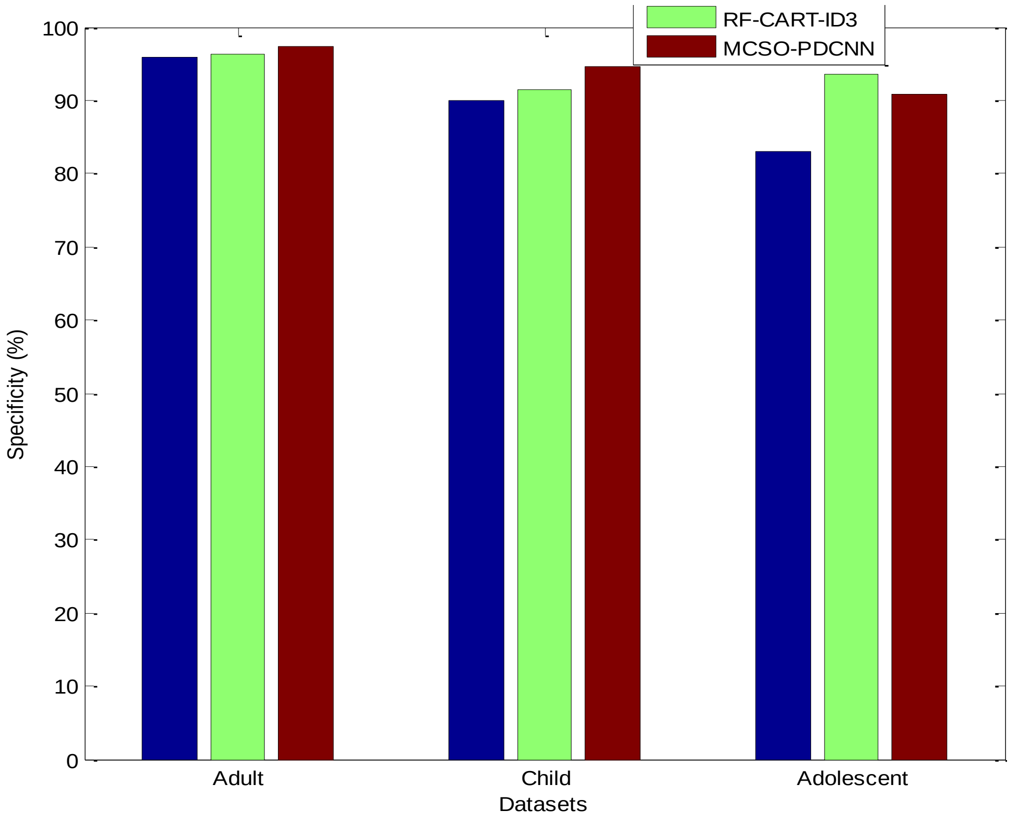

Figure 6. Specificity Comparison

Figure 6 depicts evaluation comparisons in terms of specificity where methods are in x-axis and y-axis represents their specificity values. Methods compared are RF-CART, RF-CART-ID3 and proposed MCSO+PDCNN algorithm which provides higher specificity for the given adult, child, and adolescent datasets. Thus the result concludes that the proposed MCSO+PDCNN increases the classification performance by classifying accurate results in ASD dataset.

Accuracy

Accuracy determines the overall correctness of models and is computed as the total of classifications $(T_p + T_n)$ segregated by the sum of all classification parameters $(T_p + T_n + F_p + F_n)$. Accuracy is computed as,

$$\text{Accuracy} = \frac{T_p+T_n}{(T_p+T_n+F_p+F_n)} \qquad (15)$$

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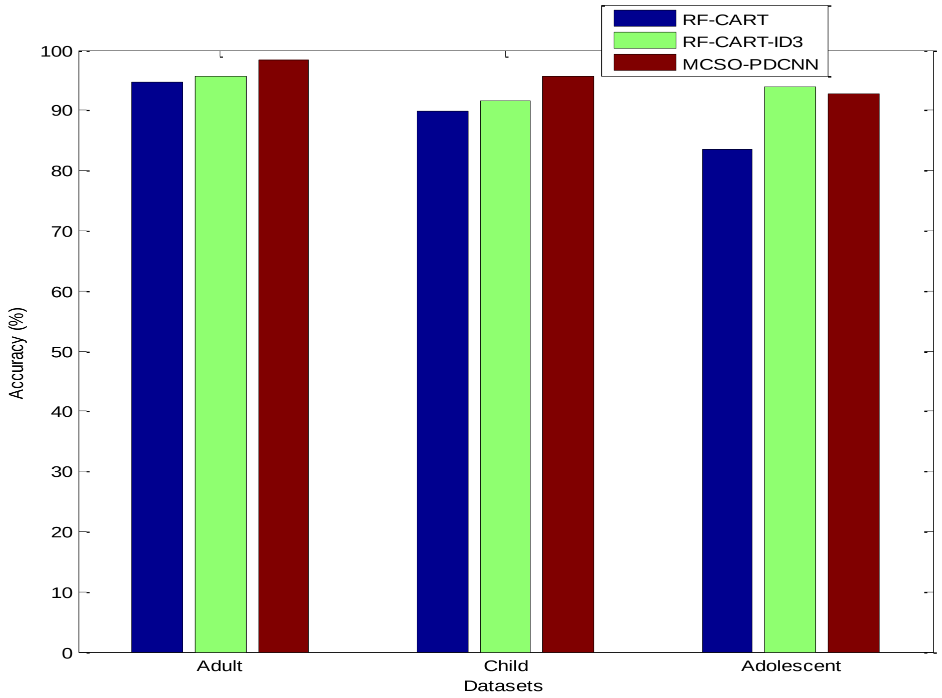

Figure 7. Accuracy

Figure 7 depicts evaluation comparisons in terms of accuracy where methods are in x-axis and y-axis represents their accuracy values. Methods compared are RF-CART, RF-CART-ID3 and proposed MCSO+PDCNN algorithm which provides higher accuracy for the given adult, child, and adolescent datasets. Thus the result concludes that the proposed MCSO+PDCNN increase the ASD classification accuracy through the optimal selection of features.

False positive rate is the ratio between the number of negative events wrongly categorized as positive (false positives) and the total number of actual negative events (regardless of classification). The false positive rate (or "false alarm rate") usually refers to the expectancy of the false positive ratio

$$\text{The false positive rate} = \frac{FP}{FP+TN} \quad (16)$$

where FP is the number of false positives, TN is the number of true negatives and N=FP+TN is the total number of ground truth negatives.

False positive Rate (FPR)

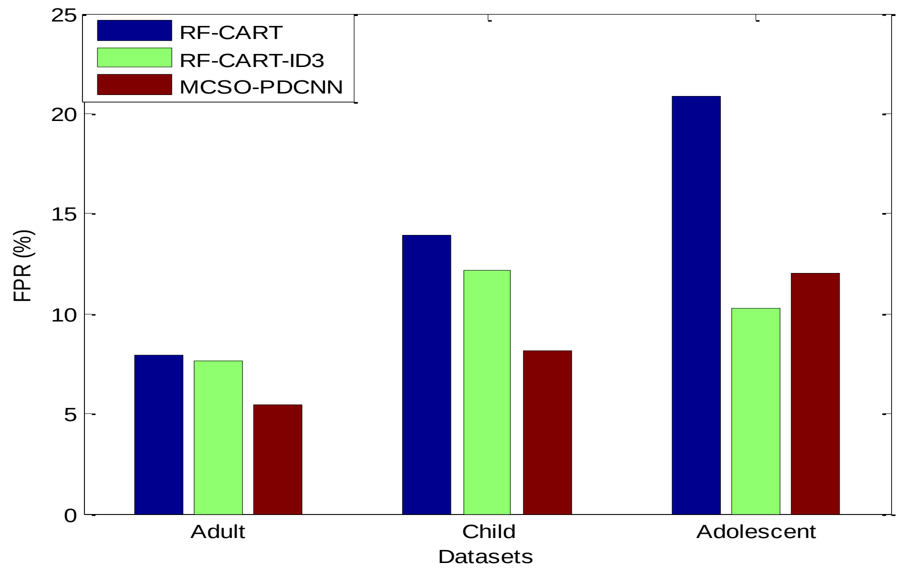

Figure 8. FPR

Figure 8 depicts evaluation comparisons in terms of FPR where methods are in x-axis and y-axis represents their FPR values. Methods compared are RF-CART, RF-CART-ID3 and proposed MCSO+PDCNN algorithm which provides lower FPR for the given adult, child, and adolescent datasets. Thus the result concludes that the proposed MCSO+PDCNN increase the ASD classification accuracy through the optimal selection of features.

Time Complexity

The system is better when the proposed algorithm executes in less time consumption.

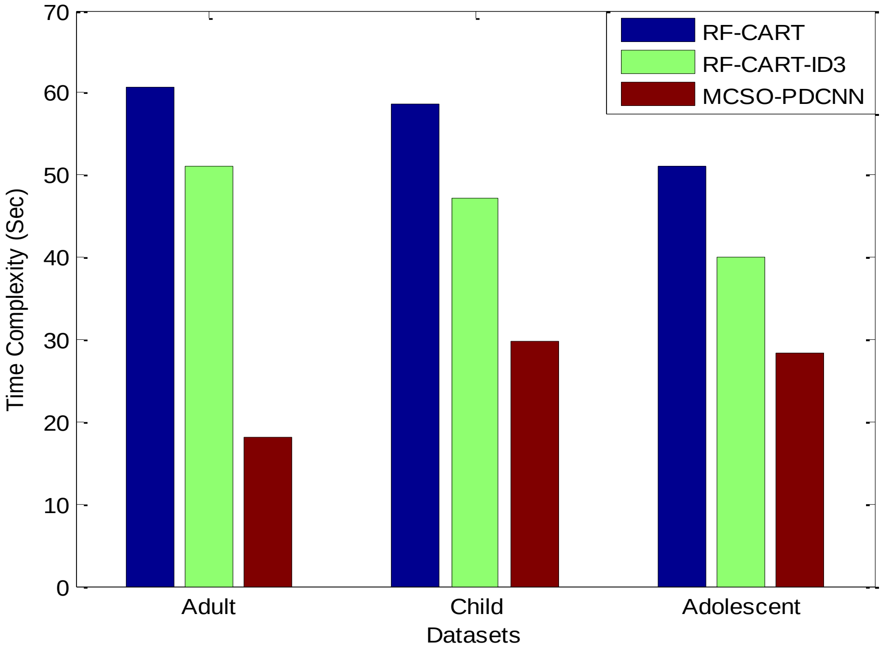

Figure 9. Time Complexity Comparison

Figure 9 depicts evaluation comparisons in terms of time complexity where methods are in x-axis and y-axis represents their time complexity values. Methods compared are RF-CART, RF-CART-ID3 and proposed MCSO+PDCNN algorithm which provides lower time complexity for the given adult, child, and adolescent datasets. Thus the result concludes that the proposed MCSO+PDCNN increases the classification performance by classifying accurate results in ASD.

The Table 1, 2 and 3 shows the comparison values of existing and proposed methods for the above mentioned performance metrics for adult, child and adolescent datasets respectively.

Table 1. Comparison values for ASD adult dataset

Methods/Metrics	RF-CART	RF-CART-ID3	MCSO+PDCNN
Accuracy (%)	94.69	95.72	98.41
Precision (%)	91.65	93.06	97.48
Sensitivity (%)	94.05	94.38	96.57
Specificity (%)	95.93	96.26	97.37
FPR (%)	7.94	7.61	5.43
Time complexity (sec)	60.69	51.13	18.08

Table 2. Comparison values for ASD child dataset

Methods/Metrics	RF-CART	RF-CART-ID3	MCSO+PDCNN
Accuracy (%)	89.82	91.57	95.65
Precision (%)	90.04	91.91	95.56
Sensitivity (%)	88.10	89.91	93.87
Specificity (%)	89.98	91.49	94.67
FPR (%)	13.89	12.18	8.12
Time complexity (sec)	58.58	47.19	29.77

Table 3. Comparison values for ASD adolescent dataset

Methods/Metrics	RF-CART	RF-CART-ID3	MCSO+PDCNN
Accuracy (%)	83.50	93.77	92.70
Precision (%)	83.10	93.70	93.06
Sensitivity (%)	81.10	91.70	89.96
Specificity (%)	82.98	93.58	90.76
FPR (%)	20.89	10.29	12.03
Time complexity (sec)	50.26	40.03	28.72

Conclusion

ASD, A neurotic disordered developmental condition occurs in young children and is associated with unusual bodily disturbances. Automation of ASD diagnosis and early predictions improves targeted treatments for ASD. This research propose MCSO+PDCNN algorithm to improve the ASD classification accuracy. In this work, preprocessing is focused to remove irrelevant features from the given dataset. Then the feature selection is performed through the MCSO algorithm. The fitness features are used to compute the more informative and relevant autism features. The classification is done by PDCNN algorithm and it is used to produce more accurate autism results in yes or no class. The training phase and testing phase is performed also during the training process, the error will be reduced until it becomes a constant. The proposed MCSO+PDCNN algorithm through its experimental results demonstrates superiority in terms of higher sensitivity, specificity, accuracy, precision values and lowered FPR, time complexity values when compared with existing methods.

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