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RESEARCH ARTICLE

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Classification of Brain Tumors Using Convolutional Neural Networks

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Abstract. Diagnosing a brain tumor usually begins with magnetic resonance imaging (MRI). If MRI detects a tumor in the brain, the type of brain tumor is usually known by looking at the results from a sample of tissue after a biopsy or surgery. This procedure can be time-consuming, tedious, and costly. This manual examination mechanism can be replaced by machine learning-based automated techniques that can save precious time and significantly reduce human effort and error. This paper aims to make multi-classification of brain tumors using deep learning. The deep learning model can classify the brain tumor into four brain tumor types as normal, glioma, meningioma, and pituitary with an accuracy of 95.26%. Satisfactory classification results are obtained using large and publicly available clinical datasets. The proposed model can be employed to assist physicians and radiologists in detecting brain tumor.

Keywords: Brain tumor, Deep learning, AlexNet.

1 Introduction

The brain tumor is considered as a deadly cancer in adults and children. A brain tumor occurs when the brain tissues develop unnaturally. The abnormal tissues overgrow compared to the healthy cells, causing the mass of cells that eventually transform tumors [1].
Many different types of brain tumors exist. Some brain tumors are noncancerous (benign), and some brain tumors are cancerous (malignant). Brain tumors can begin in the brain (primary brain tumors), or cancer can begin in other parts of the body and spread to the brain as secondary (metastatic) brain tumors [2].
Quick and timely recognition of a brain tumor is of the utmost importance for curing the tumor. It depends on the expertise and professional skills of the doctor and which method is selected to treat the patient for rapid recovery. It is challenging to determine the correct type of brain tumor in the initial phase, yet vital as it helps the physicians treat the patient accordingly [3].

Meningioma is the most common primary brain tumor, accounting for more than 30% of all brain tumors. Women are diagnosed with meningiomas more often than men. About 85% of meningiomas are noncancerous, slow-growing tumors [4]. Gliomas are brain tumours that start in glial cells. These are the supporting cells of the brain and the spinal cord [5].

Pituitary tumors are abnormal growths that develop in the pituitary gland. Some pituitary tumors result in too much of the hormones that regulate important functions of the body. Some pituitary tumors can cause the pituitary gland to produce lower levels of hormones. Most pituitary tumors are noncancerous (benign) growths [6].

The processing of medical images plays a key role in assisting humans in identifying different diseases. Computer tomography (CT) and Magnetic Resonance Imaging (MRI) are two approaches usually utilized for inspecting the irregularities in brain tissues concerning the size, location, or shape of cells, which can help in detecting the tumor in its initial stages [7]. Although MRI and CT images can clearly show the tumor in the brain, manual detection can always be time-consuming, tedious, and costly. Thus, we used the modern technique called Deep Learning to save time and cost for the doctors and to make the tumor detection fully automated.

1.1 Deep learning

Before deep learning there was machine learning, the simple machine learning algorithms work well on a wide variety of important problems. They have not succeeded, however, in solving the central problems in AI, such as recognizing speech or recognizing objects. The development of deep learning was motivated in part by the failure of traditional algorithms to generalize well on such AI tasks. The reason is that many machine learning problems become exceedingly difficult when the number of dimensions in the data is high. This phenomenon is known as the curse of dimensionality. The solution to this problem of dimensionality was to change the model we use from a parametric model to a Neural network. Deep learning algorithms are powerful and versatile algorithms used efficiently in significant research areas such as medical image processing, investment modeling, and fraud detection.
Neural networks are really just a bunch of neurons connected together. Consider a node that receives three inputs, as shown in Figure (1) [8].

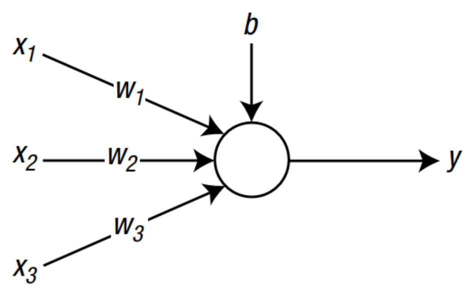

Fig. 1. A node that receives three inputs.

X1, X2, and X3 are the input signals. W1, W2, and W3 are the weights for the corresponding signals. Lastly, b is the bias, which is another factor associated with the storage of information. In other words, the information of the neural net is stored in the form of weights and bias. The input signal from the outside is multiplied by the weight before it reaches the node. Once the weighted signals are collected at the node, these values are added to be the weighted sum.
values are added to be the weighted sum. The weighted sum of this example is calculated as follows:

$$v = (w_1 \times x_1) + (w_2 \times x_2) + (w_3 \times x_3) + b$$

The equation of the weighted sum can be written with matrices as:

$$v = wx + b$$

where w and x are defined as:

$$w = \begin{bmatrix} w_1 & w_2 & w_3 \end{bmatrix} \qquad x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

Since there may be more features, it will be faster for the computer to calculate a matrix than a loop, this process is called vectorization.

A single neuron is the same as linear regression without applying activation. Finally, the node enters the weighted sum into the activation function and yields its output.

The activation function (equation(2)) determines the behavior of the node.

$$y = \varphi(v) = \varphi(wx + b) \tag{1}$$

1.2 Activation functions

The result of the weighted sum can be any number, but for some networks we want the activations to be values between some numbers. So it's common to pump this weighted sum into some function that squishes the real number line into the range we want. This function is called the Activation function. Nowadays, people tend to use a function called ReLU (Rectified Linear Unit) figure (2). ReLU output a 0 for any negative input, and doesn't change the positive inputs at all [9].

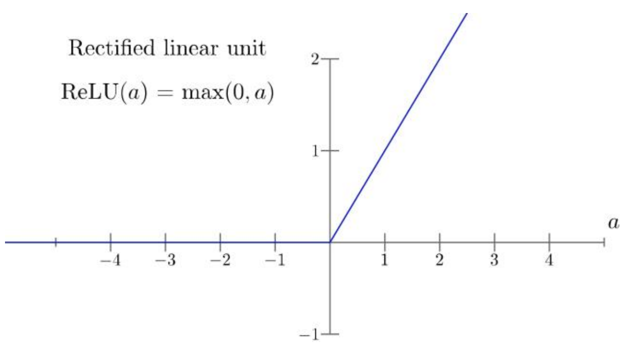

Fig.2. The ReLU function.

1.3 Convolutional neural networks

Convolutional Neural Networks (CNN's) are a popular subcategory of deep learning algorithms, specially designed for visual pattern recognition. In the last few years, thanks to the increase in computational power, the amount of available training data, and the algorithms for training deep nets, CNNs have managed to achieve superhuman performance on some complex visual tasks. They power image search services, self-driving cars, automatic video classification systems, and more.

A convolutional network is different than a regular neural network in that the neurons in its layers are arranged in three dimensions (width, height, and depth dimensions). This allows the CNN to transform an input volume in three dimensions into an output volume. Also the layers of a CNN are different from the layers of a normal neural network, a basic CNN usually contains a convolutional layer, pooling layer, and a fully connected layer. Figure (3) shows an example of a convolutional neural network.

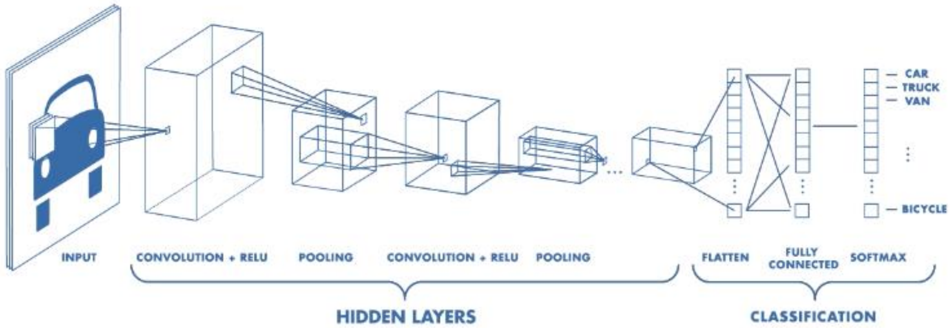

Fig. 3. Architecture of a convolutional neural network.

A practical example of a CNN is AlexNet, AlexNet is a CNN-based algorithm [10] that uses eight different layers, including maximum pooling, convolutional, and fully connected [11]. AlexNet is declared the best neural network model for image classification in the Large Scale Visual Recognition Challenge (2012) [12].

1.4 Transfer learning

It is generally not a good idea to train a very large neural network from scratch, instead, you should always try to find an existing neural network that accomplishes a similar task to the one you are trying to tackle then just reuse the lower layers of this network, this is called transfer learning. It will not only speed up training considerably but will also require much less training data [13-10]. Figure (4) shows the process of transfer learning of a neural network [14-17].

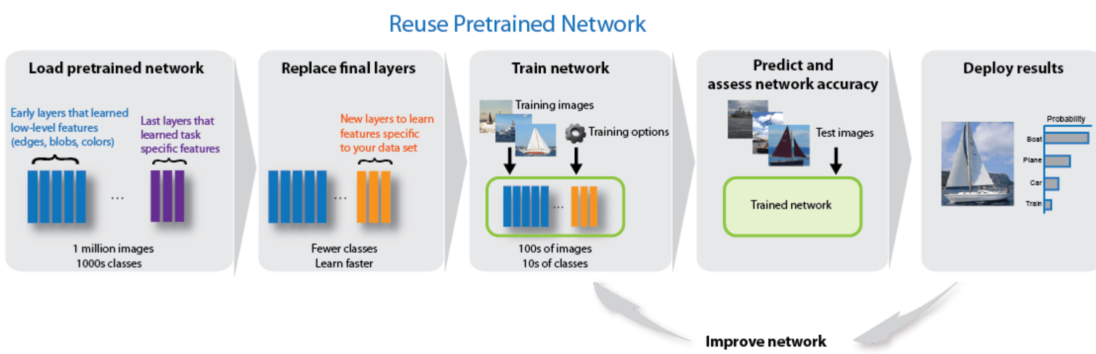

Fig. 4. Block diagram of reusing a neural network.

2 Materials and methods

In this paper we use the approach of transfer learning on the Alex-net-model to classify the previously described brain tumors. The model for the identification can classify brain tumors into four classes: meningioma, glioma, pituitary, and no-tumor. A total of 2870 images has been used in the model, including 822, 826, and 827 for meningioma, glioma, and pituitary, respectively, and 395 for the no-tumor class.
The research methodology is based on MRI image analysis for brain tumor classification, using computer vision techniques. We calculated the performance of AlexNet in terms of Accuracy, and Mean Square Error or Quadratic Loss.

The experiments are conducted on a workstation with a 2.6 GHz Core i7 10th generation CPU, NVIDIA GeForce RTX 2070 GPU and 16 GB RAM in MATLAB 2021a environment with Deep Learning toolbox.

In this section, the discussion will be about the dataset, preprocessing steps, AlexNet model, and Evaluation parameters.

2.1 Dataset

A total of 2870 images has been used in the model, including 822, 826, and 827 for meningioma, glioma, and pituitary, respectively, and 395 for the no-tumor class. The brain tumor MRI images are collected from a publicly available dataset on kaggle[15]. The dataset's properties are shown in Table 1.

Table 1. The dataset's properties.

Total classes	4
Meningioma	822
Glioma	826
Pituitary	827
Normal	395

2.2 Data preprocessing

Data preprocessing is a critical step used to check the data for experiments, the images should be prepared for the model. In our experiments, we resize every image into a 227 by 227 pixel image to feed it to the first layer of the Neural Network. After resizing the images, We choose about 80% of the remaining images for training our model and about 20% for evaluating our model.

2.3 AlexNet architecture

The AlexNet model comprises five convolutional, three maximum pooling, and three fully connected layers. The model needs a 227×227 pixel image as an input, and then ReLU (Rectified Linear Unit) activation function is applied to remove non-linearity. After that, the images are down sampled to extract rich features using pooling layers.

The first fully connected layer is then used to flatten the feature vector, which drops out 50% of the features. Each Fully Connected layer contains 4096 neurons. The last fully connected layer is known as the output layer and will produce 1000 outputs. These 1000 outputs will be passed through the SoftMax activation function. In the last phase, we trained and tested our CNN model, which classified different brain tumor types that are either normal or abnormal. We apply 100 epochs on training with 1700 iterations. Figure (5) shows the AlexNet model structure, while Table 2 shows the details of the AlexNet network [16].

Table 2. The details of the AlexNet-based model.

Algorithm	AlexNet
Epochs	100
Number of Iterations	800
Dataset	2870
Learning rate	0.001
Training data	80%
Evaluating data	20%

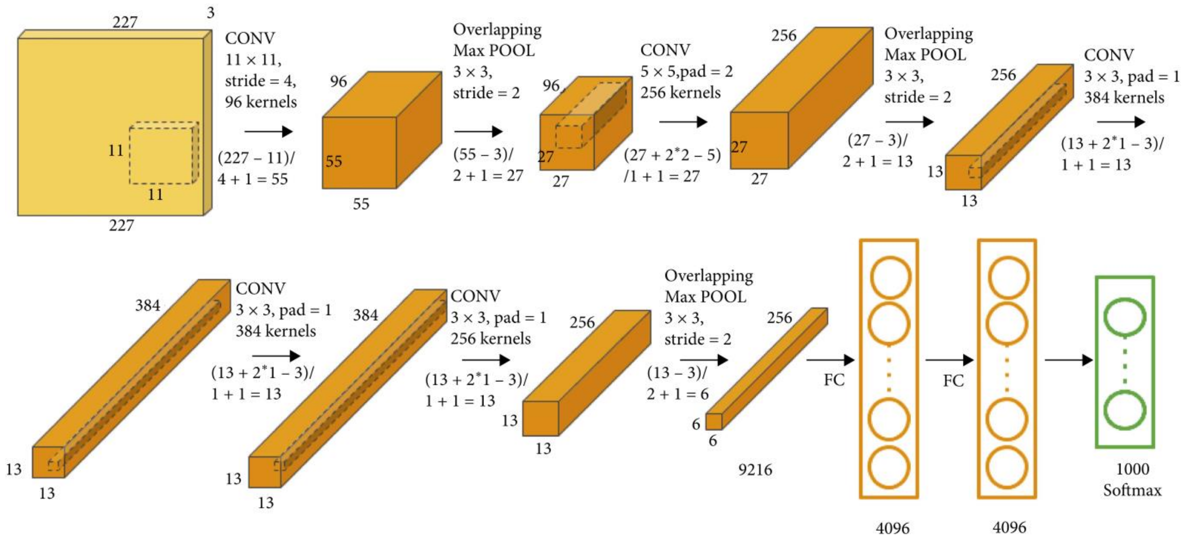

Fig. 5. structure of AlexNet model

2.4 Evaluation parameters

The proposed model's performance is calculated in both Accuracy (equation(2)) and in Mean Square Error or Quadratic Loss (equation(3)).

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}}, \quad (2)$$

$$\text{Quadratic Loss} = \frac{\sum_{i=1}^{n} \left(x_i - x_i'\right)^2}{n}. \quad (3)$$

Where in equation(2) :
True positive (TP) is the number of cases correctly identified as patient
False positive (FP) is the number of cases incorrectly identified as patient
True negative (TN) is the number of cases correctly identified as healthy
False negative (FN) is the number of cases incorrectly identified as healthy

And in equation(3):
x_i is the real output at the i'th training example.
x'_i is the hypothesis at the i'th training example.
n is the number of training examples.

3 Results and discussion

This research aims to improve the automatic detection of different types of brain tumor in MRI images. We proposed AlexNet-based CNN model for accurate detection of brain tumor and calculated its performance. In contrast, the AlexNet model has five convolutional, three maximum pooling, and three fully connected layers. The experiments are conducted with the preclassified dataset of 2870 images taken from Kaggle[15]. The data are preclassified by the experts of the field. The models' performance is evaluated in Accuracy, and Mean Square Error or Quadratic Loss.

The proposed smart detection model for brain tumor identification has been classified into four classes. meningioma, glioma, pituitary and no-tumor. Based on the experiments, the AlexNet-based model was able to correctly classify images with accuracy of 95.29%, and a minimum error of 0.0004. The accuracy and loss performance during training is shown in figure (6), while table (3) shows the Matlab training progress in Epochs and iterations.

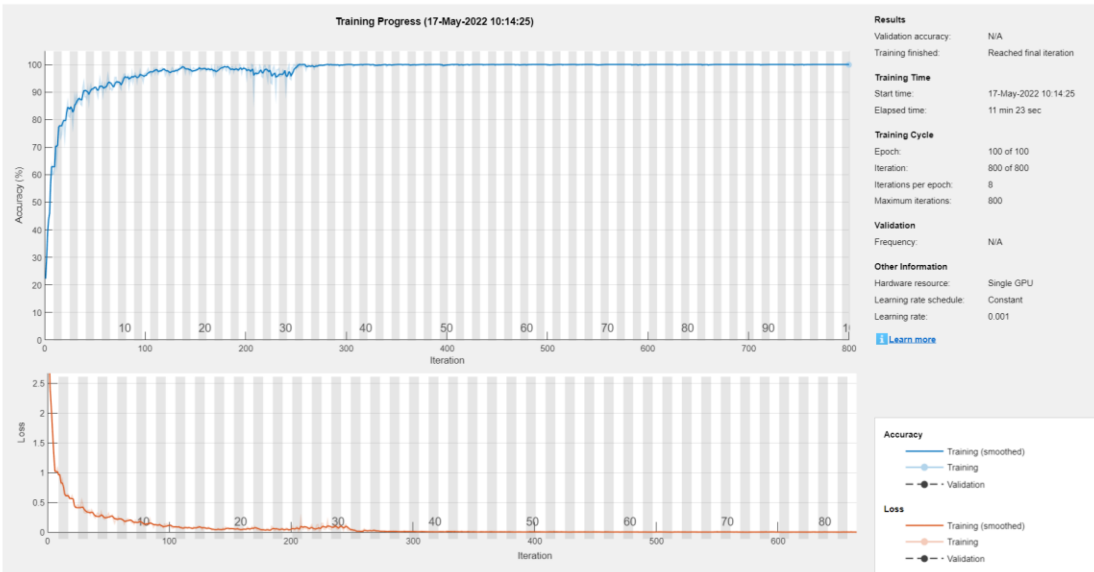

Fig.6. Accuracy and loss of the model during training

Table 3. Training process in epochs and iterations.

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch Accuracy	Mini-batch Loss	Base Learning Rate
1	1	00:00:02	22.27%	3.1985	0.0010
7	50	00:00:44	91.80%	0.3142	0.0010
13	100	00:01:26	96.88%	0.1220	0.0010
19	150	00:02:09	98.05%	0.0515	0.0010
25	200	00:02:51	98.44%	0.0546	0.0010
32	250	00:03:34	98.44%	0.0497	0.0010
38	300	00:04:16	100.00%	0.0116	0.0010
44	350	00:04:59	100.00%	0.0070	0.0010
50	400	00:05:41	100.00%	0.0046	0.0010
57	450	00:06:24	100.00%	0.0052	0.0010
63	500	00:07:07	99.61%	0.0093	0.0010
69	550	00:07:49	99.61%	0.0130	0.0010
75	600	00:08:32	100.00%	0.0004	0.0010
82	650	00:09:15	100.00%	0.0014	0.0010
88	700	00:09:58	100.00%	0.0015	0.0010
94	750	00:10:40	100.00%	0.0017	0.0010
100	800	00:11:23	100.00%	0.0010	0.0010

After training the network, we use our network on new MRI brain images that the network hasn't been trained on. For this purpose, we designed a graphical user interface (GUI) named: Brain tumor classifier v1.0. Figure (7) shows the block diagram of the application and figure (8) shows the interface of the app.

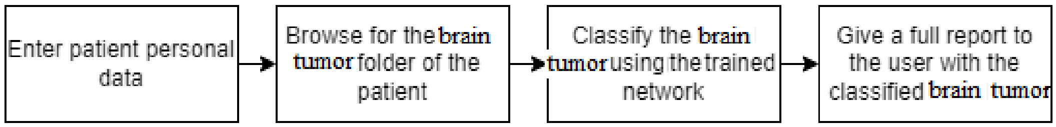

Fig. 7. Block diagram of the application

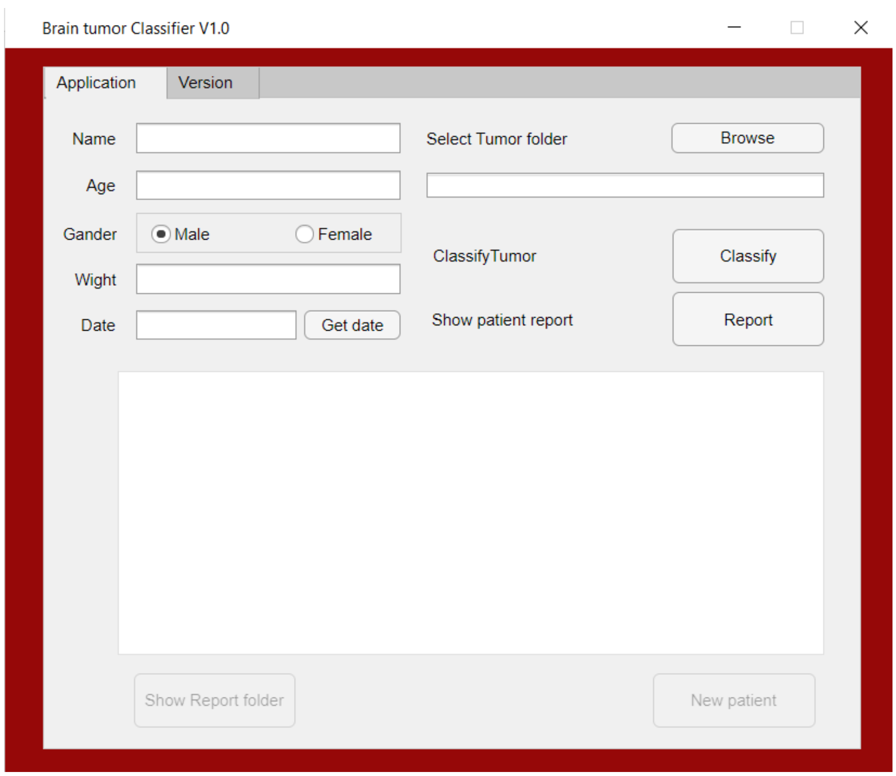

Fig. 8. Interface of the GUI.

3 Conclusion and future work

The brain tumor is considered to be fatal cancer in adults and children. The common types of primary tumors found in adults are glioma, meningioma, and pituitary. Numerous methods have been suggested and inspected in the literature for detection and classification of the brain tumor to expand the possibilities of treatment and endurance of the patients. A CNN AlexNet Based Brain Tumor Classifier is proposed in the present study. The model classified the input into four classes: glioma, meningioma, pituitary, and no-tumor. The proposed model accomplished 95.29% accuracy and a minimum error of 0.0004 superior to existing brain tumor detection and segmentation methods. The system also classifies the tumor into different classes after tumor recognition. Also we designed a Graphical User Interface (GUI) to help specialists detect different brain tumors.

Conflict of Interest

This is to certify that all authors have seen and approved the manuscript being submitted and to declare that they have no conflicts of interest.

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