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Classification of Brain Tumor using Hybrid Deep Learning Approach

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Abstract: *Diagnosis of tumor at its early stage is the most challenging task for its treatment in the area of neurology. As, brain tumor is the most common problem in the world, so tremendous research is being carried out to find out the cancer during its onset stages. The task of diagnosis as well as its automation has been extremely difficult using conventional image processing methods. In view of this, a novel technique has been proposed based on convolutional neural network architecture to classify the brain tumor which assists radiologists and physicians to make their decision fast and accurate. The proposed deep learning structure helps to analyze and produce better feature maps to classify the variations in the normal and malignant cases. The proposed method i.e. Hybrid Deep Neural Network (H-DNN) architecture is the combination of two different DNN. First Deep Neural Network (DNN-1) uses the spatial texture information of the cranial Magnetic Resonance (MR) images, whereas in the second method Deep Neural Network (DNN-2) uses the frequency domain information of the MRI scans. Finally, we combine both neural networks to produce better classification result based on prediction score. The training input to the DNN-1 is the texture which is computed by Local Binary Patterns, whereas the DNN-2 uses the frequencies, which have being calculated by Wavelet Transformation as its training input. Here two Dataset have been used for the evaluation of the proposed model i.e. Real MRI dataset and BraTS 2012 MRI Dataset for T2- weighted MRI scans. In this study, the proposed model provides 98.7% classification accuracy, which outperforms the other methods as reported in the related work. Also comparisons of Accuracy, Sensitivity and Specificity of the proposed method has been done with DNN-1 and DNN-2 architecture to indicate that the reported model gives better results when compared to the other methods.*

Keywords: *Brain tumor, convolutional neural network, deep learning, image classification, magnetic resonance imaging.*

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1. Introduction

Brain is the most complex biological structure and key support system in the human body having central nervous system for completing major activities all through our body parts (Iov et al., 2018). Tumors may occur in different body parts when there is immoderate multiplication of cells, which form shapes due to irregular grouping of cells inside a body part. These types of unusual cellule can influence the conventional functioning of the body activity and remove the useful cellule. One of the most important parts of the body is brain, where such development would be dangerous. Brain tumors can threaten the human life directly. Brain tumors are commonly classified as two types, benign tumor and malignant tumor (Dandıl, Çakıroğlu, & Ekşi, 2015). Benign tumors are non-harmful tumors, they are predictable and can be easily determined, as they are affecting limited space and don't spread beyond brain boundaries. However, malignant tumors are very harmful and multiply very fast. Brain tumor which originates in the brain only by multiplying its unusual cells is called predominant tumor. When abnormal cells extend to the other parts of the body, then they start spreading and form a structure giving another category of tumor which is called secondary tumor (metastasis). Brain tumor may be easily isolated and removed if it is spotted at an early stage. Different modalities have been used to detect the brain tumor. Here in this paper, Magnetic resonance imaging (MRI) is being used to detect the presence of tumor in their early stages (Hunnur, Raut, & Kulkarni, 2017). This modality is also very helpful to find the type of tumor. MRI modality has considerably influenced the medical image processing and analysis in detecting the normal as well as abnormal brain structure. The gravity of the cancer in any brain part is decided by the type and the stage of the tumor. Thus, utilizing an automated tumor detection framework is essential to help doctors to recognize brain tumor at an early stage (Annadurai, 2007; Akram & Usman, 2011). Researchers may focus on numerous computerized systems for the automation of classification of different MRI scans, which may leads to the finding of the tumor more accurately. However, cranial MRI scans, which have been considered here, are very complex to handle so there is a need for such a model which can easily handles such MRI images. Deep Learning model which is based on convolutional neural network, is a dynamic pattern in machine learning, as it prominently constitutes undetermined correlation without involving much nodal architecture. It is the latest technique which is being prominently used in many fields like Bio Informatics, Big Data, Networking and Medical Image Analysis etc. (Ahmadvand & Kabiri, 2016; Gao & Hui, 2016; Gao et al., 2017).

The layout of the study has been arranged as follows: The related work of the paper has been mentioned in section 2. The proposed method has been discussed in section 3. The experimental outcome has been discussed in Section 4. The conclusión of the reported paper has been discussed in section 5.

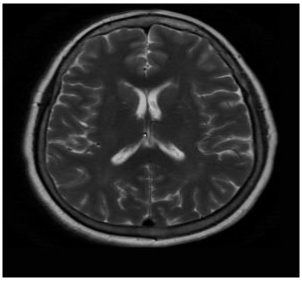
2. Related Work

This section highlights the present literature on using various feature extraction and classification approach for the detection of MRI images. It focuses on highlighting the advantages and the limitations of the methods. Ramteke et al. (2012) had proposed a technique called as K-Nearest Neighbor (KNN) to detect the normal and malignant medical images where Support Vector Machine (SVM) has been compared with proposed method of KNN. Using KNN, the accuracy achieved has been only 80% when applied on all image samples. Othman et al. (2011) proposed MRI brain classification system using support vector machine which worked well for linear data features but not for nonlinear. Zhang et al. (2016) had proposed new technique named as Glioblastoma Multiforme Prognosis Prediction as multiple kernel machine and minimum redundancy feature selection method, it helped in learning the features well but classification accuracy was not promised. Sompong et al. (2016) had proposed fusion of two segmentation techniques i.e. cellular automata model and Fuzzy-c-mean, where gray level co-occurrence matrix (GLCM) has been taken as feature selection method. BraTS 2013 dataset was used for the experimental result. The average dice coefficient metrics was 84%. Sehgal et al. (2016) had proposed an automatic method for the detection of brain tumor containing five stages i.e. MRI Acquisition, Preprocessing, Segmentation, Extraction of tumor and Evaluation of model. This experiment was conducted by BraTS 2013 MRI scans and the result was analyzed on the basis of manually segmented brain tumor. The overall performance was evaluated with average dice coefficient value i.e. 0.729. Praveen et al. (2016) had proposed a classification technique i.e. random forest to categorize normal and malignant MRI scans. If malignancy found, then again label as glioma or meningioma. In this, preprocessing was performed followed by feature extraction with the help of Gray Level Run Length Matrix, histogram and Gray Level Co-occurrence Matrix based techniques. After that, active contour model was used to implement segmentation. At last, Fast Bounding Box method was performed to detect the tumor. The classification accuracy using random forest classifier was found to be 87.62%. Abbasi et al. (2017) had proposed Random Forest classification method where Local Binary

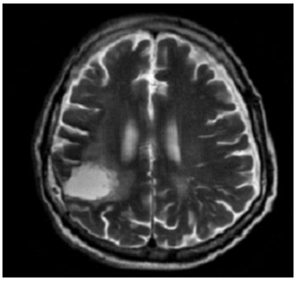
Pattern is used to extend Histogram orientation using BraTS 2013 dataset. Also the proposed framework was superior in contrast with other approach. Pereira et al. (2016) had proposed convolutional neural networks for the detection of brain tumor using brain scans. They have done segmentation, where use of small kernels makes the architecture flexible, while providing fewer numbers of weights. Also, the outcome after the classification is remarkable. Zhao et al. (2015) had proposed a framework containing two segments; in the first segment they converted multi model data into collective representation of Multi-Modal Deep Neural Networks and in segment second, Sparse Group LASSO was used to reduce the redundant features for improving the classification method. Krizhevsky et al. (2012) had proposed classification technique using Image Net, where large amount of dataset is examined with the help of five convolutional layers, but the performance of classification is not so determined. Zhao et al. (2015) had proposed multiple CNN architecture to design different 2D CNNs architecture for reducing segmentation time. In this paper, both training and testing was done with BraTS 2013 dataset. The result of this paper indicated that the accuracy, sensitivity and specificity were better than the other manual images. Işın et al. (2016) had presented review based paper where automatic segmentation techniques were presented using BraTS dataset. This paper highlighted the recent trends of deep neural network method in the area of medical imaging. Singh et al. (2019) had presented the comparison of three classification algorithm i.e. SVM, Random Forest and Artificial neural network where Fuzzy C-Mean method is used as segmentation, Discrete Wavelet Transformation is used to extract the features of MRI scans and Independent Component Analysis is used as feature reduction method. Singh et al. (2020) had proposed Ranklet Transformation as Feature extraction method and combined classification technique i.e. Auto-Encoder and SVM was used to classify the brain tumor using BraTS 2012 dataset.

3. Proposed System

This paper reports an attempt for the development of a novel technique for classifying the normal and malignant MRI scans so as to enhance the accuracy, sensitivity and specificity by means of two deep neural networks, where both the networks operate on different feature map images. The proposed Deep Neural Network-1 (DNN-1) helps to extract the deep texture features using local binary pattern in order to predict the brain tumor with better accuracy. Also, the proposed Deep Neural Network-2 (DNN-2) helps to identify the frequency domain features using wavelet transformation in order to predict the brain tumor with better accuracy, specificity and sensitivity. Normal and malignant MRI scans are shown in the Figure 1(a) and 1(b) respectively for calculating the performance of the model. The structure of the proposed model is demonstrated in Figure 2.



(a)



(b)

Figure 1. MRI Images (a) Normal MRI (b) Abnormal MRI.

Finally, after obtaining the prediction scores of both neural networks we fuse both prediction score to get the proper classification result. The classification is done based on the predictive score. This base system consists of four layers i.e. convolutional layers, pooling layers, Rectifier Linear Units (ReLU) and classification layers. Convolutional layers are the conspicuous and fundamental building structure of every CNN (Ari & Hanbay, 2018; Han & Li, 2015). The channel in all the phases of convolutional layers comprises 3*3 arrays of pixel values. Initial two phases comprise binary discrete layers of convolution each, and next two phases depicts three distinct layers of convolution. 26, 27, 28 and 29 are the fixed feature map dimension which contributes first, second, third and fourth layers of convolutional independently. The modeling of convolutional, ReLU and pooling layer has been described below.

These various convolutional layers help to save the spatial measurements better. ReLU are the enactment work, utilized toward the finish of each convolutional layer, F(x) is the function which is connected to each neuron in the convolutional neural network framework and elect the feature of particular neuron. As the data is very complex to use, non- linear property is used which covers Stochastic Gradient Descent (SGD) as optimizer since it converges much faster than all other traditional methods.

Modeling of convolutional layer (Shin et al., 2016; Tajbakhsh et al., 2016):

Convolutional layer is the core layer in CNN architecture. It is made up of group of independent filters and each filter is convolved independently with the input images and terminates with couple of relevant feature map. We first obtain the input image sample of size W1*H1*D1. It required four parameters, named as K for number of filters, S as Stride, F as spatial Extent and P as amount of zero padding. After that, D2, H2 and W2 are calculated where D2= K, H2= (H1-F+2P)/S+1 and W2= (W1- F+2P)/S+1, now the size of the image became W2*H2*D2. It also measures (F*F*D1)*K where it calculates the weight per filter and K biases. Finally, the output image is the outcome of implementing a correct convolution of dth filter (W2*H2) over the input image size with stride S. Convolutional layer also have ReLU function which alter all the negative values to 0.

Modeling of pooling layer:

To minimize the size of feature map is done by the pooling layer by reducing the parameters and computation in the system. We first obtain the input image sample of size W1*H1*DI with two parameters i.e. S and F. It also requires to generate a sample volume W2* H2* D2 as output, using W2= (W1- F)/S+1; H2= (H1- F)/S+1; D2=D1. In this, zero parameters is accepted because it evaluates the fixed function of the input. Here it is applied with Stride 2 in a single depth slice.

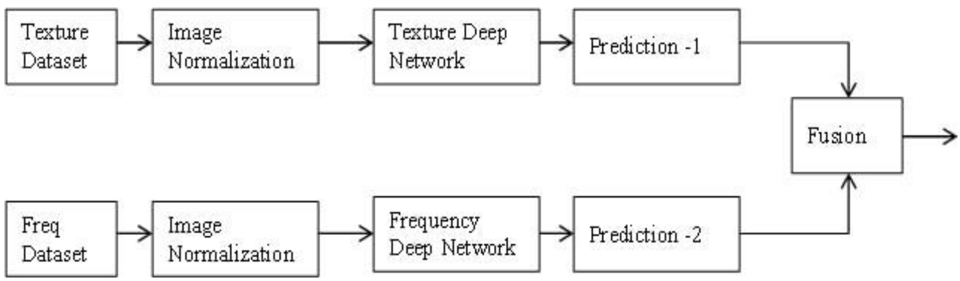


Figure 2. Proposed System Model.

3.1. Deep Texture Network

Generally, all neural networks use the raw images as a training input. But, here we have used Local Binary Patterns (LBP) images as raw images. It means that we have extracted local binary patterns features from the raw images as shown in Figure. 3 and Figure. 4 which are then fed as the training input since local binary patterns provide the texture information from the training images.

The computational analysis of Local Binary Pattern (Pawar & Belagali, 2015) has been calculated as shown in Figure. 5. This network is proficient to pull out all the features based on texture from the training MRI scans. Hence, this network, in depth analyzes the features from the texture which is helpful to enhance the performance of the model. The general structure of convolutional neural network is described in Figure. 6. Here we use this basic structure with different feature space like texture and feature information. Deep texture features play a vital role to define the proposed model of DNN-1 in an appropriate way.

The above basic structure of Deep Neural Network (DNN) acts differently at different feature space. Here, we have used dropout layer to remove the redundancy created by all other layers. Using this structure as DNN-1, feature space is calculated based on deep texture information. The screenshot of the features after training through DNN-1 is shown in Figure. 7.

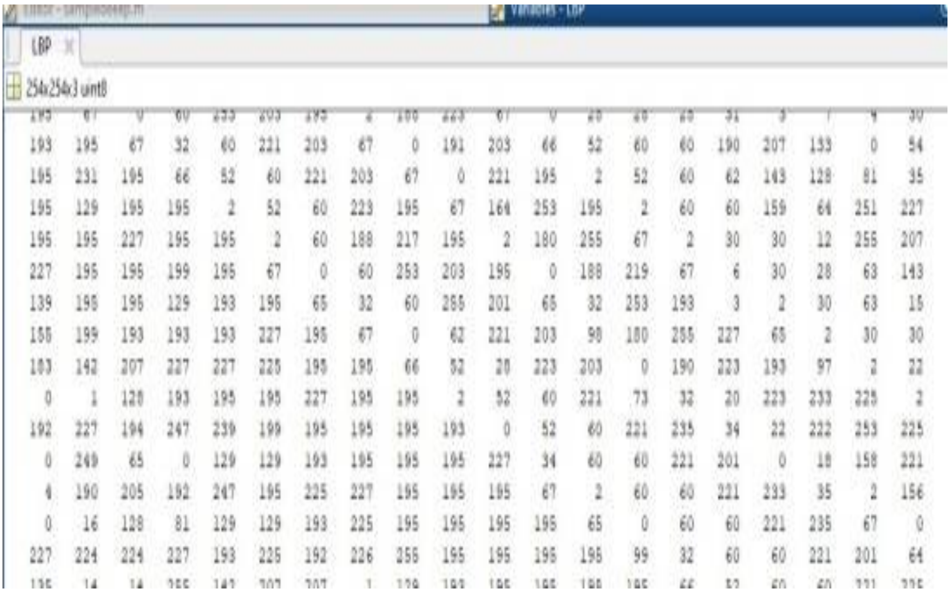


Figure 3. Screenshot of LBP features extracted from normal MRI

Figure 4. LBP MRI images

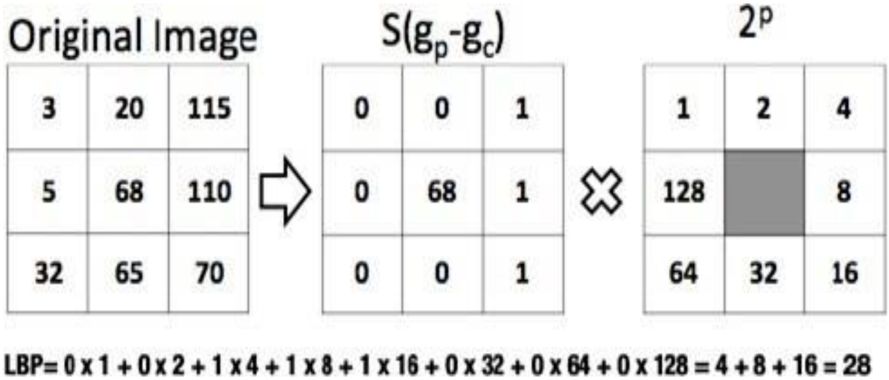


Figure 5. LBP Computation.

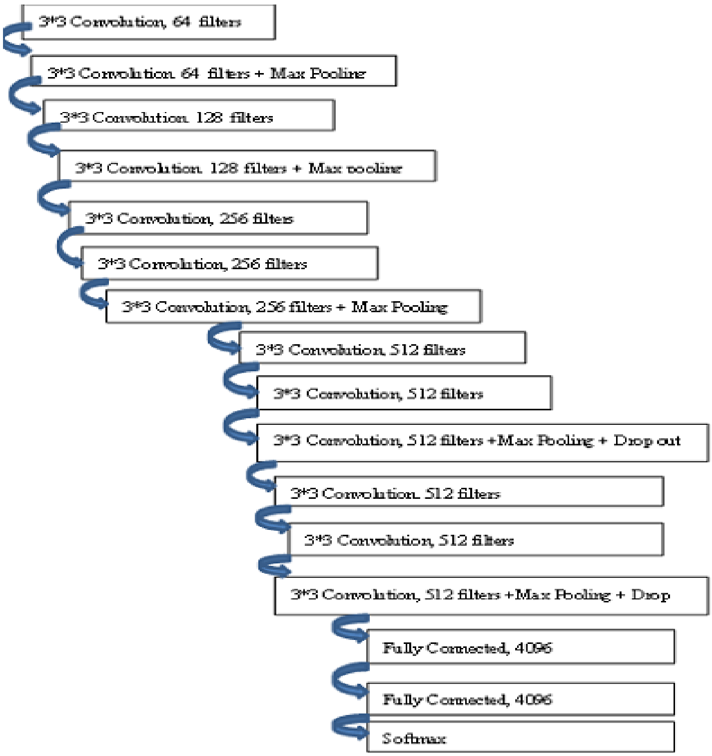
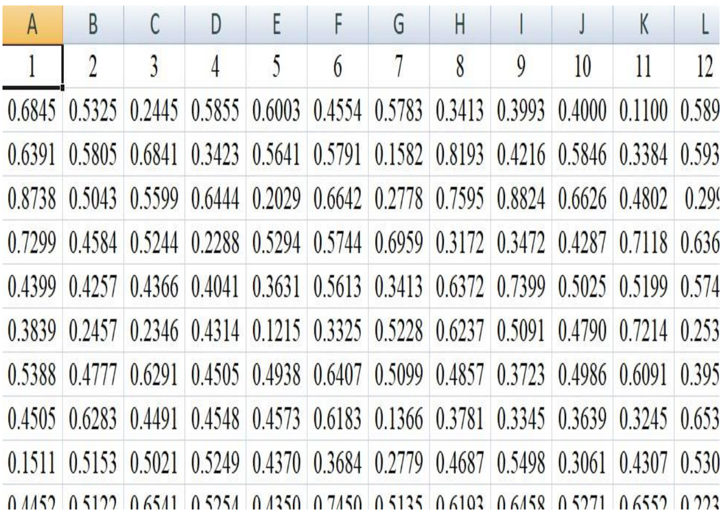


Figure 6. Basic DNN Structure.



A	B	C	D	E	F	G	H	I	J	K	L
1	2	3	4	5	6	7	8	9	10	11	12
0.6845	0.5325	0.2445	0.5855	0.6003	0.4554	0.5783	0.3413	0.3993	0.4000	0.1100	0.589
0.6391	0.5805	0.6841	0.3423	0.5641	0.5791	0.1582	0.8193	0.4216	0.5846	0.3384	0.593
0.8738	0.5043	0.5599	0.6444	0.2029	0.6642	0.2778	0.7595	0.8824	0.6626	0.4802	0.29
0.7299	0.4584	0.5244	0.2288	0.5294	0.5744	0.6959	0.3172	0.3472	0.4287	0.7118	0.636
0.4399	0.4257	0.4366	0.4041	0.3631	0.5613	0.3413	0.6372	0.7399	0.5025	0.5199	0.574
0.3839	0.2457	0.2346	0.4314	0.1215	0.3325	0.5228	0.6237	0.5091	0.4790	0.7214	0.253
0.5388	0.4777	0.6291	0.4505	0.4938	0.6407	0.5099	0.4857	0.3723	0.4986	0.6091	0.395
0.4505	0.6283	0.4491	0.4548	0.4573	0.6183	0.1366	0.3781	0.3345	0.3639	0.3245	0.653
0.1511	0.5153	0.5021	0.5249	0.4370	0.3684	0.2779	0.4687	0.5498	0.3061	0.4307	0.530
0.4452	0.5122	0.6541	0.5254	0.4350	0.7450	0.5135	0.6193	0.6458	0.5271	0.6552	0.223

Figure 7. Screenshot of LBP features value after training

3.2. Deep Frequency Network

This network is used to deeply analyze the frequency based information. Here the raw image is converted into stationary wavelet transforms to get the frequency information. Then this frequency information, as feature space, is fed to the DNN network known as DNN-2. This stationary wavelet transform is much better than other transformation like Fourier cosine and discrete wavelet (Ghazali et al., 2007; Shree & Kumar, 2018; Chaudhary & Bhattacharjee, 2020), because there is no down sampling done in the sub band creation, so all the initial information is converted into frequency information without any loss. Figure. 8 shows the screenshot of the feature values extracted from the raw MR images which are taken for further processing and Figure. 9 shows the SWT MRI image. Here we are using biorthogonal wavelet as mother wavelet to get the four sub bands, approximation coefficients are provided as input to train the frequency deep network. These approximation coefficients represent low frequencies and contain all the information of the raw image. This would help to extract different level of features from the approximation sub band image, and it would leads to improve the classification performance. Also, Figure. 10 shows the SWT Decomposition. After, calculating all the bands (HH, LH and HL) with the help of decomposition function (Lahmiri & Boukadoum, 2011), we achieved results as shown in Figure. 11. Here again we use basic structure of convolutional neural network as deep neural network (DNN-2) which is used to distinguish the frequency features and performing classification to get better outcome. The screenshot of values of different frequency features, after applying DNN-2 network is shown in Fig. 12. Here we have used dropout layer to remove the redundancy created by all other layers before fully connected layer and also used max pooling instead of average pooling.

256x256 double

	1	2	3	4	5	6	7	8	9	10	11	12	13
52	0.5000	1.5000	2.0000	3.0000	4.0000	4.0000	4.5000	3.0000	3.5000	3.5000	4.0000	3.0000	3.000
53	2.0000	3.0000	3.5000	5.0000	6.5000	6.5000	4.5000	2.5000	2.0000	2.0000	2.0000	2.5000	3.000
54	3.5000	4.0000	4.5000	5.5000	7.0000	7.0000	4.5000	1.5000	0	0.5000	2.0000	3.0000	3.000
55	3.5000	4.0000	4.0000	4.5000	6.0000	6.5000	6.0000	4.5000	2.0000	1.5000	3.5000	4.0000	3.500
56	4.0000	4.0000	5.0000	5.0000	5.5000	7.5000	8.0000	7.0000	5.0000	3.5000	3.5000	4.0000	4.500
57	5.5000	4.0000	5.5000	5.5000	5.5000	8	9.5000	7.5000	4.5000	3.5000	3.0000	3.5000	5.000
58	8.0000	6.0000	5.0000	5.0000	4.5000	4	5.5000	5.5000	4.0000	3.5000	3.0000	3.0000	4.500
59	9.0000	8.0000	5.0000	4.5000	3.5000	1.5000	2.0000	4.0000	5.5000	5.0000	3.5000	2.0000	2.500
60	6.0000	6.0000	4.0000	3.5000	3.5000	3.0000	3.5000	4.5000	5.0000	5.0000	4.5000	2.5000	1.500
61	4.5000	4.0000	4.0000	4.0000	3.5000	3.0000	3.0000	3.5000	3.0000	3.0000	4.5000	4.0000	3.500
62	6.0000	5.5000	5.0000	4.5000	3.0000	2.5000	3.0000	4.0000	4.0000	3.0000	4.0000	4.5000	4.500
63	5.0000	5.0000	5.0000	4.5000	2.5000	2.0000	4.0000	5.5000	6.0000	4.5000	4.0000	5.5000	6.500
64	2.5000	2.5000	4.0000	5.5000	4.0000	2.5000	3.5000	4.5000	5.0000	3.5000	3.5000	5.5000	7.000

Figure 8. Screenshot of SWT features value after training

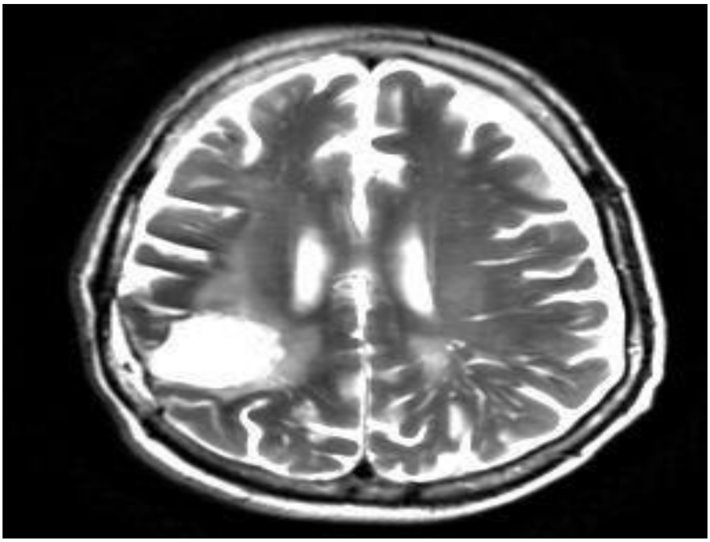


Figure 9. SWT MRI images.

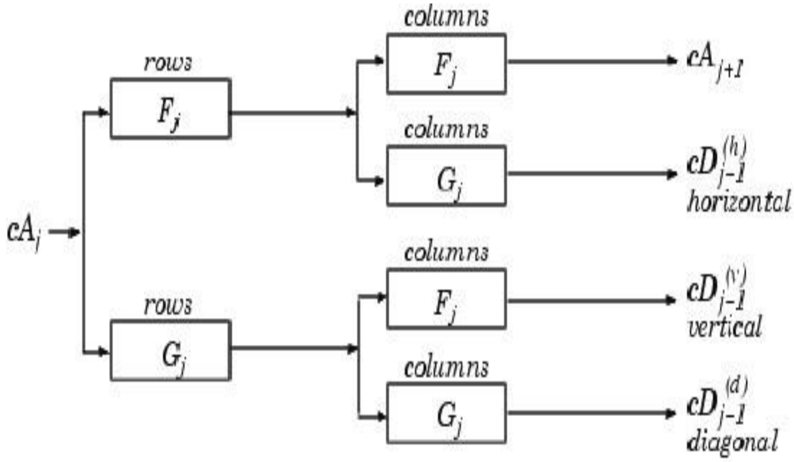


Figure 10. SWT Decomposition

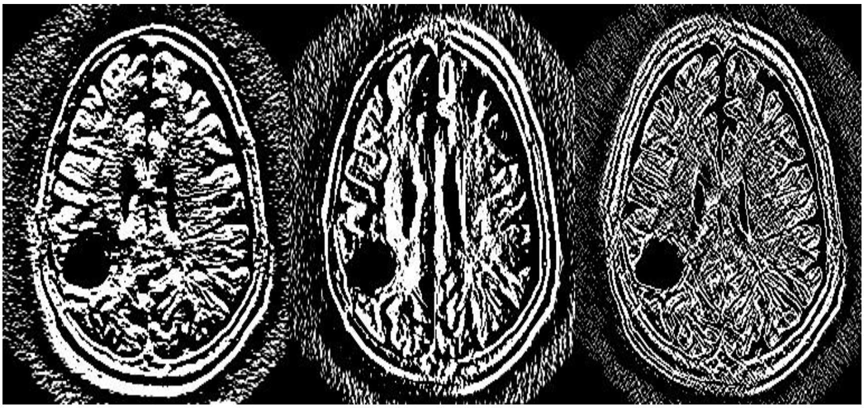
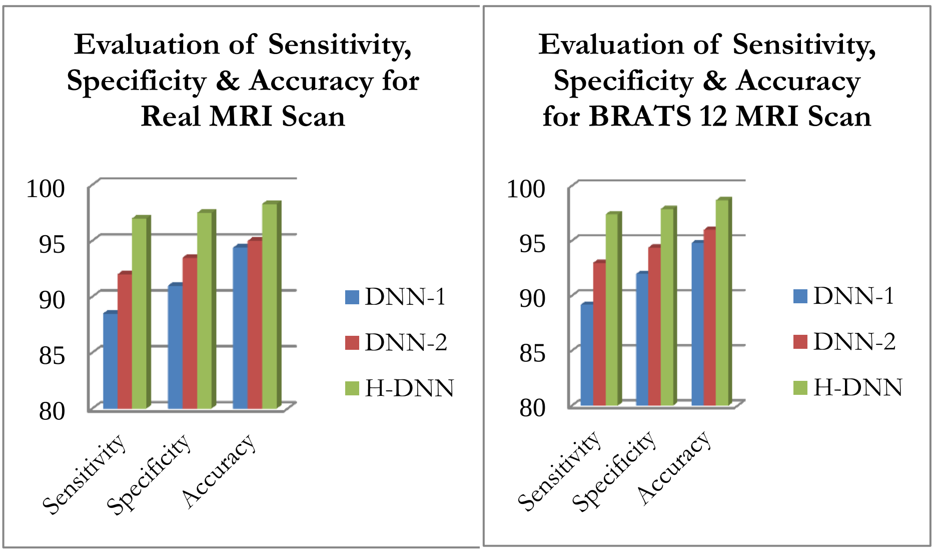


Figure 11. Abnormal LH Band, Abnormal HL Band, Abnormal HH Band.

A	B	C	D	E	F	G	H	I	J	K	L	M
1	2	3	4	5	6	7	8	9	10	11	12	13
0.6393	0.3606	0.4663	0.5665	0.5316	0.4509	0.3880	0.4508	0.7551	0.3807	0.4446	0.419	0.422
0.4487	0.5467	0.3054	0.6233	0.5651	0.2646	0.7086	0.2808	0.3046	0.2824	0.4066	0.3848	0.651
0.6013	0.2394	0.4217	0.4048	0.3273	0.5451	0.4586	0.2004	0.5287	0.3875	0.5084	0.4858	0.423
0.5621	0.4437	0.6023	0.2113	0.2811	0.4454	0.5176	0.5072	0.4669	0.3687	0.6046	0.5623	0.575
0.5326	0.4309	0.5077	0.5767	0.7233	0.5777	0.5053	0.4077	0.5641	0.5759	0.3113	0.5574	0.357
0.5429	0.5728	0.4780	0.3063	0.3493	0.7041	0.5264	0.4029	0.5403	0.564	0.5437	0.3839	0.506
0.5356	0.6591	0.3345	0.3207	0.5898	0.6197	0.2388	0.3844	0.6076	0.3909	0.2189	0.4638	0.487
0.6072	0.5634	0.5315	0.5286	0.5571	0.4605	0.5372	0.3974	0.3991	0.4844	0.5095	0.4571	0.468
0.7066	0.5813	0.4368	0.6334	0.5273	0.3912	0.5910	0.4776	0.6029	0.2170	0.5060	0.4998	0.539

Figure 12. Screenshot of SWT features value after training



(a) (b)

Figure 13. Evaluation of DNN-1, DNN-2 and H-DNN

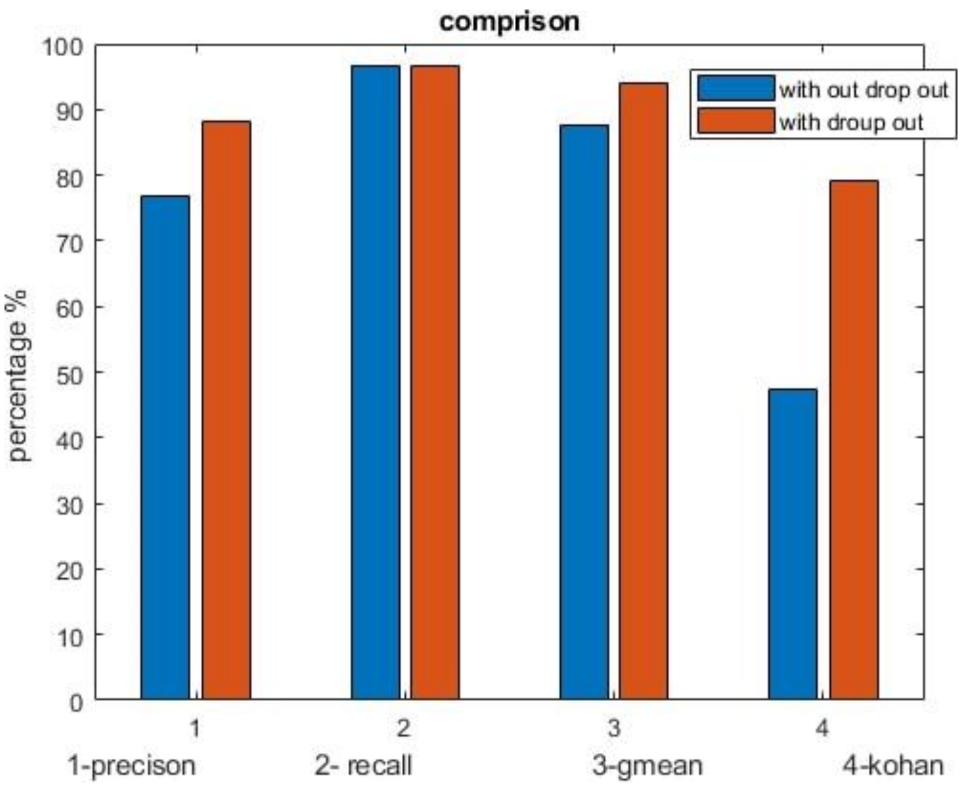


Figure 14. Performance of drop out layers of H-DNN

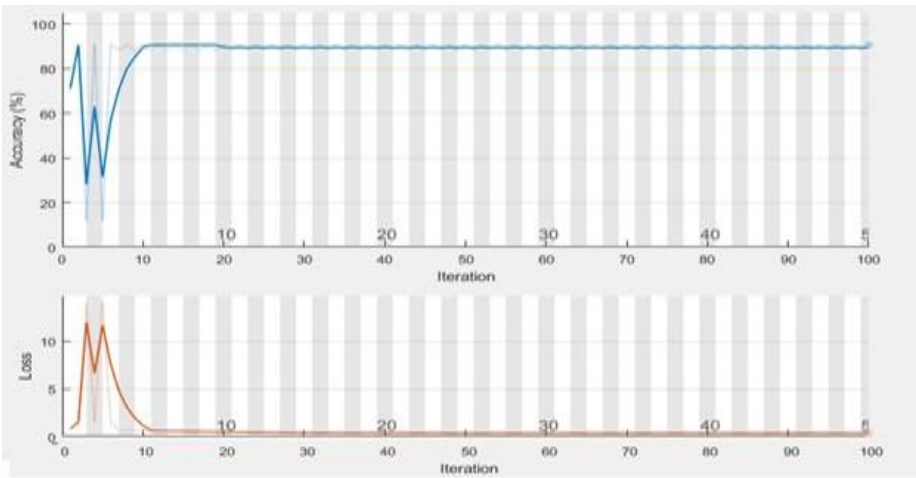


Figure 15. Training Loss and Training Accuracy

3.3. Fusion

In this stage, score level fusion is performed; therefore the predicted outcome of both the network i.e. deep texture and deep frequency networks is obtained. The obtained predictive score of both the networks are finally fused to classify the images with higher prediction score.

3.4. Data Agumentation

Here we have taken two different databases for the detection of brain tumor. One of the databases was collected from one of the renowned hospitals for better understanding and outcome. The database was collected from MRI Department of the hospital. The link of the hospital is https://mahdelhi.org/. We have taken total 1250 real MRI images, comprising 700 normal and 550 malignant brain images. For training, we have taken 600 normal and 500 abnormal images. Then we have done flip and rotation of all the training images, and thus, totally we have given 2100, 1650 normal and abnormal images respectively for training the network. For testing, we have taken 100, 50 images of normal and abnormal samples respectively, and we have resized all the images into 256x256 pixels. Second database was collected from the Medical image repository i.e. BraTS 2012. Here from this repository, total 1500 T2-weighted MRI scans are taken in which 900 scans are extracted for malignant brain and 600 for normal brain. For training, we have taken 800 malignant and 500 normal MRI scans. Again we performed flip and rotation of all the training images. Thus, we got 2700 malignant and 1800 normal MRI scans. For testing, we had taken 100 normal and 100 malignant MRI images and again executed the process of resizing of all the images before computation.

Also, the training loss is calculated by entropy loss, and we got the 100% training accuracy and training loss of 0.0003. Here the accuracy of proposed system for real MRI dataset and BraTS 2012 acquired 98.3 and 98.7 respectively. All the coding of this paper has been completed using MATLAB 2015.

4. Results & Discussion

Here, we have tested normal and malignant MRI scans to check the performance of the model, and got improved outcomes, as compared to other conventional methods. Figure. 13(a) displays Accuracy, Sensitivity and Specificity based on real MRI dataset, and which were found to be 98.3%, 97% and 97.5% respectively whereas in case of BraTS 12 MRI dataset, the Accuracy, Sensitivity and Specificity was all most similar and it was found to be 98.7%, 97.4% and 97.9% respectively, as shown in Figure. 13(b). H-DNN for BraTS 12 is much better than the real dataset as BraTS dataset is having processed and less degraded images. Figure. 14 show the accuracy of deep network with and without drop out layers in case of BraTS 12 dataset. When we use lager number of convolutional filters, then the feature map may be redundant, so the dropout layers is used to remove the redundant features which improves the classification accuracy. Table 1 and Table 2 presented the evaluation with reference to sensitivity, accuracy and specificity of DNN-1, DNN-2 and H-DNN for both the dataset to differentiate the performance of the proposed technique with the existing one. Figure. 15 showed the training loss and training Accuracy graph of the proposed network. At the end of the analysis, we found that H-DNN shows higher classification accuracy than the other methods as reported in the related work.

Table 1. Evaluation of proposed classifier with Real dataset.

Methods	**Accuracy**	**Sensitivity**	**Specificity**
DNN-1	94.4%	88.5%	91%
DNN-2	95%	92%	93.5%
H-DNN	98.3%	97%	97.5%

Table 2. Evaluation of proposed classifier with BraTS 2012 dataset.

Methods	**Accuracy**	**Sensitivity**	**Specificity**
DNN-1	94.8%	89.2%	92%
DNN-2	96%	93%	94.4%
H-DNN	98.3%	97.4%	97.9%

5. Conclusion

In the proposed methodology, Hybrid Deep Learning architecture is used to analyze the cranial MRI scans in In the proposed methodology, Hybrid Deep Learning architecture is used to analyze the cranial MRI scans in order to detect the contrast between the normal and malignant images of brain scans. Here, we divide the proposed Hybrid Deep Neural Network (H-DNN) architecture into two different DNN namely DNN-1 which is used to analyze the spatial information, whereas DNN-2 analyzes the frequency information. At last, we combine both the networks to obtain better classification results. Also, this proposed model using BraTS 2012 dataset produced 98.7% accuracy rate which is much better than the other classification methods. The Real and BraTS 2012 dataset of MRI images are used both in training and testing purpose to authenticate our proposed model.

So this method is well suitable for real time brain tumor classification of MRI images.

Computational time for processing this proposed methodology is very high but the main focus of this study is to find the accurate result of classification. Also, stacking the Hybrid Deep Learning architecture with more number of layers may improve the classification rate. But still there are many issues which remain untouched. MRI images are very complex to process as the scanning involves lots of subjectivity. So, this area is an open challenge to all the researchers. Also, we need to design a user-friendly computerized system to handle all the diagnosis at an early stage so that doctors can easily trust and operate. We also, need to focus on the type of the stage of the tumor so that it can be easily detected before any kind of incurable damage may occur. Segmentation still remains a gray area. Appropriate and accurate segmentation before classification may improve upon the result of proposed technique. Hence, this methodology is essential tools which mainly focus on many fields related to biomedical image processing applications.

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