Design of Deep Neural Architecture for Brain Cancer Classification Using Pyramid Design

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Abstract. In this study, Deep Neural Network (DNN) with Pyramid Design (PD) is developed for brain image classification. The main objective is to design a non-invasive procedure for diagnosing brain cancer using deep learning. The signal intensities obtained from the brain tissues using Magnetic Resonance Imaging (MRI) can be used for effective treatment. A pyramid consists of a predefined number of convolution layers and a max pool layer to abstract features. In the DNN-PD approach, the pyramid is stacked with an increasing number of convolution layers and convolution filters from one pyramid to the next pyramid and so on. The stacking is employed recursively to get more accurate results. It shows that the proposed architecture gives efficient results with 98.5% accuracy using REpository of Molecular BRAin Neoplasia DaTa (REMBRANDT) database. The diagnostic results of the proposed Deep Neural architecture with the expert's analysis can reduce the biopsies, a dangerous procedure with a great deal of pain.

Keywords: Brain cancer, neural network architecture, pyramid approach, MRI image classification, deep learning, REMBRANDT.

1. Introduction
The accurate classification of brain images is essential before taking any unnecessary biopsy tests. There is no ionizing radiation involved while capturing brain images using MRI scanners. The healthy and abnormal tissues can be distinguished more accurately by MRI than computed tomography images. Also, brain images are obtained from various angles that increase the diagnostic accuracy, and thus, many systems are designed to diagnose brain tumors using MRI scans.

A hybrid approach of MRI brain tumor classification has been carried out in [1]. It uses Discrete Wavelet Transform (DWT) for extracting features. The Support Vector Machine (SVM) and Genetic Algorithm (GA) tools are used for the hybrid approach. GA diminishes the feature count extracted for the classification. The hybrid approach uses geometrical parameters such as entropy; root mean square error, and smoothness to analyze the images.

The three-stage classification is analyzed to differentiate gliomas, pituitary tumors, and meningiomas brain tumors [2]. It adopts a transfer learning concept with the pre-trained GoogLeNet model to extract brain MRI image features. The integrated classifier models like SVM, GA are used for system classification, and also, the system evaluation is done with few training samples.

The Tetrolet transform [3], is used for decomposing the MRI images to extract features. SVM classifier recognizes the tumor from MRI images from the statistical features of Tetrolet transform. A CAD-based categorization of brain images with statistical feature extraction from Dual-Tree M-band
Wavelet Transform (DTMBWT) is discussed [4]. The maximum margin classifier SVM and the \(k\)-fold approach validate brain tumors in the MRI image classification.

Human soft tissue information is analyzed to detect and diagnose brain tumors [5]. T2-weighted images have difficulties in attaining sensitivity and specificity. Fluid-attenuated inversion recovery image technique is applied superiorly for accurate brain lesion detection. The T1-weighted contrast-enhanced MRI [6] is a more generic and accurate prediction method, as it does not use the dataset of any other handcrafted features. The preprocessing of brain image is followed by equalization technique for histogram-based texture feature extraction and ridge estimator with a multi logistic regression model to classify abnormal scanned images.

The combined handcrafted and deep image feature extraction for the image classification is described in [7], which uses various transformation techniques. It uses the cross-sectional views of scanned images for the feature extraction from the modified gray level co-occurrence matrix. The other efficient classification system is discussed in [8] using different wavelets like stationary wavelet transform, DWT, and DTMBWT. A coefficient selection method with SVM classifier is employed for classification. DWT-based classification of brain image is discussed in [9]. Feature vectors are extracted using Daubechies, symlets, and biorthogonal wavelet families.

An interactive diagnosis support system model is discussed in [10] for brain tumor classification to enhance the system's accuracy and robust decision. The accurate prediction is carried in three phases for extracting the features and classification by a two-stage correlated SVM classifier. It uses the hyper-column technique with Convolutional Neural Network (CNN) for feature selection, including the feature elimination method. As the deep machine learning technique has more advantages, the novel network model is integrated with pre-trained AlexNet, GoogLeNet, and VGG-16 networks.

A computer-based CNN developed in [11] with a new architecture classifying three types of tumors. The developed simple network provides high capability execution speed in the classification of MRI brain tumors and serves as an effective decision-supporting tool for radiologists. The MRI brain image classification using Deep Wavelet Auto-encoder (DWA) to detect brain cancer using the DNN [12]. In DWA, a new image compression technique is utilized with the auto encoder for feature reduction and the wavelet transform for image decomposition.

The brain tumor MRI image classification using the CNN-based complex networks [13]. It uses the computer network for diagnosis that improves tumor types' accuracy with the network structure generated by random graph algorithms instead of manual designing and optimization. The graphs generated randomly are mapped into the computable neural network for brain tumor classification by a network generator.

An automated DNN helps diagnose migraine with three measures of functions [14], homogeneity of the region, the low-frequency amplitude fluctuations, and correlation strength of regional functional. The Adam optimizer carries the brain tumor classification using nonlinear diffusion with optimized CNN [15]. Different regions of interest are used to classify manually for the identification and analysis of treatment. The preprocessing uses a canny edge detection algorithm followed by the minimum barrier and the nonlinear diffusion at multilevel.

In this study, an efficient DNN-PD is developed for the effective diagnosis of brain cancer. Followed by Section 2 details the methodologies of DNN-PD developed for the brain MRI classification system. Section 3 evaluated the DNN-PD using REMBRANDT images and compared it to other literature classification systems. Section 4 summarizes this study with main conclusions and future recommendations.

2. Methods and Materials

The DNN is an information processing system that processes the input data and finds the relationships between input (observations) and output (class labels). It is inspired by the human biological nervous systems and very effective in solving many pattern recognition systems. In this study, a PD is developed to get more accuracy for the brain MRI classification system. Figure 1 shows the proposed DNN-PD system for the brain MRI classification system.
Figure 1: Proposed DNN-PD system for brain MRI classification system

Figure 2 shows the PD to abstract features using convolution filters (CF) and max-pooling (MP) layer.

Figure 2: PD in DNN to abstract features

From Figure 2, PD-\(n\) consists of \(n\)-CF with 64x\(n\) filters, and an MP layer at the bottom of the pyramid is seen. The convolution of filters with the input data generates the feature maps, and based on the number of filters used in each PD, the feature dimension of the feature map increases. MP layer is used to reduce the feature dimension, which reduces the dimension to half by using a 2x2 window with a stride of 2. The generated feature maps inside the PD are given to the fully connected layer for the classification. Figure 3 shows fully connected layers.
A fully connected layer is simply a neural network architecture that takes inputs from the feature abstraction module after flattened. The output layer gives the predicted class, either normal or abnormal, in this study. A back propagation algorithm is employed to update the weights in the hidden neurons with cross-entropy loss. It is defined as

$$CE_{loss} = - \sum_{i=1}^{c} CL_{i} \log(PC_{i})$$  (1)

$CL_{i}$ the true label of $i$th class and $c$ is the number of classes and $PC_{i}$ the class's soft max probability.

The number of epochs is 100, and the learning rate used is 0.01. Figure 4 shows the output layer's activation function and hidden layer.

**Figure 4:** Hidden layer (a) and output layer's (b) activation functions
3. Results and Discussions
The performances of DNN-PD are evaluated using the REMBRANDT database [16]. The size of MRI scans in the database is 256x256 pixels and in DICOM format. A total of 400 images are analyze the DNN-PD (each 200 from normal and abnormal) are randomly selected. Figure 5 shows REMBRANDT database images. To train the DNN-PD architecture, 50% of MRI scans from each category are utilized, and then the architecture is tested with the remaining MRI scans.

\[
\text{Sensitivity} = \frac{TP}{TP + FN} \tag{2}
\]

\[
\text{Specificity} = \frac{TN}{TN + FP} \tag{3}
\]

\[
\text{Accuracy} = \frac{TP + TN}{TP + FN + TN + FP} \tag{4}
\]

Where the True Negative (TN) – number of correctly classified normal MRI scans,
True Positive (TP) - number of correctly classified abnormal MRI images,
False Positive (FP) - the number of wrongly classified normal MRI scanned images and
False Negative (FN) - number of wrongly classified abnormal MRI scans.

A confusion matrix using these parameters is drawn for visual analysis of the DNN-PD performance. The performance of DNN-PD is analyzed by staking the PD, which is shown in Figure 5. The term DNN-PA1 consists of PD-1 only, whereas DNN-PAn consists of stacked PD from PD-1 to PD-n. For example, DNN-PA2 consists of two PD architecture, PD-1, and PD-2. Figure 6 shows the confusion matrices and ROCs obtained for DNN-PA1 to DNN-PA5.
Figure 6: Performances of different DNN-PD for brain MRI classification
Table 1 infers a clear analysis of the performance of DNN-PD for brain MRI classification system, using the obtained performance metrics from Figure 6.

**Table 1:** Performance of DNN-PD architecture for brain MRI classification system

| Architecture | Accuracy (%) | Sensitivity (%) | Specificity (%) |
|--------------|--------------|----------------|-----------------|
| DNN-PA1      | 82           | 79             | 85              |
| DNN-PA2      | 87.5         | 85             | 90              |
| DNN-PA3      | 93.5         | 92             | 95              |
| DNN-PA4      | 98.5         | 97             | 100             |
| DNN-PA5      | 98           | 96             | 100             |

It is inferred that DNN-PA4 provides better performance than other architectures followed by DNN-PA5. The DNN-PA4 achieves 98.5% accuracy, whereas it is 98% for DNN-PA5. The feature maps generated by the DNN-PA1 are unable to differentiate the normal and abnormal tissues in the MRI scans, and thus their performance is very less compared to others. Increasing the architecture's depth by including more PAs increases the system's accuracy by 98.5% (DNN-PA4) from 82% (DNN-PA1). It is concluded that the highest accuracy achieved by the DNN-PD is due to the system's interpretation ability in the form of pyramidal architecture. Table 2 shows; the performance of DNN-PD is compared with existing systems using different classifiers.

**Table 2:** Comparison of DNN-PD with existing systems

| Techniques       | Sensitivity (%) | Accuracy (%) | Specificity (%) |
|------------------|-----------------|--------------|-----------------|
| DWT+SVM [9]      | 95              | 93.5         | 92              |
| DTMBWT+SVM [4]   | 95              | 97.5         | 100             |
| Chevrolet + SVM [3] | 96              | 98           | 100             |
| VGG16            | 97              | 97.5         | 98              |
| GoogLeNet        | 95              | 96           | 97              |
| Proposed system  | 97              | **98.5**     | 100             |

4. Conclusion

In this study, an efficient DNN-PD is designed for effective treatment for brain cancer. It is a pattern recognition system recognizing patterns in the normal and abnormal brain tissues using deep learning. The DNN-PD uses simple convolution filters for abstracting features and a fully connected layer to classify the patterns. The ability of PD improves its performance within the database. Experimental results show the performance of DNN-PD standard performance metrics of accuracy, sensitivity, and specificity. The learning of DNN-PD on REMBRANDT classifies the MRI images with 98.5% accuracy, 97% sensitivity, and 100% specificity. In the future, the DNN-PD architecture is designed with an inception module to improve the system performance to classify the scanned MRI brain images.

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