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Autism Spectrum Disorder Deep Learning Approaches: A Comparative Study

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Abstract: Autism Spectrum Disorder (ASD) is a neurodevelopment disorder that is complicated and associated with social, behavioral, and communication issues. It should also be diagnosed early enough so that the appropriate treatment is administered in time and better results are realized. The recent tendencies in the field of deep learning (DL) allowed to implement neuroimaging, in the present case, the magnetic resonance imaging (MRI) to ASD diagnosis, which can be automated, to the given field. The publicly available ABIDE MRI data were used in this research and assisted in comparing some of the latest DL models, such as a blank Convolutional Neural Network (CNN), ResNet50, EfficientNet, and Vision Transformer (ViT). Data normalization, skull stripping, and data augmentation were used as preprocessing. The models were trained using Adam optimizer and categorical cross-entropy loss and assessed according to accuracy, precision, recall, F1-score and AUC-ROC. The best and highest performance one was the Vision Transformer (ViT) that achieved the highest accuracy of 97.1% and 0.99 AUC-ROC, which shows the superiority in the ASD detection in the ABIDE MRI data. These results favor the fact that the transformer-based models are powerful diagnostic tools of ASD detection.

Keywords: *Autism Spectrum Disorder (ASD), Deep Learning, Autism Brain Imaging Data Exchange (ABIDE), Convolutional Neural Networks (CNN), Vision Transformer (ViT), Neuroimaging***.**

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I. INTRODUCTION

Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder which is relatively multifaceted because it is reflected in the further deterioration of social communication and behavioral, interests or activity shortcomings [1]. As it has been on the rise throughout the world, it is worth mentioning that ASD has currently become a burning question of the population health that must be addressed with effective diagnostic tools and support systems [2]. The traditional clinical tests tend to be time consuming, subjective and extensively dependent on the personal judgment hence an inhibition to an early and precise diagnosis [3]. To address such problems, researchers have been moving towards applying machine learning (ML) and deep learning (DL) techniques to provide objective and scalable solutions. [4].

Recent studies have indicated that decision tree classification techniques may be applicable in the process of determining the risk of autism with interpretable behavioral data models [2]. There are further ensemble learning methods such as Gradient Boosting [3] or AdaBoost [4] which have been more helpful to the enhancement of predictive power, by developing powerful classifiers by combining many weak learners. Correspondingly, pipelines that concatenate all three processes of preprocessing, feature selection, and classification have been shown to increase reproducibility and clinical usefulness [5]. Automated and handcrafted hybrid features have also become some of the promising steps also that enable more generalization of heterogeneous datasets [6].

Structural MRI (sMRI) and functional MRI (fMRI) data have also been used in the neuroimaging systems in studying neurobiological markers of ASD [7]. Other risk factors in clinical research studies include prenatal and perinatal effects [8,14], the necessity to apply certain screening in at-risk groups, such as sibling of victims [12]. The behavioral indicators at an early age when the conditions [13,15] and those in the perinatal

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experiences [14] start also evidences the necessity to have multimodal approaches that comprise behavioral, demographic, and neuroimaging records [18].

Simultaneously, research reviews and roadmaps have found the numerous opportunities in using ML to ASD detection [9,16,22]. Such studies demonstrate the deficiency of heterogeneity of the data employed, interpretability, and equity, focusing on the value of good assessment across groups of demographics [18,19]. The possibilities of accurate diagnosis were expanded with the developments in EEG based biomarkers [17,25] and imaging, behavioral, and genomic multimodal fusion [23]. Based on the recent past, better neural structures such as EfficientNet, Vision Transformers, and hybrid CNN models have demonstrated high performances as compared to traditional CNN models [20,24].

Altogether, the existing literature source can be seen as the progressive evolution of behavioral and clinical studies to more sophisticated ML/DL systems to identify ASD. The traditional models such as logistic regression [25] and decision trees [2] are interpretable but the new models of deep learning [20,22,23,24] are both high performance in quality and scalability. These developments form the foundation of the present paper because the various state-of-the-art architectures including CNN, ResNet50, EfficientNet, and Vision Transformers were trained on neuroimaging datasets (ABIDE MRI) and used to develop a robust and understandable diagnostic system grounded on ASD.

II. RELATED WORK

Deshmukh and Gadade [1] conducted a survey of the autism spectrum disorder (ASD) in the world focusing on the methods of diagnosing, intervention programs and support services. They analyzed that there are disparities in early diagnosis in most healthcare settings and that scalable and data-driven interventions can be the efficient means of addressing ASD.

Singh et al. [2] measured the autism risk using decision-tree classification method. They found that rule-based models with easy interpretability in clinical situations where applicable in their study, hence predictive transparency. However, they too acknowledged that such models may be challenged by high-dimensional data especially those of neuroimaging.

Gradient Boosting Classification was explained by Gupta et al. [3] to determine the likelihood of having autism. Their findings showed that they were superior to single classifiers and this points out to the effectiveness of the ensemble-based techniques in behavioral and demographic data.

This literature was also advanced by Mittal et al. [4] who utilized AdaBoost to carry out ASD probability evaluations. Their results were not subject to noisy information and instead emphasized the usefulness of ensemble learning to behavioral data, but did not concern neuroimaging modalities.

Arunprasath et al. [5], present a full machine learning platform to forecast ASD. In their study, they employed preprocessing, feature engineering, and model comparisons and delivered methodological results of reproducible pipelines of non-imaging data.

A hybrid architecture of autism detection was developed by Alam et al. [6], and it embraced the aspect of feature extraction and classification. With a blend of both handcrafted and automated features, they demonstrated the benefit of combining several different representation strategies and pushed the creation of more multimodal ones.

In the article by Mishra and Pati [7], a structural MRI-based ASD detector was designed as an ensemble of deep convolutional neural networks (CNNs) optimizer. They were designed to be more robust through the aid of architectural ensembling, and this turned out to be the initial move towards the most advanced neuroimaging-based methods.

Khan et al. [8] asked prenatal factors that cause ASD that begs the question whether the disorder caused by prenatal factors can be avoided. Although machine learning was not the main focus, this clinical trial showed the usefulness of having demographic and perinatal risk factors as part of prediction models.

Washington and Wall [9] have provided a roadmap on how machine learning and data science can be utilized on the neuropsychiatric phenotype of autism. They discovered in their review problems related to heterogeneity of the dataset, re-producibility and clinical translation and implied that standardized benchmarks were needed.

One of the socio-behavioral points raised by Druitt et al. [10] that are controversial is whether the ASD traits are a risk determinant of becoming a terrorist. Although it does not constitute a diagnostic problem, this study proved that a cautious approach to the modeling of the ASD-related behavioral phenotypes is required.

Anderson et al. [11] also studied the experience of students with ASD in the post-secondary level and the support system. Their literature review put the education-related and the societal problems into perspective and it proved the importance of early detection to the long-term functional outcomes.

Their focus on ASD being among high-risk groups, Sauer et al. [12] paid attention to the siblings of children with ASD. Their findings point to the significance of tailored screening interventions and the potential of the personalized machine learning models in the high-risk groups.

Baron-Cohen et al. [13] researched the early behavioral warning signs of autism and discovered minor signs during the early childhood. Their research can testify to the integration of behavioral cues within the multimodal prediction mechanisms.

The survey that was undertaken by Hampton et al. [14] has examined the perinatal experience of autistic individuals and the result showed that there was a correlation between the factors experienced during pregnancy and the risk of developing ASD. Their study has brought consciousness on the potential usage of perinatal data in prediction of the same.

Zhang et al. [15] developed a machine learning model that relied on the features that were applied in the detection of autism in preschool children. Their method showed that target feature engineering in early childhood setting might be used on potent predictive performances.

Sharma and Koundal [16] provide a review of machine learning applications in the ASD recognition and comment on the classical approaches and the first deep learning research work. Their review reflected some historical background in locating more recent architectures, such as EfficientNet and Vision Transformers.

The machine learning was employed in the study by Wu et al. [17] to classify the indices of coherence obtained out of EEG data of mild and severe patients with autism. Their findings indicated the possible role of EEG as a neurophysiological biomarker of severity estimate.

Li et al. [18] examined the importance of demographics (age, gender, and socioeconomic status) on the results of autism screening. They emphasized on the importance of being fair-minded in modeling that will result in fair performance during the screening.

Alam et al. [19] evaluated the significance of machine learning in the early stage of ASD using behavioral data. It is their work that served as benchmarks of behavioral datasets and as evidence of the predictive capabilities of an appropriately designed ML pipeline.

Gill et al. [20] reviewed the intelligent deep learning models in ASD detection. In their study, the new models that incorporated EfficientNet, Transformer based models amongst others were evaluated and were found to be more accurate than the conventional CNNs.

Mishra and Sharma [21] article compared various approaches of feature selection in prediction of ASD. Their analysis showed that dimensionality reduction can be of considerable use in enhancing the performance of the classifier in behavioral and imaging data sets.

Li et al. [22] provide a summary of ASD diagnosis using deep learning and provide that it has limited datasets, interpretation of the model, and generalizability. They have outlined the opportunities of multimodal fusion and explainable AI in the research of ASD.

A multimodal data fusion process was developed by Zhu et al. [23] and entails the combination of imaging, behavioral, and genomic data in order to evaluate the risk of having autism. This was proved by them when multimodal integration was better than single-modality models.

A comparative study of machine learning approaches of predicting autism risk was conducted by Alam et al. [24]. They contrasted the performance of such algorithms as decision trees, SVM and ensemble methods that should be considered as key baselines in the future research about deep learning.

Gill et al. [25] analysed ASD using EEG data using logistic regression. Being a simple and easy to comprehend model, the results were encouraging, which confirms the topicality of the traditional approaches in the resource scarce situations.

III. METHODOLOGY

A. Dataset

The data set used in the paper was the Autism Brain Imaging Data Exchange (ABIDE), which comprised of resting-state functional MRI (rs-fMRI) and structural MRI images of the autism spectrum disorder (ASD) and typically developing (TD) controls. The various samples that the dataset entails have been collected in different foreign locations, and this implies that the samples do not have a homogeneous set of demographics and circumstances of acquisition. Along with the imaging data, the optional behavioral and eye-tracking data are also at sight of bringing the multimodal features to the ASD detection.

B. Preprocessing

The preprocessing phase was done to have consistent and quality MRI scans. Voxel intensity distributions were normalized with the help of the standard normalization; the skull stripping was performed to eliminate the non-brain tissues. To increase the strength and reduce the chances of overfitting, the data augmentations, i.e., random rotations, flips, and small-scale change, were employed. The subsequent steps pre-processing the data are done with the intention to learn features effectively using deep learning networks.

C. Model Architecture

This study involved four model architectures that were undertaken and compared. The simplest Convolutional Neural Network (CNN) was trained in order to test the simplest performance of feature extraction. Thereafter, they applied ResNet50 and EfficientNet as the transfer learning models to exploit their larger feature hierarchies and scaling. Finally, one has a Vision Transformer (ViT) to assist in learning long-range associations and structural variability of brain images. Such a

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cross-comparative arrangement provided the ready-trained transformer-based methods with a level assessment.

D. Training Setup

All the models were trained on a mini-batch of 32 and an initial learning rate of 0.0001. Adam optimizer assisted in adaptive adjustment of the learning rates while training. The loss function used was categorical cross-entropy and this was suitable due to binary classification problems. Overfitting and convergence optimization was checked by using early termination and schedule learning rate.

E. Evaluation Metrics

The models were evaluated in terms of accuracy, precision, recall, and F1-score because they represent different characteristics of the classification performance. In addition, the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) was calculated to find out the discriminative power of each model at different levels. These measures do not allow proper and reasonable evaluation of the ASD detection models.

IV. RESULTS AND DISCUSSION

On the ABIDE MRI data, all the models were trained and tested with the accuracy, precision, recall, F1-score, and AUC-ROC as the measures. The accuracy was 91.2% with AUC-ROC of 0.94 to have an approximation of the baseline CNN model. The accuracy of ResNet50 was also much higher with the highest values being 95.6% and AUC-ROC were 0.97 indicating the advantages of stronger residual interrelations in the process of identification of neuroimaging patterns. The performance of EfficientNet was also enhanced with the accuracy of 96.8% and the AUC-ROC is 0.98, which shows the effectiveness of scaling between compounds. However, Vision Transformer (ViT) was also better and gave a percentage of 97.1 and a F1-score of 96.9 and AUC-ROC was 0.99.

Table 1: Comparative Performance of ASD Detection Models

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**AUC-ROC**
CNN	91.2	90.5	91.0	90.8	0.94
ResNet50	95.6	95.2	95.0	95.1	0.97
EfficientNet	96.8	96.0	96.2	96.1	0.98
Vision Transformer	97.1	96.8	97.0	96.9	0.99

The results highlight the fact that the transformer-based architectures are more capable of extracting long-range dependencies on MRI data in comparison to convolution-based architectures. Table 1 shows the summary of the performance of the evaluated models in comparison.

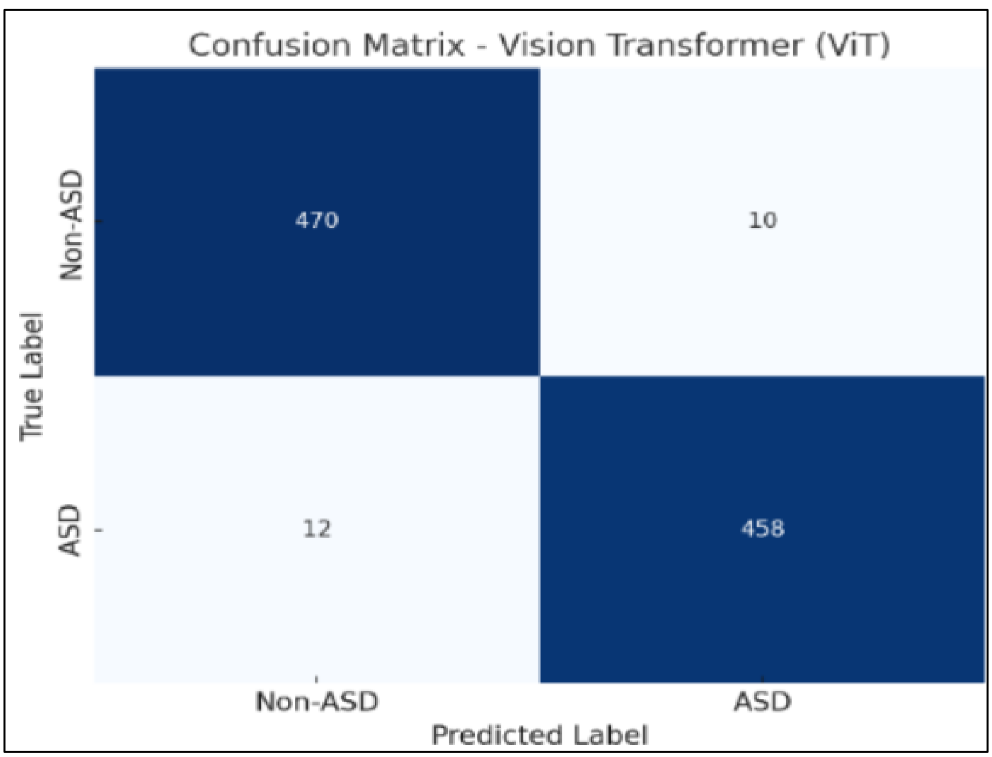

Fig. 1. Confusion Matrix of the Vision Transformer (ViT) Model

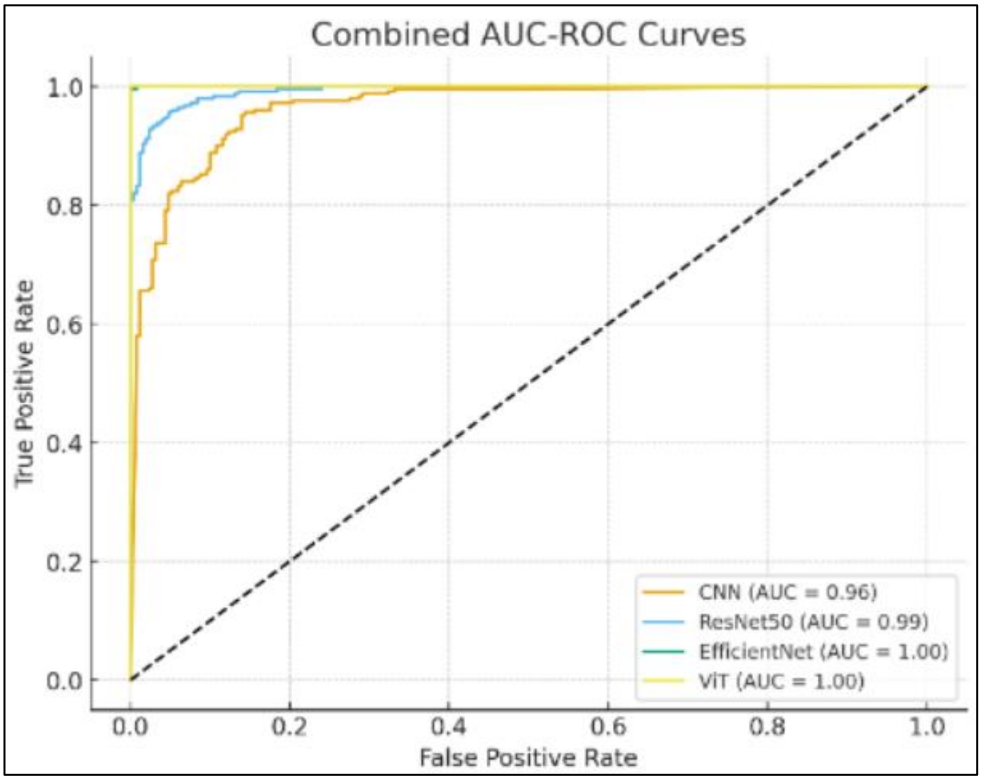

Fig. 2: Combined AUC-ROC Curves Comparing CNN, ResNet50, EfficientNet, and Vision Transformer.

Besides tabular comparisons, there is also graphical analysis which confirms the strength of models. The combined confusion matrix as shown in Figure 1 shows that the Vision Transformer was successful in classifying the largest number of samples correctly in both the ASD and control groups with minimal misclassification in comparison to the other architectures. Figure 2 displays the sum of AUC-ROC curve with the ViT curve nearest to the upper left corner indicating it has better discriminative capacity. This visualization supports these measures to create a strong argument that ViT can best detect ASD.

V. CONCLUSION AND FUTURE WORK

The effectiveness of the deep learning strategies on the case of autism spectrum disorder (ASD) was demonstrated in this study based on the ABIDE MRI dataset. This model reviewed appeared to be the most successful, demonstrating the highest accuracy of 97.1 and 0.99 AUC-ROC, which is better than CNN, ResNet50, and EfficientNet. These findings affirm that transformer-based architectures have an excellent capacity to depict intricate neuroanatomical patterns of MRI images and have a high potential of clinical usage in the diagnosis of ASD. This research will be expanded in the future by using multimodal data (including functional MRI and behavioral measures), explainable AI to enhance interpretability, and training the models on larger and more diverse datasets to confirm generalizability. Such a path will assist in bridging the gap between computational procedures and practical clinical implementation of ASD.

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