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(Research Article)

Brain Tumor Classification using CNN

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Abstract

Accurate identification of brain tumors from magnetic resonance imaging (MRI) plays an important role in clinical diagnosis and treatment planning. This paper presents a deep learning–based method for automated brain tumor classification using a Convolutional Neural Network (CNN). The proposed CNN model is trained from scratch on a publicly available brain MRI dataset containing four classes: glioma, meningioma, pituitary tumor, and no tumor. All images are resized to a uniform resolution and processed through an end-to-end learning framework without applying explicit data augmentation. The network learns relevant spatial features through convolutional and pooling layers, followed by fully connected layers for multi-class classification. Experimental results show that the proposed CNN achieves a test accuracy of about 95%, with balanced class-wise performance reflected by a macro-averaged precision, recall, and F1-score of 96%. These findings indicate that CNN-based models can effectively learn meaningful tumor characteristics from MRI scans and may serve as a useful tool to support computer-aided brain tumor diagnosis.

Keywords: Brain tumor; Medical imaging; Convolutional neural networks; Transfer learning

1. Introduction

Humans can develop nearly 200 different types of abnormal tissue growths, commonly referred to as tumors, which may be either benign or malignant. Among these, brain tumors are particularly dangerous because abnormal cell growth within brain tissue can severely disrupt normal neurological functions. Over the past three decades, mortality associated with brain tumors has increased by almost 300%, highlighting the growing need for timely and effective diagnosis and treatment. When left untreated, brain tumors can be life-threatening, making early detection crucial for improving patient survival. Due to the complexity and risks associated with brain biopsies, magnetic resonance imaging (MRI) has become the preferred diagnostic modality, as it provides a safe and reliable means of examining brain abnormalities [1–10]. Gliomas are the most prevalent type of brain tumor and originate from glial cells. They account for approximately 30% of all tumors affecting the brain and central nervous system and nearly 80% of malignant brain tumors [11]. According to the World Health Organization (WHO), gliomas are classified into four grades ranging from I to IV. Grade I tumors are typically benign and closely resemble normal tissue, grade II tumors exhibit mild structural abnormalities, grade III tumors are malignant with noticeable tissue irregularities, and grade IV tumors represent the most aggressive form, characterized by severe abnormalities [11,12]. Meningiomas arise from the membranes that cover the brain and spinal cord and generally grow slowly, with most cases being benign. Pituitary tumors originate in the pituitary gland, which plays a key role in hormone regulation; these tumors may be benign or malignant and can cause hormonal imbalances as well as visual impairments. Early detection and accurate classification of brain tumors are essential for effective diagnosis and appropriate treatment planning. However, tumor grading remains a challenging and time-consuming task for clinicians, as it requires careful visual assessment and detailed comparison of tissue

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structures. This complexity underscores the importance of computer-aided diagnosis (CAD) systems, which can assist in early detection, reduce diagnostic time, and minimize the risk of human error [11,12]. In recent years, advances in machine learning (ML), particularly deep learning (DL), have led to significant improvements in medical image analysis. Approaches such as convolutional neural networks (CNNs) and autoencoders have demonstrated strong potential in tumor detection, segmentation, and classification tasks. Nevertheless, the performance of existing DL-based methods varies across different datasets, indicating that further enhancements in model design and learning frameworks are still required.

2. Related Work

Abiniwanda et al. [13] proposed a convolutional neural network–based approach for brain tumor classification that does not require prior tumor segmentation. Their model was designed to automatically classify MRI images into three tumor categories: meningioma, glioma, and pituitary tumors. The proposed method achieved a training accuracy of 98.51% and a validation accuracy of 84.19%. A key advantage of this approach is its fully automatic nature, as it eliminates the need for manual or physical segmentation of tumor regions, thereby simplifying the overall classification process. Swaraja Kuraparthi et al. [14] investigated the effectiveness of transfer learning for brain tumor classification using three pre-trained deep convolutional neural network (DCNN) architectures: AlexNet, VGG16, and ResNet50. In their approach, features were extracted from the pre-trained networks and subsequently classified using a Support Vector Machine (SVM) classifier. To reduce overfitting and improve generalization, data augmentation techniques were applied to the magnetic resonance imaging (MRI) data. Experimental evaluations were conducted on both the Kaggle and BraTS datasets. The proposed method achieved classification accuracies of 98.28% and 97.87% without data augmentation, which increased to 99.0% and 98.86% after applying augmentation for the Kaggle and BraTS datasets, respectively. Furthermore, the model achieved high discriminative performance, with area under the ROC curve (AUC) values of 0.9978 and 0.9850. Among the evaluated architectures, ResNet50 demonstrated superior performance compared to AlexNet and VGG16 in brain tumor classification tasks**. S**eetha et al. [15] introduced a convolutional neural network (CNN) for the automatic classification of brain tumors from MR images. Their model employs a deeper architecture built with small convolutional kernels and low neuron weights to reduce computational complexity. Experimental results demonstrated that the proposed CNN achieved an accuracy of 97.5%, while maintaining lower complexity compared with other state-of-the-art methods. Ahmad Saleh et al. [16] reported a maximum accuracy of 98.75% using the Xception CNN model. The primary objective of their work was to enhance the effectiveness and reliability of MRI-based brain tumor classification and tumor type identification using artificial intelligence, CNNs, and deep learning techniques. Five pretrained models were evaluated in their study: Xception, ResNet50, InceptionV3, VGG16, and MobileNet. The study by Abd et al. [17] analyzed 25,000 brain MRI images using a deep convolutional neural network (DCNN) to identify different types of brain tumors. Their model achieved outstanding performance, reaching a training precision of 99.25%. Pashaei et al. [20] proposed a CNN-based classification framework composed of four convolution and normalization layers, three max-pooling layers, and a final fully connected layer. In their experiments, 70% of the dataset was used for training without data augmentation, while the remaining 30% was used for testing with 10-fold cross-validation. The proposed model achieved a classification accuracy of 81.0%. Afshar et al. [21] presented a Capsule Network (CapsNet) model for brain tumor classification. To enhance classification accuracy, they modified the feature mapping process in the convolutional layer of the CapsNet architecture. By using a single convolutional layer with 64 feature maps, their model achieved a maximum accuracy of 86.56%. Ankita et al. [22] achieved the accuracy of 94% and 88% respectively using VGG16 and ResNet50 on a Imaging (MRI) dataset. In this paper, they propose comparative studies of various deep learning models grounded on different types of Neural Networks (ANN, CNN, TL) to primarily identify brain tumors and then classify them into Benign Tumor, Malignant Tumor or Pituitary Tumor. Recent works highlight the widespread adoption of machine learning, deep learning, and emerging digital technologies across healthcare, cloud computing, cybersecurity, and data-intensive applications, with demonstrated effectiveness in medical imaging, IoMT systems, and intelligent decision support frameworks [23-29]. SVM and RF are used in [30].

Table 1 Comparative analysis with state-of-the-artworks.

DL Model	**Accuracy**
CNN [13]	84.19%
CNN [15]	97.5%
Xception(CNN) [16]	98.75%
ResNet50[17]	95.33%

Densenet201[18]	68.71%
ResNet101[18]	74.09%
Mobilenetv2[18]	82.61%
SqueezeNet[19]	92.08%
CNN [20]	81.0%
CapsNet [21]	86.56%

3. Methodology

This section will describe full details of the proposed methodology.

3.1. Description of Dataset

This study utilizes a publicly available [31] Brain Tumor MRI image dataset that is organized into predefined training and testing directories. The dataset contains a total of 7,023 brain MRI images, consisting of two-dimensional scans collected from different patients. Each image is labeled into one of four clinically relevant brain tumor classes.

3.1.1. Dataset Classes

The dataset contains four classes:

- Glioma
- Meningioma
- Pituitary
- No tumor

3.2. Image Distribution

Table 2 Image Distribution in the dataset

Class Levels	Training Set	Testing Set
Glioma	1321	300
Meningioma	1339	306
No tumor	1595	405
Pituitary	1457	300
Total	5712	1311

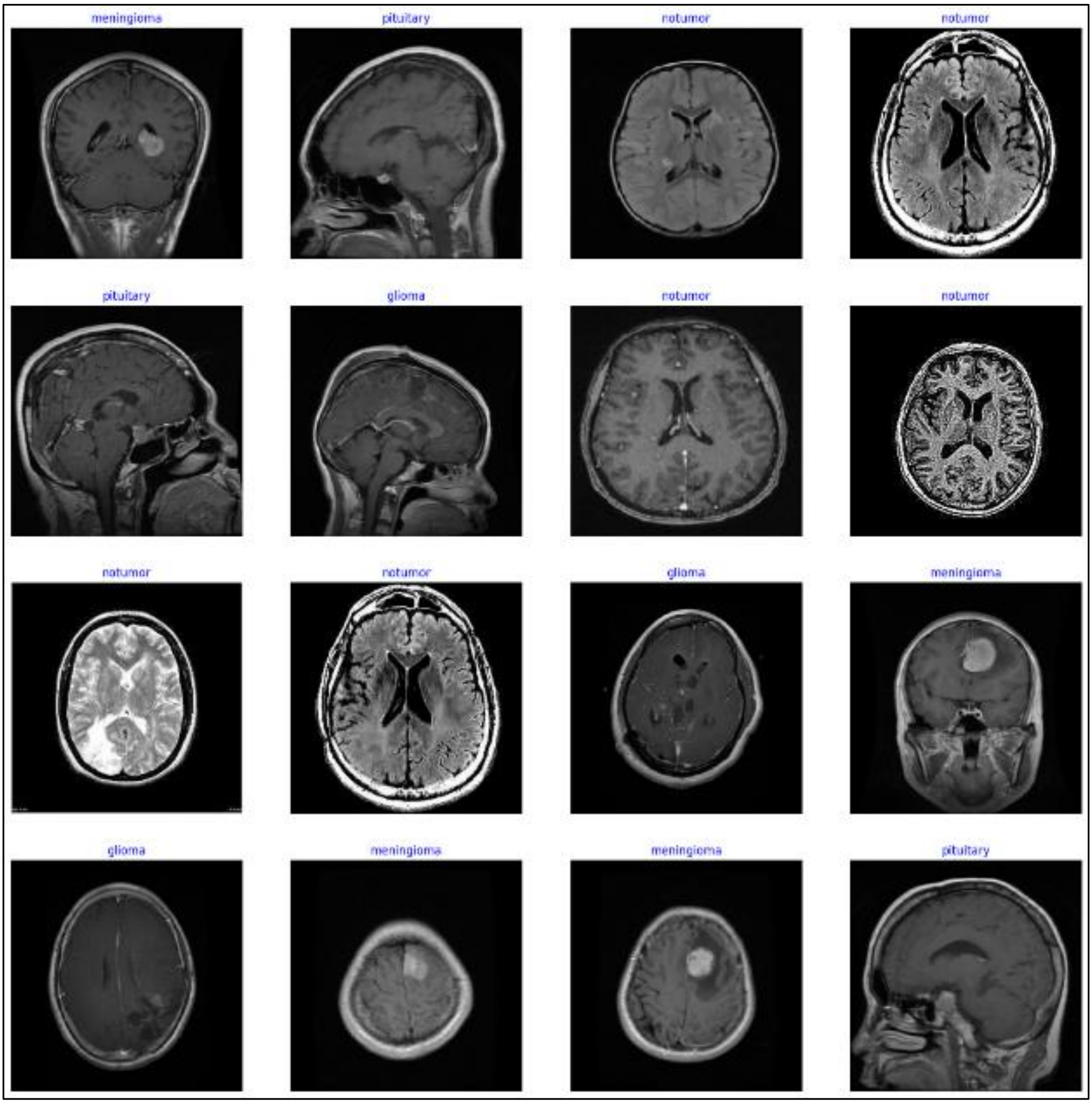

Figure 1 Visualization of Glioma, Meningioma, Pituitary, No tumor

3.3. Image Pre-Processing

To improve the consistency of classification results and the reliability of extracted features, all images in the dataset are subjected to a preprocessing step. Because deep learning models rely on extensive iterative training, a large-scale image dataset is employed to minimize overfitting and enhance the model's generalization capability.

3.4. Image Resizing and Data Augmentation

All images were resized to 224 × 224 pixels, which significantly accelerates training and inference by reducing computational cost, without causing a noticeable degradation in model performance.

In this study, explicit data augmentation was not applied. The dataset contains a relatively balanced number of samples across all classes, with more than 1,300 training images available for each tumor category. Moreover, as the data consist of MRI scans acquired under standardized clinical imaging conditions, the images share consistent orientation, scale, and anatomical structure. This uniformity contributes to stable training behavior and strong generalization performance, as reflected by the close alignment between training and validation curves.

Brain tumor classification relies heavily on clinically meaningful features such as anatomical location, shape, and intensity patterns. Applying aggressive augmentation techniques—such as large rotations or geometric distortions—could modify these features and introduce anatomically unrealistic variations. To maintain the medical validity of the images, data augmentation was therefore deliberately avoided.

While data augmentation can be beneficial in cases of limited data availability, class imbalance, or heterogeneous acquisition settings, its impact was not explored in this work. Investigating augmentation strategies and domain generalization approaches remains a potential direction for future research.

3.5. Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a deep learning approach widely used for image classification tasks due to its ability to automatically learn hierarchical feature representations from raw pixel data. CNNs exploit spatial locality by applying convolutional filters that detect low-level patterns such as edges and textures in early layers, while deeper layers capture more abstract and class-specific features. This hierarchical learning capability makes CNNs particularly suitable for medical image analysis, including brain MRI classification.

In this study, a custom CNN architecture is designed and trained from scratch for multi-class brain tumor classification using MRI images. The input images are resized to 224 x 224 x 3 with three color channels (RGB), ensuring compatibility with standard convolutional operations. The network begins with two convolutional layers, each employing 32 filters of size 5 x 5 with ReLU activation and same padding. These layers are responsible for extracting spatial features while preserving the original image dimensions.

Following the convolutional blocks, a max-pooling layer with a 2 x 2 window is applied to reduce spatial dimensionality and computational complexity. Dropout regularization is then introduced to mitigate overfitting by randomly deactivating a fraction of neurons during training. The resulting feature maps are flattened into a one-dimensional vector and passed through a fully connected dense layer with 256 neurons and ReLU activation, enabling high-level feature learning. A final dropout layer further improves generalization before the output layer.

The output layer consists of four neurons with softmax activation, corresponding to the four brain tumor classes: glioma, meningioma, pituitary, and notumor. The model is trained using the Adamax optimizer with a learning rate of 0.001 and categorical cross-entropy loss. Training is conducted over 20 epochs using data generated via an image data generator without explicit augmentation.

Table 3 illustrates the basic parameters used in order to train the CNN mode lwhere adamax is used. Categorical Cross-entropy is used as loss function.

Table 3 Parameter for the CNN model

Method	**Value (as used in code)**
Type of Learning	From Scratch
Transfer Learning	No
Trainable Layers	All layers
Model Architecture	Custom CNN
Number of Convolution Layers	2
Type of Learning	From Scratch
Transfer Learning	No
Trainable Layers	All layers
Model Architecture	Custom CNN
Optimizer	Adamax
Learning Rate	True
Loss Function	Categorical Cross-Entropy

Batch Size	32
Epochs	19

4. Results

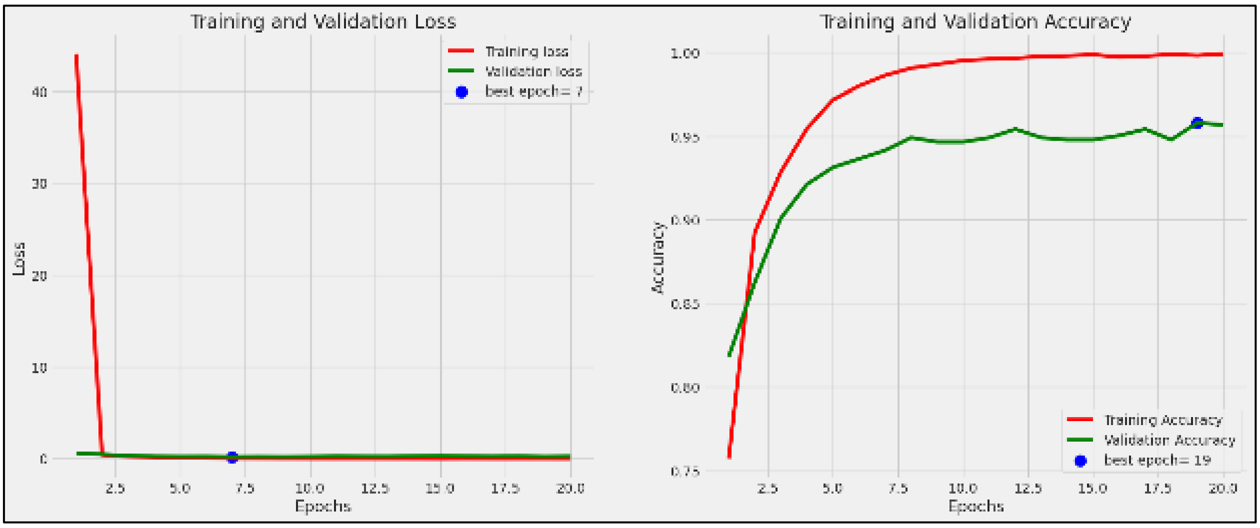

Figure 2 Learning Curve of CNN Model

Figure 2 illustrates the training behavior of the CNN model, where the training loss decreases sharply during the initial epoch and approaches near zero, indicating rapid learning and strong fitting to the training data. In contrast, the validation loss drops early and reaches its minimum around epoch 7 before showing small fluctuations, suggesting that the model's best generalization in terms of loss occurs relatively early. The training accuracy increases steadily and eventually reaches nearly 100%, while the validation accuracy rises quickly and stabilizes around 95–96%, achieving its highest value near epoch 19.

Table 4 CNN Model

Class	Precision	Recall	F1-Score
Glioma	0.97	0.93	0.95
Meningioma	0.89	0.92	0.90
No Tumor	0.96	0.97	0.97
Pituitary	0.98	0.99	0.99
Overall accuracy			0.95

Table 5 Comparison of proposed methods with other models

DL Model	Accuracy
CNN	95.0%
CNN [13]	84.19%
CNN [15]	97.5%
Xception [16]	98.75%
ResNet50 [17]	95.33%

Densenet201 [18]	68.71%
ResNet101 [18]	74.09%
Mobilenetv2 [18]	82.61%
SqueezeNet [19]	92.08%
CNN [20]	81.0%
CapsNet [21]	86.56%

5. Conclusion

A convolutional neural network (CNN) was developed to automatically classify brain tumors from MRI images. The model was trained from scratch to distinguish between glioma, meningioma, pituitary tumor, and normal cases, without using explicit tumor segmentation or data augmentation. The results show that the CNN performs reliably, achieving an overall accuracy of 95% with consistent performance across all classes. These findings suggest that a simple CNN architecture can effectively support brain tumor classification, while future improvements may include testing on larger datasets, applying data augmentation, and exploring more advanced network design.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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