

Brain Tumor Detection Using Convolution Neural Networks

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ABSTRACT

Early diagnosis of brain tumors is important for improving patient prognoses; however, traditional diagnostic methods like biopsies require invasive surgical procedures. In this paper, we introduce two deep learning-based methods—a new two-dimensional Convolutional Neural Network (CNN) and a convolutional auto-encoder network—that enable the accurate classification of brain tumors from magnetic resonance imaging (MRI). A data set of 7,000 T1-weighted contrast-enhanced MRI images was utilized, including glioma, meningioma, pituitary gland tumor, and normal brain samples. Preprocessing and augmentation procedures were carried out on the data set in order to enhance the generalization ability of the models. The suggested architecture of the 2D CNN includes eight convolutional layers, four pooling layers, and utilizes batch normalization with a uniform 2×2 kernel across the network. The auto-encoder architecture combines feature extraction and classification by utilizing the last output of the encoder. Experimental results show that the 2D CNN achieved a training accuracy of 96.47% with an average recall of 95%, showing good performance and efficiency in computation. The simplicity and effectiveness of the proposed CNN make it a promising tool for real-time clinical applications, offering a non-surgical and highly reliable tool for the assistance of radiologists in the diagnosis of brain tumors.

INTRODUCTION

Brain tumors, malignant or benign neoplasms, pose a perilous threat to human health, with over 200 known types in the brain and central nervous system. Brain tumors, according to the American Cancer Society, are abnormal tissue growth that disrupts normal brain functions, typically causing extreme or fatal consequences. In a surprising turn of events, National Brain Tumor Foundation statistics indicate a 300% increase in mortality rates for brain tumors over the past three decades. Left untreated, brain tumors develop rapidly, thus the importance of early detection and immediate treatment. Brain tumor diagnosis, however, is largely based on biopsy, a surgical process far more complex than biopsies on other organs. Such a need has spurred the development of diagnostic tools that are more accessible, accurate, and non-invasive.

Magnetic Resonance Imaging (MRI) is at present the most salient and most used imaging modality for the diagnosis of brain tumors. MRI provides clear images of soft tissues because of which it is especially well suited for the identification of structural abnormalities in the brain. Although MRI scan interpretation is very specialized and is likely to be dependent on the experience and expertise of radiologists, tumor morphology variability and human errors like fatigue may cause variability and diagnostic errors. Thus, the use of computational techniques in medical imaging analysis has assumed increasing importance. Recent advances

in machine learning, particularly in the field of deep learning, have revolutionized the analysis of medical images. Such approaches have the ability to automatically detect patterns and features from huge sets of data and allow effective as well as accurate classification without relying solely on features detected by experts. Convolutional Neural Networks (CNNs), a popular class of deep learning models, have been shown unparalleled effectiveness in issues of medical image classification, as a result of their ability to learn complex spatial hierarchies as well as feature extraction. Another neural network-based approach, Autoencoders, have been successful in learning representations in an unsupervised manner and have been applied in issues of tumor detection as well.

Some efforts have been made to use deep learning and machine learning techniques for brain tumor classification. Nonetheless, they have several limitations such as high computation time, excluding normal brain images from the model or not being compared with others in terms of performance. In addition, the majority of previous work only differentiates between tumor types such as glioma, meningioma, and pituitary gland tumors, ignoring normal cases, which are inevitable for real-world diagnostic systems.

In order to meet these challenges, for this study, we put forward deep learning models—a specially designed 2D CNN to classify brain tumors from MRI images. The suggested models are trained to classify three types of tumors and normal brain images for enhanced diagnostic range and accuracy. By designing models with optimized architecture and conducting rigorous evaluation, this study will be able to offer a robust, accurate, and computational-efficient solution for brain tumor detection to aid radiologists in clinical decision-making.

Contributions of this work

The significant contributions of this work are detailed below:

(1) Our networks are performed on an extensive data set of 7000 T1-weighted contrast-enhanced MRI images, which are desirable for the training and testing phases.

(2) The internal architecture of the modified 2D CNN and convolutional auto-encoder neural network are adjusted in terms of the number of layers, how the layers are positioned next to each other, the type of parameters and hyperparameters, and their values that can be varied to fine-tune our models to enhance accuracy.

(3) Extracted essential features are utilized to classify three types of brain tumors and healthy brains (no tumor) by 2D CNN, auto-encoder network, and six common machine learning techniques.

(4) In the modified 2D CNN, several convolution layers are considered; all layers in this hierarchical network have a 2×2 kernel function. This network consists of eight convolutional layers and four pooling layers; after all convolution layers, batch-normalization layers were applied. The training process was accomplished over 50 training epochs

(5) The developed networks achieved optimal accuracy of approximately 95% to 96%, and areas under the receiver operating characteristics curves (AUROC) are 0.99 or 1. Performance analysis proposes a renovation of our proposed techniques by comparing related papers.

RELATED WORKS

In the research published in recent years relating to the segmentation of brain tumors, there is two branches of machine learning methods: Supervised learning and unsupervised learning. The difference between these models is simple, in supervised learning human intervention is needed at least to label the data appropriately, the machine learning model learns through iterating the operations of prediction of the labeled data communicated as input and improves the results by adjusting the response each time [24].

In unsupervised method-based segmentation, the human touch always needed for validating output variables [25], among its techniques there is the support vector machine (SVM) method and the fuzzy clustering approach are used. These methods have achieved the best performance when it comes to predicting or detecting a tumor, on the other hand the performance obtained is a little weak when the border between the normal tissue and the tumor area is blurred. Also, the extraction process usually takes time because the extraction algorithms have to extract a lot of information and details related to these edges and a lot of essential features. Segmentation is the process of separating the image into distinct regions and is one of the most vital and demanding aspects of computer-aided clinical diagnostic tools.

Although brain tumor segmentation is primarily done manually, it is very time consuming and the segmentation is subject to variations both between observers [26]. Therefore, an automatic and robust brain tumor segmentation will have a significant impact on brain tumor diagnosis and treatment. Convolutional neural networks (CNN) differ from other machine learning techniques in the fact that the segmentation is done automatically and does not require the intervention of an expert as well as the feature extraction which is done with precision, on the other hand there are several parameters to be learned by a neural network (CNN) which results in expensive computation time and requires process graphics units (GPU) to train the model [27]. The role of a CNN network consists of two main tasks: feature extraction and data classification, the convolution and pooling layer are responsible for feature extraction, fully connected layers help to achieve the classification task [28]. In [29], the authors presented a convolutional neural network for brain tumor detection, 2 CNNs models were made as a comparison to find the best model for classification. The first model includes one convolution layer, the second includes two layers. This study showed that increasing convolutional

layers improves the model performances and resulted in accuracy of 93% and a loss value of 0,23.

Among the techniques for using artificial neural networks, there is also transfer learning, the principle is simple, instead of designing a new CNN model and training it from scratch, existing architectures which are well trained on large dataset and which have demonstrated their performance are used, this makes it possible to use each transfer learning model and adapt it to the desired stain according to the nature of the task and the characteristic to be detected or classified [30]. Due to their ability to self-learn without the intervention of an expert, CNN models based on Transfer learning techniques have achieved excellent performance, the use of the weight sharing technique provides an adequate network and allows to automatically detect the tumor through the MRI images [31]. Research published in [32], Aimed boosting accuracy by the use of transfer learning strategy they implemented three transfer learning approaches using pre-trained CNN models, namely: VGG19, Inception V3 and MobileNet V2, they obtained respectively an accuracy rate of 88,22%, 91% and 92%. The authors concluded that the MobilnetV2 is the most efficient Model compared to the other models.

Using the ANN approach, Authors in [33], worked on two classes named benign tumors and malignant tumors, they started by preprocessing the images with the filters, then applied the average colour moment technique on the images to extract the characteristics. After the transmission of these characteristic maps to the ANN, the classification was made with an accuracy rate of 91.8%. A study published in [34], the model uses the histogram statistical equalization technique which consists in applying a transformation to each pixel of the image by calculating several statistical characteristics such as the average sum, the variance, the entropy, the dissimilarity, this model is therefore used for low-grade and high-grade class images of cervical glioma. The results

obtained from the proposed method of accuracy, sensitivity and specificity reached 83.6% accuracy, 80.88% sensitivity and 86.84% specificity. One of the techniques used in the detection of characteristics and classification of images consists in combining the concept of deep learning, CNNs, with other methods of preprocessing, these techniques include data augmentation, edge detection, genetic algorithm (GA), discrete wavelet transform (DWT) and principal component analysis (PCA).

Authors in [35] have combined the two techniques of data augmentation and edge detection, data augmentation makes it possible to increase the amount of data artificially, other images are generated from the first images provided. The edge detection will allow finding the region of interest (ROI), the extraction of the characteristics is done thanks to a simple CNN model. They obtained 89% classification accuracy. The results of these searches are classified in Table I, highlighting the classification model with a description of the chosen preprocessing technique, as well as the scores obtained based on the metrics used in each work.

MATERIAL AND METHODS

The research process of this study is explained in Figure 1. The key steps of the research are selecting an appropriate brain tumor dataset, pre-processing the MRI images, feature extraction, and classification through different models

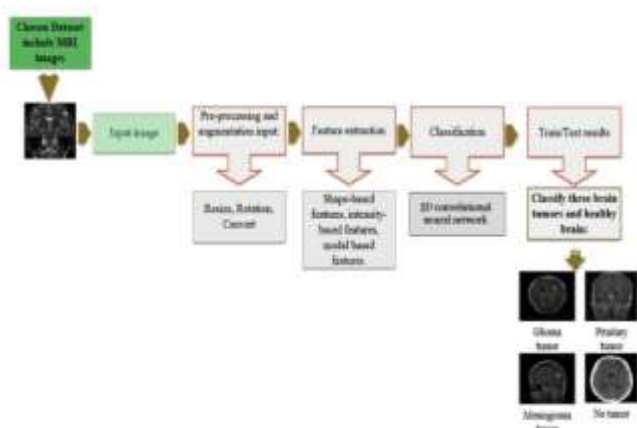


Fig. 1 Stages of the proposed methodology

DATASET

Our research utilized three publicly available brain tumor MRI datasets from Kaggle. The details of the datasets and their divisions (i.e., training and testing) are listed in Table 1. The table presents three MRI datasets, their respective class distributions, and the number of images in the training and testing sets. Dataset 2 includes classes labeled as yes and no, with 239 images. The training set of Dataset 2 comprises 201 images, and the testing set contains 38 images. Dataset 3 focuses on the tumor classes, with 1500 images. The training set of Dataset 3 has 1200 images, and the testing set consists of 300 images. Dataset 3 also has an additional set of 3000 images, with 2400 in the training set and 600 in the testing set. Dataset 1 contains images of glioma, meningioma, pituitary, and no tumor classes, with a total of 7023 images. The training set of Dataset 1 consists of 5712 images, while the testing set has 1311 images.

Dataset 1				Dataset 2				Dataset 3			
Class	Images	Train	Test	Class	Images	Train	Test	Class	Images	Train	Test
Glioma	1621	1321	300	Yes	155	135	20	Yes	1500	1200	300
Meningioma	1645	1339	306	No	84	66	18	No	1500	1200	300
Pituitary	1757	1457	300								
No Tumor	2000	1595	405								
Total	7023	5712	1311	Total	239	201	38	Total	3000	2400	600

Table I: Dataset Distribution

PREPROCESSING

A set of procedures was utilized to preprocess the MRI scans, thus allowing accurate identification of brain tumors and producing meaningful results. The procedure addressed issues associated with inconsistencies in image resolutions and intensity levels contained in the dataset. Normalization of intensity levels, using techniques like z-score normalization and scaling of pixel intensities to a target range (e.g., 0 to 1), enhances the accuracy of machine learning models. Since there were inconsistencies in patient positioning and image orientation, it was important to register the scans to a standard reference frame. Image registration techniques were utilized to enable spatial consistency, thus allowing for more reliable

comparisons and analyses. Additionally, artifacts and interferences caused due to patient movement or inconsistencies in the equipment were dealt with. Denoising algorithms like Gaussian smoothing and non-local means filtering were utilized to remove unwanted distortions without degrading essential image characteristics.

Fine-Tuning of CNN Hyperparameter	
Step 1:	Find the best hyperparameters to train the final model.
Step 2:	Develop new model instances for the best hyperparameters.
Step 3:	Train the model with the specified parameters.
Step 4:	Test and evaluate the CNN model.
Step 5:	Find the best performance metrics (e.g., accuracy).

Fig. 2 Steps of fine tuning the CNN

PROPOSED SOLUTION

2D CNN

The design of the proposed two-dimensional Convolutional Neural Network (2D CNN) architecture is explained in this research. Training and testing were performed on a database of 7,000 MRI images, 90% (6,300 images) of which was used for training and the rest, 10% (700 images), was used for testing. The network consists of various layers, among which some are convolutional layers—two having 64 filters, another set with 32 filters, and some other layers designed with 16 filters. The last two convolutional layers have filters of an 8-dimensional size. All the convolutional layers utilize a 2×2 kernel for spatial feature extraction. The CNN is hierarchical in structure, connecting convolutional layers with periodic pooling and fully connected layers. Note that not all convolutional layers have a pooling layer following them, as is evident with the structure. The network in total has eight convolutional layers and four pooling layers. The last pooling layer's output is flattened into a one-dimensional vector to be fed into the fully connected layers. Padding is carried out using the same values in neighbouring cells so that the dimensions of the output of the convolutional layers and edge information are preserved. In the classification stage, the network architecture consists of a fully connected layer of 1024 neurons and then a layer of 4 neurons corresponding to the

four provided output classes. The last classification stage uses a softmax activation function. Batch normalization layers are used after each convolutional layer for enhancing the training stability and avoiding overfitting. Dropout layers with a rate of 0.1 are also used after each pooling and dense layer for regularization. ReLU activation function is used in all the layers except the last dense layer. The model is optimized with Adam optimizer, and some different learning rates (0.01, 0.001, 0.0001) are tried out to determine the most effective setting. It was found that the optimal learning rate is 0.001. The training process was performed over 100 epochs total, batch size 16, each epoch lasting about 7 seconds. The feature extraction that occurs through the convolutional layers results in input to the first dense layer $U_{fc} = 1024$ neurons. Computation of the weights (W_{conv}) of the dense layer is derived from the dimensions of the convolution output ($y_1 \times y_2$), the number of filters (k), and the dense layer number of neurons. $W_{conv} = y_1 \times y_2 \times k \times U_{fc} = 5 \times 5 \times 8 \times 1024 = 204,800$

Including the biases (1024), the first dense layer's total number of parameters is 205,824. The total number of trainable parameters in the entire network, calculated by summing all layer parameters, is 243,924. All of these parameters are optimized during training.

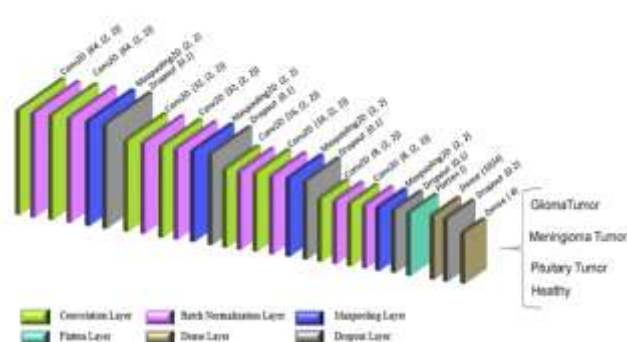


Fig. 3 Architecture/Layers of Convolutional Neural Network

PERFORMANCE EVALUATION METRICS:

Several common measures of evaluation are used to measure the performance of the system. Some of them are Accuracy, Precision, Recall, F1-score, Area Under the Curve (AUC), the Confusion

Matrix, and the Receiver Operating Characteristic (ROC) curve. Each one provides a different perspective on the performance of the model. The definitions and the corresponding mathematical equations for these measures are explained in the next section.

Confusion Matrix:

A confusion matrix is a tabular display describing the output of a classification model's predictions. The matrix aids in differentiating correctly classified instances from misclassified instances, making it possible to identify potential errors made by the model. Being a performance-measuring tool, it categorizes predictions into four fundamental categories: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). These categories of information are critical in describing the ability of the model and are presented in Table II.

TABLE II. ELEMENTS OF THE CONFUSION MATRIX

Element	Description
TP	Images containing the tumor and correctly classified.
NP	Images not containing the tumor and correctly classified.
FP	CNN classifies images as containing tumors but that does not contain any tumor.
FN	CNN classifies images as not containing any tumor but are containing a tumor.

Loss Function:

A loss function quantifies the extent to which the outputs of the predictions of the neural network are distant from the values in the training set. The performance of the network enhances as the loss function value decreases. Minimization of the function is done by minimizing the difference between the predicted and actual values, and this is done by the adjustment of the internal weights of the network during training.

RESULTS & DISCUSSION

Several standard evaluation metrics are generally introduced to evaluate the performance of the system, among these metrics there is Accuracy,

Precision, Recall, F1_score, confusion matrix and Receiver Operating Characteristic curve (ROC).

Training Results:

The CNN model was trained using a notebook on the Google Colab platform, which provides access to widely used Python libraries such as TensorFlow and Keras. Colab executes the code on Google's cloud infrastructure, utilizing high-performance hardware. This significantly boosts training efficiency which is particularly beneficial given the large number of parameters in the proposed CNN architecture. The progression of accuracy and loss over the training and validation phases is illustrated in Fig. 4 and Fig. 5, respectively.

The accuracy plot in Fig. 4 shows the trend during both training and validation. It is evident that the training accuracy consistently outperforms the validation accuracy. Similarly, as seen in the loss curve presented in Fig. 5, the training loss is lower than the validation loss throughout. These observations indicate that the model generalizes well and does not suffer from overfitting.

Testing Results:

The performance of the proposed methodology was evaluated by the measures of precision, specificity, accuracy and, above all, the ROC curve for two classes (normal and abnormal brains) and compared to the performance of other classifiers, the metrics mathematical equations are detailed below. Also, the confusion matrix as shown in fig 6 shows how well the model is able to classify and detect true positives and true negatives.

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (1)$$

$$\text{Sensitivity} = \frac{TP}{FN+TP} \quad (2)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (4)$$

$$F1 - \text{Score} = 2 * \frac{\text{Precision} * \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}} \quad (5)$$

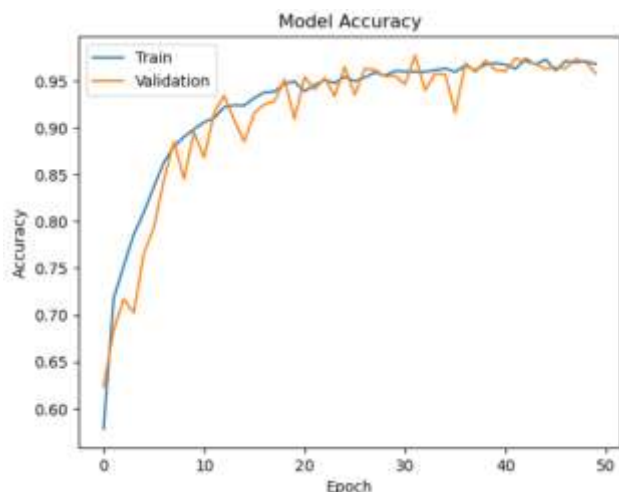


Fig. 4 Model Accuracy Graph

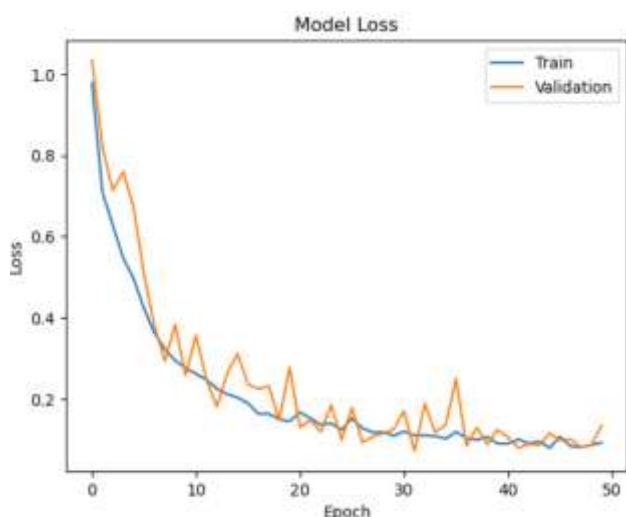


Fig. 5 Model Loss Graph

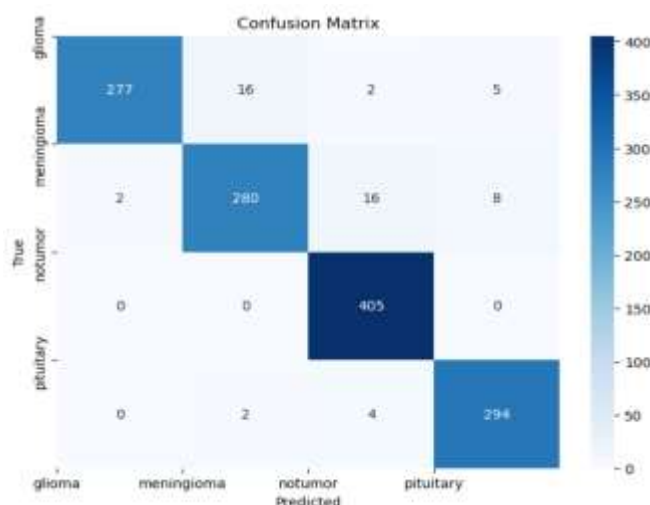


Fig. 6 Confusion Matrix

CONCLUSION & PERSPECTIVES

In this study, we developed and evaluated a novel 2D Convolutional Neural Network (CNN) architecture, alongside traditional machine learning models, for the accurate classification of brain tumors using T1-weighted, contrast-enhanced MRI scans. The proposed CNN model demonstrated high training accuracy of 96.47% and effectively distinguished between three tumor types—glioma, meningioma, and pituitary—as well as healthy brain images. Comparative analysis showed that the CNN outperformed conventional classifiers such as KNN, Random Forest, and SVM in both accuracy and execution time, highlighting its efficiency and generalization capability.

Furthermore, we validated the model on an extensive MRI dataset, where preprocessing and normalization played a key role in enhancing performance. The CNN achieved superior results in segmentation and classification tasks, with overall accuracy rates reaching up to 97%, outperforming other existing models across various evaluation metrics. These outcomes confirm the robustness of CNN-based architectures in medical image analysis and support their use as reliable decision-support tools for radiologists in clinical settings.

Future work will focus on refining the proposed architecture and assessing its scalability and performance across larger, more diverse datasets to further strengthen its applicability in real-world diagnostics.

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