An Effective Sparse Autoencoders based Deep Learning Framework for fMRI Scans Classification

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Abstract: Deep Learning (DL) identifies features of medical scans automatically in a way very near to expert doctors and sometimes over beats in treatment procedures. In fact, it increases model generalization as it doesn't focus on low level features and reduces difficulties (eg: overfitting) of training high dimensional data. Therefore, DL becomes a prioritized choice in building most recent Computer-Aided Diagnosis (CAD) systems. From other prospective, Autism Spectrum Disorder (ASD) is a brain disorder characterized by social miscommunication and confusing repetitive behaviours. The accurate diagnosis of ASD through analysing brain scans of patients is considered a research challenge. Some appreciated efforts has been reported in literature, however the problem still needs enhancement and examination of different models. A multi-phase learning algorithm combining supervised and unsupervised approaches is proposed in this paper to classify brain scans of individuals as ASD or controlled patients (TC). First, unsupervised learning is adopted using two sparse autoencoders for feature extraction and refinement of optimal network weights using back-propagation error minimization. Then, third autoencoder act as a supervised classifier. The Autism Brain fMRI (ABIDE-I) dataset is used for evaluation and cross-validation is performed. The proposed model recorded effective and promising results compared to literatures.

1 INTRODUCTION

Deep Learning is an artificial intelligence approach that offers automatic learning features similar to experts in many fields but especially in computer vision and imaging domains. The potential satisfying feedback of applying deep learning methods in medical imaging encouraged many researchers to prioritize the approach while solving their research challenges and faced problems (Krizhevsky et al., 2012, Najafabadi et al., 2015;Litjens et al., 2017, Ravì D., et al., 2017). Many neural network models of varies number of layers to transform input images to outputs through accurate extraction of most discriminative features were proposed. However, the convolutional neural network (CNN) (Bengio et al., 2013) is highly a recommended selection. CNN contains layers that transform the input with convolution filters of a small extend. It is preferred as it doesn't waste time in learning separate detectors for identical objects placed differently in an image, and it reduce the number of network training parameters as weight have no direct relation with image size.

For many years, autism disorder has received more attention as an important disease. It is a significant crisis for many families in Arabic society because unknown reasons for causing and poor background of the characteristic of the disease. Autism appears since birth and it recorded a variant and multiple symptoms of illness. Many researches tried to diagnose the disease from different data types using machine learning techniques (SE. Schipul et al., 2012; M. Plitt et al,2015; A. Abraham,

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et al.,2017;). ABIDE-I is a large autism brain scans images dataset. Knowledge discovery in this datasets is a challenge for many researchers. Therefore several machine learning approaches (G. Chanel, et al., 2016; XA. Bi,2018; G. Chanel, et al.,2019) and deep learning (Xi. Li, et al., 2018; H. Li, et al., 2018) have been reported on ABIDE dataset. The data contains 1035 individuals between autistic (ASD) and controlled patients (TCs). These models may suffer from lack of generalization of low reported classification accuracy. Also, some researchers used the full set of data while others used it partially due to availability of resources and/or characteristics of the used technique. However, the domain still opens and encourages competition with different novel hybridization methods and/or enrichment of knowledge extraction or mining results from medical data such ABIDE.

In this paper, an attempt to build a generalized model for dealing with large medical imaging data is proposed. It is a new Deep Learning framework based on sparse autoencoder where it allows machines to learn very complex data representation that can subsequently be used to perform accurate data classification in a fully treatment for ABIDE datasets. Two conventional sparse autoencoders (SAE) are unsupervised learning used in training to extract discriminative features. The third one is a supervised learning used to classify the extracted features and to diagnose the ASD. These three stages were jointed to form a stacked framework. The rest of the paper is as follow: Section 2 presents related work on ABIDE. Section 3 shows our contributions framework construction, features extraction and images classification. Section4 discusses computational results and section 5 concludes the paper.

2 RELATED WORK

Autism is neurological developmental disorderthat affect many families and recently, the disorder .spread due to many unclarifed reasons More attention focuses on rehabilitation of families to handle their cases however an intensive research currently focusing on the treatment and/or knowledge discovery in autism medical imaging. fMRI scans of brain are a kind of medical imaging. Each fMRI scan is actually a group of tiny cubic elements called voxels(X,Y, Z or 3D) and if time is added during data gathering , it become 4D. A time series is extracted from each voxel to save its activity change over time. One of the famous brain scans for autism is ABIDE. In the following, some related work on ABIDE with different techniques.

(H. Chen, et al., 2016), investigated the effect of different frequency bands for constructing brain functional network, and obtained 79.17% accuracy using SVM technique applied to 112 ASD and 128 healthy control subjects. (Brown et al., 2018), proposed framework based on an element-wise layer for deep neural networks. Then they incorporate the data-driven structural priors. They select 1013 of 539 healthy control and 474 with ASD and reported 68.7%. (XA. Bi, et al., 2018), selected the support vector machines (SVM) as a classifier but used multiply SVM architecture to enhance the results as single SVM gives poor results. Their selected samples included 46 TC and 61 ASD and recorded 96.15%. (Bi Xia-an, et al, 2018), proposed genetic-evolutionary SVM and validated by data of 157 participants (86 AS and 71 TC). The classification accuracy reached to 97.5%. (XA. Bi, et al, 2018), presented multiple Random Neural network (NNs) based model on ABIDE. They focused on 50 ASD and 42 TCs samples. A random 5 NN clusters were built using 5 different NNs. The highest accuracy cluster is selected as the best base classifier. Then, valuable features were used to retrieve abnormal brain regions.

In addition, several deep learning models have been proposed recently. (Xi. Li, et al, 2018), used 3D CNN to detect features based on the spatial characteristics, then they voted the results through visualization and interpretation to choose the most competent for ASD or TCs output. They implemented their proposed on subset of 82 diagnosed with autism child and 48 controlled. They obtained higher accuracy. (X. Guo, et al., 2017), proposed a DNN with a novel method for extraction of features for high dimensional rs-fMRI. They used multiple trained sparse auto-encoders for feature extraction, and then used DNN for high-quality representations of the whole-brain function connectivity patterns. They considered 110 samples (55 ASD and 55 TCs) and recorded 86.36%. (M. Khosla, et al., 2018), proposed 3D deep learning model and used subset of data. They classified healthy controld individuals by76 67% classifcation accuracy ofusing subset of 178 samples for training. However generalization of proposed models is affected by small samples.

A two phase's method was proposed in (Xi. Li, et al., 2018). First, a deep neural network classifier was trained with original scans. Then a corruption on the regions of interest (ROIs) of the brain scans

were feed to the trained network to enhance perdition. Their approach was tested on 82 subset and reached 85.3% accuracy. (Heinsfeld et al., 2018), proposed the usage of respective neural patterns of functional connectivity in rs-fMRI as a main discriminative features guide in classifying healthy versus autism patients. They implemented unsupervised phase, where they used 2 stacked denoising autoencoders. Then they used multi-layer perceptron as a supervised classifier. They applied the proposed method on the whole data set and reported 70%, it is considered an improvement with almost full data.

(H. Li,, et al., 2018), proposed a deep transfer learning NN framework. They trained a stacked sparse autoencoder offline extract the functional connectivity patterns. They selected a subset of 310 samples, and reported a range between 62.3% and 70.4%. (Eslami, T., et al., 2019), proposed a new joint learning procedure combining autoencoder and a single layer perceptron. Then continued with results of first phase and applied a data augmentation strategy, based on linear interpolation to produce synthetic training datasets. They used only 13 sites from 17 and reported 80%.

The literature showed that a few studies have considered sparse autoencoder in the classification of individuals with autism based on fMRI. Also, only one reference implemented their proposed system on the dataset fully. Hence, the motivation of our proposed method where a full treatment of ABIDE database is evaluated.

3 PROPOSED SPARSE AES BASED DL FRAMEWORK

3.1 Sparse Autoencoder

Autoencoder consists of basically three-layers, input, hidden, and output, respectively. The hidden layer is fully connected to the input and output layers through weighted connections. It is trained to reconstruct similar input at output layer effectively. One of autoencoders disadvantages is the limited number of hidden units. The Spar Autoencoder (SAE) (Makhzani & Frey., 2013; fgJanowczyk, A.., et al., 2017; Hou, L., et al., 2019) tried to solve this by adding a sparsity constraint, to tune a large number of neurons with low average output and hence neurons appear schematic inactive most of the time. This can be implemented by setting a loss function during training. Assume hidden neurons activation function = haj, then average activation of it is in Eq.1

$$A_f = \frac{1}{m}\sum_{n=1}^{m}[h_{aj}x_n] \quad (1)$$

The objective of sparsity constraints is to minimize A_f so that A_f =A , where A is a sparsity constraint between 0 such as 0.05 , $\hat{A_j}$, the average activation of hidden unit j (in the sparse autoencoder), p_t is the penalty term and N= number of neurons in the hidden layers

$$p_t = \sum_{aj}^{N} KL(A||\hat{A}_{aj}) \quad (2)$$

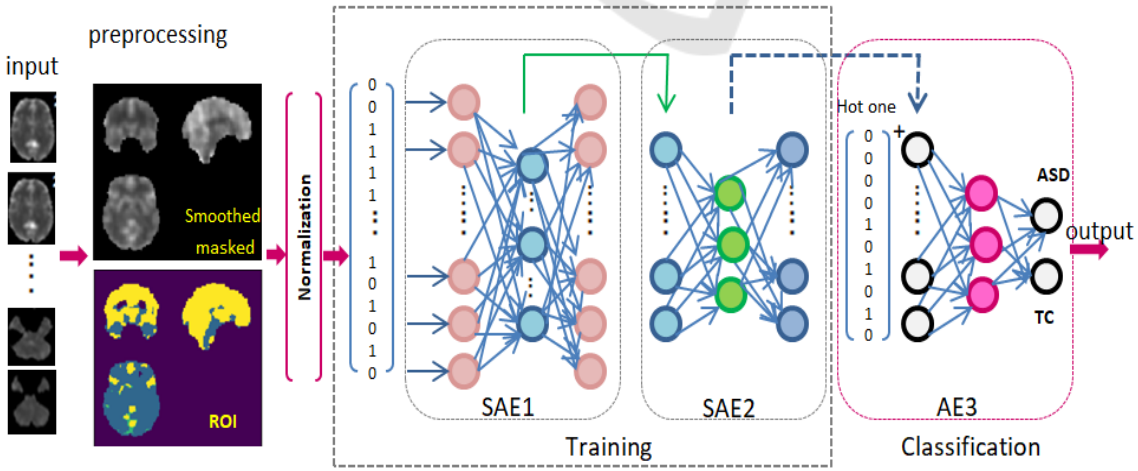

Figure 1: Proposed Sparse autoencoder based deep learning model for medical data classification.

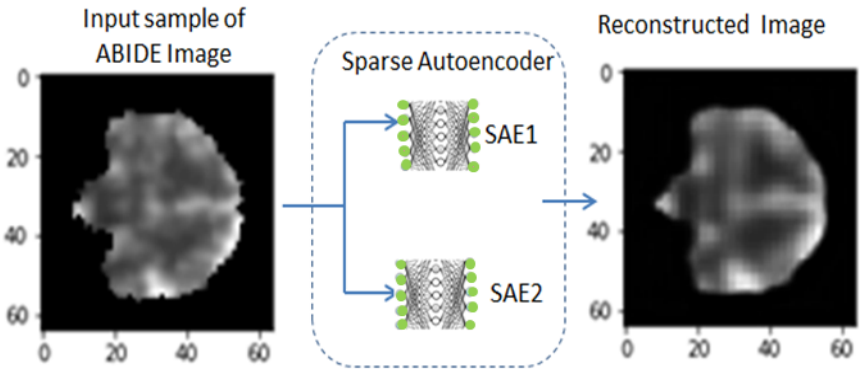

Figure 2: Un-supervised sparse autoencoders for feature extraction.

To enforce sparsity constraints regularizes complexity and prevent over-fitting, a penalty term is added to cost function which penalizes $A\hat{}$, de-weighting significantly from A. Since A and $A\hat{}$, can be seen as the probabilities of Bernoulli random variables, a Kullback-Leibler (KL) divergence (Shin et al.,2013), represented by Eq.3.

$$\mathrm{KL}(\mathrm{A}||\widehat{\mathrm{A}}_{\mathrm{aj}}) = \mathrm{A}\log\frac{\mathrm{A}}{\widehat{\mathrm{A}}_{\mathrm{j}}} + (1-\mathrm{A})\log\frac{1-\mathrm{A}}{1-\widehat{\mathrm{A}}_{\mathrm{j}}} \quad (3)$$

3.2 Proposed Architecture & Extracting Features

The proposed architecture is shown in Figure 1. It is composed of two Sparse AEs as unsupervised learning for feature extraction and followed by AE for classification task:

- *Input layer*: receiving the pre-processed fMRI scans.
- *Two Sparse AEs*: are two unsupervised autoencoders; for deeper feature extraction and refinement of highly important set of unique features. Figure 2, shows the unsupervised role of the two SAE to reconstruct input while learning most valuable feature.
- *Output layer*: is a supervised autoencoder to classify cases into ASD or TC.

The unsupervised Sparse AEs receives data without labels. Each Sparse autoencoder contains two convolutional (CNN) layers. Normalization and Max-pooling are necessary for smoothing the learning process. Then the identical set of parameters are kept for decoding phase (eg: kernel size (3,3,3) for dimensionality reduction). To reach the nearest reconstruction of its input at the output layer, the AE is forced to infer major information preserving a reduction while representing the input in the hidden layer, then mapped to the output layer. Therefore, each hidden node represents a feature of a reduced but accurate copy and this can be evaluated through visualization, See figure 2. SAE has a sparsity constraint that is imposed on the mean activity of hidden layer (Shin et al.,2013) to overcome overfitting.

The input and output layers for the first autoencoder have 17668 features fully connected to hidden bottleneck of 3015 units from the hidden layer. The second autoencoder maps 3015 inputs from the output of the previous autoencoder to outputs through a hidden layer of 983 units and then to 271 units. The batch size=256 and epoch=80. To classify the individuals with ASD, we used supervised autoencoder, inserted in the last layer (output layer) of the proposed neural network. The discriminative features were injected to last autoencoder, in addition to the correspondence vector of numbers for each class of output (one-hot). The vector consists of only 1 for the class it represents and all others are zeros. Softmax function is used for regression of output. Batch size=1024 and epoch=100, are used.

3.3 Training, Validation and Testing

First, each raw rs-fMRI data was preprocessed, and the whole-brain function connectivity patterns (FCP) were obtained by calculating the Pearson's Correlation coefficient (CC) of Time series (TSs) from any pair of ROIs. Given two times series, T_{s1} and T_{s2}, each of length T_L, the Pearson's correlation can be computed Eq.4

$$\rho_{T_{S1},T_{S2}} = \frac{\sum_{t=1}^{T}(T_{s1_t}-\overline{T_{S1}})(T_{s2_t}-\overline{T_{S2}})}{\sqrt{\sum_{t=1}^{T}(T_{s1_t}-\overline{T_{S1}})^2}\sqrt{\sum_{t=1}^{T}(T_{s2_t}-\overline{T_{S2}})}} \quad (4)$$

Multiple SAEs were used in training phase to conclude low but valuable and most discriminative representations of data. In fact single SAE usually gives less expectation, however two SAEs deeper the learning and enrich result. These in turn will affect the classifier positively. Training, testing, optimizing parameters, and 10-fold cross validation flow of the proposed model, is shown in Figure 3.

First, the original fMRI is consisting of a number of slices. Applying region segmentation on each slice, then calculating functional connectivity analysis. The normalization of input is necessary for autoencoder in general.

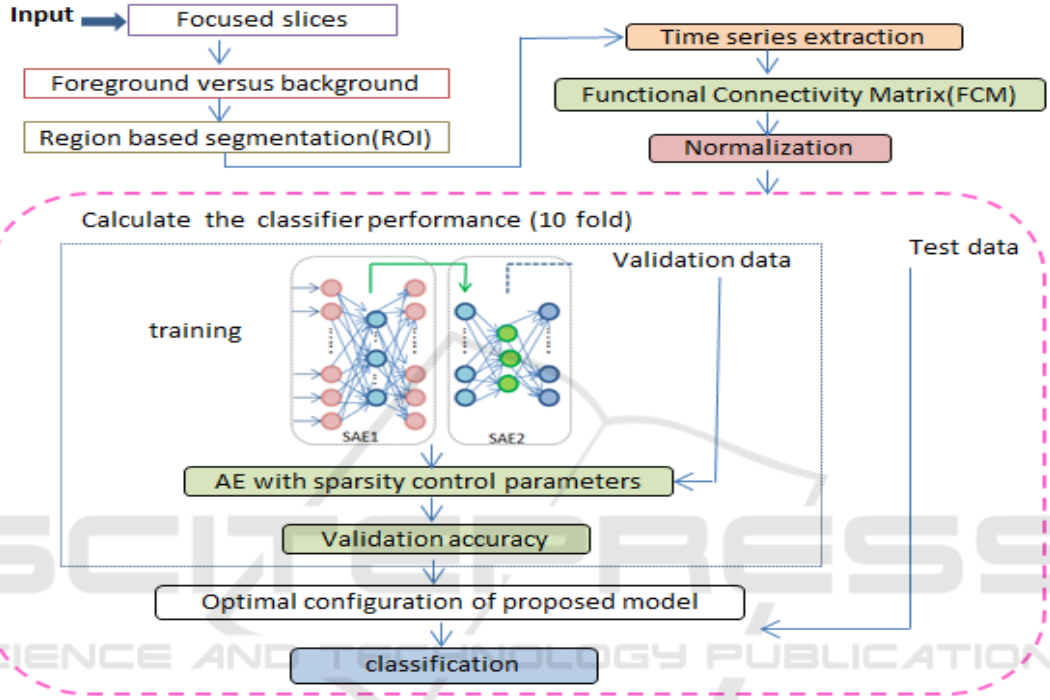

Figure 3: The proposed Deep framework for training, validation, and testing.

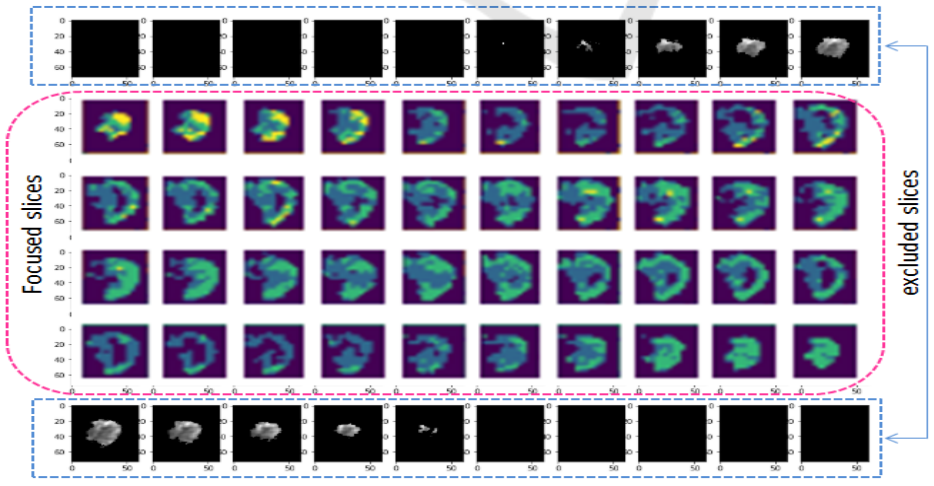

Figure 4: Sample of focused and excluded slices during training.

Table 1: ABIDE-I providers class distribution of genders, ASD and TC.

Site	Caltech	CMU	KKI	Leuven	MaxMun	NYU	OHSU	OLIN	PITT	SBL	SDSU	STANFORD	TRINITY	UCLA	UM	USM	YALE
Ts	37	27	48	63	52	175	26	34	56	30	36	39	47	98	140	71	56
ASD	19	14	20	29	24	75	12	19	29	15	14	19	22	54	66	46	28
Male	15	11	16	25	21	65	12	15	25	15	13	15	22	48	57	46	20
Female	4	3	4	3	3	10	0	3	4	0	1	4	0	6	9	0	8
TC	18	13	28	34	28	100	14	15	27	15	22	20	25	44	74	25	28
Male	14	9	20	29	27	73	14	13	23	15	16	16	25	38	57	25	20
Female	4	4	8	5	1	27	0	2	4	0	6	4	0	6	17	0	8

Accuracy versus number of epoch (1-100) (b) classification loss and validation loss versus number of epoch (1-100).

After training and validation are accomplished, an optimized set of parameters are saved for later testing. The data were divided 70% training and 30% testing.

The performance of the system was evaluated based on the four criteria: Sensitivity (SE), Specificity (SP), Accuracy (ACC) and Matthew's Correlation Coefficient (MCC). These are calculated based on the accurate identification of positive (ASD) or negative (TC) samples. A True Positive (TP) would indicate that autism fMRI labeled and identified correctly through data description, while a False Positive (FP) indicates that fMRI is identified as normal individual. Conversely, True Negatives and False Negatives (FN) are calculated for controlled individual. The metrics are defined by the following equations:

$$A_{cc} = \frac{T_P+T_N}{N}, S_e = \frac{T_P}{T_P+F_N}, S_P = \frac{T_N}{T_N+F_P} \quad (5)$$

$$M_{cc} = \frac{{}^{T_P}/_{N-S\times P}}{\sqrt{P\times S\times(1-S)\times(1-P)}} \quad (6)$$

Where $N=T_N+T_P+F_N+F_P$, $S=(T_P+F_N)/N$ and $P=(T_P+F_P)/N$.

4 DATA ACQUISITION & EXPERMINTES

The Autism data ABIDE I used in this paper was acquired public through request for Autism Brain Imaging Data Exchange to use it in research purpose only. Table 1, shows the class and gender from 17 sites participation of (ABIDE I), (ADi. Martino, et al., 2014) Pre-processed Connectomes Project (http://preprocessed-connectomesproject.org/). C-PAC pipeline was chosen for pre-processed version (Y. Behzadi, et al., 2007). Actually, the project offers four pipelines to download data all provide basic requirement of handling data but they are different in the pre-processing algorithm. C-PAC was chosen to compare our results with other research paper that used same pipeline data.

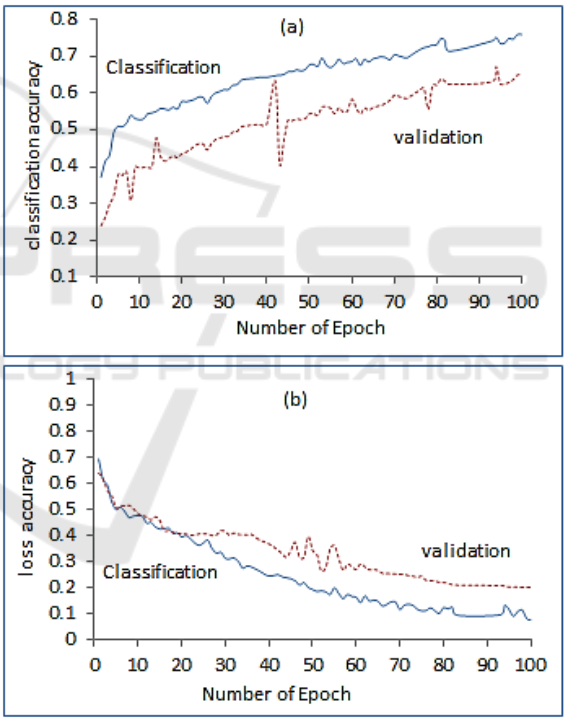

Figure 5: (a) Classification accuracy and validation, (b) loss accuracy and validation.

For more details about pre-processing the raw data please read (ADi. Martino, et al., 2014). 1035 samples were obtained after excluding the corrupted samples, 505 ASD and 530 TC. Technical Implementation All aspects of data pre-processing, analysis, feature extraction and building the classifier are implemented using python and colaboratory resources. The used lab top is with intel

(R) core (TM) i5, 7200 U processor 2.5 GHz and 8 GB of RAM specification.

The data 3D volume is 61×73 ×61. First, during visualization, the centred slices provides clearer and consistent information while the beginning 10 slices and last as well seems to be a burden while training, validating and testing and provide no valuable information from our prospective. Therefore, the centred 40 slice were chosen as in figure 4. Additionally, the data was smoothed and masked, and ROI are calculated from time difference in slices as seen in figure 1. Sparse autoencoder like the basic autoencoder needs normalization (scaling issues and vectors flatten) for data to be suitable for neural network. The model was trained over 70% of the data and 30% for testing and was used in a cross-validation 10-fold schema.

The main performance measure is the accuracy of correctly classify ASD from TC patients. Therefore the proposed network training accuracy and validation accuracy, training loss and validation loss, versus epochs is depicted in Figure 5. The mean values are higher with increase of epoch number. The results are reasonable as more training epoch increase the classification and validation accuracy and reduce the loss as in Figure 5(b).

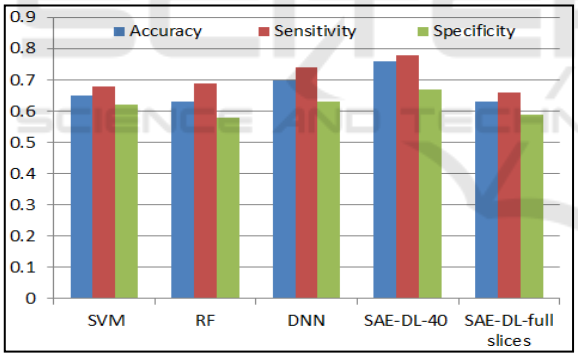

Figure 6: Results comparison of Techniques in (A. Heinsfeld, et al., 2018) and SAE-DL.

Also, a comparison of accuracy, sensitivity and specificity with author that applied Support Vector Machine (SVM, Acc=0.65, Se=0.68, Sp=0.62), Random Forest (RF, Acc=0.63, Se=0.69, Sp=0.58) and Deep Neural Network (DNN, Acc=0.70, Se=0.74, Sp=0.63), on the full data set (A. Heinsfeld, 2018). Figure 6, shows these values in comparison with our method in two cases. Case1: selecting 40 centred slices (SAE-DL-40, Acc=0.76, Se=0.78, Sp=0.67), and Case2: using full slices (SAE-DL-full slices(73), Acc=0.65, Se=0.67, Sp=0.57),). Based on mentioned literatures, and the depicted similar case of using full database sample, the proposed classification accuracy in case1, reported higher classification accuracy due to removing the burden of useless slices of patients that provide poor information and reduces the learning capabilities.

5 CONCLUSIONS

In the present paper, a two sparse autoencoders deep learning framework was developed for classifying ASD individuals and TD controls based on fMRI brain scans. The first contribution of this work is the proposed architecture for feature selection based on multiple sparse AEs to improve the quality of the extracted features and treats issues like over fitting and generalization. The second contribution is using full data sets with accompany complexities, where many researchers avoid full set and preferred a partial sub set of ABIDE. The proposed framework trained and evaluated by the 10-fold evaluation was implemented. An accuracy of 76% was achieved with fMRI data, thus achieving higher predicative performance than the literatures of techniques applied on the same data.

REFERENCES

A. Abraham, MP. Milham, A. Martino, RC. Craddock, D. Samaras, B. Thirion and G. Varoquaux. 2017, Deriving reproducible biomarkers from multi-site resting-state data: An Autism-based example, *NeuroImage* vol.147, pp.736–745

ADi. Martino, et al., 2014, The autism brain imaging data exchange: towards large-scale evaluation of the intrinsic brain architecture in autism. vol.6, pp.659.-667.

A. Heinsfeld, et al., 2018, Identification of autism spectrum disorder using deep learning and the ABIDE dataset. *NeuroImage: Clinical*. vol.17, pp. 16-23.

Bengio, Y., Courville, A., Vincent, P., 2013. Representation learning: A review and new perspectives. *IEEE Trans Pattern Anal Mach Intell*, vol.35 (8), pp.1798–1828.

Bi Xia-an, et al, 2018, Analysis of Asperger Syndrome Using Genetic-Evolutionary Random Support Vector Machine Cluster, *Frontiers in Physiology journal*, vol.9, pp:1646.

C. J. Brown, J. Kawahara, and G. Hamarneh, 2018, Connectome priors in deep neural networks to predict autism, in *Biomedical Imaging (ISBI 2018), IEEE 15th International Symposium on. IEEE*, pp. 110–113

Eslami, T., Mirjalili, V., Fong, A., Laird, A., and Saeed, F., 2019, ASD-DiagNet: A hybrid learning approach

for detection of Autism Spectrum Disorder using fMRI data , arXiv preprint arXiv:1904.07577

G. Chanel, et al., 2016, Classification of autistic individuals and controls using cross-task characterization of fMRI activity. *NeuroImage*: Clinical, vol.10, pp. 78-88.

G Litjens, T Kooi, BE Bejnordi, AAA Setio, F Ciompi, M Ghafoorian, 2017, A survey on deep learning in medical image analysis, *Medical image analysis*, vol, 42, pp.60-88

H. Chen, X. Duan, F. Liu, F. Lu, X. Ma, Y. Zhang, L. Q. Uddin, and H. Chen, 2016, Multivariate classification of autism spectrum disorder using frequency-specific resting-state functional connectivity—a multicenter study, Progress in *Neuro-Psychopharmacology and Biological Psychiatry*, vol. 64, pp. 1–9.

H. Li, N. Parikh and L. He. , 2018, A Novel Transfer Learning Approach to Enhance Deep Neural Network Classification of Brain Functional Connectomes. Front. Neurosci. vol.12, pp.491.

Krizhevsky, A., Sutskever, I., Hinton, G.E., 2012. Image-net classification with deep convolutional neural networks, in: *Advances in neural information processing systems*, pp. 1097–1105.

Makhzani, Alireza and Frey, Brendan. 2013, k-sparse autoencoders. *CoRR, abs/1312.5663*.

M. Khosla, K. Jamison, A. Kuceyeski and M. Sabuncu., 2018, 3D Convolutional Neural Networks for Classification of Functional Connectomes, *arXiv: 1806.04209*

MN. Parikh, H. Li and L. He. 2019, Enhancing Diagnosis of Autism With Optimized Machine Learning Models and Personal Characteristic Data. *Frontiers in Human Neuroscience*. vol.13, pp.1-5.

M. Plitt, KA. Barnes and A. Martin., 2015, Functional connectivity classification of autism identifies highly predictive brain features but falls short of biomarker standards. *NeuroImage*: Clinical, vol.9, pp. 359-366.

Najafabadi M.M., Villanustre F., Khoshgoftaar T.M., Seliya N., Wald R., and Muharemagic E., 2015. Deep learning applications and challenges in big data analytics. *Journal of Big Data*, vol. 2, no. 1, pp. 1-21.

Ravì D., et al., 2017. Deep learning for health informatics. *IEEE Journal of Biomedical and Health Informatics*, vol. 21, pp. 4-21.

SE. Schipul, DL. Williams, TA. Keller, NJ. Minshew & MA.Just, 2012. Distinctive Neural Processes during Learning in Autism, *Cereb Cortex.* vol, 22(4), pp.937.

Shin, H.-C., Orton, M. R., Collins, D. J., Doran, S. J., and Leach, M. O. 2013. Stacked autoencoders for unsupervised feature learning and multiple organ detection in a pilot study using 4D patient data. *Pattern Anal.Mach. Intell. IEEE Trans*. vol.35, pp.1930–1943.

XA. Bi, Y. Wang, Q. Shu, Q. Sun, and Q. Xu. , 2018, Classification of Autism Spectrum Disorder Using Random Support Vector Machine Cluster. *Frontiers in Genetics*. vol.9.

XA. Bi, Y. Liu, Q. Jiang, Q. Shu, Q. Sun and J Dai., 2018, The Diagnosis of Autism Spectrum Disorder Based on the Random Neural Network Cluster. *Frontiers in Human Neuroscience*, vol.12, pp. 257.

Xi. Li, N. Dvornek, et al., 2018, 2-Channel Convolutional 3d Deep Neural Network (2CC3D) For fMRI Analysis: ASD Classification and Feature Learning. *IEEE 15th International Symposium on Biomedical Imaging (ISBI): Washington, D.C., USA.*

Xi. Li, N. Dvorneky, J. Zhuang, P. Ventolaz and J. Duncan. 2018, Brain Biomarker Interpretation in ASD Using Deep Learning and fMRI. Int. Conference on Medical Image Computing and Computer-Assisted Intervention, *MICCAI*, pp. 206-214,.

X. Guo, KC. Dominick, AA. Minai, H. Li, CE. and LJ. Lu, 2017, Diagnosing Autism Spectrum Disorder from Brain Resting-State Functional Connectivity Patterns Using a Deep Neural Network with a Novel Feature Selection Method, Front. *Neurosci*. vol.11, pp 460.

Y. Behzadi, K. Restom K, J. Liau, TT. Liu. , 2007, A component based noise correction method (CompCor) for BOLD and perfusion based fMRI. *NeuroImage*, vol.37 (1), pp. 90- 101.