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# MEDICAL IMAGE COMPUTING FRAMEWORK FOR NOICE COMPONENT DETECTION IN FUNCTIONAL MRI

RATHI B[1], BENZIGAR ANTONY F[2]

[1]Assistant Professor, Department of Computer Science, College of Applied Science, Vadakkencherry

[2] Lecturer, Department of Computer Science, College of Applied Science, Vadakkencherry

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**Abstract -** Deeplearning attempts medical image denoisinge it herby directly learning the noise present or via first learning the image content. We observe that residual learning (RL) often suffers from signal leakage while dictionary learning (DL) is prone to Gibbs (ringing) artifacts. In this paper, we propose an unsupervised noise learning framework that enhances denoising by augmenting the limitation of RL with the strength of DL and vice versa. To this end, we propose a ten-layer deep residue network (DRN) augmented with patch-based dictionaries. The input images are presented to patch-based DL to indirectly learn the noise via sparse representation while given to the DRN to directly learn the noise. An optimum noise characterization is captured by iterating DL/DRN network against proposed loss. The denoised images are obtained by subtracting the learned noise from available data.We show that augmented DRN effectively handles high-frequency regions to avoid Gibbs artifacts due to DL while augmented DL helps to reduce the overfitting due to RL. Comparative experiments with many state-of-the-arts on MRI and CT datasets (2D/3D) including low-dose CT (LDCT) are conducted on a GPU-based supercomputer. The ablation studies are carried out that demonstrate enhanced denoising performance with minimal signal leakage and least artifacts byproposed augmented approach.

***Key Words:*** residual learning, patch-based DL, denoising

## 1. INTRODUCTION

An image can be defined as a two-dimensional light intensity function *f(x,y)*, where *x* and *y* denote spatial (plane) coordinates.The value at any point *(x,y)* is in proportion to the brightness of the image at that point. Images can be two dimensional (photograph or screen display) or three dimensional (statue or hologram). A continuous image can be digitized at sampling points. The sampling points are arranged in the plane and the geometric relation of the sampling points is known as a grid. A digital image is usually in a matrix form. A small sampling point, which is not further divisible, in the grid is a pixel. A pixel corresponds to one picture element. An image is built of a set of pixels. For digital image processing, operations are performed on the pixels. Broadly, digital image processing can be classified into two classes: processing and analysis. Processing involves enhancement in the appearance and representation of the image. Analysis comprises of extraction of features, quantification of shapes, registration and recognition of the image. Efficient processing and analysis of an image allows efficient image processing. The same holds true for the brain tumor. The brain tumor has to be successfully processed, analyzed and then detected.

## 2. RELATED WORKS

**[1]** This work done by Umme Sara, Morium Akter, Mohammad Shorif Uddin "Image Quality Assessment through FSIM, SSIM, MSE and PSNR—A Comparative Study" in the year 2019.

Quality is a very important parameter for all objects and their functionalities. In image-based object recognition, image quality is a prime criterion. For authentic image quality evaluation, ground truth is required. But in practice, it is very difficult to find the ground truth. Usually, image quality is being assessed by full reference metrics, like MSE (Mean Square Error) and PSNR (Peak Signal to Noise Ratio). In contrast to MSE and PSNR, recently, two more full reference metrics SSIM (Structured Similarity Indexing Method) and FSIM (Feature Similarity Indexing Method) are developed with a view to compare the structural and feature similarity measures between restored and original objects on the basis of perception. This paper is mainly stressed on comparing different image quality metrics to give a comprehensive view. Experimentation with these metrics using benchmark images is performed through denoising for different noise concentrations. All metrics have given consistent results. However, from representation perspective, SSIM and FSIM are normalized, but MSE and PSNR are not; and from semantic perspective, MSE and PSNR are giving only absolute error; on the other hand, SSIM and PSNR are giving perception and saliency-based error. So, SSIM and FSIM can be treated more understandable than the MSE and PSNR.

## 3. PROPOSED SYSTEM

In our proposed work we will take MRI scanned image and apply following steps on it for detection and classification of brain tumor.

### 3.1. STEPS OF PROPOSED SYSTEM

**Image Acquisition:** In our proposed approach we first will consider that the MRI scan images of a given patient are either color, Gray-scale or intensity images herein are displayed with a default size of 220×220. If it is color image, a Gray-scale converted image is defined by using a large matrix whose entries are numerical values between 0 and 255, where 0 corresponds to black and 255 to white for instance. Then the brain tumour detection of a given patient consist of two main stages namely, image segmentation and edge detection.

**Image Segmentation:** The objective of image segmentation is to cluster pixels into image region. The segmentation is useful for identifying region of interest i.e. locate tumor and other abnormalities. The proposed system is based on information about anatomical structure of healthy parts and compares it with healthy parts. The comparison done with reference image of normal candidate brain scan image. After comparison it will locate abnormal parts of brain tumour patient.

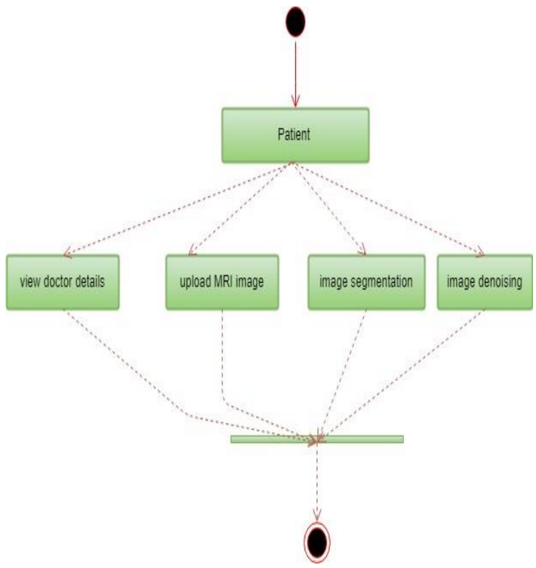
**Skull Part Removal:** This is a pre processing step which is required to produce better results. Skull is outer part of the brain surrounding. The main problem in skull-stripping is the segmentation of the non-cerebral and the intracranial tissues due to their uniform intensities. So it may affect the result of seed point selection.

**Thresholding:** Thresholding of image takes place by considering a threshold value of the total pixel value and assigning "0" to thevalues below the threshold.

**Smoothing of image:** There are different types of noise encountered by different techniques, depending on noise nature and characteristics namely Gaussian noise and impulse noise .We will use smoothing image filters for reducing Gaussian noise from MRI images & sharpening filters for highlighting edges in an image. It was observed that smoothing and sharpening filter does not remove noise completely from original image.

**Edge detection:** Edge is the property attached to an individual pixel. The purpose of edge detection is to finding Region of Interest. While preserving structural properties to be used for further image processing. We will apply edge detection algorithm and calculate region of interest as Our region of interest is tumor i.e. abnormal part present on brain. The white portion.is the tumor, since our focus is on this portion it will help full to significantlyreduce amount of data in an image. After identifying tumor we will apply Canny Edge Detection algorithm in order to classify brain tumor.

**Identify Brain Tumour Using contours:** Contours can be explained simply as a curve joining all the continuous points (along the boundary), having same color or intensity. The contours are a useful tool for shape analysis and object detection and recognition. In proposed work we will take MRI scanned image. It can be in the form color or gray, if it is not in gray color the system will convert image into gray format. This gray image is given to the image segmentation. Segmented image is compared with stored data sets. After comparing we can detect brain tumor. For classification we will give this compared image to the neural network. By using probabilistic classification we can classify the tumor is in normal state or abnormal state process..

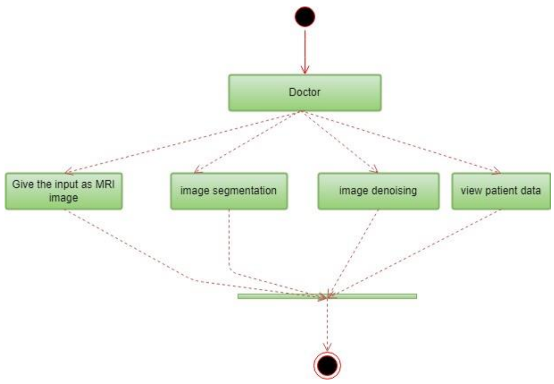



## 4. ACTIVITY DIAGRAM AND COMPONENT DIAGRAM

### 4.1. ACTIVITY DIAGRAM

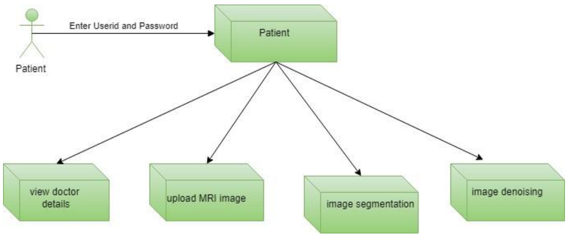
**Patient**

**Doctor**

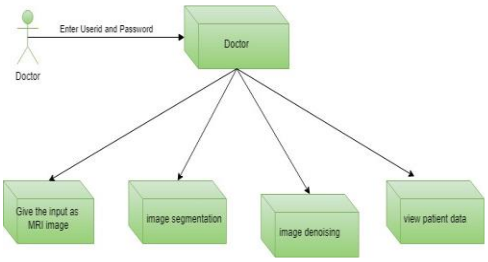



### 4.2. COMPONENT DIAGRAM

**Patient**




**Doctor**




## 5. RESULTS AND OBSERVATION

The MRI and CT data are available in the form of a 3D image cube. We develop a model for both 3D and 2D processing of the MRI/CT including LDCT data considering different generations of the scanning machines. Note that while the proposed framework is generalized for 3D and 2D processing, nevertheless, user can choose to perform either 3D block or 2D image processing.

## 6. CONCLUSION

We have presented a novel augmented unsupervised noise learning approach for enhancing medical image denoising considering input as 2D and 3D for image/voxel processing. The proposed dictionary based DRN handles both the Rician noise and Poisson noise present in the MRI and CT/LDCT images, respectively. Our model learns the patch based dictionaries in order to learn noise indirectly and augment with the residue(noise) contents learn directly from the available MRI/CT/LDCT images using proposed DRN. Note that the proposed approach does not require the clean (denoised) images for training the model, unlike many deep learning-based recent approaches. We have better handled the ill-posed nature of the problem by choosing the optimum regularization parameters that have been estimated from the data. Dictionary-based DRN reduces the noise from the images by preserving the edges of the images and maintaining their visual quality (without losing details) which is evident from the results. Ablation study conducted on DL and DRN parts further evaluate the efficiancy of the proposed augmented noise learning process. We further showed that the proposed method has minimal signal leakage with least Gibbs(ringing) artifacts in the estimated denoised image, and enhances the medical image denoising. In future, one would like to design unsupervised framework for restoration of medical images that would address any degradation in the multimodal images along with the noise.

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