Counter-propagation Neural Network for Brain Tumor Classification

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Abstract. Brain tumor is a condition in which abnormal cells grow unnaturally in the brain. Depending on the size and type, the abnormal cells called tumors can be life-threatening if the patient does not take immediate treatment. The cause of tumor growth in the brain is the presence of risk factors such as family history and ionization radiation. Patients with brain tumors will experience several symptoms of a headache, nausea, memory loss, and changes in vision, speech, and hearing. Detection of brain tumors can be performed with the help of the medical device of Magnetic Resonance Imaging (MRI) Scan. Through the image of MRI Scan results, radiology specialists will interpret and analyze the brain condition. However, analysis and conclusions for this matter take a long period of time. Therefore, a method is required to classify the brain tumors through MRI images automatically. The method used in this research is Counter-propagation Neural Network. Prior to classification, the brain's MRI image will be used as the input for the image pre-processing stage then go through the segmentation and feature extraction processes. Based on the test, it can be concluded that the proposed method can identify brain tumors with an accuracy of 92.5%.

1. Introduction

The brain tumor is one of the diseases that occur when abnormal cells grow unnaturally in the brain [1]. The shape and size of the tumor are varied and can be found in any part of the brain. The cause of tumor growth in the brain is the presence of risk factors such as family history or ionization radiation. Patients with the brain tumor will experience some symptoms of a headache, nausea, memory errors, and changes in vision, speech, and hearing.

Brain tumors can be detected by examination using a medical device of Magnetic Resonance Imaging (MRI) Scan. MRI Scan is a medical device that uses magnetic technology and radio waves to see the human organs. After the patient undergoes the examination process, the radiology specialist will analyze and draw the conclusions based on the MRI image manually.

One of the classification methods is Counter-propagation neural network method. Counter-propagation is a neural network that studies two-way mapping between the input layer and the output layer. When the input data is put into the input layer to generate a pattern classification in the output layer, the output layer will receive an additional input vector and generate a classification output on the network input layer [2].

Another research was conducted by Rohmah, et al. on the Several techniques to classify the types of brain tumors have been performed in the past, such as Backpropagation (BP) and Principle Component Analysis (PCA). The MRI image was processed through pre-processing, segmentation and Gray Level Co-occurrence Matrix (GLCM) processes to extract features in segmented imagery. Once
the noise is removed and the segmentation method has been applied to the image, the tumor area will be isolated and separated from the rest of the image. Afterward, the two methods of classification of BP and PCA will be implemented [3].

Subsequent research used Adaptive Neuro-Fuzzy Inference System (ANFIS) method to classify the types of brain tumors. MRI images of the brain were processed using artefact removal and noise reduction. Then the feature of the processed image will be extracted to reduce the redundancy of information. The final result of the image was classified using ANFIS [4].

Another study implemented Discrete Wavelet Transformation (DWT) for feature extraction, and image features were recompressed using Principles Component Analysis (PCA). Feed Forward Backpropagation Artificial Neural Network (FP-ANN) and K-Nearest Neighbor (KNN) were served as the classification methods[5].

Further research utilized the Hyperbolic Hopfield Neural Network (HHNN). CT brain scan was used as input. The noise in the image was removed using a bilateral filter and then segmented using Enhanced Markov Random Field Approach (EMRF). The process continued to the feature extraction stage using the Texture Descriptor and ended with the classification process [6].

Another research applied Probabilistic Neural Network (PNN) method. MRI image was used as input and then processed through the grayscale process and Gaussian filter in the pre-processing process. Canny Edge Detection and PNN method were used as image segmentation and classification methods respectively [7].

Another research was conducted using Counter-propagation Neural Network (CPNN) technique in a system to classify defects in knitting fabric. The image of defective knit fabric was used as the input image; then the image was processed using grayscale technique and convolution mask filter. The process continued to threshold technique to generate a binary image. Then, the defect types of the knit fabrics were classified using the CPNN method [8].

Brain tumors can be categorized into two main types, namely benign tumors and malignant tumors. Detection and classification of brain tumor types are performed by doctors and radiologists by examining, analyzing and drawing conclusions from MRI Scan results. The examination conducted manually and took a long time. Therefore, A system is mandatory to simplify the classifying process of the brain tumor automatically. Based on this, authors proposed a study on brain tumor classification using counter-propagation neural network as the algorithm.

2. Methodology

The method proposed by the authors to classify the type of brain tumor consists of several stages. These stages start from acquiring MRI image data of normal brain, benign brain tumor and malignant brain tumor to be used as the training and test images. The image will then go through the image pre-processing stage. In this stage, the image resizing was performed to determine the size of the input image. Then it will be further processed using contrast enhancement technique to correct and improve the image contrast. The following stage is image segmentation using the threshold to get a binary image. The process continues to a skull stripping stage to select a part of the tumor and separate it from other unnecessary parts. The process continues to feature extraction that calculates the metric and eccentricity values to obtain the feature value of the segmented image. After the result of feature extraction acquired, the tumor will be classified using Counter-propagation Neural Network. After the stages were performed, the system will generate the classification result of the brain types. The general architecture of the methodology for this study is shown in Figure 1.
2.1. Data

The data for this research were in the form of MRI scanned images. Sample of MRI Scan image can be seen in Figure 2.

2.2. Pre-processing
Pre-processing is a stage in image processing that will produce a better image quality to obtain maximum results. In this research, the image pre-processing methods are image resizing and contrast enhancement.

Resizing aims to obtain the same size images for the input data. The images obtained from the MRI Scan have different length and width, so it is mandatory to determine the length and width of the input image so the size could match the resolution view of the system. The specified size for the image in this study is 300 x 300 pixels.

Contrast enhancement has the purpose to generate a better quality images. The brain tumor images obtained from MRI Scan are less clear and difficult to distinguish from other parts of the brain. By increasing the contrast of the image, the shape of the brain tumor will be more apparent and will ease the next process. The contrast enhancement process of the MRI brain image is shown in Figure 3.

![Fig 3. Pre-processed image](image3.png)

2.3. Segmentation

After pre-processing, the process continues to the segmentation stage. The image segmentation is performed to simplify the image to make it easier to analyze. Through the segmentation process, the tumor area can be separated from other parts of the brain so it will facilitate the classification process in the next stage. Segmentation stage consists of thresholding and skull stripping processes.

Thresholding technique aims to change the MRI image which initially in the form of a grayscale image into black and white with sharper quality. The threshold result of MRI brain image is shown in Figure 4.

![Fig 4. Thresholding sample](image4.png)

Images generated from the threshold process still have information that is not needed, because, in addition to tumors, bone and brain tissue are still displayed. Skull stripping is performed to obtain the tumor area and remove unnecessary parts. The skull stripping process of MRI brain image is shown in Figure 5.

![Fig 5. Skull stripping](image5.png)
2.4. Feature extraction

Feature extraction is a process to extract the value of features or information from an object of a segmented image to be distinguished from other objects. The proposed feature extraction technique is metric & eccentricity calculation.

Eccentricity function is utilized to get the value of eccentricity where the stats are derived from the regionprops () function to obtain the size of an object. While the metric value obtained using equation below.

$$W_{ij}(x) = \frac{1}{2\pi d/\sigma} \exp \left[ -\frac{\| (x - x_{ij}) \|^2}{2\sigma^2} \right]$$

The calculation of metric and eccentricity values can be seen in Table 1.

| No. | Image | Metric | Eccentricity |
|-----|-------|--------|--------------|
| 1   | ![Image 1](image1.png) | 0.81   | 0.53         |
| 2   | ![Image 2](image2.png) | 0.90   | 0.64         |
| 3   | ![Image 3](image3.png) | 0.80   | 0.79         |
| 4   | ![Image 4](image4.png) | 0.92   | 0.60         |
| 5   | ![Image 5](image5.png) | 0.93   | 0.61         |
2.5. Classification

The classification algorithm is applied to classify an object into its grouping. The classification algorithm is tested using sample data based on information received from the training data according to its type. At the classification stage, the value of feature extracted from the previous stage is used as the input. The method implemented in this study is Counter-propagation Neural Network. The architecture can be seen in Figure 6.

| No. | Image | Metric | Eccentricity |
|-----|-------|--------|--------------|
| 6   | ![Image 6](image) | 0.89   | 0.76         |
| 7   | ![Image 7](image) | 0.98   | 0.61         |
| 8   | ![Image 8](image) | 0.88   | 0.77         |
| 9   | ![Image 9](image) | 0.88   | 0.67         |
| 10  | ![Image 10](image) | 0.86   | 0.71         |

The steps taken in the Counter-propagation training process are as follows:

Step 1: Initialize the weights and learning rate.
Step 2: As long as the first phase stop condition has not been met, perform steps 3-8.
Step 3: For each input pair of x: y, do step 4-6.
Step 4: Enter the input vector x on the X layer.
Step 5: Enter the input vector y on layer Y.
Step 6: Find the winning unit hidden layer using equation 2, save the result as J variable.
\[ z_j = \sum (x_i - v_{ij})^2 + \sum (y_k - w_{kj})^2 \]

Step 6: Update weights for the unit using equations as follows.

\[ v_{ij}^{\text{new}} = (1 - \alpha) v_{ij}^{\text{old}} + \alpha x_i; \quad i = 1 \ldots n \]
\[ w_{kj}^{\text{new}} = (1 - \beta) w_{kj}^{\text{old}} + \beta y_k; \quad k = 1 \ldots m \]

Step 7: Reduce learning rate \((\alpha, \beta)\).

Step 8: Check if the stop condition for the first phase is met.

Step 9: As long as the stopping condition for the second phase has not been met, do Step 10-16 (the values of \(\alpha\) and \(\beta\) are very small and constant during the second phase).

Step 10: For each input pair of \(x, y\), do Step 11-14.

Step 11: Enter the input vector \(x\) on the X layer.

Step 12: Find the winning hidden layer unit with equation 2, save the result as \(J\) variable.

Step 13: Update the weights that go into \(z_j\) using equations 3 and 4.

Step 14: Update the weights that go from \(z_j\) to the output layer using equations below.

\[ u_{jk}^{\text{new}} = (1 - \alpha) u_{jk}^{\text{old}} + \alpha y_k; \quad k = 1 \ldots m \]
\[ t_{ji}^{\text{new}} = (1 - \beta) t_{ji}^{\text{old}} + \beta x_i; \quad i = 1 \ldots n \]

Step 15: Reduce learning rate \((\alpha, \beta)\).

Step 16: Check if the stop condition for the second phase is met.

3. Result and Discussion

At this stage, a test was performed on the data and system. The data were tested using ten normal brain images, ten images of the benign brain tumor and ten images of the malignant brain tumor while the training data was performed using the data of 30 normal brain images, 30 images of the benign brain tumor and 30 images of the malignant brain tumor.

Testing was conducted with network parameters such epoch total of 1000, a learning rate of 0.2 and various number of hidden nodes. The results of the test can be seen in Figure 7. Testing with different node values aims to get the value of nodes that can classify types of brain tumors with a high level of accuracy.

![Fig 7. Accuracy result graph](image)

Based on the test results as shown in Figure 7, the smaller the node value, the lower the accuracy. While the greater the value of the node, the higher the accuracy will be obtained. So the best accuracy is obtained from node value of \(\geq 25\). The data of test result can be seen in Table 2.
Table 2. Test results

| No | Actual | Result |
|----|--------|--------|
| 1  | Benign | Benign |
| 2  | Benign | Benign |
| 3  | Benign | Benign |
| 4  | Benign | Benign |
| 5  | Benign | Benign |
| 6  | Benign | Benign |
| 7  | Benign | Normal |
| 8  | Benign | Benign |
| 9  | Benign | Malignant |
| 10 | Benign | Benign |
| 11 | Malignant | Malignant |
| 12 | Malignant | Malignant |
| 13 | Malignant | Malignant |
| 14 | Malignant | Benign |
| 15 | Malignant | Malignant |
| 16 | Malignant | Malignant |
| 17 | Malignant | Malignant |
| 18 | Malignant | Malignant |
| 19 | Malignant | Malignant |
| 20 | Malignant | Malignant |
| 21 | Normal | Normal |
| 22 | Normal | Normal |
| 23 | Normal | Normal |
| 24 | Normal | Normal |
| 25 | Normal | Normal |
| 26 | Normal | Normal |
| 27 | Normal | Normal |
| 28 | Normal | Normal |
| 29 | Normal | Normal |
| 30 | Normal | Normal |

Based on data of test result on the classification system of brain tumor type through MRI Scan image using Counter-propagation Neural Network, the accuracy of brain rumor classification can be obtained in an average value of percentage.

\[
\text{Accuracy} = \frac{\text{Number of correctly identified data}}{\text{Total data}} \times 100\%
\]
From the above calculation, the accuracy of Counter-propagation Neural Network method in classifying the type of brain tumor through image MRI Scan is at 90%.

In addition to the percentage of accuracy, system performance can be calculated using precision and recall calculations. Precision is the accuracy level of information requested by users and recall is the level of system success in rediscovering information.

Table 3. Calculation of system performance

| TP | TN | FP | FN | Recall | Precision | F-score |
|----|----|----|----|--------|-----------|---------|
| 17 | 10 | 0  | 3  | 85%    | 100%      | 92.5%   |

Based on Table 2, the values of precision and recall are at 100% and 85% respectively. From these two values can be calculated system performance using the value of f-score. The f-score value is the accuracy value to declare whether a system has worked effectively or not. The f-score value obtained for the system is 92.5%. With the f-score value that has exceeded 50%, the performance of the system is considered to have run effectively.

4. Conclusion

In this research, the system accuracy is at 92.5%; it shows that Counter-propagation Neural Network method is able to classify the type of brain tumor through MRI Scan image well. Based on the system testing, the number of hidden nodes greatly affects the percentage of system accuracy. Based on the test, the smaller the value of the hidden node the smaller the level of accuracy, the higher the value of the hidden node, the higher the accuracy. The value of hidden node ≥ 25 is suitable as the parameter for classifying the type of brain tumor using Counter-propagation Neural Network. In addition, the quality of the image used as input on the system will affect the image pre-processing and classification process.

For future work, other imaging techniques are required to generate a better segmentation result. Further research can also implement other feature extraction techniques to obtain more specific information values of the tumor. Adding more images into the training data will also improve the identification process. A study on brain tumor classification using other neural network methods can be conducted to make a comparison on the accuracy result to Counter-propagation Neural Network.

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