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CNN-based MRI Brain Tumor Detection Application

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***Abstract*—Brain tumors are usually diagnosed manually by the doctors from the Magnetic Resonance Images, which decreases the efficiency of the diagnosis process. Facing the situation that diagnosis of brain tumors from Magnetic Resonance Images needs effective methods to increase the speed and enhance the accuracy, we proposed algorithms using Convolutional Neural Network, the MobileNet, and AlexNet models to help classify the tumor while also developed an interface system to connect the algorithm directly to hospital system. We utilized grouped dataset and developed the algorithm to classify whether there is brain tumor occurred in the Magnetic Resonance images. The patients can employ the interface system developed through Tkinter by simply typing the information and automatically get the final results appears on the screen. From our result, compared with other models such as MobileNet and AlexNet, the proposed Convolutional Neural Network algorithm reaches the highest accuracy and lowest loss. Our interface system enables the patients of the hospital to directly and conveniently access the diagnosis of our algorithm.**

Keywords- Convolutional Neural Network; AlexNet; MobileNet; Brain Tumor; MRI; Interface; Tkinter

I. INTRODUCTION

Brain tumors are one of the deadliest cancers and pose a threat to human life, appearing in areas or related parts of the brain [1][2]. Rapid and accurate diagnosis is essential for the treatment of brain tumors. Magnetic Resonance Images (MRI) is the standard technique for brain tumor diagnosis [1]. As MRI is a non-invasive technique that provides excellent anatomical information and is sensitive to key components of tumor physiology, it is essential for early detection, monitoring, and diagnosis [3]. Clinically, MRI can be used in combination with imaging techniques to provide the most accurate information about tumor morphology and metabolism such as computed tomography (CT) [1]. However, CT may miss structural lesions, especially in the posterior fossa [4]. So far MRI is the accepted standard for brain tumors [1].

The problem in radiological is still the need to manually analyse the results of MRI brain tumor manually, thus it takes a long time to find out the diagnostic from the doctor. In addition, more pathological tests are often required to distinguish brain tumors from other diseases in the brain because of the similar color [5].

Recently, with the advancement in deep learning and the strong feature extraction ability of CNN models, many CNN-based methods are used in brain tumor diagnosis [6-8]. Laukamp et al. [6] detected meningiomas by using conventional MRI based on deep learning. The deep learning model is able to detect 55 cases out of 56 cases successfully. Similarly, Charron et al. [7] developed a CNN-based model for automatic detection and segmentation of MRI brain metastases, which had an average Dice similarity coefficient of 0.77. In addition, Abd-Ellah et al. [8] used convolutional neural network to extract data features from 19 patients' MRI images and used SVM for classification, and finally achieved automatic diagnosis of brain tumor on MRI which accuracy is 99.55% and a Dice coefficient is 0.87. However, the sample size of this study [8] was only 19 cases, which is easily prone to error. Deep learning training usually requires a large amount of high-quality medical data, so further expansion of sample diversity and sample size is needed to improve this study. In addition, these studies mentioned above just focused on the simulation of the models and ignored the implementation of the interoperable industrial systems. In fact, it is also important for doctors or specialists to have such a system, which can help them to reduce the analytical time and get higher accuracy.

Therefore, in order to overcome the above shortcomings, a user-interactive interface is built to facilitate patients to query results, which can also save time for the doctor's accurate judgment. In summary, our main contributions of this paper are as follows:

1) We employ three different models for image analysis and tumor determination, which are self-defined CNN, MobileNet and AlexNet. The self-defined CNN work best for the highest accuracy for 98.8% and loss for 1.96.

2) We deploy Tkinter to build an interactive user interface for patients and physicians to view the tumor analysis results conveniently.

II. METHOD

A. Dataset

The dataset we used comes from Brain MRI Images for Brain Tumor Detection [9] which is provided by Kaggle. The

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dataset has already been classified into two types, that 115 images have brain tumor and 98 images do not.

The data augmentation technology can be used to expand the size of the data set, so that the expanded data can be used to build a better deep learning model [10]. The amount of existing Brain MRI data is insufficient for deep learning model training. Thus, the first step is to expand our data set through rotating, changing brightness, and flipping. After data augmentation, the amount of image data reached 2783. One of the characteristics of human brain MRI is that there is a black area e.g. background information around the brain in the image, which is invalid for medical diagnosis and deep learning training. The model can be focused on the brain part by cropping off the invalid area to extract effective features. The images in the original data set with different sizes, thus resize the images to the same size is also necessary.

After that, the dataset is shuffled and divided into the training set, validation set and testing set.

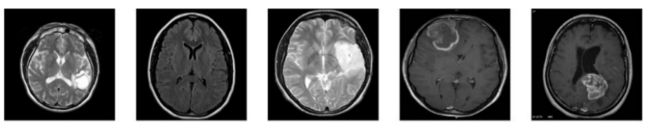

Figure 1. Original images displayed in the same size

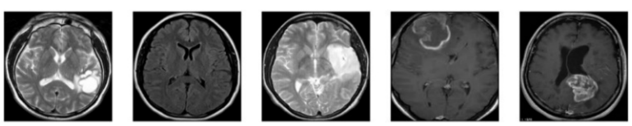

Figure 2. Images after cropping and resize processing

B. Algorithm

Convolutional Neural Network (CNN) [11] is a feedforward neural network that usually includes an input layer, convolution layer, pooling layer, and ReLu-activation layer. It has been proved that it can perform well in medical image processing e.g., intracranial hemorrhage [12]. CNN uses convolution algorithm instead of traditional matrix multiplication neural network, which makes it important in the field of image processing. In the convolution layer, CNN employs a filter and applies convolution algorithm to it to get new characteristic images. Pooling layer mainly performs the work of downsampling, compressing the characteristic image, that helps simplifying the calculation and elicit main characteristics.

To achieve better results, both AlexNet and MobileNet models are also used in this study for data analysis. AlexNet can achieve efficient GPU convolutional structure and solve the overfitting problem of deep neural network by many skills, such as dropout, RELU and data augmentation, so that the network can still converge well with 60 million parameters. Unlike traditional neural networks, AlexNet uses RELU as the activation function, which makes the speed of training improve approximately 6 times more.

Even the AlexNet model is good at the recognition, but the number of parameters and computation of the model is huge and not suitable for running on mobile, embedded devices. There are more lightweight and faster CNN designs, and Google's MobileNet is one of them. MobileNet describes an efficient network architecture that allows the direct construction of very small, low-latency models that easily meet the requirements of embedded devices through two hyperparameters. MobileNet abandons the pooling layer and directly uses stride of 2 for convolutional operations and two hyperparameters, the width adjustment parameter and the resolution parameter, to control the network computation speed and accuracy. Therefore, MobileNet is also employed in our study.

C. Interface

As for the output of the result, Tkinter is used to build an interactive interface. It is Python’s important graphical user interface package that largely been used to achieve user interaction with the program. The users just need to input their names and answer the question to tell the system whether they need to know the result of detection, and then this system will give the proper feedback. Even though Tkinter is simpler than other GUI packages e.g., pyqt5, we still choose to use it since we don’t need to design a very complex application, it is enough for the industrial demand.

In addition, Natural Language Processing (NLP) techniques [13] can be used to divide the words received, search for keywords inside the words to gain information, and create active communication with the user. NLP techniques ate used to identify whether the user needs to know the detection. NLP techniques technology can be used to solve many problems, such as sentiment analysis, trend analysis, and event extraction. In our project, we just focus on information extraction.

D. Implementation Details

We firstly proposed CNN network realized by TensorFlow in Python. Our CNN model has in total 11 layers. The model first contains two repeated combination of layers of convolution layer, batch normalization layer, and max pooling layer to filter the characteristic from the images. At the end of the model, a convolution layer and a batch normalization layer are connected to flatten, dropout and dense layer to achieve the final classification of the image.

The second model we used is the MobileNet. It contains four layer, one mobilenet layer, one global average pooling layer, connected to a dropout and dense layer to employ the MobileNet algorithm and dense to final binary classification. The third model is AlexNet. AlexNet model we built has 19 layers. It begins with two repeated combination of convolution layer, connected to the max pooling layer. After the first four layers, there are repeated combination of two convolution layer connected to the max pooling layer. At last, is flatten layer, dense layer, dropout layer, dense layer, dropout layer, and final dense layer that output the classification.

1) Loss Function: The loss function we employed is binary cross-entropy loss function [14]. It is normally used in binary classification with the following formula:

$$J_{bce} = -\frac{1}{M}\sum_{m=1}^{M}[y_m \times +(1-y_m) \times \log(1-h_\theta(x_m))] \quad (1)$$

The activation function we employed is sigmoid [15] function with the following formula:

$$\sigma(x) = \frac{1}{1+\exp(-x)} \quad (2)$$

2) Training detail: We chose to use 70 percent of data for training, 15 percent of data for validation, and 15 percent data for testing. We performed in total 40 epochs for each method, and we used Adam optimizer. The learning rate we utilized is 0.001.

III. RESULT AND DISCUSSION

A. Performance Comparison

After the training, the results of our methods, including AlexNet, MobileNet, and proposed CNN, are shown in the Table 1:

TABLE I. ACCURACY IN DIFFERENT MODELS.

Model	Evaluation Indicator	
	Accuracy	Loss
AlexNet	0.9640	0.0838
MobileNet	0.9712	0.1473
Proposed CNN	0.9880	0.0196

To evaluate the performance of different classical CNN models in the brain images. We measured the accuracy and loss between them, which can be seen in Table I. Table I shows that our proposed CNN achieved the highest accuracy of 98.80% and lowest loss among the three models after training, followed by the MobileNet of which accuracy is 97.12%. The possible reason for this phenomenon is that the architecture of the proposed CNN is shallower than the MobileNet and AlexNet, which has fewer parameters and can better fit our dataset distribution. In fact, the feature of our dataset is not so complex, which is suitable to be processed by the model with fewer layers and a small number of parameters.

The accuracy and loss of the three models in the validation set change with epochs shown as following figures:

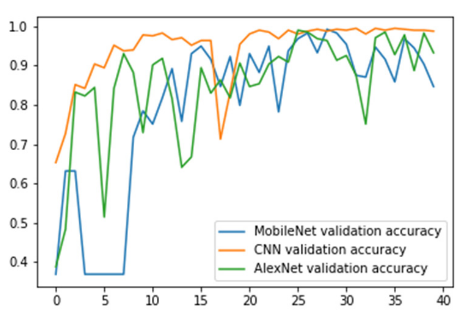

Figure 3. Trend of accuracy in different models.

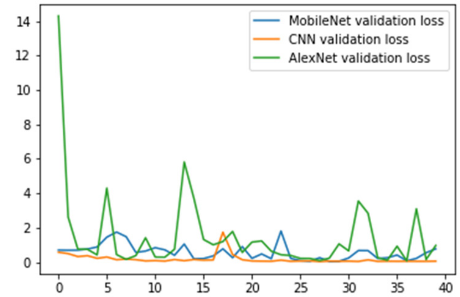

Figure 4. Trend of loss in different models.

B. Interface presentation

Our interface system is supposed to be connected to the hospital, so that the Tkinter interface can access directly to the hospital's library. After requesting names from the patients, received the string and matching it with the names in the hospital library, the interface is able to find the corresponding patients' information inside the hospital library. Then Tkinter will directly output the picture of the MRI of the brain tumor to the patients and ask whether the patient want to access the diagnosis. By using splitting and matching method from nature language processing, the interface system then can match the word it needs. If the words the patients typed in include yes, the interface system will output the result gained from the algorithm, else it will terminate. The pictures of the interface are shown in Figure 5 and Figure 6:

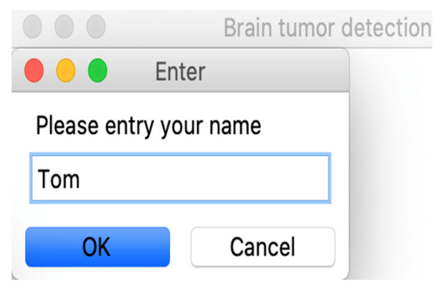

Figure 5. Interface system requests the name from patients and access the information of the patients from the hospital system.

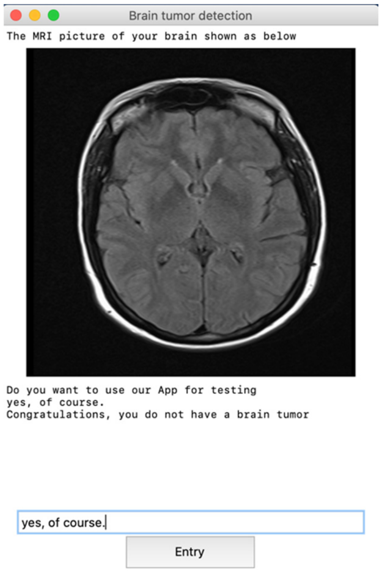

Figure 6. Interface system displays the MRI; after the patient's approval, the system will inform the diagnosis.

IV. Conclusion

In this paper, we proposed a self-designed CNN brain tumor classification method, which uses binary group data of brain tumor to train the brain tumor classification model in order to increase efficiency in classifying brain tumor in hospital system. In addition, we also employed the classical Alexnet and MobileNet models to test the performance of the brain tumor classification and compared them with our proposed CNN. Extensive experiments were conducted to evaluate the proposed CNN model. Experimental results showed that the models trained with our method have comparable accuracy than the results gained under various different settings, which achieved the accuracy of 98.8%. We also developed the interface system via Tkinter that could be connected to hospital system for broader complication. In the future, we plan to design a more robust method to decrease the overfitting problem in order to gain higher accuracy, broaden the usage of the interface system and serve more brain tumor classification tests.

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