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Brain tumour MRI detection and classification based on the convolutional neural network

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Abstract. Magnetic Resonance Imaging (MRI) has emerged as a widely used diagnostic technique for brain tumour detection. However, the diagnosis of brain tumours poses significant challenges due to their occurrence in diverse locations and various types. Furthermore, MRI generates images that require manual analysis by physicians, which can be laborious and prone to errors. To enhance the efficacy and accuracy of brain tumour detection, recent advances in artificial intelligence have led to the development of machine learning algorithms. In this study, a convolutional neural network (CNN) based method was proposed for brain tumour detection and classification through the preprocessing of raw MRI images. The customized CNN model achieves an accuracy of 98% on a dataset consisting of four types of MRI images, including three types of brain tumours and healthy brain images, with preprocessing applied to all images. The CNN model demonstrates an accuracy of 95% in classifying raw MRI images from the dataset. The CNN model's performance is further improved by training the model with preprocessed images that have been transformed into the same colour space and object area zoomed in. These findings provide a promising avenue for the development of automated and efficient brain tumour detection systems using CNN and MRI.

Keywords: brain tumour, MRI, CNN, machine learning, deep learning.

1. Introduction

Brain Tumor, also known as intracranial tumour, is an abnormal and uncontrollable growth of cells in the brain or near the brain tissue. As the most complex organ of the human body, the brain consists of different units: the forebrain including the cerebrum and tissue below it, the midbrain, and the hindbrain including the brain stem, upper spinal cord, and cerebellum. Brain tumours are not restricted to a fixed location, they can be found in any part of the brain and the skull. They may be classified as primary, originating from brain tissue or nearby, or metastatic, originating from other regions of the body. Brain tumours vary in many types and will cause pain and problem in people's life. People with Brain tumours are like to experience symptoms such as dizziness, headache, thought disorder, loss of hearing, vision changes, and memory loss. Nervous system cancer including brain tumours is the 10th leading cause of death for humans [1]. Worldwide, approximately 251, 329 deaths are caused by primary malignant nervous system tumours. Estimatively 24810 adults are diagnosed with primary malignant brain tumours in the U.S. in 2023 [2]. Brain tumours can exert pressure on and damage other parts of the brain tissue, leading to brain dysfunction and can also spread to other parts of the body. Magnetic Resonance Imaging

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(MRI) is the most popular technology for diagnosing. Determining the specific type of tumour usually requires surgery to test the brain tissue sample taken out from the body.

However, the process of diagnosis and classification of brain tumours is complex, and invasive which is associated with significant labour costs. In addition, MRI and Computerized Tomography (CT) scans do not always provide sufficient resolution to fully characterize the properties of the tumours, which will possibly cause misdiagnosis of the tumour. Delayed diagnosis, invasion, misdiagnosis, and high labour costs are all factors that reduce the recovery rate of brain tumours. Fortunately, recent advances in Artificial Intelligence (AI) have led to the development of novel techniques that hold promise for improving the diagnosis of brain tumours.

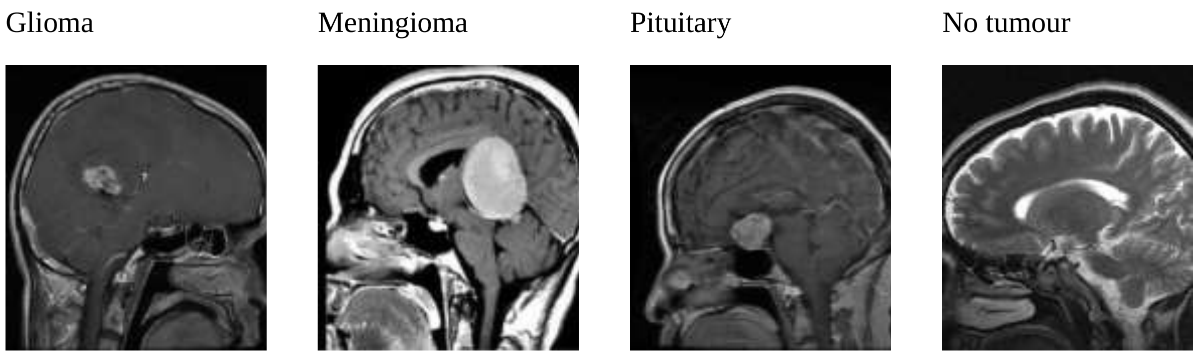
AI is a technique in that machines can work dynamically as if they had human intelligence relying on the AI algorithm. AI techniques include machine learning, deep learning, natural language processing, computer vision, and robotics. When working with a huge amount of data, well-developed AI algorithms can improve accuracy and precision, increase efficiency and productivity and reduce labour costs, freeing up human labour for more complicated work with low substitutability. Now, AI has been applied in various areas including the medical field. AI has shown its ability to improve the accuracy of the diagnosis of brain tumours. For instance, Alrashedy et al. employed the BrainGAN framework to generate and classify brain tumour images and reached an accuracy of 99.09% with ResNet152V2 [1].

In this paper, the convolutional neural network (CNN) will be used in MRI brain tumour classification after applying a preprocessing algorithm to raw data. Data is obtained from consisting of 7, 023 pictures divided into four categories: glioma, meningioma, pituitary and no tumour. For each class, the training and testing data can be accessed [2]. The study trains the models using training raw data and preprocessing data, evaluates the accuracy as well as the loss of the model and compares the performance of the models on the dataset in the two experiments. The result shows that the customized CNN model proposed in this study works well on the dataset without any data preprocessing before the training and reached an accuracy of 95%. With preprocessing algorithm applied to the data before training, the model performs even better and achieves an accuracy of 98%.

2. Method

2.1. Dataset

The dataset used in this study was sourced from [3]. It contains 7, 023 MRI images of human brains in total, categorized into four classes meningioma, glioma, pituitary, and no tumour. The dataset consists of a training set and a testing set for the purpose of training and evaluating the model, respectively. Sample images of these four classes are shown in Figure 1.



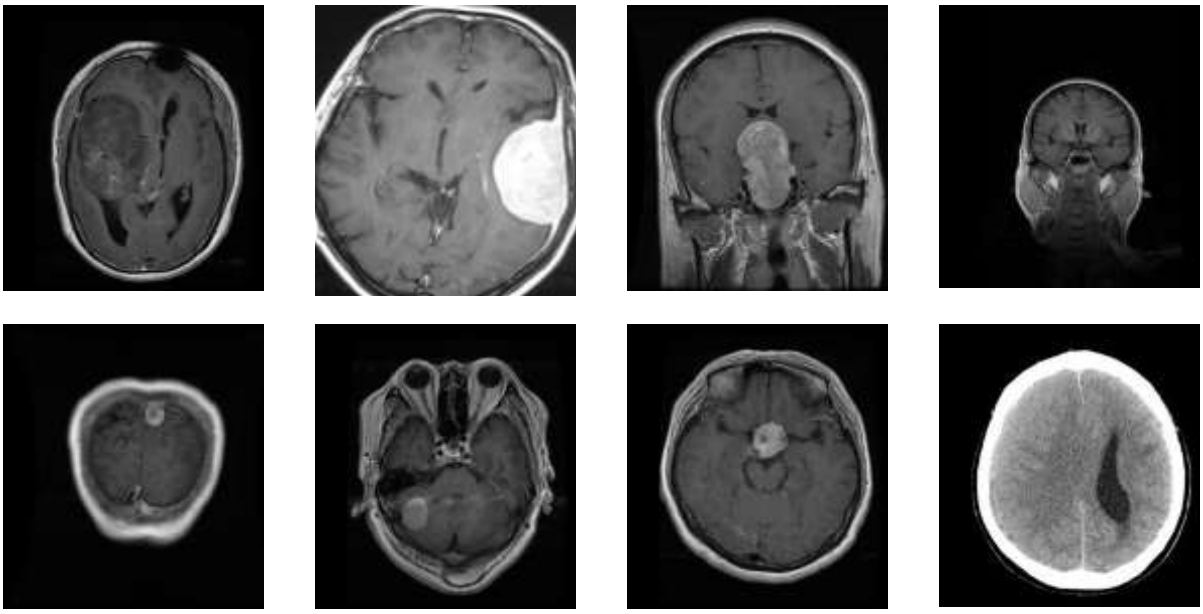


Figure 1. The sample images of the collected dataset.

To ensure the accuracy of the classification related to the grey-scaled MRI images in the dataset, the resizing operation was carried out first. The other preprocessing operation used Python packages called numpy, tqdm, cv2, os and imutils. For each image in the training set and testing set, the extreme points were found and then the rectangle out of them will be cropped. To accomplish this, cv2.cvtColor() method is applied first to convert all the images to cv2.COLOR_BGR2HSV colour space. Then, cv2 GaussianBlur() applies Gaussian smoothing to the converted images with kernel size [3 × 3]. When thresholding the images, cv2.threshold() is applied to the blurred images so that all pixel values above 45 are set to 255. After that comes morphological operations erosion and dilation. Erosion is performed twice on each image by cv2.erode() and dilation is performed twice by applying cv2.dilate() with the number of iterations set to 2 for both. Functions cv2.findContours() and imutils.grab_contours are used to find contours in the thresholded images and then grab the largest. Then the extreme points are found, by which images are cropped. Then, all the images are resized to size (100 × 100). So far, in each image of the dataset, the object area has been increased and the features of images are accentuated.

2.2. CNN model

Convolutional Neural Network (CNN) is a deep learning algorithm which is commonly used for image processing and analysis in different tasks [4-8]. A CNN model can be specified as a sequential model consisting of a series of neural layers. On each layer, computations are performed on the input data of this layer and the output of the layer is provided to the next layer as input [9]. In this way, the input data goes through the layers one after one, sequentially. The CNN model constructed in this study comprises 12 layers of three types, which are the convolutional layer, max pooling layer, and fully-connect layer [10].

The convolutional layer with a kernel of a specific size is the layer where the convolution is performed. The kernel is shifted across the input image. Each time, the kernel is applied to an area of the input, and the dot product between the covered pixels and the kernel is calculated and recorded. In this project, each convolutional layer has a 3 × 3 kernel. Rectified Linear Unit (ReLU) is used as the activation function for each convolutional layer. The max pooling layer is often used after a convolutional layer and is the place where a filter is shifted across the image and keeps only the pixel with the highest value each time. The fully connected layer) learns a set of weights and biases during

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training and updates these weights and biases. Every neuron in the dense layer is connected to each neuron in the previous layer. The CNN model of this project has the structure shown in Table 1.

Table 1. The strcuture of the proposed CNN.

Layer-1	Convolutional layer of 64 3 × 3 filters
Layer-2	Max pooling layer
Layer-3	Convolutional layer of 64 3 × 3 filters
Layer-4	Max pooling layer
Layer-5	Convolutional layer of 128 3 × 3 filters
Layer-6	Max pooling layer
Layer-7	Convolutional layer of 256 3 × 3 filters
Layer-8	Max pooling layer
Layer-9	Flatten layer
Layer-10	Dense layer (ReLU)
Layer-11	Dropout (0.5)
Layer-12	Dense layer (softmax)

2.3. Implementation details

The CNN model is constructed by using Tensorflow. The model is instantiated by creating an object of TensorFlow.keras.Sequential class. Layers are created by tensorflow.keras.layers and added to the model sequentially from the first to the last. The CNN model is compiled using Adam as the optimizer and sparse_categorical_crossentropy as the loss function. The metric to be evaluated by the model during training and testing is accuracy. In this study, the model is trained by original data that is not preprocessed in 200 epochs and by preprocessed data in 200 epochs.

Data generators for training and testing sets are created using ImageDataGenerator() from TensorFlow.keras, and then the flow_from_dirctory method is used to take the path to a directory and generates batches of augmented data. With the raw data and preprocessed data, the data generators will pass the original data and preprocessed data to train the model respectively. The four classes in the training and testing set are labelled as pituitary -> 4, no tumour -> 3, glioma -> 1, and meningioma -> 2.

3. Result and discussion

The loss to the index of epochs and the accuracy to the index of epochs of the model trained by non-preprocessed data and preprocessed data are plotted in Figure 2.

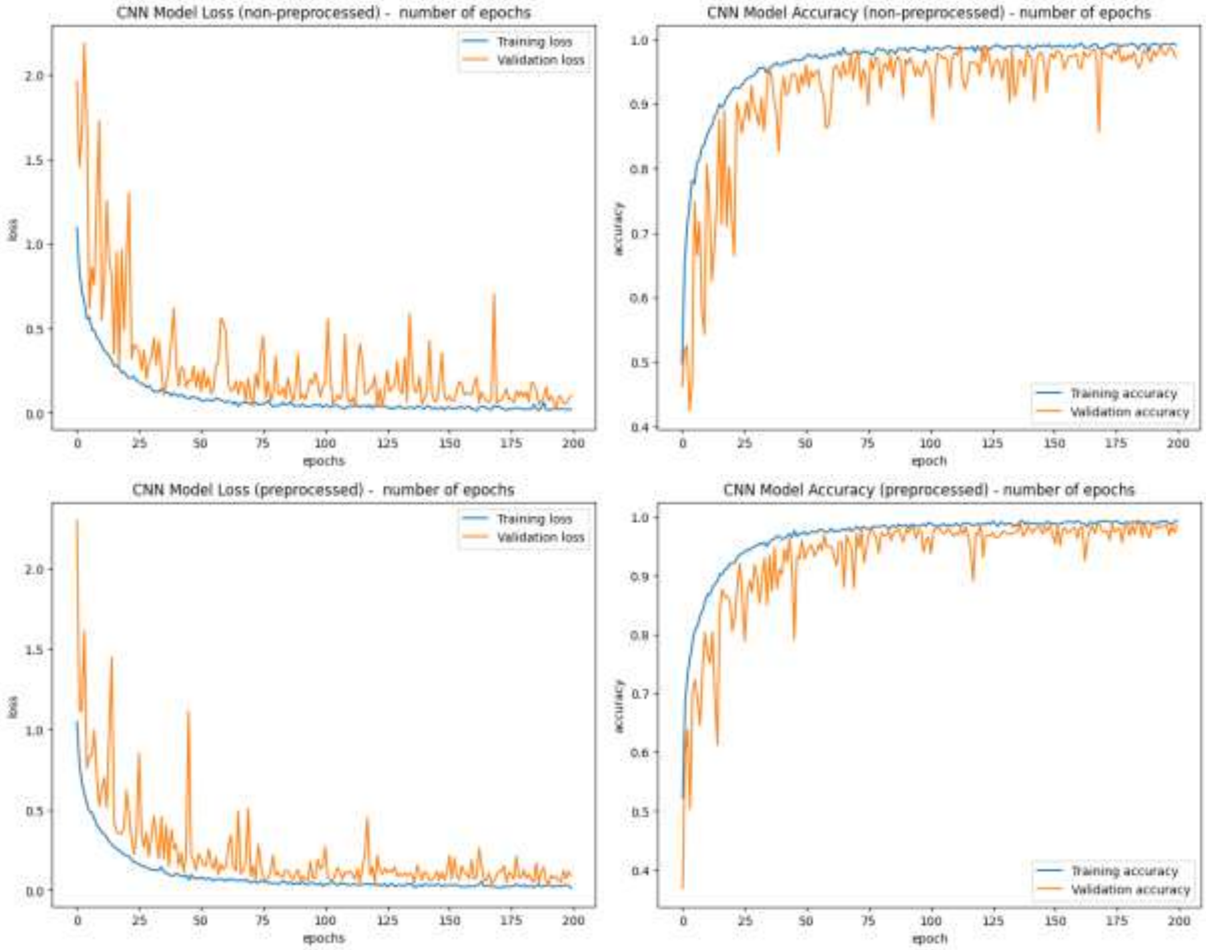

Figure 2. The performance of the model during the training process.

From the graphs, in the first 75 epochs, the training loss and validation loss of the model trained by original data and the model trained by preprocessed data both significantly decreased, the training accuracy and validation accuracy of the model trained by original data and the model trained by preprocessed data both significantly increased. Comparing the two pairs of graphs, it is clear that the accuracy of the model trained by data without preprocessing has a larger fluctuation when growing with a slower rate of growth than the model trained by the preprocessed data. The model trained by original data reached an accuracy of 98% and the accuracy stayed around 94%. However, the loss and accuracy of the model trained by preprocessed data have a smaller fluctuation during the decrease and growth. In addition, the curve of validation loss/accuracy and the curve of training loss/accuracy are more matched by using preprocessed data to train the CNN model. With preprocessed data, the accuracy of the model reached 98% earlier and stayed close to 98%.

The results suggest that preprocessing the data enables the model to attain similar levels of accuracy in fewer epochs and achieve higher accuracy overall. This is possible because the preprocessing operation converts the images into the same colour space, detect the object area and zoom in, and crop the images by extreme points. However, the non-preprocessed images vary in colour space, size, margin, and area of the objects. Thus, the preprocessed data has higher consistency with larger, more centred object areas, and less interference than the original data.

4. Conclusion

In this work, a customized CNN model is proposed to help diagnose and classify brain tumours using brain MRI images from. This study constructed a CNN model, preprocessed data with a preprocessing algorithm, and trained the model with both raw and preprocessed data. Experiments were carried out to evaluate and compare the performance of this CNN model trained by raw and preprocessed data covering 4 types of brain tumour MRI images. Results showed that the customized model trained with the preprocessed data performs better with higher accuracy and lower loss than that trained with raw data. In the future, the further study is looking forward to developing and testing the proposed method on datasets of more types of brain MRI images and then adapting the method to assist doctors with brain tumour diagnosis.

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