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BRAIN TUMOR DETECTION USING BACKPROPAGATION NEURAL NETWORKS

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Abstract A study of brain tumor detection has been done by making use of backpropagation neural networks with Gray Level Co-Occurrence Matrix (GLCM) feature extraction. CT-Scan images of the brain consist of 12 normal and 13 abnormal (tumor) brain images are analyzed. The preprocessing stage is begins with cropping the image to a 256 x 256 pixels picture, then converting the colored images into grayscale images, and equalizing the histogram to improve the quality of the images. GLCM is used to calculate statistical features determined by 5 parameters i.e., contrast, correlation, energy and homogeneity for each direction. In these backpropagation neural networks, the [12 2 1] architecture is used. The correlation coefficient between the target and the output for the training data is 0.999, while the correlation coefficient for the testing data is 0.959 with an accuracy of 70%. The results of this research indicate that backpropagation neural networks can be used for the detection of brain tumors.

Keywords Brain Image, backpropagation neural networks, GLCM, Tumor

INTRODUCTION

Brain tumor is the second most deadly disease for men between the age of 20-30 years and is the fifth most deadly disease for women between the age of 20-30 years (ABTA, 2012). According to data from the International Agency for Research on Cancer, more than 126,000 people in the world suffer from brain tumors each year and more than 97,000 people die due to this disease (Al-Tamimi, MSH, 2014). In its early stages, the tumor is very difficult to identify because of its unclear appearance and low contrast which makes the tumor look like normal tissue.

Among others, a medical device that can be used to detect brain tumor is Computed Tomography Scanner (CT-Scan) (Ravenel, 2003). CT Scan uses X-rays to produce an image of human organs. CT-Scan image analysis of brain tissue has to be very accurate so the appropriate therapy needed to cure the brain tumor can be performed.

The neural networks can be used to recognize the patterns of a brain tumor, including complex patterns. Neural networks use perceptron methods that can identify benign tumor patterns. Moreover, backpropagation neural networks use waterfall model that can be used to recognize brain cancer cells (Handayani, 2013).

This research combines feature extraction of 4-direction GLCM (0˚, 45˚, 90˚ and 135˚) with distance d=1 and backpropagation neural networks to identify normal and abnormal (tumor) brain images. GLCM is a matrix describing the frequency of occurrence of two pixels pair with a particular intensity, in distance (d) and orientation of angle (θ) (Gadkari, 2004). GLCM is used because it has been proved as the best feature extraction (Nithya and Santi 2011). This method can be used to classify masses on mammogram images on 4-directions GLCM with distance d=1 and d=2, 8-direction GLCM with distance d=1 and 16-direction GLCM with distance d=2 (Listia, R, 2014). The identification method applied in this study is backpropagation neural networks. This method is chosen because it is suitable for identification and classification (Eskaprianda, Isnanto, & Santoso, 2011)(Nurkhozin & Irawan, 2011). Backpropagation neural networks trains the network to balance its ability to recognize the patterns used in the training and its ability to provide the correct response to the inputs respect to the patterns used during the training.

MATERIAL AND METHODS

Data

The data used in this study are CT-Scan images of brain (film) which have been converted into digital images of 256 x 256 pixels in JPEG format. There are 25 images used consisting of 20 training data images (10 normal images and 10 tumor images) and 5 test images (2 normal images and 3 tumor images).

Image Processing

Image processing, also called prepossessing, is the processing of an image to improve its quality for further processing step. In general, types of images that can be produced and processed by computer, are binary, grayscale and color images.

The preprocessing consists of following steps:

Cropping

A film image is converted into a digital image and then cropped to define the input area of interest. Cropping is used to select certain parts of the image to be analyzed. The images are cropped to a size of 256 x 256 pixels.

Grayscale

In this step, the colored image is converted to a grayscale image. Value of the gray level varies between 0 to 255. This value is related to the intensity of the incoming x-ray. In the figure, a value of 0 represents complete black and 255 represents white, while values in between, represents varying degrees of gray.

Histogram

A histogram is calculated to display the distribution of grayscale values. The histogram then be used to determine the range of values to distinguish between brain tissue and the background. This can be done to exclude bones in the image.

Histogram Equalization

Histogram equalization is an important part of image processing. This process aims to produce a uniform histogram image by redistributing the intensity distribution of the initial histogram.

Image Segmentation

Image segmentation is a process that divides the image into a number of regions or objects. Segmentation aims to seperate the image into parts containing important information i.e. separation of the object from the background. The image segmentation method used in this study is called thresholding. Thresholding is used to separate bones and tissues in the image based on the value of the image gray scale level.

Feature Extraction

Feature extraction is a process of extracting features of an object in an image. Feature extraction is done by making use of Gray Level Co-Occurrence Matrix (GLCM). This process forms a 4-direction GLCM (0°, 45°, 90° and 135°) with distance d=1 to determine the direction coordinate. After determining the direction, co-occurrence matrix is formed by calculating the frequency of pairs of reference values of reference pixels and neighboring pixels at a given distance and direction. Then, the sum all the elements to calculate the probability of each element by dividing each GLCM element by the total of all elements. Moreover, calculate the GLCM statistical feature consisting of contrast, correlation, energy and homogeneity. The statistical features obtained are used as inputs on backpropagation neural networks.

Identification Using Neural Networks

Neural networks is a method of information processing inspired by biological nerve systems, i.e., the way the brain processes information (Hermawan 2006). Neural networks consist of several neurons that are connected to each other and organized in layers. Each neuron on the network receives and sends signals from or to other neurons. Signal transmission is done through the connector and the strength of the neurons connection is represented by weights (Anggriyani 2015).

The architecture of backpropagation neural networks used is presented in Fig. 1. This architecture consists of 1 input layer, 2 hidden layers, and 1 output layer. The input layer consists of 5 neurons, the first hidden layer consists of 12 neurons with bipolar sigmoid activation function (tansig), while the second hidden layer consists of 2 neurons with a binary sigmoid activation function (logsig). The output layer consists of 1 neuron with an identity activation function (Purelin). Thus, the architecture of neural networks used is [12 2 1].

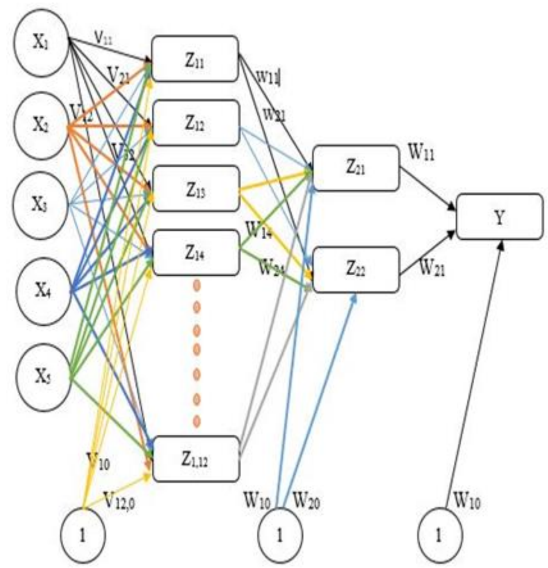
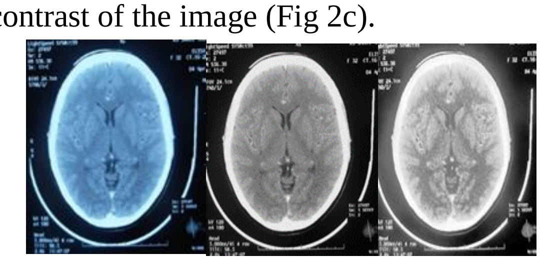


Fig. 1. Architecture of neural networks

RESULTS AND DISCUSSION

Image processing in this research is done in several stages which comprise of preprocessing, segmentation and feature extraction. The preprocessing stage is initiated by cropping to take the area of interest in the figure (See Fig 2a). The next step is converting the image to a grayscale image (Fig 2b). The histogram is then created from the grayscale image to get the information of gray level distribution. Finally, histogram equalization is invoked to improve image quality by increasing the contrast of the image (Fig 2c).



(a) (b) (c)

Fig. 2. (a) Brain Image after Cropping,
(b) Grayscale, (c) Histogram Equalization

The image segmentation process in this research is done by using the thresholding method. This process aims to separate the bone with the tissue to obtain brain image without the skull (Fig 3).

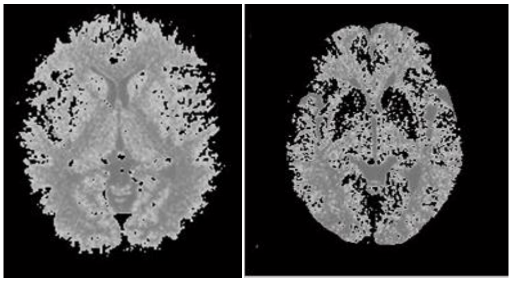


Fig 3. Brain Image without a skull

Feature extraction in this research is done by making use of GLCM. The size of GLCM used is 64x64 with angles 0˚, 45˚, 90˚ and 135˚. In this step, a statistical feature of the image consisting of contrast, correlation, energy and homogeneity for each direction can be obtained. From this statistical feature, we can obtain the minimum and maximum value of each normal and abnormal (tumors) brain image.

The method of neural networks is used to identify brain images. A statistical feature obtained from GLCM and angles are used as input data, whereas normal and tumors brain images are used as target data. The architecture used in this research consists of 1 input layer, 2 hidden layers, and 1 output layer.

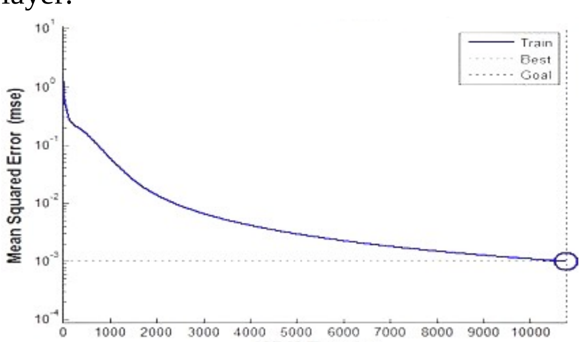


Fig. 4. Training process

Fig. 4. shows that the Mean Squared Error (MSE) value decreases for each iteration indicating the network learns well. The training process is stopped at 10.748 iterations because it reached MSE 0.001.

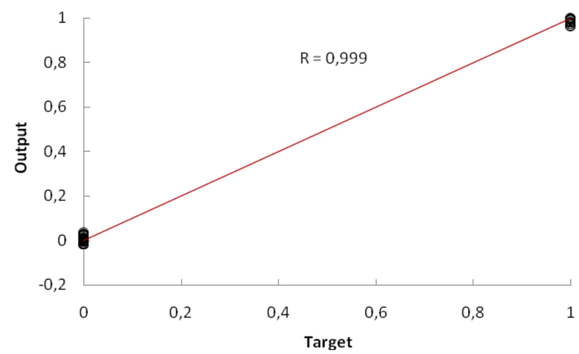


Fig. 5. Relation of target and output (training data)

Figure 5. shows the relation between the target and the output for a set of training data. Relation of the output and the target of neural networks is analyzed using linear regression to obtain the correlation coefficient. Doing so, we obtained a correlation coefficient of 0.999 which indicates a good relationship between the target and the output.

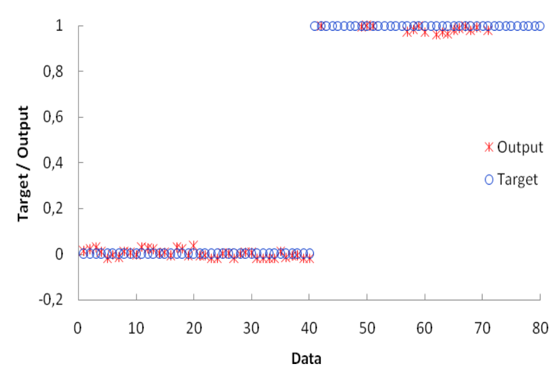


Fig. 6. Comparison between target and networks output (training data)

The comparison between target and output of the training data for normal and abnormal brain images can be seen in Figure 6. As is shown, it can be inferred that the output (*) and the target (o) are mostly coincidental. This indicates the that the training process is successful.

After the training, the next process is testing. The results of network testing are shown in Fig. 7 and Fig. 8.

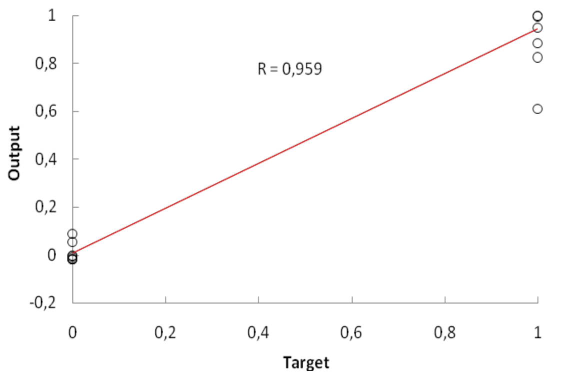


Fig. 7. Relation of target and output (testing data)

Fig. 7 shows the relation between the target and the output for neural networks testing data. Using linear regression analysis we obtain a correlation coefficient of 0.959. This shows a good relationship between the target and the output.

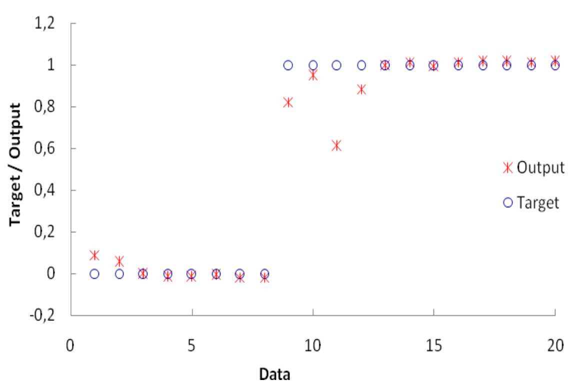


Fig. 8. Comparison between target and networks output (testing data)

The comparison between the target and the output for normal and abnormal brain image testing data can be seen in Figure 8. From the 20 samples of data used in the study, 6 show slight deviation. Thus, the conformity percentage of neural networks used in this study to identify brain tumors is 70%.

CONCLUSION

To conclude, we performed an extraction feature of CT-Scan brain image using 4-direction GLCM (0˚, 45˚, 90˚ and 135˚) with distance d=1. From these parameters, we obtain four statistical features, i.e., contrast, correlation, energy and homogeneity for each direction. The statistical features are then used to detect brain tumors using backpropagation neural networks. The results show the correlation coefficient for training data is 0.999 and the correlation coefficient for testing data of 0.959. While the accuracy of backpropagation neural networks was determined to be 70%.

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