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HYBRID METHOD ARCHITECTURE DESIGN OF MRI BRAIN TUMORS IMAGE SEGMENTATION

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Abstract. *Image segmentation is still an important and interesting issue for researchers today, and one of MRI issues is image segmentation of brain tumors. MRI images of brain tumors have quite high complexity both from variable size and structure, low contrast, bad boundaries, and low homogeneity. In some cases noise appears like blur, miss focus, and miss alignment of images. Manually image segmentation requires high accuracy, since each pixel contains important information. In addition, it will potentially lead to different interpretations of each expert. The tools that are used by experts to read MRI images of the brain nowadays, can present images into several regions namely sagittal, coronal, and cross sectional. The division into these three regions is actually quite helpful during the diagnosis process, since the doctor can see the brain tissue in the three regions, but the display cannot lead to an object that is found slightly different from particular area or focus on one particular object or area that shows a difference or abnormality. The expected outcome of this initial research is an architecture design for segmenting MRI images of brain tumors by involving two algorithms, MDWT and CNN. Combination both of MDWT and CNN provides new approaches in medical images analysis including brain image tumor segmentation. Researchers use literature study and laboratory experiment as the research methods.*
Keywords: Magnetic resonance image, Image segmentation, Multi directional wavelet transform, Convolution neural network, Architecture

1. **Introduction.** The problem arises in many cases of brain tumors since its growth is very difficult to detect early, because the symptoms are similar to ordinary headaches. In most cases, the patient will be treated after having advanced symptoms, such as frequent headaches with increasing pain, vomiting, visual disturbances, speech and walking disorders and other disorders until the death. If this further disruption has occurred, the patient has definitely a malignant tumor of third or fourth stadium.

The condition above can actually be minimized by early detection of brain tumors. Brain tumor patients can do a variety of medical action to help diagnose by doctors, and one of them is scanning (radiological imaging) using an MRI machine (magnetic resonance image). MRI is relatively safe because the gadolinium injection process of contrast material reduces the allergic reaction of iodinated contrast material. MRI images show contrast better than other radiological devices [1]. MRI can present anatomical parts imaging separately in vivo with high resolution of arbitrary planes and non-invasive

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imaging. MRI results have a higher sensitivity for detecting the existence or changes in tumor size. MRI can show the presence of abnormal tissue with high resolution and good contrast [2]. MRI machines can display digital images into 3 sides, namely sagittal, coronal, and cross sectional. Sagittal MRI shows a side view or profile of the body, while cross sectional or cross section incision shows the slices of human body. The thin horizontal slices show human body from top to bottom.

The division into the three sides is supposed to be quite helpful during the diagnosis process, because doctors can see brain tissue from three sides, but the MRI display is not enough to guarantee the accuracy of the diagnostic results. Something difference from the appearance of the image does not represent definitely the existence of the tumor. The display on the reader cannot direct to one object that is found to be slightly different from other areas. So the device has not been able to focus on one particular object or area (ROI/region of interest) that shows a difference or abnormality. In addition, each side of the MRI image still consists of several image displays. Hence, there are a lot of MRI images that need to be analyzed for the diagnosis process. The condition consumes much time if the images are analyzed individually. In addition, the issue of accuracy of the analysis results between each expert could be different potentially. MRI images of brain tumors have quite high complexity both from variable size, structure (tissue morphology), and other features. MRI images of brain tumors are also intensity inhomogeneity or different intensity ranges, low contrast, and bad boundaries. And in some cases, brain tumor MRI images contain blur, miss focus, and miss alignment noise. The conditions will affect the accuracy of the image segmentation results, which affect the results of diagnosing the presence of brain tumors in human brain tissue. This study proposes an architecture design of brain tumor image segmentation system.

One solution to solve the problems is to conduct the segmentation process of the MRI image. Segmentation becomes an important issue in medical image analysis, because the process of segmentation involves images with sensitive areas, that the results of segmentation must be accurate, precise and efficient. The accuracy of the results of segmentation can give consideration to the patient's care plan, plan of patient's action, and other plans for the patient [3]. One of the benefits of image segmentation is the brain tumor MRI image in order to assist the process of diagnosing the existence of a brain tumor.

Image segmentation means dividing an image into homogeneous regions based on certain similarity features (criteria) and particular similarity with the aim of simplifying or representing images in a form to be easy to analyze and meaningful. Segmentation has a role to facilitate the depiction of important areas in an image or known as ROI (region of interest) [4]. Image segmentation can be done based on intensity, features, and atlas of the image, and others.

In 2015, a study was carried out using a combination of several types of wavelets to carry out each process in order to improve the medical image of the heart, liver and kidney. Several types of wavelets and proposed methods were implemented to obtain boundaries or edges of the image object. The results of the evaluation of the three types of medical images showed quite significant, about 50-57% PSNR value for other wavelets and about 79-88% for the proposed method [5]. Wavelet transformation was also used to remove noise from MRI images in a 2018 study. The exact wavelet transformation used is dual tree complex wavelet transform. The evaluation results between ODI and PSNR values were 0.9165 ± 0.0536 and the comparison of ODI values with SSIM was 0.9050 ± 0.0452 [6]. Other studies used the directional wavelet transform algorithm to restore old document images. Research that was conducted in 2017 used to exploit all pixels from old document images. Evaluation of the algorithm was done subjectively by experts who understood about old documents [7]. Zhao and several other experts integrated two architectures in deep learning to conduct segmentation, namely FCNN and CRF. The parameters that were obtained after training with FCNN were used by

CRF to train image slices. The evaluation results are shown by the dice similarity value [8]. In 2016, Pereira and his friend conducted a study to segment brain tumor MRI images with CNN. The results of implementation of the algorithm showed that DCS was 88%, PPV was 91%, and sensitivity was 86% [9]. In 2019, Mittal and other researchers used GCNN to segment brain MRI images. This study was conducted in several stages (pre-processing, skull stripping, feature extraction, and segmentation). The precision and recall values of applying the GCNN algorithm were 98% [10]. Alharbi and Albahar in 2019 proposed continuous wavelet transform to detect anomalies of network traffic data based on the lowest percentage deviation value. These two researchers mentioned that Morlet transform gave better result than other mother wavelet families [11].

Based on the ability of wavelet and CNN transformations in analyzing medical images, this study proposes the merging of two algorithms of wavelet transformation and deep learning approach. The two proposed algorithms are multi directional wavelet transform and convolution neural network. As an initial stage of research, the output of this study is a system architecture design for segmenting MRI brain tumor images on gray scale and RGB images. In further research, the developing method or algorithm will be proposed.

This research was conducted using literature study and laboratory experiments method. Literature study was used to identify state of the art relates to the algorithm used in segmenting brain tumor images, while laboratory experiments were used to develop the proposed image segmentation algorithm. The stages in this study began from the study of literature, analysis of proposed algorithms, algorithm development, implementation with some simulations, and evaluations. The initial research publication consists of the result of the literature study stage up to the stage of proposed algorithm analysis. The next publication will be carried out after further research will have carried out, consisting of the algorithm development stage to the results evaluation stage. Figure 1 explains the whole research stages.

The organization of this paper consists of paper introduction, problem statement and preliminaries, main results, control design, and conclusions. Introduction contains information about research background and existing literature related to the topic. Second session explains why these two algorithms are proposed. While the third session contains

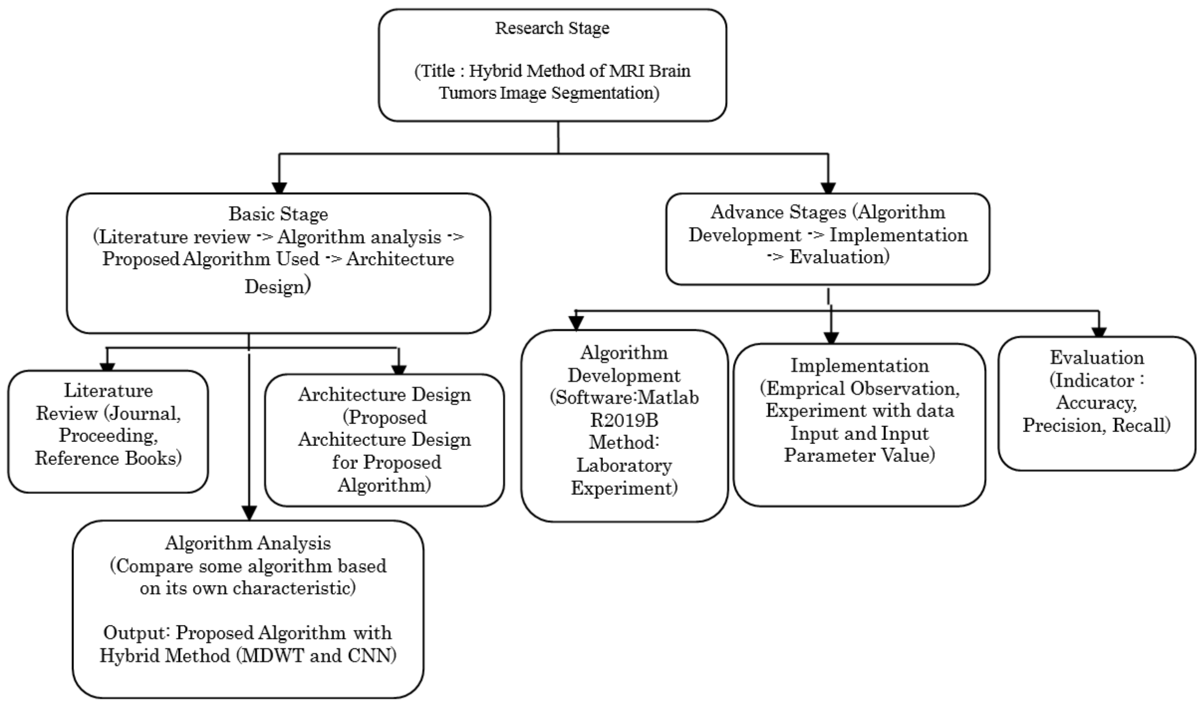

Figure 1. Research stages

the output of this study. Control design explains about input parameter value of each algorithm as a control. And the paper ends with conclusion session.

2. **Problem Statement and Preliminaries.** The problem statement of this research is how to design the architecture model to segment MRI images of brain tumors both gray scale and RGB images with a combination of multi directional wavelet transform and CNN algorithms.

The literature study shows that the multi directional wavelet transform algorithm is an algorithm that is able to exploit directional characters of an image. Hence, the algorithm is able to separate the desired features of the unexpected ones. In other words, the multi directional wavelet transform algorithm is able to separate images based on different wavelet domain frequencies. In addition, the CNN algorithm has the ability to recognize objects of an image. CNN algorithm is able to separate the features contained in an image through a series of convolution processes.

Based on the results of the literature study, the two proposed algorithms had advantages and abilities in analysis of medical images, and one of them was the process of image segmentation. So the preliminaries that will be developed in this study are a hybrid methods architecture design which is a combination of MDWT and CNN algorithms that can be implemented to segment the MRI images of brain tumors.

3. **Main Results.** Based on the above problems, this study proposes a hybrid method architecture design to segment brain tumor MRI images with multi directional wavelet transform (MDWT) algorithm and the CNN algorithm. This architectural design will be developed in Matlab R2019 programming language in the next stages. Figure 2 shows a hybrid method architecture design that is proposed in this study which consists of:

1) Input image

   The input image uses gray scale image and RGB (red green blue). There are 50 input images.

2) Image segmentation algorithm

   a. Image transformation with MDWT algorithm

      The input parameters of the MDWT algorithm are the level of decomposition, wavelet function, and the degree of convolution. While the wavelet function is used to filter (low pass filtering and high pass filtering) in order to analyze the signals from the input image. Filtering is done by convolution using a matrix. The degree of convolution is a vector that will be compared to the convolution matrix.

   b. Feature extraction with CNN algorithm

      To implement the CNN algorithm, it is necessary to identify the layer architecture that is best to suit the input image. The most appropriate layer architecture is done through several experiments. The output of this stage consists of some important features that represent the input image. This important feature represents the category of several types of brain tumors and normal conditions without brain tumors.

3) Output image (segmented image)

   The output of the proposed architecture design is an image that has been segmented using two algorithms (hybrid methods). The image is segmented based on the features possessed by the input image.

4) Algorithm evaluation results

   Evaluation of the proposed algorithm uses indicators of accuracy, precision, and recall.

5) Results early diagnosis of a tumor

   If the image has been segmented, it can be used to diagnose the existence of a brain tumor. From the output image, ROI will be clearly seen.

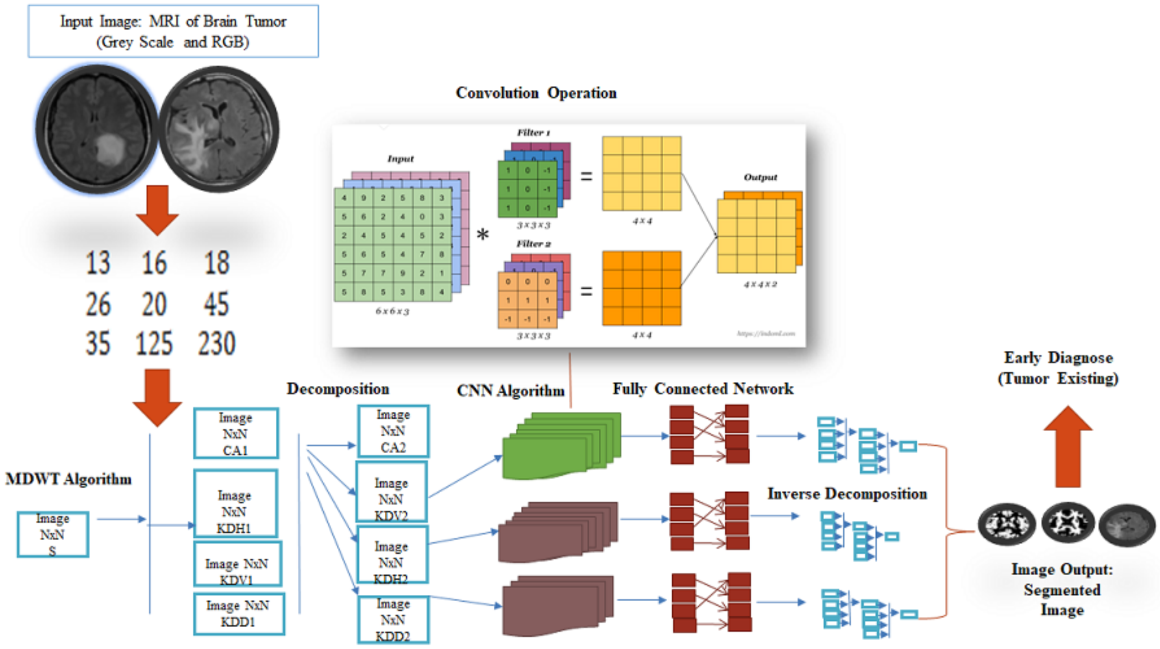

FIGURE 2. Hybrid method architecture design of MRI brain tumors image segmentation

The implementation of the two algorithms produces output as features of the input and output image. When the features contained have been identified, the algorithm can partition the image area based on the feature homogeneity. If the image has been segmented based on the features, it can be known an area in the MRI image that shows normal or abnormal tissue.

MDWT algorithm uses the wavelet transform approach. Wavelet transform can transform images to the form of other images that are meaningful. The results of the wavelet transform are four sub band images, namely the approximation of sub band, the horizontal detail sub band, the vertical detail sub band, and the diagonal detail sub band. Transformation can be done in several levels. At the second decomposition level, the approximation sub band will be transformed back to be 4 sub band. Transformation is done through a convolution process involving a matrix and wavelet functions that match the input image. Then the process of generating a sub band is done by multi directional techniques that the image is transformed into several directions from each generated sub band (sub image). With the algorithm, much information (features) of the image can be obtained, so that the segmentation process can be done easily, because the discovery of these features will affect the homogeneous generated regions. Figure 3 shows the decomposition process.

Convolution neural network (CNN) algorithm works with deep learning techniques, because it has a layered algorithm structure (Multilayer Perceptron) to solve the problems of object recognition, classification, and others. Deep learning has the ability to extract many things such as abstracts, and features of a set of data by building complex models, even though the very simple data is used [12]. Deep learning compiles complex architectures of simple concepts, so that deep learning has the ability to represent problems of formed high flexibility [13]. Deep learning techniques have been widely used in the medical or health sciences as a tool for analyzing medical images such as the classification of medical images, detection of objects in medical images, and segmentation. On CNN, the learning process is carried out by using several convolution matrices (external mask/sub windows) to produce new images that represent the features of input image. Figure 4 shows an illustration of the convolution process in CNN algorithm.

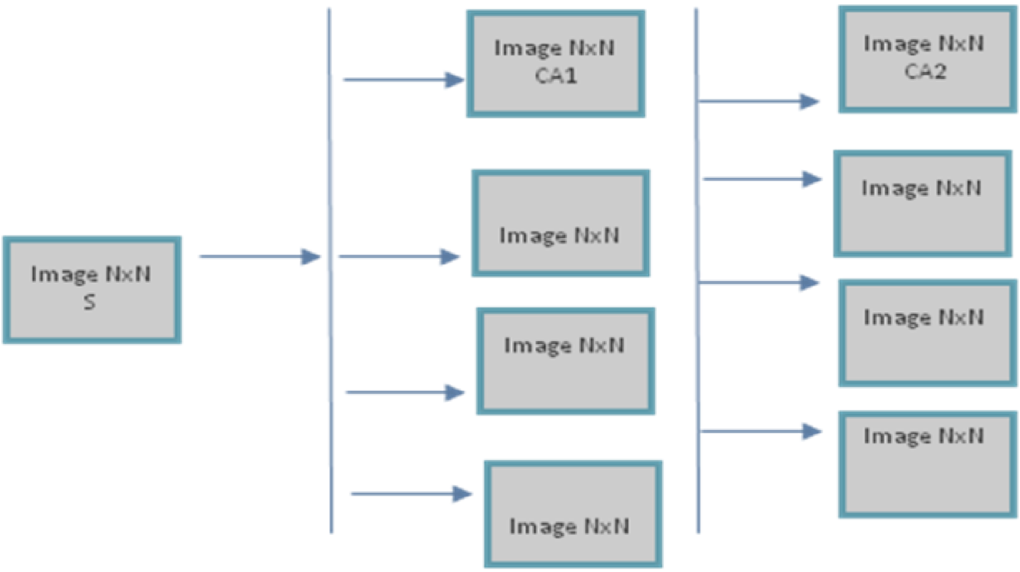

FIGURE 3. Decomposition process of image using wavelet transformation

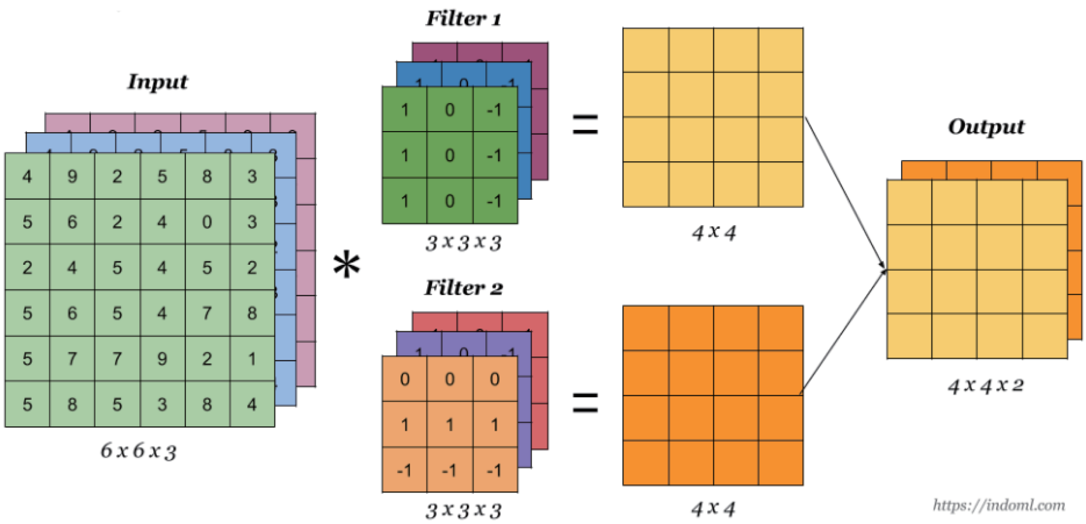

FIGURE 4. Convolution process using CNN

4. **Control Design.** The design control of this study is the input parameters of each proposed algorithm, because the exact value of each parameter will determine the quality of the output image.

Input parameter for MDWT algorithm is the level of decomposition, the size of the convolution matrix, kind of wavelet function, and the degree of orientation (direction) of the convolution matrix. This MDWT algorithm equation shows relation of all input parameters of this algorithm.

$$\Phi_{j,m,n}(x,y) = \phi_{j,m}(x_1)\phi_{j,n}(y_1) \tag{1}$$

$$\Psi^1_{j,m,n}(x,y) = \Psi_{j,m}(x_1)\phi_{j,n}(y_1) \tag{2}$$

$$\Psi^2_{j,m,n}(x,y) = \phi_{j,m}(x_1)\Psi_{j,n}(y_1) \tag{3}$$

$$\Psi^3_{j,m,n}(x,y) = \Psi_{j,m}(x_1)\Psi_{j,n}(y_1) \tag{4}$$

$$\phi_{j,m}(x) = \frac{1}{\sqrt{2^j}}\phi\left(\frac{x}{2^j} - m\right), \ \Psi_{j,m}(x) = \frac{1}{\sqrt{2^j}}\Psi\left(\frac{x}{2^j} - m\right) \tag{5}$$

Φ represents wavelet function used, Ψ is 1 dimesional scaling function, x & y are pixel coordinates for the image, and $\Phi_{j,m,n}(x,y)$ indicates intensity level at coordinates x, y.

While the input parameters of the CNN algorithm are layer architectures and kernel function (convolution function). With the right number of network layers, it will produce optimal features or information of the input image. Each stage consists of three layers, namely the convolution layer, the activation layer, and the pooling layer. The equation for carrying out convolution operations on input images after applying the MDWT algorithm can be seen as follows. x is input image, $s(t)$ is function of convolution results, and w is weight next stages.

$$s(t) = (x * t)(\tau) = \sum_{\alpha=-\infty}^{\infty} x(\alpha) * w(t - \alpha) \tag{6}$$

5. **Conclusions.** With the ability of the MDWT algorithm to perform as many as decomposition using transformation techniques based on the wavelet function, this algorithm can obtain potentially all the meaningful information (features) of the input image. Also, with the CNN algorithm, multi-layered learning capabilities allow the CNN algorithm to extract more detailed information of the generated images after the implementation of the MDWT algorithm. This means that the application of these two methods can produce detailed feature information of the image, so that the segmentation process can be done easily. The segmentation algorithm can partition the image area into homogeneous areas based on features extracted by the proposed hybrid method easily. In accordance with Figure 1, this study will be continued by developing this hybrid method architecture design into a system that can segment the brain tumor MRI images. Performance evaluation algorithm will be carried out after the system has been developed, and will be resolved soon.

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