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

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ABSTRACT Brain tumors are abnormal cell growths in the brain, some of which may lead to cancer. Magnetic Resonance Imaging (MRI) is the usual way to detect a brain tumor. We use MRI images to identify information about the abnormal growth of tissue in the brain. In various research papers, machine learning and deep learning algorithms apply to detect brain tumors. They can predict Brain tumors very quickly when these algorithms are applied, and the high accuracy helps provide treatment to patients. A fantastic performance has been demonstrated by Deep Neural Networks (DNN), to date, in classification and segmentation tasks. With this idea in mind, in this paper, we propose to use a Deep Wavelet Autoencoder (DWA) that blends the core feature reduction characteristic of the autoencoder along with wavelet transform image decomposition to compress images. The Merging of both has a significant impact on reducing the size of the feature set to take on more classification tasks using DNN. In the existing non-deep learning method, the primary problems of tumor detection of images are Loss of edge details due to shifting variant properties, Poor discriminatory power, High computational load, and lower accuracy in the classification of medical Resonance images containing a noise happened because of the operator performance which can lead to critical inaccuracies classification.

INDEXTERMS Deep Neural Network (DNN), Deep Wavelet Auto-encoder (DWA), Magnetic Resonance Imaging (MRI), Segmentation, image classification.

1. INTRODUCTION

The brain is the most important organ in the human body which controls the entire functionality of other organs and helps in decision-making. It is primarily the control center of the central nervous system and is responsible for performing the daily voluntary and involuntary activities in the human body [1]. The tumor is a fibrous mesh of unwanted tissue growth inside our brain that proliferates in an unconstrained way. The initial detection of the malignant region always helps in the 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 [2]. The latest advances in machine learning (especially deep learning) help identify, classify, and measure patterns in medical images.

The most common methods used to analyze a tumor in the brain are positron emission tomography (PET), magnetic resonance imaging (MRI), and computerized tomography (CT) [3]. MRI is a familiar applicator is used for diagnosing and analyzing many diseases like brain tumors, neurological disorders, epilepsy, etc. Generally, a system all right processed by hardware, computer assists automate this operation to obtain exact and rapid results [4]. MRI is a very suitable technique for brain analysis studies and is widely accepted for providing and uploading anatomical information. MRI Images are used for understanding and trusting research analysis and tests and are large-scale used by radiologists for analyzing brain tumors [4].

Image segmentation is the process of dividing a digital image into multiple image segments [5]. The goal of segmentation is to ease and fast analyze. On the other side, image segmentation is a pioneering task in various computer vision and image processing applications [6]. The hypothesis of the segmentation process is to divide the image into diverse regions based on some measures for further processing. Image segmentation has a pivotal role in abnormality detection and surgical planning [5] .

Brain tumor segmentation in medical image processing is needful and generally ruled by factors like missing boundaries, noise, and low contrast. One of the pioneer issues so that many segmentation techniques flunk due to noise.

Brain imaging segmentation is a complex and challenging task in the segmentation field. However, if the accurateness has maintained during a segmentation task, then it would enormously help in tumors detection, neurotic tissue, etc. [5]

MRI segmentation with learning strategies and pattern recognition techniques has been highly successful in analyzing brain image.

The aim of this work is to build a system that determines and detects the brain MRI image through the process of the proposed image classifier. So, we recommend a DNN for classification and segmentation. In this paper, a technique for image compression is a DWA [4] used to divide input data slice as a tumor (abnormal) or no tumor (normal) that combines the ability to minimize the primary function of automatic encoders with the image degradation property of the wavelet transform. The combination of the two (DWADNN) has a crucial impact on reducing the size of the function set to withstand in addition to classification tasks with DNN [4].

The objective of the DWA is to set a high-level feature learning and automatic fault diagnosis technique. [7]

2. PROBLEM DEFINITION

Brain tumors are a heterogeneous group of central nervous system neoplasms that arise within or adjacent to the brain. Moreover, the location of the tumor within the brain has a profound effect on the patient’s symptoms, surgical therapeutic options, and the likelihood of obtaining a definitive diagnosis [8]. The location of the tumor in the brain also markedly alters the risk of neurological toxicities that alter the patient’s quality of life.

Currently, many people die as a result of a lack of early detection of tumors, particularly brain tumors, because the brain is the primary controller of all body organs and their activities [3]. As a result, we propose a method for early detection of this disease**.**

In this paper, we use DNN-DWA, where DNN [9] is used for classification and DWA [10] is used for image compression**.**

We build a model based on the integration of DNN and DWA that takes a brain MRI image as input, performs operations on it, and then shows whether it is infected or not**.**

3. BACKGROUND

A brain tumor is a mass or growth of abnormal cells in your brain. The abnormal cells can be benign and malignant tumors vary in their structural representation. The benign tumors do not have active cancerous cells and have uniformity in structure. It has less destruction in the human body as it has quite a slow movement and does not penetrate the human tissue. But the malignant cells are non-uniform in structure and usually have active cells**.** It spreads anywhere in the body very fast and removing the tissue from the human body is not easy**.**

The initial detection of malignant region always helps in early diagnosis it can increase the chances of the patient's recovery and one of the factors for reducing death. Brain tumor detection received much attention due to its clinical significance for early treatment. Accurate diagnosis and classification of brain tumors are still challenging despite many major contributions are available. The process of diagnosing brain tumors is overly complicated for many reasons, including the brain's synaptic structure, size, and shape [11]. Imaging tests can help doctors find out if the tumor is a primary brain tumor or if it is cancer. Processing MRI is overly complex and constantly studied by the researchers to give doctors better ability to diagnose the patients [12]. The goal of brain tumor segmentation is to identify the brain tumor and extract the patient specifically clinical information to help later interventions that exist in multidimensional MRI images [5]. An MRI scan is a painless test that produces truly clear images of the organs and structures inside your body. MRI uses a large magnet, radio waves and a computer to produce these detailed images. It does not use X-rays (radiation)**.**
[13]

MRI is a well-known medical device used to diagnose and analyze many diseases such as brain tumors, neurological diseases, epilepsy, etc**.** [3]

The mechanism of image processing has widespread usage in the area of medical science for improving the early detection and treatment phases [14]**.**

DNN have attracted rapid attention in past few years, are able to solve far more complex problems through a wide range of architectures other than simple feed-forward, fully connected networks [3]. DNN have demonstrated wonderful performance in classification and segmentation task**.**

In this paper, we used a DWA as a technique for image compression. DWA model is used for training and testing using different databases. DWA model, employed to divide input data slice as a tumor (abnormal) or no-tumor (normal), which blends the basic feature reduction property of auto-encoder along with the image decomposition property of wavelet transform is proposed [4]. The combination of both has a tremendous effect on sinking the size of the feature set for enduring further classification tasks by using DNN

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 to the above exiting techniques. This makes the process of image classification for analyzing cancer detection quite accurate and easy way.

Modern life is amazingly hassled due to the increasing percentage of manufactured diseases like cancer, diabetes, and manifold sclerosis. Different natures of cancers including brain tumors are spreading among children and adults. The efficient, reliable, and safe tumor detection provides quality care and saves expensive time. The Deep auto-encoder learning procedure shows promising results in diagnosing tumors through MRI images. It is very efficient and reliable to overcome the problem of brain image segmentation and classifications. This motivates us to develop an efficient brain tumor detection model based on DL.

Auto-encoder is a type of artificial neural network used to learn data encoding in an unsupervised manner [4]. The aim of an auto-encoder is to learn a lower dimensional representation (encoding) for higher-dimensional data, typically for dimensional reduction, by training the network to capture the most important parts of the input image [4].

Auto-encoder consist of three parts: [3]

1) Encoder: a module that compresses the train-validate-test set input data into an encoded representation that is typically several orders of magnitude smaller than the input data.
2) Bottleneck: a module that contains the compressed knowledge representations and is therefore the most important part of the network.
3) Decoder: a module that helps the network “decompress” the knowledge representations and reconstructs the data back from its encoded form. The output is then compared with the ground truth.

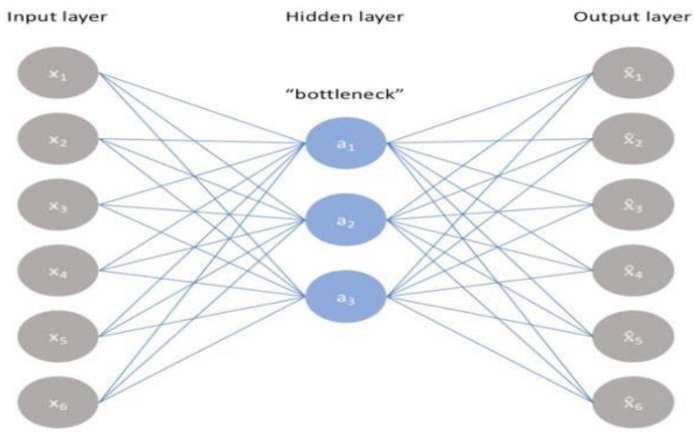


Fig. 1. The architecture as a whole look something like this.

Finally, auto-encoders provide a useful way to greatly reduce the noise of input data, making the creation of deep learning models much more efficient. They can be used to detect anomalies, tackle unsupervised learning problems, and eliminate complexity within datasets**.** [3]

4. RELATED WORK

Image segmentation is one of the most important tasks in the field of machine learning, and it is thought to be one of the most important clinical applications. Many researchers have conducted extensive research on image segmentation and analysis**.**

Allaouni and Mohammed [15] proposed an evolutionary algorithm-based segmentation method based on region growth. Despotovic et al [16]. provided an extensive review of the various segmentation techniques that are used for brain analysis in a medical image or brain image. They emphasized the differences between various segmentation techniques, MRI image pre-processing steps, and so on. Hiralal and Menon [17] Additionally, a detailed overview of the various brain image segmentation methodologies for brain MRI images was provided. They emphasized a very clear discussion for selecting an appropriate segmentation method for MRI brain images for analysis and prognosis. Using the Fuzzy C-Means (FCM) and Support Vector Machine (SVM) algorithms, Xiao and Tong [18] created an image segmentation algorithm. They combined the two algorithms mentioned above and proposed a segmentation technique that was shown to benefit the high noise and high bias field in a brain image. Yazdani et al. [19] presented a bird's overview of the brain image segmentation methodologies, keeping intensity inhomogeneity, noise, partial volume, etc. into consideration. Shalini et al. [20] proposed a method that used weighted fuzzy to segment the brain tumour from the given images and the kernel metric to improve segmentation performance. It outperformed any other existing method in this domain in terms of efficiency and accuracy.

Tiwari [21] proposed a new binary classification model inspired by quantum mechanics, and the proposed model outperforms all baselines in the majority of cases. Tiwari et al. [22] proposed a DCLNN model to classify the blood cell image dataset and improved the existing result. Chen et al. [23] proposed an MRI segmentation method. They combined fuzzy clustering and Markov random field and integrated the original image's fuzzy clustering membership into the Markov random field function. Nayak et al. [24] conducted another extensive survey on brain MRI image segmentation, providing a comprehensive review of the technique used to detect brain tumours using brain MRI images. This merging functioned as segmentation supporting information, and the proposed method was more efficient. Ganesh and Palanisamy [25] 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 in the noise factor**.**

Jose et al. [26] suggested a technique where the fuzzy c-means and kmeans algorithms were combined for brain tumor detection and detection of 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. Shen et al. [27] proposed an 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 tumors from the images. An effective neural network-based brain tumor detection technique was proposed by Damodharan and Raghavan which focused on brain tissue segmentation. The proposed method provided the desired efficiency and accuracy in relevance to brain tissue and tumor segmentation, feature extraction and classification etc**.**

A Wavelet-like Auto Encoder (WAE) using a neural network was proposed by Chen et al. [28] that decomposes the original image into low-resolution images for the purpose of classification. These low-resolution channels or images are further used as input to the Convolutional Neural Network (CNN) [4] for the reduction of computational complexity without altering the accuracy factor. Vincent et al. [4] established a stack-denoising autoencoder by using a denoising criterion for learning the needed representation of a deep learning network. A deep neural network approach was considered where the scattering wavelet transformation technique was used for the extraction of audio features for the musical dataset, this whole idea was proposed by Klec and Korzinek [4] where a classifier was used for validating. Lebedev et al. [4] proposed a TensorFlow decomposition method to enhance the speedup of the convolutional neural network, where a two-step optimization method was implemented**.**

Kumar et al. [4]proposed a compression technique based on a deep wavelet auto-encoder, which combines the fundamental feature reduction property of the auto-encoder and the image decomposition property of wavelet transform. These methods significantly affect the feature set's size for undertaking another classification task using DNN. A brain image database was obtained, and the proposed DWA-DNN image classifier was considered. They compared the DWADNN classifier with the other classifiers such as DNN and auto-encoder and achieved better results.

5. METHODOLOGIES/TECHNIQUES USED

5.1. AUTOENCODER

An autoencoder is an unsupervised learning technique of a neural network that trains the network to ignore signal" noise" as it learns effective data representations (encoding) [3]**.** The goal of an autoencoder is to copy its inputs into its outputs [4]. They operate by compressing the input into a latent-space representation, which is subsequently used to reconstruct the output. There are two components to this type of network [4]:

1) ENCODER This is the part of the network that compresses the input into a latent-space representation. It can be represented by an encoding function *h=f(x)*.
2) DECODER: This part aims to reconstruct the input from the latent space representation. It can be represented by a decoding function *r=g(h)*.

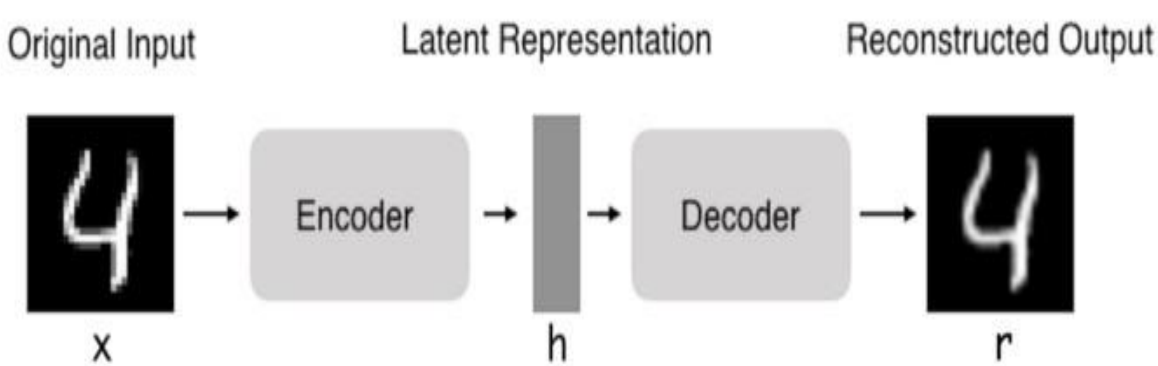


Fig. 2 Architecture of an Autoencoder

The autoencoder as a whole can thus be described by the function *g(f(x))* = *r* where you want ***r*** as close as the original input ***x***.

Autoencoders can be used for Image extraction, compression, de-noising, etc. [4] In the case of large data distribution, autoencoders can be thought of as optimization approaches that can be used to extract and learn principal components. In this work, we used the autoencoding technique. Because the data set that is being worked on and entered the form are images, and because the size of the data set is very large and needs to be compressed into images for easy handling and the extraction of information from them, this algorithm is appropriate, and it is expected to produce results with high accuracy when using it. An autoencoder is often considered the most effective pre-processing technique for exploiting a deep neural network for image classification (as in Figure 3).

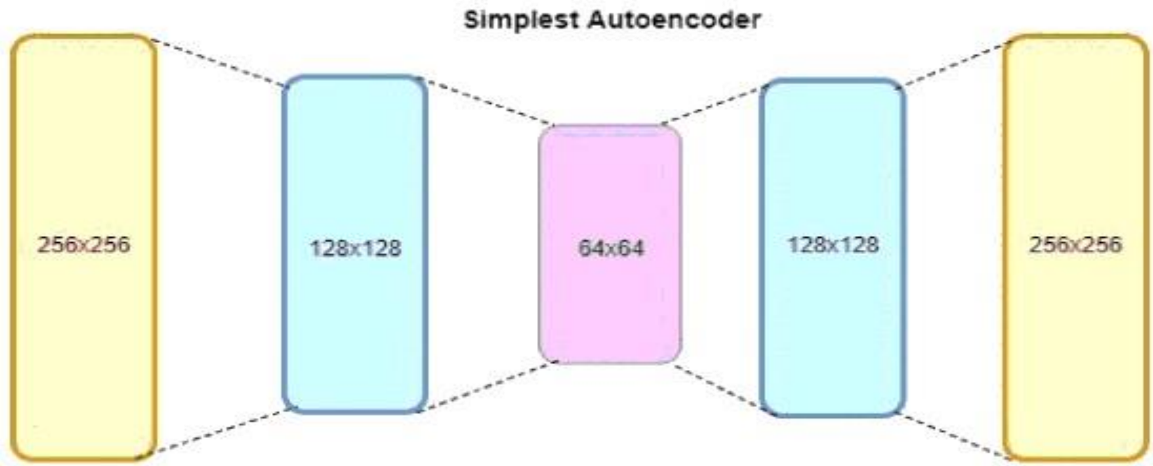


Fig. 3. Simple autoencoder model with 3 hidden layers for encoding and decoding of images.

We compress the input image by converting it into a vector with a manageable number of elements. For example, each image in the dataset is 256x256 in size. That is, there are 65536 elements in each image. When each image is reduced to only two elements, we saved 65534 elements and, as a result, (65534/65536) *100=99.9969.

Due to the very large input size, we, therefore, considered adding an intermediate hidden layer for encryption and decryption (Figure 4). The middle layer contains the 64x64 encoded image. Mathematically, let Xi represent the input, hi represent the hidden layer (here I range from 1 to 3). and Yi represents the output. Set the activation functions [4]used as given in the equation. (1):

$$hi = fi\ (WiFi + bi),\ \mathrm{i} = 1to4 \tag{1}$$

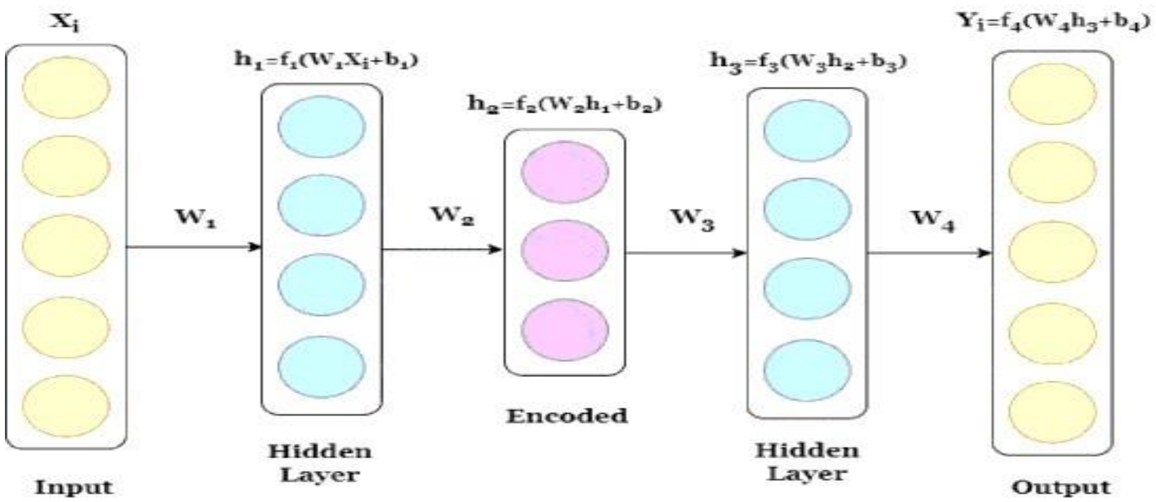


Fig. 4. Autoencoder model with different layers, functions, and parameters**.**

where, Wi is the weight vector between Xi to H1, H1 to H2, and Yi**.**

Types of Autoencoder

In this article, the two following types of autoencoders will be described:

1) Regularized autoencoder

2) Deep Wavelet autoencoder

5.1.1 REGULARIZED AUTOENCODER

Regularized autoencoders utilize a loss function that enables the model to have other features outside the ability to copy its input to its output, as opposed to limiting the model's capacity by keeping the encoder and decoder shallow and the code size small. The sparse autoencoder and the denoising autoencoder are the two common varieties of regularized autoencoders.

Types Of Regularized Autoencoder:

1) SPARSE AUTOENCODER

Sparse autoencoders are often employed to learn features for a different job, like classification. Instead of just serving as an identity function, an autoencoder that has been regularized to be sparse must react to certain statistical properties of the dataset it was trained on. In this method, a model that has learned valuable characteristics as a byproduct can be produced by training to execute the copying task with a sparsity penalty. [4]

It uses sparsity to control information bottlenecks. In particular, the loss function is designed such that activations within the layer are penalized. The sparse encoder learning algorithm usually automatically learns features from the unlabeled data. As shown in Figure 3 (a simple autoencoder), simply Implementing a sparsity constraint on the hidden unit gives autoencoders reveal a lot of interesting information data. This type of autoencoder has sparse coefficients. We maintain a single layer network with the goal of understanding and finding matching dictionary codes. Rebuild errors due to concurrent limits of a code language for designing them. Rather, Classification can be expressed as a kind of specification algorithm that reduces inputs that are basically fed to a single

$$X = f(W_v + s) \quad (2)$$

$$v' = f(W^t X + b') \quad (3)$$

class to Reduce error in prediction. Mathematically, A basic sparse autoencoder (see Figure 5) consists of: A single hidden layer H connected to the input, A vector, v, and a weight matrix w. It is usually represented as a coding step. Output is generated from behind-the-scenes layers as vectors to be reconstructed, using the new v' weight matrix wt [4]

Given the learning process of error propagation in the formula below in eq. (4): [4]

$$min\|v - v'\|_2^2 \quad (4)$$

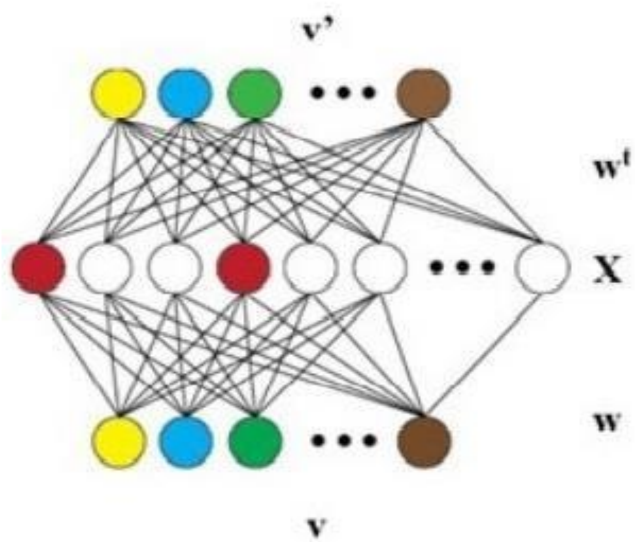


Fig. 5. Sparse autoencoder network

2) DE-NOISING AUTOENCODER

By altering the reconstruction error term of the loss function, we can create an autoencoder that learns something helpful in place of penalizing the loss function. To accomplish this, one can introduce some noise to the input image and train the autoencoder to eliminate it. The encoder will be able to extract the most crucial features and learn a more reliable representation of the input this way.(As shown in Figure 6 below). extension of the standard autoencoder is a denoising autoencoder introduced as a base for deep networks.

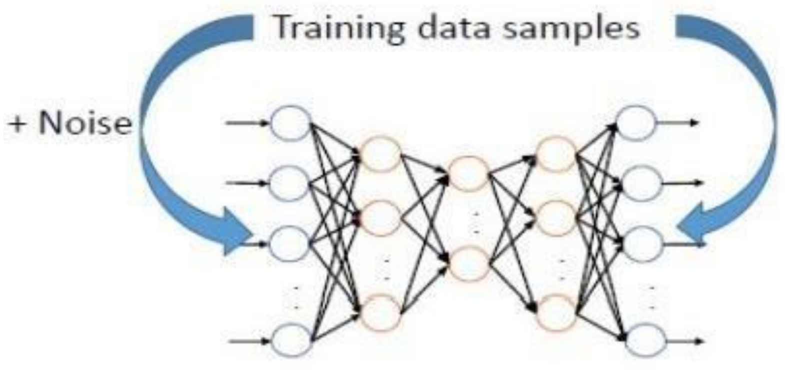


Fig. 6. A schematic overview of denoising autoencoder.

The idea underlying denoising autoencoder [3]: - It is used to allow data to be reconstructed from corrupted/corrupted data inputs. This is a kind of force effect placed in the hidden layer to identify robust features and prevent them from simply learning. So here the autoencoder is trained to design the input from the corrupted version of the input data. This makes the output more sophisticated than the input data. He also does two things.

1) Encode the input.
2) mitigate the effects of corruption processes applied to the input.

Here is how the denoising autoencoder is trained: -

1) that the autoencoder can be trained alongside the original dataset.
2) destroying data by only deleting part of the data; This produces an autoencoder that predicts missing inputs.

Autoencoders with denoising can also be stacked on top of each other for an iterative learning process to balance inputs and outputs.

5.1.2 DEEP WAVELET AUTOENCODER

Deep autoencoders [4]: A deep autoencoder is composed of two symmetrical deep belief networks having four to five shallow layers. One of the networks represents the encoding half of the net and the second network makes up the decoding half.

Figure 7 shows one layer of the proposed DWA architecture. This structure can be extended further to make the model deeper. In this technique, the encoded image generated from the original image is processed by a discrete wavelet transform (DWT) using a second order Daubechies wave mother to obtain the approximate and detailed coefficients by multiplication. It passes through low and high pass filters. Among these coefficients, only the approximation coefficients are considered for classification by the deep neural network model.

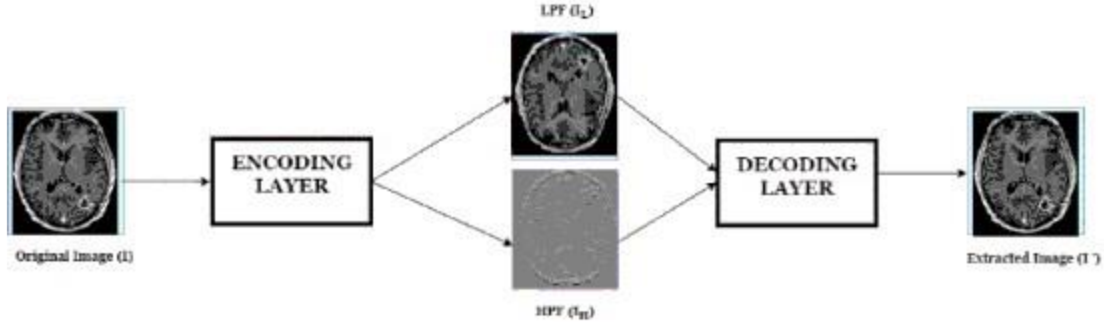


Fig. 7. The proposed architecture of a single layer of Deep Wavelet Autoencoder.

5.2 Classification Techniques Used

For our research purposes, several classifiers were used such as ELM, RBFNN, MLPNN, PNN, and TDNN. Multilayer Perceptron Neural Network (MLPNN) [29] [4] is a network having three layers that are input, hidden, and output layers. This is the basic algorithm used for the error propagation function and is also known as a layered network. The synapse strength of the network here can be varied using a backpropagation algorithm to get the desired output, which also acts as an optimization technique. Some of the disadvantages of the above network include error propagation in convergent local minima and thus can create problems that can occur in the real application domain. (RBFNN) [4] operates mainly in two training phases, which are supervised as well as unsupervised phases. In the unsupervised phase, a clustering algorithm is often applied to decide the centre and propagation coefficient, and pseudo-inverse weights are used to associate the final product of the network with the sense fields. The performance is basically calculated using the original mean squared error.

The Extreme Learning Machine(ELM) [30] is another type of classifier, which is essentially a single-layer energy neural network. Here, the output is reasonably determined using generalized operations, since the hidden layers are not resolved. ELM is often separated from the concept of iteration. This allows the method to be quite fast and take less time than any traditional NN. It has fewer training errors and a small weight standard than any other algorithm.

On the other hand, Probabilistic Neural Network (PNN) [4] is one of the most famous classification techniques for image analysis and it is quite effective for all multidimensional data. Here, Bayesian probability is used to store weights and functions and is optimized by gradient descent. Time Delay Neural Network (TDNN) [31], the interconnection of hidden units plays a central role. The units are connected to a fairly small number of input units representing a given sample, and the hidden layer is connected to the output layer by a path. Here, hidden units are feature units that distinguish certain features in the input, regardless of their location. Activation functions are often different from this network**.**

6. RESULTS AND DISCUSSION

Table 1 compares the proposed DWA-DNN model's performance with that of other traditional classification methods. Accuracy, Specificity, Sensitivity, and FScore are the four characteristics used to measure performance.

TABLE I

PERFORMANCE COMPARISON BETWEEN DEEP LEARNING VS. NON-DEEP LEARNING-BASED APPROACHES

Classification Technique	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 2 provides experimental evidence that the DWA-DNN technique works better than other traditional non-deep learning techniques. It is evident that the DWA-DNN technique outperforms the TDNN or PNN algorithms in terms of accuracy, and that it also performs well in terms of specificity, sensitivity, and Fscore measurement. Additionally, a comparison between DNN, Autoencoderbased DNN, and the suggested DWA-DNN approach has been made. All experiments have been carried out using 10-fold cross-validation**.**

TABLE II PERFORMANCE COMPARISON BETWEEN TRADITIONAL DNN, AE-DNN AND PROPOSED DWA- DNN.

Classification Technique	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**

6.1 STATISTICAL ANALYSIS

DNN vs. DWA-DNN and AE-DNN vs. DWA-DNN performance comparison using McNemar's statistical test. To test whether the two techniques behave statistically differently, McNemar's test, a base standardized normal test statistic, is utilized. The statistic is calculated in accordance with eq (5),

$$MN_{ij} = \frac{mn_{ij} - mn_{ji}}{\sqrt{mn_{ij} + mn_{ji}}} \qquad (5)$$

where mnij denotes the number of samples misclassified by i classifier but not by j classifier. Similarly, mnji denotes the 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):

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

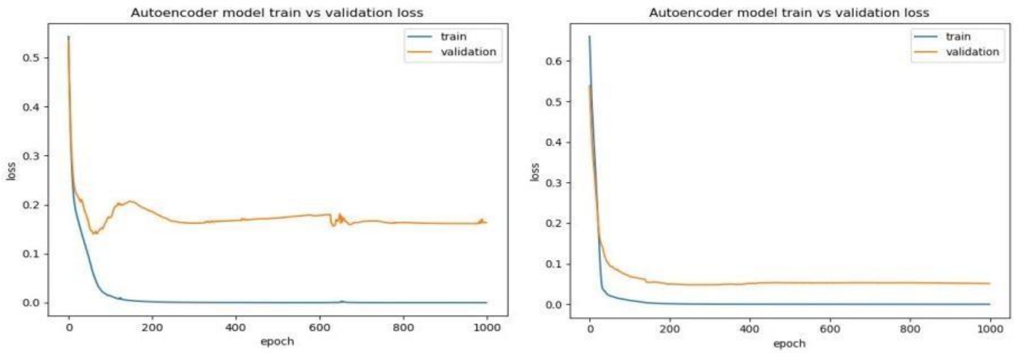
Under the null hypothesis, mnij is equal to mnji. That is equivalent to the number of counts for

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

Table 3 below displays measurements of the overall accuracies (OAs), average accuracies (AAs), and Kappa statistics (Kappa) of 10 training and testing runs of DNN, AE-DNN, and DWA-DNN.

TABLE III
MEASURE OF CLASSIFICATION TECHNIQUES.

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



(a) (b)

Fig. 7. Loss graph for Autoencoder model. (a) Simple AE model. (b) Wavelet AE model.

The accuracy gap between the two approaches (DNN and DWA-DNN) is significant at the 95% level of confidence since |MNij| = 3.841, which is greater than 1.96. As a result, the null hypothesis can be rejected. The accuracy difference between the two techniques (AE-DNN and DWA-DNN) is also significant at the 95% level of confidence since |MNij| = 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.

7. CONCLUSION AND FUTURE WORK

In recent years, demand for image-processing-based diagnostic computer systems has grown, enabling radiologists to speed up diagnosis while simultaneously assisting patients. The most deadly and life-threatening cancer, which affects many individuals globally, is a brain tumor. A variety of brain tumor segmentation and classification methods have been suggested to enhance medical image analysis.

Deep learning network models have obtained good results in recent years in the medical image analysis field. Interpretation of medical image datasets has always been a time-consuming process and handling them is itself a challenge. In this paper, the solutions dealt with made us think from 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 to the existing classifiers like DNN, AE, etc. The advantage of this proposed method is its excellent ability to analyze large data from magnetic resonance images of the brain without technical problems and with very high accuracy, which will help doctors in the accurate diagnosis of brain tumors. Our proposed model achieved a great overall performance on brain tumor identification and classification stages, allowing the model to be used in computing techniques for the early detection of brain tumors. The results of the proposed DWA-DNN technique show that its accuracy and statistical measure are far more competing than any other non-deep learning technique. It would be far more interesting to explore the possibility of combining the DNN with many other variations of the auto-encoder to see the effect or performance in the same brain MRI dataset.

6. References

[1] R. a. M. S. J. S. a. K. M. a. K. S. R. Hashemzehi, "Detection of brain tumors from MRI images base on deep learning using hybrid model CNN and NADE," *biocybernetics and biomedical engineering,* vol. 40, pp. 1225-1232, 2020.

[2] Xu, Liyun and Xu, Zhubo, "Application of Image Processing Technology in the Diagnosis of Football Injury," *Applied Bionics and Biomechanics*, vol. 2022, 2022.

[3] Abd El Kader, I., Xu, G., Shuai, Z., Saminu, S., Javaid, I.,Ahmad, I. S., & Kamhi, S., "Brain tumor detection and classification on MR images by a deep wavelet autoencoder model," *Diagnostics,* vol. 11, p. 1589, 2021.

[4] Mallick, Pradeep Kumar and Ryu, Seuc Ho and Satapathy, Sandeep Kumar and Mishra, Shruti and Nguyen, Gia Nhu and Tiwari, Prayag, "Brain MRI image classification for cancer detection using deep wavelet autoencoder-based deep neural network," *IEEE Access*, vol. 7, no. 4, pp. 46278--46287, 2019.

[5] Hesamian, Mohammad Hesam and Jia, Wenjing and He, Xiangjian and Kennedy, Paul, "Deep learning techniques for medical image segmentation: achievements and challenges," *Journal of digital imaging,* vol. 32, pp. 582--596, 2019.

[6] Gao, Mingchen and Huang, Junzhou and Huang, Xiaolei and Zhang, Shaoting and Metaxas, Dimitris N, "Simplified labeling process for medical image segmentation," in *International Conference on Medical Image Computing and Computer-Assisted Intervention*, Springer, 2012, pp. 387--394.

[7] Zongliang Xie and Jinglong Chen and Yong Feng and Kaiyu Zhang and Zitong Zhou, "End to end multi-task learning with attention for multi-objective fault diagnosis under small sample," *Journal of Manufacturing Systems,* vol. 62, pp. 301316, 2022.

[8] Mezzacappa, Frank M and Thorell, William, "Neuronal Brain Tumors," in *StatPearls [Internet]*, tatPearls Publishing, 2021.

[9] LeCun, Yann and Bengio, Yoshua and Hinton, Geoffrey and others, "Deep learning. nature, 521 (7553), 436-444," *Google Scholar Google Scholar Cross Ref Cross Ref,* 2015.

[10] Haidong, Shao and Hongkai, Jiang and Ke, Zhao and Dongdong, Wei and Xingqiu, Li, "A novel tracking deep wavelet auto-encoder method for intelligent fault diagnosis of electric locomotive bearings," *Mechanical Systems and Signal Processing,* vol. 110, pp. 193--209, 2018.

[11] Sathya, A and Senthil, S and Samuel, Anudevi, "Segmentation of breast MRI using effective fuzzy c-means method based on support vector machine," in *World Congress on Information and Communication Technologies*, IEEE, 2012, pp. 67-72.

[12] Alexander Selvikvåg Lundervold and Arvid Lundervold, "An overview of deep learning in medical imaging focusing on MRI," *Zeitschrift für Medizinische Physik,* vol. 29, pp. 102-127, 2019.

[13] Hussain, Shah and Mubeen, Iqra and Ullah, Niamat and Shah, Syed Shahab Ud Din and Khan, Bakhtawar Abduljalil and Zahoor, Muhammad and Ullah, Riaz and Khan, Farhat Ali and Sultan, Mujeeb A, "Modern Diagnostic Imaging Technique Applications and Risk Factors in the Medical Field: A Review," *BioMed Research International*, vol. 2022, 2022.

[14] Rabaan, A. A., Bakhrebah, M. A., AlSaihati, H., Alhumaid, S.,Alsubki, R. A., Turkistani, S. A., ... & Mutair, A. A., "Artificial Intelligence for Clinical Diagnosis and Treatment of Prostate Cancer," *Cancers,* vol. 14, p. 5595, 2022.

[15] Allaoui, A. E., & Mohammed, M., "Evolutionary region growing for image segmentation," *International Journal of Applied Engineering Research,* vol. 13, pp. 2084-2090, 2018.

[16] Despotović, I., Goossens, B., & Philips, W., "MRI segmentation of the human brain: challenges, methods, and applications," *Computational and mathematical methods in medicine,* vol. 2015, no. 16, 2015.

[17] Hiralal, R., & Menon, H. P., "A survey of brain MRI image segmentation methods and the issues involved," in *The international symposium on intelligent systems technologies and applications*, Springer, 2016, pp. 245-259.

[18] Xiao, J., & Tong, Y., "Research of brain MRI image segmentation algorithm based on FCM and SVM," in *The 26th Chinese Control and Decision Conference (2014 CCDC)*, IEEE, 2014, pp. 1712-1716.

[19] Yazdani, S., Yusof, R., Karimian, A., Pashna, M., & Hematian, A., "Image segmentation methods and applications in MRI brain images," *IETE Technical Review,* vol. 32, pp. 413-427, 2015.

[20] Shalini, R., Muralidharan, V., & Varatharaj, M., "MRI brain tumor segmentation using kernel weighted fuzzy clustering," *Int. J. Eng. Res. Technol.,* vol. 3, pp. 121125, 2014.

[21] Tiwari, P., & Melucci, M., "Multi-class classification model inspired by quantum detection theory," *arXiv preprint arXiv:1810.04491,* 2018.

[22] Tiwari, P., Qian, J., Li, Q., Wang, B., Gupta, D., Khanna, A., ... &de Albuquerque, V. H. C., "Detection of subtype blood cells using deep learning," *Cognitive Systems Research,* vol. 52, pp. 1036-1044, 2018.

[23] M. Chen, Q. Yan, and M. Qin,, "A segmentation of brain MRI images," *Comput. Assist. Surg.,*, vol. 22, pp. 200-211, oct. 2017.

[24] 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, pp. 4-13, 2015.

[25] Ganesh, M., & Palanisamy, V, "A multiple kernel fuzzy c-means clustering algorithm for brain mr image segmentation," *A multiple kernel fuzzy c-means clustering algorithm for brain mr image segmentation,* vol. 5, p. 406, 2012.

[26] Joseph, R. P., Singh, C. S., & Manikandan, M., "Brain tumor MRI image segmentation and detection in image processing," *International Journal of Research in Engineering and Technology,* vol. 3, pp. 1-5, 2014.

[27] Shen, S., Sandham, W., Granat, M., & Sterr, A., "MRI fuzzy segmentation of brain tissue using neighborhood attraction with neural-network optimization," *IEEE transactions on information technology in biomedicine,* vol. 9, pp. 459-467, 2005.

[28] Chen, T., Lin, L., Zuo, W., Luo, X., & Zhang, L., "Learning a wavelet-like autoencoder to accelerate deep neural networks," in *Proceedings of the AAAI Conference on Artificial Intelligence*, 2018.

[29] Mishra, P., Mishra, S., Nanda, J., & Sajith, K. V., "Multilayer perceptron neural network (MLPNN) controller for automatic generation control of multiarea thermal system," in *2011 North American Power Symposium*, IEEE, 2011, pp. 1-7.

[30] Huang, G. B., Zhou, H., Ding, X., & Zhang, R. (2011)., "Extreme learning machine for regression and multiclass classification," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics),* vol. 42, pp. 513-529, 2011.

[31] Waibel, A., Hanazawa, T., Hinton, G., Shikano, K., & Lang, K. J., "Phoneme recognition using time-delay neural networks," *IEEE transactions on acoustics, speech, and signal processing,* vol. 37, pp. 328-339, 1989.