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Brain Image Classification by Deep Neural Network with Pyramid Design of Inception Module

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Abstract. In Deep Neural Network (DNN), the convolution filters of different sizes are stacked to abstract features from the input data, making weight updating difficulties and causes overfitting. A conventional Inception Module (IM) overcomes the abovementioned drawbacks by designing the architecture wider rather than deeper. In this study, DNN with Pyramid Design of Inception Module (PDIM) is designed for brain image classification using Magnetic Resonance Imaging (MRI). Depth of the architecture is increased by stacking PDIM units, and their performances are evaluated. This study's MRI images are obtained from the REpository of Molecular BRAin Neoplasia DaTa (REMBRANDT) database. The newly proposed architecture achieves 99% accuracy with 98% and 100% sensitivity and specificity. The performance comparison shows the system's effectiveness that could help the physicians for accurate brain cancer classification.
Keywords: Deep neural network, artificial neural network, backpropagation algorithm, brain image classification, inception module.

1. Introduction

The human brain is the primary organ of our body. A primary brain tumor (Gliomas) starts in the brain, whereas secondary tumors can randomly start elsewhere in the body and spread to the brain. As brain cancer causes are still unknown, an early diagnosis with the highest accuracy is required to decrease the mortality rate. In MRI scanned brain images, the Glioma tumor is classified into the normal, low, and high grades using Convolutional Neural Networks (CNN) [1] includes preprocessing unit where the primary feature extraction of image datasets is followed by a CNN network where the extracted features are mapped with secondary features and fed for classification.

The automated MRI brain tumor classification is done for specifying meningiomas, pituitary, and gliomas type diseases using the CNN and Support Vector Machine (SVM) classifiers [2]. In this, the confusion matrix-based polynomial and linear SVM classifiers are used. As the datasets are downsized and reduced for computation, the salty noise is added to make a robust performance analysis model.

The wavelet autoencoder-based DNN technique is used for compressing the brain image dataset [3], integrates the autoencoder feature reduction with the decomposed wavelet transform the image to resize the image feature set for enhancing DNN classification. In [4], the brain MRI scanned image classification using various techniques such as decision tree, K-nearest neighbor, SVM, artificial neural network, and CNN are reviewed. The classification and identification of abnormal brain and normal brain images with various neurological disorders are analyzed.

Various wavelet transformation techniques like stationary wavelet transform, discrete wavelet transform and Dual-Tree M-band Wavelet Transform (DTMBWT) [5] are used for rank-

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based feature extraction and coefficient selection of MRI image datasets. The decomposed sub-band images with ranked features use an SVM classifier for abnormal and normal image classification. The automated binary classification of MRI brain images enables a high-resolution image of living tissues to provide important structural information of tumors[6]. It utilizes the integration of CNN and transfers learning pre-trained sixteen layered network model. The efficient automated diagnosis and classification of test data image accuracy are assured.

The Neural Network (NN) based MRI brain image classification employs WT to extract the image features, and then the Principle Component Analysis (PCA) technique [7] is applied to reduce the feature dimensionality. The reduced features are sent to a Back Propagation NN (BPNN) to find the optimal weight by adopting the NN's scaled conjugate gradient. The NN technique's three stages are preprocessing, reducing the dimensionality, and classification [8]. In this stage, the MRI brain image data is converted into encoded information stored, computed, and transmitted through digital devices. The second stage is dimensionality reduction by PCA; finally, the BPNN is used to classify the subjected image as normal or abnormal.

A computer-Aided Diagnosis (CAD) system, an efficient system is presented [9], which analyzes the normal and abnormal MRI brain image using the DTMBWT for statistical feature extraction. An SVM classifier, the maximum margin classifier with a k-fold approach, is used to classify and validate the extracted feature dataset. The four-stage statistical analysis is employed to enhance MR image quality, which comprises preprocessing stage, feature extraction method, feature reduction model, and classification network [10]. The DWT-based image enhancement technique is used for feature extraction with three sub-stages, including a median filter for noise removal. The image contrast is enhanced using the histogram equalization technique by RGB conversion gray-scale image. Finally, to categorize the scanned brain MRI images, pathological details utilize an advanced trained DNN.

Gliomas image classification based on hybrid statistical and wavelet feature extraction [11] is discussed. The statistical features are extracted based on multi-layer Perceptron classifier MRI modalities and DWT. DWT is also used with SVM for brain image classification in [12]. Another frequency domain transformation named Tetrolet transform is utilized in [13]. The energy-based features are extracted and given to the SVM classifier for classification.

The internet of medical things is the healthcare domain with IT systems linking through the computer networks via medical devices and other applications [14]. An optimized DL classifier model with an opposition-based crow search algorithm picks the optimal features from the preprocessed image and classifications based on these featured images.

The newly automated multiclass diagnosis system is used to classify pathological brain MRI into various categories [15]. The texture feature subset extraction is done using the entropy and sub-bands within the MRI, plays a significant role in the detection and segregation of pathological brain images. Fast curvelet transform is used for simple and fast feature extraction that is finally to kernel-based machine learning model for classification.

DWT and SVM based hybrid approach are integrated to classify the MR brain tumor images [16]. It includes feature extraction, followed by feature reduction using genetic algorithm and SVM classifier for brain tumor image classification that classifies benign or malign type. The CAD system helps doctors and radiologists diagnose the proper tumor types using artificial intelligence [17]. The deep learning algorithm gives the optimum performance in the computerized world that enhances the CAD-based deep learning approach for classifying the various types of brain tumors using residual networks.

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In this study, an effective brain image classification system by DNN-PDIM for brain cancer diagnosis is developed. The paper follows DNN-PDIM architecture methodologies in section 2. The results obtained from the analysis of DNN-PDIM on MRI images are discussed in section 3, and the final section summarizes the conclusions of this study with future recommendations.

2. Methods and Materials

NNs are structures of interconnected nodes capable of receiving input, processing it, and producing some output. Input can either be external or from other nodes' output, so in this sense, a task is performed collectively and concurrently by the whole network rather than a node on its own. It is inspired by how biological networks of neurons function in humans and mammals and offer a new computation model. They are a mathematical tool for pattern recognition for classification. The field of applications is now very diverse, with many different methods. In DNN, features are abstracted deeply using convolutional filters before using BPNN to update the weights. Figure 1 shows the architecture of DNN-PDIM.

Although many of the DNN methods are considerably different, they have many common features. All provide a non-linear mapping from an 'input' feature space to some unique output corresponding to that input. NNs learn in a method analogous to that perceived to be employed by the human brain. The mapping from input to output is derived by experience of previously defined and classified mappings. The method of learning is therefore supervised. The Visual Geometry Group (VGG) [18] architectures use deeper architecture with small-sized convolution layers (only 3x3). Due to the deeper structure of VGG, VGG is computationally expensive as well as overfitting. To avoid this, GoogLeNet[19] uses IM to allow more computation through a dimension reduction with stacked convolutions of 1x1. The architecture of IM is shown in Figure 2. A single IM is used in PDIM-1, and two IMs are used in PDIM-2. Thus the DNN-PDIM system is stacked with PDIM-n to form a pyramid design.

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Figure 1: DNN-PDIM architecture

Figure 2: Architecture of IM (MPL – Max Pooling Layer)

In a BPNN, data (inputs) are admitted at the inputs and travel in one direction towards the outputs with one or more hidden layers trained to perform virtually any regression or discrimination task [22]. Figure 3 shows two hidden layers in the architecture of a multi-layered FFNN.

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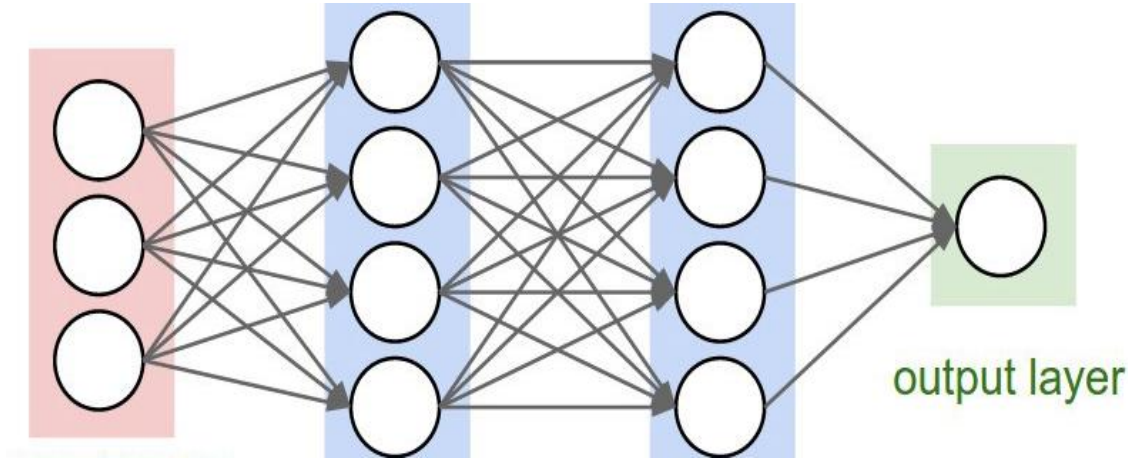

Figure 3: A multi-layered FFNN (Input layer (pink), Hidden layers (blue), Output layer (green))

The backpropagation algorithm compares the network output to that expected. It computes an error-based measure on squared differences and then minimizes gradient descent by altering the network's weights. Denoting a training member of the set by v^i, the actual output by y^i , and the desired outputs by x^i, the error is:

$$E = \sum_i \sum_j (y_j^i - x_j^i)^2 \tag{1}$$

And the algorithm performs iterative weight updating until the error is small:

$$w_{ij}(k+1) = w_{ij}(k) - \in \frac{\partial E}{\partial w_{ij}} \tag{2}$$

The convergence algorithm can be very slow, and there is extensive literature on speeding the algorithm. The best-known technique is the introduction of momentum, which controls behavior so that the process does not get stuck in local minima. Equation 2 is rewritten as,

$$w_{ij}(k+1) = w_{ij}(k) + \in \delta_j z_i(k) + \alpha[w_{ij}(k) - w_{ij}(k-1)] \tag{3}$$

Here α is the constant momentum and is chosen to be between zero and one. In general, BPNNs are good candidates for tackling almost any image processing task. This study uses a momentum factor of 0.9 with 20 epochs. The optimizer used is stochastic gradient descend with backpropagation. The input layer's and output's layer activation functions are rectified linear unit and softmax functions

3. Results and Discussions

In this section, the performances of the DNN-PDIM system are discussed. It uses 400 MRI- DICOM images obtained from the REMBRANDT database [20]. Each DICOM image has a resolution of 256x256 pixels, and they are converted to bitmap images initially. The obtained MRI images are grouped into two groups; normal (200) and abnormal (200). A randomly chosen 100 images from each category are used for training the DNN-PDIM system, while the remaining is used for testing the DNN-PDIM system. Figure 4 shows sample images from the REMBRANDT database[21].

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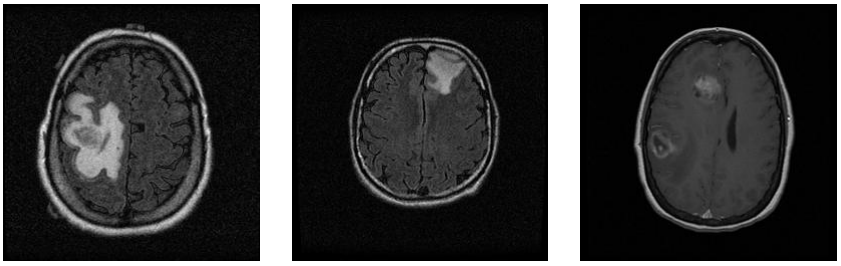
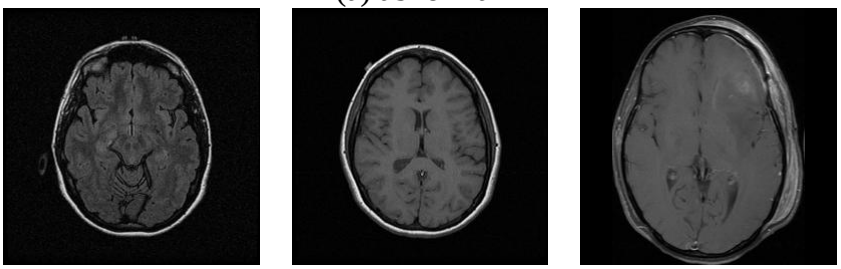


(a) abnormal



(b) Normal

Figure 4: Sample images from REMBRANDT database

Table 1 shows the performance metrics and their corresponding formulae used to analyze the DNN-PDIM system on the REMBRANDT database.

Table 1: Performance metrics of the DNN-PDIM system

Performance metrics	Formula	Description
Accuracy	$\frac{TP+TN}{TP+FN+TN+FP}$	It gives overall performance of the system.
Specificity	$\frac{TN}{TN+FP}$	It gives the DNN-PDIM system performance on normal cases.
Sensitivity	$\frac{TP}{TP+FN}$	It gives the DNN-PDIM system performance on abnormal cases.
True Negative (TN) – number of correct classification of normal cases True Positive (TP) - number of correct classification of abnormal cases False Positive (FP) - number of incorrect classification of normal cases and False Negative (FN) - number of incorrect classification of abnormal cases.		

The performance of the DNN-PDIM system is analyzed by randomly chosen training and testing images. Hence, for proper validation of the DNN-PDIM system, the system is executed ten times with randomly chosen images, and the obtained performance accuracies are shown in Table 2.

Table 2: Obtained Accuracies of the DNN-PDIM system

Run	DNN-PDIM-1	DNN-PDIM-2	DNN-PDIM-3	DNN-PDIM-4	DNN-PDIM-5
1	82.5	90	96	99	99

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2	84.5	89.5	95.5	99.5	98.5
3	86.5	94	97.5	99	98.5
4	81.5	89	95	99.5	98
5	79.5	87	92	99.5	99
6	79.5	85	91	99	98
7	84.5	91.5	96.5	98	99
8	82.5	88.5	94.5	99	98
9	86.5	92	96.5	99.5	99
10	87.5	94	98	98	98
Avg	**83.5**	**90.05**	**95.25**	**99**	**98.5**

It is inferred from Table 2 that the average classification accuracies increase while increasing the depth of the architectures. The architecture is initialized with DNN-PDIM-1 that gives only 83.5% average accuracy. DNN-PDIM-4 obtains maximum accuracy of 99% and further increases the depth; the accuracy is reduced to 98.5%, and it is due to the redundant data by the higher depth of the architecture. Tables 3 and 4 show the sensitivities and specificities of DNN-PDIM.

Table 3: Obtained Sensitivities of the DNN-PDIM system

Run	DNN-PDIM-1	DNN-PDIM-2	DNN-PDIM-3	DNN-PDIM-4	DNN-PDIM-5
1	80	87	94	98	98
2	82	85	92	99	97
3	84	91	97	98	97
4	79	86	93	99	96
5	77	85	90	99	98
6	77	83	90	98	96
7	82	89	94	96	98
8	80	87	94	98	96
9	84	88	96	99	98
10	85	92	98	96	96
Avg	**81**	**87.3**	**93.8**	**98**	**97**

Table 4: Obtained Specificities of the DNN-PDIM system

Run	DNN-PDIM-1	DNN-PDIM-2	DNN-PDIM-3	DNN-PDIM-4	DNN-PDIM-5
1	85	93	98	100	100
2	87	94	99	100	100
3	89	97	98	100	100
4	84	92	97	100	100
5	82	89	94	100	100
6	82	87	92	100	100
7	87	94	99	100	100
8	85	90	95	100	100
9	89	96	97	100	100
10	90	96	98	100	100
Avg	**86**	**92.8**	**96.7**	**100**	**100**

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It is observed from Tables 3 and 4 that DNN-PDIM-4 and DNN-PDIM-5 give the highest specificity of 100%, whereas DNN-PDIM-1 obtains the lower specificity is 86%. Though DNN-PDIM-5 gives 100% specificity, its sensitivity is 97% which is 1% lower than the sensitivity obtained by DNN-PDIM-4 (sensitivity of 98%). Figure 5 visually shows the performances of different DNN-PDIM architectures. A comparative study of the DNN-PDIM system with other classification systems is made and shown in Figure 6.

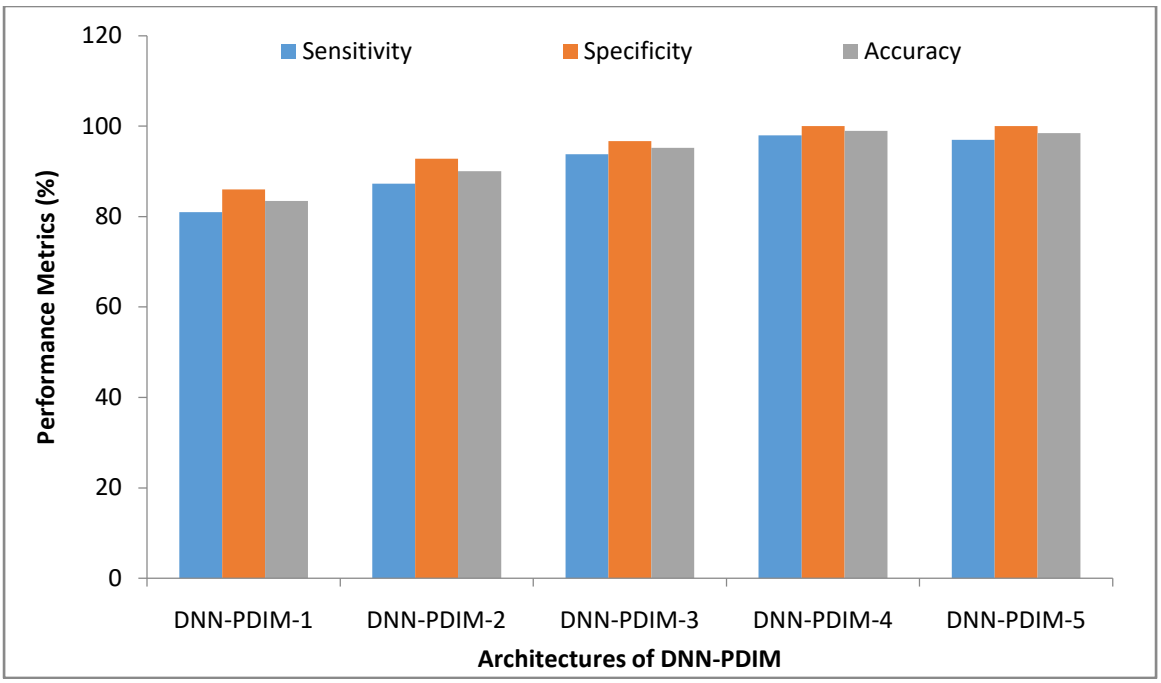

Figure 5: Performance of different DNN-PDIM architectures

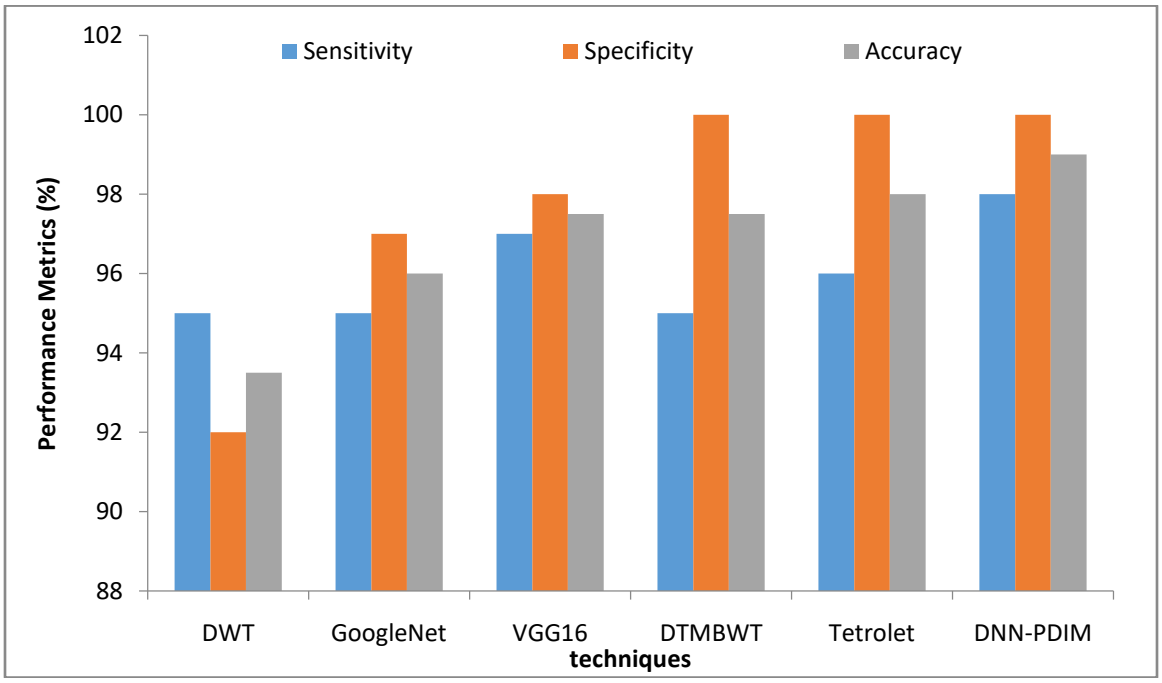

Figure 6: Performance comparison of the DNN-PDIM system

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It is observed from Figure 6 that the DNN-PDIM gives better results than other classification systems. When compared to GoogLeNet[19], VGG16 [18] improves the classification from 96% to 97.5%. The proposed deep learning system, DBB-PDIM, further improves the accuracy to 99%. Other classification systems, which do not consider deep learning provides a maximum classification of 98% by Tetrolet, transform [13], 97.5% by DTMBWT [9], and 93.5% by DWT [12].

4.Conclusion

A new deep learning architecture, DNN-PDIM is developed for brain cancer diagnosis in this paper. The depth of the architecture is increased in each module to extract features. And then, the backpropagation with cross-entropy loss is employed for classification. The maximum average accuracy of 99% is obtained for classification, the sensitivity of 98%, and specificity of 100% are obtained by DNN-PDIM-4 architecture. The results contained in this study demonstrate that the DNN-PDIM can induce adverse effects on MRI brain image classification. The outcomes of the DNN-PDIM system may help the physician to diagnose brain cancer more accurately. Further, the DNN-FDIM will provide useful tools to design new architectures for medical image diagnosis. To further analyze the DNN-PDIM architecture, a residual module can be implemented to classify the MRI brain scans more accurately.

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