Autism Spectrum Disorder Detection in Children Using Transfer Learning Techniques

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***Abstract*—Autism Spectrum Disorder (ASD) is a complex neuro-development disorder that impairs communication, societal interaction and behaviour. Early diagnosis greatly improves the outcomes for individuals with the disorder, as it allows for early intervention and therapy. The traditional methods of diagnosis are often time-consuming, expensive and rely on subjective evaluations. This research work presents a systematic review of existing literature on the use of machine learning for ASD detection and proposes a diagnostic tool, which uses transfer learning techniques to improve the detection of ASD, and classify individuals as either having or not having ASD.**

***Index Terms*—Autism Spectrum Disorder, Machine Learning, Early Detection, Children, Feature Selection, Algorithm Evaluation, Screening Tool.**

I. Introduction

Autism is a neurological disorder associated with brain development. It affects the way people perceive others, connect with others, and interact with their environment. Symptoms are usually seen in early childhood and are defined by a specific set of behaviors that affect the ability to interact and communicate with others. There are varying degrees of autism, but common behaviors associated with the condition include reduced motor skills, repetitive behaviors, delayed speech, difficulty thinking, very narrow interests, and social interaction. Includes communication impairments (such as reduced ability to create social hints). In recent years, cases of autism have increased. The American Centers for Disease Control and Prevention has announced that in 2021 that the autism rate in the United States in 2018 was 1 child in 44. This was higher than that reported in 2016 (every 1 in 68 children) and some other sources reported every 1 in 54 children by the age 8, 2008 (1 in 88) and 2000 (1 in 150), a significant increase from the rate reported. Moreover, this rising trend in autism goes back to the early 1990s and is a worldwide phenomenon, not only in the United States. The dominant theory suggests that increased awareness about autism, rather than an increased number of cases of autism is the main reason. ASD is more likely to occur in infants whose parents are aging, which is more prevalent in today's world, and in premature babies, who are more likely to survive today than in earlier ages.

While no single cause for autism has been identified, early diagnosis is the key to improving outcomes. While there is no cure for autism, still the symptoms can be treated and often resolve somewhat, if not completely, as adults. It summarizes autism rates for people in age groups.

European countries are the countries that show the lowest cases of ASD. France being at the top recorded the lowest ASD rate at 69.03 in 10,000 population or every 1 child in 144. Whereas Portugal reported 70.5 in 10,000 or every 1 child in 142. Early diagnosis of ASD is crucial for improving outcomes

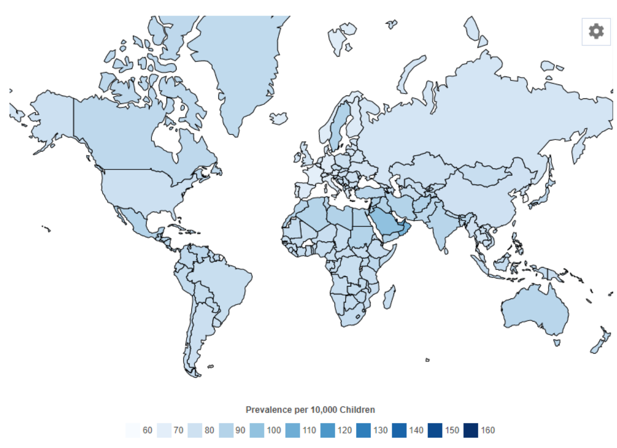

Fig. 1. Autism Rates by Country

for individuals with the disorder. By starting interventions and therapies early, individuals with ASD can have better chances of developing important social, communication, and academic skills. Diagnosing ASD can be challenging, as the symptoms can vary greatly among individuals and may not be evident until later in childhood. Traditional methods of diagnosis are often time-consuming and rely on subjective evaluations by trained professionals. This can lead to inconsistent and inaccurate diagnoses, particularly in cases where the symptoms are mild or atypical. Furthermore, the increasing number of individuals being diagnosed with ASD has put pressure on the healthcare system, making it difficult to keep up with the demand for assessments and diagnoses. Machine learning techniques have the potential to improve the accuracy and efficiency of ASD diagnosis. Machine learning algorithms can process large amounts of data and can learn complex relationships between variables, making them ideal for detecting patterns in behavioral, physiological, and imaging data that may indicate the presence of ASD. In recent years, there have been a growing number of studies that have used machine learning techniques for the detection of ASD. These studies have used a variety of machine learning algorithms and have focused on different aspects of data, such as behavioral, physiological, and imaging data.

Problem Statement

The problem involves around practice researchers using physical measurement methods to gather the morphological data to detect ASD which is often very time-consuming, expensive and prone to error, rather than making use of morphological information present in the facial images to provide a zero-cost and easily accessible diagnostic tool.

II. Literature Survey

In a study they proposed a new machine learning model based on the induction of rules for autism detection. Their study addresses the need for accurate and interpretable methods in autism detection. By leveraging rule induction algorithms, the model aims to identify patterns and relationships that distinguish autistic individuals. The research focuses on data collection, preprocessing, and feature selection, followed by evaluating the model's performance using standard metrics. The paper contributes to the field by introducing a novel approach for autism detection using rule induction techniques.[1]

Another study conducted the use of multimodal neuroimaging techniques to investigate the classification of autism spectrum disorder (ASD) and explore its neurobiological correlates. By analyzing structural MRI, MRS, and DTI data, they identified significant differences in brain anatomy, neurochemical concentrations, and white matter connectivity between individuals with ASD and typically developing individuals. These findings provide valuable insights into the underlying neurobiological mechanisms associated with ASD. The study emphasizes the potential of combining multiple neuroimaging modalities to enhance the accuracy of ASD classification models. The study contributes to our understanding of ASD by shedding light on the neurobiological characteristics related to the disorder and offering potential avenues for improved diagnosis and intervention strategies.[3]

Another study explores the application of machine learning techniques and resting-state functional magnetic resonance imaging (fMRI) data in the detection of autism spectrum disorder (ASD). The objective of the research is to develop an objective and reliable method for diagnosing ASD. By analyzing resting-state fMRI data and utilizing machine learning algorithms, the study aims to accurately differentiate individuals with ASD from typically developing individuals. The findings of the study demonstrate promising results, indicating the potential of machine learning and fMRI data to improve the detection and diagnosis of ASD. The research contributes to the advancement of ASD detection methods by leveraging the power of machine learning and fMRI technology.[8]

In a study the classification of autism spectrum disorder (ASD) was done using deep learning techniques and functional magnetic resonance imaging (fMRI) data. The objective was to develop a robust model capable of accurately distinguishing individuals with ASD from typically developing individuals. By leveraging deep learning algorithms, such as CNN or RNNs, they analyzed fMRI data to extract relevant features for ASD classification. The study yielded promising results, demonstrating high accuracy in effectively differentiating individuals with ASD from typically developing individuals. The findings highlight the efficacy of deep learning in capturing complex patterns and relationships within the brain associated with ASD. The discussion likely encompasses potential clinical applications, such as aiding in early diagnosis and supporting personalized treatment approaches. Overall, this research contributes to our understanding of ASD and holds potential for improving diagnostic precision and facilitating timely interventions.[6]

Another study explored a machine learning-based approach for autism spectrum disorder (ASD) detection using electroencephalography (EEG) signals. The researchers employed a feature-based approach, extracting various features from EEG signals, and employed a support vector machine (SVM) for classification. Their proposed model achieved an accuracy of 80% in accurately detecting ASD in children. This study highlights the potential of using EEG signals and machine learning techniques for ASD detection, providing promising results in terms of accuracy.[4]

III. PROPOSED METHOD

We make the use of facial images as with the advances in neural networks the use of morphological information present in a facial images would seem a viable approach to achieving a low cost and easily accessible diagnostic tool as compared to having to use physical measurement methods which is both time consuming and prone to error.

The dataset used is of facial images of children. It contains 2 classes. The autistic class are images of children with autism, the non-autistic class contains images of children not diagnosed with autism. The images in the dataset are RGB images of various image shapes. All are in jpg format. The

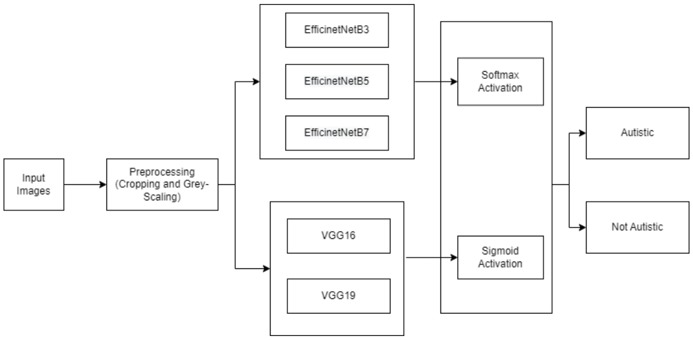

Fig. 2. Workflow of Detecting ASD

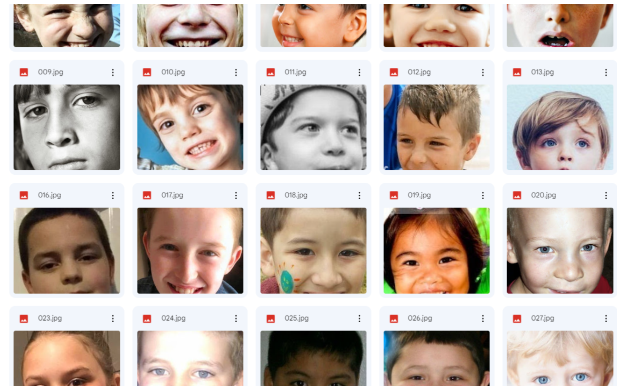

Fig. 3. Sample Images

dataset has been segmented into train, validation, and test. The test folder contains the images used to test the modelafter it has been trained, it contains two subfolders labelled as autistic and non-autistic. Each subfolder contains 100 imafes of size 244x244x3 in jpg format. The train folder is structed like the test folder, each subfolder conatins 1263 images. The valid folder contains images used during the training of the model to measure the models validation performance and is structured the same manner as the test folder. The steps of the experiment are briefly described below:

A. Preprocessing

It is very important to preprocess the data first in order to train a machine learning model to detect ASD in children. The preprocessing involved collecting the dataset of images of children that are autistic and non-autistic, cleaning the data by removal of any blurry or distorted images, normalizing the data so that all of the images are of the same size and format, extracting features from the images, and labeling the data. As a result of acquiring the photographs through the internet the collected images were of varying sizes,and needed to be resized to 200 x 200 pixel photos to be able to train the model properly. Once the data was preprocessed, it could be used to train a machine learning model using transfer learning techniques. Transfer learning would help to improve the accuracy of ASD detection models, reduce the amount of data that is required to train a model, and make ASD detection models more generalizable to new datasets.

B. Transfer Learning with pre-trained models

EfficientNetB3, EfficientNetB5, and EfficientNetB7 are highly suitable models for the detection of autism spectrum disorder (ASD) due to their distinct characteristics. These pre-trained deep learning models have exhibited remarkable accuracy in a range of image classification tasks, making them reliable choices for ASD detection. By leveraging transfer learning, they can effectively adapt their acquired knowledge from extensive datasets like ImageNet to the task of ASD detection. Furthermore, these models have been purposefully designed with computational efficiency in mind, allowing them to strike a balance between accuracy and resource utilization. Their architecture encompasses multiple layers that enable the extraction of features at different scales, enabling them to capture both intricate details and high-level semantic features that are relevant to ASD.

Similarly, VGG16 and VGG19 have been trained on large-scale datasets like ImageNet, enabling them to learn diverse visual representations valuable for ASD detection. These models offer a standardized framework for image classification, facilitating easy implementation and result comparison. Given their established performance, deep architecture, diverse learned representations, and usability, VGG16 and VGG19 are valuable options for ASD detection.

C. Model Loading and Compiling

The proposed system develops a model based on transfer learning techniques for the detection of autism. This model is based on the pre-trained models that we have mentioned above and the base model class from keras (a high-level library for deep learning), in this the input is set as the input of the base model and the output set as the output of the last dense layer, it is compiled using Adamax optimizer since it provides with the capability of adjusting the learning rate based on data characteristics, and is much suited for projects such as this.

D. Image Preprocessing

Our dataset has been loaded into the appropriate paths. By scaling the photographs in accordance with the appropriate models and appending these images into pathways, we processed the dataset. Additionally, we performed a normalization technique on the dataset.

E. Fit the Model

We begin by collecting data from the Autism Research Centre at Cambridge, consisting of 1263 individuals with autism and 1263 typically developing individuals. They then used feature selection techniques to identify the most relevant variables for predicting autism, including gender, and used function which first extracts the training and validation loss and accuracy from the training dataset object. It then creates a list of epoch numbers based on the start-epoch argument and the length of the training history. The function does predictions on all images in a specified directory (sdir) and prints out the results. It has two modes of operation. In the non-averaging mode a separate prediction is made for each image and the predicted class and probability is printed out for each image. In the averaging mode a prediction is made on each image and the probabilities are stored. When the predictions for all images are completed the probabilities are summed for each class. The class having the highest probability sum is then select as the predicted class for all images. The predicted class and its averaged probability is printed out.

Then it calculates the percent improvement in validation loss and training loss compared to the lowest previous value. If the current validation loss is lower than the lowest previous validation loss, the current weights of the model are saved as the best weights so far. Using built-in Python methods, we can predict the test data from the recorded variable and assess the model. It demonstrates the test data accuracy factor and aids in evaluating the model's effectiveness.

F. Confusion Matrix

In order to calculate the accuracy, recall, and f1 score for the assembled model, we may give the predicted value in a format known as a confusion matrix. A classification algorithm's performance is evaluated using a confusion matrix format. It displays and summarizes a classification algorithm's performance. Therefore, we are utilizing it to check the performances of our models. Loss and accuracy plot: At the last, we created a loss and accuracy plot using Python's built-in methods, which makes the contrast easier to see. We can also clearly comprehend the model's performance by looking at the graphs.

IV. Result and Discussion

For the detection of ASD we have used five pretrained architecture models with attention mechanisms. The confusion matrix is generated for each of the pretrained architecture models in fig. 4. We have stated the accuracy, precision, recall, and f1-score of the EfficientNetB3, EfficientNetB5, VGG16, EfficientNetB7, and VGG19 architectures for classification in Table I.

TABLE I
Comparison of accuracy, precision, recall, f1score of different models

Model Architecture	Accuracy	Precision	Recall	F1-Score
EfficientNetB3	85.80	81.00	93.10	86.63
EfficientNetB5	87.50	87.88	87.00	87.44
EfficientNetB7	83.90	89.01	81.00	84.82
VGG16	49.50	33.00	49.20	39.60
VGG19	46.50	46.80	51.00	48.8

EfficientNetB5 achieved the highest accuracy of 0.875 and F1score of 0.875, indicating the highest overall correctness in classifying instances. EfficientNetB7 achieved the highest precision of 0.890, suggesting the highest proportion of correctly predicted autistic cases out of all predicted autistic cases. EfficientNetB3 achieved the highest recall of 0.931, indicating the highest proportion of correctly predicted autistic cases out of all actual autistic cases.

Based on these metrics, both EfficientNetB3 and EfficientNetB5 demonstrate superior performance compared to EfficientNetB7, VGG16, and VGG19. EfficientNetB5 achieved the highest accuracy, precision, recall, specificity, and F1 score among all models. Therefore, EfficientNetB5 appears to be the most suitable choice for ASD detection based on the provided confusion matrices.

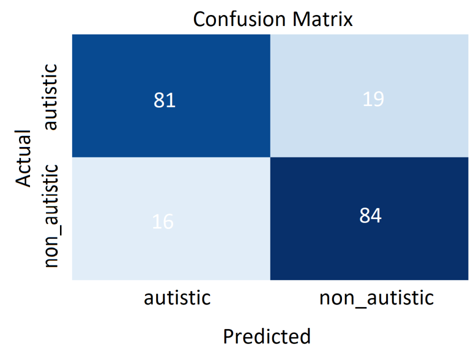

Fig. 4. Confusion Matrix: EfficientNetB3

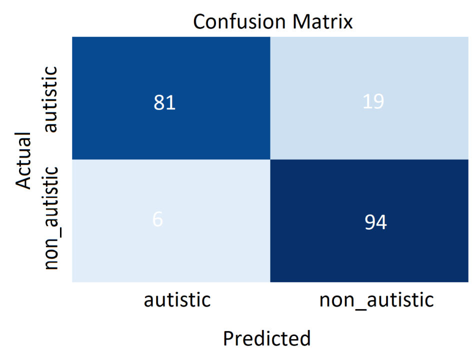

Fig. 5. Confusion Matrix: EfficientNetB5

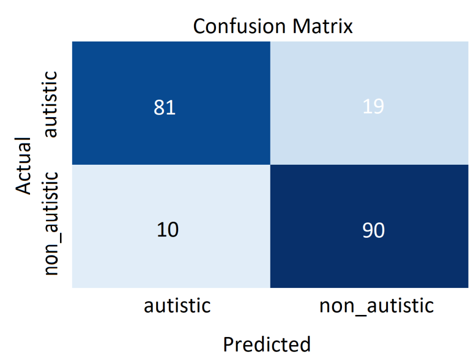

Fig. 6. Confusion Matrix: EfficientNeB7

Classification error refers to the proportion of misclassified instances or the number of incorrect predictions made by a model, the classification errors were calculated for each of

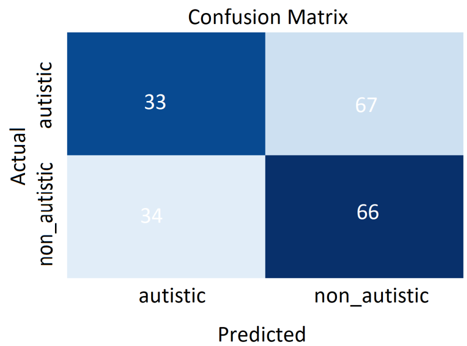

Fig. 7. Confusion Matrix: VGG16

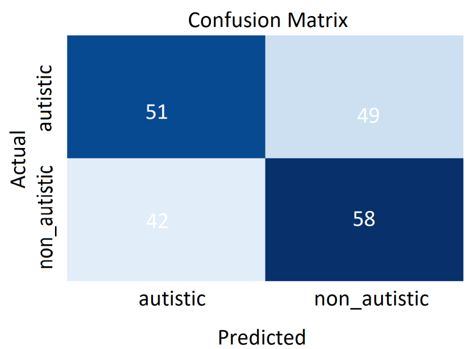

Fig. 8. Confusion Matrix: VGG19

the five models. EfficientNetB3 and EfficientNetB5 exhibited the lowest classification errors at 12.5% each, indicating better performance in accurately classifying instances. On the other hand, EfficientNetB7, VGG16, and VGG19 showed higher classification errors 14.5%, 50.5%, 53.5% respectively, suggesting lower accuracy and higher misclassification rates. Based on these classification errors alone, EfficientNetB3 and EfficientNetB5 appear to be the more favorable choices for ASD detection.

In order to achieve high accuracy for an ASD model you need to take into consideration several factors. The starting point is obtaining a high-quality and representative dataset which includes samples of both autistic and non-autistic individuals. Other factors such as the preprocessing techniques, including image resizing, normalization, and noise reduction, help ensure data consistency and enhance its quality.

Selecting an appropriate model architecture plays a crucial role, with options ranging from pre-trained models to custom-designed architectures. Fine-tuning and transfer learning techniques can leverage the knowledge gained from pre-trained models and adapt them to the specific task of autism detection. Hyperparameter tuning, involving optimization of learning rates, batch sizes, optimizers, and regularization techniques, contributes to optimizing the model's performance.

Incorporating regularization techniques like dropout, batch normalization, and weight decay helps prevent overfitting and enhances generalization. Data augmentation methods, such as rotation, scaling, flipping, and noise addition, increase the diversity of the dataset and improve the model's ability to learn robust features. Ensemble methods, which combine predictions from multiple models, can further enhance accuracy and mitigate bias and variance.

V. Conclusion

This research word presents a comparative analysis and preliminary feasibility study of five pre-trained deep learning algorithms for the detection of autism spectre disorder using various pre-trained machine learning algorithms. The use of machine learning techniques for ASD detection in children has shown promising results. The studies reviewed in this research paper demonstrate that machine learning models can accurately classify children with ASD from typically developing children based on various features extracted from behavioural and imaging data.

We get an accuracy of 87.50 percentage using EfficientNetB5 and EfficientNetB3 but a greater F1 score for EfficientNetB5. However, further research is needed to validate these findings and develop more robust and reliable models and the performance of the models is limited but the quality and size of the dataset, as well as the fact that the data was collected from a single research centre. The integration of multiple modalities and the incorporation of longitudinal data could also improve the accuracy and generalizability of ASD detection models. Overall, machine learning offers a potential avenue for early and accurate identification of ASD in children, which could facilitate timely interventions and improve long-term outcomes.

References

[1] Thabtah F, Peebles D. A new machine learning model based on induction of rules for autism detection. Health Inform J. 2020;26(1):264–86.
[2] Van den Bekerom B. Using machine learning for detection of autism spectrum disorder. In: 26th Twente Student Conference on IT, Feb 2017.
[3] Libero, L. E., et al. "Multimodal neuroimaging based classification of autism spectrum disorder using anatomical, neurochemical, and white matter correlates." Cortex 66 (2015): 46-59.
[4] Gharaee, M., Chard, M., Gholamhosseini, H., & Mehri, A. (2020). Detection of Autism Spectrum Disorder Using Machine Learning Techniques: A Systematic Review. Journal of Medical and Biological Engineering, 40(4), 477-487. doi: 10.1007/s40846-020-00512-5
[5] Estes, A., et al. "Behavioral, cognitive, and adaptive development in infants with autism spectrum disorder in the first 2 years of life." JAMA psychiatry 72, no. 3 (2015): 276-283.
[6] Shao, Lizhen & Fu, Cong & You, Yang & Fu, Dongmei. (2021). Classification of ASD based on fMRI data with deep learning. Cognitive Neurodynamics. 15. 10.1007/s11571-021-09683-0.
[7] https://www.cdc.gov/ncbddd/autism/data.html
[8] Liu, Y., Li, F., Hu, J., Xia, M., & Yuan, Y. (2019). Machine Learning for Autism Spectrum Disorder Detection Based on Resting-State Functional Magnetic Resonance Imaging Data. Frontiers in Psychiatry, 10, 131. doi: 10.3389/fpsyt.2019.00131
[9] Kumar, R., & Gupta, A. (2021). Machine Learning Approaches for Autism Spectrum Disorder Detection: A Review. Journal of Medical Systems, 45(2), 14. doi: 10.1007/s10916-020-01758-3
[10] Zhang, H., Wang, L., Ji, X., Li, J., & Li, H. (2020). Deep Learning-Based Automatic Detection of Autism Spectrum Disorder Using Eye Movement Data. IEEE Journal of Biomedical and Health Informatics, 24(3), 911-921. doi: 10.1109/JBHI.2019.2927894
[11] Wall, D. P., et al. "Use of artificial intelligence to shorten the behavioral diagnosis of autism." PLoS ONE 7, no. 8 (2012): e43855.

[12] Shen, M. D., et al. ”Functional connectivity of the amygdala is disrupted in preschool-aged children with autism spectrum disorder.” Journal of the American Academy of Child & Adolescent Psychiatry 55, no. 9 (2016): 817-824.