Autism Spectrum Disorder Detection Using Parallel DCNN with Improved Teaching Learning Optimization Feature Selection Scheme

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***Abstract*— The identification of a neurological disorder known as autism spectrum disorder (ASD) is essential and vital for improving the quality of life and providing appropriate medical care for those with autism. Good health and well-being are essential for individuals with autism, just like anyone else. In the last decade, numerous machine learning (ML) and deep learning (DL) based techniques and methods were used for Autism Disorder Detection (ASD) with the help of magnetic resonance images (MRI). The performance of this technique is susceptible to poor feature representation, redundant features, complexity of DL frameworks, and poor visual quality of the images. This paper presents ASDD based on a parallel Deep Convolution Neural Network (PDCNN). It includes image enhancement, feature extraction, feature selection, deep feature representation, and ASDD. It presents an improved double-stage Gaussian Weiner Filtering scheme to minimize blur, contrast, and uneven illumination in some images. Further, it offers the shape and texture feature extraction of functional MRI (fMRI) with gray level co-occurrence matrix (GLCM), local binary pattern (LBP), and histogram of oriented gradient (HOG), and local directional pattern (LDP). Afterward, an improved teaching-learning-based scheme is utilized to select prominent features to minimize the computational intricacy of the PDCNN. The outcomes of the system are validated on the ABIDE-I dataset.**

***Index Terms*— Autism spectrum disorder, Good health and well-being, Deep Convolution Neural Network, Deep learning, Local Binary Pattern, Medical Imaging, and Histogram of Oriented Gradients**

I. INTRODUCTION

The World Health Organization, which is an eminent apex body at the international level, estimated that one in 160 children has Autism Spectrum Disorder (ASD), along with anxiety, concentration problems, mental abnormality, and depressive deficit hyperactivity disorder are likely to accompany this condition [1]. Most kids with autism disorder, which is a neurological abnormality that impacts hugely on social interaction and sometimes communication disabilities, are generally observed between the ages of six and seventeen. The disease Autism Spectrum Disorder describes a group of conditions that impair mental strength and nervous system development. Early symptoms of autism disorder include interest restriction, inappropriate social connectivity and emotional regulation, hypo- or hyper-reactivity to sensory inputs, and repetitive behaviors [2][3].

Autism often prevents many individuals from learning, developing, controlling, interacting, or performing some fundamental life tasks. The financial toll that ASD takes on both the affected families and society is substantial. To distinguish ASD patients from normal conditions, a slightly earlier and more precise diagnostic framework is necessary. Researchers who engage in supplementary diagnoses for ASD have increasingly been drawn to various non-invasive and in vivo neuroimaging methods. ASDs are frequently identified with the help of brain imaging modalities. They may be structural and functional, which mainly includes structural MRI, which is known as sMRI [4], fMRI [5], diffusion MRI, electroencephalography (EEG) [6] [7], magnetoencephalography (MEG) [8], and electrocardiography (ECG) [9].

The most suitable structural properties of the brain may be precisely defined using structural MRI. Early detection of ASD is essential as it benefits children by enhancing their communication quality and social abilities, ultimately improving their quality of life [10] [11]. Treatment and management of sickness depend on an early diagnosis. An essential first step in diagnosing and analyzing neurological disorders that are commonly observed, such as epilepsy, Alzheimer's, and autism, is the development of a model that can interact between functional or anatomical parts of the brain [12] [13] [14]. The brain and its architecture are examined using the fMRI. The (BOLD) signals obtained from several brain regions can be used to detect coordinated blood oxygen level-dependent changes. It has been analyzed and demonstrated that Autism Spectrum disorder impacts the functional links separating multiple brain regions and areas, affecting global brain networks. Consequently, the ongoing research is to use functional connectivity patterns in the brain to classify people with ASD and healthy controls [15]. Early diagnosis of ASD may aid in providing patients with the appropriate medical and psychosocial care. The behavioral analysis and monitoring that are part of the standard ASD identification techniques are laborious, time-consuming, and dependent on the expertise of the experts. ASD detection and

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population expansion has resulted in the development of an automated system for ASD identification that is more dependable, rapid, and efficient [16].

Recently, much attention has been paid to using CNN for effective classification and representation learning. CNNs are always available, robust classifiers that work well in various applications because they have many relevant free parameters. A CNN model can also handle many essential parameters and has enhanced feature extraction accuracy to a greater extent. The deep CNN model comprises many layers: pooling, normalization, convolutional, and fully connected. The CNN approach may examine brain biomarkers in people with ASD using fMRI. Compared to MRI scans, CNN models provide a superior depiction of spatial and spectral alterations, making it easier to identify subtle differences in the brain regions affected by autism. By balancing the local and global components, CNN can provide a better MRI image. Nevertheless, some constraints limit the CNN's performance, such as the need for extensive hyperparameter tuning, a larger number of critical trainable parameters, problems with data scarcity, insufficient feature discrimination, etc. [17] [18].

The shortcomings of the existing approaches, which include difficulties with data scarcity and substantial hyperparameter tweaking, necessitate a more effective and precise ASD detection technique. This research suggests a unique approach that uses parallel deep learning networks (PDCNN).

This article presents the PDCNN-based system to improve the ASD detection rate. The key contributions of the work are summarized as follows:

1) Feature representation of the brain fMRI using GLCM, LBP, LDP, and HOG to describe the texture and shape of the brain MRI
2) Feature selection using improved Elite-Learning based Teaching Learning based algorithm
3) ASDD using novel PDCNN to improve the generalization capability, feature distinctiveness, and autism disorder detection rate.

The arrangement of the remaining article is as follows: Section 2 offers a survey of recent work carried out for ASD detection. Section 3 provides the detailed methodology encompassing feature extraction, selection, and PDCNN. Further, section 4 gives the experimental results and discussions. Finally, section 5 depicts the findings from the work and offers the future scope for the possible improvement in the method.

II. RELATED WORK

Using structural Magnetic Resonance Imaging (sMRI) and functional magnetic resonance imaging (fMRI), several DL approaches have found ASD. These techniques are excellent and exceptional because they can identify brain MRIs' important functional and anatomical characteristics. Deep neural networks (DNN), which use anti-correlation between the posterior and anterior parts of the brain, were used by Heinsfeld et al. [19] to examine the identification of ASD.

ASD detection methods employed a 2-stacked denoising auto-encoder (SDA) for pre-training and a deep neural network (DNN) for classification to improve subjectivity and generalization ability in larger datasets. The paracingulate gyrus and supramarginal regions of the ASD subject show higher levels of anti-correlation. ASD detection method based on DNN with A.E. was described by Kong et al. [20]. This method uses connection maps to access the A.E. Grey matter volume and Destrieux atlas, which were used to differentiate between different cortical areas to determine ASD.

Using the correlation properties of rs-fMRI, Sherkatghanad et al. [21] introduced a parallel CNN for ASD identification. It has a sizeable trainable parameter (4,398,802) and struggles with data scarcity, yet despite this, it has been shown to improve the accuracy of ASD diagnosis significantly; nonetheless, its performance is restricted. Wang et al. [22] employed Ensemble Learning (E.L.) and Multilayer Perceptron (MLP) classifiers to identify ASD. SDA and a multi-atlas deep feature characterization of fMRI are used together to extract the features. The system is heavily computationally burdened by numerous categorization approaches and feature representations based on deep learning. To determine the uniqueness of the standard and ASD samples, Dvornek et al. [23] used a recurrent neural network based on long short-term memory (LSTM). Work was accomplished via the use of time series fMRI for ASD identification.

Anatomical regions significantly impact the performance of the network with considerable variability. High-order morphological Network Construction (HON) and a supervised ensemble classifier were used to create Soussia et al.'s proposed ASD detection technique [24]. A morphological brain network, or MBN, was constructed using structural information gathered from various cortical regions. Functional connectivity measures were used in a DNN by Faria et al. [25] to detect ASD. The ABIDE-I dataset showed an accuracy of 88.0%.

. Eslami et al. [26] also looked at the ASD-DiagNet framework for ASD identification. This framework was built on correlation features and included an autoencoder to capture lower-dimensional patterns using functional connectivity characteristics. It was observed that the data augmentation helped to improve the accuracy of the ASD diagnosis by 3%. The data augmentation was performed using the Extended Frobenius Norm (EROS). The study by Zhang et al. [27] explored improving deep neural networks (DNNs) for malware classification using GAN-based adversarial training. The proposed model enhanced DNNs by using generative adversarial networks (GANs) to generate adversarial malware samples for training, improving resistance to evasion attacks. The study by Yamashita et al. [28] provided an overview of convolutional neural networks (CNNs) and their applications in radiology. CNNs achieve high accuracy in tasks like tumor detection, image segmentation, and classification, often surpassing traditional machine learning methods. The study by Chattopadhyay and Maitra [29] presented a convolutional neural network (CNN) based deep learning method for detecting brain tumors in MRI images. Jayaprakash et al. [30] have shown that multinomial logistic regression increases the performance of the LR for ASD and provides better classification accuracy. It shows 89% accuracy on the childhood autism rating scale. Awate et al. [31] developed an eNidan application for ASD detection using logistic regression (LR). It provided 67% accuracy for the ASD detection. The reliability of the system for real-time implementation is lower.

Shrivastav et al. [32] classified instances of typically developing TD and ASD using ASD datasets from all age groups. Following preprocessing using KNN Imputer and One-Hot encoding, classifiers such as SVM, KNN, RF, and ANN were used. Unlike complicated models like DNN and CNN, Random Forest achieved 100% accuracy without overfitting, guaranteeing superior generalization for real-time ASD diagnosis. Ahmad et al. [33] compared several CNN models that have already been trained using models like ResNet34, ResNet50, Alex Net, and VGG16. Using transfer learning to improve performance resulted in ResNet50 obtaining the maximum accuracy of 92%. In terms of both accuracy and computing efficiency, the technique came out on top of the most advanced models currently available. Jahani et al. [34] investigated the use of multi-contrast magnetic resonance imaging (MRI) to classify young individuals with ASD. These findings suggested that combining structural and functional neuroimaging data can enhance the accuracy of ASD classification in young individuals. Subtirelu et al. [35] discussed the roles of sMRI, fMRI, and positron emission tomography (PET) in identifying biomarkers for ASD.

PDCNN provides Diversified feature extraction, redundancy in the learned feature, reduces the overfitting problem, increases gradient propagation, and helps in optimization as it consists of multiple parallel convolution branches with different kernels and filter sizes.

Robert Subtirelu et al. [36] explore how different neuroimaging techniques aid in the early diagnosis of ASD, along with challenges like small sample size, lack of standardized protocol, and variability in data analysis. Vadamodula Prasad et al [37] present an innovative approach for ASD detection with an optimization algorithm, Hybrid Sewing Training Optimization (HSTO); however, they acknowledge validation of results over larger and diverse datasets. Juan Manuel Mayor Torres et al. [38] investigated individuals with ASD by analyzing EEG signal data. The challenges are facial emotion recognition in ASD are solely due to impaired neural encoding. A. Saranya and R. Ananda [39] proposed fuzzy hybrid deep convolutional neural networks and fusion of facial expressions and human gaits based on input video sequences, however, the performance can be improved using a fuzzy optimizer to reduce dimensionality and increase the classification and prediction performance. Shweta Jain et al. [40] proposed a deep Convolutional Neural Network (CNN) with Dwarf Mongoose optimized Residual Network (DMResNet). They observed that the model fails to handle variability in multi-site datasets, generalizing, and balancing the model leads to complexity and interpretability.

Mayank Mishra et al. [41] proposed a DCNN with an on-the-fly data augmentation approach. However, they can avoid the overfitting issue to produce generalization. Pranav Reddy et al. [42] aim at ASD detection using transfer learning. They focus on facial phenotypes. They have achieved binary classification only. Investigating bias and fairness will be more promising. Yang Ding et al. [43] present a systematic review and meta-analysis aimed at evaluating the diagnostic accuracy of deep learning (DL) models in predicting ASD, study limits to generalizability, and introduces potential for selection bias. High Data Heterogeneity problem observed.

Some gaps are identified from an extensive literature survey, i.e., lack of standardized dataset, inconsistent evaluation methodology, sometimes narrow focus on single methodology, insufficient interoperability, underutilization of hybrid models, optimization algorithm, and less generalization.

As shown in Table 1, a synopsis of the many current methods employed to identify ASD is offered. The deep learning framework focuses on the approach used for identifying ASD and the dataset, performance metrics, and total trainable parameters. ASD detection methods based on deep learning have far outperformed those based on machine learning. However, major trainable parameters, poor feature discrimination, data scarcity issues, lengthy hyperparameter adjustment, etc., limit the performance of the DL architecture. This paper integrates the conventional fMRI texture and shape features to enhance the deep learning framework's feature distinctiveness. It offers a unique fMRI enhancement method to improve the image's visual quality and reduce the impact of blur, uneven lighting, and low contrast.

III. METHODOLOGY

The proposed methodology encompasses four crucial stages: MRI image enhancement, texture and shape feature extraction, feature selection, and feature enrichment using parallel DCNN and ASD/TD classification. The preprocessing stage includes an improved double-stage Gaussian Weiner Filtering scheme to enhance MRI images. LDP, and HOG techniques. Further, various texture and shape features are extracted using GLCM, LBP. Improved teaching, Learning-based optimization is utilized to select the salient features from the available features. The Parallel DCNN improves the feature distinctiveness capability of the fMRI images raw texture and shape features. Finally, the SoftMax classifier provides the ASD and TD classification. The flow diagram of the methodology is shown in Fig. 1. The proposed IDSGWF encompasses three parallel layers that enhance the texture, contrast, and edges and minimize blur and noise in the MRI images.

A. Improved Double Stage Gaussian Weiner Filtering (IDSGWF)

The quality of the radiographic fMRI images is often subjected to poor contrast, poor texture representation, and high-frequency noise. The proposed IDSGWF focuses on texture enhancement, edge smoothing, contrast enhancement, and high-frequency noise minimization, as shown in Fig. 2. The first layer consists of double-stage Gaussian filtering that smoothens the edges and minimizes the high-frequency noise in the MRI images. The Weiner filter assists in reducing the blur and low-frequency noise in the MRI images.

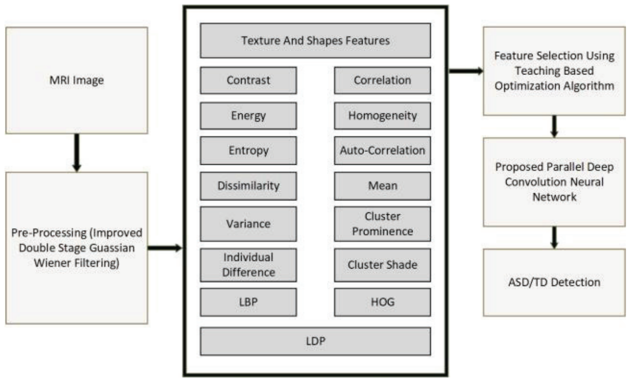

Fig. 1. Flow diagram of Methodology

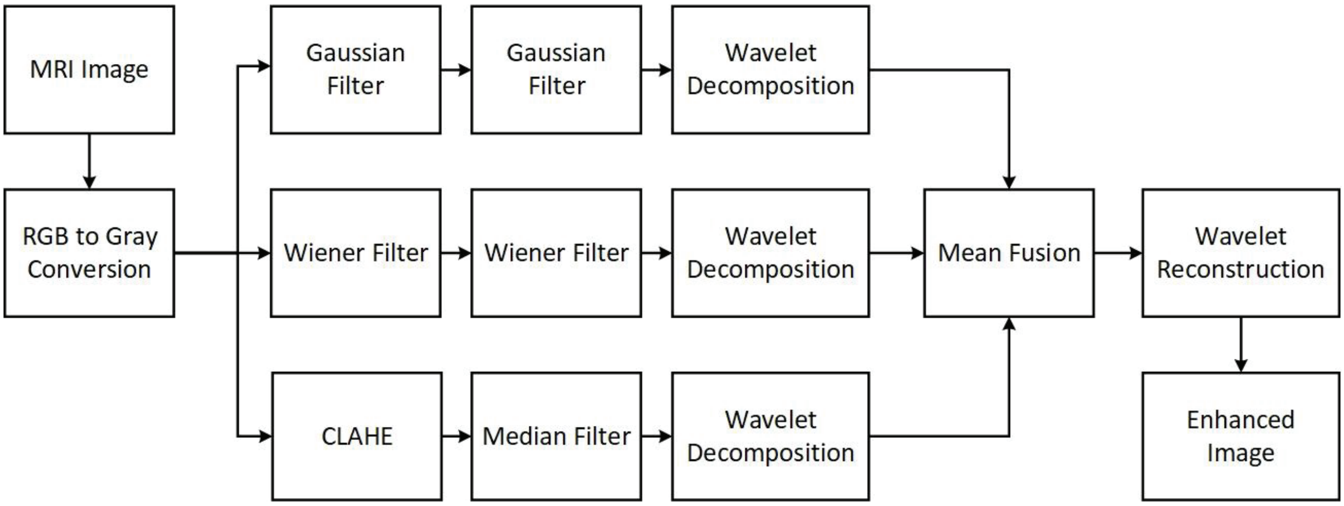

Fig. 2. Process diagram of proposed IDSGWF

The contrast-limited adaptive histogram equalization (CLAHE) improves the contrast of the fMRI images by enhancing the local region of the image. The median filter is applied for texture smoothing, followed by CLAHE. The discrete wavelet transform is used to fuse the outputs of the three IDSGWF layers to maintain the image's texture quality. The effectiveness of the IDSGWF is estimated based on mean square error (MSE), peak signal-to-noise ratio (PSNR), and structural similarity index (SSIM) metrics.

B. Feature Extraction

The proposed scheme extracts the texture features using GLCM, LBP, and LDP to characterize the impact of autism on fMRI. It offers the changes in homogeneity of the fMRI texture. The GLCM provides different texture measures such as contrast, correlation, energy, homogeneity, entropy, autocorrelation, dissimilarity, individual difference, mean, variance, cluster prominence, and cluster shade. The LBP provides the local texture features, which provide minor variations in the texture of the fMRI. The HOG features provide the shape characteristics of the fMRI images. The GLCM, LBP, LDP, and HOG features are concatenated to form the final feature vector, as shown in Table 1.

TABLE I
TEXTURE AND SHAPE FEATURES OF fMRI

Features	**Number of Features**	**Position of Feature in Feature Vector**
Contrast	1	1
Correlation	1	2
Energy	1	3
Homogeneity	1	4
Entropy	1	5
Autocorrelation	1	6
Dissimilarity	1	7
Individual Difference	1	8
Mean	1	9
Variance	1	10

Cluster Prominence	1	11
Cluster Shade	1	12
LBP	256	13-268
HOG	8100	269-8368
LDP	256	8369-8624

The final feature set is represented using equation 1, where $Feat_{GLCM}$ donotes GLCM features, $Feat$ indicate total features, $Feat_{LBP}$ stands for LBP features, $Feat_{LTP}$ denotes LTP features, and $Feat_{HOG}$ symbolizes HOG features.

$$Feat = \{Feat_{GLCM}, Feat_{LBP}, Feat_{LTP}, Feat_{HOG}\} \quad (1)$$

C. Feature Selection using EL-TLBO

The feature selection using improved EL-TLBO is represented in Fig. 3.

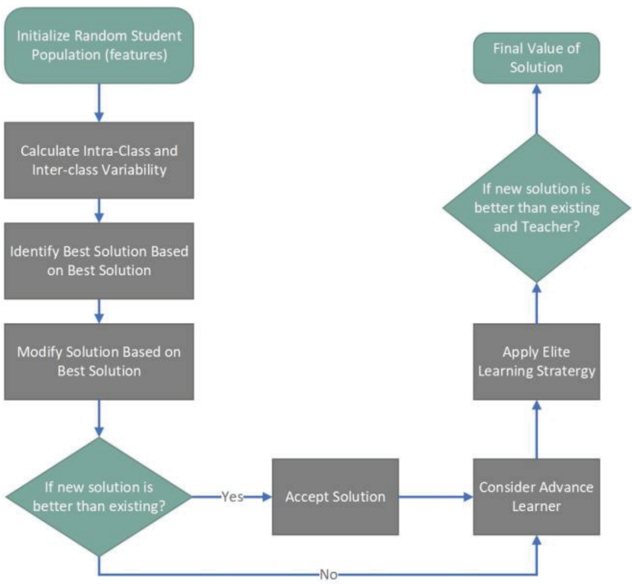

Fig. 3. Improved ELTLBO-based feature selection scheme

Teaching learning-based optimization (TLBO) is a population-based meta-heuristic optimization method that optimizes a given objective function by simulating a classroom setting.

The instructor/teacher works diligently in a classroom to ensure that every student is educated. The students then engage in self-interaction to refine and enhance their acquired information. This algorithm is divided into two stages: **Teacher stage:** Every student gains information and learns from the instructor.

Student Stage: Students engage in conversation with one another to exchange information. The traditional TLBO suffers from unguaranteed convergence, limited exploration and exploitation, sensitivity to initial solution, scalability challenges, and lack of robustness for higher-dimensional data. Thus, the proposed elite learning-based TLBO considers the knowledge-sharing strategy among elite learners, improving exploration and exploitation. Elite learning helps

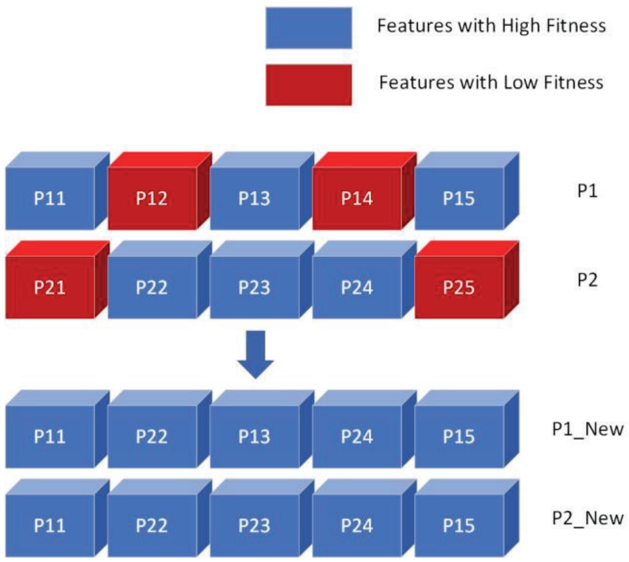

Fig. 4. Elite learning scheme for TLBO

to achieve better convergence compared with traditional TLBO. The representation of the elite learning strategy for TLBO is shown in Fig. 4. The algorithm for the EL-TLBO is given as follows:

Algorithm: EL-TLBO
Inputs: Random features positions
Output: optimized feature positions

1: Initialize a population of candidate solutions with random values.
Evaluate the fitness of each candidate solution in the population.
2: for n=1: max_iter
3: Sort the population based on fitness in ascending order
4: Calculate the mean of the best and worst solutions:
5: best_solution = population[0]
6: worst_solution = population[n-1]
7: mean_solution = (best_solution + worst_solution) / 2
8: For each solution in the population (excluding the best solution):
9: Generate a new solution by combining the current solution and the mean solution:
10: For end
new_solution = current_solution + rand() * (mean_solution - current_solution)
11: Evaluate the fitness of the new_solution.
12: Apply the proposed elite learning scheme

13: If the new_solution is better than the current solution:
14: Replace the current solution with the new solution.
15: Update the best_solution if necessary
16: End Repeat
17: Return the best_solution found.

D. Proposed Elite Learning Strategy

The elite learning strategy involves selecting and preserving the best-performing individuals, often called the elite individuals in each generation, to enhance the search process and improve the quality of the solutions. In optimization algorithms, the term elite refers to the top individuals with the highest fitness or objective function values. It helps to attain faster convergence, better balance in exploration and exploitation, well-optimized solutions, etc. The algorithm for elite learning is described as follows:

Algorithm: Proposed Elite Learning Strategy
Input: Two Elite Solutions, P1 and P2
Output: Global Best solution

1: Select two elite members from the top 5% of the population
2: E1: Random learner from the elite group
3: E2: Random learner from the elite group
4: If E1~=E2
5: Apply a knowledge-sharing strategy
6: Replace the weak members of one solution with strong members of the other solution to generate a modified new solution E1_new and E2_new
7: Calculate the fitness of updated E1 and E2
8: If fitness (E1_new)> Global_Best_fitness
9: Global_Best = E1_new
10: End
11: If fitness (E2_new)>Global_Best_fitness
12: Global_Best = E2_new
13: End

The flowchart for the proposed ELS scheme is shown in Fig. 5

E. PDCNN

The suggested PDCNN consists of three parallel DCNN layers with varying kernel sizes at each layer. Better feature distinctiveness is achieved using 3×3, 5×5, and 7×7 filter kernels at different arms, like the first, second, and third parallel arms. Each parallel arm includes three-layered DCNNs consisting of 32, 64, and 128 filters at each layer.

The DCNN provides the spatial features of the image. It gives the hierarchical features using a convolution operation. The convolution layer provides the connectivity features that help to characterize texture, edges, and more complex input image features. In this layer, the N convolution filters with a size of w × w are convolved with the input image. This layer helps acquire complex features of the input image. The ReLU activation function helps improve the non-linear nature of the convolution features. It replaces all negative values with 0. It assists in tackling the problem of vanishing gradient and accelerates the network training. The Batch Normalization (B.N.) layer standardizes the features by scaling and adjusting the activations. It supports minimizing the exploding or vanishing gradient problem during the training process.

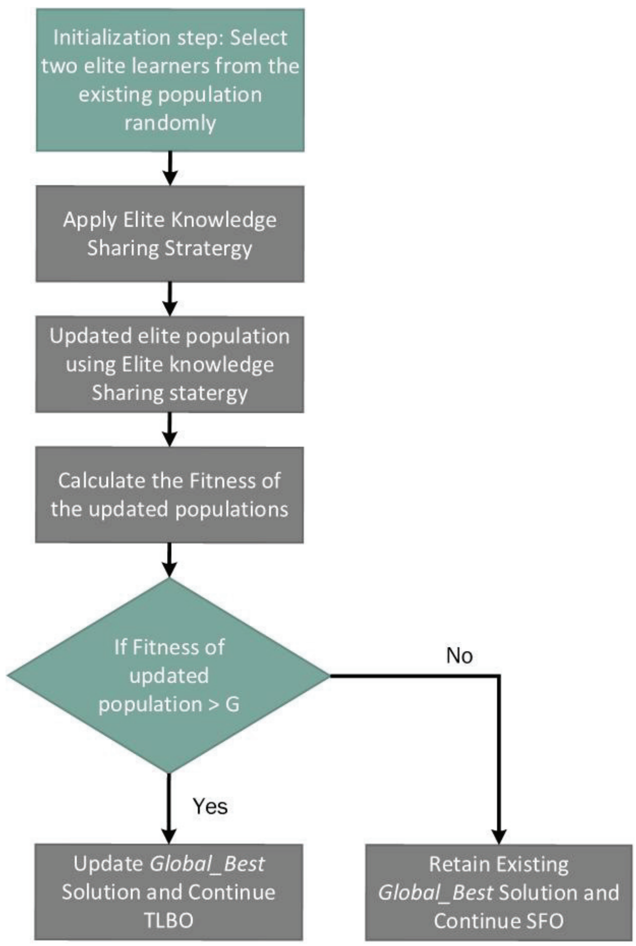

Fig. 5. Flowchart for the proposed ELS scheme

During the learning process, the B.N. layer normalizes the input by mathematically subtracting it from the mean of the batch taken and dividing it by the batch standard deviation.

Further, it shifts and scales the normalized values using learnable parameters such as beta and gamma. The B.N. layers speed up and stabilize the training process. The B.N. layer addresses the internal covariance shift, providing faster convergence and improved generalized performance. The MaxPool layer minimizes the spatial dimensions by selecting the maximum value from the 2 × 2 window. It helps reduce the network's computational complexity and regulates the overfitting. The maximum value from the non-overlapping region of 2 × 2 provides salient features that decrease the dimensions by exactly half their original size. The MaxPool layer provides translation-invariant hierarchical features. The equation for convolution operation is represented in equations 2 and 4, where Feat denotes the input features where Feat denotes the total features, w indicate the filter windows, z denotes the convolution filter output, σ stands for activation function, b denotes bias, and R indicate ReLU output.

$$z(n) = Feat(n) \times w = \sum_{m=0}^{i-1} Feat(m).w(n-m) \quad (2)$$

$$z_i^l = \sigma\left(b_i^l + \sum_j z_j^{l-1} \times w_{ij}^l\right) \quad (3)$$

$$R(z) = (0, z) \quad (4)$$

An FC layer, often called a dense layer, is employed to improve the connectivity of feature maps. In this, each neuron is connected to all other neurons of other layers. This layer helps for high-level reasoning and decision-making using extracted features. The SoftMax provides a probability distribution (S) for input vector z. The SoftMax function for components z_i is given as equation 5.

$$S(Z)_i = \frac{e^{z_i}}{\sum_j e^{z_j}} \quad (5)$$

The class with the most significant probability function is declared the final prediction.

IV. RESULTS AND DISCUSSION

The proposed system uses MATLAB-2023 on a computer with 20GB of RAM and a Windows operating environment.

A. Dataset: ABIDE-I

The ABIDE dataset consists of neuroimaging and phenotypic data gathered from 1,112 individuals. For detecting autism symptoms and examining possible biomarkers, it is the most data-driven method currently available. ABIDE-I's global multisite database comprises 1,112 structural, resting-state functional magnetic resonance imaging (fMRI) samples and phenotypic data from 16 sites. Five hundred seventy-three people without autism spectrum disorder (ASD) and 539 people with ASD make up these samples [27–30]. The experimentation for ASD detection with the proposed technique is performed on the ABIDE-I dataset [44]. The photos are shrunk to 128 by 128 pixels, allowing the computation to run more smoothly.

The parameter configuration of the suggested PDCNN is summarized in Table II.

TABLE II
PARAMETER CONFIGURATIONS OF PDCNN

Parameter	Specification
Learning Algorithm	Adam
Initial Learning Rate	0.001
Loss Function	Cross-entropy
Epoch	200

A. Discussion on Results

The accuracy, recall, precision, and F1-score of the proposed ASDD for different features selected using EL-TLBO for the ABIDE dataset are illustrated in Fig.6 to Fig 9. It is observed that the proposed model provides better results for the 800 features. Increasing the number of features enhances the accuracy of the system. For 100 features, the ELTBO-PDCNN provides an overall accuracy of 83.29%, whereas the TLBO-PDCNN provides an overall accuracy of 81.14%. The ELTLBO-PDCNN offers the highest accuracy of 96.71% for 800 features. Increasing the features beyond 800 increases the redundancy and non-salient features, which results in a significant drop in the overall accuracy of the system.

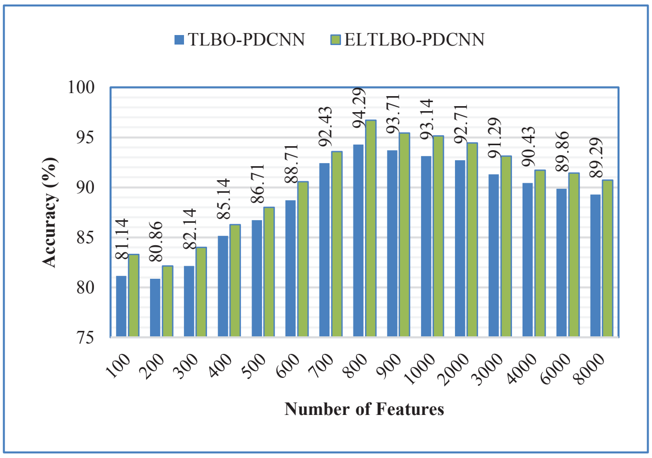

Fig. 6. Accuracy of proposed EL-TLBO-PDCNN for ASDD

The results of the Performance of PDCNN, PDCNN-TLBO, and PDCNN-ELTLBO are summarized in Table III.

The PDCNN-EL-TLBO provides an improved recall of 0.97, precision of 0.97, F1-score of 0.97, and accuracy of 96.71%. The feature selection helps to select the prominent features from the available features that minimize the complexity of the PDCNN. The elite learning helps improve the TLBO's convergence and provides a superior solution. It enhances the balance between exploring and exploiting the TLBO algorithm by utilizing the existing population. The better convergence and population diversity assists to choose the prominent set of the features having higher distinctive power. The results of the proposed scheme are compared with existing traditional techniques using CNN-based frameworks for the ASDD for the ABIDE-I dataset, as described in Table IV.

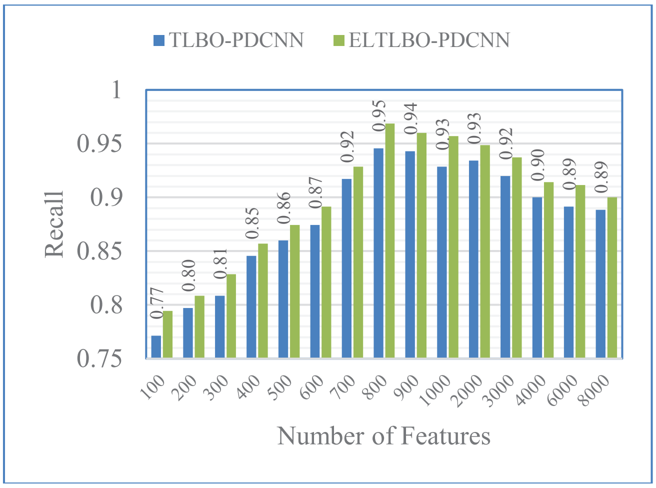

Fig. 7. Recall of proposed EL-TLBO-PDCNN for ASDD

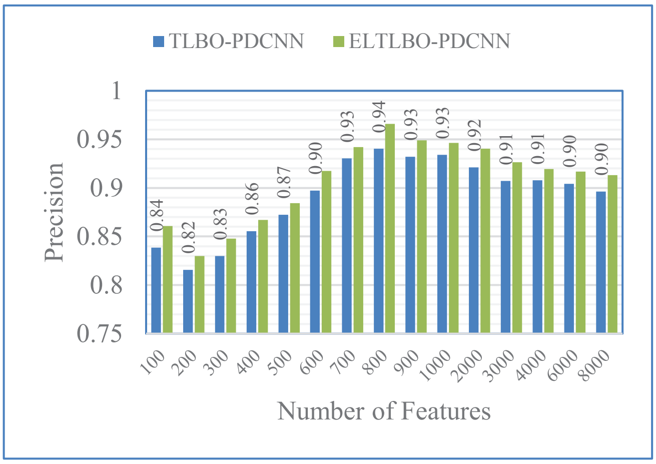

Fig. 8. Precision of proposed EL-TLBO-PDCNN for ASDD

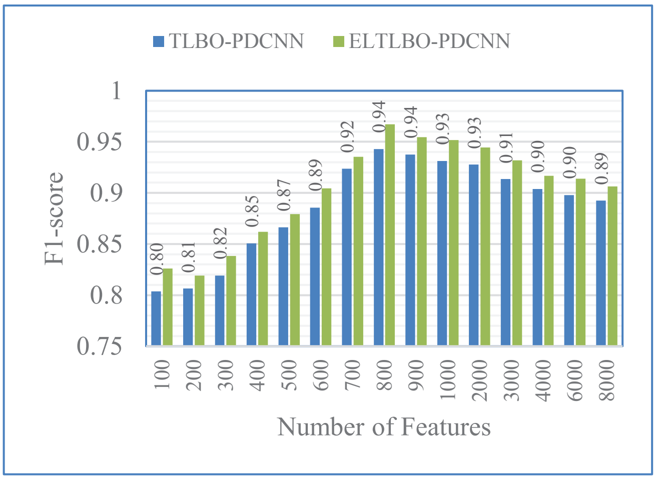

Fig. 9. F1-score of proposed EL-TLBO-PDCNN for ASDD

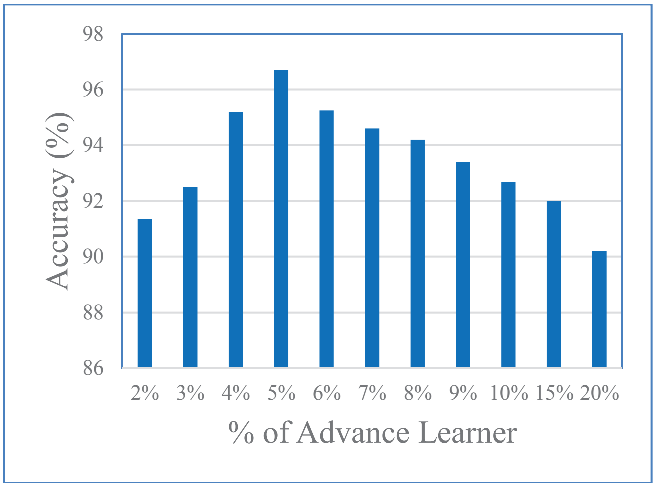

Fig. 10. Effect of % of advanced learners for elite learning

TABLE III
PERFORMANCE OF PDCNN, PDCNN-TLBO AND PDCNN-ELTLBO

Algorithm	Precision	Recall	F1-score	Accuracy
PDCNN	0.91	0.90	0.91	90.71
PDCNN-TLBO	0.95	0.94	0.94	94.29
PDCNN-EL-TLBO	**0.97**	**0.97**	**0.97**	**96.71**

Wang et al. (2020) used MLP with Ensemble Learning, achieving 74.52% accuracy, while Heinsfeld et al. (2018) and Dvornek et al. (2017) applied DNN and RNN-LSTM, obtaining 70% and 68.50%, respectively, without reporting parameters.

Rajat Mani Thomas et al. [23] used 3D CNN with 62% accuracy and 257,585 parameters, whereas Zeinab Sherkatghanad et al. [20] employed Parallel CNN, achieving 70.22% accuracy with 4,398,802 parameters. Faria Subah et al. [25] applied DCNN, reaching 88% accuracy without parameter details. Ahmad et al. [34] used ResNet50 with the highest accuracy of 92% but required 23M parameters. Awate et al. applied LR, achieving 67% accuracy, while Jayprakash et al. used MLR, reaching 89%, with no parameter details.

Subtirelu et al. [36] highlight the potential of neuroimaging modalities in elucidating the neural correlates of ASD. Results imply that integrating neuroimaging data with cutting-edge analytical methods may improve ASD early diagnosis and intervention tactics. Prasad, V et. al. [37] got the accuracy of 98.6 % using the Hybrid Sewing Training Optimization (HSTO) algorithm in detecting ASD from brain MRI images. Saranya, A et al. [39] used the integration of facial and gait features, which addresses the limitations of traditional behavioral assessments, offering a more objective and quantifiable approach to ASD detection with 95% accuracy.

Jain et al. [40] presented an approach that integrates advanced preprocessing, feature extraction, and classification techniques to achieve a high diagnostic accuracy of 99.8%. Mayan Mishra et al. [41] applied Real-time augmentation techniques during training to increase data diversity and prevent overfitting and got an accuracy of 95.7%. Reddy P et al. [42] used EfficientNetB0 with 87.9% accuracy with 138 M trainable parameters.

This comparison highlights the trade-off between accuracy and model complexity. The proposed PDCNN with a 3-parallel layer provides 92.50% accuracy. The PDCNN helps to improve the feature distinctiveness, generalization capability, multi-level features, and representation capability.

The feature selection scheme using TLBO helps to select the crucial features and gives enhanced accuracy of 94.29%. The PDCNN-TLBO provides noteworthy improvement over the PDCNN for 800 features.

TABLE IV
COMPARISON OF THE PROPOSED METHODOLOGY WITH THE EXISTING STATE OF THE ART

Author and Year	Method	Accuracy (%)	Total Trainable Parameters
Heinsfeld et al. (2018) [18]	DNN	70	-
Zeinab Sherkatghanad et al. (2020) [20]	Parallel CNN	70.22	4398802
Wang et al. (2020) [21]	MLP and Ensemble Learning	74.52	-
Dvornek et al. (2017) [22]	RNN-LSTM	68.50	-
Rajat Mani Thomas et al. (2020) [23]	3D CNN	62.00	257585
Faria Subah et al., (2021) [24]	DCNN	88	-
Jayprakash et al. (2024) [30]	MLR	89	-
Awate et al. (2024) [31]	LR	67	-
Ahmad et al. (2024) [34]	ResNet50	92	23000000
Prasad, V et. al (2023) [37]	HSTO	98.6	62000000
Saranya, A et. al. (2022) [39]	VGG-Net	95	16000000
Mayank Mishra et al. (2023) [41]	DCNN	95.7	-
Reddy P et al. (2023) [42]	EfficientNetB0	87.9	13800000
Proposed Method	PDCNN (3L)	92.50	3245184~ 3.24 M
Proposed Method	PDCNN+TLBO	94.29	1862784 ~ 1.86 M
Proposed Method	PDCNN+EL-TLBO	96.71	

The elite learning scheme for the TLBO-based feature selection provides a better balance between exploiting and exploring the TLBO population. It efficiently uses the elite population to achieve better fitness. The PDCNN-EL-TLBO delivers 3.94% and 2.56% improvement over PDCNN and PDCNN-TLBO, respectively. The PDCNN needs a total of 3.24M trainable parameters for 8000 features and lower 1.86 M trainable parameters for 800 features selected using EL-TLBO and TLBO algorithms—the feature selection based on EL-TLBO helps to minimize the computational intricacy of the system.

V. CONCLUSION AND FUTURE SCOPE

The article presents the ASDD system focusing on preprocessing, feature extraction, feature selection, and deep feature representation. The novel IDSGWF assists in enhancing the quality of the MRI images by minimizing blur, noise, contrast, and uneven illumination. It helps to improve the texture, smoothness, edges, and contrast of the MRI images. Further, the texture features using GLCM, LBP, and LDP describe the abnormalities caused by fMRI due to ASD. The shape features using HOG depict the changes in the shape of the volume, corpus callosum, and other parts of the brain. The TLBO-based feature selection scheme selects the crucial features and helps reduce the computational intricacy of the system. The PDCNN architecture provides better feature representation, superior generalization capability, and a better correlation between fMRI images' global and local characteristics to depict autism.

Future improvements to the suggested PDCNN for massive data may enhance ASD detection accuracy precisely. We may analyze the system's ability and performance in natural settings to generalize the suggested technique using dataset samples. The proposed method may be tested for different genders and ages. The PDCNN approach may also categorize ASD grades and assess illness risk and severity. In the future, the performance of the proposed system can be evaluated and validated on real-time MRI images.

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