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BrainNet: A Deep Learning Approach for Brain Tumor Classification

Tripty Singh[a,*], Rekha R Nair[b], Tina Babu[b], Atharwa Wagh[a], Aniket Bhosalea[a], Prakash Duraisamy[c]

[a]*Department of Computer Science and Engineering, Amrita School of Computing, Bengaluru, Amrita Vishwa Vidyapeetham, India*
[b]*Department of Computer Science and Engineering, Alliance University, Bengaluru, India*
[c]*University of Wisconsin-Green Bay Wisconsin, USA*

Abstract

Cancer, regardless of its type, represents a formidable threat to human life and disrupts the delicate balance of normal bodily functions. Among the various forms of cancer, malignant brain tumors stand out as a leading cause of mortality in both adult and pediatric populations. The timely identification of these brain tumors is crucial for attaining precise diagnoses. Brain tumour identification and diagnosis are now made possible by the use of magnetic resonance imaging (MRI). However, the intricate and irregular shapes and locations of these tumors often pose challenges for complete comprehension. Typically, the expertise of neurosurgical specialists is required for the precise analysis of MRI scans. Unfortunately, in many developing countries, a shortage of skilled medical professionals and limited awareness about brain tumors compound the difficulties associated with obtaining timely and accurate MRI results. To address these notable challenges, this research introduces BrainNet, an innovative Convolutional Neural Network (CNN) architecture specifically designed for the classification of brain tumors into distinct categories. The established transfer learning models VGG13, VGG19, VGG16, InceptionResV2, and Squeeznet, all of which were pretrained on the Imagenet dataset, are outperformed by BrainNet in both how well it handles these problems and how well it outperforms them. The performance of the BrainNet CNN architecture is particularly impressive, with a precision score of 94.75 percent and accuracy rates of 99.96 percent during training and 97.71 percent during testing. This accomplishment has the potential to significantly improve brain tumour diagnosis and classification, particularly in areas with limited access to medical resources and knowledge.

Keywords: Brain tumor; Deep Learning; Transfer Learning; Brain MRI scans; Convolution Neural Network

* Corresponding author. Tel.: +0-000-000-0000 ; fax: +0-000-000-0000.
E-mail address: tripty singh@blr.amrita.edu

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1. Introduction

Brain tumors (BT) are a diverse medical condition affecting a significant global population [1]. Among brain cancers, they are considered highly dangerous. The incidence of brain cancer is generally lower compared to other types of malignancies [2]. Brain tumours are now categorised by the World Health Organisation (WHO) as a distinct subtype of malignancies that affect the central nervous system following a revision to its classification in 2020. Common types of brain tumours comprises gliomas, meningiomas, acoustic neuromas, and pituitary tumours. Studies indicate that Glioma, Meningioma, and Pituitary tumors collectively account for 75% of all brain tumors [3].

The degree of malignancy in each of these tumour forms varies. A cancer known as a meningioma can grow on a protective layer which covers the brain's cortex and the vertebral column or the spinal cord. Glioma is a type of brain tumor that originates from glial tissues in the brain and spinal cord. Pituitary tumors, on the other hand, develop in the area of the pituitary gland [4].

According to Tandel et al., during the initial assessment of brain tumours, oncologists routinely use medical imaging techniques including Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scans as part of their normal protocol. These modalities provide comprehensive insights into the structure of the brain, facilitating the detection of any irregularities or abnormalities. Recent progress in brain tissue imaging techniques has resulted in enhanced image quality, contrast, and resolution. These advancements empower radiologists to identify even minute lesions, thereby elevating the precision of diagnostic assessments [5, 6].

The timely identification of brain cancer is pivotal for successful treatment and rehabilitation. In the realm of IoT healthcare, researchers and medical experts have devised numerous non-invasive techniques for categorizing brain tumors and identifying brain cancer. Computer-based automated diagnostic systems (CADS) created towards the detection of tumours in the brain heavily rely on machine learning (ML) and deep learning (DL) models.

In response to these pressing issues, the scientific community has ventured into the realm of artificial intelligence (AI) and deep learning to craft innovative solutions. Conventional techniques, such as manual feature extraction, rule-based systems, and classical machine learning algorithms, have been deployed to tackle brain tumor classification. However, these methods are plagued by inherent limitations. Classical machine learning algorithms, although capable of handling diverse data, are limited by their dependence on handcrafted feature vectors. This reliance often leads to suboptimal performance, especially when faced with the high-dimensional and complex nature of medical images.

Considering these limitations, there is a compelling need for a paradigm shift. Deep learning, with its ability to autonomously acquire complex patterns and representations from raw data, has emerged as a transformative force in the field of medical image analysis. In this paper, "BrainNet," a cutting-edge CNN architecture created specifically with regard to multiclass classification of cancers of the brain is introduced. BrainNet not only addresses the shortcomings of traditional methods but also establishes new benchmarks in terms of accuracy and efficiency. CNN models are widely applied in image classification and analysis, especially in the domain of medical image data. They have gained recent prominence for diagnosing brain cancer using image data[7, 8]. The ability of CNN to distinguish closely related features from the data allows it to classify images accurately [9]. In the IoT healthcare industries, data augmentation and transfer learning approaches can also enhance the prediction potential of deep learning models for precise brain cancer diagnosis and brain tumour categorisation [10].

The research objectives for the study on brain tumor classification using the BrainNet CNN can be outlined as follows:

- Design and build the BrainNet Convolutional Neural Network, including the required layers and parameters, for the precise classification of brain tumours. This is known as the BrainNet CNN architecture.
- Dataset Preprocessing: The collected comprehensive dataset of brain MRI scans contains diverse tumor types and variations. Preprocess the dataset to ensure consistency and suitability for training.
- Model Training and Optimization: Train the BrainNet model using the prepared dataset, and employ optimization techniques to enhance its performance, including hyperparameter tuning and data augmentation.
- Performance Evaluation: Evaluate the performance of BrainNet in terms of accuracy, precision, recall, F1-score, and other relevant metrics for multiclass brain tumor classification.
- Comparison with Transfer Learning Models: Compare the performance of BrainNet against established transfer learning models (VGG13, VGG19, VGG16, InceptionResV2, Squeeznet) to demonstrate its superiority.

The remainder of the text has been laid out as per. The most recent advancements in this research area are described in Section 2. The proposed technique is elaborated in Section 3, followed by the dataset description in Section 4. Performance measures that are used to evaluate the model in mentioned in Section 5. Section 6 provides examples of the experiment's findings. The paper concludes in Section 7.

2. Research Review

Recently, a range of imaging modalities, with a focus on MRI scans, were considered to recognise and categorise cancers of the brain using ML and DL algorithms [11, 12, 13]. Zacharaki and colleagues created a brain cancer identification mechanism that utilized machine learning models such as SVM and KNN for the classification of various glioma types. They achieved classification accuracies of 85% and 88%, respectively. [14]. To further enhance classification performance, A classification scheme for brain tumours was put forth by Cheng et al., which enhanced the definition of the tumour territory. The accuracy of their method, which combined three feature discovery techniques (Grey level co-occurrence matrix, intensity histogram and bag of words), was 91.28 percent. [15].

Convolutional neural networks (CNN) were trained using axial brain tumour pictures by Paul et al. The suggested approach's ultimate classification phase included two convolution layers, two completely linked layers, two max-pooling layers, and attained a recognition rate of 91.43 percent [7]. El-Dahshan et al. utilized 80 MRI brain images with brain tumors for classification. They used the discrete wavelet transform and PCA approaches to deduct the dimensionality concerning the data, using ANN and KNN machine learning classifiers to differentiate between benign and malignant tumors. The classification accuracy for ANN and KNN classifiers was 97% and 98%, respectively [16].

Febrianto presented a deep CNN-based system for automated brain cancer identification and grading, as well as fuzzy C-Means (FCM) for brain segmentation. Segmented regions' shape, texture, and characteristics were retrieved, then fed into SVM and DNN classifiers, resulting in a 97.5 percent accuracy rate [17]. In a different study, Afshar et al. developed a capsule network and brain MRI scans with coarse cancer borders to classify brain tumours. The system had an accuracy of 90.89% [18].

In order to classify brain tumours with an accuracy of 94.2 percent, Anaraki et al. employed a GA-CNN framework that merged GA and CNN [19]. Khan et al. reported accuracy rates of 94.82 percent for their CNN-Transfer learning system for identifying brain tumours [20]. The proposed multi-classification method demonstrated good results by combining deep features and ML methods. For the purpose of accurately detecting brain tumours from MRI scans, the scientists proposed a Convolutional Neural Network (CNN) structure. This study also compares a number of models, including as VGG16, ResNet-50, and Inception V3, to the suggested architecture [21]. Methil et. al introduced a novel approach for brain tumor detection in diverse brain images. This method initiates with the application of distinct image preprocessing techniques, including histogram equalization and opening, followed by the utilization of a convolutional neural network [22].

A review of the literature found that current methods for diagnosing brain cancer lack the predictive ability necessary to accurately and consistently identify the illness, allowing for the commencement of therapy and the patient's recovery. Consequently, a trustworthy method to precisely detect brain tumours is required.

In this research, a novel CNN architecture is introduced for brain tumor classification. The performance of this newly designed CNN is compared with two pre-trained benchmark architectures, VGG16 and Inception ResNetV2. The aim is to assess the effectiveness and efficiency of the proposed CNN in accurately classifying brain tumors compared to these well-established benchmark models.

3. Proposed work

An extensive explanation of the BrainNet approach is given in this section, along with details on the preprocessing procedures, CNN architecture, and training procedure. The general workflow is shown in Fig. 1.

3.1. Image Preprocessing

Prior to feeding the brain images into the CNN, we employ a series of preprocessing techniques to enhance the quality and suitability of the input data. These techniques include histogram equalization and morphological open-

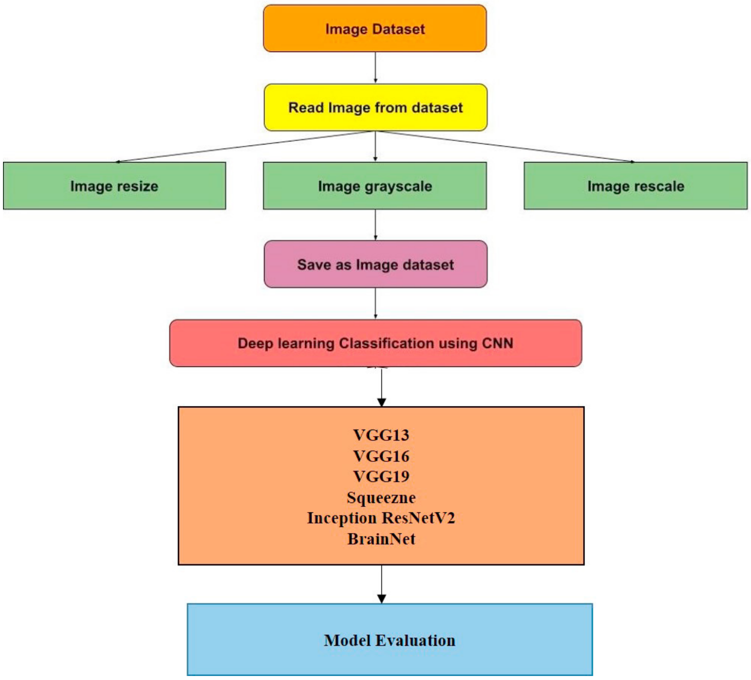


Fig. 1: Typical process flow for tumor classification

ing. Histogram equalization enhances the contrast of the images, making it easier for the network to discern critical features. Morphological opening aids in noise reduction and smoothes the images for improved feature extraction.

3.2. BrainNet architecture

BrainNet leverages the power of deep learning through a meticulously designed CNN architecture.The CNN uses several convolutional layers to extract hierarchical characteristics from the input images, which are then followed by max-pooling layers. In the pursuit of enhancing network convergence and mitigating the vanishing gradient problem, techniques like batch normalization and the utilization of rectified linear units (ReLU) are incorporated into the model.

Fig. 2 illustrates the newly designed CNN architecture, which comprises seven convolution layers. After each convolutional layer, a sequence of layers consisting of a Batch Normalization layer and a max pooling layer is applied. Within the convolutional layer, the image matrix undergoes convolution with a filter or kernel matrix. Each filter plays a vital role in extracting unique features from the image. This convolution process results in the feature map.

Following matrix multiplication, the dimensions of the feature map are as follows:

$$\left(\frac{m - f + 2a}{s + 1}\right) \times \left(\frac{m - f + 2a}{s + 1}\right) \tag{1}$$

The size of the original picture ($mtimesm$), the size of the kernel or filter (f), the stride (s), which controls how the kernel progresses over the image, and the amount of padding (a) are some of the variables that affect the feature map's dimensions. The dimensions of the feature map gradually change during the multiplication of the matrix operation among the image matrix and filters, frequently resulting in a reduction in size. Padding is used, which involves incorporating zero layers to the image matrix's outer edges in order to keep the image's size constant with the input.

In each of the seven convolution layers, LeakyRelu is used as the activation function. LeakyRelu helps to address the dying Relu problem, ensuring that neurons do not become inactive during training. Mathematically, LeakyRelu can be represented as:

$$f(x) = max(0.1x, x) \tag{2}$$

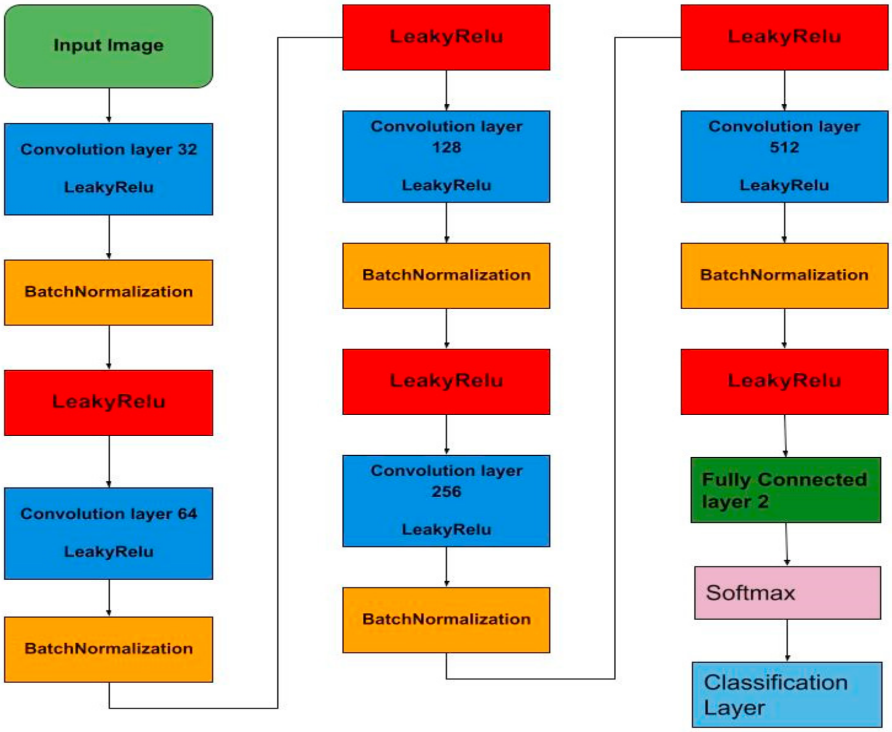


Fig. 2: Architecture of the proposed model

After the convolutional layer, a Batch Normalization layer is incorporated into the network. Deep neural networks commonly encounter an issue known as multi-covariate shift during training. This issue arises when the distribution of inputs to each layer undergoes variations, particularly as the number of filters employed in each layer varies. As a result, the input to consecutive layers changes in each iteration, leading to random distribution and causing instability and slow learning in the network. Batch normalization is employed to address this issue by stabilizing the network and accelerating training.

Following the batch normalisation layer in the network is the max pooling layer. In the max pooling layer, a predetermined stride is employed to traverse the convoluted matrix or feature map, identifying and extracting the most prominent pixel value, which corresponds to the largest value within the designated kernel. This operation serves the purpose of mitigating overfitting and noise within the data by isolating the most crucial features. In the architecture under consideration, the pooling kernel size is established at 2×2.

The initial convolution layer consists of 32 filters, each with a size of 3×3. The second and third convolution layers contain 64 filters, both with a size of 7×7. The fourth and fifth convolutional layers are equipped with 128 filters, each with dimensions of 7×7. In the sixth convolutional layer, there are 256 filters, each with dimensions of 7×7, and in the seventh convolutional layer, 512 filters are used, again with the same dimensions of 7×7.

Following the convolutional layers, a flattening layer is introduced within the network. It is primarily responsible for transforming the complex feature matrix into a single linear vector made up of pixel values. In order to accomplish this, the subsequent rows of the complicated matrix are concatenated to the end of the first row by concatenating them after the initial row. As a result, the original $N \times N$ matrix undergoes a transformation into an $N^2 \times 1$ matrix, commonly referred to as a column vector. This flattening process is a standard procedure employed to prepare the data for the subsequent fully connected layers within the neural network.

The network moves on to the dense levels or fully connected layers after the flattening layer. These layers combine to create a Recurrent Neural Network (RNN), which is in charge of categorizing the picture vectors into different groups. In this architecture, two dense layers are incorporated, each followed by dropout layers characterized by a dropout rate of 25%. These dropout layers serve to enhance the network's robustness and mitigate overfitting. The LeakyRelu activation function is utilized in these dense layers.

To address overfitting observed during training, dropout layers were introduced after the dense layers. When employing a dropout rate of 25%, it means that during training, approximately 25% of the neurons within the fully connected layers are effectively ”deactivated” or rendered inactive. This implies that their weights will not undergo updates during the training process. This random dropout of neurons helps reduce overfitting as a different set of 25% neurons is set to be ”dead” for each epoch.

At the conclusion of the network architecture, the output layer, serving as the final layer, comes into play. In the context of this multi-class classification problem, the output layer employs the softmax activation function. This choice of activation function allows for the computation of probabilities associated with the input's membership in each class, ultimately yielding the definitive classification output.

3.3. Training Process

We elaborate on the training process, which involves the use of labeled brain image data to optimize the network's parameters. The training process for BrainNet employs a robust optimization algorithm, like stochastic gradient descent (SGD), coupled with a suitable loss function, such as categorical cross-entropy, which is specifically tailored to facilitate multiclass classification.

3.4. Model evaluation

This section discuss the rigorous evaluation protocol employed to assess BrainNet's performance. This includes metrics such as training and test accuracy, precision, recall, F1-score, and confusion matrices. The proposed model's predictability and robustness are guaranteed by the evaluation procedure.

The proposed model was compared against five well-known pre-trained benchmark architectures—specifically, VGG19, VGG16, VGG13, ResNetV2, Inception, and Squeeznet—in order to assess its efficacy. These benchmark models have been widely used in various image classification tasks and serve as reference points for evaluating the effectiveness of the newly designed CNN architecture. The comparison allows researchers to understand how well the proposed model performs in comparison to well-established and widely recognized models in the field of image classification, helping to validate its performance and potential advantages.

4. Data set

The dataset used for the study comprises training and testing folders, with each folder containing four subfolders representing the classes: Meningioma, Glioma, no Tumor and Pituitary, as depicted in Fig. 3. The training set consists of approximately 1400 images in each class, while the testing set contains 300 images in each class.

Class	Test set images	Training set images
No Tumor	405	1595
Glioma	300	1321
Pituitary	300	1457
Meningioma	306	1339
Overall outcome	1311	5712

Table 1: Dataset distribution

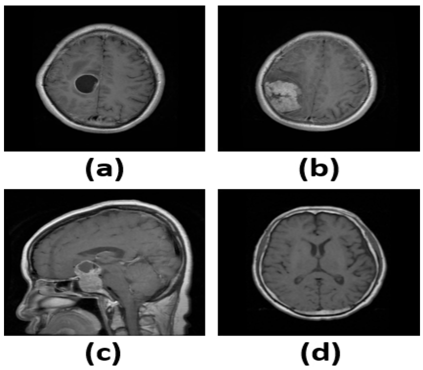


Fig. 3: Model Accuracy for SelectKBest

The information for the dataset was taken based on the webpage https://figshare.com/articles/dataset/brain_tumor_dataset/1512427. For a comprehensive overview of the dataset's characteristics, please refer to Table 1, which furnishes details regarding the quantity of images and the distribution of classes.

5. Performance measures

In evaluating the effectiveness of the proposed BrainNet model, a comprehensive a group of 4 evaluation measures was employed: Accuracy, F1 score, Precision, and Recall. The confusion matrix must be created and represented visually in order to compute the specified metrics correctly. This matrix serves as a detailed and informative summary of the model's classification outcomes for each class, facilitating a thorough analysis of its performance

The percentage of transactions that the algorithm correctly classifies is measured by the most important component of accuracy. Its calculation is as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

Precision is an important metric, particularly when the cost of False Positives is significant and needs to be minimized. It is calculated as follows:

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

Recall holds significant importance as a metric, particularly when there are significant consequences associated with False Negatives that demand careful consideration. Its calculation is as follows:

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

Precision and Recall are combined using their harmonic mean to create the F1-score. It proves especially valuable in situations where datasets are imbalanced. This is especially important because relying solely on accuracy can yield biased results when the majority class overwhelms the dataset. The F1 score provides a balanced evaluation that considers both Precision and Recall, making it more appropriate for such scenarios. It is calculated as follows:

$$F1\_Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{6}$$

6. Experimental Findings and Assessment

6.1. Configuration for Experiments

Entire experimentation was conducted using Google Colab as the computing environment. The optimization technique employed was Stochastic Gradient Descent (SGD), with a consistent learning rate set at 10^{-3}. Categorical cross-entropy was used as the loss function for this model.

Random shuffling was enabled and the training set was divided into a validation set and a training set.m This ensures that different sets of images are used for validation in each epoch, preventing overfitting.

Table 2 provides a thorough overview of the performance of the suggested model by summarising the findings from these experiments.

It is clear from the metrics listed in Table 3 and the confusion matrix shown in Figure 4 that the proposed model is the best option for correctly categorising tumours in this dataset. Additionally, a closer examination of the accuracy plots for all three models highlights the remarkable capability of the proposed model to rapidly grasp the dataset's intricacies compared to the pre-trained models. The proposed model achieved convergence in only 10 epochs, after which both the training and validation accuracy curves progressed smoothly and in parallel, indicating stable learning.

The pre-trained models, on the other hand, show considerable variations during the whole training process as seen in the accuracy plots, in contrast to the smooth and stable behaviour seen in the suggested model. This suggests that the pre-trained models had a more challenging time learning and adapting to the dataset compared to the proposed model. Overall, the proposed model demonstrated superior performance in terms of accuracy and learning efficiency.

Framework	Testing accuracy (%)	Training accuracy(%)
VGG19	93.05	90.62
VGG16	88.52	89.82
VGG13	88.93	89.01
Squeeznet	90.69	91.26
BrainNet	97.71	99.96
Inception ResNetV2	95.86	96.09

Table 2: Comparison for model performance

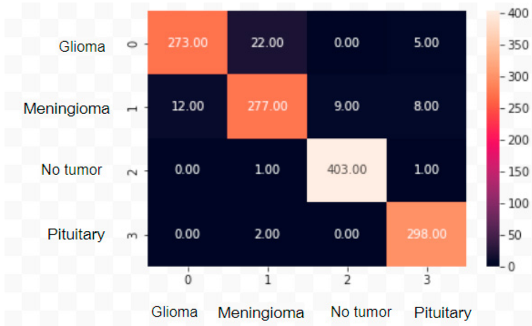
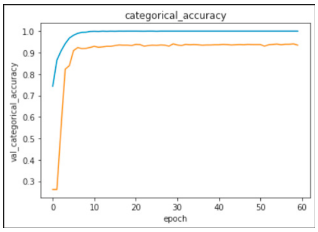


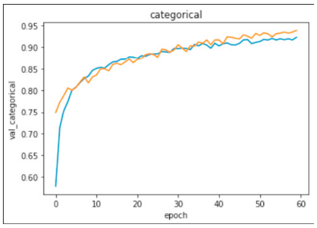
Fig. 4: Analysis of the confusion matrix for the BrainNet model

Table 3: An assessment of the proposed model performance on a class-by-class basisl Performance

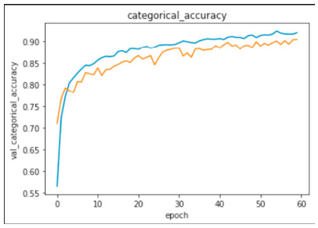
Category/Measure	F1 score	Recall	Precision
Pituitary	0.98	0.99	0.96
No Tumor	0.98	0.99	0.97
Meningioma	0.90	0.87	0.93
Glioma	0.93	0.93	0.93



(a) Accuracy graph BrainNet

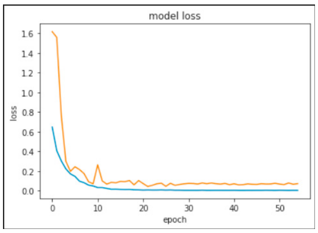


(b) Accuracy graph InceptionResNet V2

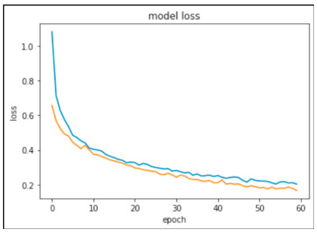


(c) Accuracy graph VGG16

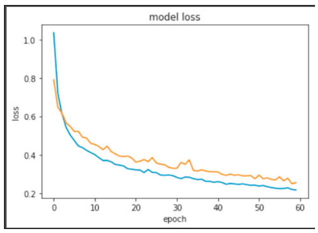
Fig. 5: Accuracy of various networks



(a) Loss graph of BrainNet



(b) Loss graph of InceptionResNetV2



(c) Loss graph of VGG16

Fig. 6: Loss of various networks

In this research, a novel model for brain tumor classification employing brain MRI scans was introduced. To gauge its effectiveness, the proposed model was subjected to a rigorous comparison alongside five prominent models: Squeeznet, VGG19, VGG16, VGG13, ResNetV2, and Inception. The proposed model consistently outperformed the other architectural options in a thorough comparatives analysis, demonstrating its effectiveness in the task of classifying brain tumours.

To ensure an equitable and unbiased comparison, all six models were assessed under identical conditions on the same platform. It's important to note that ResNetV2 and VGG models are typically designed for RGB images, while the brain MRI scans utilized in this study are in grayscale format. To make the comparison feasible, the dataset was modified to have extra channels added to the grayscale images, converting them to 3-channel images similar to RGB images. This allowed the use of the existing pre-trained weights of the models without any modifications.

To ensure uniformity throughout training process, a consistent learning rate of 10^{-3} was applied to all six models, coupled with the utilization of categorical cross-entropy loss function. Each of the six models underwent an extensive training regimen spanning 60 epochs, a duration carefully chosen to provide ample iterations for the models to effectively discern and classify the intricate patterns within the data.

The performance of the suggested model was assessed by taking into account a number of important metrics:

1. The key parameters under evaluation include the model's classification accuracy, computational load, and learning rate. The latest results demonstrate that the proposed model surpasses the performance of the previous five pretrained models in terms of classification accuracy.
2. The model's computational complexity, which is measured by the number of learnable parameters it possesses, is the second metric. Now, parameters are simply the weights that the network learns to use during training. As the number of parameters to be learned increases, so does the model's complexity. In other words, a model that has fewer trainable parameters can learn the dataset more rapidly and effectively. When compared to VGG16, which has approximately 133 million of parametrs for training, ResNetV2, Inception, with around 58 million parameters, the suggested model is notably more lightweight, consisting of just 10 millions of parameters. There are thus the fewest trainable parameters in the model that is being given.
3. The model's learning rate makes up the third measure.The proposed model attained an accuracy surpassing 90% during just 10 epochs and consistently maintained this high level of accuracy throughout the following epochs up to 60, according to the examination of accuracy plots for all three models. The other two models, on the other hand, needed more epochs (more than 20) to reach about 90% accuracy and still weren't stable.
   In particular, the accuracy graph of Inception ResNetV2 shows instances where the validation accuracy surpassed the training accuracy, which is not expected and indicates poor learning of the model.

These results lead to the conclusion that the proposed model showed the greatest learning potential for the given dataset. Its rapid convergence to high accuracy and stable performance throughout training showcase its efficiency and effectiveness in learning the complex patterns of brain tumor classification from the data.

In considering the three criteria that have been addressed, it is evident that the proposed model has performed better than the other models in comparison. It is the most suitable choice for the task of classifying brain tumors due to its greater accuracy, reduced computing intensity with fewer parameters, and effective learning behavior.

7. Conclusion

The classification of tumors holds immense significance in the early detection of diseases. In this research work, a pioneering Convolutional Neural Network (CNN) architecture named BrainNet is introduced. BrainNet is a specialized system created with the primary objective of accurately classifying and diagnosing brain tumors. The proposed model exhibits rapid and efficient learning, attributed to its smaller number of trainable parameters compared to other architectures. The proposed model exhibits remarkable performance, surpassing all other pre-trained models with an outstanding training accuracy of 99.96% and an equally impressive testing accuracy of 97.71%.

Future applications of the proposed methodology in tumour categorization show substantial promise beyond its current focus on brain tumours. This potential also applies to radiological pictures, providing intriguing chances to improve tumour diagnosis across different medical imaging datasets.

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