ELM Autoencoder using Neuron Selection and Activation Functions for Effective Compression

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Abstract

The neural network depends on the structure of the human brain, which includes the connected neurons. An autoencoder is a popular stream in neural networks. The process of the Autoencoder depends on unsupervised Machine learning algorithms. It has three main factors to reconstruct the image, such as encoder, hidden layer, and output layer. In that case, the encoder constructs with the help of input data and the hidden layer. The decoder builds with the hidden layer and output layer of the neural network. The process of the neural network focuses on the activation function, which refers to the weighting function. The feasibility of the algorithm is related to that weighting function and neuron selection. The state-of-art method includes the approach of Extreme Learning Machine (ELM) based on Autoencoders for achieving high performance. Also, it specifies the various weighting function and selection of neurons for finding better outcomes. The goal of the state-of-art work is to achieve high performance depends on the accuracy rate and time complexity. The choice of our state-of-art work reveals high accuracy with the minimization of computation complexity.

Keywords: Deep learning, ELM-autoencoder, Autoencoder, Image Compression

1. Introduction

Deep learning is an efficient technique in machine learning, where multiple abstract layers are communicating with each other. Also, it is a subset of artificial intelligence which modeled with neural pathways of the human brain. Machine learning is modeled based on the neural pathways of the human brain system. Deep refers to the multiple layers between the input and output layers. In deep learning, the algorithm automatically learns what features are useful. Each layer is deeply connected to the previous layer and makes its decisions based on the output fed by the last layer.

In recent decades, data reduction is an essential factor for efficient transmission. Autoencoders are neural networks that help to learn useful data automatically. The process of Autoencoder plays an ideal role in simplifying the process of feature engineering. The Autoencoder applies backpropagation, setting the target values to be equal to the inputs. The process is copying its information to the output. The hidden layer describes a code used to represent the input.

The neural network is an application of supervised learning. A set of unlabeled training data consider as,

$\{ X(1),X(2),X(3),\ldots X(n)\}$ where, $X(i) \in Rnx(i) \in Rn$

The autoencoder neural network applies the backpropagation method to set the target value to be nearest to the input as,

$Y(i) = X(i)$.

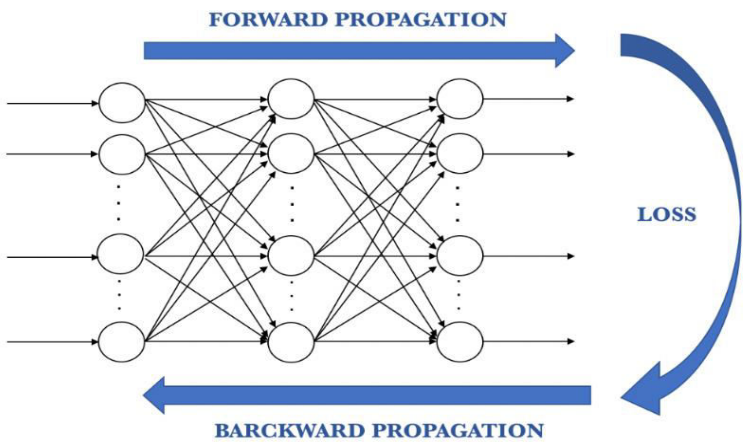


Fig.1. Learning Process of Neural Network

In this research work, focus on the various weighting function which deals with the accuracy rate to compare with each. There are some accessible weighting functions used to calculate the accuracy rate. ELM achieves state-of-art results which, shortens the training time. Almost it faces difficulties in making such performance by conventional learning techniques. Specifically, this method is essential for applying a feed-forward neural network approach. The structure of ELM consists of hidden nodes in a single layer representation. Also, ELM distributed the weights between the input and hidden nodes randomly.

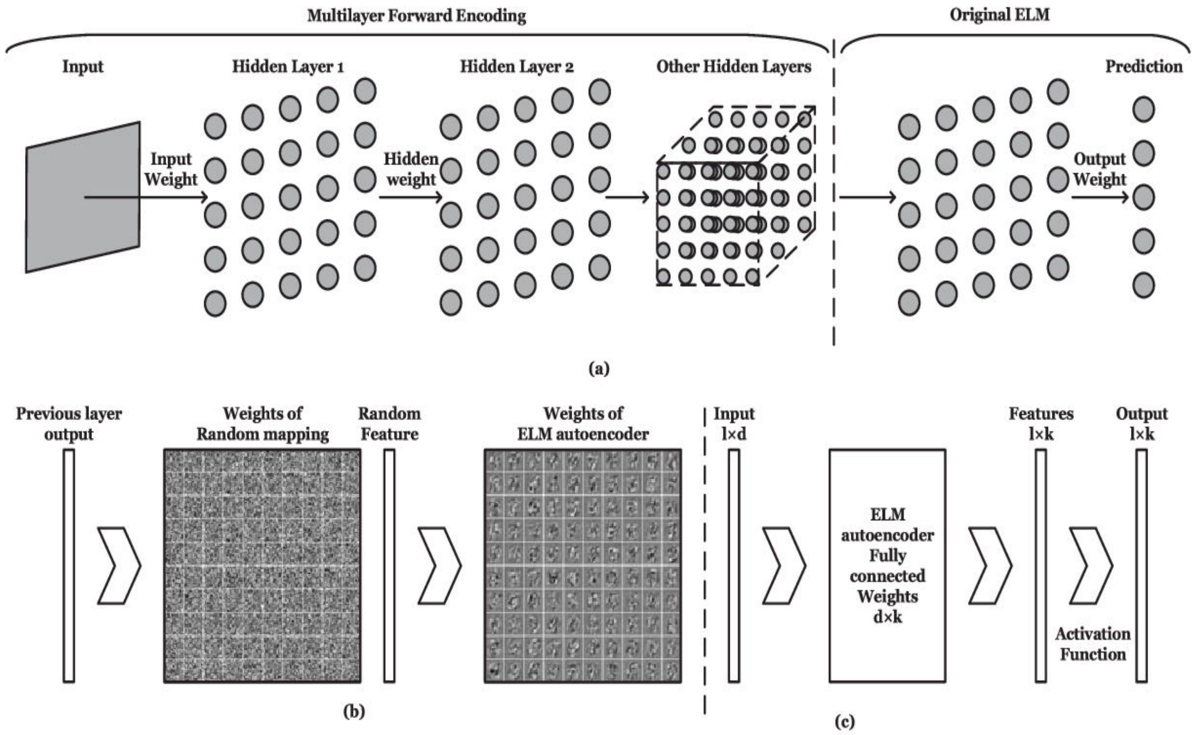


Fig.2. Multilayer Perceptron of Extreme Learning Machine

1.1. Neuron selection Process

In neural network architecture, the neuron selection process conducts randomly. The accuracy of the outcomes depends on the neuron selection when the changes to be held in the neuron selection process the accuracy get changes.

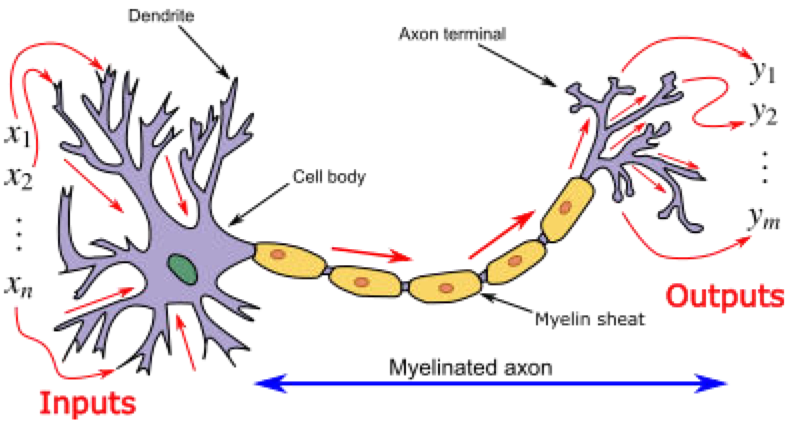


Fig.3. Biological Representation of Neurons

The process of the neural network is split the training data into k equal-size parts which refer as a fold. Typically, the number of k belongs to 3 and 10. The next step is to fix the suitable amount of dimensionality of the hidden layer. Mostly, the neurons select as 40 neurons, 50 neurons, etc. Each of the dimensionality has trained the network k times using k-1 folds as training data and the kth one as testing data. The number of neurons that performs the average testing error over the k-trails based on the lowest point.

1.2. Activation Weighted Function

The activation function of the neural network plays a vital role in the minimization of training time required to execute an algorithm. There is some popular function to accelerate the neural network architecture like Linear/identity, Non-linear, Sigmoid/Logistic, Tann/hyperbolic tangent, ReLu, ELU, and Softplus, etc.

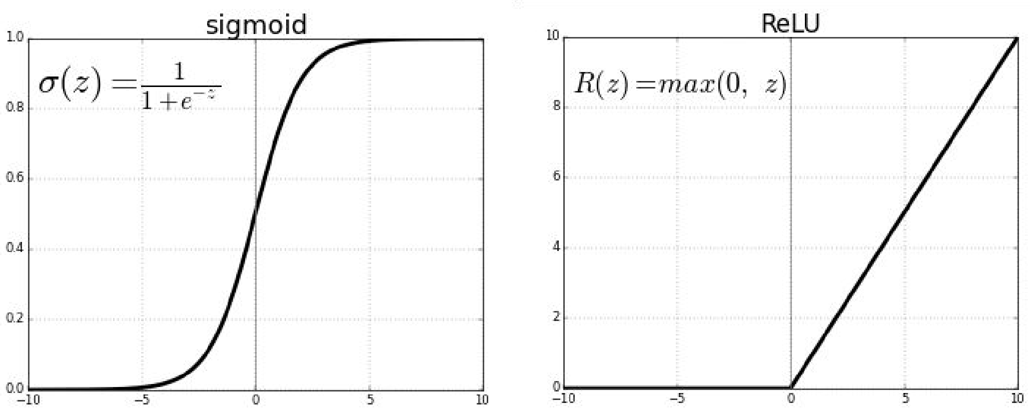


Fig.4. Logistic Sigmoid v/s ReLu Activation Function

The above figure represents the process of logistic sigmoid and the ReLu activation function process graphically. From the observation of the figure indicates the ReLU is half rectified (from bottom). Also, the R (z) is zero when z is less than zero, and R (z) is equal to z when z is above or equal to zero.

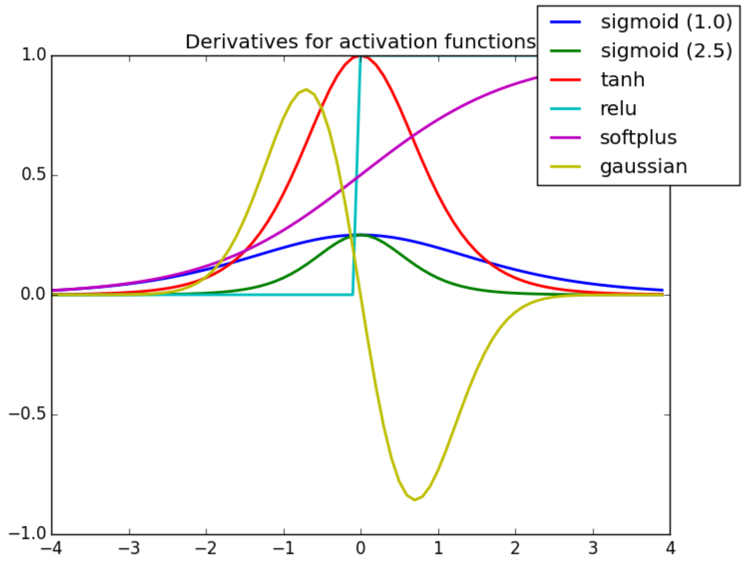


Fig.5.Derivatives for Activation Functions in Neural Networks

In this research work deals with comparative analysis using various activation functions. Notably, the ReLu function minimizes the training time than the other activation functions. The rectified linear unit (ReLU) is a compelling transformation that activates a single node if the input is above a certain threshold. The default and more usual behavior are that, as long as the data value which is below zero, the output is zero when the output is a linear function with the form of f(x)=x. The ReLU activation function has proven to work in many different situations and is currently widely used. The ReLu activation function formula has presented in Eq. (1).

$$f(x) = \begin{cases} 0 & for\ x<0 \\ x & for\ x\geq 0 \end{cases} \qquad (1)$$

where, f(x) denotes the function of ReLu, and x refers as an input. From that equation, all the negative values become zero immediately, which decreases the ability of the model to fit or train from the data correctly. That means any negative input given to the ReLU activation function turns the value into zero immediately in the graph, which in turn affects the resulting figure by not mapping the negative values appropriately.

2. Related Work

This section provides various literature reviews for improving the proposed algorithm. Also, each method has its own strength with the merits and demerits. Duan, L., et al. (2016) [9] proposed a feature extraction of motor imagery EEG based on extreme learning machine auto-encoder. Ge, H., et al. (2019) [10] examined a concept of stacked denoising extreme learning machine autoencoder based on graph embedding for feature representation. Hashmi, A. S., & Ahmad, T. (2019) [11] proposes an optimal Replicator Neural Network using ELM learning and Garson algorithm for anomaly detection.

Dimensionality reduction is a major issue for reducing the complexity of data while retaining the relevant information for the analysis. Haut, J. M., Paoletti, et al. (2018) [12] proposed a method for fast dimensionality reduction and classification of hyperspectral images with extreme learning machine. Also, the author enquires a real-time method for dimensionality reduction and classification of hyperspectral images which are used to develop a fast compressor based on the extreme learning machine. Kasun, L. L. C., et al. (2013) [13] proposed a representational learning with extreme learning machine for big data. Khatab, Z. E., et al. (2017) [14] presented a fingerprint method for indoor localization using autoencoder based deep extreme learning machine. Luo, X., et al. (2018) [15] discussed about the combination of Graph cut liver segmentation and Fuzzy with MPSO tumor segmentation algorithms. The system determines the elapsed time for the segmentation process. The accuracy of the proposed system is higher than the existing system. Tang, J., et al. (2015) [16] proposed a method using extreme learning machine for multilayer perceptron. [17] discussed that Biomedical and anatomical data are made simple to acquire because of progress accomplished in computerizing picture division. More research and work on it has improved more viability to the extent the subject is concerned. A few tech- niques are utilized for therapeutic picture division, for example, Clustering strategies, Thresholding technique, Classifier, Region Growing, Deformable Model, Markov Random Model and so forth. Yan, X., et al. (2017, May) [18] proposed a MIMO-OFDM system based on auto encoder and extreme learning machine for signal detection. It is evident that the proposed work achieves higher accuracy during the selection of maximum neurons, and a low accuracy range identifies when the neuron is minimum. Also, the compression efficiency is high, using the minimum neuron selection in the field of 10 neurons.

3. Proposed Work

The proposed work presents the ELM autoencoder algorithm with the various activation weighting function and neuron selection process, which deals with the number of trials to solve the ambiguous of the algorithm. In the first unit of the proposed algorithm deals with the neuron selection process with various weighted function. Also, it finds the finite level of neurons, which reveals high accuracy. In the meanwhile, the weighting functions also compared to produce low computation complexity which could be taken to that accounts to select the better weighting function.

The first unit of the proposed work is composed using the neuron selection process for checking accuracy. The trial and error method has been established to check whether the best selection of the neurons. In our method, the neurons are selected as 10,20,30,40 and 50 accordingly. The best neurons are selected in the range of 50 for the accuracy with low compression ratio. Also, the neurons are selected as 10 neurons yields high compression ratio with low accuracy. From the observation, the neuron selection process plays a vital role to perform the overall accuracy decision of the data.

The next unit of the proposed work focuses the activation functions to be incorporated to reveal the computation complexity. The training time has been evaluated using the activation function. This method using six activation function like ReLu, Sigmoid, Sine, Hardlim, Tribas, and Radbas are using to validate the duration of the training time. From this list, the sigmoid activation function reveal high accuracy than the other activation functions. Also, it reaches low computation complexity than the others. Almost, the ReLu and Sigmoid activation function matches the performance with the minimum difference. The experimental results has proven that the proposed work achieves higher accuracy with low computation complexity using sigmoid activation function for the selection of 50 neurons.

4. Results and Discussion

The performance of the proposed work presents the outperformance with the result tables, graphical representation, and visual representation, which has used on the outcome of the method. The performance of the proposed work evaluates using the standard metrics, which brings accuracy, compression ratio, and computation complexity. In this evaluation process for accuracy checking the algorithm used the error metric is Mean Squared Error (MSE), from the error rate the Peak Signal to Noise Ratio (PSNR) is measured the image quality. The compression efficiency of the algorithm identifies using the Compression Ratio (CR), and the processing time also measured for the feasibility.

From the observation of table 1, the proposed achieves higher accuracy for the maximum number of neuron (50 neurons) selection, and also it accomplishes some amount of compression ratio. Also, table 1 describes the performance using the ReLu activation function for a better outcome.

Table 1 Different Neuron Selection Scheme with ReLu Activation Function using MRI-T2 Brain Image Dataset

Evaluation Metrics	Selection of Neurons				
	10	20	30	40	50
Accuracy (In db.)	68.63	71.05	73.45	75.55	77.53
Compression Ratio (%)	25.60	12.80	8.53	6.40	5.12
Computation Time (In Sec)	3.48	6.49	10.31	13.55	16.67

It is evident that the proposed work achieves higher accuracy during the selection of maximum neurons, and a low accuracy range identifies when the neuron is minimum. Also, the compression efficiency is high, using the minimum neuron selection in the field of 10 neurons.

Table 2 Various Activation Function using 50 neurons using MRI-T2 Brain Image Dataset

Metrics	Activation Function in Neural Network					
	ReLu	Sigmoid	Sine	Hardlim	Tribas	Radbas
Accuracy (In db.)	77.16	77.53	76.62	76.19	76.14	76.63
Computation Time (In Sec)	17.76	16.67	19.43	17.92	17.75	18.15

Table 2 examines the result using various activation functions using the ELM-autoencoder technique. In particular, the ReLu activation function reveals a high accuracy rate and a good compression ratio than the other activation functions. Furthermore, the state-of-art method shows higher performance than the existing process using the ELM-Autoencoder technique so that the state-of-art process could be an ideal choice for medical image diagnosis.

The outcome of the state-of-art work illustrates in Fig.6. Also, it shows high and low accuracy using different neuron selection.

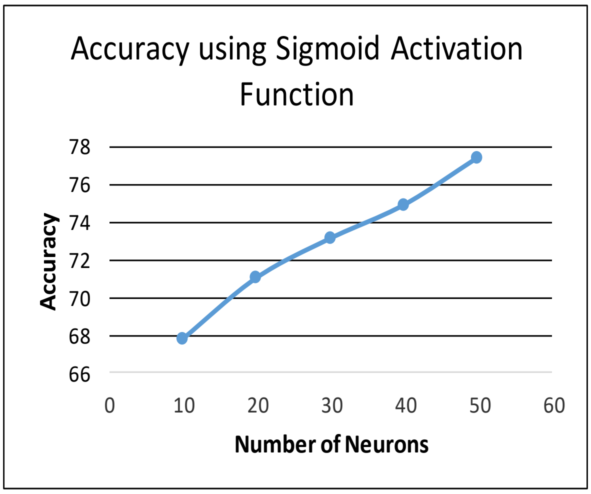


Figure.6. Representation of Sigmoid Function Using Accuracy

The compression efficiency pictorially represented in the figure (Fig.7.) From the figure, the minimum and maximum range of compression ratios shown to exhibit better performance.

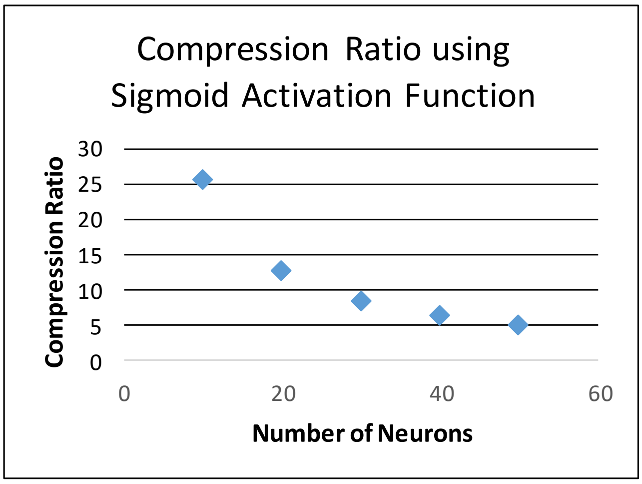


Fig.7. Representation of Sigmoid function using Compression Ratio

The computation time illustrated using a figure (Fig.8.), which shows the long and short span using the proposed method.

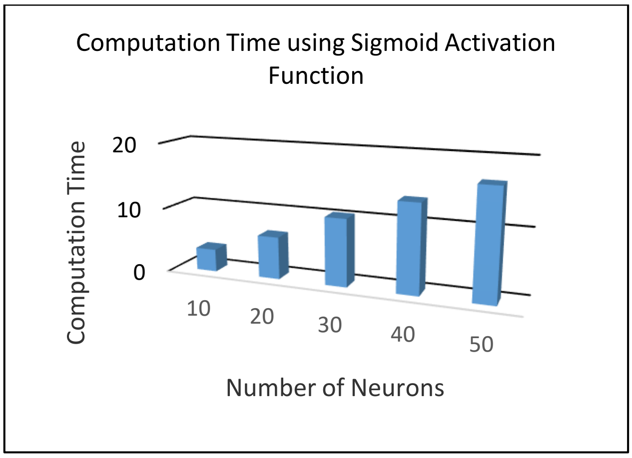


Figure.8. Representation of Sigmoid function using Computation Time

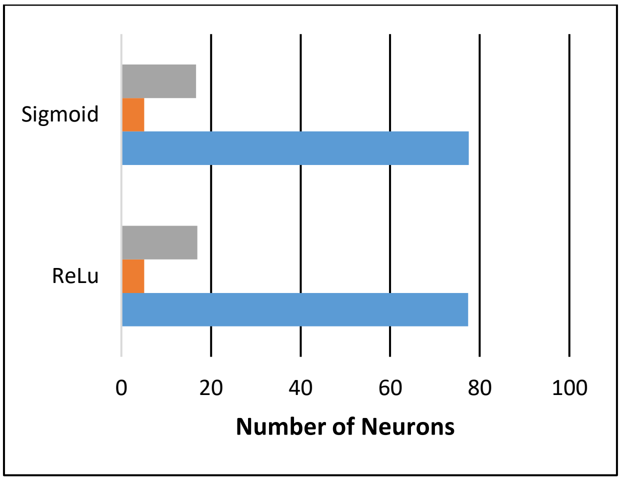
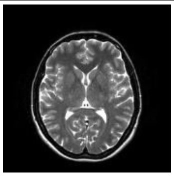
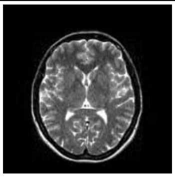
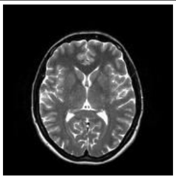
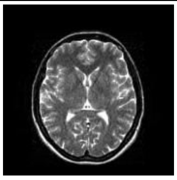
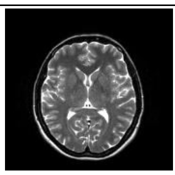
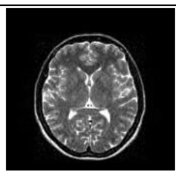


Fig.9. Sigmoid vs ReLu using Compression Ratio

The above figure (Fig.9.) represents the comparative analysis using sigmoid and ReLu activation function for analysing the performance.

The performance of the reconstructed image is visually presented in the following figure (Fig.10). The image quality has proven that the proposed work achieves high accuracy.

Activation Function	Input and Output Image
ReLu	 original image  regenerated
Sigmoid	 original image  regenerated
Sine	 original image  regenerated

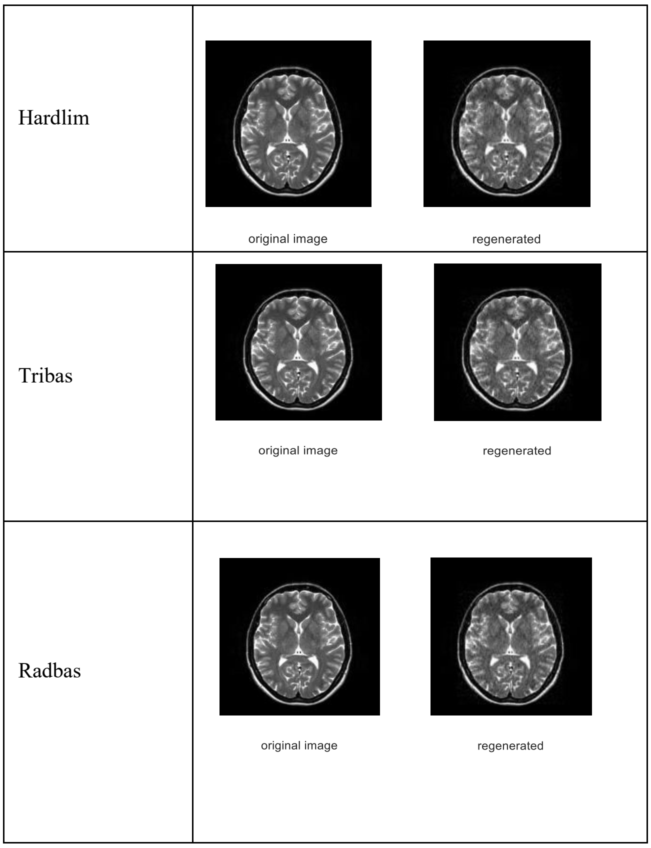


Fig.10. Visual Representation of the proposed work using Input and Output Image

5. Conclusions

The state-of-art method exhibits higher performance using the ReLu activation function, and the compression efficiency also increased. It proves that our novel method outperforms the other existing work. In future enhancement is to be directed with the implementation of hybrid technology to improve the compression efficiency without losing the accuracy.

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