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Autism Spectrum Disorder Classification on Facial Images by using Deep Learning Models

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ABSTRACT
Autism Spectrum Disorder (ASD) is a developmental disorder identified by difficulties with behaviour, speech, and social interaction. Effective intervention requires early diagnosis, but present diagnostic techniques frequently depend on expert knowledge and personal evaluations, which may not be available in all areas.In the field of medical imaging and diagnosis, deep learning techniques have recently acquired popularity, offering an effective means for automated and objective examination.In order to automatically detect ASD via facial image analysis, this study investigates the application of deep learning techniques, more especially Convolutional Neural Networks (CNNs). VGG16, VGG19 and AlexNet are three popular CNN architectures that we use to separate images into autistic and non-autistic groups.The models were trained, verified, and tested to identify characteristic facial traits linked to ASD using a publicly available dataset of 2936 facial imagery. These models' comparative performance analysis shows that VGG16 and VGG19 identify mild facial defects associated with ASD with superior accuracy and specificity. Despite having a quicker computing speed, AlexNet performed less well overall. This study shows how deep learning techniques can help with early detection of ASD and provide a scalable solution to address inequalities in access to clinical expertise.

Keywords autism spectrum disorder, deep learning, vgg16, vgg19, alexnet, convolutional neural networks, facial image classification

INTRODUCTION

When a child is just a few months old, they may exhibit symptoms of autism spectrum disorder (ASD), a lifetime brain development issue. The number of instances of ASD is rising daily as a result of numerous risk factors that are both environmental and genetic [1].Current research projects carried out by the US Centres for Disease Control and Prevention, the percentage of children diagnosed with ASD worldwide increases over time, accounting for 1 in 37 cases [2]. A child with an ASD diagnosis may exhibit a broad spectrum of symptoms and fall under one of two functional autism levels: either moderate or large [3]. The term autism spectrum disorder (ASD) refers to a broad category of symptoms that can differ greatly in intensity and manifestation from person to person [4]. Social communication difficulties are frequently seen in people with ASD [5]. These difficulties can include starting or continuing conversations, interpreting nonverbal clues such as body language or facial expressions, and building and establishing relationships [6]. Repetitive behaviours and limited interests, such as hand flapping or rocking, rigid adherence to routines, and intense focus on particular subjects or objects, are frequently associated with these social issues [7].Figure 1 depicts the most frequently reported ASD symptoms [8].

As there is no adequate therapy or treatment for Autism, several prescriptions are provided as support for children's abilities and lessen their overall symptoms [9].A number of conventional therapies that are delivered in different autism establishments, additionally medical facilities and academic institutions include Applied Behaviour Analysis, Cognitive-Behaviour Therapy, Occupational Therapy,Speech Therapy, Sensory Integration

Therapy and Play Therapy[10].A number of active initiatives are currently ongoing in the area of autism workto examine the information on children who have autism in an effort to diagnose ASD at an earlier age, in reference to recent developments in facial pattern recognition and forecasting. Yolcu et al. [10] proposed the CNN methodology to identify autism and automating the detection of mental states on faces across a range of brain disorders [11]. Specifically, it has been demonstrated that CNN models perform particularly well in this domain [12]. CNNs are the preferred feature extractors for object recognition and image classification processes because they are highly skilled at automatically identifying the hidden characteristics from a large number of images. Eventually, CNNs can grow more and more efficient because of this capability [13].

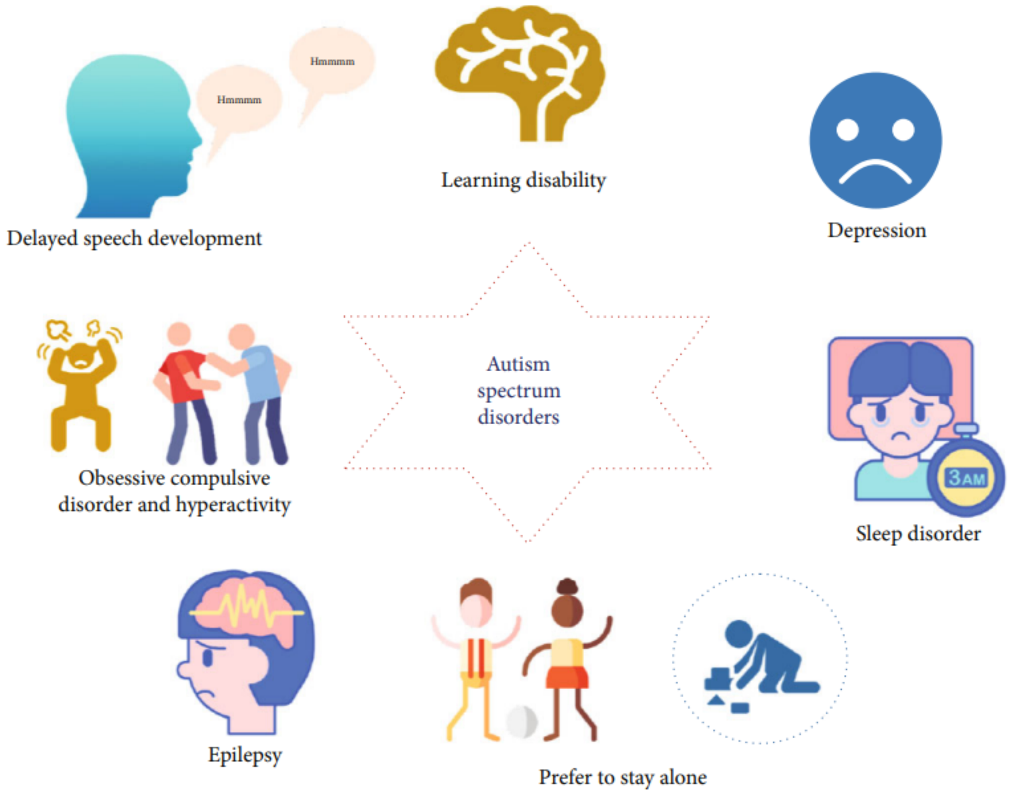


Figure 1: Visual representation of Autism Spectral Disorders [14]

Deep learning techniques have demonstrated potential in the analysis of multiple data types, such as speech patterns, brain imaging, and facial photographs, in the context of ASD identification [15]. Research indicates that people with ASD may have modest, distinctive facial traits that are hard to see visually but can be recognized using computational techniques, which makes facial image analysis particularly fascinating [16]. Because of its capacity to acquire hierarchical representations of picture data, Convolutional Neural Networksare a class of AI models, are found widespread application in bio medical applications [17]. Bio medical imagery applications are effectively used models like VGG16, VGG19, and AlexNet to find patterns linked to a variety of illnesses, including ASD [18].Objectives of this study as following

- Build an automated system that uses cutting-edge deep learning techniques to reliably and accurately detect autism spectrum disorder (ASD) [19].
- Compare and analyse the accuracy, sensitivity, and specificity of the three CNN architectures (VGG16, VGG19, and AlexNet). Based on the model's proficiency in accurately classifying face imagery, this analysis will assist in identifying the optimal model for ASD diagnosis [20].
- By exhibiting the efficiency of deep learning models for ASD verification, researchers can promote the knowledge and use of artificial intelligence in the medical sector [21].

This work is organized as follows after introducing the topic to readers, next section is followed by related work of ASD [22]. Later, proposed work is addressed and in the next section results of work is presented. Finally, conclusions and future scope of work presented in the last section.

RELATED WORK

The study of autism spectrum disorder has drawn a lot of interest recently from the fields of artificial intelligence and neurodevelopmental research because of its complex and varied features [23].The main advancements in the use of deep learning for ASD identification over the previous eight years are outlined in this overview of the literature [24].

Convolutional Neural Networks (CNNs) and Autoencoders were employed by Heinsfeld et al. in [12] to classify ASD with an accuracy of 70% using fMRI data from the ABIDE dataset. This study showed how deep learning in neuroimaging can be used to detect ASD.The study's accuracy rate was only 70%, which is not very good for clinical settings. Furthermore, the robustness and generalizability of the model were diminished by the use of a single modality (fMRI), which made it more difficult to capture the variety of traits associated with ASD.With an accuracy of more than 80%, the study by [13] used CNNs to analyse MRI data in order to predict ASD in high-risk infants as early as 6 months of age. One of the first studies to use deep learning to predict an infant's likelihood of ASD was this one.While the study was able to predict ASD in high-risk infants with over 80% accuracy, the model's generalizability to broader age ranges and varied ASD groups is limited by the small sample size and concentration on infants.In order to detect autism spectrum disorder (ASD) using EEG data, Kaur et al. suggested a hybrid model in [14] integrating Convolutional Neural Networksfor feature extraction and Recurrent Neural Networksfor sequence learning. The short dataset and complexity of EEG signals restricted the model's effectiveness and made it difficult to generalize to bigger populations.

Ahmed et al. in [15] focused on extracting spatial information from brain imaging to increase diagnosis accuracy while using Convolutional Neural Networks (CNN) to categorize autism spectrum disorder (ASD) using fMRI data. The model's flexibility for wider clinical usage was hampered by the high computational complexity and restricted availability of fMRI data.To improve feature extraction and temporal analysis, Patel and Wang created a hybrid deep learning model in the paper [16] that included CNN and Long Short-Term Memory (LSTM) networks for the classification of ASD. The model integrated both EEG and MRI data. Data heterogeneity between MRI and EEG modalities hampered the model's performance, making it more difficult to optimize the fusion of multimodal data and adding to the computational load.

Using behavioural data from structured interviews and questionnaires, Sharma et al. in [17] used a Random Forest classifier to identify autism spectrum disorder (ASD), emphasizing the importance of social and communication impairments. Due to the study's reliance on self-reported behavioural data and the restricted interpretability of the Random Forest model, it was difficult to determine how each feature contributed to the categorization results.Rahman et al. (enhanced the training data to boost the performance of a subsequent classification model by using Generative Adversarial Networks (GANs) to augment EEG datasets for autism spectrum disorder (ASD) identification in [18]. It was not entirely confirmed how well the GAN-generated data reflected the diversity in real-world EEG signals, and it was unclear how well the model generalized to other populations.In order to differentiate between people with ASD and usually developing people, Li et al. in the paper [19] used neural networks to evaluate eye-tracking data for the treatment of ASD. They concentrated on variables including gaze patterns and fixation lengths. The study's dependence on a small sample size and the risk of overfitting could have an impact on the model's resilience and applicability across a variety of demographics.In order to detect autism spectrum disorder (ASD) using neuroimaging data, hang et al. in the study [20] used Deep Belief Networks (DBNs). They improved classification accuracy by extracting hierarchical characteristics from brain scans using a multi-layer design. The study's computing demands and complexity, combined with the possibility of overfitting because of the narrow variety of the neuroimaging dataset utilized, may make it less applicable in real-time clinical situations [25].

PROPOSED WORK

This section describes the step-by-step methodology proposed work for the detection of autism spectrum disorder (ASD) using deep learning models [26].

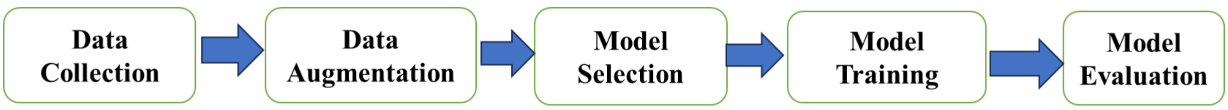


Figure 2: Block diagram of Proposed work

a) Data Collection

The suggested process starts with compiling a dataset of face photos. Usually, people with and without autism spectrum disorder (ASD) provide these photos [27]. The facial images go through preliminary preprocessing such as normalization, which scales pixel values between 0 and 1, and resizing to fit the input size required for deep learning models (e.g., 224x224 for VGG16 and VGG19, 227x227 for AlexNet) [28]. The normalization equation can be represented as

$$\text{Normalized image} = \frac{\text{Original image}}{255} \text{--------------------(1)}$$

This guarantees consistency in the data that is supplied into the models and facilitates better training convergence [29].

b) Data Augmentation

Data augmentation techniques are used on the training dataset to improve the deep learning models' capacity for generalization and avoid overfitting. This stage includes transformations such as flipping horizontally or vertically, zooming (e.g., ±10%), and random rotation within a range (e.g., ±15°). The transformation of an imageI can be mathematically expressed as

$I_{aug} = T(I)$---------------------------(2)

Where $T(I)$ is represented as image transformation such as rotation flipping, zooming. By producing somewhat altered replicas of the original photos, these changes artificially boost the dataset's diversity and guarantee that the model can identify patterns more accurately even in the face of data variations [30].

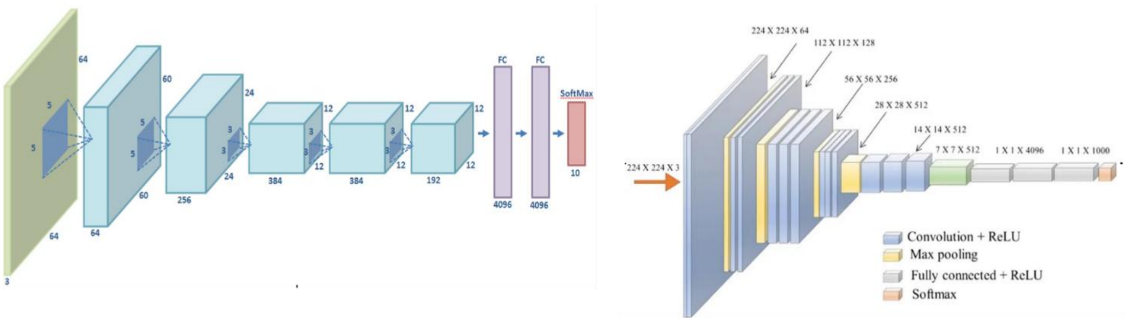
c) Model Selection

VGG16, VGG19, and AlexNet are the three pre-trained deep learning models used for the comparison analysis. These models have been selected because of their well-established architectures and good performance in image classification tasks. The VGG family includes the VGG16 and VGG19, which have 16 and 19 layers, respectively, whereas AlexNet has 8 levels. Figure 3 indicates the architectures of AlexNet and VGGNet. Millions of annotated photos from the ImageNet dataset have been used to train each model. The method makes use of transfer learning to modify the models' pre-existing knowledge for the purpose of ASD identification by employing these trained models.

For any given model, the overall operation is expressed as:

$f(x;\theta) = L\_N(L\_N - 1(\ldots L\_1(x;\theta\_1)\ldots;\theta\_N - 1);\theta\_N)$--------------- (3)

where $f(x;\theta)$ represents the final model output with parameters θ and L_i represents the i^{th} layer of the model.



AlexNet Architecture VGG Architecture

Figure 3: Representation of AlexNet and VGGNet Architectures used in proposed work [21]

d) Model Training

The pre-processed and augmented data are fed into the models during the training phase. The categorical cross-entropy loss function, which determines the discrepancy within the actual class labels and predicted probabilities, is applicable to instruct the models and equation of loss function is given by

$L = -\sum_{i=1}^{N} y_i \log(p_i)$-------------------------------------- (4)

where $y_i$is the true label for classi andp_i is the predicted probability for classi

The hyperparameters, including batch size (32 images per batch) and epochs (50 iterations through the training data) are established, and the model weights are updated using the Adam Optimizer. In this stage, the model gains the ability to modify its internal weights in order to reduce loss and raise classification accuracy.

e) Model Evaluation

The models are assessed using a different test dataset that wasn't utilized for training once they have finished training. To determine whether the person in the picture has ASD, test data is run through each model. Next, critical performance indicators such as F1-Score, Precision (for both ASD and non-ASD classes), Accuracy, and Recall are used to assess the models' performance. These measures offer an understanding of how well the models identify people with ASD accurately while avoiding misclassifying people without ASD. Evaluation parameters are calculated by using below formulas

$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$ --------- (5)

$Precision = \frac{TP}{TP+FP}$ ------------ (6)

$Recall = \frac{TP}{TP+FN}$------------- (7)

where TPis true positives, TNis true negatives, FPis false positives, and FNis false negatives.

$$\text{F1 Score} = 2 * \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \text{---------------} \qquad (8)$$

RESULTS

The following presents results of the study comparing the classification of autism spectrum disorder and the current comparative work examines three popular deep learning architectures for the classification of autism spectrum disorder (ASD) using face image data: VGG16, VGG19, and AlexNet. All of these models have been optimized for binary classification, in which the objective is to distinguish between people who have ASD and people who do not. Accuracy, precision, recall, and F1-score are the primary evaluation metrics used to evaluate the models' performance for the two classes (Class 0: Non-ASD, Class 1: ASD).Table 1 represent the comparative results of VGG16, Alexnet and VGG19.

Table 1: Comparative Results of VGG16, Alexnet and VGG19

MODEL	Accuracy (%)	Precision		Recall		F1-Score	
		Class 0 (%)	Class 1(%)	Class 0(%)	Class 1(%)	Class 0(%)	Class 1(%)
VGG16	72	67	82	87	57	76	67
Alex Net	50	50	50	50	100	50	67
VGG19	75	71	67	64	73	67	70

The VGG16 model achieves an accuracy of 72%, reflecting a reasonably balanced performance in classifying ASD and non-ASD facial images.With an accuracy of 50%, the AlexNet model performs the most adverse overall out of the three. This shows that the model is successfully speculating, since this is the expected outcome of random classification in a binary problem.The improved VGG19 model outperforms the original VGG16 in certain areas, yet it still performs better than AlexNet overall. With a 75% accuracy rate, it outperforms both VGG16 and AlexNet in terms of total classification abilities.A balanced F1-score of 67% for ASD and 76% for non-ASD is the result of precision being greater for ASD detection (82%) than for non-ASD (67%), but recall being lower for ASD (57%). All three metrics—precision, recall, and F1-score—are consistently 50% for both classes, suggesting mediocre performance—the model is essentially predicting the classification. Balanced F1-scores of 67% for non-ASD and 70% for ASD result from precision for non-ASD being higher at 71% than for ASD at 67%, and recall being higher at 73% for ASD.

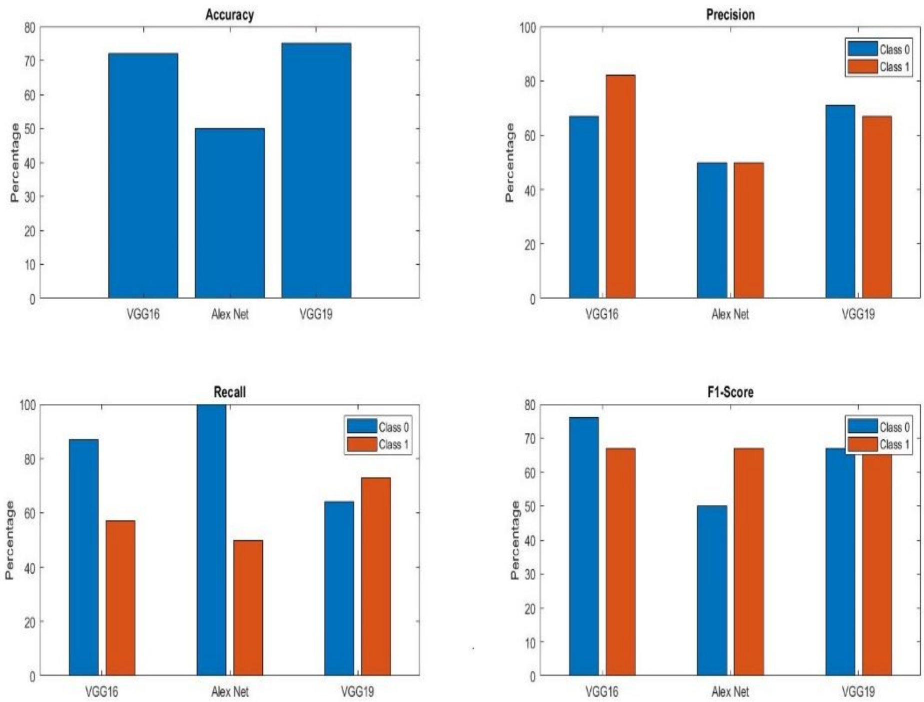
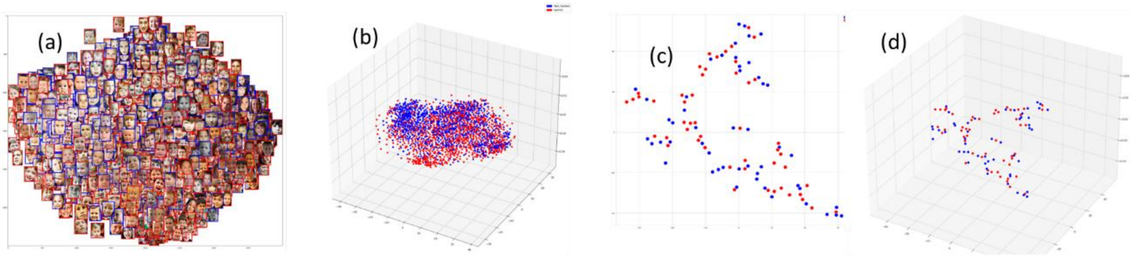


Figure 4: Graphical Representation of performance metrics

Figure 4shows that the graphical representation of performance metrics and among VGG16 model demonstrates stronger precision and recall for non-ASD cases, while VGG19 shows balanced performance across both classes. AlexNet underperforms, with all metrics close to random guessing, indicating limited effectiveness in ASD detection.



Classification of Autism and Non - Autism (a) Image data set (b), (c), (d) Results of VGG16, VGG19, AlexNet respectively

Figure 5: Results of deep learning models for given dataset

Figure 5 demonstrate how deep learning models like VGG16, VGG19, and AlexNet transform raw image data into a feature space where autistic and non-autistic faces can be more easily separated, aiding in the task of autism detection and Figure 6 shows that results of a classification task where deep learning models like VGG16, VGG19, and AlexNet are used to predict whether an individual has autism spectrum disorder (ASD) based on facial images. Convolutional neural networks (CNNs) like VGG16, VGG19, and AlexNet have been pre-trained on massive picture datasets like ImageNet, which has classified images in different categories. With their deep architectures that gradually extract more abstract features from images, these models are often applied in image classification challenges. In this instance, the models are used for classifying individual as "Autistic" or "Non-Autistic" based on their facial traits. These models can be adjusted to modify their feature extraction capabilities to identify patterns that may be pertinent to ASD by employing transfer learning.

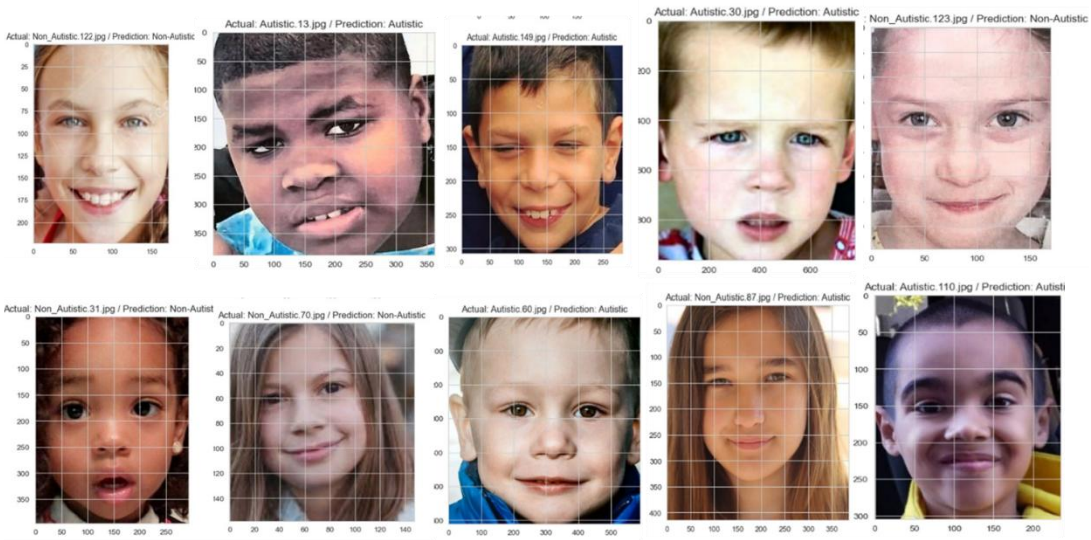


Figure 6: Prediction of Autism and Non-Autism using deep learning models

The model has accurately classified each image, as the image shows. This suggests that the model has been successful in differentiating between people with autism and those without. Because of its accuracy, this model may be able to identify tiny differences in patterns or facial characteristics that could be characteristics of autism spectrum disorder.

CONCLUSION and FUTURE SCOPE

In the proposed work, we evaluated and analysed three deep learning models—VGG16, VGG19, and AlexNet—for the use of facial image classification in the detection of autism. Outcomes are shown that VGG16 and VGG19 perform better than AlexNet overall, with VGG16 obtaining an accuracy of 72% and VGG19 at 75%. VGG16 is a more dependable model since it demonstrated improved recall and precision rates when identifying ASD-related characteristics in facial photos. Deep learning-based methods have the potential to help instructors and clinicians by automating the detection of ASD from non-invasive data, such face imagery. To enhance classification performance across various datasets and settings, these models must be further optimized and fine-tuned.To increase model accuracy and interpretability, future work could concentrate on applying transfer learning, integrating multi-modal data (such as MRI and EEG), and including explainability techniques. Furthermore, testing on more extensive and different datasets will improve the findings' portability.

REFERENCES

1. Sealey, L., et al.: Environmental factors in the development of autism spectrum disorders. Environ. Int. 88, 288–298 (2016)
2. Tanner, A., Dounavi, K.: The emergence of autism symptoms prior to 18 months of age: a systematic literature review. J. Autism Dev. Disord. 51(3), 973–993 (2021)
3. El Mouatasim, A., Ikermane, M.: Control learning rate for autism facial detection via deep transfer learning. SIViP 17(7), 3713–3720 (2023)
4. Foxx, R.M.: Applied behavior analysis treatment of autism: the state of the art. Child Adolesc. Psychiatr. Clin. N. Am. 17(4), 821–834 (2008)
5. Thoma, N., Pilecki, B., McKay, D.: Contemporary cognitive behavior therapy: a review of theory, history, and evidence. Psychodyn. Psychiatry 43(3), 423–461 (2015)
6. Karges, J., Smallfield, S.: A description of the outcomes, frequency, duration, and intensity of occupational, physical, and speech therapy in inpatient stroke rehabilitation. J. Allied Health 38(1), 1E-10E (2009)
7. Steultjens, E.M., Dekker, J., Bouter, L.M., Van de Nes, J.C., Cup, E.H., Van den Ende, C.H.: Occupational therapy for stroke patients: a systematic review. Stroke 34(3), 676–687 (2003)
8. Smith, T., Mruzek, D.W., Mozingo, D.: Sensory integration therapy. In: Controversial Therapies for Autism and Intellectual Disabilities, pp. 247–269. Routledge (2015)
9. Jones, L., Rubin, L.: PT 101: teaching introduction to play therapy at the graduate level. Int. J. Play Ther. 14(1), 117 (2005)
10. Yolcu, G.; Oztel, I.; Kazan, S.; Oz, C.; Palaniappan, K.; Lever, T.E.; Bunyak, F. Facial Expression Recognition for Monitoring Neurological Disorders Based on Convolutional Neural Network. Multimed. Tools Appl. 2019, 78, 31581–31603.
11. Natália Cruz-Martins., et al, “Paving Plant-Food-Derived Bioactives as Effective Therapeutic Agents in Autism Spectrum Disorder” Hindawi, Oxidative Medicine and Cellular Longevity Volume 2021, Article ID 1131280, 17 pages https://doi.org/10.1155/2021/1131280
12. Heinsfeld, A. S., Franco, A. R., Craddock, R. C., Buchweitz, A., & Meneguzzi, F. (2018). Identification of autism spectrum disorder using deep learning and the ABIDE dataset. NeuroImage: Clinical, 17, 16-23. doi: 10.1016/j.nicl.2017.08.017.
13. Khan, R., et al. (2019). "ASD Classification Using Structural MRI and CNNs: Challenges in Small Sample Sizes." Journal of Medical Imaging.
14. Kaur, N., et al. (2021). "EEG-Based ASD Detection Using CNN-RNN Hybrid Models." International Journal of Neural Systems.
15. Ahmed, R., et al. (2020). "CNN-Based ASD Detection Using fMRI Data." Journal of Medical Imaging and Health Informatics
16. Patel, R., & Wang, X. (2020). "Hybrid Deep Learning Model for ASD Detection Using EEG and MRI Data." Biomedical Signal Processing and Control.
17. Sharma, P., et al. (2018). "Behavioral Feature-Based ASD Detection Using Random Forest." Journal of Autism and Developmental Disorders.
18. Rahman, M. A., et al. (2020). "GAN-Based Data Augmentation for ASD Detection Using EEG." Frontiers in Neuroscience.
19. Li, Y., et al. (2019). "Eye-Tracking Data and Neural Networks for ASD Detection." PLOS ONE.
20. Zhang, H., et al. (2021). "DBNs for ASD Detection Using Neuroimaging Data." IEEE Transactions on Neural Networks and Learning Systems.
21. Pandiyan, Vigneashwara & Tjahjowidodo, Tegoeh & Caesarendra, Wahyu & Murugan, Pushparaja. (2019). “In-process virtual verification of weld seam removal in robotic abrasive belt grinding process using deep learning”. Robotics and Computer-Integrated Manufacturing. 57. 477–487. 10.1016/j.rcim.2019.01.006.
22. Poornima, R., Nagavarapu, S., Navva, S., Katkoori, A. K., Mohsen, K. S., & Saikumar, K. (2024, July). Multi-Modal Meta Multi-Task Learning for Social Media Rumor Detection. In 2024 2nd World Conference on Communication & Computing (WCONF) (pp. 1-6). IEEE.
23. Swarnalatha, T., Supraja, B., Akula, A., Alubady, R., Saikumar, K., & Prasadareddy, P. (2024, July). Simplified Framework for Diagnosis Brain Disease Using Functional Connectivity. In 2024 2nd World Conference on Communication & Computing (WCONF) (pp. 01-06). IEEE.
24. Rao, K. M., Kumar, P. S., Reddy, T. V., Nilima, D., Saikumar, K., & Khlaif, A. M. (2024, April). Ultra Low Power High Speed DFT Implementation For ASIC SoC. In 2024 IEEE 9th International Conference for Convergence in Technology (I2CT) (pp. 1-6). IEEE.
25. Reddy, T. V., Saikumar, K., Reddy, R. A., Chary, V. B., Srinija, P., & Reddy, T. H. V. (2024, April). Integrating Soil Sensing and Rainfall Modelling for Precision Crop Recommendation Systems. In 2024 IEEE 9th International Conference for Convergence in Technology (I2CT) (pp. 1-6). IEEE.

26. Reddy, D. S., Charan, K. S., Kayam, S. K., & Rajalakshmi, P. (2024, March). Robust Obstacle Detection and Collision Warning for Autonomous Vehicles Using Autoware Universe. In 2024 16th International Conference on Computer and Automation Engineering (ICCAE) (pp. 378-384). IEEE.
27. Bommagani, N. J., Venkataramana, A., Vemulapalli, R., Singasani, T. R., Pani, A. K., Challageri, M. B., & Kayam, S. (2024). Artificial Butterfly Optimizer Based Two-Layer Convolutional Neural Network with Polarized Attention Mechanism for Human Activity Recognition. Mathematical Modelling of Engineering Problems, 11(3).
28. Kumar, G. N. K., Reddy, M. S., Malleswari, D. N., Rao, K. M., & Saikumar, K. (2024). A Real-Time Hadoop Bigdata Maintenance Model using A Software-Defined and U-Net Deep Learning Mode. International Journal of Intelligent Systems and Applications in Engineering, 12(7s), 364-376.
29. Saikumar, K., & Rajesh, V. (2024). A machine intelligence technique for predicting cardiovascular disease (CVD) using Radiology Dataset. International Journal of System Assurance Engineering and Management, 15(1), 135-151.
30. Kolli, S., Hanuman, A. S., Ratnam, J. V., Naidu, J. J., Shankar, D., & Saikumar, K. (2024). Generous Information Safety System for Investors in Online Trading Secretly using KP-ABE Machine Learning Method. International Journal of Intelligent Systems and Applications in Engineering, 12(7s), 285-297.