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Research Article

Polynomial Regressive Quadratic Gradient Optimized Deep Belief Classifier for Autism Spectrum Disorder Identification

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ABSTRACT

ASD is neurological chaos which affects individual's brain development, influencing their communication skills, and behavior. Premature recognition as well as interference considerably enhances results for individuals through ASD. Interventions may include behavioral therapy, and so on. ML methods have applied to classification as well as diagnosis of ASD to analyze large datasets. However, conventional models have faced major challenges, leading to inaccuracies and increased time consumption. To address this challenge, a novel deep learning model called the Polynomial Regressive Quadratic Gradient Optimized Deep Belief Classifier (PRQGODBC) is developed to enhance accuracy of ASD identification. The proposed deep belief classifier is kind of DL ANN with numerous layers of nodes (neurons) organized into an input layer, one or more hidden layers, output layer. These processes are integrated into the proposed Deep Belief Classifier to enhance accuracy and minimize time in Autism Spectrum Disorder (ASD) identification. During data acquisition stage, patient data points are gathered as of database. These collected data points are then fed into input layer of deep belief classifier. Input is subsequently transferred to the hidden layers of deep belief classifier, where preprocessing, feature selection, categorization are performed. In preprocessing steps, two processes are considered such as handling missing data and removing noisy data using polynomial regression-based data imputation technique and greatest normalized residual test. After preprocessing, feature selection is performed by Quadratic Discriminant Analysis to choose the most relevant attributes from dataset. Through chosen features, classification tasks are carried out using Tucker’s congruence coefficient and provide classification outcomes for normal or autism identification. After classification, a fine-tuning is applied to reduce error rate by optimizing hyperparameters using the stochastic adaptive gradient method. Finally, accurate classifications of ASD patients are attained at output layer. An experimental assessment is conducted through various factors. Obtained outcomes show that PRQGODBC is more efficient in achieving higher accuracy while maintaining time compared to existing approaches.

Keywords: Autism Spectrum Disorder (ASD), Deep Belief Classifier, polynomial regression-based data imputation, maximum normalized residual test, Quadratic Discriminant Analysis, Tucker's congruence coefficient

1. INTRODUCTION

ASD is multifaceted growth chaos which influences individuals distinguish world as well as interact through others. Individuals through ASD have trouble at various domains, including social interactions, communication, play,stereotypical activities. Premature ASD diagnosis minimize developmental and so on. Healthcare professionals often produce extensive communications during patient behavioral assessments, which time-utilizing to procedure as well as document. Timely detection of Autism Spectrum Disorder contributes to an improved quality of life through suitable treatment as well as care. ML methods have been employed to explore feasibility of recognizing key aspects and assessing incidence or nonexistence of autism.

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The ASD recognition model using transfer learning through the GTO (ASD²-TL* GTO) was developed in [1] with the aim of detecting autism spectrum disorders. However, the model did not utilize a larger dataset, which limited its effectiveness in detecting autism spectrum disorders while minimizing time consumption. HCAN method was developed in [2] to classify ASD by integrating aggregated features. However, the HCAN model acquired a high computational cost.

Recommender method through multiple classifiers was designed [3] to improve precision at detecting ASD and to evaluate the model's performance. But, it did not implement deep learning algorithms for effective ASD detection with minimal processing time. Diverse machine learning techniques were developed in [4] to identify traits associated through ASD, for enhancing and automating diagnostic process. The techniques designed were applied to relatively small datasets related to ASD. A Federated Learning (FL) technique was developed in [5] for early as well as precise diagnosis of ASD in children , adults. But, various DL methods have not used for the early detection of ASD with improved accuracy.

Numerous supervised ML methods were developed in [6] to produce classification method which predicts likelihood of ASD by higher precision. However, deep feature learning process was not addressed to further improve accuracy of ASD prediction. In [7], ML structural design was designed that efficiently predicts the characteristics of autistic children and accurately classifies and identifies traits associated through ASD. But, model did not address the issue of time complexity. Comparative evaluation of ML classifiers was conducted in [8] to examine and classify ASD at toddlers as well as adolescents. But, the issue of error rates was not addressed. A Convolutional Neural Networks were developed in [9] with the aim of facilitating the early diagnosis of ASD. But, it did not effectively utilize a larger dataset for training and testing the deep learning networks with both ASD and non-ASD subjects. An explainable model for ASD recognition at toddlers as well as children was designed based on deep learning [10]. However, the hyperparameters and optimization aspects remain unresolved, which affects the model ability to reduce biases and errors while enhancing its generalization capabilities. A functional brain network was developed in [11] for detecting patients with Autism Spectrum Disorder. However, the techniques employed were tested on a limited dataset.

Logistic Regression approach and SVM were developed in [12] for achieving huge stage of accuracy through improved effectiveness of individual patients. But it failed to apply the deeper analysis of complex disease. A one-dimensional CNN was developed in [13] for the classification of ASD detection. But, it was not applied to a more diverse and larger sample size at database to analyze method result. Decision-making model depend on linguistic neutrosophic fuzzy sets was developed in [14] with the aim of diagnosing Autism Spectrum Disorder. But, it did not enhance accuracy as well as reliability of classification for enhancing autism detection. A machine-learning approach was developed in [15] to distinguish ASD within individuals across different age groups. But it failed to apply better database connected to ASD as well as recognition of other neuro-developmental chaos.

1.1 major contribution of work

This paper presents major contributions, including as follows:

- To enhance accuracy of ASD detection, new PRQGODBC method has been developed with deep belief network.
- To reduce processing time of ASD detection, PRQGODBC model carry out data preprocessing where the missing data and outlier detection process is executed with the help of polynomial regression-based data imputation and maximum normalized residual test respectively. Quadratic Discriminant Analysis is also employed for choosing more important features as of database.
- To improve accuracy of ASD detection, Tucker's congruence coefficient is employed in Deep Belief Network for analyzing the data samples. Stochastic adaptive gradient method is also employed to reduce error rate of data classification. This approach enhances accuracy and minimizes incorrect classifications.
- Extensive valuation is conducted to calculate result of PRQGODBC and other related works with various evaluation metrics

1.2 Organization of the work

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Manuscript is organized as follows: Section 2 evaluation literature review, while Section 3 describes PRQGODBC method, along with a detailed diagram. Section 4 outlines the experimental setup and gives explanation of database. In Section 5, the results for various parameter sets are discussed. Lastly, the conclusion is given in Section 6.

2. LITERATURE REVIEW

An automated ASD classification system was developed in [16] using the owl search algorithm to identify and classify autism. But, it did not incorporate an ensemble of deep learning approaches to enhance the classifier's performance. An enhancement approach was designed in [17] integrating deep learning with CNN for accurate detection of ASD. However, it was unable to achieve early diagnosis of the Autism. A machine learning-based tool was designed in [18]. But, it did not succeed in improving prediction models or identifying factors to enhance the recognition of ASD. Graph CNN with a residual connectivity approach was proposed in [19] to improve recognition of ASD at children and reduce errors. However, it did not incorporate feature importance scores in the ASD detection process. A novel DASD model was developed [20] to rapidly and precisely identify children with ASD through feature selection and outlier rejection processes. But, it did not implement an efficient approach for the precise selection of feature sets.

fMCDM method was introduced in [21] to detect ASD patients depend on harshness of their disorder. But, it faced challenges in selecting psychologists and the assessment process for multiple patients with more time consumption. An integrated ensemble model combining Random Forest and XGBoost classifiers was introduced in [22] for accurate identification of ASD with higher precision. But, it did not achieve improved detection accuracy while maintaining minimal time complexity. A deep transfer learning model was developed in [23] for premature recognition of ASD depend on facial aspects, achieving higher detection accuracy. However, it was applied to a small dataset. A Support Vector Machine (SVM) was introduced in [24] to identify ASD more accurately across different age groups and feature subsets. But, it did not developing a more efficient ASD diagnosis system for early-stage detection at a lower cost. A modified bat algorithm depend on ANN was developed in [25] for the accurate classification of ASD and to enhance precision. However, the algorithm was not effective in detecting and diagnosing other diseases with improved efficiency.

A multinomial logistic regression was developed [26] for identifying children through ASD. But it failed to enhance accuracy of ASD in diagnostic processes. Various machine learning models were developed in [27] for classifying individuals with ASD. However, these models did not provide a comprehensive clinical study for every patients, to offer enhanced classification of each individual's status within AS. Optimized machine learning models were developed in [28] with the aim of detecting autism. But, hybrid feature selection was not employed to improve autism detection while minimizing time consumption. A novel Self-Organizing Map (SOM) model was developed in [29] to achieve significantly higher accuracy in the classification of ASD. But, it did not attain high levels of predictive performance. Discriminant analysis and binary logistic regression method were designed [30] for accurate prediction of ASD. But, these models did not effectively maximize sensitivity across diverse patient populations.

3. PROPOSAL METHODOLOGY

ASD is neurological disease distinguished through complex through social relations, and so on. Premature recognition is vital, ML offers quicker as well as additional cost-efficient diagnosis. This study uses diverse ML techniques to recognize vital ASD traits, to improve and automate diagnostic procedure. This PRQGODBC model explores deep learning techniques to recognize key ASD traits, to improve as well as automate diagnostic procedure, thereby facilitating faster and more cost-effective assessments.

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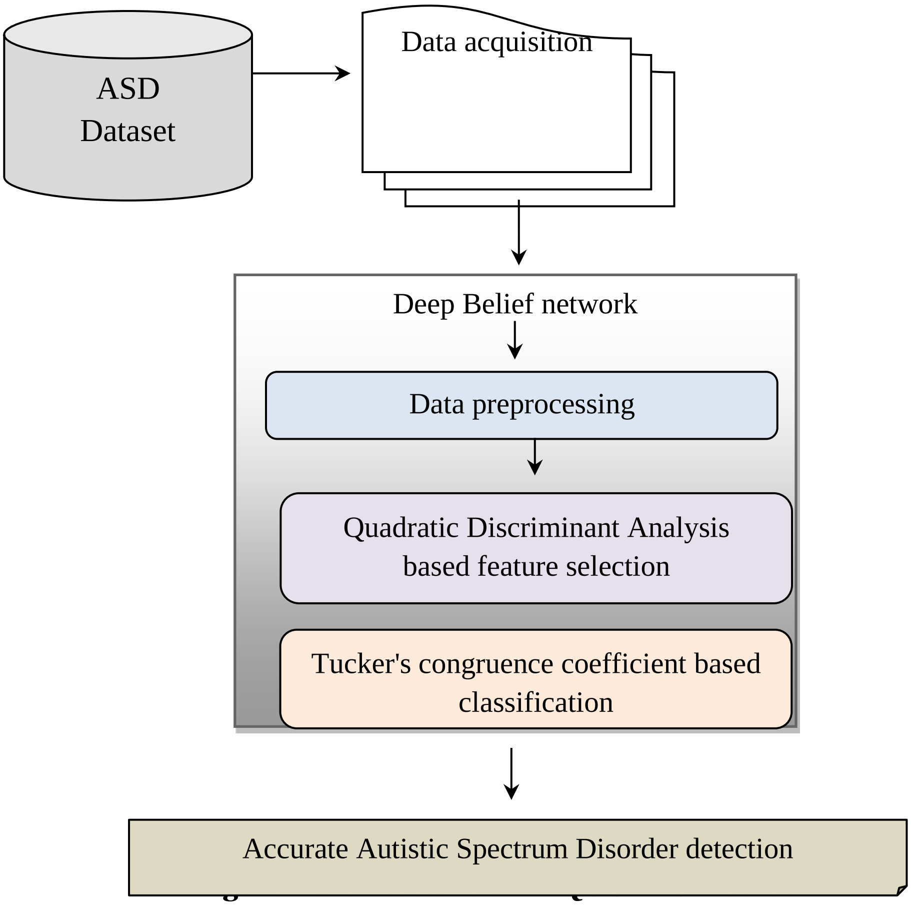

Figure 1 depicts architecture diagram of PRQGODBC model for precise detection of Autistic Spectrum Disorder detection. [31] The accurate detection process is implemented into the Deep Belief network where the preprocessing, feature selection and classification is performed. Based on the analysis, the Autistic Spectrum Disorder detection results are obtained at the output layer.

3.1 data acquisition

It refers to process of collecting data samples from ASD Classification dataset from database https://www.kaggle.com/competitions/abide/data for analysis and processing. The objective of this dataset was to use DL methods to recognize ASD patients using brain imaging data, focusing exclusively on their brain establishment patterns of ASD patients as of globally sourced, multi-site ABIDE database. This dataset explored patterns of functional connectivity which independently distinguish ASD contributor as of brain imaging information, with the goal of revealing the neural patterns underlying this classification.

3.2 Deep Belief network

DBNs are type of DL technique designed to enhance classification process particularly in sequential data processing. A DBN contain numerous layers of stacked RBMs, forming a hierarchical generative model. This hierarchical structure helps to reduce computational complexity while supporting huge number of data samples. Moreover, advantage of deep belief model efficiently reduces the errors throughout the learning process. The advantage of Stacked RBMs are capable of handling high-dimensional data efficiently by capturing correlations between large numbers of input variables, making them suitable for classification.

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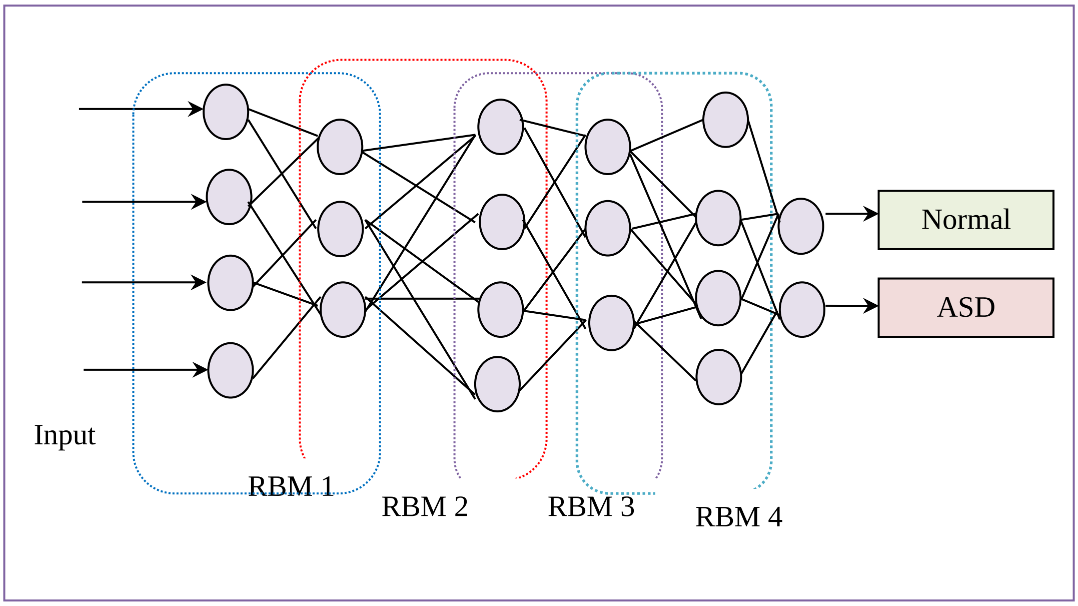

Figure 2 depicts schematic structure of DBN for classification of normal or disorder samples. In layer-wise training stage, each layer processes weighted inputs, applies a series of transformations, and then transmits the output to the next layer. Fine-tuning occurs after the initial training, where the network's hyperparameters are adjusted using error backpropagation to enhance the overall performance. In the layer-by-layer training method, the Deep Belief Network (DBN) architecture utilizes RBMs, which are stochastic NN consist of two layers namely visible layer and hidden layer. The visible layer contains neurons (nodes) that receive the input data samples, with connections established between layers but not within the same layer [32].

From the figure 2, visible layer in RBM consider which training set $\{DS, Y\}$ where DS indicates training data samples '$DS = DS_1, DS_2, DS_3, \dots DS_N$' from the dataset and label or output 'Y' denoting category that belongs to normal and Autism Spectrum Disorder (ASD). [33]The input training data samples are provided to input layer. In the training phase, the neuron in the input layer assigns weight related with the correlation between the visible (input) unit and the hidden unit.

$$Q = A(\sum_{i=1}^{n} DS_i \ * \ W_{vh}) + b_{vh} \quad (1)$$

Where, Q indicates an activity of the neuron in RBM, DS_i indicates an input training data samples, W_{vh} refers to a weight between visible and hidden unit, b_{vh} indicates a bias, A denotes a sigmoid activation function to determine the activation state of each hidden unit given the input from the visible layer. If the output 'A' is close to 1, the hidden unit is activated; if it is close to 0, the hidden unit remains inactive. Then the input is transferred from the visible unit to active hidden unit.

3.1 Preprocessing

It is an essential phase at ASD that involves preparing as well as transforming raw information to spotless and usable design. Therefore, an efficient preprocessing is necessary to significantly enhance the performance of models.

Let us assume data samples $DS_1, DS_2, DS_3, \dots DS_n$ collected from database. Number of information samples and

Therefore, the input matrix is formulated in matrix,

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$$M = \begin{bmatrix} fet_1 & fet_2 & \dots & fet_m \\ DS_{11} & DS_{12} & \dots & DS_{1n} \\ DS_{21} & DS_{22} & \dots & DS_{2n} \\ \vdots & \vdots & \dots & \vdots \\ DS_{m1} & DS_{m2} & \dots & DS_{mn} \end{bmatrix} \quad (2)$$

Where, M denotes input data matrix, every column represents number of features$fet_j = fet_1, fet_2, fet_3 \dots\dots fet_m$, every row denotes number of information samples instances $DS_1, DS_2, DS_3, \dots DS_n$ respectively. These input data matrix is given to the hidden layer for preprocessing. In the preprocessing steps, two processes are considered such as handling missing data and removing noisy data.

• Missing data imputation

It is common issue at information analysis that occurs when no value is recorded for one or more features in a dataset. Handling missing data is essential, as it significantly impact result of ML methods and validity of analyses. PRQGODBC model utilizes the polynomial regression-based data imputation for managing missing data in the database to enhance the quality and usability of the dataset for further processing.

Polynomial regression-based data imputation is technique employed to load at missing values at database through measuring relationship between data samples. Determine which values in the dataset are missing. Then the imputation process is carried out with the available data points.

$$R = \alpha_0 + \alpha_1 DS_1 + \alpha_2 {DS_2}^2 + \cdots \alpha_n {DS_n}^n + \epsilon \quad (3)$$

R indicates output of Polynomial regression, $DS_1, DS_2, DS_3, \dots DS_n$ represents number of data samples, $\alpha_0, \alpha_1, \alpha_3, \dots \alpha_n$ symbolizes coefficients of regression equation, ϵ denotes error term that reduces sum of squared differences among examined 'R_o'and forecasted values 'R_p'.

$$\epsilon = arg\ min\ (R_o - R_p)^2 \quad (4)$$

The regression function is used for discovering values of coefficients which reduce i.e. $arg\ min$ deviation among observed 'R_o'and forecasted values 'R_p. Like this, these proposed imputation method efficiently finds the every missing values at provided database.

• Outlier detection

It is significant process at information analysis which involves recognizing information points that diverge considerably as of majority of other data within the dataset. Outliers indicate variability in measurement, experimental errors, and it significantly affects statistical analyses and modeling. In this proposed PRQGODBC model, maximum normalized residual test is used for outlier detection which defined two hypotheses such as no outliers at database and outlier in database**.** Test is formulated as follows,

$$NT = \arg max \left[\frac{|DS_i - \mu|}{\sigma}\right] \quad (5)$$

$$\mu = \frac{\sum_{i=1}^{n} DS_i}{n} \quad (6)$$

Where, NT indicates a normalized residual test, $arg\ max$ indicates an argument of maximum function which measures absolute dissimilarity among some individual information point (DS_i) and sample mean 'μ', σ represent deviation, n indicates number of data samples. The absolute dissimilarity among data samples is higher than utmost allowable deviation, after that it is set the hypotheses as outlier data samples. Or else, data samples are no outliers. This data points are detached as of database and it filled through the missing data imputation.

3.2 Quadratic Discriminant Analysis based feature selection

After data preprocessing, feature selection is carried out to reduce time required for ASD identification. Feature selection includes recognizing as well as choosing subset of appropriate features from a dataset that contribute to ASD identification. This process helps improve model performance by decreasing training time. Quadratic

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Discriminant Analysis is used as a dimensionality reduction technique in the hidden layer of the deep belief **c**lassifier to choose most relevant features as of database.

Quadratic Discriminant Analysis considers which every class follows Gaussian distribution through its own mean and covariance matrix. The probability of a data point samples with two different classes such as relevant and irrelevant are measured as follows. The individual features or combinations of features contribute to distinguishing between the two groups based on the decision rule derived from the likelihood ratio test.

$$L \quad = \frac{1}{(2\pi\, v)^{-1}} \exp\left[-0.5 * \left(\, fet_j - M\right)^T v^{-1}\left(\, fet_j - M\right)\right] \qquad (7)$$

$$Z = arg\ max \ \ L \qquad (8)$$

From (7), L denotes an outcome of likelihood analysis between the feature ‘ fet_j’ and mean ‘M’ of the respective class, $arg\ max$ denotes maximum likelihood score, ‘v ‘specifies a variance, Z denotes an outcomes of Quadratic Discriminant Analysis, likelihood ratio presents outcomes from ‘0’ to ‘1. The likelihood ratio provides values from ‘0’ to ‘1,’ where features through values closer to 1 indicate a higher likelihood of belonging to a relevant class. In this approach, features with the highest likelihood values, which are most representative of the relevant class, are selected for classification. Conversely, features with lower likelihood ratios, which contribute less to distinguishing the relevant class from other classes, are considered irrelevant and are removed from the dataset.

3.3 **classifications**

After the feature selection, classification task is carried out by applying Tucker's congruence coefficient in hidden layer to analyze both the training and testing data. Tucker's congruence coefficient is statistical measure employed to assess similarity among two data matrices (training data samples and testing data samples). In context of ASD identification, the congruence coefficient helps quantify the similarity between feature representations from training as well as testing data samples within dataset.

Coefficient is applied to measure the similarity between the data samples as given below,

$$\rho = \frac{\sum DS_t * DS_r}{\sqrt{\sum DS_t^{\,2} \sum DS_r^{\,2}}} \qquad (9)$$

Where, ρ indicates similarity coefficient, $\sum DS_t * DS_r$ denotes sum of product of paired score of two data samples, DS_t denotes a testing data samples, DS_r indicates a training data samples, $\sum DS_t^{\,2}$ symbolizes a squared score of DS_t and $\sum DS_r^{\,2}$ signifies a squared score of DS_r. The coefficient (ρ) provides the values between ‘-1’ and ‘+1’. Based on the coefficient results, the normal or ASD data samples are classified.

3.4 Fine tuning

After the classification, a fine-tuning is employed to reduce error rate by optimizing the hyperparameters (i.e. weight) using the stochastic adaptive gradient method. This iterative method optimizes an objective function, such as classification error, with suitable smoothness properties. The error is calculated depend on actual as well as predicted classification results.

$$E = [Y - Y_p] \quad (10)$$

Where, E indicates error,Y denotes an actual classification outcome and Y_p denotes an predicted outcomes. Back propagate the error across the extended network and update the weights using adaptive gradient function.

$$W_{new} = W_t - \eta \left[\frac{\partial E}{\partial W_t}\right] \quad (11)$$

Where, W_{new} denotes updated new weight, W_t represent current weight, η indicates learning rate($\eta < 1$), $\left[\frac{\partial E}{\partial W_t}\right]$ denotes partial derivative of the error ‘E’ with present weight ‘W_t’. Hidden state is updated at each time step and retains information. After the fine-tuning process is completed, output from last hidden layer is transferred to output layer.

$$Y = A\,(H_{out}\,W_{ho}) \quad (12)$$

Where, Y denotes output of the deep belief work, A denotes a sigmoid activation function, H_{out} indicates a hidden layer output, W_{ho} indicates weight among hidden as well as output layer. In classifying individuals as either normal or having autism spectrum disorder (ASD), the sigmoid function transforms the similarity coefficient results into probabilities.

$$A = \begin{cases} 1; & ASD \\ 0; & normal \end{cases} \quad (13)$$

Finally, the outcomes denoting presence or absence of ASD disease are obtained. This ensures which method forecast are interpretable and suitable for making classification decisions based on the learned features during both pre-training as well as fine-tuning stages. Algorithm of data classification for ASD detection is given below,

// Algorithm 1: Polynomial Regressive Quadratic Gradient Optimized Deep Belief Classifier

Input: dataset, number of features $fet_j = fet_1, fet_2, fet_3 \ldots .. fet_m$, number of data samples $DS_1, DS_2, DS_3, \ldots DS_n$
Output: Increase the ASD detection accuracy

Begin
Number of selected features fet_m with training data samples DS_n taken **at the input layer**
For each samples DS_i –**[hidden layer]**
Assign weight 'W_{vh}' and bias 'B'
End for
Formulate input vector matrix 'M' using (2)
If missing value in dataset **then**
Apply the polynomial regression using (3)
Replace missing value
End if
For each data sample DS_i
Perform maximum normalized residual test using (5)
Detect **o**utlier data samples
End for
For each feature 'fet_m'
Measure the likelihood using (7)
$\boldsymbol{if}$ arg max **then**
Features are said to be relevant
Else
Features are said to be irrelevant
End if
For each training and testing data samples
Measure similarity using (9)
Classify normal or ASD
End for
Measure the error rate 'E' using (10)
Update the weight 'W_{new}' using (11)
If ($A = 1$) **then**
Correctly detected as presence of ASD
else
Correctly detected as normal
End if
Obtain the final classification results **at the output layer**
End

Algorithm 1 describes the various processes involved in detecting Autism Spectrum Disorder (ASD) using a Polynomial Regressive Quadratic Gradient Optimized Deep Belief Classifier. At first, number of data samples is gathered as of database and input into hidden layer. Preprocessing is then carried out to address missing data and detect outliers. Subsequently, relevant features are identified using the likelihood ratio measure. Following this,

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Tucker's congruence coefficient is employed to assess similarity among training and testing information samples. Based on coefficient results, the classification of ASD and normal data samples is then obtained. After classification, the error is computed by comparing the actual output results through predicted outputs. To minimize this error, the adaptive gradient method is applied in fine tuning process to optimize the weights between the layers. The optimal weight values are determined to reduce the overall error rate of the classifier. After the fine-tuning process, classification outcomes are obtained at output layer using sigmoid activation function. Consequently, accurate detection of ASD is achieved with minimal error.

4. EXPERIMENTAL SETUP

Experimental evaluation of PRQGODBC and conventional methods with dataset description is presented. The proposed PRQGODBC and ASD²-TL*GTO [1] and HCAN [2] are implemented using java program language with ASD Classification database https://www.kaggle.com/competitions/abide/data. The objective of dataset is to leverage DL methods to recognize patients with ASD using brain imaging data, focusing on their brain activation patterns. ASD brain imaging information was sourced from the worldwide multi-site database called as ABIDE.

4. Performance Comparison Analysis

Performance of PRQGODBC and conventional ASD²-TL*GTO [1] and HCAN [2] are evaluated through different parameters with different number of data samples.

Accuracy: it is referred as ratio of number of data samples which are properly classified to total number of data samples.

$$\boldsymbol{Acc} = \frac{\boldsymbol{N_{correct}}}{\boldsymbol{N}} * \mathbf{100} \qquad (14)$$

Where, $\boldsymbol{Acc}$ denotes an accuracy, '$\boldsymbol{N_{correct}}$' represents number of data samples properly classified as normal or ASD, '$\boldsymbol{N}$' symbolizes the number of data samples. It is calculated in percentage (%).

Precision: It is defined as ratio of detecting the normal and normal ASD samples. It expressed as follows,

$$\boldsymbol{Pr} = \left(\frac{\boldsymbol{Tp}}{\boldsymbol{Tp+Fp}}\right) \qquad (15)$$

Where, Pr denotes precision, Tp indicates true positive, Fp denotes false positive.

Recall: It refers to a method ability to precisely classify all samples in a dataset. This metric is defined as ratio of Tp predictions to sum of Tp and false negatives. Mathematically, it expressed as follows:

$$Rc = \left(\frac{Tp}{Tp+Fn}\right) \qquad (16)$$

Where, Rc denotes a recall, Tp indicates true positive, Fn represents false negative.

F1 score: it calculated as average of Pr and Rc. It offers a single value that balances these two metrics, giving more complete assessment of classifier's result. It is measured as below,

$$F1\_S = \left[2 * \frac{Pr * Rc}{Pr + Rc}\right] * 100 \qquad (17)$$

Where$F1_S$ denotes an F1 score, Pr indicates precision, 'Rl represent recall. F-measure is measured in percentage (%).

Processing time: It is calculated as amount of time utilized through method for identifying ASD and normal samples through classification. It is calculated as follows,

$$PT = N * T(ASD) \quad (18)$$

Where, PT denotes a processing time depend on data samples 'DP_i' and 'N' symbolizes the number of data samples. '$T(ASD)$' represent the time consumed for identifying the single autism spectrum disorder data samples. It is calculated in milliseconds (ms).

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4.1 Performance parameter Analysis

Performance of PRQGODBC and ASD²-TL*GTO [1] and HCAN [2] are estimated through different parameters with different number of samples.

Table 1 comparison of *Acc*

Number of data samples	Accuracy (%)		
	PRQGODBC	ASD²-TL*GTO	HCAN
100	94	91	90
200	96.33	91.23	89.05
300	96.78	92.66	90.06
400	95.26	92.45	90.11
500	97.89	95.02	93.05
600	98.05	96.05	92.36
700	98.02	96.55	93.06
800	98.22	95.03	92.12
900	98.89	96.45	92.12
1000	99.02	96.08	92.07

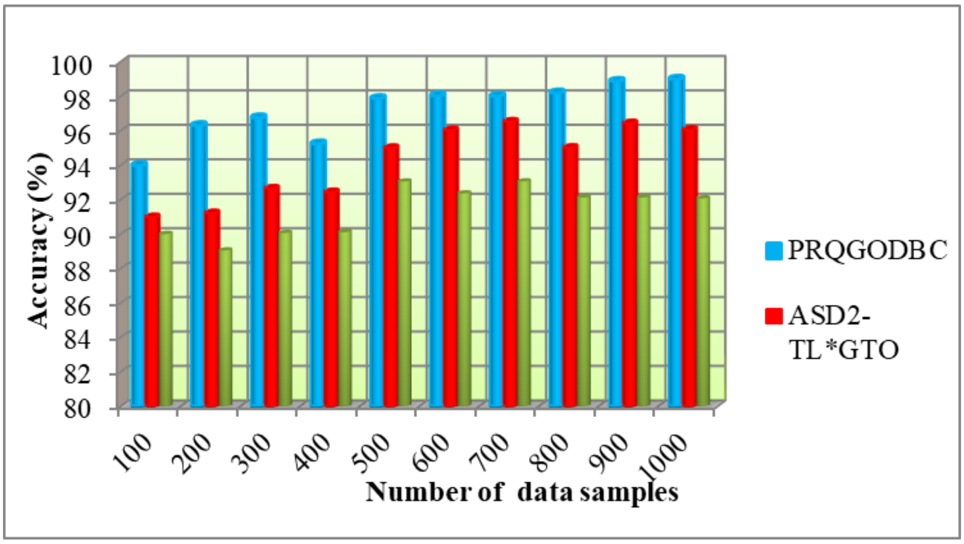

Figure 3 graphical results of accuracy

Figure 3 illustrates a performance analysis of *Acc* versus number of samples. Numbers of samples are taken in horizontal axis and ASD detection accuracy was observed on vertical axis. Graphically observed result proves that the accuracy of proposed PRQGODBC was observed to be higher than the [1] and [2]. Let us assume initial iteration involving 100 samples, the accuracy using the PRQGODBC was found to be 94%. Subsequently, 91% and 90% of accuracy were observed by applying [1] and [2], respectively. Multiple runs were carried out for every technique through various numbers of data samples. The performance outcomes of PRQGODBC were compared to outcomes of conventional methods. Overall comparison outcomes prove PRQGODBC increased accuracy by 3% compared to

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[1] and 6% compared to [2]. The PRQGODBC employs a Deep Belief Classifier to improve accuracy. The proposed DL classifier model examines the testing and training data samples with Tucker's congruence coefficient in the hidden layer. This process helps to accurately classify the given data samples as either normal or ASD. Furthermore, the fine-tuning of the Deep Belief Classifier minimize error rate during classification, leading to enhanced accuracy.

Table 2 comparison of precision

Number of data samples	Precision (%)		
	PRQGODBC	ASD²-TL*GTO	HCAN
100	93.10	90.47	89.02
200	94.05	89.05	87.25
300	93.74	90.03	88.41
400	94.22	91.22	87.32
500	93.74	90.57	88.04
600	93.66	91.33	87.41
700	94.12	90.46	88.05
800	95.05	91.34	89.41
900	94.78	91.36	88.06
1000	94.12	91.35	89.41

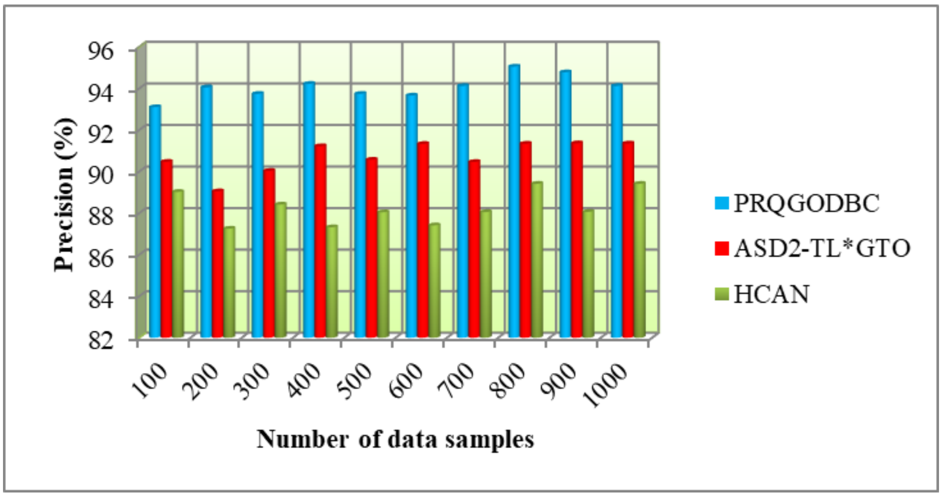

Figure 4 graphical results of precision

Figure 4 shows graphical analysis of precision using PRQGODBC and ASD²-TL*GTO [1] and HCAN [2]. The overall outcomes denote PRQGODBC outperforms existing [1] and [2] respectively. In experiment performed with 100 data samples, the precision was found to be 93.10% for the proposed PRQGODBC model, precision was 90.47% and 89.02% for the two existing [1],[2]. Overall, analysis of ten performance results illustrates that the precision using the proposed PRQGODBC is enhanced by 4% and 7% than the [1], [2]. This is because of application of DL classifier model for identifying normal or ASD samples. This model analyzes testing and training features using a

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similarity coefficient, resulting in classification with superior true positive rates as well as reduced false positive rates, finally enhancing precision.

Table 3 comparison of recall

Number of data samples	Recall (%)		
	PRQGODBC	ASD²-TL*GTO	HCAN
100	96.42	91.56	87.95
200	95.36	92.56	89.05
300	95.05	92.22	90.12
400	96.05	92.06	90.45
500	95.77	91.11	89.33
600	96.07	92.33	89.41
700	95.88	91.05	88.45
800	96.12	91.17	89.64
900	96.07	92.05	90.04
1000	95.89	92.32	90.36

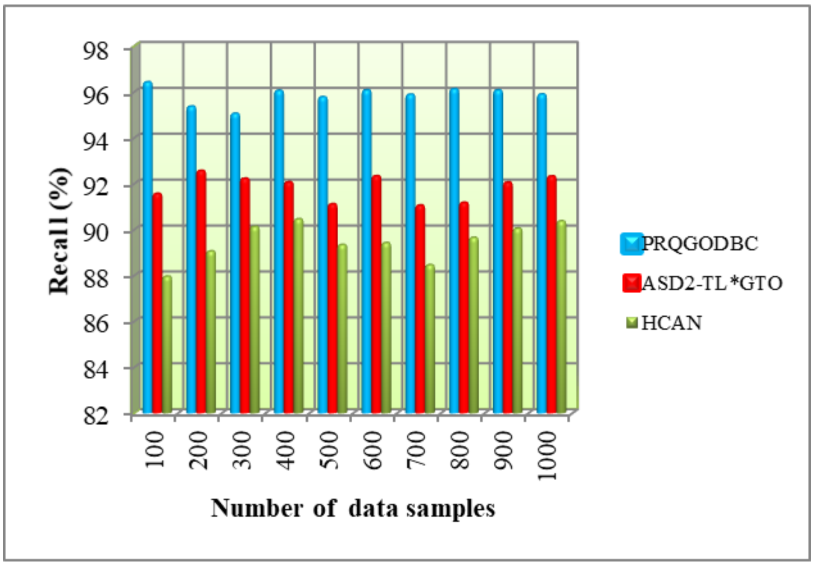

Figure 5 graphical results of recall

Figure 5 depicts result outcomes of recall versus number of data samples taken from dataset, ranging from 100 to 1000. The recall is calculated with PRQGODBC and ASD²-TL*GTO [1] and HCAN [2] respectively. For each method, ten dissimilar outcomes were observed, and the corresponding outcomes are depicted in figure 5. For example, when 100 data samples were used for experimentation, recall with PRQGODBC model was 96.42%. On the other hand, by applying [1] and [2], the recall performance was found to be 91.56% and 87.95% respectively. Similarly, dissimilar performance outcomes were examined for every technique. These results were compared, showing a considerable improvement of 4% and 7% using the PRQGODBC model compared to [1] and [2],

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respectively. This was achieved by accurately improving the true positives and minimizing the false negatives in data sample classification. The number of data samples classified with higher Tp and minimal false negatives helps to improve Rec.

Table 4 comparison of F1 score

Number of data samples	F1 score (%)		
	PRQGODBC	ASD²-TL*GTO	HCAN
100	94.73	91.01	88.48
200	94.70	90.77	88.14
300	94.39	91.11	89.25
400	95.12	91.63	88.85
500	94.74	90.83	88.68
600	94.84	91.82	88.39
700	94.99	90.75	88.24
800	95.58	91.25	89.52
900	95.42	91.70	89.03
1000	94.99	91.83	89.88

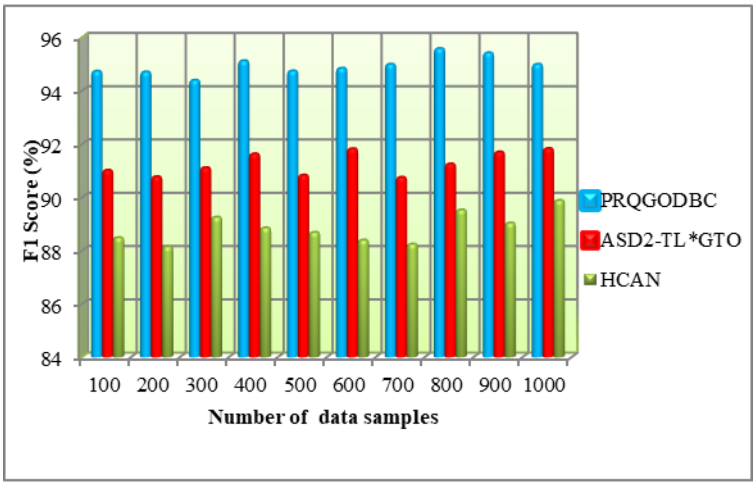

Figure 6 graphical results of F1 score

Figure 6 illustrates F1-score result for ASD detection using three methods namely PRQGODBC, ASD²-TL*GTO [1], and HCAN [2]. Graphical depiction demonstrates which PRQGODBC outperforms other two methods, [1] and [2], in terms of F1-score. This improvement is achieved to PRQGODBC's ability to enhance Pre and Rec through ASD detection. An average of ten comparison outcomes shows F1-score of PRQGODBC is considerably improved by 4% and 7% than the [1] and [2]. This development highlights efficiency of PRQGODBC model in a balanced trade-off among Pre and Rec for classification.

Table 5 comparison of processing time

Number of data samples	Processing time (ms)		
	PRQGODBC	ASD²-TL*GTO	HCAN
100	12	15	18
200	15	18	22
300	17	20	23
400	20	24	27
500	22	27	30
600	24	30	33
700	27	34	37
800	30	37	40
900	33	40	44
1000	35	43	47

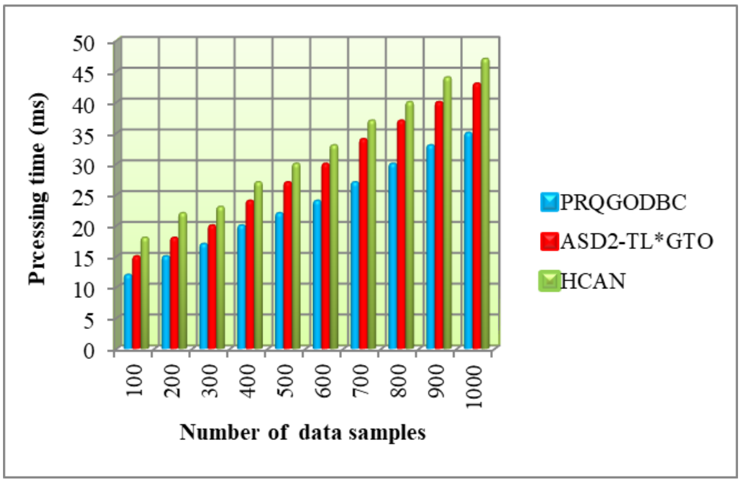

Figure 7 graphical results of processing time

Figure 7 depicts performance analysis of processing time using namely PRQGODBC, ASD²-TL*GTO [1], and HCAN [2].Especially, processing time for PRQGODBC model is considerably reduced compared to existing [1] and [2]. The outcomes attained as of PRQGODBC model are then compared to conventional methods. The average comparison results indicate denote processing time is significantly reduced by 18% and 27% than the [1],[2]. This is because of PRQGODBC model performing data preprocessing steps, including missing data imputation and outlier recognition. Following this, outlier recognition is carried out. These preprocessing steps in the PRQGODBC model help to reduce the time consumption for ASD detection. Additionally, the PRQGODBC model utilizes Quadratic Discriminant Analysis to choose relevant features as of database and remove irrelevant ones, further minimizing time utilization.

5. CONCLUSION

Autism is the fastest-growing developmental and neurological disorders. Early diagnosis is crucial for managing the condition and improving outcomes for children. New PRQGODBC model has designed to enhance accuracy of diagnostic assessments. The PRQGODBC model reduces the time required for ASD detection through effective data preprocessing and relevant feature selection from the dataset. Following this, the proposed deep belief network within the PRQGODBC model accurately analyzes both testing and training data samples, classifying them as either normal and ASD with minimal error. A comprehensive experimental assessment is performed with various metrics with number of data samples. Outcomes of analysis show proposed PRQGODBC model achieves improved accuracy in ASD detection, with reduced processing time compared to conventional models.

REFERENCES

[1] Abdulqader M. Almars, Mahmoud Badawy, Mostafa A. Elhosseini, "ASD2-TL* GTO: Autism spectrum disorders detection via transfer learning with gorilla troops optimizer framework", Heliyon, Elsevier, Volume 9, Issue 11, 2023, Pages 1-15. https://doi.org/10.1016/j.heliyon.2023.e21530

[2] Lizhen Shao, Cong Fu and Xunying Chen, "A heterogeneous graph convolutional attention network method for classifcation of autism spectrum disorder", BMC Bioinformatics, Springer, Volume 24, 2023, Pages 1-17. https://doi.org/10.1186/s12859-023-05495-7

[3] Anita Vikram Shinde, Dipti Durgesh Patil, "A Multi-Classifier-Based Recommender System for Early Autism Spectrum Disorder Detection using Machine Learning", Healthcare Analytics, Elsevier, Volume 4, 2023, Pages 1-10. https://doi.org/10.1016/j.health.2023.100211

[4] Rownak Ara Rasul, Promy Saha, Diponkor Bala, S.M. Rakib Ul Karim, Md. Ibrahim Abdullah, Bishwajit Saha, "An evaluation of machine learning approaches for early diagnosis of autism spectrum disorder", Healthcare Analytics, Elsevier, Volume 5, 2024, Pages 1-16. https://doi.org/10.1016/j.health.2023.100293

[5] Muhammad Shoaib Farooq, Rabia Tehseen, Maidah Sabir & Zabihullah Atal, "Detection of autism spectrum disorder (ASD) in children and adults using machine learning", Scientific Reports, volume 13, 2023, Pages 1-13. https://doi.org/10.1038/s41598-023-35910-1

[6] Dhuha heyaa Khudhur, Saja Dheyaa Khudhur, "The classification of autism spectrum disorder by machine learning methods on multiple datasets for four age groups", Measurement: Sensors, Volume 27, 2023, Pages 1-6. https://doi.org/10.1016/j.measen.2023.100774

[7] Md. Jamal Uddin, Md. Martuza Ahamad, Prodip Kumar Sarker, Sakifa Aktar, Naif Alotaibi, Salem A. Alyami, Muhammad Ashad Kabir and Mohammad Ali Moni, "An Integrated Statistical and Clinically Applicable Machine Learning Framework for the Detection of Autism Spectrum Disorder", Computers, Volume 12, Issue 5, 2023, Pages 1-19. https://doi.org/10.3390/computers12050092

[8] Jyotismita Talukdar, Deba Kanta Gogoi, Thipendra P. Singh, "A comparative assessment of most widely used machine learning classifiers for analysing and classifying autism spectrum disorder in toddlers and adolescents", Healthcare Analytics, Elsevier, Volume 3, 2023, Pages 1-16. https://doi.org/10.1016/j.health.2023.100178

[9] Amna Hendr, Umar Ozgunalp and Meryem Erbilek Kaya, "Diagnosis of Autism Spectrum Disorder Using Convolutional Neural Networks", Electronics, Volume 12, Issue 3, 2023, Pages 1-15. https://doi.org/10.3390/electronics12030612

[10] El-Sayed Atlam, Mehedi Masud, Mahmoud Rokaya, Hossam Meshref, Ibrahim Gad and Abdulqader M. Almars, "EASDM: Explainable Autism Spectrum Disorder Model Based on Deep Learning", Journal of Disability Research, Volume 3, 2024, Pages 1-15. DOI: 10.57197/JDR-2024-0003.

[11] Caroline L. Alves, Thaise G. L. de O. Toutain, Patricia de Carvalho Aguiar, Aruane M. Pineda, Kirstin Roster, Christiane Thielemann, Joel Augusto Moura Porto & Francisco A. Rodrigues, "Diagnosis of autism spectrum disorder based on functional brain networks and machine learning", Scientific Reports, Volume 13, 2023, Pages 1-20. | https://doi.org/10.1038/s41598-023-34650-6

[12] Puneet Bawa, Virender Kadyan, Archana Mantri, Harsh Vardhan, "Investigating multiclass autism spectrum disorder classification using machine learning techniques", e-Prime - Advances in Electrical Engineering, Electronics and Energy, Elsevier, Volume 8, 2024, Pages 1-9. https://doi.org/10.1016/j.prime.2024.100602

[13] Aythem Khairi Kareem, Mohammed M. AL-Ani and Ahmed Adil Nafea, "Detection of Autism Spectrum Disorder Using A 1-Dimensional Convolutional Neural Network", Baghdad Science Journal, Volume 20, Issue 3, 2023, Pages 1182-1193. https://dx.doi.org/10.21123/bsj.2023.8564

[14] M. E. Alqaysi, A. S. Albahri, Rula A. Hamid, "Evaluation and benchmarking of hybrid machine learning models for autism spectrum disorder diagnosis using a 2-tuple linguistic neutrosophic fuzzy sets-based decision-

making model", Neural Computing and Applications, Springer, Volume 36, 2024, Pages 18161–18200. https://doi.org/10.1007/s00521-024-09905-6

[15] Mahmoud M. Abdelwahab, Khamis A. Al-Karawi, E. M. Hasanin and H. E. Semary, "Autism Spectrum Disorder Prediction in Children Using Machine Learning", Journal of Disability Research, Volume 3, Issue 1, 2024, Pages 1-9. DOI: 10.57197/JDR-2023-0064

[16] Hanan Abdullah Mengash, Hamed Alqahtani, Mohammed Maray, Mohamed K. Nour, Radwa Marzouk, Mohammed Abdullah Al-Hagery, Heba Mohsen and Mesfer Al Duhayyim, "Automated Autism Spectral Disorder Classification Using Optimal Machine Learning Model", Computers, Materials and Continua, Elsevier, Volume 74, Issue 3, 2022, Pages 5251-5265. https://doi.org/10.32604/cmc.2023.032729

[17] Fatima Zahra Benabdallah, Ahmed Drissi El Maliani, Dounia Lotfi and Mohammed El Hassouni, "A Convolutional Neural Network-Based Connectivity Enhancement Approach for Autism Spectrum Disorder Detection", Journal of Imaging, Volume 9, Issue 6, 2023, Pages 1-12. https://doi.org/10.3390/jimaging9060110

[18] Kim Steven Betts , Kevin Chai , Steve Kisely, Rosa Alati, "Development and validation of a machine learning-based tool to predict autism among children", Autism Research, Wiley, Volume 16, Issue 5, 2023, Pages 941-952. https://doi.org/10.1002/aur.2912

[19] Mingzhi Wang , Jifeng Guo , Yongjie Wang , Ming Yu , and Jingtan Guo, "Multimodal Autism Spectrum Disorder Diagnosis Method Based on DeepGCN", IEEE Transactions on Neural Systems and Rehabilitation Engineering , Volume 31, 2023, Pages 3664 – 3674. **DOI:** 10.1109/TNSRE.2023.3314516

[20] Asmaa H. Rabie and Ahmed I. Saleh, "A new diagnostic autism spectrum disorder (DASD) strategy using ensemble diagnosis methodology based on blood tests", Health Information Science and Systems, Springer, Volume 11, 2023, Pages 1-23. https://doi.org/10.1007/s13755-023-00234-x

[21] Shahad Sabbar Joudar, A.S. Albahri, Rula A. Hamid, "Intelligent triage method for early diagnosis autism spectrum disorder (ASD) based on integrated fuzzy multi-criteria decision-making methods", Informatics in Medicine Unlocked, Elsevier, Volume 36, 2023, Pages 1-21. https://doi.org/10.1016/j.imu.2022.101131

[22] Fahima Hajjej, Sarra Ayouni, Manal Abdullah Alohali, Mohamed Maddeh, "Novel Framework for Autism Spectrum Disorder Identification and Tailored Education With Effective Data Mining and Ensemble Learning Techniques", IEEE Access, Volume 12, 2024, Pages 35448 – 35461. **DOI:** 10.1109/ACCESS.2024.3349988

[23] Taher M. Ghazal, Sundus Munir, Sagheer Abbas, Atifa Athar, Hamza Alrababah and Muhammad Adnan Khan, "Early Detection of Autism in Children Using Transfer Learning", Intelligent Automation & Soft Computing, Volume 36, Issue 1, 2023, Pages 11-22. https://doi.org/10.32604/iasc.2023.030125

[24] Mousumi Bala, Mohammad Hanif Ali, Md. Shahriare Satu, Khondokar Fida Hasan, and Mohammad Ali Moni, "Efficient Machine Learning Models for Early Stage Detection of Autism Spectrum Disorder", Algorithms, Volume 15, Issue 5, 2022, Pages 1-22. https://doi.org/10.3390/a15050166

[25] Mohemmed Sha, Abdullah Alqahtani, Shtwai Alsubai and Ashit Kumar Dutta, "Modified Meta Heuristic BAT with ML Classifiers for Detection of Autism Spectrum Disorder", Biomolecules , Volume 14, Issue 1, 2024, Pages 1-28. https://doi.org/10.3390/biom14010048

[26] D. Jayaprakash, C.S. Kanimozhiselvi, "Multinomial logistic regression method for early detection of autism spectrum disorders", Measurement: Sensors, Elsevier, Volume 33, 2024, Pages 1-9. https://doi.org/10.1016/j.measen.2024.101125

[27] Daniel, Nicholas Dominic, Tjeng Wawan Cenggoro, Bens Pardamean , "Machine Learning Approaches in Detecting Autism Spectrum Disorder", Procedia Computer Science, Elsevier, Volume 227, 2023, Pages 1070-1076. https://doi.org/10.1016/j.procs.2023.10.617

[28] Maraheb Alsuliman and Heyam H. Al-Baity, "Efficient Diagnosis of Autism with Optimized Machine Learning Models: An Experimental Analysis on Genetic and Personal Characteristic Datasets", Applied Sciences, Volume 12, Issue 8, 2022, Pages 1-22. https://doi.org/10.3390/app12083812

[29] Fadi Thabtah, Robinson Spencer, Neda Abdelhamid, Firuz Kamalov, Carl Wentzel, Yongsheng Ye & Thanu Dayara, "Autism screening: an unsupervised machine learning approach", Health Information Science and Systems, Springer, Volume 10, 2022, Pages 1-13. https://doi.org/10.1007/s13755-022-00191-x

[30] Wail M. Hassan, Abeer Al-Dbass, Laila Al-Ayadhi, Ramesa Shafi Bhat & Afaf El-Ansary, "Discriminant analysis and binary logistic regression enable more accurate prediction of autism spectrum disorder than principal

component analysis", Scientific Reports, Volume 12, 2022, Pages 1-13. https://doi.org/10.1038/s41598-022-07829-6 .

[31] S. Subash Chandra Bose, Rajesh Natarajan, Gururaj H L, Francesco Flammini & P. V. Praveen Sundar , "Iterative Reflect Perceptual Sammon and Machine Learning-Based Bagging Classification for Efficient Tumor Detection" , MDPI ,Sustainability ,Vol.15,Issue.5, Pp.1-17 , March 2023 , https://doi.org/10.3390/su15054602 .

[32] S Subash Chandra Bose, Badria Sulaiman Alfurhood, Francesco Flammini, Rajesh Natarajan & Sheela Shankarappa Jaya , "Decision Fault Tree Learning and Differential Lyapunov Optimal Control for Path Tracking", MDPI,Entropy,Vol.25,Issue.3,pp.1-15,March2023, https://doi.org/10.3390/e25030443 .

[33] Rajesh Natarajan, Santosh Reddy, Subash Chandra Bose, HL Gururaj, Francesco Flammini, and Shanmugapriya Velmurugan , "Fault detection and state estimation in robotic automatic control using machine learning", Elsevier , Array , Vol.19 , Issue , pp.1-9 , June 2023, https://doi.org/10.1016/j.array.2023.100298.