A Convolutional Neural Network for Automatic Brain Tumor Detection

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Abstract

Magnetic resonance imaging (MRI) combined with artificial intelligence (AI) algorithms to detect brain tumors is one of the important medical applications. In this study, a Convolutional neural network (CNN) model is proposed to detect meningioma and pituitary, which was tested with a dataset consisting of two categories of tumors with 1,800 MRI images from several persons. The CNN model is trained via a Python library, namely TensorFlow, with an automatic tuning approach to obtain the highest testing accuracy of tumor detection. The CNN model used Python programming language in Google Colab to detect sensitivity, precision, the area under the PR and receiver operating characteristic (ROC), error matrix, and accuracy. The results show that the proposed CNN model has a high performance in the detection of brain tumors. It achieves an accuracy of 95.78% and a weighted average precision of 95.82%.

Keywords: artificial intelligence, MRI, convolutional neural network, brain tumors

1. Introduction

One of the vital topics in the medical field is brain tumor detection [1-2]. Therefore, it is necessary to evaluate the tumor and select a proper treatment decision according to the classes. Classification of brain tumors is a challenging problem for physicians because of the heterogeneous nature of tumor cells. Physicians contribute to the diagnosis of brain tumor diseases; however, they need an efficient and helpful tool for their diagnosis. Computer-aided devices are widely used for brain tumor explorations-based tomography CT scan images, but these devices have low-accuracy diagnoses [3].

In recent years, a robust solution for computer-aided diagnosis devices has been introduced for diagnosing brain tumors via magnetic resonance imaging (MRI) [4]. MRI is the most useful technique in the detection of brain tumors as it has high image quality [5]. Furthermore, artificial intelligence (AI) algorithms are considered a key enabler in assisting brain tumor detection, especially the advance of high-performance deep learning (DL). The DL algorithms with high levels of testing accuracy are a significant phase-oriented and high-precision approach to detecting brain tumor patients. The study aims to provide an accurate and efficient method to differentiate between meningioma and pituitary cases. It helps radiologists and doctors in screening brain tumor cases as well.

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Machine learning (ML) and DL algorithms are used to classify brain tumors [6]. However, the low accuracy of existing algorithms needs to be improved [7]. Convolutional neural network (CNN) has played an effective role in diagnosing brain tumors. It classifies the tumor type through medical imaging of the human brain. MRI is a good instance that it has discovered many patients with brain tumors.

DL algorithms were presented to classify brain tumor patients based on brain MRI images, but a sufficient testing accuracy level was not achieved. Afshar et al. [8] proposed a CapsNet algorithm to detect brain tumor diseases via a capsule neural network approach. This algorithm was applied to a 3,064-image dataset and had a maximum accuracy of 86.56%. Anaraki et al. [9] implemented a CNN algorithm to recognize brain tumors. This algorithm was trained on a dataset of 600 various images and reached an overall testing accuracy of 94.2%. Saxena et al. [10] examined VGG-16, Inception-V3, and ResNet-50 algorithms with a 253-image dataset split into 183, 50, and 20 for training, validation, and testing. The maximum accuracy of Inception-V3 and VGG-16 were 55% and 90%, respectively, while the ResNet-50 reached a total accuracy of 95%. Zhou et al. [11] developed a combination of LSTM-DenseNet algorithms to identify brain tumors that were tested on a dataset of 930 pituitary, 708 meningioma, and 1,426 glioma patients with a maximum accuracy of 92.13%.

DL and ML architectures have been introduced to predict brain tumors in patients. Cheng et al. [12] proposed a support vector machine (SVM) algorithm that reached a total precision of 91.28% with a dataset of 930 pituitaries and 1,426 glioma images. A CNN algorithm was utilized, which reached a testing accuracy of 84.19% with 3,064 MRI images [13]. Kaplan et al. [14] implemented a k-nearest neighbor (KNN) algorithm with the nLBP feature extraction approach, which achieved a 95.56% testing accuracy. Pashaei et al. [15] presented a CNN algorithm with an extreme learning machine (ELM) technique to train 70% of a 3,064 brain tumor cases dataset, then utilized the algorithm to assess the rest 30%, reaching a testing accuracy of 93.68%. Zacharaki et al. [16] employed SVM-KNN algorithms to classify brain tumors, which were applied to 102 MRI images and reached a maximum testing accuracy of 85%.

In this study, a CNN model is developed to detect brain tumors. The CNN performance is assessed via several assessing metrics, i.e., sensitivity, precision, the area under the PR and receiver operating characteristic (ROC), error matrix, and accuracy. The tumors are categorized into two groups: meningioma and pituitary. The accuracy of the CNN reached 95.78%, while the sensitivity and F1-score were 95.78%. A hyper-parameter tuning approach is utilized to achieve the best performance of the CNN. The paper is organized as follows: The methodology is explained in Section 2. The results are presented with the discussion of the paper in Section 3. Finally, Section 4 concludes the study.

2. Methodology

In this paper, a CNN model is implemented using a TensorFlow library. The CNN is built to classify two types of brain tumors: meningioma and pituitary. This model is utilized due to its proper with images dataset where it captures spatial features of these images. All layers of the CNN are tuned via its hyperparameters, and the activation functions used for the CNN are ReLU and sigmoid.

2.1. The proposed model

This study proposed a CNN model for classifying MRI brain tumors because the advantage of CNN architecture is the convenience of capturing spatial data. Fig. 1 demonstrates the CNN architecture, which has four convolutional layers, three max-pooling layers, four dropout layers, a flattened layer, a fully connected layer, and an output layer. The input shape of the MRI images has a height of 224 pixels and a width of 224 pixels. A two-dimensional convolutional layer has been used for each MRI image with a ReLU activation function, which is used to extract spatial features. The layers used in the step are described as follows:

(1) The convolutional layer includes 32 filters and a 3 × 3 kernel; the other has 64 filters with a ReLU function. A max-pooling layer includes a 2 × 2 pool, which minimizes the convolutional output complexity to perform a down-sampling process. A dropout layer is used to tackle the over-fitting problem [17].

(2) A 2-D convolutional layer has 64 filters and a 3 × 3 kernel, which is implemented to enable the CNN to classify more features that are lost in the previous convolutional layers. A max-pooling layer has a 2 × 2 pool and a dropout layer with a 25% drop rate from neurons.

(3) A 2-D convolutional layer has 128 filters, a 3 × 3 kernel, a max-pooling layer, and a dropout layer with a 0.25 drop rate.

(4) A flattened layer is utilized to transform the data into one dimension. The fully connected layer is initialized with 64 neurons with a ReLU activation function. A dropout layer with a drop rate of 50%, the output layer is configured with a sigmoid function to minimize the output to 2 classes. The proposed model uses a cross-entropy loss function to calculate the error among the actual and prediction values, and the optimizer uses the Adam algorithm [18]. The CNN batch size and training iterations are 32 and 50, respectively. The total number of parameters for the implemented CNN is 5,668,162. Table 1 shows the used layers of the proposed CNN.

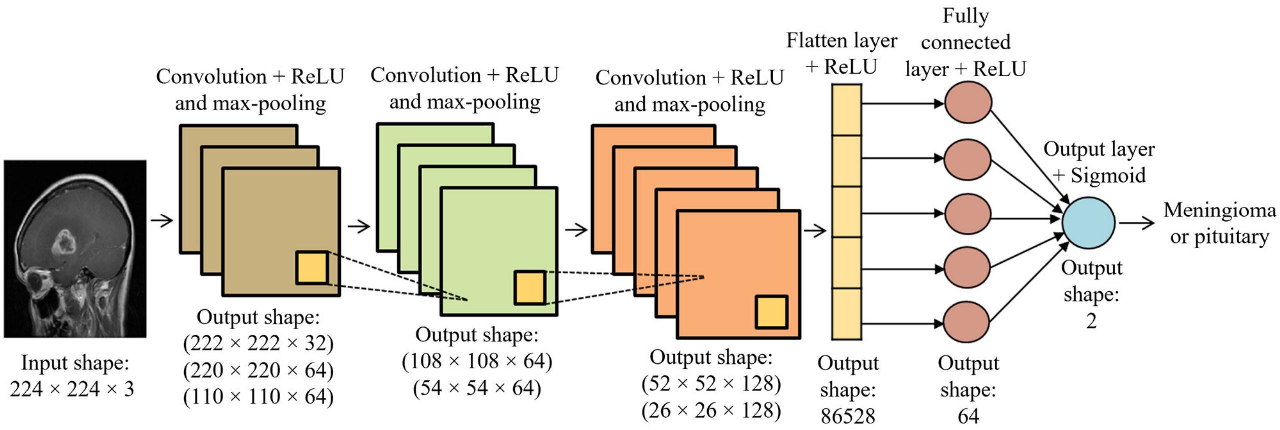

Fig. 1 The structure of the CNN model

Table 1 The layers of the CNN

Layer	Type	Kernel size	Output shape	Trainable parameters
1	Conv2D	3 × 3	222 × 222 × 32	896
2	Conv2D	3 × 3	220 × 220 × 64	18496
3	MaxPooling2D	2 × 2	110 × 110 × 64	0
4	Dropout	-	110 × 110 × 64	0
5	Conv2D	3 × 3	108 × 108 × 64	36928
6	MaxPooling2D	2 × 2	54 × 54 × 64	0
7	Dropout	-	54 × 54 × 64	0
8	Conv2D	3 × 3	52 × 52 × 128	73856
9	MaxPooling2D	2 × 2	26 × 26 × 128	0
10	Dropout	-	26 × 26 × 128	0
11	Flatten	-	86528	0
12	Fully connected	-	64	5537856
13	Dropout	-	64	0
14	Output	-	2	130

2.2. *Dataset description*

The MRI dataset collected from the repository of Kaggle [19] includes 900 images of the meningioma and 900 images of the pituitary. The proposed model is evaluated through the MRI dataset collected for testing and training. 1,800 MRIs are divided into 20% of the dataset utilized for testing, while 80% remaining is used for training, where the purpose of the testing is to assess the CNN model, while the purpose of the training is to learn the CNN model features of the MRI images. The difference between meningioma and pituitary images is the intensity of their pixels or their features.

3. Results and Discussion

The CNN model is implemented by running Python programming language in Google Colab. The CNN is trained using a high-speed laptop with Intel Core i3, two central processing units (CPU), and 4GB of RAM. Fig. 2 shows CNN's training and testing accuracy curves. At 50 epochs, the accuracy percentage for training is 93.6%; the accuracy percentage for testing is 95.78%. These values mean that the CNN performs better based on the testing and training dataset at 50 training epochs. Fig. 3 demonstrates learning curves for the loss of CNN. At 50 epochs, the loss rate for training is 0.1734; the loss rate for testing is 0.1476. Analyzing the performance of the model can be described as [20]:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

$$F1\text{-}score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

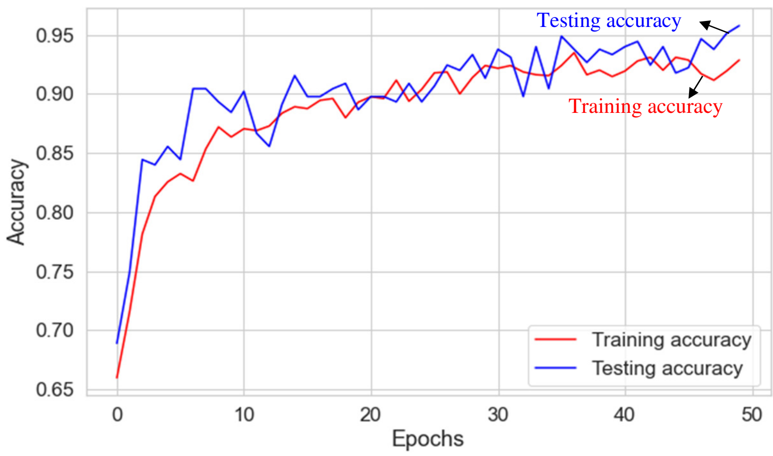

Fig. 2 Accuracy curves for the CNN

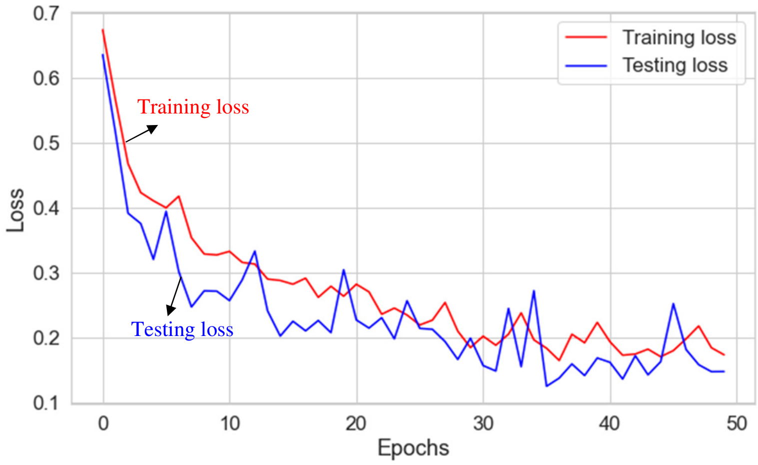

Fig. 3 Loss curves for the CNN

Table 2 presents a classification report of the brain tumors with evaluation metrics of the recall, precision, and F1-score for the CNN model. In this work, the weighted average of precision, sensitivity, and F1-score are 95.82%, 95.78%, and 95.78%, respectively. These values mean that the CNN performs better based on the testing and training dataset at 50 training epochs. These results are estimated from the confusion matrix that is used to assess the performance of the CNN model.

Table 2 Classification report for the CNN model

Class	Precision	Recall	F1-score
Meningioma	0.9440	0.9733	0.9584
Pituitary	0.9725	0.9422	0.9571
Macro average	0.9582	0.9578	0.9578
Weighted average	0.9582	0.9578	0.9578

Fig. 4 describes the confusion matrix determined based on the CNN. In this part, the diagonal values are the testing accuracy to classify the MRI images. The matrix lists data of the true positives of meningioma as 219; the true positives of the pituitary are 212. These values mean that the CNN performs better for the meningioma class than the pituitary class. The normalized confusion matrix of the CNN is introduced in Fig. 5. The proposed CNN for the accuracy of meningioma is 0.97; the accuracy of the pituitary is 0.94. Therefore, classification errors of 0.058 and 0.027 for meningioma and pituitary, respectively. These values mean that the CNN achieves fewer error results for the meningioma class than the pituitary class.

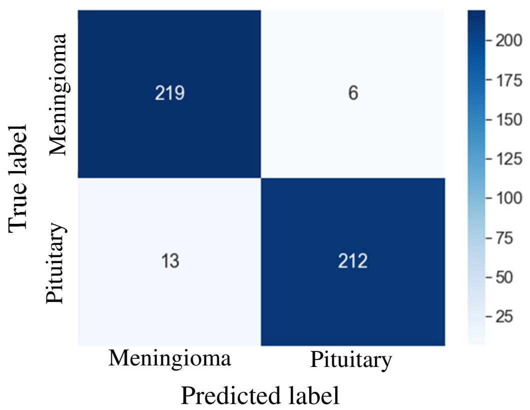

Fig. 4 Confusion matrix for CNN

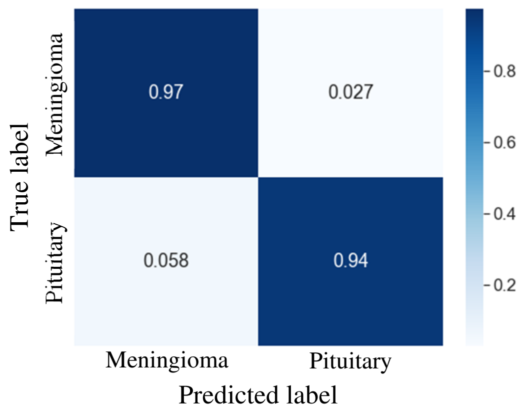

Fig. 5 Normalized confusion matrix for CNN

Fig. 6 illustrates the PR curves for each class. The PR curve of class meningioma has the lowest area of 0.987, while the PR curve of class pituitary has the highest area of 0.989. Thereby, the micro-average PR curve has an area of 0.998. Fig. 7 presents the ROC curves, where the area values of the meningioma and pituitary tumor classes are 0.99. The micro-average area for the ROC curve is 0.99; thus, it proves that CNN achieves high performance based on these curves. The ROC curve is described by the true positive rate (TPR) to the false positive rate (FPR). The PR curve is the ratio between the precision and the recall.

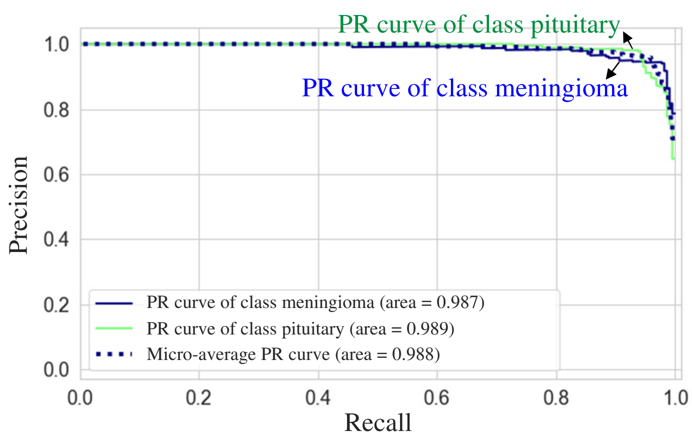

Fig. 6 PR curves of the CNN

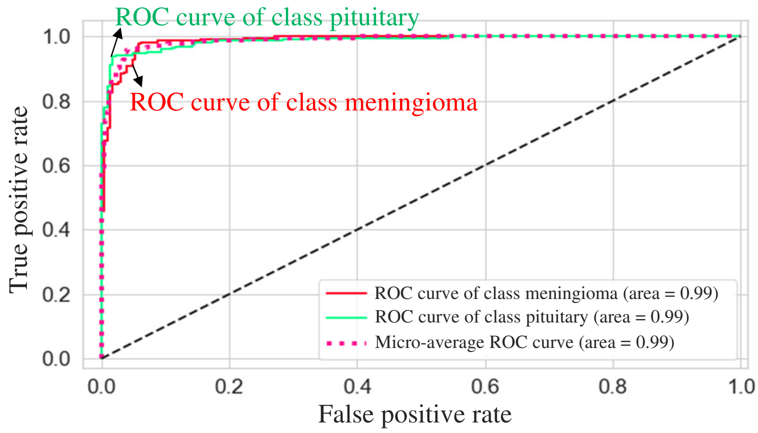

Fig. 7 Area under ROC curves for the CNN

The PR curves, normalized confusion matrices, and ROC curves show that the accurate classification of brain tumor patients is achieved by using the CNN model. Additionally, CNN had a low loss rate and high accuracy when testing and training. Table 3 introduces a comparison of the accuracy achieved by previously published works [8-16] and this work. In this study, the CNN achieved a maximum accuracy of 95.78%, which is better than the previous models.

Table 3 Comparison between previous works and the proposed work

Reference	Model	Testing accuracy (%)
[8]	CapsNet	86.56
[9]	CNN + GA	94.2
[10]	VGG-16 Inception-V3 ResNet-50	90 55 95
[11]	DenseNet + LSTM	91.28
[12]	SVM	91.28
[13]	CNN	84.19
[14]	KNN + nLBP	95.56
[15]	CNN + KELM	93.68
[16]	SVM	85
Proposed work	CNN	95.78

4. Conclusions

This paper has proposed a new CNN model to classify two brain tumors “meningioma” and “pituitary” from MRI image patients. It obtains a high testing accuracy of 95.78% in the image dataset of 900 meningioma images and 900 pituitary images. The normalized confusion matrix, recall, precision, F1-score, the area under the PR, and ROC curves evaluate the efficiency of the CNN. The CNN has a precision of 95.82%, a recall of 95.78%, and an F1-score of 95.78%. The PR curves with an area of 98.7% for the meningioma class and 98.9% for the pituitary class; the average area under the ROC curve is 99% for the meningioma and pituitary classes for CNN. The results show that the new CNN model can improve the detection of brain tumors.

Conflicts of Interest

The author declares no conflict of interest.

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