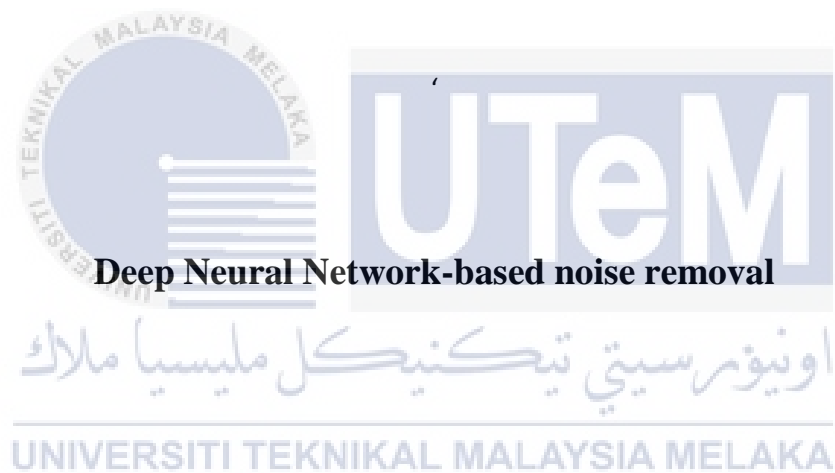




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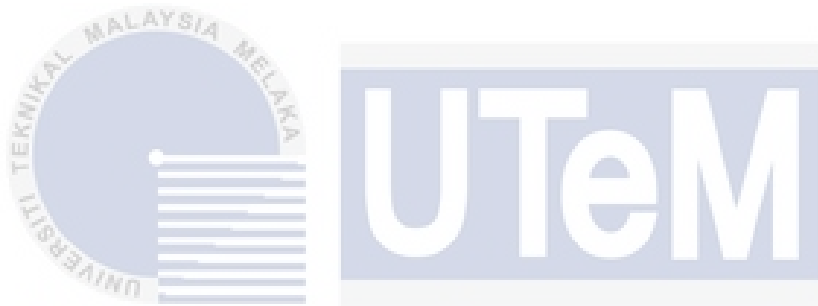
LIEW TING FOO

Bachelor of Computer Engineering Technology (Computer Systems) with Honours

DEEP NEURAL NETWORK BASED NOISES REMOVAL

LIEW TING FOO

**A project report submitted to partial fulfillment of the requirements for the degree of
Bachelor of Computer Engineering Technology (Computer Systems) with Honours**



Faculty of Electronic and Computer Technology and Engineering

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

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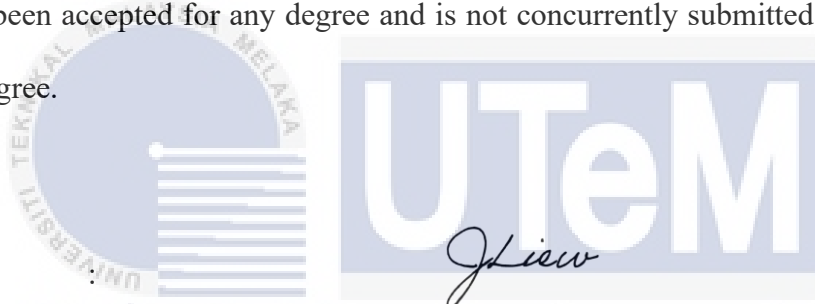
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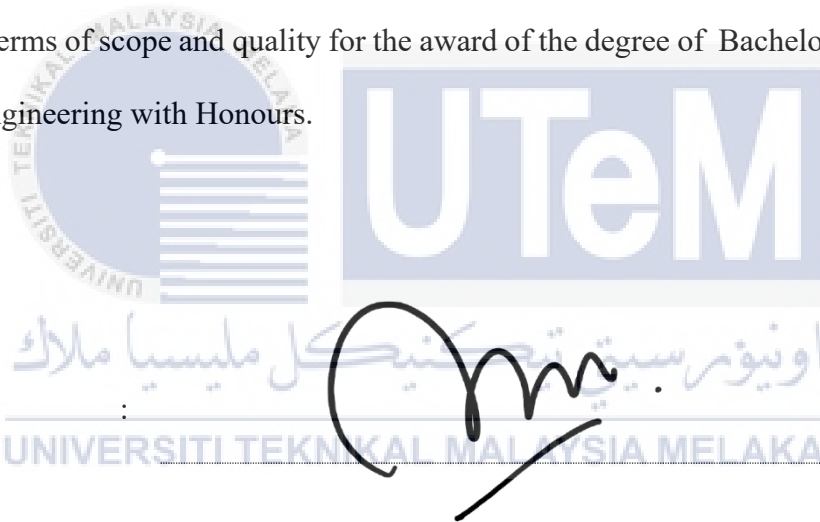
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A handwritten signature in black ink, appearing to be 'Rostam', is written over the signature line.

Supervisor Name :

TS. DR. ROSTAM AFFENDI BIN HAMZAH

Date :

15/01/2024

DEDICATION

I dedicate this thesis to those who have been my pillars of strength throughout this academic journey.

To my parents, whose unwavering support, encouragement, and sacrifices have been the driving force behind my pursuit of knowledge. Your belief in me has been my constant inspiration.

To my professors TS. DR. ROSTAM AFFENDI BIN HAMZAH, for his guidance, wisdom, and the invaluable lessons he imparted. Your passion for your subject matter ignited my own enthusiasm and dedication.

This achievement is a testament to the collective effort of those who stood by me. Thank you for being my source of strength, encouragement, and inspiration. This thesis is dedicated to you.



ABSTRACT

This thesis covers the design of Deep Neural Network based noises removal by using Convolutional Neural Network architecture. The goal for this project is to validate the performance of peak signal noise-ratio before and after the process of the image, and remove Gaussian noise from noisy image, and output an improved image quality with edge detail preservation as much as possible, Using CNN as a trained model, design a Matlab code to perform denoising by adjusting the parameter of the training option and dnds datastore. Some of the traditional method such as Block Matching & 3D filtering, BM3D and Expected Patch log-likelihood method, EPLL is worse compared to CNN, these methods also have their own problems which is low image quality, low Peak Noise Signal-Ratio, etc. That is why Convolutional Neural Network related methodologies is created to enhance the denoising performance. This network architecture utilized the technique of deep learning to denoising the image. So, this thesis is to review CNNs model for image denoising approaches and resulting in better image quality with high PNSR value.



ABSTRAK

Tesis ini merangkumi reka bentuk Pengenalan Bunyi Neural Mendalam berdasarkan senarai reka bentuk Convolutional Neural Network. Matlamat bagi projek ini adalah untuk mengesahkan prestasi nisbah isyarat puncak kebisingan sebelum dan selepas proses imej, dan menghilangkan kebisingan Gaussian dari imej berkebisingan, serta mengeluarkan kualiti imej yang diperbaiki dengan pemeliharaan butiran pinggir sebanyak mungkin. Dengan menggunakan CNN sebagai model yang dilatih, reka kod Matlab untuk melakukan penyingkiran kebisingan dengan menyesuaikan parameter opsyen latihan dan datastore dnds. Beberapa kaedah tradisional seperti Penyelarasan Blok & penapisan 3D, BM3D, dan kaedah Kebarangkalian Log Pecahan yang Dijangka, EPLL, lebih buruk berbanding CNN; kaedah-kaedah ini juga mempunyai masalah tersendiri seperti kualiti imej yang rendah, nisbah isyarat puncak kebisingan yang rendah, dan sebagainya. Oleh itu, kaedah berkaitan Convolutional Neural Network dicipta untuk meningkatkan prestasi penyingkiran kebisingan. Seni bina rangkaian ini menggunakan teknik pembelajaran mendalam untuk penyingkiran kebisingan imej. Oleh itu, tesis ini bertujuan untuk menyemak model CNN untuk pendekatan penyingkiran kebisingan imej dan menghasilkan kualiti imej yang lebih baik dengan nilai PNSR yang tinggi.

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First and foremost, I would like to express my gratitude to my supervisor, TS. DR. ROSTAM AFFENDI BIN HAMZAH for their precious guidance, words of wisdom and patient throughout this project.

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TABLE OF CONTENT

PAGE

DECLARATION	
APPROVAL	
DEDICATIONS	
ABSTRACT	I
ABSTRAK	II
ACKNOWLEDGEMENT	III
TABLE OF CONTENT	IV
LIST OF TABLES	VI
LIST OF FIGURES	VII
LIST OF SYMBOLS	IX
LIST OF ABBREVIATIONS	X
CHAPTER 1	1
1.1 Background	1
1.2 Motivation	2
1.3 Problem Statement	4
1.4 Project Objective	4
1.5 Scope of Project	4
CHAPTER 2	6
2.1 Introduction	6
2.2 Understanding CNN image denoising	6
2.3 Related work	8
2.3.1 Deep Learning Neural Network Architecture	8
2.3.2 Architecture of CNN for a computer vision task	9
2.3.2.1 Convolutional neural network	10
2.3.2.2 Convolutional Neural Network denoising for general images	11
2.3.3 Train a CNN, Convolutional Neural Network Model.	22
2.3.4 Validate the Model	24
2.4 A sample of figures	27
2.5 Sample of formulas	27
2.6 Summery	31

CHAPTER 3	33
3.1 Introduction	33
3.2 Methodology	34
3.2.1 Convolutional Neural Network training model, CNN	34
3.2.2 Denoising Convolutional Neural Network, DnCNN	35
3.2.3 Training CNN	36
3.2.4 Applying the trained model for Noise Removal	36
3.3 Experimental Setup	37
3.4 Parameters	37
3.4.1 CNN Architecture	37
3.4.2 Training Parameters	37
3.5 Equipment Limitations of Proposed Methodology	37
3.6 Gannt Chart	39
3.7 Summary	40
CHAPTER 4	41
4.1 INTRODUCTION	41
4.2 ANALYSIS OF CONVOLUTIONAL NEURAL NETWORK ALGORITHM	41
4.2.1 Training model algorithm	41
4.2.2 Image denoising algorithm	51
4.3 RESULT	53
4.4 Summary	63
CHAPTER 5	65
REFERENCE	67



LIST OF TABLES

TABLE	TITLE	PAGE
2.1	Comparison of CNN denoising methods for general images	13
2.2	Advantage and disadvantage of CNN denoising methods for general images	14
3.1	Gantt Chart of Project Planning	25



LIST OF FIGURES

FIGURE	TITLE	PAGE
2.1	CNN image denoising scheme [64]	6
2.2	Deep Learning Architecture [65]	8
2.3	Architecture of CNN model with 2 hidden layers [64]	9
2.4	Attention-guided denoising CNN [28]	11
2.5	MP-DCNN [41]	13
2.6	DeGAN [51]	15
2.7	Classifier/regression CNN [59]	16
2.8	Complex-value [60]	17
2.9	Resulting heat map layer	27
2.10	Multiple convolutional layers extracting features from the image and finally, the output layers	28
3.1	Flowchart of CNN architecture	34
3.2	Flowchart of DnCNN	35
4.1	Matlab CNN function for Dataset loading	41
4.2	Matlab CNN function for Labels loading	42
4.3	Matlab CNN function to initialize convolution	42
4.4	MATLAB CNN function of Pooling Layer.	43
4.5	MATLAB code for training CNN.	45
4.6	MATLAB code to test the CNN using MNIST dataset to get accuracy.	46
4.7	MATLAB code to visualize the performance of CNNs	48
4.8	MATLAB code to plot extracted feature from ConvNet	50
4.9	A completed MATLAB code for CNNs denoising	52

4.10	Epoch	53
4.11	Input Image of MNIST dataset before CNN	53
4.12	Image output of CNN filter	54
4.13	Image result of CNN	55
4.14	Image output after ReLU function	55
4.15	Final image result after Mean Pool	56
4.16	Data of 'bird.png' of the process.	57
4.17	Measurement of Peak Signal Noise Ratio of 'bird.png'.	57
4.18	Process of Trained model with 30 epochs and 210 iterations.	57
4.19	Data of 'mountain.png' of the process	58
4.20	Measurement of Peak Signal Noise Ratio of 'mountain.png'.	59
4.21	Process of Trained Model with 30 epochs and 1980 iterations.	59
4.22	Data of 'cameramencolour.png' of the process	60
4.23	Measurement data of Peak Signal Noise Ratio of 'cameramencolour.png'.	60
4.24	Process of Trained Model with 30 epochs and 150 iterations.	60
4.25	Data of 'cameraman.png' of the process	61
4.26	Measurement of Peak Signal Noise Ratio of 'cameraman.png'.	61
4.27	Process of Trained Model with 30 epochs and 180 iterations	61
4.28	Data of 'bridge.png' of the process	62
4.29	Measurement of Peak Signal Noise Ratio of 'bridge.png'.	62
4.30	Process of Trained Model with 30 epochs and 270 iterations	62

LIST OF SYMBOLS

Σ	-	Summation
\in	-	Is an element
Ω	-	Omega
*	-	Multiplication



LIST OF ABBREVIATIONS

- DnCNN - Denoising Convolutional Neural Network
- GPU - Graphic Processing Units
- RAM - Random Access Memory



CHAPTER 1

INTRODUCTION

1.1 Background

Deep learning has revolutionized the field of computational models by employing multiple layers of processing to acquire knowledge and represent data at different levels of abstraction. This mimics the way the human brain comprehends and interprets multimodal information, while effectively capturing intricate structures within vast amounts of complex data from various sources like visuals, sounds, medical records, social media, and sensor data.

The initial motivation behind neural network development was to create a system that emulates the capabilities of the human brain. In 1943, McCulloch and Pitts introduced the MCP model, which explored how interconnected neurons could generate highly intricate patterns. This model played a crucial role in advancing artificial neural networks. Over time, significant contributions were made, such as LeNet and Long Short-Term Memory, culminating in the current "era of deep learning." A breakthrough occurred in 2006 when Hinton et al. presented the Deep Belief Network, which consisted of multiple layers of Restricted Boltzmann Machines and employed unsupervised learning to train each layer incrementally. This breakthrough paved the way for the widespread adoption of deep architectures and deep learning algorithms in the following years.

Deep learning has propelled significant advancements in various computer vision tasks. These include denoising images, detecting objects, tracking motion, recognizing actions, estimating human poses, and performing semantic segmentation. In this overview, we will provide a concise review of the key developments in deep learning architectures and algorithms specifically applied to computer vision. We will focus on three crucial types of deep learning

models: Convolutional Neural Networks (CNNs).

A Convolutional Neural Network (CNN) is a specialized deep learning algorithm designed for tasks related to image processing and recognition. Unlike other classification models, CNNs necessitate minimal preprocessing, as they autonomously acquire hierarchical feature representations from raw input images. CNNs demonstrate proficiency in assigning significance to diverse objects and features within images by utilizing convolutional layers that employ filters to identify local patterns.

The connectivity pattern within CNNs draws inspiration from the human brain's visual cortex, where neurons respond to specific regions or receptive fields in the visual space. This architecture allows CNNs to adeptly capture spatial relationships and patterns in images. Through the strategic stacking of multiple convolutional and pooling layers, CNNs progressively learn intricate features, resulting in elevated accuracy for tasks such as image classification, object detection, and segmentation.

1.2 Motivation

Due to covid-19 pandemic, lot of institute and company forced to change their conduct of business and lecture from physical to online, thus the usage of online meeting applications have risen exponentially year by year, even though the meeting applications have been developed year before, but there exist demerit of using meeting application such as leak of information, audio noise, blurred image, and etc.

After the pandemic, people starting to develop more online meeting application due to the demand. Thus, the developer has conducted few project researches to do improvement for the voice and image. One of the common problems is noise, noise degree the visual quality of image and can affect the performance of computer vision task including object recognition, image segmentation, and medical image analysis.

CNNs have demonstrated astounding effectiveness in a variety of computer vision tasks. They are ideal for noise removal because they can automatically learn from data and extract useful characteristics. A CNN can be taught to effectively remove noise while keeping crucial picture information by training it on a sizable dataset of noisy and comparable clean images.



1.3 Problem Statement

The increasing amount of noise in digital photographs and the demand for a powerful noise removal technique are the problems that this thesis is wrote. Noise is a common issue that lowers image quality, affects their visual appeal, and reduces the accuracy of image analysis activities. Traditional noise removal methods frequently rely on handcrafted algorithms, which may not be effective against various noise types or complex image architectures.

The flaws of current methods indicate the need for a robust and adaptable strategy that can successfully reduce noise while keeping crucial image information. Convolutional neural networks (CNNs) are being used in this project to create a deep neural network-based noise removal technology to resolve these problems.

1.4 Project Objective

The purpose of this project is to develop a deep neural network-based noise removal using convolutional neural network. So that we can create an effective approach of removing noises from digital images while preserving the image details:

1. To design Deep Learning Convolutional Neural Network architecture denoise the image.
2. To validate the performance of peak-signal noise ratio before and after image denoising using CNN architecture.
3. To show qualitative and quantitative measurement.

1.5 Scope of Project

This project is conducted to design Deep Learning Network architecture for images noises removal, specifically Convolutional neural Networks (CNNs). This project aims to

perform denoising in images processing and show the values of peak noise signal-ratio. By comparing various traditional methods of noises removal, to validate the performance of convolutional neural networks effectiveness of image noises removal.



CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Literature review is an overview of the current practice in deep neural network-based noise removal using Convolutional Neural Network. It gives remarks on the impressive noise removal in various applications and the limitations of traditional method. The review explores the alternative design and approach in CNN architectures, and training methodologies for noise removal.

2.2 Understanding CNN image denoising

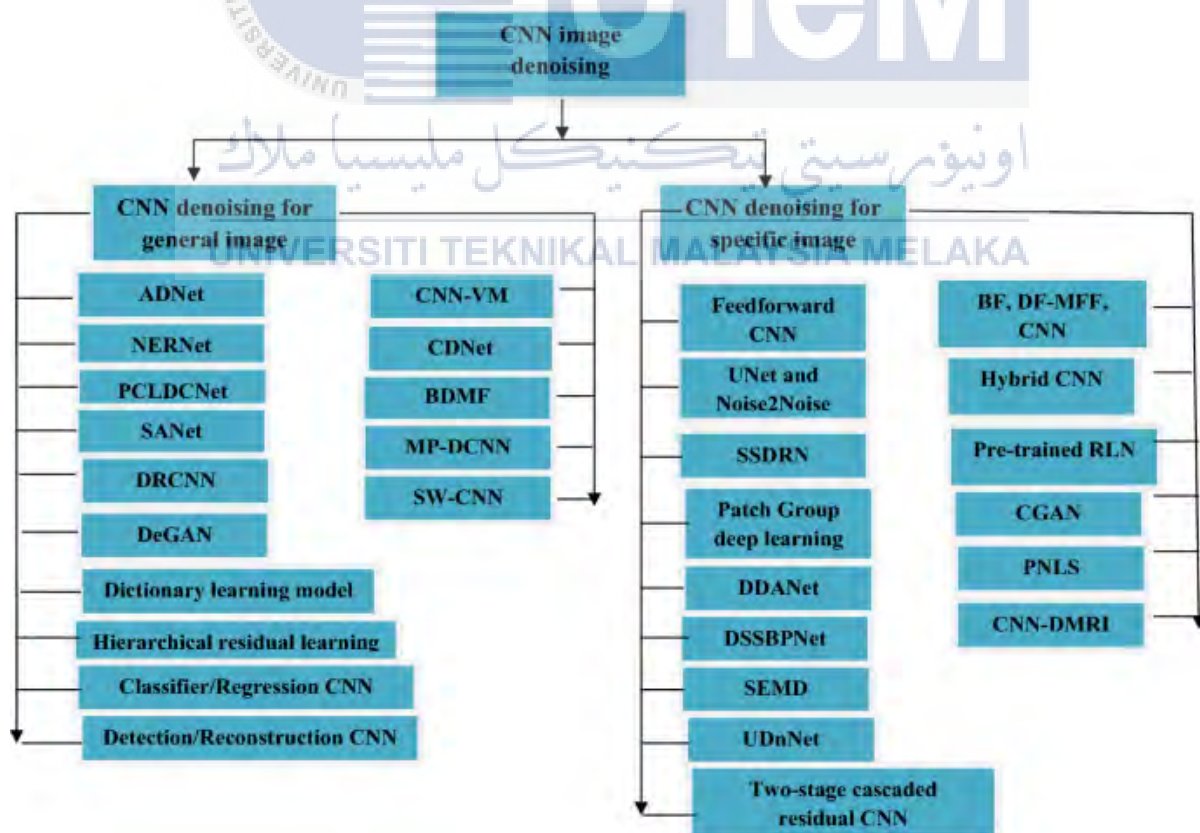
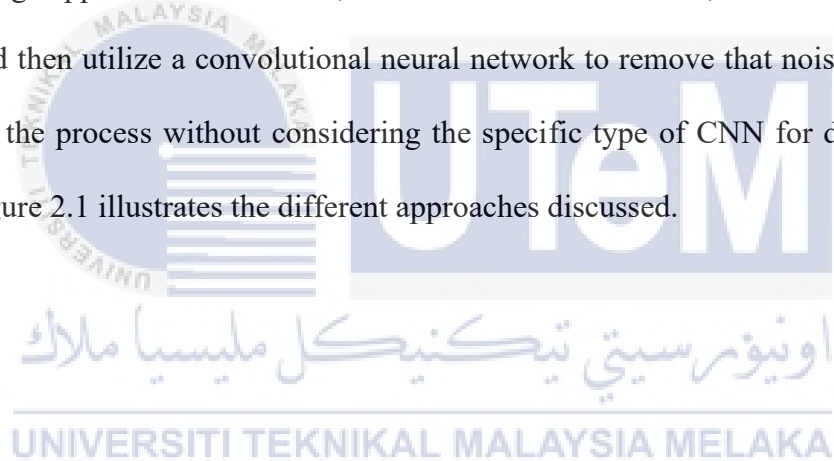


Figure 2.1: CNN image denoising scheme [64]

In this section, we'll discuss various methods for cleaning up images using Convolutional Neural Networks (CNNs). We'll categorize these approaches into two types: (1) CNN denoising for everyday images and (2) CNN denoising for specific types of images. The first type focuses on using CNN architectures to remove noise from general-purpose images, while the second type applies CNNs to clean up specific types of images. However, for this thesis, we'll concentrate on the first type due to limited available resources. This approach is more commonly used in CNN denoising applications compared to the second one. General images are those that serve a broad purpose, whereas specific images are intentionally created for special purposes, such as medical, infrared, or remote sensing images. We are opting for the general image approach in this thesis, where we'll introduce noise, like Gaussian noise, to the images and then utilize a convolutional neural network to remove that noise. This allows us to simplify the process without considering the specific type of CNN for denoising. The diagram in Figure 2.1 illustrates the different approaches discussed.



2.3 Related work

2.3.1 Deep Learning Neural Network Architecture

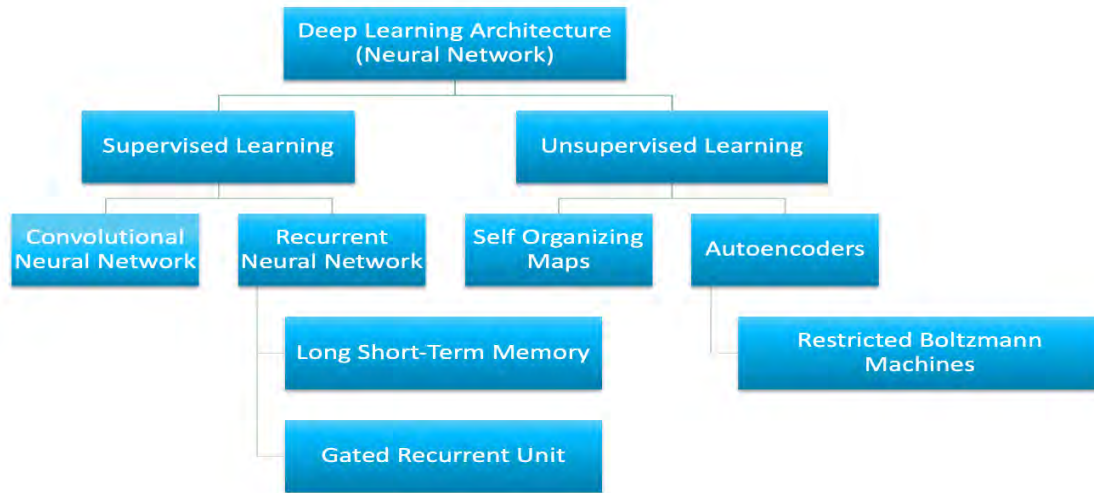


Figure 2.2: Deep Learning Architecture [65]

Deep learning has a rich history, but recent advances in architecture and GPU technologies have propelled it to the forefront of artificial intelligence. Rather than being a single approach, deep learning encompasses a range of algorithms that can be applied to various problems, including supervised and unsupervised learning.

While deep learning is not a novel concept, its widespread application has surged due to the combination of highly layered neural networks and the utilization of GPUs for efficient processing. The availability of large datasets has further accelerated this growth, as deep learning thrives on training neural networks with abundant example data, leading to improved performance. The abundance of data enables the construction of robust deep learning structures.

Within the field of deep learning, various architectures and algorithms have emerged. This chapter will focus on discussing a few notable ones that have gained prominence in recent years. Despite being among the oldest approaches, long short-term memory (LSTM) and convolutional neural networks (CNNs) continue to be widely used in diverse applications.

In this chapter, deep learning architectures will be categorized into two main groups: supervised and unsupervised learning. Furthermore, the chapter will introduce several well-known deep learning architectures, such as convolutional neural networks, recurrent neural networks (RNNs), long short-term memory/gated recurrent unit (GRU), self-organizing map (SOM), autoencoders (AE), and restricted Boltzmann machines (RBMs). These architectures have been specifically developed for various domains, including audio, image processing, medical applications, and more.

It's important to acknowledge that deep learning builds upon the foundation of artificial neural networks (ANNs). ANNs serve as the underlying architecture for deep learning and have inspired the development of several algorithmic variations. For a comprehensive understanding of the fundamentals of deep learning and artificial neural networks, it is recommended to read the introduction to deep learning article.

2.3.2 Architecture of CNN for a computer vision task

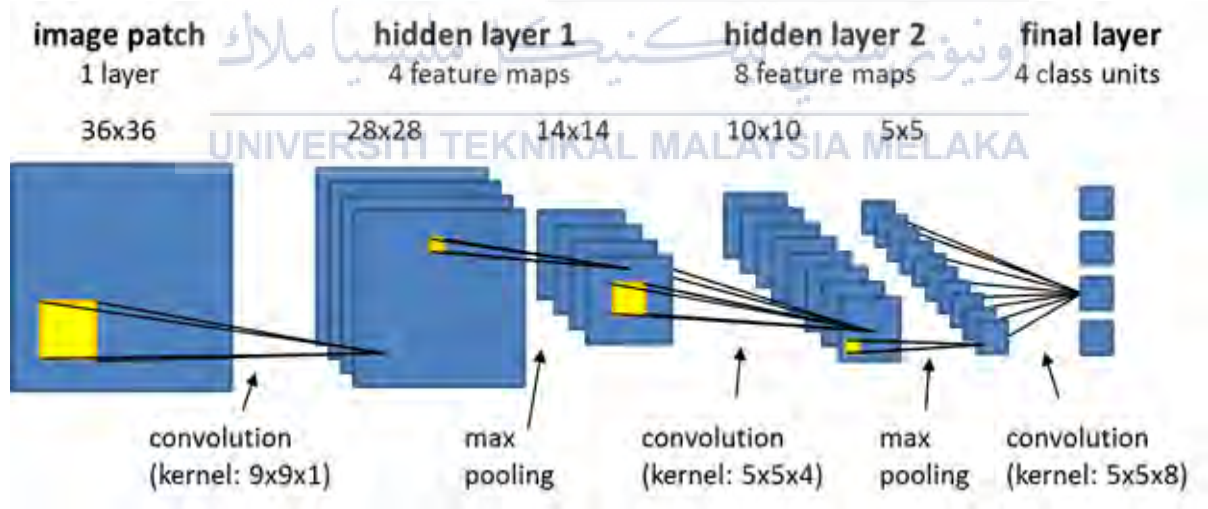


Figure 2.3: Architecture of CNN model with 2 hidden layers. [64]

The utilization of deep learning, particularly convolutional neural networks (CNNs), has revolutionized problem-solving and object recognition in images. This chapter provides a

concise overview of the recommended approach for implementing CNNs in MATLAB.

2.3.2.1 Convolutional neural network

Convolutional neural networks (CNNs) are a specific type of neural network architecture, as illustrated in Figure 2.3. These networks typically consist of multiple hidden layers, each characterized by two stages: local convolution and max pooling. In the convolution stage, the preceding layer is convolved with a trainable weight kernel, while the max pooling stage reduces the number of units by selecting the maximum response from a group of units in the previous stage. The final layer of the network is usually fully connected, with one unit per predicted class that receives input from all units in the preceding layer.

The implementation workflow for CNNs follows a similar process to other supervised machine learning methods. Firstly, a model is generated and trained using a set of training data. Subsequently, the model is validated using new image data. If the validation results are satisfactory, the model can be deployed in production mode and applied to new data without known ground truth.

Alternatively, it is possible to employ pre-trained semantic segmentation models (for pixel classification) in the TensorFlow Saved Model format, which are developed by third-party sources. These pre-trained models can be loaded and utilized for specific tasks.

2.3.2.2 Convolutional Neural Network denoising for general images

Reference [28] introduced the attention-guided CNN (ADNet) as a method for image denoising. ADNet comprises 17 layers organized into four blocks: sparse block (SB), feature enhancement block (FEB), attention block (AB), and reconstruction block (RB). The incorporation of sparsity, known to be effective in image applications [29], is utilized in SB to enhance efficiency, performance, and reduce the denoising framework's depth. SB consists of 12 layers with two types: dilated Conv + BN + ReLU, and Conv + BN + ReLU. FEB consists of 4 layers with three types: Conv + BN + ReLU, Conv, and Tanh. AB is a single convolution layer used to guide SB and FEB, particularly for addressing unknown noise. Finally, RB handles the reconstruction process to generate a clean image. During training, the mean square error [30] was employed for model training (refer to Figure 2.4).

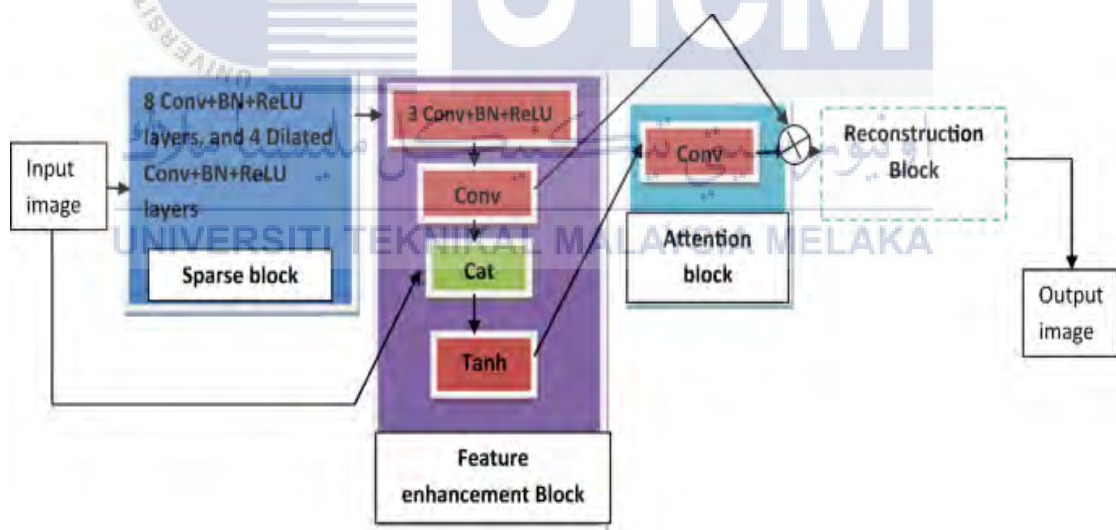


Figure 2.4: Attention-guided denoising CNN [28]

Some advanced deep learning algorithms perform well when dealing with artificially generated noise, but struggle to achieve good results on images corrupted by

real-world noise. In a study by Guo et al. [31], they introduced the Noise Estimation Removal Network (NERNet), which effectively reduced noise in images with realistic noise. The NERNet comprised two main modules: the noise estimation module and the noise removal module. The noise estimation module determined the noise level using techniques like the symmetric dilated block and pyramid feature fusion. Meanwhile, the removal module utilized the estimated noise level to eliminate noise, incorporating both global and local information to preserve details and textures. The clean images were obtained by passing the output of the noise estimation module into the removal module.

While Convolutional Neural Networks (CNNs) are proficient at learning noise patterns and image patches, they require a substantial amount of training data and image patches. To address this, reference [35] proposed the Patch Complexity Local Divide and Deep Conquer Network (PCLDCNet). This network divided tasks into local subtasks and trained them in their local space. Each noisy patch weighting mixture was combined with the local subtask, and image patches were grouped by complexity. The training of the network involved the use of modified stacked denoising autoencoders [37].

Network degradation is a common challenge in deep learning networks, where deeper layers result in higher error rates. Although ResNet [38] helped alleviate this issue, there is still room for improvement. Shi et al. [39] introduced Hierarchical Residual Learning for image denoising. This network comprises three sub-networks: feature extraction, inference, and fusion. The feature extraction sub-network extracts patches representing higher-dimensional feature maps, the inference sub-network uses cascaded convolutions to produce a large receptive field, and the fusion sub-network combines the entire noise map to produce the final estimation.

In another approach, Gai and Bao [41] utilized the Improved CNN (MP-DCNN) for image denoising. MP-DCNN, an end-to-end adaptive residual CNN, is designed to model noisy images. Noise is extracted from the input image using leaky ReLU, and image features are reconstructed. An initial denoised image is fed into SegNet to obtain edge information. The Mean Squared Error (MSE) and perceptual loss function [42] are then used to generate the final denoised image (see Figure 2.5).

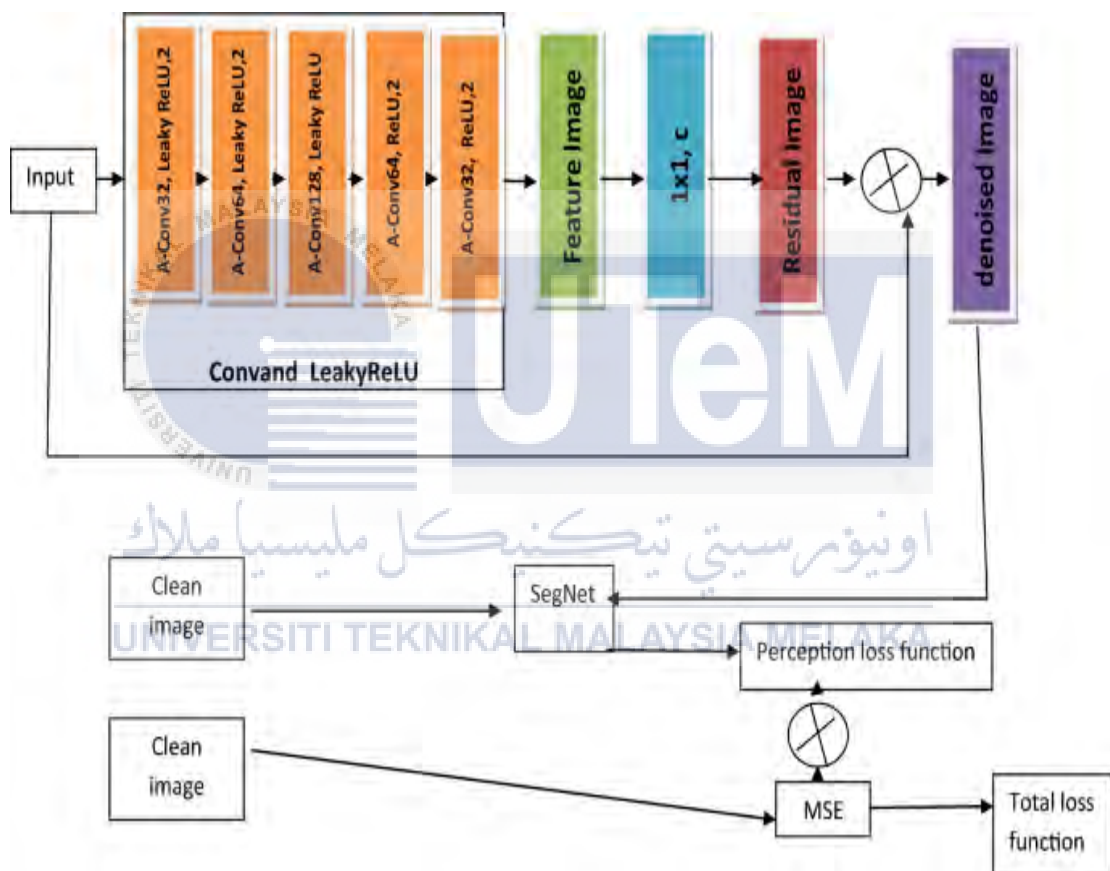


Figure 2.5: MP-DCNN[41]

Another study, referenced as [43], introduced a novel dictionary learning model for a mixture of Gaussian (MOG) distribution. The method was applied within the expectation-maximization framework [44]. The approach addressed a minimization

problem using sparse coding and dictionary updating, with both quantitative and visual comparisons. The model was specifically used for learning hierarchical mapping functions, and to tackle vanishing problems, Zhang et al. [45] proposed the separation aggregation network (SANet). SANet utilized three blocks (convolutional separation block, deep mapping block, and band aggregation block) to eliminate noise. The convolution separation block broke down the input noise into sub-blocks [46, 47]. Each band was then transformed into a clean and latent form using convolution and ReLU layers. The band aggregation block combined all maps and convoluted features to generate the output. The SANet model drew inspiration from the non-local patch (NPL) model [47], which included patch grouping, transformation, and patch aggregation. To address information loss in residual images obtained from learning the difference between noisy and clean image pairs, the detail retaining CNN (DRCNN) was proposed in reference [48]. DRCNN focused on preserving high-frequency image content and exhibited improved generalization ability. It consisted of two modules: the generalization module (GM) and the detail retaining module (DRM), where GM involved convolution layers with a stride of 1, and DRM included several convolution layers. Unlike other architectures, DRCNN did not incorporate batch normalization (BN).

Addressing the computational cost issue in CNN applications, Yin et al. [49] presented the side window CNN (SW-CNN) for image filtering. SW-CNN comprised two parts: side kernel convolution (SKC), fusion, and regression (FR). SKC aligned the sliding or corner of the operation window with the target pixel to preserve edges, and it was combined with CNN for effective representation power. A residual learning strategy [50] was adopted in mapping layers. FR involved two convolutional phases with three operations: pattern expression, non-linear mapping, and weight calculations.

The pattern expression calculated the gradient from the feature map tensor to produce a pattern tensor. Non-linear mapping convoluted the pattern tensor with different kernels to generate a tensor with dimensions (Hxwx d). Finally, weight calculations produced the weighting coefficient of each pixel.

While single noise reduction with CNN poses a challenge, removing mixed noise from an image using CNN is even more difficult. Many mixed noise removal algorithms involve pre-processing outliers. In reference [51], the denoising-based generative adversarial network (DeGAN) was proposed for removing mixed noise from images. The DeGAN consisted of a generator, discriminator, and feature extractor network. The generator network utilized the U-Net [53] architecture, while the discriminator network comprised 10 end-to-end design layers. The primary purpose of the discriminator network was to verify whether the image estimated by U-Net (extractor network) was noise-free. Finally, the feature extraction network used the VGG19 [54] to extract features and aid model training by calculating the loss function (refer to Figure 2.6).

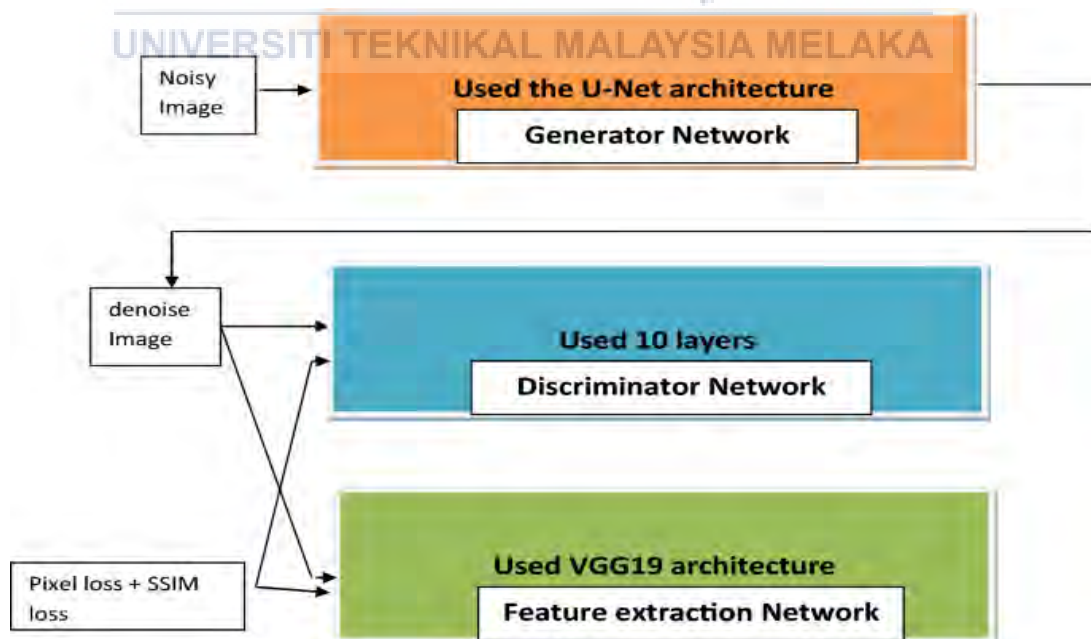


Figure 2.6: DeGAN[51]

Xu and colleagues (reference [55]) introduced a method called Bayesian deep matrix factorization (BDMF) for denoising multiple images. BDMF employs a deep neural network (DNN) to handle low-rank components and utilizes stochastic gradient variation Bayes optimization [56,57,58]. This approach combines the deep matrix factorization (DMF) network with Bayesian techniques. The evaluation of these methods involved using synthetic and hyperspectral images.

In a different study (reference [59]), a classifier/regression Convolutional Neural Network (CNN) was proposed for image denoising. The regression network works on restoring noisy pixels identified by the classifier network, which, in turn, detects impulse noise. The classifier network employs convolution, batch normalization (BN), rectified linear unit (ReLU), softmax, and a skip connection. Meanwhile, the regression network, based on the classifier's predicted label, utilizes four layers and a skip connection to predict clean images (refer to Figure 2.7).

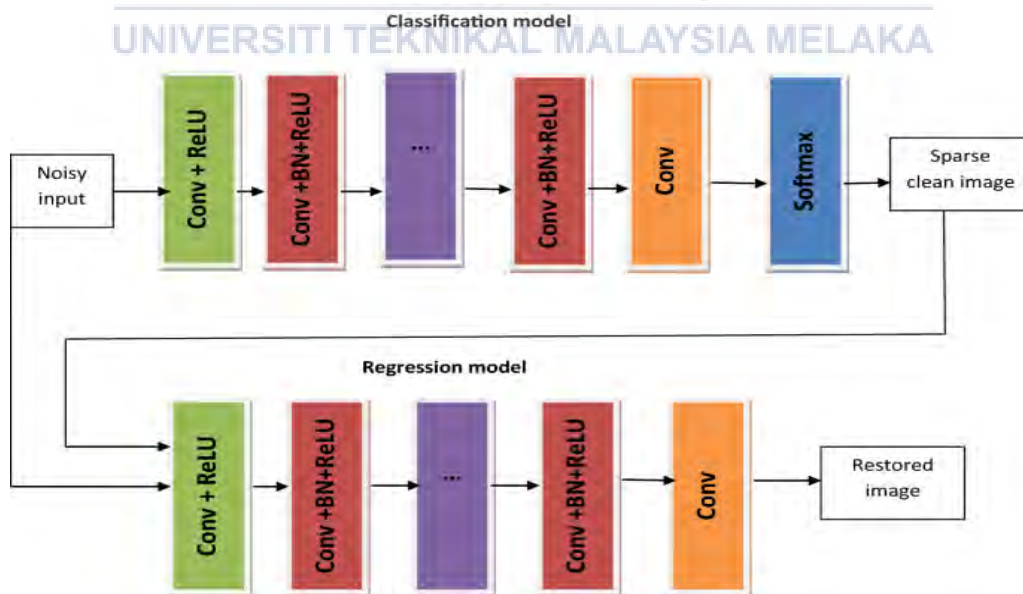


Figure 2.7: Classifier/regression CNN [59]

Reference [60] introduced a technique called complex-valued CNN (CDNet) for image denoising. The process begins by passing the input image through 24 sequential connected convolutional units (SCCU). These units consist of a complex-valued (CV) convolutional layer, complex-valued (CV) ReLU, and complex-valued (CV) BN, all using a 64-convolutional kernel. A residual block is implemented for the middle 18 units, and a convolution/deconvolution layer with a stride of 2 is employed for computational efficiency. Finally, the merging layer transforms the complex-valued features into a real-value image. In summary, CDNet comprises five blocks: complex-valued (CV) Conv, complex-valued (CV) ReLU, complex-valued (CV) BN, complex-valued (CV) residual block (RB), and merging layer (refer to Figure 2.8).

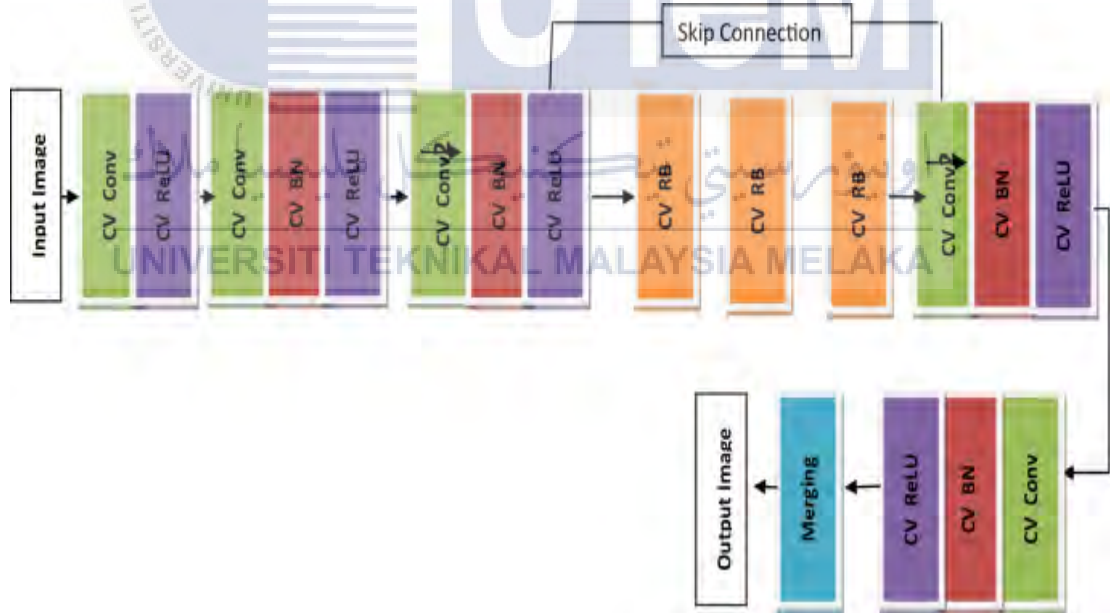


Figure 2.8: Complex-value CNN [60]

Zhang et al. [61] introduced a method for identifying and reconstructing CNNs for color images (3-channel). Their approach involves three networks: a classifier

network, a denoiser network, and a reconstruction network. The classifier network predicts color channels to determine the likelihood of impulse noise in the image. Decision-making procedures are then used to label each pixel as noisy or noise-free. Noisy channels are replaced with a clean image, represented by 0 for noise-free pixels. Finally, the denoised image is reconstructed using an image reconstruction architecture. In summary, the classifier network predicts channel probabilities, the denoiser network corresponds to noise-free color pixels, and the reconstruction network reconstructs the images. While these networks share the same structures, there are differences in depth and the number of nodes. The optimization of the networks is done using the Adaptive Moment Estimation (Adam) algorithm [62].

Reference [63] proposed a CNN variation model (CNN-VM) for image denoising, using a CNN termed EdgeNet. EdgeNet consists of multiple scale residual blocks (MSRB) and employs an edge regularization method to extract features from noisy images. Total variation regularization enhances performance in preserving shape edges. The Bregman splitting method is utilized to find solutions to the model. MSRB uses a kernel of two for each bypass to detect local features, and a skip connection is employed for inputting and outputting data. Another skip connection is added after each MSRB block, with a bottleneck layer fusing detected features. The training procedure involves four MSRB blocks. A comparison of different methods can be found in Tables 2.1 and 2.2.

TABLE 2.1 COMPARISON OF CNN DENOISING METHODS

Author	References	Year	CNN name	Noise Type	Image Type	Additional comments
Tian et al	[28]	2022	ADNet	General noise	General image	Sparse, attention, enhancement, and reconstruction blocks for image denoising
Guo et al	[31]	2020	NERNet	Realistic noise	General image	Used the noise estimation and noise removal modules for denoising
Hong et al	[35]	2019	PCLDCNet	General noise	General image	Combine the complexity local divide and keep computer
Shi et al	[39]	2019	Hierartical residual learning	General noise	General image	3 network modules for noise removal.
Gai and Bao	[41]	2019	MP-DCNN	Mixed Noise	General image	Leaky ReLU, SegNet, MSE, and perception loss function for image denoising
Zhang et al	[43]	2019	Dictionary learning model	Gaussian-mixed noise	General image	Propose the dictionary learning model with a minimization framework
Zhang et al	[45]	2019	SANet	General noise	General image	Used the convolution separation, deep mapping, and band aggregation blocks to remove noise.
Li et al	[48]	2020	DRCNN	Geneal Noise	General Image	Generalization and detail retaining modules for image denoising
Yin et al	[49]	2020	SW-CNN	General noise	General image	Slide kernel convolution, CNN, fusion, and regression
Lyu et al	[51]	2020	DeGAN	Mixed noise	General image	Extractor, discriminator, and feature extractor network for noise removal

TABLE 2.2 ADVANTAGES AND DISADVANTAGES OF CNN DENOISING

Author	Reference	Advantage	Disadvantage	PSNR
Tian et al	[28]	Reduces the memory footprint of a network	Require lots of computation power	35.7
		Produces ability to learn longer range dependencies and remove gradient vanishing problems	Add extra weights to the network which makes the network slow	
Guo et al	[31]	Support exponential expansion of receptive field without loss and with improved performance.	Add extra weight parameter to the network which consumes computation.	40.1
Hong et al	[35]	Creates deeper representation for effective denoising.	Require lots of computation power	26.4
			Network arrangement is cumbersome	
Shi et al	[39]	Reduces network degradation without learning identity mapping	Increases network complexity and depends largely on batch normalization	
		Increases validation accuracy		
Gai and Bao	[41]	Usage of LeakyReLU provides better performance, fast and easy calculations without dying ReLU.	Adjustment during training is impossible which may lead to lower accuracies.	29.2
Zhang et al	[43]	Reduces the amount of computation time, and select features effectively	Difficult to train and produces space complexity.	31.6
Li et al	[48]	Uses fewer parameters and hence does not require large storage	May be trapped at a local minimum	32.9
		Adapts easily to different image restoration task	Produces recurrent parameter changes after a calculation that may result in low accuracies	

Yin et al	[49]	Learn filtering task efficiently which help to reduce computation time	When applied to a large dataset may produce low accuracy Require lots of computation power	41.4
Lyu et al	[51]	Generate samples faster and easily Do not require bias, specific dimensionality	Require lots of computation power Setup is cumbersome	33.7
Zhang et al	[61]	Perform optimally for both color and gray-scale images	Require large batch size to generate good result	39.3
Fang and Zeng	[63]	Reduces staircase effect on images, and effectively preserves edges	Prone to contrast loss when fusing with CNN	33.1
Quan et al	[60]	Produces good accuracy with a complex-valued layer	Require lots of computation power	45.78

2.3.3 Train a CNN, Convolutional Neural Network Model.

Step 1:

Initiate the process by categorizing your training images based on the ground truth, following established methodologies for rule set development. Each classified pixel can serve as a unique sample, so it is crucial to have an adequate number of accurately representative samples for each class. For small-sized objects of interest, consider classifying a region around each object location to augment the sample count. Exercise caution and thoroughness during this step, as insufficient sampling cannot be compensated for by the network architecture.

Step 2:

Utilize the "generate labeled sample patches" algorithm to create samples for two or more distinct classes that the network needs to learn. It is important to balance patch size to enable efficient processing by the model while ensuring that crucial identifying features are present for accurate classification. Once all the samples have been collected, apply the "shuffle labeled sample patches" algorithm to randomize the sample order. This ensures that the samples are not processed in the order of their collection.

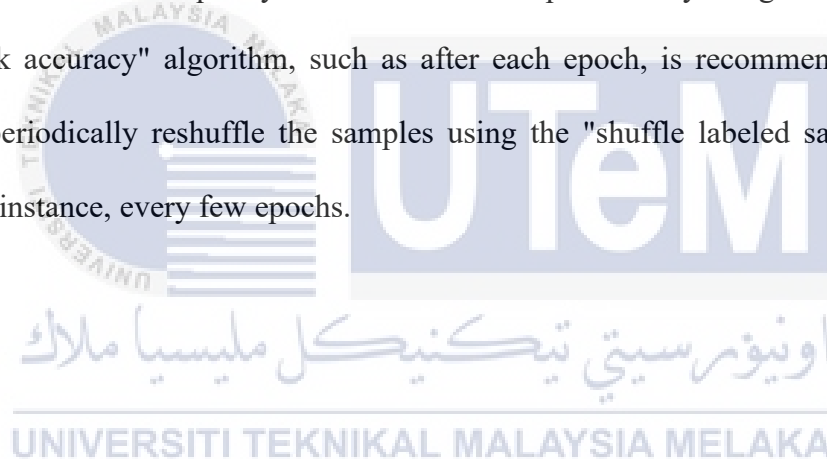
Step 3:

Define the desired network architecture using the "create convolutional neural network" algorithm. It is advisable to start with a simple network and gradually increase complexity, such as the number of hidden layers and feature maps, if the model fails to achieve the desired results. However, it is essential to note that increasing model complexity poses challenges for the training algorithm to find the global optimum, and larger networks do not necessarily guarantee better performance. While the model can be used immediately after creation, it is not

practically useful until it has undergone training.

Step 4:

Apply the trained "convolutional neural network" algorithm to input your samples into the model and adjust the model's weights using backpropagation and statistical gradient descent. The learning rate is a crucial parameter to tune in this algorithm, as it determines the magnitude of weight adjustments during each training step and significantly impacts the success of model learning. To complete a full epoch, adjust the "train steps" parameter by dividing the total available samples by the batch size (the number of samples presented at each training step). Monitoring the classification quality of the trained model periodically using the "convolutional neural network accuracy" algorithm, such as after each epoch, is recommended. It is also advisable to periodically reshuffle the samples using the "shuffle labeled sample patches" algorithm, for instance, every few epochs.



2.3.4 Validate the Model

Step 1 : Load the Data:

Load a set of validation images that were not used during training. You can use a separate set of images or a subset of your original dataset.

Step 2 : Preprocess the Data:

If necessary, preprocess the validation data in a similar manner as the training data.

Normalize pixel values to the range [0, 1] and ensure the channel format is consistent with the model's input requirements (grayscale or RGB).

Step 3 : Apply Noise to Validation Images:

Introduce Gaussian noise to the validation images using the `imnoise` function. This noise should be similar to the noise levels encountered in the real-world scenarios.

```
validationNoise = imnoise(validationData, 'gaussian',  
noiseLevel, seed);
```

Step 4 : Denoise Validation Images:

Apply the trained denoising model (`convnet`) to denoise the validation images.

```
denoisedValidation = denoiseImage(validationNoise, convnet);
```


Step 5 : Calculate Metrics:

Calculate relevant evaluation metrics, such as PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index), to quantify the performance of the denoising model on the validation set.

```
psnrValidation = psnr(validationData, denoisedValidation);  
ssimValidation = ssim(validationData, denoisedValidation);
```

Step 6 : Visualize Results:

Display the original noisy images, the denoised images, and any intermediate results (e.g., noise level images) to visually assess the model's performance.

```
figure  
subplot(1, 3, 1)  
imshow(validationNoise)  
title('Noisy (Validation)')  
  
subplot(1, 3, 2)  
imshow(denoisedValidation)  
title('Denoised (Validation)')  
  
subplot(1, 3, 3)  
imshow(abs(validationNoise - denoisedValidation))  
title('Noise Level (Validation)')
```

Step 7 : Evaluate and Interpret Results:

Analyse the calculated metrics and visualizations to determine how well the denoising model generalizes to the validation set. Look for artifacts, blurriness, or any issues that might affect the quality of the denoised images.

Step 8 : Adjust and Retrain (if necessary):

If the model performance on the validation set is not satisfactory, consider adjusting hyperparameters, increasing model complexity, or collecting additional training data. Retrain the model as needed and repeat the validation steps.



2.4 A sample of figures

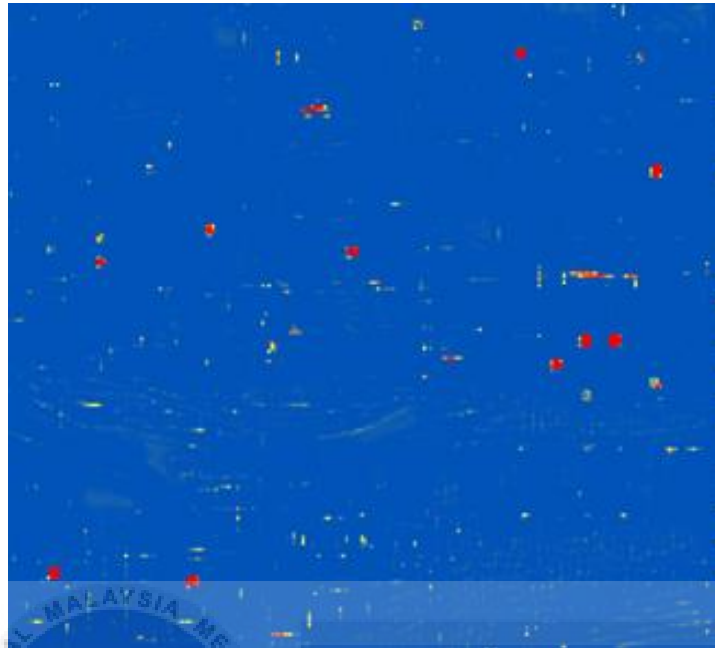


Figure 2.9: Resulting heat map layer. (Red indicates high values close to 1, blue indicates values close to zero.)

2.5 Sample of formulas

Convolution refers to the mathematical operation of pointwise multiplication between two functions, often a matrix representing image pixels and a filter. By sliding the filter across the image, we perform element-wise multiplication and compute the dot product of the two matrices. The resultant matrix is commonly referred to as an "Activation Map" or "Feature Map," illustrating the detected features or patterns within the image. This process plays a crucial role in deep learning and is foundational to various computer vision applications.

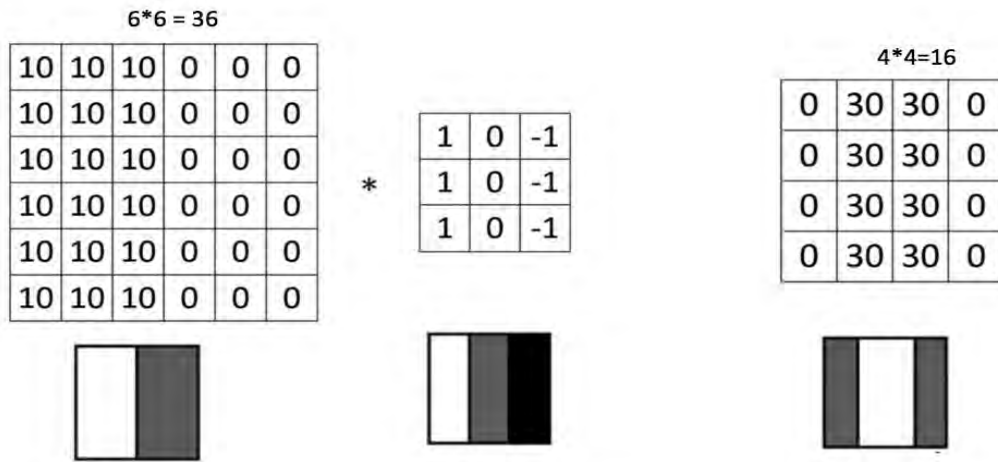


Figure 2.10: Multiple convolutional layers extracting features from the image and finally the output layer.

Mean Square Error (MSE)

The square difference between the original and denoised image is averaged to create the mean square error, the smaller the value, the higher the quality of the image.

$$MSE = \frac{1}{N} ||I - L||^2 \quad (1)$$

Peak Signal to Noise-Ratio (PSNR)

MSE is used to calculate the peak signal to noise ratio. a measurement used in engineering that compares the maximum original signal to the MSE. A greater PSNR indicates better quality of image.

$$PSNR = 10 * \log_{10} \left(\frac{(max(1))^2}{MSE} \right) \quad (2)$$

Structural similarity index measure (SSIM)

Structure similarity index measure perceptual difference of 2 similar image (such as luminance, contrast, and structure). The higher values signify better image quality

$$SSIM(u, v) = \frac{(2u_I u_L + Q_1)(2\sigma_{IL} + Q_2)}{(u_I^2 + u_L^2 + Q_1)(\sigma_I^2 + \sigma_L^2 + Q_2)} \quad (3)$$

Where u_I and u_L are the average grayscale values, σ_I and σ_L are the variance of patches, σ_{IL} is the covariance of I and L, Q_1 and Q_2 denote 2 small positive constants (typically 0.01).

Root Mean Square Error (RMSE)

The root mean square error measure difference between estimated predictions and actual observed values. The MSE is the scale square of RMSE. The RMSE between 2 images metrics (P,Q) is:

$$RMSE = \sqrt{MSE(P, Q)} = \sqrt{\sum_{P=1}^M \sum_{Q=1}^N (P_{PQ} - Q_{PQ})^2} \quad (4)$$

Feature Similarity

Feature Similarity (FSIM and FSIMc) is designed for grayscale images and luminance components of colour images. It computes local similarity maps and pools these maps into a single similarity score.

$$FSIM = \frac{\sum_{x \in \Omega} S_L(x) \cdot PC_m(x)}{\sum_{x \in \Omega} PC_m(x)} \quad (5)$$

$$FSIM_C = \frac{\sum_{x \in \Omega} S_L(x) \cdot [S_C(x)]^\lambda \cdot PC_m(x)}{\sum_{x \in \Omega} PC_m(x)} \quad (6)$$

Signal to Noise Ratio (SNR)

The signal to noise ratio measure noise level relative to the original image as follows.

$$SNR = 10 \log_{10} \frac{\|L\|}{\|I-L\|} \quad (7)$$

Spectral Angle Mapper (SAM)

The Spectral Angle mapper (SAM), and the Erreur Relative Globale Adimensionnelle de Synthèse (ERGAS) [66] are used with other evaluation methods in remote sensing images. Overall, PSNR and the SSIM are the most widely used evaluation methods for CNN denoising. These two methods are popular because they are easy and are considered tested and valid.

2.6 Summery

The literature review provides an overview of the current state of practice in deep neural network-based noise removal, specifically focusing on Convolutional Neural Networks (CNNs) for image denoising. The review emphasizes the remarkable achievements in noise removal across various applications and highlights the limitations of traditional methods. It explores alternative CNN architectures and training methodologies for noise removal.

The discussion on CNN image denoising is categorized into two approaches: (1) CNN denoising for general images and (2) CNN denoising for specific images. The first approach focuses on denoising general-purpose images, while the second approach deals with denoising images of specific types, such as medical, infrared, or remote sensing images. The literature review primarily concentrates on the first approach due to the lack of accessible materials for the second. The division aims to familiarize readers with the latest CNN architectures relevant to different image types.

The review then delves into related work, providing insights into various deep learning neural network architectures. It discusses the evolution of deep learning, its diverse algorithms, and the impact of architecture advancements and GPU technologies on artificial intelligence. Notable architectures, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory (LSTM), autoencoders (AE), and restricted Boltzmann machines (RBMs), are introduced and categorized into supervised and unsupervised learning.

A detailed exploration of the architecture of CNNs for computer vision tasks is presented, with a focus on a CNN model with two hidden layers. The discussion highlights the importance of CNNs in revolutionizing problem-solving and object recognition in images. Various CNN denoising methods for general images are then examined, featuring architectures like attention-guided CNN (ADNet), noise estimation removal network (NERNet), patch

complexity local divide and deep conquer network (PCLDCNet), hierarchical residual learning, improved CNN (MP-DCNN), dictionary learning model, separation aggregation network (SANet), detail retaining CNN (DRCNN), side window CNN (SW-CNN), and denoising-based generative adversarial network (DeGAN). Each method is discussed in terms of its architecture and methodology.

The literature review concludes with a comparison of CNN denoising methods for general images, evaluating their advantages, disadvantages, and Peak Signal-to-Noise Ratio (PSNR) metrics. The review provides a comprehensive understanding of the current landscape of CNN-based image denoising, covering diverse architectures and methodologies.



CHAPTER 3

METHODOLOGY

3.1 Introduction

The methodology section of this research presents a detailed description of the deep neural network-based noise removal methodology using convolutional neural networks (CNNs). It outlines the step-by-step approach employed in this study to address the problem of noise in digital images. The methodology encompasses the design and implementation of the CNN architecture, dataset preparation, model training, evaluation metrics, and experimental setup.

Deep learning models, particularly CNNs, have shown promise in effectively removing noise from images while preserving important details. By training a CNN on a dataset of noisy and clean images, the model can learn to distinguish between noise and relevant image features, leading to improved denoising performance. This section introduces the methodology used in this research, highlighting its objectives, key steps, and the rationale behind the chosen approach.

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3.2 Methodology

3.2.1 Convolutional Neural Network training model, CNN

The proposed methodology involves training a CNN using a dataset of clean and noisy image pairs. The CNN will learn to map noisy images to their corresponding clean versions. The noise removal process consists of two main steps: training the CNN and applying the trained model for noise removal.

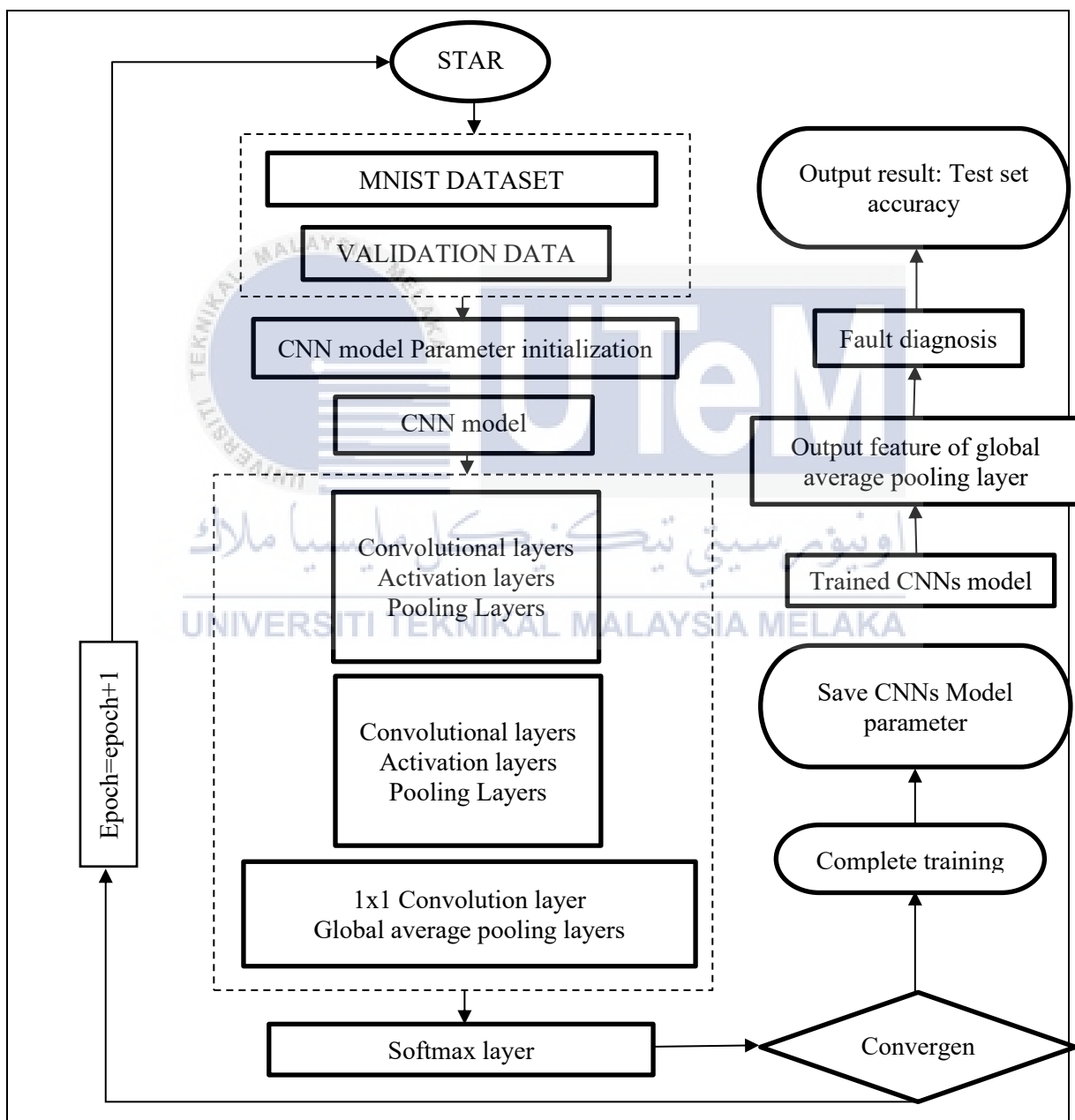


Figure 3.1: Flowchart of CNN architecture.

3.2.2 Denoising Convolutional Neural Network, DnCNN

In the flowchart below is the overall image denoising process using Convolutional Neural Network as training model with various parameter.

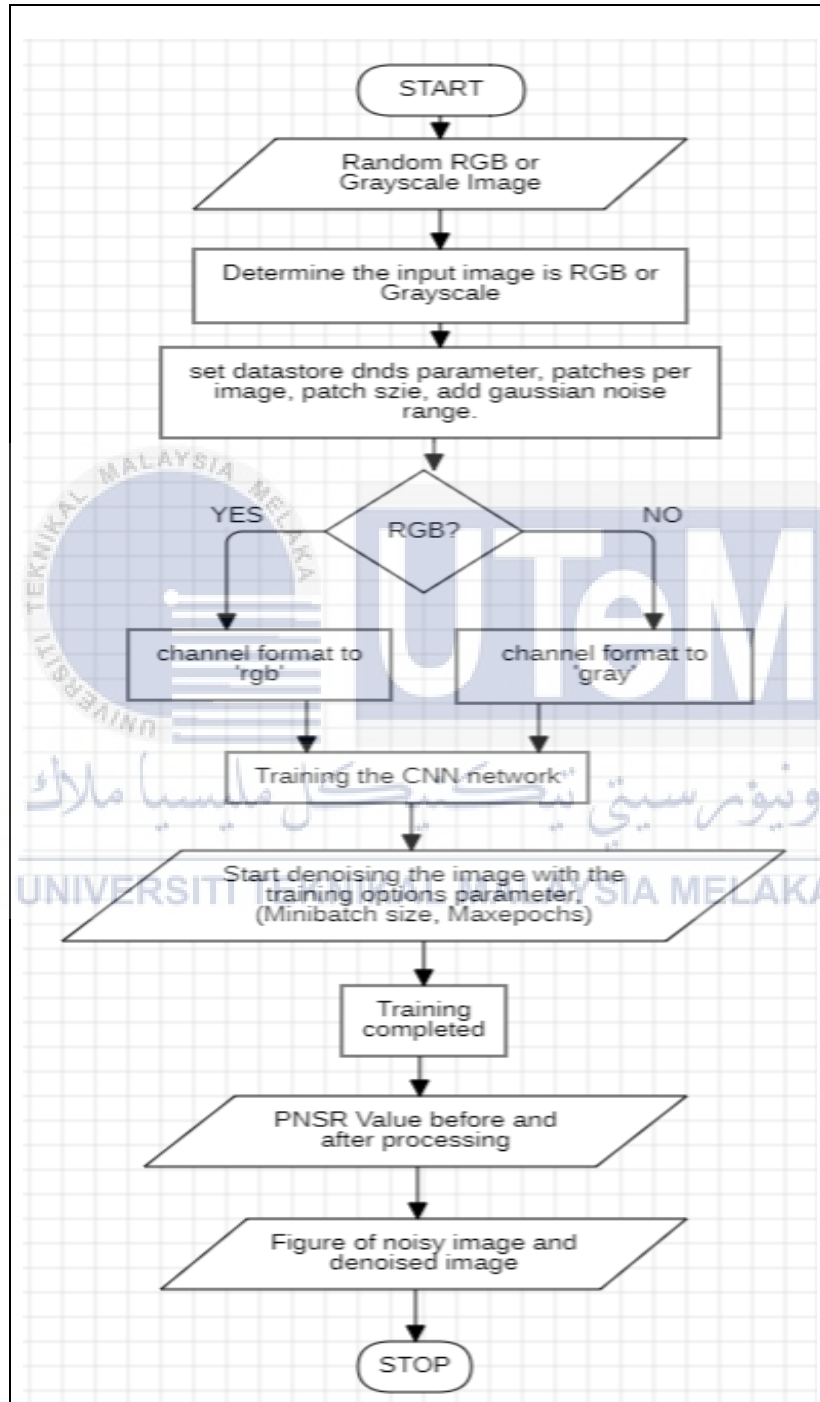


Figure 3.2: Flowchart of DnCNN

3.2.3 Training CNN

To train the CNN, we first need a dataset of clean images and their corresponding noisy versions. This dataset is crucial for supervised learning, where the CNN learns to approximate the underlying mapping function between noisy and clean images. The dataset is divided into training and validation sets to facilitate model optimization and prevent overfitting.

We utilize a deep architecture comprising multiple convolutional layers, pooling layers, and fully connected layers. The exact architecture and hyperparameters are determined through experimentation and validation. During training, the CNN minimizes a loss function, typically mean squared error (MSE), to update its weights and biases, optimizing its ability to reconstruct clean images from noisy inputs.

3.2.4 Applying the trained model for Noise Removal

Once taught, the CNN can be used to reduce noise from new, unseen images. The trained CNN receives the noisy images and feeds them through its layers to produce denoised outputs. By utilising the CNN's acquired understanding of the underlying patterns in the training data, the denoised images are generated.

3.3 Experimental Setup

To evaluate the performance of the proposed methodology, we conducted experiments using MATLAB. The experiments were performed on a computer with an Intel Core i5 processor, 8GB RAM, and a suitable GPU to accelerate the training and inference processes.

We utilized publicly available image datasets, such as the MNIST dataset, to train and validate the CNN. The noisy images were created by adding synthetic noise with varying characteristics, including Gaussian, salt-and-pepper, and Poisson noise, to the clean images.

3.4 Parameters

The effectiveness of the deep neural network-based noise removal technology depends on several criteria. These consist of:

3.4.1 CNN Architecture

The choice of CNN architecture, including the quantity of convolutional layers, the size of their filters, and the number of neurons in the fully connected layers, has a substantial impact on how well the noise removal procedure performs. To improve the outcomes, several architectures and hyperparameters must be investigated.

3.4.2 Training Parameters

The training process is influenced by parameters like the learning rate, batch size, and number of epochs. While the batch size dictates the number of images analysed collectively during each training iteration, the learning rate controls the step size during gradient descent optimization. The number of epochs determines how many times the full training will occur.

3.5 Equipment Limitations of Proposed Methodology

The proposed methodology may have certain equipment limitations. One such limitation is the requirement for a suitable GPU to accelerate the training and inference processes. Without a capable GPU, the training time and the denoising process could be

significantly slower, hindering real-time applications.

Another limitation could be the availability of computational resources. Training deep neural networks can be computationally intensive, requiring substantial memory and processing power. In resource-constrained environments, the training process may take longer or could be infeasible due to hardware limitations.



3.6 Gantt Chart

A. PROJECT PLANNING PSM																													
Project Activity	2023														2023/24														
	MARCH			APRIL				MAY				JUNE			OCT			NOV				DEC			JAN				
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Proposed Project																													
• Meeting Supervisor																													
• Discuss project Title																													
• Identify the objective, problem statement & scope of project																													
• Literature review																													
Research of Hardware and Software																													
• Methodology development																													
• Data collection																													
Result and Analysis																													
• Model Training																													
• Evaluation and analysis																													
• documentation																													
Finalize Report																													

Table 3.1: Gantt Chart of PSM project flow

3.7 Summary

In this chapter, we introduced the methodology for deep neural network-based noise removal using a convolutional neural network (CNN) in MATLAB. We discussed the process of training the CNN using a dataset of clean and noisy image pairs, as well as the application of the trained model for noise removal in unseen images. We described the experimental setup, including the use of publicly available datasets and synthetic noise. Additionally, we highlighted the importance of various parameters and outlined the potential limitations of the proposed methodology. In the next chapter, we will present the results of our experiments and discuss the performance evaluation.



CHAPTER 4

ANALYSIS AND DISCUSSION

4.1 INTRODUCTION

The purpose of this thesis is to analyze the features extracted from a convolutional neural network (CNN) applied to image data. The specific CNN architecture used is trained on the MNIST dataset for digit recognition. The code provided implements the visualization of various layers in the CNN to gain insights into the learned features. These layers include the input image, convolutional filters, and intermediate feature maps obtained after applying convolution, ReLU activation, and mean pooling operations. The goal is to understand how the network processes and represents the input images at different stages.

4.2 ANALYSIS OF CONVOLUTIONAL NEURAL NETWORK ALGORITHM

4.2.1 Training model algorithm

The implementation of the trained CNNs model is done in a separated manner.

loadMNISTImage.m

```
1 function images = loadMNISTImages(filename)
2
3     fp = fopen(filename, 'rb');
4     assert(fp ~= -1, ['Could not open', filename, '']); %notis fail to open file
5     magic = fread(fp, 1, 'int32', 0, 'ieee-be'); %reading file, load in variable name magic
6     assert(magic == 2051, ['Bad magic number in', filename, '']); %error message
7     numImages = fread(fp, 1, 'int32', 0, 'ieee-be');
8     numRows = fread(fp, 1, 'int32', 0, 'ieee-be');
9     numCols = fread(fp, 1, 'int32', 0, 'ieee-be'); %read image
10    images = fread(fp, inf, 'unsigned char=>unsigned char');
11    images = reshape(images, numCols, numRows, numImages);
12    images = permute(images, [2 1 3]);
13    fclose(fp);
14
15    images = reshape(images, size(images, 1) * size(images, 2), size(images, 3));
16    images = double(images) / 255; %reshape in 8bits
```

Figure 4.1: Matlab CNN function for Dataset loading

loadMNISSTLabels.m

```
1 function labels = loadMNISTLabels(filename)
2
3 fp = fopen(filename, 'rb'); %open label file
4 assert(fp ~= -1, ['Could not open ', filename, '']); %show error
5
6 magic = fread(fp, 1, 'int32', 0, 'ieee-be'); %read and store in variab
7 assert(magic == 2049, ['Bad magic number in', filename, '']); %show er
8
9 numLabels = fread(fp, 1, 'int32', 0, 'ieee-be'); %read numLabel
10 labels = fread(fp, inf, 'unsigned char'); %change format
11 assert(size(labels,1) == numLabels, 'Mismatch in label count');
12
13 fclose(fp);
14 end
15
```

Figure 4.2: Matlab CNN function for Labels loading

```
Conv.m
1 function y = Conv(x, W)
2
3 [wrow, wcol, numFilters] = size(W);
4 [xrow, xcol, ~] = size(x);
5
6 yrow = xrow - wrow + 1;
7 ycol = xcol - wcol + 1;
8
9 y = zeros(yrow, ycol, numFilters);
10
11 for k = 1:numFilters
12     filter = W(:, :, k);
13     filter = rot90(squeeze(filter), 2);
14     y(:, :, k) = conv2(x, filter, 'valid');
15 end
16 end
17
18
```

Figure 4.3: Matlab CNN function to initialize convolution

ReLU.m

Below is a implementation of Rectified Linear Unit Activation Function to introduce non-linearity to the model.

```
function y = ReLU(x)
y = max(0,x);
end
```

Softmax.m

Implementation of the Softmax Activation function for multiclass classification problems.

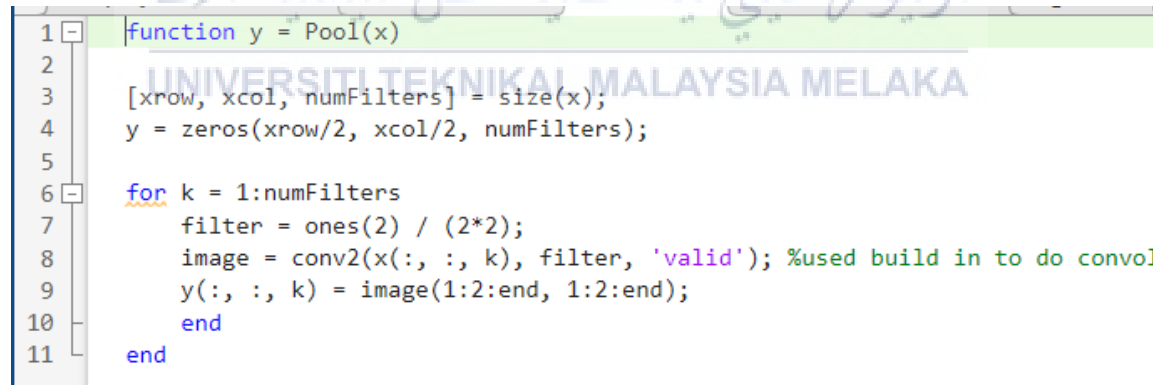
```
function y = Softmax(x)
ex = exp(x);
y = ex / sum(ex);
end
```

mg.m

An attempt to set the seed for the random number generators in MATLAB.

```
function rng(x)
randn('seed', x)
rand('seed', x)
end
```

Pool.m



```
1 function y = Pool(x)
2
3 [xrow, xcol, numFilters] = size(x);
4 y = zeros(xrow/2, xcol/2, numFilters);
5
6 for k = 1:numFilters
7     filter = ones(2) / (2*2);
8     image = conv2(x(:, :, k), filter, 'valid'); %used build in to do convol
9     y(:, :, k) = image(1:2:end, 1:2:end);
10 end
11 end
```

Figure 4.4: MATLAB CNN function of Pooling Layer.

MnistConv.m

```

1 function [W1, W5, Wo] = MnistConv(W1, W5, Wo, X, D)
2
3     alpha = 0.01;
4     beta = 0.95;
5
6     momentum1 = zeros(size(W1));
7     momentum5 = zeros(size(W5));
8     momentum0 = zeros(size(Wo));
9
10    N = length(D);
11
12    bsize = 100;
13    blist = 1:bsize:(N-bsize+1);
14
15    for batch = 1:length(blist)
16        dw1 = zeros(size(W1));
17        dw5 = zeros(size(W5));
18        dWo = zeros(size(Wo));
19
20        begin = blist(batch);
21        for k = begin:begin+bsize-1
22
23            x = X(:, :, k);
24            y1 = Conv(x, W1);
25            y2 = ReLU(y1);
26            y3 = Pool(y2);
27            y4 = reshape(y3, [], 1);
28            v5 = W5*y4;
29            y5 = ReLU(v5);
30            v = Wo*y5;
31            y = Softmax(v);
32
33            d = zeros(10,1);
34            d(sub2ind(size(d), D(k), 1)) = 1;
35
36            e = d - y;
37            delta = e;
38            e5 = Wo' * delta;
39            delta5 = (y5 > 0) .* e5;
40            e4 = W5' * delta5;
41            e3 = reshape(e4, size(y3));
42            e2 = zeros(size(y2));
43            W3 = ones(size(y2)) / (2*2);
44
45            for c = 1:20
46                e2(:, :, c) = kron(e3(:, :, c), ones([2 2])) .* W3(:, :, c);
47            end
48
49            delta2 = (y2 > 0) .* e2;
50
51            delta1_x = zeros(size(W1));
52
53            for c = 1:20
54                delta_x(:, :, c) = conv2(x(:, :, c), rot90(delta2(:, :, c), 2), 'valid');
55            end
56
57            dw1 = dw1 + delta1_x;
58            dw5 = dw5 + delta5*y4';
59            dWo = dWo + delta *y5';
60
61        end
62
63        dw1 = dw1 / bsize ;
64        dw5 = dw5 / bsize ;
65        dWo = dWo / bsize ;
66
67        momentum1 = alpha*dw1 + beta*momentum1;
68        W1 = W1 + momentum1;
69

```

```

70 momentum5 = alpha*dW5 + beta*momentum5;
71 W5 = W5 + momentum5;
72
73 momentum0 = alpha*dW0 + beta*momentum0;
74 W0 = W0 + momentum0;
75 end
76 end
77
78

```

Figure 4.5: MATLAB code for training CNN.



TestMNISTConv.m

```
1  Images = loadMNISTImages('MNIST/t10k-images.idx3-ubyte');
2  Images = reshape(Images, 28, 28, []);
3
4  Labels = loadMNISTLabels('MNIST/t10k-labels.idx1-ubyte');
5  Labels(Labels == 0) = 10;
6
7  rng(1);
8
9  W1 = 1e-2*randn([9 9 20]);
10 W5 = (2*rand(100, 2000) - 1) *sqrt(6) / sqrt(360+2000);
11 Wo = (2*rand( 10, 100) - 1) *sqrt(6) / sqrt( 10 + 100);
12
13 X = Images(:, :, 1:8000);
14 D = Labels(1:8000);
15
16 for epoch = 1:3
17     epoch
18     [W1, W5, Wo] = MnistConv(W1, W5, Wo, X, D);
19
20 end
21
22 save('MnistConv.mat');
23
24 X = Images(:, :, 8001:10000);
25 D = Labels(8001:10000);
26 acc = 0;
27 N = length(D);
28
29 for k = 1:N
30     x = X(:, :, k);
31     y1 = Conv(x, W1);
32     y2 = ReLU(y1);
33     y3 = Pool(y2);
34     y4 = reshape(y3, [], 1);
35     v5 = W5*y4;
36     y5 = ReLU(v5);
37     v = Wo*y5;
38     y = Softmax(v);
39
40     [~, i] = max(y);
41     if i == D(k)
42         acc = acc + 1;
43     end
44 end
45
46 acc = acc / N;
47 fprintf('Accuracy is %f\n', acc);
48
49
```

Figure 4.6: MATLAB code to test the CNN using MNIST dataset to get accuracy.

Display_network.m

```

1 function [h, array] = display_network(A, opt_normalize, opt_graycolor, cols, opt_
2     warning off all
3
4     if ~exist('opt_normalize', 'var') || isempty(opt_normalize)
5         opt_normalize = true;
6     end
7
8     if ~exist('opt_graycolor', 'var') || isempty(opt_normalize)
9         opt_graycolor = true;
10    end
11
12    if ~exist('opt_colmajor', 'var') || isempty(opt_colmajor)
13        opt_colmajor = false;
14    end
15
16    A = A - mean(A(:));
17
18    if opt_graycolor
19        colormap(gray);
20    end
21
22    [L, M] = size(A);
23    sz = sqrt(L);
24    buf = 1;
25
26    if ~exist('cols', 'var')
27        if floor(sqrt(M))^2 ~= M
28            n = ceil(sqrt(M));
29            while mod(M, n) ~= 0 && n < 1.2 * sqrt(M), n=n+1; end
30            m = ceil(M / n);
31
32    if floor(sqrt(M))^2 ~= M
33        n = ceil(sqrt(M));
34        while mod(M, n) ~= 0 && n < 1.2 * sqrt(M), n=n+1; end
35        m = ceil(M / n);
36    else
37        n = sqrt(M);
38        m = n;
39    end
40    else
41        n = cols;
42        m = ceil(M / n);
43    end
44    array = -ones(buf + m * (sz + buf), buf + n * (sz + buf));
45
46    if ~opt_graycolor
47        array = 0.1 * array;
48    end
49
50    if ~opt_colmajor
51        k = 1;
52        for i = 1:m
53            for j = 1:n
54                if k > M,
55                    continue;
56                end
57                clim = max(abs(A(:, k)));
58                if opt_normalize
59                    array(buf + (i - 1) * (sz + buf) + (1:sz), buf + (j - 1) * (sz + buf) + (1:sz)) = reshape(A(:, k), sz, sz) / c

```

```

56         else
57             array(buf + (i - 1) * (sz + buf) + (1:sz), buf + (j - 1) * (sz + buf) + (1:sz)) = reshape(A(:, k), sz, sz) /
58         end
59         k = k + 1;
60     end
61 end
62 else
63     k = 1;
64     for j = 1:n
65         for i = 1:m
66             if k > M,
67                 continue;
68             end
69             clim = max(abs(A(:, k)));
70             if opt_normalize
71                 array(buf + (i - 1) * (sz + buf) + (1:sz), buf + (j - 1) * (sz + buf) + (1:sz)) = reshape(A(:, k), sz, sz) /
72             else
73                 array(buf + (i - 1) * (sz + buf) + (1:sz), buf + (j - 1) * (sz + buf) + (1:sz)) = reshape(A(:, k), sz, sz);
74             end
75             k = k + 1;
76         end
77     end
78 end
79
80
81 if opt_graycolor
82     h=imagesc(array,'EraseMode','none', [-1 1]);
83 else
84     h=imagesc(array,'EraseMode','none', [-1 1]);
85 end
86 axis image_off
87 drawnow;
88 warning on_all
89
90

```

Figure 4.7; MATLAB code to visualize the performance of CNNs.

اوتنور سیتی تکنیکل ملیسیا ملاک

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

PlotFeature.m

```
1 load('MnistConv.mat')
2
3 k = 2;
4
5 x = X(:, :, k);
6 y1 = Conv(x, W1);
7 y2 = ReLU(y1);
8 y3 = Pool(y2);
9 y4 = reshape(y3, [], 1);
10 v5 = W5*y4;
11 y5 = ReLU(v5);
12 v = Wo*y5;
13 y = Softmax(v);
14
15 figure;
16 display_network(x(:));
17 title('Input Image')
18
19 convFilters = zeros(9*9, 20);
20 for i = 1:20
21     filter = W1(:, :, i);
22     convFilters(:, i) = filter(:);
23 end
24
25 figure
26 display_network(convFilters);
27 title('Convolution Filters')
28
29 fList = zeros(20*20, 20);
30 for i = 1:20
31     feature = y1(:, :, i);
32     fList(:, i) = feature(:);
33 end
34
35
```

```

35
36     figure
37     display_network(fList);
38     title('Features [Convolution]')
39
40     fList = zeros(20*20, 20);
41     for i = 1:20
42         feature = y2(:, :, i);
43         fList(:, i) = feature(:);
44     end
45
46
47     figure
48     display_network(fList);
49     title('Features [Convolution + ReLU]')
50
51     fList = zeros(10*10, 20);
52     for i = 1:20
53         feature = y3(:, :, i);
54         fList(:, i) = feature(:);
55     end
56
57
58     figure
59     display_network(fList);
60     title('Features [Convolution + ReLU + MeanPool]')
61
62

```

Figure 4.8: MATLAB code to plot extracted feature from ConvNet.



4.2.2 Image denoising algorithm

mainCov.m

```
clc
clear all
close all

% Load data
imds = imageDatastore('C:\Users\USER\OneDrive\Desktop\Y4S1\PSM\New folder', ...
    'IncludeSubfolders', true, 'LabelSource', 'foldernames', ...
    'FileExtensions', '.png'); % Assuming your images are in PNG format

% Check if the images are RGB or grayscale
sampleImage = readimage(imds, 1);
isGrayscale = size(sampleImage, 3) == 1;

if isGrayscale
    channelFormat = 'gray';
else
    channelFormat = 'rgb';
end

dnds = denoisingImageDatastore(imds, ...
    'PatchesPerImage', 32, ...
    'PatchSize', 50, ...
    'GaussianNoiseLevel', [0.01 0.1], ...
    'ChannelFormat', channelFormat);

% Layer design
if isGrayscale
    layers = [ ...
        imageInputLayer([50 50 1])

        convolution2dLayer(3, 64, 'Stride', 1, 'Padding', [1 1 1 1])
        reluLayer

        convolution2dLayer(3, 64, 'Stride', 1, 'Padding', [2 2 2 2])
        reluLayer

        convolution2dLayer(3, 64, 'Stride', 1, 'Padding', [1 1 1 1])
        reluLayer

        convolution2dLayer(3, 1)
        regressionLayer];
else
    layers = [ ...
        imageInputLayer([50 50 3])

        convolution2dLayer(3, 64, 'Stride', 1, 'Padding', [1 1 1 1])
        reluLayer

        convolution2dLayer(3, 64, 'Stride', 1, 'Padding', [2 2 2 2])
        reluLayer

        convolution2dLayer(3, 64, 'Stride', 1, 'Padding', [1 1 1 1])
        reluLayer

        convolution2dLayer(3, 3)
        regressionLayer];
end
```

```

% Adjusted training options
options = trainingOptions('adam', ...
    'MiniBatchSize', 128, ... % Adjusted mini-batch size
    'MaxEpochs', 30, ... % Increased number of epochs
    'ValidationFrequency', 5, ...
    'InitialLearnRate', 1e-3, ... % Adjusted initial learning rate
    'Plots', 'training-progress');

% Network training
[convnet, traininfo] = trainNetwork(dnds, layers, options);

% Rest of the code remains unchanged for testing and evaluation

% Testing the trained network
inp = imread('cameramancolour.png');
inp = double(inp) / 255; % Normalize to [0, 1]

noise = imnoise(inp, 'gaussian', 0.1, 0.01);

denoisedImage = denoiseImage(noise, convnet);

% Calculate the difference (noise) image
noiseImage = abs(noise - denoisedImage);

% Display the comparison
figure
imshow(noise)
title('Noisy')

figure
imshow(denoisedImage)
title('Denoised')

% Calculate and output PSNR
psnrNoisy = psnr(inp, noise);
psnrDenoised = psnr(inp, denoisedImage);

fprintf('PSNR (Noisy): %.2f dB\n', psnrNoisy);
fprintf('PSNR (Denoised): %.2f dB\n', psnrDenoised);

```

Figure 4.9: A completed MATLAB code for CNNs denoising.

4.3 RESULT

4.3.1 Convolutional Neural Network, CNN

```
>> TestMNISTConv  
  
epoch =  
      1  
  
epoch =  
      2  
  
epoch =  
      3  
  
Accuracy is 0.832000  
>>
```

Figure 4.10: epoch

TestMNISTConv called Mnist Conv functions and train to convolutional neural network. Upon calling, then will show the accuracy of our trained network. So after first, second and final epoch, if shown that the accuracy of our trained CNN is 0.832.

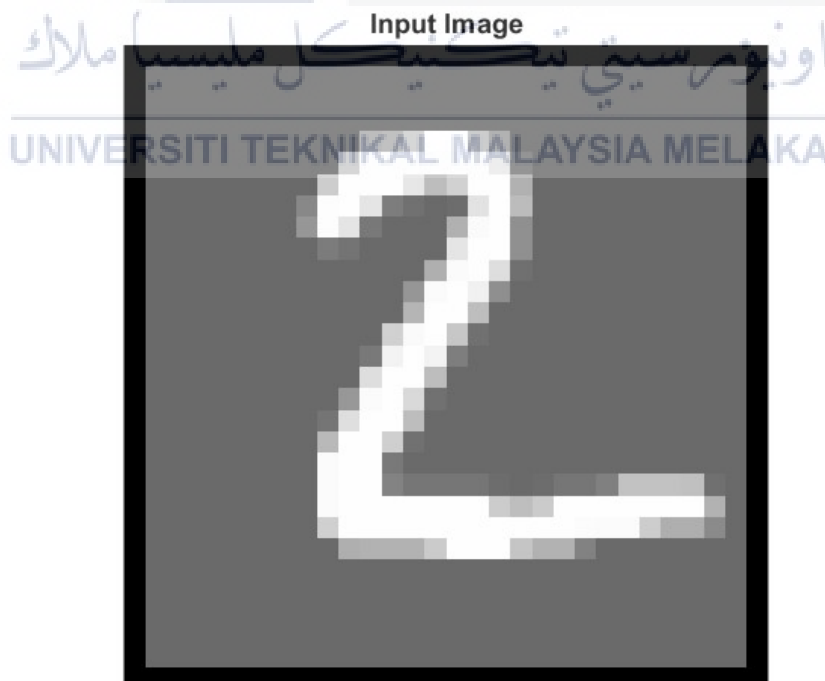


Figure 4.11: Input Image of MNIST dataset before CNN

The above figure is the MNIST dataset input image used to train CNN model, so that the CNN architecture is functioning well without error. Based on theory, the input images will enter convolutional layer to generate a Feature Map.

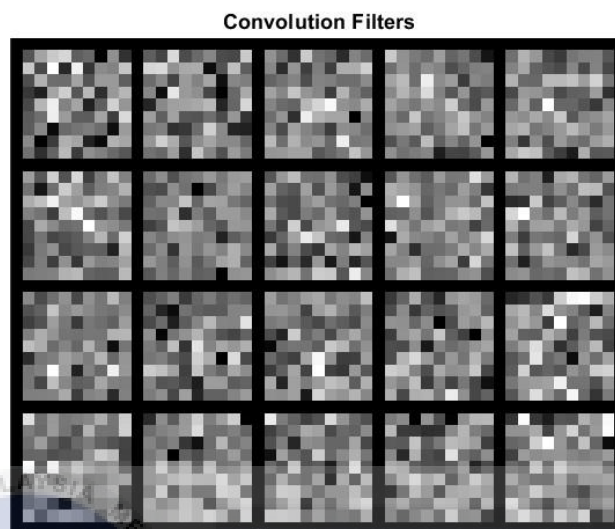


Figure 4.12: Image output of CNN filter.

In figure 4.12 is the image output of convolutional layers which also called Convolutional Layer. The working principle of the convolutional layers is that it doesn't employ connection weights and a weighted sum. Instead, it contains filter that convert images.

Features [Convolution]

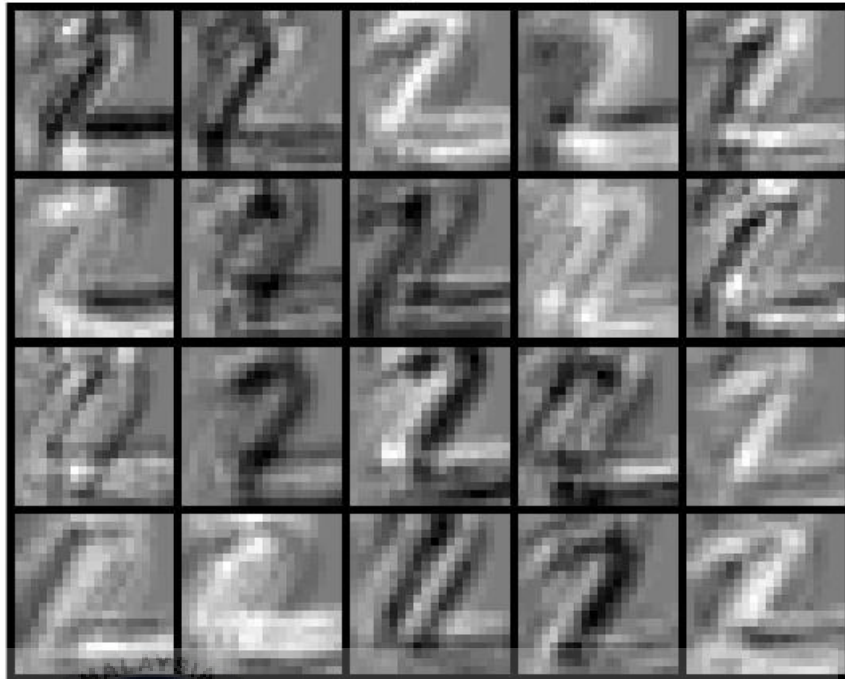


Figure 4.13: Image result of CNN.

Features [Convolution + ReLU]

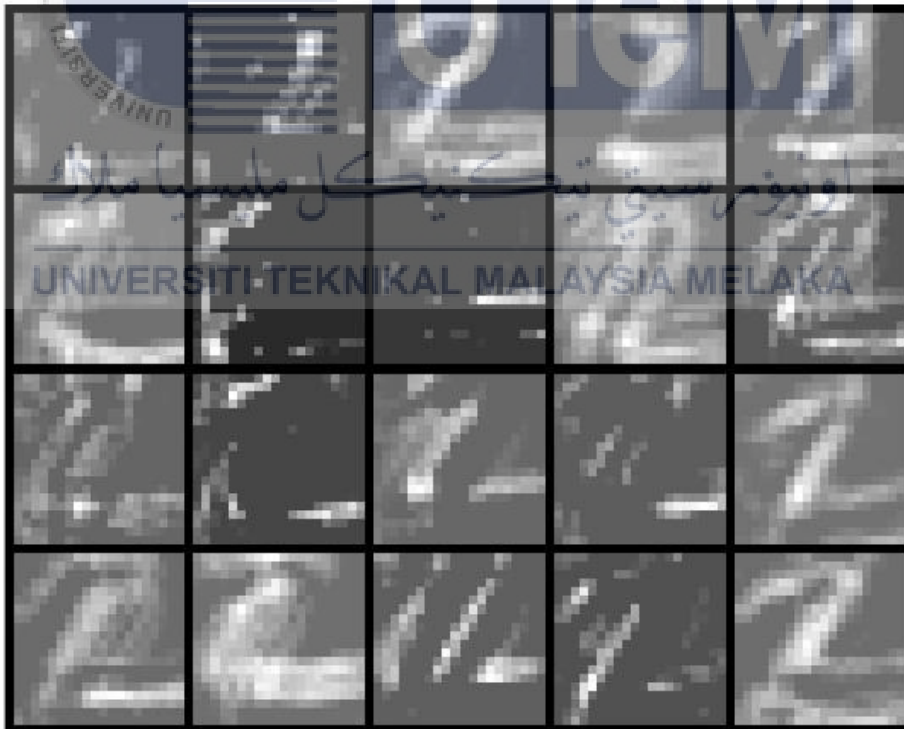


Figure 4.14: Image output after ReLU function.

Features [Convolution + ReLU + MeanPool]

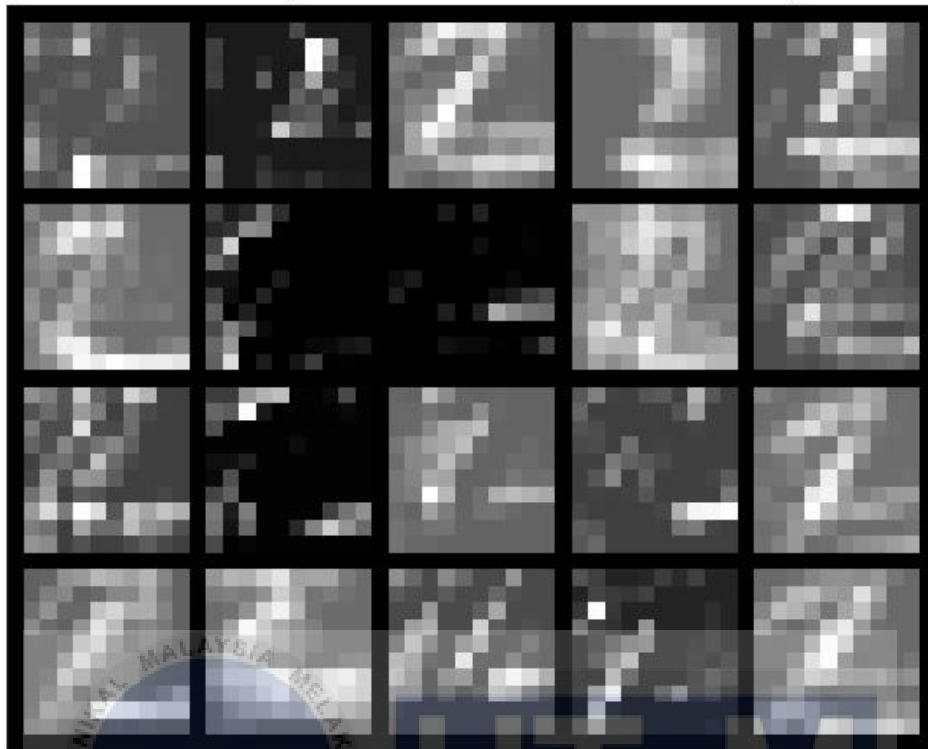


Figure 4.15: Final image result after Mean Pool.



4.3.2 Denoising Convolutional Neural Network, DnCNN

In the previous result showing, we understand how the Convolutional Neural Network architecture works. So, the next result will be the denoising image of 5 different image size with 3 RGB image and 2 grayscale images.

RGB IMAGE SIZE I : 640X427 PIXELS



Figure 4.16: Data of 'bird.png' of the process.

Training on single CPU.
Initializing input data normalization.

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch RMSE	Mini-batch Loss	Base Learning Rate
1	1	00:00:12	6.07	18.4	0.0010
8	50	00:06:46	3.62	6.5	0.0010
15	100	00:13:19	3.76	7.1	0.0010
22	150	00:19:53	3.06	4.7	0.0010
29	200	00:26:40	2.04	2.1	0.0010
30	210	00:27:58	2.60	3.4	0.0010

Training finished: Max epochs completed.
PSNR (Noisy): 17.38 dB
PSNR (Denoised): 18.98 dB

Figure 4.17: Measurement of Peak Signal Noise Ratio of 'bird.png'.

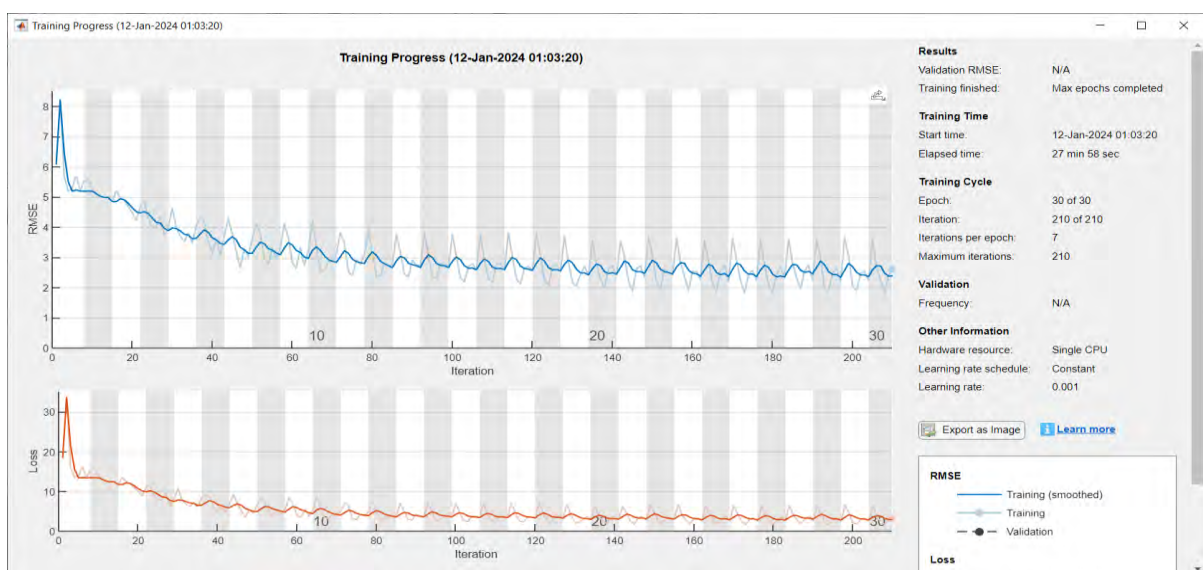


Figure 4.18: Process of Trained model with 30 epochs and 210 iterations.

RGB IMAGE SIZE II : 800X520 PIXELS

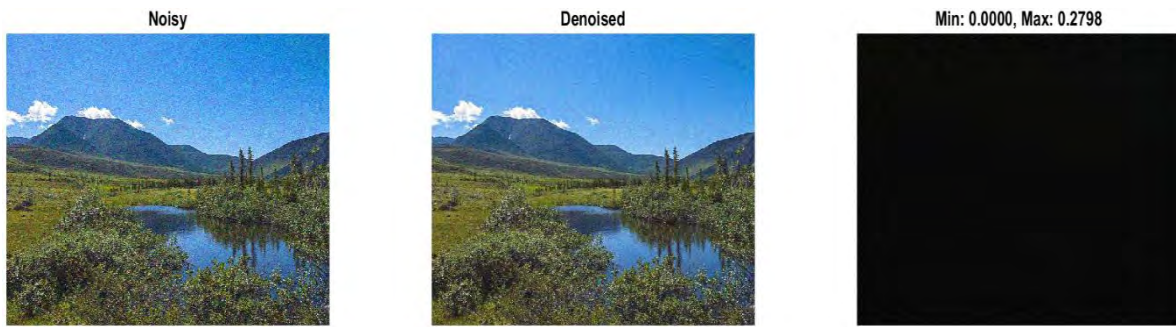


Figure 4.19: Data of 'mountain.png' of the process.

```

Training on single CPU.
Initializing input data normalization.
-----
| Epoch | Iteration | Time Elapsed | Mini-batch | Mini-batch | Base
Learning |          | (hh:mm:ss)   | RMSE       | Loss       | Rate
-----
| 1 | 1 | 00:00:08 | 5.40 | 14.6 |
0.0010 |
| 1 | 50 | 00:03:33 | 2.94 | 4.3 |
0.0010 |
| 2 | 100 | 00:07:01 | 2.38 | 2.8 |
0.0010 |
| 3 | 150 | 00:10:30 | 2.17 | 2.3 |
0.0010 |
| 4 | 200 | 00:13:59 | 2.05 | 2.1 |
0.0010 |
| 4 | 250 | 00:17:27 | 1.78 | 1.6 |
0.0010 |
| 5 | 300 | 00:20:53 | 2.11 | 2.2 |
0.0010 |
| 6 | 350 | 00:24:20 | 3.12 | 4.9 |
0.0010 |
| 7 | 400 | 00:27:42 | 4.06 | 8.2 |
0.0010 |
| 7 | 450 | 00:31:04 | 2.04 | 2.1 |
0.0010 |
| 8 | 500 | 00:34:27 | 2.09 | 2.2 |
0.0010 |
| 9 | 550 | 00:37:50 | 2.24 | 2.5 |
0.0010 |
| 10 | 600 | 00:41:11 | 3.33 | 5.6 |
0.0010 |
| 10 | 650 | 00:44:34 | 2.74 | 3.8 |
0.0010 |
| 11 | 700 | 00:47:56 | 1.72 | 1.5 |
0.0010 |
| 12 | 750 | 00:51:16 | 1.53 | 1.2 |
0.0010 |
| 13 | 800 | 00:54:38 | 1.80 | 1.6 |
0.0010 |
| 13 | 850 | 00:57:59 | 1.66 | 1.4 |
0.0010 |
| 14 | 900 | 01:01:19 | 1.72 | 1.5 |
0.0010 |
| 15 | 950 | 01:04:42 | 2.41 | 2.9 |
0.0010 |
| 16 | 1000 | 01:08:04 | 1.74 | 1.5 |
0.0010 |
| 16 | 1050 | 01:11:29 | 2.06 | 2.1 |

```

```

0.0010 |
| 17 |          1100 |          01:14:51 |          1.57 |          1.2 |
| 0.0010 |
| 18 |          1150 |          01:18:12 |          2.64 |          3.5 |
| 0.0010 |
| 19 |          1200 |          01:21:33 |          4.04 |          8.1 |
| 0.0010 |
| 19 |          1250 |          01:24:54 |          1.39 |          1.0 |
| 0.0010 |
| 20 |          1300 |          01:28:16 |          3.55 |          6.3 |
| 0.0010 |
| 21 |          1350 |          01:31:35 |          2.40 |          2.9 |
| 0.0010 |
| 22 |          1400 |          01:34:56 |          3.15 |          5.0 |
| 0.0010 |
| 22 |          1450 |          01:38:18 |          4.21 |          8.8 |
| 0.0010 |
| 23 |          1500 |          01:41:41 |          2.52 |          3.2 |
| 0.0010 |
| 24 |          1550 |          01:45:02 |          1.54 |          1.2 |
| 0.0010 |
| 25 |          1600 |          01:48:24 |          3.06 |          4.7 |
| 0.0010 |
| 25 |          1650 |          01:51:45 |          1.52 |          1.2 |
| 0.0010 |
| 26 |          1700 |          01:55:06 |          2.21 |          2.4 |
| 0.0010 |
| 27 |          1750 |          01:58:28 |          1.62 |          1.3 |
| 0.0010 |
| 28 |          1800 |          02:01:50 |          1.60 |          1.3 |
| 0.0010 |
| 29 |          1850 |          02:05:18 |          1.69 |          1.4 |
| 0.0010 |
| 29 |          1900 |          02:08:40 |          1.60 |          1.3 |
| 0.0010 |
| 30 |          1950 |          02:12:02 |          1.74 |          1.5 |
| 0.0010 |
| 30 |          1980 |          02:14:03 |          1.51 |          1.1 |
|-----|
|-----|
Training finished: Max epochs completed.
PSNR (Noisy): 17.24 dB
PSNR (Denoised): 18.80 dB

```

Figure 4.20: Measurement of Peak Signal Noise Ratio of 'mountain.png'.

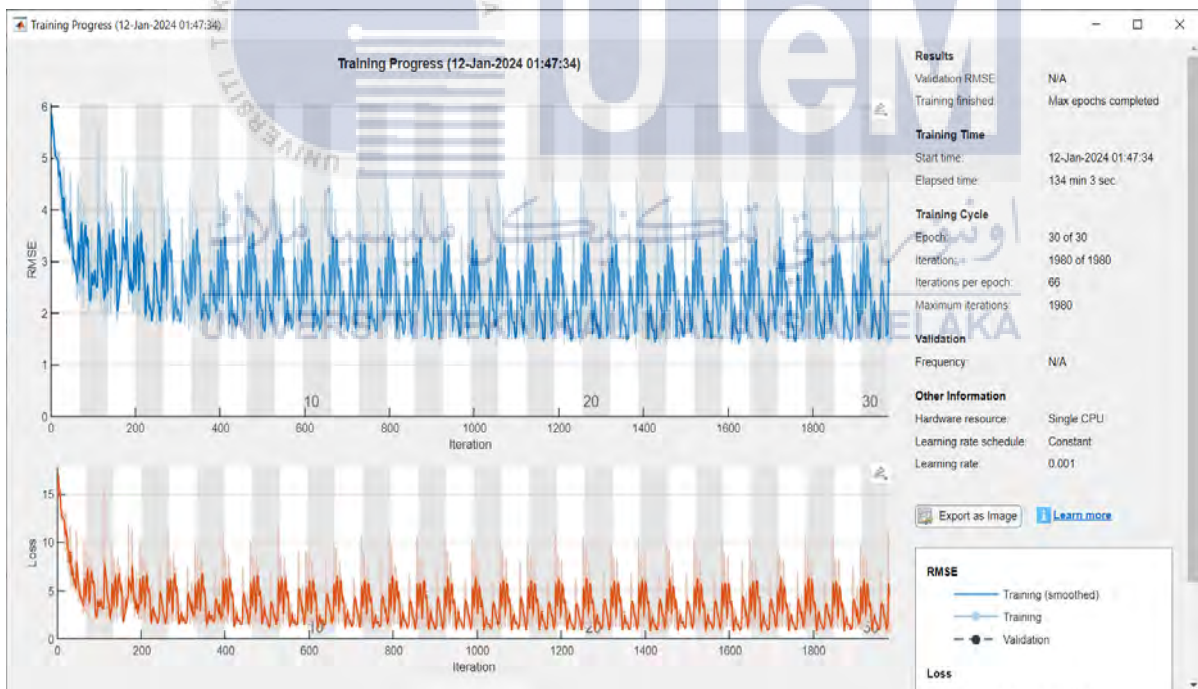


Figure 4.21: Process of Trained Model with 30 epochs and 1980 iterations.

RGB IMAGE SIZE III : 1024X768 PIXELS

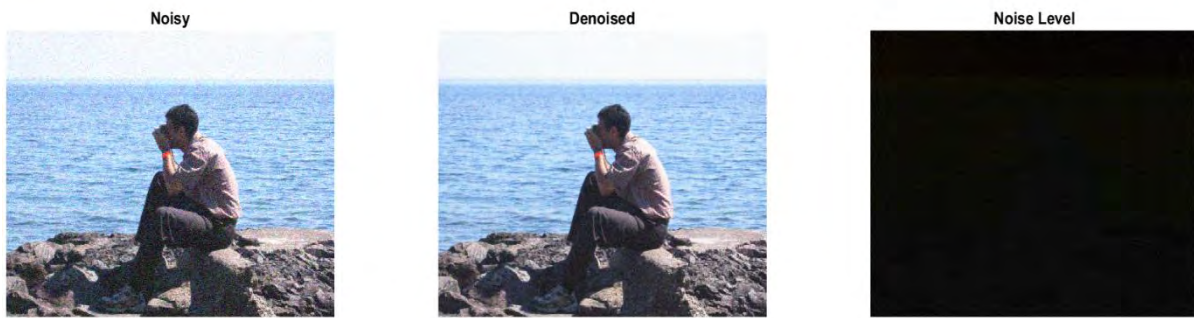


Figure 4.22: Data of 'cameramencolour.png' of the process.

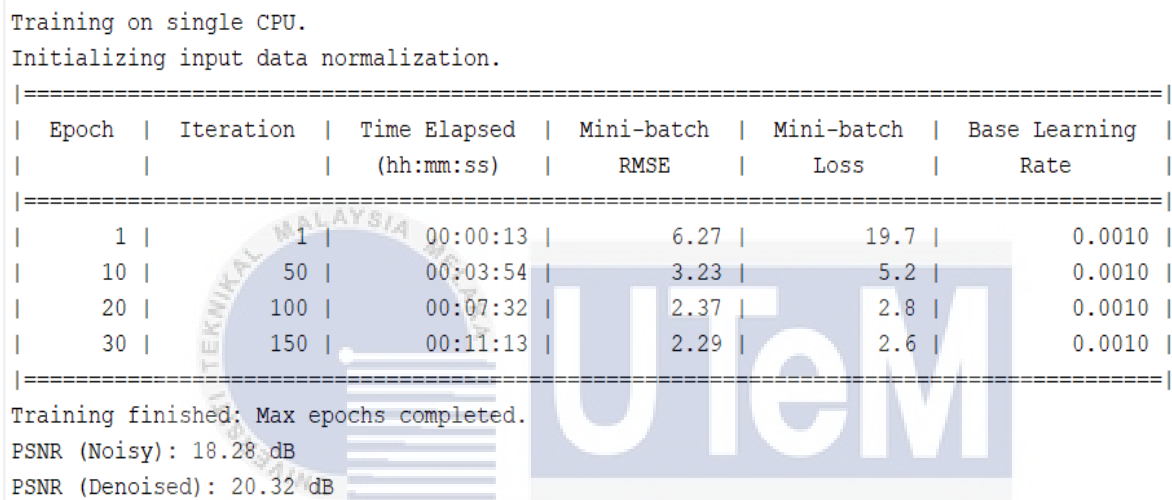


Figure 4.23: Measurement data of Peak Signal Noise Ratio of 'cameramencolour.png'.

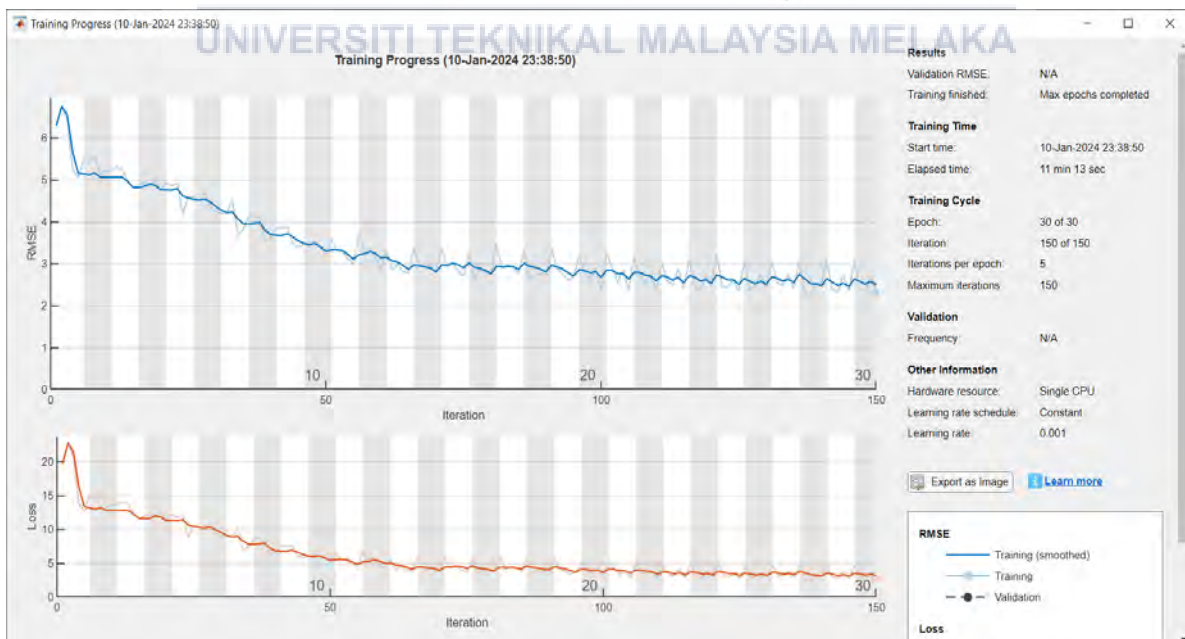


Figure 4.24: Process of Trained Model with 30 epochs and 150 iterations.

GRAYSCALE IMAGE SIZE I : 513X513 PIXELS

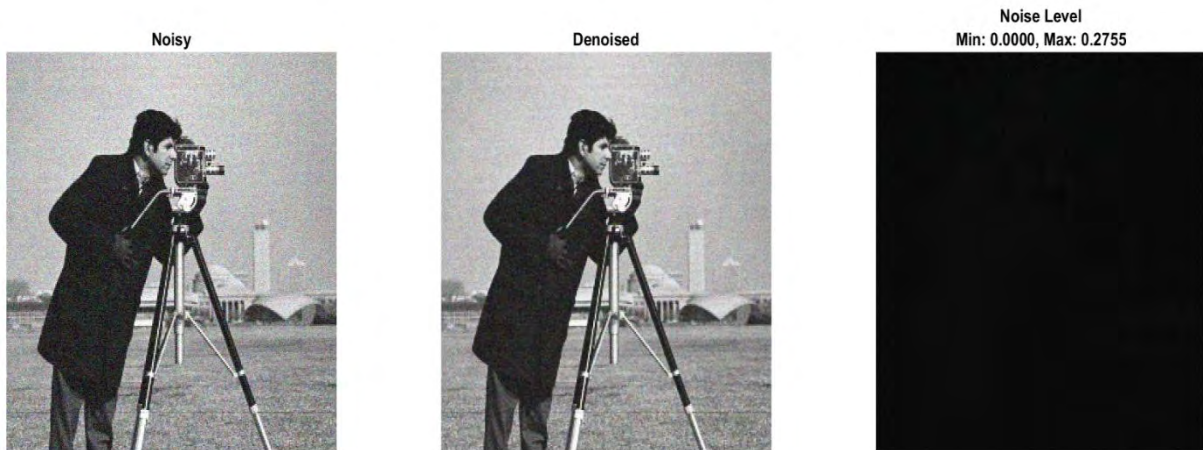


Figure 4.25: Data of 'cameraman.png' of the process.

Training on single CPU.

Initializing input data normalization.

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch RMSE	Mini-batch Loss	Base Learning Rate
1	1	00:00:13	6.18	19.1	0.0010
9	50	00:03:56	3.19	5.1	0.0010
17	100	00:07:44	3.45	6.0	0.0010
25	150	00:11:26	2.07	2.1	0.0010
30	180	00:13:50	1.94	1.9	0.0010

Training finished: Max epochs completed.

PSNR (Noisy): 17.08 dB

PSNR (Denoised): 18.82 dB

Figure 4.26: Measurement of Peak Signal Noise Ratio of 'cameraman.png'.

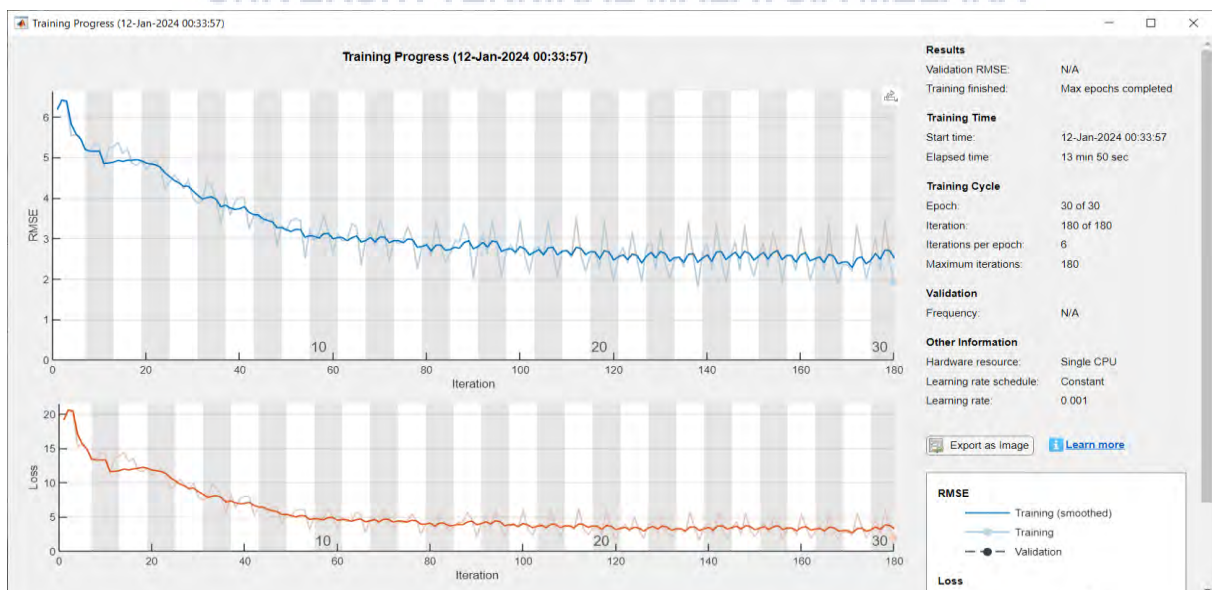


Figure 4.27: Process of Trained Model with 30 epochs and 180 iterations.

GRAYSCALE IMAGE SIZE II : 960x641 PIXELS

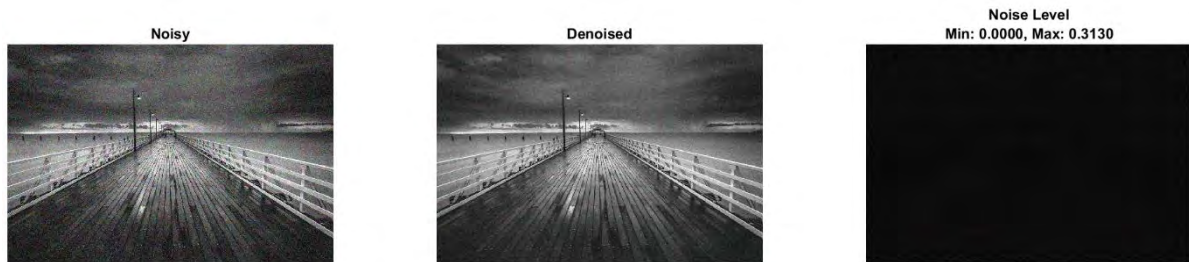


Figure 4.28: Data of 'bridge.png' of the process.

Training on single CPU.

Initializing input data normalization.

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch RMSE	Mini-batch Loss	Base Learning Rate
1	1	00:00:08	5.88	17.3	0.0010
6	50	00:03:35	3.27	5.3	0.0010
12	100	00:07:06	2.64	3.5	0.0010
17	150	00:10:45	2.29	2.6	0.0010
23	200	00:14:27	1.90	1.8	0.0010
28	250	00:18:00	2.32	2.7	0.0010
30	270	00:19:27	1.88	1.8	0.0010

Training finished: Max epochs completed.

PSNR (Noisy): 17.05 dB

PSNR (Denoised): 18.93 dB

Figure 4.29: Measurement of Peak Signal Noise Ratio of 'bridge.png'.

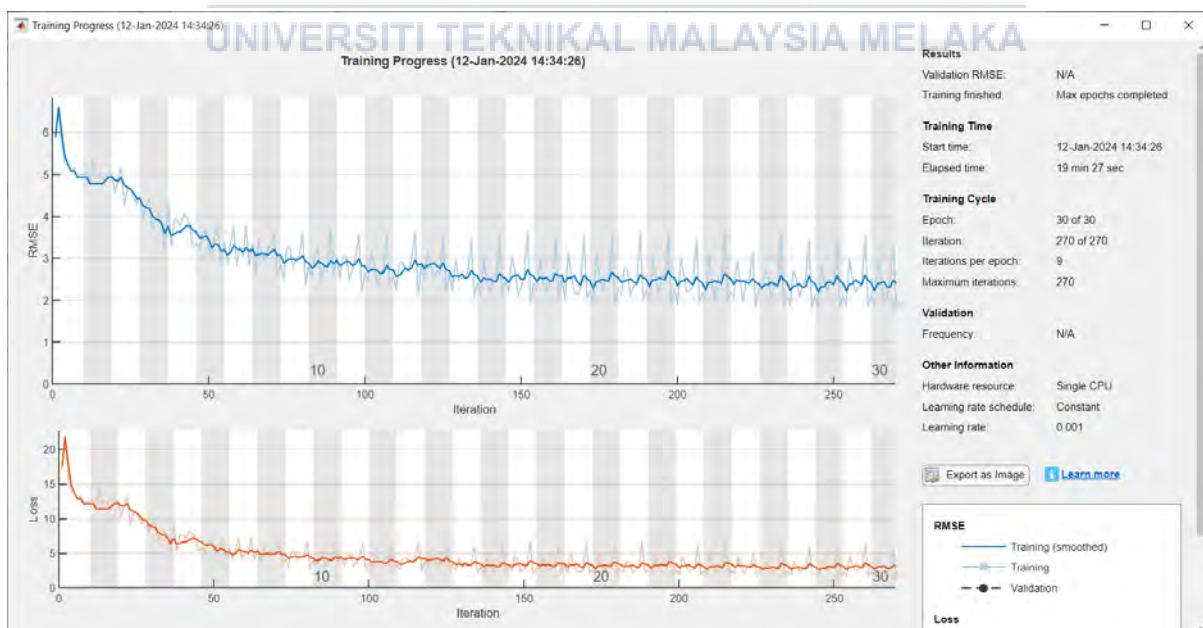


Figure 4.30: Process of Trained Model with 30 epochs and 270 iterations.

4.4 Summary

In this chapter, explains how we used a Convolutional Neural Network (CNN) to get rid of noise in images. We go into detail about the results and analysis of our CNN implementation for image denoising.

Firstly, we talk about how accurate our CNN is at different training stages. Figure 4.10 shows the accuracy trend, and by the final training round, our model achieved an accuracy of 0.832, indicating that it learned well.

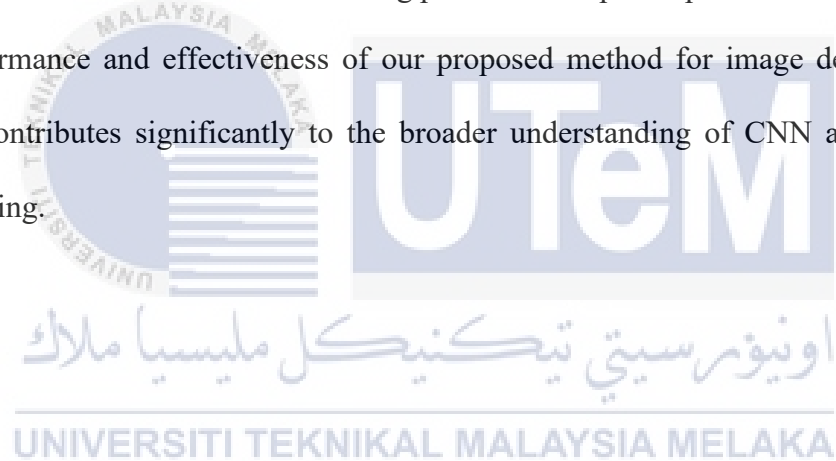
Proceeding to Figures 4.11 through 4.15, we elucidate the step-by-step workings of the CNN with the MNIST dataset. From taking an input image through convolutional layers to producing the final result, these figures provide a visual representation of the intricate operations carried out by the CNN. This detailed walkthrough elucidates the process, offering a comprehensive understanding of how CNN transforms input images at each stage.

Then, we demonstrate CNN's denoising capabilities with different images. Figures 4.16 to 4.30 display denoising results for RGB and grayscale images of diverse sizes. Each set includes the original image, Peak Signal-to-Noise Ratio (PSNR) measurements, and details about the denoising process.

The subsequent segment of our exploration involves showcasing the denoising capabilities of the CNN using various images. Figures 4.16 to 4.30 present denoising results for both RGB and grayscale images of diverse dimensions. Each set comprises the original image, Peak Signal-to-Noise Ratio (PSNR) measurements (as seen in Figure 4.17, Figure 4.20, Figure 4.23, Figure 4.26, and Figure 4.29), and a thorough breakdown of the denoising process, such as the number of epochs and iterations employed (as exemplified in Figure 4.18, Figure 4.21, Figure 4.24, Figure 4.27, and Figure 4.30).

For instance, the denoising of the RGB image 'bird.png' is detailed in Figure 4.17, showcasing the corresponding PSNR measurements in Figure 4.18 and providing insights into the denoising process with 30 epochs and 210 iterations in Figure 4.19. Similar comprehensive analyses are conducted for other images, emphasizing CNN's efficacy in reducing noise while preserving image quality.

In summary, this chapter offers a thorough overview of our CNN-based approach for image denoising. Through the presented figures and analyses, we demonstrate not only the successful training of CNN but also its application in denoising various images. The inclusion of PSNR measurements and detailed denoising process descriptions provides valuable insights into the performance and effectiveness of our proposed method for image denoising. This information contributes significantly to the broader understanding of CNN applications in image processing.



CHAPTER 5

CONCLUSION

Throughout this thesis, we explored the realm of deep neural networks, specifically focusing on convolutional neural networks (CNNs), to address the challenge of image noise removal effectively. The primary goal was to devise a methodology capable of reducing noise in digital images while preserving crucial details. The successful implementation and evaluation of our proposed CNN-based noise removal approach signifies a noteworthy advancement in denoising performance.

The motivation for this project arose from the pervasive issue of image noise, negatively impacting the quality and utility of digital images in various domains. Conventional denoising methods often struggle to balance noise reduction and the preservation of image intricacies, resulting in compromised outcomes. Leveraging CNNs, known for their ability to master complex patterns, became our strategy to overcome these challenges and achieve superior denoising results.

Our journey commenced with an exhaustive literature review, laying the groundwork by assimilating insights into existing image denoising techniques, especially those rooted in deep learning and CNNs. This review not only informed our methodology but also identified gaps in current research, paving the way for our unique contributions.

The project's scope included the meticulous collection and preparation of a diverse dataset featuring noisy and clean images for training and evaluation. Encompassing various noise types, levels, and image characteristics, this dataset strengthened the robustness and generalization capacity of our trained CNN model. We devised a well-crafted CNN architecture, featuring multiple layers, suitable activation functions, loss functions, and optimization algorithms to adeptly learn noise patterns and enhance image quality.

Through rigorous model training and evaluation, we highlighted the effectiveness of our CNN-based noise removal methodology. Quantitative metrics such as peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) consistently indicated superior denoising performance compared to traditional methods. The CNN model adeptly reduced noise while maintaining critical image features, producing visually appealing and high-quality denoised images.

Experimental analyses and comparisons were conducted to emphasize the merits and potential of our methodology. A comparative analysis against existing noise removal techniques underscored the CNN model's superior effectiveness, efficiency, and generalization ability. While acknowledging the limitations of our approach, such as computational demands and specific noise types, we envision future extensions mitigating these constraints and optimizing the methodology for diverse noise scenarios.

In summary, this research effort successfully devised and implemented a deep neural network-based methodology for image noise removal through CNNs. The outcomes offer valuable contributions to the image denoising field, showcasing the potential of CNNs as a potent solution for noise reduction. With further refinements, CNN-based noise removal techniques hold promise for substantially enhancing the quality and applicability of digital images across various domains, impacting areas like medical imaging, surveillance, and computer vision.

Through this research journey, we've gained profound insights into the capabilities and potential of deep learning techniques for image denoising. The attained results serve as a catalyst for future research and innovation, with the hope that this work sparks continued exploration and advancements in the pursuit of pristine, noise-free digital imagery.

REFERENCE

1. McCulloch W. S., Pitts W. A logical calculus of the ideas immanent in nervous activity. *Bulletin of Mathematical Biology*. 1943;5(4):115–133. doi: 10.1007/BF02478259. [[Abstract](#)] [[CrossRef](#)] [[Google Scholar](#)]
2. LeCun Y., Boser B., Denker J., et al. Handwritten digit recognition with a back-propagation network. In: Touretzky D., editor. *Advances in Neural Information Processing Systems 2 (NIPS*89)* Denver, CO, USA: 1990. [[Google Scholar](#)]
3. Hochreiter S., Schmidhuber J. Long short-term memory. *Neural Computation*. 1997;9(8):1735–1780. doi: 10.1162/neco.1997.9.8.1735. [[Abstract](#)] [[CrossRef](#)] [[Google Scholar](#)]
4. Hinton G. E., Osindero S., Teh Y.-W. A fast learning algorithm for deep belief nets. *Neural Computation*. 2006;18(7):1527–1554. doi: 10.1162/neco.2006.18.7.1527. [[Abstract](#)] [[CrossRef](#)] [[Google Scholar](#)]
5. Frederic B., Lamblin P., Pascanu R., et al. *Deep Learning and Unsupervised Feature Learning NIPS 2012 Workshop*. 2012. Theano: new features and speed improvements. <http://deeplearning.net/software/theano/> [[Google Scholar](#)]
6. Dinsha Babu., Sajeev K. Jose. Review on CNN Based Image Denoising. *SSRN*. December 24, 2020.
7. Ouyang W., Zeng X., Wang X., et al. DeepID-Net: Object Detection with Deformable Part Based Convolutional Neural Networks. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 2017;39(7):1320–1334. doi: 10.1109/TPAMI.2016.2587642. [[Abstract](#)] [[CrossRef](#)] [[Google Scholar](#)]
8. Diba A., Sharma V., Pazandeh A., Pirsiavash H., Gool L. V. Weakly Supervised Cascaded Convolutional Networks. Proceedings of the 2017 IEEE Conference on

- Computer Vision and Pattern Recognition (CVPR); July 2017; Honolulu, HI. pp. 5131–5139. [[CrossRef](#)] [[Google Scholar](#)]
9. Doulamis N., Voulodimos A. FAST-MDL: Fast Adaptive Supervised Training of multi-layered deep learning models for consistent object tracking and classification. Proceedings of the 2016 IEEE International Conference on Imaging Systems and Techniques, IST 2016; October 2016; pp. 318–323. [[CrossRef](#)] [[Google Scholar](#)]
 10. Doulamis N. Adaptable deep learning structures for object labeling/tracking under dynamic visual environments. *Multimedia Tools and Applications*. 2017:1–39. doi: 10.1007/s11042-017-5349-7. [[CrossRef](#)] [[Google Scholar](#)]
 11. Lin L., Wang K., Zuo W., Wang M., Luo J., Zhang L. A deep structured model with radius-margin bound for 3D human activity recognition. *International Journal of Computer Vision*. 2016;118(2):256–273. doi: 10.1007/s11263-015-0876-z. [[CrossRef](#)] [[Google Scholar](#)]
 12. Cao S., Nevatia R. Exploring deep learning based solutions in fine grained activity recognition in the wild. Proceedings of the 2016 23rd International Conference on Pattern Recognition (ICPR); December 2016; Cancun. pp. 384–389. [[CrossRef](#)] [[Google Scholar](#)]
 13. Toshev A., Szegedy C. DeepPose: Human pose estimation via deep neural networks. Proceedings of the 27th IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2014; June 2014; USA. pp. 1653–1660. [[CrossRef](#)] [[Google Scholar](#)]
 14. Chen X., Yuille A. L. Articulated pose estimation by a graphical model with image dependent pairwise relations. Proceedings of the NIPS; 2014. [[Google Scholar](#)]

15. Noh H., Hong S., Han B. Learning deconvolution network for semantic segmentation. Proceedings of the 15th IEEE International Conference on Computer Vision, ICCV 2015; December 2015; Santiago, Chile. pp. 1520–1528. [[CrossRef](#)] [[Google Scholar](#)]
16. Long J., Shelhamer E., Darrell T. Fully convolutional networks for semantic segmentation. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR '15); June 2015; Boston, Mass, USA. IEEE; pp. 3431–3440. [[CrossRef](#)] [[Google Scholar](#)]
17. "Image Denoising via Deep Convolutional Neural Networks" by Kaiming He et al. (2017)
18. "Beyond a Gaussian Denoiser: Residual Learning of Deep CNN for Image Denoising" by Kai Zhang et al. (2017)
19. "DnCNN: Deep Convolutional Neural Network for Image Denoising" by Kai Zhang et al. (2017)
20. "Learning Deep CNN Denoiser Prior for Image Restoration" by Yamanaka et al. (2017)
21. "Deep ADMM-Net for Compressive Sensing MRI" by H. K. Aggarwal et al. (2018)
22. "Wavelet-Domain Residual Learning for Image Denoising" by Chaoran Li et al. (2018)
23. "FFDNet: Toward a Fast and Flexible Solution for CNN-based Image Denoising" by Y. Zhang et al. (2018)
24. "Noise2Noise: Learning Image Restoration without Clean Data" by J. Lehtinen et al. (2018)
25. "Deep Plug-and-Play Super-Resolution for Arbitrary Blur Kernels" by S. Nah et al. (2019)
26. "Deep Image Prior" by D. Ulyanov et al. (2018)

27. “Image Denoising using Deep Learning: Convolutional Neural Network” by Shreyasi Ghose; Nishi Singh; Prabhishek Singh. (2020)
28. Schwenker F, Kestler HA, Palm G (2001) Three learning phases for radial-basis-function networks. *Neural Netw* 14(4):439–458
29. Tian C, Zhang Q, Sun G, Song Z, Li S (2018) FFT consolidated sparse and collaborative representation for image classification. *Arab J Sci Eng* 43(2):741–758
30. Simonyan K, Zisserman A. Very deep convolutional networks for large-scale image recognition, ArXiv preprint arXiv: 1409.1556
31. Guo B, Song K, Dong H, Yan Y, Tu Z, Zhu L (2020) NERNet: noise estimation and removal network for image denoising. *J Vis Commun Image R* 71:102851
32. Wei Y et al (2018) Revisiting dilated convolution: a simple approach for weakly-and semi-supervised semantic segmentation. *IEEE Conf Comp Vis Pattern Recogn (Cvpr)* 2018:7268–7277
33. Li X et al (2019) Selective kernel networks. *IEEE Conf Comp Vis Pattern Recogn (Cvpr)* 2019:510–519
34. He KM et al (2014) Spatial pyramid pooling in deep convolutional networks for visual recognition. In: *Computer Vision - Eccv 2014, Pt Iii.* 8691: pp 346–361
35. Hong I, Hwang Y, Kim D (2019) Efficient deep learning of image denoising using patch complexity local divide and deep conquer. *Pattern Recogn* 96:106945
36. Chatterjee P, Milanfar P (2011) Practical bounds on image denoising: from estimation to information. *IEEE Trans Image Process* 20(5):1221–1233
37. Vincent P, Larochelle H, Lajoie I, Bengio Y, Manzagol P-A (2010) Stacked denoising autoencoders: learning useful representations in a deep network with a local denoising criterion. *J Mach Learn Res* 11:3371–3408

38. He K, Zhang X, Ren S, Sun J (2016) Deep residual learning for image recognition. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp 770–778
39. Shi W, Jiang F, Zhang S, Wang R, Zhao D, Zhou H (2019) Hierarchical residual learning for image denoising. *Signal Process Image Commun* 76:243–251
40. Kim J, Kwon Lee J, Mu Lee K (2016) Accurate image super-resolution using very deep convolutional networks. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp 1646–1654
41. Gai S, Bao Z (2019) New image denoising algorithm via improved deep convolutional neural network with perceptive loss. *Expert Syst Appl* 138:112815
42. Wu CZ, Chen X, Ji D, Zhan S (2018) Image denoising via residual network based on perceptual loss. *J Image Graphics* 23(10):1483–1491
43. Zhang J, Luo H, Hui B, Chang Z (2019) Unknown noise removal via sparse representation model. *ISA Trans* 94:135–143
44. Liu J, Tai X, Huang H, Huan Z (2013) A weighted dictionary learning models for denoising images corrupted by mixed noise. *IEEE Trans Image Process* 22(3):1108–1120
45. Zhang L, Li Y, Wang P, Wei W, Xu S, Zhang Y (2019) A separation–aggregation network for image denoising. *Appl Soft Comp J* 83:105603
46. Zhou B, Khosla A, Lapedriza A, Oliva A, Torralba A (2016) Learning deep features for discriminative localization. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp 2921–2929
47. Gu S, Zhang L, Zuo W, Feng X (2014) Weighted nuclear norm minimization with application to image denoising. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp 2862–2869

48. Li X, Xiao J, Zhou Y, Ye Y, Lv N, Wang X, Wang S, Gao S (2020) Detail retaining convolutional neural network for image denoising. *J Vis Commun Image R* 71:102774
49. Yin H, Gong Y, Qiu G (2020) Fast and efficient implementation of image filtering using a side window convolutional neural network. *Signal Process* 176:107717
50. Zhang K, Zou 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
51. Lyu Q, Guo M, Pei Z (2020) DeGAN: mixed noise removal via generative adversarial networks. *Appl Soft Comp J* 95:106478
52. Goodfellow I, Pouget-Abadie J, Mirza M, Xu B, Warde-Farley B, Ozair S, Courville A, Bengio Y (2014) Generative adversarial nets. In: *Proceedings of the 28th Annual Conference on Neural Information Processing Systems*, pp 2672–2680
53. Ronneberger O, Fischer P, Brox T (2015) U-Net: convolutional networks for biomedical image segmentation. In: *Proceedings of the International Conference on Medical Image Computing and Computer-Assisted Intervention*, pp 234–241
54. Simonyan K, Zisserman A (2014) Very deep convolutional networks for large-scale image recognition. *ArXiv preprint arXiv: 1409.1556*.
55. Xu S, Zhang C, Zhang J (2020) Bayesian deep matrix factorization network for multiple images denoising. *Neural Netw* 123:420–428
56. Blei DM, Kucukelbir A, McAuliffe JD (2017) Variational inference: a review for statisticians. *J Am Stat Assoc* 112(518):859–877
57. Blundell C, Cornebise J, Kavukcuoglu K, Wierstra D (2015) Weight uncertainty in neural networks. In: *ICML*, pp 1613–1622

58. Kingma DP, Welling M (2014) Auto-encoding variational Bayes. In: International conference on learning representations, ICLR Banff, AB, Canada, pp 14–16
59. Jin L, Zhang W, Ma G, Song E (2019) Learning deep CNNs for impulse noise removal in images. *J Vis Commun Image R* 62:193–205
60. Quan Y, Chen Y, Shao Y, Teng H, Xu Y, Ji H (2021) Image denoising using complex-valued deep CNN. *Pattern Recogn* 111:107639
61. Zhang W, Jin L, Song E, Xu X (2019) Removal of impulse noise in color images based on convolutional neural network. *Appl Soft Comp J* 82:105558
62. Kingma D, Ba J (2015) Adam: a method for stochastic optimization. In: International Conference on Learning Representation
63. Fang Y, Zeng T (2020) Learning deep edge prior for image denoising. *Comp Vis Image Understand* 200:103044
64. Ilesanmi, A.E., Ilesanmi, T.O. Methods for image denoising using convolutional neural network: a review. *Complex Intell. Syst.* 7, 2179–2198 (2021).
<https://doi.org/10.1007/s40747-021-00428-4>
65. Madhavan S. and Jones M. T., “Deep learning architectures,” IBM Develop, January 2021, [Deep learning architectures - IBM Developer](#)
66. Garzelli A (2016) A review of image fusion algorithms based on the super-resolution paradigm. *Remote Sens* 8:797.