Journal of Neonatal Surgery
ISSN(Online): 2226-0439
Vol. 14, Issue 15s (2025)
https://www.jneonatalsurg.com

A Deep Learning Framework for Building Social Connections in Individuals with Autism

Anita Vikram Shinde[1], Dipti Durgesh Patil[2], Arati Vinayak Deshpande[3]

[1]Department of Computer Engineering, Marathwada Mitra Mandal's College of Engineering, Savitribai Phule Pune University,Pune, India.

Email ID: anitavshinde8@gmail.com

[2]Department of Information Technology, MKSSS's Cummins College of Engineering for Women, Pune, India. Savitribai Phule Pune University, Pune, India.

Email ID: diptid@gmail.com

[3]Department of Computer Engineering. VIT, Savitribai Phule Pune University India

Email ID: arati.deshpande1@vit.edu

.Cite this paper as: Anita Vikram Shinde, Dipti Durgesh Patil, Arati Vinayak Deshpande, (2025) A Deep Learning Framework for Building Social Connections in Individuals with Autism. *Journal of Neonatal Surgery*, 14 (15s), 901-912.

ABSTRACT

Biomedical images and social media data can be incorporated to detect Autism Spectrum Disorder (ASD), a type of neurological or brain-related problem. A neurological condition called autism spectrum disorder (ASD) is linked with brain progress and consequently affects how the face looks on the outside. ASD children differ significantly from normal children called typically developed (TD) children in that they have different facial landmarks. The proposed research is novel that aims to create a system based on facial recognition and social media for autism spectrum disorder detection. Deep learning techniques are used to identify these landmarks, but they need precise technology to extract and create the right patterns of the facial features. This study uses a deep learning algorithm that is, a convolutional neural network (CNN) with transfer learning to facilitate communities and psychiatrists experimentally detect autism based on facial features. Pre-trained models such as EfficientNet, Xception, Visual Geometry Group Network (VGG19) and NASNETMobile were applied to the classification task. Performance assessment standards such as accuracy, specificity, and sensitivity were used to compare the outcomes of these models. With the accuracy result of 92.33%, VGG19 model outperformed EfficientNet (78.57%), NASNETMobile (62.24%) and Xception (78.91%) in autism detection in patients.

Keywords: *Deep Learning; Transfer Learning; Social Network; Recommender System; Autism Spectrum Disorder (ASD)*

1. INTRODUCTION

Autism Spectrum Disorder (ASD) is a group of complex neuro-developmental disorders differentiated by a scope of symptoms and varying range of intensity [1]. The phrase "spectrum" presents the wide diversity of challenges and strengths that ASD patients may have. This developmental disorder has symptoms such as difficulty in societal interaction and conversation and by limited and recurring behavior etc. This is a rare condition in which a child develops typically for the first few years of life and then experiences a significant loss of skills and abilities [2] [3] [4] [5]. Individuals with Asperger's often have difficulties with social interaction and may display repetitive behaviors, but they typically have average to above-average intelligence. The symptoms of ASD can manifest in a variety of ways, and they often become apparent in the early stages of a child's development. These early signs include missing eye-to-eye contact, lack of reply to name calling etc. Other common features of ASD include challenges in public interaction, difficulties in communication (both verbal and non-verbal), and monotonous behaviors or intense interests in specific topics.

Artificial intelligence (AI) models in recent information technology assisted in diagnosing ASD using facial pattern recognition. Convolutional neural network (CNN) algorithm is used in [6] to train dataset for taking out features from human face expressions and such algorithms are proposed to find facial expressions in various neurological diseases [7]. Facial Expression Recognition 2013 dataset was updated using deep leaning techniques to recognize facial expression of autistic patients [8]. Important characteristics of autism have been found in a number of investigations using a variety of diagnostic techniques, including voice recognition [10], facial recognition, medical picture analysis[7], eye tracking [9], and feature extraction [11] . But face recognition is a better indicator of autism than an individual's emotional condition. A typical method of identifying someone and demonstrating whether they are normal or odd is facial recognition. Facial recognition is a very commonly used method to discover patients and to categorize as regular or irregular. It involves excavating available content to present conduct structure [12].

Machine learning and artificial intelligence have many practical uses that aim to address societal issues. AI has been incorporated in all areas of medicine to support medical professionals in handling conditions like autism. An artificial neural network has drawn attention in classifying patients as ASD and no ASD. Recurrent neural networks (RNNs) and CNNs, as well as the bidirectional long short-term memory (BLSTM) model, are examples of deep learning approaches that have been applied or advisable for the purpose of discovering autism in children [13] [14]. Machine learning techniques [15] [16] have been used in more research recently to diagnose ASD. These include data analysis on physical biomarkers [17] [18] [19] [20] [21], brain imaging [22] [23] [24], evaluation of the behavior of persons with autism etc.

In order to have early Autism spectrum Disorder (ASD) screening in children, prediction model [25] was presented so relevant therapies, medications can be suggested by medical practitioners to sufferers for flourishing living. Detailed study of recommender systems techniques and challenges was conducted using Big Data Analytic and performance evaluation metrics, several applications in various domains were presented and discussed [26]. A Recommender System with Multi-Classifier was proposed for speedy Autism Spectrum Disorder Detection [27] and literature study of different Machine Learning methods used in Autism spectrum disorder detection was presented with experimentation on autism dataset.

A model having Feature selection using Principal Component Analysis along with AdaBoost classifier was proposed [28] with decrease information loss and better performance. Experimentation was carried out on Autism Brain Imaging Data Exchange (ABIDE) [29] for sMRI and fMRI using machine learning classifiers to classify patients as autistic or not autistic. Different machine learning algorithms are implemented on non-clinical autism dataset for early detection [30] giving more impressive intervention. For early and accurate diagnosis of autism, various ML techniques were used [31] and result comparison was presented in order to select best accuracy method for prediction [32] [33]. Autism Spectrum Disorder using machine learning and deep learning [34] was presented and performance analysis showed that CNN worked better than other methods.

This study investigated the effects of early autism detection in patients to ensure healthy lifestyle. While earlier studies have explored autism detection in victims, they have not explicitly addressed its influence of detection using facial images of them. Our research showed how to identify autism from a child's image using a well-trained classification model (using transfer learning). With the development of very specific mobile devices, this model may easily take an image with a camera and perform a diagnostic test of potential autistic symptoms.

The research contributions of our work include:

a. Four pre-trained deep learning algorithms were applied on selected image dataset for ASD identification namely EfficientNet, NASNetMobile, Xception, and VGG19.

b. The VGG19 model outperformed the four pre-trained deep learning algorithms in terms of performance.

c. A system was proposed to assist medical professionals in identifying ASD patients by examining their facial expression and eyes.

The paper is structured as follows. Section 2 presents the proposed research methodology. Section 3 explains experimentation performed on the input dataset. Section 4 presents results and discussion on the same. Section 5 concludes the paper with pointers to future work.

2. REARCH METHODOLOGY

Detecting autism in victims is a critical job and it has to be performed with accuracy and precision. The aim of this study is to employ EfficientNet, Xception, NASNetMobile, and VGG19 as a deep learning models with transfer learning to recognize autism based on the facial characteristics of autistic and normal / typically developed children. It is possible to diagnose autism or normalcy in children based on their facial qualities. Important facial features were retrieved from the

pictures by the models. The capability of deep learning algorithms to extract minute features from images, that are invisible to the human sight, is one of their benefits, playing crucial role in detection. Proposed Methodology Framework presented in Figure 1 consists of data gathering, data preprocessing, and preparation of the model, ASD detection and finally performance evaluation.

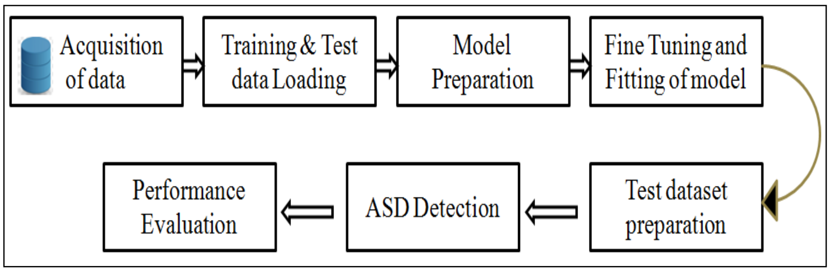


Figure 1. Proposed Methodology Framework

2.1 Dataset Used: Experimentation is carried out on facial image dataset of autistic and normal children publicly available in Kaggle repository [35]. Dataset contains total 2,940 facial images (50 % of autistic & 50 % of normal children). The dataset was prepared by collecting face images through internet resources like web pages and social media such as Facebook. Distribution of dataset in training, testing and validation is depicted in Table 1 and Figure 2.

Table1 : Dataset distribution into training, testing, and validation

Sr No	Dataset	Number of Images
1	Whole dataset	2,940
2	Training dataset	2,540
3	Test dataset	300
4	Validation dataset	100

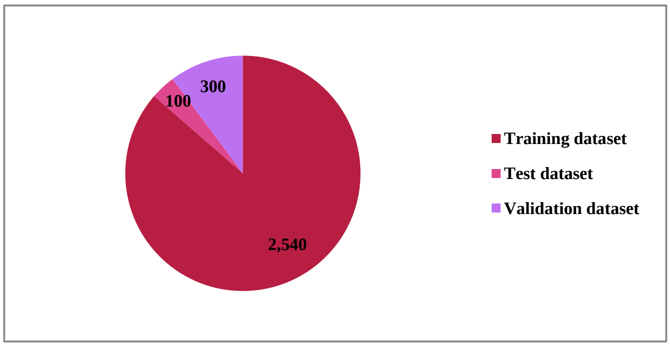


Figure 2. Distribution of dataset

2.2 Preprocessing on Dataset: Data preprocessing plays very important role in cleaning and cropping the images in dataset. Image dataset is collected from internet, social media hence preprocessing is vital step before using it in training of deep learning models. Whole dataset containing 2940 images is split as 2540 in training, 294 in validation and 106 in testing.

2.3 Convolutional Neural Network Models: Artificial intelligence (AI) has advanced outstandingly to help people with everyday tasks in healthcare applications, which rely on a subset of AI known as "computer vision". Thus, the CNN algorithm has aided in behavioral and psychological research as well as disease detection. The convolutional neural network (CNN) takes the input picture and applies value to learnable weights and biases for image classification.

Using max pooling or average pooling, the number of weights was decreased due to the convolution layer's large number of parameters. Max pooling depends on the greatest qualities in every window, whereas the average pooling depends on the mean worth of every window in the step. Figure 3 describes the pooling in CNN. A Softmax output of 0 indicates a class 0 image, while a Softmax output of 1 indicates a class 1 image.

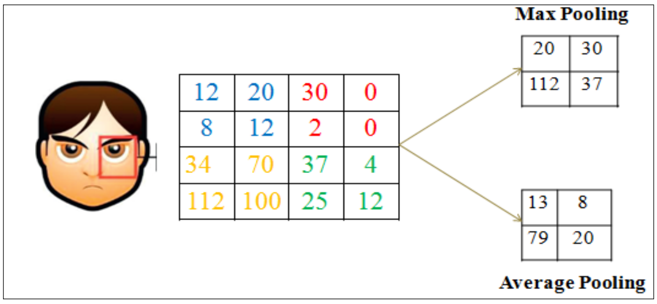


Figure 3. Max pooling and Average Pooling of Convolution Layer

2.4 Deep Learning Models: Four pre-trained models namely VGG19, NASNetMobile, Xception and EfficientNetB3 are used for autism spectrum detection using face pictures dataset.

2.4.1 VGG19: VGG19 (Visual Geometry Group Network Model) is a deep artificial neural network consists of around 19 layers deep with 16 convolution layers and 3 fully connected to categorize the image into 1000 classes. It is CNN model implemented on dataset ImageNet. It has become very useful and acceptable for image classification since it uses multiple of 3 X 3 filters in each convolutional layer. Fig 4 shows its architecture.

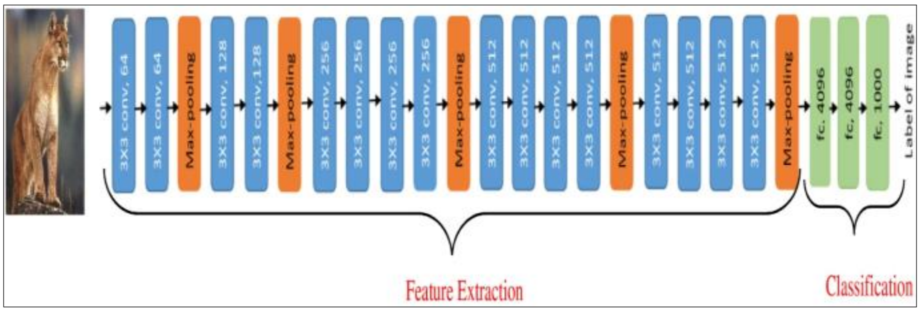


Figure 4. Architecture of VGG19 Model [36]

Input layer accepts 224 × 224 × 3 size image as input. Minimal receptive field, or 3 X 3, which is the smallest size that is likely to still release left/right and up/down is used by VGG's convolutional layers. As VGG lengthens training times and uses more memory, it rarely affects Local Response Normalization (LRN). Moreover, it doesn't improve the model's overall accuracy. From 3 fully connected layers, the 4,096 channels are present in first two FC layers, while the 1,000 channels are present in third layer.

2.4.2 NASNetMobile: It incorporates the concept of Neural Architecture Search (NAS), a gradient-based method for discovering proficient network design [37]. The compact and more competent edition of NASNet, NASNetMobile model is particularly implemented for mobile appliances. Reinforcement learning approach was used to create this architecture.

2.4.3 Xception: This model as shown in fig 5 has trained on the dataset ImageNet for purpose of picture identification and classification. It is a deep CNN model that offers new inception layers. The pre-training model, trained on the standard dataset, was used in the feature extraction method to extract the feature from the new dataset and to eliminate the upper layers of the model [38].

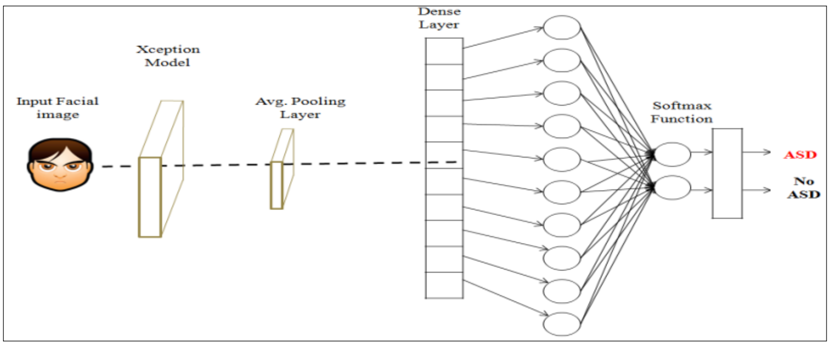


Figure 5. Architecture of Xception [38]

To enable custom classification based on the number of classes, new top layers were added to the model. To prevent overwriting, fine tuning of the generic features is done to fit a specific class.

2.4.4 EfficientNet: The eight models in the EfficientNet group, ranging from B0 to B7, show that accuracy increases significantly but the number of calculated parameters does not increase significantly with model number [39]. Fig 6 shows model architecture.

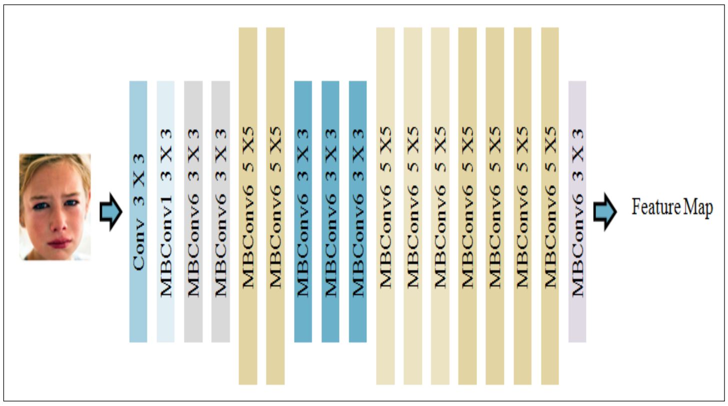


Figure 6. EfficientNet Model

3. EXPERIMENTATION

Experimentation is carried out using python libraries (e.g. Panda seaborn, Keras library, TensorFlow library etc.) to build smart autism detection system. Table 2 lists hyper parameters for models. Different performance evaluation matrices used for selected pre-trained models include confusion matrix, accuracy, specificity, sensitivity, precision, recall, f1-score etc. The classification model is evaluated using confusion matrix. It displays the outcomes of classification.

Table 2 : Hyper parameter for models

Sr No	Hyper parameter	Value
1	Image Size	224 x 224
2	Weight	ImageNet
3	Epochs	50
4	Batch size	32
5	Optimizer	Adam
6	Learning rate	0.001
7	Loss	Categorical cross-entropy

The equations of metrics are as following:

$$Sensitivity = \frac{TP}{TP+FN} * 100 \quad \ldots\ldots\ldots\ldots \quad (1)$$

$$Specificity = \frac{TN}{TN+FP} * 100 \quad \ldots\ldots\ldots\ldots \quad (2)$$

$$Accuracy = \frac{TP+TN}{(TP+TN+FP+FN)} * 100 \quad \ldots\ldots\ldots\ldots \quad (3)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad \ldots\ldots\ldots\ldots \quad (4)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad \ldots\ldots\ldots\ldots \quad (5)$$

$$\text{F1-score} = \frac{2*\text{Precision}*\text{Recall}}{\text{Precision}+\text{Recall}} \quad \text{……………………………………………………} (6)$$

Sensitivity is the capability of the model to appropriately recognize autistic patients. Specificity is the capability of the model to properly recognize the typically develop (TD) or normal patient.

4. RESULTS AND DISCUSSIONS

This part comments on the testing results of experimentation to diagnose autism in patients. Individuals with mental imbalance face hardships and difficulties in understanding their general surroundings and in understanding their contemplation, sentiments, and necessities. Identifying autism is very vital step to save the existences of numerous youngsters. An AI-based intelligent system can support in early autism detection. In this experimentation, we found that the process of autism detection correlates with facial expressions of patients. The proposed method in this study has employed four high level modern deep learning models, EfficientNet, Xception, VGG19 and NASNetMobile for diagnosing autism spectrum disorder. These pretrained are tested to classify patients as ASD and as no ASD using their facial attributes. The experimental outcomes of these models were shown in Table 3 & Table 4, and our study suggests that the VGG19 model was the most accurate compared with other models. Figure 7 depicts comparison of Accuracy metric with various Deep Learning models.

Table3. Pre-trained Deep Learning Models Classification Results

Deep Learning Model	TP	FP	FN	TN
EfficientNet	122	25	38	109
VGG19 model	121	26	23	124
NASNetmobile model	131	16	122	25
Xception model	123	24	38	109

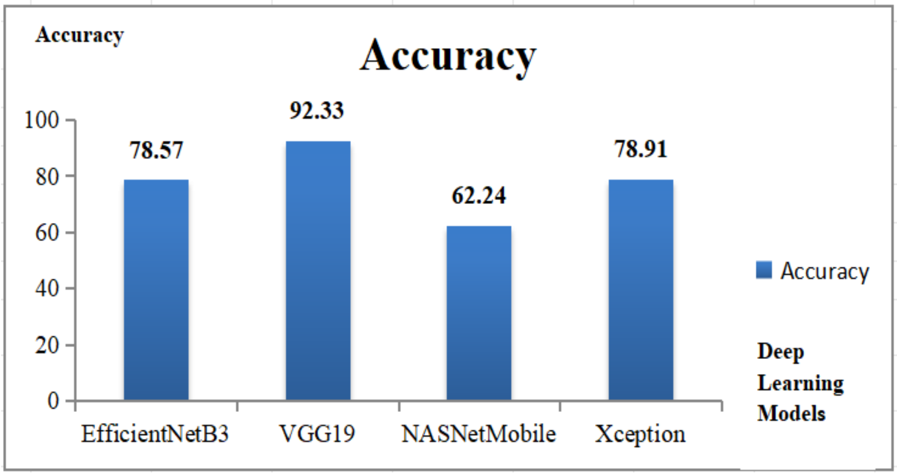


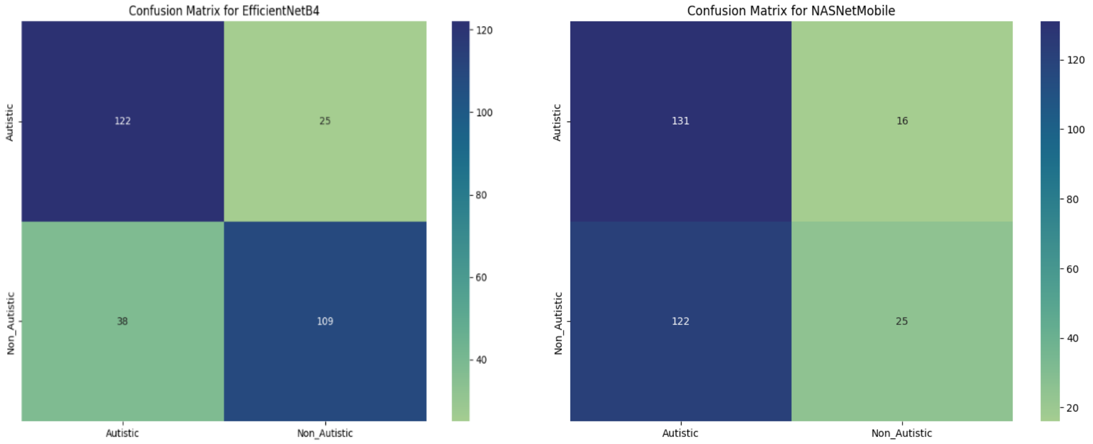
Figure 7. Comparison of Accuracy metric with Deep Learning models

Figure 8 and Figure 9 depict the confusion metrics of these four deep learning models. VGG19 model has maximum accuracy of 92.33% of these four models whereas NASNetmobile model has the minimum performance of 62.22%.

Table 4. Pre-trained Deep Learning Models Performance metrics

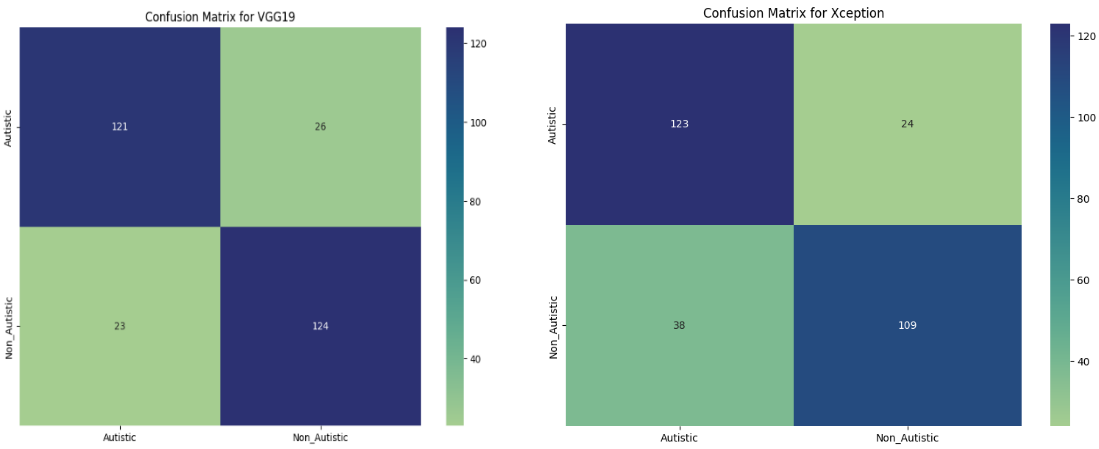
Deep Learning Model	Specificit y	Sensitivit y	Accurac y
EfficientNet	81.343284	76.25	78.57
VGG19 model	82.666667	84.02777 8	92.33

NASNetmobile model	60.97561	51.778656	62.24
Xception model	81.954887	76.397516	78.91



(i) **(ii)**

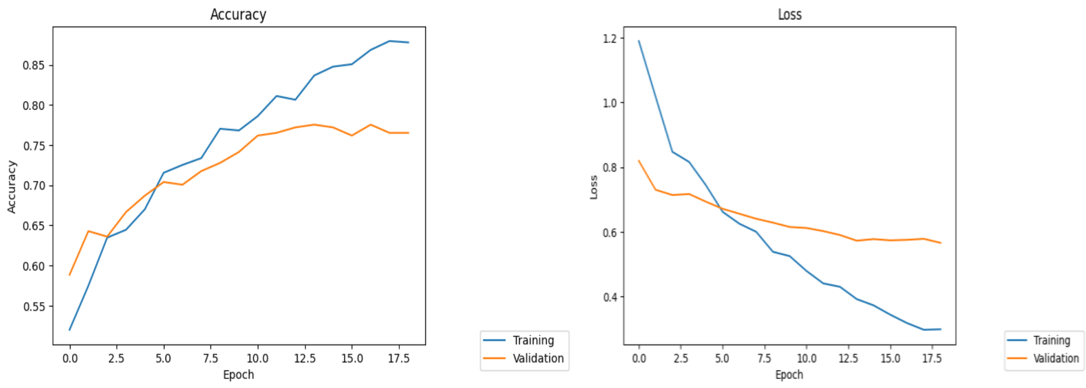
Figure 8. Confusion matrices for the (i) EfficientNet (ii) NASNetmobile model



(iii) **(iv)**

Figure 9. Confusion matrices for the (iii) VGG19 model and (iv) Xception model.

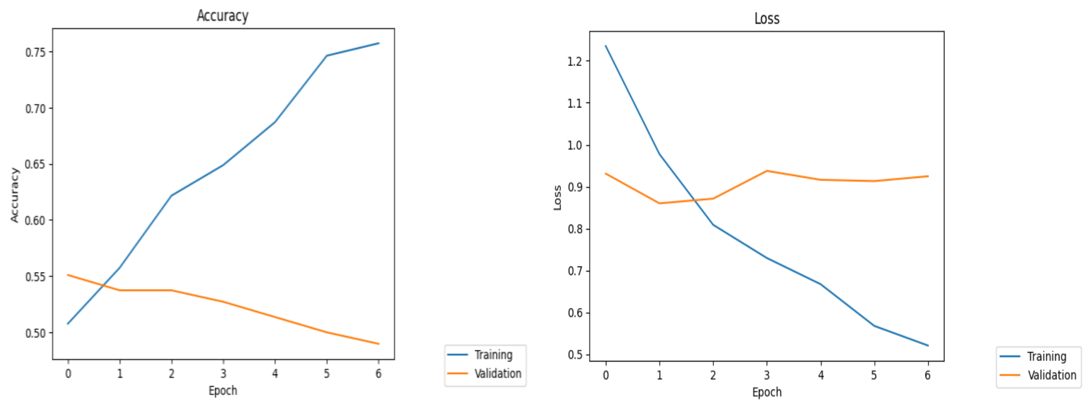
The operation of the EfficientNet model for the training data for Autism Spectrum Disorder Detection is shown in Figure 10 where x-axis is representing the epoch number and y-axis is representing % score. In the training step, the accuracy has increased from 55% to 85% after 17 epochs whereas in validation step, accuracy was 75%. Its training loss was 1.2 and validation loss was 0.8.



(a) **(b)**

Figure 10. Performance graph for the EfficientNet model (a) Accuracy performance (b) Model loss

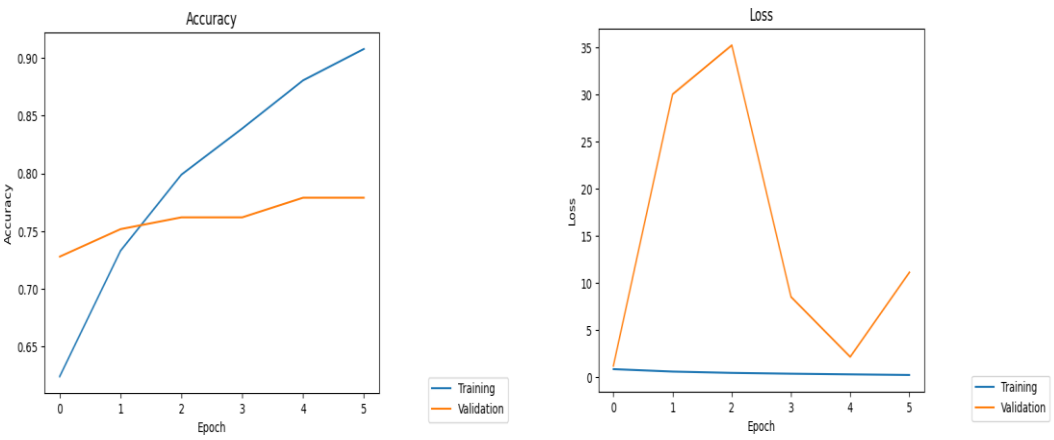
Figure 11 shows the performance of the NASNetMobile model in identifying ASD. Its accuracy in training phase was 50-75% and in validation phase was 50-55%. Its training loss was 1.2 and validation loss is 0.9.



(b)

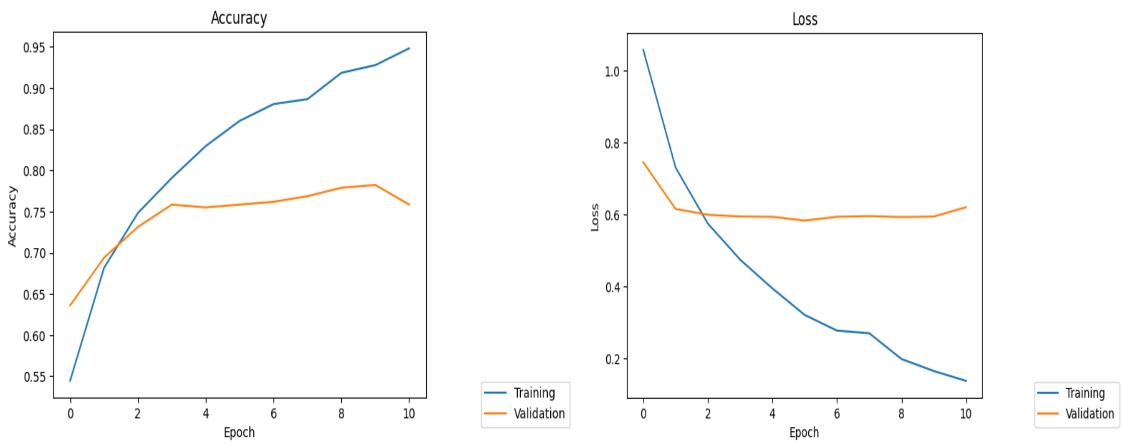
Figure11. Performance graph for the NasnetMobile model (a) Accuracy performance (b) Model loss

Figure 12 shows the performance of the VGG19 model in identifying ASD. Its accuracy in training phase was 65-90% and in validation phase was 70-75%. Its training loss was 1 and validation loss is 1. Figure 13 shows the performance of the Xception model in identifying ASD. Its accuracy in training phase was 55-95% and in validation phase was 55-75%. Its training loss was 1 and validation loss was 0.8. It was observed that for detecting ASD , Xception model is most suitable deep learning model.



(a) **(b)**

Figure 12. Performance graph for the VGG19 model (a) Accuracy performance (b) Model loss



(a) **(b)**

Figure 13. Performance graph for the Xception model (a) Accuracy performance (b) Model loss

This study explored a extensive use of pre-trained models with facial image dataset. However, further and in-depth studies may be needed to confirm its applicability, especially regarding use of social networking information in autism detection.

5. SUMMARY

The significant awareness of autism in children is an outcome of advancements in global health knowledge and capabilities. Researchers and academicians have also stepped up to identify the root cause of autism and diagnose it at an early age to offer treatment programmes that should assist autistic people to mix into the society and get away from the loneliness of the autistic world.

Recent observations suggest that there has been a major rise in the number of autistic children in recent years. Our findings provide conclusive evidence that how well the four deep learning models—EfficientNet, NASNETMobile, Xception, and VGG19—performed in identifying ASD using face features. Training of every model was performed using a publicly accessible dataset from the Internet, with the VGG19 model achieving the highest classification accuracy (92.33%). The outcomes of the model categorization offered a possibility that these deep learning and computer vision-based models will be used as smart tools to assist families and medical practitioners to diagnose autism more quickly and precisely. Detailed behavioral and emotional investigations for autism diagnosis that take a lot of time and work can be conducted more successfully with the use of computer based approaches. Our study demonstrates that facial data are more live than textual data. Future studies may explore in using facial information with feasible ways of detecting autism in patients.

REFERENCES

[1] AC. S. Paula, S. H. Ribeiro, E. Fombonne, and M. T. Mercadante, “Brief report: prevalence of pervasive developmental disorder in Brazil: a pilot study,” Journal of Autism and Developmental Disorders, vol. 41, no. 12, pp. 1738–1742, 2011

[2] https://doi.org/10.1007/s10803-011-1200-6

[3] Apa–American Psychiatric Association, “Diagnostic and statistical manual of mental disorders (DSM –5),” 2020, https://www.psychiatry.org/psychiatrists/practice/dsm

[4] R. Carette, F. Cilia, G. Dequen, J. Bosche, J.-L. Guerin, and L. Vandromme, “Automatic autism spectrum disorder detection thanks to eye-tracking and neural network-based approach,” in Proceedings of the International Conference on IoT Technologies for Healthcare, pp. 75–81. 4, Springer, Angers, France, 24–25 October 2017. DOI:10.1007/978-3-319-76213-5_11

[5] L. Kanner, “Autistic disturbances of affective contact,” Nerv. Child, vol. 2, pp. 217–250, 1943.

[6] E. Fombonne, “Epidemiology of pervasive developmental disorders,” Pediatric Research, vol. 65, no. 6, pp. 591–598, 2009.

[7] G. Yolcu, I. Oztel, S. Kazan et al., “Deep learning-based facial expression recognition for monitoring neurological disorders,” in Proceedings of the 2017 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), pp. 1652–1657, Kansas City, MO, USA, 13–16 November 2017. DOI: 10.1109/BIBM.2017.8217907

[8] G. Yolcu, I. Oztel, S. Kazan et al., “Facial expression recognition for monitoring neurological disorders based on convolutional neural network,” Multimedia Tools and Applications, vol. 78, no. 22, pp. 31581–31603, 2019. DOI: 10.1007/s11042-019-07959-6 M. I. U. Haque and D. Valles, “A facial expression recognition approach using DCNN for autistic children to identify emotions,” in Proceedings of the 2018 IEEE 9th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON), pp. 546–551, Vancouver, Canada, 1–3 November 2018. DOI: 10.1109/IEMCON.2018.8614802

[9] Q. Guillon, N. Hadjikhani, S. Baduel, and B. Rog´e, “Visual social attention in autism spectrum disorder: insights from eye tracking studies,” Neuroscience & Biobehavioral Reviews, vol. 42, pp. 279–297, 2014. https://doi.org/10.1016/j.neubiorev.2014.03.013.

[10] T. Akter, M. S. Satu, L. Barua, F. F. Sathi, and M. H. Ali, “Statistical analysis of the activation area of fusiform gyrus of human brain to explore autism,” International Journal of Computer Science and Information Security, vol. 15, pp. 331–337, 2017.

[11] M. S. Satu, F. Farida Sathi, M. S. Arifen, M. Hanif Ali, and M. A. Moni, “Early detection of autism by extracting features: a case study in Bangladesh,” in Proceedings of the 2019 International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST), pp. 400–405, Dhaka, Bangladesh,10–12 January 2019. DOI:10.1109/ICREST.2019.8644357

[12] S. Schelinski, K. Borowiak, and K. von Kriegstein, “Temporal voice areas exist in autism spectrum disorder but are dysfunctional for voice identity recognition,” Social Cognitive and Affective Neuroscience, vol. 11, no. 11, pp. 1812–1822, 2016 DOI: 10.1093/scan/nsw089

[13] M. Li, D. Tang, J. Zeng et al., “An automated assessment framework for atypical prosody and stereotyped idiosyncratic phrases related to autism spectrum disorder,” Computer Speech & Language, vol. 56, pp. 80–94, 2019. https://doi.org/10.1016/j.csl.2018.11.002

[14] F. B. Pokorny, B. W. Schuller, P. B. Marschik et al., “Earlier identification of children with autism spectrum disorder: an automatic vocalisation-based approach,” in Proceedings of the Annual Conference of the International Sp, August 2017. Computational Intelligence and Neuroscience 9 doi: 10.21437/Interspeech.2017-1007

[15] F. Eyben, K. R. Scherer, B. W. Schuller et al., “The Geneva minimalistic acoustic parameter set (GeMAPS) for voice research and affective computing,” IEEE Transactions on Affective Computing, vol. 7, no. 2, pp. 190–202, 2016. DOI: 10.1109/TAFFC.2015.2457417

[16] A. Jack, “Neuroimaging in neurodevelopmental disorders: focus on resting-state fMRI analysis of intrinsic functional brain connectivity,” Current Opinion in Neurology, vol. 31, no. 2, pp. 140–148, 2018. *DOI:* 10.1097/WCO.0000000000000536

[17] W. Liu, M. Li, and L. Yi, “Identifying children with autism spectrum disorder based on their face processing abnormality: a machine learning framework,” Autism Research, vol. 9, no. 8, pp. 888–898, 2016. DOI: 10.1002/aur.1615

[18] M. Alcañiz Raya, I. A. Chicchi Giglioli, J. Mar´ın-Morales et al., “Application of supervised machine learning for behavioral biomarkers of autism spectrum disorder based on electro dermal activity and virtual reality,” Frontiers in Human Neuroscience, vol. 14, p. 90, 2020. https://doi.org/10.3389/fnhum.2020.00090

[19] J. Hashemi, G. Dawson, K. L. H. Carpenter et al., “Computer vision analysis for quantification of autism risk behaviors,” IEEE Trans. Affect. Comput.vol. 3045, pp. 1–12, 2018. DOI: 10.1109/TAFFC.2018.2868196

[20] A. V. Dahiya, C. McDonnell, E. DeLucia, and A. Scarpa, “A systematic review of remote telehealth assessments for early signs of autism spectrum disorder: video and mobile applications,” Practice Innovations, vol. 5, no. 2, pp. 150–164,2020. https://doi.org/10.1037/pri0000121

[21] S. R. Shahamiri and F. -abtah, “Autism AI: a new autism screening system based on artificial intelligence,” Cognitive Computation, vol. 12, no. 4, pp. 766–777, 2020. https://doi.org/10.1007/s12559-020-09743-3

[22] C. H. Y. Fu and S. G. Costafreda, “Neuroimaging-based biomarkers in psychiatry: clinical opportunities of a paradigm shift,” Canadian Journal of Psychiatry, vol. 58, no. 9, pp. 499–508, 2013. DOI: 10.1177/070674371305800904

[23] S. J. Moon, J. Hwang, R. Kana, J. Torous, and J. W. Kim, “Accuracy of machine learning algorithms for the diagnosis of autism spectrum disorder: systematic review and meta-analysis of brain magnetic resonance imaging studies,” JMIR Mental Health, vol. 6, no. 12, Article ID e14108, 2019. doi: 10.2196/14108.

[24] S. Sarabadani, L. C. Schudlo, A. A. Samadani, and A. Kushski, “Physiological detection of affective states in children with autism spectrum disorder,” IEEE Transactions on Affective Computing, vol. 11, no. 4, pp. 588–600, 2020. DOI: 10.1109/TAFFC.2018.2820049

[25] Shinde, A.V., Patil, D.D. (2023). Content-Centric Prediction Model for Early Autism Spectrum Disorder (ASD) Screening in Children. In: Tuba, M., Akashe, S., Joshi, A. (eds) ICT Infrastructure and Computing. Lecture Notes in Networks and Systems, vol 520. Springer, Singapore. https://doi.org/10.1007/978-981-19-5331-6_38

[26] Shinde A. V., Patil, D. D., & Tripathi, K. K. (2024). A Comprehensive Survey on Recommender Systems Techniques and Challenges in Big Data Analytics with IOT Applications. Revista De Gestão Social E Ambiental, 18(2), e05195. https://doi.org/10.24857/rgsa.v18n2-097

[27] Anita Vikram Shinde, Dipti Durgesh Patil, A Multi-Classifier-Based Recommender System for Early Autism Spectrum Disorder Detection using Machine Learning, Healthcare Analytics, Volume 4,2023, 100211, ISSN 2772-4425, https://doi.org/10.1016/j.health.2023.100211.

[28] M. B. Mohammed, L. Salsabil, M. Shahriar, S. S. Tanaaz and A. Fahmin, "Identification of Autism Spectrum Disorder through Feature Selection-based Machine Learning," *2021 24th International Conference on Computer and Information Technology (ICCIT)*, Dhaka, Bangladesh, 2021, pp. 1-6, doi: 10.1109/ICCIT54785.2021.9689805.

[29] M. Lohar and S. Chorage, "Automatic Classification of Autism Spectrum Disorder (ASD) from Brain MR Images Based on Feature Optimization and Machine Learning," *2021 International Conference on Smart Generation Computing, Communication and Networking (SMART GENCON)*, Pune, India, 2021, pp. 1-7, doi: 10.1109/SMARTGENCON51891.2021.9645785.

[30] N. BalaKrishna, M. B. Mukesh Krishnan, S. M. Reddy, S. K. Irfan and S. Sumaiya, "AUTISM Spectrum Disorder Detection Using Machine Learning," *2023 3rd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)*, Greater Noida, India, 2023, pp. 1645-1650, doi: 10.1109/ICACITE57410.2023.10183095

[31] A. S. Teja, A. S. Abhay, D. Mounika and M. V. Pujitha, "Autism Spectrum Disorder Detection Techniques," *2022 International Conference on Communication, Computing and Internet of Things (IC3IoT)*, Chennai, India, 2022, pp. 1-4, doi: 10.1109/IC3IOT53935.2022.9767927.

[32] N. Zaman, J. Ferdus and A. Sattar, "Autism Spectrum Disorder Detection Using Machine Learning Approach," *2021 12th International Conference on Computing Communication and* Networking Technologies (ICCCNT), Kharagpur, India, 2021, pp. 1-6, doi: 10.1109/ICCCNT51525.2021.9579522.

[33] S. Raj and S. Masood, “Analysis and detection of autism spectrum dis-order using machine learning techniques,” Procedia Computer Science,vol. 167, pp. 994–1004, 2020.

[34] Hosseini MP, Beary M, Hadsell A, Messersmith R, Soltanian-Zadeh H. Deep Learning for Autism Diagnosis and Facial Analysis in Children. Front Comput Neurosci. 2022 Jan 20;15:789998. doi: 10.3389/fncom.2021.789998. Retraction in: Front Comput Neurosci. 2023 May 16;17:1215827. doi: 10.3389/fncom.2023.1215827.

[35] G. Piosenka, “Detect autism from a facial image,” 10 December 2021, https://www.kaggle.com/datasets/cihan063/autism-image-data

[36] Bansal, M., Kumar, M., Sachdeva, M. et al. Transfer learning for image classification using VGG19: Caltech-101 image data set. J Ambient Intell Human Comput 14, 3609–3620 (2023). https://doi.org/10.1007/s12652-021-03488-z

[37] Ghodekar, Anil and Kumar, Akhil, LightLeafNet: Lightweight and Efficient NASNetmobile Architecture for Tomato Leaf Disease Classification. 20 Sep 2023 Available at SSRN: https://ssrn.com/abstract=4570347 or http://dx.doi.org/10.2139/ssrn.4570347

[38] Gülmez, B. A novel deep neural network model based Xception and genetic algorithm for detection of COVID-19 from X-ray images. Ann Oper Res 328, 617–641 (2023). https://doi.org/10.1007/s10479-022-05151-y

[39] Ümit Atila, Murat Uçar, Kemal Akyol, Emine Uçar, Plant leaf disease classification using EfficientNet deep learning model, Ecological Informatics, Volume 61, 2021, 101182, ISSN 1574-9541, https://doi.org/10.1016/j.ecoinf.2020.101182