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RESEARCH ARTICLE

AUSD-XVGG: AUTISM SPECTRUM DISORDER CLASSIFICATION USING DEEP LEARNING BASED XCEPTION AND VGG16

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Abstract – Autism Spectrum Disorder (ASD) is a neurological disorder which might have a lifelong impact on the language learning, speech, cognitive, and social skills of an individual. However, the current ViT-ARDNet-LSTM model is mostly dependent on standardized, high-quality images and scans, which might not always be accessible in a variety of medical facilities. The generalizability and robustness of the model in real-world medical environments may also be limited by how differently images and scans acquisition techniques, scanner types, and image resolutions vary throughout institutions. In this paper, a novel DL-based AUSD-XVGG model is proposed for ASD classification using Xception and VGG16. Initially, the input images are preprocessed using log transformation and normalization to enhance the image and remove the noise. MobileNetV2 is used for feature extraction of ASD images to extract the features. The hybrid classification is Xception and VGG16, which captures the depth and spatial features of facial expressions. The AUSD-XVGG approach classifies as autism and normal. The performance of the AUSD-XVGG approaches was assessed using the metrics such as F1 score, specificity, recall, accuracy, and precision. The AUSD-XVGG approach achieves a high accuracy of 99.07% for ASD. The AUSD-XVGG improves the accuracy range of 26.09%, 5.35% and 2.96% better than DNN, ViT-ARDNet-LSTM, and IMFRCNN respectively.

Keywords *– Autism Spectrum Disorder, MobileNetV2, VGG16, Xception, log transformation.*

1. INTRODUCTION

Autism spectrum disease (ASD) is a complicated neurodevelopmental syndrome characterized by repetitive activities, a lack of interest, and impaired social communication [1]. Although it is typically detected in early childhood, some persons may not be diagnosed until later in life [2]. ASD is distinguished by qualitative deficiencies in social behavior, such as difficulties developing relationships with peers, difficulties interpreting nonverbal cues such as body language and facial expressions, a lack of spontaneous social initiation, and abnormalities in emotional reciprocity [3, 4].

ASD is predicted by the World Health Organization (WHO) to affect one out of every 68 children. Because of this, there are more than 68 million people with ASD globally, including over 2 million in the United States [4]. ASD is a developmental disease that affects 1% to 2% of children worldwide and is distinguished by repetitive activities, communication issues, and difficulty engaging with others [5, 6].

Machine learning (ML) and artificial intelligence (AI) are becoming more widely acknowledged to be effective techniques to enhance the healthcare diagnosis process. These techniques can assist professionals by screening large populations, identifying high-risk individuals, and reducing diagnostic times [7]. Deep Learning (DL) [8] techniques are being used in speech, behavioral observations, neuroimaging, and early ASD detection. DL neural networks (NN) have shown to be incredibly powerful tools for image analysis applications such as facial image (FI) identification [9]. Deep NN, specifically convolutional neural network (CNN) models, are utilized to diagnose ASD [10]. CNNs are widely used to extract features [11] of the ASD images.

However, the proposed two-phase DL approach is based on balanced and well-structured datasets, which may not accurately reflect the noise and unpredictability observed in actual clinical data. Furthermore, the continuous availability of user-specific information and participation is critical to the effectiveness of the personalized lifestyle guidance system, which may not always be available in settings with limited resources or diverse patients. To overcome this problem, the CAD-SULOR approach for CVD. The important contributions of the CAD-SULOR approaches are as follows:

- The input images are denoised using the log transformation (LR) and normalization to enhance the facial images, and MobileNetv2 is used to extract the features of the image.
- The Xception and VGG16 are used to improve the accuracy and classify the ASD, such as autism and normal.
- The AUSD-XVGG model efficiency was assessed using metrics like F1 score, specificity, recall, accuracy, and precision.

The structure of this paper and other parts of this work is as follows: Section 2 presents the literature review. The ASD classification is explained in Section 3, while the findings and discussion of the AUSD-XVGG approaches are explained in Section 4. The conclusion and recommendations for further research are included in Section 5.

2. LITERATURE SURVEY

In this paper, researchers have proposed a number of advanced ML and DL designs for ASD. ViT, LSTM, and ResNet 50 have been used with various techniques and designs for ASD in the research studies that have been proposed. Some of the research are examined in the following section.

In 2025 Prakash et al. [12] proposed an could evaluate raw behavioral film to recommend activities that may assist youngsters with ASD in receiving functional and diagnostic detection. The behavior action recognition (BAR) pipeline encompasses temporal action location, child detection, and the identification and classification of acts of interest. The Self-Stimulatory Behavior Dataset (SSBD), an independent benchmark, achieved a top-1 accuracy of 78.57% respectively.

In 2025 Parvathy et al. [13] introduced a DL model ViT-ARDNet-LSTM for ASD classification using MRI images. For effective ASD classification, this framework combines the benefits of LSTM models, adaptive residual dense nets, and ViT. When the sigmoid activation function was considered, the experimental results revealed that the proposed model attained 94% accuracy.

In 2025 Alutaibi et al. [14] developed a Capsule DenseNet++ (CDN++) was used to the upgraded ASD system that combined DL and reinforcement learning-based lifestyle improvements. CDN++, a sophisticated DL model that improves feature representation efficiency and interpretability, was used to classify these improved features for exact ASD identification. The accuracy of the detection model's performance was measured at 98.90%.

In 2025 Meera [15] presented the ASD Using Thermal Imaging and DL of an enhanced detection system. The efficiency of the ResNet 50 system and IMFRCNN in categorizing thermal images of people with ASD and people without ASD. Reliability was 90% for the ResNet 50 and 96% for the IMFRCNN.

In 2025 Saranya et al. [16] introduced an ASD detection using used spatial patterns of EEG signals and a quantum-based ML technique. The C4-Cz pair performed best in SVM classification, with the highest accuracy. The QSVM with amplitude embedding feature map performed better than the others, with an accuracy of 94.7%.

In 2025 Sha et al. [17] proposed a multimodal fusion method for early detection of ASD through the analysis of demographic and facial feature images. AlexNet CNN was proposed for prediction and evaluated using the multiactivation function (MAF) framework. The proposed strategy outperforms existing methods with an accuracy rating of 98.99%.

In 2025 Farhat et al. [18] proposed a deep ensemble model that overcomes restrictions in existing datasets by thorough preprocessing, leveraging the benefits of VGG16 and Xception net trained on FI for ASD detection. The model achieved an outstanding 97% accuracy on the dataset by combining Xception and VGG16's feature extraction capabilities with fully linked layers.

In the literature review, these current approaches have several limitations like difficulty in classifying ASD because of low-quality images, especially in real-world clinical settings where data variability is high. To overcome this problem, the AUSD-XVGG approach in ASD.

3. PROPOSED METHODOLOGY

T In this paper, a novel AUSD-XVGG approach classify the ASD in Facial images. The facial images are denoised using the log transformation (LR) and normalization. MobileNetv2 is employed to extract features and edge identification for real-time classification in ASD. The hybrid classification is used in Xception and VGG16, improving accuracy and classification, such as distinguishing between autism and normal. The overall process of the AUSD-XVGG approach is displayed in Figure 1.

3.1. Dataset

In this research, the Autistic Children Facial Dataset [19] was taken from the Kaggle for Autism spectrum disorder classifcation. Although the children in the sample ranged in age from two to fourteen, the majority were between the ages of two and eight. 2D RGB images with a roughly 3:1 male-to-female ratio and roughly equal numbers of autistic and control groups made up the dataset. The images were divided into three groups: training, testing, and validation. The training set included 2536 images, the testing set contained 300 images, and the validation set contained 100 images. Gerry Piosenka, the image provider, obtained the images from an internet portal. Regretfully, there is no known clinical history for the children in the sample, including information on socioeconomic background, ethnicity, and the severity of ASD.

3.2. Data augmentation

The initial step in data preparation is to clean the data, which involves removing errors, duplicates, and outliers, as well as deleting extraneous data points, providing structure to the information, and managing missing numbers. However, no values are missing from this dataset because duplication has already been deleted. The images in the dataset must be enhanced with rotation, magnification, horizontal flipping, and height and breadth alteration to increase training efficacy. As a result, there are more images in the training and validation datasets.

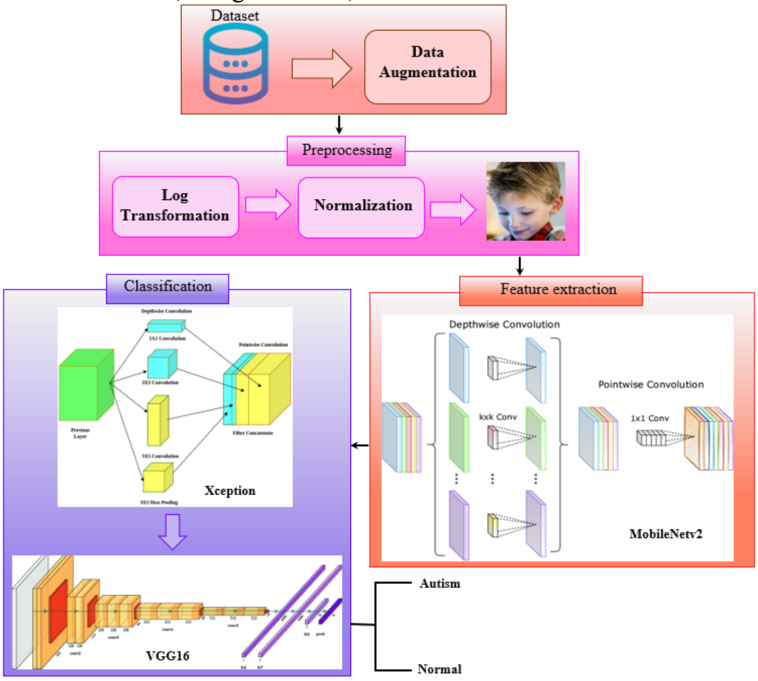

Figure 1. overall workflow of the AUSD-XVGG Model

3.3. Preprocessing

Logarithmic transformation (LT) is a basic image enhancement technique that improves image contrast. This approach converts narrow-range, low frames into a wider range of output levels. Brightening darker intensities improves visual aspects and makes them more noticeable to the natural vision.

$$D_{tNorm} = \frac{D_t}{255} \tag{1}$$

$$D_{tL} = c * log(1 + D_{tNorm}) \tag{2}$$

where D_{tNorm} is the dataset utilized for normalization, D_{tL} is the dataset after log transformation for image enhancement, and c is a scaling constant whose value varies depending on the application.

3.4. Feature extraction

MobileNetV2 is a lightweight CNN architecture designed for mobile and embedded devices with limited computational resources. MobileNetV2 improves on the original MobileNet model by adding depthwise separable convolutions to reduce the number of parameters and computations required for mobile devices. It also introduced the concept of linear bottlenecks to reduce computation while maintaining accuracy. Figure 2 depicts the MobileNetV2 display the architecture.

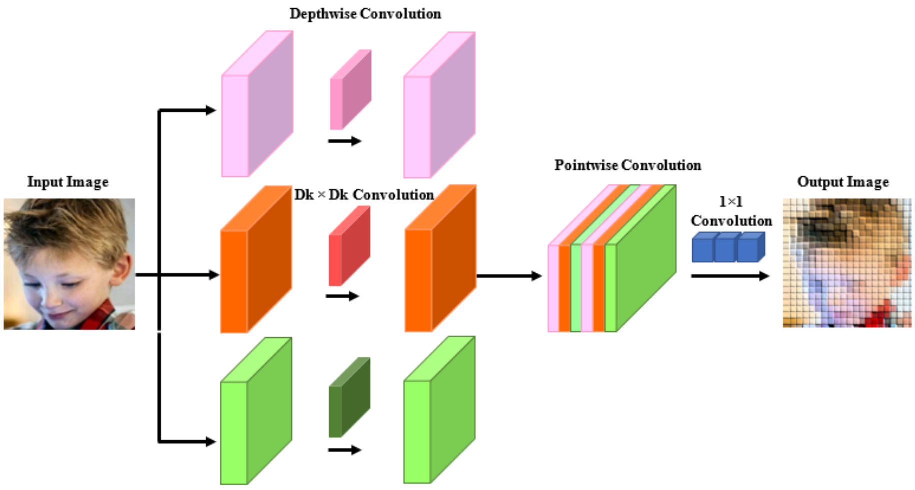

Figure 2. Architecture of MobileNetv2

$$Y_{i,j,k} = \sum_{m,n} X_{i+m,j+n,k} \times K_{m,n,k} \quad (3)$$

The input feature map is represented by X, while the intermediate feature map following the depthwise convolution is represented by Y. The low-level features are extracted such as edges, textures, and shapes, already learned by these models, are transferred to extract high-level discriminative features relevant to ASD classification.

3.5. Classification

The Xception deep CNN introduces additional levels of inception. The depth-wise convolution layers that make up the inception layers are followed by a point-wise convolution layer. The Xception flowchart is displayed in figure 3 is made the advantage of the features maps and featured two dense layers with rule activation functions (128 and 64 layers deep, respectively), as well as a global max pooling layer. The dense layer's output was then transferred to the flatten layer, which accepts a feature map as input and returns a vector. Batch normalization improved the findings by reducing overfitting. In the last layer, the Softmax function was employed to forecast the result.

A well-known and highly regarded architecture for deep CNNs, VGG16 is commended for its exceptional performance in image classification tasks. The final convolution layer is taken into consideration in order to avoid using a fixed size input (224 x 224) for the model. VGG creates a sequence of values by analyzing input values. The VGG16 is categorized as both ASD and Normal. The VGG16 convolution layer model receives a 224 x 224 x 3-pixel image as input. Two convolutional layers, each measuring 224 x 224 x 64 pixels, and pooling layers with a smaller peak, measuring 112 x 112 x 64 pixels, were discovered. Once more, two convolutional convolution128 layers measuring 112 x 112 x 128 were discovered, along with pooling layers with a smaller peak of 56 x 56 x 128.

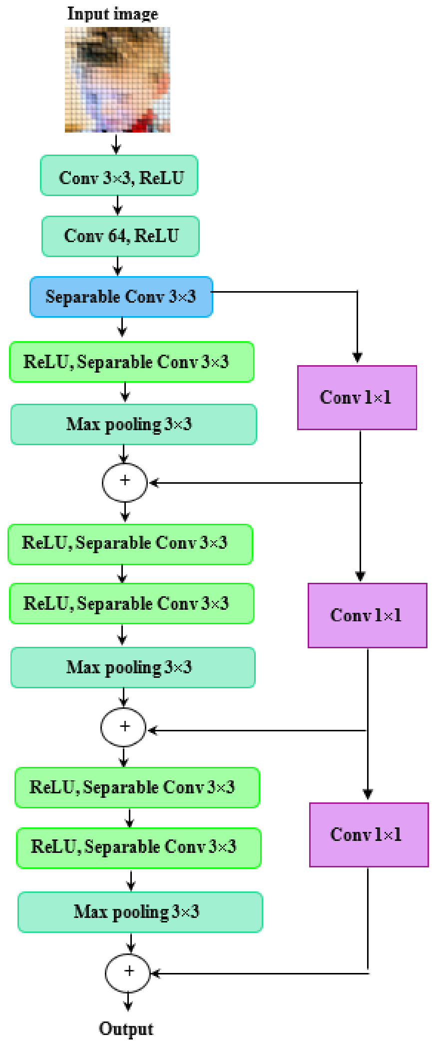

Figure 3. Flowchart of Xception

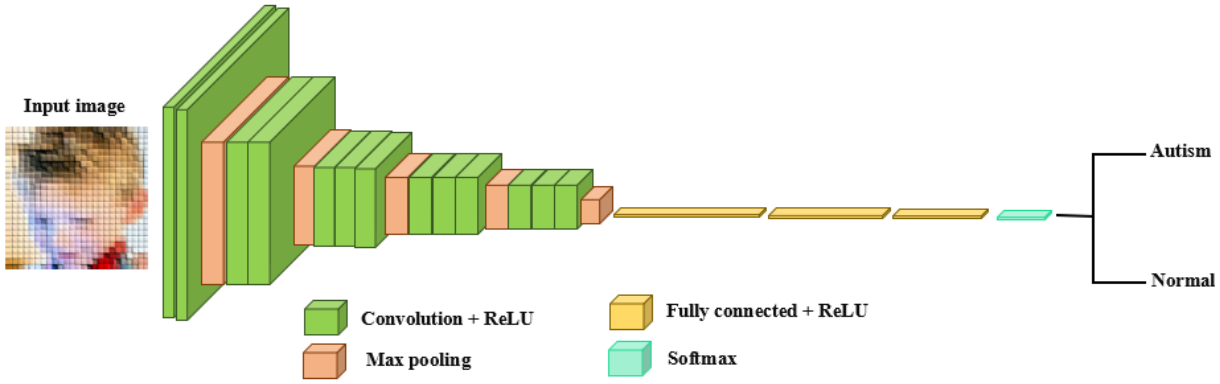

Figure 4. Architecture of VGG16

$$\hat{X} = \hat{x}_0, \hat{x}_2, \hat{x}_3, \hat{x}_4, \cdots, \hat{x}_n \quad (4)$$

$$P\left(y = j \middle| \Theta^{(i)}\right) = \frac{e^{\Theta^{(i)}}}{\sum_{j=0}^{k} e^{\Theta_k^{(i)}}} \quad (5)$$

The classification is finalized using three dense layers following the stack of convolutional and max pooling layers. The dense layers use ReLU activation functions, while the final dense layer uses Softmax for binary or multi-class classification.

$$E = \frac{1}{3}\left(min_i d(c_i, G_1) + min_i d(c_i, G_2) + min_i d(c_i, G_3)\right) \quad (6)$$

where G denotes the ground truth classes and $d(.)$ is a distance metric used for matching predicted class centroids c_i with the ground truth G_j. The maximum pooling layer is used at multiple stages to reduce spatial dimensions. The Xception and VGG16 is used to ASD classification such as autism and normal.

4. RESULT AND DISCUSSION

In this section, the experimental setup of the AUSD-XVGG was implemented using MATLAB 2020b, and the ensuing experimental findings are represented. The AUSD-XVGG to evaluate the model on the collected ASD images, a number of measures were employed, including F1 score, recall, accuracy, specificity, and precision.

Input	Preprocessing	Feature Extraction	Classification
			Autism
			Normal
			Autism
			Normal

Figure 5. Experimental result of the Proposed AUSD-XVGG

The input images are obtained from the Autistic Children Facial dataset, as shown in column 1. In column 2, the Logarithmic transformation (LT) is applied as a preprocessing step to enhance image quality. In Column 3 Feature extraction using MobileNetV2, and Classification, Xception and VGG16 is used to process the from column 4. Finally, FCNN is utilized for classification to determine whether the ASD is autism and normal. The experimental results of the AUSD-XVGG approach, are display in Figure 5.

4.1 Performance Analysis

The AUSD-XVGG approach was evaluated in this section utilizing several measurements like recall, specificity, F1 score, accuracy, and precision, in the gathered dataset.

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (7)$$

$$Specificity = \frac{TN}{TN+FP} \quad (8)$$

$$Precision = \frac{TP}{TP+FP} \quad (9)$$

$$recall = \frac{TP}{TP+FN} \quad (10)$$

$$f_1 = 2\left(\frac{precision*recall}{precision+recall}\right) \quad (11)$$

where T_{pos} and T_{neg} indicates the True positive and negative of the provided images, F_{pos} and F_{neg} shows the sample images false positives and negatives.

Table 1. Performance analysis of the AUSD-XVGG model

Classes	Accuracy	Specificity	Precision	Recall	F1 score
Normal	99.11%	97.98%	98.57%	98.97 %	97.58 %
Autism	99.03%	98.11%	97.75%	97.32 %	96.67 %

Table 1 presents various classes, the proposed technique was evaluated for its recall, F1 score, specificity, accuracy, and precision. The accuracy of the AUSD-XVGG approach is 99.11% for normal and 99.03% for autism in ASD.

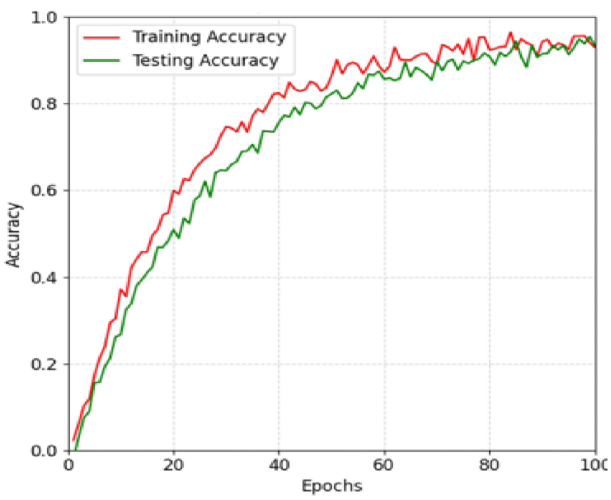

Figure 6. Accuracy of the proposed AUSD-XVGG model

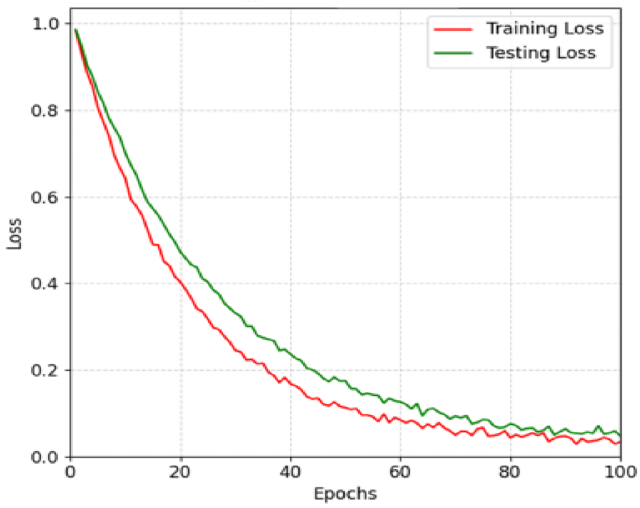

Figure 7. Loss of the proposed AUSD-XVGG model

Figure 6 displays the accuracy of the training and testing, with accuracy on the y-axis and Epochs on the x-axis. The proposed framework shows an accuracy level of 99.07% for times when considering the correctness of its evaluation and training curves. Figure 7 displays the loss graph displayed against epochs, demonstrating that the loss decreases as epochs increase. The proposed approach has a low loss of 0.93% while achieving great precision.

4.2 Comparative Analysis

The AUSD-XVGG methods accuracy and efficiency were demonstrated by comparing it to other existing methods. The Xception and VGG16 approach was used to identify ASD images as autism and normal in order to measure the efficiency. Using metrics of recall, F1 score, accuracy, and specificity, the efficacy of the proposed approach is assessed. The accuracy rate demonstrates that the recommended approach of the existing methods. The AUSD-XVGG approach is contrasted with the existing techniques, including DNN [12], ViT-ARDNet-LSTM [13], and IMFRCNN [15].

Table 2. Comparison of the existing model and proposed model

Techniques	Accuracy	Specificity	Precision	Recall	F1 score
DNN [12]	78.57 %	79.8%	75.2%	76.3 %	79.9 %
ViT-ARDNet-LSTM [13]	94.03 %	75.5%	79.6%	73.7 %	76.8 %
IMFRCNN [15]	96.22 %	96.7%	95.3%	96.1 %	98.1 %
Proposed	99.07 %	98.04%	98.16 %	98.14 %	97.26 %

Table 2 presents the various techniques of the existing model and compare the proposed model. The AUSD-XVGG technique improves the accuracy 78.57%, 94.03% and 96.22% better than the DNN [12], ViT-ARDNet-LSTM [13], and IMFRCNN [15] respectively. The AUSD-XVGG approach outperforms the current methods with an accuracy of 99.07%. The AUSD-XVGG improves the accuracy range of 26.09%, 5.35% and 2.96% better than DNN [12], ViT-ARDNet-LSTM [13], and IMFRCNN [15] respectively.

Table 3. Accuracy comparison of the existing models and proposed model

Authors	Method	Accuracy
Saranya et al., [16]	QSVM	94.71%
Farhat et al., [18]	Xception	97.24%
Proposed	AUSD-XVGG	99.07%

Table 3 shows an Accuracy comparison of existing models and the AUSD-XVGG model. The AUSD-XVGG technique maintains high accuracy levels of 99.07%. The AUSD-XVGG approach enhances the total accuracy by 4.61%, and 1.88% better than QSVM [16], and Xception [18] respectively. The comparison above indicates that the AUSD-XVGG model is more accurate than the existing models.

5. CONCLUSION

In this research, a novel AUSD-XVGG approach was proposed for the autism spectrum disorder classification using an Xception and VGG16. The input images are pre-processed using the LT and normalization to reduce the noise and enhanced images. The MobileNetv2 is used to extract the features of a facial images. The Xception and VGG16 is used to improve the accuracy and classification such as autism and normal. The performance of the AUSD-XVGG approaches was assessed using the metrics such as F1 score, specificity, recall, accuracy, and precision. The AUSD-XVGG approach accomplishes a higher accuracy of 99.07% respectively. The AUSD-XVGG improves the accuracy range of 26.09%, 5.35% and 2.96% better than DNN, ViT-ARDNet-LSTM, and IMFRCNN respectively. The AUSD-XVGG approach enhances the total accuracy by 4.61%, and 1.88% better than QSVM, and Xception respectively. Future work will focus on enhancing the AUSD-XVGG model for ASD by implement an advanced optimization technique to detect the ASD.

CONFLICTS OF INTEREST

No financial or interpersonal conflicts have been reported by the authors that would have affected the study's findings.

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