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Analysis of Brain Imaging Data for the Detection of Early Age Autism Spectrum Disorder using Transfer Learning Approaches for Internet of Things

Adnan Ashraf, Qingjie Zhao, Waqas Haider Bangyal and Muddesar Iqbal

***Abstract*— In recent years, advanced magnetic resonance imaging (MRI) methods including functional magnetic resonance imaging (fMRI) and structural magnetic resonance imaging (sMRI) have indicated an increase in the prevalence of neuropsychiatric disorders such as autism spectrum disorder (ASD), effects one out of six children worldwide. Data driven techniques along with medical image analysis techniques, such as computer-assisted diagnosis (CAD), benefiting from deep learning. With the use of artificial intelligence (AI) and IoT-based intelligent approaches, it would be convenient to support autistic children to adopt the new atmospheres. In this paper, we classify and represent learning tasks of the most powerful deep learning network such as convolution neural network (CNN) and transfer learning algorithm on a combination of data from autism brain imaging data exchange (ABIDE I and ABIDE II) datasets. Due to their four-dimensional nature (three spatial dimensions and one temporal dimension), the resting state- fMRI (rs-fMRI) data can be used to develop diagnostic biomarkers for brain dysfunction. ABIDE is a collaboration of global scientists, where ABIDE-I and ABIDE-II consists of 1112 rs- fMRI datasets from 573 typical control (TC) and 539 autism individuals, and 1114 rs-fMRI from 521 autism and 593 typical control individuals respectively, which were collected from 17 different sites. Our proposed optimized version of CNN achieved 81.56% accuracy. This outperforms prior conventional approaches presented only on the ABIDE I datasets.**

***Index Terms*— MRI analysis, Autism assisted diagnosis, early age detection, deep learning.**

I. INTRODUCTION

DATA analysis in internet of things (IoT) have rapidly evolved in the recent few decades due to the tremendous input of multimodality of data. In internet of medical things data-driven machine learning models are gaining more popularity[1]. Due to the higher complexity of the neural network in human brain[2], there are innumerable cell types working in specific regions [3]. Brain disorder occurs when a part of the brain stops responding to brain activities, caused by malfunctioning of the brain's tissues and nerves. Brain diseases are mostly occurs due to genealogical factors and environmental risks attenuating factors that affect the working of specific brain region of nervous system [4]. Similarly, lack of executive functions (EFs) is a common cause of socio interactive and academic failure in children, related to a wide range of neurological and brain developmental issues. Recently, data-driven approaches have been used to discover unique clusters of children with shared EF-related issues and brain structure features [5]. Common brain diseases include Alzheimer [6], brain cancer [7], schizophrenia [8, 9], Autism [10], and psychiatric disorders [11-13] [8, 9, 14] etc.

Autism spectrum disorder (ASD) is a common brain disease which affects many parts of the brain and causes neurological and developmental disability in a child (12-18 months) that can last throughout their life span [10, 15]. ASD shows various symptoms including learning disability, behavioural disability, abnormal body posture and facial expressions and poor eye contact etc. Neurological illnesses effect one in six persons and cost almost one trillion dollars to treat them across the globe, according to the American Brain Foundation [16]. Due to brain intricacy, curing brain diseases are relatively difficult and complex. Hence, brain disease research has been a broad field for last twenty year [17].

ASD is one of the neurological disorder that is a behavioural disease characterized by poor verbal interaction, Restricted and Repetitive Behaviours (RRBs) [18], with neurodevelopment that leads to permanent impairment [19, 20]. ASD has increased rapidly during the past three decades, matching the 1.7 percent rate of autism in American children only. Boys have four times more autism than girls due to its rapid growth. Autism families have a 5–10% chance of having another autistic child and 0.1% to 0.2% of families without autistic children will have one (CDC, 1943-2004) [21, 22]. Physical inactivity and poor diet may increase the risk of chronic non-communicable diseases like ASD, they risk violence, injury, and abuse etc. Other childhood vaccinations do not increase ASD risk (WHO, 2021) [23]. During the last decade's neuroimaging research has shed light on ASD's neurobiology. The use of task-based functional MRI (fMRI) has revealed aberrant activity in crucial regions involved in social communication and RRBs in several studies. fMRI detects blood oxygen and flow changes that result from cerebral activity, an actively functioning brain consumes more oxidizing, so blood flow increases in the active area to meet this demand.

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In recent years, fMRI is used to study brain development in infants [2, 24-28]. rs-fMRI, gray matter (GM), and white matter (WM) MRI [29] has been used to diagnose brain abnormalities that cause ASD in several studies. Alongside the rapid advancement of both medical and computing technologies, there has been a corresponding rise in the commercial and educational interest in the field of healthcare. The internet of things enables computer systems to monitor and evaluate the mental and physiological health of user conditions such as ASD, Alzheimer's disease, and schizophrenia. When people and machines collaborate, medical institutions derive more benefit from the data they collect [30], such as in the case of the autistic brain imaging data exchange (ABIDE).

Deep learning's success in computer vision has led scientist's interest to investigate its neuroimaging applications. [31-37]. Standardized ASD tests are needed for clinical diagnostic approaches [38-41], which adds more time to the diagnostic process alongside increases treatment cost [24]. This research work applies artificial intelligence (AI) inspired transfer learning (TL) approaches to classify neuroimaging fMRI images to favour a supportive environment for autistic youngsters to communicate easily and in an adaptable manner [42-44]. Our study aims to propose an automatic early age detection and prediction tool of ASD using convolutional neural network (CNNs) [45-50] as one of the most powerful deep learning methods [51-55] and transfer learning [11, 56, 57] to overcome the challenges of a comprehensive dataset in the medical imaging domain based on rs-fMRI data ABIDE I-II [58]. Following key gaps are observed and properly catered:

- Early age ASD detected using ABIDE data set.
- Complete ABIDE_I and ABIDE_II dataset are used.

The most crucial aspect of ASD treatment is an early diagnosis. ASD has traditionally been diagnosed in young children by in-depth interviews with clinicians and careful observation of their behaviours [59, 60]. Hence, there is a pressing need to lessen reliance on conventional diagnostic methods to make an accurate diagnosis of this condition as early as possible, ideally before the emergence of any behavioural disorder signs. The contributions of our research work are summarized below:

- To provide an automated detection method with high confidence results.
- To develop a robust and generic method for quantitative analysis of brain MRI using Convolution Neural Network and Transfer Learning Approaches.
- To optimize the performance of transfer learning approaches with conventional ones are compared by analysis and experiments.

The prime purpose of this research article was to implement deep neural network and transfer learning approaches to classify autistic individuals from typical control individuals using ABIDE-I and ABIDE-II dataset. Collection and processing of ABIDE-I & ABIDE-II dataset was one of the most difficult and crucial part of this research work.

Furthermore, this paper continues as Section II elaborates the literature review, Section III explains about dataset and methodology, Section IV gives description about the results and discussion and Section V concluded this research work.

II. Literature Review

X. Yang et. al [18] reviews ASD categorization using classic machine learning and deep learning approaches for implementation on ABIDE data. This study aimed to compare brain networks between ASD and typical developing (TD) people. The correlation metric produced this result, Specificity is 73.61% and accuracy is 69.43%.

F. Zhang *et. al.* [61] proposes an rs-fMRI-based early age ASD detection and classification methodology, for functional connectivity features. The authors employed a multi-layer perceptron (MLP) that had been pretrained with a variational autoencoder (VAE), a less complex form of recurrent neural networks. Proposed model was evaluated using 10x10-fold cross-validation and achieved 78.12% accuracy.

The diagnosis of Autism Spectrum Disorder (ASD) involves the utilisation of video footage including newborns ranging from six to thirty-six months of age, as outlined in reference [62]. A total of 2000 three-minute films have been subjected to manual classification by proficient raters to identify and categorise various activities. The problem of machine learning (ML) is addressed in a two-stage manner. The initial phase involves the construction of deep learning models with the purpose of automatically detecting clinically significant newborn behaviours during individualised interactions with parents or medical professionals. The study presents findings on two different models: an image-based model and a facial behaviour feature-based model. The baseline results of these models are presented. The researcher achieved an accuracy rate of 70% for identifying smiles, 68% for recognising people, 67% for classifying objects, and 53% for discerning vocalisations. Upon identification of the most pertinent statistical behavioural traits and subsequent adjustment for class imbalance, a baseline machine learning classifier is developed, resulting in an autism spectrum disorder detection accuracy of 82%.

Early diagnosis and intervention play a crucial role in the care of young children diagnosed with autism spectrum disease [63]. This study employs eye-tracking data obtained from youngsters during unrestricted gazing tasks using natural stimuli. Among the two machine learning strategies being considered, the initial strategy involves employing a generative model that simulates synthetic saccade patterns. These patterns are then utilised to provide a deep learning classifier with an approximation of the typical scan-path observed in individuals without Autism Spectrum Disorder (ASD). The second approach involves the utilisation of a convolutional neural network (CNN) or a recurrent neural network (RNN) to process the input image in conjunction with fixation maps. According to our research findings, the

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accuracy of ASD prediction on the validation dataset is 67.23%, while on the test dataset it is 62.1%.

In their [64] study, Wu et al. (2019) employed scan path data obtained from a cohort of young individuals to develop an automated method for the detection of Autism Spectrum Disorder (ASD). To begin, a simulation environment with artificial motor imagery patterns is employed to simulate the baseline scan route of a person without ASD and then entered into a deep learning classifier. The second approach utilises a convolutional neural network for the purpose of analysing pictures and fixation maps. The results obtained from our validation dataset indicate an accuracy rate of 65.4%.

The training and testing of machine learning models for autism classification are conducted utilising the ABIDE database [65]. The present study introduces a novel approach for autism classification by proposing a multi-input deep neural network model. Deep learning models have demonstrated exceptional performance in the detection of Autism Spectrum Disorder (ASD) [66, 67]. This model is cross-validated using 1,038 real individuals and 10,038 samples. The author's classification of genuine data yielded an accuracy rate of 78.07%, while the supplemented data achieved a better accuracy rate of 79.13%, representing a 9% improvement compared to the previous results.

Sherkatghanad et al., 2020 [68] proposed a CNN architecture for automated detection of ASD using CC400 functional parcellation and ABIDE dataset. Preprocessing steps included slice timing correction, correction for motion, and normalization of voxel of MRI images that were passed through 400 filtered of different dimensions in CNN. The whole obtained result from CNN was fed to multilayer perceptron to complete the classification process which achieved accuracy of 70.22%.

According to the findings of this research [69], around 1.6% of children aged 8 in the United States have autism spectrum disorder. The use of automated diagnostic processes allows for the early detection of ASDs. Uncovering multimodal data correlations needs a multichannel deep attention neural network (DANN). 809 individuals tested the multichannel DANN model by using the ABIDE repository as their resource (408 ASD patients and 401 typical development controls). When compared to other machine learning models, our model scored 0.732 points higher in a k-fold cross validation test.

(Yang, Islam, & Khaled, 2019) [70] proposed a cross validation grid search method to find optimal parameter for each classifier to classify brain images data of ASD and TD (Typically Developed) patients. They investigated four classifiers—support vector machines with a Gaussian kernel, logistic regression, Ridge, and ABIDE rs-fMRI data—and compared their performance. Proposed system showed a slightly higher accuracy 71.98% than previously obtained using deep learning approaches that was 70%.

(El Gazzar, Cerliani, Van Wingen, & Thomas, 2019) [48] used rsfMRI data taken from ABIDE to classify brain images data of ASD patients. The proposed method was able to achieve cross-validated accuracies of 68% with an average accuracy of 65.1%, which is somewhat over the state-of-the-art median.

(Maryam et al., 2019) [71] used convolutional neural networks (CNNs) with a classifier combination of dynamic (mixing of experts) and static (basic Bayes) methods and a transfer learning methodology. They were able to achieve an approximate Accuracy of ~0.67-0.7 on ABIDE-II dataset using two Optimization techniques Adam & Adamax.

(Rajat et al., 2020) [72] used 2,000 data points from the ABIDE to train a 3D-CNN model using one of three approaches: I each measure was fed into a separate 3D-CNN (single-measurement models; SM-models); ii) the results from all nine 3D-CNNs were pooled into a single output (multi-model ensemble; MM-ensemble); or iii) Rajat used a single 3D-CNN to analyze.

Increasing the sample sizes in neuroimaging studies conducted on the general population has the effect of reducing dimensionality [73]. The potential advantages of greater sample sizes in machine learning-based diagnostic categorization may be limited. The ComBat method effectively mitigates inter-site disparities in data distributions through the application of empirical Bayes techniques. Researchers have successfully distinguished individuals with Autism from a control group of healthy individuals by utilising resting state functional magnetic resonance imaging (fMRI) data to analyse functional connectivity.

Table 1 shows the literature reviews covering data from 2018-2022. Search terms used for collecting articles were “CNN bases image classification”, “MRI data processing for brain diseases”, “Autism detection using MRI” etc.

TABLE I
LITERATURE REVIEW SUMMARY TABLE

Year	Author	Algorithm	Diseases
2023	(E. Helmy et al.,) [74]	Survey	ASD
2023	(R. Ma *et al.*,) [75]	Contrastive Variational Autoencoder (CVAE)	ASD
2022	(Yang, Xin) [18]	(kSVM)	ASD
2019	(Ahmed El Gazzar et al,.) [48]	1-D CNN atlas Schaefer-400 and Harvard Oxford	ASD
2022	(Zhang, F., et al.,)[61]	DNN	ASD
2021	(C. Wu *et al.,*) [62]	ResNet-18, SDG optimizer	ASD

2021	(Liaqat, S., et al.,)[63]	MLP, CNN, LSTM	ASD
2019	(Wu, C., et al) [64]	Machine Learning	ASD
2021	(T. M. Epalle,) [65]	MISO-DNN & PNN	ASD
2020	(Sherkatgh anad et al.,)[68]	CNN with MLP	ASD
2020	(K. Niu *et al.*,)[69]	multichannel DANN, MLP	ASD
2019	(Yang, Islam,) [70]	SVM, LR, Ridge,Gaussian kernel	ASD
2019	(Maryam A. A. et al,.)[71]	CNNs, and transfer learning using two Optimization techniques Adam & Adamax	ASD
2020	(Rajat M.T. et al.)[72]	a combined nine channel 3D-CNN model	ASD
2021	Ingalhalikar, M., et al., [73]	ANN-Deep Learning	ASD

III. Methodology

This section provides an overview of the ABIDE datasets, followed by an explanation of the classifiers employed in this research study. Various scholars engage in discourse regarding the practical implementations of their respective studies. Subsequently, all performance factors pertaining to resources, early age, and performance are assessed. Performance indicators and evaluation criteria are universally applicable to all types of data. This part closes by presenting the recommended research technique, accompanied by comprehensive explanations and graphics.

A. Dataset

The dataset utilized in this study was derived from the Autism Brain Imaging Data Exchange (ABIDE) in order to facilitate subsequent research. The ABIDE dataset has been widely employed by numerous researchers in order to differentiate individuals with Autism Spectrum Disorder (ASD) from control people, utilizing magnetic resonance imaging (MRI) scan images. The ABIDE-I dataset is composed of 1112 resting-state functional magnetic resonance imaging (rs-fMRI) datasets. Among these, 573 datasets belong to typically developing persons, while 539 datasets belong to individuals with autism. On the other hand, the ABIDE-II dataset consists of 1014 resting-state functional magnetic resonance imaging (rs-fMRI) datasets. Out of these, 521 datasets are from individuals with autism, and 593 datasets are from typically developing control individuals. These datasets were collected from a total of 17 distinct sites [76]. Mentioned below in Table 2.

TABLE II
DESCRIPTION OF ABIDE-I AND ABIDE-II DATASET

Sr#	Characteristics	Values	
1	**Dataset (Version)**	ABIDE-I	ABIDE-II
2	**No of Images**	1112	1014
3	**Autism**	539	521
4	**Typical Control (TC)**	573	593
5	**Age Group**	7-64 Years	5-64 Years

The Autism Brain Imaging Data Exchange I (ABIDE I) denotes the initial release of data within the ABIDE dataset [76]. The ABIDE I study encompassed 17 international sites, which collectively contributed pre-existing data sets consisting of Functional Magnetic Resonance Imaging (R-fMRI), anatomical, and phenotypic data. These data sets were made accessible for the purpose of sharing with the global research community. The present study gathered a total of 1112 data sets, consisting of 539 data sets from individuals diagnosed with Autism Spectrum Disorder (ASD) and 573 data sets from individuals without ASD (referred to as typical controls). The age range of participants in both groups was from 7 to 64 years, with a median age of 14.7 years across all groups. The previously mentioned statistic was made public in August of 2012.

The primary objective of ABIDE II is to enhance the scope of investigation regarding the role of brain imaging in Autism Spectrum Disorder (ASD). As of the present time, ABIDE II has amassed a collection of over 1000 supplementary data sets that exhibit enhanced phenotypic characterisation, specifically focusing on core measurements of Autism Spectrum Disorder (ASD) and its related symptoms [76]. Moreover, the collections encompass longitudinal samples of data obtained from a cohort of 38 individuals at intervals spanning 1 to 4 years. The ABIDE II study encompasses a total of 19 websites, consisting of 10 founding institutions and seven new members. These websites have together contributed 1114 data sets, which include information from 521 individuals diagnosed with Autism Spectrum Disorder (ASD) and 593 control subjects. The age range of the participants spans from 5 to 64 years.

B. Classifier

A classifier refers to a function or hypothesis that is employed to categorize instances associated with a class by assigning them distinct labels. Instances are assigned labels based on specific attributes, and subsequently, a classifier categorizes them. The present research work utilizes the following classifiers.

In recent years, CNN models have quickly emerged in medical data analysis, lesion segmentation, anatomical segmentation, and classification (Castro-Godinez et al., 2020) [77, 78]. CNN is a deep learning method that gives weights to picture features and separates them. CNNs require less preparation than other classification techniques. CNNs can learn filters/characteristics if trained. CNN uses filters to

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capture spatial and temporal connections in images. Reusing weights and decreasing parameters helps the architecture adapt to the picture dataset. Thus, the network may learn image complexity.

Transfer learning is a process which allows us to build more accurate and precise models in less time period with less data required. Using transfer learning, the model starts from patterns instead of scratch. Transfer learning utilizes already built models which are known as pre-trained models. Pre-trained models are trained on large datasets. Thus, transfer learning classifiers didn't require more data and required less time to train.

C. Proposed Methodology

Classifier Fundamentally, a research technique is a set of procedures utilized to solve a problem. Each and every one of the methods used in this research are laid out and explained in detail here. An algorithm is provided that can classify datasets into two groups and then make predictions based on that information. Beginning with data collection and ending with data classification for predictive modelling, the study process was broken down into six distinct phases. Listed below are descriptions of each phase.

Collecting the Abide dataset was a challenging task as the online data repository is only accessible for Neuro Informatics Tools and Resources Collaboratory (NITRC) members. Firstly, applied for data access to NITRC through E-mail and submitted the thesis title, supervisor contact, problem statement and research objectives. Luckily, upon success after a couple of days that made us eligible to download available datasets. Collected dataset was organized in three groups:

- ABIDE I
- ABIDE II
- ABIDE I+II

The groups were subsequently formed manually, taking into consideration criteria such as resources and age. Various approaches have been employed in an attempt to reduce dimensionality in resting-state functional magnetic resonance imaging (rs-fMRI) data, owing to the inclusion of spatiotemporal signals. In the neuroimaging literature, it is a frequent practice to minimize brain sizes by summarizing the temporal domain while preserving the three-dimensional spatial dimensions. There are various methodologies employed to extract attributes from time series data. In essence, these strategies can be categorized into two distinct approaches: temporal compression and spatial compression. Figure 1 illustrates the recommended methodology for transfer learning approaches.

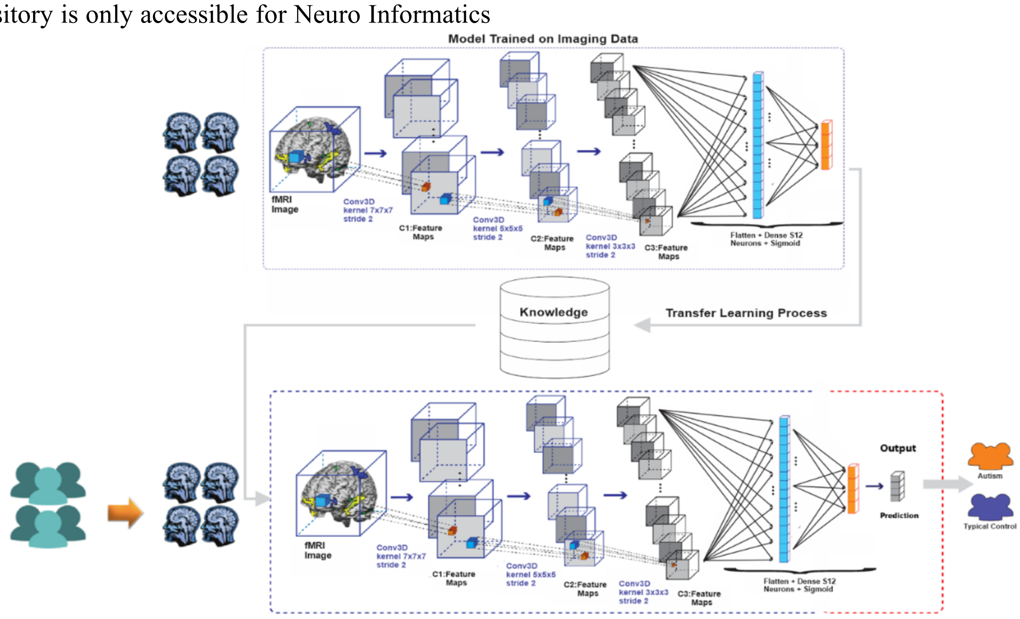

Fig. 1. Proposed Methodology for Transfer learning.

IV. RESULTS AND DISCUSSION

This part of the study contains detailed results of CNN, and transfer learning classifiers on all three datasets. This section presents performance matrixes such as precision, recall, accuracy, and F1-score for every classifier on each dataset. Heat maps and accuracy graphs for each dataset are also presented. In the last, discussion is stated for each classifier on each dataset.

A. Performance Metrics

Evaluating a machine learning model is crucial to measuring its performance. Machine learning model evaluation uses several metrics. Choosing the most appropriate metrics is important for fine-tuning a model, based on its performance. Detection of any disease is considered as binary classification which categories our data as positive or negative results. The evaluation metrics employed to assess the performance of CNN and transfer learning classification models are as follows. The subsequent terminologies are employed to delineate supplementary metrics.

- True positive (TP): Actually positive (true truth), predicted to be positive (correctly classified) .
- True negative (TN): Actual negative (basic truth), predicted as negative (correctly classified) .

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- False positive (FP): Actual negative (true truth), predicted to be positive (in-correctly classified) .
- False negative (FN): Actual positive (true truth), predicted to be negative (in-correctly classified).

By using these metrics, we can further find Precision, Recall, F1-score, Sensitivity and Accuracy. These are the commonly used metrics in machine learning, deep learning, and transfer learning classification problems. This enables researchers to evaluate a classification algorithm from multiple perspectives.

B. Experimental Setup

This section contains results for both CNN and transfer learning classifiers. This section has three parts. The first part presents all CNN classifier's results including precision, recall, F1-score, accuracy, heat maps and accuracy graph of all models. Second part contains results for all Transfer learning classifiers the same as machine learning classifiers. The third part compares results gathered from both CNN and Transfer Learning algorithms.

C. Results for ABIDE-I

This section contains results for both CNN and transfer learning classifiers. This section has three parts. The first part presents all CNN classifier's results including precision, recall, F1-score, accuracy, heat maps and accuracy graph of all models. Second part contains results for all Transfer learning classifiers the same as machine learning classifiers. The third part compares results gathered from both CNN and Transfer Learning algorithms.

1) **ABIDE-I Resource Based Analysis**
This section contains evaluation metrics, accuracy graph and heat map of CNN. The performance of ASD classification based on resources is illustrated in Fig. 2. a sampling dataset containing subject data from four resources, children of different ages were used to test results. Table 3 acquires accuracy, sensitivity, and specificity results. Discussion and comparative analysis shows our model performance compared with other similar architectures.

TABLE III
CLASSIFICATION ACCURACY OF CONVOLUTION NEURAL NETWORK FOR ABIDE-I

Resource	Model	Acc	Sensitivity	Specificity	F1-Score
UM	CNN	78.5%	79.5%	72.5%	87.0%
	DTL-NN	81.0%	81.3%	75.5%	83.0%
UCLA	CNN	78.7%	78.3%	78%	81.0%
	DTL-NN	81.3%	80.9%	79.4%	82.0%
USM	CNN	76.5%	77.3%	75.3%	79.0%
	DTL-NN	79.9%	80.9%	82.5%	82.0%
LUEVEN	CNN	77.5%	78.4%	78.4%	79.0%
	DTL-NN	81.7%	82.8%	79.9%	83.0%

Our models attained an average of 79.09% accuracy, 80.71 % sensitivity, and 78.71% specificity, which exceeded several other state-of-the-art techniques in terms of performance ([71, 72, 79]). Models perform well on a larger training dataset as compared to small datasets.

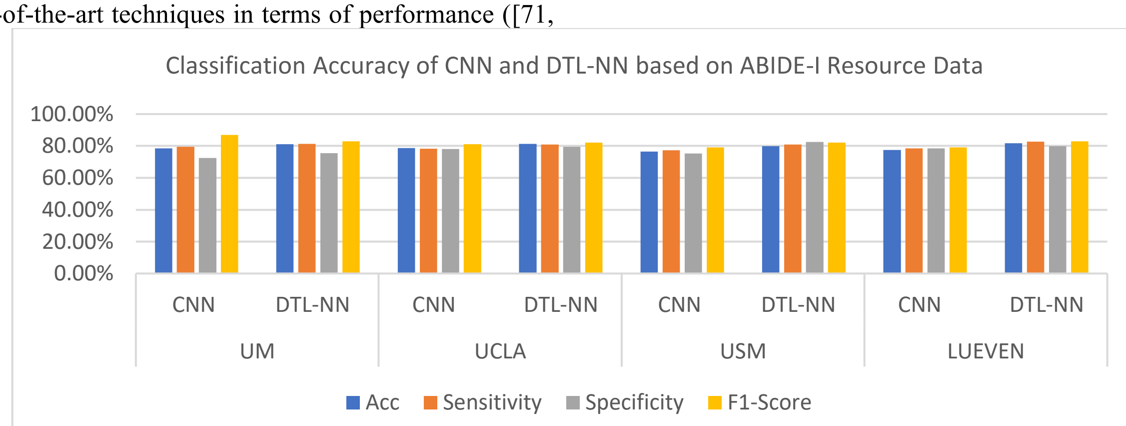

Fig. 2. Classification accuracy of CNN and DTL-NN based on ABIDE-I resource labelled Dataset.

a) **Comparative Analysis:** Table 4 shows comparative analysis with respect to ABIDE-I research work on convolution neural network. By comparing the suggested study to similar prior work, it becomes abundantly evident that the proposed models are more effective than the prior work when it comes to learning models.

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TABLE IV
COMPARATIVE ANALYSIS WITH RESPECT TO CNN RESULTS ON ABIDE-I

Yu Zhao et al,.2019 [79]	2019 Maryam et al,.2019 [71]	Rajat etal,. 2020[72]
CNN	CNN	CNN
65.30%	67%-70.0%	~66%

2) **ABIDE-I Complete**
This section contains evaluation metrics and accuracy graphs of complete ABIDE-I dataset analysis regardless of Resources or early age. The complete dataset contains 1112 images, after cleaning, missing and broken images we used 938 MRI scans.

The performance of ASD classification based on resources, which is illustrated in Fig. 3. a sampling dataset containing subject data from four resources, both genders and of different ages was used to test results. Table 5 shows the accuracy, sensitivity, and specificity results. Discussion and comparative analysis shows our model performance with other similar architectures.

TABLE V
COMPARATIVE ANALYSIS WITH RESPECT TO CNN RESULTS ON ABIDE-I

Dataset	Model	Acc	Sensitivity	Specificity	F1-Score
ABIDE-I	CNN	78.5%	79.5%	79.5%	87.0%
	DTL-NN	80%	81.3%	74.5%	88.0%

The models in our study demonstrated an average accuracy of 78.5%, sensitivity of 79.5%, and specificity of 79.5%, surpassing the performance of most contemporary approaches [72]. Transfer learning models demonstrated superior accuracy in comparison to convolutional neural networks (CNNs). Models demonstrate superior performance when trained on larger datasets in comparison to smaller datasets.

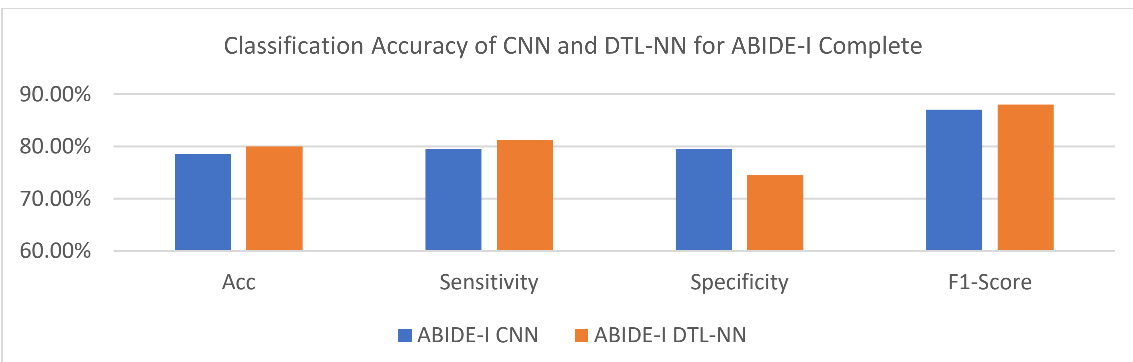

Fig. 3. Classification accuracy of CNN and DTL-NN based on complete ABIDE-I Dataset.

a) **Comparative Analysis:** Table 6 shows comparative analysis with respect to ABIDE-I research work on convolution neural Network. Proposed research work is compared with previously done work of the same nature which clearly shows that proposed models work efficiently as compared to previously done work for learning models.

TABLE VI
COMPARATIVE ANALYSIS WITH RESPECT TO CNN RESULTS ON ABIDE-I

Ahmed El Gazzar et al,. 2019 [48]	Maryam et al,. 2019 [71]
CNN	CNN
65.1%	73.04%

D. Results for ABIDE-II

This section contains results for both CNN and transfer learning classifiers for ABIDE_II dataset. The ABIDE_II dataset was categorized further in two major groups based on resources and age. Each set was analyzed separately to test and compare results of both models.

1) **ABIDE-II Resource Based Analysis**
This section presents an analysis of evaluation metrics, an accuracy graph, and a heat map pertaining to the Convolutional Neural Network (CNN). The performance of Autism Spectrum Disorder (ASD) classification, with respect to available resources, is depicted in Figure 4. To assess the outcomes, a sampling dataset comprising subject data from

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four distinct resources, encompassing individuals of varying ages and both genders, was utilized. Table 7 contains accuracy, sensitivity, and specificity results. Discussion and comparative analysis shows our model performance compared with other similar architectures.

TABLE VII
CLASSIFICATION ACCURACY OF CNN AND DTL-NN BASED ON ABIDE-II RESOURCE DATASET

Resource	Model	Acc	Sensitivity	Specificity	F1-Score
BNI	CNN	79.5%	77.5%	72.5%	87.0%
	DTL-NN	80%	81.3%	78.5%	82.0%
EMC	CNN	79.3%	79.3%	78%	81.0%
	DTL-NN	79.9%	78.9%	79.4%	84.0%
ETH	CNN	78.8%	77.3%	78.3%	79.0%
	DTL-NN	76.4%	81.5%	79.9%	82.0%
GU	CNN	78.5%	78.4%	79.4%	80.0%
	DTL-NN	80.7%	79.8%	79.9%	84.0%

ABIDE-II data download and labelling was a challenging task. Each image was manually labelled and assigned a group. Each group was tested separately to compare and analyze results of each set. Four chosen resources contained the highest number of images available and contained early age data. CNN again outperformed the previous results and showed better accuracy then other state of the art methods.

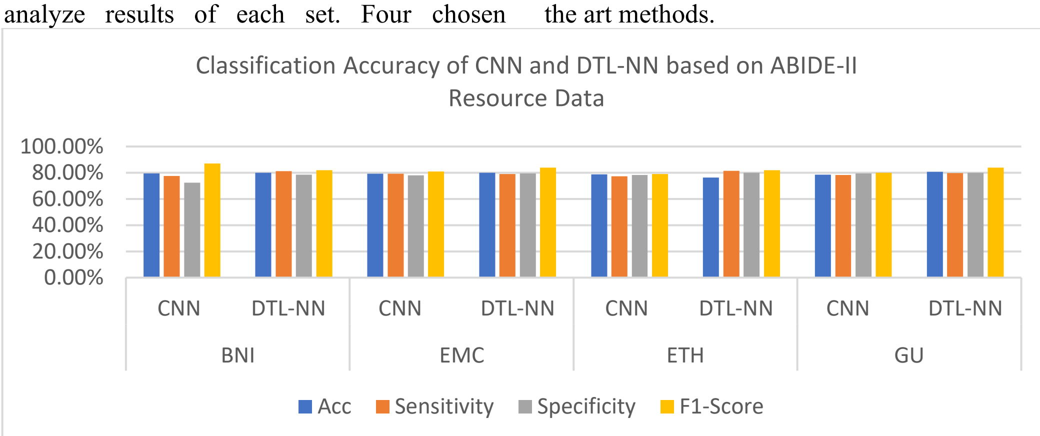

Fig. 4. Classification accuracy of CNN and DTL-NN based on ABIDE-II resource labelled Dataset.

a) **Comparative Analysis:** Table 8 shows comparative analysis with respect to ABIDE-II research work on convolution neural Network. The proposed research work is compared with the earlier work of the same nature which clearly shows that the proposed model works efficiently as compared to the work done earlier for the learning model.

TABLE VIII
COMPARATIVE ANALYSIS WITH RESPECT TO CNN RESULTS ON ABIDE-II DATA RESOURCE

Sherkatghanad et al., 2020 [68]	Yang, Islam, & Khaled, 2019 [70]
CNN	CNN
70.22%	70%

2) **ABIDE-II Complete**

This section includes evaluation metrics and accuracy graphs for the entire ABIDE-II dataset analysis, regardless of resource or early age. The performance of ASD classification based on resources is illustrated in Fig. 5. a sampling dataset containing subject data from four resources and different ages was used to test results. Table 9 is listed with accuracy, sensitivity, and specificity. Discussion and comparative analysis shows our model performance compared with other similar architectures.

TABLE IX
CLASSIFICATION ACCURACY OF CONVOLUTION NEURAL NETWORK FOR ABIDE-II

Dataset	Model	Acc	Sensitivity	Specificity	F1-Score
ABIDE-II	CNN	80.5%	82.5%	79.5%	87.0%
	DTL-NN	83%	84.3%	78.5%	85.0%

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Our models achieved an average of 79.09% for accuracy, 80.71% for sensitivity, 78.71% for specificity which outperformed in results as compared to many other state of the art techniques ([79] [71] [72]). Models perform well on a larger training dataset as compared to small datasets.

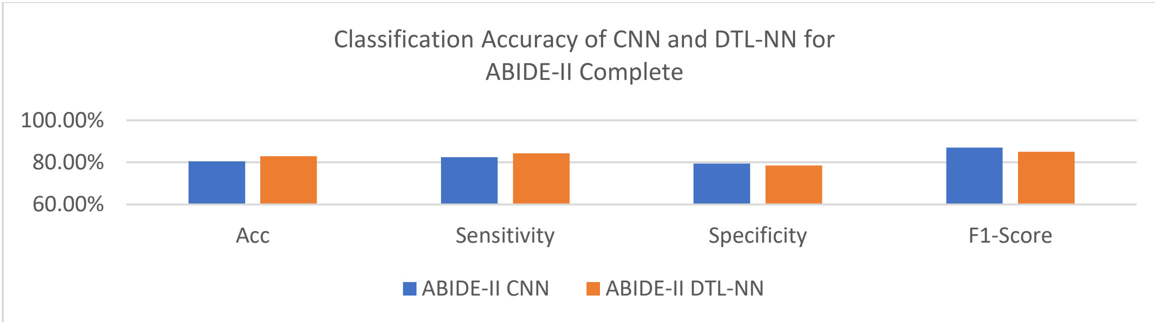

Fig. 5. Classification accuracy of CNN and DTL-NN based on complete ABIDE-II.

a) **Comparative Analysis:** Table 10 shows a comparative analysis with respect to ABIDE-II research work on convolution neural Network. Proposed research work is compared with previously done work of the same nature which clearly shows that proposed models work efficiently as compared to previously done work for learning models.

TABLE X
CLASSIFICATION ACCURACY OF CONVOLUTION NEURAL NETWORK FOR ABIDE-II

Sherkatghanad et al., 2020 [68]	El Gazzar, Cerliani, Van Wingen, & Thomas, 2019 [48]
CNN	CNN
70.22%	~68%

E. Results for ABIDE - I + II

This section contains results for both CNN and transfer learning classifiers on a combined dataset from Abide I and II. The performance of ASD classification based on resources is illustrated in Fig. 6. a sampling dataset containing subject data from four resources, both genders and of different ages was used to test results. Below Table 11 contains accuracy, sensitivity, and specificity results. Discussion and comparative analysis shows our model performance compared with other similar architectures.

TABLE XI
CLASSIFICATION ACCURACY OF CONVOLUTION NEURAL NETWORK FOR ABIDE-II

Dataset	Model	Acc	Sensitivity	Specificity	F1-Score
ABIDE - I+II	CNN	81.56	81.5%	80.5%	88.0%
	DTL-NN	82.31%	83.3%	80.7%	87.0%

Our models achieved an average of 79.09% for accuracy, 80.71% for sensitivity, 78.71% for specificity which outperformed in results as compared to many other state of the art techniques ([79] [71] [72]). Models perform well on a larger training dataset as compared to small datasets.

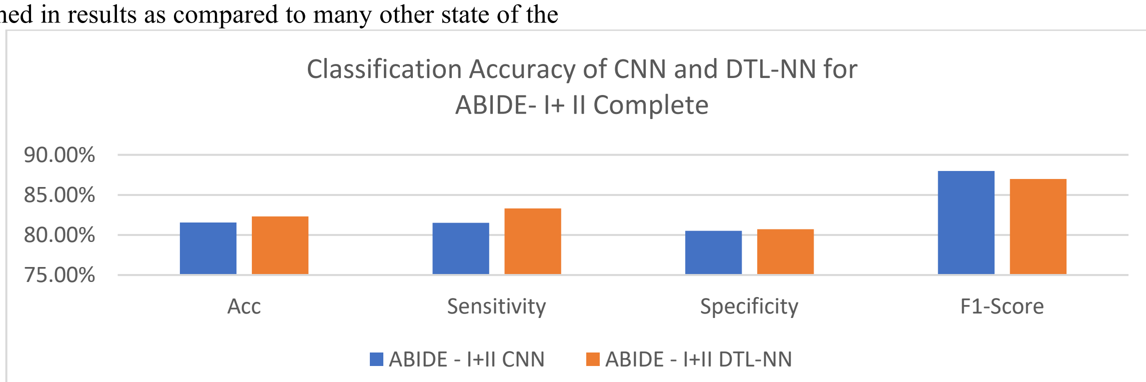

Fig. 6. Classification accuracy of CNN and DTL-NN based on ABIDE-I+II Data

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a) **Comparative Analysis:** Table 12 contains a comparative analysis with respect to the ABIDE-I+II research work on Convolutional Neural Networks and Transfer Learning. The proposed research work is compared with the earlier work of the same nature which clearly shows that the proposed models work efficiently as compared to the work done earlier for the learning model.

TABLE XII
COMPARATIVE ANALYSIS WITH RESPECT TO CNN RESULTS ON ABIDE-I+II

Sherkatghanad et al., 2020 [68]	**Maryam et al,. 2019 [71]**
CNN	CNN
70.22%	67%-70.0%

b) **Comparative Analysis:** Below mentioned Table 8, is comparative analysis table with respect to ABIDE-II research work on convolution neural Network. As compared to previous studies of a similar kind, the presented research demonstrates that the proposed model outperforms its predecessors in terms of learning efficiency.

V. CONCLUSIONS

The functional magnetic resonance imaging (fMRI) approach is a modern medical imaging approach that has greatly contributed to the identification and assessment of neurological and neurodevelopmental difficulties. An optimized version of convolution neural network turned out to be a breakthrough for ASD classification tasks. Transfer Learning classifiers achieved better results with ABIDE-I 81.7%, ABIDE-II 80.7%, ABIDE-I+II 82.31% of accuracy on experimented datasets and outshines among compared machine learning and deep learning ASD classification literatures. Our analysis is limited by the method utilised to collect ABIDE data from 17 foreign clinical and research sites. Another limitation is picture data availability. The dataset has 851 subjects, which is significant. However, in order to optimise the performance of deep learning algorithms, it is advisable to augment the dataset by increasing its size. The current focus of study lies on the early detection of autism, with the aim of utilising tracking outcomes to enhance patient well-being in both healthcare facilities and domestic settings through the implementation of remote medical devices and recommended treatment strategies. In future research, it is recommended to focus on the development of an assistive tool for individuals with autism, with the aim of improving their overall well-being and enhancing their efficiency in daily activities.

VI. ACKNOWLEDGMENT

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APPENDIX

1) **Accuracy**
Accuracy is a fraction of, total number of predictions a model predicts right and calculated using below (1).

$$\text{Accuracy} = \frac{TN+TP}{TP+TN+FP+FN} \tag{1}$$

2) **Precision**
Precision is the fraction of relevant instances among all recovered instances and calculated using below (2).

$$\text{Precision}=\frac{TP}{TP+FP} \tag{2}$$

3) **Sensitivity**
Recall or positive class or sensitivity is the fraction of related instances which are recovered and is calculated using below (3).

$$\text{Recall}=\frac{TP}{TP+FN} \tag{3}$$

4) **Specificity**
Negative class recall is also called specificity and is defined as the relationship between the negative and functions of actual negative cases and is calculated using below (4).

$$\text{Recall}=\frac{TN}{TP+FN} \tag{4}$$

5) **F1 Score**
It is a combination of precision and recall and is calculated using below (5).

$$\text{F1-Score}=2*\frac{\text{Precision*Recall}}{\text{Precision+Recall}} \tag{5}$$

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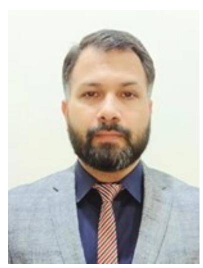

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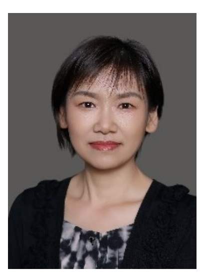

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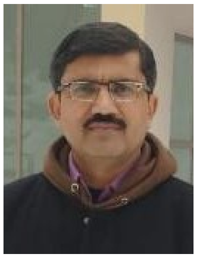

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