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Adaptive Deep Convolution Neural Network for Early Diagnosis of Autism through Combining Personal Characteristic with Eye Tracking Path Imaging

Revathi Kesavan [a], Naveen Palanichamy [b,*], Su-Cheng Haw [b], Kok-Why Ng [b]

[a] *Department of Artificial Intelligence and Data Science, Dhanalakshmi College of Engineering, Manimangalam, Chennai, India*
[b] *Faculty of Computing and Informatics, Multimedia University, Selangor, Malaysia*
Corresponding author: [*]p.naveen@mmu.edu.my

***Abstract*—Autism is a large set of illnesses related to brain development, also referred to as autism spectrum disorder (ASD). According to WHO reports, 1 in 100 children is expected to have ASD. Numerous behavioral domains are affected, including linguistic, interpersonal skills, stereotypical and repetitive behaviors which represent an extreme instance of a neurodevelopmental abnormality. Identifying ASD can be difficult and exhausting because its symptoms are remarkably identical to those of many other disorders of the mind. Medical professionals can improve diagnosis efficiency by adapting deep learning practices. In clinics for autism spectrum disorders, eye-tracking scan pathways (ETSP) have become a more common instrument. This approach uses quantitative eye movement analysis to study attentional processes, and it exhibits promising results in the development of indicators that can be used in clinical studies for autism. ASD can be identified by comparing the abnormal attention span patterns of children's having the disorder to the children's who are typically developing. The recommended model makes use of two publicly viable datasets, namely ABIDE and ETSP imaging. The proposed deep convolutional network consists of four hidden convolution layers and uses 5-fold cross-validation strategy. The performance of the proposed model is validated against multilayer perceptron (MLP) and conventional machine learning classifiers like decision tree (DT), k-nearest neighbor (KNN) and Random Forest (RF) using metrics like sensitivity, specificity and area under curve (AUC). The findings demonstrated that without the need for human assistance, the suggested model is capable of correctly identifying children with ASD.**

***Keywords*—Autism spectrum disorder; convolutional neural network; early diagnosis; eye-tracking scan path; machine learning.**

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I. Introduction

ASD is a neurodevelopmental disease caused by differences in the brain. Social engagement and involvement, as well as restricted or repetitive behaviors or hobbies, can be problematic for people with ASD. Additionally, people with ASD may move, pay attention, or learn differently. For those with ASD, social interaction and communication skills might be difficult. Some people with ASD may exhibit peculiar habits or hobbies. Many ASD sufferers also exhibit comparable traits. These could consist of seizure conditions, unusual sleeping and eating patterns, delayed language acquisition, movement and learning or cognitive abilities.

Millions of youngsters worldwide suffer with ASD, and India is not an exception. The long-term results for impacted children are greatly improved by prompt intervention and support, which is made possible by earlier identification plus accurate diagnosis of autism [1]. In India, the frequency of autism has been rising significantly. A 2021 study that was written up in the Indian Journal of Pediatrics states the following:

a. In India, it is believed that 1 in 68 children have autism
b. There is a roughly 3:1 male-to-female ratio in cases of autism, with boys being more frequently affected than females

A blood test or any other medical test cannot be used to detect ASD, which makes diagnosis difficult. Medical practitioners consider a child's developmental history and behavior when making a diagnosis. Sometimes, even in children as young as 18 months old, ASD can be recognized. By the age of two, a diagnosis from a trained specialist can be relied upon. However, many children don't receive a conclusive diagnosis until much later in life. Some people wait until they are adults or teenagers before receiving a diagnosis. This delay may prevent people with ASD from receiving the essential early assistance.

It's critical to diagnose ASD in children as early as possible to ensure they receive the support and assistance they require to realize their full potential [2]. Autism early diagnosis is revolutionary for a number of reasons:

a. Early Intervention: Early diagnosis makes it possible to put early intervention plans in place that are customized to the individual requirements of the child. This can greatly accelerate their growth in important domains like behavior, social skills, and communication.
b. Brain Plasticity: The brain is very malleable throughout the first few years of life, allowing it to more easily adjust and develop new connections. An excellent chance to positively impact the growth of a child's brain exists at this phase. Early identification of ASD allows for better utilization of the ability of the brain to improve a child's cognitive function.
c. Parental Training and Assistance: Early diagnosis gives parents and other caregivers a better grasp of their children's requirements as well as the information and tools they need to help them successfully.

Early intervention of ASD greatly helps parents of the child to procure treatment plans where the child's brain also easily shaped due to the plasticity and learn skills to face challenges. The existing efforts in early diagnosis of ASD majorly focused on brain imaging datasets. Whereas the proposed attempt makes use of personal characteristic of ASD patient with ETSP images to attain promising accuracy.

The article is organized according to the following structure: A review of latest studies which have established particular models for ASD identification is presented in Section 2. Furthermore, Section 3 offers a thorough explanation of the deep learning methods and datasets used in this investigation. The outcomes of the experiments are provided and analysed in Section 4. Finally, Section 5 offered a conclusion**.**

II. Materials and Method

The summarization of renowned efforts of investigators contributed towards early detection of ASD is discussed in this section. The need for automated systems to predict ASD and significance of machine learning algorithms in detecting ASD is deeply investigated by several studies [3], [4], [5], [6]. The machine learning algorithms like DT, naïve bayes (NB), KNN and support vector machine (SVM) grasped its popularity due to its performance [7], [8], [9], [10]. Roggala et al. [11] addressed the way to improvising the diagnosis of ASD through account EEG signal analysis. Khudhur and Khudhur [12] exercised different machine learning models that classified the ASD over multiple datasets extracted from Kaggle and UCI repository pertaining to four age groups namely toddler, child, adolescent and adult. The results demonstrated that the decision tree, logistic regression and random forest classification algorithms are the most prevalent models after applying various ML techniques to the pre-processing datasets mentioned above. For every dataset that is used, these dominant models obtain the maximum prediction accuracy of almost 100% when compared to other analyzed models.

In supporting earlier detection of ASD, Ulhaq et al. [13] demonstrated the efficiency of machine learning algorithms through adapting feature scaling namely quantile, power, normalizer and max abs scalar in their work. As an outset Ada Boost exhibited the promising the result when comparing all others. To improve the prediction accuracy Jhanjhi et al. [14], applied the stochastic gradient decent model and obtained the accuracy of 99.7% for adult dataset in UCI ML repository. Ada boost algorithm is renowned as an efficient machine learning algorithm and applied in enormous efforts of past researchers like Suhas et al. [15]. The promising way to increase the detection accuracy of ASD by adapting personality characteristics in the dataset is discussed by Parikh et al. [16]. Further the application of discriminant analysis for obtaining high accuracy with reduced computational complexity is narrated by Nishat et al. [17].

Deep learning (DL) is especially helpful for picture identification and other jobs where the characteristics are hard to identify. DL techniques can handle huge composite datasets which would be challenging for customary machine learning models to comprehend. Automatic feature extraction from the data eliminates the need for human feature engineering, which is only one of the many advantages of deep learning. Salari [18] attempted to apply 2D convolutional neural network (CNN) to bring better prediction rate. Whereas Selah and Chern [19] investigated the effectiveness of 3D Convnets / CNN for detecting ASD and they noticed the performance accuracy of CNN as 97.07% as the highest one comparing to conventional machine learning algorithms.

The role of deep learning and adaptation of optimization techniques for increasing the prediction accuracy is exercised by Adinew et al. [20]. Meneguzzi et al. [21] built a deep neural network (DNN) by stacking autoencoders for diagnosing the ASD over the brain images obtained from ABIDE dataset. The resultant DNN provided 70% accuracy while compared to other state-of-art techniques.

The eye-tracking device delivers useful information about kids' visual activity for a timely and precise diagnosis. Its working process is initiated by scanning the eye's path to produce a series of eye projection points on the image, which is then used to examine the behavior of kids with autism. Raseem et al. [22] conducted an experiment to demonstrate the outcome of deep learning models enriched with a feature extraction mechanism. The result evidenced that feature extraction preceded by classifier highly impacts the overall accuracy.

Kanhirakadavath and Chandran [23] built a deep network, allowing feature selection with help of principal component analysis (PCA) algorithm before CNN. This model presented its overall accuracy as 97%. The importance of early intervention and the efficacy of using the eye tracking paths in determining ASD are explained by Lanvin et al. [24]. The impact analysis of eye patterns over the years greatly influences the prediction rate of ASD and is done by Kong et al. [25]. The significant past efforts carried out in this domain are summarized as Table 1.

TABLE I

SUMMARY OF SIGNIFICANT EFFORTS IN DETECTING AUTISM

Name of the Author	Dataset	Methods	Accuracy
Khudhur and Khudhur [12]	Kaggle and UCI ML Repository	c. DT d. SVM e. KNN f. NB g. Logistic Regression (LR) h. RF	Among other models DT, LR and RF provided 100% accuracy
Ulhaq et al. [13]	UCI ML Repository	i. Ada Boost (AB) j. DT k. Gaussian Naïve Bayes (GNB) l. KNN m. LR n. NB o. RF p. SVM	AB - 99.25% (for toddlers) and 97.95% (for children)
Jhanjhi et al. [14]	UCI ML Repository	q. AB r. CN2 rule induction s. KNN t. NB u. RF v. Stochastic gradient decent (SGD) w. SVM	AB - 99.8% (for toddler) SGD - 99.7% (for adult)
Kumar et al. [15]	AQ-10	x. AB y. RF z. SVM	-
Salari et al. [18]	ABIDE	CNN (2D Convnets)	70.22%
Saleh and Chern [19]	ABIDE	CNN (3D Convnets)	97.7%
Meneguzzi et al. [21]	ABIDE	DNN (Two stacked autoencoders)	70%
Raseem et al. [22]	Figshare Data Repository (Eye tracking scan-path imaging)	aa. Artificial neural network (ANN) bb. Feed forward neural network (FFNN) cc. Hybrid model (Enriched hybrid feature selection which combines local binary pattern (LBP) and grey level co-occurrence matrix (GLCM))	FFNN & ANN – 99.8%
Kanhirakadavath and Chandran [23]	Eye tracking Dataset by M. Elbattah	CNN with PCA	97%

The dataset comprises eye tracking habits of informed consents is presented by Cilia et al. [26]. Apart from eye movement, facial features can be used in diagnosing the ASD patients demonstrated by Alam et al., [27]. For an accurate diagnosis and course of treatment, structural magnetic resonance imaging (sMRI) must be used to identify trustworthy biomarkers for ASD. A comparative study of machine learning algorithms with sMRI is carried out by Bahathiq et al. [28]. The early intervention of ASD detection helps a lot and the accuracy of detection rate is improved by adapting deep learning practices accounting ETSP images with personality characteristic of the person.

The primary goals of the proposed model and structural details of the proposed mechanism are presented below.

A. Primary Goals of the Proposed Model

The primary goals of the proposed model are listed below:

a. To diagnose ASD in early stage by combining personality characteristics and eye tracking path (behavioral pattern) of the individual
b. To improve the prediction rate through deploying promising deep learning techniques

B. Adaptive Deep Model: Structure and Details

The overall structure of the proposed deep network is captured in Figure 1. Pre-processing, the initial phase in the process, entails three separate operations: converting RGB to grayscale, resizing images and addressing missing values in ABIDE dataset. Using Equation 1, the following expression is used to convert an RGB image to a grayscale image. The generated grayscale photos are then resized from 640 x 480 to 100 x 100. By taking this step, the computer's processing load is lessened, enabling speedier computing.

$$GS\,\mathrm{Im}age = \left(R/3.0\right) + \left(G/3.0\right) + \left(B/3.0\right) \quad (1)$$

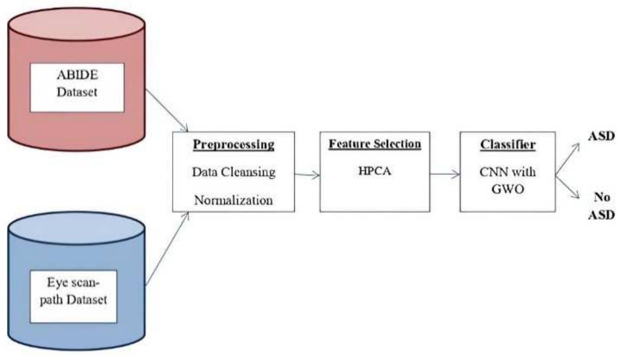

Fig. 1 The structure of the proposed model for detecting autism

The application of Discrete Wavelet Transform Techniques (DWT) lowers the dimensionality of the image, chooses relevant features, and efficiently extracts them. To increase process efficacy, DWT is coordinated using kernel Principal Component Analysis (PCA) [29]. By finding just a few principal components (orthogonal linear combinations) of the input variables with the largest variance, PCA reduces the dimension. Thus, the proposed feature extractor is named as HPCA.

Next step is applying classifier to predict ASD. The four alternating convolutional and max-pooling layers that make up the CNN's structure are designated as Levels 1 through 4 is utilized here. Convolution layers are made up of numerous kernels that work together to extract characteristics from digital images through a mathematical process called convolution. The feature maps' size is decreased by combining the max-pooling layers with convolutional layers [30], [31]. This process is also referred to as down-sampling. A flatten layer is accessible at the output terminal of all CNN-based classification models to reformat the output matrix and prepare it for the following step. Here, the spatial data from the features at level 4 is deleted and substituted with a channel dimension. Consequently, distinct channels are created for every retrieved feature map. The configuration of the CNN is provided in Table 2.

TABLE III
CONFIGURATION OF CNN

Layer ID	Function	Dimensions (No. of Kernel and Size)	Dimension of Output
Layer 1	2D Convolution	16, 3*3	16, 100*100
	Activation - ReLU		
	Max Pooling	16, 2*2	16, 50*50
Layer 2	2D Convolution	32, 3*3	32, 50*50
	Activation - ReLU		
	Max Pooling	32, 2*2	32, 25*25
Layer 3	2D Convolution	64, 3*3	64, 25*25
	Activation - ReLU		
	Max Pooling	64, 2*2	64, 12*12
Layer 4	2D Convolution	128, 3*3	128, 12*12
	Activation - ReLU		
	Max Pooling	128, 2*2	128, 6*6
	Flatten Layer	-	1*4608
	Dense Layer 1	128	-
	Dense Layer 2	256	-
	Output Layer	1	-

Furthermore, to increase prediction accuracy, grey wolf optimization (GWO) is exercised in this model. It is one of the population-based meta-heuristics algorithms and it was introduced by Mirjalili et al. [31] and Revathi and Samydurai [32] by the year 2014. The process flow of GWO is best illustrated in Figure 2.

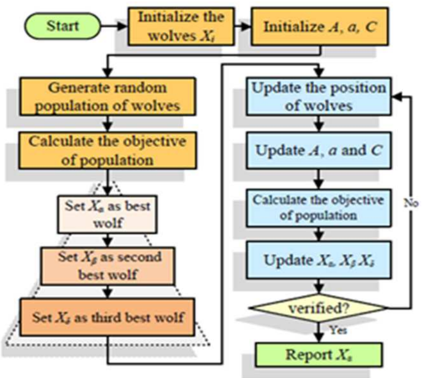

Fig. 2 The generic flow of GWO

It imitates the hierarchy of command and hunting style of adult grey wolves. The four types of grey wolves that are utilized to model the leadership hierarchy are alpha, beta, delta, and omega [30]. Grey wolves' social structure and hunting patterns are mathematically modelled in order to produce GWO. Omega wolves adjust their placements in each iteration according to positions α, β, and δ alpha, beta, and delta because prey is more likely to be found at these positions. In order to mathematically mimic the grey wolves' last hunting strategy of attacking their prey once it stops moving, we need to decrease the value of $\vec{a}$. When a drops from 2 to 0 in the interval [-2a, 2a], a random number $\vec{A}$ is assigned to it throughout the repetitions.

III. RESULT AND DISCUSSION

For examining the personal characteristic, Autism Brain Imaging Data Exchange (ABIDE) database is utilized. The personal characteristics taken into account are age, sex, verbal IQ, performance IQ, Full scale IQ and handedness (left, right or ambidextrous). The second dataset is composed by Mahmoud Elbattah that includes 547 eye-tracking scan path images extracted from 59 participants. The ASD dataset, which includes ETSP images, was used to test the suggested algorithms. A total of 547 images is found in the collection that is split into two classes: ASD with 219 images and 328 with No ASD. Here is a mapping of personal characteristics of ASD with respective ETSP images and No ASD is performed.

The dataset was split up as follows: 20% was put aside for testing, while the remaining 80% was used for training and validation which is called as 80:20 validation strategies. To assess the performance of the optimized deep neural network is evaluated using the parameters as follows: Positive Prediction Rate (PPR) represents the probability of getting the condition following the positive outcome of the test. In the event of an adverse test result, the Negative Prediction Rate (NPR) indicates the likelihood of not possessing the ailment.

Sensitivity, also called recall, is the ratio known as RC, which is calculated by dividing the total number of true positive and false negative values by the number of true positive predictions. The same is expressed as Equation (2).

$$R_C = \frac{T_P}{T_P + F_N} \tag{2}$$

The ratio known as Specificity SP is the proportion of accurate negative predictions to all negative forecasts and is specified as Equation (3).

$$S_P = \frac{T_N}{T_N + F_N} \tag{3}$$

Area under the ROC Curve (AUC) determines the complete two-dimensional area from (0, 0) to (1, 1) beneath the entire ROC curve, through applying integral computation. AUC provides an overall performance score over all possible categorization criteria. The AUC and cross-validated ROC curve for the deep model using the ETSP dataset is displayed in Figure 3 and 4 respectively.

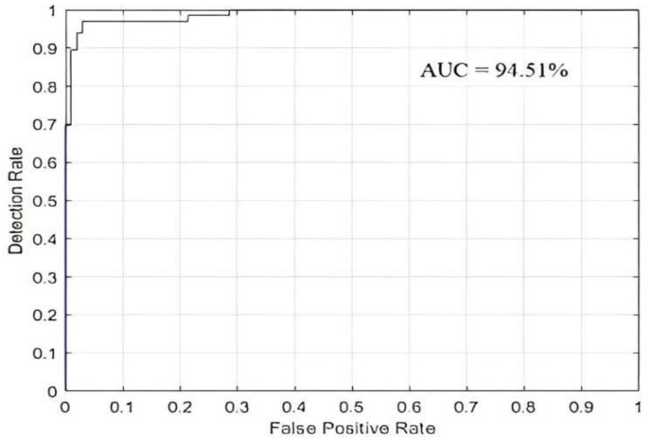

Fig. 3 AUC of the proposed model

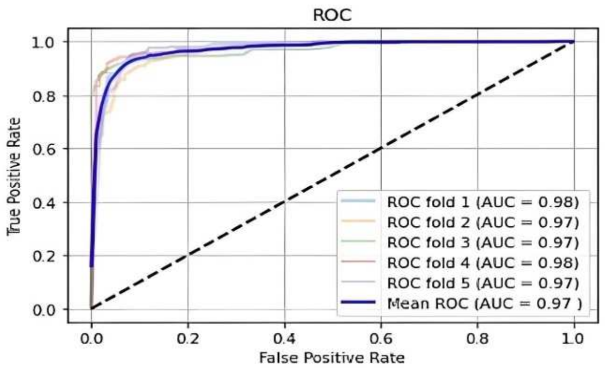

Fig. 4 Cross-validated ROC on the proposed deep model

The performance analysis of proposed model is best evident by comparing the same with traditional ML algorithms like CNN, DT, KNN, MLP, RF and two stacked denoising autoencoders (TDSA) which is a kind of ensemble method. The resultant analysis is summarized in Table 3. The graphical chart of the performance is better arrested in Figure 5.

TABLE IIIII
COMPARATIVE ANALYSIS OF EVALUATION RESULTS

Model	Measures in %				
	PPR	**NPR**	**Sensitivity**	**Specificity**	**AUC**
DT	55.23	44.07	38.28	84.15	64.25
KNN	52.86	42.65	43.90	87.28	66.37
MLP	64.80	55.93	49.80	89.20	71.35
RF	57.27	57.52	54.33	91.07	74.60
Two Stacked Denoising Autoencoders	58.25	59.37	74.02	69.04	77.80
CNN	76.69	62.50	76.20	85.32	86.05
Proposed Model (CNN with GWO)	86.45	61.20	92.38	91.09	94.51

The trapezoidal rule can be applied to determine AUC. AUCs of 0.5 typically show no discrimination (i.e., the ability to distinguish between patients who have the illness or disorder and those who do not, based on the tests); values in the range of 0.7 to 0.8 are viewed as acceptable; values in the range of 0.8 to 0.9 are regarded excellent; and values greater than 0.9 are weighed remarkable.

From this figure, it is clearly observed that the deep model built outperformed against machine learning models. The suggested model ensures approximately 30% increased AUC rate as compared to DT, 28% greater than KNN, 23% than MLP, 20% than RF, 17% than TDSA and 8% than CNN.

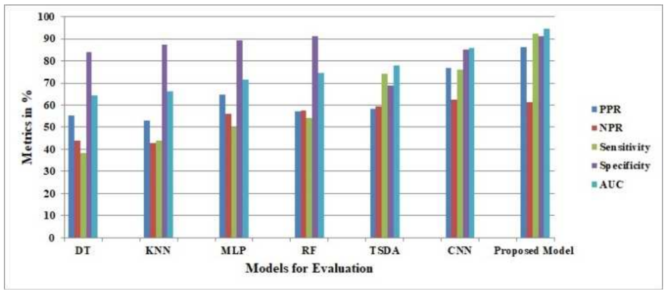

Fig. 5 Analysis chart of proposed model

Furthermore, employing metrics like accuracy and ROC can be troublesome when the classifications under consideration have non-uniform distributions. We have an unbalanced dataset when one class significantly dominates the distribution of all the data classes in it. It is therefore more reasonable to use metrics like sensitivity, specificity and Unweighted Average Recall (UAR) to assess the performance of the classifiers in the presence of an unbalanced data distribution. The UAR is recently developed evaluation metric. It is predominantly used to address the class imbalance issue. Without taking the number of occurrences into account, it simultaneously takes into account the mean sensitivity for one class and the mean specificity for another.

IV. CONCLUSION

Classifying ASD, employing deep learning as a method is the primary objective of this work. The outcomes unequivocally demonstrate that using deep learning is effective at identifying ASD. The pre-processed image information is collected, filtered based on personality characteristics and eye scan pattern with the help of HPCA. The CNN algorithm empowered with GWO is implemented over the Jupyter Notebook, to categorize the ASD and non-ASD patients. Lastly, a statistical analysis is done to assess the performance of the deep network built as proposed model. The greatest prediction rate obtained by this investigation in terms of AUC was 94.51%.

Further, to make more clinically ready approach along with personal characteristics and ETSP, the brain imaging of ASD can be annotated. To improve the dataset quality, transfer learning techniques can be applied. Moreover, to obtain acute performance of the classifier, new evaluation metrics like UAR can be utilized. Lastly, it is a good idea to combine professional analysis using statistical hypothesis validation.

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