A PRELIMENERY REPORT ON

Image Denoising for 3D MRI Images

SUBMITTED TO THE SAVITRIBAI PHULE PUNE UNIVERSITY, PUNE
IN THE FULFILLMENT OF THE REQUIREMENTS
FOR THE AWARD OF THE DEGREE

OF

BACHELOR OF ENGINEERING (COMPUTER ENGINEERING)

SUBMITTED BY

Rohan Tagare	Exam No : 71701252C
Shreyas Chidrawar	Exam No : 71700786D
Vindeep Chaudhari	Exam No : 71700800C
Devendra Sathe	Exam No : 71701188H

DEPARTMENT OF COMPUTER ENGINEERING

PUNE INSTITUTE OF COMPUTER TECHNOLOGY

DHANKAWADI, PUNE - 411043

SAVITRIBAI PHULE PUNE UNIVERSITY

2019-2020

CERTIFICATE

This is to certify that the Project Entitled

Image Denoising of 3D MRI Images

Submitted by

Rohan Tagare	71701252C
Shreyas Chidrawar	71700786D
Vindeep Chaudhari	71700800C
Devendra Sathe	71701188H

are bonafide students of this institute and the work has been carried out by them under the supervision of **Dr. A. R. Buchade**, approved for the fulfillment of the requirements of Savitribai Phule Pune University, for the award of the degree of **Bachelor of Engineering** (Computer Engineering).

Dr. A. R. Buchade
Guide,
Dept. of Computer Engg.

Prof. Mrs. M. S. Takalikar
Head,
Dept. of Computer Engg.

Dr. P. T. Kulkarni
Principal,
Pune Institute of Computer Technology

Place: Pune

Date:

Acknowledgements

It gives us great pleasure in presenting the preliminary project report on **'Image Denoising of 3D MRI Images '**.

We would like to take this opportunity to thank our internal guide **Dr. A. R. Buchade** for giving us all the help and guidance we needed. We are really grateful to them for their kind support. Their valuable suggestions were very helpful.

We are also grateful to **Prof. Mrs. M. S. Takalikar**, Head of Computer Engineering Department, PICT for her indispensable support, suggestions.

In the end our special thanks to the college for providing various resources such as laboratory with all needed software platforms, continuous Internet connection, for our Project.

Rohan Tagare
Shreyas Chidrawar
Vindeep Chaudhari
Devendra Sathe
(B.E. Computer Engg.)

Abstract

Magnetic resonance imaging (MRI) plays an important role on the diagnosis of pathological and physiological alterations in living tissues and organs of human body. The quality of MR images can, however, easily be degraded due to random noise generated while acquiring them. Increased noise level affects the accuracy of diagnosis and also the reliability of quantitative image processing. To avoid these problems it is essential to remove the noises of magnetic resonance images before further processing. With the help of Denoising Convolutional Neural Networks Deep Convolutional Neural Network (DCNN), denoisation of 3D MRI Images is proposed.

Keywords: Image Processing, Image Denoising, MRI, Rician Noise, Convolutional Neural Network (CNN)

Contents

List of Abbreviations **i**

List of Figures **ii**

1 Introduction **1**

1.1 Overview 1

1.2 Motivation 2

1.3 Problem Definition and Objectives 2

1.4 Project Scope and Limitations 2

2 Literature Survey **3**

2.1 Literature Survey 3

3 Software Requirements Specification **7**

3.1 Introduction 7

3.1.1 Project Scope 7

3.1.2 User Classes and Characteristics 7

3.1.3 Assumptions and Dependencies 8

3.2 Functional Requirements 9

3.2.1 Accepting of input as MRI image 9

3.2.2 Noise Removal 9
3.2.3 Residual Learning of CNN 9
3.3 Non-Functional Requirements 9
3.3.1 Performance Requirement 9
3.3.2 Efficiency 10
3.3.3 Scalability 10
3.4 System Requirements 10
3.4.1 Software Requirements 10
3.4.2 Hardware Requirements 11
3.5 Analysis Models: SDLC Model to be applied 11

4 System Design **12**
4.1 System Architecture 12
4.2 Mathematical Model 13
4.3 Data Flow Diagrams 15
4.3.1 DFD Level 0 15
4.4 UML Diagrams 16
4.4.1 Use Case Diagram 16
4.4.2 Activity Diagram 17
4.4.3 Sequence Diagram 18

5 Project Plan **19**

6 Project Implementation **20**
6.1 Method 20

6.2 Colaboratory Jupyter Notebook 21
6.3 Dataset 21
6.3.1 Brainweb Dataset 21
6.3.2 IXI Hammersmith Dataset 21

7 Testing **22**
7.1 Unit Testing 22
7.2 Integration Testing 22
7.3 Testing on Platforms 23

8 Results **24**
8.1 Outputs 24
8.2 Accuracy 26

9 Other Specifications **28**
9.1 Advantages 28
9.2 Limitations 28
9.3 Applications 28

10 Conclusion and future scope **29**
10.1 Conclusion 29
10.2 Future Scope 29

Annexure A Feasibility Study **30**
A.1 Problem Statement Feasibility 30

Annexure B Plagiarism Report **31**

List of Abbreviations

BN Batch Normalization

CNN Convolutional Neural Network

Conv Convolitional

DCNN Deep Convolutional Neural Network

DnCNN Denoising Convolutional Neural Network

EPLL Expected Patch Log-Likelihood method

MRI Magnetic Resonance Imaging

ReLU Rectified Linear Unit

WNNM Weighted Nuclear Norm Minimization

List of Figures

2.1 Rician Noise 4

3.1 SDLC Model 11

4.1 System Architecture 12
4.2 Rician Noise Formula 13
4.3 L2 Loss Function 13
4.4 PSNR Function 14
4.5 DFD Level 0 15
4.6 Use Case Diagram 16
4.7 Activity Diagram 17
4.8 Sequence Diagram 18

5.1 Gantt Chart 19

8.1 20 percent noise removal 25
8.2 PSNR values of 20 percent Rician noise removal 26
8.3 PSNR values of 3D MRI noise removal 27

CHAPTER 1

INTRODUCTION

1.1 Overview

Magnetic resonance imaging (Magnetic Resonance Imaging (MRI)) of the body uses a powerful magnetic field, radio waves and a computer to produce detailed images of the inside of your body. It may be used to help in the diagnosis or monitoring the treatment for a variety of conditions within the chest, abdomen and pelvis.
Magnetic Resonance Imaging (MRI) plays an important role in clinical diagnosis producing high quality 2-D and 3-D images of the body and is also affected by noise. Image quality may get degraded while capturing, processing and storing. Removing noise from the original magnetic resonance images is still a challenge for researchers because noise removal may result in introduction of artifacts and blurs them . [1]
According to the probability theory Rician distribution of Rice Noise distribution is the distribution of the magnitude of a circular bivariate normal random variable which has potentially non-zero mean[2]. The image intensity in magnetic resonance magnitude images in the presence of noise is dominated by a Rician Noise distribution. Low signal intensities are therefore biased due to this noise.[3] It is shown how the underlying noise could be estimated from these images. The noise characteristics in phase images are also studied and shown to be very different from the magnitude images. The Image Denoising 3D MRI Images using residual learning of multi-channel deep CNN is Proposed in given project.[4]

1.2 Motivation

Magnetic resonance Imaging is the popular medical imaging modalities at present to diagnose various diseases. However this imaging modality is suffering with a big problem called noise. Rician noise is present in the Magnetic resonance imaging (MRI). The noise present in the images will degrade the contrast of the image which will create problems in the diagnostic phase. Hence we are proposing this denoising method. [5]

1.3 Problem Definition and Objectives

To denoise 3D Magnetic Resonance Images using residual learning of deep convolutional neural network. [4]

1.4 Project Scope and Limitations

To denoise 3D Magnetic Resonance Images using residual learning of deep convolutional neural network. [4]

CHAPTER 2

LITERATURE SURVEY

2.1 Literature Survey

Various types of noises along with their nature were studied in order to denoise image more accurately.

Gaussian noise
Gaussian noise is a type of noise having a probability distribution function equal to that of a normal distribution function which is also known as Gaussian distribution. Gaussian noises can be caused due to thermal vibrations of atoms in the environment. Following is an image which displays the Gaussian noise. There are two types of noises. Gaussian noise only deals with additive noises.

Rician noise
In probability theory Rician distribution is the magnitude of a circular bivariate normal random variable having potentially non-zero mean. The image intensity in magnetic resonance magnitude images in the presence of noise is dominated by the Rician Noise distribution. Low signal intensities are therefore biased due to this noise. The noise characteristics in phase images are also studied and it is observed to be very different from the magnitude images.

Speckle Noise
Speckle noise is a type of multiplicative noise. It occurs in all coherent imaging systems, such as Synthetic Aperture Radar and medical images. Speckle noise is generated in various ways in images. In case of ultrasound images, speckle noise arises when a sound wave beats arbitrary interferes with little particles or on a scale equivalent to sound wavelength. In case of conventional radar images, it arises due to random variation in return signaling. Speckle Noise is actually quite random in nature. Many researchers use noise removal techniques for speckle noise

reduction. Speckle noise degrades the quality of the medical images. It reduces the effectiveness of human observation to recognize the details of the diagnostic examination. Speckle noise reduces the contrast of the image, making it difficult to perform further image processing operations.

Salt and Pepper Noise

Salt-pepper noise refers to a wide variety of processes that result in the same basic image degradation: only a few pixels are noisy, but they are actually very noisy. The effect is similar to sprinkling white and black dots on the image. One example where salt and pepper noise arises is during transmission of images over digital links. Salt and pepper noise is an example of heavily tailed noises. Salt-pepper noise is also called impulse noise. This noise can be caused due to sharp disturbance in the image signal. It presents itself as occurring white and black pixels.

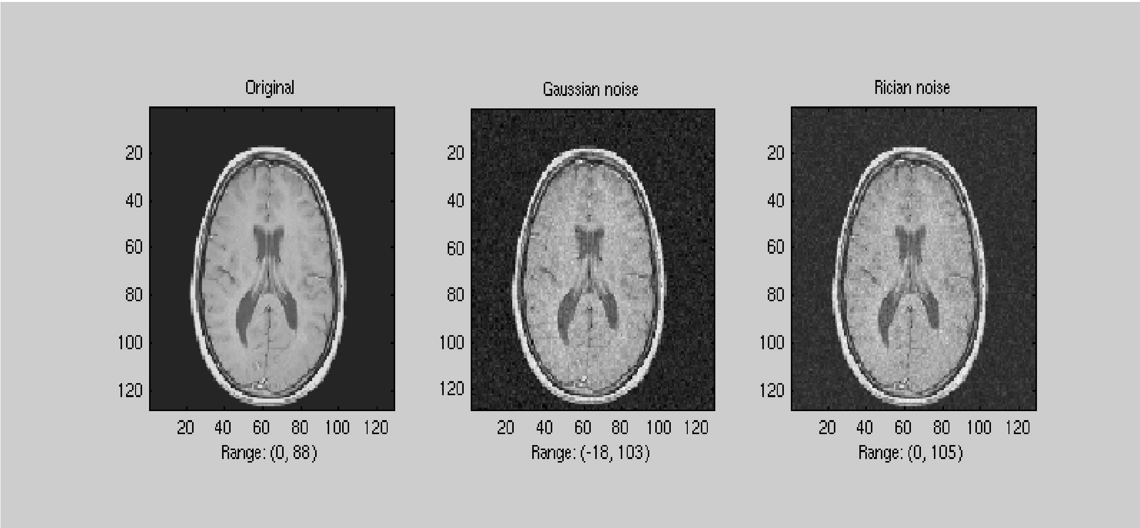

Figure 2.1: Rician Noise

- Kai Zhang, Wangmeng Zuo, Yunjin Chen, Deyu Meng, and Lei Zhang : Beyond a Gaussian Denoiser: Residual Learning of Deep CNN for Image Denoising :IEEE[4]

  A deep convolutional neural network is proposed for image denoising, where residual learning is adopted for separation of noise from noisy observations. The batch normalization and residual learning techniques have been integrated to speed up the training process and boost the performance of denoising. Unlike traditional discriminative models that train specific models at certain noise levels, this single Deep CNN model has the capacity for handling the blind Gaussian denoising with unknown noise level. Experimental results demonstrated that the proposed method not only produces favorable image denoising performance quantitatively and qualitatively but it also promises a good run time by GPU implementation.

- Chang YN, Chang HH : Automatic brain MR image denoising based on texture feature-based artificial neural networks :content.iospress.com [6]

  An artificial neural network based bilateral filter associated with image texture feature analysis is proposed for automatically denoising brain related MR images. A variety of MR images with various scenarios were adopted for evaluation of the performance of the proposed framework. Experimental results indicate that this new automation method accurately predicts the bilateral filtering parameters and effectively removes the noise in MR images with adequate quantity and quality. In comparison to the manually tuned filtering process, this approach not only produces better denoised results but also saves significant amount of processing time. In future, the proposed framework can be extended to 3D for volumetric filtering process.

- Ajay Kumar Boyat , Brijendra Kumar Joshi, " A Review Paper: Noise Models in Digital Image Processing" : ResearchGate.[7]

  Enhancement and restoration are necessary tasks in digital image processing. There are various noise models available that can distort the images up to large extent. In order to restore such noisy images there are many image restoration and filtering techniques available for recovery of the original image from the degraded image. In this paper maximum noise models have been covered that gives a detailed understanding of all the perspectives of the noise including their pros and cons. Apart from noise a detailed comparative study of image restoration and filtering techniques are also given. This helps to understand the various aspects of the image restoration that will create interest and lead them to work in specified hybrid technique.

- Lovedeep Gondara : Medical Image Denoising Using Convolutional Denoising Autoencoders : IEEE[8]

  In this paper denoising autoencoder is constructed using convolutional layers. It can be used for efficient denoising of medical images such as MR images. It would also be interesting, if we are given only a few images and we can combine them with other readily available images from datasets such as ImageNet for better denoising performance by increasing the size for training sample. Different algorithms are proposed with varying denoising performances. Deep learning based models have shows a great promise. We observe that using small sample size, denoising autoencoders constructed by using convolutional layers can be used for efficient denoising. Heterogeneous images should be combined for boosting sample size for increased denoising performance.

- GengChen, PeiZhang, YafengWu, DinggangShen, Pew-ThianYap : Denoising Magnetic Resonance Images Using Collaborative Non-Local Means : Elsevier [5]

  It is observed that experiments on synthetic data have shown that the proposed method works significantly better than the classical NLM algorithm. The BrainWeb image that have been used for evaluation is the only noise-free image with sufficiently structural complexity for realistic evaluation. Various levels of Rician noise are added to the image for studying the effects of noise on denoising performance. This only satisfies partly the requirements of an ideal synthetic evaluation dataset because all the noisy image realizations are perfectly aligned. Hence, in this paper spatial misalignment is introduced via random transformations to the dataset for creating a more challenging dataset for evaluation. Both qualitative and quantitative results using the real data support the notion that images from different individuals contain common structural information used for mutual denoising. The results given by this method clearly showed less structural blurring.

- H. Gudbjartsson, S. Patz : The Rician distribution of noisy MRI data : Magn. Reson. Med.[9]

  It is shown that the underlying noise can be estimated from the images and a simple correction scheme is provided to reduce the bias. In this paper we observe that the noise characteristics in phase images are also studied and shown to be very different from those of the magnitude images.

CHAPTER 3

SOFTWARE REQUIREMENTS SPECIFICATION

3.1 Introduction

3.1.1 Project Scope

The Scope of our Project is limited to denoise 3 dimensional MR images with Rician and Gaussian noise robustly.We are analysing it on data with different noise levels. In particular, our method will show abilities for both noise suppression and structure preservation.

3.1.2 User Classes and Characteristics

- Expected user to our project are MRI and CT scan centers,Doctors to get more clear MRI Image for analyzing and generating Medical reports.
- Users are generally highly qualified doctors of Radiology as MRI scans requires to be read and reported by very much accuracy and precision by Radiology Specialists.

3.1.3 Assumptions and Dependencies

- Input Images must be MRI images with Rician noise and Gaussian noise
- Input images must be 3D images.
- Noise level in the images should not be more than 15 Percent.

3.2 Functional Requirements

3.2.1 Accepting of input as MRI image

The system should be able to accept Images of MRI as Input entered through smart phone or computer.The Image input is then passed to our CNN Model and we will get MRI image with less noise as output.

3.2.2 Noise Removal

The System should be able to reduce significant amount of Rician noise.

3.2.3 Residual Learning of CNN

Residual learning of CNN was proposed for solving the performance degradation issues, even the training accuracy begins to degrade along with the increase in depth of network. By assuming that the residual mapping easy to be learned than the original unreferenced mapping, the network learns residual mapping for a few layers. With this residual learning strategy, Deep CNN can be easily trained and can help in significant reduction of noise.

3.3 Non-Functional Requirements

3.3.1 Performance Requirement

System performance is dependent on the accuracy of the system which is based on removal of noise from image . The neural network performs correctly when the noise of the system is reduced after the image is given as input to the network . Accuracy can be checked by comparing the noise levels in input and output images.

3.3.2 Efficiency

Algorithm efficiency measured in terms of response time after giving the image and the accuracy of the algorithm . It is better to have a quick response time for the output. For machine learning algorithms training time is also an important factor in deciding the efficiency of the algorithm . Less time for training , better is the efficiency of training process.

3.3.3 Scalability

Algorithm needs help of GPU's for faster computations . Thus if more GPU's are to be used the process can be parallelised to a greater extent . This will help us to decrease training time and will increase response time as well.

3.4 System Requirements

3.4.1 Software Requirements

- Language
  - Python 3.6
- Frameworks and libraries used
  - Jupyter Notebook
  - Tensorflow Framework
  - Keras Library
  - Machine learning python libraries
- Datasets
  - IXI-Hammersmith dataset
  - Brainweb dataset
- Google Colaboratory Jupyter Notebook can also be used in case computational power is not sufficiently available.

3.4.2 Hardware Requirements

- NVIDIA GPU GTX 1050
- i7 quad core processor

3.5 Analysis Models: SDLC Model to be applied

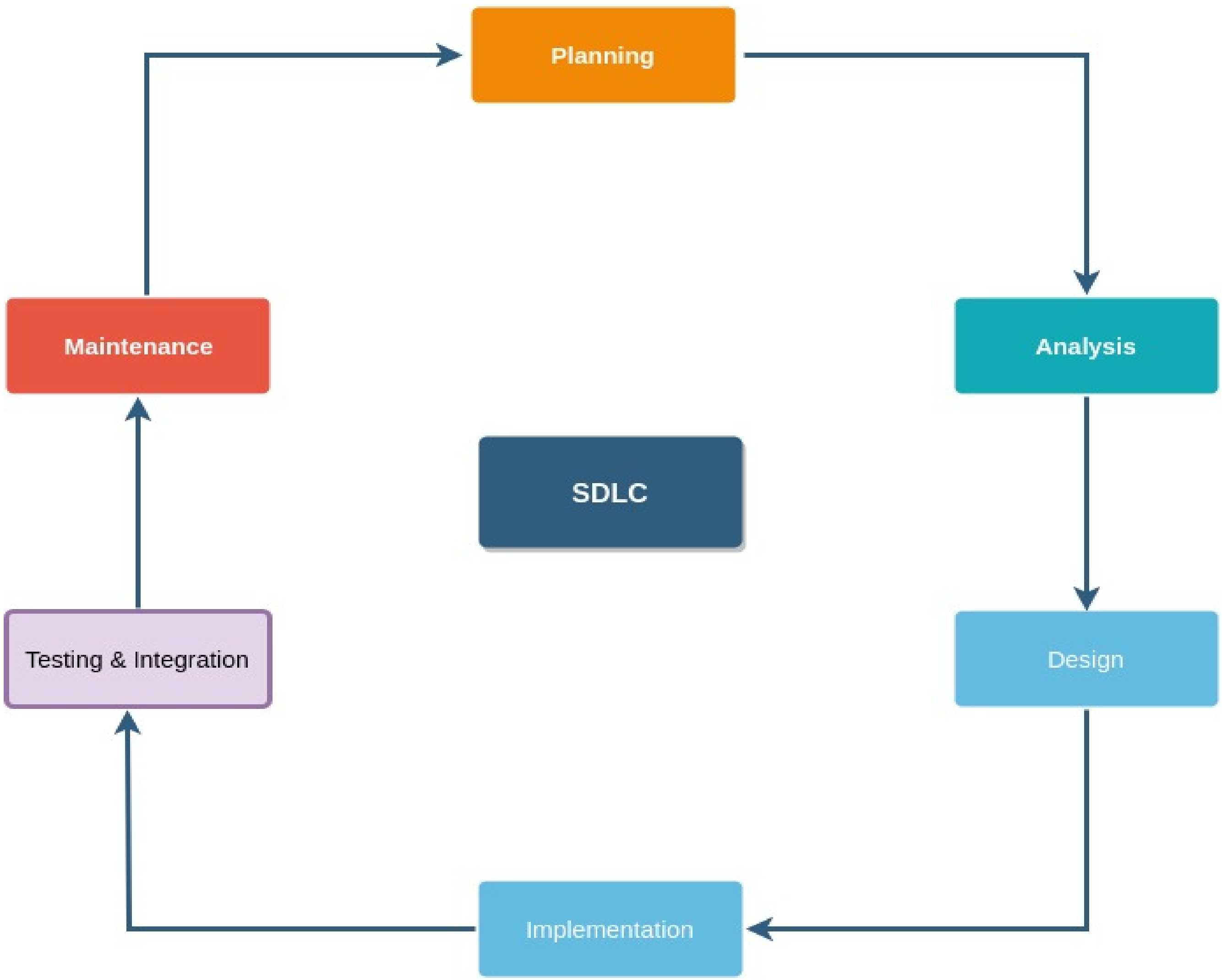

Figure 3.1: SDLC Model

CHAPTER 4

SYSTEM DESIGN

4.1 System Architecture

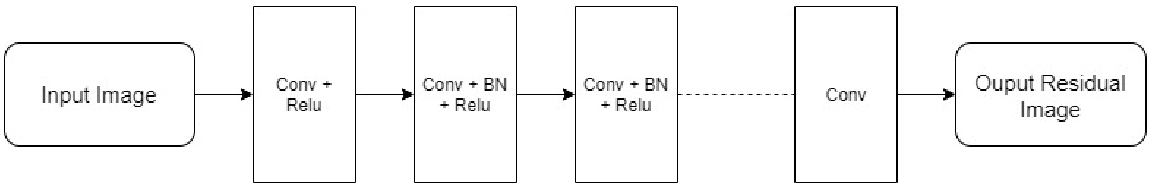

Figure 4.1: System Architecture

Proposed Architecture consists of one input layer of convolution with rectified linear unit, multiple layers of convolution with batch normalization and ReLU and one final output layer of convolution. As output layer generates an image with same size as that of the input, proposed network does not include any layer of max-pooling.
To adapt with the 3D volume, we apply a multi-channel approach for learning while we expect that multi-channel information will lead to a fast and more stable training and more robust denoising performance.
The residual learning formulation is adopted to learn R(y), and batch normalization is incorporated for speeding up training as well as boosting the denoising performance. By incorporating convolution with Rectified Linear Unit (ReLU), Denoising Convolutional Neural Network (DnCNN) can gradually separate image structure from the noisy observation through the hidden layers. This mechanism is similar to the iterative noise removal strategy adopted in methods like Expected

Patch Log-Likelihood method (EPLL) and Weighted Nuclear Norm Minimization (WNNM).

4.2 Mathematical Model

$$
\begin{aligned}
f(x,\nu,\sigma) &= \frac{x}{\sigma^2}\exp\left(\frac{-(x^2+\nu^2)}{2\sigma^2}\right) I_0\left(\frac{x\nu}{\sigma^2}\right) \\
&\text{is} \\
&\frac{x}{\sigma^2}\exp\left(\frac{-(x^2+\nu^2)}{2\sigma^2}\right)\sqrt{\frac{\sigma^2}{2\pi x\nu}}\exp\left(\frac{2x\nu}{2\sigma^2}\right)\left(1+\frac{\sigma^2}{8x\nu}+\cdots\right) \\
&\to \frac{1}{\sigma\sqrt{2\pi}}\exp\left(-\frac{(x-\nu)^2}{2\sigma^2}\right)\sqrt{\frac{x}{\nu}}, \quad \text{as } \frac{x\nu}{\sigma^2}\to\infty
\end{aligned}
$$

Figure 4.2: Rician Noise Formula

$$
L2LossFunction = \sum_{i=1}^{n}(y_{true} - y_{predicted})^2
$$

Figure 4.3: L2 Loss Function

$$PSNR = 10 \log_{10}\left(\frac{MAX_I^2}{MSE}\right)$$

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2$$

Figure 4.4: PSNR Function

4.3 Data Flow Diagrams

4.3.1 DFD Level 0

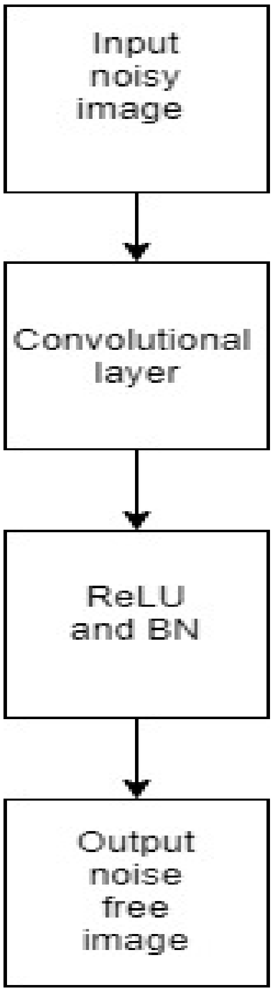

Figure 4.5: DFD Level 0

We input noisy images to the machine learning algorithm. The algorithm has several layers of both convolutional layer Convolitional (Conv) and ReLU unit with Batch Normalization Batch Normalization (BN). Model uses several such layers . Then at the end model will output noise free image.

4.4 UML Diagrams

4.4.1 Use Case Diagram

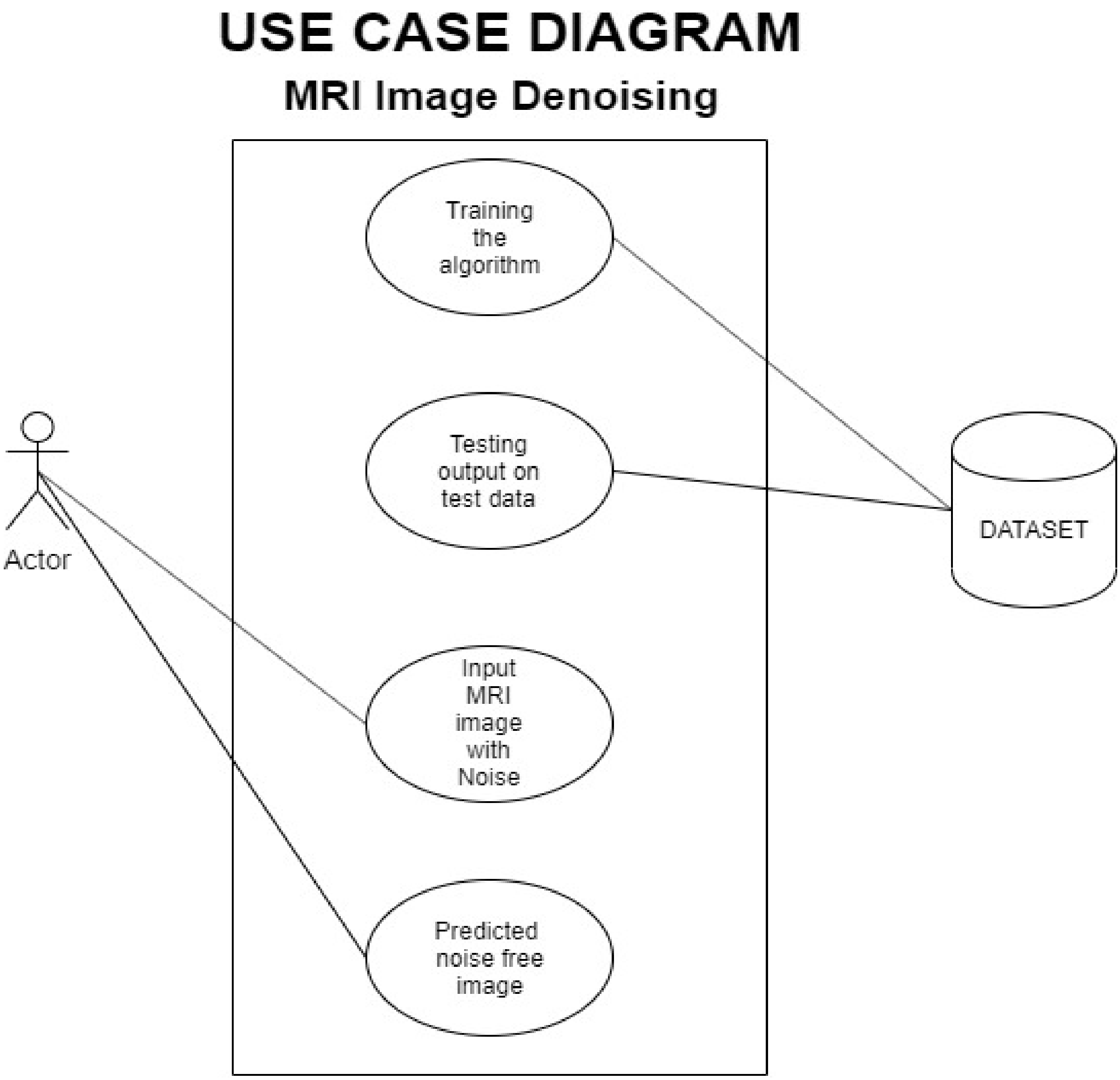

Figure 4.6: Use Case Diagram

Denoising algorithm uses dataset images for training and testing purposes. After this process the algorithm is ready to be used on outside image. Once we input this image then the algorithm will output noise free image.

4.4.2 Activity Diagram

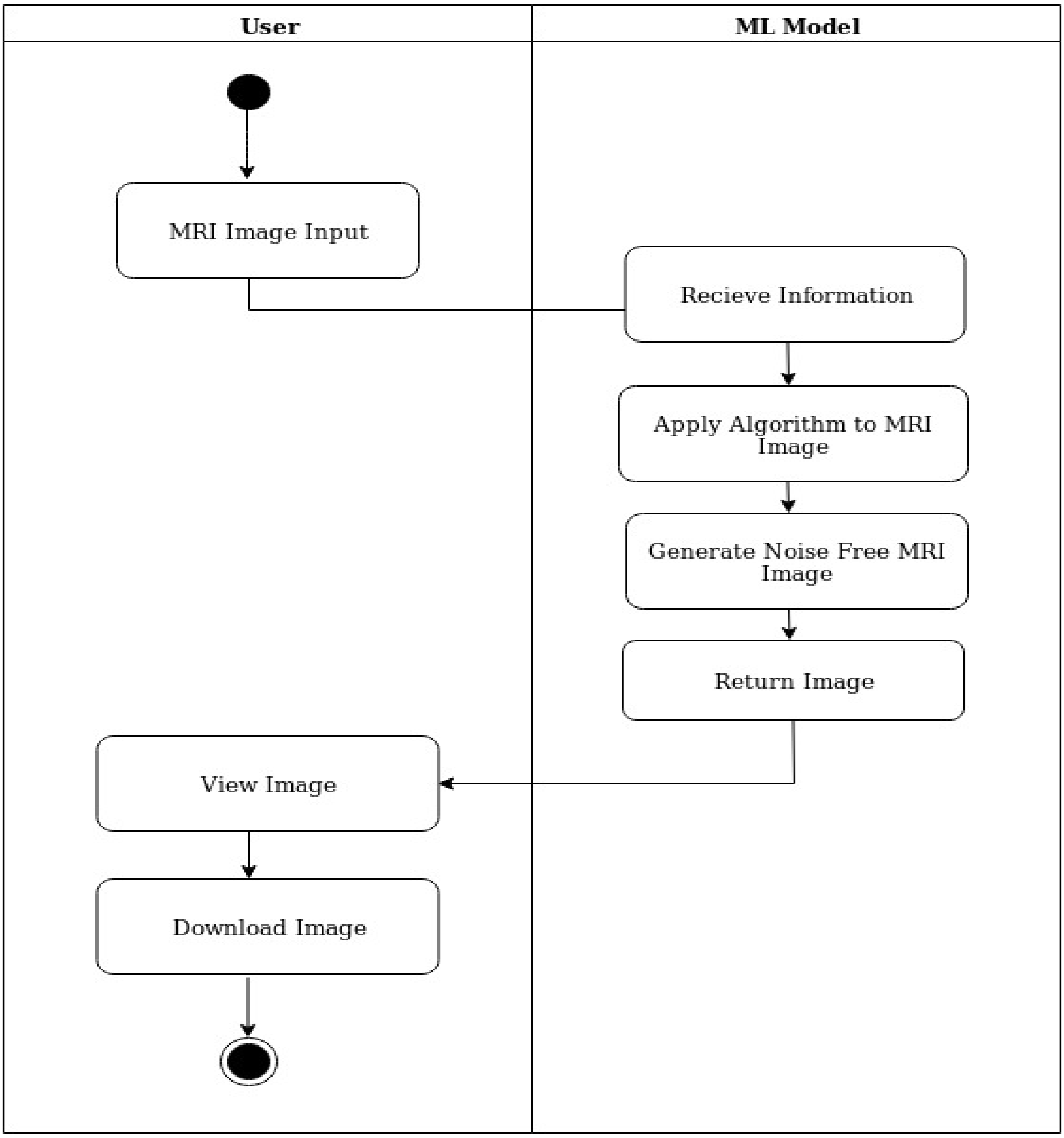

Figure 4.7: Activity Diagram

Denoising algorithm uses dataset images for training and testing purpose. We apply algorithm to generate noise free image. Once we input this image then the algorithm will output noise free image. This image will be downloaded by the doctor.

4.4.3 Sequence Diagram

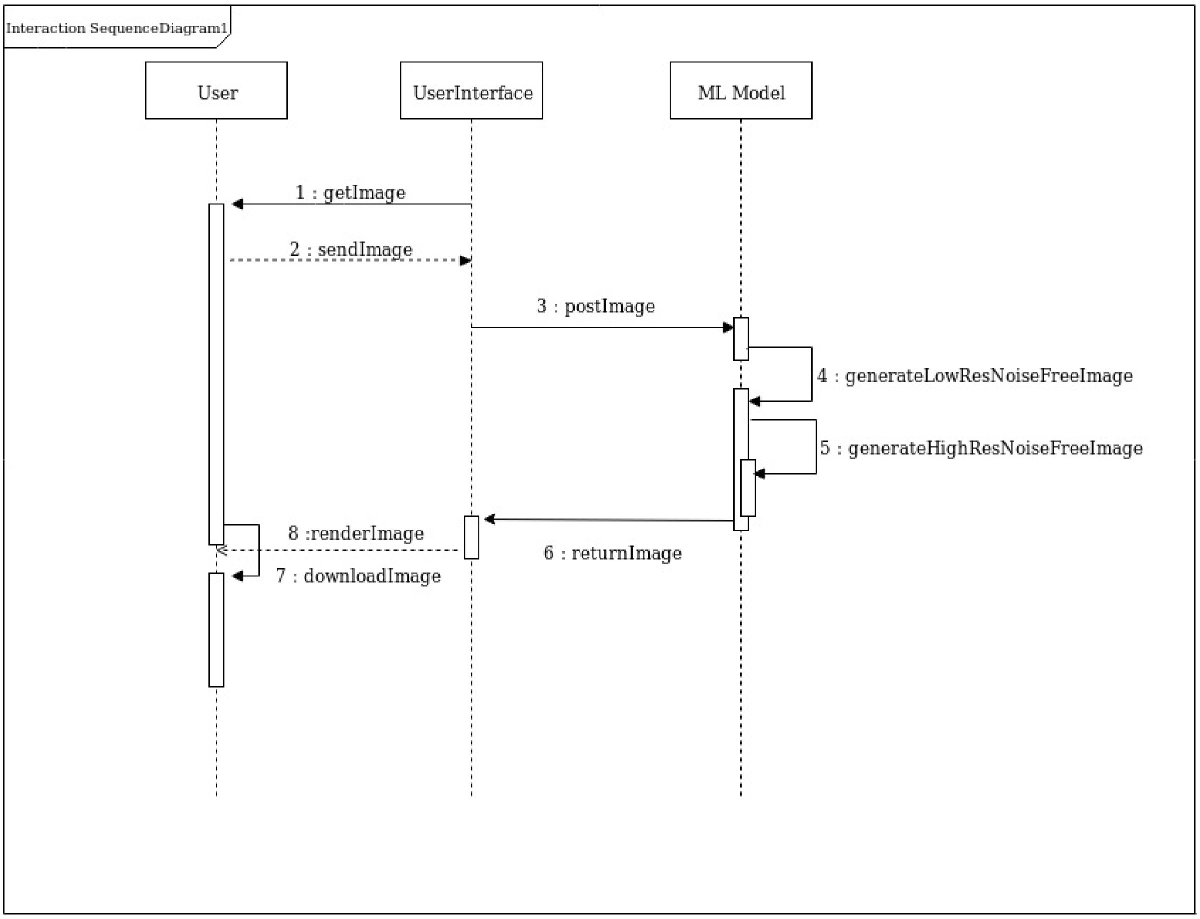

Figure 4.8: Sequence Diagram

Denoising algorithm uses dataset images for training and testing purpose. We apply algorithm to generate noise free image. Once we input this image then the algorithm will output noise free image. This image will be downloaded by the doctor.

CHAPTER 5

PROJECT PLAN

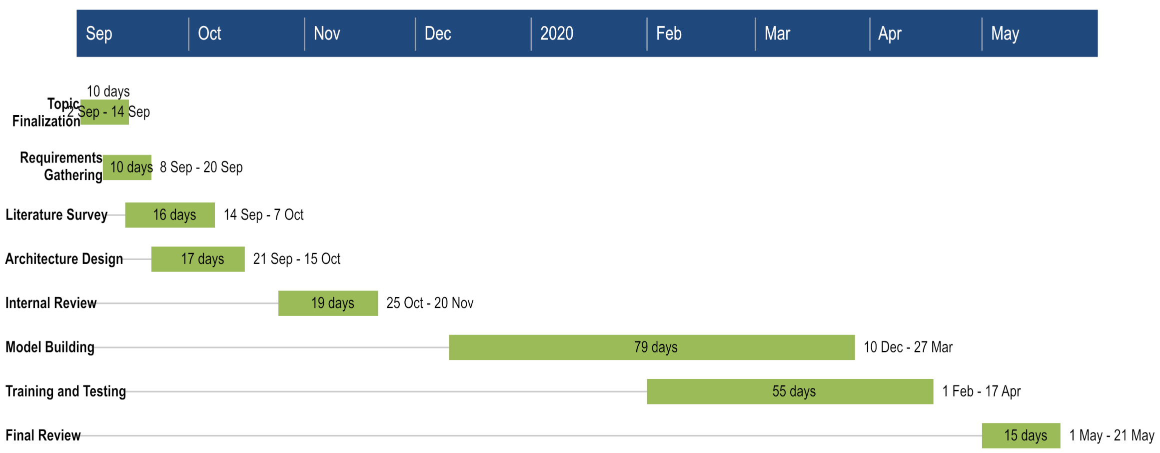

Figure 5.1: Gantt Chart

Following is the timeline for the project expressed using the Gantt Chart. We have given the approximate timeline for different modules of the project.

CHAPTER 6

PROJECT IMPLEMENTATION

6.1 Method

Our neural network consists of one input layer of convolution along with rectified linear unit, eight layers of convolution with batch normalization and RelU and one output layer of convolution. The output layer will generate an image with the same size as the input. This network does not contain any max-pooling layer because the output should be of the same size as the input. For the first layer there are 64 kernels of size 3 3 k where k is the number of channels of the 2 dimensional image. For grey level 2 dimensional images k is set to 1. Here we are dealing with MR volume. We are processing these images slice by slice. The kernels of the rest of layers are set to have a size of 3 3 64. We have added two key features to this network, residual learning technique and batch normalization so as to speed up the training and to boost the denoising performance.

For optimizing the parameters, the square error between the desired residual image and the estimated image from the noisy input is calculated as the loss function. The loss function that we used is the l2 loss function.

6.2 Colaboratory Jupyter Notebook

Google Colaboratory Jupyter Notebook is a free online Jupyter notebook environment based on cloud allowing us to train our machine learning and deep learning models on CPUs, GPUs, and TPUs. Colab Notebook gives a decent GPU for free, which can continuously run for 12 hours. We can run multiple CPU, GPU, and TPU instances simultaneously.

We have used Google's Colaboratory Jupyter Notebook to train and test our neural network as we did not have the sufficient recources on our local machines. We used the GPU services provided by Colab editor.

6.3 Dataset

6.3.1 Brainweb Dataset

Brainweb is a simulated brain dataset (SBD, http://brainweb.bic.mni.mcgill.ca/brainweb/). The SBD contains a set of realistic MRI data volumes produced by an MRI simulator which was widely used to evaluate the performance of denoising approaches.

6.3.2 IXI Hammersmith Dataset

Hammersmith dataset is a subset of IXI dataset (http://braindevelopment.org/ixidataset/). We used 47 3 dimensional MR Images from this Hammersmith dataset and trained and tested them on Google's Colaboratory Jupyter Notebook.

CHAPTER 7

TESTING

7.1 Unit Testing

We have performed unit testing in our project. We initially tested the noise removal of individual 2 dimensional slices of one of the 3 dimensional MR Image. One 2 dimensional slice was added with certain percentage of Rician noise and tested for noise removal. Later on the slice was tested by adding variable noise percentage of Rician noise. Brainweb's simulated dataset was also used as a standard MR Image for reference.

7.2 Integration Testing

We combined certain number 2 dimensional slices of 3 dimensional MR Images to form a block and collectively tested these blocks with a fixed percentage of Rician noise and then later on with variable percentage of Rician noise.

7.3 Testing on Platforms

Initially the 2 dimensional slices were tested on local machines. They showed significant results. However when the number of images increased it became difficult to test on the machines. Hence we used Google's Colaboratory Jupyter Notebook. It allowed us to test more number of images and also use the GPU services provided. Also the 3 dimensional MR Images with multiple slices arranged as blocks were tested on Google's Colab Jupyter notebook. We have used total of 47 3-dimensional MR Images on this platform. Out of these 30 were used for training and rest for testing.

CHAPTER 8

RESULTS

8.1 Outputs

Following images show outputs for noise removal of 2 dimensional MR Image which contained 20 percent Rician noise.

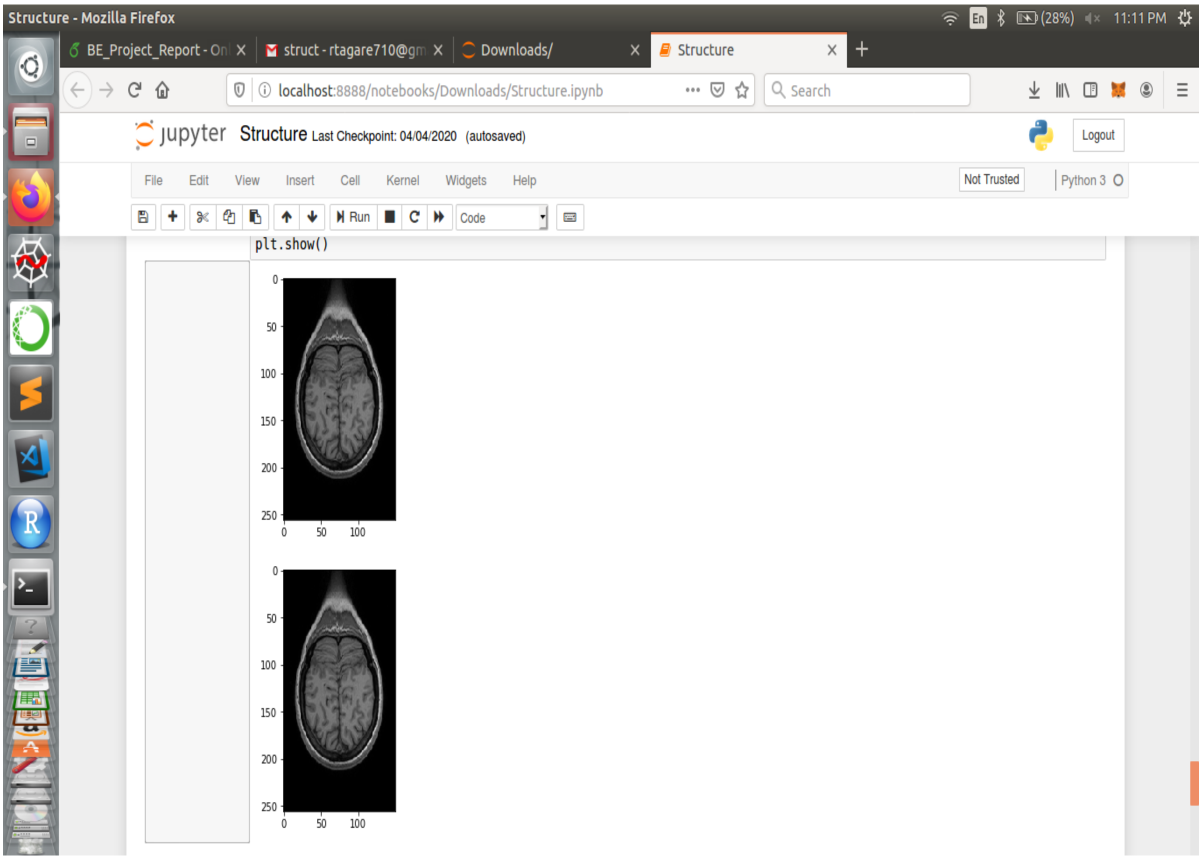

Figure 8.1: 20 percent noise removal

Following image shows he PSNR value obtained as output for 2 dimensional MR Image denoising.

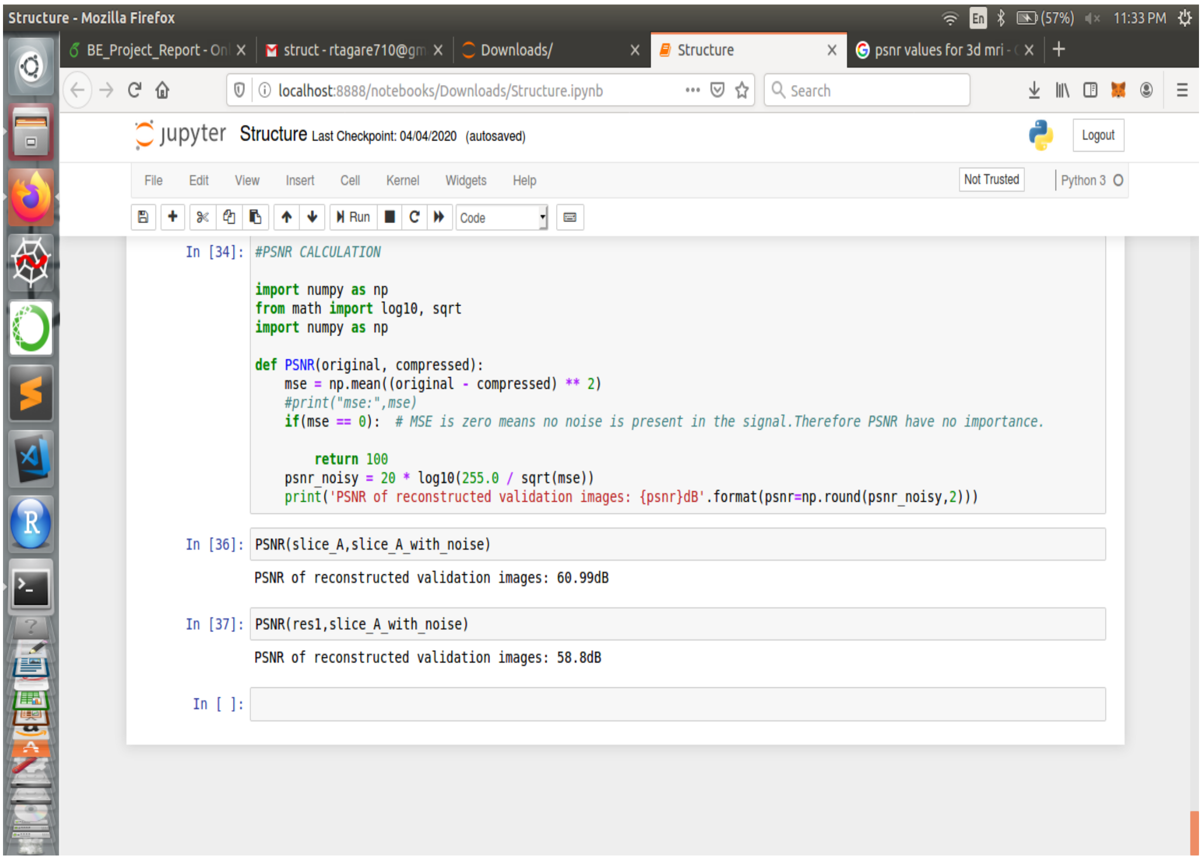

Figure 8.2: PSNR values of 20 percent Rician noise removal

8.2 Accuracy

We have measured accuracy of our model in terms of PSNR values obtained. Peak Signal To Noise ratio is a term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the representation. Many signals have a very dynamic range. PSNR is usually expressed in logarithmic decibel. This ratio is used as a quality measurement between the original and a corrupted image. The higher the value of the PSNR the better quality of the compressed, or reconstructed image.

Noise percentage	Noise inserted	Noise removed
10	67 db	68 db
15	63 db	66 db
20	62 db	61 db

Figure 8.3: PSNR values of 3D MRI noise removal

Above table shows PSNR ratio for 10 , 15 and 20 percentage of Rician noise removal. These values are significantly high values. These values are obtained by testing the model over 20 images. Images were having 3 channels as the third dimension.

CHAPTER 9

OTHER SPECIFICATIONS

9.1 Advantages

- Multiple channels help to remove variety of noise percentages in 3 dimensional MR Images.
- Can also be extended using other filters to remove noises from any given images other than MR Images.
- Helps in further medical diagnosis.

9.2 Limitations

- Takes long time to train the algorithm.
- It needs GPUs to speed up the process.
- It needs large image dataset for training purposes.

9.3 Applications

- To identify Rician noises in MR images.
- To give noise free MR Images.

CHAPTER 10

CONCLUSION AND FUTURE SCOPE

10.1 Conclusion

General methods only take care of one noise at a time. Also current approach work by training the models for a certain level of a particular noise and then use this model to predict and denoise the image. But in this method we are using multiple levels of noises in the convolutional neural networks. Also we are trying to improve the accuracy of our model and make it better than the current models.

10.2 Future Scope

Time needed to train the neural network is high. To improve time required we can execute the algorithm in parallel on multiple GPUs . Also large amount of dataset is needed for training which may be reduced by learning features with small amount of images. Resultant model for denoised image can be further used to predict fatality of disease.

ANNEXURE A

FEASIBILITY STUDY

A.1 Problem Statement Feasibility

Magnetic Resonance Imaging MRI is widely used at present to diagnose various diseases. Rician noise also known as Rice noise is a prominant noise int he MR images. We will be denoising 3 dimensional MR images in this method which will have Rician and Gaussian noises robustly. We are using multiple levels of noises in the CNN. We have referred datasets of MR images of brain and lungs for making this project. Time needed to train neural network is still high in this model. Parallel GPU implementation of algorithm can help to reduce it.

ANNEXURE B

PLAGIARISM REPORT

SmallSEOTools

PLAGIARISM SCAN REPORT

Words	804	Date	April 28,2020
Characters	5177	Exclude Url	

0% Plagiarism	100% Unique	0 Plagiarized Sentences	43 Unique Sentences

Content Checked For Plagiarism

Magnetic resonance imaging (MRI), as an attractive non-invasive medical imaging technique, plays an important role on the diagnosis of pathological and physiological alterations in living tissues and organs of human body. The quality of MR images can, however, easily be degraded by random noise generated while acquiring them. Increased noise level could dramatically

SmallSEOTools

PLAGIARISM SCAN REPORT

Words	869	Date	April 28,2020
Characters	5541	Exclude Url	

2% Plagiarism	98% Unique	1 Plagiarized Sentences	44 Unique Sentences

Content Checked For Plagiarism

An artificial neural network based bilateral filter associated with image texture feature analysis is proposed for automatically denoising brain related MR images. A variety of MR images with various scenarios were adopted for evaluation of the performance of the proposed framework. Experimental results indicate that this new automation method accurately predicts

SmallSEOTools

PLAGIARISM SCAN REPORT

Words	967	Date	April 28,2020
Characters	5841	Exclude Url	

2% Plagiarism	98% Unique	1 Plagiarized Sentences	48 Unique Sentences

Content Checked For Plagiarism

Proposed Architecture consists of one input layer of convolution with rectified linear unit (ReLU), multiple layers of convolution with batch normalization and/or ReLU and one final output layer of convolution. As output layer generates an image with same size as the input, proposed network does not include any max-pooling layer. To adapt to 3D volume, we

CHAPTER 11

REFERENCES

[1] H. R. Golshan HM, "An optimized lmmse based method for 3d mri denoising," *IEEE/ACM transaction on computational biology and bioinformatics*, vol. 12, no. 4, pp. 861–870, 2014.

[2] W. Y. G. m. S. F. g. W. X. Weisheng Dong, Peiyao Wang, "Denoising prior driven deep neural network for image restoration :ieee.," *IEEE Transaction on pattern analysis and machine intelligence*, vol. 41, no. 10, pp. 2305–2318, 2018.

[3] R. K. F. A. J. G. Gerig, O. Kubler, "Nonlinear anisotropic filtering of mri data," *IEEE Transactions on medical imaging*, vol. 11, no. 2, pp. 221–232, 1992.

[4] Y. C. D. M. Kai Zhang, Wangmeng Zuo and L. Zhang, "Beyond a gaussian denoiser: Residual learning of deep cnn for image denoising," *IEEE Transactions on Image Processing*, vol. 26, no. 7, pp. 3142–3155, 2017.

[5] Y. D. P.-T. GengChen, PeiZhang, "Denoising magnetic resonance images using collaborative non-local means : Elsevier," *Neurocomputing*, vol. 177, pp. 215–227, 2016.

[6] C. H. Chang YN, "Automatic brain mr image denoising based on texture feature-based artificial neural networks : content.iospress.com," *Biomedical Materials and Engineering*, vol. 26, no. s1, pp. S1275–S1282, 2015.

[7] B. K. J. Ajay Kumar Boyat, "Review paper: Noise models in digital image processing : Researchgate," *arXiv preprint arxiv:1505.03489*, 2015.

[8] L. Gondara, "Medical image denoising using convolutional denoising autoencoders," *2016 IEEE 16th International Conference on Data Mining Workshops (ICDMW)*, 2016.

[9] S. P. H. Gudbjartsson, "The rician distribution of noisy mri data : Magn.reson. med," *Magnetic Resonance in medicine*, vol. 34, no. 6, pp. 910–914, 1995.