Application of Computer-Aided Diagnosis Technology in Brain Tumour Detection

Fengmei Gao¹*, Tao Lin²

ABSTRACT
Accurate segmentation of brain tumour means that surgeons accurately remove the tumour without damaging other healthy tissues. At present, due to the differences in human brains, the widely used manual brain tumour segmentation method cannot guarantee its accuracy and reliability. Therefore, it is of great social and practical significance to work out an automatic and accurate brain tumour segmentation method based on the computer-aided technology. This paper proposes a novel brain tumour segmentation method based on the deep learning model of stacked de-noising auto-coder. Firstly, by model training, it obtains the parameters of the deep learning network, and then it extracts high-level abstract features of the input image data through the network and uses these features to translate the segmentation of brain tumour to the classification of image blocks. Finally, this paper applies the proposed method for the MRI images of real brain tumour patients to carry out segmentation of brain tumours, and then compares it with the manual brain tumour segmentation method. The results show that the computer-aided brain tumour segmentation method is more effective and accurate and can provide reliable basis for the removal of brain tumours by surgeons without damaging normal tissues.

Key words: Computer-aided, Brain Tumour Detection, Brain Tumour Segmentation

Introduction
According to statistics, every year, about 250,000 people in the world develop primary brain tumours (Majós et al., 2004), and about 52,000 to 130,000 people in China become new brain tumour patients. What is worse, brain tumour ranks the 10th (accounting for about 2%) among all the malignant tumours that cause deaths. In real life, brain tumour (Bauer et al., 2013), which most people have little knowledge about, is also one of the most difficult tumours to be completely resected in neurosurgery operations, but if it is identified through detection in the early stage (Parveen et al., 2016), the chances of survival for brain tumour patients can be greatly improved (Shanthi et al., 2008). If the tumour can be segmented (Zacharaki et al., 2009) in the brain image (Saritha et al., 2013) of a patient and observed for its relationship with other tissues before surgery, surgeons will be able to develop a more reliable and comprehensive operative plan to remove the tumour without damaging other normal tissues. This will help patient’s recovery more quickly and reduce their complications and recurrence rate. Therefore, the computer-aided (El-Dahshan, 2014) detection of brain tumours is of great social and practical value.

At present, the widely used tumour segmentation in clinical diagnosis and treatment (Prastawa et al., 2004) is the manual segmentation method, which is neither reliable nor accurate (Menze et al., 2015). With the continuous development of computer hardware, doctors can use relevant computer programs to process some. Medical images or other clinical indicators to obtain objective data.
and diagnostic results. Such computer-aided diagnosis (Kuo et al., 2002) can improve the diagnosis accuracy of doctors to a certain extent. Nowadays, the increasingly sophisticated MRI technology can provide us with better and clearer images. All these technologies are making the computer-aided detection of brain tumours possible (Arakeri, 2015). At present, the main technologies used in the computer-aided detection of brain tumours (Chiou et al., 2009) include computer image processing, feature extraction and selection, medical image segmentation, classification and recognition. However, few studies have been conducted on the application of medical image classification and recognition technologies in the detection of brain tumours (Kleesiek et al., 2016), and in recent years, many medical imaging methods for brain tumour segmentation (Corso, 2008) still have a lot of problems, such as the need for human intervention or inaccurate segmentation results.

This paper presents a novel brain tumour segmentation method based on the medical imaging technology and the deep learning theory. It consists of three steps - preprocessing (i.e. medical image de-noising), brain tumour segmentation based on the deep learning mode of the stacked de-noising auto-coder and post-processing. In addition, this paper applies this method to segment the brain tumours in the MRI images of real patients to prove the effectiveness and accuracy of this method.

**Deep learning**

*Basic idea of deep learning*

As a hot subject in the field of computer science, machine learning can not only make computers execute commands, but also train machines to learn human’s thinking patterns and methods to obtain new knowledge based on past experience and data (Babič, 2017). However, medical data are usually high-pixel image data, which are highly dimensional, which are quite difficult and challenging to the traditional machine learning. The emergence of deep learning, which allows machines to learn abstract high-dimensional data, well solves this problem (Prastawa et al., 2003). Take images for example. To the computer, an image is just a number of pixels. It cannot understand the meaning of each object in the image. Figure 1 shows how the brain conducts its thinking activity when a person is looking at pictures. When human eyes see an image, the pixel blocks in the image are first perceived by the optic nerve and then transmitted to the brain, and then the perceived pixels are processed by specific tissues in the cerebral cortex. Through analysis, the brain further abstracts the image and determines what the objects are based on their edges.

![Figure 1. Human’s abstract thinking Process](image)

**Figure 2. Layer-by-layer initialisation process**

The deep learning process is inspired the human’s abstract thinking process, as shown in the figure above. It attempts to simulate the thinking process of human by a hierarchical approach. The deep learning superimposes multiple hidden layers, each of which can obtain high-level features by combining low-level features. In this way, it obtains the abstract features to gradually approach our true target. Deep learning, as an improvement of the artificial neural network, has a similar structure as that of
the latter one – which consists of an input layer, hidden layers and an output layer. There are only connections between the nodes of adjacent layers. In order to overcome the local convergence of the training results caused by random initialization in the artificial neural network, Hinton et al. proposed an unsupervised layer-by-layer initialization algorithm, as shown in Figure 2. It can be seen from the figure that this is a hybrid network where the top two layers are connected in an undirected manner and the other layers weighted bidirectionally. The connection from bottom to top is used to infer a potential representation from the bottom, and the connection from top to bottom is to map the associative memory of the top layer into an image. Each training of this layer-by-layer initialization algorithm only focuses on one layer of the hybrid network, in order to minimise the errors in the bi-directional input and restoration of a single-layer network. In this way, the initial parameters of each layer are generated accordingly. After the initialization of the parameters of all the layers, the tagged data are used to adjust the network parameters from top to bottom to generate the final network parameters. Compared with artificial neural network, the biggest advantage of deep learning is that the results of initialisation are closer to the optimal region, and deep learning is a nonlinear network structure, which can use fewer parameters to approximate complex functions and extract more discriminative features.

Deep learning model of stacked auto-coding

Deep learning is a learning method by which machines use the network model containing multiple hidden layers to accurately classify useful features. There are many models, such as convolutional neural networks and deep belief network. The model used in this paper is a deep learning model of stacked auto-coding, which is a simple deep learning model composed of an input layer, multiple hidden layers and an output layer. The training process for stacked auto-coder is divided into the following two parts:

1. Input untagged data and perform unsupervised pre-training on each layer in the network. The training process is shown in the following Figure 3.

First pre-train the input layer and the first hidden layer. Between these two layers, there is an encoder and decoder, respectively. After the input is placed into the encoder, we will obtain an input representation, and then through decoding, we will obtain the restored input from the input presentation. We compare this result with the original input to measure the accuracy of the input representation, and then minimise the reconstruction errors by adjusting relevant parameters. Each time we use the output from the last layer as the input to the next level to carry out the layer-by-layer training. The number of layers trained is subject to the total number of layers in the network until all the hidden layers are trained, at which time, the initialised parameters of the network are fully generated.

![Figure 3. Automatic encoder principle](image)

(2): Adjust the given tagged data from top to bottom.

Through the previous step, the network obtained can only extract features but cannot perform classification. Therefore, we add an output layer at the top of the network that can fine-tune the network with tagged data to link the input to its classification result. In addition, the stacked de-noising auto-coding proposed by Vincent can achieve de-noising by reading data. The biggest difference is that the input raw data are destroyed. Using this measure is to force the machine to automatically learn how to restore the original input data and enhance its learning and generalisation ability, as shown in the following Figure 4.

Deep learning is a kind of machine learning method that mimics human's thinking ability. As a hotspot in artificial intelligence field, it is mainly used in speech analysis and image recognition and now also gradually applied in computer-aided diagnosis.
This paper proposes a computer-aided brain tumour detection method based on the deep learning of machines. What distinguishes it from other segmentation methods is that it converts segmentation into classification. It uses the features of the neighbourhood around the pixel to determine whether the pixel is part of the brain tumour. The structure of the proposed computer-aided brain tumour detection method is shown in Figure 5. The system consists of three parts – pre-processing, brain tumour detection and post-processing.

**Pre-processing**

Before the brain tumour detection, in order to make the experiment go well, we must first process the images to ensure that the experimental data are consistent in brightness and contrast. Therefore, we need to make some pre-processing changes to the images, including brightness transform, histogram processing, image de-noising and spatial filtering.

(1): Brightness transform

We mainly use the three curves in Figure 6 below to process the brightness of the original images. Figure 6(a) shows that a lower input grey value leads to a higher output value, which is used to compress the high end and extend the low end of the grey scale; the curve shown in Figure 6(b) can be used to increase the brightness of the area that we are interested in; the curve shown in Figure 6(c), where a lower input grey scale value leads to more darkness, is used to extent the high end and compress the low end of the grey scale.

**Brain tumour detection method**

**Brain tumour detection method based on deep learning**
(2): Histogram processing
Histogram processing usually refers to histogram equalisation and histogram matching. In order to eliminate the differences in the appearances of the images of the same kind, the grey levels of the images are normalised through histogram equalisation, which is accomplished using the cumulative distribution function, whose formula is as follows:

\[ s = T(r) = \int_{0}^{r} p_{r}(r)dr, 0 \leq r \leq 1 \]  

Where, \( r \) represents the grey value of the original image; \( s \) represents the grey value of the equalised image; \( p_{r}(r) \) is used to represent the probability density of the grey level in the image. It can be seen from the above equation that the density function of the transformed output grey level is evenly distributed, that is, the transformed grey level is evenly distributed and has high contrast.

Since it is relatively difficult to control the enhancement of histogram equalisation, histogram matching is also often required to help us selectively expand the contrast of the area needed. The steps of histogram matching are as follows: the first step is to carry out histogram equalisation of the image, with the formula shown as (1), to obtain the density function \( p_{s}(s) \) that outputs the grey level; and the second step is to select a matching histogram shape to obtain the histogram equalisation result equivalent to \( s \):

\[ H(z) = \int_{0}^{s} p_{z}(z)dz = s \]  

From equations (1) and (2), we obtain the third step:

\[ z = H^{-1}(s) = H^{-1}[T(r)] \]  

According to the above equation, as long as \( H^{-1}(s) \) is obtained, the original histogram can be mapped to the histogram we need. Processed by this method, the image will have enhanced effect and natural transition without any false contour.

(3): Spatial filtering
Spatial filtering is also to enhance the image effect and improve its quality. This paper uses a Laplacian filter, whose computing template is shown in Figure 7 below:

\[ \begin{array}{ccc}
0 & 1 & 0 \\
1 & -4 & 1 \\
0 & 1 & 0 \\
\end{array} \]

Figure 7. Two kinds of Laplacian filters

The images processed by the Laplacian filters are shown in Figure 8 below. (a) is the original MRI image of brain tumour, and (b) and (c) are the images processed by the Laplacian filters with a centre of -4 and -8, respectively. Through comparison, it can be seen that the processed images are clearer than the original image, and that the one process by the Laplacian filter with a centre of -8 is obviously better than the one processed by the filter with a centre of -4 - the enhancement effect is more obvious and the image details are clearer.

(4): Image de-noising
The image will inevitably generate noise during its generation. In actual practice, in order to achieve the best de-noising result, we will select the most suitable filter according to the actual situation, including the colour and size of the noise, and then adjust the parameters through experiments.

Figure 8. Two kinds of Laplacian filters
Detection of brain tumour

This paper uses the stacked de-noising auto-coder mentioned in the previous section to perform layer-by-layer pre-training. Unlike the traditional auto-coder, in this method, the input will be subjected to man-made noise pollution. By training of corrupted input data, the network can learn how to deal with these noises and learn more robust features.

We add the input vector $x$ into the noise randomly according to the distribution of $q_D$ to obtain $\tilde{x} \sim q_D((\tilde{x} | x))$. The corrupted input $\tilde{x}$ will be mapped as shown in equation (4):

$$y = f_\theta(\tilde{x}) = \text{sigm}(W \tilde{x} + b)$$

(4)

After reconstruction, we obtain:

$$z = g_{\theta'}(y) = \text{sigm}(W'y + b')$$

(5)

The training parameters are used to minimise the average reconstruction error. And the objective function obtained is as follows:

$$\argmin_{\theta} \frac{1}{n} \sum_{i=1}^{n} L(x_i, g_{\theta'}(f_\theta(\tilde{x}_i)))$$

(6)

Figure 9. Training process diagram

After training of a layer, we take the output as the input to the next layer, and so on. Then we can obtain the initialised parameters of this coder. The neural network structure using the initialised parameters is shown in the following Figure 9. The number of nodes in the topmost output layer is set as 2, with one indicating a point that is part of the brain tumour and one indicating a point that is not. This new deep network has the optimal initialised parameters. We use this network to classify the image blocks and then proceed to the next step.

Post-processing

After the initial classification results are obtained through pre-processing and the deep learning model, there will be a few points that are part of normal tissues near the tumour in the image included in the scope of tumour, like those blank spots or isolated points in other parts of the tumour area. To solve this problem, we use morphological operations to process binary images, including open and closed operations. Through these operations, we can fill in the blank parts of the tumour area and remove extra spots, making the contour of the brain tumour smoother. This is the post-processing of the image.

Experimental results and analysis

Experimental data processing

Based on the steps described in the previous section, this section uses the test data to determine the specific network structure. In addition, the segmentation results based on the deep learning network are compared with those under other methods.

(1): Experimental data pre-processing

The test data in this paper are MRI images of 10 patients with real brain tumours, and each group of images contain data in both traverse and coronal directions. Each image is pre-processed. The extracted image block size is 25X25, with the centre point as the tag of the entire image block. Firstly, we use the non-linear filter to reduce the noise. Then in order to expand the grey range of the image, we use the brightness curve to change the brightness of the image so as to increase the contrast of the tissues in various parts of the brain and make the tissues clearer and easier to distinguish. The image before and after brightness change is shown in Figure 10 below, where (a) is the original image, and (b) is the one after brightness change.

Figure 10. Images before and after brightness change
In order to mitigate the difference in contrast and brightness caused by the different instrument parameters during shooting, we carried out histogram specification to the images with brightness changes. The comparison of the images before and after the processing is shown in the Figure 11, where (a) is the image before processing and (b) is the one after it. It can be found that the processed images have basically the same grey level, with significantly smaller differences in brightness.

(2): Parameter setting of deep learning network
In the deep learning network, important parameters include the number of hidden layers used to extract high-level features of input data and the number of hidden layer nodes that determine the number of network parameters per layer. Through the experimental results, we find that the training effect is best when the number of nodes is 20, and the accuracy and efficiency of the network can be well balanced with two hidden layers. The relationship between the number of hidden layers and the accuracy for different patients is shown in Figure 12.

(3): Analysis of post-processing results
Post-processing mainly includes threshold segmentation and morphological image processing. It can be seen from Figure 13 that the contour of the post-processed image segmentation is very smooth and accurate and close to the outline of the brain tumour. (a) is an unprocessed image; (b) is an image mapped through deep learning; (c) is a threshold-segmented image, and (d) is the last image after processing.

**Analysis of brain tumour detection test results**
In order to objectively evaluate this method, we compare its segmentation results with true values. Let DL denote the set of brain tumour points segmented by this method, GT denote the set of brain tumour points in the manually segmented brain tumour images, TP denote the overlap between the two, and FN denote the points that are originally part of the tumour but excluded from the tumour, and FP denote the points mistaken for tumour points. This is more clearly illustrated by Figure 14.
We use the matching degree to indicate the percentage of true values in the region that is correctly segmented (i.e., overlapping parts in Figure 10): \[ MP = \frac{#TP}{#GT} \] (7)

The comparison results are shown in Table (1). The larger #TP is, the more correctly segmented parts there will be. The smaller #FP is, the fewer segmentation errors there will be. As can be seen from the table below, the average value of MP is as high as 97.17%.

In order to display the segmentation results more visually, in Figure 15, (a) shows the original MRI image before segmentation, (b) shows the manually sketched outline, (c) is the tumour area marked green, (d) the binary image of the hand-sketched tumour and (e) is the binary image of the brain tumour region segmented based on the deep learning model. It is found that the experimental results obtained by this method are very close to the true values.

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<th>Patient No.</th>
<th>#TP</th>
<th>#FP</th>
<th>#FN</th>
<th>#GT</th>
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![Figure 14. Diagram of test result sets](image)

![Figure 15. Comparison of segmentation results](image)
Conclusions
Based on the deep learning model, this paper studies the computer-aided brain tumour segmentation method and obtains the following conclusions:

(1): This paper proposes the framework and process flow of a computer-aided brain tumour segmentation based on deep learning, and applies the deep learning model of the stacked denoising auto-coder in the segmentation of brain tumour. With the help of the model, this paper translates the segmentation of brain tumour into the classification of pixels in the images, and establishes a complete brain tumour detection method with appropriate pre-processing and post-processing.

(2): Through the experiment, this paper determines the parameters in the deep learning network used to detect brain tumours and compares them with the true values. The results prove that the MP of this method is up to over 97%. In the segmentation process, this method can automatically extract the brain tumours from the brain MRI images of the patients without any manual intervention and the segmentation results are accurate and can serve as strong references and basis for surgeons in their diagnosis and treatment. This method can help surgeons remove brain tumours thoroughly without damaging other normal tissues.

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References