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Diagnosis of Autism in Children Using Deep Learning Techniques by Analyzing Facial Features †

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Abstract: Autism spectrum disorder (ASD) is a complex neurological disorder that results in aberrant personality traits, cognitive function, and interpersonal relationships. It impacts the child's linguistic and social skills, interaction abilities, and capacity for logical thought. It is possible to use the human face as a physiological identifier since it can serve as an indicator of brain function, thus helping with early diagnosis in a simple and effective way. The purpose of this study is to detect autism from facial images using a deep learning model. To accurately identify autism in children, we used three pre-trained CNN models, VGG16, VGG19 and, EfficientnetB0, as feature extractors and binary classifiers. The suggested models were trained using a publicly available dataset from Kaggle that included 3014 images of children characterized as autistic and non-autistic. The models yielded accuracies of 84.66%, 80.05%, and 87.9%, respectively.

Keywords: autism spectrum disorder; deep learning; facial images; detection; CNN

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1. Introduction

Autism spectrum disorder (ASD) is a developmental disorder caused by neurobiological abnormalities [1]. ASD is a complex medical condition that is not entirely comprehended. Environmental and genetic factors may play roles in causing this disorder. Autism is estimated to affect 1 in 160 individuals worldwide according to the World Health Organization. This represents approximately 2% of the global population. According to 2022 statistics, the United States has the highest prevalence of ASD, with 1 in 44 children afflicted. It is most commonly diagnosed in children older than three years [1]. Children with autism often face difficulties with social interaction and communication, as well as restricted interests or behaviors. They may also have unique cognitive, gestural, and attentive styles [2]. There is currently no known cure for autism spectrum disorder, but early diagnosis is essential if we are to provide expeditious treatment to alleviate the severity of symptoms and enable the child to develop the necessary skills to function in the future [1].

Researchers at the University of Missouri conducted a study examining the diagnosis of autism in children by analyzing their facial features. Their investigation revealed that children with autism possess a set of distinct facial characteristics that differ from those observed in non-autistic children. The features include an exceptionally expansive upper face, encompassing widely spaced eyes, and a comparatively shorter central facial region, covering the cheeks and nose [3]. Figure 1, sourced from the Kaggle database, demonstrates the differences in facial attributes between the two groups, with the first row depicting autistic children, and the second row showing non-autistic children [4].

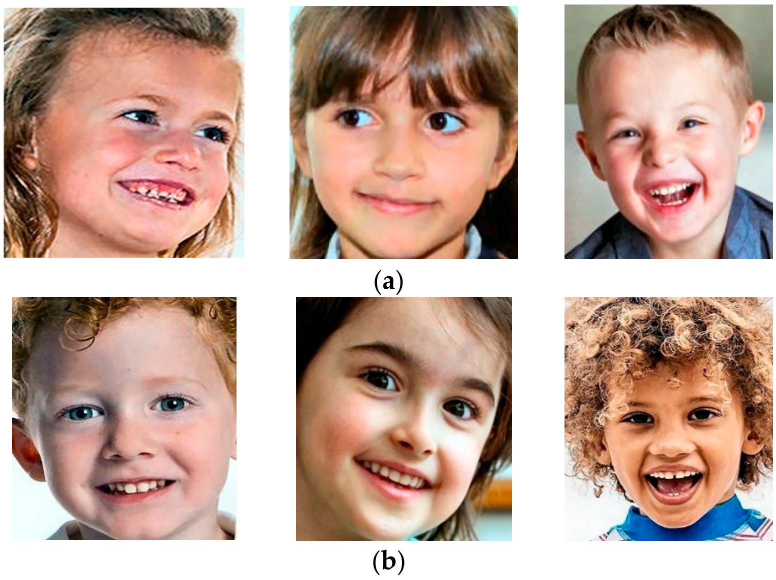

Figure 1. (**a**) Children with autism; (**b**) children without autism.

Research into diagnosing autism spectrum disorder (ASD) using facial features is rapidly expanding, particularly due to its significance for developing nations. This method can serve as an initial screening tool for early ASD detection in both typically developing children and those with ASD. Recent studies underscore the potential of deep neural networks, particularly CNN models, in diagnosing various diseases [5–14]. To extract features, convolutional neural networks (CNNs) are widely utilized. CNNs are excellent for image detection or classification as their ability to learn from a substantial corpus of images is noteworthy [15]. CNNs are extremely precise and efficient, however they require a lot of time and computing power to train [7]. Hence, instead of beginning from scratch, utilizing models pre-trained on supercomputers and extensive datasets proves more efficient. Enhanced classification or prediction can be attained by adjusting the weights and parameters of these pre-trained models through transfer learning, tailored to the specific requirements of the desired tasks [16].

However, the majority of proposed CNN models involve a greater number of hyperparameters, resulting in an increase in complexity, and are frequently not applicable for datasets of varying sizes [15]. Therefore, to create a successful CNN-based ASD diagnosis model, it is imperative to develop a CNN architecture capable of detecting ASD with minimal hyperparameters. This opportunity being presented, we used pre-trained deep learning models and 2D facial images to diagnose ASD early. To extract image features, we used the Kaggle dataset coupled with the transfer learning technique.

Contributions made in this work including the following:

1. Pre-processing is performed on the dataset, which includes data augmentation and resizing of the images, before it is given to the model for training.
2. Import the pre-trained networks, modify the layers to accommodate the ASD dataset, and train the deep learning model.
3. Analyze the performance of various models to determine the optimal model for classifying the image dataset into two classifications—autistic and non-autistic.

Section-Wise Summary

The ensuing Section 2 provides an overview of the extensive scholarly investigation conducted on the subject matter, encapsulating the advancements made in this particular domain. Following that, the subsequent Section 3 expounds upon the methodologies employed in this study, and] elucidating the alterations made to the underlying pre-trained frameworks. Following this, a comprehensive analysis and discussion of the outcomes are presented in the results and discussion Section 4, ultimately culminating in the presentation of the conclusion in Section 5.

2. Literature Review

2.1. Diagnosis Using Machine Learning Models

In recent years, there has been a growing emphasis on evaluating facial expressions in individuals with autism spectrum disorder (ASD) to enable early diagnosis, particularly in children. Jaine et al. [17] employed machine learning and deep learning techniques for this purpose. They concentrated on analyzing human faces, with a particular focus on the eye regions, using images sourced from YouTube videos. Their methodology involved employing computer vision techniques to extract image frames and curate the dataset. The extracted features were then subjected to analysis using classical machine learning algorithms, specifically decision trees and k-nearest neighbors (KNNs). The resulting heterogeneous ensemble model achieved a peak accuracy of 74.84%. Notably, the research team suggested that further refinement could be achieved by filtering the dataset based on factors such as age (>18), gender, or autism severity level. This selective approach has the potential to enhance the accuracy of ASD diagnosis through facial expression analysis.

2.2. Diagnosis Using Deep Learning Models

The increasing popularity of utilizing deep learning for autism detection can be attributed to its capability to analyze intricate patterns and derive valuable insights from diverse data sources. This enables the achievement of greater precision and the timely identification of autism, fostering improved diagnostic outcomes. Fedari et al. [18] utilized a modified CNN model to scrutinize the eye-tracking scan paths of 59 school children, leveraging the characteristic elements of eye fixation. The model achieved a notable accuracy score of 90%. However, the primary limitation of their study was the small scale of the dataset. Romu et al. [19] employed a similar but relatively limited dataset and integrated advanced deep learning techniques. Their experimentation revealed that a single-layer artificial neural network (ANN) model attained the most elevated level of accuracy, which amounted to 92%.

The utilization of transfer learning is increasingly favored as a method for identifying autism spectrum disorder (ASD) in children as it allows for effective adaptation to ASD-specific tasks, even when confronted with limited specialized data, contributing to enhanced efficiency and accuracy in ASD diagnosis. Fawaz et al. [20] implemented CNN models and transfer learning methodology to identify autism in children by analyzing static facial images from the Kaggle dataset. They utilized three pre-existing networks—Xception, VGG19, and NASNETMobile—to train their model. The Xception network achieved an accuracy of 91%. However, Monica et al. [2] took a similar approach but improved upon it by integrating deep neural networks (DNNs) with CNNs. Their Xception model accomplished a significantly higher accuracy rate of 96.62%.

2.3. Diagnosis Using Hybrid Models

Hybrid models, which merge deep learning (DL) and machine learning (ML) techniques, effectively harness the advantages of both approaches in the detection of autism spectrum disorder (ASD). DL excels in capturing intricate patterns inherent in complex data, such as facial images, while ML contributes interpretability and generalization capabilities. Through the amalgamation of these techniques, hybrid models enhance the accuracy, resilience, and interpretability of ASD detection systems [21].

In a study conducted by Tania et al. [2], a model was developed for detecting autism in children. The researchers utilized the facial image dataset available on Kaggle and employed a total of 17 classifiers, including 10 machine learning and 7 deep learning models, along with pre-trained models, to evaluate the model's performance. Additionally, the classifiers were utilized to differentiate between different autism spectrum disorder (ASD) groups by applying the k-means clustering technique exclusively to autism image data. Notably, the improved MobileNet model achieved the highest accuracy of 91%. In a similar vein, Eman et al. employed comparable methodologies, classifiers, and datasets while also incorporating AutoML techniques. The AutoML model outperformed the others, yielding the highest accuracy of 96%.

3. Methodology

The aim of this study was to utilize a transfer learning-based framework for recognizing autistic facial traits, with the ultimate goal of detecting the occurrence of autism spectrum disorder (ASD) in children during their early years. To accomplish this goal, we employed pre-existing deep learning models that could automatically extract sturdy characteristics that would otherwise be difficult to identify through visual scrutiny due to their complexity. These features were then processed through multiple layers, with the dense uppermost layer yielding the diagnosis of ASD.

3.1. System Architecture

Figure 2 illustrates the workflow in the form of a block diagram.

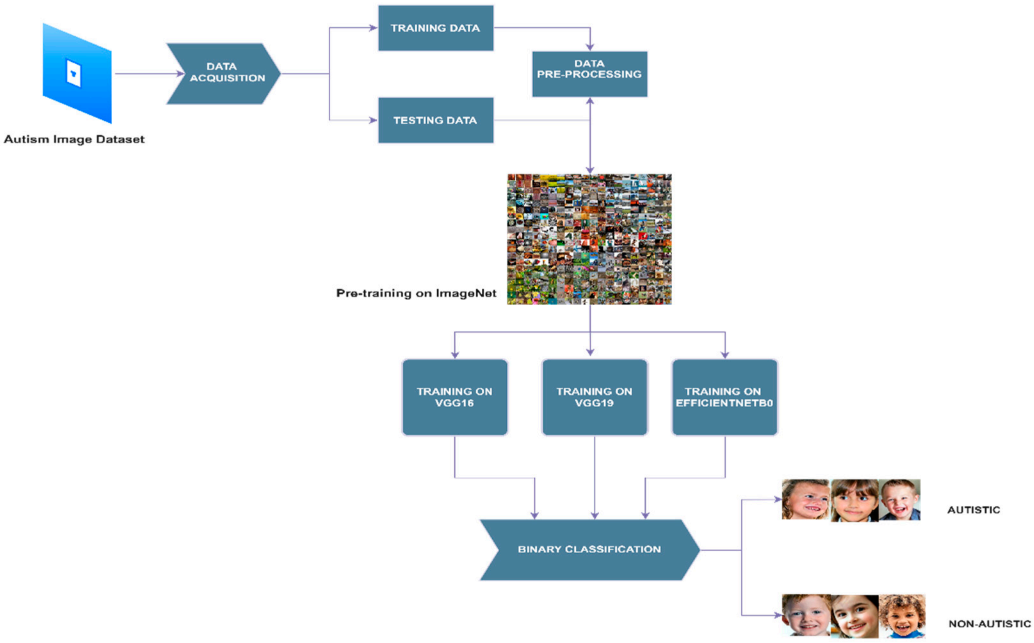

Figure 2. Architecture overview of the methodology.

3.2. Dataset Details

To achieve optimal performance in deep learning models, a large dataset is essential for providing comprehensive training in diverse scenarios [6]. This training process results in a significantly higher level of accuracy. Our recommended models were developed using the autistic children dataset, which is the only free resource of its kind available online in the Kaggle repository [22]. The age of the children in the dataset ranged from 2 to 14 years, with the majority being between 2 and 8 years old. The dataset consisted of 2D RGB images, with an almost equal ratio of the autistic class to the normal control class, and a male-to-female ratio of approximately 3:1. The images were categorized into three groups, which included the training set, testing set, and validation set. The training set contained 2536 images (86.38%), while the testing set and validation set contained 300 images (10.22%) and 100 images (3.41%), respectively. In each group, the ASD and NC classes were equally represented. The provider of the images, Gerry Piosenka, sourced them from an online platform. Unfortunately, no clinical history pertaining to the children depicted in the dataset, including factors such as ASD severity, ethnicity, or socioeconomic status, is available for reference.

3.3. Data Augmentation

The preliminary stage of data preparation involves data cleaning, which encompasses the removal of errors, duplicates, and outliers, as well as the elimination of extraneous data points, the imposition of structure on the dataset, and the handling of missing values. However, in the case of this particular dataset, duplication has already been eradicated, and no values are missing. Subsequently, to enhance training efficacy, the dataset's images necessitate data augmentation through the implementation of rotating, horizontal flipping, zooming, and height and width shifting, resulting in an augmented set of images for training and validation sets. Additionally, the dataset's images must be resized to $227 \times 227 \times 3$ dimensions to ensure compatibility with the specified architecture.

3.4. Transfer Learning Models for Feature Extraction

The present investigation rests upon the existing scholarly literature as there is a lack of standardized protocols or universal benchmarks to ascertain the optimal pre-trained algorithms. Consequently, the research is founded upon three pre-trained deep learning models that employ convolutional neural networks (CNNs): VGG19, VGG16, EfficientNetB0. The selection of these models is based on their impressive performance, as attested by numerous references in the literature.

3.5. VGG16

VGG16 is widely recognized as a highly acclaimed architecture for deep convolutional neural networks, praised for its remarkable capabilities in image classification tasks. This distinguished model comprises a total of 16 layers, consisting of 13 convolutional layers alongside 3 fully connected layers. Notably, the uniform structure of VGG16, incorporating 3×3 convolutional filters, facilitates effective deep learning while maintaining manageable parameters. VGG16 has gained popularity as a favored option for a range of computer vision tasks, such as object recognition and localization, owing to its impressive performance and uncomplicated architecture. Furthermore, the pre-existing weights of VGG16 are commonly employed in transfer learning scenarios, enabling the integration of knowledge acquired from extensive datasets to enhance the performance of other models across diverse tasks and datasets [23].

3.6. VGG19

VGG19 is a convolutional neural network architecture that employs small convolution filters of 3×3 dimensions. The network has 19 weighted layers and represents a significant improvement over previous designs, demonstrating the benefits of increasing network depth. Developed by Karen Simonyan and Andrew Zisserman for the 2014 ImageNet Challenge, VGG19 achieved state-of-the-art performance in both localizing and classifying tasks. To promote further research in computer vision involving deep visual representations, the authors have released the VGG19 model for public use. This model requires input images of size 224×224 in RGB format. The only preprocessing step needed is to subtract the mean RGB value, calculated from the training set, from each pixel in the input image. The VGG19 architecture processes input images through a sequence of convolutional layers, each featuring a small receptive field of 3×3. Spatial pooling is conducted using five max-pooling layers applied after certain convolutional layers. Following the convolutional layers, three fully connected layers are employed. The depth of the convolutional layers varies depending on the specific architecture. The first two fully connected layers consist of 4096 channels each, while the third layer comprises 1000 channels and incorporates a softmax function. This final layer is used for making predictions based on the learned features from the preceding layers, typically in tasks such as image classification [24].

3.7. EfficientNetB0

EfficientNet is a neural network architecture that has been specifically developed to balance accuracy and computational efficiency, providing a state-of-the-art solution for various computer vision tasks. Utilizing compound scaling of depth, width, and resolution, the mobile inverted bottleneck MBConv constitutes the primary layer of EfficientNetB0. The constants associated with each of these components (α, β, and γ) must be determined to achieve the best results, with larger models requiring greater system resources. One advantage of EfficientNetB0 is its ability to find scaling coefficients despite having limited system capacity due to its smaller size. Once found, these same coefficients can then be used for larger and more complex models [25].

4. Results

4.1. Experimental Analysis

4.1.1. Modification of the Architectures

Upon importing the three pre-trained models, namely VGG16, VGG19, and EfficientNetB0, into the Keras framework, a bespoke model was meticulously constructed and incorporated with these pre-existing neural networks in order to undergo a process of fine-tuning. This optimization aimed to enhance their compatibility with the autism image dataset. The customized model was augmented with an additional 9 layers, comprising a global max pooling layer, 5 dense layers with varying neuron counts per layer, and 3 drop-out layers featuring a dropout rate of 0.2. Notably, the final layer was equipped with the softmax activation function, thereby facilitating the binary classification of images into two distinct classes, namely autistic and non-autistic.

4.1.2. Hyperparameter Tuning

To determine the best combination of hyperparameters and optimizer, we evaluated the accuracy and area under the curve (AUC) through a series of ablation studies. The deep transfer learning models and Keras API Library were utilized in our training process. Additionally, we incorporated data processing libraries including matplotlib, sklearn, and pandas to analyze and present visual representations of the models' performance. A fixed set of hyperparameters, namely 20 epochs, a learning rate of 0.001, and a batch size of 64 were employed to evaluate the effectiveness of CNN-based models with different optimizers. Table 1 summarizes the validation accuracy for optimizers. The optimizers Adagrad, Adam, and Adamax were chosen because numerous cited studies demonstrate that these three optimizers produce a superior model performance [17]. The highest accuracy and AUC values, as shown in Table 1, are 88.33% and 95.44%, respectively. We obtained the best result with the Adamax optimizer.

Table 1. Model performance for different optimizers.

Model	Adamax		Adam		Adagrad	
	Accuracy	**AUC**	**Accuracy**	**AUC**	**Accuracy**	**AUC**
VGG19	50.00%	50.16%	51.44%	50.00%	87.66%	93.06%
VGG16	52.74%	54.16%	57.89%	60.29%	84.67%	90.73%
EfficientNetB0	88.33%	95.44%	87.66%	94.32%	82.66%	88.68%

As a result, the optimizer chosen to facilitate the training of the model in the following experiments was Adamax. With the optimizer set as Adamax, we employed various learning rates, namely, 0.01, 0.001, and 0.0001. The outcomes of the diverse learning rates on the test results are presented in Table 2.

As demonstrated in Table 2, the accuracy and AUC values were improved when the learning rate was set to 0.001.

An optimal accuracy of 88.33% was achieved by utilizing a learning rate of 0.001 during the training of the EfficientNetB0 model for a duration of 20 epochs.

Table 2. Model performance for different learning rates.

Model	Learning Rate					
	0.01		0.001		0.0001	
	Accuracy	**AUC**	**Accuracy**	**AUC**	**Accuracy**	**AUC**
VGG19	74.00%	81.50%	50.74%	50.00%	84.66%	91.98%
VGG16	76.22%	83.00%	52.74%	54.15%	80.05%	87.83%
EfficientnetB0	87.37%	92.01%	88.33%	95.44%	87.9%	93.31%

Using the optimum learning rates and optimizers for each model obtained the results shown in Figure 3.

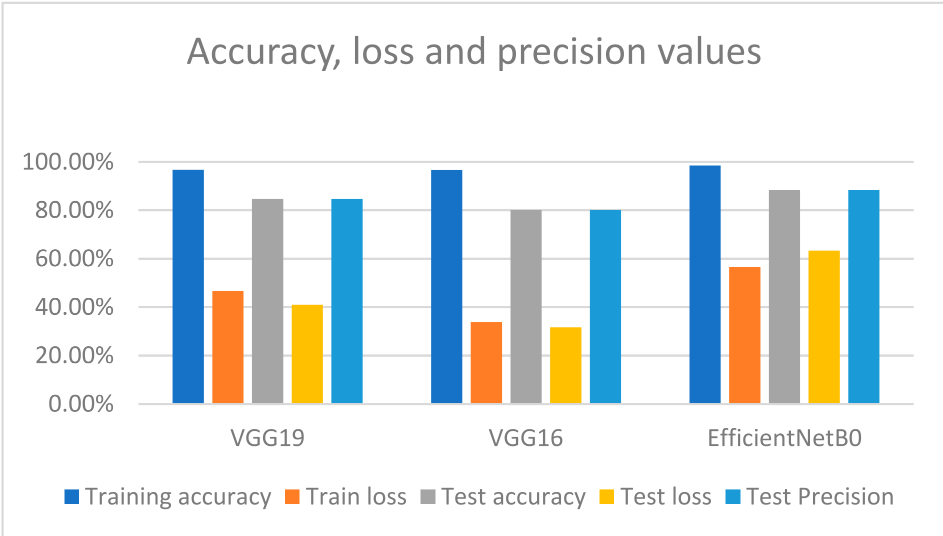

Figure 3. Model performances.

Consequently, we generated the ensuing graphs as shown in Figures 4–7 for the EfficientNetB0 model to conduct a more thorough investigation of the training and testing procedures for this model.

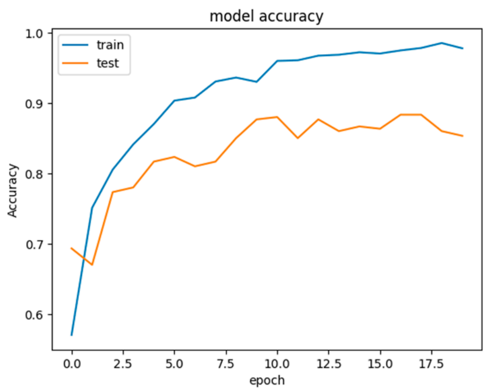

Figure 4. Train vs. Test accuracy.

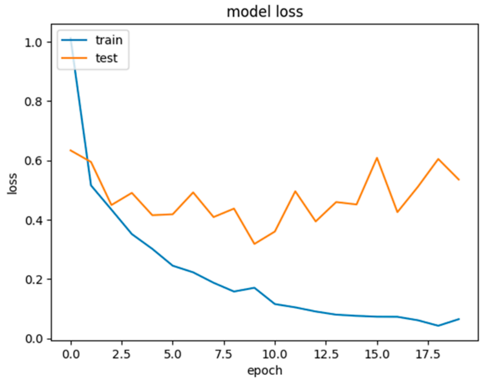

Figure 5. Train vs. Test loss.

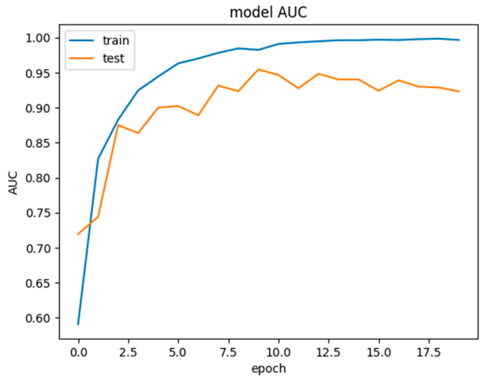

Figure 6. Train vs. Test AUC.

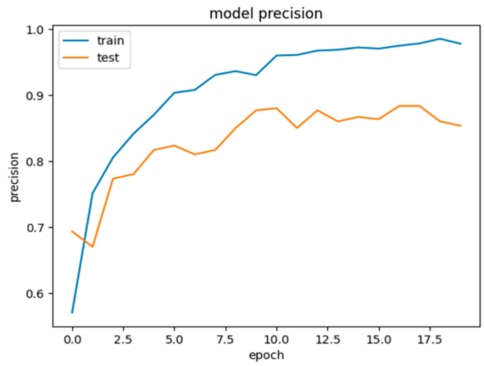

Figure 7. Train vs. Test Precision.

5. Conclusions

The objective of this study was to identify the optimal transfer learning model for the classification of autism spectrum disorder (ASD). To this end, an empirical investigation was carried out, encompassing the fine-tuning of hyperparameters and optimizers for model training. Three CNN-based models, namely VGG19, VGG16, and EfficientNetB0, were the main focus of this study. These are well-established and widely used in the field. The investigation involved the utilization of three optimizers, namely Adam, Adamax, and Adagrad, to determine the optimal optimizer for each model. Additionally, three learning rates, specifically 0.01, 0.001, and 0.0001, were employed to determine the most effective one.

Our study revealed that, when utilizing the Adagrad optimizer, the VGG16 model attained the highest performance with an accuracy rate of 84.67% and an AUC of 90.73%. The VGG19 model also exhibited notable performance, with an accuracy rate of 87.66% and an AUC of 93.06% when the Adagrad optimizer was employed. These findings highlighted the efficacy of the Adagrad optimizer in improving the performance of the VGG16 and

VGG19 models. In contrast, the EfficientNet model achieved the highest accuracy of 88.33% and an AUC of 95.44% when trained with Adamax optimizer.

Overall, the EfficientNetB0 model demonstrated the most effective performance when trained with 20 epochs. Utilizing Adamax as the optimizer and a learning rate of 0.001, this resulted in a training accuracy of 98.51% and a test accuracy of 88.33%.

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References

1. Ghazal, T.M.; Munir, S.; Abbas, S.; Athar, A.; Alrababah, H.; Khan, M.A. Early Detection of Autism in Children Using Transfer Learning. *Intell. Autom. Soft Comput.* **2023**, *36*, 11–22. [CrossRef]
2. Akter, T.; Ali, M.H.; Khan, M.I.; Satu, M.S.; Uddin, M.J.; Alyami, S.A.; Ali, S.; Azad, A.K.; Moni, M.A. Improved Transfer-Learning-Based Facial Recognition Framework to Detect Autistic Children at an Early Stage. *Brain Sci.* **2021**, *11*, 734. [CrossRef] [PubMed]
3. Alkahtani, H.; Aldhyani, T.H.H.; Alzahrani, M.Y. Deep Learning Algorithms to Identify Autism Spectrum Disorder in Children-Based Faci-al Landmarks. *Appl. Sci.* **2023**, *13*, 4855. [CrossRef]
4. Autistic Children Facial Image Data Set. Available online: https://www.kaggle (accessed on 19 January 2024).
5. Yang, M.; Cao, M.; Chen, Y.; Chen, Y.; Fan, G.; Li, C.; Wang, J.; Liu, T. Large-Scale Brain Functional Network Integration for Discrimination of Autism Using a 3-D Deep Learning Model. *Front. Hum. Neurosci.* **2021**, *15*, 687288. [CrossRef] [PubMed]
6. Ahsan, M.M.; Alam, T.E.; Trafalis, T.; Huebner, P. Deep MLP-CNN Model Using Mixed-Data to Distinguish between COVID-19 and Non-COVID-19 Patients. *Symmetry* **2020**, *12*, 1526. [CrossRef]
7. Ahsan, M.M.; Gupta, K.D.; Islam, M.M.; Sen, S.; Rahman, M.L.; Hossain, M.S. COVID-19 Symptoms Detection Based on NasNetMobile with Explainable AI Using Various Imaging Modalities. *Mach. Learn. Knowl. Extr.* **2020**, *2*, 490–504. [CrossRef]
8. Ahsan, M.M.; Ahad, M.T.; Soma, F.A.; Paul, S.; Chowdhury, A.; Luna, S.A.; Yazdan, M.M.; Rahman, A.; Siddique, Z.; Huebner, P. Detecting SARS-CoV-2 From Chest X-Ray Using Artificial Intelligence. *IEEE Access* **2021**, *9*, 35501–35513. [CrossRef] [PubMed]
9. Ahsan, M.; Mahmud, M.; Saha, P.; Gupta, K.; Siddique, Z. Effect of Data Scaling Methods on Machine Learning Algorithms and Model Per-formance. *Technologies* **2021**, *9*, 52. [CrossRef]
10. Ahsan, M.M.; Nazim, R.; Siddique, Z.; Huebner, P. Detection of COVID-19 Patients from CT Scan and Chest X-ray Data Using Modified MobileNetV2 and LIME. *Healthcare* **2021**, *9*, 1099. [CrossRef] [PubMed]
11. Ahsan, M.M.; Luna, S.A.; Siddique, Z. Machine-Learning-Based Dis-ease Diagnosis: A Comprehensive Review. *Healthcare* **2022**, *10*, 541. [CrossRef] [PubMed]
12. Ahsan, M.M.; Siddique, Z. Machine learning-based heart disease diagnosis: A systematic literature review. *Artif. Intell. Med.* **2022**, *128*, 102289. [CrossRef] [PubMed]
13. Haque, R.; Islam, N.; Islam, M.; Ahsan, M.M. A Comparative Analysis on Suicidal Ideation Detection Using NLP, Machine, and Deep Learning. *Technologies* **2022**, *10*, 57. [CrossRef]
14. Pham, H.; Jones, M.A.; Gai, T.; Islam, W.; Danala, G.; Jo, J.; Zheng, B. Identifying an optimal machine learning generated image marker to predict survival of gastric cancer patients. In *Medical Imaging 2022: Computer-Aided Diagnosis*; Iftekharuddin, K.M., Drukker, K., Mazurowski, M.A., Lu, H., Muramatsu, C., Samala, R.K., Eds.; SPIE: Bellingham, WA, USA, 2022; p. 79. [CrossRef]
15. Alam, M.S.; Rashid, M.M.; Roy, R.; Faizabadi, A.R.; Gupta, K.D.; Ahsan, M.M. Empirical Study of Autism Spectrum Disorder Diagnosis Using Facial Images by Improved Transfer Learning Approach. *Bioengineering* **2022**, *9*, 710. [CrossRef] [PubMed]
16. Mishra, P.; Passos, D. Realizing transfer learning for updating deep learning models of spectral data to be used in new scenarios. *Chemom. Intell. Lab. Syst.* **2021**, *212*, 104283. [CrossRef]
17. Budke, J.R. Face Biometrics for Differentiating Typical Development and Autism Spectrum Disorder: A Methodology for Collecting and Evaluating a Dataset. Master's Thesis, Universidade Federal do Rio Grande do Norte, Lagoa Nova, Brazil, 2022.

18. Cilia, F.; Carette, R.; Elbattah, M.; Dequen, G.; Guérin, J.L.; Bosche, J.; Vandromme, L.; Le Driant, B. Computer-Aided Screening of Autism Spectrum Disorder: Eye-Tracking Study Using Data Visualization and Deep Learning. *JMIR Hum. Factors* **2021**, *8*, e27706. [CrossRef] [PubMed]
19. Carette, R.; Elbattah, M.; Cilia, F.; Dequen, G.; Guérin, J.-L.; Bosche, J. Learning to Predict Autism Spectrum Disorder based on the Visual Patterns of Eye-tracking Scanpaths. In Proceedings of the 12th International Joint Conference on Biomedical Engineering Systems and Technologies, SCITEPRESS—Science and Technology Publications, Prague, Czech Republic, 22–24 February 2019; pp. 103–112. [CrossRef]
20. Alsaade, F.W.; Alzahrani, M.S. Classification and Detection of Autism Spectrum Disorder Based on Deep Learning Algorithms. *Comput. Intell. Neurosci.* **2022**, *2022*, 8709145. [CrossRef] [PubMed]
21. Ahmed, I.A.; Senan, E.M.; Rassem, T.H.; Ali, M.A.; Shatnawi, H.S.; Alwazer, S.M.; Alshahrani, M. Eye Tracking-Based Diagnosis and Early Detection of Autism Spectrum Disorder Using Machine Learning and Deep Learning Techniques. *Electronics* **2022**, *11*, 530. [CrossRef]
22. Piosenka, G. Detect Autism from a Facial Image. Available online: https://cutt.ly/ibIXt5a (accessed on 27 January 2021).
23. Rohini, G. Everything You Need to Know about VGG16. Available online: https://medium.com/@mygreatlearning/everything-you-need-to-know-about-vgg16-7315defb5918 (accessed on 19 January 2024).
24. Simonyan, K.; Zisserman, A. Very Deep Convolutional Networks for Large-Scale Image Recognition. September 2014. Available online: http://arxiv.org/abs/1409.1556 (accessed on 19 January 2024).
25. Tan, M.; Le, Q.V. EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks. In Proceedings of the 36th International Conference on Machine Learning, Long Beach, CA, USA, 9–15 June 2019.