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

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

***Abstract*—In recent years, advanced magnetic resonance imaging (MRI) methods including as functional magnetic resonance imaging (fMRI) and structural magnetic resonance imaging (sMRI) have indicated an increase in the prevalence of neuropsychiatric disorders. Data driven techniques along with medical image analysis techniques, such as computer-assisted diagnosis, can benefit from deep learning. With the use of artificial intelligence (AI) and IoT-based intelligent approaches, it would be convenient to make it easier for autistic children to adopt the new atmospheres. In this study, we have tried to classify and represent learning tasks of the most powerful deep learning network such as Convolution Neural network (CNN) and Transfer Learning algorithm for 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 rs-fMRI data can be used to develop diagnostic biomarkers for brain dysfunction. ABIDE is a global collaboration of scientists, as ABIDE-I and ABIDE-II consists of 1112 rs-fMRI datasets comprising 573 typically developing and 539 autism individuals, 1014 rs-fMRI containing 521 austistic and 593 typical control (TC) respectively, collected from 17 different sites. Our proposed optimized version of CNN achieved 81.56% accuracy. This outperforms prior conventional approaches presented on the ABIDE I datasets.**

***Index Terms*—Autism spectrum disorder, ASD, early age ASD, gender base ASD, deep neural network, transfer learning.**

I. Introduction

DATA analytics in Internet of things has evolved fast in the recent few decade due to the tremendous input of multimodality data. In Internet of medical things machine learning-based analytical, data-driven models are increasingly becoming more popular [1]. Due to the high complexity of neural network contained in the 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 which can be caused by malfunctioning of the brain's tissues and nerves. Brain diseases are mostly caused by genealogical factors, environmental risks attenuating factors that affect the working of specific brain region of nervous system [4]. Lack of executive functions (EFs) is a common cause of socio interactive and academic failure in children and has been connected to a wide range of neurological and developmental issues. Data-driven approaches have been used to discover unique clusters of children with shared EF-related issues and subsequently found brain structure features that separate these data-driven groups [5]. Common brain diseases include Alzheimer [6], brain cancer [7], schizophrenia [8], [9] Autism [10], and psychiatric disorders [11], [12], [13] etc.

Alzheimer's disease (AD) is characterized by brain cell death, which eventually affects memory and thinking [6]. Between 30 and 60, early AD symptoms occur. Memory, eyesight, problem-solving, and peanut butter tests are used to detect AD.

Neuroanatomical cell growth, called tumor cells, causes issues in solid skulls that enclose the brain [7]. Early symptoms of Brain Tumer (BT) include nausea, vomiting, headache, bodily weakness, and memory issues. Early detection and treatment of BT can save lives. Neurologic exams, CT scans, MRIs, and Angiograms detect BT.

Schizophrenia impacts thinking, behaviour, and emotion. Early illness symptoms may begin between 16-30 and continue a lifetime. Antipsychotics, psychosocial treatments, and coordinated specialist care (CSC) help treat schizophrenia in early stages [8], [9], [14].

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 his life [10], [15]. ASD shows a large number of symptoms which include learning disability, behavioral disability, abnormal body posture and facial expressions and poor eye contact etc. Neurological illnesses affect one in six people and cost almost one trillion dollars to treat, according to the American Brain Foundation [16]. Due to brain intricacy, brain disease treatment is difficult. That's why brain disease research has been a broad field for last 20 years [17].

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Adnan Ashraf and Zhao Qingjie are with the School of Computer Science and Technology, Beijing Institute of Technology, Beijing 100081, China (e-mail: adnannashraf@gmail.com; zhaoqj@bit.edu.cn).

Waqas Haider Khan Bangyal is with the Department of Computer Science, Kohsar University, Murree 40000, Pakistan (e-mail: waqas.bangyal@kum.edu.pk).

Muddesar Iqbal is with the Department of Communication and Network Engineering, College of Engineering, Prince Sultan University, Riyadh 11586, Saudi Arabia (e-mail: miqbal@psu.edu.sa).

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ASD is one of the neurological disorder that is a behavioural disease characterized by repetitive behaviour, poor verbal interaction, Restricted and repetitive behaviours (RRBs) [18], 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. 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 has revealed aberrant activity in crucial regions involved in social communication and RRBs in a number of studies. fMRI detects blood oxygen and flow changes that result from cerebral activity, a more active brain consumes more oxidizing, so blood flow increases in the active area to meet this demand.

In recent years, fMRI is used to study brain development in infants [2], [24], [25], [26], [27], [28]. rs-fMRI, gray matter (GM), and white matter (WM) MRI [29] have 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 users, including conditions such as ASD, Alzheimer's disease, and schizophrenia. When people and machines collaborate, medical institutions may derive more benefit from the data they collect [30], such as in the case of the autistic brain imaging data exchange (ABIDE).

Since deep learning has been so effective in computer vision, researchers have begun to explore how they may apply it to neuroimaging [31], [32], [33], [34], [35], [36], [37]. Standardized ASD tests are needed for clinical approaches [38], [39], [40], [41] of diagnosis, which adds time to the diagnostic process and costs more money to treatment [24]. This research work uses IoT, Artificial intelligence inspired transfer learning approaches to classify neuro-imaging fMRI images in the favour of a supportive environment for autistic youngsters to communicate easily and in an adaptable manner [42], [43], [44]. Our study aims to find an automatic early prediction tool for the detection of ASD using convolutional neural network (CNNs) [45], [46], [47], [48], [49], [50] as one of the most powerful deep learning methods [51], [52], [53], [54], [55] and Transfer Learning (TL) [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.

ASD is a broad research area where progress has been made, but there is still much work to do. 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]. As a result, there is a pressing need to lessen reliance on conventional diagnostic methods in order to make an accurate diagnosis of this condition as early as possible, ideally before the emergence of any behavioral disorder signs. The contributions of our research work are summarized below:

- We provide an automated detection method with high confidence results.
- We develop a robust and generic method for quantitative analysis of brain MRI using Convolution Neural Network and Transfer Learning Approaches.
- The performance of transfer learning approaches with traditional 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. Further the paper continue below as Section II elaborates the literature review, Section III explains about materials and methods, Section IV gives description about results and discussion and Section V concluded this discussion.

II. Literature Review

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 normally developing people (TD). The correlation metric produced this result, Specificity is 73.61% and accuracy is 69.43%.

Reference [61] proposes an rs-fMRI-based early age ASD detection and classification methodology, for functional connectivity features, they employed an 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.

ASD is being started diagnosed using video of infants aged from six to thirty six months is presented in [62]. There are 2000 3-minute movies with experienced raters hand coding these actions. The ML issue is approached in two stages. First step, we build deep learning models to automatically identify clinically important newborn behaviors in one-on-one interactions with parents or doctors. (1) image-based model (2) facial behavior feature-based model baseline findings are reported. We get 70% accuracy for smiles, 68% for faces, 67% for objects, and 53% for vocalizations. After identifying the most relevant statistical behavioral characteristics and compensating for class imbalance, we create a baseline ML classifier that achieves an ASD diagnostic accuracy of 82%.

For young children with autism spectrum condition, early diagnosis and intervention are critical [63]. This work, utilizing eye-tracking data collected from children during free-viewing activities with natural visuals. Out of two machine learning techniques, The first approach uses a generative model of synthetic saccade patterns to feed a deep learning classifier an approximation of a normal, non-ASD person's baseline scan-path. In the second method, a CNN or RNN is fed the input picture along with fixation maps. Our research indicates that the ASD prediction accuracy on the validation dataset is 67.23 percent and on the test dataset it is 62.1%.

Reference [64] uses scan path data from youngsters viewing natural photos to automatically detect ASD. To begin, a simulation environment of artificial motor imagery patterns is used to mimic the baseline scan path of a person without ASD and then input into a deep learning classifier. The second method employs a convolutional neural network to process images and fixation maps. Our validation dataset tests reveal 65.4% accuracy.

Machine learning models for autism classification are trained and tested using the (ABIDE) database [65]. This research proposes a multi input deep neural network autism classification model. Generally deep learning models perform outstandingly for ASD detection [66], [67]. Our model is cross-validated using 1,038 real participants and 10,038 samples. We classify genuine data at 78.07% and augmented data at 79.13%, 9% higher than 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 et al., 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%.

Gazzar et al., 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.

Aghdam 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.

Thomas et al., 2020 [3] 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.

Larger public neuroimaging sample sizes minimize dimensionality [72]. Machine learning-based diagnostic categorization may not benefit from larger samples. ComBat removes inter-site discrepancies in data distributions using empirical Bayes. Using resting state fMRI functional connectivity data, we differentiate Autism from healthy controls.

Table I 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.

III. Methodology

This section covers ABIDE datasets and then, the classifiers utilized in this re-search work are explained. Different researchers discuss their applications. Then all performance indicators based on resources, early age, and performance are measured. Performance indicators and evaluation criteria apply to all data. This section concludes with the proposed research methodology with detailed diagrams explanations.

A. Dataset

We collected data from Autism Brain Imaging Data Exchange (ABIDE) to develop a dataset for further analysis. ABIDE dataset has been used by many researchers to classify ASD patients versus control subjects based on MRI scan images. ABIDE-I consists of 1112 rs-fMRI datasets comprising 573 typically developing and 539 autism individuals, while ABIDE-II consists of 1014 re-fMRI dataset comprises of 521 autistic and 593 typical control individuals [75] collected from 17 different sites. Mentioned below in Table II.

Autism Brain Imaging Data Exchange I (ABIDE I) represents the first ABIDE release data [75]. ABIDE I involved 17 international sites that shared previously collected Functional Magnetic Resonance Imaging (R-fMRI), anatomical and phenotypic data sets made available for data sharing with the wider scientific community. This effort collected 1112 data sets, including 539 from individuals with ASD and 573 from typical controls (7–64 years, median 14.7 years across groups). This total was released in August 2012.

ABIDE II was created to further expand the research field of brain imaging role in ASD. To date, ABIDE II has collected more than 1000 additional data sets with greater phenotypic characterization, particularly in terms of core ASD measurements and associated symptoms [75]. In addition, collections contain longitudinal samples of data collected from 38 people at times (1-4 years interval). ABIDE II has 19 websites—ten

TABLE I
LITERATURE REVIEW SUMMARY TABLE

Year	Author	Algorithm	Diseases
2023	(E. Helmy et al.,) [73]	Survey	ASD
2023	(R. Ma *et al.*,) [74]	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.)[3]	a combined nine channel 3D-CNN model	ASD
2021	Ingalhalikar, M., et al., [72]	ANN-Deep Learning	ASD

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

founding institutions and seven additional members—donating 1114 data sets from 521 persons with ASD and 593 controls (age range: 5-64 years).

B. Classifier

Classifier is a function or hypothesis which is used to categorize the instances of a class by assigning them specific labels. Instances are labelled using certain parameters and then classifier categories them. These are the following classifiers which are used in this research work.

In recent years, CNN models have quickly emerged in medical data analysis, lesion segmentation, anatomical segmentation, and classification (Castro-Godinez et al., 2020) [76], [77]. 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 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

Each group was further manually organized based on Resources and Age factors. Several methods have been tried to decrease dimensionality in rs-fMRI data because of the

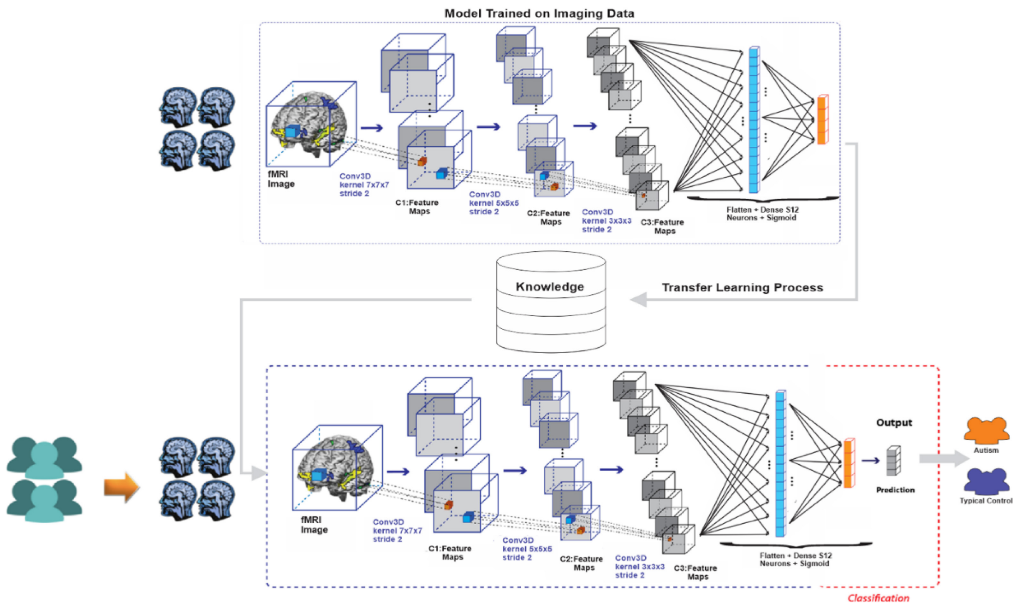

Fig. 1. Proposed methodology for transfer learning.

spatiotemporal signal they include. In neuroimaging literature, brain sizes are commonly reduced by summarizing the temporal domain while keeping three-dimensional spatial dimensions. Several approaches extract time series properties. Essentially, they may be broken down into methods that focus on either temporal compression or spatial compression. Fig. 1 represents the proposed methodology for transfer learning approaches.

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. To measure the performance of CNN and Transfer learning classification models following evaluation metrics are used. The following terms are used to define additional 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).
- 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).

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 III acquires accuracy, sensitivity, and specificity results. Discussion and comparative analysis shows our model performance

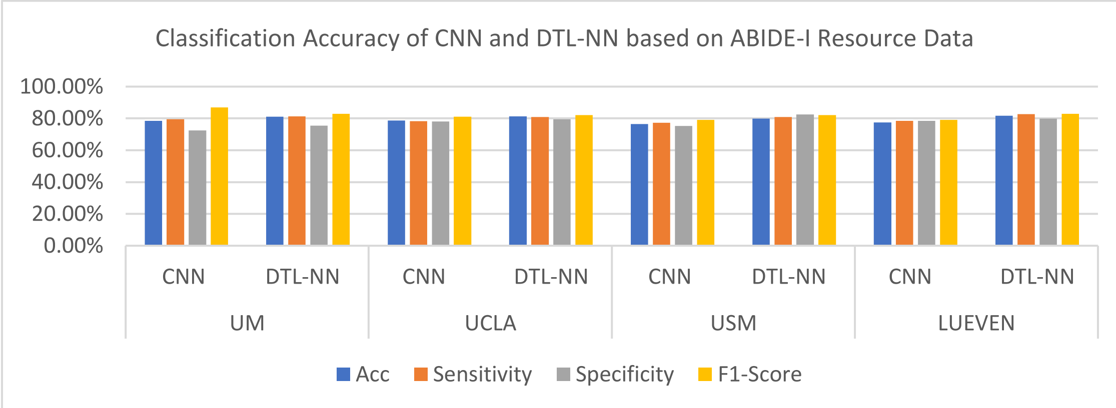

Fig. 2. Classification accuracy of CNN and DTL-NN based on ABIDE-I resource labelled dataset.

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%

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[3]
CNN	CNN	CNN
65.30%	67%-70.0%	~66%

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%

compared with other similar architectures. 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 [3], [71], [78]. Models perform well on a larger training dataset as compared to small datasets.

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 [3], [71], [78]. Models perform well on a larger training dataset as compared to small datasets.

a) *Comparative Analysis:* Table IV 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.

2. *ABIDE-I Complete:* This section contains evaluation metrics and accuracy graphs of complete ABIDE-I dataset analysis regardless of Resources or early age. Complete dataset contain 1112 images, after cleaning missing and broken images we used 938 MRI scans. The performance of ASD classification based on resources 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 V shows the accuracy, sensitivity, and specificity results. Discussion and comparative analysis shows our model performance compared with other similar architectures.

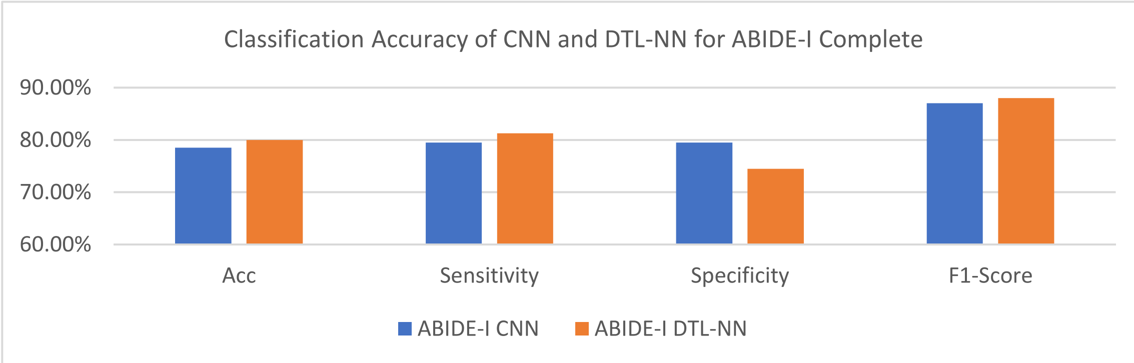

Fig. 3. Classification accuracy of CNN and DTL-NN based on complete ABIDE-I dataset.

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%

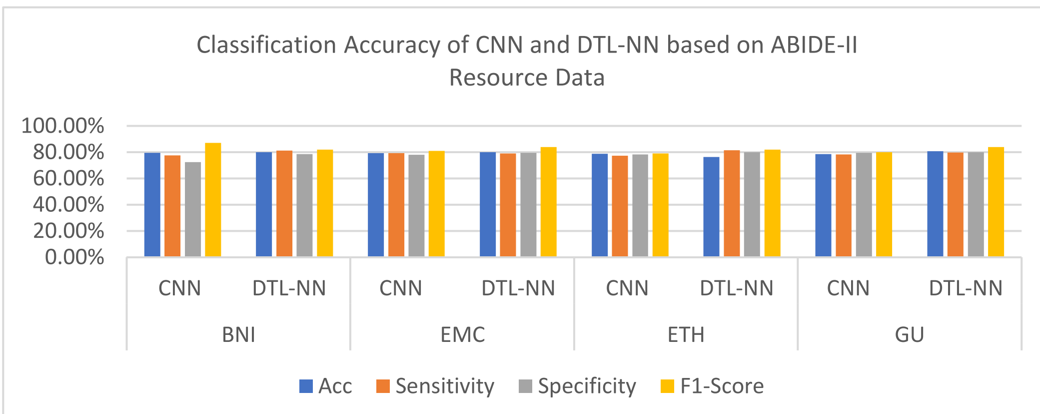

Fig. 4. Classification accuracy of CNN and DTL-NN based on ABIDE-II resource labelled Dataset.

Our models achieved an average of 78.5% for accuracy, 79.5% for sensitivity, 79,5% for specificity which outperformed in results as compared to many other state of the art techniques [3]. Transfer Learning models showed even better accuracy as compared to CNN. Models perform well on a larger training dataset as compared to small datasets.

a) *Comparative Analysis:* Table VI 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.

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 contains evaluation metrics, accuracy graph and heat map of CNN. The performance of ASD classification based on resources is illustrated in Fig. 4. a sampling dataset containing subject data from four resources, both genders and of different ages was used to test results. Table VII contains accuracy, sensitivity, and specificity results. Discussion and comparative analysis shows our model performance compared with other similar architectures.

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.

a) *Comparative Analysis:* Table VIII 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

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%

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%

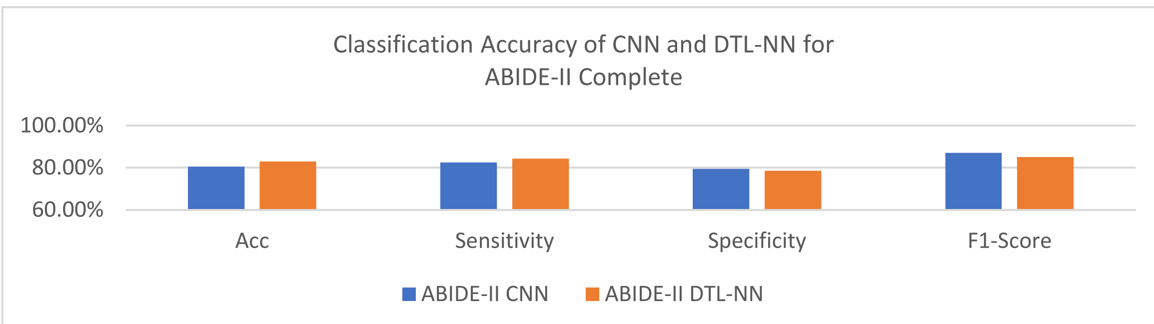

Fig. 5. Classification accuracy of CNN and DTL-NN based on complete ABIDE-II.

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%

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%

works efficiently as compared to the work done earlier for the learning model.

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 IX is listed with accuracy, sensitivity, and specificity. Discussion and comparative analysis shows our model performance compared with other similar architectures.

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 ([3], [71], [78]). Models perform well on a larger training dataset as compared to small datasets.

a) *Comparative Analysis:* Table X 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

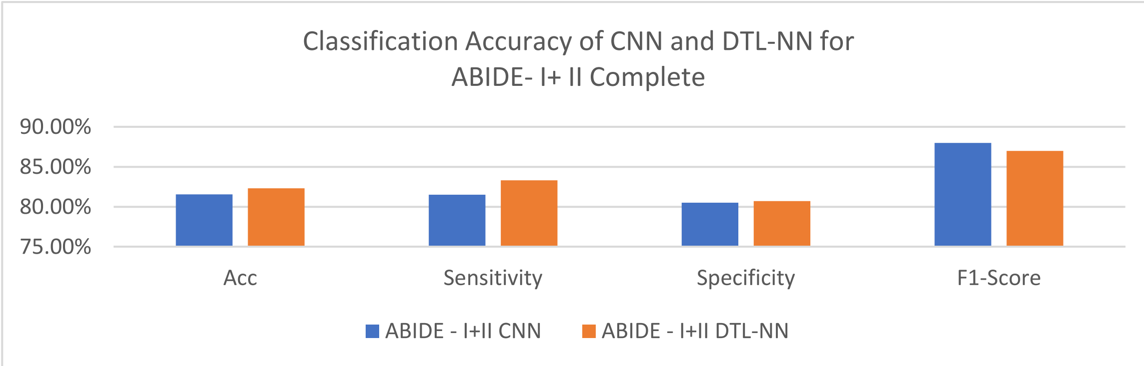

Fig. 6. Classification accuracy of CNN and DTL-NN based on ABIDE-I+II Data.

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%

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%

efficiently as compared to previously done work for learning models.

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 XI contains accuracy, sensitivity, and specificity results. Discussion and comparative analysis shows our model performance compared with other similar architectures.

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 [3], [71], [78]. Models perform well on a larger training dataset as compared to small datasets.

a) *Comparative Analysis:* Table XII 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.

b) *Comparative Analysis:* Below mentioned Table VIII, 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. CONCLUSION

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.

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).

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

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

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

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).

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

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

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

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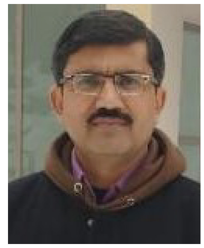
Adnan Ashraf received the undergraduate degree in computer science from the Virtual University of Pakistan in 2014, and the master's degree in computer science from the University of Gujrat, Pakistan, in 2018. He is currently pursuing the Ph.D. degree in computer science with the Beijing Institute of Technology, Beijing, China. His research is concentrated on evolutionary computing, AI, swarm AI, ANNs, image processing, and video processing using deep learning and transfer learning.

Zhao Qingjie received the B.S. degree in control science and engineering from the China University of Petroleum in 1988, the M.S. degree in control science and engineering from Shandong University in 1996, and the Ph.D. degree in computer science and technology from Tsinghua University in 2003. She was a Visiting Fellow with the School of Computer Science and Electronic Engineering, University of Essex, U.K., from 2008 to 2009, and a Senior Visiting Scholar with the Department of Information, University of Hamburg, Germany, from 2017 to 2018. She is currently a Professor with the School of Computer Science and Technology, Beijing Institute of Technology. Her research areas are computing intelligence, image and signal processing, and pattern recognition.



Waqas Haider Khan Bangyal received the Ph.D. degree in computer science in 2018. He is currently an Associate Professor and the In Charge Dean of the Faculty of Computing and Applied Sciences, Kohsar University, Murree, Pakistan. He has 20+ years of global experience in computer science, computer vision, artificial intelligence, IoT, big data, and block chain. His research interests include optimization, machine learning & meta-heuristics, image processing, bio informatics, NLP, and pattern recognition.

Muddesar Iqbal is an academic entrepreneur who has always found his Teaching, R&D, and Enterprise activities working hand-in-hand to produce innovative technologies. He has been PI, Co-PI, and Coordinated more than 17 research and capacity building projects. He has co-invented four patented technologies with more than 100 research articles published in reputed journals and conferences. His research interests include 5G, B5G, 6G, Smart IoT and FPGAs, blockchain, collaborative cognitive-communication systems, AI-enabled recommendation systems, and Chatbots.