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Brain Tumour Biomarkers by Deep Learning Architectures

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Abstract:

Brain tumour may be detected by the use of different medical imaging modalities such as Computed Tomography (CT) and Magnetic Resonance Imaging (MRI). MRI has been shown to be effective in screening brain tumour than CT. Deep features have been proposed for brain image classification on the basis of two different architectures; Visual Geometric Group (VGG) and Inception Architectures (IA). The need to characterize the brain images as normal or abnormal leads to different deep learning algorithms for the extraction of deep features. The MRI brain image dataset REpository of Molecular BRAin Neoplasia DaTa (REMBRANDT) is studied in this work for the classification. It contains 200 brain images with 100 related to normal and 100 to abnormal. For the analysis, same set of training and testing samples obtained via random split of 50:50 are used by the VGG-16, VGG-19, IA-V1 (GoogleNet) and IA-V3.The classification performance in percentage accuracy, sensitivity and specificity with the above architectures are recorded. Results show that IA-V3 provides best average performance of 95.1% accuracy.

Keywords: brain images, brain tumour, visual geometry group, inception module, neural networks.

1. Introduction

The automatic diagnosis of brain tumour using a computerized system is the need for the hour as the brain cancer increases day-by-day. In image based classification, the VGG architecture is the mostly used architecture. It is modified in [1] for MRI brain image classification. The standard max pool layer is modified to median pool layer for reducing the dimension of the extracted deep features. The convolution dictionary learning is discussed in [2] for brain tumour diagnosis that includes the local constraint. It integrates the dictionary learning to extract deep features into a Convolution Neural Network (CNN).

A multi-scale CNN is described in [3] for the classification of brain images after tumour segmentation. The prediction is made by pixel wise observation based on the highest intensity values from the tumour segmented using CNN architecture. MRI brain images of bilingual and monolingual people are employed for classifying brain tumours in [4]. Artificial Neural Networks (ANN) are employed which takes tract based spatial statistics for the classification. It uses different number of neurons for the performance analysis until the best accuracy is reached.

A deep CNN with additional differential operator is used in [5] for brain image classification. It generates an additional feature map due to the differential operator used in deep CNN. It uses contrast calculations to extract the pixel direction pattern for effective classification. Transfer learning is utilized in [6] for brain image classification. It uses IA as basic deep CNN architecture and the brain images are classified using transfer learning. At first the images are normalized and down-sampled before classification.

An approach to classify MRI images into cancerous or normal by the CNN is discussed in [7]. It uses transfer learning with VGG-16, ResNet50 and IA-V3 as base for the classification. Also, data augmentation is introduced to increase the images in the database. A blended ANN is implemented in [8] for effective classification of MRI brain images. The features obtained from wavelet transform are reduced using statistical calculation before applying to blended ANN for classification.

A feed forward ANN with random forest classifier is discussed in [9] for efficient classification. At first, median filter based pre-processing is applied to remove noises and then wavelets and colour moments are treated as features. Then optimal set of features are selected as inputs

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for ANN classification. A deep leaning model is discussed in [10] for brain image classification. Two models; IA-V3 and DenseNet201 are analyzed. The softmax layer is used to classify the combined deep features from the pretrained IA-V3 model and DenseNet201 model.

The aim of this work is to increase the accuracy of screening of brain tumour using MRI brain images. The rest of the paper is as follows: Section 2 describes the deep learning architectures to obtain the biomarker for brain tumour diagnosis. Section 3 evaluates the different architectures applied to brain tumour diagnosis by a number of experiments using random split and provides the obtained performances. Section 4 summarizes the work with the conclusion arrived.

2. Methods and materials

This section concentrates on the classification brain tumour via the use of deep learning architectures. The use of deep learning is advantageous as it is designed to specifically extract deep features and classify them in a single module rather than using two separate modules in the conventional machine learning approaches. The dimension of the extracted deep features from the brain images is much larger than the conventional feature extraction techniques such as moments, statistical and spectral features. The main difference in the deep learning architectures lies in the layer's arrangement. In general, convolution and max pooling layers are utilized for the extraction of deep features and then a fully connected layer which has a neural network design for the classification. Figure 1 clearly shows the arrangements of layers for VGG16 [11] and IA-V3 [12] architectures.

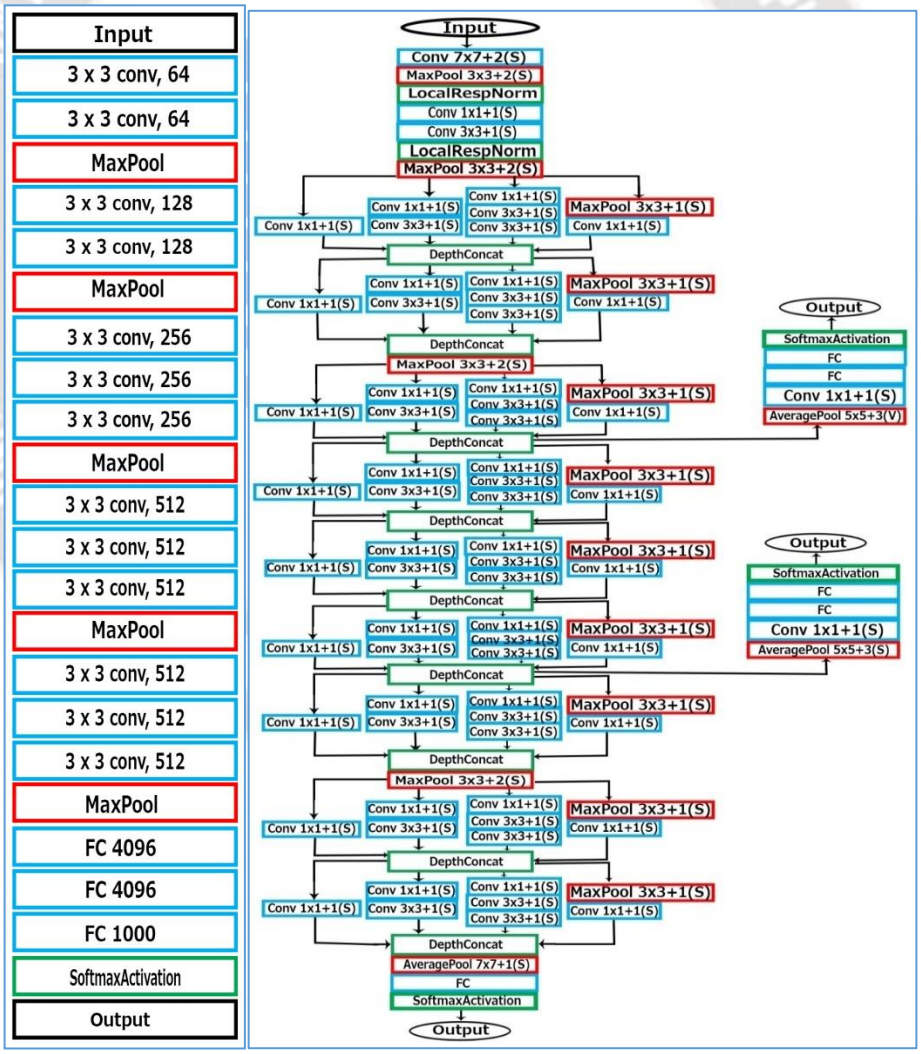

Figure 1. Arrangement of layers in VGG16 and IA-V3

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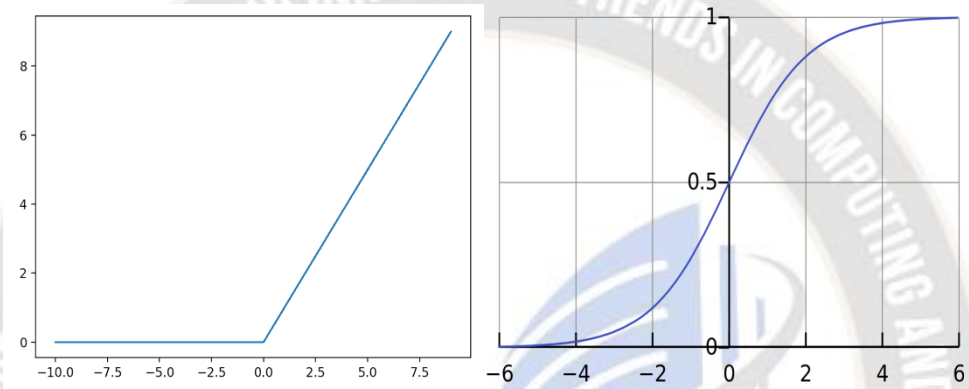
The classification performance of a system depends on the process of picking the best dominant values or features from the images. This leads to a nontrivial process that needs deeper features that explores only a finite subset of features. To extract deep features, many convolution filters with different kernel size are used, In VGG architecture, kernel size of 3x3 is used throughout the design whereas IA-V3 uses 3x3 and 5x5 sized kernel. Also, pooling is used to reduce the deep feature dimension.

Neural networks are highly successful in solving non-linear and non-separable problem such as glaucoma diagnosis [13], facial emotion detection [14] and pneumonia classification [15]. For an NN, choosing suitable parameters are imperative to the success of the learning process. Activation functions are also important to overcome the vanishing gradient. Also, other important parameters such as learning rate, loss function and batch size also makes the learning process more effectively to produce a good system. Figure 2 shows the activation functions used in both architectures.



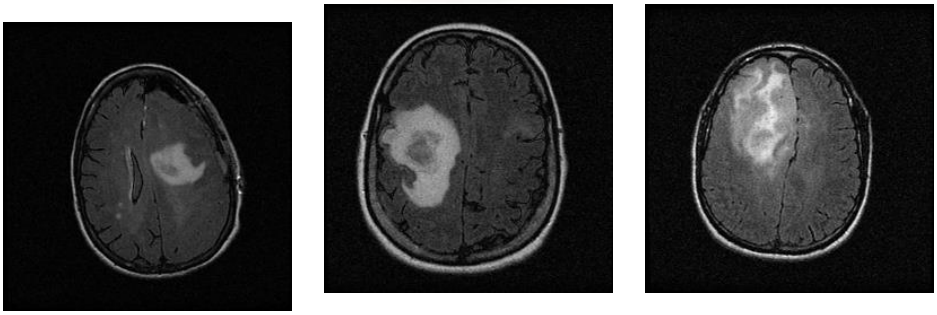
(a) (b)

Figure 2 Activation functions (a)Input layer (ReLu) (b) output layer (softmax)

The stochastic gradient descend algorithm is used as an optimization in the hidden layer that greatly relates to the setting of the initial values and the stopping condition. An inappropriate setting may cost cost more time to converge, or lead to a convergence towards other unexpected local minima. So different initial settings of are investigated and the one that gives the maximum accuracy is chosen.

3. Results and Discussions

The deep learning techniques presented in the previous section are employed to perform deep feature extraction and pattern classification so as to identify or classify the abnormal MRI brain images from the REMBRANDT database [16-17]. It contains images from 130 subjects. A total of 200 images are selected [18] with 100 related to normal and 100 to abnormal. Figure 3 shows samples used in this study.



(a) abnormal

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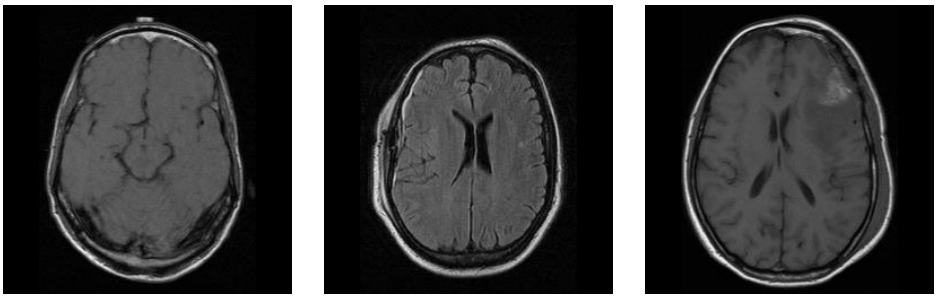

(b) normal

Figure 3 Samples used in this study

In this work, the deep learning architectures using VGG and IA based on random split with 50% for both training and testing is evaluated using the REMBRANDT benchmark database images. The available samples are randomly divided ten times. In each trial, the selected 50% samples are used for test and 50% for training. The mean values of the ten test accuracies, precisions and recalls are used to evaluate the final performance evaluation. The obtained measures based on the random split are summarized in Table 1 and compared with different architectures of VGG and IM.

Table 1 Accuracy of the biomarkers by deep learning architectures

#Run	Accuracy			
	VGG-16	VGG-19	IA-V1	IA-V3
1	91	90	91	93
2	97	95	95	96
3	95	94	92	93
4	96	95	95	97
5	92	90	93	94
6	90	89	95	97
7	92	91	94	95
8	88	86	95	96
9	94	92	92	94
10	93	92	94	96
Avg	92.8	91.4	93.6	95.1

Table 2 Sensitivity of the biomarkers by deep learning architectures

#Run	Sensitivity (%)			
	VGG-16	VGG-19	IA-V1	IA-V3
1	92	90	93	94
2	98	96	94	96
3	96	95	93	94
4	98	96	96	98
5	94	91	95	96
6	90	89	96	98
7	92	91	95	96
8	88	85	97	98
9	96	93	94	96
10	94	93	94	96
Avg	93.8	91.9	94.7	96.2

Table 3 Specificity of the biomarkers by deep learning architectures

#Run	Specificity (%)			
	VGG-16	VGG-19	IA-V1	IA-V3
1	90	90	89	92
2	96	94	96	96
3	94	93	91	92
4	94	94	94	96
5	90	89	91	92
6	90	89	94	96
7	92	91	93	94
8	88	87	93	94
9	92	91	90	92
10	92	91	94	96
Avg	91.8	90.9	92.5	94

It can be seen from Table 1 that the performance of all architectures are over 90% and the IA-V3 architectures gives an average accuracy of 95.1% with 10 runs of testing with random split. The average sensitivity of IA-V3 is 96.2% and the specificity is 94%. The performance of the systems are in the order of IA-V3 < IA-V1 < VGG-16 < VGG-19. Also, it is noted that IA architectures provide promising results than VGG architectures. Figure 4 shows the average performances of the system for brain image classification.

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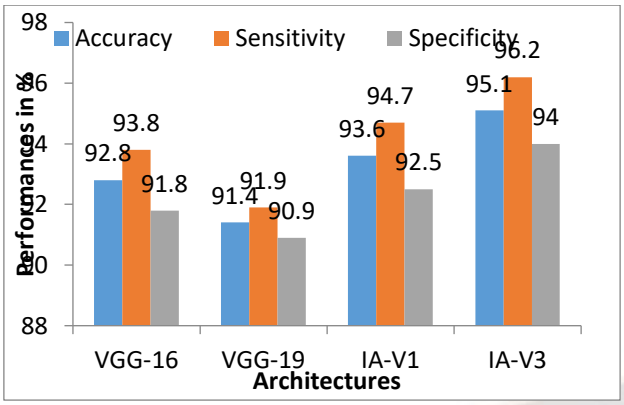

Figure 4 Average performances of the architectures for brain image classification

4. Conclusion

In this work, biomarker for brain image classification employing deep learning architectures is presented. The biomarker seeks deep features from the architectures corresponding to normal and abnormal patterns in the brain image. Four different architectures are studied including VGG-16, VGG-19, IA-V1 and IA-V3. All of these architectures are considered for the classification of MRI brain images. The effectiveness of the proposed biomarker from the deep learning architectures is demonstrated using REMBRANDT database to identify the abnormality present in it. The classification performances are shown in terms of accuracy, sensitivity and specificity for ten rums and their average performances are also computed. Results show that IA-V3 provides higher performance than the famous VGG architectures.

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