# Application of Machine Learning in Digital Communication.

Author

MUHAMMAD SUFIAN

FALL 2016-MS-16(CSE) 00000172053

Supervisor

DR. AIMAL KHAN

DEPARTMENT OF COMPUTER & SOFTWARE ENGINEERING

COLLEGE OF ELECTRICAL & MECHANICAL ENGINEERING

NATIONAL UNIVERSITY OF SCIENCES AND TECHNOLOGY

ISLAMABAD

JULY 2019

# Application of Machine Learning in Digital Communication.

Author

MUHAMMAD SUFIAN

FALL 2016-MS-16(CSE) 00000172053

A thesis submitted in partial fulfillment of the requirements for the degree of

MS Software Engineering

Thesis Supervisor:

DR. AIMAL KHAN

Thesis Supervisor's Signature:

________________________________________

DEPARTMENT OF COMPUTER & SOFTWARE ENGINEERING

COLLEGE OF ELECTRICAL & MECHANICAL ENGINEERING

NATIONAL UNIVERSITY OF SCIENCES AND TECHNOLOGY,

ISLAMABAD

JULY 2019

# DECLARATION

I certify that this research work titled *Application of Machine Learning in Digital Communication* is my own work under the supervision of Dr. Aimal Khan. This work has not been presented elsewhere for assessment. The material that has been used from other sources has been properly acknowledged / referred.

Signature of Student

Muhammad Sufian

00000172053

# LANGUAGE CORRECTNESS CERTIFICATE

This thesis is free of typing, syntax, semantic, grammatical and spelling mistakes. Thesis is also according to the format given by the University for MS thesis work.

Signature of Student
Muhammad Sufian
00000172053

Signature of Supervisor
Dr. Aimal khan

# Plagiarism Certificate (Turnitin Report)

This thesis has been checked for Plagiarism. Turnitin report endorsed by Supervisor is attached.

Signature of Student

Muhammad Sufian

00000172053

Signature of Supervisor

Dr. Aimal khan

# COPYRIGHT STATEMENT

## ACKNOWLEDGEMENTS

I am thankful to my Creator Allah Subhana-Watala to have guided me throughout this work at every step and for every new thought which You setup in my mind to improve it. Indeed, I could have done nothing without Your priceless help and guidance. Whosoever helped me throughout the course of my thesis, whether my parents or any other individual was Your will, so indeed none be worthy of praise but You.

I am profusely thankful to my beloved parents who raised me when I was not capable of walking and continued to support me throughout in every department of my life.

I would also like to express my gratitude to my supervisor **Dr. Aimal Khan** for his incredible cooperation and providing help at every phase of this thesis. He has guided me and encouraged me to carry on and has contributed to this thesis with a major impact. Thank you for guiding me, often with big doses of patience. I would also like to thank my co-supervisor **Dr. Farhan Hussain** for their constant motivation and help throughout this thesis.

Some special words of gratitude go to my wife **Takreem Saeed** who has always been a major source of technical support and cooperation when things would get a bit discouraging.

*“Dedicated to my exceptional parents whose tremendous support and cooperation led me to this wonderful accomplishment”*

# ABSTRACT

Digital communication depends on channel coding for the integrity and correct reception of the data. The traditional communication techniques ignore the context and content associated with the received data while mitigating the channel effects. Image transmission in digital communication have many major constraints. Image quality degrades over wireless channel due to limited characteristic of transmitted data. To mitigate the effects of the noisy channel on the images different image denoising techniques are used such as Convolutional Denoising Autoencoders, Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT), Fast Fourier Transform (FFT), Non-Local Means (NLM), Block-matching and 3D filtering (BM3D) and Deep Learning. The goal of this thesis is to study the application of machine learning in digital communication to correct errors and remove the effects of channel degradation. This will help us improve the energy consumption, resource utilization, and the Bit Error Rate. It will enable us to communicate with low bandwidth and using minimum resources. Machine learning for denoising the image has attracted substantial attentions because of its high denoising performance. We have constructed a Convolutional Neural Network that will denoise the image which is corrupted by the noisy channel. By using the methods of batch normalization and residual learning the denoising performance is increased. The existing traditional models only denoise the image for a specific noise type (Gaussian noise) and certain noise level $\sigma = 25$, but our trained network denoise the image for unknown noise level and for burst errors as well. Experiments prove that our trained model displays high efficiency in image denoising. The proposed network is trained in MATLAB and Python with the help of GPU computing which accelerates the overall performance of the neural network. The application areas of this thesis mainly are in the domains related to digital communications. This include wireless communications, optical communications and line communications. However, as the wireless communications (especially underwater wireless) is extremely error prone, so this domain will be highly benefited. The applications can include military communications, Underwater Communication and Noisy Industrial Communication.

**Keywords:** Digital Communication, Machine Learning, Image Transmission, Image Denoising, Deep Learning, Convolutional Neural Network, Residual Learning, Batch Normalization

# TABLE OF CONTENTS

# LIST OF FIGURES

# LIST OF TABLES

# Chapter 1

# Introduction

# CHAPTER 1: INTRODUCTION

This section provides a detail introduction about the research and research concepts. This section is organized in multiple sub sections. **Section 1.1** provides the background study, **Section 1.2** presents the problem statement of research, **Section 1.3** discuss the proposed methodology, **Section 1.4** gives the detail about research contribution, and Thesis organization is presented in **Section 1.5**.

## 1.1.Background Study

The purpose of this section is to introduce the background study of multiple concepts which has been used in this research. These concepts include:

- Machine Learning
- Digital Communication
- Image Transmission
- Image Denoising

### 1.1.1. Machine Learning

Arthur Samuel used this term of "Machine Learning" for the first time in history in 1959, he was an American pioneer who did a lot of work in the area of artificial intelligence AI and computer gaming. He once quoted about the machine learning that "it gives computers the ability to learn without being explicitly programmed". Then in 1997, another computer geek Tom Mitchell presented a "well-posed mathematical and relational definition that A computer program is said to learn from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E. Machine Learning is a latest buzzword floating around. It deserves to, as it is one of the most interesting subfields of Computer Science".

Machine learning operations can be categorized into three main classes, conditional on the type of the learning "signal" or "response" accessible to a learning method. In first category of **Supervised learning** which can be define as "an algorithm learns from example data and associated target responses that can consist of numeric values or string labels, such as classes or tags, to later predict the correct response when posed with new examples comes under the category of Supervised learning.

This method is just like human beings who study under the supervision of a instructor or a teacher. The instructor delivers good instances for the pupil to remember, and the pupil then originates general rules from these detailed instances.

The second category of learning is **Unsupervised learning** which can be defined as **"**an algorithm learns from plain examples without any associated response, leaving to the algorithm to determine the data patterns on its own". This sort of process inclines to reorganize the data into nearly new format, for example innovative features that can characterize a class. This type of unsupervised learning is pretty valuable in providing us the insights of statistics and new valuable inputs to the algorithms of supervised learning. It is a type of learning, which is similar to the human learning methods when humans find out that specific events or objects are from the exact class. For example, finding out the resemblance between events or items. Some machine learning systems that are also called recommenders we discover on the internet are dependent on unsupervised learning.

**Reinforcement learning** is another type of learning which can be define as "an algorithm is presented with examples that lack labels, as in unsupervised learning". Though, we can define an example by feedback of negative and positive comments, which suits the best for the algorithm method. This lies in the group of Reinforcement learning. In this type of learning the algorithm's necessity is to make results, which turns into decisions and decisions have always consequences. If we talk about the real-life world, we can say this reinforcement learning is learning by trial and error. We make some mistakes and then we learn from our mistakes. Wrong decisions aid us to learn and grow just because the errors have a penalty added in form of resources. For example, loss of time, increment in cost and many others. And these consequences teach us a specific sequence of action. Another fascinating instance of this learning category happens when our machines (PCs) learn how to play computer games by themselves.

The **Semi-supervised learning** can be defined as "an incomplete training signal is given to a training set with some often many of the target outputs missing". This type of learning can be further explained by a case which is known as "Transduction" in which full set of instances problem is provided at the time of learning, excluding that some part of the outputs is missing.

ML can also be classified according to the required outcome, when the desired outcome is expected by the system of machine learning.

**Classification**: When the values of inputs are divided into three or more than two classes, and the learner system must generate a model that allocates unseen values of inputs to two or more than two of these classes. Classification is generally attempted in a supervised learning. Filtering the spam emails is an instance of classification, when the inputs are messages or emails and "spam" and "not spam" are the classes.

**Regression**: also belongs to the problem of supervised learning, in this case the outcomes or the values of output are continuous instead discrete.

**Clustering**: When the number of input values are divided into clusters. Dissimilar with classification, the clusters are not known prior, and this makes clustering associated with the unsupervised learning.

Machine Learning is used when the problems and issues cannot be solved by traditional approaches. Figure 1 shows the applications of ML in different areas of communication".

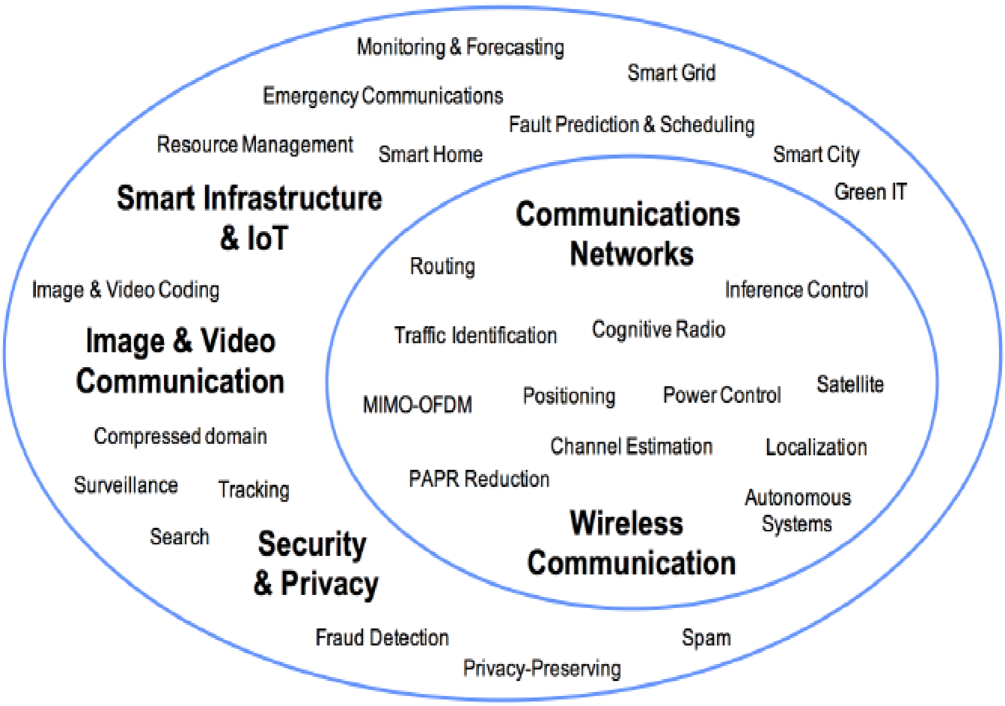



**Figure 1:** Applications of machine learning in different areas of communications**.**

### 1.1.2. Digital Communication

Digital communication can be defined as a type of communication in which the data and information first “encoded digitally as discrete signals” then send to the receiver electronically. This communication type is usually used in the modern era. Organizations usually depend on this type of communication for their business communications inside and outside the organization. Steps involved in digital communication are as follows:

**Input source:** it can be any data type like picture or text and it can be in any form of digital or analog.

**Source Encoder** Output of the input source is the input to this step in which the data or information is converted into signal which consists of 0′s and 1′s. To precisely represent the digital signal, the most accurate practice is to use few binary digits if possible. As a result, the problem of data redundancy is solved, and the process becomes more efficient. Binary digits make a sequence before converting into signal which is known as information sequence.

**Data Compression** this step of data compression involves the conversion of any signal type into the binary digits efficiently. The purpose of data compression is to protect the data from the communication channel errors.

**Chanel Encoder**: this step helps the receiver to recover the output data which was affected by the errors during the communication medium. this method works in a controlled manner and the information of binary sequence have some redundancy.

**Digital Modulator**: To transmit the received sequence in the form of signal over the electric media, it is passed through the modulator. Modulator transform the sequences received from the cannel encoder into the form of signal wave. For example, the 1’s and 0’s are represented by sin and cos.

**Channel:** media between the receiver and the sender which have some physical properties as well is the communication channel.

**Digital Demodulator**: Digital demodulator works inversely as the digital modulator.

**Channel Decoder**: original information is reconstructed in the form of sequence, and the knowledge present in the code is used for controlling the redundancy of the output data.

**Source Decoder**: the receiver, receives the approximate same output as the input in this step.

**Output Transducer**: At the end, we receive the desired output in the desired format.

**Figure 2** represent a generic digital communication system.

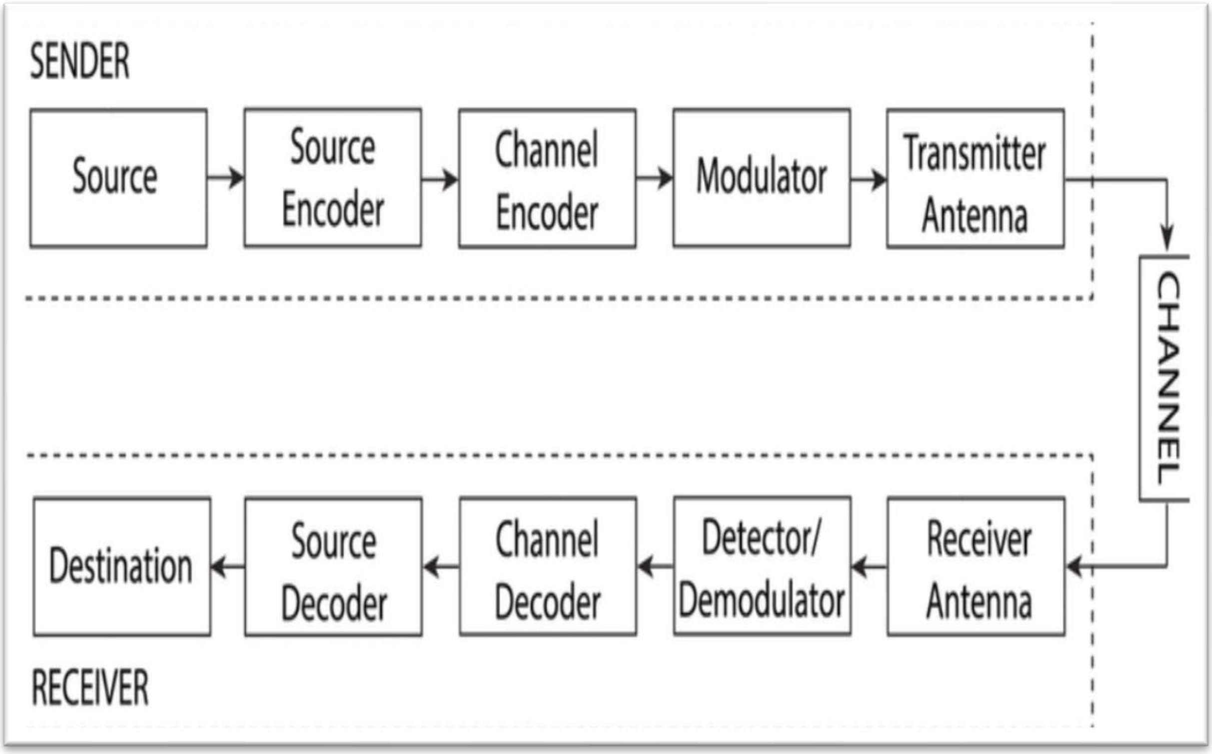



**Figure 2:** Block diagram representing the Digital Communication System

### 1.1.3. Image Transmission

The fundamentals of this system used in our research work are presented in **figure 3**. The source encoder encodes the source image using appropriate image compression technique. For the protection of coded image in Fig. 1 channel encoder adds redundancy to the coded image by using appropriate channel coding technique. Modulator modulates the coded image and transmits through the wireless channel. QAM is invariably used as the modulation technique. The channel introduces noise and distortion to the transmitted image. demodulator receives the image data with error and demodulates it. After channel decoding, the coded image is decompressed.

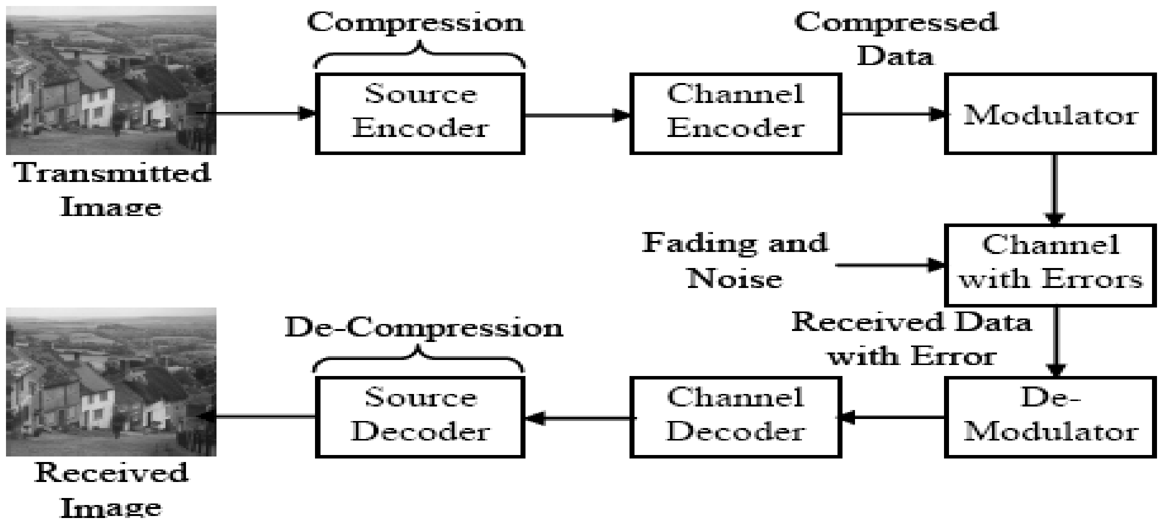



**Figure 3:** Image Transmission System

### 1.1.4. Image Denoising

In low level vision, Image denoising is the main theme where the objective of denoising is to reconstruct the noise corrupted image. Different techniques and different algorithms are used in the e previous work to clean the noisy observation. Currently, machine learning, and CNN based techniques are used which have different denoising results. Due to different requirements, all these models have varying performances because the training dataset, the computational costs and resources may vary.

## 1.2.Problem Statement

Image transmission over wireless communication channel has two major constraints. First, channel bandwidth has fluctuations. Second, most likely channel error produces for this reason the image data must be protected from errors to maintain image quality. In general, High quality image transmission demands more storage capacity and high bandwidth requirements. The image quality degrades over wireless channel due to limited characteristic of transmitted data. To mitigate the effects of the noisy channel on the images different image denoising techniques are used e.g. Convolutional Denoising Autoencoders, DCT, DWT, FFT, Transform Methods, NLM, BM3D and Deep Learning. So denoising the image which is corrupted by the noisy channel with the use of machine learning application is the problem statement of this thesis.

## 1.3.Proposed Methodology

Entire research is done in a very systematic way. **Figure 4** represent the flow of research step by step. In first step we identify the problem. Then proposed the ideal solution for the problem identified in first step. We carry out a detailed and comprehensive literature review which helps us to identify the optimal solution for the problem. We reviewed the researches carried out related to our proposed solution, analyze and compared it."

The proposed solution includes the image transmission through a noisy channel, which corrupts the image by multiple degradations and then construct a model using Deep Learning that consists of different layers to obtain denoise image (reconstructive image). The Model is trained using Residual Learning Method and it includes the Convolutional Layers, Batch Normalization and RELU Layers. We optimized the Model using Back propagation with Stochastic gradient descent. The proposed methodology has been validated by comparing the model with two other state of the art models of image denoising.

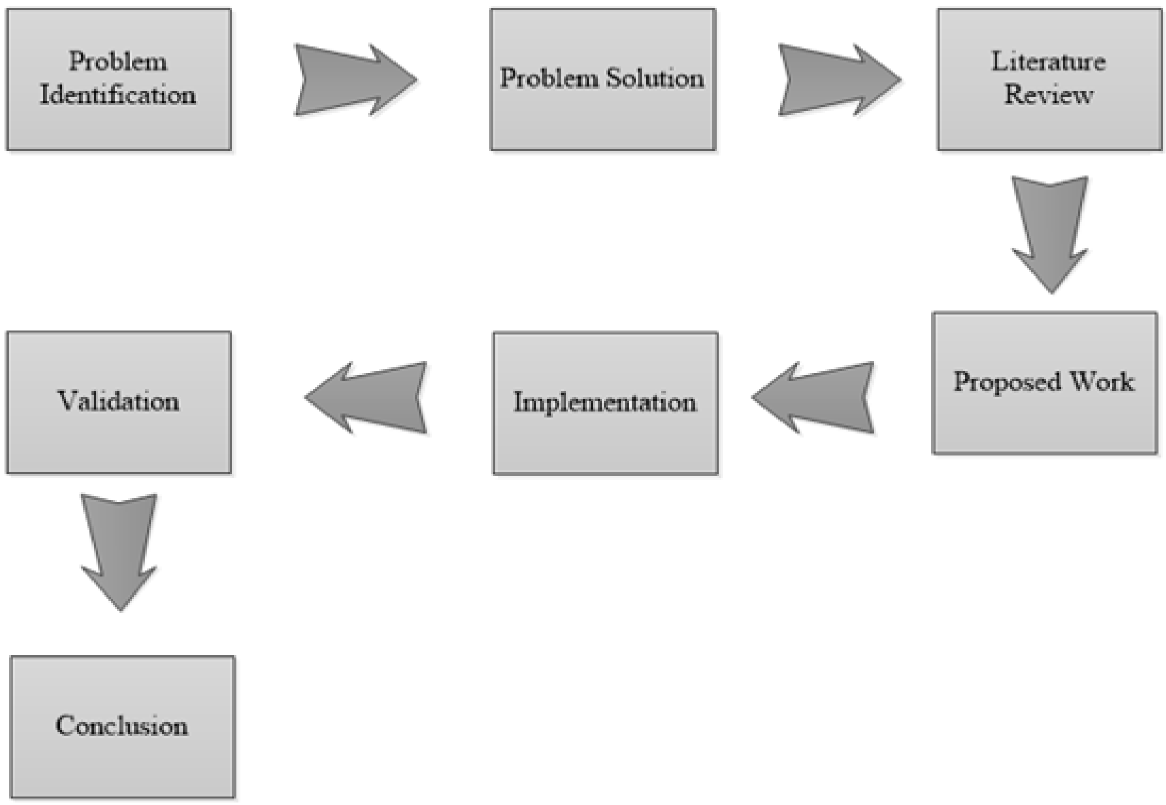



**Figure 4:** Research Flow

## 1.4. Research Contribution

Contributions of this research are; denoise the image, corrupted by the noisy channel in the digital communication by using the applications of machine learning. Detailed set of contributions of the proposed approach are as follows:

- We have presented a model which denoise the image which is corrupted during the digital transmission
- This model consists of a convolutional neural network which first learn from the training data
- The image is denoise by the technique of residual learning, in which latent clean image is removed from hidden layers by the Neural Network.
- We have provided validation of our work by comparing the results with two modern image denoising models, TNRD and BM3D.

## 1.5. Thesis Organization

**Figure 5** represent the organization of thesis**. Chapter 1** deals with introduction having detailed background study about the concepts used in the research, problem statement, research contribution and thesis organization. **Chapter 2** contains the literature review which provide a description of work done in the field of image denoising using machine learning. In Literature review we also highlights the research gaps that we encountered. Error! Reference s ource not found. covers the details of proposed methodology used for identification of problem. Error! Reference source not found. **4** presents the detailed implementation regarding the proposed model, image transmission, image retrieval and image denoising. Error! Reference source not found. provides the validation performed for our proposed methodology by comparing with two other denoising models. **Chapter 5** contains a brief analysis of our proposed work with previous researches. **Chapter 6** contains a brief discussion on the work done and contains the limitations to our research and concludes the research and recommends a future work for the research.

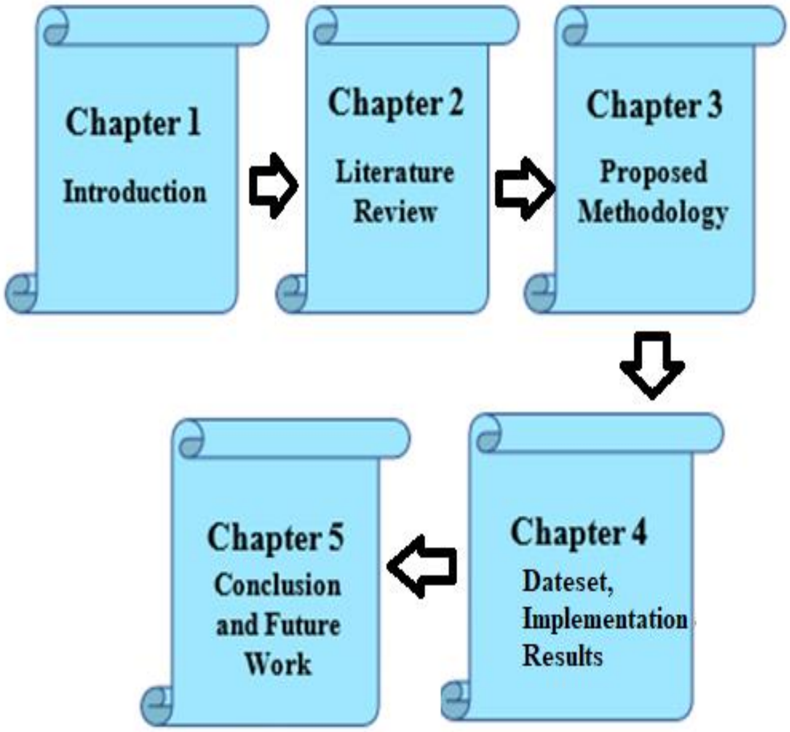



**Figure 5:** Thesis Outline

# Chapter 2

# Literature Review

# CHAPTER 2: LITERATURE REVIEW

This chapter presents brief review of reliable digital communication and existing work in image denoising techniques using machine learning applications. After a brief literature review of work conducted in this area we enlightened the research gaps that we found in previous works.

## 2.1.Literature Review

Digital communication can be divided into two main categories. First type is wireless communication which includes deep space, satellites and cellular while the second type is wireline communication that includes DSL modems, cables and ethernet. Reliable Digital communication is the prime pillar for the modern information era. Reliable Digital communication depends on different critical aspects that involves the transmission of data under noisy circumstances. Different types of data are transferred over the communication media. In our work, we have just focused on one type of data that is images. When images are sent and received in digital communication, it become dirty because of the noisy conditions present in the communication media. Cleaning that dirty image is generally known as image denoising.

Image denoising is a traditional problem of image processing. In low-level-vision image denoising is still an active subject. In many applications images denoising is a crucial step. The main objective of image denoising is to get the clean image from the noise corrupted observation. It can be defined by the degradation model of images $\boldsymbol{y} = \boldsymbol{x} + \boldsymbol{v}$, where $\boldsymbol{x}$ is the clean image, $\boldsymbol{y}$ and $\boldsymbol{v}$ is any type of noise. Generally, it is assumed that the $\boldsymbol{v}$ is the gaussian noise also knows as Additive White Gaussian Noise (AWGN) where $\sigma$ is the standard deviation. In last couples of years several models have been developed for image denoising such as Sparse Models, Nonlocal Self-Similarity, MRF and gradient models. Particularly, nonlocal self-similarity models are state of the art methods. NSS methods includes WNNM, NCSR, LSSC and BM3D. All these models have high quality of denoising, but these models also have two major drawbacks.

Complex optimization, that is the first major problem of these models. It creates issues at the testing stage and the process consumes more time while denoising. That is why these models do not get high performance uncles they sacrifice on computational resources. Second major drawback is to choose the different parameters manually.

For overcoming the drawbacks of these models' different discriminative models have been developed in recent years. These models are developed to overcome the iterative optimization process at the testing stage. Roth and Schmidt proposed a method (CSF) which is known as cascade of shrinkage fields. It merges the arbitrary field-based method. This method develops single learning framework by unfolding the half-quadratic optimization algorithm. Trainable nonlinear reaction diffusion (TNRD) method was proposed by Chen et al. This model acquires an altered field of expert's image prior by disclosing static sum of gradient descent inference phase. Other work related to this was found in [13], [25].

Both the above described methods (TNRD and CSF) showed prominent outcome toward linking the gap b/w denoising quality and computational efficiency. Performance of these models are inherently limited prior's specified form. Explicitly, for image structures in order to capturing the full characteristics TNRD and CSF are priors adopted which are purely grounded on the analysis model. Moreover, stage wise greedy training is used to learn parameters while manual parameters are intricate. One more non-neglecting disadvantage is that, at certain noise level specific model is trained and unknown level of noise removing is limited. In this work, they took denoising models as a bare discriminating model issue as an alternative of image prior. The reasons are three folded of using CNN. First, for manipulating image characteristics CNN is very effective in increasing the flexibility and capacity with very deep architecture [19]. Second, batch normalization [21], ReLU [38] and RL [13] included for training CNN through learning methods and regularization in order to achieve considerable advances. In CNN, these methods may be adopted to improve denoising performance and speed up training process. Third, CNN can be oppressed to progress the run time performance as it is well-suited on modern powerful GPU for parallel computation.

We refer CNN Image Denoiser for denoising convolutional neural network. The proposed CNN image denoiser is considered to predict the residual image vˆ, instead of directly outputting the denoised image xˆ, i.e., difference between the latent clean image and noisy observation. In other words, operations in the hidden layers are implicitly used to remove the latent clean image in the proposed CNN image denoiser. Training performance of CNN Image

Denoiser is enhanced and stabilize through the batch normalization technique. It chances out that batch normalization and residual learning can beneficial from each other and their incorporation is much effective in boosting the denoising performance and speeding up the training. To structure a progressively compelling and denoising the additive white Gaussian noise, v is the variance of the bicubic up sampling of the low pixels image and the ground truth high pixels image, for Guassian denoising the picture degradation model can be changed over to a SISR issue; “JPEG picture deblocking problem can be demonstrated by the same picture degradation model in which v taking as the difference between the compressed image and the original image. In this case, JPEG and SISR image deblocking may be treated as two distinct cases of a general picture denoising problem, however in JPEG and SISR deblocking the noise vs from AWGN are much different.”

It is normal to ask whether is it conceivable to prepare a CNN model to deal with such broad picture denoising issue? By examining the connection between TNRD and CNN Image Denoiser [16], we propose to broaden CNN Image Denoiser for dealing with a few general picture denoising assignments, as well as Guassian denoising, JPEG and SISR image deblocking. Broad investigations demonstrate that, our CNN Image Denoiser prepared with a specific noise level can yield preferred Gaussian denoising results overstate-of-the-art techniques, for example, BM3D [2], TNRD [16] and WNNM [13]. For Gaussian denoising with obscure noise level (i.e., daze Gaussian denoising), CNN Image Denoiser with a solitary model can even now beat TNRD [16] and BM3D [2] prepared for a particular noise level. The CNN Image Denoiser can likewise acquire promising outcomes when reached out to a few general picture denoising assignments. In addition, we demonstrate the adequacy of training just a solitary CNN Image Denoiser model for three general picture denoising undertakings, i.e., daze Gaussian denoising, JPEG deblocking with various quality elements and SISR with various upscaling variables. The commitments of this work are outlined as follows: 1) for Guassian denoising they proposed an end-to-end trainable dep CNN. Rather than the current deep neural system-based strategies which straightforwardly approximate the latent clean picture, the system receives the residual learning technique to expel the latent clean picture from noisy perception. 2) They discover that batch normalization and residual learning can incredibly profit the CNN learning as they can accelerate the training as well as lift the denoising performance. CNN Image Denoiser beats state-of-the-art methods for Guassian denoising at a specific noise level in terms of both visual quality and quantitative metrices. 3) Our CNN Image Denoiser can be effectively stretched out to deal with general picture denoising assignments. We can train a solitary CNN Image Denoiser model for visually impaired Gaussian denoising, and accomplish preferable execution over the contending techniques prepared for a particular commotion level. “Besides, it is promising to illuminate three general picture denoising errands, i.e., visually impaired Gaussian denoising, JPEG deblocking and SISR, and, with just a solitary CNN Image Denoiser model. The rest of the paper is sorted out as pursues. Area II gives a concise review of related work. Area III first shows the proposed CNN Image Denoiser model, and after that extends it to general picture denoising. In Section IV, broad tests are led to assess CNN Image Denoisers. Finally, a few finishing up comments are given in Section V.

## II. RELATED WORK

For Image Denoising a Deep Neural Networks in which there have been numerous tries to deal the denoising problem. In [23], Seung and Jain proposed for image denoising to use CNNs and demanded that CNNs have better or similar illustration power than the MRF model. In [24], for image denoising the multilayer perceptron (MLP) was effectively applied. In [25], stacked inadequate denoising auto-encoders strategy was received to deal with Gaussian noise evacuation and accomplished similar outcomes to K-SVD [5]. In [16], a trainable nonlinear reaction diffusion (TNRD) a trainable nonlinear response dissemination (TNRD) model was proposed and it very well may be communicated as a feed-forward profound system by unfurling a fixed number of inclination descent induction steps. Among the above deep neural systems-based strategies, TNRD and MLP can accomplish promising execution and can contend with BM3D. In any case, for TNRD [16] and MLP [24], a particular model is trained for a specific noise level. As far as we could possibly know, it remains uninvestigated to create CNN for general picture denoising. Batch Normalization and Residual Learning recently, determined by the simple access to huge scale dataset and the advances in profound learning strategies, the convolutional neural systems have demonstrated extraordinary accomplishment in taking care of different vision undertakings. The delegate accomplishments in preparing CNN models incorporate Rectified Linear Unit (ReLU) [20], tradeoff among profundity and width [19], [26], parameter introduction [27], angle based streamlining calculations [28], [29], [30], bunch standardization [21] and remaining learning [22]. Different components, for example, the effective preparing usage on present day ground-breaking GPUs, likewise add to the accomplishment of CNN. In any case, for TNRD [16] and MLP [24], a particular model is trained for a specific noise level. As far as we could possibly know, it remains uninvestigated to create CNN for general picture denoising. Batch Normalization and Residual Learning recently, determined by the simple access to huge scale dataset and the advances in deep learning strategies, the CNN have demonstrated extraordinary accomplishment in taking care of different vision undertakings. The delegate accomplishments in training CNN models incorporate Rectified Linear Unit (ReLU) [20], gradient-based optimization algorithms [28], [29], [30], parameter initialization [27], tradeoff among width and depth [19], [26], deep learning [22] and batch normalization [21]. Different components, for example, the effective training usage on present day ground-breaking GPUs, likewise add to the accomplishment of CNN. For Gaussian denoising, from a set of high quality pictures, sufficient training data is easy to generate. For image denoising this work focuses on learning and design of CNN. Below, we review two methods that are related to CNN Image Denoising 1) Residual Learning:

This learning [22] of CNN was at first present to clear up the performance degradation problem i.e. along with the increasing of network depth even the preparation exactness starts to devalue. By supposing that the residual mapping is a lot simpler to be scholarly than the first unreferenced mapping, residual system expressly learns a residual mapping for a couple of stacked layers. With such a residual learning procedure, very profound CNN can be effectively prepared and improved precision has been accomplished for picture arrangement and object recognition [22]. The recommended CNN Image Denoiser model acquires the residual learning formulation. Dissimilar to the residual system [22] that utilization numerous residual units (i.e. identity shortcuts), our CNN Image Denoiser utilizes a solitary residual unit to anticipate the residual image. We further clarify the method of reasoning of residual learning plan by examine its link with TNRD [16] and extend it to unravel a few general picture denoising tasks. It ought to be noted that, before the residual system [22], the methodology of foreseeing the residual image has just been received in some low-level vision issues, for example, shading picture demosaicking [32] and single picture super resolution [31].

In any case, as far as we could possibly know, there is no work which straightforwardly predicts the residual image for denoising. 2) Batch Normalization: Mini-batch stochastic gradient descent (SGD) has been generally utilized in preparing CNN models. In spite of the effortlessness and adequacy of mini-batch SGD, its preparation productivity is to a great extent decreased by inside covariate shift [21], i.e. changes in the dispersions of interior nonlinearity contributions during preparing. Batch normalization [21] is proposed to ease the interior covariate shift by fusing a normalization step and a scale and shift venture before the nonlinearity in each layer. For batch normalization, just two parameters for each actuation are included, and they can be refreshed with back-spread. Batch normalization appreciates a few benefits, for example, quick preparing, better execution, and low affectability to introduce. For further factors on batch normalization, it would be ideal if you allude to [21]. By a wide margin, no work has been done on considering batch normalization for CNN-based image denoising. We experimentally find that, the coordination of residual learning and batch normalization can result in quick and stable preparing and better denoising execution.

## 2.2.Research Gap

The proposed solution includes the image transmission through a noisy channel, which corrupts the image by multiple degradations and then construct a model using Deep Learning that consists of different layers to obtain denoise image (reconstructive image). The Model is trained using Residual Learning Method and it includes the Convolutional Layers, Batch Normalization and RELU Layers.

# Chapter 3

# Proposed Methodology

# CHAPTER 3: PROPOSED METHODOLOGY

When the image is transferred over the transmission medium it is compressed to minimize the usage and bandwidth issues. Digital images transmission is still a challenge because of the mounting number of images, their sizes and diversity of bandwidths. As a result, the image quality is compromised.  Transmission techniques are used to mitigate these effects. Delivering the compressed high-resolution image in the sequential manners could increase the arrival time of the image. The more efficient way is to transfer the image in the bit stream. The flow diagram below shows the steps involved in the digital communication where a clean image is passed through the noisy channel and noisy image is retrieved at the end. The basic concept of this image transmission process is that the image gets dirty when its travelling through the channel in the form of binary digits. Generally, image denoising techniques only assume one noise type i.e. Additive White Gaussian Noise (AWGN) but in our work we have added burst error as well in the image. The figure 7 below shows the clean and dirty image with White Gaussian Noise addition while figure 8 shows the clean JPEG image and its dirty version by burst error. The retrieved dirty images are denoised by using the Convolutional Neural Network which is further described in this chapter. Figure 9 shows the flowchart of complete methodology.

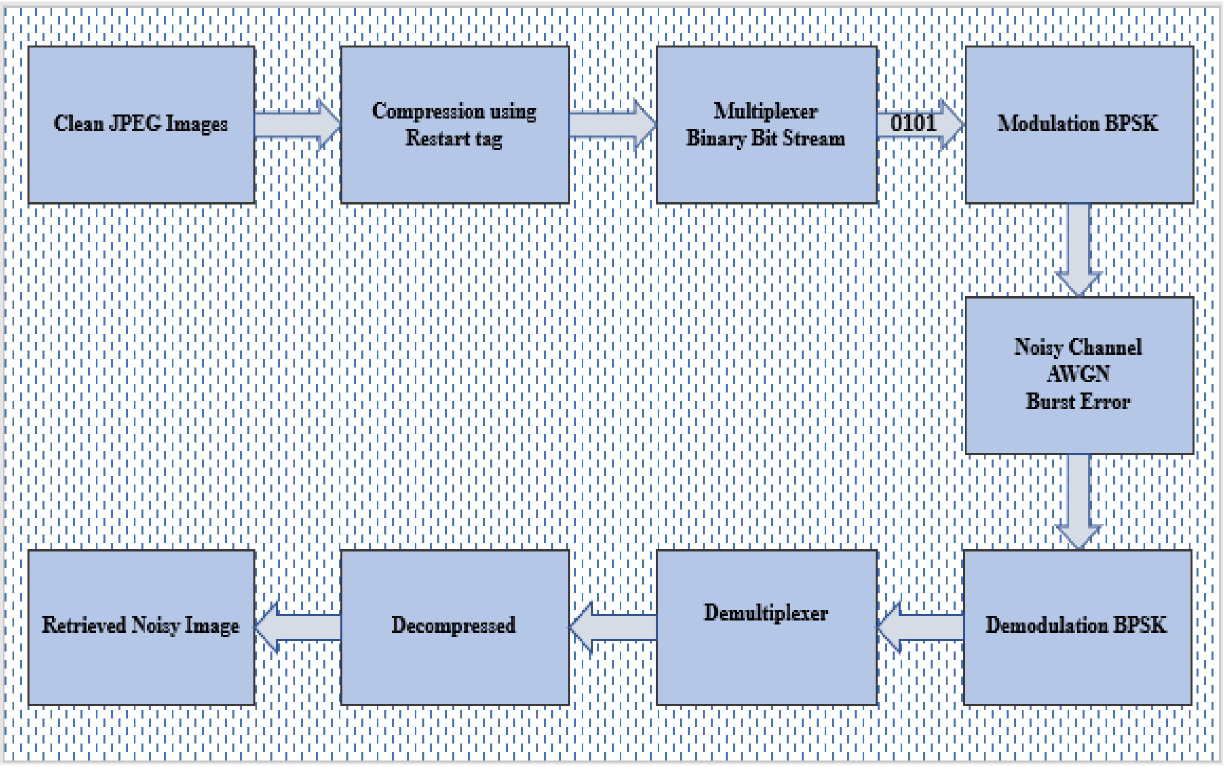



**Figure 6:** Image transmission over noisy channel (Digital Communication)

## 3.1. Image transmission over noisy channel (Digital Communication)

### 3.1.1. Clean JPEG Image:

The input image which we will use to transfer over the wireless communication medium. This image is original, without noise and any corruption.

### 3.1.2. Compression of JPEG image by adding Restart Marker:

Before transmitting the clean JPEG Image over the wireless channel, we have compressed the image and added the restart marker by using the JPEC Imager 2 software. The purpose of compressing and restart marker is that if an error occurs then resynchronization will be allowed. Since the wireless communication medium in our work is noisy with burst error so without adding the restart marker will results in wrong output i.e. the burst error will not show up at the pixels where we placed it. The value of the restart marker indicates when the large portion of data is missed.

### 3.1.3. Multiplexer:

After loading and compressing the image we got a matrix of n x n size. In order to transfer these values over the channel we need to convert it first into the binary bit stream. So, we used the multiplexer which receives many inputs and generate one particular output that is the bit stream.

### 3.1.4. Modulation:

The received digital bit stream will be modulated by using Binary Phase Shift Keying (BPSK). In this technique of digital modulation one bit per symbol will be send over the channel.

### 3.1.5. Noisy Wireless Channel:

The wireless communication channel is corrupted with additive white gaussian noise (AWGN). For AWGN we have randomly added blink noise to the channel.

### 3.1.6. Demodulation:

The received signal which is corrupted with the AWGN is demodulated using the BPSK technique. Which converts it into a bit stream.

### 3.1.7. Demultiplexer:

Bit stream which is corrupted now demultiplex from a stream to matrix. This step is inverse of the multiplexer step.

### 3.1.8. Decompressed:

The last step before getting the retrieved dirty image is to decompress the image, which is done by inversing the compression function.

### 3.1.9. Retrieved Dirty Images:

After completing the steps of figure 6, the input clean image is not corrupter with the AWGN and burst errors as shown in the figure 7 and 8 below.

**Figure 7: (a)**: Input Clean Image **(b)** Retrieved Dirty Image with AWGN

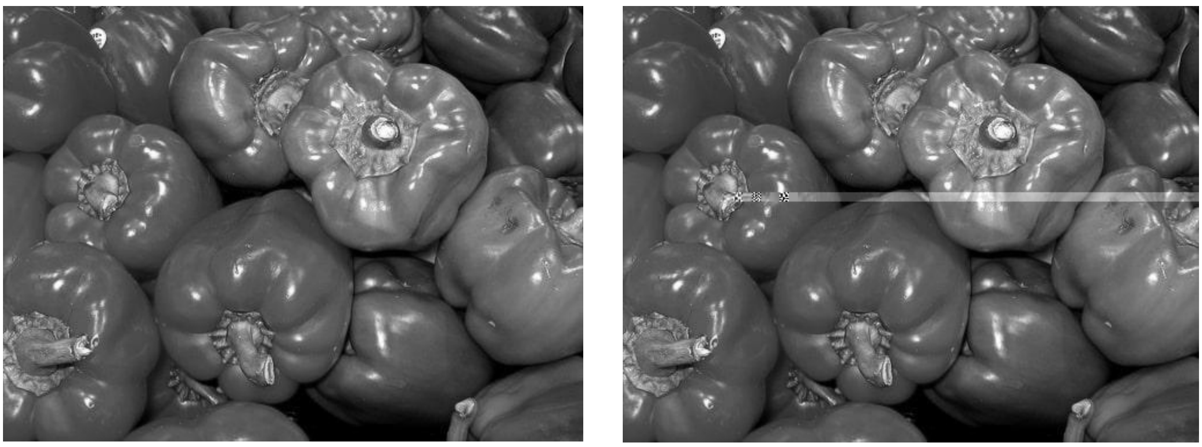


**Figure 8: (a)**: Input Clean Image **(b)** Retrieved Dirty Image with Burst Error

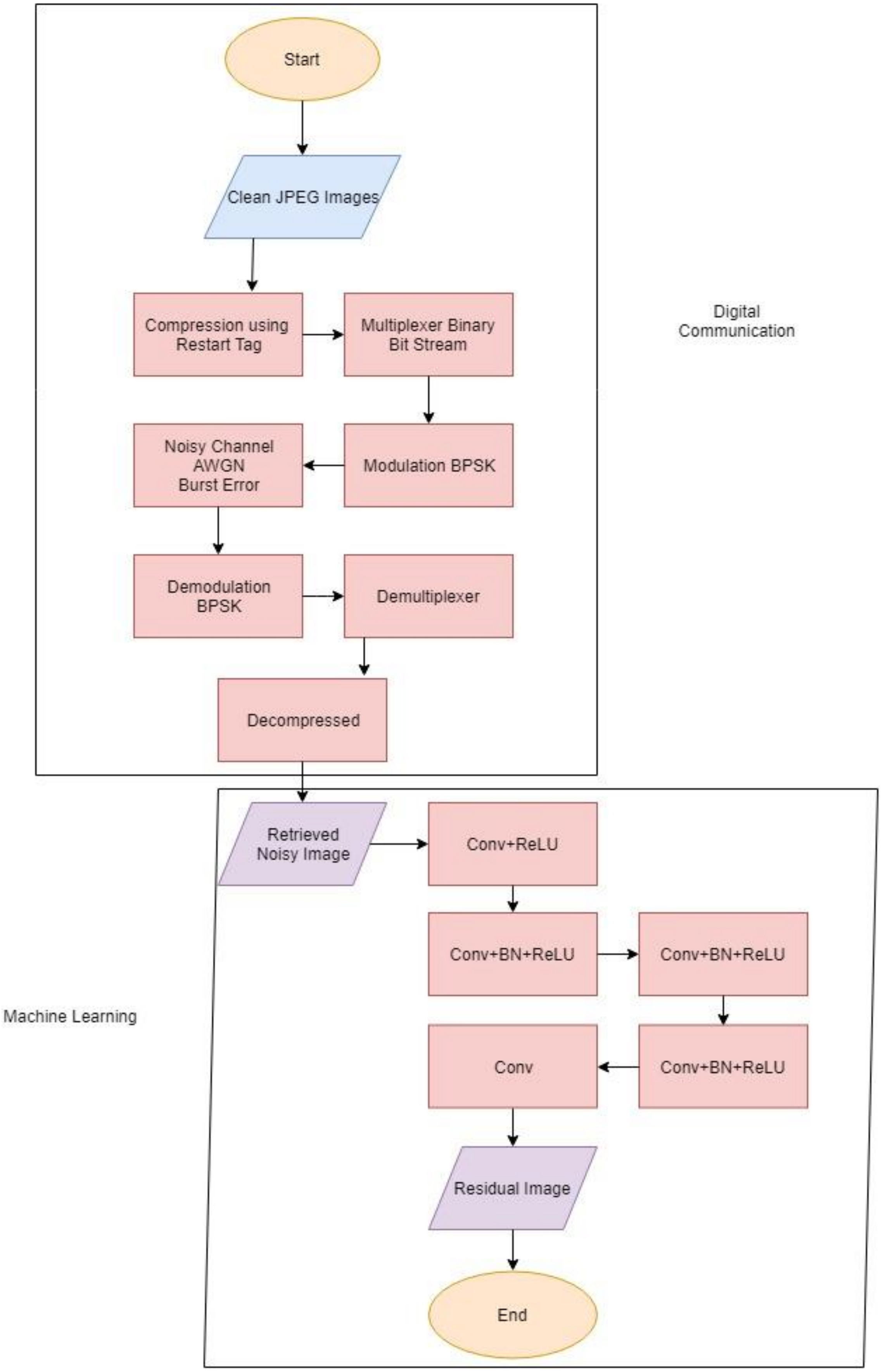



**Figure 9:** Flowchart of Proposed Methodology

We have organized the rest of the chapter by first introducing the simple convolutional neural network that denoise the images by progressive learning, the next section describes the designing of the convolutional neural network. For the gaussian noise removal Batch Normalization and Residual Learning are very useful. Our proposed CNN can remove the unknown level of gaussian noise by mapping the input image.

The incredible progress in the CNNs theses few years have observed the dramatic increase of exploring convolutional neural networks for solving the image denoising problems. convolutional neural networks have the advantages of great performance and fast processing when CNNs are compared with the traditional methods which are model based. The image denoising CNN can be explained by these three points:

a. Can we study the convolutional neural network as a image denoiser?
b. Can the CNNs learn for denoising the image of unknown level?
c. Can we use the CNNs for other tasks related to image restoration?

Noise in images can be very sophisticated than the simple gaussian noise. The current convolutional neural network denoisers usually have low performance on real time noisy images. So, it is very interesting to study the problems related to image restoration such as gaining of noise clear images and unsupervised CNN for real images denoising.

## 3.2. Denoising the Images with Deep CNN

Discriminative models or conditional models which are used for image denoising is attracting significant attentions because of the promising image denoising performance. These models are opposed to generative models. Distribution of conditional probability P(y|x), which is used for the prediction of **y** from the **x**. Conditional or Discriminative models are inherently supervised (used with label data only). modeling the dependence of unobserved (target) variables Y on observed variables ***x***. In this section we will discuss the feed forward CNN for image denoising which has embraced the progress in the learning algorithm.

## 3.3. Architecture Design: CNN Image Denoiser

Figure 9 below shows the architecture design of CNN Image Denoiser**.** Noisy image which we retrieved from the digital communication is the input observation. As the equation elaborates y = x + v, where dirty image is **y**, and the clean image is x with addition of the noise v.

Cascade of Shrinkage Fields (CSF) and Multi-Layer Perceptron (MLP) are the two-conditional image denoising models which directly get the F(y) = x (mapping function) for the prediction of latent clean original image.

In the Convolutional Neural Network Image Denoiser, Residual Learning is used for training the residual mapping as shown in the equation R(y) = v, where x will be calculated by this equation x = y − R(y). According to learning models, size of the convolutional filters is 3 × 3. So, accessible network field of Convolutional Neural Network where the depth (**d**) must equal to (2d + 1) × (2d + 1). Network depth d can be increased to negotiate the computational burden cost by using the larger image context information.

Proper depth setting of the Denoising Convolutional Neural Network in the architecture design is the most important issue. Because the proper depth setting has improved trade-off between efficiency and performance. The size of the receptive field in the Denoising Convolutional Neural Network is set to 35 X 35 where the corresponding depth is 17. With the given depth of D, three kinds of layers are shown in the figure 9 below with 3 different colors.

(i) First layer contains the Convolutional and rectified linear unit layers with 64 filters. Every filter size is 3 × 3 × c in order to generate the 64 feature maps. Furthermore (ReLU, max(0, ・)) are used for nonlinearity. Here image channels are represented by the c such as c =1 when the image is grayscale and 3 when the image is colored.

(ii) For the second layers 2 ~ (D − 1), Convolutional and rectified linear unit are used by adding Batch Normalization layer between them. 64 filters are used with the size of 3 × 3 × 64.

(iii) The last layer contains convolutional, where the filters c are having the size of 3 × 3 × 64 for image reconstruction.

To conclude Convolutional Neural Network Image Denoiser has 2 major features. First one is the adoption of Residual Learning R(y) and the second one is Batch Normalization to increase the speed of the training as well as boosting the performance of denoising process. Batch Normalization and Residual Learning benefit from each other. And the integration of these both can effectively speed up the performance and training of the image denoising process.

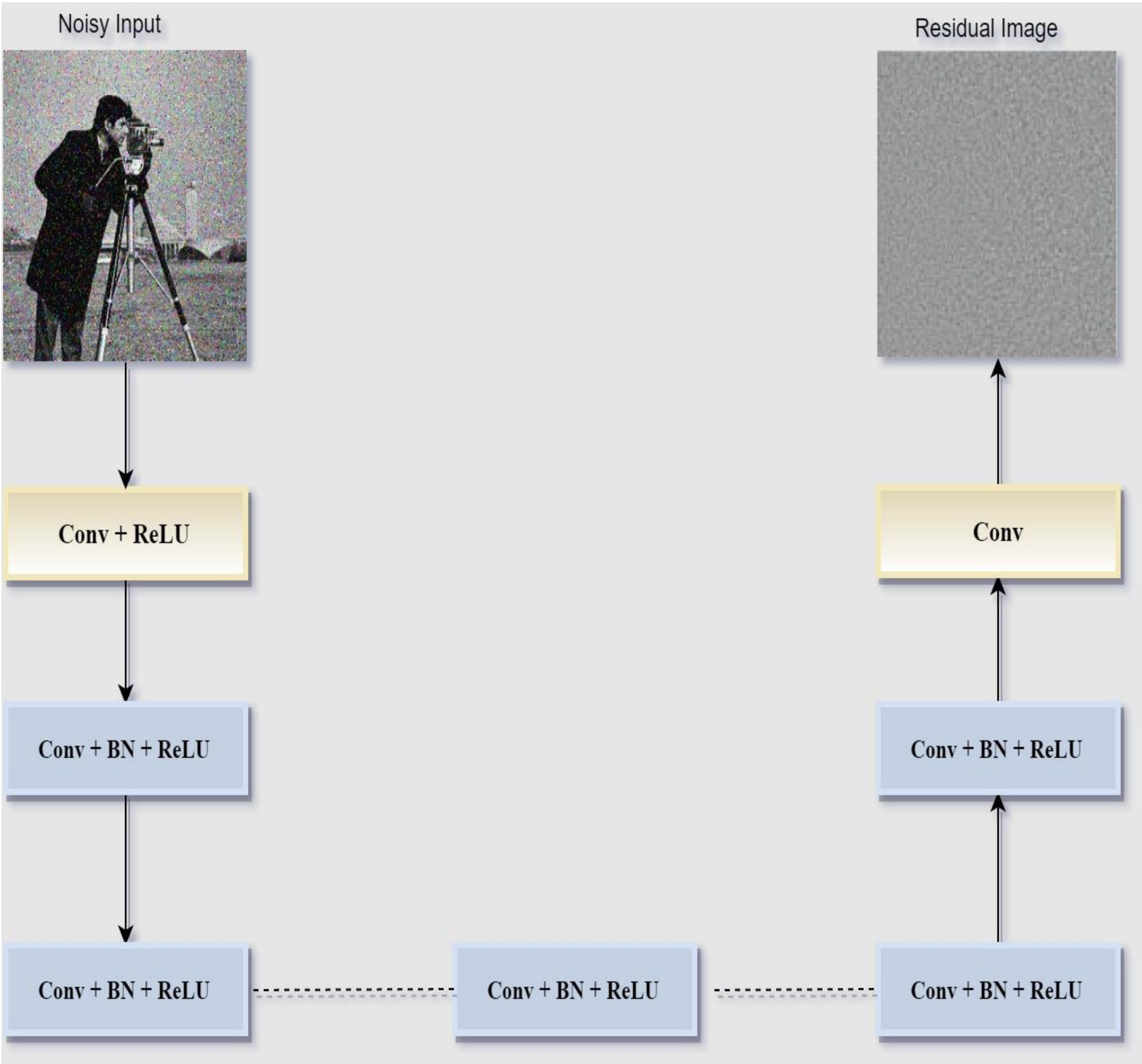



**Figure 10:** Architecture of CNN Image Denoiser

**

Conv = Convolutional Layer

ReLU = Rectified Linear Units

BN = Batch Normalization Layer

## 3.4. Batch Normalization

For the improvement of internal covariate shift the idea of Batch Normalization was presented. It has many advantages like low initialization sensitivity, better performance and fast training. The training process of deep neural network is very complex because the input of every layer changes in the process of training when the previous layer's parameters changed. This causes lower learning rates which can slows down the process of training. Saturating nonlinearities and the parameter initializations make its very complicate to train the network, this is known as internal covariate shift. By making batch normalization as a part of the architecture the model gains strength. For each mini-batch the normalization is performed. We can use high learning rates without caring much about the initialization by using the Batch Normalization. When Batch Normalization is applied to the advanced models of image classification, it gets the same level of accuracy as the original model with less training steps and blows the original model by a substantial margin.

## 3.5. Residual Learning

The main purpose of using the Residual Learning is because its mapping is very easy as compared to original image mapping. Residual network usually stacks several units to lessen the degradations of the accuracy. With the help of residual network, the Convolutional Neural Network for image denoising can be trained and its accuracy can be improved along with the image classification. While typical residual network uses several residual units our convolutional neural network only uses one residual unit for the prediction of the residual image. This approach of getting the residual image has implemented in many areas of low-level vision issues such as SISR.

By using the CNN Image Denoiser the network can be trained for mapping the original image **y** for the prediction of **x** or by using the R(y) residual mapping for the prediction of **v**. According to the research work of [23], when the mapping of original image is same as the identity mapping the optimization of residual mapping could become easier. Because of the similarity of noisy observation which is **y** and the latent clean image which is **x** than the **v** which is residual image, F(**y**) will near to identity mapping than the R(y). That is why the RL is appropriate formulation of CNN Image Denoiser.

Residual Learning is very helpful in stabilizing the network training with BN. CNN Image Denoiser which used Residual Learning to eliminate the latent clean image from the hidden layers. That means the inputs from each layer are less corelated, Gaussian-like distributed and less related with the content of the image. At the end, BN and RL help each other for the denoising of the Additive White Gaussian Noise.

Figure 10 displays the average values of PSNR which are obtained by using 2 learning formulations without/with Batch Normalization. The settings for both optimization algorithms of gradient based and model architecture were same. Optimization algorithms which are gradient based are adopted. First is the ADAM and the second one is the SGD. These both optimization algorithms have best results when the RL and BN are enabling in the model. The incorporation of BN and RL lead towards best performance in image denoising instead the optimization algorithms (ADAM or SGD). Figure 10 shows the four Image denoising models which have different structures of BN and RL layers. 68 Images from the Berkeley dataset were trained for a specific level of noise.

## 3.6. Boundary Artifacts Reduction:

In low level image processing generally, it is demanded to have the same output size image just like the input image. This can create the boundary artifact problem. In other image denoising models such as TNRD and MLP corrupted image is regularly padded in the stage of preprocessing. But in our model, we pad zeros directly before Convolutional just for the surety that feature mapping of both input and middle layers have same size of image. This strategy of zero padding results in mitigating the problem of boundary artifacts.

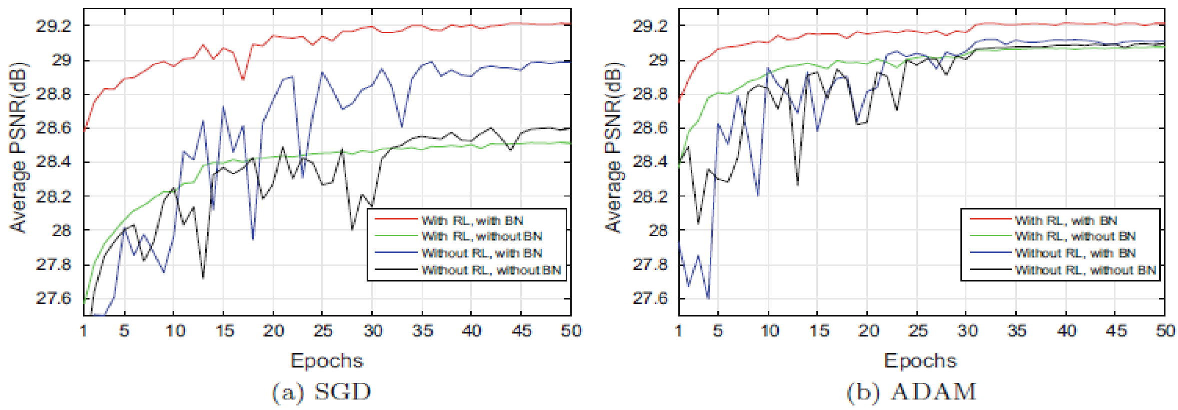



**Figure 11:** Results of four models for AWGN denoising using two optimization algorithms which are gradient based i.e. ADAM and SGD

### 3.7. CNN Image Denoise for unknown Gaussian Level

The existing image denoising models denoise the images for a specific noise level. These models only train the neural network for constant value of noise, i.e., $\sigma = 15$. Our trained model denoise the images for unknown level of noise, i.e. if the noise is not even gaussian distributed. For the training of our CNN model for AWGN removal many quality factors and downsapmled images along with the upscaling factors are used. Experiments show that the trained CNN image denoiser model can yield outstanding results for unknown noise level. Figure 11 displays our CNN model for blind image denoising. Different parts of the input image are corrupted with different level of noises, the retrieved image doesn't have apparent artifacts.

**Figure 12:** Corrupted Input with multiple noise levels

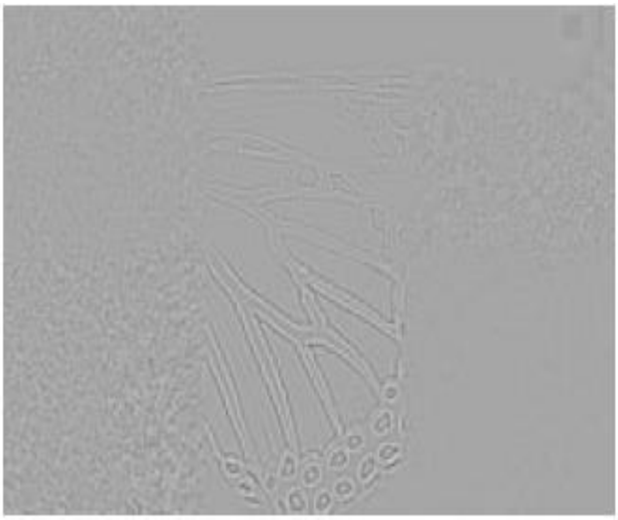


**Figure 13:** Residual of input Image

# Chapter 4

# Dataset, Implementation and Results

# CHAPTER 4: DATASET, IMPLEMENTATION AND RESULTS

This chapter deals with the dataset details, a brief description of implementation and the results of our proposed methodology.

## 4.1. Dataset Description:

AWGN removal for blind noise level, we have followed the work of TNRD. For the network training purpose, the 400 images of 180 x 180 sizes are used. By using the large dataset for the training purpose can only show slight improvement. To train our CNN image denoiser the patch size is set to 50 x 50, and then cropped to 128 x 3000 patches. State of the art image denoising models used 2 specific datasets for the evaluation of the performance. We have used the same sets of images. First one is Berkeley segmentation dataset (BSD68) which contains 68 natural images and the second dataset have 12 images as figure 14 displays. These 2 datasets are not included in the training of our CNN image denoiser.

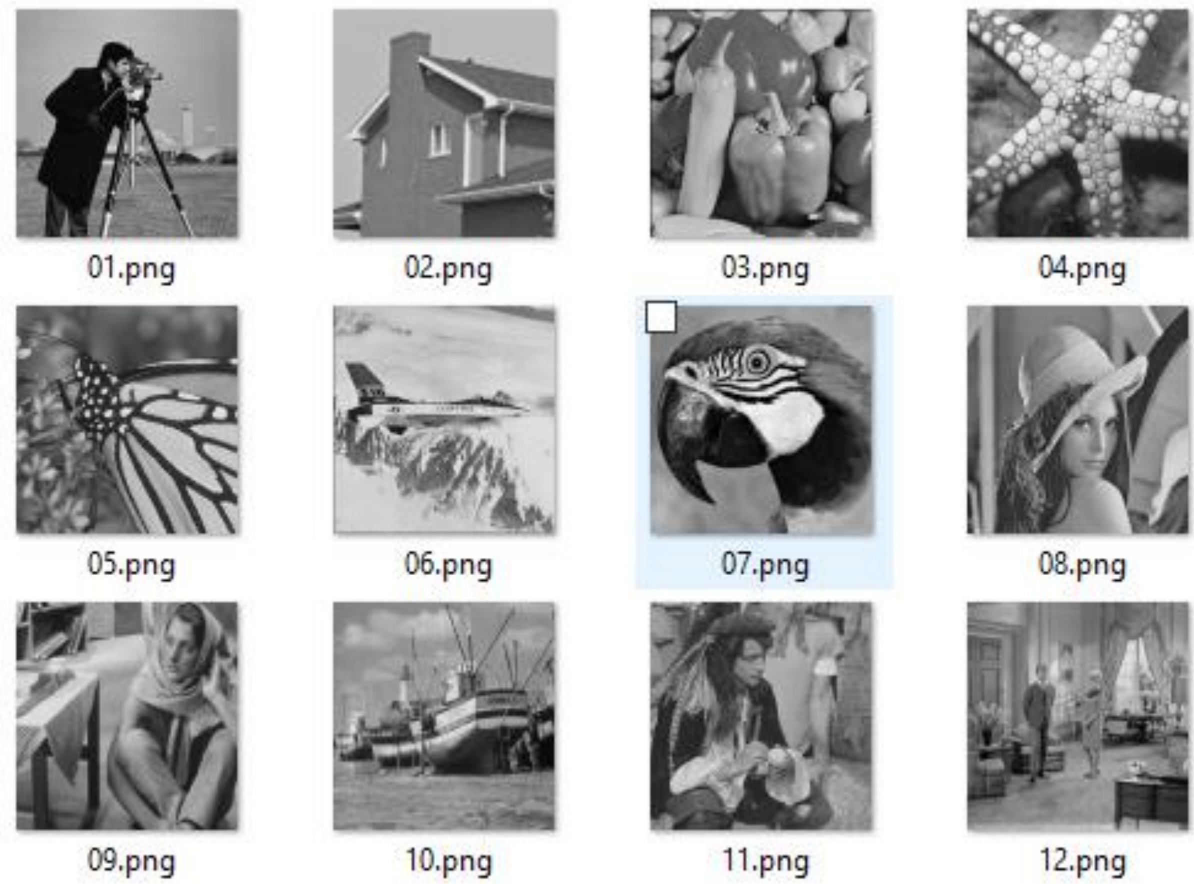



**Figure 14:** Most commonly used dataset of 12 images for performance evaluation of Image denoising models

## 4.2. Training of CNN image denoiser and setting of parameters:

The network depth of CNN Image Denoiser is set to 20 as described in the chapter 3 of proposed methodology. For capturing denoising spatial information this depth will be enough. We have adopted the following equation in order to get the loss function and learning residual mapping R(y) for the residual **v** prediction. 50 epochs were trained for our CNN Image Denoiser and the learning rate decreased from from 1e – 1 to 1e – 4. Weights were initialized as it were in the work of "" and the mini-batch of 128 size.

Corrupted or noisy image is the input to our CNN Image Denoiser y = x + v. Residual learning was adopted by our model for the residual mapping training R(y) = v, and by replacing the value of v, we have x = y - R(y). The difference between the noisy image and residual image is avrg. Mean Square Error, which we adopted as loss function in our model. In equation (1) $\{(y_i; x_i)\}^{N}_{i=1}$ signifies N noisy-clean training image (pair) patches.

$$\ell(\mathbf{\Theta}) = \frac{1}{2N} \sum_{i=1}^{N} \|\mathcal{R}(\mathbf{y}_i; \mathbf{\Theta}) - (\mathbf{y}_i - \mathbf{x}_i)\|_F^2 \qquad (1)$$

In image restoration, visual quality is also an important factor which is considered by calculating the run time testing speed of the code. Our model is well suited for processing on GPU. Because of the use of Batch Normalization layers parallel computing is necessary. Our model has very high speed on the CPU for the digital communication part. Table I below shows the implementation properties of our trained model. The comparison of our model is made with two modern image denoising models Block Match 3-D Filtering BM3D and Trainable Nonlinear Reaction–Diffusion TNRD.

## 4.3. Implementation

Table 1 below shows the implementation properties of our trained model.

**Table 1**: Implementation Requirements

| | |
|---|---|
| **Package** | MatcConvNet |
| **Environment** | MATLAB (R2015b) |
| **GPU** | Nvidia Titan X |
| **Time Consumed** | 24 hours |
| **PC** | CPU 3.30GHz Intel(R) Core (TM) i7-5820004B |

## 4.4. Compared Models

We have compared our model with two state of the art image denoising models. Block-matching and 3D filtering (***BM3D***) and Trainable Nonlinear Reaction–Diffusion (**TNRD**). We have downloaded the codes of these two models from the authors websites and run it against the default parameters setting for getting the comparison results.

## 4.5. Results

### 4.5.1. Quantitative Evaluation:

The average PSNR results of our model and two comparison models are shown in the table below. Our model has achieved best results and competed the two comparison models.

**Table 2:** The Average PSNR (dB) of different models on Dataset BSD68

| **Methods** | **BM3D** | **TNRD** | **CNN Image Denoiser** |
|---|---|---|---|
| **Noise Level [0-55]** | 25.62 | 25.97 | 26.23 |

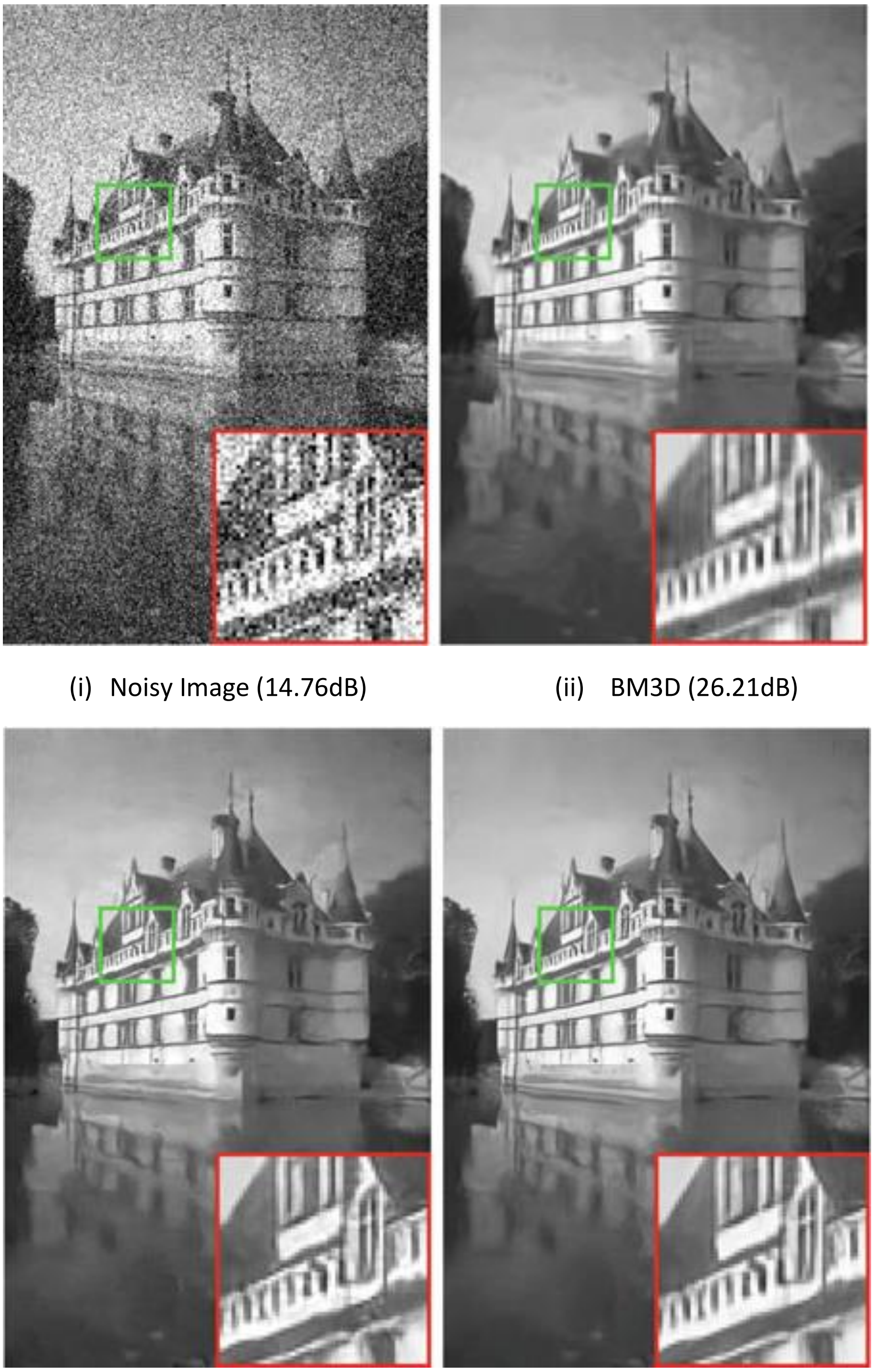
**Table 3(a):** Average PSNR (dB) of different models on dataset 12

| Images | C.man | House | Peppers | Starfish | Monar. | Airpl. | Parrot |
|---|---|---|---|---|---|---|---|
| **BM3D** | 26.13 | 26.13 | 26.68 | 25.04 | 25.82 | 25.10 | 25.90 |
| **TNRD** | 26.62 | 29.48 | 27.10 | 25.42 | 26.31 | 25.59 | 26.16 |
| **CNN Image Denoiser** | 27.03 | 30.02 | 27.39 | 25.72 | 26.83 | 25.89 | 26.48 |

**Table 3(b):** Average PSNR (dB) of different models on dataset 12

| Images | Lena | Barbara | Boat | Man | Couple | Average |
|---|---|---|---|---|---|---|
| **BM3D** | 29.05 | 27.22 | 26.78 | 26.81 | 26.46 | **26.46** |
| **TNRD** | 28.93 | 25.70 | 26.94 | 26.98 | 26.50 | **26.50** |
| **CNN Image Denoiser** | 29.38 | 26.38 | 27.23 | 27.23 | 26.91 | **26.91** |

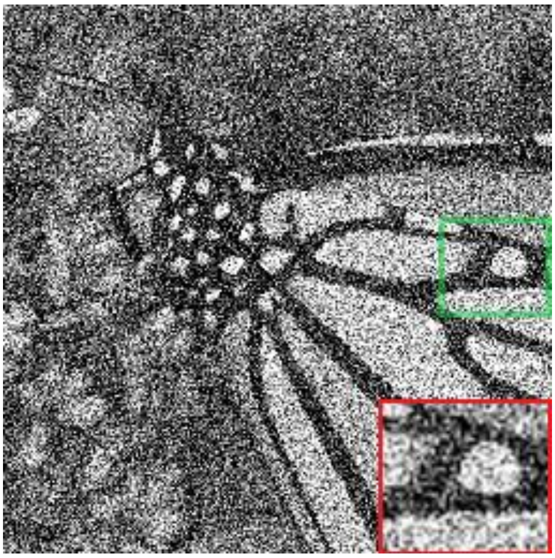
### 4.5.2. Qualitative Evaluation:



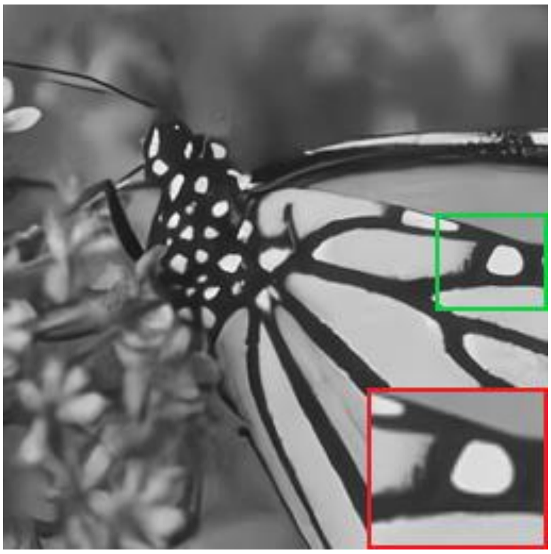
(i) Noisy Image (14.76dB) (ii) BM3D (26.21dB)

(iii) TNRD (26.59dB) (iii) CNN Image Denoiser (26.90dB)

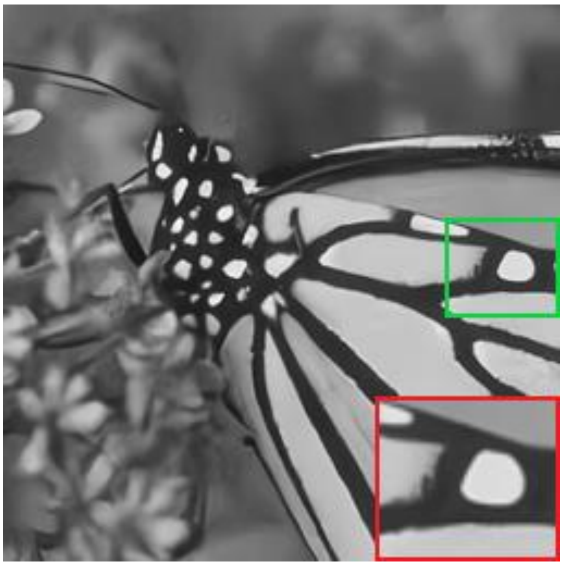
**Figure 15:** Denoising results of three models



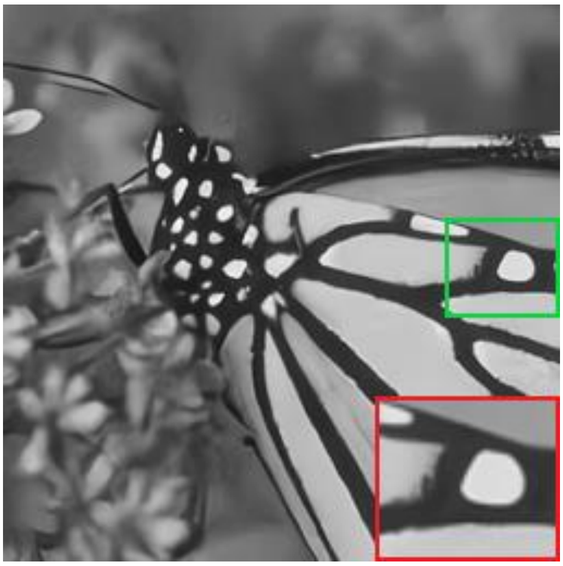
(i) Noisy Monarch Image



(ii) BM3D [25] (25.82 dB)



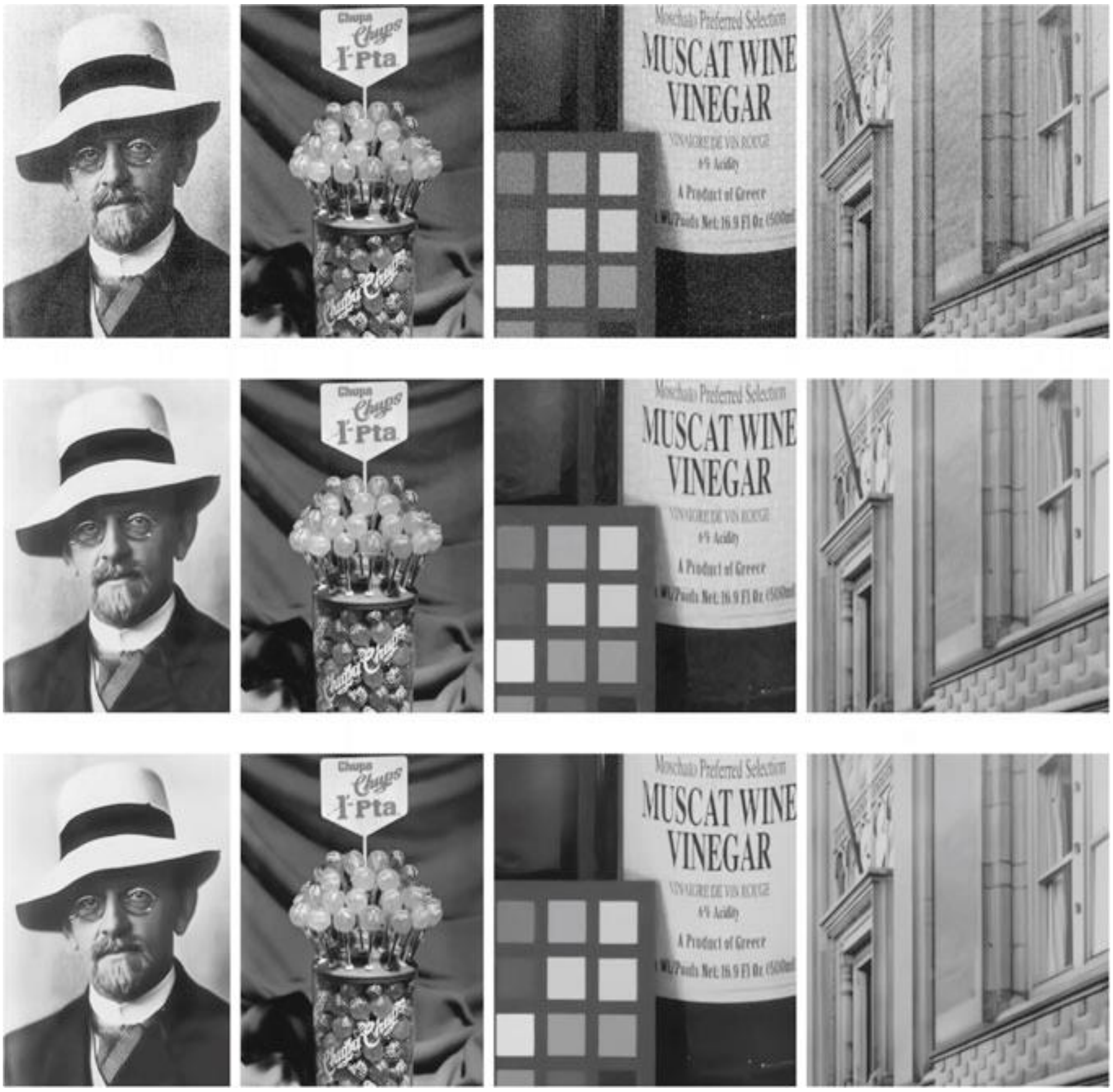
(iii) TNRD (26.31 dB)



(iv) CNN Image Denoiser (26.83 dB)

**Figure 16:** Denoising results of BM3D, TNRD and CNN Image Denoise

Figure 15 and 16 shows the results of denoising of or model CNN image denoiser, BM3D and TNRD. While figure 17 shows the real time corrupted images and their denoised versions by CNN image Denoiser, TNRD and BM3D.




(a) *David Hilbert* (b) *Chupa Chups* (c) *Vinegar* (d) *Building*

**Figure 17:** Denoising results of CNN image denoiser and BM3D on real time corrupted images

# Chapter 5

# Conclusion, Challenges and Future Work

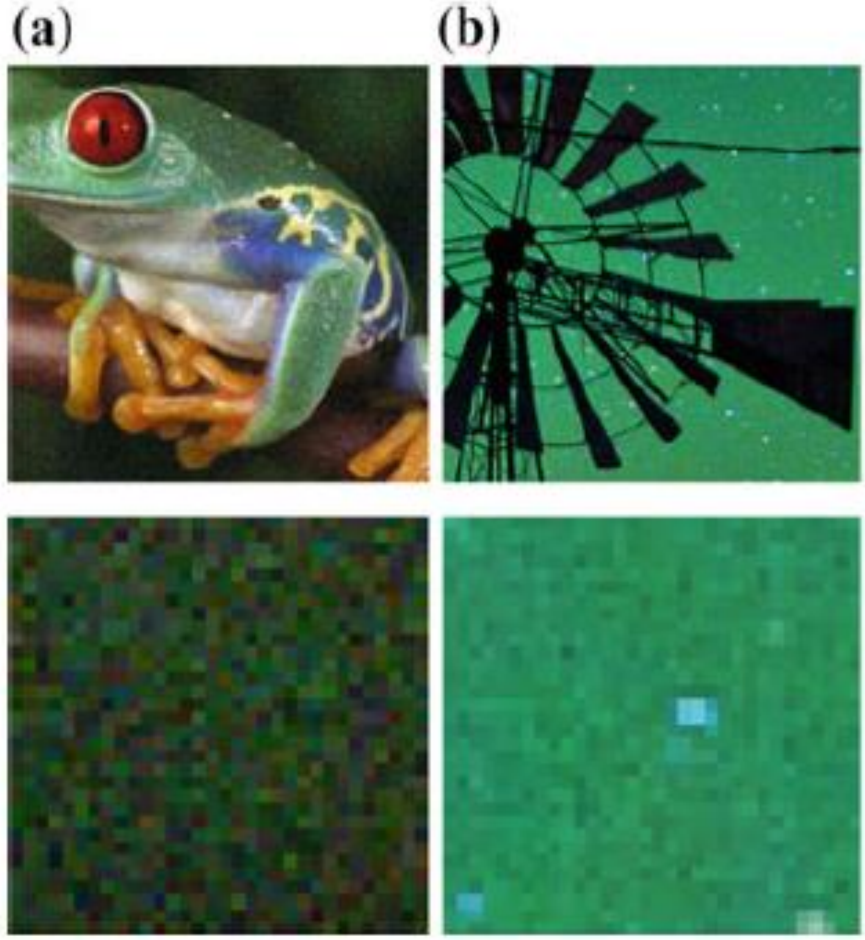
# CHAPTER 5: CONCLUSION, CHALLENGES AND FUTURE WORK

In our research thesis, first we have comprehensively described the characteristic of a noise corrupted channel of digital communication and its effect on the content of the data. The detailed overview of image transmission over noise corrupted channel is illustrated. Then we showed the architecture and implementation of CNN for denoising the wireless channel (AWGN) corrupted images. We have compared our method with modern denoising models and results shows that our method performed better. Our research paper offers significant cues on digital communication methods and for image processing applications.

A lot of research work has been done on removal of Additive White Gaussian Noise, but only few authors have studied the denoising of natural images. Performance evaluation of the image denoiser is very difficult that is why denoising the natural images face many issues since the natural and real time images are very much sophisticated. Figure below shows the other types of noises which corrupt the real time images. As one can witnessed that the properties of such noise’s types are much diverse, and model trained with the fix noise can not deal with these noise types.

Generally, image denoiser model can denoise the image for a specific amount of noise. A model which is trained with a specific value of standard deviation cannot remove the poison/ blind noise. The reason behind that drawback is Convolutional Neural Network can only be used as general denoiser. Even still, this general image denoise for Additive White Gaussian Noise removal is a valuable research because of the reason that it’s an ideal benchmark for effectively evaluating the different CNN Image denoisers. The other reason is that a lot of image reconstruction issues can be solved by linearly solving the AWGN problems, that broadens the field of application. To increase the performance of Convolutional Neural Network based image denoising model, straightforward method is to get enough information of actual clean and noisy training pairs. This method has many pros because no need to worry about complicated degradation method. Though, capturing the equivalent clean observation of a noise corrupted image is not a minor task because many postprocessing steps are required to carefully handle this.

On the other hand, simulation can be done on the real images and on the degradation method to synthesize noise corrupted observations for a clean one. Though, it's not an easy task to precisely model the complicated degradation method. The said image denoising model could be dissimilar for diverse cameras.



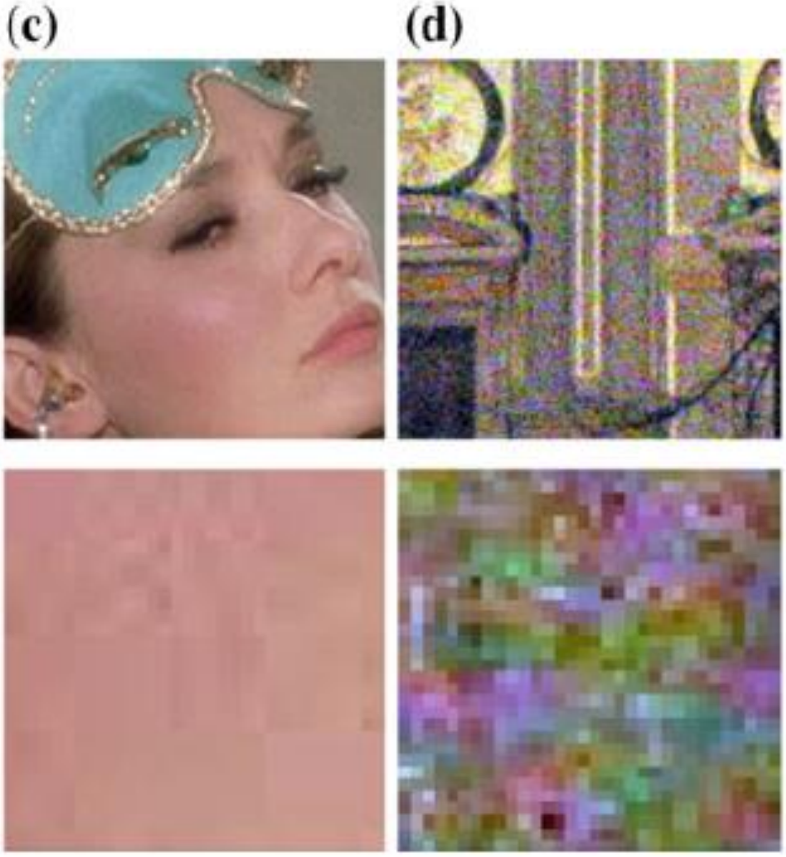



Fig. 18 Noise of different types. (a). Additive white Gaussian Noise (AWGN); (b) inter channel correlated Gaussian; (c) JPEG compression noise; (d) low-frequency noise

# References


[1] Ahn B, Cho NI (2017) Block-matching convolutional neural network for image denoising. arXiv:1704.00524

[2] Bae W, Yoo J, Ye JC (2017) Beyond deep residual learning for image restoration: persistent homology-guided manifold simplification. In: The IEEE conference on computer vision and pattern recognition (CVPR) workshops, pp 145–153

[3] Bako S, Vogels T, McWilliams B, MeyerM, Novák J, Harvill A, Sen P, DeRose T, Rousselle F (2017) Kernel-predicting convolutional networks for denoising Monte Carlo renderings. ACM Trans Gr 36(4):97

[4] Barbu A (2009) Training an active random field for real-time image denoising. IEEE Trans Image Process 18(11):2451–2462

[5] Burger HC, Schuler CJ, Harmeling S (2012) Image denoising: can plain neural networks compete with BM3D? In: IEEE conference on computer vision and pattern recognition, pp 2392–2399

[6] Chambolle A, Pock T (2011) A first-order primal-dual algorithm for convex problems with applications to imaging. J Math Imaging Vis 40(1):120–145

[7] Chan SH, Wang X, Elgendy OA (2017) Plug-and-Play ADMM for image restoration: fixedpoint convergence and applications. IEEE Trans Comput Imaging 3(1):84–98

[8] Chen Y, Pock T (2017) Trainable nonlinear reaction diffusion: a flexible framework for fast and effective image restoration. IEEE Trans Pattern Anal Mach Intell 39(6):1256–1272

[9] Choi JH, Elgendy O, Chan SH (2017) Integrating disparate sources of experts for robust image denoising. arXiv:1711.06712

[10] ColomM,LebrunM,BuadesA, MorelJM(2014)Anon-parametric approach for the estimation of intensity-frequency dependent noise. In: IEEE international conference on image processing, pp 4261–4265

[11] Dabov K, Foi A, Katkovnik V, Egiazarian K (2007) Image denoising by sparse 3-D transformdomain collaborative filtering. IEEE Trans Image Process 16(8):2080–2095

[12] Godard C, Matzen K, Uyttendaele M (2017) Deep burst denoising. arXiv:1712.05790

[13] Gu S, Zhang L, Zuo W, Feng X (2014) Weighted nuclear norm minimization with application to image denoising. In: IEEE conference on computer vision and pattern recognition, pp 2862–2869

[14] He K, Zhang X, Ren S, Sun J (2015) Delving deep into rectifiers: surpassing human-level performance on imagenet classification. In: ICCV, pp 1026–1034

[15] He K, Zhang X, Ren S, Sun J (2016) Deep residual learning for image recognition. In: IEEE conference on computer vision and pattern recognition, pp 770–778

[16] Heide F, Steinberger M, Tsai YT, Rouf M, Pajak D, Reddy D, Gallo O, Liu J, Heidrich W, Egiazarian K et al (2014) FlexISP: a flexible camera image processing framework. ACM TransGr 33(6):231

[17] Ioffe S, Szegedy C (2015) Batch normalization: accelerating deep network training by reducing internal covariate shift. In: International conference on machine learning, pp 448–456

[18] Jain V, Seung S (2009) Natural image denoising with convolutional networks. In: Advances in neural information processing systems, pp 769–776 122 W. Zuo et al.

[19] Kim Y, Jung H, Min D, Sohn K (2017) Deeply aggregated alternating minimization for image restoration. In: IEEE conference on computer vision and pattern recognition, pp 6419–6427

[20] Kingma D, Ba J (2015) Adam: a method for stochastic optimization. In: Internationa conference for learning representations

[21] Kligvasser I, Shaham TR, Michaeli T (2017) xUnit: learning a spatial activation function for efficient image restoration. arXiv:1711.06445

[22] Krizhevsky A, Sutskever I, Hinton GE (2012) ImageNet classification with deep convolutional neural networks. In: Advances in neural information processing systems, pp 1097–1105

[23] Lebrun M, Colom M, Morel JM (2015) The noise clinic: a blind image denoising algorithm. Image Process On Line 5:1–54. http://demo.ipol.im/demo/125/ Lee JS (1981) Refined filtering of image noise using local statistics. Comput Gr Image Process 15(4):380–389

[24] Lefkimmiatis S (2017) Non-local color image denoising with convolutional neural networks. In: IEEE conference on computer vision and pattern recognition, pp 3587–3596

[25] Lefkimmiatis S (2018) Universal denoising networks: a novel CNN-based network architecture for image denoising. In: IEEE conference on computer vision and pattern recognition

[26] Levin A, Nadler B (2011) Natural image denoising: optimality and inherent bounds. In: IEEE conference on computer vision and pattern recognition, pp 2833–2840

[27] LiuC, Szeliski R, Kang SB,ZitnickCL, FreemanWT(2008) Automatic estimation and removal of noise from a single image. IEEE Trans Pattern Anal Mach Intell 30(2):299–314

[28] Mildenhall B, Barron JT, Chen J, Sharlet D, Ng R, Carroll R (2017) Burst denoising with kernel prediction networks. arXiv:1712.02327

[29] Pan J, Hu Z, Su Z, Yang MH (2014) Deblurring text images via L0-regularized intensity and gradient prior. In: IEEE conference on computer vision and pattern recognition, pp 2901–2908

[30] Remez T, Litany O, Giryes R, Bronstein AM (2017) Deep class-aware image denoising. In: International conference on sampling theory and applications, pp 138–142

[31] Riegler G, Schulter S, Ruther M, Bischof H (2015) Conditioned regression models for nonblind single image super-resolution. In: IEEE international conference on computer vision, pp 522–530

[32] Romano Y, Elad M, Milanfar P (2016) The little engine that could: Regularization by denoising (RED). SIAM J Imaging Sci (submitted)

[33] Roth S, Black MJ (2005) Fields of experts: a framework for learning image priors. In: IEEE computer society conference on computer vision and pattern recognition, vol 2, pp 860–867

[34] Roth S, Black MJ (2009) Fields of experts. Int J Comput Vis 82(2):205–229

[35] Samuel KG, Tappen MF (2009) Learning optimized MAP estimates in continuously-valued MRF models. In: IEEE conference on computer vision and pattern recognition, pp 477–484

[36] Santhanam V, Morariu VI, Davis LS (2017) Generalized deep image to image regression. In: IEEE conference on computer vision and pattern recognition, pp 5609–5619

[37] Schmidt U, Roth S (2014) Shrinkage fields for effective image restoration. In: IEEE conference on computer vision and pattern recognition, pp 2774–2781

[38] Shi W, Caballero J, Huszár F, Totz J, Aitken AP, Bishop R, Rueckert D, Wang Z (2016) Realtime single image and video super-resolution using an efficient sub-pixel

convolutional neural network. In: IEEE conference on computer vision and pattern recognition, pp 1874–1883

[39] Simonyan K, Zisserman A (2015) Very deep convolutional networks for large-scale image recognition. In: International conference for learning representations

[40] Sreehari S, Venkatakrishnan S, Wohlberg B, Drummy LF, Simmons JP, Bouman CA (2015) Plug-and-play priors for bright field electron tomography and sparse interpolation. arXiv:1512.07331

[41] Sun J, TappenMF (2011) Learning non-local range Markov random field for image restoration. In: IEEE conference on computer vision and pattern recognition, pp 2745–2752

[42] Sun J, Tappen MF (2013) Separable Markov random field model and its applications in low level vision. IEEE Trans Image Process 22(1):402–407

[43] Vedaldi A, Lenc K (2015) MatConvNet: convolutional neural networks for matlab. In: ACM conference on multimedia conference, pp 689–692 Convolutional Neural Networks for Image Denoising and Restoration 123

[44] Vogel C, Pock T (2017) A primal dual network for low-level vision problems. In: German conference on pattern recognition. Springer, pp 189–202

[45] Wang T, Qin Z, Zhu M (2017) An ELU network with total variation for image denoising. In: International conference on neural information processing. Springer, pp 227–237

[46] Wang T, SunM, Hu K (2017) Dilated residual network for image denoising. arXiv:1708.05473

[47] Yang D, Sun J (2018) Bm3d-net: a convolutional neural network for transform-domain collaborative filtering. IEEE Signal Process Lett 25(1):55–59

[48] Yu F,KoltunV(2016) Multi-scale context aggregation by dilated convolutions. In: International conference on learning representations

[49] Zhang K, Zuo W, Chen Y, Meng D, Zhang L (2017) Beyond a Gaussian denoiser: residual learning of deep CNN for image denoising. IEEE Trans Image Process 26(7):3142–3155

[50] Zhang K, ZuoW, Gu S, Zhang L (2017) Learning deep CNN denoiser prior for image restoration. In: IEEE conference on computer vision and pattern recognition, pp 3929–3938

[51] Zhang K, Zuo W, Zhang L (2018) Learning a single convolutional super-resolution network for multiple degradations. In: IEEE conference on computer vision and pattern recognition

[52] Zoran D, Weiss Y (2011) From learning models of natural image patches to whole image restoration. In: IEEE international conference on computer vision, pp 479–486