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Brain MRI Image Classification for Cancer Detection Using Deep Wavelet Autoencoder-Based Deep Neural Network

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ABSTRACT Technology and the rapid growth in the area of brain imaging technologies have forever made for a pivotal role in analyzing and focusing the new views of brain anatomy and functions. The mechanism of image processing has widespread usage in the area of medical science for improving the early detection and treatment phases. Deep neural networks (DNN), till date, have demonstrated wonderful performance in classification and segmentation task. Carrying this idea into consideration, in this paper, a technique for image compression using a deep wavelet autoencoder (DWA), which blends the basic feature reduction property of autoencoder along with the image decomposition property of wavelet transform is proposed. The combination of both has a tremendous effect on sinking the size of the feature set for enduring further classification task by using DNN. A brain image dataset was taken and the proposed DWA-DNN image classifier was considered. The performance criterion for the DWA-DNN classifier was compared with other existing classifiers such as autoencoder-DNN or DNN, and it was noted that the proposed method outshines the existing methods.

INDEX TERMS Neural network (NN), deep neural network (DNN), autoencoder (AE), image classification.

I. INTRODUCTION

The initial detection of malignant region always helps in early diagnosis of an affected person which is one of the factors for reducing death. The image processing technique has made a sudden garner from all quarters of the section and the application of image processing mechanism have risen up in recent years [1]. The storage and capturing of the medical images are largely preserved in a digital environment and understanding the necessary inside information about it has always been tiring and time consuming operation [2]–[3]. Brain Magnetic Resonance (MRI) is a very familiar medical activity that is used for analysis and diagnosis of many neurological diseases like brain tumor, sclerosis, epilepsy, etc [4]. A system fully handled by machines/computers usually helps in automating this process in order to receive accurate and fast result [5].

MRI is extremely suitable for brain analysis studies and it is widely accepted for providing and transmitting anatomical information. It is quite non-invasive and depicts a high spatial resolution. Segmenting brain image is one of the most challenging problems. On the other hand, image segmentation is a major task in various computer vision and image processing application. The premise of the segmentation process is to divide the image into varied regions based on some measures for further processing [6]. Image segmentation plays a pivotal role in abnormality detected, surgical planning, etc. But one of the major issues due to which many segmentation techniques fails is because of noise. The MRI images themselves

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undergo numerous noise because of transmission or recording medium, quantization error, etc. There is also an issue of poor image contrast in medical image due which image segmentation becomes a difficult task.

Brain imaging segmentation is quite a challenging and complicated task in the area of segmentation. But if the accuracy is maintained during the task of segmentation then it would tremendously help in detecting tumors, neurotic tissue, etc. Brain structure identification through MRI is of utmost importance in neuroscience and it has many applications such as brain development study, analysis of neuroanatomical study of the brain etc. Hence, mostly MRI images are used for the purpose of understanding and carrying out the research analysis in medical Image segmentation. MRI segmentation using learning strategies and pattern recognition techniques has been highly successful for brain image analysis. The approach technically state a parametric model that considers selected features based on density function [7].

Deep neural networks (DNN) [8] have attracted rapid attention in past few years. Autoencoder are basically a type of Artificial Neural Network (ANN) [9]–[11] for learning efficient data encoding in an unsupervised way. The basic auto encoder is typically robust and have unsupervised feature learning ability, whereas wavelet function has a wonderful time frequency localization property and facial features. When mixed together they are practically able to solve many real life matters. The wavelet auto encode has a wavelet function as the activation function instead of the standard sigmoid function which basically explain various signal characters with variable resolution. When several trained wavelet auto encoders (WAEs) [12] are extended to further enhance and improved improve the quality of the learned features, deep WAE was constructed that is typically same as that standard deep auto encode. The objective of the deep wavelet encode is to establish a high level feature learning and automatic fault diagnosis technique.

The aim of this paper is to build a system that would help in cancer determination and detection of the Brain MRI image through the process of the proposed image classifier. The theme is further exploited to use a deep wavelet auto encode for extracting high level features for the typical brain structure MRI images. The proposed image classifier DWA-DNN was tested and compared with many other existing classification methods, like DNN, AE-DNN etc. It was observed that DWA-DNN outperforms in the context of accuracy when compared with the above exiting techniques. This makes the process of image classification for analyzing the cancer detection in a quite accurate and easy way.

Section 2, minutiae out the theoretical aspects of the existing research and study done in the field or domain of DNN, AE, image classification, etc. Section 3, provides us an insight about the proposed methodology and the way it can be carried out. In section 4, the strategies and the techniques/methods are discussed that can be utilized for the design of image classification. Section 5, presents the thorough experimental setup where the specific techniques and dataset used are defined clearly. In section 6, we present a thorough analysis and discussion about the results generated from the proposed method, and we also discuss the statistical analysis and its implication. In the final part, a complete generalized view is indicated along with the future directions towards this research field.

II. RELATED WORK

Image segmentation is one of the crucial task in the field of machine learning and is alleged to be one of the critical application in the clinical area. Many researchers have done extensive research in the field of image segmentation and analysis. Despotovic *et al.* [13] provided an extensive review on the various segmentation techniques that are used for brain analysis in medical image or brain image. They highlighted differences between various segmentation techniques, steps related to preprocessing of MRI images, etc. Allaouni and Mohammed [14] proposed a segmentation method based on evolutionary algorithms and region growing. The suggested technique was carried out and was validated on around 1000 synthetic images based on approximately 6 criteria of valuation.

Hiralal and Menon [15] also provided a detailed overview about the various brain image segmentation methodologies of brain MRI images. They highlighted a very clear discussion for the selection of appropriate segmentation method for MRI brain images for the purpose of analysis and prognostication. Yazdani *et al.* [16] presented a brid's overview about the brain image segmentation methodologies, keeping intensity inhomogeneity, noise and partial volume, etc. into considerations. In the work, they divided the problem into five different groups based on their workflow process and segmentation principles. Xiao and Tong [17] designed an image segmentation algorithm based on Fuzzy C-Means (FCM) algorithm and Support Vector Machine (SVM) algorithm. They merged the above two algorithms and proposed a segmentation technique that was tested to be beneficial to the high noise and high bias field in a brain image. Tiwari [39]–[43] proposed a new binary classification model which is inspired from quantum mechanics and proposed model performance is better than all the baselines in the most of the cases. Tiwari *et al.* [44] proposed DCLNN model to classify the blood cell image dataset and improved the existing result. Another extensive survey was made by Nayak *et al.* [18] on the brain MRI image segmentation where a comprehensive review about the technique was worked to detect brain tumors using brain MRI images. An MRI segmentation approach was proposed by Chen *et al.* [19]. They combined fuzzy clustering and Markov random field and integrated the fuzzy clustering membership of the original image into Markov random field function. This merging acted as a segmentation supporting information and the proposed method achieved higher efficiency. Jose *et al.* [20] suggested a technique where the fuzzy c-means and k-means algorithm were combined together and for the brain tumor detection and detecting the area of tumor spread using brain MRI images. The method worked fine except with a limitation where determining fuzzy membership was hard and intense.

Ganesh and Palanisamy [21] used and proposed multiple kernel fuzzy C- means clustering algorithm for MRI images fuzzy segmentation. The proposed method aimed at refining the classification accuracy by lessening the number of iterations and is quite effective to the noise factor. Shen *et al.* [22] proposed a MRI fuzzy segmentation with neural network optimization for brain tumor detection. It used the neighborhood attraction with the above optimization technique to help in the accurate detection of brain tumor from the images. Shalini *et al.* [23] suggested a method where the weighted fuzzy was used to segment the brain tumor from the given images and the kernel metric was used to increase the segmentation performance. It provided a high efficiency and accuracy as compared to any other prevailing method in this domain. An effective neural network based brain tumor detection technique was proposed by Damodharan and Raghavan [24] which focused on brain tissue segmentation. The proposed method provided a desired efficiency and accuracy in relevance to brain tissue and tumor segmentation, feature extraction and classification and etc.

A Wavelet-like Auto Encoder (WAE) using neural network was proposed by Chen *et al.* [25] that decomposes the original image into low resolution images for the purpose of classification. These low resolution channels or images are further used as an input to the Convolutional Neural Network (CNN) for reduction of computational complexity without altering the accuracy factor. Vincent *et al.* [26] established a stack denoising auto encoder by using a denoising criterion for learning needed representation of a deep learning network. A deep neural network approach was considered where scattering wavelet transformation technique was used for extraction audio features for musical dataset. This whole idea was proposed by Klec and Korzinek [27] where a classifier was used for validating. Lebedev *et al.* [28] proposed a tensor flow decomposition method to enhance the speedup of the convolutional neural network, where two step optimization method was implemented.

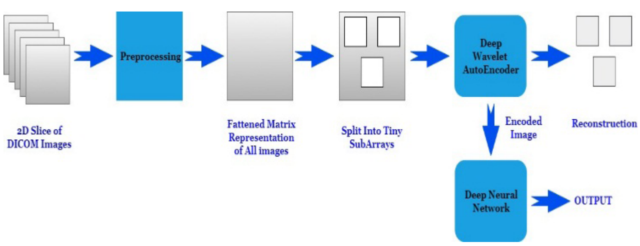


FIGURE 1. **Proposed architecture of a DICOM image classifier for brain disease detection based on DWA-DNN model.**

III. PROPOSED MODEL

Figure 1 represents the architecture of our suggested model for Brain MRI image classification for disease detection based on Deep Wavelet Autoencoder (DWA) based Deep Neural Network. The images collected are mostly present in DICOM format, which is a medical file format for computer memory. These DICOM files first should be processed to extract images from it. After preprocessing of these images, all images are shown in the 2-D array format. Again, these 2D arrays are flattened to represent all images in a 2D dataset format. Since the amount of the images is very high, so they have been split into a number of tiny sub arrays for better performance. These image sub arrays are then processed through DWA to get the encoded images (Approximation and Detailed coefficients). In the final stage only encoded approximation images are further considered for training and testing of a predefined deep neural network

IV. METHODOLOGIES/TECHNIQUES USED

A. AUTOENCODER

Autoencoder [29]–[30] can be seen as optimization techniques that can be used to extract and learn principal components in case of large data distribution. It is mostly regarded as a deep learning technique as it possesses the power to make a deeper network, which can manage itself the network structure to conform to the desired environment. Generally it is used for image extraction, compression, de-noising, etc. In this research study, we have utilized this technique as an image compression technique which can be used as a feature selection technique. Autoencoder can be regarded as the best pre-processing technique for image classification using deep neural network (as depicted in figure 2).

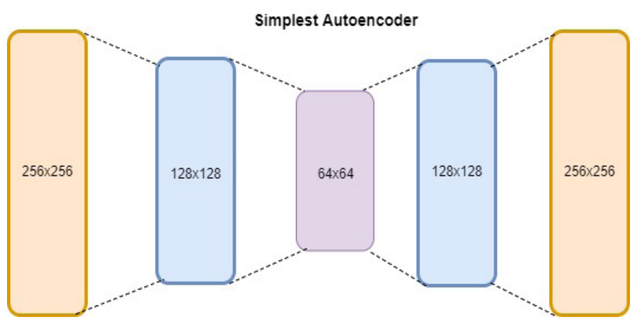


FIGURE 2. **Simple autoencoder model with 3 hidden layers for encoding and decoding of images.**

As the input size is very high, hence we have considered one extra intermediate hidden layer for encoding and for decoding as well (figure 3). The middle layer which actually contains the encoded image with a size of 64 × 64. Mathematically let X_i represents the input, H_i represents Hidden Layer (here I is 1 to 3) and Y_i represents the output. Let the activation functions used I as shown in eq (1):

$$h_i = f_i(W_i X_i + b_i), \quad i = 1 \textit{ to } 4 \tag{1}$$

where, W_i is the weight vector between X_i to H_1, H_1 to H_2 and Y_i.

B. REGULARIZED AUTOENCODER

1) SPARSE AUTOENCODER

Supervised learning has always garnered a huge admiration from all the quarters of AI as it is one the most powerful

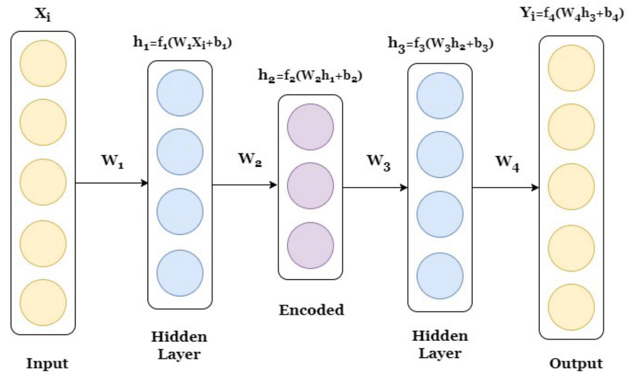


FIGURE 3. Autoencoder model with different layers, functions and parameters.

tool that exist. But irrespective of its accomplishment it is extremely circumscribed. Many algorithms till date do exist where the input characteristics are run manually for the purpose of reading. But there are domains where this manual intensive methodology will not scale well. Hence, it is highly needed that there should be some supervised learning method that should overcome the above problem. A vast number of algorithms exist in rich learning that utilizes a number of neural network techniques to discover and interpret the features for the purpose of sorting. The original and standard auto encoders are a bit hard to train as compared to any extended autoencoder versions. Sparse autoencoder [31] is competitive as compared to the standard auto encoder as they have a high number of hidden units as compared to the input units, but with an imposed restriction that only a few numbers of hidden units can be active at any point of time. Sparse encoder learning algorithm, usually automatically learn features from the unlabeled data.

As depicted in figure 2 (simple autoencoder), if we simply implement a sparsity constraint on the hidden units, then the autoencoder will uncover many interesting information from the data. This type of autoencoder having sparsity [32] factor guides a single layer network for the purpose of understanding and finding out a dictionary code that scales down the reconstruction error while posing a restriction of the number of code language for designing the same. Rather, the task of classification can be represented as a kind of specifying the algorithm to lessen the input fed to a single class that basically reduces the error at the time of prediction. Mathematically, the basic sparse autoencoder (shown in figure 4) consists of a single hidden layer, H, which is connected to the input vector, v with a weight matrix w. This normally is called as an encoding step. The output is generated from the hidden layer as a vector which is reconstructed, v' that uses a new weight matrix w^t. The bias is denoted as s and the activation function is slated as f. The formulation is depicted below in eq. (2) and eq. (3):

$$X = f(W_v + s) \tag{2}$$

$$v' = f(W^t X + b') \tag{3}$$

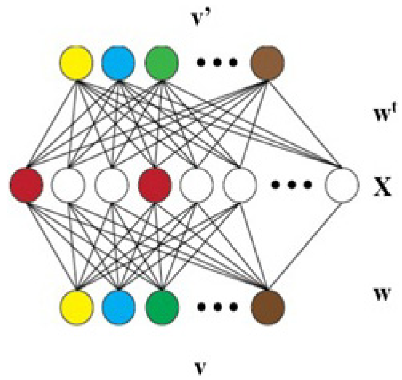


FIGURE 4. Sparse autoencoder network.

The learning process for the error propagation is stated below in eq.(4):

$$min\|v - v'\|_2^2 \tag{4}$$

2) DE-NOISING AUTOENCODER

The deep neural networks are quite nonlinear in nature and therefore, they are not worthy enough for major challenges. Hence, pre-training with the noisy data was highly required. This led to a process where noise was added artificially to each layer to provide better performance and rapid training (as shown in figure 5 below). An extension of the standard autoencoder is a denoising autoencoder [33] that was introduced as a base for deep network [17].

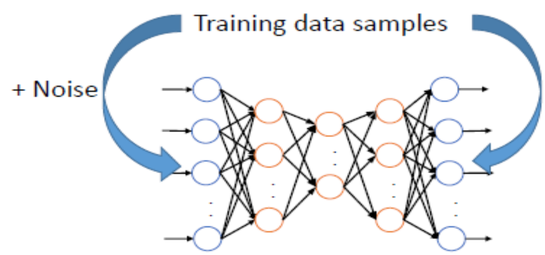


FIGURE 5. A schematic overview of denoising autoencoder.

The idea underlying denoising autoencoder is quite straightforward and bare. it is used to be able to reconstruct data from an input of a ruined/corrupted data. This is a form of force effect laid on the hidden layer to identify robust features and prevent it from merely learning. Hence, the autoencoder here is trained to design the input from a corrupted version of the input data. This makes the output more polished as compared to the input data. This denoising autoencoder is said to be a stochastic version of the standard autoencoder where it implements two things: it encodes the input; and it loosen the effect of corruption process that is applied to the input. The training process of the denoising autoencoder is quite a simple task. One way to train it is, by stochastically ruining the datasets and then feeding it to the neural network.

Based on this, the autoencoder can be trained beside the original dataset. Another way is to, ruin the data by simply remove parts of the data. This would result in an autoencoder to predict the missing input. To provide an equilibrium between input and output, denoising autoencoders can also be stacked upon each other for the process of iterative learning.

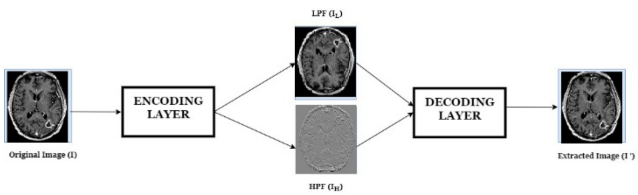


FIGURE 6. **Proposed architecture of a single layer of Deep Wavelet Autoencoder.**

C. DEEP WAVELET AUTOENCODER

Figure 6, represents a single layer of proposed DWA architecture. This architecture can be further extended to make the model deep. In this technique the encoded image generated from the original image is processed through a Discrete Wavelet Transform (DWT) [34] using Daubechies mother wavelet of order 2 to get approximate and detail coefficients by passing through low pass and high pass filters respectively. Out of these coefficients only approximation coefficients are further considered for classification using a Deep Neural Network model.

D. CLASSIFICATION TECHNIQUES USED

For the purpose of our study, some of the classifiers were used like ELM, RBFNN, MLPNN, PNN, and TDNN. Multilayer Perceptron Neural Network (MLPNN) [35] is a network having three layers that are input, hidden and output layers. It is the basic algorithm that is used for the purpose of error propagation and is also known as the layered network. The synaptic strength of the network here can be modified using the back propagation algorithm to get the desired output which also acts as an optimization technique. Few of the disadvantages of the above network include the propagation of error into the local minima which converges and hence, that may create possible issues in the field of real applications. The Radial Basis Function Neural Network (RBFNN) mostly works in two training phases, which is supervised as well as unsupervised phases. In the unsupervised phase, clustering algorithm is typically applied for deciding the center and the spread factor and the pseudo inverse weights are used that connects the end product of the net with the sensory fields. The performance is basically calculated using the mean squared error.

Another types of classifier is Extreme Learning Machine (ELM) [36] that is basically a single layer feed neural network. Here, the output is determined rationally by using generalized operations, as the hidden layers are not tuned. ELMs are usually detached from the concept of iterations. This enables this method to be quite fast and less time consuming than any traditional feed forward NN. It has less training error and small weight norm as compared to any other algorithms. Probabilistic Neural Network (PNN) on the other hand, is one of the famous classification technique for image analysis and it is quite efficient for any high dimensional data. Here, the Bayesian probability is used for backing the weights and the functions and the same is optimized using the gradient descent method. Time Delay Neural Network (TDNN) [37], the connection of hidden units plays a pivotal role. The units are connected to a quite fewer number of input units that represents a certain pattern and the hidden layer is connected to the output layer using a feed forward path. Here, the hidden units are the feature unit that makes out a certain features in the input irrespective of its position. Activation functions are usually different from this network.

V. EXPERIMENTAL AND MODEL EVALUATION

A. EXPERIMENTAL SETUP

The model proposed have been validated through different experimental results that had been carried out on the particular dataset. For the experimental purpose Python 3.6 platform was considered with some basic packages taken like numpy, scilpy, matplotlib. Also, the data analysis packages like keras, scikit-learn and tensorflow was taken in an i7 core processor with 3.4 GHz speed and with 4 GB RAM. For the purpose of validating our experiment, the proposed hybridized autoencoder and the image classifier with standard heterogeneous non-deep learning based classifiers such as MLPNN, RBFN, ELM, PNN, TDNN etc. was compared. Some of the validation procedure is discussed in section 6 for the specific datasets that is used in this experimental work.

B. DATASET DESCRIPTION

For this research work, we have used RIDER (Reference Image Database to Evaluate Therapy Response) [38] Neuro-MRI which contains imaging data on 19 patients with recurrent glioblastoma who underwent repeat imaging sets. These images were obtained approximately 2 days apart (with the exception of one patient, RIDER Neuro MRI-1086100996, whose images were obtained one day apart). All 19 patients had repeat dynamic contrast-enhanced MRI (DCE-MRI) datasets on the same 1.5T imaging magnet. On the basis of T2-weighted images, technologists chose 16 image locations using 5mm thick contiguous slices for the imaging. For T1 mapping, multi-flip 3D FLASH images were obtained using flip angles of 5, 10, 15, 20, 25 and 30 degrees, TR of 4.43 ms, TE of 2.1 ms, 2 signal averages. Dynamic images were obtained during the intravenous injection of 0.1mmol/kg of Magnevist intravenous at 3ccs/second; started 24 seconds after the scan had begun. The dynamic images were acquired using a 3D FLASH technique, using a flip angle of 25 degrees, TR of 3.8 ms, TE of 1.8 ms using a $1 \times 1 \times 5$mm voxel size. The 16 slice imaging set was obtained every 4.8 sec. Seventeen of the 19 patients also obtained repeat diffusion tensor imaging (DTI) sets. Whole brain DTI were obtained using TR 6000ms, TE 100 ms, 90 degree flip angle, 4 signal averages, matrix 128 × 128, 1.72 × 1.72 × 5 mm voxel size, 12 tensor directions, iPAT 2, b value of 1000 sec/mm2. All 19 patients underwent whole brain 3D FLASH imaging in the sagittal plane after the administration of Magnevist. For this sequence, TR was 8.6 ms, TE 4.1 ms, 20 degree flip angle, 1 signal average, matrix 256 × 256; 1mm isotropic voxel size. All 17 patients who had repeat DTI sets also had 3D FLAIR sequences in the sagittal plane after the administration of Magnevist. For this sequence, the TR was 6000 ms, TE 353 ms, and TI 2200ms; 180 degree flip angle, 1 signal average, matrix 256 × 216; 1 mm isotropic voxel size. Before transmission to NCIA, all image sets with 1mm isotropic voxel size were defaced using MIPAV software or manually.

All the images collected are in DICOM format and they have been processed using python program and the total size of the image dataset is 7.3GB. The sample image dataset is shown in figure 7.

C. PARAMETRIC SETUP

The parametric setup of the work is described in table 1 below:

D. ALGORITHMIC DESCRIPTION

Step1: Pre-processing of DICOM images to extract the specific image matrix only.
Step2: Flattening of image matrices to construct image dataset.
Step3: Splitting of dataset to sub arrays
Step4: for each sub array continue the steps 5 to 9
Step5: Input the image sub array to Deep Wavelet Autoencoder for encoding
Step6: Pass the encoded image through low pass and high pass filter using discrete wavelet transform for decomposition.
Step7: Apply inverse wavelet transform to combine and decode the images to get original image
Step8: Run the Autoencoder for number of epochs to get optimized weight and bias values
Step9: Extract approximation coefficients from the hidden layer, combine them and provide as input to a deep neural network for classification.
Step10: Train the DNN with the inputs provided by step9 and test the network for different metrics measurement.

VI. RESULTS AND DISCUSSION

Table 2, shows the performance comparison between proposed DWA-DNN model and other traditional classification techniques. The performance has been measured with four parameters those are Accuracy, Specificity, Sensitivity and F-Score. From the table 3, it has been experimentally proved that DWA-DNN technique outperforms compared to other traditional non-deep learning techniques. It can be clearly seen that the DWA-DNN technique have an overtly good accuracy when compared to TDNN or PNN algorithm and also the specificity, sensitivity and F-score measure is quite good as compared to the previous two. Further a comparison has been made between DNN, Autoencoder based DNN and proposed DWA-DNN technique. All experiments have been carried out using a 10-fold cross validation.

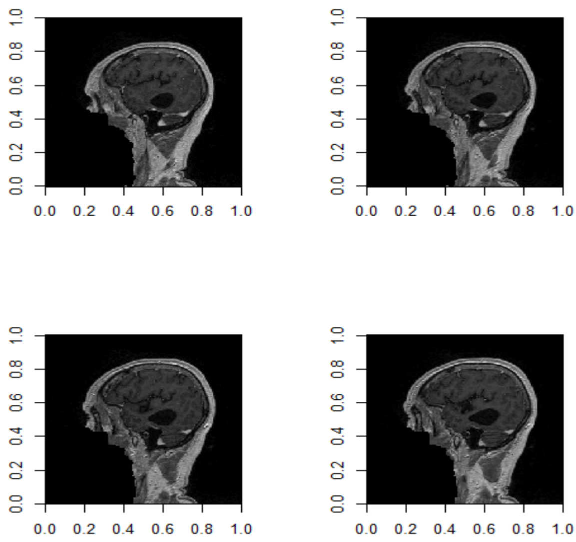


FIGURE 7. Sample image of the data collected.

TABLE 1. Parametric setup.

Techniques	Parameters	Values
Autoencoder	No. of layers	5
	No. of encoded units	64x64
	Unit type	Logistics
	Lambda (Weight decay parameter)	0.002
	Beta(Weight of sparsity penalty term)	6
	Rho(sparsity parameter)	0.01
	Epsilon(parameter for initializing weights)	0.001
	Optimization method	BFGS Algorithm
	Maximum iterations	2000
Deep Neural Network	Activation function	Sigmoid
	Learning rate	0.8
	Momentum	0.5
	No. of epochs	1000
	Batch size	100

A. STATISTICAL ANALYSIS

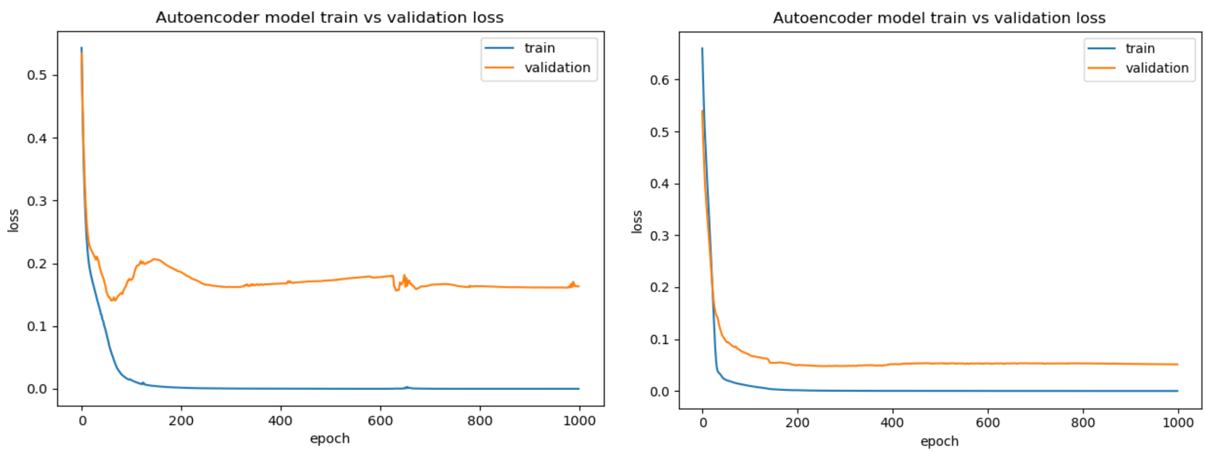
McNemar's statistical test to compare the performances of DNN vs DWA-DNN and AE-DNN vs DWA-DNN performances. The McNemar's test, which is based upon the

TABLE 2. Performance comparison between deep learning vs. non deep learning based approaches.

Classification Techniques	Accuracy	Specificity	Sensitivity	F-Score
MLPNN	0.85±0.33	0.83±0.26	0.87±0.22	0.84±0.30
RBFNN	0.67±0.22	0.75±0.23	0.74±0.34	0.74±0.21
ELM	0.90±0.15	0.87±0.32	0.91±0.22	0.89±0.25
PNN	0.89±0.18	0.90±0.28	0.87±0.29	0.88±0.32
TDNN	0.86±0.32	0.85±0.25	0.88±0.23	0.86±0.29
DWA-DNN	**0.93±0.14**	**0.92±0.16**	**0.94±0.26**	**0.93±0.15**

TABLE 3. Performance comparison between traditional DNN, AE-DNN and proposed DWA- DNN.

Classification Techniques	Accuracy	Specificity	Sensitivity	F-Score
DNN	0.89±0.18	0.88±0.26	0.91±0.19	0.90±0.22
AE-DBN	0.90±0.19	0.89±0.24	0.91±0.18	0.90±0.23
DWA-DNN	**0.93±0.14**	**0.92±0.16**	**0.94±0.26**	**0.93±0.15**



(a) (b)

FIGURE 8. Loss graph for Autoencoder model. (a) Simple AE model. (b) Wavelet AE model.

standardized normal test statistic, is used to demonstrate whether the two methods perform differently in the statistical sense. The statistic is computed as shown in eq. (5),

$$MN_{ij} = \frac{mn_{ij} - mn_{ji}}{\sqrt{mn_{ij} + mn_{ji}}} \tag{5}$$

where, mn_{ij} denotes number of samples misclassified by i classifier but not by j classifier. Similarly $\mathrm{mn_{ji}}$ denotes number of samples misclassified by j classifier but not by i classifier. This is basically derived from the *chi-squared* distribution shown in eq.(6):

$$\chi^2 = \frac{(b-c)^2}{b+c} \tag{6}$$

Under the null hypothesis mn_{ij} is equal to mn_{ji}. That is equivalent to the number of counts for

$$mn_{ij} = mn_{ji} = (mn_{ij} + mn_{ji})/2 \tag{7}$$

TABLE 4. Measure of classification techniques.

Classification Techniques	Overall Accuracy	Average Accuracy	Kappa Statistics
DNN	91%	89%	0.4811
AE-DNN	93%	91%	0.5732
DWA-DNN	**96%**	**93%**	**0.6522**

At 95% level of confidence, the difference of accuracies between the two methods (DNN and DWA-DNN) is significant as $|MN_{\rm ij}| = 3.841$ which is greater than 1.96. Hence, the null hypothesis can be rejected. Similarly, at 95% level of confidence the difference of accuracies between the two methods (AE-DNN and DWA-DNN) is significant as $|MN_{\rm ij}| = 2.147$ which is greater than 1.96. Hence, the null hypothesis can be rejected and the alternative hypothesis can be accepted that states there is a significant difference between the corresponding two different classifiers.

Measuring the overall accuracies (OAs), average accuracies (AAs), and Kappa statistics (Kappa) of ten runs of trainings and tests of DNN, AE-DNN and DWA-DNN is presented below in table 4.

VII. CONCLUSION AND FUTURE WORK

Interpretation of medical image dataset has always been a time consuming process and handling them is itself a challenge. In this paper, the solutions dealt made us to think in the perspective of DNN, AE and wavelet transformation. The proposed DWA-DNN classifier have achieved a great result in terms of accuracy, specificity, sensitivity and other performance measure when compared the existing classifiers like DNN, AE etc. The results of the proposed DWA-DNN technique shows that its accuracy and the statistical measure is far more competing than any other non-deep learning techniques. It would be far more interesting to explore the possibility of combining the DNN with many other variation of the autoencoder to see the effect or performance in the same brain MRI dataset.

REFERENCES

[1] B. Alhadidi, M. H. Zu'bi, and H. N. Suleiman, "Mammogram breast cancer image detection using image processing functions," *Inf. Technol. J.*, vol. 6, no. 2, pp. 217–221, 2007.

[2] D. L. Pham, C. Xu, and J. L. Prince, "Current methods in medical image segmentation," *Annu. Rev. Biomed. Eng.*, vol. 2, no. 1, pp. 315–337, 2000.

[3] V. B. Langote and D. S. Chaudhuri, "Segmentation techniques for image analysis," *Int. J. Adv. Eng. Res. Stud.* vol. 2, no. 1, pp. 252–255, 2012.

[4] A. Sathya, S. Senthil, and A. Samuel, "Segmentation of breast MRI using effective fuzzy C-means method based on support vector machine," in *Proc. Inf. Commun. Technol.*, 2012, pp. 67–72.

[5] M. Singh, A. Verma, and N. Sharma, "An optimized cascaded stochastic resonance for the enhancement of brain MRI," *Innov. Res. BioMedical Eng.* vol. 39, no. 5, pp. 334–342, 2018.

[6] T. X. Pham, P. Siarry, and H. Oulhadj, "Integrating fuzzy entropy clustering with an improved PSO for MRI brain image segmentation," *Appl. Soft Comput.* vol. 65, pp. 230–242, Apr. 2018.

[7] J. Tong, Y. Zhao, P. Zhang, L. Chen, and L. Jiang, "MRI brain tumor segmentation based on texture features and kernel sparse coding," *Biomed. Signal Process. Control* vol. 47, pp. 387–392, Jan. 2018.

[8] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature* vol. 521, no. 7553, pp. 436–444, 2015.

[9] S. K. Satapathy, A. K. Jagadev, and S. Dehuri, "An empirical analysis of training algorithms of neural networks: A case study of EEG signal classification using java framework," in *Intelligent Computing, Communication and Devices*. New Delhi, India: Springer, 2015, pp. 151–160.

[10] S. Mishra and D. Mishra, "SVM-BT-RFE: An improved gene selection framework using Bayesian T-test embedded in support vector machine (recursive feature elimination) algorithm," *Karbala Int. J. Mod. Sci.*, vol. 1, no. 2, pp. 86–96, 2015.

[11] A. Jyoti, M. N. Mohanty, and M. P. Kumar, "Morphological based segmentation of brain image for tumor detection," in *Proc. Int. Conf. In Electron. Commun. Syst. (ICECS)*, 2014, pp. 1–5.

[12] B. Abraham and S. M. Nair, "Computer-aided diagnosis of clinically significant prostate cancer from MRI images using sparse autoencoder and random forest classifier," *Biocybern. Biomed. Eng.*, vol. 38, no. 3, pp. 733–744, 2018.

[13] I. G. B. Despotović, B. Goossens, and W. Philips, "MRI segmentation of the human brain: Challenges, methods, and applications," *Comput. Math. Methods Med.*, vol. 2015, Oct. 2015, Art. no. 450341.

[14] A. E. L. Allaoui and M. Mohammed, "Evolutionary region growing for image segmentation," *Int. J. Appl. Eng. Res.* vol. 13, no. 5, pp. 2084–2090, 2018.

[15] H. Hiralal and H. P. Menon, "A survey of brain MRI image segmentation methods and the issues involved," in *Proc. Int. Symp. Intell. Syst. Technol. Appl.*, 2016, pp. 245–259.

[16] S. Yazdani, R. Yusof, A. Karimian, M. Pashna, and A. Hematian, "Image segmentation methods and applications in MRI brain images," *IETE Tech. Rev.*, vol. 32, no. 6, pp. 413–427, 2015.

[17] J. Xiao and Y. Tong, "Research of brain MRI image segmentation algorithm based on FCM and SVM," in *Proc. 26th Chin. Control Decis. Conf.*, 2014, pp. 1–6.

[18] S. K. Nayak, Y. Karali, and S. C. Panda, "A study on brain MRI image segmentation techniques," *Int. J. Res. Stud. Comput. Sci. Eng.*, vol. 2, no. 9, pp. 4–13, 2015.

[19] M. Chen, Q. Yan, and M. Qin, "A segmentation of brain MRI images utilizing intensity and contextual information by Markov random field," *Comput. Assist. Surg.*, vol. 22, pp. 200–211, Oct. 2017.

[20] A. Jose, S. Ravi, and M. Sambath, "Brain tumor segmentation using k-means clustering and fuzzy c-means algorithms and its area calculation," *Int. J. Innov. Res. Comput. Commun. Eng.*, vol. 2, no. 3, pp. 3496–3501, 2014.

[21] M. Ganesh and V. Palanisamy, "A multiple kernel fuzzy c-means clustering algorithm for brain mr image segmentation," *Int. J. Adv. Eng. Technol.*, vol. 5, no. 1, pp. 406–415, 2012.

[22] S. Shen, W. Sandham, M. Granat, and A. Sterr, "MRI fuzzy segmentation of brain tissue using neighborhood attraction with neural-network optimization," *IEEE Trans. Inf. Technol. Biomed.*, vol. 9, no. 3, pp. 459–467, Sep. 2005.

[23] R. Shalini, V. Muralidharan, and M. Varatharaj, "MRI brain tumor segmentation using kernel weighted fuzzy clustering," *Int. J. Eng. Res. Technol.*, vol. 3, no. 4, pp. 121–125, 2014.
[24] S. Damodharan and D. Raghavan, "Combining tissue segmentation and neural network for brain tumor detection," *Int. Arab J. Inf. Technol.*, vol. 12, no. 1, pp. 42–52, 2015.
[25] L. Chen, L. Lin, W. Zuo, X. Luo, and L. Zhang, "Learning a wavelet-like auto-encoder to accelerate deep neural networks," in *Proc. 32nd AAAI Conf. Artif. Intell.*, 2018, pp. 1–8.
[26] P. Vincent, H. Larochelle, Y. Bengio, and P.-A. Manzagol, "Extracting and composing robust features with denoising autoencoders," in *Proc. 25th Int. Conf. Mach. Learning. (ICML)*, 2008, pp. 1096–1103.
[27] M. Kleć and D. Koržinek, "Pre-trained deep neural network using sparse autoencoders and scattering wavelet transform for musical genre recognition," *Comput. Sci.* vol. 16, no. 2, pp. 133–144, 2015.
[28] V. Lebedev, Y. Ganin, M. Rakhuba, I. Oseledets, and V. Lempitsky, "Speeding-up convolutional neural networks using fine-tuned CP-decomposition," in *Proc. Int. Conf. Learn. Represent.*, 2014, pp. 1–11.
[29] C.-Y. Liou, J.-C. Huang, and W.-C. Yang, "Modeling word perception using the Elman network," *Neurocomputing*, vol. 71, nos. 16–18, pp. 3150–3157, 2008.
[30] C.-Y. Liou, W.-C. Cheng, J.-W. Liou, and D.-R. Liou, "Autoencoder for words," *Neurocomputing*, vol. 139, pp. 84–96, Sep. 2014.
[31] Y. Xiao, J. Wu, Z. Lin, and X. Zhao, "A semi-supervised deep learning method based on stacked sparse auto-encoder for cancer prediction using RNA-seq data," *Comput. Methods Programs Biomed.*, vol. 166, pp. 99–105, Nov. 2018.
[32] H. Liu, T. Ma, D. Tao, and J. You, "HSAE: A Hessian regularized sparse auto-encoders," *Neurocomputing*, vol. 187, pp. 59–65, Apr. 2018.
[33] P. Vincent, H. Larochelle, I. Lajoie, Y. Bengio, and P.-A. Manzagol, "Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion," *J. Mach. Learn. Res.* vol. 11, pp. 3371–3408, 2010.
[34] A. N. Akansu, W. A. Serdijn, and I. W. Selesnick, "Wavelet transforms in signal processing: A review of emerging applications," *Phys. Commun.* vol. 3, no. 1, pp. 1–18, 2010.
[35] P. Mishra, S. Mishra, J. Nanda, and K. V. Sajith, "Multilayer perceptron neural network (MLPNN) controller for automatic generation control of multiarea thermal system," in *Proc. North Amer. Power Symp.*, 2011, pp. 1–8.
[36] G.-B. Huang, H. Zhou, X. Ding, and R. Zhang, "Extreme learning machine for regression and multiclass classification," *IEEE Trans. Syst. Man, Cybern. B, Cybern.*, vol. 42, no. 2, pp. 513–529, Apr. 2012.
[37] A. Waibel, T. Hanazawa, G. Hinton, K. Shikano, and K. J. Lang, "Phoneme recognition using time-delay neural networks," *IEEE Trans. Acoust., Speech, Signal Process.* vol. 37, no. 3, pp. 328–339, Mar. 1989.
[38] D. Barboriak. (2015). *Data From RIDER_NEURO_MRI. The Cancer Imaging Archive*. [Online]. Available: http://doi.org/10.7937/K9/TCIA.2015.VOSN3HN1
[39] P. Tiwari and M. Melucci, "Towards a quantum-inspired framework for binary classification," in *Proc. 27th ACM Int. Conf. Inf. Knowl. Manage.*, Oct. 2018, pp. 1815–1818.
[40] E. Di Buccio, Q. Li, M. Melucci, and P. Tiwari, "Binary classification model inspired from quantum detection theory," in *Proc. ACM SIGIR Int. Conf. Theory Inf. Retr.*, Sep. 2018, pp. 187–190.
[41] P. Tiwari and M. Melucci. (2018). "Multi-class classification model inspired by quantum detection theory." [Online]. Available: https://arxiv.org/abs/1810.04491
[42] P. Tiwari and M. Melucci, "Binary classifier inspired by quantum theory," in *Proc. AAAI*, Jan. 2019. Hawaii, USA.
[43] Q. Li, M. Melucci, and P. Tiwari, "Quantum language model-based query expansion," in *Proc. ACM SIGIR Int. Conf. Theory Inf. Retr.*, Sep. 2018, pp. 183–186.
[44] P. Tiwari *et al.*, "Detection of subtype blood cells using deep learning," *Cognit. Syst. Res.*, vol. 52, pp. 1036–1044, Dec. 2018.

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