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DYNAMIC ADAPTIVE WITH ANT LION OPTIMIZATION FOR AUTISM DISORDER FACIAL IMAGE CLASSIFICATION

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ABSTRACT

Autism Spectrum Disorder (ASD) is a complex neurodevelopmental disorder that affects social interaction and communication with others. However, similarity among facial images of individuals with autism impacts the classification accuracy and difficult for the model to effectively learn the images. In this research, a proposed Dynamic Adaptive Boundary Adjustment with Ant Lion Optimization (DALO) and Softmax loss to enhance performance of Convolutional Neural Network (CNN) for classification. DALO effectively balances exploration and exploitation, optimizing the search of hyper parameter space in SCNN. The SCNN technique enhances loss function by using softmax to address overfitting. The softmax loss function is used by optimization algorithm to update model weights during training. The Autistic Children dataset (ACD) and ASD Dataset and pre-processing to ensure all pixel values contribute equally during learning process. Feature extraction using MobileNetV2 which utilizes depth-wise while maintaining model capacity. The proposed DALO-SCNN method achieves a precision of 0.982, recall of 0.98 and f1-score of 0.93 and accuracy 97% on ACD dataset. The SCNN method achieves better accuracy of 93.12%, precision of 92.56% of precision, 92.01% of recall and 92.25% of f1-score on ASD dataset, when compared to the existing methods such as CNN and ResNet 50 techniques.

Keywords: *Ant Lion Optimization, Autistic Children Facial Dataset, Autism Spectrum Disorder, Convolutional Neural Network, MobileNetV2*

1. INTRODUCTION

Autism Spectrum Disorder (ASD) is crucial for early planning in special education, treatment, family support, and providing appropriate medical care for both children and adults [1]. Diagnosing and treating ASD is a major global public health concern that has attracted considerable attention. The main cause of ASD remains unknown, with diagnosis highly dependent on behavioral assessments and diagnostic scales [2]. Common behavioral issues in ASD patients include impaired expressive gestures, lack of responsiveness to sound, inadequate eye contact, insensitivity to pain and agitation with changes in daily routines [3]. Of the various theories about the causes of ASD, like the extreme male brain theory and the protective effect of female brains, there is no definitive cure exists. The diagnosis and treatment process for ASD is lengthy and complex. [4, 5]. The process is labor-intensive and costly, requiring both skilled and unskilled workers [6]. Additionally, symptoms of ASD are often subtle and challenging to recognize, especially in young children, making effective communication with autistic children a critical aspect of treatment [7].

To address these issues, Deep Learning (DL) methods are increasingly being used to analyses ASD in children [8]. There is a pressing need for an intelligent, automated detection tool that enhances efficiency and accuracy in classifying ASD images [9]. Children with ASD often struggle with social interactions, particularly with verbal communication aspects such as eye contact and sharing facial expressions [10]. However, ASD images contain a wide range of data due to the overlapping nature of symptoms. [11-12]. The identification of diagnosis using the ACD and ASD Dataset involved complex and challenging image classification [13]. The pre-processed image involves extracting various features using a pre-trained model to efficiently analyses ASD images [14]. These features are used to analyses ASD data and explore treatment options by identifying functional patterns to distinguish between autism and non-autism [15]. However, similarity among facial images of individuals with autism affects classification accuracy of classification, making it challenging to derive meaningful insights from these images. In this research, a proposed method called Dynamic Adaptive Boundary Adjustment with Ant Lion Optimization (DALO) and Softmax loss is used to enhance the Convolutional Neural Network (SCNN) for improved classification accuracy. DALO effectively balances exploration and exploitation, optimizing the hyper parameter space and making it suitable for tuning SCNN hyper parameters. The SCNN enhanced loss function helps manage overfitting, while the softmax loss provides gradients that the optimization algorithm uses to update model weights during training.

The main contributions of this research are considered as follows:

- MobileNetV2 performs feature extraction, particularly for mid-level features and the shape of ASD facial images, enabling effective feature extraction.
- The proposed DALO provides a balanced approach to global exploration, making it effective for searching the hyper parameter space and tuning CNN hyper parameters.
- Enhancing CNN with the softmax loss function helps manage overfitting, while the softmax loss provides gradients for optimization algorithm to update model weights during training.

The paper is organized as follows: Section 2 provides a literature review that summarizes ASD classification. Section 3 introduces the proposed method utilized by DALO-SCNN. Section 4 discusses the result and comparative analysis. The conclusion of this research is given in Section 5.

2. LITERATURE REVIEW

This research conducts studies on ASD facial image classification, providing insights into various techniques along with their advantages and limitations.

Mouatasim and Ikermane [16] presented a DL-based Convolutional Neural Network (CNN) to classify facial images as indicative of ASD, involving the Dense Net model for classifying facial images. This connectivity pattern of the dense net allows for better feature propagation as each layer accesses features from all preceding layers, thus improving the network's ability to learn discriminative features. However, Dense Net connection requires large amounts of data to train on ASD and the bottleneck approach results in the loss of essential features, leading affect the classification accuracy.

Elshoky et al. [17] designed a classification model autism spectral disorders based on automated ML algorithms. The designed automated ML approaches utilized for identification and classification of autism from the facial images with help of pipeline optimization. The main advantage of the designed automated ML model extracts complex features from facial images effectively without manual intervention which results in improve classification process. However, the feature selection for autism classification by automated ML approaches was done by manually, which failed to capture features with subtle differences that lead to inaccurate classification.

Alkahtani et al. [18] developed a DL based model to identify autism spectrum disorder by facial images. The developed pre-trained models such as Visual Graph Geometry (VGG-19), MobileNET-v2 and CNN with various ML algorithms to assess the performance. The main advantage of the developed model that adapts variations in facial images like lighting, angles, and face expression that results in increase classification performance. However, the developed pre-trained models with poor hyper parameter tuning lead to suboptimal results that impact on accurate classification results.

Ahmad et al. [19] presented an ASD classification using various pre-trained CNN-based techniques such as ResNet, Mobile Net and VGG 16 &19 to diagnose ASD. This was the construction of the DL technique adjusted for different performance accuracy and helped to analyses the facial image efficiently to access the ASD classification. However, insufficient training data leads to overfitting, making it challenging to learn the facial features due to the similarity of the disorder and complex to learn the feature.

Shinde and Patil [20] introduced facial image identification for ASD classification in young children, analyzing their behaviors using DL-based CNN techniques. The introduced method automatically classifies the essential feature and allows parameter sharing across the entire image. However, CNN requires high computational power and large amounts of labelled data. Limited data hinder the effectiveness of classification and insufficient training data reduces the accuracy of ASD image classification.

For overall analysis, existing techniques struggle with similarity among facial images of individuals with autism, which affects classification accuracy and makes learning from this image challenging. This research proposed the DALO method and Softmax loss to enhance the SCNN for improved classification accuracy. DALO balances exploration and exploitation, effectively searching the hyper parameter space, making it well-suitable for tuning SCNN hyper parameters.

3. PROPOSED METHODOLOGY

In this section, proposed DALO with SCNN method effectively analyses the facial image and achieves high accuracy of the ASD. Initially, data from the ACD & ASD dataset is acquired and pre-processed through normalization, resizing and augmentation of autistic image of children diagnosed.

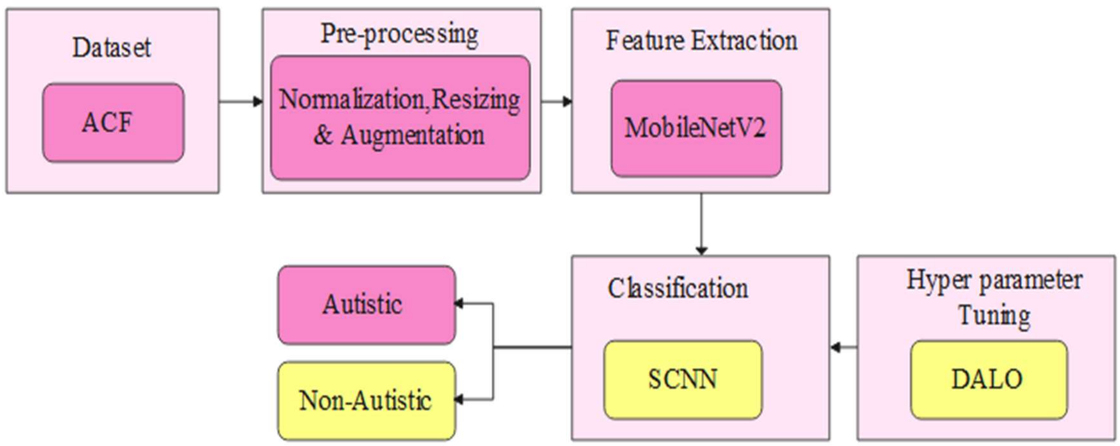

Figure 1: Block diagram of the proposed method

The feature extraction is performed efficiently using MobileNetV2, focusing on extracting mid-level features, facial, shape and expression for classification. Hyper parameter tuning is conducted with DALO algorithm, which balanced exploration to avoid the local optimal and achieve high accuracy. The SCNN technique is involved in classification, enhancing the softmax loss function to address overfitting and achieve high accuracy of facial image classification. Figure 1 shows block diagram of proposed method.

3.1Data collection

The ACD [21] dataset contains 2,936 images with labels for two classes: autistic and non-autistic children. This dataset is appropriate for younger individuals and includes pictures of both girls and boys. Almost every image is captured with the subject posing straight-faced in front of the camera. There are consider the 224x224 pixels with two class labels. The images come in two different sizes: 224x224 pixels with two class labels

The ASD [22] dataset was used where it was physically divided into 2 phase, training and testing and divided into ratio of 80:10:10 with 80%, 10%, 10% for training, testing and validation. The autistic and non-autistic class had 147 image and total image is 2940 image. The each subfolder contained 100 images $224 \times 224 \times 3$ in size in a jpg format. The dataset contained 2940 image where 1327 image were of autistic children and 1613 were of non-autistic children. Figures 2 and 3. Sample image of ACD and ASD dataset.

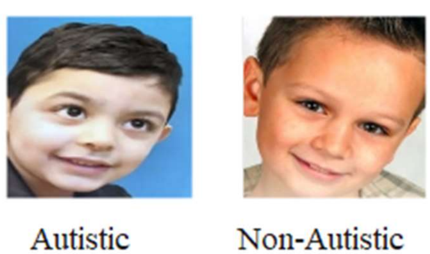

Figure 2: Sample image of ACD dataset

Figure 3: Sample image of ASD dataset

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3.2Pre-processing

The collected data undergoes normalization, resizing and augmentation and is sequentially applied to the facial image of the children diagnosed with ASD [23]. The image has been augmented using flipping and rotation techniques to maximize the size of training data.

3.2.1 Normalization

The data normalization [23] using Z-score is considered to mean and standard deviation measures. The instance, $x'_{i,n}$ as follows and different features or pixel values in an image have different ranges. Normalization rescales the pixel values to the standard range, usually between 0 and 1 or -1. The mathematical formula for min-max normalization is given in Equation (1),

$$x'_{i,n} = \frac{x_{i,n} - \mu_i}{\sigma_i} \quad (1)$$

In the above a (1), μ and σ denoted the mean and standard deviation of ith feature respectively.

This normalized image ensures that all pixel values contribute equally during the learning process and prevent features with large scales from the model training.

3.2.2 Data augmentation

Data augmentation is essential in enhancing machine learning performance, especially in facial image analysis where labelled data is limited or when the model's ability to generalize is crucial. By applying transformations like rotation, scaling and flipping, data augmentation significantly increases effective dataset size by generating multiple variations of the original image. This process allows the model to learn a broader range of patterns and representations. Additionally, resizing ensures that all images have consistent dimensions, which is typically required by the input layer of a neural network.

3.3Feature extraction

The augmented image is involved in the feature extraction using MobileNetV2 [24] a state-of-the-art network architecture. This process utilizes a depth-wise separable Convolutional (Conv) layer to extract Mobile Net V1, offering greater efficiency by involving depth-wise separable Conv. In this approach, the Conv layer is split into a depth-wise convolution and a pointwise Conv of size 1×1, which is combined to create the depth-wise separable Conv block, which functions similarly to a traditional CNN structure. The architecture includes a global average pooling layer followed by either a fully connected layer or 1×1 Conv layer with a softmax function for classification. A depth multiplier controls the amount of channels in each layer further enhancing network efficiency.

The structure of MobileNetv2 building blocks includes residual connections and consists of three Conv layers. This first layer is an 1×1 Conv expands number of channels; the next layer is a depth-wise separable Convolution layer and a third layer is channels which reduces the number of parameters. MobileNetV2 consists of 17 such building blocks followed by a standard 1×1 Conv layer, a global average pooling layer and a classification layer. The extracted features are then fed into the classification layer to improve accuracy.

3.4Classification

The ASD facial classification using the DALO-SCNN technique is performed efficiently to achieve better accuracy. The hyper parameter turning using DANO efficiently updates the optimal solution from local to global and manages the iteration with limited data to evaluate the iteration. The population parameters are adjusted based on the CNN iteration count. The SCNN techniques enhance the softmax loss function to reduce overfitting during the training of essential facial images leading to achieving high accuracy. The hyper parameter tuning helps achieve high accuracy by optimizing iteration, epochs and batch size.

3.4.1 Optimizing Hyper parameter tuning using Ant Lion Optimization

The hyper parameter tuning using the DALO algorithm helps to perform balance exploration and exploitation, leading to fast convergence, and reducing training time and computational resources. Figure 4 shows the overall process of classification.

The DALO algorithm improved the exploration and achieved high classification accuracy while effectively handling local optima.

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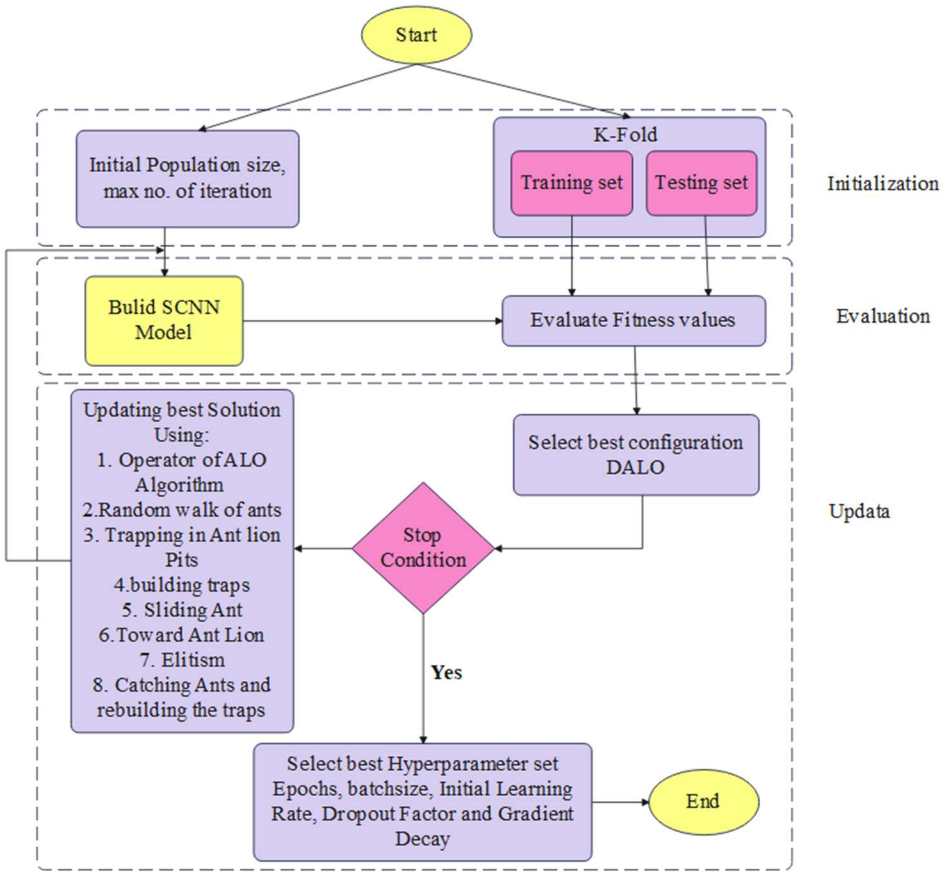

Figure 4: The overall process of classification

3.4.1.1 Operators of ALO algorithm

The ALO algorithm is interaction between ant lions and ants in traps that interactions ants are required to move over search space. The modelling of ants' movement and their random walks is defined by Equation (2).

$$Y(t) = [0, cumsum(2r(t_1) - 1, \ldots\ldots, cumsum(2r(T) - 1)] \quad (2)$$

Where, arbitrary walk of ants in exploration space shown in Equation (2) and $cumsum$ is phase length, t denoted the phase of the arbitrarily walk, T denoted increase iteration, $r(t)$ denoted the arbitrary function expressed by Equation (3).

$$r(t) = \begin{cases} 1, rand > 0.5 \\ 0, rand \leq 0.5 \end{cases} \quad (3)$$

The velocity of ants are stored and used during optimization process $rand$ denoted an arbitrary solution between zero and one and iteration of position and fitness of antlion and other ants are contained by n is represented matrix.

3.4.1.2 Random Walks of Ants

The ant changes their position for exploration of the space in lion walk arbitrarily and it is expressed the Equation (4) which is effectively performed in the hunt because it changes the place frequently for the hunting process.

$$Y_i^t = \frac{(Y_i^t - a_i)(d_i^t - c_i^t)}{(b_i - a_i)} + c_i^t \quad (4)$$

Where, a_i and b_i denoted minimum and maximum of the arbitrarily walk of ith parameter, d_i^t and C_i^t are denoted parameters of the upper and lower bound of arbitrarily walk of iteration.

3.4.1.3 Trapping in Ant Lion Pits

Antlions build traps by considering the roulette selection of antlions to optimize the fitness function using the accuracy performance achieve better in other optimization. Roulette selection helps to improve the chance of encountering different antlions, thereby increasing population diversity. However, this approach leads to local optima, affecting the random movement of ants and dynamic is described by Equations (5) and (6).

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$$C_i^t = AntLion_i^t + c^t \quad (5)$$

$$d_i^t = AntLion_i^t + d^t \quad (6)$$

Where, $AntLion_i^t$ denoted position of ith antlion at iteration of tth, d_i^t and $C_i^t$are considered upper and lower bound of every parameter has iteration of tth respectively.

3.4.1.4 Building Trap

The roulette wheel is used to model the ability of the ant lion which involves roulette wheel operator selecting the ant lion based on fitness (accuracy) during iteration. The mechanism shows better ant lion for catching ants.

3.4.1.5 Sliding Ants Towards Ant Lion

The Sliding behavior of ants towards the antlion, preventing them from escaping boundary of trap and adapting to local optima is expressed by Equations (7) to (10) shown below.

$$c^t = \frac{c^t}{I} \quad (7)$$

$$a^k = \frac{a^k}{I} \quad (8)$$

$$I = 10^w \frac{t}{T} \quad (9)$$

$$w = \begin{cases} 2, t > 0.1T \\ 3, t > 0.5T \\ 4, t > 0.75T \\ 5, t > 0.9T \\ 6, t > 0.95T \end{cases} \quad (10)$$

Where, t denoted recent iteration, T denoted higher iteration and w indicated constant fixed on by iteration.

3.4.1.6 Elitism

The Elitism Strategy is an essential part of ALO during in elitism process in antlion to fit from every iteration and then handle other lion. The elite antlion influences arbitrary walks of ants during in-position iteration and chooses the roulette of the circle to hurt the other animal that is expressed in Equation (11).

$$Ant_i^t = \frac{R_A^t + R_E^t}{2} \quad (11)$$

Where, Ant_i^t denoted position of the ith position, tth denoted the iteration, R_A^t and R_E^t are arbitrarily walk in the velocity around antlion choose by roulette circle of elite.

3.4.1.7 Catching Ants and Rebuilding Traps

When an ant is caught by an antlion, its new position is updated. If the ant achieves maximum fitness then the corresponding antlion captures prey, replaces its position with ant's position, and rebuilds its trap. This process is shown in Equation (12).

$$Antlion_j^t = Ant_i^t if\ f(Ant_i^t) > f(Antlion_j^t) \quad (12)$$

Where new traps have large modifications to catch ants to expressed by Equation (12).

3.4.2 Dynamic adaptive Boundary Adjustment with Ant Lion Optimization Algorithm

The dynamic adaptive boundary adjustment of ant lion trap, which is adjusted step-by-step around elite ants, ensures convergence of optimization process. This leads to a loss of population diversity and results in algorithm falling into local optima, thereby diminishing its global exploration ability. The improved algorithm avoids falling into local optimum and enhances convergence precision. The dynamic strategy adjusts size of trap boundary, decreasing linearly as the number of iterations approaches its maximum. This adjustment is described by equations (7) to (10) with Equation (9) specifically addressing boundary adjustment to improve the performance as detailed in Equation (13).

$$I = 10^w \frac{t}{T} * \left(1.5 - \cos\left(\frac{t\pi}{2T} * rand\right)\right) \quad (13)$$

Where, rand is the arbitrary number of the uniformly distributed numbers between the (0,1). The ant lion adjusted the proportion and used roulette selected by ants at various phases. The weight is defined by Equations (14) and (15).

$$\delta = \delta_{max} - t\frac{\delta_{max} - \delta_{min}}{T} + \xi * rand \quad (14)$$

$$Ant_i^t = \frac{(2-\delta) * R_A^t + \delta * R_E^t}{2} \quad (15)$$

Where, $rand$ is the arbitrarily stable transfer between (0,1) and enhanced expression to include a dynamic variable, which makes the size of the trap boundary show a non-linear is minimized. The dynamic range is adjusted to the trap boundary of diversity and global exploration ability in ALO and selected 1020 feature selected by the optimization approach. The weighted elitism in the ALO algorithm balances wandering weight during different phases, effectively enhancing algorithm exploration capabilities.

3.4.3 Softmax Convolutional Neural Network

The classification using SCNN effectively extracts the mid-level distinct feature from facial images, leading to high accuracy. The neural network involves various layers to analyses each facial image and the large number of neurons in these layers result in a vast number of parameters.

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Managing these large parameters is crucial, as it leads to overfitting, especially when the training data is insufficient. To mitigate overfitting, it is essential to train the model with a sufficient amount of data. In hyper parameter tuning range such as epochs of 30-500, batch size of 25-40, Dropout factor of 0.1-0.5, Gradient Decay of 0-1 and Initial Learning Rate of 0.2-0.5 range is consider in the optimization approach for learning efficiently in classification. The softmax loss enhances the performance of the method focus on the class individual for facial image and it is expressed by Equation (16) shown below.

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N} log \frac{e^{w_{yi}^{T} x_i^{\theta_i} + b_{y_i}}}{\sum_{j=1}^{M} e^{w_{yi}^{T} x_i^{\theta_i} + b_{y_i}}} \quad (16)$$

Where, $\mathcal{L}$ denoted the loss function and mini-batch and the number of classes is N and M. Normalized deep feature of ith sample is $X_i^{\theta_i}$, y_i is the class of the ith sample and column of the weights in the previous connected fully layer is W_j, T represents the transpose and bias term is b respectively. The cross-entropy technique is involved to prevent overfitting during training, while regularization techniques are used to improve the model accuracy in classification. This approach helps avoid both overfitting and under fitting in the training data, thereby enhancing the model's performance in facial image classification as expressed in Equation (17).

$$R(W_j) = \frac{\lambda}{N} W_j^2 \quad (17)$$

Where, coefficient of the weight and parameter isW_j, the regularization parameter is λ and the number of samples is N respectively. The identified autistic facial image is modified for the identification of loss to evaluate the softmax function. The softmax is modified and used as a loss function to resolve the overfitting in the facial image, its mathematical formula is in Equations (18) and (19) shown below.

$$EI(W_i) = -\frac{1}{N}\sum_{n=1}^{N} 1\{y_n = n\} log \frac{\exp(W_{i,n}^{T} \cdot x_n)}{\sum_{m=1}^{M} \exp\left(W_{i,n}^{T} \cdot x_n\right)} + \frac{\lambda}{N} W_i^2 \quad (18)$$

$$EI(W_i) = MI(W_i) + R(W_i) \quad (19)$$

Where, the number of the samples is N and M is classes, fusion feature from the CNN for queried image is x_n and y_n is the queried image of mapped. The learned coefficients of W_i and transpose is T and regularization parameter is λ and regularization of loss is the $R(W_i)$ respectively.

4. EXPERIMENTAL RESULT

In this research, the DALO-SCNN technique is simulated using MATLAB (R2020b), RAM: 16 GB, PROCESSOR: INTEL i5, OPERATING-OS: Windows 10, GPU: 6 GB, SSD: 1TB. The performance measures used for evaluating the different optimization and classification are explained in section 4.1. The performance of the proposed method is calculated using various performance metrics, like Accuracy, Precision, F1-score, and Recall, [13] respectively.

4.1 Performance analysis

In this section, the proposed DALO-SCNN approaches is evaluated with several performance metrics like Accuracy, F1-score, Recall and Precision, which are presented in Tables 1 - 3. The performance of various optimization techniques on the ACD and ASD dataset is evaluated based on accuracy, F1-score, recall and precision which are defined by equations (20) to (23) as shown below. The existing methods using various optimization techniques such as PSO, BWO, ABO and ALO are evaluated. The DALO technique achieves a precision of 986%, recall of 98% and f1-score of 90% and accuracy 97% on ACD dataset. The SCNN method achieves better accuracy of 93.12%, precision of 92.56% of precision, 92.01% of recall and 92.25% of f1-score on ASD dataset.

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (20)$$

$$Precision = \frac{TP}{(TP + FP)} \quad (21)$$

$$F1 - score = 2 * \frac{(Precision * Recall)}{Precision + Recall} \quad (22)$$

$$Recall = \frac{TP}{TP + Fn} \quad (23)$$

Where, TP, TN, FP, and FN illustrate True Positive, True Negative, False Positive, and False Negatives respectively.

Table 1: Performance analysis of various optimization on the SCNN algorithm on datasets

Methods	Dataset	Accuracy (%)	Recall (%)	F1-score (%)	Precision (%)
PSO	ACD	93	90	86	94
BWO		94	91	87	95
ABO		95	96	88	96
ALO		96	97	89	97

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DALO		97	98	90	986
PSO	ASD	89.06	88.23	88.03	88.64
BWO		90.78	89.36	89.13	89.53
ABO		91.48	90.78	90.86	90.79
ALO		92.53	91.45	91.45	91.43
DALO		93.12	92.01	92.25	92.56

In this section, classification using SCNN technique is evaluated with several performance metrics like Accuracy, F1-score, Recall and Precision, which are presented in Tables 2 based dataset. The existing methods using classification techniques such as CNN, RNN, DNN, MLP evaluated. The SCNN method performed efficiently after feature selected 1020 feature fed to classification, it achieves a precision of 986%, recall of 98% and f1-score of 90% and accuracy 97% on ACD dataset. The DALO achieves better accuracy of 93.12%, precision of 92.56% of precision, 92.01% of recall and 92.25% of f1-score on ASD dataset is given in Table 2.

Table 2: Performance analysis of classification using DALO on datasets

Methods	Dataset	Accuracy (%)	Recall (%)	F1-score (%)	Precision (%)
CNN	ACD	93	90	86	94
DNN		94	91	87	95
RNN		95	96	88	96
MLP		96	97	89	97
SCNN		97	98	90	986
CNN	ASD	89.06	88.23	88.03	88.64
DNN		90.78	89.36	89.13	89.53
RNN		91.48	90.78	90.86	90.79
MLP		92.53	91.45	91.45	91.43
SCNN		93.12	92.01	92.25	92.56

In this section, the proposed DALO-SCNN method is evaluated with several performance metrics like Accuracy, F1-score, Recall and Precision, which are presented in Tables 3. The performance of various optimization techniques on the ACD and ASD dataset is evaluated based on accuracy, F1-score, recall and precision as detailed in Table 3 The existing methods using various optimization techniques such as CNN, RNN, PSO-CNN, BWO-RNN are evaluated. The SCNN achieves precision of 986%, recall of 98% and f1-score of 90% and accuracy 97% on ACD dataset. The SCNN method achieves better accuracy of 93.12%, precision of 92.56% of precision, 92.01% of recall and 92.25% of f1-score on ASD dataset.

Table 3: Performance analysis of proposed method on datasets

Methods	Dataset	Accuracy (%)	Recall (%)	F1-score (%)	Precision (%)
CNN	ACD	93	90	86	94
RNN		94	91	87	95
PSO-CNN		95	96	88	96
BWO-RNN		96	97	89	97
DALO-SCNN		97	98	90	986
CNN	ASD	89.06	88.23	88.03	88.64
RNN		90.78	89.36	89.13	89.53
PSO-CNN		91.48	90.78	90.86	90.79
BWO-RNN		92.53	91.45	91.45	91.43
DALO-CNN		93.12	92.01	92.25	92.56

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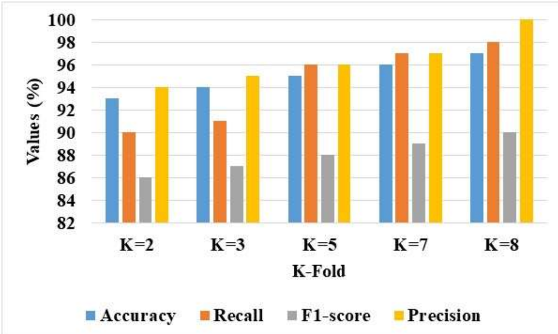

Figure 5: Graphically represented DALO-SCNN method with K-fold values on ACD dataset

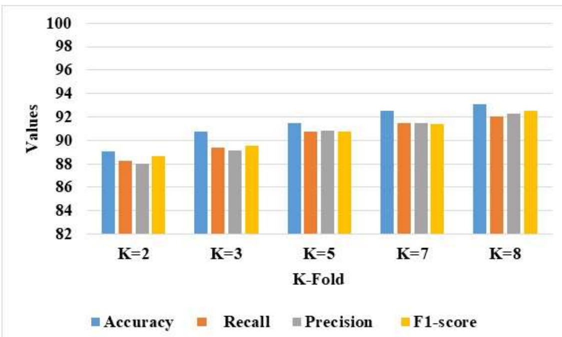

Figure 6: Graphically represented DALO-SCNN method with K-fold values on ASD dataset

Figure 5 & 6 illustrates the classification outcomes of the proposed method using various performance metrics on the ACD and ASD dataset, evaluated with different K-fold values. The analysis shows that the DALO-SCNN method combined with statistical techniques achieves the best performance when the K-fold values are set to 5, respectively.

Figure 7 and 8 displays the results of the ROC which are the crucial parameters in ACD and ASD dataset for DALO-SCNN classification. The ROC curve visually represents the performance by comparing the false and true positive rates. The proposed method significantly outperforms other existing methods.

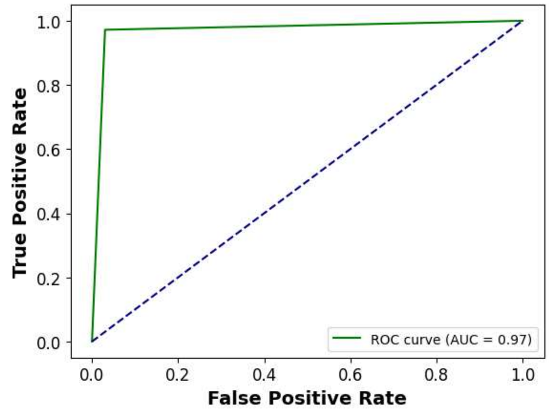

Figure 7: Graphical representation of ROC curve on ACD dataset

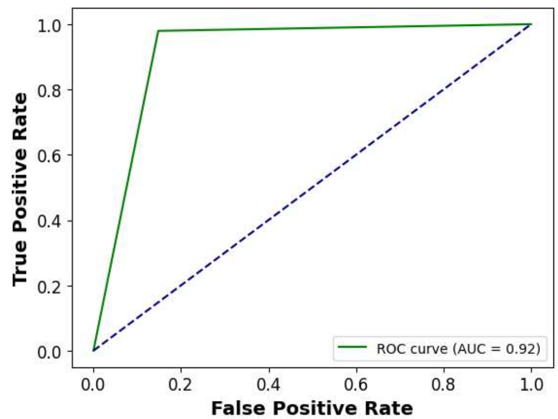

Figure 8: Graphical representation of ROC curve on ASD dataset

4.2 Comparative analysis

The performance of proposed method DALO-SCNN technique is compared to existing methods, including DenseNet121 [16], AutoML [17], CNN [18] and ResNet 50 [19]. In this research, the proposed DALO-SCNN method achieves a precision of 0.982, recall of 0.98 and f1-score of 0.93 and accuracy 96% on ACD dataset. The SCNN method achieves better accuracy of 93.12%, precision of 92.56% of precision, 92.01% of recall and 92.25% of f1-score on ASD dataset. Table 4 to 6 presents a comparative analysis of the proposed method.

Table 4: Comparative analysis of proposed method on ACD dataset using accuracy metric

Methods	Accuracy (%)
DenseNet 121 [16]	91
AutoML [17]	96
Proposed DALO-SCNN method	97

Table 5: Comparative analysis of proposed method on ACD dataset to evaluated the performance metric

Methods	Recall	F1-score	Precision
DenseNet 121 [16]	0.97	N/A	0.98

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Proposed DALO-SCNN method	0.98	0.90	0.986

Table 6: Comparative analysis of proposed method on ASD dataset

Methods	Accuracy (%)	Recall (%)	F1-score (%)	Precision (%)
CNN [18]	92	92	92	92
ResNet 50 [19]	92	N/A	N/A	N/A
Proposed DALO-SCNN method	93.12	92.01	92.25	92.56

4.3 Discussion

The advantages of the proposed DALO-SCNN technique are discussed in this section. The DALO-SCNN technique is used to analyse the effectiveness of classifying different ASD facial images using the ACD and ASD dataset image. Initially, pre-processing involves normalization, resizing and augmentation of the children's facial image. The feature extraction using MobileNetV2 focuses on mid-level features, capturing shapes and expressions like edges and contours. The DALO algorithm performs hyper parameter tuning to achieve high classification accuracy. The DALO algorithm helps to achieve high accuracy compared to other optimization techniques such as PSO and ACO. Classification using SCNN efficiently handles sufficient trained data to avoid the overfitting of the ASD facial image and enhance the softmax loss function to further reduce overfitting and then achieve better classification accuracy. Moreover, DALO-SCNN techniques have better outcomes than existing approaches such as DenseNet121 [16], AutoML [17], CNN [18] and ResNet 50 [19] approaches. The proposed method efficiently handle the exploration and exploitation which helps in finding the optimal solution for complex optimization involved the hyperparameter tuning in facial image classification then it achieve better acucuracy. The dynamic adaptive variant improves the standard ALO by allowing the algorithm to adapt its serch behavior based on the facial data. Dense Net [16] connection requires large amounts of data to train on ASD and the bottleneck approach results in the loss of essential features, leading affect the classification accuracy. The AutoML [17] autism classification by automated ML approaches was done by manually, which failed to capture features with subtle differences that lead to inaccurate classification. The CNN models with poor hyper parameter tuning lead to suboptimal results that impact on accurate classification results. The ResNet 50 [19] insufficient training data leads to overfitting, making it challenging to learn the facial features due to the similarity of the disorder and complex to learn the feature.

5. CONCLUSION

In this research, a DALO and SCNN method is proposed for classification to improve the accuracy. DALO balances exploration and exploitation, effectively searching the hyper parameter space, making it suitable for tuning SCNN hyper parameters. The SCNN enhancement of the loss function helps to handle overfitting and the softmax loss provides gradients that the optimization algorithm uses to update model weights during training. Initially, data obtained from the ACD and ASD Dataset undergoes normalization during pre-processing to ensure all pixel values contribute equally during the learning process. Feature extraction is performed by using MobileNetV2 involves depth-wise separable feature is minimized amount of parameters when maintaining model capacity. The proposed method enhances the model's ability to generalize across various facial image characteristics associated with autism, which is improve the classification accuracy. The combination of ALO and a dynamic adaptive mechanism lead to more precise classification and reduce the high dimensionality issue. The performance of the proposed DALO-SCNN method achieves a precision of 0.982, recall of 0.98 and f1-score of 0.93 and accuracy 97% on ACD dataset. The SCNN technique achieves better accuracy of 93.12%, precision of 92.56% of precision, 92.01% of recall and 92.25% of f1-score on ASD dataset, when compared to existing methods such as CNN and ResNet 50 techniques. Future work will focus on developing an enhanced deep learning (DL) technique to further improve classification accuracy.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

The paper conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, writing—review and editing, visualization, have been done by 1st author. The supervision and project administration, have been done by 2nd author.

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