Reviving Images

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Submitted to the department of computer engineering in the partial fulfillment of the requirements for the degree of Bachelors in Computer Engineering.

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UNDERTAKING

I certify that research work titled "***Reviving Images***" is my own work. The work has not been presented elsewhere for assessment. Where material has been used from other sources it has been properly acknowledged / referred.

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DEDICATION

We would like to dedicate our project to our parents as well as our supervisor Sir Engr. Muhammad Nauman, both of whom have been a reliable source of support and a shoulder to lean on over the course of this project. They have served as a source of motivation for us, enabling us to approach each and every challenge with zeal, passion, and resolve. Their steadfast faith in our capabilities and their unending support have been critical to our achievement, and we are very grateful to them for that. Their counsel and insight molded our thinking and assisted us in overcoming challenges, something we could not have done without. We will be eternally thankful to them for their love, their patience, and their comprehension. Their contributions to this endeavor cannot be overstated in terms of their significance. Their unwavering commitment to our growth and development instilled in us a strong work ethic and a dedication to excellence. Their guidance has enhanced not only our technical abilities but also our personal and professional development. We owe them gratitude for the innumerable hours they invested in us by providing guidance, constructive criticism, and invaluable insights. This endeavor reflects their profound influence on our lives and ambitions.

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We want to thank Allah Almighty first and foremost for the knowledge that He has given us, and we owe our boss a debt of respect and appreciation. supervisor, Muhammad Nauman, for sharing his skills with us throughout this endeavor. We owe a great debt of gratitude to our supervisor for inspiring this initiative and providing us with invaluable direction. We owe Muhammad Nauman an enormous debt of gratitude for his unwavering enthusiasm and guidance throughout the duration of our thesis and project. Our manager was a fantastic role model who encouraged us to stretch ourselves professionally, and he helped us set and reach our goals. Supplied with us.

Our sincere gratitude also extends to our devoted friends and family members, without whose encouragement and backing none of our dreams could have come to fruition. Please accept our sincere gratitude.

ABSTRACT

In the domain of digital imagery, image restoration is crucial for revitalizing degraded images and recovering their former splendor. The “Reviving Images” project concentrates on developing an innovative method for restoring and improving pictures with different kinds of deterioration, like noise, blurring, and color distortion. Utilizing the power of advanced image processing techniques and machine learning algorithms, our methodology seeks to produce high-quality restoration results in a practical and efficient manner. By employing cutting-edge deep learning models and integrating them with conventional image processing techniques, we aim to reveal previously concealed details, improve visual quality, and breathe new life into once-damaged images. Through extensive experimentation and analysis, we intend to demonstrate the efficacy and potential of our method for reviving images in a variety of applications. This project has the potential to have a significant impact on disciplines such as photography, medical imaging, and historical preservation, thereby creating new avenues for image restoration and preservation. Besides, the Resuscitating Pictures project endeavors to lay out coordinated efforts with social foundations, files, and galleries to digitize and reestablish authentic photos and craftsmanship’s. By safeguarding and rejuvenating these important visual records, we add to the aggregate comprehension and enthusiasm for social legacy, guaranteeing that people in the future can investigate and draw in with our common history in a distinctive and vivid way.

Keywords:

Noise reduction , Edge Detection , Image Retrieval , Image synthesis , Image Authentication , Image based modeling , Denoising , Computer vision , image reconstruction.

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CHAPTER 1

INTRODUCTION

The field of image processing has long been dedicated to restoring and enhancing degraded images, which can suffer from issues like noise, blur, and color distortion, leading to diminished visual quality and usability. Traditional techniques such as filtering and deconvolution have been used, but their limitations often result in suboptimal outcomes. On the other hand, modern approaches findings based on deep learning have been encouraging. although they can be computationally intensive and data-hungry. This thesis proposes a novel method that combines traditional image processing techniques with deep learning to effectively tackle various image degradation problems. By harnessing the strengths of both approaches, we aim to overcome their limitations and achieve superior results in a more efficient and practical manner. This research has the potential to advance image restoration solutions, benefiting fields like digital photography, surveillance, and medical imaging.

1.1 Background

Techniques for reviving and enhancing images by leveraging advancements in image processing, specifically focusing on the integration of traditional methods and deep learning approaches. Several research papers have made significant achievements in the field.

Zhou et suggested a convolutional neural network (CNN)-based method for color image restoration, highlighting the potential of deep learning in image processing. Similarly, Chen et al. [2] presented an approach for image restoration utilizing deep CNNs and adaptive gradient methods. These papers demonstrate the effectiveness of deep learning models in addressing image degradation issues. Laine and Simonyan [3] introduced temporal resembling for semi-supervised learning, which can be relevant for incorporating semi-supervised techniques in image restoration tasks. Liu et al. [4] explored blind image restoration using deep CNNs, showcasing the potential of deep learning for handling complex restoration challenges. Zhang et al. [5] proposed a combined CNN approach for denoising and deblurring images, illustrating the benefits of integrating multiple tasks in image restoration. Dong et al. [6] introduced the concept of using generative adversarial networks (GANs) for image restoration, providing an alternative perspective on utilizing deep learning for image enhancement. Wang and Li [7, 10] conducted surveys on deep learning techniques for image super-resolution, highlighting the advancements and trends in this specific domain. Chen et al. [8] and Kim et al. [9] also explored recent advances in deep learning for image super-resolution, offering insights into the state-of-the-art techniques. Other studies, such as those by Xu et al. [12, 13], Dong et al. [14], and Huang et al. [18], focused on various aspects of image restoration, including sparse representations, collaborative filtering, and self-exemplars. These papers contribute to the broader understanding of image restoration techniques and their applications.

The field of image processing has long been concerned with the restoration and enhancement of degraded images. Image degradation can occur due to a variety of factors, such as noise, blur, and color distortion, and can significantly affect the visual quality and usefulness of an image. To address these issues, a range of techniques have been developed over the years, including traditional methods such as filtering and deconvolution, as well as modern methods based on machine learning, such as deep learning. While traditional methods are typically simple and fast, they can often produce suboptimal results due to the limitations of their underlying models However, they can be computationally expensive and necessitate a significant quantity of training data. Modern approaches, on the other hand, have produced outstanding results on a range of image processing applications. A rising number of people are now interested in using both conventional and cutting-edge techniques to improve and restore images. By combining the advantages of both strategies, it is possible to achieve improved results with a more efficient and practical approach. This thesis presents a new method for image restoration and enhancement that combines image processing techniques and deep learning methods to effectively address a range of image degradation issues.

on the benefits offered by both conventional image processing techniques and deep learning methods. We hope to be able to overcome the limits of both approaches by combining more conventional techniques, such as filtering and deconvolution, with deep learning algorithms. This will allow us to produce greater outcomes. By using a hybrid method, we are able to take advantage of the speed and simplicity of traditional procedures while also utilizing the capability of deep learning models for more complicated image restoration work.

The deep learning aspect of our approach entails training a convolutional neural network (CNN) with the use of a huge dataset that contains paired examples of images that have been degraded and those that serve as references. The underlying picture restoration process is effectively captured by the network as it learns to map the damaged images to their corresponding high-quality references. Backpropagation is used to optimize the parameters of the network, which enables the model to become excellent at repairing various sorts of image deterioration, such as noise reduction, blur removal, and color correction. Traditional image processing methods, such as pre-processing and post-processing, are incorporated into our system in addition to the deep learning component. The total efficiency and effectiveness of the process of restoration can be improved thanks to the application of these strategies. Before feeding the input photos into the deep learning model, for instance, we use denoising filters to reduce the amount of noise that is present in those images. In a similar manner, we use deconvolution methods to enhance the images that have been recovered. This helps to reduce artefacts while simultaneously increasing the overall visual quality. Our method for restoring and improving images attempts to deliver a solution that is more comprehensive and applicable to real-world scenarios by fusing the strengths of conventional image processing with those of deep learning. When compared to employing either method on its own, it has the potential to provide significantly superior restoration results, significantly lower computational requirements, and significantly faster processing times. The experimental evaluation and comparison with other approaches will reveal that our suggested method is successful and efficient when used in a variety of image restoration circumstances.

In the end, this research helps to develop image processing techniques by bridging the gap between classic methods and contemporary deep learning approaches. This research bridges the gap between traditional methods and modern approaches. It lays the groundwork for the development of image restoration solutions that are more resilient and efficient, which will be beneficial to a variety of fields, including digital photography, surveillance, and medical imaging, among others.

1.2 Problem Statement

In the realm of image processing, the issue of picture degradation is a serious concern since it can negatively impact an image's visual quality and utility. While numerous approaches have been devised to deal with this issue, they frequently have shortcomings that prohibit them from producing high-quality restoration outcomes. The objective of this project is to create a novel method for image enhancement and restoration that successfully solves a variety of difficulties with image degradation, such as noise, blur, and color distortion.. The suggested strategy seeks to create effective and workable solutions for enhancing the visual quality of degraded photos by integrating image processing techniques and deep learning approaches. The suggested approach makes an effort to overcome the shortcomings of existing approaches by bridging the gap between traditional image processing techniques and deep learning approaches. It needs convolutional neural network (CNN) training. with a large dataset of degraded and reference images so that the network can learn the underlying image restoration process. By incorporating image processing techniques as pre- and post-processing steps, such as denoising filters and deconvolution algorithms, the method seeks to achieve efficient and practical solutions for improving the visual quality of degraded images. This project seeks to contribute to the field of image processing by developing a novel method that combines the advantages of conventional techniques and deep learning. By integrating image processing techniques and leveraging the power of deep learning models, we aim to surmount the limitations of existing approaches and provide efficient and practical methods for restoring and enhancing degraded images.

haze, and color distortion. Through this project, we aspire to advance the field of image processing by proposing a novel approach that effectively addresses image degradation issues, providing enhanced visual quality and improved usability of degraded images.

1.3 Objective

Project goal is to develop a new approach for image restoration and enhancement that combines image processing techniques and deep learning methods to effectively address a range of image degradation issues, including noise, blur, and color distortion. The proposed method seeks to achieve efficient and practical high-quality restoration outcomes, and to show the efficacy of this method through extensive experimental findings on a range of photos. This project's ultimate objective is to present a promising method for enhancing the visual quality of damaged photos in a variety of applications. The project will also research cutting-edge ways to combine image processing technologies as pre- and post-processing phases, optimising their parameters for the most effective restoration performance..

Extensive tests are performed on a variety of datasets comprising different types and levels of image deterioration in order to assess the effectiveness of the proposed strategy. In order to assess the visual quality of the restored photographs, we will use both objective and subjective measurements.

The ultimate objective of the project is to contribute to the field of image processing by developing a practical and effective method for image restoration and enhancement. This strategy has the potential to benefit a variety of applications, such as medical imaging, surveillance, and digital photography. It intends to equip researchers and practitioners with a dependable set of tools to address the challenges posed by image degradation and enhance the visual quality and usability of degraded images in real-world scenarios. The project seeks to advance the state-of-the-art in image restoration and enhancement by combining image processing techniques and deep learning, thereby benefiting a variety of fields and applications.

1.4 Tools and Techniques

Following are few of the techniques and tools which we have used for out project, their scope and details are discussed here.

1.4.1 WordPress

WordPress is a popular PHP-based CMS. PHP's backend scripting powers WordPress. WordPress makes website development strong and versatile by enabling dynamic content production, database connectivity, and server-side scripts. WordPress, based on PHP, lets people build, customize, and manage websites without programming. WordPress' PHP-based architecture integrates seamlessly with plugins, themes, and extensions, providing a wide range of functionality and design possibilities. PHP's flexibility and large function library make it perfect for WordPress. It simplifies database interfaces, file handling, form processing, and other web development operations. PHP's flexibility with many operating systems and web servers makes WordPress websites accessible and easy to deploy. WordPress's open-source nature and active PHP community ensure ongoing development, upgrades, and security updates. PHP's widespread acceptance and copious documentation give developers plenty of resources and help for WordPress-based website development. WordPress and PHP allow users to construct dynamic, interactive, and feature-rich websites quickly and easily.

1.4.2 Python

Python's readability and versatility make it a popular programming language. Its clear syntax and large standard library make it a versatile tool. Python is adaptable enough for web development, computational science, data analysis, and more. The ecosystem of outside libraries for Python such as NumPy, Pandas, and Tensor Flow, improves its capabilities and simplifies specialized jobs. Developers can choose between procedural, object-oriented, and functional programming paradigms. The language's code readability encourages developer collaboration and maintainability. Indentation-based syntax ensures good code organization.

Python’s interpreted nature makes it ideal for rapid prototyping and iterative development. Python programmers are cross-platform-compatible. Python’s vibrant community further boosts its popularity. Developers can use vast documentation, tutorials, and forums to learn and share. Python’s simplicity, versatility, and huge ecosystem make it a popular language for developers to create a wide range of applications quickly and efficiently.

1.4.3 CNN (Convolutional Neural Networks)

CNNs are deep learning algorithms for video and image analysis. They revolutionised object detection, image recognition, and computer vision. Convolutional, pooling, and fully linked layers are present in CNNs.. The convolutional layers filter incoming data to extract features, capturing spatial patterns and local relationships. Pooling layers minimize spatial dimensions and computational complexity while keeping critical properties. Using retrieved features, fully linked layers

CNNs automatically identify key characteristics and patterns by learning hierarchical representations from raw data. CNNs back propagate their weights to minimize the discrepancy between expected and actual outputs during training. CNNs excel in image classification, object detection, facial recognition, and medical image analysis. They efficiently analyze complex, high-dimensional data. In scenarios with little training data, transfer learning—where previously trained CNN models are adjusted for particular tasks—improves performance. Computer vision, artificial intelligence, and visual data processing have all been revolutionised by CNNs.

1.4.4 Collab

Users can write, run, and share code with ease using Google Colab, a cloud-based platform. It offers a Jupyter notebook interface that enables interactive Python coding. Users may store and access their notebooks with ease because to its powerful integration of Google Drive. Colab is perfect for machine learning and data analysis jobs since it provides free access to GPU and TPU resources. Multiple users can operate on the same notebook concurrently, making collaboration simple.

Its extensive library support, preinstalled packages, and ability to import data directly from Google Sheets make it a popular choice among researchers, students, and developers.

It offers numerous benefits that make it a preferred choice for many users. It eliminates the need for local installations and configurations, as it runs entirely on the cloud, making it accessible from any device with an internet connection. Colab supports version control, allowing users to save and manage different versions of their notebooks easily. It also provides a wide range of pre-installed libraries and allows users to install additional packages effortlessly. Colab's integration with Google Drive enables seamless data storage and sharing,

CHAPTER 2

LITERATURE REVIEW

A literature review is a crucial part of any research effort because it offers a thorough assessment and analysis of the body of literature already published on the subject under inquiry.

It involves systematically reviewing and synthesizing relevant literature, including academic articles, books, and other published materials. The literature review serves multiple purposes, such as establishing the context and background of the research, identifying gaps and research questions, evaluating methodologies and findings from previous studies, and demonstrating the researcher's familiarity with the existing knowledge in the field. By critically examining previous works, the literature review helps researchers build on existing theories and frameworks, avoid duduplicatingfforts, and contribute new insights to the body of knowledge. It also aids in the formulation of hypotheses, research design, and methodology selection.

2.1 Related Work

For many years, conventional image restoration techniques, such as filtering and deconvolution, have been extensively employed. They rely on mathematical models and heuristics to restore degraded images, but their ability to achieve optimal results is frequently limited. Deep learning has revolutionized image restoration by leveraging large datasets and potent neural networks to effectively learn complex patterns and restore images. By integrating traditional and contemporary techniques, researchers hope to develop more effective and practical image restoration and enhancement strategies. Incorporating traditional methods as pre- and post-processing steps in deep learning-based architectures to enhance overall performance is an example of a hybrid approach. These developments contribute to the continuous growth of the discipline, allowing for improved restoration results in various image processing applications. The combination of traditional and contemporary image restoration techniques

Researchers have investigated various methods of integrating these approaches, capitalizing on their respective strengths to produce superior restoration outcomes. Traditional methods, for instance, can be utilized as preliminary estimation or refinement stages in deep learning-based frameworks. This strategy combines the speed and simplicity of conventional methods with the high-level feature extraction capabilities of deep neural networks. In addition, hybrid methods have been proposed to surmount the limitations of conventional models by incorporating priors or constraints derived from machine learning. By training deep learning models using conventional techniques, the resulting models are better equipped to manage various types of degradation and produce more precise restoration results. In addition, researchers have investigated the transfer learning method, in which pre-trained deep learning models are fine-tuned using a limited quantity of data that is often domain- or application-specific. This knowledge transfer from pre-trained models to target tasks improves restoration performance while reducing the need for extensive training data.

In addition, the development of hybrid methods highlights the significance of benchmark datasets and evaluation metrics. Robust datasets containing a variety of image degradation scenarios enable thorough performance evaluation and comparison of various approaches. Objective metrics, such as peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM), provide quantitative assessments, whereas subjective evaluations by human observers ensure the perceptually appealing visual quality of restored images. Researchers seek to improve the visual quality and usability of degraded images across a variety of applications, including medical imaging, surveillance, and digital photography, by combining traditional and modern techniques. These developments not only contribute to the advancement of image restoration but also to the enhancement of the overall user experience and the extraction of information from visual data.

2.2 PSO and K-Means Grouping Algorithm

Younus et al. [23] present a content-based comparable image repossession system that incorporatesparticle swarm optimization (PSO) and K-meansalgorithms in their study.

To facilitate efficient image retrieval, the system seeks to extract various features from color images, including histograms, co-occurrence matrices, color moments, and texture moments. The Wang dataset, which contains 100 images for each of the 10 label classes, serves as the evaluation standard for this study. Precision and recall metrics are calculated to evaluate the query and retrieval processes.

In addition, the effectiveness and superiority of the proposed method are determined by comparing its outcomes with those of existing techniques. The system provides a content-based approach to image retrieval by employing the PSO and K-means algorithms for feature extraction and similarity comparison, respectively. The combination of various feature descriptors enables an exhaustive representation of image content, thereby improving the precision and relevance of retrieval results. The experimental evaluation of the Wang dataset offers insight into the efficacy of the proposed system. The comparison with existing methods facilitates the identification of its competitive advantages and potential contributions to the field of image repossession.

Overall, Younus et al. present a content-based image retrieval system that incorporates the PSO and K-means algorithms, providing a promising method for retrieving visually similar images based on their content features.

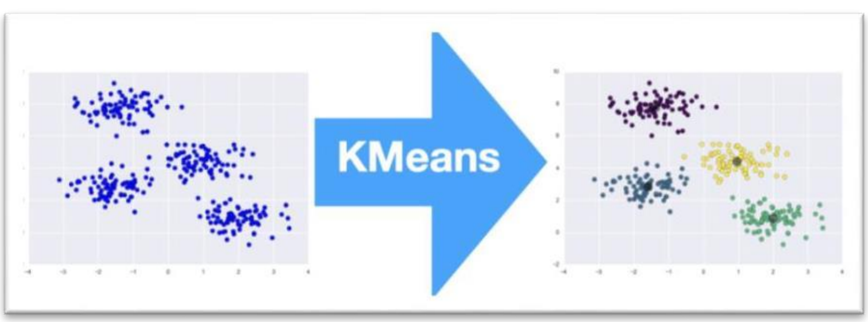

Fig 2.1: K Means Clustering

The figure presents a content-based image retrieval system that combines the PSO and K-means algorithms and offers a promising approach.

2.3 Proposed System

In our project, we created a model that integrates a convolutional neural network (CNN) and a recommender system based on nearest neighbors to detect and correct image distortions. To extract features from the input image, we used a ResNet-50 model that had been trained to recognize various visual patterns and objects using the ImageNet dataset. We were able to extract high-level features from the input image using the ResNet-50 model. Our convolutional neural network (CNN) model was then trained with the extracted features. The CNN model was created to learn and reproduce the underlying distortion patterns of the input images. By training the model on a large dataset of distorted images, CNN learned to effectively identify and classify various varieties of distortion. Using the Gaussian Blur() function, we applied a Gaussian blur to the images to improve their quality. This technique assisted in reducing disturbance and smoothing out the image, resulting in an enhanced visual appearance. Image processing frequently employs Gaussian blur to reduce the effects of noise and enhance the overall image quality. By combining the feature extraction capabilities of ResNet-50, the distortion identification and enhancement capabilities of the CNN, and the Gaussian blur technique, our model seeks to provide effective and aesthetically pleasing solutions for identifying and enhancing image distortions.

The incorporation of the pre-trained ResNet-50 model, CNN training, and the application of Gaussian blur permits our model to effectively resolve distortions, thereby improving the visual quality of the images. This method demonstrates the compatibility between deep learning-based feature extraction, aberration identification, and conventional image processing techniques for comprehensive image enhancement. In our proposed system, we developed a model that combines a convolutional neural network (CNN), a recommender system, and the application of Gaussian blur to detect and correct image distortions. We utilized a pre-trained ResNet-50 model for feature extraction and trained a CNN to learn distortion patterns. The application of Gaussian blur further improved image quality by reducing noise and deep learning and traditional image processing techniques for comprehensive image enhancement.

CHAPTER 3

DESIGN AND METHODOLOGY

This Chapter a systematic framework for conducting research. It involves planning the overall structure, data collection methods, analysis techniques, and procedures for interpreting results. A well-designed study ensures reliability, validity, and reproducibility, while the chosen methodology outlines the specific approaches and tools used to address research objectives and answer research questions.

3.1 Neural Networks

The computational framework known as Artificial Neural Networks (ANN) is heavily influenced by the human brain [49] and is made up of stacked multi-layers made of interconnected nodes. Numerous scientific disciplines, including computer vision [37], speech recognition [24], and natural language processing [10], have widely adopted neural networks. The basic construction of a simple NN is shown in this section along with many proposed current NN architectures, particularly CNN architectures. Additionally, several cutting-edge neural network training techniques are covered.

3.1.1 Simple Neural Network Model

The perceptron is the basic building block that enables neural nodes to learn. Each perceptron receives external signals and executes linearly separable functions depending on its learning weights and optional biases. Figure 2.1 illustrates this procedure. The model's output is calculated as

$$y = (\sum_{i=1} n \, w_i x_i + \mathrm{b})$$

where x_1, x_2, x_3.., x_n are input signals, w_1, w_2, w_3.., w_n wn are learning weights, b is the optional bias, and f () is an activation function (such as sigmoid [46], ReLU [46]). A trainable Multilayer Perceptron (MLP) is the foundation of an artificial neural network. Figure 2.2 depicts an easy-to-understand ANN with three layers.

The weights of the perceptron are randomly initialized and created with the intention of connecting the values of the previous layers and estimating the output for the following layers or the output of the network. Multiple forward and backward iterations are used to adaptively estimate the weight values. Until they reach the weights' ideal values, which enables the neural networks to produce very respectable results.

The five phases that make up the ANN algorithm are shown in Figure 2.3:

Step 1:

Using certain techniques such as zero-mean Gaussian distribution [37], orthonormal matrix initialization , etc., the values of the neural nodes or weights () are randomly initialized. The model can increase accuracy and training speed with the right neural weight initialization .

Step 2:

The forward propagation determines the output by the given inputs based on the networks' specified weights.

Step 3:

A loss function calculates the separation between the expected outputs from step 2 and the supplied inputs.

Step 4:

Employ a back propagation approach to estimate the gradient $\nabla_\theta J(\theta)$ for network weights.

Step 5:

Each interaction step's weights are modified appropriately. The neural weights can be updated using a variety of techniques. The one that is most widely used is gradient descent , in which the values of are updated in a decreasing order after each iteratio n step.

$$\theta = \theta - \eta * \nabla_{\theta} J(\theta)$$

Where θ, ŋ, $\nabla_{\theta} J(\theta)$ are, respectively, the weights values, learning rates, and gradient with respect to θ.

Up until the model converges, the neural weights are modified through a number of iterations. The learning rates and optimization methods' settings affect how many interactions there are.

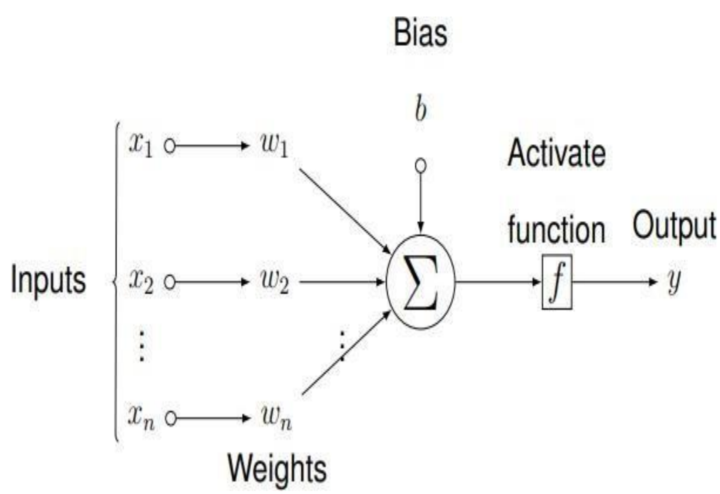

Fig 3.1 : A Simple Preceptor Model

3.1.2 Convolutional Neural Networks

The first CNN version taught by the gradient-based learning algorithm to do handwriting recognition for digits was published by LeCun in the 1990s, which is when CNN started to gain popularity [38]. The three concepts that make up CNN architectures are local receptive fields, shared weights, and spatial subsampling. Two different types of convolutional layers, including convolutional and subsampling ones, are used to represent these concepts. The convoluted and subsampling layers are distributed across various planes known as feature maps. The operations of each unit inside a feature map are the same for the various local receptive fields of images. CNN draws inspiration from the following when extracting feature maps from its data:

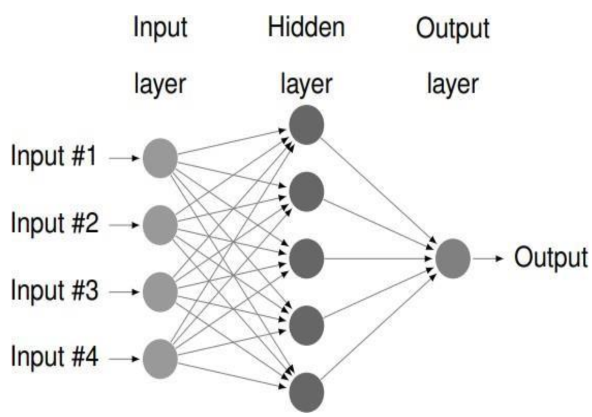

Fig 3.2: Typical Working Process of ANNs

The term "local receptive fields" and discuss the human visual system. Neurons may extract basic visual properties from pictures, such as aligned edges and corners, using local receptive fields. Higher-level features are obtained by combining the features that were retrieved from the layers. A particular local receptive field can extract a variety of features from each convolution layer, which is made up of a stack of several feature maps. In Figure 4, a typical CNN design is displayed.

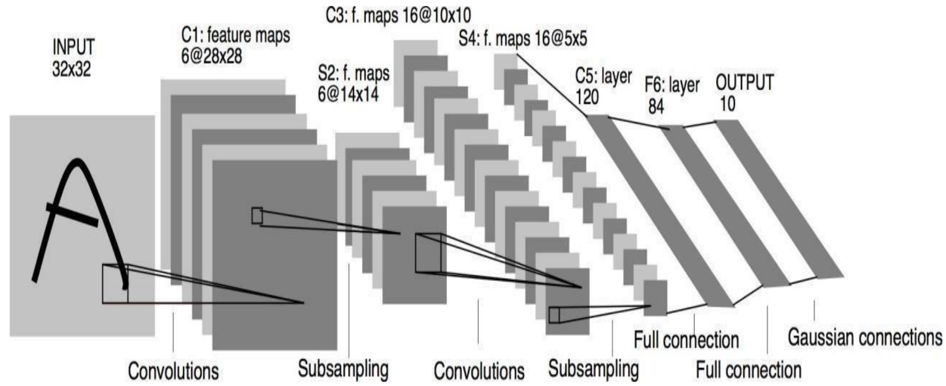

Fig 3.3: Convolutional Neural Networks

LeCun et al.'s first CNN (LeNet-5) is shown in Figure 2.4. 32x32 pixels are the size of the input data. Three convolutional layers, C1, C3, and C5, are created from 6, 16, and 120 feature maps, respectively. Two subsamples, S2, S4, are created from 6 and 16 feature maps, respectively. The classification task is processed by the full linked layer F6, which is the last layer. [38].

Each convolutional unit in a layer of convolution is coupled to a tiny input region known as the local receptive field in the preceding layers. Convolutional operations produce comparable feature maps from various local receptive fields from prior convolutional layers. With a same feature map, all convolutional units extract data from various regions of the entire picture. [38].

Each convolutional layer in LeNet-5 operated on a local receptive field, which was a small input region connected to the preceding layer. This local connectivity allowed the network to extract relevant features by convolving kernels with the input data. As a result, comparable feature maps were produced, capturing different aspects of the input image.

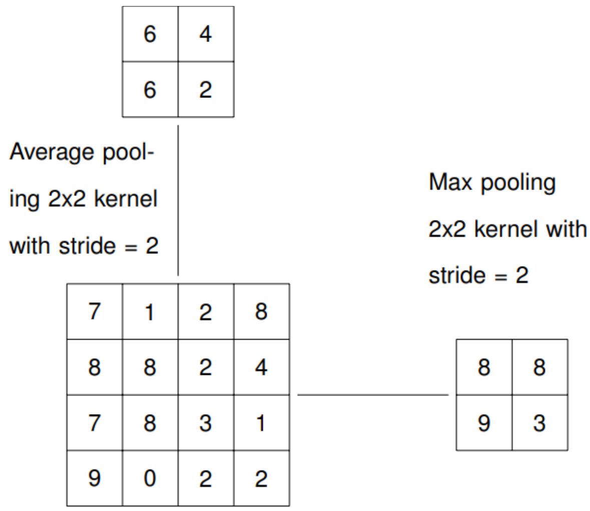

Fig 3.4: Conceptual Design of the Subsampling

The feature maps are down sampled, and the resolution is decreased for the subsampling or pooling layers to achieve spatial invariance. The subsampling S2 down samples feature maps from C1 (28x28) to 14x14 in Figure 4, whereas the subsampling S4 down samples feature maps to 5 x 5 from earlier convolution layers. The average pooling method and maximum pooling are two common subsampling techniques. Figure 5 illustrates the conceptual design of these subsampling techniques.

The classification layer, which comes after a series of convolutional and subsampling layers, is in charge of carrying out the classification tasks.

CNN can be viewed as a model that can synthesis its own feature extractor because all of its weights are learned using the back-propagation method [38]. The next section discusses a number of cutting-edge deep CNN architectures that are based on the initial CNN architecture's mechanism.

3.1.3 CNN Designs

In this part, both the suggested CNN designs for image denoising and the most recent CNN architectures that are often utilized for image denoising are introduced.

3.1.3.1 VGGNet Network

VGGNet is a deep neural network that won first place in the Image Net Large Scale Visual Recognition Challenge 2014 (ILSVRC2014) [53] and can demonstrate the beneficial correlation between the network's great depth and model performance, as improving neural model depth results in better model accuracy.

As seen in Figure 2.6, the basic building block of a VGGNet is composed of one or more convolutional layers, followed by activation functions like ReLU.

A VGG block is created by a series of these fundamental units, followed by a max pooling layer, as depicted in Figure 2.7.

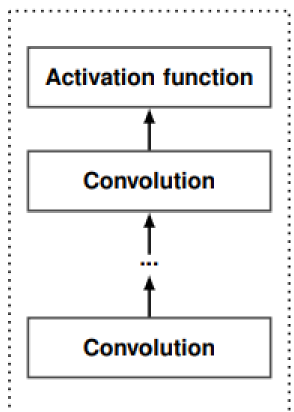

Fig 3.5: 9 The Fundamental Unit of VGGNet

Finally, a fundamental VGGNet architecture is constructed using VGGNet building blocks, and it includes thick layers and the soft-maxfunction. ResNet [28] and DnCNN [72] are two examples of typical deep CNN architecture that were influenced by the VGGNet design ideas.

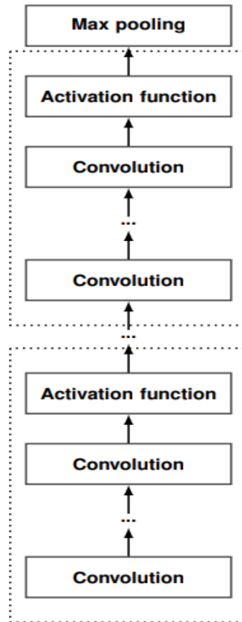

Fig 3.6 : A Simple VGGNet Block

3.1.3.2 Network in Network (NIN)

A suggested neural structure called Network In Network (NIN) enables discriminating models to extract more characteristics from local receptive fields and avoids the overfitting issue [42]. NIN can be thought of as a micro-network created by MLPs that connects the local patches of the preceding neural layer and the appropriate convolutional output. In contrast to Figure 2.8.b, which depicts a micro-network connecting the subsequent convolutional output and the preceding filter, Figure 2.8.b depicts the convolutional layer as being in the middle and receiving features from the previous layer directly in order to pass to the subsequent layer. The concept of inception networks, which is presented in the following section, is heavily influenced by NIN architecture.

3.1.3.3 Residual Learning Network

The primary issues in training great deep neural networks, like the vanishing/exploding problems, are addressed by the residual learning network. Such issues result in gradient values that are noticeably small/big, which has a poor impact on training accuracy [28]. By stacking a sizable number of network layers with residual learning network, the model can scale up while retaining the learning capability of the training model. The residual approach uses a shortcut link to map the previous layer with one or more earlier layers rather than directly stacking layers on top of one another. The output of the residual network, denoted by the letters x for the input, F for the layers, and y for the output, is y = F(x) + x rather than y = F(x), as seen in Figures 2.9.a and 2.9.b. In order for the shortcut connection to conduct linear operations between layers, it is also crucial to make sure that the output and input of residual layers havethe same dimensions [28].

DenseNet [31], DnCNN [72], Inception CNN , and other very deep advanced CNN architectures all considerably benefit from the residual learning approach.

3.1.3.4 Network Inception

Due to its success in the ILSVRC 2014 competition, the "Inception" deep convolution network has grown in popularity since that year . While retaining the depth of the networks, inception networks enable models to drastically reduce the number of training parameters. . Figure 2.10 illustrates how to maximize learning capacity for the naive inception module by widening the layers by concatenating several kernel sizes, including 1 x 1, 3 x 3, 5 x 5, and max pooling with a 3x3 kernel. Different versions sustain and build inception networks. Inception-v4 and Inception-Resnet are now the most recent versions [59].

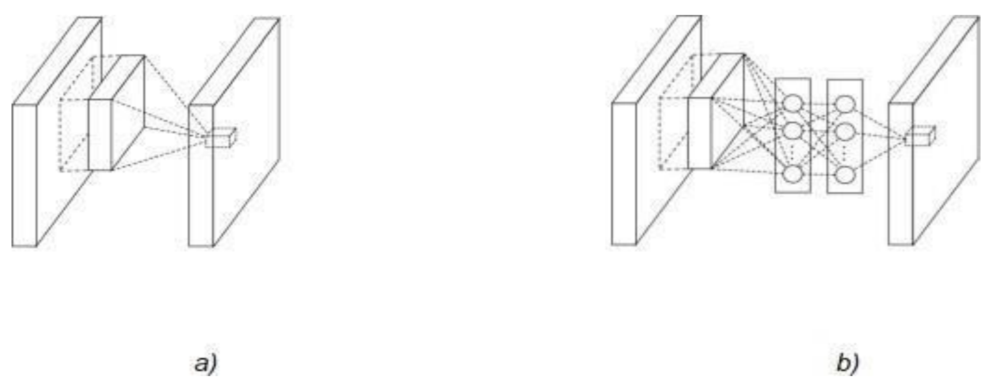

Fig 3.7 : The tradition Convolutional Network and Convolutional Network

As illustrated in Figures 2.1 and 2.12 [7], the modified versions produce higher performance and efficiency since each Inception block's size is equally determined in this version. The most pertinent submissions for the ImageNet challenge, as well as their most recent accuracy scores in comparison to other well-known designs, are shown in Figure 2.11. The computational costs and accuracy values of various model architectures are displayed in Figure 2.12. These numbers demonstrate how Inception-V4's performance has greatly improved to attain high accuracy while using acceptably low amounts of computer resources [7].

We concentrate on Inception-Resnet for the Inception-V4 because the suggested denoising networks use this neural topology. Figure 2.13 illustrates two common Inception-Resnet topologies. A residual shortcut connection in Figure 2.13 performs the operation of merging the previous layer with a layer aggregated from inception branches by connecting the previous input layer with each inception branch. Each branch manages several processes made up of the stacking of kernels with various filters. The 1x1 convolution technique can be used to ensure that the input and output after of the operating blocks have the same dimensions since the residual shortcut implemented by the res-inception module improves training performance. Prior to completing the subsequent convolution procedures, the dimension of the input is additionally reduced using the 1x1 convolution. Two 3x3 convolutions in Figure 2.13.a act as a 5x5 convolution because they are stacked on top of one another. The diverse sizes of kernels are combined in this method, which enhances the module's capacity for learning and avoiding. losing learning characteristics due to processes that reduce dimension . In Figure 2.13.b, the 1 x n kernel that comes after the n x 1 kernel functions as a n x n convolution; this strategy greatly reduces the number of parameters.

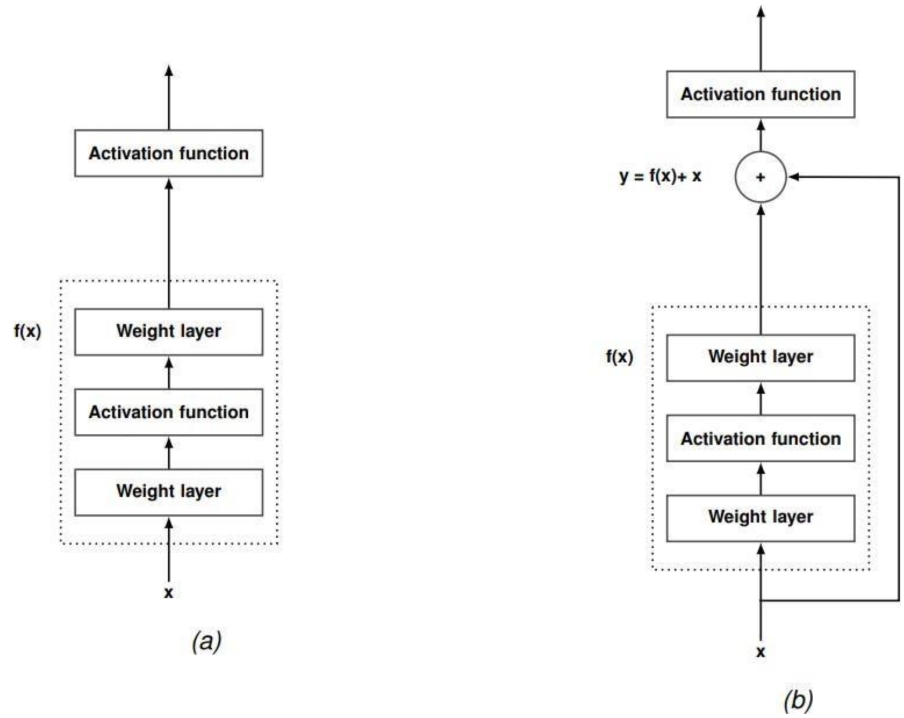

Fig 3.8 : Typical Plain and Residual Network Structures

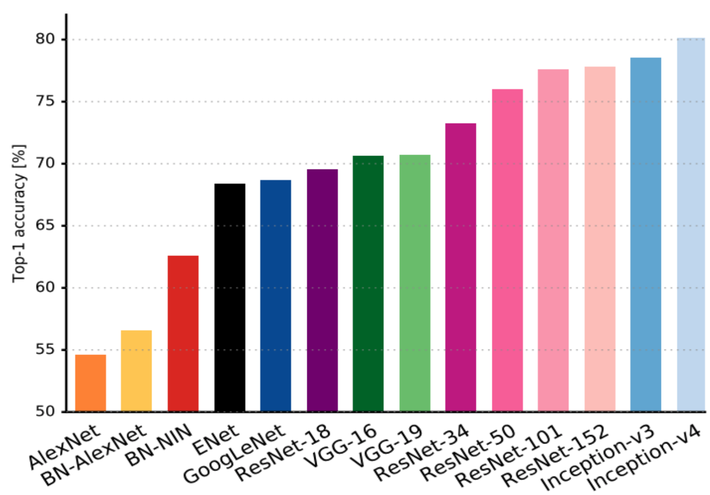

Fig 3.9 : The comparison of Inception-V4 with other popular Neural Networks [7]

3.1.3.5 Wide Residual Networks

A common issue with deep residual networks is diminishingfeature reuse, which refers to the restriction on learning practical features that correspond to the depth of the network. By enlarging ResNet blocks, Sergey suggests a solution to the issue of the deep residual networks' diminishing feature reuse. Since it lowered the number of layers, training parameters, and time, widening the residual network offers greater advantages for improving the depth of networks. The suggested technique, which is shown in Figure 2.14, develops by boosting the Resnet block's power [29], often employing a 3x3 filter.

Three strategies—increasing the number of convolutional layers, the quantity of learning features for convolutional layers, and kernel sizes—are used to improve the learning capacity of the Resnet block.

By using a dropout mechanism inside a Resnet block, the suggested method also proposes a novel strategy to avoid overfitting. Figure displays the suggested architectural design.

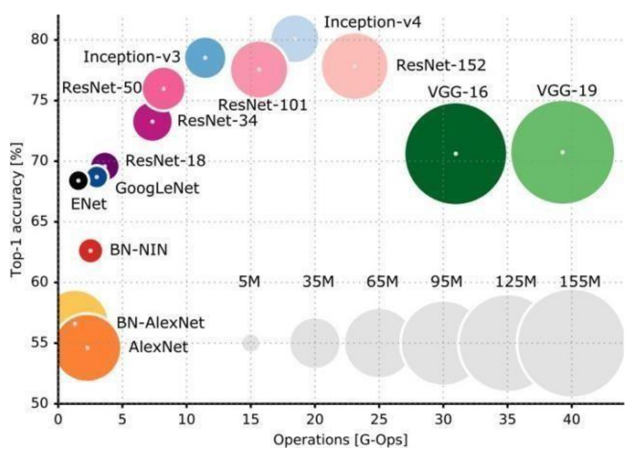

Fig 3.10 : A comparison of the amount of computing operations and the accuracy of common neural networks [7]

3.1.4 Cutting-Edge Methods For Neural Network Training

State of the art techniques for brain network preparing incorporate exchange learning, GANs, self-directed learning, and support learning. These methods upgrade model execution, work with information move between assignments, empower unaided learning without express names, and empower specialists to learn through cooperation with the climate. By pushing the limits of man-made intelligence abilities, these techniques drive headways in regions, for example, PC vision, normal language handling, and mechanical technology, cultivating leap forwards in AI exploration and applications.

3.1.4.1 Data Augmentation

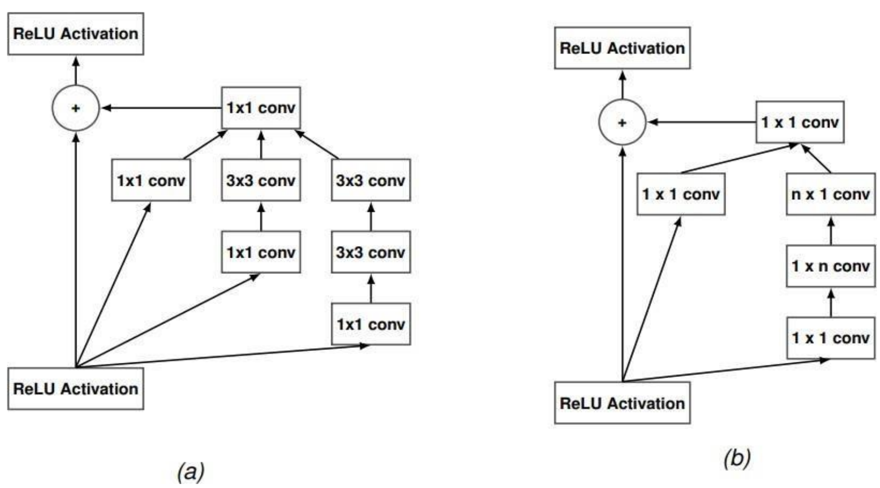

Fig 3.11: Typical Res-Inception structures

Expanding the training dataset using image modification techniques is one of the effective ways to get rid of overfitting for the training process. To improve the amount of learning data during training, real-time data augmentation modifies the data somewhat. For instance, the training image is replicated using cropping, rotation, and horizontal and vertical flipping. Using this method, the models can access more data.

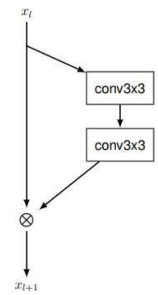

Fig 3.12 : The input and output of the l-th unit in the network are represented by the fundamental Resnet block

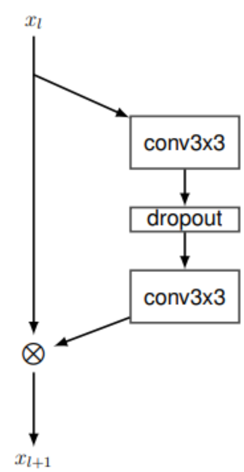

Fig 3.13: The input and output of the l-th unit in the network are represented by the fundamental Dropout Resnet block.

3.1.4.2 Initialization of Deep Neural Networks

$$Var(W_i) = \frac{2}{n_{in} + n_{out}},$$

Initializing the values of the neural weights is the first and most important step in correctly training a neural network. Vanishing/exploding gradient problems and poor training convergence are both brought on by improper network initialization [36]. A small random initialization is the standard technique for initializing neuronal weights [26]. To overcome the common problems of training deep models, more complex initialization procedures are needed for the large deep network [28, 50]. This section discusses a number of effective initialization techniques, including Xavier [21], He [27], Orthogonal [45], and LSUV initialization . The Xavier initialization [21] mitigates the initial weight values from being too small or too large over various layers, preventingthe models from the vanishing/explodingdifficulties. Given the weights w_i, n_{in} and n_{out}, as well as the number of the neural weights are distributed by a normal distribution with a mean of 0 and a variance determined as the input and output of the layers, respectively.

This is intended to perform Sigmoid activation [46]. He [27] created a particular initialization for the networks with ReLU activation function [46] by altering the variance of the neural weights distribution of Xavier initialization as follows,

$$Var(W_i) = \frac{2}{n_{in}}.$$

By using gradient norm-preserving and de-correlate neural layer properties, orthogonal initialization [45] addresses the common issues with deep learning networks and enables the models to learn more features from training data. Later, Layer-sequential unit-variance (LSUV) [67] was created as an extension of orthogonal initialization, implementing unit normalization for each layer after orthogonal initialization.

3.1.4.3 Learning Rates

An important parameter for training networks is the learning rate, which sets the numerical values that should be added to or subtracted from weights for each training period [4]. Setting an appropriate learning rate can greatly enhance training performance because an incorrect learning rate might cause models to diverge or fail to converge [57]. Conversely, an incorrect learning rate can cause training to take a long time. Additionally, a low learning rate can cause the training to continue in local minima [3]. Learning rate schedules and adaptive learning rates are two common ways to optimize learning rates.

There are three common ways to set a learning rate schedule: a constant, a step decay, and an exponential decay learning rate. The learning rate for the first technique is manually set. After a few epochs, the learning rate will, for the step decay, lower the value by a certain amount. The learning rate, for instance, is decreased by 50% after every 5 epochs or by 0.1 after every 20 epochs [12]. A = a0ekt is the formula for the exponential decay learning rate, where a0, k are hyper-parameters, and t is the iteration step [12]. Using the same updated learning rate values for all parameters is a prevalent flaw in learning rate schedule methods, however adaptive learning rate approaches offer potential answers to this issue.

The common adaptive learning rate techniques covered in this section include Adam, RMSprop, Adagrad, and Adadelta.It establishes several learning rates for various parameters for the Adagrad [18] adaptive learning rate algorithm. Since the proposed strategy is effective for extra data, enables the learning rate to change according to the frequency of learning features. For features that occur frequently, the algorithm sets relatively low learning rates; in contrast, it sets high learning rates for features that occur less frequently. Given that the diagonal matrix G contains the diagonal value at step t, g_t is the gradient value at step θ, G_t contains the diagonal value at step t, g_t is the very small value to ensure that the denominator value is not equal to zero, and is the vector product between G_t and g_t. Each epoch's weight values are updated as [18].

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt[2]{G_t + \epsilon}} \odot g_t$$

The fundamental flaw in this approach is similarly caused by the accumulation of the magnitude in G. This is because excessively large values for the next diagonal g_t cause learning rates to drop to extremely low levels, which causes the training process to stack. The Adadelta technique, which enables the learning process to continue to make progress even when the number of epochs dramatically increases, addresses the drawbacks of Adagrad [18]. Given that p is a decay constant and that, $E[g^2]_t$ is the running average at time t, $E[g^2]_t$ can be calculated as

$$\nabla\theta_t = -\frac{\eta}{\sqrt{E[g^2]_t + \epsilon}} g_t.$$

Adadelta updates new weights by substituting $E[g^2]_t$ for G_t in the denominator as follows:

$$E[\nabla\theta^2]_t = \rho E[\nabla\theta^2]_{t-1} + (1-\rho)\nabla\theta_t^2,$$

The next stage in the Adadelta approach is to match the same fictitious units for each updated weight. To do this, use the formulas

RMSprop is the following well-liked technique for adaptive learning rate. Geoff Hinton [47] proposed this unpublished technique in his online course . This approach can solve the Adagrad method's issue with declining learning rates. The estimated method for the running average at time t and the updated weight values $E[g^2]_t$ is Adadelta.

Individual learning rates for each parameter are estimated using Adaptive Moment Estimation (Adam) [35] base m_t on the first and second moments v_t of the gradient, respectively. Given that g_t is the gradient at time t and that α_1, β_2 are the hyper-parameters, mt and v_t are estimated as

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t,$$
$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2.$$

Following that, the values of m_t and v_t are changed to account for these biases by estimating bias correction as

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t}$$

$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t},$$

The parameters' values are updated by the final step, which is In actual use, the Adam technique [35] for optimizing deep learning training grows popularity and produces

3.1.4.4 Batch Normalization

Because it favorably smooths the training optimization landscape, batch normalization (BN), a training approach, enables expediting the training process while keeping the stability of the deep neural networks . By scaling the mini-batch variance and adjusting the mini-batch mean for each training mini-batch, the neural model's output is modified [33].

$$BN_{\gamma,\beta}(x_i) = \gamma \frac{x_i - \mu_x}{\sqrt{\sigma_x^2 + \epsilon}} + \beta,$$

Implementing BN enables much higher learning rates to be set for the training process, less thought to be given to initial neural parameters, and also functions as "dropout" layers; as a result, it shortens training time, strengthens training networks, and avoids the overfitting learning phenomenon [33]. The combination of BN and residual learning, when used to create neural networks for denoising, mutually supports one another to improve the quality of denoising and the performance of neural models . The implementation of Batch Normalization (BN) in neural networks brings several advantages to the training process. Firstly, it allows for higher learning rates to be set, which accelerates convergence and reduces the training time. With BN, there is less need to carefully initialize neural parameters, as the normalization process mitigates the effects of parameter initialization to some extent.

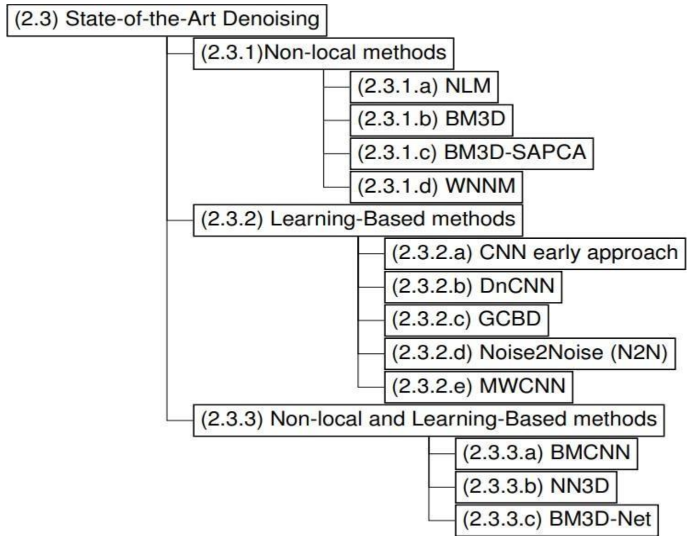

Fig 3.14: structure of the chosen state-of-the-art denoising techniques.

3.2 Denoising of Images

In the context of this thesis, three denoising approaches—non-local, learning-based, and the combination of non-local and learning-based strategies—are chosen to characterize the state-of-the-art denoising methodologies. In Figure 2.16, the structure of a few denoising categories is displayed.

3.3 Modern Denoising Methodologies

Non-local self-similarity (NLS) and CNN-based methods are now two of the most popular denoising techniques. By utilizing redundant characteristics in real images and estimating the correlation values from other blocks in the same images, NLS reduces noise [44]. The method has gained popularity for years since it is so effective at denoising chores. The most successful approaches that come from this strategy are BM3D [13] and WNNM [25], where NLM [6] is regarded as the first method .

CHAPTER 4

IMPLEMENTATION AND METHODOLOGY

The FLCNN approach for picture denoising, which uses an extremely deep CNN constructed using a combination of residual and inception layers, is introduced in this chapter. By tackling common deep neural network training issues that appear when there are much more training parameters than there are in base-line networks made up simply of residual neural layers, the suggested method aims to increase learning capacity. The suggested learning-based strategy is described in general terms in this part, along with the implementation steps.

4.1 The Suggested Network Background

DnCNN is the foundation of several effective learning-based techniques for image denoising . However, due to the declining feature reuse issue that restricts the contribution of the most recent neural networks, it is ineffective for those networks to increase their performances by increasing the number of learning parameters. The DnCNN and Inception-Resnet designs served as inspiration for the FLCNN neural network that is suggested in this thesis work. It uses inception layers to raise the total number of parameters in a way that leads to better overall performance, skip connections to retain the learning capacity of very deep neural networks, and both. By overcoming diminishing feature reuse and expanding the network's receptive field, our technique is able to outperform DnCNN architecture and improve the limitations of DnCNN-based networks.

4.2 The Suggested Network Structure

The goal of FLCNN is to denoise AWGN-corrupted gray-scale images. It consists of two cascading phases: boost and warm up. Regular convolutional layers are used in the warm-up phase, whereas customized inception layers are stacked to form the boost phase. Fig. 3.1 depicts a warm-up. Each layer in the warm-up stage produces 64 feature maps in a series of sequential levels. 3x3 kernels are used in the first few layers, and the latter ones employ five kernels. Before the boost phase, the network can progressively grow and widen the receptive fields by increasing the size of the kernels during this phase. Batch normalization and Rectifier Linear Unit (ReLU) are used after each CNN layer.

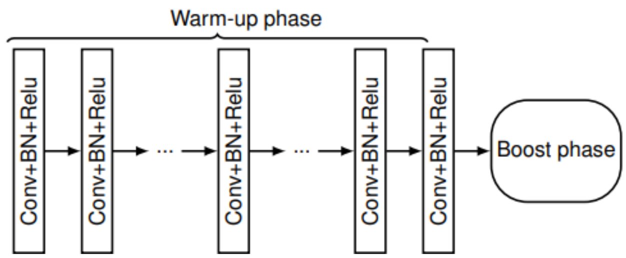

Fig 4.1: The warm-up phases

The boost step consists of the series of inception layers shown in Fig. 3.2, which widens the network and enhances its ability to learn features from training data.

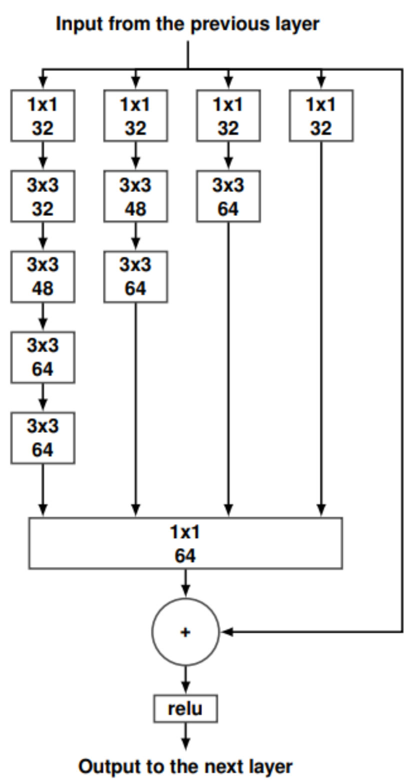

Fig 4.2: Inception layer used in the proposed architecture.

Convolution (Conv), BN, and ReLU are the three processes that make up each inception layer. At the very end of the inception layers, a 1 x 1 convolutional operation is used to aggregate the various filter branches and match the output dimensions to the input dimensions. In order to extract features at various scales, expand the receptive field, and benefit from the correlation between branches, each filter branch in this layer is built of one or more stacked kernels. Each inception layer has a shortcut link that enables it to take advantage of the residual learning technique.

When compared to the usage of convolutional layers with a similar receptive field, the model is able to obtain more features and save on computational costs through the growth of the receptive field through inception layers and the use of 1 x 1 convolutional operation to lower the data dimensions.

The term Flashlight CNN was inspired by the boost stage, which ultimately results in a substantially larger increase in the size of the receptive field than the warm-up stage. The proposed neural network for image denoising tasks is shown in Fig. 3.3.

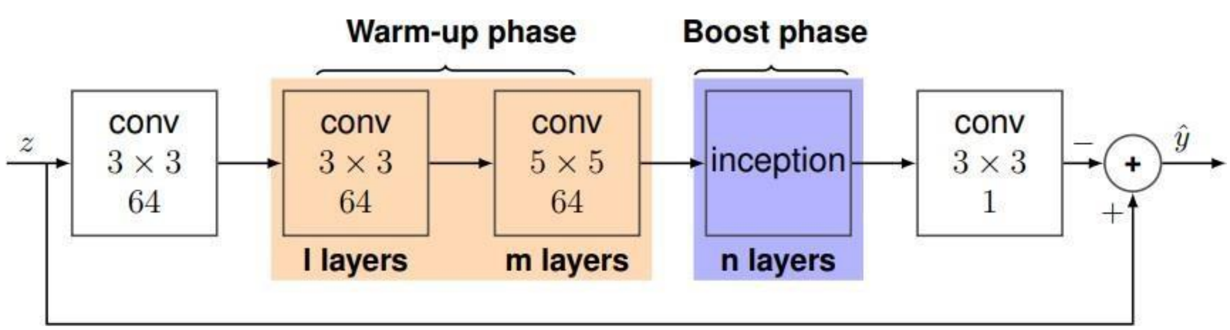

Fig 4.3: The proposed FLCNN architecture for denoising

On the validation set DIV2K [1], a large number of training experiments were conducted in order to choose the number of layers (l, m, and n) for each phase. The other numbers of layers are restricted to the ranges of 3, 4, 5 and 3, 4, 5, 6, 7 for m and n, respectively, in order to keep the experiments manageable. L is fixed at 5. Table 3.1 displays the findings. The numbers of phases are chosen as l = 5, m = 4, and n = 6 based on the findings of these tests. The chosen network has 15 layers and 1629905 trainable parameters with this configuration.

In order to observe the behavior of the network and compare FLCNN and DnCNN like networks when the number of networks' parameters is raised, we also conduct experiments that stack more layers for DnCNN-like networks. The findings demonstrate that even though the performance of a DnCNN-like network starts to decline dramatically at around 1 million parameters, the suggested architecture can still make use of the additional parameters to boost performance, as shown in Fig 3.4.

4.3 Training

The techniques for gathering training data for the suggested deep neural network and the steps involved in its implementation are discussed in this section.

Validation performance vs number of parameters

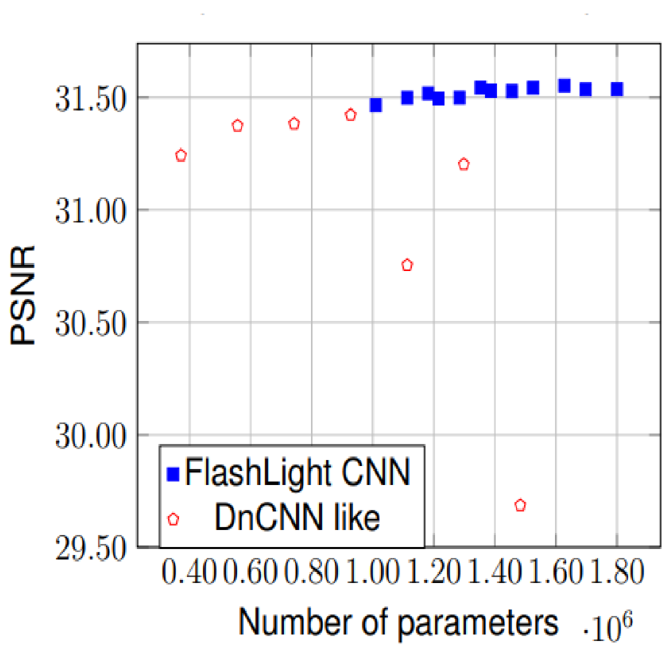

Fig 4.4: Validation performances vs number of parameters, with the number of parameters

Table 4.1: The configuration of the proposed network

Experiment	Layers	Total-Layers	Params	PSNR
1	5-3-3	11	1009793	31.47
2	5-3-4	12	1181633	31.52
3	5-3-5	13	1353473	31.54
5	5-3-7	15	1697153	31.54
7	5-4-3	12	1112385	31.50
8	5-4-4	13	1284225	31.50
9	5-5-3	13	1214977	31.49
10	5-5-4	14	1386817	31.53
11	5-3-6	14	1525313	31.54
12	5-4-5	14	1456065	31.53
13	5-4-6	15	1627905	31.55
14	5-4-7	16	1799745	31.54
15	5-5-7	17	1902337	30.55

4.3.1 Preprocessing of Data

Before feeding the training data to the training models, we present here the data separation and augmentation methods.

4.3.1.1 Data Separation

From the DIV2K [1] dataset, 800 photos are downloaded and made grayscale. Each image is divided into 64x64-pixel-sized tiny patches. The view_as_windows function from the scikit-image package handles the process of dividingimages into small pieces . By moving nearby windows through images, the view_as_windows function enables splitting up large images into closely spaced sections. A new picture block is created with each moving step of a particular size. Figure 7 shows the separated blocks from Figure 6, while Figure 6 serves as the original image used to illustrate the separating image process.

Fig 4.5: The sample image from the dataset

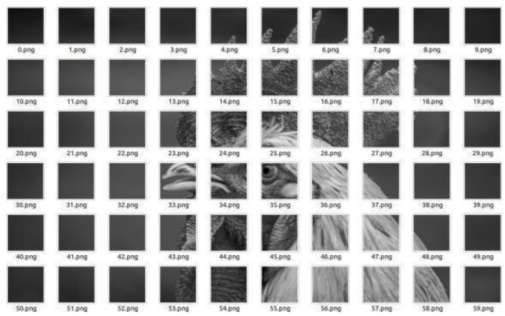

Fig 4.6: Separating blocks

The created images are used as the ground truth, or labels, following the separation procedure. The next step is to add AWGN noise with a certain noise level () to the ground truth in order to create the noisy images. The proposed models are trained and evaluated with respect to three different noise levels: 15, 25, and 50.

4.3.1.2 Data Augmentation

Online data augmentation processes are used to alter training images before they are fed to the training models. The Keras Image Preprocessing Library [9] handles the data argumentation process and is set up to randomly flip the provided images' horizontal and vertical axes. These augmentation methods enable the training models to access more data while maintaining the quality of the training images.

4.3.1.3 Training Setting

On top of the Tensorflow 1.10 architecture, Keras 2.20 prototypes and implements networks. On a server running Ubuntu 18.04 LST with AMD Ryzen Thread ripper 1950X 16-Core Processor, GeForce GTX 1080 Ti, the proposed models are trained.

4.3.2 Stabilized setting variables

The orthogonal approach is used to initialize network weights, while Adam Optimization and learning rate schedulers are used to update them. During the training procedure, the learning rates decline exponentially from 1e-1 to 1e-4.

4.4 Evaluation

The performance of the suggested method for image denoising based on PSNR , structural similarity index measure (SSIM) , and visual appearance of the recovered images is provided and discussed in this section.

4.4.1 Quantitative Evaluation

The proposed FLCNN is tested on three well-known datasets, Set12, BSD68, and Urban100 [48], with noise levels of 15, 25, and 50. It is then compared to state-of-the-art techniques, such as BM3D [14], DnCNN [72], FFDNet [75], and IRCNN [74]. Figure 4.1 depicts the entire Set12 for reference. Table 4.1 displays the evaluation's findings in terms of PSNR and SSIM values. In the comparison, the suggested method performs better than the other methods. In particular, it outperforms DnCNN in all noise levels and datasets by a wide margin.

Table 4.2: Performance comparison in terms of PSNR

		BM3D [13]		DnCNN [72]		FFDnet [75]		IRCNN [73]		FLCNN	
Dataset	σ	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
set12	15	32.41	0.8959	32.87	0.9030	32.77	0.9033	32.77	0.9009	32.97	0.9053
	25	30.00	0.8505	30.44	0.8616	30.45	0.8639	30.38	0.8597	30.66	0.8673
	50	26.76	0.7660	27.19	0.7822	27.33	0.7896	27.14	0.7795	27.51	0.7955
bsd68	15	31.13	0.8741	31.74	0.8908	31.62	0.8902	31.63	0.8881	31.78	0.8928
	25	28.61	0.8024	29.23	0.8279	29.19	0.8290	29.14	0.8247	29.33	0.8326
	50	25.69	0.6881	26.23	0.7183	26.30	0.7242	26.18	0.7162	26.40	0.7291
urban100	15	32.40	0.9232	32.68	0.9250	32.44	0.9277	32.49	0.9244	33.02	0.9323
	25	29.77	0.8790	29.97	0.8789	29.95	0.8895	29.82	0.8839	30.53	0.8962
	50	26.08	0.7797	26.28	0.7864	26.55	0.8060	26.24	0.7927	27.05	0.8183

Table 4.3: Performance comparison in terms of PSNR[2]

	BM3D [13]		DnCNN [72]		FFDnet [75]		IRCNN [73]		FLCNN	
Image	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Camera	31.95	0.8994	32.55	0.9113	32.39	0.9115	32.49	0.9118	32.60	0.9149
House	34.96	0.8922	35.07	0.8900	35.19	0.8930	34.97	0.8845	35.32	0.8916
Peppers	32.74	0.9095	33.27	0.9164	33.21	0.9165	33.24	0.9124	33.26	0.9145
Starfish	31.16	0.8963	32.17	0.9107	31.96	0.9086	31.99	0.9125	32.25	0.9158
Butterfly	31.97	0.9371	33.16	0.9484	32.70	0.9466	32.92	0.9471	33.26	0.9499
Airplane	31.08	0.9037	31.69	0.9109	31.56	0.9107	31.66	0.9071	31.74	0.9099
Parrot	31.53	0.8996	31.99	0.9090	31.92	0.9091	31.99	0.9051	32.02	0.9081
Lena	34.28	0.8960	34.61	0.9012	34.63	0.9021	34.52	0.8986	34.74	0.9039
Barbara	33.07	0.9222	32.65	0.9188	32.54	0.9186	32.43	0.9169	32.89	0.9234
Boat	32.10	0.8534	32.38	0.8602	32.35	0.8606	32.30	0.8578	32.47	0.8633
Man	31.95	0.8675	32.42	0.8799	32.37	0.8795	32.35	0.8779	32.46	0.8818
Couple	32.12	0.8733	32.43	0.8791	32.44	0.8823	32.37	0.8785	32.57	0.8860
Mean	32.41	0.8959	32.87	0.9030	32.77	0.9033	32.77	0.9009	32.97	0.9053

Fig 4.7: Example Images

For levels of 15, 25, and 50, respectively, the denoising findings for each image in Set12 are displayed in Tables 4.2, 4.3, and 4.4. On 11 out of 12 noisy photos, the suggested technique outperforms BM3D and achieves superior PSNR results. As expected, BM3D yields better PSNR results than learning-based techniques for images with repeating textures, such as Barbara in Set12. For all of the photos in Set12, the proposed technique yields better SSIM findings. When the noise level is $\alpha = 15$, DnCNN, FFDnet, and IrCNN display higher PSNR and SSIM results for the Peppers image than FLCNN by 0.01 dB and 0.0015, respectively. The suggested strategy yields higher quantitative findings across all experiments for the noise levels of $\alpha = 25$ and $\alpha = 50$.

4.4.2 Qualitative Evaluation

In comparison to BM3D (32.93 dB) and DnCNN (33.18 dB), FLCNN has the greatest PSNR values (33.64 dB) for the house image in Figure 4.2. All of the methods that have been tested have produced outcomes that are excessively smooth. With regard to the boat picture in Figure 4.3, FLCNN produces higher PSNR (30.35 dB) values.

Table 4.4 : Performance comparison in terms of PSNR and SSIM

	BM3D [13]		DnCNN [72]		FFDnet [75]		IRCNN [73]		FLCNN	
Image	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Camera	29.49	0.8489	30.15	0.8705	30.06	0.8724	30.04	0.8713	30.28	0.8787
House	32.93	0.8627	33.18	0.8662	33.43	0.8686	33.13	0.8602	33.64	0.8661
Peppers	30.20	0.8712	30.79	0.8835	30.87	0.8871	30.82	0.8803	30.93	0.8862
Starfish	28.62	0.8452	29.38	0.8617	29.26	0.8605	29.22	0.8646	29.57	0.8704
Butterfly	29.39	0.9020	30.33	0.9171	30.19	0.9186	30.18	0.9165	30.54	0.9232
Airplane	28.37	0.8597	29.06	0.8732	28.99	0.8744	29.05	0.8691	29.17	0.8732
Parrot	29.06	0.8551	29.57	0.8674	29.56	0.8685	29.54	0.8601	29.65	0.8657
Lena	32.08	0.8621	32.47	0.8702	32.60	0.8746	32.44	0.8687	32.79	0.8779
Barbara	30.68	0.8853	30.02	0.8763	30.04	0.8786	29.94	0.8750	30.52	0.8886
Boat	29.83	0.7974	30.15	0.8080	30.20	0.8115	30.11	0.8069	30.35	0.8163
Man	29.58	0.8013	30.07	0.8201	30.07	0.8217	30.00	0.8184	30.15	0.8247
Couple	29.73	0.8154	30.10	0.8254	30.18	0.8306	30.06	0.8256	30.32	0.8367
Mean	30.00	0.8505	30.44	0.8616	30.45	0.8639	30.38	0.8597	30.66	0.8673

On the wall and roof, the brick pattern practically vanishes. As seen in the first and second rows of the recovered image, FLCNN maintains superior features and shapes of the roof as well as the shadow line of the roof when compared to DnCNN. The white windows in the final row of Figure 4.2 are more or less equally recovered by each denoising technique.

Table 4.5: Performance comparison in terms of PSNR and SSIM[2]

	BM3D [13]		DnCNN [72]		FFDnet [75]		IRCNN [73]		FLCNN	
Image	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Camera	26.44	0.7772	27.12	0.7982	27.12	0.8047	26.97	0.7994	27.30	0.8143
House	29.64	0.8127	30.16	0.8273	30.60	0.8366	30.12	0.8196	30.94	0.8375
Peppers	26.72	0.7925	27.25	0.8120	27.41	0.8189	27.24	0.8071	27.36	0.8194
Starfish	25.14	0.7428	25.63	0.7636	25.63	0.7663	25.49	0.7651	25.84	0.7792
Butterfly	26.00	0.8240	26.87	0.8485	26.89	0.8539	26.68	0.8434	27.09	0.8613
Airplane	25.24	0.7813	25.78	0.8033	25.81	0.8067	25.80	0.7976	25.93	0.8043
Parrot	26.02	0.7841	26.60	0.8002	26.70	0.8057	26.64	0.7926	26.79	0.8016
Lena	28.92	0.7954	29.38	0.8115	29.65	0.8224	29.39	0.8090	29.81	0.8268
Barbara	27.09	0.7852	26.20	0.7652	26.41	0.7777	26.22	0.7676	26.98	0.7971
Boat	26.74	0.6964	27.17	0.7146	27.30	0.7223	27.12	0.7125	27.41	0.7297
Man	26.76	0.7005	27.20	0.7208	27.26	0.7254	27.14	0.7176	27.32	0.7295
Couple	26.45	0.6997	26.94	0.7212	27.13	0.7342	26.91	0.7221	27.30	0.7449
Mean	26.76	0.7660	27.19	0.7822	27.33	0.7896	27.14	0.7795	27.51	0.7955

SSIM (0.8163), in contrast to other techniques. FLCNN performs better at recovering the texture lines in the first and second rows of Figure 4.3. The final row demonstrates that the sand is recovered using all techniques, and the outcomes for this pattern are nearly identical.

FLCNN also had greater PSNR and SSIM than other examined methods for the aircraft in Figure 4.4. The patterns above the text, as seen in the first row, and the texts, as shown in the second row, are recovered more effectively by FLCNN. In the final row, FLCNN and DnCNN both have superior visual outcomes to BM3D.

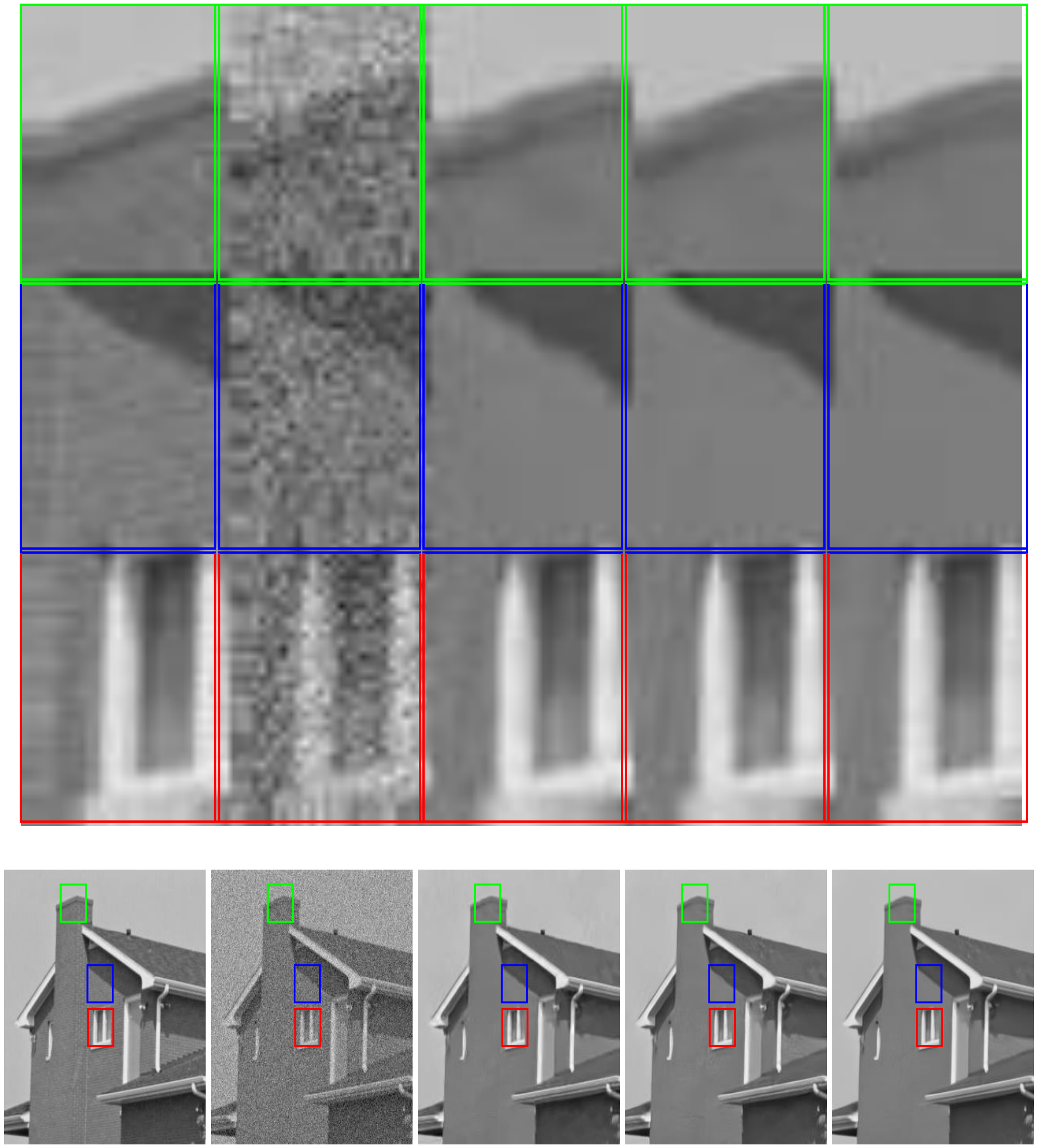

Fig 4.8: Denoising results for house

Ground Truth

Noisy = 20.25 dB

BM3D = 32.92 dB

DnCNN = 33.16 dB

Flash Light = 33.63 dB

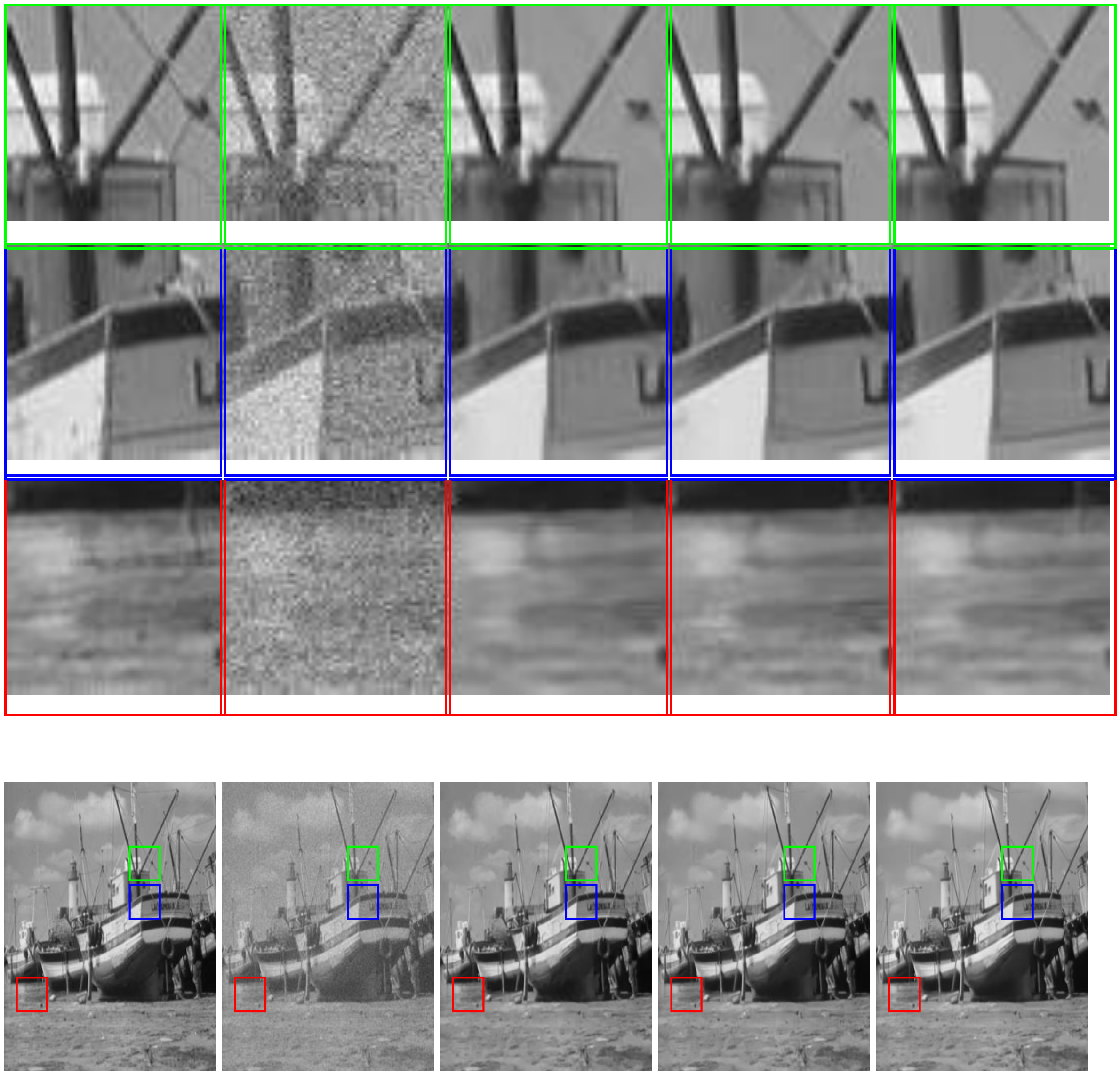

Fig 4.9: Denoising results for boat

Ground Truth

Noisy = 20.28 dB

BM3D = 29.82 dB

DnCNN = 30.14 dB

Flash Light = 30.34 dB

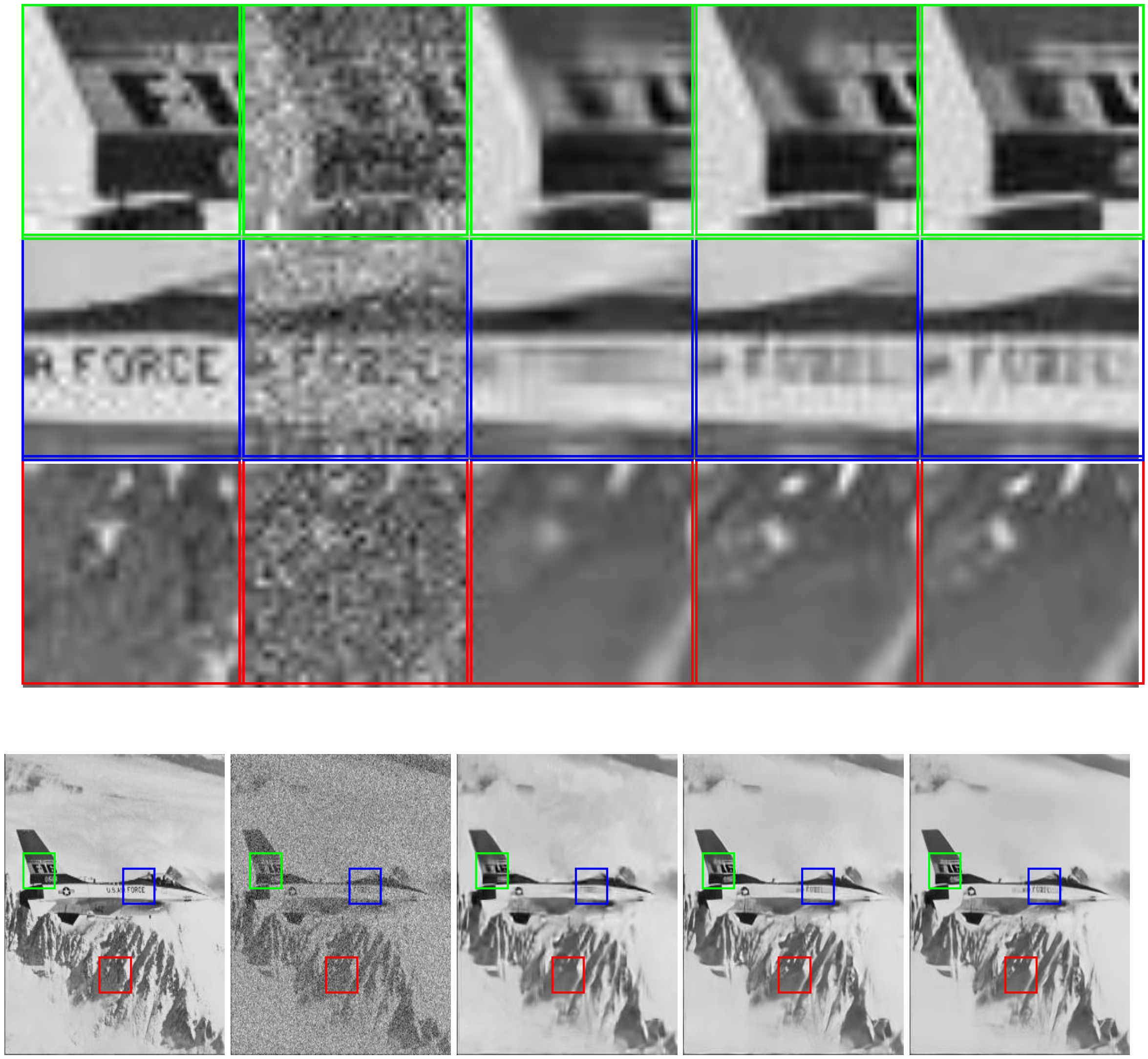

Fig 4.10: Denoising results for Plane

Ground Truth

Noisy = 14.61 dB

BM3D = 25.24 dB

DnCNN = 25.78 dB

Flash Light = 25.93 dB

CHAPTER 5

RESULTS AND DISCUSSION

This chapter will analyse the outcomes of our suggested technique and assess how well it functions.. We will assess the performance of our trained model in predicting similar images with detailed output. By inputting blurry or noisy images into the system, we will observe the transformation achieved through several processes applied to the picture. These processes aim to enhance the image quality and generate the desired output, showcasing the effectiveness of our methodology in addressing image degradation and producing improved results.

5.1 Input Image

An image with noise and damaged pixels refers to an image that has been corrupted or distorted, resulting in the presence of unwanted artifacts and pixel-level irregularities. This can occur due to various factors such as sensor limitations, transmission errors, or physical damage. Addressing such issues requires image processing techniques, including denoising algorithms and image restoration methods, to remove noise and repair damaged pixels, restoring the image to its original quality.

Fig 5.1: Input Image

5.2 Processing Images

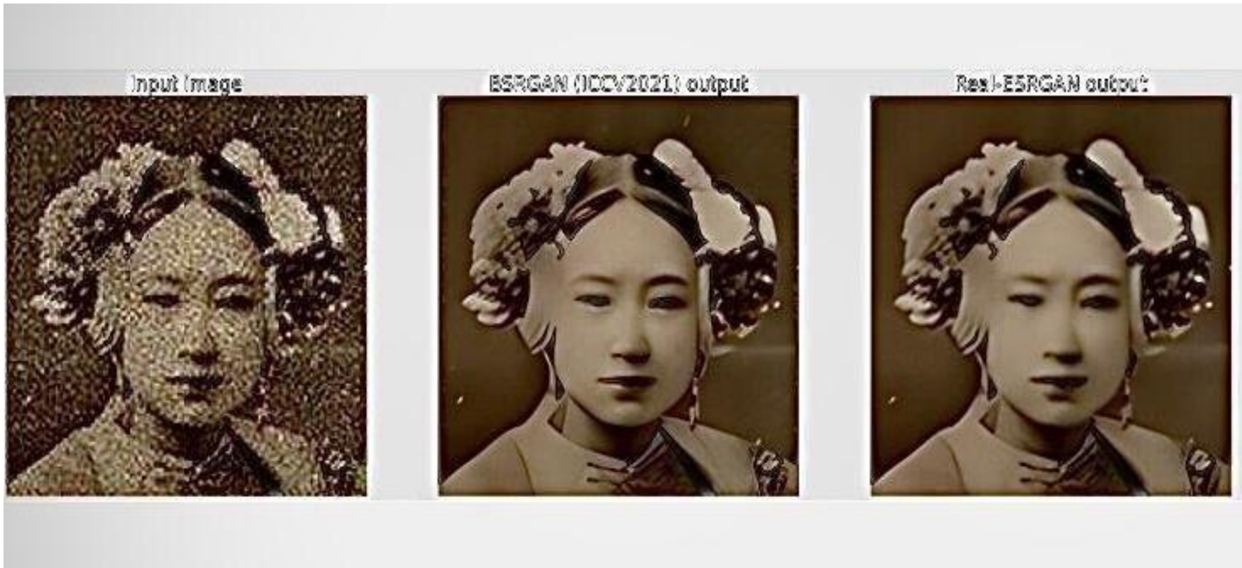

Fig 5.2: Processing Images

5.3 Output Image

As you can see the output picture which is crystal and clear from the input one, the pixel is must efficient and clear than the previous one.

Figure 5.3: Output Image

5.4 Input Image

The given blurry image displays a lack of sharpness and clarity, with indistinct details and reduced contrast.

Fig 5.4: Input Image

5.5 Output Image

The resultant images is much enhanced on the basis of sharpness, blur factor and contrast

Fig 5.5: Output Image

CHAPTER 6

CONCLUSION

The research on image restoration has cast light on the transformative power of visual representation in various fields. This thesis has examined the significant role that reviving images plays in preserving cultural heritage, improving communication, and fostering artistic expression by examining the historical context, technological advancements, and creative processes involved. By reviving old photographs, paintings, and other visual artifacts, We can close the time gap, enabling future generations to communicate with their forebears and gain important insights into the complex fabric of human history.. The use of digital tools and techniques has created new opportunities for restoring damaged or degraded images, ensuring their longevity and accessibility for future generations. In addition, the revival of images has proved instrumental in facilitating effective communication across a variety of professional fields. In disciplines such as journalism, advertising, and education, reimagined visuals have the ability to captivate audiences, communicate complex messages, and elicit emotions. Individuals and organizations can effectively communicate ideas, influence public opinion, and establish meaningful connections with their intended audiences by maximizing the potential of images.

Image resurrection allows artists to reinterpret, recreate, and revitalize existing visual resources. Artists can challenge conventions, explore personal histories, and spark thought-provoking conversations using collage, digital manipulation, and mixed media. Reviving pictures inspires artists to experiment and find new methods to express themselves. However, this thesis also acknowledges the ethical implications of reviving images. It stresses the significance of respecting the integrity and original intent of the creators, as well as taking into account the potential consequences and implications of altering visual content.

Authenticity and historical veracity of the original material should be maintained, while still allowing for meaningful reinterpretations and adaptations, when reviving images. Reviving images can preserve cultural history, improve communication, and inspire creativity. It connects us to the past, empowers us now, and inspires us to shape the future. As technology advances and our grasp of visual representation develops, images will enrich our lives, extend our perspectives, and improve our collective human experience. Picture reclamation and its extraordinary power stretch out past protection and correspondence. It significantly affects fields like medication, criminology, and even space investigation. In medication, the improvement of clinical pictures aids exact analysis and treatment arranging. By reestablishing clearness and detail to X-beams, X-rays, and histopathological pictures, clinical experts can recognize inconspicuous irregularities, distinguish infections at a beginning phase, and come to informed conclusions about quiet consideration. forensic investigations, image restoration techniques can aid in analyzing surveillance footage, enhancing images of crime scenes, and identifying crucial details or suspects. The ability to recover obscured or degraded visual information can significantly contribute to solving crimes, bringing justice, and ensuring public safety. While picture rebuilding holds gigantic potential, moral contemplations stay crucial. Protecting the respectability of authentic pictures, regarding social responsive qualities, and defending security are fundamental perspectives to consider. Finding some kind of harmony among rebuilding and conservation permits us to respect the past while embracing the conceivable outcomes representing things to come.

CHAPTER 7

FUTURE WORK

Future research in image restoration should focus on advancing existing methods and exploring new approaches to enhancing the authenticity and clarity of the photos that have been restored. This can involve investigating novel algorithms, deep learning models, and hybrid techniques that combine multiple methods. Additionally, incorporating semantic information during the restoration process can enhance the intelligence of the system by using computer vision and natural language processing methods to understand the content and context of the picture. Current picture restoration techniques primarily concentrate on single-modal data, such as grayscale or color images. Future research can explore multi-modal image restoration, where different types of data, such as infrared or hyper spectral images, are combined to restore a more comprehensive representation of a scene. This has practical applications in fields like historical document restoration and medical imaging. Future research should focus on developing efficient algorithms and parallel processing techniques to restore large image collections or handle real-time image streams effectively. Scalability and computational efficiency will be crucial considerations in such scenarios. Standardized evaluation metrics and benchmark datasets are essential for fair comparison and objective evaluation of image restoration techniques. Future work should involve the development of comprehensive evaluation frameworks that cover various aspects of restoration, including noise reduction, in painting, super-resolution, and artifact removal. This will facilitate advancements in the field and promote the adoption of effective techniques. The ethical and legal implications of image restoration, such as privacy concerns and the potential for deep fakes, need to be addressed. Future research should investigate these implications and develop guidelines or frameworks to ensure responsible use of image restoration technologies. Collaboration with professionals from diverse disciplines can provide valuable insights in this regard. Image restoration techniques can find applications in virtual and augmented reality environments.

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