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Preliminary Analysis on the Effect of Different Denoising Techniques towards Texture Features of MRI Images of Alzheimer's Disease

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ABSTRACT

Early detection of Alzheimer's disease (AD) has become one of the major research topics nowadays. The utilization of the computerized system may help medical experts to better understand and analyse the magnetic resonance imaging (MRI) images of AD patients for early detection. One of the commonly steps taken for the analysis of the image is image denoising using certain filters. However, finding shows that previous researchers use different approaches. This study aims to analyse the effect of different denoising techniques towards detection of Alzheimer's disease. Data of two different groups (AD patients and Normal Control) were collected from Alzheimer's Disease Neuroimaging Initiative (ADNI). Then brain extraction and skull stripping were performed. Several image denoising techniques were implemented for both groups namely median filter, Wiener filter, histogram equalization filter and Gaussian low pass filter. After that, all images underwent texture feature extraction process and analysis were made to see the effect of those denoising techniques towards the features of Gray-Level Co-occurrence Matrix (GLCM) extracted which are the contract, correlation, energy and homogeneity features. The result shows that the use of mentioned denoising filters do not give effect to the extracted features. All values of contrast, correlation, energy and homogeneity cannot clearly distinguish between AD and NC groups. Without any filters on the other hand, contrast feature gives the best output in distinguishing between AD and NC groups with the normalized value of 0.1. The result from this study may help in thorough investigation of other features or hybrid features that could be used for the purpose of detection and classification of AD.

1. Introduction

Alzheimer's disease (AD) is a neurological disease affecting the brain function that may lead to memory loss in patients and could affect the daily life of both patients and caretakers [1]. This disease has no cure and the patients' condition may worsen due to the progression of the disease, which may in the end lead to death. Researchers all over the world try to come up with a simple and more accurate approach in order to identify AD before the symptoms become visible but most often, AD

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detection is not that accurate. Usually, accuracy will be improved once the patient has started to show the signs of the disease. Therefore, detection of AD at its earliest stage is essential so that proper treatment could be introduced thus slowing down or even preventing the patients from further brain damage [2].

Over the past few decades, magnetic resonance imaging (MRI) has been progressively used in exploring brain anatomy including for AD [3]. In the diagnosis of AD using medical imaging modalities, specifically using MRI images, some lesion areas in the brain could be determined with the help of expert radiographers. Image processing technology in addition can be used to for a better quality of reconstruction and measurement process, especially for brain, soft tissues and lesions. With the help of sophisticated and high-end computers, medical experts can analyze multiple areas of interest qualitatively and quantitatively [4]. Current practice on detecting AD is by looking into the brain scans, performing a clinical assessment, and eventually asking questions of the patient and their relatives [5,6]. This is a very challenging process as identifying the parts of the brain that are affected by AD by using the bare eyes is not an easy task. Moreover, one of the AD symptoms, such as brain shrinkage, can be observed as well in healthy, elderly normal control (NC) groups [7].

Therefore, computer-aided diagnosis (CAD) systems which utilize computerized and digital image analysis can be used as an alternative solution to the problem. CAD can be developed based on image analysis techniques using deep learning methods or common traditional methods [8]. Utilization of deep learning frameworks for detection of AD in MRI images can be seen as in previous studies [2,4,8]. Even though the deep learning methods can give great output when dealing with brain MRI analysis, finding a robust and more generic algorithm still remain as a challenge. Pre-processing stage can also affect the performance of deep learning techniques [3]. On the other hand, the common framework which uses the pipeline of pre-processing, segmentation, feature extraction and classification can be utilized using supervised or unsupervised machine learning approaches such as Support Vector Machine (SVM) [9,10]. Detecting AD using these algorithms has their own issues as well including the low image quality, issues in the brain segmentation and pre-processing steps, and the complexity of medical images [11]. Thus, detailed analysis is needed to thoroughly investigate each step involved in the pipeline.

Image pre-processing is usually performed before any further image analysis to remove any possible noise or unwanted data, as well as to highlight and enhance important features for feature extraction process. Due to the complexity of medical images construction, the images may contain noise and distortion which may generally cause by the variations in the detector sensitivity, diminished illumination of the object, limitation of the images, and spontaneous variations in the radiation signal [12,13]. Therefore, it is crucial to pre-process the data to enhance its quality or to optimize its geometric and intensity patterns [12]. The pre-processing step will help the researchers to improve the quality which will then highlight the essential information that is required in the feature extraction and classification process. There are many available image pre-processing steps including intensity normalization, contrast enhancement, image denoising, brain extraction, skull stripping, and others. Some researchers performed the pre-processing steps using secondary tools/software such as the Brain Extractor Tools (BET2), Freesurfer Statistical Parameter Mapping (SPM12), and Computer Anatomy Toolbox (CAT12) [2,14-17]. The implementation of image denoising step is also varies between researchers where there were previous reported studies which uses the more common filters such as median filter, Wiener filter, histogram equalization, and Gaussian low pass filter [9,10,18,19]. There was also a study that implemented other types of filters such as Lucy-Richardson approach [20,21]. Besides, there were some past studies which did not even implement any image denoising process [8,22-24]. Due to these stated inconsistencies in the process, the effect of these denoising techniques to image feature extraction and classification between AD patients and normal patients remains unclear.

Therefore, this study aims to analyze the effect of different denoising techniques towards detection of Alzheimer's disease. The objective is to implement the image denoising step and assess its effect on the later process of feature extraction for two different groups of images. Data of two different groups (AD patients and Normal Control) were first collected from Alzheimer's Disease Neuroimaging Initiative (ADNI). Then brain extraction and skull stripping were performed. Several image denoising techniques were implemented for both groups. After that, all images underwent texture feature extraction process and analysis were made to see the effect of those denoising techniques towards the features of GLCM extracted. The rest of this paper is organized as follows. Section 2 discusses the methodology in detail, while Section 3 reports the experimental results and finally, in Section 4, the findings are concluded.

2. Methodology

Figure 1 shows the general block diagram involved in this particular study. The MRI images of the brain were gathered from the ADNI database. Both data of AD and NC (normal control) groups were gathered. The image samples were then undergoing the pre-processing steps including brain extraction, skull stripping and image denoising. Then, the output of each denoising technique was analyzed by extracting some common features that could be used for the purpose of image classification between AD and NC. The detail of each step is explained in the following sections.

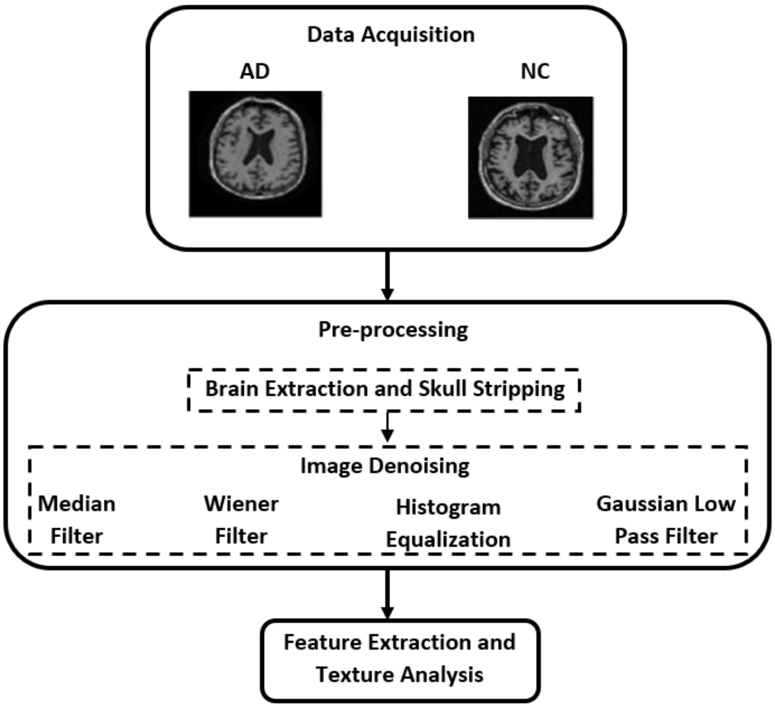


Fig. 1. Block diagram of the study

2.1 Data Acquisition

The MRI data used in this study were gathered from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database (adni.loni.usc.edu). The ADNI was launched in 2003 as a public-private partnership, led by Principal Investigator Michael W. Weiner, MD. The primary goal of ADNI has been to test whether serial magnetic resonance imaging (MRI), positron emission tomography (PET), other biological markers, and clinical and neuropsychological assessment can be combined to measure the progression of mild cognitive impairment (MCI) and early Alzheimer's disease (AD). For up-to-date information, see www.adni -info.org.

In this study, for the analysis purpose, MRI data of two different classes were gathered which were from the AD patients (Group Name: AD) and normal control patients (Group Name: NC). 20 images were collected from each group for this preliminary analysis as shown in Table 1.

Table 1
Brain MRI dataset considered in this study

Image Class	Number of images
Alzheimer’s Disease (AD)	20
Normal (NC)	20
Total	40

2.2 Image Pre-processing

Image pre-processing is normally applied to the original images before any further image analysis techniques took place. The purpose of image pre-processing is to eliminate possible noises and enhance the important features exist in the respected images. The pre-processing step may help the researchers to improve the quality of the image for further processes such as feature extraction and classification. There are various pre-processing techniques available as in researches by Angkoso *et al.,* [14], Raju *et al.,* [15], Mehmood *et al.,* [16], Acharya *et al.,* [18], and Kumari *et al.,* [19] but, in this study, only a few being explored including brain extraction, skull stripping and image denoising as explained in the next following sections.

2.2.1 Brain extraction and skull stripping

The pre-processing techniques of brain extraction and skull stripping is the process that can be used to remove other tissues in brain including eyes, necks, and skulls. This step simplifies the images further as it removes the unwanted regions that might affect the later step especially during feature extraction and texture analysis. In order to remove those other tissues, the dark spaces in between the brain and the skull can be used as the segmentation region. There are many software and tools as presented by Arafa *et al.,* [25], that can be used for extraction of the brain. For example, the brain extraction tool ROBEX algorithm which utilizes machine learning. It may use deep learning also, but the computational process is very extensive and complicated thus specific hardware is needed to run the algorithm.

In this study, the brain extraction technique was implemented based on Khademi *et al.,* [26] which used the binary segmentation mask to extract the brain. The purpose of the brain extraction algorithm from Khademi *et al.,* [26] is to find a binary segmentation mask that can identify voxels from the brain tissue class. That mask can then be multiplied with the original image in order to extract the brain region out of the whole volume [26].

2.2.2 Image denoising

There are many denoising techniques available including the use of different types of filters such as Median filter, Wiener filter, CLAHE filter, Histogram Equalization and Gaussian filter. The median filter is a denoising technique which minimizes the appearance of the noise without blurring the edges [25]. This filter is a good option for the enhancement purpose of MRI images. This filter is able to identify pixels as noise by comparing and matching each of the image pixel to its neighboring pixels [25]. This median filter contains a specific size filter that can control the passing of each pixel value. Then, it will replace it with the respected median value. Further details on median filter can be seen as in related previous studies [18,27]. Wiener filter on the other hand is a filter type which is used to create an estimate of a targeted random process based on linear time-invariant (LTI) filtering of an observed noisy process, with the knowledge of stationary signal and noise spectra, and additive noise. This filter can minimize the mean square error between the estimated random process and the desired process [9]. Histogram equalization is a technique in image processing of contrast adjustment using the image's histogram and it is being used by Kamal *et al.,* [10] in his brain MRI study of AD [28]. Gaussian filtering on the other hand is a technique that can help to denoise the image and is implemented by detecting the mask size as shown in Eq. (1) [25].

$$g(x, y) = \frac{1}{2\pi\sigma^2} . e^{-\frac{x+y}{2\sigma^2}} \tag{1}$$

where x, y is the distance between the origin and vertical, horizontal axes while σ is the standard deviation of the Gaussian function.

In this study, four types of images denoising techniques were selected namely median filter, Wiener filter, intensity histogram as well as Gaussian low pass filter. The analysis in terms of texture features will also be compared with the original images that do not use any filters.

2.2.3 Feature extraction and texture analysis

Feature extraction and texture analysis (TA) is the methodology that uses mathematical approaches to detect any information in the MRI output where they may not be visible in the image pixels. The TA method can provide a quantitative and reproducible method to extract any needed image features [29,30]. The texture of the images is the spatial variation in pixel intensity levels within a tissue. The analysis methods can be grouped as statistical, structural, model-based, and transform-based, depending to the approach used when evaluating the relationships between the pixels [30].

Statistical-based TA specifically utilizes properties which is able to control the distribution and relation of gray-level values in the image [30]. First-order statistical TA is known as a histogram, where it extracts the image intensity values of the images. Many features may be derived including mean, standard deviation, skewness, kurtosis, entropy, energy and mean of positive pixel. Second-order statistical methods analyze the spatial relationship or co-occurrence of the pixel intensity values. Several methods exist to analyze second-order statistics, the two most common are gray-level co-occurrence matrix (GLCM) and gray-level run-length matrix (GLRLM) methods [30]. The GLCM analyzes the gray-level distribution of pairs of pixels in a specified distance and a specified image orientation, where two-dimensional (2D) GLCM is usually quantified in 4 directions (0°, 45°, 90°, and 135°) and three-dimensional (3D) GLCM in 13 directions. Some of the GLCM features include entropy, energy, contrast, correlation, inverse different moment, homogeneity, and cluster shades. GLRLM estimates the spatial relationships between groups of pixels with similar gray-level values, where run-length features allow evaluation of the coarseness of texture in a predetermined direction [30].

In this study, TA is performed to see the effect towards the features extracted due to the usage of multiple image denoising step. For this study, the gray-level co-occurrence matrix (GLCM), a second order statistical method is implemented to extract four properties/features including contrast, energy, homogeneity and correlation. The GLCM method is chosen not only because of its being commonly used in previous Alzheimer disease literature on texture, but also because it is easily interpreted compared to other texture methods. Besides that, its reliance on the relative rather than absolute value of the voxels in an image makes it less susceptible to interscan variability in signal-intensity values [30]. Contrast is used to measure the intensity contrast between a neighboring pixel in the whole image. Energy shows the sum of squared elements in the GLCM while homogeneity shows the measure the closeness of the GLCM element distribution with respect to the GLCM diagonal. Finally, correlation is used to measure the level of relation between a pixel and its neighbor for the whole image. Eq. (2) to Eq. (5) show the equations for each contrast, energy, homogeneity, and correlation, respectively.

Contrast

$$\sum_{i,j=0}^{N-1} P_{i,j}(i,j)^2 \tag{2}$$

Energy

$$\sum_{i,j=0}^{N-1} P_{i,j}^2 \tag{3}$$

Homogeneity

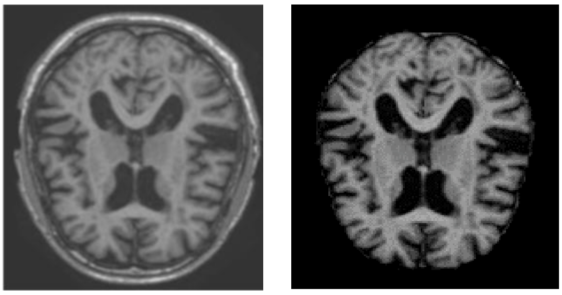
$$\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2} \tag{4}$$

Correlation

$$\sum_{i,j=0}^{N-1} P_{i,j}\left[\frac{(i-\mu_i)(j-\mu_j)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}}\right] \tag{5}$$

3. Results

The MRI image of the brain shows brain tissue as well as some non-brain parts including the head, eye, fat, spinal cord, and skull [3]. Therefore, the skull stripping process is needed to segment brain tissue from those non-brain tissues. Figure 2 shows the images before and after the brain extraction process. The output image shows that the skull has been removed from the original image. The output image from this step were used as the input image in the denoising step.



(a) (b)

Fig. 2. Image before (a) and after (b) brain extraction and skull stripping step

For this preliminary analysis purposes, four image denoising methods were selected to be tested namely median filter, Wiener filter, histogram equalization as well as Gaussian low pass filter as in Table 2. The selection of the type of the filters used are based on the previous studies as mentioned in the previous section. For both AD and NC groups, all output images from this step were then fed to GLCM feature extraction process. No measurement of filters performance was made as this step is mainly for the purpose of preparing the images for texture analysis.

Table 2
Output images for different denoising filters for both AD and NC groups

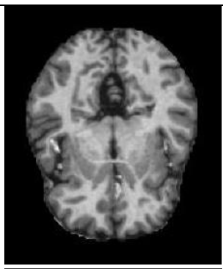
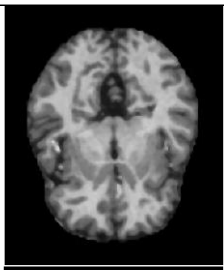
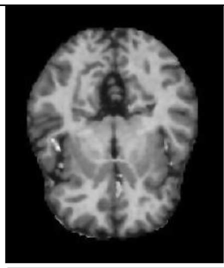
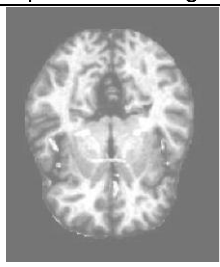
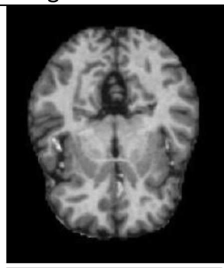
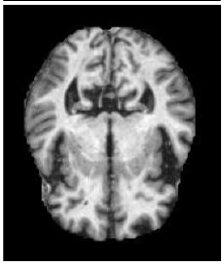
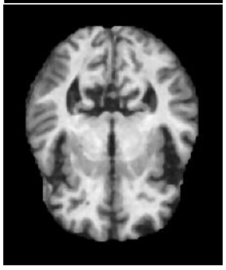
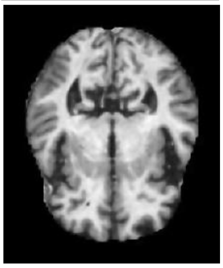
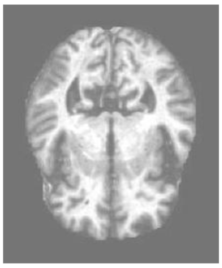
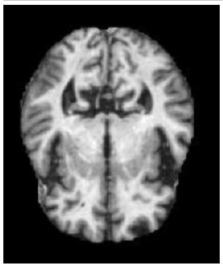
	Original Image	Median Filter Image	Wiener Filter Image	Histogram Equalization Image	Gaussian Filter Image
NC					
AD					

Figure 3 shows the result of feature extraction by using contrast, correlation, energy and homogeneity of GLCM features for both AD and NC groups for original images. The values indicate the average values for 20 images in each group. As can be seen from Figure 3, without the use of any filter for image denoising, contrast feature gives the best separation values between AD and NC as the difference is 0.1. Energy and homogeneity features can only slightly separate between the two groups with the difference value of 0.02 only while correlation feature cannot be used to distinguish between AD and NC.

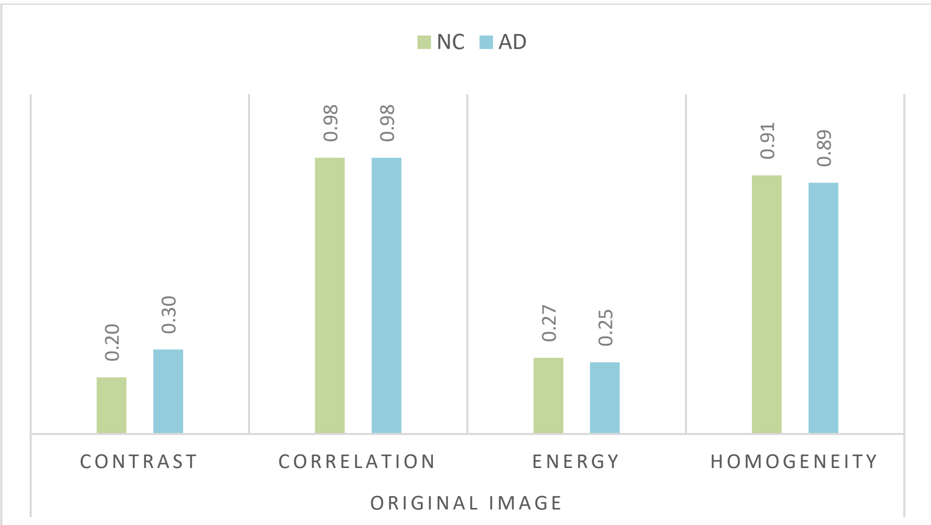


Fig. 3. Graph of GLCM features for AD and NC groups for Original Image

Figure 4 shows the feature extraction by using contrast, correlation, energy and homogeneity of GLCM features for both AD and NC groups for images after different denoising approaches. The values indicate the average values for 20 images in each group. As the graphs shown in Figure 4, for median filter, Wiener filter and Gaussian filter used in image denoising step, contrast feature gives the best separation values between AD and NC as the difference is 0.07, 0.08 and 0.08, respectively. Energy and homogeneity features can only slightly separate between the two groups with the difference value of 0.01 to 0.02 only. As the one without the filter, correlation feature also cannot be used to distinguish between AD and NC since the values for both groups are the same (0.98). Interestingly for histogram equalization filter, contrast feature and homogeneity feature cannot be used to distinguish between AD and NC as both gives the same output values, 0.15 and 0.93, respectively. Correlation feature and energy feature can only slightly separate between the two groups with the difference value of 0.01.

Overall, from this preliminary analysis, this study proves that the usage of common denoising filters (median filter, Wiener filter, histogram equalization filter and Gaussian low pass filter) give only small effect to the feature extraction process. Based on the values of the features calculated, contrast feature with no filter can best be used to distinguish between AD and NC groups. It is recommended that further study need to be done especially on testing other types of filters available. Perhaps the usage of previous four denoising filters may be beneficial for the later step such as image segmentation or registration which are not tested in this particular study. It is also recommended that further analysis could be performed using different types of feature extraction techniques such as intensity histogram features, or gray level run length matrix (GLRLM) features before a thorough conclusion could be made. Besides that, a hybrid approach combining common feature extraction techniques and deep learning approach may also be taken into considerations in order to find the best methods in detecting and classifying between AD and NC groups.

(a) (b) (c) (d)

Fig. 4. Graph of GLCM features for AD and NC groups for Images after Different Denoising Approaches, (a) Median filter, (b) Wiener filter, (c) Histogram Equalization Filter and (d) Gaussian Low Pass filter

4. Conclusions

In conclusion, this preliminary study was able to analyse the effect of different denoising techniques on feature extraction and texture analysis for detection and classification of Alzheimer's disease. From the result, it can be concluded that contrast feature with no filter gives the best output where it can best separate between AD and NC groups. Other features with denoising filters of median filter, Wiener filter, histogram equalization filter and Gaussian low pass filter give only small effect towards distinguishing between AD and NC groups. This preliminary study has shown that, for specific purpose of extracting the features from the images, selection of appropriate filter needs to be performed. It is recommended that further study need to be done especially on testing other types of filters available including those that focusing on removing Rician noise in MRI images. It is also recommended that thorough feature extraction and analysis could be performed to the images to seek for other possible prominent features or even hybrid method utilizing deep learning framework that could be used for detection and classification of AD.

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