

Deep Learning for Neuroimaging-based Diagnosis and Rehabilitation of Autism Spectrum Disorder: A Review

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Abstract—Accurate diagnosis of Autism Spectrum Disorder (ASD) is essential for its management and rehabilitation. Neuroimaging techniques that are non-invasive are disease markers and may be leveraged to aid ASD diagnosis. Structural and functional neuroimaging techniques provide physicians substantial information about the structure (anatomy and structural connectivity) and function (activity and functional connectivity) of the brain. Due to the intricate structure and function of the brain, diagnosing ASD with neuroimaging data without exploiting artificial intelligence (AI) techniques is extremely challenging. AI techniques comprise traditional machine learning (ML) approaches and deep learning (DL) techniques. Conventional ML methods employ various feature extraction and classification techniques, but in DL, the process of feature extraction and classification is accomplished intelligently and integrally. In this paper, studies conducted with the aid of DL networks to distinguish ASD were investigated. Rehabilitation tools provided by supporting ASD patients utilizing DL networks were also assessed. Finally, we presented important challenges in this automated detection and rehabilitation of ASD.

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I. INTRODUCTION

ASD is a disorder of the nervous system that affects the brain and results in difficulties in speech, social interaction and communication deficits, repetitive behaviors, and delays in motor abilities [1]. The disease can generally be distinguished with extant diagnostic protocols from the age of three onwards. Autism influences many parts of the brain. This disorder also involves a genetic influence via the gene interactions or polymorphisms [2], [3]. One in 70 children worldwide is affected by autism. In 2018, the prevalence of ASDs was estimated to occur in 168 out of 10,000 children in the United States, one of the highest prevalence rates worldwide. Autism is significantly more common in boys than in girls. In the United States, about 3.63 percent of boys aged 3 to 17 have autism spectrum disorder, compared with approximately 1.25 percent of girls [4].

Diagnosing ASD is difficult because there is no pathophysiological marker, relying instead just on psychological criteria [5]. Psychological tools can identify individual behaviors, levels of social interaction, and consequently facilitate early diagnosis. Behavioral evaluations embrace various instruments and questionnaires to assist the physicians to specify the particular type of delay in a child's development, including clinical observations, medical history, autism diagnosis instructions, and growth and intelligence tests [6].

Several investigations for the diagnosis of ASD have recently been conducted on neuroimaging data (structural and functional).

Analyzing anatomy and anatomical connections of brain areas with structural neuroimaging is an essential tool for studying structural disorders of the brain in ASD. The principal tools for structural brain imaging are magnetic resonance imaging (MRI) techniques [7], [8], [9]. Cerebral anatomy is defined by structural MRI (sMRI) images and anatomical connections are assessed by diffusion tensor imaging MRI (DTI-MR) [10]. Investigating the activity and functional connections of brain areas using functional neuroimaging can also be used for studying ASD. Brain functional diagnostic tools are older approaches than the previous two methods for studying

ASD. The most basic modality of functional neuroimaging is electroencephalography (EEG), which records the electrical activity of the brain from the surface of the head with a high temporal resolution (in milliseconds order) [11]. Studies have shown that employing EEG signals to diagnose ASD have been useful [12], [13], [14]. Functional MRI (fMRI) is one of the most promising imaging modalities in functional brain disorders, used as a task-based (T-fMRI) or restingstate (rs-fMRI) [15], [16]. fMRI-based techniques have a high spatial resolution (in the order of millimeters) but a low temporal resolution due to slow response of the hemodynamic system of the brain as well as fMRI imaging time constraints and is not ideal for recording the fast dynamics of brain activities. In addition, these techniques have a high sensitivity to motion artifacts. It should be stressed that in consonance with studies, three less prevalent modalities of electrocorticography (ECoG) [17], functional near-infrared spectroscopy (fNIRS) [18], and Magnetoencephalography (MEG) [19] can also attain reasonable performance in ASD diagnosis. An appropriate approach is to utilize machine-learning techniques alongside functional and structural data to collaborate with physicians in the process of accurately assessing ASD. In the field of ASD, applying machine learning methods generally entail two categories of traditional methods [20] and DL methods [21]. As opposed to traditional methods, much less work has been done on DL methods to explore ASD or design rehabilitation tools.

This study reviews ASD assessment methods and patients' rehabilitation with DL networks. The outline of this paper is as follows. Section 2 is search strategy. Section 3 concisely presents the DL networks employed in the field of ASD. In section 4, existing computer-aided diagnosis systems (CADS) are reviewed using brain functional and structural data. In section 5, DL-based rehabilitation tools are introduced to support ASD patients. Section 6 discusses the reviewed papers. Section 7 reveals the challenges of ASD diagnosis and rehabilitation with DL. Finally, the paper concludes and suggests future work in section 8.

II. SEARCH STRATEGY

In this review, IEEE Xplore, ScienceDirect, SpringerLink, ACM, as well as other conferences or journals were used to acquire papers on ASD diagnosis using DL methods. Further, the keywords "ASD", "Autism Spectrum Disorder" and "Deep Learning" are used to select the papers. The papers are analyzed till June 03th, 2020 by the authors (AK, SN). Figure 1 depicts the number of considered papers using DL methods for the automated detection of ASD each year.

III. DEEP LEARNING TECHNIQUES FOR ASD DIAGNOSIS AND REHABILITATION

Nowadays, DL algorithms are used in many areas of medicine including structural and functional neuroimaging. The application of DL in neural imaging ranges from brain MR image segmentation [22], detection of brain lesions such as tumors [23], diagnosis of brain functional disorders such as ASD [24], and production of artificial structural or functional brain images [25]. Machine learning techniques are categorized into

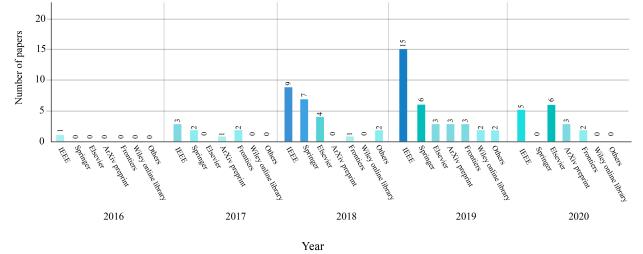


Fig. 1: Number of papers published every year for ASD diagnosis and rehabilitation.

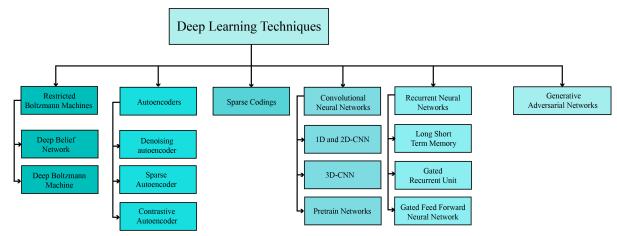


Fig. 2: Illustration of various types of DL methods.

three fundamental categories of learning: supervised learning [26], unsupervised learning [27], and reinforcement learning [28], and a variety of DL networks are provided for each type. So far, most studies applied to identify ASD using DL have been based on supervised or unsupervised approaches. In Figure 2 illustrates generally employed types of families with DL networks with supervised or unsupervised networks to study ASD.

IV. CADS-BASED DEEP LEARNING TECHNIQUES FOR ASD DIAGNOSIS BY NEUROIMAGING DATA

A traditional artificial intelligence (AI)-based CADS encompasses several stages of data acquisition, data pre-processing, feature extraction, and classification [29], [30], [31], [32]. In these investigations [33], [34], [35] existing traditional algorithms have been used for diagnosing ASD. In DL-based CADS, however, feature extraction, and classification are performed intelligently within the model. Also, due to the structure of DL networks, using large dataset to train DL networks and recognize intricate patterns in datasets is incumbent. The components of DL-based CADS for ASD detection are shown in Figure 3. It can be noted from the figure that, large and free databases are first introduced to diagnose ASD. In the second step, various types of pre-processing techniques are used on functional and structural data to be scrutinized. Finally, the DL networks are applied on the preprocessed data.

A. Neuroimaging ASD Datasets

Datasets are fed as input to the development of CADS and the power of CADS depends primarily on the affluence of the

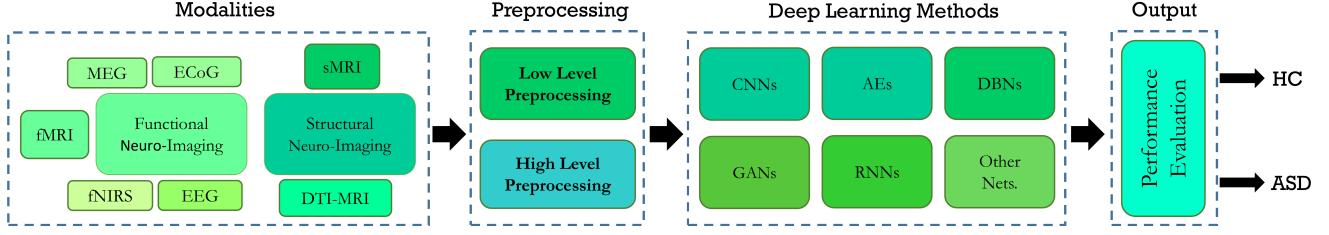


Fig. 3: Block diagram of CAD system using DL architecture for ASD detection.

input data. To diagnose ASD, varied brain functional and structural datasets are available. The most complete free dataset available is ABIDE [36] dataset with two subsets: ABIDE-I and ABIDE-II, which encompasses sMRI, rs-fMRI, and phenotypic data. ABIDE-I involves data from 17 international sites, yielding a total of 1112 datasets, including 539 from individuals with ASD and 573 healthy individuals (ages 64-7). In accordance with HIPAA guidelines and 1000 FCP / INDI protocols, these data are anonymized. In contrast, ABIDE-II contains data from 19 international sites, with a total of 1114 datasets from 521 ASDs individuals and 593 healthy individuals (ages 5-64). Also, preprocessed images of the ABIDE-I series called PCP [37] can be freely downloaded by the researchers. The second recently released ASD diagnostic database is called NDAR, which comprises variant modalities, and more information is provided in [38].

B. Preprocessing Techniques

Neuroimaging data (especially functional ones) is relatively complicated structure, and if it is not pre-processed properly, it may affect the final diagnosis. Preprocessing of this data typically entails multiple common steps performed by different software as standard. Indeed, occasionally prepared pipelines are applied on the dataset to yield pre-processed data for future research. In the following section, preprocessing steps are briefly explained for fMRI data.

1) Standard (Low-level) fMRI preprocessing steps: Low-level pre-processing of fMRI images normally has fixed number of steps exerted on the data, and prepared toolboxes are usually used to reduce execution time and yield better accuracy. Some of these reputable toolboxes contain FMRIB software libraries (FSL) [39], BET [40], FreeSurfer [41], and SPM [42]. Also, important and vital fMRI preprocessing incorporates brain extraction, spatial smoothing, temporal filtering, motion correction, slice timing correction, intensity normalization, and registration to standard atlas, which are summarized.

BRAIN EXTRACTION: the goal is to remove the skull and cerebellum from the fMRI image and maintain the brain tissue [43], [44], [45].

SPATIAL SMOOTHING: involves averaging the adjacent voxels signal. This process is persuasive on account of neighboring brain voxels being usually closely related in function and blood supply [43], [44], [45].

TEMPORAL FILTERING: the aim is to eliminate unwanted components from the time series of voxels without impairing the signal of interest [43], [44], [45].

REALIGNMENT (MOTION CORRECTION): During the fMRI test, people often move their heads. The objective of motion correction is to align all images to a reference image so that the coordinates and orientation of the voxels be identical in all fMRI volumetric images [43], [44], [45].

SLICE TIMING CORRECTION: The purpose of modifying the slice time is to adjust the time series of the voxels so that all the voxels in each fMRI volume image have a common reference time. Usually, the corresponding time of the first slice recording in each fMRI volume image is selected as the reference time [43], [44], [45].

INTENSITY NORMALIZATION: at this stage, the average intensity of fMRI signals are rescaled to compensate for global deviations within and between the recording sessions [43], [44], [45].

REGISTRATION TO A STANDARD ATLAS: The human brain entails hundreds of cortical and subcortical areas with variant structures and functions, each of which is very time-consuming and complex to study. To overcome the problem, brain atlases are employed to partition brain images into a confined number of ROIs, following which the mean time series of each ROI can be extracted [46]. ABIDE datasets exert a manifold of atlases, including Automated Anatomical Labeling (AAL) [47], Eickhoff-Zilles (EZ) [48], Harvard-Oxford (HO) [49], Talaraiach and Tournoux (TT) [50], Dosenbach 160 [51], Craddock 200 (CC200) [52] and Craddock 400 (CC400) [53] and more information is provided in [54]. Table I provides complete information on preprocessing tools, atlases, and few other preprocessing information.

2) Pipeline Methods: Pipelines present preprocessed images of ABIDE databases. They embrace generic preprocessing procedures. Employing pipelines, distinct methods can be compared with each other. In ABIDE datasets, preprocessing is performed by four pipeline techniques: neuroimaging analysis kit (NIAK) [55], data processing assistant for rs- fMRI (DPARSF) [56], the configurable pipeline for the analysis of connectomes (CPAC) [57], or connectome computation system (CCS) [58]. The preprocessing steps carried out by the various pipelines are comparatively analogous. The chief differences are in the particular algorithms for each step, the software simulations, and the parameters applied. Details of each pipeline technique are provided in [54]. Table I demonstrates the pipeline techniques used in autism detection

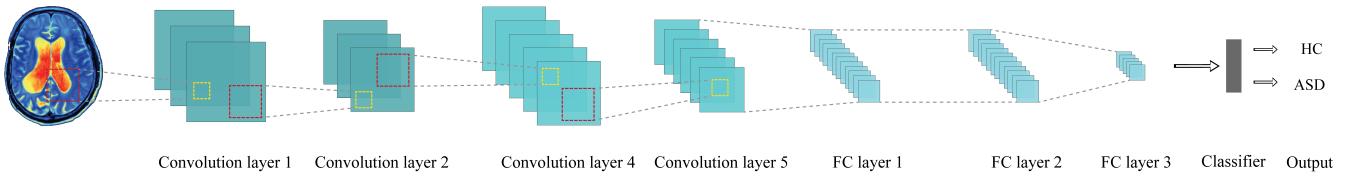


Fig. 4: Overall block diagram of 2D-CNN used for ASD detection.

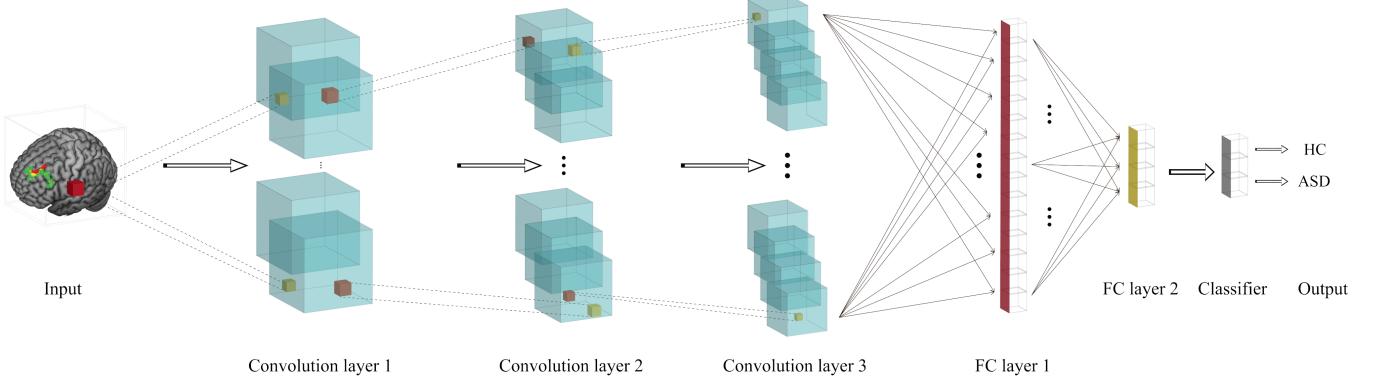


Fig. 5: Overall block diagram of a 3D-CNN used for ASD detection.

investigation exploiting DL.

3) High-level preprocessing Steps: High-level techniques for pre-processing brain data are important, and using them accompanying preliminary pre-processing methods can enhance the accuracy of ASD recognition. These methods are applied after the standard pre-processing of functional and structural brain data. These include sliding window (SW) [24], data augmentation (DA) [59], functional connectivity matrix (FCM) [60], [61] and fast Fourier transformation (FFT) [62]. Furthermore, some research utilized feature extraction [63] techniques and other feature selection methods. Precise information on assayed studies in Table I is indicated in detail.

C. Deep Neural Networks

Deep learning in various medical applications, including the diagnosis of ASD, has become extremely popular in recent years. In this section of the paper, the types of Deep Learning networks used in ASD detection are examined, which include CNN, RNN, AE, DBN, CNN-RNN, and CNN-AE models.

1) Convolutional Neural Networks (CNNs) : In this discussion, the types of popular convolutional networks used in ASD diagnosis are surveyed. These networks involve 1D-CNN, 2D-CNN, 3D-CNN models, and a variety of pre-trained networks such as VGG.

1D AND 2D-CNN

There are many spatial dependencies present in the data and it is difficult to extract these hidden signatures from the data. Convolution network uses a structure alike to convolution filters to extract these features properly and contribute to the knowledge that features should be processed taking into account spatial dependencies, and the number of network parameters are significantly reduced. The principal application of these networks is in image processing and due to the two-dimensional (2D) image inputs, convolution layers form 2D

structures, which is why these networks are 2D convolutional neural network (2D-CNN). By transforming data, in to one-dimensional signals, the convolution layers' structure also resembles the data structure [64]. In convolution networks, assuming that variant data sections do not require learning different filters, the number of parameters are markedly lessened and make it feasible to train these networks with more bounded databases [21]. Figure 4 shows the block diagram of 2D-CNN used for ASD detection.

3D-CNN

By transforming the data into three dimensions, the convolution network will also be altered to a three-dimensional format (Figure 5). It should be noted that the manipulation of three dimensional CNN (3D-CNN) networks is less beneficial than 1D-CNN and 2D-CNN networks for diverse reasons. First, the data required to train these networks must be much large which conventionally such datasets are not utilizable and methods such as pre-training, which are extensively exploited in 2D networks, cannot be used here. Another reason is that with more complicated structure of networks, it becomes much tougher to fix the number of layers, and network. The 3D activation map generated during the convolution of a 3D CNN is essential for analyzing data where volumetric or temporal context is crucial. This ability to analyze a series of frames or images in context has led to the use of 3D CNNs as tools for action detection and evaluation of medical imaging. [65].

2) Deep Belief Networks (DBNs): Although DBNs are not popular today as they used to be, and have been substituted by new models to perform various applications (autoencoders for unsupervised learning , generative adversarial networks (GAN) for generative modes [66], variational autoencoders (VAE) [67]), disregarding the restricted use of this network in this era, their influence on the advancement of neural networks cannot be overlooked. The use of these networks in this paper

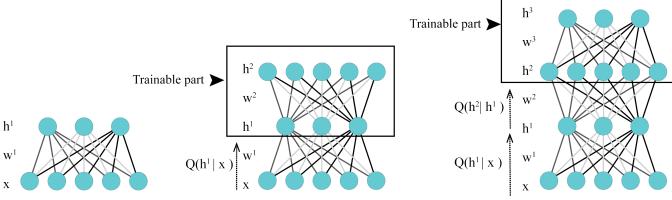


Fig. 6: Overall block diagram of DBN used for ASD detection.

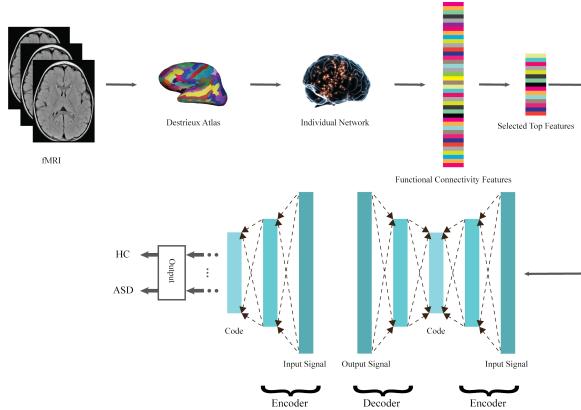


Fig. 7: Overall block diagram of an AE used for ASD detection.

is related to the feature extraction without a supervisor or pre-training of networks. These networks serve as unsupervised, consisting of several layers after the input layer, which is shown in Figure 6. The training of these networks is done greedily and from bottom to top, in other words, each separate layer is trained and then the next layer is appended. After training, these networks are used for feature extraction method or a network with trained weights [21].

3) *Autoencoders (AEs)*: Autoencoders (AEs) are more than 30 years old, and have undergone dramatic changes over the years to enhance their performance. But the overall structure of these networks has remained the same [21]. These networks consist of two parts: coder and decoder so that the first part of the input leads to coding in the latent space, and the decoder part endeavors to convert the code into preliminary data (Figure 7). Autoencoders are a special type of feedforward neural networks where the input is the same as the output. They compress the input into a lower-dimensional code and then reconstruct the output from this representation. The code is a compact summary or compression of the input, also called the latent-space representation. Various methods have been proposed to block the data memorizing by the network, including sparse AE (SpAE) and denoising AE (DAE) [21]. If the Autoencoder is properly trained, the coder layer can extract the features in unsupervised pre-training in this type of networks.

4) *Recurrent Neural Networks (RNNs)*: In convolution networks, a kind of spatial dependencies in the data is addressed. But interdependencies between data are not confined to this model. For example in time-series dependencies may be highly distant from each other, on the other hand, the long-term and variable length of these sequences results in that the ordinary

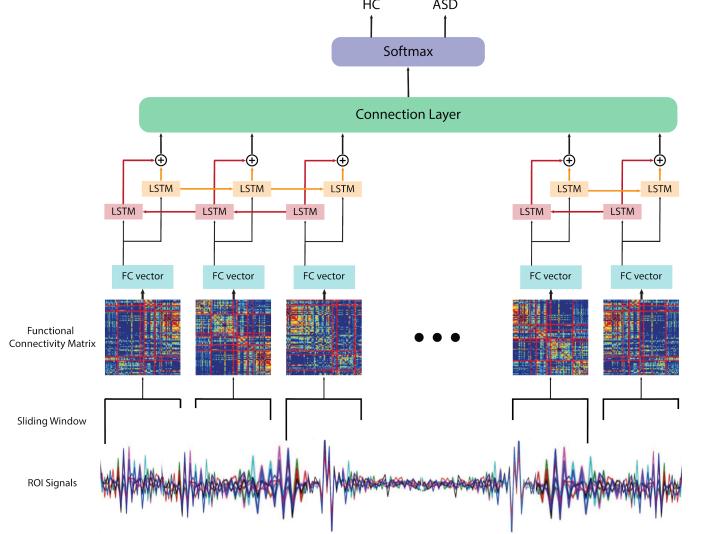


Fig. 8: Overall block diagram of LSTM used for ASD detection.

networks do not perform well enough to process these data. To overcome these problems, RNN networks can be used. LSTM structures are proposed to extract long term and short term dependencies in the data (Figure 8). Another well-known structure called GRU is developed after LSTM, and since then, most efforts have been made to enhance these two structures and make them resistant to challenges (eg GRU-D, [68] is used to find the lost data).

5) *CNN-RNN* : The initial idea in these networks was to utilize convolution layers to amend the performance of RNNs so that the advantages of both networks can be applied; CNN-RNN, on the one hand, makes it achievable to receive temporal dependencies with the relief of RNN, and on the other hand, it discovers the possibility of receiving spatial dependencies in data with the help of convolution layers [69]. These networks are highly beneficial for analyzing time series with more than one dimension (such as video) [70] but further to the simpler matter, these networks also yield the analysis of three-dimensional data so that instead of a more complex design of a 3D-CNN, a 2D-CNN with an RNN network is occasionally used. The superiority of this model is due to the feasibility of employing pre-trained models. Figure 9 demonstrates the CNN-RNN model.

6) *CNN-AE*: In the construction of these networks, the principal aim and prerequisite have been to decrease the number of parameters. Just changing the network layers of convolution markedly lessens the number of parameters, combining AE with convolution structures also makes significant contribution. This helps to exploit more dimensional data and extracts more information from the data without changing the size of the database. Similar structures, with or without some modification, are widely deployed in image segmentation [71], and likewise unsupervised network can be applied for network pre-training or feature extraction. Figure 10 depicts the CNN-AE network used for ASD detection. In Tables I and

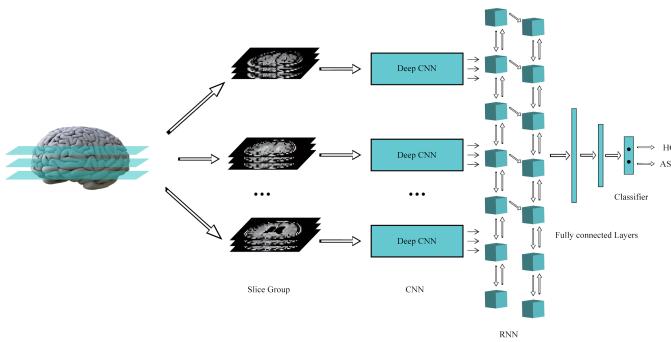


Fig. 9: Overall block diagram of CNN-RNN for ASD detection.

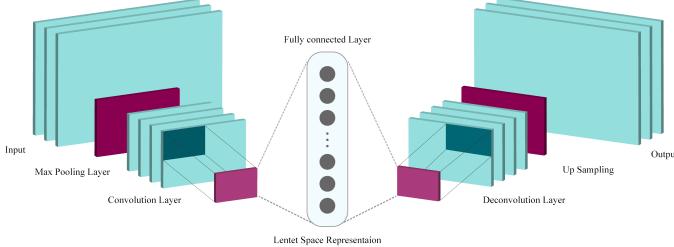


Fig. 10: Overall block diagram of a CNN-AE for ASD detection.

II, provide the summary of papers published on detection and rehabilitation of ASD patients using DL respectively.

V. DEEP LEARNING TECHNIQUES FOR ASD REHABILITATION

Rehabilitation tools are employed in multiple fields of medicine and the main purpose is to help the patients to recover after the treatment. Various and multiple rehabilitation tools using DL algorithms have been presented. Rehabilitation tools used to help ASD patients using mobile, computer applications, robotic devices, cloud systems, and eye tracking, which will be discussed below. Also, the summary of papers published on rehabilitation of ASD patients using DL algorithm are shown in table II.

A. Mobile and Software Applications

Facial expressions are a key mode of non-verbal communication in children with ASD and play a pivotal role in social interactions. Use of BCI systems provides insight into the user's inner-emotional state. Valles et al. [72] conducted research focused on mobile software design to provide assistance to children with ASD. They aimed to design a smart iOS app based on facial images according to Figure 11. In this way, people's faces at different angles and brightness are first photographed, and are turned into various emoji so that the autistic child can express his/her feelings and emotions. In the group's major investigation [72], Kaggle's (The Facial Expression Recognition 2013) and KDEF (Kaggle's FER2013 and Karolinska Directed Emotional Faces) databases were used to train the VGG-16 is established. In addition, the LEAP system has been adapted to train the model at the University

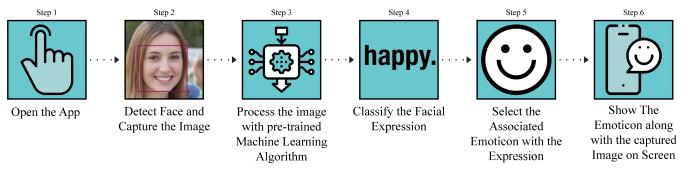


Fig. 11: Block diagram of ios application for ASD rehabilitation.



Fig. 12: Cloud system design for ASD rehabilitation.

of Texas. The research provides the highest rate accuracy of 86.44%. In another similar study, they achieved an accuracy of 78.32% [73].

B. Cloud Systems

Mohammadian et al. [74] have proposed a new application of DL to facilitate automatic stereotypical motor movement (SMM) for identification by applying multi-axis inertial measurement units (IMUs). They have applied CNN to transform multi-sensor time series into feature space. An LSTM network is then combined with CNN to obtain the temporal patterns in SMM identification. Finally, they employed the classifier selection voting approach to combine an ensemble of the best base learners. After various experiments, the superiority of their proposed procedure over other base methods has been proven. Figure 12 shows the real-time SMM detection system. First, IMUs, which are wearable sensors, are used for data collection; the data can then be analyzed locally or remotely (using Wi-Fi to transfer data to tablets, cell phones, medical center servers, etc.) to identify SMMs. If abnormal movements are detected, an alarm will be sent to a therapist or parents.

C. Eye Tracking

Wu et al. [75] proposed a model of DL saliency prediction for autistic children. They used DCN in their proposed paradigm, with a SM saliency map output. The fixation density map (FDM) is then processed by the single-side clipping (SSC) to optimize the proposed loss function as a true label along with the SM saliency map. Finally, they exploited an autism eye-tracking dataset to test the model. Their proposed model outperformed other base methods. Elbattah et al. [76] aimed to employ unsupervised machine learning to detect clusters in ASD. Their key goal was to learn eye-tracking scan paths based on visual representation clusters. The first step involved the visualization of the eye-tracking path, and the images captured from this step were fed to an autoencoder to learn the features. Using autoencoder features, clustering models are developed using the K-Means algorithm. Their method performed better than other state-of-art techniques.

TABLE I: Summary of articles published using DL methods for ASD detection.

Work	Datasets	Neuroimaging Modalities	Number of Cases	Pipelines	Image Atlas	Preprocessing Toolbox	High level Preprocessing	Inputs DNN	DNN Toolbox	DNNs	Number of Layers	Classifier	K fold	Performance Criteria (%)
[24]	Clinical Acquisition	T-fMRI residual -fMRI	82 ASD 48 HC	NA	MN1152	BET	SW	Single Mean Channel Input Single STD Channel Input Combined 2-Channel Input	NA	2CC3D	17	Majority Voting	No	F1-Score = 89
						FSL								
[77]	Clinical Acquisition	T-fMRI	82 ASD 48 HC	NA	AAL	NA	SVE, C-SVE, H-SVE, Monte Carlo Approximation	Mean Channel Sequence STD Channel	NA	2CC3D	14	Sigmoid	NA	Acc = 97.32
[78]	HCP Dataset in the HAFNI Project	T-fMRI rs-fMRI	68 Subjects with 7 Tasks and 1 rs-fMRI Data	NA	NA	FSL	Dictionary Learning and Sparse Coding	Functional RNS Maps	NA	3D-CNN	8	Softmax	NA	Acc = 94.61
[59]	Clinical Acquisition	T-fMRI(T1-Weighted MP-RAGE s-MRI, BOLD T2*-Weighted fMRI Sequence)	21 ASD 19 HC	NA	AAL	FSL	DA	ROIs Time-Series	Keras	LSTM	7	Sigmoid	10	Acc=69.8
[79]	Different Datasets	T-fMRI rs-fMRI Phenotype	1711 ASD 15903 HC	A	AAL	SPM	Wavelet and Different Techniques	FCMs	Keras	CNN	14	Softmax	NA	Ensemble AUROC=0.92 Ensemble Acc=85.19
						SpeedyPP								
[80]	Clinical Acquisition	T-fMRI	82 ASD 48 HC	NA	AAL	Neurosynth	SW Corrupting Strategy Prediction Distribution Analysis Corrupt a ROI of Original Image	Original fMRI Sequence Mean-Channel Sequence std-channel sequence Concatenating Voxel-Level Maps of Connectivity Fingerprints	NA	2CC3D	16	Sigmoid	NA	Acc= 8.7.1
[80]	ABIDE-I	rs-fMRI	41 ASD 54 HC	NA	AAL	FSL								
[81]	ABIDE-I ABIDE II	rs-fMRI	379 ASD, 395 HC 163 ASD, 230 HC	CPAC	All Atlases ABIDE	NA	Connectivity Matrix Calculation	Masking Correlations	PyTorch	AE	NA	SLP	10	Acc= 73.3 Acc=70.1 Sen=67.8 Spec=7.28
[82]	ABIDE-I	rs-fMRI	505 ASD 530 HC	CPAC	CC-200 AAL Dosenbach160	NA	FCM, DA	Raw Images	NA	G-CNNs BrainNetCNN with Proposed Layers	5	Softmax	10	Acc=70.86 Acc= 68.7 Sen= 69.2 Spe= 68.3
[83]	ABIDE-I	rs-fMRI	872 subjects											
[84]	ABIDE-I	rs-fMRI	474 ASD 539 HC	CCS	AAL	NA	FCM	Functional Connectomes	NA	G-CNNs BrainNetCNN with Proposed Layers	15	Softmax	5	Acc= 68.7 Sen= 69.2 Spe= 68.3
[85]	ABIDE-I	rs-fMRI	13 ASD 22 HC	NA	AAL	SPM8 REST DPARSF	Qcut, NMI Statistic Matrix	Pearson Correlation Coefficient Matrix NMI Matrix	NA	DAE	NA	NA	NA	Acc=54.49
[86]	ABIDE	rs-fMRI	11 ASD 16 HC	NA	NA									
[87]	ABIDE-I	rs-fMRI	55 ASD 55 HC	NIAK	AAL	NA	FCM, Feature Selection	Whole-Brain FCPs	NA	Multiple SAEs	4	Softmax regression	5	Acc=86.36
[62]	ABIDE-I ABIDE-II ABIDE-I + II	rs-fMRI	54 ASD 62 HC 156 ASD 187 HC	NA	NA	SPM8	Dimension Reduction	Images with 95 68, 79 68, and 79 95 Dimensions, Around the x, y, and z Axes	Keras with Theano backend	MCNNes	9	Binary SR	10	Acc=72.73 Sen=71.2 Spec=73.48
							FFT							
[88]	ABIDE	rs-fMRI	542 ASD 625 HC	CPAC	All Atlases	NA	Creating Stochastic Parcellations by Poisson Disk Sampling	Gray Matter Mask Parcellations	NA	3D-CNN	6	Various Methods	10	Acc=72
[89]	ABIDE-I	rs-fMRI	465 ASD 507 HC	DPARSF	AAL	NA	FCM	Edge Weights of Subjects' Brain Graph	Keras	VAE	3	NA	NA	NA
[90]	ABIDE-I	rs-fMRI	539 ASD 573 HC	CCS	Craddock 200	Neurosynth	DA	Mean Time Courses from ROIs	Keras	LSTM	5	Sigmoid	10	Acc=68.5
[91]	ABIDE	Rs-fMRI, Phenotypic Info	505 ASD 530 HC	NA	CC200	DPABI	Slicetiming, Spatial Standardization, Smoothing, Filtering, Removing Covariates, FCM, AE-MKFC	4005-Dimensional Eigenvector	NA	SAE	3	Clustering	NA	Acc=61 NMI=3.7 F-measure=60.2
[92]	ABIDE	rs-fMRI	42 ASD 42 HC	NA	NA	FSL	Independent Components (Time Course, Power Spectrum and Spatial Map)	time courses of each subject	NA	SAE	9	Softmax	21	Acc=87.21 Sen=89.49 Spec=83.73
[93]	ABIDE-I	rs-fMRI	NY site UM site US site UC site	CCS	AAL	Neurosynth	DA	fMRI ROI Time-Series, Functional Connectivity	Keras	LSTM	6	Sigmoid	10	Acc=74.8
[94]	ABIDE-I	rs-fMRI	408 ASD 401 HC											
[95]	ABIDE	rs-fMRI	At Least 60 Subjects	CCS	AAL	FMRIB's Linear & Nonlinear Image Registration Tools	DTL-NN Framework: Offline Learning, Transfer Learning FCM Using Pearson's Correlation	3 Different FCM+ Demographic Data	Keras	DANN	25	Sigmoid	10	Acc=73.2 Sen=74.5 Spec=71.7
[96]	ABIDE I+II	rs-fMRI	993 ASD 1092 HC	NA	AAL Schaefer-100 HO Schaefer-400	FAST	NA	Mean Time-Series within Each ROI	NA	ID-CNN	5	Softmax regression	5	Avg Acc= 67.1 Avg Sen=65.7 Avg spec=68.3 AUC=0.71

[97]	ABIDE-I	rs-fMRI	529 ASD 573 HC	All Pipelines	NA	NA	Single Volume Image Generator	Glass Brain and Stat Map Images	Keras	4 Deep Ensemble Classifier techniques (CNN)	16	Sigmoid	NA	Acc=87 F1-score=86 Recall=85.2 Precision=86.8
[98]	ABIDE-II	rs-fMRI	303 ASD, 390 HC	NA	NA	FSL	NA	ID Time Series from Voxels	NA	ID-CAE	14	NA	NA	Acc= 65.3
[99]	ABIDE	rs-fMRI	40 ASD, 40 HC	CCS	NA	NA	Threshold Segmentation	WM, GM, CSF	NA	AlexNet	Standard	Softmax	NA	Acc=82.61
[100]	ABIDE	rs-fMRI	Whole Dataset	All Pipelines	Parcelled into 200 Regions	NA	DA Using SMOTE and Graph Network Motifs, FCM Calculation	Upper Triangle Part of the Correlation Matrix	NA	ASD-DiagNet	Proposed	SLP	NA	Acc=82 Sen=79.1 Spec=83.3
[60]	ABIDE-I	rs-fMRI	12 ASD 14 HC	C-PAC	SCSC	NA	Time Series Extraction from Different Regions, Connectivity Matrix, SMOTE Algorithm	FCM	PyTorch	Auto-ASD-Network	Proposed	SVM	5	Acc=80 Sen=73 Spec=83
[61]	ABIDE-I	rs-fMRI	505 ASD 530 HC	CPAC	CC400	NA	FCM Computation	FCM	NA	CNN	20	MLP	10	Acc=70.20 Sen=77.00 Spec=61.00
[101]	ABIDE	rs-fMRI	505 ASD 530 HC	NA	NA	NA	Connectivity Matrix	Converting Connectivity Matrix to One Dimensional Vector	NA	ID CNN -AE	7	Softmax	NA	Acc=70 Sen=74 Spec=63
[102]	ABIDE-I	rs-fMRI	539 ASD 573 HC	NA	NA	FreeSurfer	NA	Single 3D Image	Theano	3D-FCNN	13	Softmax	6	Mean DSC=91.56 Mean MHD=14.05
[103]	ABIDE-I	rs-fMRI	501 ASD 553 HC	DPARSF	AAL	NA	Converting FCM to One Dimensional Vector	1000 Features Selected by the SVM-RFE	NA	SSAE	3	Softmax	Different Folds	Acc=93.59 Sen=92.52 Spec=94.56
[104]	ABIDE-I	rs-fMRI	100 ASD 100 HC	NA	NA	FSL FEAT	Online Dictionary Learning and Sparse Representation Techniques, Generating Spatial Overlap Patterns	4D Matrix with 150 3D Network Overlap Maps	Theano	3D-CNN	14	NA	10	Average Acc= 70.5 Average Sen= 74 Average Spec= 67
[105]	ABIDE-I	rs-fMRI & Phenotypic	529 ASD 571 HC	CPAC	HO	FSL	Population Graph Construction, Feature Selection Strategies (RFE, PCA, MLP, AE)	Population Graph	Scikit-learn	GCN	11	Softmax	10	Acc=80.0
[106]	ABIDE-I	rs-fMRI & Phenotypic	403 ASD 468 HC	CCS	CC200	NA	DA	Mean Time-Series from ROIs	Keras	LSTM	6	Sigmoid	10	Acc=70.1
[107]	ABIDE-I	rs-fMRI & S-MRI & Phenotypic (T1 Weighted)	505 ASD 530 HC	CPAC	Craddock 200	NA	Flattening FCM	1D Vector	NA	Two SdAE + MLP	NA	Softmax	10	Acc=70 Sen=74 Spec=63
[108]	Clinical acquisition	rs-fMRI Fetal BOLD fMRI	75 Qualified Subjects	NA	NA	FSL Brainsuite SPMR CONN	Extraction of Fetal Brain fMRI Data, SW	Mean Time Series of 3D fMRI Volumes	PyTorch	3D-CNN	7	Sigmoid	NA	F1-score=84 AUC=91
[109]	ABIDE-I	rs-fMRI	116 ASD 69 HC	NA	AAL	SPM8	Segmentation, Average Mean Time Series of Each ROI	Rs-fMRI + GM+WM Data Fusions	Theano	DBN	6	LR	10	Acc=65.56 Sen=84 Spec=32.96
[110]	IMPAC	rs-fMRI s-MRI	418 ASD 497 HC	NA	All atlases	NA	Flattening FCM from Rs-fMRI, Features Extraction from S-MRI	FCM Vector Anatomical Features Combination of Both Anatomical and Connectivity FCM Vector	Keras Tensor-Flow Caffe	Different Networks	8	Various Methods	3	AUC= 80
[111]	ABIDE-I	rs-fMRI s-MRI	368 ASD 449 HC	CPAC	AAL CC200 Destrieux	Freesurfer	FCM Computation and Flattening into a 1D Vector, Fisher Score	1D vector	NA	Ensemble of 5 Stacked AEs and MLP for Classification	31	Label Fusion Using the Average of Softmax Probabilities	10	Acc= 85.06 Sen= 81 Spec= 89
[112]	NDAR	rs-fMRI MRI (T1-Weighted MR Images)	61ASD 215 HC	NA	NA	NA	Data-Driven Landmark Discovery Algorithm, Patch Extraction	50 Patches Extracted from 50 Landmarks	NA	Multi-Channel CNN	13	Softmax	10	Acc=76.24
[63]	NDAR	All Modalities	78 ASD 124 HC	NA	Proposed Atlas	FSL BET	PICA, Extraction of PSD	PSDs of 34 Components	NA	34 SAEs	Each SAE Has 2 Layers	PSVM	NA	Acc=88.5 Sen=85.1 Spec=90.4
[113]	NDAR	T1-Weighted MR Images	60 ASD, 211 HC	NA	NA	In-House Tools	3D Patches Extraction	Patch Size 166416	NA	DDUNET	11 Blocks	NA	5	NA
[114]	ABIDE-I NDAR/Pitt NDAR/IBIS	s-MRI	-21 ASD, 21 HC 16 ASD, 16 HC 10 ASD, 10 HC	NA	NA	FSL iBEAT	Segmentation, Shape Feature Extraction	CDF Values of Features	NA	SNCAE	NA	Softmax	NA	Acc=96.88

[115]	ABIDE-I	s-MRI	78 ASD 104 HC	NA	Destrieux	FreeSurfer	Construction of Individual Network, F-score	3000 Top Features	NA	SAE	3	Softmax	10	Acc=90.39 Sen=84.37 Spec=95.88
[116]	HCP	s-MRI	1113 HC	NA	Desikan Killia	FreeSurfer	Normalization, Apply One-Hot Coding	Preprocessed Images	Tensor-Flow Keras	DEA	3	NA	10	AUC-ROC=63.9
	ABIDE-I		83 ASD 105 HC											
[117]	ABIDE	s-MRI	1112 Subjects	NA	NA	SPM12	NA	32 Slices Along Each Axial, Coronal, and Sagittal	Keras	DCNN	17	Sigmoid	NA	Acc=84 Sen=77 Spec=85
	CombiRx		1112 Subjects											
[118]	ABIDE-II	MRI	NA	NA	DKT	FreeSurfer	Segmentation	Coronal, Axial and Sagittal 2D Slices	PyTorch	FastSurfer CNN	Proposed	Softmax	NA	NA
[119]	ABIDE-I	MRI	500 ASD 500 HC	NA	HO Cortical and Subcortical Structural Atlas	FSL	GABM Method, New Chromosome Encoding Scheme	Preprocessed MRI Scans	NA	3D-CNN	11	Softmax	5	Acc=70
[120]	Clinical acquisition	MRI	48 HC	NA	NA	FreeSurfer	Sparse Annotations, DA	Image Patch	Caffe	3D-CNN	18	Softmax	NA	Acc=91.6 ROC=94.1
[121]	ABIDE-I	rs-fMRI	270 ASD 305 HC	C-PAC	Brain-Netome Atlas (BNA)	NA	Filtering, Calculating Mean Time Series for ROIs Using BrainNetome Atlas (BNA), Normalization	Mean Time Series Data Stacked Across ROIs	NA	CNN-GRU	14	Sigmoid	5	Acc=74.54 Sen=63.46 Spec=84.33
[122]	Clinical acquisition	fNIRS	25 ASD 22 HC	No	No	No	Transformation of the Time Series to Three Variants	PM, GM, SM	Keras	1D CNN-LSTM	NA	Bagging	NA	Acc=95.7 Sen=97.1 Spec=94.3
[123]	Clinical acquisition	fNIRS	25 ASD 22 HC	No	No	No	SW Converted into the 3D Tensor	3D tensor	NA	CGRNN	7	NA	NA	Acc=92.2 Sen=85.0 Spec=99.4
[124]	Different datasets	MRI	NA	NA	Various Methods	FreeSurfer FSL, SPM12, VolBrain	Geometric DA	3D cortical mask	Theano	ConvNet	U-Nets	NA	8	NA
[125]	ABIDE I+II	rs-fMRI	620 ASD 2085 HC	C-PAC	HO	FSL	Performed an Automatic Quality Control, Visually Inspection, 9 Temporal Summary Measures, Mean and STD of the Summary Measures, Normalization, Occlusion of Brain Regions	Each Summary Measure	NA	MM-ensemble (3D-CNN)	7	Majority Voting	5	Acc=64 F1-score=66
[126]	ABIDE-I	rs-fMRI Phenotypic Information	184 ASD 110 HC	C-PAC	NA	NA	Down Sampling	Raw 4D Volume	NA	3D-CNN C-LSTM	21	Softmax	5	Acc=77 F1-score=78
[127]	ABIDE-I	rs-fMRI and T1-Weighted Images	403 ASD 468 HC	NA	264 ROIs Based Parcellation Scheme	AFNI FSL MATLAB	Connectivity Matrix, Feature Extraction (Different Features)	Normalized Features	NA	AE	7	DNN	10	Acc= 79.2 AUC= 82.4
[128]	ABIDE-I	rs-fMRI	505 ASD 530 HC	C-PAC	CC200	NA	FCM	Vector of FC Measures	PyTorch	CapsNet	Standard	K-Means Clustering	10	Acc=71 Sen=73 Spec=66

TABLE II: Summary of papers published on rehabilitation of ASD patients using DL algorithm.

Work	Datasets	Type of Applications	Number of Cases	Preprocessing	Inputs DNN	DNN Toolbox	DNNs	Number of Layers	Classifier	K fold	Performance Criteria (%)
[129]	OSIE	—	20 ASD 19 HC	HFM Construction, Filtering Normalizing, DA	HFMs, Natural Scene Images	Caffe TensorFlow	VGGNeT	50	Softmax	13	Acc=85 Sen=80 Spec=89
[73]	KDEF	Facial Expression Recognition	70 Individuals	DA	RGB Images (562762)	Keras	DCNN	44	Softmax	NA	Acc=78.32
[130]	Clinical Acquisition	Detect Audio Regimes That Directly Estimate ASD Severity Social Affect scores	33 ASD	MFCC Spectrograms	32 Spectrograms	NA	Noisemes Network DiarTK Diarization Network	Standard Network	Synthetic RF	—	Acc=84.7
[72]	Kaggle's FER2013 KDEF	Facial Expression Recognition	NA	No	4848-Pixel Images	Keras (TensorFlow Backend)	DCNN	44	Softmax	NA	Acc=86.44
[131]	SALICON	ASD Classification	14 ASD 14 HC	SalGAN Model, Feature Extraction	Sequence of Image Patches	NA	SP-ASDNet	11	NA	NA	Acc=57.90 Rec=59.21 Pre=56.26
[132]	BigFaceX	Facial Expression Recognition	196 Subjects	SW, Merge in the Channel Dimension, DA	5-channel Sub-Sequence Stacks within a Specific Time Window	Keras	TimeConvNet	PreTrain Nets	Softmax	NA	Acc=97.9
[133]	Different Datasets	Suitable Courseware for Children with ASD	NA	Interactive and Intelligent Chatbot , NLP, Visual Aid	Different Inputs	NA	Different Nets	NA	NA	NA	NA
[134]	Camera Images	Estimating Visual Attention in Robot-Assisted Therapy	6 ASD and ID	Resizing, Frame Extraction, Visual Inspection Face Detection (ViolaJones), Feature Extraction (HOG Descriptors)	5 Facial Landmarks - 36 HOG Descriptors	NA	R-CNN MTCNN	VGG-16 Cascaded CNNs Architecture	K-NN Nave	10	Acc= 88.2 Pre=83.3 Sen=83.0 Spec=87.3
[135]	Sensor Data	Automatic SMM detection	6 ASD 5 HC	Resampling, Filtering, SW	Time-Series of Multiple Sensors	Keras	CNN-LSTM	13	Majority Voting	NA	NA
[136]	KOMAA	Facial Expression Recognition	55 subjects	Segmentation, Different Features, Z-scores	Greedy Forward Feature Selection	NA	CNN	9	SVM	NA	Acc=96
[137]	Story-Telling Narrative Corpora	ASD Classification	31 ASD 36 HC	DA, ChineseWord2Vec	32-Dimensional Word Vector	NA	LSTM	1	Coherence Representation of LSTM Forget Gate	NA	Acc=92
[138]	Ext-Dataset (video dataset)	ASD Classification using Eye Tracking	136 ASD 136 HC	TLD Method, Accumulative Histogram Computation	Angle Histogram, Length Histogram and Fused Histogram,	Keras	LSTM	4	NA	10	Acc=92.6 Sen=91.9 Spec=93.4
[139]	MIT1003	Predicting Visual Attention of Children with ASD.	300 Images	NA	Raw Images	NA	DCN	26	NA	NA	SIM=67.8 CC=76.9 AUC-J=83.4
[75]	Scan Path Data, Including Location and Duration	ASD Classification	14 ASD 14 HC	DA Methods	Image, Data Points	Pytorch	ResNet18)	Standard	Softmax	NA	Acc=55.13 Sen=63.5 Spec=47.1
[140]	UCI Machine Learning Repository	ASD classification	Number of Instances= 704	Different Methods	Preprocessed Data	NA	CNN	7	NA	NA	Acc=99.53 Sens=99.39 Spec=100
[76]	Eye Tracking Scanpath	ASD Classification	29 ASD 30 HC	Visualization of Eye-Tracking Scanpaths Scaling Down, PCA	100*100 Image	Keras, Scikit-Learn	AE	8	K-Means Clustering	NA	Silhouette score=60
[141]	Video Data	Engagement Estimation of Children with ASD During a Robot-Assisted Autism Therapy	30 children	NA	cropped face images (256 *256)	Keras with TensorFlow Backend	CultureNet	R-CNN + ResNet50+ 5FC layers	Softmax	Na	ICC=43.35 CCC=43.18 PC=45.17
[142]	YouTube ASD Dataset	Modeling Typical and Atypical Behaviors in ASD Children	68 video Clips	Different Methods	Sequences of Individual Frames at a Rate of 30 fps	openCV, Caffe	DCNN	NA	DT	5	Avg Pre=73 Avg Recall=75 Avg Acc=71
[143]	Video Dataset	Behavioral Data Extracted from Video Analysis of Child-Robot Interactions.	5 ASD 7 HC	Segmentation, Upper Body tracking, Laban Movement Analysis to Drive Weight, Different features	3 Movement Features with 68 Facial Key-Points	NA	CNN	10	Softmax	NA	Acc=88.46 Pre=89.12 Recall=88.53
[144]	Video Dataset	Developing Automatic SMM Detection Systems	6 ASD	Resampling, Filtering, SW, Data Balancing, Normalizing	Time-Series of Multiple Accelerometer Sensors	Deepy Library	CNN	8	SVM	NA	F1-score=95
[145]	ASD Screening	Autism Screening	513 ASD 189 HC	Cleaning Missing Values and Outliers, Visualization, Identity Mapping	The Embedded Categorical Variables are Concatenated with Numerical Features as New Feature Vectors	NA	DENN	4	Sigmoid	NA	Acc=100 Spec=99 Sen=100 F1-score=99
[146]	ASD Screening Datasets	Classification of Adults with ASD	—	Handling of Missing Values, Variable Reduction, Normalization, and Label Encoding	Normalized Variables	Keras	DNN	7	Sigmoid	NA	Acc=99.40 Sen=97.89 Spec=100

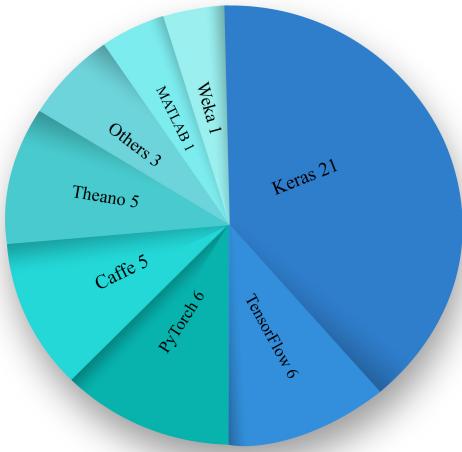


Fig. 13: Number of DL tools used for the diagnosis and rehabilitation of ASD patients in reviewed papers.

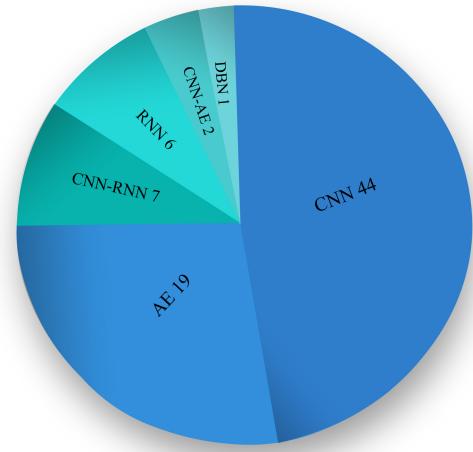


Fig. 14: Number of of DL networks used for ASD detection in the reviewed works.

VI. DISCUSSION

In this study, we performed a comprehensive overview of the investigations conducted in the scope of ASD diagnostic CADS systems as well as DL based rehabilitation tools for ASD patients. In the field of ASD diagnosis, numerous papers have been published using functional and structural data as well as rehabilitation tools, as illustrated in table III in the appendix. A variety of DL toolboxes have been proposed for implementing deep networks. In tables I and II the types of DL toolboxes utilized for each study are depicted, and the total number of usage is demonstrated in Figure 13. The Keras toolbox is used in the majority of the studies due to its simplicity. Keras offers a consistent high-level application programming interface (APIs) to build the models more straight forward, and by using powerful backends such as TensorFlow, its performance is sound. Additionally, due to all pre-trained models and available codes on platforms such as GitHub, Keras is quite popular among researchers.

Number of DL networks used for the ASD detection in the reviewed works is shown in Figure 14. Among the various DL architectures, CNN is found to be more popular as it has achieved more promising results compared to other deep methodologies. The autoencoder, as well as RNN, have yielded favorable results.

The number of various classification algorithms used in DL networks are shown in Figure 15. One of the best and most widely used is the Softmax algorithm (Tables I and II). It is most popular as it is differentiable in the entire domain and computationally less expensive.

VII. CHALLENGES

Some of the most substantial challenges in ASD diagnosis scope have been addressed using DL-based techniques in this section, which comprise database and algorithmic problems. There are only two-class brain structural and functional

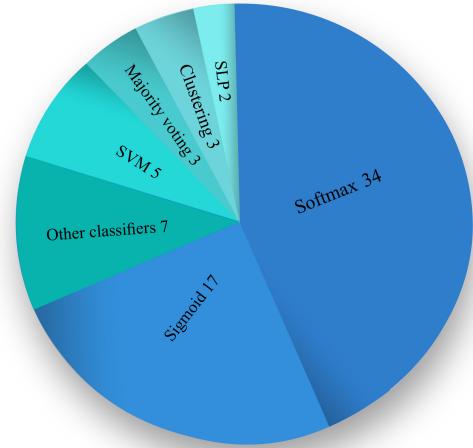


Fig. 15: Illustration of number of various algorithms used for the detection of ASD in DL.

datasets (ASD and healthy) available in the public domain. Hence, researchers are not able to broaden their investigation to other types of ASD disorders. One of the cheapest and most pragmatic functional neuro-screening modalities for diagnosis are ASD are EEG, and fNIRS. But unfortunately the deficiency of freely available datasets has resulted in little research in this area. Another obstacle is that multi-modality databases such as EEG-fMRI are not available to researchers to evaluate the effectiveness of incorporating information in different imaging modalities to detect ASD. However, although fMRI and sMRI data are ubiquitous in the ABIDE dataset, the results of merging these structural and functional data for ASD diagnosis with DL have not yet been investigated. Another problem grappling the researchers is designing the DL-based

rehabilitation systems with hardware resources. Nowadays, researchers are allocated with assistive tools such as Google Colab to improve the processing power, the problems still prevail when implementing these systems in the real world scenarios.

VIII. CONCLUSION AND FUTURE WORKS

ASD is typically characterized by social disorders, communication deficits, and stereotypical behaviors. Numerous computer-aided diagnosis systems and rehabilitation tools have been developed to assist patients with autism disorders. In this survey, research on ASD diagnosis applying DL and functional and structural data were first assessed. The researchers have taken advantage of deep CNNs, RNNs, AEs, and CNN-RNN networks to improve the performance of their system. Boosting the accuracy of the system, the capability of generalizing and adapting to differing data and real-world challenges, as well as reducing the hardware power requirements to the extent that the final system can be utilized by all are the principal challenges of these systems. To enhance the accuracy and performance of CADS for ASD detection in the future, deep reinforcement networks (RL) or GANs can be exploited. Scarcity of data is always a paramount problem in the medical field that can be resolved relatively with the help of these deep GANs.

Many researchers have proposed various DL-based rehabilitation tools to aid the ASD patients. Designing a reliable, accurate, and wearable low power consumption DL algorithm based device is the future tool for ASD patients. The achievable rehabilitation tool is to wear smart glasses to help the children with ASD. These glasses with the built-in cameras will acquire the images from the different directions of environment. Then the DL algorithm processing these images and produces meaningful images to the ASD child to better communicate with their surroundings.

APPENDIX A STATISTICAL METRICS

This section demonstrates the equations for the calculation of each evaluation metric. In these equations, True positive (TP) is the correct classification of the positive class, True negative (TN) is the correct classification of the negative class, False positive (FP) is the incorrect prediction of the positives, False negative (FN) is the incorrect prediction of the negatives.

$$\text{Accuracy}(\text{Acc}) = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$\text{Specificity}(\text{Spec}) = \frac{TN}{TN + FP} \quad (2)$$

$$\text{Sensitivity}(\text{Sen}) = \frac{TP}{TP + FN} \quad (3)$$

$$\text{Precision}(\text{Prec}) = \frac{TP}{TP + FP} \quad (4)$$

$$F1 - \text{Score} = 2 * \frac{\text{Prec} * \text{Sens}}{\text{Prec} + \text{Sens}} \quad (5)$$

$$\text{Avg}_{\text{Acc}} = \frac{\sum^n \frac{TP+TN}{TP+TN+FP+FN}}{n} \quad (6)$$

where n is the total number of outputs of the system.

RECEIVER OPERATING CHARACTERISTIC CURVE (ROC-CURVE)

The receiver operating characteristic curve (ROC-curve) depicts the performance of the proposed model at all classification thresholds. It is the graph of true positive rate vs. false positive rate (TPR vs. FPR). Equations for calculation of TPR and FPR are presented below.

$$\text{TPR} = \frac{TP}{TP + FN} \quad (7)$$

$$\text{FPR} = \frac{FP}{FP + TN} \quad (8)$$

AREA UNDER THE ROC CURVE (AUC)

AUC presents the area under the ROC-curve assimilated from (0, 0) to (1, 1). It provides the aggregate measure of all possible classification thresholds. AUC has a range from 0 to 1. A 100% wrong classification will have AUC value 0.0, while a 100% correct classified version will have the AUC value 1.0. It has two folded advantages. One is that it is scale-invariant, which implies how well the model is predicted rather than checking the absolute values. The second advantage is that it is classification threshold invariant as it will verify the models performance irrespective of the threshold being selected.

APPENDIX B

Table III shows details about all the works reviewed in this study.

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TABLE III: Details of Deep Nets. For ASD diagnosis and Rehabilitation.

Author	Network	Details for Deep Networks	Dropout	Classifier	Optimizer	Loss function
[24]	2CC3D	CNN Layers (6) + Pooling Layers (4) + FC Layers (2)	2 (rate=0.5) 2 (rate=0.65)	Sigmoid	NA	BCE
[77]	2CC3D	CNN Layers (6) + Pooling Layers (4) + FC Layers (3)	NA	Sigmoid	NA	NA
[78]	3D-CNN	CNN Layers (2) + LReLU Activation + Pooling Layers (1) + FC Layers (1)	3 (rate=NA)	Softmax	SGD	MNLL
[59]	LSTM	LSTM Layers (1) + Pooling Layers (1) + FC Layers (3)	1 (rate=0.5)	Sigmoid	Adadelta	MSE
[79]	CNN	CNN Layers (2) + ReLU Activation + BN Layers (4) + FC Layers (3)	2 (rate=0.3) 2 (rate=0.7)	Softmax	Adam	NA
[80]	2CC3D	CNN Layers (6) + Pooling Layers (4) + FC Layers (2)	2 (rate=NA)	Sigmoid	NA	NA
[81]	CNN	CNN Layers (2) + ELU Activation + Pooling Layers (2) + FC Layers (2)	NA	Sigmoid	SGD	NA
[82]	AE	Standard AE with Tanh Activation	NA	SLP	NA	MSE BCE
[83]	G-CNN	Proposed G-CNN with 3 Layer CNN	(rate=0.3)	Softmax	Adam	NA
[84]	BrainNetCNN with proposed layers	Element-wise layer (1) + E2E layers (2) + E2N layer (1) + N2G layer (1) + FC layers (3)+ Leaky ReLU activation+ htat activation	5 (rate=0.5) 1 (rate= 0.6)	Softmax	Adam	Proposed Loss Function
[85]	DAE	Standard DAE	NA	NA	NA	Proposed Loss function
[86]	LeNet-5	Standard LeNet-5 Architecture	NA	Softmax	NA	NA
[87]	SAE	SAE with LSF Activation	NA	Softmax	L-BFGS	NA
[62]	MCNNES	CNN Layers (3) + ReLU Activation + Pooling Layers (3) + FC Layers (1)	1 (rate=0.5)	Binary SR	Adam Adamax	BCE
[88]	3D-CNN	CNN Layers (2) + ELU Activation + Pooling Layers (2) + FC Layers (3)	NA	Sigmoid	SGD Adam	BCE MSD
[89]	VAE	VAE with 3 Layers	NA	NA	Adadelta	Proposed loss function
[90]	LSTM	LSTM Layers (1) + Pooling Layers (1) + FC Layers (1)	1(rate=0.5)	Sigmoid	Adadelta	BCE
[91]	SAE	SAE Layers (3) + Sigmoid Activation	NA	Clustering	Proposed Opt.	NA
[92]	SAE	SAE Layers (8) + Sigmoid Activation	NA	SR	L-BFGS	MSE
[93]	LSTM	LSTM Layers (2) + Pooling Layers (1) + FC Layers (2)	NA	Sigmoid	Adam	BCE MSE
[94]	Multichannel DANN	3 MLP (1 dropout layer and 4 dense layers) + Self-attention (3) + Fusion (3) + Aggregation layer + dense layer (1) + relu, elu, tanh activations	1 (rate=NA)	Sigmoid	NA	CE
[95]	SSAE	3 SSAE Layers	NA	Softmax	scaled conjugate gradient descent	Proposed loss function
[96]	1D-CNN	CNN Layers (1) + Pooling Layers (1) + FC Layers (1)	(rate=0.2)	Softmax	Adam	NA
[97]	CNN	CNN layers (6) + pooling layers (4) + BN layers (2) + FC layers (2)	1 (rate=0.25)	Sigmoid	Adam	Propose loss function
[98]	1D CAE-CNN	Encoder (4 layers) + Decoder (4 layers) + CNN layers (2) + pooling layers (2) + FC layers (2)	NA	NA	NA	NA
[99]	AlexNet	Standard AlexNet Architecture	NA	Softmax	NA	CE
[100]	ASD-DiagNet	Proposed DiagNet	NA	SLP	NA	NA
[60]	Auto-ASD-Network	Proposed Auto-ASD-Network	NA	SVM	NA	NLLF
[61]	CNN	CNN layers (7) + Pooling layers (7) + FC layers (3)	1 (rate=0.25)	MLP	NA	NA
[101]	2 SdAE-CNN	Proposed SdAE-CNN with 7 Layes CNN	NA	Softmax	NA	NA
[102]	3D-FCNN	CNN Layers (9) + PReLU Activation + FC Layers (3)	NA	Softmax	SGD	CE
[103]	SSAE	2 Layers SSAE	NA	Softmax	NA	NA
[104]	3D-CNN	CNN layers (7) + Pooling Layers (3) + FC Layers (2) + log-likelihood activation	2 (rate=0.2)	NA	SGD	MNLL
[105]	GCN	GCN with ReLU and Sigmoid Activation	(rate=0.3)	Softmax	NA	CE
	AE	SAE wth Tanh Activation				MSE
[106]	LSTM	Proposed Deep Nework	(rate=0.5)	Sigmoid	Adadelta	BCE MSE
[107]	2 SdAE-MLP	Proposed 2-SdAE-MLP Network	NA	Softmax	NA	MSE
[108]	3D-CNN	CNN Layers (2) + ReLU Activation + Pooling Layers (2) + FC Layers (2)	NA	Sigmoid	SGD	BCE
[109]	DBN	DBN with 5 Hidden Layers	NA	LR	NA	NA
[110]	FeedFWD	Dense layers (5) + LReLU activation	3 (rate= NA)	NA	Adam	BCE
[111]	ensemble of 5 SAE and MLP	5 [AE (3) + MLP (2)] + softmax activation	5 (rate=NA)	averaging the softmax activation probabilities	NA	NA
[112]	Multi-Channel CNN	CNN Layers (5) + ReLU Activation + Pooling Layers (2) + FC Layers (5)	NA	Softmax	NA	CE
[63]	34 SAEs	34 [SAE network (2)]	NA	PSVM	L-BFGS	NA
[113]	DDUNET	Proposed DDUNET with 11 blocks and ReLU activation	(rate=0.1)	NA	SGD	CE
[114]	SNCAE	Propose SNCAE Newtork	NA	Softmax	NA	NA
[115]	SpAE	SpAE with 2 Networks	NA	Softmax	NA	MSE
[116]	DAE	AE (3) + SELU Activation	NA	Adam	Sum of MSE + 2 CE + CC	
[117]	DCNN	CNN Layers (6) + ReLU Activation + Pooling Layers (6) + FC Layers (4)	NA	Sigmoid	Adam	BCE
[118]	FastSurfer CNN	Proposed FastSurfer CNN Network	NA	Softmax	Adam	Logistic & Dice Losses
[119]	3D-CNN	CNN Layers (3) + ReLU Activation + Pooling Layers (3) + FC Layers (2)	2 (rate=0.5)	Softmax	Adadelta	CE
[120]	3D-UNET	DCNN Layers (7) + ReLU Activation + Pooling Layers (2) + BN Layers (6)	2 (rate=0.5)	Softmax	SGD	weighted CE
[121]	CNN-GRU	CNN Layers (4) + GRU Layers (2) + ReLU Activation + Pooling Layers (2) + FC Layers (5)	NA	Sigmoid	Adam	BCE
[122]	1D CNN - LSTM	Proposed 1D-CNN LSTM with ReLU Activation	(rate=0.2)	Softmax	Adam	CCE
[123]	CGRNN	CNN layers (3) + ReLU activation + Pooling layers (1) + GRU layers (1) + sigmoid activation + FC layer (1)	1 (rate=0.5)	NA	Adam	BCE
[124]	ConvNet	variation of the U-net convolutional architecture	NA	NA	ADAM	Proposed Loss function
[125]	3D-CNN	CNN Layers (2) + ELU Activations + Pooling Layers (2) + FC Layers (2)	NA	Sigmoid	SGD	BCE
[126]	3DCNN C-LSTM	CNN Layers (8) + Conv-Bi LSTM Layers (2) + Sigmoid Activation (for LSTM) + Pooling Layers (1) + FC Layers (1)	8 (rate=0.2)	Softmax	Adam	CE
[127]	AE	Proposed AE with 7 Layers	NA	DNN	NA	NA
[128]	CapsNets	Standard Architecture	NA	K-Means Clustering	Adam	Proposed loss function
[129]	VGGNets + ASDNet	CNN Layers (27) + ReLU Activation + Pooling Layers (10) + FC Layers (6)	6 (rate=0.5) 7 (rate=0.25) 3 (rate=0.5)	Softmax	SGD	CE
[73]	DCNN	CNN Layers (7) + activation+ Pooling Layers (13) + FC Layers (3) + BN Layers (10)	NA	Softmax	SGD	NA
[130]	Noisemess net DiarTK Diarization net	Standard networks	NA	RF	NA	NA
[72]	DCNN	CNN Layers (7) + ELU Activation + Pooling Layers (13) + FC Layers (3) + BN Layers (10)	7 (rate=0.25) 3 (rate=0.5)	Softmax	SGD	NA
[131]	SP-ASDNet	CNN Layers (2) + LSTM Layers (2) + Pooling Layers (3) + FC Layers (2)	2 (rate=NA)	NA	Adam	BCE
[132]	TimeConvNet	convolutional spatiotemporal encoding layer+ backbone convolutional neural network architecture (mini-ception, ResNet20, MobileNetV2)	NA	Softmax	Adam	CCE
[133]	Different Networks	Proposed structure	NA	NA	NA	NA
[134]	RCNN	VGG-16	NA	K-NN	NA	NA
	MTCNN	cascaded CNNs architecture	NA	Nave		
[135]	CNN-LSTM	CNN Layers (3) + LSTM Layers (1) + ReLU Activation + Pooling Layers (3) + FC Layers (3)	1 (rate=0.5) 1 (rate=0.2)	Softmax	SGD	NA
[136]	CNN	CNN Layers (4) + Pooling Layers (2) + FC Layers (2)	NA	Softmax	NA	NA
[137]	LSTM	LSTM layer (1)	NA	coherence representation	NA	NA
[138]	LSTM	LSTM Layers (3) + Sigmoid Activation + FC Layers (1)	NA	NA	NA	CE
[139]	DCN	CNN Layers (17) + Pooling Layers (3) + deconvolution layers (3) + learned priors (3)	NA	NA	NA	Proposed loss Function
[75]	Pretrained resnet18	Standard ResNet-18 Architecture	Standard	Standard	Adam	BCE
[140]	CNN	CNN Layers (2) + ReLU Activation + Pooling Layers (2) + FC Layers (2)	1 (rate=0.5)	NA	Adam	BCE
[76]	AE	AE with 8 layers	NA	K-Means Clustering	NA	NA
[141]	CultureNet	Faster R-CNN + modified ResNet50 + 5FC layers	NA	Softmax	Adelta	Proposed loss function
[142]	DCNN	Proposed DCNN Architecture with Different Layers	NA	Decision Tree (DT)	Manual Optimization	NA
[143]	CNN	CNN Layers (2) + ReLU Activation + FC Layers (3)	4 (rate=0.2)	Softmax	NA	NA
[144]	SA-B3D with LSTM model	CNN Layers (5) + LSTM Layers (1) + Pooling Layers (4) + FC Layers (1)	NA	Sigmoid	Adam	CE
[74]	CNN	CNN Layers (3) + ReLU Activation + Pooling Layers (3) + FC Layers (1)	NA	SVM	SGD	NA
[145]	DENN	Proposed DENN Architecture with ReLU Activation + FC Layers (2)	NA	Sigmoid	mini-batch SGD	CCE
[146]	DNN	Proposed DNN with ReLU Activation + FC Layers (2)	(rate=0.2) (rate=0.4)	Sigmoid	Adam	BCE

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