ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com
International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 9, Issue 6, June 2022

BRAIN TUMOUR

OVIYA B[1] VINOSHINI M[2] SABAREESWARI B[3] SIVASAKTHI S[4]
Department of Electronics and Communication Engineering
Bharathiyar Institute of Engineering for Women, Deviyakurichi
oviyabala19@gmail.com[1] vinoshinimohankumar@gmail.com[2]
sabarish172001@gmail.com[3] ssivasakthi976@gmail.com[4]

SANGEETHA E[4] AP/ECE
AP/ Department of Electronics and communication Engineering,
Bharathiyar Institute of Engineering for Women, Deviyakurichi
sangeta.r@gmail.com

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 the brain anatomy and functions. The mechanism of image processing has a widespread usage in the area of medical science for improving the early detection and treatment phases. Deep Neural Network (DNN), till date have demonstrated a 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 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 like Autoencoder-DNN or DNN, and it was noted that the proposed method outshines the existing methods.

Keywords: Neural network (NN); Deep Neural Network (DNN); Autoencoder (AE); Image Classification.

1. INTRODUCTION

Automated classification and detection of tumors indifferent medical images is motivated by the necessity of high accuracy when dealing with a human life. Also, the computer assistance is demanded in medical institutions due to the fact that it could improve the results of humans in such a domain where the false negative cases must be at a very low rate. It has been proven that double reading of medical images could lead to better tumor detection. Butte cost implied in double reading is very high, that's why good software to assist humans in medical institutions is of great interest nowadays. Conventional methods of monitoring and diagnosing the diseases rely on detecting the presence of particular features by a human observer. Due to large number of patients in intensive care units and the need for continuous observation of such conditions, several techniques for automated diagnostic systems have been developed in recent years to attempt to solve this problem. Such techniques work by transforming the magnetic resonance images by using some prior knowledge like pixel intensity and some anatomical features is proposed. Currently there are no methods widely accepted therefore automatic and reliable methods for tumor detection are of great need and interest. The application of PNN in the classification of data for MR images problems are not fully utilized. These included the clustering and classification techniques especially for MR images problems with huge scale of data and consuming times and energy if done manually. Thus, fully understanding the recognition, classification or clustering techniques is essential to the developments of Neural Network systems particularly in medicine problems.

Segmentation of brain tissues in gray matter, white matter and tumor on medical images is not only of high interest in serial treatment monitoring of "disease burden" in oncologic imaging, but also gaining popularity with the advance of image guided surgical approaches. Outlining the brain tumor contour is a major step in planning spatially localized radiotherapy (e.g., Cyber knife, iMRT) which is usually done manually on contrast enhanced T1-weighted magnetic resonance images (MRI) in current clinical practice. On T1 MR Images acquired after administration of a contrast agent (gadolinium), blood vessels and parts of the tumor, where the contrast can pass the blood–brain barrier are observed as hyper intense areas. There are various attempts for brain tumor segmentation in the literature which use a single modality, combine multi modalities and use priors obtained from population atlases.

2. PROPOSED METHOD

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

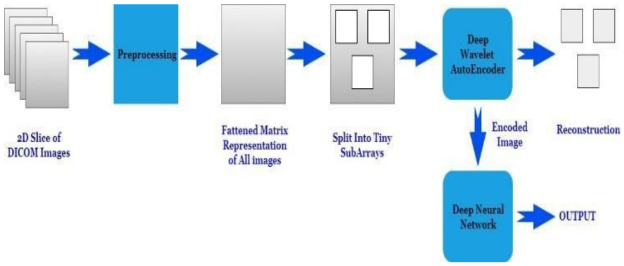

FIGURE 1. Proposed architecture of a DICOM image classifier for brain disease detection based on DWA-DNN model

3.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).

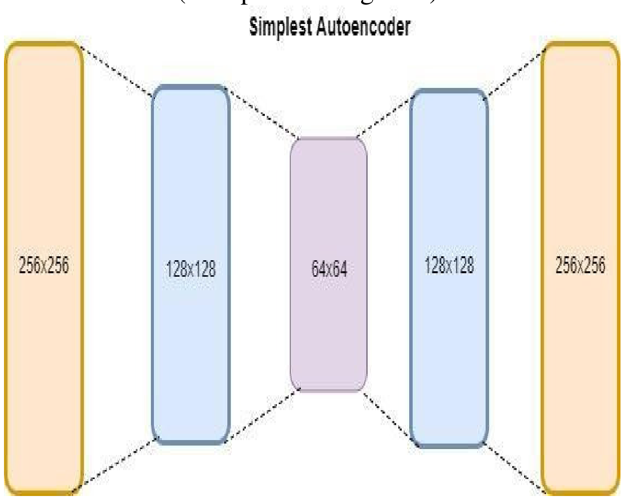

FIGURE 2: Simple Autoencoder model with 3 hidden layers for encoding and decoding of images

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 64x64. Mathematically let Xi represents the input, Hi represents Hidden Layer (here I is 1 to 3) and Yi represents the output.
Let the activation functions used

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 64x64. Mathematically let Xi represents the input, Hi represents Hidden Layer (here I is 1 to 3) and Yi represents the output. Let the activation functions used

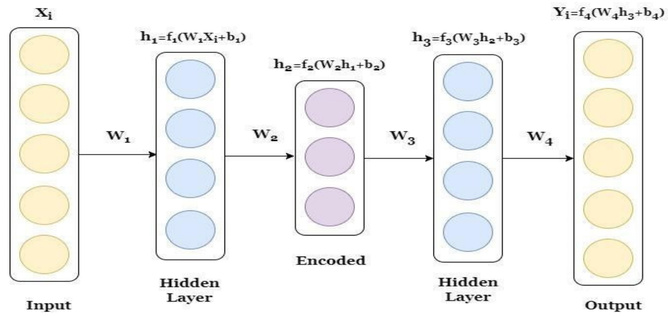

FIGURE 3. Autoencoder model with different layers, functions and parameters

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 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.

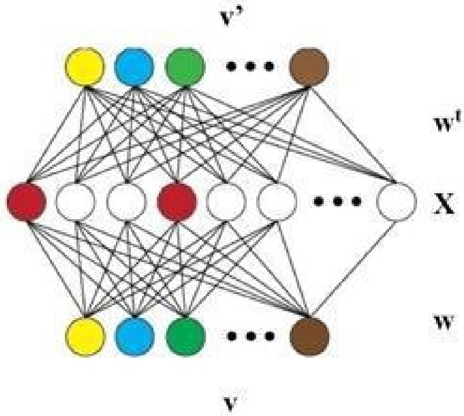

FIGURE 4. Sparse Autoencoder Network

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].

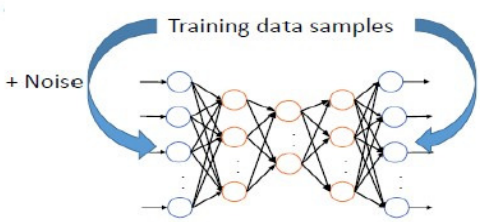

FIGURE 5. A schematic overview of denoising autoencoder

The idea underlying denoising autoencoder is quite straightforward and bare. [3] discussed that In surgical planning and cancer treatment, it is crucial to segment and measure a liver tumor's volume accurately. Because it would involve automation, standardisation, and the incorporation of complete volumetric information, accurate automatic liver tumor segmentation would substantially affect the processes for therapy planning and follow-up reporting. Based on the Hidden Markov random field, Automatic liver tumor detection in CT scans is possible using hidden Markov random fields (HMRF-EM). 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.

C. DEEP WAVELET AUTOENCODER ss

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

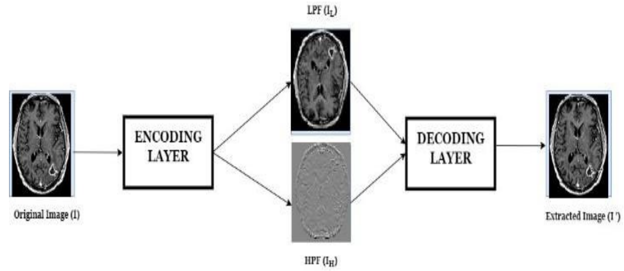

FIGURE 6. Proposed architecture of a single layer of Deep Wavelet Autoencoder

4.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. [1] discussed that Liver tumor division in restorative pictures has been generally considered as of late, of which the Level set models show an uncommon potential with the advantage of overall optima and functional effectiveness. The Gaussian mixture model (GMM) and Expected Maximization for liver tumor division are introduced. In the early liver division process Level set models are utilized.. 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.

5.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.

6.METHODOLOGY

The algorithm has two stages, first is pre-processing of
given MRI image and after that segmentation and then perform morphological operations. Steps of algorithm are as following:-

1) Give MRI image of brain as input.
2) Convert it to gray scale image.
3) Apply high pass filter for noise removal.
4) Apply median filter to enhance the quality of image.
5) Compute threshold segmentation.
6) Compute watershed segmentation.
7) Compute morphological operation.
8) Finally output will be a tumour region. All above steps are explained here in detail.

7.RESULT & CONCLUSION

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

8.REFERENCE

[1] Christo Ananth, M Kameswari, Densy John Vadakkan, Dr. Niha.K., "Enhancing Segmentation Approaches from Fuzzy-MPSO Based Liver Tumor Segmentation to Gaussian Mixture Model and Expected Maximization", Journal Of Algebraic Statistics, Volume 13, Issue 2, June 2022,pp. 788-797.
[2] Pham DL, Xu C and Princo JL (2000) A Survey On
Current Methods In Medical Image Segmentation, Annual Review of Biomedical Engineering 2.
[3] Christo Ananth, S. Amutha, K. Niha, Djabbarov Botirjon Begimovich, "Enhancing Segmentation Approaches from Super Pixel Division Algorithm to Hidden Markov Random Fields with Expectation Maximization (HMRF-EM)", International Journal of Early Childhood Special Education, Volume 14, Issue 05, 2022,pp. 2400-2410.
[4] Sathya A, Senthil S, Samuel A. (2012) Segmentation of breast MRI using effective Fuzzy C-Means method based on Support Vector Machine. Information and Communication Technologies (WICT) 67-72.