

BRAIN MRI IMAGES FOR BRAIN TUMOR DETECTION USING DEEP LEARNING

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Abstract

Artificial Intelligence through advanced algorithms, such as deep learning, has recently been applied in medical imaging, representing an emerging area in the classification of medical pathologies. Deep learning has been widely applied in medical imaging to help automate and improve medical image analysis. Medical imaging techniques such as MRIs, CT scans, and X-rays produce large amounts of data that can be difficult for human experts to accurately interpret and analyze. Deep learning algorithms can be trained to recognize patterns in medical images, identify abnormal features, and make predictions about

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patient outcomes. The present research work exposes an automatic classification model to detect brain tumors in brain magnetic resonance images (MRI). The data set is found in the Kaggle repository, which consists of 253 MRI images: 155 with brain tumors and 98 without. The proposed model can classify brain tumor MRI images with 91% accuracy. Therefore, the model represents an auxiliary tool to existing conventional methods for the diagnosis of brain tumors.

Keywords: deep learning, MRI images, automatic classification model.

1. Introduction

A brain tumor is a mass or lump of abnormal cells found in the brain. There are two main types of tumors: cancerous (malignant) tumors and benign tumors. Cancerous tumors can be divided into primary tumors, which start within the brain, and secondary tumors, which have spread from elsewhere, known as brain metastasis tumors. Today, deep learning, a subfield of Artificial Intelligence, is capable of classifying, diagnosing, segmenting, and providing a medical diagnosis, in other words, it is a computer-aided diagnosis (Abd-Ellah et al. [1]).

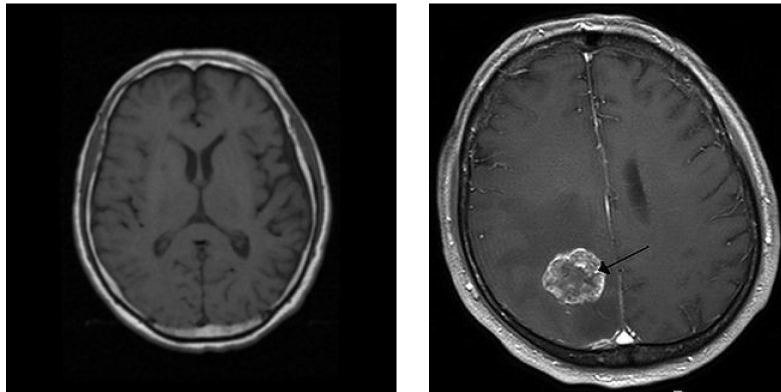


Figure 1. Set of images divided into benign (left) and malignant (right) tumors.

Source: <https://www.kaggle.com/datasets/navoneel/brain-mri-images-for-brain-tumor-detection>

The early detection of brain tumors is crucial for successful treatment and improved patient outcomes. Brain tumors can be difficult to diagnose due to their location, size, and shape. Deep learning algorithms can help automate the process of analyzing medical images and accurately identifying brain tumors (Paul et al. [17]). Deep learning algorithms can quickly analyze large amounts of medical imaging data and identify patterns that may be difficult for human experts to detect. This can lead to earlier detection of brain tumors and help doctors make more informed decisions about treatment options. In addition, deep learning algorithms can help differentiate between different types of brain tumors, which can have different treatment approaches and outcomes (Tandel et al. [21]). Accurately identifying the type of brain tumor can help doctors plan the most effective treatment for the patient. Overall, the use of deep learning in detecting brain tumors can lead to earlier detection, more accurate diagnoses, and improved patient outcomes. Our model represents a valuable alternative in medical diagnosis because it helps physicians make more informed and accurate decisions about the diagnosis and treatment of patients. In the past, physicians had to rely on the interpretation of MRI images performed by a specialist, which can lead to human error and sometimes late diagnosis (Liu et al. [11]). With our model, clinicians can get accurate and fast results, which can save time and ultimately improve patient outcomes. The model can process large amounts of MRI images in a short time, this represents an added value. On the other hand, it helps clinicians to identify patterns and trends in data more efficiently and effectively. In summary, our automatic classification model for MRI images is a promising alternative in medical diagnosis because it improves accuracy, efficiency, and patient outcomes (Naser [15]).

2. Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are advanced algorithms that have been widely used in the detection of brain tumors in medical imaging (Wu [23]). CNNs are particularly well-suited to image recognition tasks, making them ideal for analyzing MRI scans and

detecting brain tumors. CNNs use a series of convolutional layers to extract features from an image, followed by fully connected layers that perform the classification task. In the context of brain tumor detection, a CNN can be trained to recognize patterns in medical images that indicate the presence of a tumor, such as changes in tissue density or irregularities in the shape of the brain (Albawi et al. [3]). One of the key advantages of using CNNs for brain tumor detection is their ability to learn and adapt to new data. As more MRI scans are added to the training dataset, CNN can continue to improve its accuracy and become better at detecting tumors. In addition, CNNs can help reduce the need for manual interpretation of MRI scans by medical professionals, which can save time and reduce the risk of human error (Chauhan et al. [5]). By automating the process of tumor detection, CNNs can help improve the efficiency and accuracy of the diagnostic process. Overall, CNNs are a powerful tool for the detection of brain tumors in medical imaging. They offer the potential to improve accuracy, efficiency, and speed in the diagnosis and treatment of brain tumors, ultimately leading to better outcomes for patients. A Convolutional Neural Network is built using several layers (Li et al. [9]), including (see Figure 2):

- Convolution layer: This layer uses filters to extract features from the input image. Each filter is convolved with the image to produce a “feature map” that highlights a specific feature of the image.
- Pooling layer: This layer reduces the size of the “feature maps” and decreases the number of model parameters. Pooling can be done using various techniques, such as max pooling, which selects the maximum value within an area of the feature map.
- Flatten layer: This layer converts the “feature map” resulting from the pooling layer into a one-dimensional vector.
- Feature extraction layer: This layer uses various filters and convolution layers to extract more abstract features from the image.

- Fully connected layer: This layer takes the extracted features and combines them to produce an output. This layer connects to all the neurons in the previous layer.

- Classification layer: This layer uses an activation function, such as the softmax function, to produce a probability of each possible class in the data set.

In short, a CNN uses layers of convolution, pooling, flattening, feature extraction, fully connected, and classification to extract features from input images and produce output that can be used to perform a specific task, such as detecting brain tumors in images of MRI.

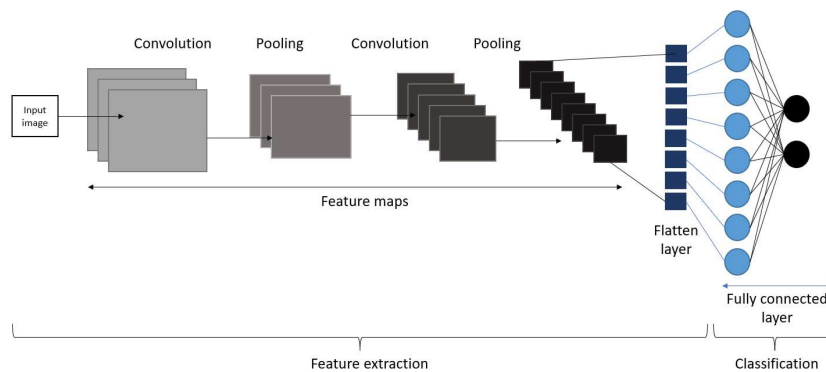


Figure 2. A typical CNN.

3. Proposed Model

The proposed model consists of three parts: Data set acquisition and pre-processing, feature vector and classification system, and evaluation and diagnostic metrics. The images are collected from Kaggle datasets of Brain MRI Images. The dataset is labeled into two classes of YES and NO based on the presence of tumors, as shown in Figure 1. Overall, there are 155 images with brain tumors and the remaining 98 images are of normal brains.

3.1. Data set acquisition and pre-processing

The image data that was used for this model is Brain MRI Images for Brain Tumor Detection which is located in the Kaggle repository (Chakrabarty [4]). It consists of MRI scans of two classes:

- (1) No tumor, benign.
- (2) Tumor, malignant.

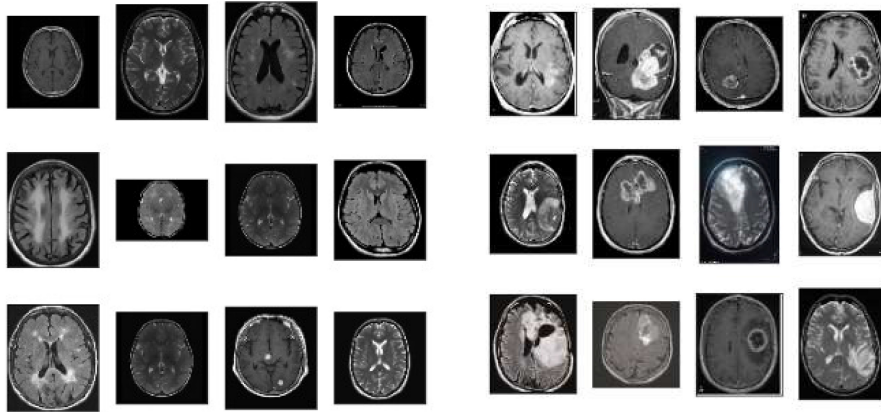


Figure 3. Data set.

As you can see in Figure 3, images have different widths and heights. For this reason, it is necessary to pre-process the images in size, since a pre-trained convolutional neural network is used. A pre-trained network is a neural network that has been previously trained on a large data set to perform a specific task, such as image classification or object detection (Lopes et al. [12]). Instead of training a neural network from scratch on a particular data set, a pre-trained network can be used as the basis for a related deep learning task (Masud et al. [13]). Since the image size for the VGG16 input layer is (224, 224), all images from the data set are resizing at this size.

3.2. Feature vector

The convolutional base of a pre-trained network called VGG16 was used by transfer learning, as a feature extractor and to obtain the feature vector that enters the classification system. VGG16 is a deep convolutional neural network architecture that was proposed by a group of researchers from the Visual Geometry Group (VGG) at the University of Oxford in 2014 (Simonyan & Zisserman [19]). Its architecture is composed of 16 convolutional and fully connected layers. The main feature of VGG16 is its depth since it uses 3×3 convolution layers with a stride of 1 pixel and padding of 1 pixel to maintain the size of the input, which allows the network to learn features of different scales in the picture. The pooling layers are done with 2×2 filters with a stride of 2 to reduce the dimension of the learned features. Also, it uses regularization to avoid overfitting, by using the dropout technique. In addition, it uses the ReLU activation function to activate neurons and speed up training. This network is commonly used as a pre-trained base in transfer learning tasks due to its high performance in image classification tasks (Gardezi et al. [8]).

Figure 4 shows the convolutional basis of the VGG16 network that was used as a feature extractor.

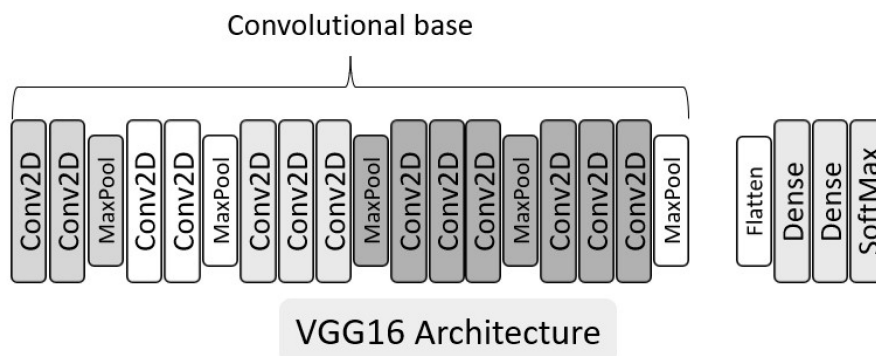


Figure 4. Convolutional base of the VGG16 network.

3.3. Classification system

The classification system is composed of two classification techniques: training and test set (Consonni et al. [7]), as well as cross-validation (Afendras, Markatou, & Inference, 2019). In addition, the two techniques were evaluated with three types of classifiers: Support Vector Machine (SVM) (Suthaharan et al. [20]), Naive-Bayes (NB) (Rish [18]), and Centroid-Based Classification (CBC) (Chen et al. [6]), and measured with four metrics to report the performance of the model, these were: accuracy, precision, recall, and F1 score (Palacio-Niño & Berzal [16]). Training/test set is a technique in which the data set is divided into two parts: a training set used to train the model and a test set used to evaluate the performance of the model. The training set is used to fit the model's parameters, while the test set is used to evaluate its performance. The test set is a final evaluation of the model before it is used in the real world. Cross-validation is a technique in which the data set is divided into multiple parts, called "folds", and an iteration is performed in which each fold is used as a test set and the others as a training set. This allows for a more accurate assessment of the model's performance by using all the data in the training and testing set. Cross-validation also helps to reduce the impact of randomness in the split of the training/test set. The classifiers used and the evaluation metrics have been studied and reported in the literature with optimal values in the performance of models that classify and detect brain tumors (Mohsen et al. [14]).

3.4. Experimental setup

The convolutional base of VGG16 is used as a feature extractor to classify the images. The model is illustrated in Figure 5.

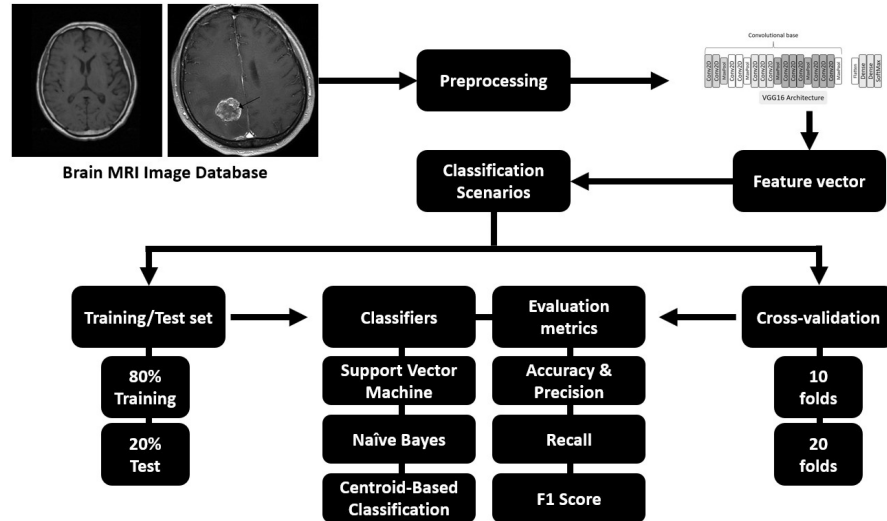


Figure 5. Proposed model to detect brain tumors.

4. Results

According to Figure 5, the proposed model was evaluated on four evaluation metrics, which are based on the confusion matrix (Visa et al. [22]). The confusion matrix is a tool used in data classification analysis to assess the performance of a classification model. This matrix is a table showing the number of correct and incorrect predictions made by the model in each of the classes being classified.

The confusion matrix is made up of four main elements:

- True Positives (TP): Number of cases in which the model correctly predicted the positive class.

- False Positives (FP): Number of cases in which the model incorrectly predicted the positive class (false alarms).
- True Negatives (TN): Number of cases in which the model correctly predicted the negative class.
- False Negatives (FN): Number of cases in which the model incorrectly predicted the negative class (omission failures).

The confusion matrix is presented in a two-by-two table, with the model predictions in the rows and the true classes in the columns. An example of a confusion matrix is shown below:

Table 1. Confusion matrix

	Positive class (tumor)	Negative class (no tumor)
Positive prediction	TP	FP
Negative prediction	FN	TN

Here's how these metrics relate to the confusion matrix (Liang [10]):

- Accuracy: It is the proportion of correct predictions of the model about the total number of samples. It is calculated as $(TP + TN) / (TP + FP + TN + FN)$.
- Precision: It is the proportion of true positives (TP) about the total positive predictions, that is, the model's ability to correctly predict positive cases. It is calculated as $TP / (TP + FP)$.
- Recall (sensitivity): It is the proportion of true positives (TP) about the total number of true positive cases, that is, the model's ability to correctly identify positive cases. It is calculated as $TP / (TP + FN)$.
- F1-score: It is a measure of the precision and recall of the model, which combines both metrics in a single value. It is the harmonic mean of precision and recall and is calculated as $2 * ((precision * recall) / (precision + recall))$.

The results of the model are presented in Tables 2 and 3.

Table 2. Training/test set

Evaluation metrics	SVM	NB	CBC
Accuracy	0.89	0.83	0.79
Precision	0.90	0.83	0.80
Recall	0.90	0.84	0.80
F1 Score	0.89	0.83	0.79

Table 3. Cross-validation

Folds	Evaluation metrics	SVM	NB	CBC	Folds	SVM	NB	CBC
10	Accuracy	0.88	0.83	0.80	20	0.90	0.83	0.79
	Precision	0.89	0.83	0.81		0.91	0.84	0.80
	Recall	0.87	0.83	0.81		0.89	0.83	0.79
	F1 Score	0.88	0.83	0.80		0.90	0.83	0.79

5. Discussion

The proposed model for detecting brain tumors using a combination of image pre-processing, feature extraction, and classification techniques appears to be promising. The results that have been obtained indicate that the model has achieved a high level of accuracy in the classification of brain tumor images in the training and test sets, which is impressive. The model makes use of the VGG16 pre-trained neural network as a feature extractor, as it is known for its ability to extract useful features from images, as shown in the evaluation. Furthermore, the inclusion of two classification techniques, training set, and test and cross-validation, is a good practice to evaluate the performance of the model and ensure that the results are reliable.

Regarding the results, it is important to highlight that the Support Vector Machine (SVM) classifier obtained the best values in the training and test set technique, and in particular, a high level of precision of 90%. This suggests that SVM is a good candidate for this type of brain tumor classification task. It is also interesting to note that the results in the cross-validation technique improved with increasing folds and that the SVM also had an outstanding performance in this technique. This finding suggests that using a higher number of folds in cross-validation could be beneficial to further improve the accuracy of your model. In fact, in 20 folds with the cross-validation technique, up to 91% was achieved, the maximum value of the model. Regarding the evaluation metrics, the four that have been used are commonly used to evaluate the accuracy of classification models. Importantly, accuracy is an important metric in this context, as accurate detection of tumors is critical for effective treatment.

In summary, the results suggest that the proposed model is promising for the automatic detection of brain tumors using imaging. The use of pre-processing, feature extraction, and classification techniques has proven to be effective, and the SVM seems to be a good candidate for this type of task. In the future, one could consider increasing the number of folds in the cross-validation and testing other classifiers to further improve the performance of the model.

6. Conclusions

In conclusion, the results obtained from the proposed model for the automatic detection of brain tumors by using MRI images suggest that the combination of image pre-processing, feature extraction, and classification techniques may be effective in this task. The SVM stood out as the classifier with the best performance, obtaining an accuracy of 90% in the training and test set technique, and 91% with 20 folds in cross-validation. Furthermore, increasing the folds in the cross-validation

further improved the accuracy of the model. Importantly, accuracy is a critical metric in this context, as accurate detection of tumors is critical for effective treatment. In the future, other improvements to the model could be considered, such as exploring other classifiers and image pre-processing techniques to further improve performance.

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