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Convolutional neural network denoising technique on MRI examination using parallel imaging grappa (Generalized autocalibrating partial parallel acquisition): A study on axial brain MRI T_2 fat saturation flair

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Abstract
Background: Approximately more than 25% of MRI examinations are Brain MRI. One of the important Brain MRI sequences is FLAIR Fatsat, but the image results of FLAIR Fatsat Brain MRI sequences have noise and long scanning time. To overcome this, the parallel imaging technique GRAPPA and denoising convolutional neural network (CNN) post processing can be used so as to reduce scanning time and reduce noise in the image results of the FLAIR Fatsat Brain MRI sequence.
Objective: Knowing the difference in image quality between before and after the application of CNN denoising technique on MRI examination using parallel imaging GRAPPA on axial T_2 FLAIR Fatsat Brain MRI.
Methods: This study uses retrospective data by collecting 3362 axial T_2 Flair Fatsat GRAPPA Brain MRI images, with a sample size of 92 images, comparing the original image with the denoising image using CNN and assessing the Peak Signal Noise Ratio (PSNR), Structural Similarity Index (SSIM), Signal to Noise Ratio (SNR) and Contrast to Noise Ratio (CNR).
Results: The research proves that of the 92 samples obtained, the performance of the CNN denoising technique has a difference in image quality between before and after the application of the CNN denoising technique, with an SNR value of 13.40, CNR value of 24.95, PSNR value of 32.62, SSIM value of 0.82.
Conclusion: CNN denoising technique can be considered as post processing of MRI Brain image quality improvement, there is a difference in the value of SNR, CNR, and obtained good average PSNR and SSIM values indicating the quality of the resulting image after the application of CNN denoising technique is getting better.

Keywords: Brain MRI, denoising, convolutional neural network

Introduction
Magnetic resonance imaging (MRI) examination is a routine examination in major hospitals. According to the International Society for Magnetic Resonance in Medicine, approximately 10 million patients undergo MRI examinations every year. MRI examination has become an important medical diagnostic examination especially in Brain MRI, more than 25% of MRI examinations are Brain MRI examinations, the Canadian for Health Information (CIHI) has data that the national average of MRI examinations is 41.4 per 1000 people. Fluid Attenuated Inversion Recovery (FLAIR) is a sequence that aims to suppress fluid to appear dark while tissues that have a long T_2 relaxation time will appear bright [1].
With the dark cerebrospinal fluid (CSF) image on FLAIR, the lesion adjacent to the CSF will be clearly visible. FLAIR image quality is good and sensitive to pathology but requires a long scanning time [2]. Research conducted states that high signal due to fat can cause artifacts, by suppressing artifacts, noise can also be suppressed [3]. SNR is the ratio of signal amplitude and noise amplitude, with minimal noise, the SNR value will increase, the average SNR value on axial cut MRI Brain is 2.07, causing the micro-image of lesions, white matter, and gray matter in the FLAIR sequence to look vague with indistinct boundaries, so it is necessary to use denoising techniques to reduce noise and MRI examination time must be considered, one of which is by using parallel imaging in the imaging process so that the

scanning time is faster. FLAIR sequences are often combined with Fat Saturation techniques. Fat Saturation is a fat suppression technique by providing selective frequency saturation pulses that have the same resonance frequency as the fat resonance frequency. The combination of FLAIR sequences and Fat Saturation techniques is called FLAIR Fat Saturation sequences, this aims to avoid artifacts from subcutaneous fat, so in one sequence there is suppression of water signals and fat signals at the same time [4].

Some alternatives to reduce the long scanning time by using parallel imaging. Parallel imaging is a technique to increase the speed of MRI data acquisition by passing through several phase encoding lines in k-space with the encoding frequency direction remaining fully sampled [5]. Parallel imaging reconstruction methods can be categorized into two groups, namely reconstruction that takes place in image space (image space) for example, SENSE, PILS and k-space reconstruction such as SMASH, GRAPPA [6]. Of the parallel imaging reconstruction methods, there are generally only two methods promoted by vendors, namely SENSE and GRAPPA. The GRAPPA technique during the data acquisition process allows for loss of phase encoding of the information received by the various coil elements. The data acquisition method in GRAPPA is by combining underesampled k-space signals to fill in the missing information from undersampled k-space [7] GRAPPA has a special parameter called acceleration factor that will affect image quality, including SNR which affects diagnostic information and scanning time [8, 9]. The SENSE technique uses image reconstruction formed by a phased array coil. The use of SENSE when coil sensitivity maps are obtained accurately will provide an optimal signal to noise ratio (SNR), in SENSE examinations are often better at examining the brain when compared to GRAPPA using the same r-factor, but many vendors use the GRAPPA technique compared to SENSE. The disadvantage of GRAPPA is that it results in a longer scanning time than SENSE because it requires a longer time that will worsen the low-resolution image where the calibration time occupies a larger presentation of the total acquisition time because the image matrix results in size, this disadvantage is relatively decreased. Parallel imaging works by utilizing the spatial information on the coil phased array to reduce the acquisition time. While it has benefits in reducing scanning time and increasing resolution, parallel imaging also causes SNR loss [2].

This study aims to determine the difference in image quality between before and after the application of CNN denoising technique on MRI examination using parallel imaging GRAPPA on MRI brain axial T_2 FLAIR fat saturation. This research is expected to produce optimal scanning time, improve the quality of Brain MRI images by minimizing noise from the influence of convolutional neural network denoising techniques.

Materials and Methods

This study is an analytical study with a numerical measurement scale in one paired group with a type of pre-experimental research using a one group pretest and post-test without control research design. The study was conducted by applying the GRAPPA parallel imaging technique at an acc factor value of 2. The acc factor value of 2 is often used in the application of GRAPPA in MRI examinations.

The sequence used is T_2 FLAIR Fat Saturation on axial cut Brain MRI examination. MRI Brain T_2 FLAIR Fat Saturation images were improved with convolutional neural network (dnCNN) denoising technique to produce images with better quality. Each image is measured before and after the denoising technique. Image quality is assessed quantitatively by measuring SNR, CNR, PSNR, and SSIM. The population of this study is the target population, namely MRI images with T_2 FLAIR fat saturation GRAPPA acc factor 2 axial sequences, while the affordable population is the target population that meets the inclusion criteria, namely, 1) Brain MRI patient images with T_2 FLAIR fat saturation GRAPPA acc. factor 2 axial sequences from January 2022 to July 2023; 2) Confounding variables that have been controlled are: spatial resolution, fov, slice thickness, accelaration factor value, matrix. while the exclusion criteria of this study are Brain MRI images with sequences other than T_2 FLAIR fat saturation GRAPPA acc factor 2 axial samples taken with purposive sampling technique and obtained a bear sample of 92 images of Brain MRI patients T_2 FLAIR fat saturation GRAPPA acc factor 2axial.

Results

An experimental analytical study has been conducted with the application of the Convolutional Neural Network (CNN) denoising technique to MRI examinations using parallel imaging grappa on MRI brain axial T_2 flair fat saturation. In this study, the data used is secondary data with the samples used are MRI Brain images stored in the Radiology MRI Installation PACS system, taken from January 2021 - July 2023. The research subjects taken were 92 MRI Brain patient images with axial T_2 flair fat saturation grappa sequences or according to the inclusion criteria. The study was conducted by making MRI images of the Brain axial T_2 flair fat saturation sequence applying parallel imaging GRAPPA. Brain MRI images that have been selected are stored on CD/DVD in Dicom format, all MRI parameters are controlled to remain the same in each sample. Brain MRI images of T_2 flair fat saturation axial GRAPPA sequences were then subjected to image information improvement with Convolutional Neural Network (CNN) denoising technique. This study was conducted to assess the quality of Brain MRI images by calculating the SNR and CNR values and testing the performance of CNN filters by calculating the MSE, PSNR, and SSIM values. This research has obtained permission from the Health Ethics Committee of the Poltekkes Kemenkes Semarang, Indonesia.

Creation and Assessment of the Application of Convolutional Neural Network (CNN) Denoising Technique

In the initial stage, the creation and Operational Design of the Application of Convolutional Neural Network (CNN) Denoising Technique was carried out by searching for image data from the results of examinations on MRI Brain image patients with axial T_2 flair fat saturation grappa sequences. In the next stage, image storage is carried out in the form of Digital Imaging and Communication in Medicine (DICOM) into CD / DVD. The image is stored in the form of Digital Imaging and Communication in Medicine (DICOM). MRI image of Brain T_2 sequence flair fat saturation axial application of parallel imaging GRAPPA that has been stored on DVD_R, then image quality improvement is carried out. Noise in the image is made noise reduction efforts and contrast enhancement with Convolutional Neural Network (CNN) denoising technique. In this research using a tool using matlab application with Convolutional Neural Network (CNN) denoising technique. Identification of Brain MRI images with the matlab program, then given denoising techniques with the application of Convolutional Neural Network (CNN). Matlab or what is commonly called (matrix laboratory) is a program for analyzing and computing numerical data.

Matlab is also an advanced mathematical programming language formed on the premise of using the properties and shape of matrices. Matlab's Image Tool provides an interactive environment for investigating and navigating images, displaying detailed information about pixel values. To start the Image Tool, use the Imtool function to read the image from a file using the main window. Image filtering is a process to reduce noise in MRI images to improve an image or digital image.

A deep learning CNN model was created using the MatConvNet architecture. The MRI brain image is associated with the first layer. The parameters of the CNN deep learning model using the MatConvNet architecture used are with a max epoch value of 100, minibatch size 128, momentum 0.9 and learning rate 0.0001 and using the MatConvNet Package. The parameters used are parts that function to control the course of the CNN deep learning model function in order to produce classification predictions correctly. The process of preparing the MatConvNet architecture so that it can produce output in the form of classification consists of two steps.

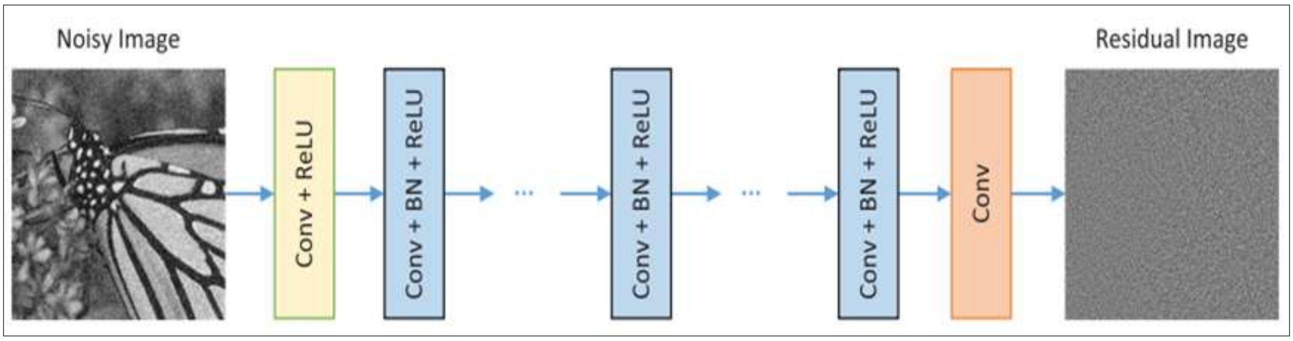

Fig 1: Process Illustration of MatConvNet Architecture

The next stage is the process of training the brain MRI image data set using 3234 brain MRI images. Before the image is entered for the training process, the brain MRI image is preprocessed. Next, the parameters are formed and inputted as needed. Then the training process is carried out on the training data and then records the output results and saves the network that has been generated by the training process. then continue the assessment Performance Assessment of Deep Learning CNN Models MatConvNet architecture The performance assessment of this CNN deep learning model uses a k-fold cross validation test with a k value. The data set used is 3234 MRI brain T_2 flair fat saturation grappa images.

The matconvnet architecture deep learning classification model is trained using training data that has been input into the folder according to its classification. Then validation is carried out using testing data using datasets that are taken automatically and randomly by the deep learning model with a ratio of training data and test data, namely 90: 10. In the CNN algorithm architecture, it can be seen that the coding process is carried out for the cross-validation process. This training process occurs as many as 100 iterations, according to the epoch setting of 100 and learning rate 0.0001.

Epoch is the number of times the training process occurs until all data is completed. Learning rate is one of the training parameters to calculate the weight correction value during the training process. The greater the learning rate value, the faster the training process will run. The greater the learning rate, the less accurate the network will be, but vice versa, if the learning rate is smaller, the accuracy of the network will be greater or increase with the consequence that the training process will take longer.

Calculation of the Average Signal to Noise Ratio (SNR) between Before and After the Convolutional Neural Network (CNN) Denoising Technique on Brain MRI Images

SNR is the ratio between the amplitude of the signal and the amplitude of the noise. To calculate the SNR value, the Region of Interest (ROI) is determined. In this study, the SNR value before denoising ranged on average 8.34 and the SNR value after denoising ranged on average 13.40. The results of the SNR value after denoising have a high average value compared to before denoising.

Calculation of Average Value of Contrast to Noise Ratio (CNR) Between Before and After Denoising Technique Convolutional Neural Network (CNN) on Brain MRI Image

CNR is the ratio of SNR between neighboring organs. A good CNR can show the difference between pathological areas and normal areas [10]. CNR assessment is obtained from the intensity difference value between the object and the background object divided by the standard deviation of the background [11]. In this study, the average CNR value of axial MRI Brain T_2 flair fat saturation grappa image, where each image is calculated CNR between before and after the application of CNN denoising. The CNR value before the application of CNN denoising ranges on average 18.24 while the CNR value after the application of CNN denoising ranges on average 24.95.

Calculation of Mean Square Eror (MSE) Value on Brain MRI Image with the Application of CNN Denoising Technique

Quantitative testing is done to calculate the MSE and PSNR to the image to see the quality of the image produced by the

CNN denoising process. The MSE value of the Brain T_2 flair fat saturation grappa axial MRI image after the application of CNN denoising can be seen describing the average MSE value of the Brain T_2 flair fat saturation grappa axial MRI image. Each image is calculated by combining the MSE between the image before and after the application of CNN denoising. The MSE value with the merging between the image before and after the application of CNN denoising ranges on average 35.60.

Fig 2: The calculation score of MSE on Matlab software

Calculation of Average Peak Signal to Noise Ratio (PSNR) Value on Brain MRI Image with the application of CNN denoising technique

The calculation of the PSNR value is done in the Matlab application by entering the formula in the GUI, after which the combined PSNR value of the image before and after CNN denoising will appear in the window. In this study, the average PSNR value of MRI Brain T_2 flair fat saturation grappa axial image. Each image is calculated by combining the image before and after the application of CNN denoising. The calculation of PSNR value is done in Matlab application by entering the formula in the available GUI. The PSNR value with the merging image between before and after the application of CNN denoising ranges on average 32.62.

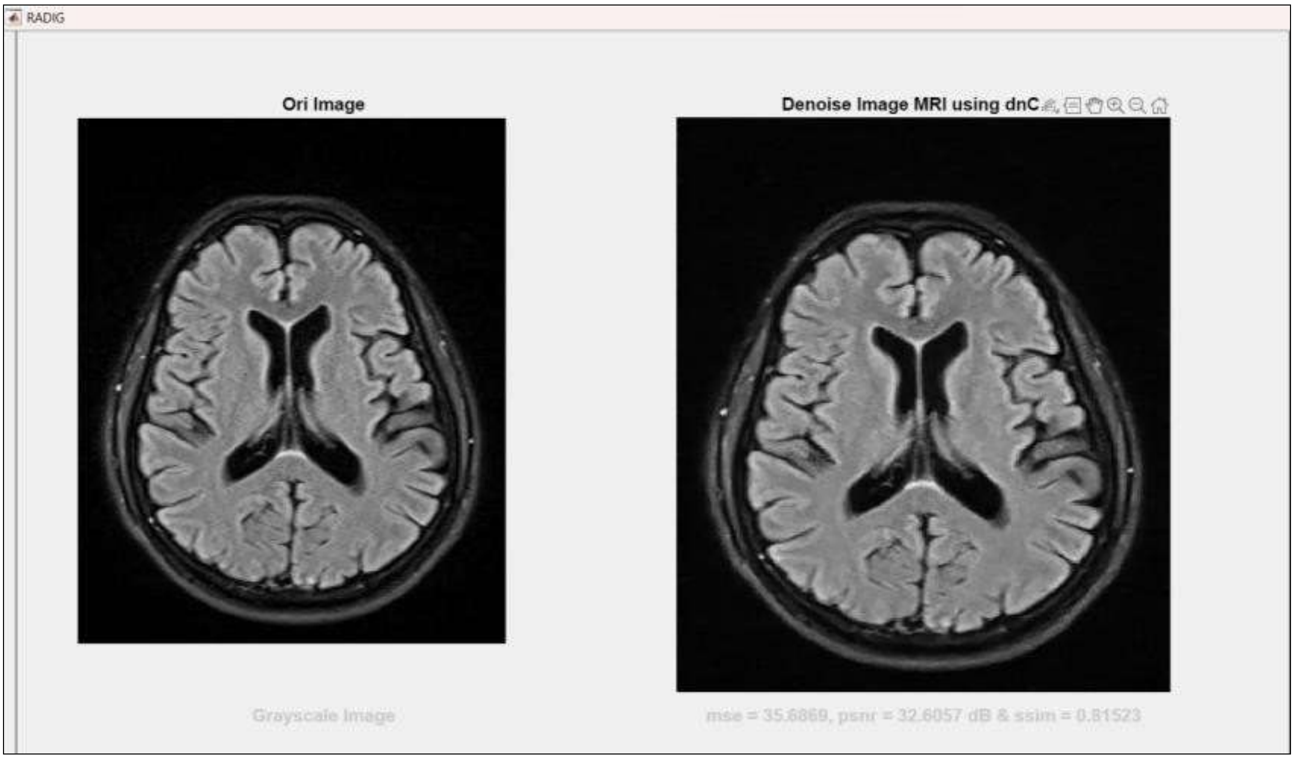

Fig 3: The calculating score of PSNR on GUI

Calculation of Structural Similarity Index Measure (SSIM) Value on Brain MRI Image with the application of CNN denoising technique

Each image is calculated by combining the SSIM between the image before and after the application of CNN denoising. The calculation of the SSIM value is done in the Matlab application by entering the formula in the available GUI. The SSIM value with the merged image between before and after the application of CNN denoising ranges on average 0.82.

Differential Test of Signal to Noise Ratio (SNR) Value on MRI Brain T_2 Flair Fat Saturation Grappa Axial Image between Before and After the Application of CNN Denoising Technique

Table 1: Difference test of SNR value of MRI Brain Image

SNR	Mean Rank	P value Wilcoxon	Significance
SNR Pre	0,00	0,000	There is difference
SNR Post	46,50		

From the table above, the results of the t-test show that there is a difference in SNR values on MRI images of Brain T_2 Flair Fat Saturation Grappa Axial between before and after the application of CNN denoising techniques with a p value of 0.000. This value is smaller than 0.05 ($p=0.000 <0.05$) so there is a significant difference between the SNR values before and after the application of CNN denoising technique.

Differential Test of Contrast to Noise Ratio (CNR) Value on MRI Brain T_2 Flair Fat Saturation Grappa Axial Image between Before and After the Application of CNN Denoising Technique

Table 2: Difference Test of CNR Value of Brain MRI Image

CNR	Mean	P value Paired T Test	Significance
CNR Pre	18,2428	0,000	There is difference
CNR Post	24,9551		

From the table above, the t-test results show that there is a difference in CNR values on MRI images of Brain T_2 Flair Fat Saturation Grappa Axial between before and after the application of CNN denoising techniques with a p value of 0.000. This value is smaller than 0.05 ($p=0.000<0.05$), so there is a significant difference between the CNR value before and after the application of CNN denoising technique.

Discussion

The study was conducted on MRI brain image T_2 flair fat saturation axial cut GRAPPA sequence with the application of Convolutional Neural Network (CNN) denoising technique deep learning model MatConvNet architecture in Matlab R2022a program. Image samples obtained retrospectively on the radiology PACS system, obtained brain MRI image data T_2 flair fat saturation axial cut GRAPPA sequence which is divided into CNN denoising training data sets as much as 3234 image data. The image samples used for this study amounted to 92 MRI brain T_2 flair fat saturation axial GRAPPA images. The image samples obtained are in accordance with medical image standards, namely the DICOM format and then converted into JPG form. This is because in the image encoding process, the DICOM image format has a large matrix size so that it can cause a slow training and testing process with the MatConvNet architecture CNN deep learning model. Therefore, an image preprocessing stage is carried out first to produce a better image picture [12].

DICOM can specify non-proprietary data exchange, digital image formats, file structures for biomedical images, and image information related to images. Despite its advantages, DICOM cannot be read by all software so it needs to be converted into other forms such as JPG or PNG. Images in JPG format have been widely used in previous studies to diagnose various diseases. From the previous research [13], JPG-formatted images generated from DICOM conversion were used to detect hand structures. Another study [14] showed that JPG format images can be used for OA detection with deep learning models, indicating that images in DICOM format need to be converted into JPG format for easier processing. Due to the many uses and advantages of images in JPG format, the researcher was inspired to use this image format for the research process of CNN denoising technique on MRI brain T_2 flair fat saturation axial GRAPPA image using MatConvNet architecture.

The research results were obtained by running the MatConvNet architecture CNN deep learning model through the MATLAB version R2022a program. Running the CNN deep learning program starts with inputting the training data set, then the training data set that has been carried out the training process is then stored, followed by the testing process so that the test classification results appear along with the accuracy value of the test. Previous research [13] In this study, the training data set and the testing data set use images that are not specific or general, in this study the training data set and the testing data set use specific images, namely the MRI brain T_2 flair fat saturation axial GRAPPA image. Training for the CNN deep learning model architecture of this research is using parameters with a max epoch value of 100, minibatch size 128, momentum 0.9, learning rate 0.0001, iteration 3100 and training time 144 minutes 52 seconds using the NVIDIA GeFORCE RTX 3050 GPU.

The MatConvNet architecture CNN deep learning model through the MATLAB version R2022a program in this study, can denoise the structure of the ventricle, white matter, and gray matter regions in the MRI Brain T_2 flair fat saturation axial GRAPPA image marked by quantitative assessment, namely the PSNR value above 30db, SSIM value is close to 1, Increasing SNR and CNR values by removing or reducing noise in the image through a combination of feature learning, non-linear transformations, data driven approaches, making it a powerful tool to improve the quality of MRI images of Brain T_2 flair fat saturation axial cut GRAPPA. Although the deep learning CNN denoising model MatConvNet architecture has many advantages in removing or reducing noise in images, there are some disadvantages, namely: heavy computation, requiring large training data, and tuning parameters such as the number of layers of the kernel size becomes a time-consuming experiment.

In this research analysis, filter performance evaluation is also carried out with error sensitivity measures [15]. The most widely used sensitivity measures are Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE) [16]. Each image is calculated PSNR and MSE by combining the image before and after the application of CNN denoising technique. The PSNR value with the merging image between before and after the application of CNN denoising ranges on average 32.62 the results of the PSNR calculation are still above 30 db indicating the quality of the image produced after WMF denoising is very good. The PSNR parameter has units of decibels (dB) where two images are said to have a low level of similarity if the PSNR value is below 30 dB. PSNR values falling below 30 dB indicate relatively low quality, where the distortion due to insertion is clearly visible. High image quality is at values close to 30 dB [17].

PSNR is the ratio between the maximum value of the measured signal and the amount of noise that affects the signal. PSNR is usually measured in decibels (db). PSNR is used to determine the comparison of image quality before and after the message is inserted. To determine PSNR, the Mean Square Error (MSE) value must first be determined. MSE is the average square error value between the original image and the manipulated image. MSE is the average square error value between the original image and the inserted image. SNR and PSNR are very useful in measuring image contrast but PSNR is more useful when dealing with contrast adjustment in regions of interest. SNR is not very good for homogeneous images, so for reconstruction evaluation PSNR is preferred. PSNR is defined as relative to the peak dynamic range which is 255 for an 8bit image. PSNR is used to measure the image quality after reconstruction where higher PSNR indicates good reconstruction and hence, ensures high image enhancement. PSNR is expressed in dB [18].

The convolutional neural network denoising method tends to produce good denoised images not only in terms of visual perception but also in terms of quality matrices such as PSNR and SNR. The higher the PSNR value and the higher the SNR value, indicating that the proposed filter is superior to other denoising methods. In this study, the MRI brain image of T_2 flair fat saturation grappa axial cut sequence has noise reduction and image quality improvement after CNN denoising. Denoising method. In this research analysis, an evaluation of filter performance is also carried out using SSIM. SSIM is known as the quality matrix used to measure the similarity between two images and correlates with the quality of perception of the Human Visual System (HVS). The SSIM model is created by considering 3 factors, namely loss of correlation, luminance distortion and contrast distortion. The SSIM value with the merging of images between before and after the application of CNN denoising ranges on average 0.82 the results of the SSIM calculation, according to the SSIM theory has a value with a range of 0-1. SSIM with a value close to 1 means that the tested image is close to the original image, indicating better image quality. This study evaluates brain MRI images quantitatively using SNR assessment on brain MRI images in T_2 flair fat saturation grappa sequences of selected axial cuts. Signal to Noise Ratio (SNR) is a measure to compare the object signal level with the background noise level. The higher the signal and the less noise, the SNR will increase. The calculation of SNR value is done before and after the application of CNN denoising technique on MRI brain image in T_2 flair fat saturation grappa axial cut sequence. The data normality test was performed first using the Kolmogorov Smirnov test because the number of samples was more than 50. The results showed that the data was not normally distributed, so the analysis test used was the Wilcoxon non-parametric test. The Wilcoxon t-test results showed a significant difference between the images before and after the application of the CNN denoising technique, with a p-value of 0.000. The average SNR rating also showed an increase after the application of CNN denoising technique. In MRI examination of the Brain in the T_2 flair fat saturation sequence, the use of parallel imaging GRAPPA features can speed up image acquisition time, but can also reduce image quality and increase noise. Therefore, denoising was performed using CNN to remove noise and improve image quality [19]. The results show significant improvements in inter-organ boundaries, object structure, texture, and image smoothness. The SNR values obtained from MRI are used to compare hardware imaging, protocol imaging, and sequences. The difference in SNR in both images before and after the application of CNN denoising technique is caused by different image quality. The CNN denoising method produces good denoised images, both visually and in image quality matrices such as PSNR, SNR, and MSE. Therefore, this algorithm can be used for MRI examination of Brain in T_2 flair fat saturation GRAPPA axial cut sequence.

CNR calculation on MRI brain images was performed before and after the application of CNN denoising technique. Data normality test was conducted before the CNR difference test because it is numerical data. The normality test used the Kolmogorov-Smirnov test because the number of samples was more than 50. The normality test results showed that the CNR data before and after denoising had a normal distribution. Therefore, the non-parametric paired sample T-test was used. The paired sample T-test results showed a p-value of 0.000. This shows that there is a significant difference between the image before and after denoising using the CNN technique. The decrease in noise in the image after CNN denoising causes an increase in CNR value [20, 21]. The application of CNN denoising technique affects the noise in MRI images. Noise on MRI can arise due to the image acquisition process and the use of hardware. This noise affects the contrast of image resolution. The lower the noise, the contrast resolution will increase. Filtering, especially with the CNN denoising method, can reduce noise, but not eliminate it completely. The low noise in the image increases the spatial resolution. This makes the boundaries between different objects clear. Images with good CNR can distinguish pathological and healthy areas. In the CNN denoising image, the edge boundaries between adjacent organs are clearer and more defined.

Conclusion

Through research using Convolutional Neural Network (CNN) denoising technique on MRI Brain image of T_2 flair fat saturation GRAPPA axial cut sequence, several things can be concluded. First, there is a significant difference in the Signal to Noise Ratio (SNR) value after the application of CNN denoising technique. Second, there is a significant difference in the value of Contrast to Noise Ratio (CNR) after the application of CNN denoising technique. Third, the calculation results show that the average value of Peak Signal to Noise Ratio (PSNR) in the MRI image of Brain T_2 flair fat saturation GRAPPA axial sequence after CNN denoising is about 32.62. This result is still above 30db, indicating high image quality after CNN denoising. Fourth, the calculation results show that the average value of Structural Similarity Index Measure (SSIM) in the image is about 0.82. The SSIM value is close to 1, indicating better image quality.

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