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We express all our respect to the juries who will do the honour of appreciating this work

Dedication

I dedicate this modest work to my dear parents, who have continuously encouraged me throughout my studies and supported me in every aspect of my life, always worrying greatly to offer me a better life. May God protect them

To my sister Sabrina.

And my brothers Walid, Billel, Aissa, and Moussa especially.

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To all my family.

Finally, I dedicate this work to everyone who knows me, whether closely or from afar.

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Abstract

This master's thesis investigates the implementation of single image super-resolution (SISR) algorithms. Two categories of image super resolution are considered: conventional methods based on interpolation and methods based on deep learning networks. Three interpolation methods are used, namely: Bicubic, bilinear and nearest algorithms. The implemented deep learning SR networks are: Very deep learning SR (VDSR), Enhanced Deep Super-Resolution Network Algorithm (EDSR) and Enhanced Super Resolution Generative adversarial network (ESRGAN). The considered SR algorithms are applied on the same and well known datasets, for the sake of comparison. The performance assessments are accomplished in terms of PSNR and SSIM in addition to the visual quality of the processed images. The obtained results indicate that deep learning SR algorithms offer significant improvements in LR image quality, outperforming other algorithms in terms of both PSNR and SSIM.

Résumés

Cette thèse de master examine la mise en œuvre des algorithmes de super-résolution d'image unique (SISR). Deux catégories de super-résolution d'image sont considérées : les méthodes conventionnelles basées sur l'interpolation et les méthodes basées sur les réseaux de Dee Learning. Trois méthodes d'interpolation sont utilisées, à savoir : les algorithmes Bicubic, bilinéaire et du plus proche voisin. Les Roseau SR de deep learning mis en œuvre sont : Very Deep Learning SR (VDSR), Enhanced Deep Super-Resolution Network Algorithm (EDSR) et Enhanced Super Resolution Generative Adversarial Network (ESRGAN). Les algorithmes SR considérés sont appliqués aux mêmes ensembles de données bien connus, à des fins de comparaison. Les évaluations des performances sont réalisées en termes de PSNR et de SSIM en plus de la qualité visuelle des images traitées. Les résultats obtenus indiquent que les algorithmes SR de deep Learning offrent des améliorations significatives de la qualité des images basse résolution, surpassant les autres algorithmes en termes de PSNR et de SSIM.

ملخص

تتناول هذه الأطروحة البحثية تطبيق خوارزميات تحسين دقة الصورة الواحدة (SISR). يتم النظر في فئتين من تحسين دقة الصورة: الطرق التقليدية المبنية على الاستيفاء والطرق المبنية على شبكات التعلم العميق. تم استخدام ثلاث طرق استيفاء، وهي: الخوارزميات التكعيبية الثنائية، الخطية الثنائية، وأقرب الجيران. الشبكات العميقة لتحسين الدقة المطبقة هي: شبكة تحسين الدقة العميقة جدًا (VDSR)، خوارزمية شبكة تحسين الدقة العميقة المحسنة (EDSR)، وشبكة تحسين الدقة التوليدية المحسنة (ESRGAN). تم تطبيق خوارزميات تحسين الدقة المدروسة على نفس مجموعات البيانات المعروفة جيدًا لغرض المقارنة. تم تقييم الأداء من حيث PSNR و SSIM بالإضافة إلى الجودة البصرية للصور المعالجة. تشير النتائج التي تم الحصول عليها إلى أن خوارزميات تحسين الدقة المبنية على التعلم العميق تقدم تحسينات كبيرة في جودة الصور منخفضة الدقة، متفوقة على الخوارزميات الأخرى من حيث PSNR و SSIM.

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List of Abbreviations

AI Artificial intelligence

ANN A neural network

BCI Cubic Interpolation

BLI Bilinear Interpolation

CNN Convolutional Neural Network

DL Deep Learning

EDSR Enhanced Deep Super Resolution

ESRGAN Enhanced Super-Resolution generative adversarial network

HR High Resolution

GAN's generative adversarial network

LR Low Resolution

MSE Mean Square Error

ML Machine Learning

NN's Neural Networks

PSNR Peak Signal-to-Noise Ratio

ReLU Rectified Linear Unit

SR super-resolution

SRCNN Super-Resolution Convolution neural network

SRGAN Super-Resolution generative adversarial network

SSIM Structural Similarity

SSIR single-image super-resolution

General Introduction

The field of image super-resolution (SR) is pivotal in various domains such as medical imaging, satellite imagery, and digital photography. This study aims to explore and enhance single image super-resolution (SISR) techniques, with the ultimate objective of developing a novel hybrid method that combines the strengths of existing approaches to achieve superior results.

Initially, we formulate the problem of SISR, outlining the challenges and objectives in enhancing the resolution of a single low-resolution image. We then discuss performance assessment criteria that are essential for evaluating the effectiveness of SR algorithms. Conventional SR algorithms are reviewed, setting the stage for understanding the limitations that have driven the development of more sophisticated methods.

In the subsequent sections, we explore machine learning and deep learning, focusing on Neural Networks (NNs) and Convolutional Neural Networks (CNNs). We review key super-resolution (SR) models, starting with the foundational Super Resolution Convolutional Neural Network (SRCNN) and advancing through the Very Deep Super Resolution (VDSR) and the Enhanced Deep Super-Resolution Network (EDSR). The introduction of Generative Adversarial Networks (GANs) represents a significant leap in SR technology, particularly with the SRGAN and its enhanced version, ESRGAN, which set new benchmarks for image quality by using adversarial training to generate highly realistic images.

Our study includes a detailed comparative analysis of deep learning-based SR methods, both CNN-based and GAN-based, highlighting their strengths and limitations through qualitative and quantitative assessments. We also discuss experimental results to provide deeper insights into the performance of these methods.

Ultimately, our objective is to develop a new hybrid approach that integrates the advantages of existing SR techniques to create a more robust and effective solution. This work concludes with a summary of our findings and outlines future research directions, emphasizing the potential of hybrid methods to drive further advancements in image super-resolution. This comprehensive exploration aims to provide a solid foundation for ongoing research and innovation in this dynamic field.

This manuscript is organized through three chapters:

First chapter Basic Concepts of Single Image Super Resolution second one Deep learning neural networks application to single image super resolution and third chapter was an Implementation of single image super resolution algorithms based on CNN & GAN

Chapter 1

Basic Concepts of Single Image Super Resolution

Summary

In this Chapter, we review the basic concepts of image super resolution problem. A focus on image enhancement approaches will be presented. Furthermore, single image super resolution (SISR) algorithms based on deep learning will be detailed before concluding this Chapter.

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1.1 Introduction

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1.1 Introduction

Super-resolution (SR), particularly single-image super-resolution (SISR), is a type of image transformation task that has garnered growing interest in both academic and industrial spheres. [1] its objective is to reconstruct a high-resolution image from a single low-resolution image.[2] It finds wide application across various computer vision domains, encompassing tasks such as security and surveillance imagery, medical image reconstruction, video enhancement, and image segmentation. [1]

Many single-image super-resolution (SISR) methods, including conventional interpolation, have been studied extensively in the past [1]. However, SISR presents an inherently ill-posed problem, with multiple high-resolution images potentially corresponding to a single original low-resolution image. [1] Recent advances in deep learning have resulted in the development of powerful super-resolution methods utilizing various deep learning architectures such as the generative adversarial Network (GANs) [3] and Convolutional Neural Networks (CNNs) [2], which offer superior solutions compared to classical methods.

This chapter presents image enhancement approaches, focusing on the problem formulation of the image super-resolution process. We explore conventional SR algorithms, compare their methodologies and its performances. A big focus on deep learning SR algorithms is set at the second section of this Chapter. Concluding remarques are presented at the end of this Chapter.

1.2 Problem Formulation of Single Image Super-Resolution Process

Image super-resolution aims to reconstruct high-resolution (HR) images from low-resolution (LR) inputs. This process involves addressing an inherently ill-posed problem due to the lack of unique solutions when attempting to reverse the degradation process that led to the LR representation [4].

Define that $I_x \in \mathbb{R}^{h\times w}$ which is the $LR\ image$ and $HR\ image$ as $I_y \in \mathbb{R}^{H\times W}$ where $H > h$ and $W > w$ [1] the general setup for image super-resolution can be described as follows:

$$I_x = D\left(I_y;\ \delta\right) \qquad (1.1)$$

Where D represents the degradation mapping function, and δ encompasses the parameters of the degradation process, such as scaling factors or noise levels [4]. The goal is to estimate an HR approximation $\hat{I}_y$given the LR imageI_x :

$$\hat{I}_y = F(I_x; \theta) \qquad (1.2)$$

Here, F is the super-resolution model parameterized by θ [4].

While the degradation process is unknown and subject to influence by numerous factors (such as compression artefacts, anisotropic degradations, sensor noise, and speckle noise), researchers endeavour to formulate the degradation mapping. Many studies opt to model the degradation directly as a singular downsampling operation, depicted as follows [4]:

$$D(I_y; \delta) = (I_y) \downarrow_s, \{s\} \subset \delta \qquad (1.3)$$

Where $\downarrow_s$ is downsampling operation involves a scaling factor denoted as 's'. In fact, the majority of datasets designed for general Super-Resolution (SR) adhere to this pattern, employing Bicubic interpolation with anti-aliasing as the predominant downsampling method. Nevertheless, alternative approaches have been explored, which model the degradation as a composite of several operations [4] :

$$D(I_y; \delta) = (I_y \otimes k) \downarrow_s + n_\varsigma, \{k, s, \varsigma\} \subset \delta \qquad (1.4)$$

Where $I_y \otimes k$ represents the convolution between a blur kernel k and the HR image I_y , and n_ς is some additive white Gaussian noise (AWGN) with standard deviation ς.

Recently, researchers have reimagined SISR as an end-to-end learning process, drawing upon extensive training data and refined loss functions. Concurrently, the proliferation of DL-based models has surged, driven by the potent representational capabilities of CNNs and their computational efficiency in both forward and backward computations. As a result, the SISR objective can now be succinctly framed as follows [1]:

$$\hat{\theta}_F = arg_{\hat{\theta}_F} \min \mathcal{L}\left(\hat{I}_y, I_y\right) + \lambda\Phi(\theta) \qquad (1.5)$$

where $\mathcal{L}$ denotes the loss function between the generated SR image $\hat{I}_y$ and the HR image I_y , Φ(θ) denotes the regularization term, and λ is the trade-off parameter that is used to control the percentage of the regularization term[1].

1.3 Conventional SR Algorithms: ISR Based on interpolation methods

These algorithms encompass a wide array of methodologies, including interpolation-based methods, namely Nearest neighbor, Bilinear and Bicubic interpolation. A comparative study between these approaches sheds light on their respective strengths, weaknesses, and applicability in different scenarios.

1.3.1 Nearest neighbor

Nearest neighbor interpolation stands out as the simplest and quickest among interpolation algorithms. [7] It resamples an image by assigning the value of the nearest sample to the processed samples of the new grid [8]. Essentially, new pixels are generated to match nearby ones, often resulting in pixilation or jagged edges that disrupt smooth curves. This method typically yields unsatisfactory results when enlarging or reducing images. [7]

The nearest neighbor interpolation of a function v is defined as the piecewise constant function [9]:

$$u(x, y) = v_{[x],[y]}, \qquad (1.11)$$

Where the interpolation kernel for nearest neighbour as shown in Figure 1.1 [9]

$$k(x, y) = k_1(x)k_2(y), \qquad (1.12)$$

$$k_1(t) = \begin{cases} 1 & if -\frac{1}{2} \leq t < \frac{1}{2} \\ 0 & otherwise \end{cases} \qquad (1.13)$$

100	150	200
125	175	225
150	200	250

100	100	150	150	200	200
100	100	150	150	200	200
125	125	175	175	225	225
125	125	175	175	225	225
150	150	200	200	250	250
150	150	200	200	250	250

Figure 1.1 Nearest neighbor Interpolation

This method is also known as "pixel duplication" because it simply duplicates the value of the nearest input sample [9]

1.3.2 Bilinear interpolation

Bilinear interpolation computes its interpolated value by averaging the weighted values of the four neighbouring pixels [10]. This method produces a smoother image compared to the original. When the known pixel distances are equal, the interpolated value is the sum of these values divided by four. Bilinear interpolation operates in both horizontal and vertical directions, offering superior results to nearest neighbor interpolation while requiring less computational time than Bicubic interpolation. [7]

If we got p_0, p_1, p_2, p_3 are the four closest neighbors of p, we will determinate the final value of the interpolated pixel using the following equation:

$$I(p) = \frac{\left(\sum_{i=0}^{3} \omega_i . \mathrm{I}(p_i)\right)}{\left(\sum_{i=0}^{3} \omega_i\right)} \qquad (1.14)$$

Where coefficients ω_i are inversely proportional to the distance between p and $p_i$with their sum totaling 1. [11]

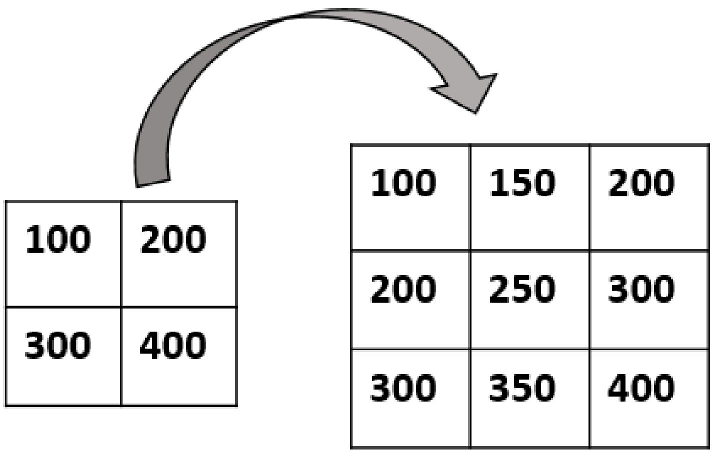

Figure 1.2 Bilinear interpolation

The interpolation kernel are presented in Figure 1.3 [9]

$$k(x, y) = k_1(x)k_2(y), \qquad (1.15)$$

Where

$$k_1(t) = (1 - |t|)^+, \qquad (1.16)$$

1.3.3 Bicubic interpolation

Bicubic interpolation advances from bilinear interpolation by incorporating the nearest 4x4 neighbourhood of known pixels, totalling 16 pixels. Weighting in the calculation prioritizes closer pixels due to their varying distances from the unknown pixel. As a result, Bicubic interpolation generates markedly sharper images compared to its predecessors, offering an optimal balance between processing time and output quality. This superior performance has established it as a standard feature in numerous image editing programs, including Adobe Photoshop, printer drivers, and in-camera interpolation. [7]

Bicubic interpolation uses the interpolation kernel as shown in Figure 1.3

$$k_1(t) = \begin{cases} (\alpha + 2)|t|^3 - (\alpha + 3)|t|^2 + 1 & if \ |t| \le 1 \\ \alpha|t|^3 - 5\alpha|t|^2 + 8\alpha|t| & if \ 1 < |t| < 2 \\ 0 & otherwise \end{cases} \qquad (1.17)$$

Where α is a free parameter [9].

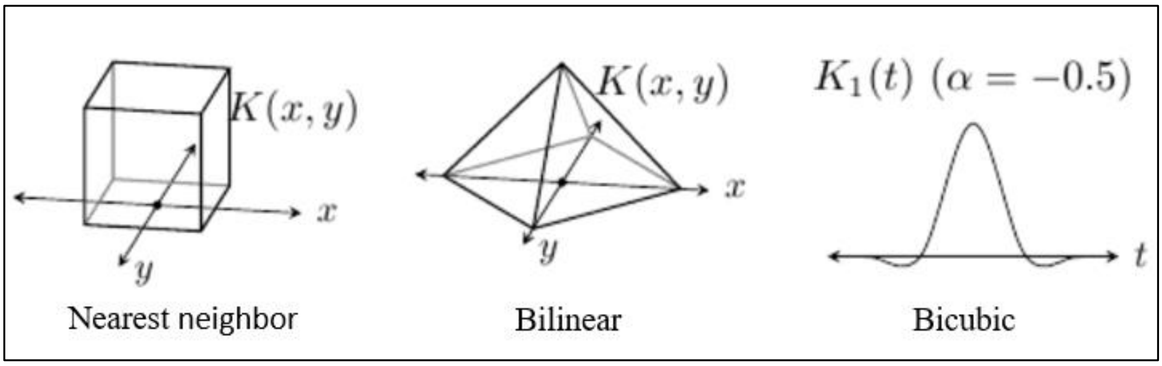

Figure 1.3 Interpolations kernels [9]

1.4 Performance Assessment

There are numerous techniques for assessing image quality, including MSE (Mean Square Error), UIQI (Universal Image Quality Index), PSNR (Peak Signal-to-Noise Ratio), SSIM

(Structural Similarity Index Method), HVS (Human Vision System), FSIM (Feature Similarity Index Method), and many others. These methods are widely utilized to evaluate and analyse the quality of images across various applications and domains. In this these, we have used SSIM and PSNR methods to evaluate the algorithms performance.

- **Structural Similarity Index (SSIM)**

  is a metric used to measure the similarity between two images. It aims to capture the perceived change in structural information, luminance, and contrast of the images, which are key factors in human perception of image quality. SSIM compares local patterns of pixel intensities that have been normalized for luminance and contrast.

  The SSIM index varies between -1 and 1, where 1 indicates perfect similarity between the images. A score closer to 1 implies that the images are highly similar, while a score closer to -1 indicates dissimilarity.

  Mathematically, the SSIM index between two images x and y is calculated as follows:

  $$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \qquad (1.6)$$

  Whereμ_x, μ_y are the average pixel intensities σ_x^2, σ_y^2 are the variances of pixel intensities in images x and y respectively, σ_{xy} is the covariance of pixel intensities between images x and y. And c_1, c_2 are small constants added to avoid instability issues when the denominator is close to zero.[5]

- **DSSIM (Structural Dissimilarity)**

  It is a distance metric derived from the Structural Similarity (SSIM) index. SSIM measures image quality by considering three main components: luminance, contrast, and structural or correlation term. DSSIM extends this concept to quantify dissimilarities between images. [5] It can be expressed as:

  $$DSSIM(x,y) = \frac{1 - SSIM(x,y)}{2} \qquad (1.7)$$

- **Mean Squared Error (MSE)**

  It measures the average squared difference between the pixel values of the original image and the corresponding pixel values of the reconstructed or denoised image.

  Mathematically, for a grayscale image with dimensions$M \times N$ MSE is calculated as [6]:

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(I_{ij} - \hat{I}_{ij})^2 \qquad (1.8)$$

Where M is the height of the image, N is the width of the image, I_{ij} is the intensity (pixel value) of the original image at position $(i,\ j)$ and $\hat{I}_{ij}$ is the intensity of the reconstructed or denoised image at position $(i,\ j)$

For colour images, the same formula can be applied independently to each colour channel (e.g., red, green, blue), and the MSE values can be averaged across all channels.[5]

As with other applications, a smaller MSE value indicates a better quality reconstruction or denoising, implying that the reconstructed or denoised image is closer to the original image.

- **Root Mean Squared Error (RMSE)**

  Represents the square root of the MSE, Root Mean Square Error (RMSE) is a widely employed technique for measuring the disparities between predicted and actual values generated by an estimator. It assesses the magnitude of errors and serves as an excellent indicator of accuracy. RMSE is particularly useful for comparing forecasting errors across different estimators for a specific variable. [5]

$$RMSE = \sqrt{MSE} \qquad (1.9)$$

- **Peak Signal-to-Noise Ratio (PSNR)**

  is another commonly used metric for evaluating the quality of reconstructed or denoised images. It measures the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. In the context of images, PSNR is often used to compare a reconstructed or denoised image to the original image. [4]

  The formula for PSNR in the context of images is:

$$PSNR(\text{dB}) = 10 \times log_{10}\left(\frac{Max^2}{MSE}\right) \qquad (1.10)$$

Where Max is the maximum possible pixel value of the image (for example, 255 for an 8-bit grayscale image or 1 for a normalized image)

A higher PSNR value indicates higher image quality, as it implies that the reconstructed or denoised image is closer to the original image in terms of pixel values.

- **Visual Information Fidelity (VIF)**

  Evaluates the perceptual similarity between two images by comparing their local luminance and contrast characteristics, providing insights into visual fidelity.

In this work we have used the two criteria PSNR and SSIM in addition to the visual quality of the processed image

1.5 Super Resolution based on deep learning [12], [13]

Deep learning-based super-resolution (SR) algorithms have emerged to enhance the quality of low-resolution images by generating high-resolution counterparts. These techniques uses deep neural networks to understand the relationship between low and high-resolution images, consistently achieving cutting-edge results across diverse fields like medical imaging, computer vision, and image processing.

Several deep learning architectures have been developed for SR, including convolutional neural networks (CNNs), residual networks, dense networks, and generative adversarial networks (GANs). For example, Very Deep Super Resolution (VDSR) employs a very deep CNN to extract complex features, while Enhanced Deep Super-Resolution (EDSR) combines global and local residual learning for improved performance. GANs have also shown promising results by leveraging adversarial training to generate high-quality, realistic super-resolved images. These models are trained using large datasets of paired low and high-resolution images, with the goal of minimizing the difference between the predicted high-resolution output and the ground truth

Deep learning-based SR has numerous applications, such as enhancing the resolution of medical images for improved diagnosis, super-resolving images captured by telescopes to reveal more details of celestial bodies, and upscaling low-resolution videos for a better viewing experience. However, challenges remain, such as the need for large datasets of paired low and high-resolution images for training, and the computational complexity of deep models

Overall, deep learning has revolutionized the field of image super-resolution, enabling the recovery of high-frequency details and the generation of high-quality, high-resolution images from low-resolution inputs. As deep learning techniques continue to advance, we can expect to see even more impressive results and broader applications of SR in the future.

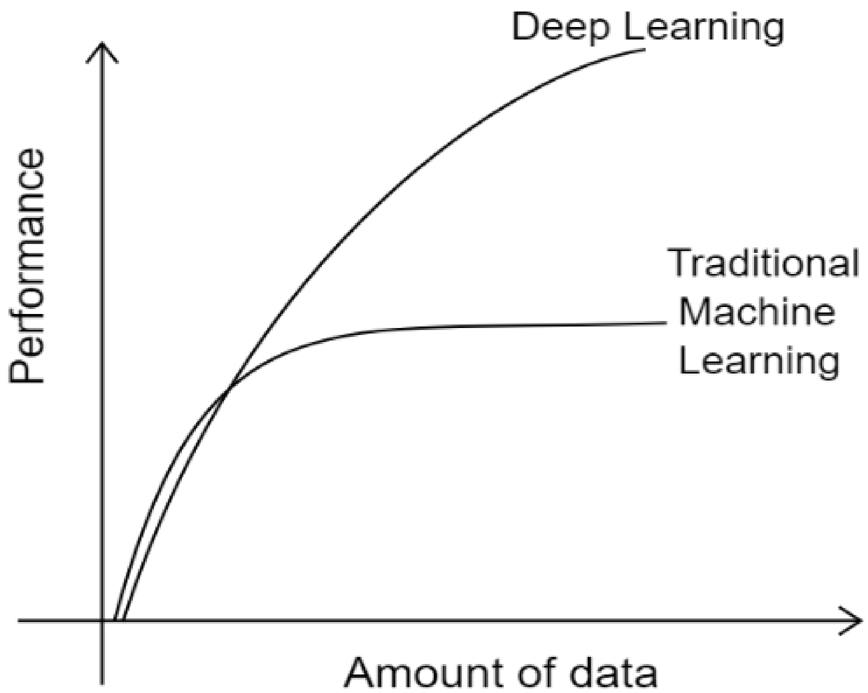

Figure1.4 Deep learning performance VS machine learning performances

Figure 1.4 represents the difference between Traditional Machine learning and Deep Learning performances using amount data.

1.6 Conclusion

In conclusion, this chapter serves as a comprehensive primer on image enhancement techniques, where we focused on image super-resolution (SISR). By dissecting the problem formulation and exploring the inherently ill-posed nature of SISR, we highlighted the complexities involved in accurately reconstructing high-resolution images from low-resolution inputs. With mentioning for the performance assessment section where we provided insight into the metrics used to evaluate SISR methods, emphasizing the importance of both objective and perceptual quality measures.

The review of conventional SR algorithms showcased the foundational approaches that paved the way for current advancements, illustrating their limitations in preserving fine details and textures. via the examination conventional algorithms, and delving into the transformative impact of deep learning we equip readers with a nuanced understanding of the evolution, challenges, and future directions in the field of image super-resolution in the next chapter .

Chapter 2

Deep learning neural networks application to single image super resolution

Summary

In this chapter, we will explore the evolution of image super-resolution techniques, starting with foundational concepts in machine learning and deep learning. passing on Neural Networks (NNs), focusing on Convolutional Neural Networks (CNNs) and their application in super-resolution through models like SRCNN, VDSR, and EDSR. The chapter highlighted the advancements brought by Generative Adversarial Networks (GANs), based on ESRGAN.

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2.1 Introduction

Deep learning, as a subset of machine learning algorithms, is designed to learn hierarchical representations of data. Deep learning neural networks have been extensively applied to single image super-resolution (SISR) tasks, aiming to enhance the resolution of low-resolution images. Recent research has focused on developing efficient neural network architectures and effective optimization objectives for deep SISR learning [14]. One approach involves employing convolutional neural networks like SRDenseNet to perform SISR on images, such as MR brain images, achieving notable results [15]. Various deep learning algorithms have been explored for SISR, including models like SRCNN, VDSR, EDSR, CRN, ERN, DRCN, DRRN, GLRL, FGLRL, DRDN, SRDenseNet, RDN, Dilated-RDN, DSAN, DBCN, and SICNN [16]. These algorithms utilize different network architectures and strategies to enhance image resolution effectively. This chapter aims to elucidate the evolution and impact of these models, showcasing how each advancement builds upon the previous ones to push the boundaries of what is possible in image super-resolution. Through this journey, we gain a deeper understanding of the technological innovations that have transformed this field, paving the way for future research and applications.

2.2 Machine learning

Machine learning (ML) is a branch of artificial intelligence, it is the practice of instructing computers to learn from data through a diverse array of algorithms, capable of iteratively enhancing, elucidating, and forecasting outcomes. Through the absorption and analysis of training data, machine learning algorithms iteratively refine their understanding, culminating in the creation of more precise models. The culmination of this process yields a machine learning model, representing the outcome of training the algorithm with the provided data [17].

There exist two primary categories within machine learning: Supervised Learning, which stands as the predominant paradigm in both Machine Learning (ML) and Deep Learning (DL). This method entails furnishing the machine learning algorithm with exemplars (data) of the task it's tasked to perform, Figure 2.1 enabling it to learn in a guided manner from these instances. Supervised learning boasts a broad spectrum of applications spanning computer vision, regression, and classification, among others. The lion's share of challenges in both Machine Learning and Deep Learning hinges on supervised learning as the principal approach [18].

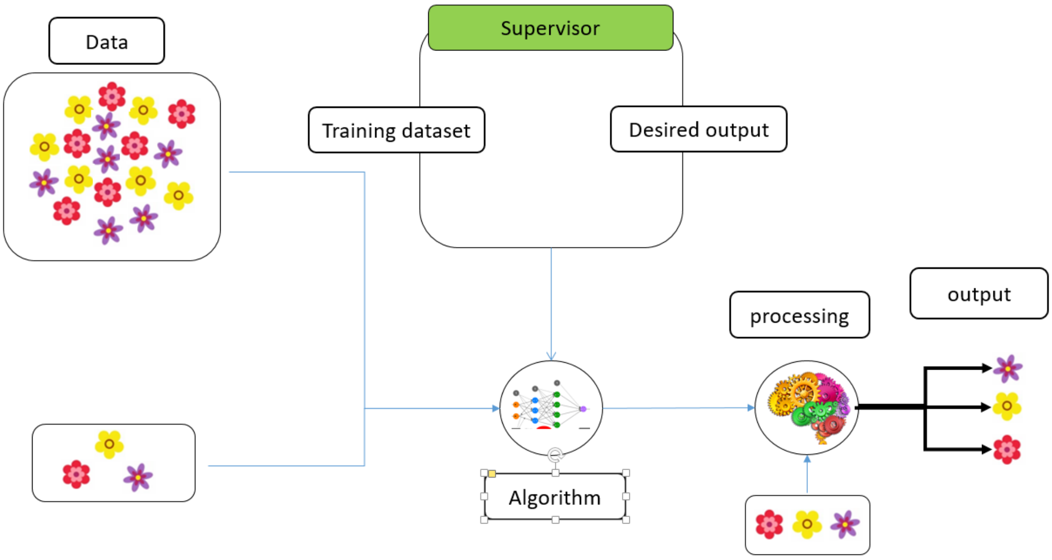

Figure 2.1 supervised learning

On the other hand, we encounter Unsupervised Learning, which operates distinctively. Here, unlabelled data is utilized to train models, affording them the capacity to discern patterns and features from the data sans predefined outputs. as it is shown in Figure 2.2 This methodology finds particular utility in handling copious amounts of unlabelled data and is employed for tasks such as clustering and dimension reduction.

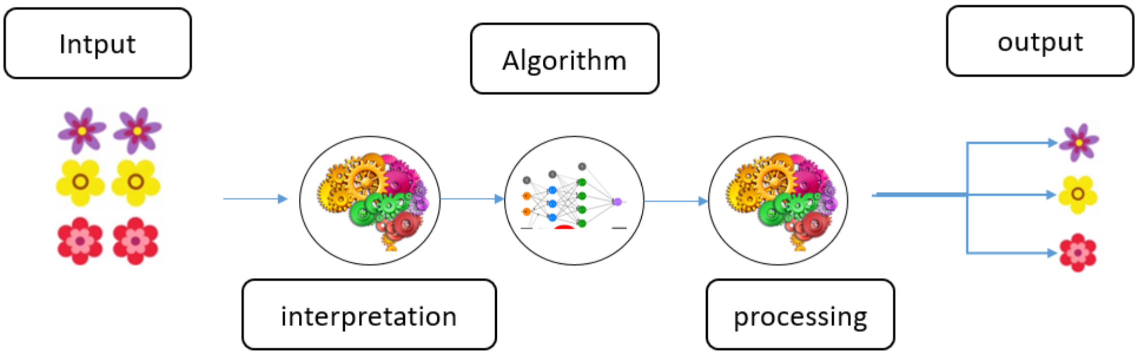

Figure 2.2 unsupervised learning

2.3 Deep learning

Deep learning (DL) is a subset of machine learning algorithms focused on acquiring hierarchical representations of data. It has demonstrated significant advantages over other machine learning approaches across various artificial intelligence domains,[14] due to the utilization of more intricate algorithms, (deep neural networks), and the capability to handle unstructured data such as images, text, or video...[19]. Deep learning models draw inspiration from the structure and functionality of biological neural networks, employing artificial networks to replicate the human brain's capacity for information processing [20].

As deep learning models receive more data, their accuracy improves. Yet, training these models demands substantial computational resources, as they navigate data across multiple hidden layers utilizing parameters known as weights, which denote the strength of connections between layers. Deep learning finds application in diverse fields like fraud detection, supply chain management, and natural language processing [21].

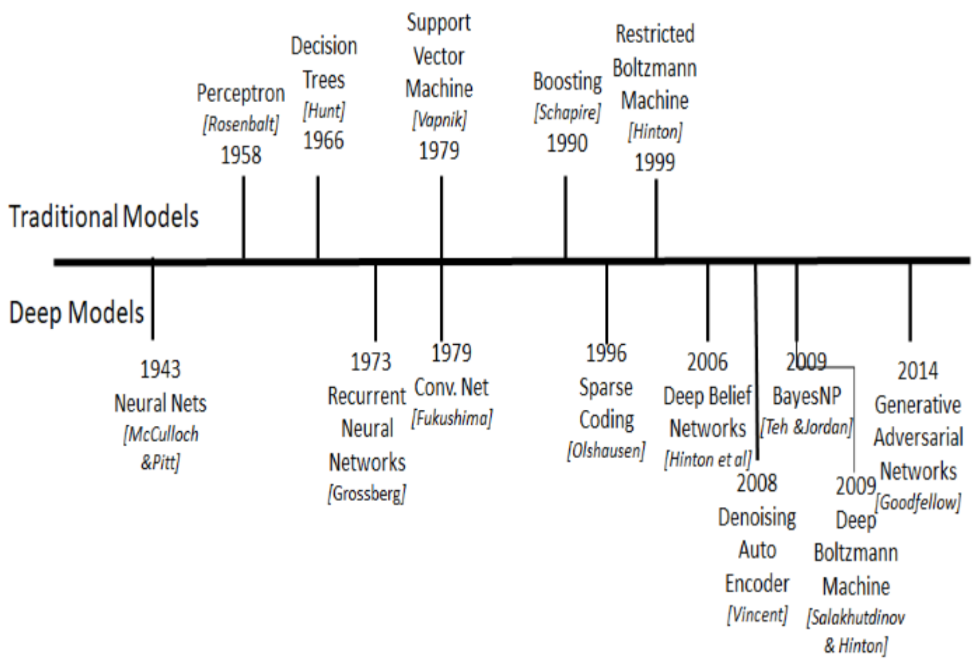

Figure 2.3 Evolution of deep learning models [21]

2.4 Neural Networks (NNs)

A neural network consists of interconnected layers of nodes or neurons, including an input layer, one or more hidden layers, and an output layer. The input layer receives data, which is subsequently processed within the hidden and output layers using weights assigned to the nodes. A typical neural network can comprise thousands or even millions of interconnected simple processing nodes [22].

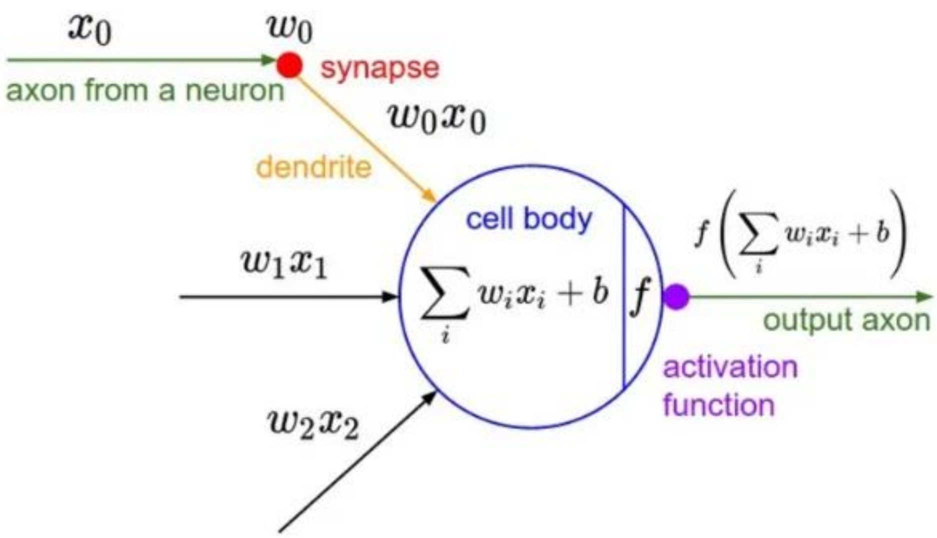

Figure 2.4 Neuron components

2.4.1 Basic Principles of Neural Networks

- **Weight and bias** In neural networks, each connection between nodes has a weight and bias associated with it. The weight determines the connection's strength, while the bias adds flexibility to the output [23].
- **Activation function** Activation functions are crucial in neural networks as they introduce non-linearity, enabling the network to learn complex patterns in the data. The activation functions like the rectifier function are popular for introducing non-linearity, while the sigmoid function is suitable for binary predictions. [23].
- **Backpropagation** is a technique used to train neural networks by adjusting the weights and biases based on the error between predicted and actual outputs [27].
- **Gradient Descent** is a widely used optimization algorithm in machine learning and deep learning that minimizes the cost function of a neural network model during

training. It works by iteratively adjusting the weights in the direction of the steepest descent of the loss function until it reaches a minimum. The learning rate determines how big the steps are in the direction of the negative gradient, which is crucial to balance convergence speed and avoiding overshooting the optimal solution

- **Hyperparameters** are set before training and include variables that determine the network structure and training process. The article from Towards Data Science explains hyperparameters related to network structure, such as the number of hidden layers and learning rate, and discusses techniques like grid search for tuning hyperparameters [25].
- **Overfitting and regularization** Overfitting occurs when a model learns the training data too well, leading to poor performance on new data. Regularization techniques like dropout and L1/L2 regularization are used to prevent overfitting [24].
- **Epoch** The epoch count is a hyperparameter determining the frequency of the learning algorithms processing of the entire training dataset. Within each epoch, the model's internal parameters are adjusted for every sample in the training set. Typically, an epoch comprises one or more batches. [28]
- **Batch size** The batch size in machine learning is the number of training examples used in each iteration or batch during the training process. It is a hyperparameter that affects training efficiency, memory usage, and model performance. Choosing an appropriate batch size is crucial for balancing training speed and model accuracy. Common batch sizes include powers of 2, such as 32, 64, and 128, but the optimal size can vary based on the specific dataset and model architecture [29][30]

2.4.2 Forward propagation

Forward propagation in a neural network is the process through which information flows from the input layer through one or more hidden layers to the output layer. During this process, each neuron receives input from the neurons in the preceding layer, processes it using its activation function, and then passes the output to the neurons in the next layer. The journey begins at the input layer, where the network receives input data typically represented as a vector. The data then traverses through one or more hidden layers, each composed of multiple neurons. Within these layers, neurons process input from the previous layer, apply activation functions, and transmit the output to the subsequent layer. Finally, the output layer, which is the last layer of the network, produces the final output. It consists of one or more neurons, each processing input from the preceding layer, applying activation functions, and generating the ultimate result of the neural network. [22]

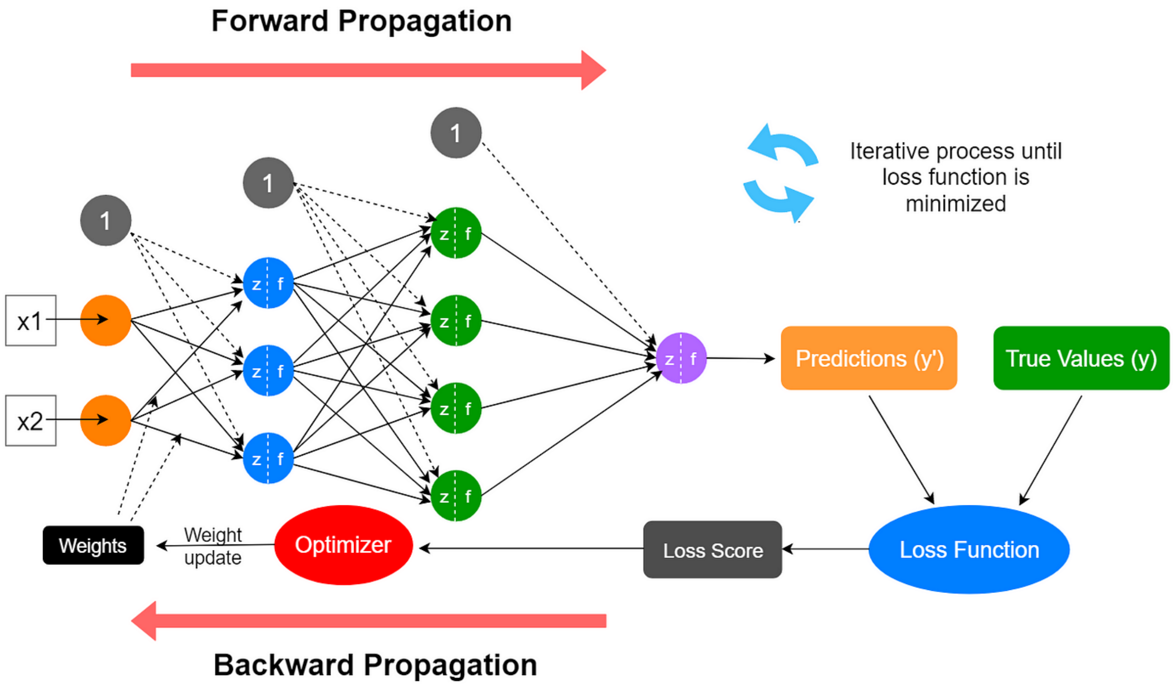

Figure 2.5 Neural network

2.4.3 Training a neural network

Training a neural network involves several key steps. The primary goal of training is to adjust the weights and biases of the network to minimize the difference between the network's predictions and the actual output so that it can make better predictions in the future. This process is typically done using a training dataset that includes input data and corresponding labels or outputs. The process typically involves feeding the network a set of inputs (generally big data sets) and comparing its predicted output to the true one. [32]

2.5 Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a specialized type of feed-forward neural network that excels in learning feature engineering through filters or kernels. CNNs are widely used in various applications such as image and video recognition, recommender systems, image classification, segmentation, medical image analysis, natural language processing, brain-computer interfaces, and financial time series analysis. They are designed to prevent issues like vanishing and exploding gradients by using regularized weights over fewer connections. CNNs are known for their ability to extract higher-layer features from wider context windows compared to lower-layer features, making them efficient for processing complex data like images and videos.

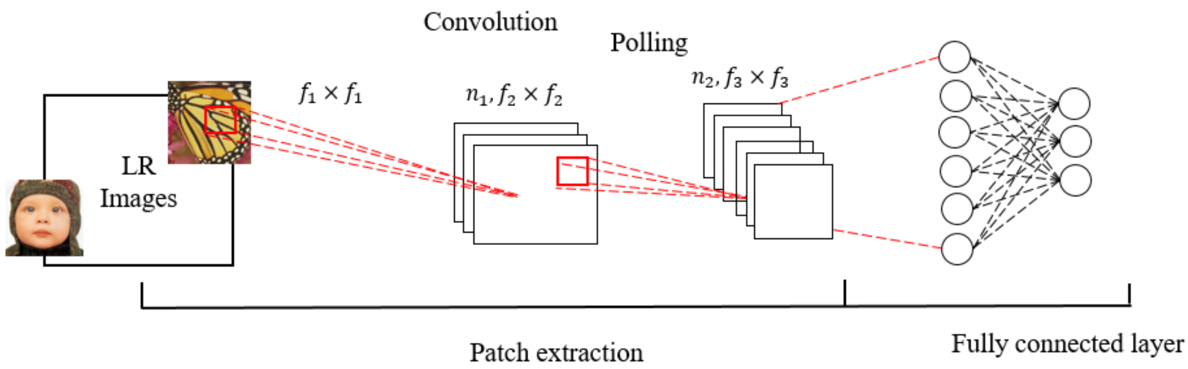

Figure 2.6 Conventional architecture of a convolutional neural network

2.6 Super Resolution Convolutional Neural Network (SRCNN)

The Super-Resolution Convolutional Neural Network (SRCNN) is a deep learning method that reconstructs high-resolution images from low-resolution images. It directly learns an end-to-end mapping between the low-resolution (LR) and high-resolution (HR) images, significantly outperforming previous non-deep learning methods [2]. Figure 2.7 Illustrate the architecture of a SRCNN

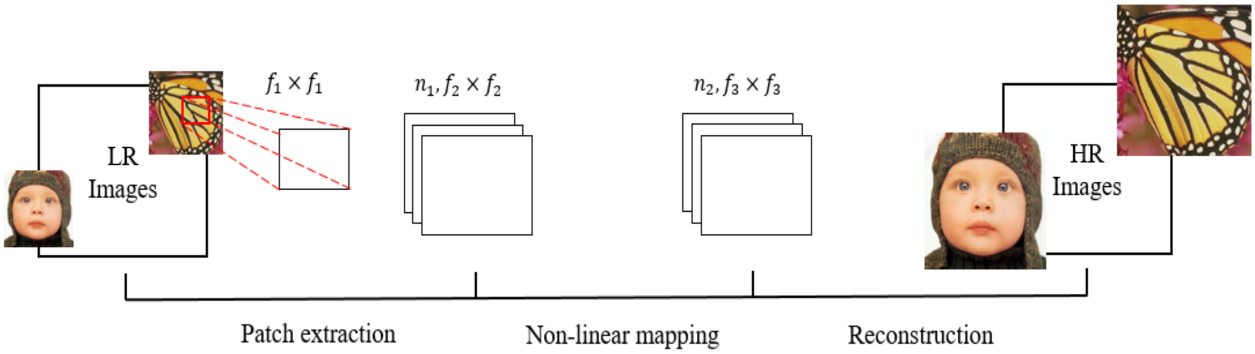

Figure 2.7 SRCNN architecture

2.7 Very Deep Super Resolution VDSR

VDSR is a deep learning approach for single image super-resolution that uses a very deep convolutional neural network (CNN) to generate high-resolution images from low-resolution inputs [32]. The network consists of 20 weight layers, which is significantly deeper than previous methods like SRCNN [32]

By stacking numerous 3x3 convolutional layers, VDSR is able to capture complex relationships between low-resolution (LR) and high-resolution (HR) images, allowing it to enhance fine textures and sharp edges [32]. The network learns a residual mapping, predicting the difference between the bicubic-upscaled LR image and the ground truth HR image [32][33][34]. This residual learning strategy enables faster convergence during training compared to directly learning the HR output [32].

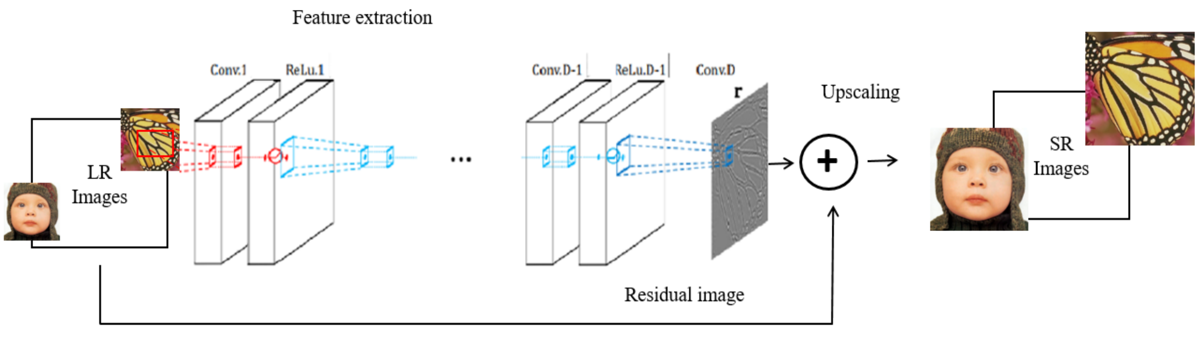

Figure 2.8 VDSR architecture

VDSR is versatile, as it can handle multiple upscaling factors (e.g. x2, x3, x4) by training on images of different scales [32]. It also benefits from parallel computing using GPUs for faster processing during inference [32].

. 2.8 Enhanced Deep Super-Resolution Network Algorithm (EDSR)

EDSR (Enhanced Deep Residual Networks for Single Image Super-Resolution) is a deep learning-based super-resolution method that achieves state-of-the-art performance. The EDSR network consists of three main components: ResamplerNet, which estimates content-adaptive resampling kernels and offsets for each pixel in the downscaled image; a downscaling module, which applies the estimated resampling kernels to downscale the input image; and SRNet the differentiable up sampling operation, which guides the training of ResamplerNet by minimizing the super-resolution error through. The entire framework is trained end-to-end by back propagating error, resulting in enhanced image quality and detail [14][34]. Figure2. Shows the EDSR network architecture.

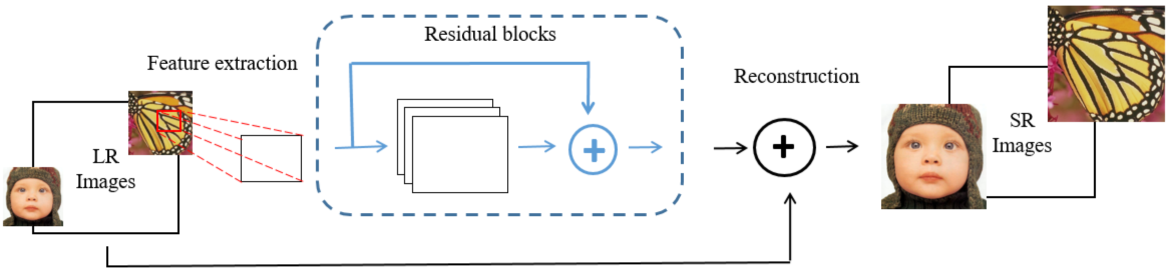

Figure 2.9 EDSR architecture

2.9 Generative adversarial network (GAN)

Generative Adversarial Networks (GANs) are a powerful class of deep learning models used for enhancing the statistics of a prior Probability Density Function (PDF) set by generating fake PDF replicas. GANs operate through a competitive process involving a generator and a discriminator network. The generator aims to produce data instances that resemble the training set, while the discriminator learns to differentiate between real and generated data. This adversarial training process enables GANs to autonomously identify patterns in input data and generate new examples that closely resemble the original dataset. Figure 2. Explains the Discriminator Principe of work [35].

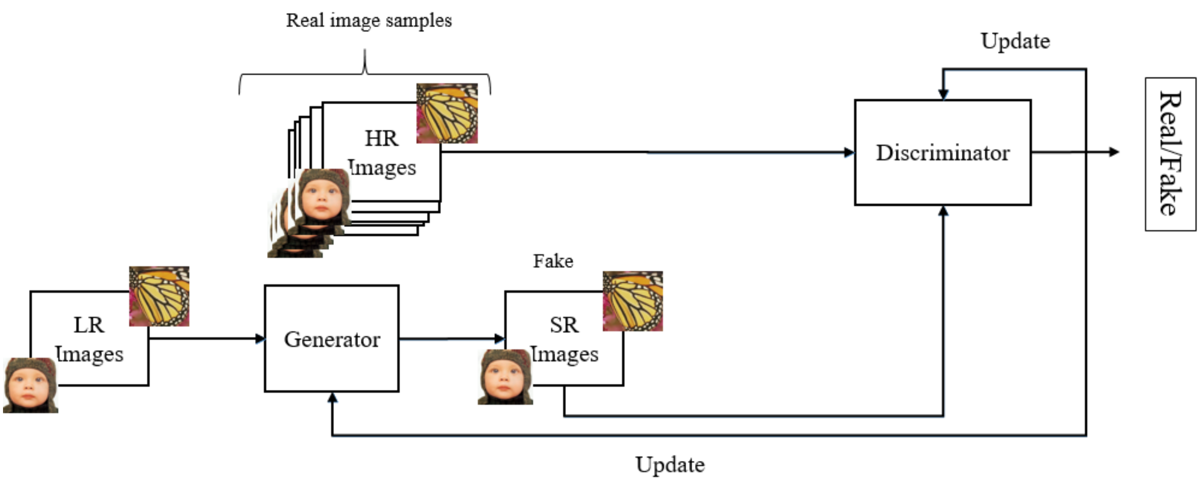

Figure 2.10 Discriminator operation

2.10 Super Resolution Generative adversarial network (SRGAN)

The Super-Resolution Generative Adversarial Network (SRGAN) is a deep learning model designed for single image super-resolution, focusing on recovering finer textures from images during upscaling without compromising quality. SRGAN consists of two key components: the Generator and the Discriminator [36].

2.10.1 Generator

The generator in SRGAN is responsible for producing high-resolution images from low-resolution inputs. It utilizes a residual network with skip connections, making it easier to train and enabling deeper architectures for better results. The generator optimizes the generated data to deceive the discriminator by producing realistic images [36].

As shown in Figure 2.10 the generator comprises B residual blocks (16 in total), each containing two convolutional layers with 3x3 kernels and 64 feature maps. Batch normalization and ParametricReLU activation functions are used within the blocks.

2.10.2 Discriminator

The discriminator's role is to differentiate between real high-resolution images and generated super-resolution images. It employs a network architecture similar to DCGAN with LeakyReLU activation. The discriminator uses strided convolutions to reduce image resolution and features, followed by dense layers and a final sigmoid activation for classification.

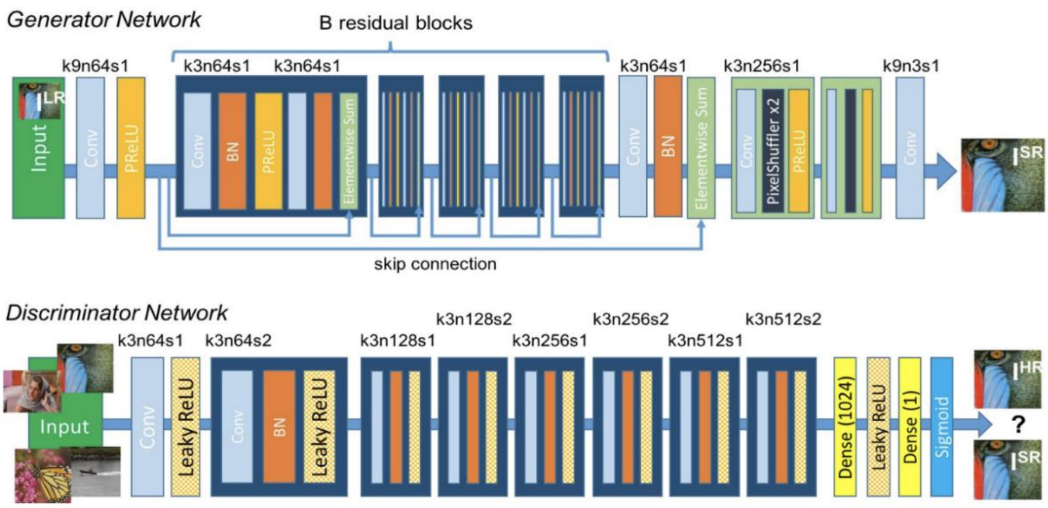

Figure 2.11 Generator and Discriminator architectures [35]

The discriminator consists of eight convolutional layers with 3x3 filter kernels, increasing from 64 to 512 kernels. Strided convolutions are utilized to reduce image resolution, and the network ends with two dense layers, LeakyReLU activation, and a sigmoid function for classification. Figure 2.10

2.10.3 Loss Function:

SRGAN utilizes a perceptual loss function, which combines content loss and adversarial loss.

- **Content Loss** In SRGAN, content loss includes pixelwise Mean Squared Error (MSE) loss and VGG loss based on pre-trained VGG network layers to capture high-frequency content in images.
- **Adversarial Loss** This loss function compels the generator to produce images more similar to high-resolution images by training a discriminator to differentiate between the two.

2.11 Enhanced Super Resolution Generative adversarial network (ESRGAN)

The Enhanced Super-Resolution Generative Adversarial Network (ESRGAN) is an advancement over the Super-Resolution Generative Adversarial Network (SRGAN) that focuses on improving visual quality by enhancing network architecture, adversarial loss, and perceptual loss components. ESRGAN introduces the Residual-in-Residual Dense Block (RRDB) without batch normalization as the basic building unit, incorporates the idea of relativistic GAN for discriminator predictions, and enhances the perceptual loss by using features before activation. These enhancements result in ESRGAN consistently achieving better visual quality with more realistic and natural textures compared to SRGAN [37].

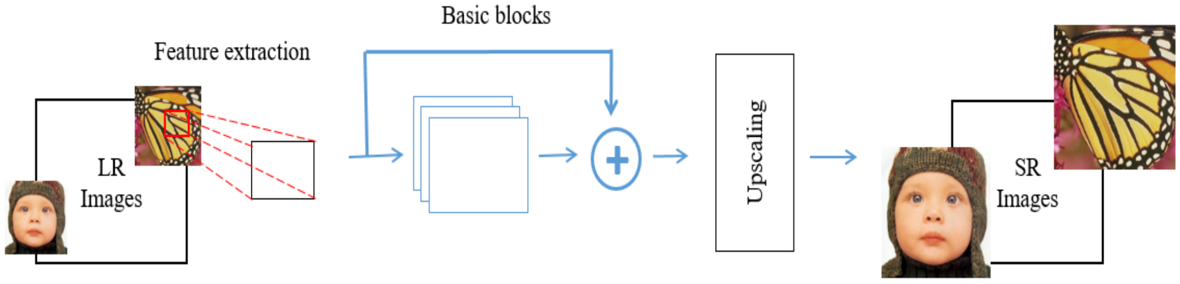

Figure 2.12 ESRGAN architectures [35]

2.12 Conclusion

In this chapter, we have systematically explored the fundamental concepts and advanced techniques in the field of image super-resolution through machine learning and deep learning methodologies. We began with a foundational overview of machine learning and deep learning, setting the stage for a deeper dive into Neural Networks (NNs). We discussed the basic principles of neural networks, forward propagation, and the essential aspects of training a neural network. Our focus then shifted to Convolutional Neural Networks (CNNs), which form the backbone of many state-of-the-art image processing techniques. We delved into specific models designed for super-resolution tasks, beginning with the Super Resolution Convolutional Neural Network (SRCNN). We then examined the Very Deep Super Resolution (VDSR) model, highlighting its enhanced capability to capture complex image features.Further, we explored the Enhanced Deep Super-Resolution (EDSR) network, which pushes the boundaries of image quality and detail preservation. The introduction of Generative Adversarial Networks (GANs) marked a significant milestone in super-resolution research, leading us to discuss SRGAN and ESRGAN, two models that leverage adversarial training to achieve remarkable visual fidelity.

Throughout this chapter, we have seen how the evolution from traditional CNN-based methods to GAN-based approaches has significantly improved the quality of super-resolved images. Each model builds upon its predecessors, incorporating novel techniques and optimizations to enhance performance. This progression underscores the dynamic nature of research in this field and sets the stage for future innovations in image super-resolution.

Chapter 3

Implementation of single image super resolution algorithms based on CNN & GAN

Summary

In this chapter, we first implement the conventional image super resolution algorithms, namely: Bicubic, Nearest Neighbor, and Bilinear interpolation. Then we implement the deep learning SR algorithms based on CNN (VDSR, EDSR). Finely we implement the deep learning SR algorithms based on GAN (ESRGAN). A comparative study is established in terms of Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) in addition to the visual quality. We have performed many simulation experiments with the most used datasets in this field. The obtained results are very close to those of the recent works and highlight the benefit of deep learning networks.

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3.5 Deep Learning SR methods Based on CNN

3.6 Deep Learning SR methods Based on GAN

3.7 Global qualitative and quantitative comparative study

3.8 Future work

3.9 Conclusion

3.1 Introduction

In this chapter, we present the results of our simulation experiment, focusing on various super-resolution (SR) algorithms. More precisely we implement the following single image super resolution SISR algorithms of SR algorithms. Initially, we employed conventional methods (Bicubic, bilinear, and nearest neighbor). Subsequently, we delved into SISR algorithms based on deep learning techniques in two categories (based on CNN, based on GAN), the implemented SISR algorithms based on CNN are Very Deep Learning SR (VDSR) and EDSR. The implements SISR based on generative adversarial networks (GANs) is Enhanced Super-Resolution Generative Adversarial Network (ESRGAN).

For all the SR algorithms the first step is the generation of LR images. And to ensure an objective comparison, identical datasets were employed for all considered SR algorithms. Note that in our study we have considered only down sampling degradation, the generation of LR images are accomplished with Bicubic interpolation

We conducted a quantitative comparative study using two well-established metrics: PSNR and SSIM. Additionally, we evaluated the visual quality of the reconstructed images. Notably, these metrics were computed for each test image acquired. The average PSNR and SSIM values were computed at the conclusion of each simulation experiment. And we highlighted the concluding remarks in the end of this chapter

3.2 Software material

The primary code sources were developed and executed on Google Colab and in a DELL laptop with a RAYZEN5 processor running Windows 10 Professional. The large datasets were efficiently processed through the utilization of the online GPU T4 resources in Google Colab. PyTorch was the main programming package used in Python3.8, specifically designed for deep learning implementations.

The PSNR and SSIM were calculated with its function on MATLAB R2021a for better resolution.

3.3 Datasets

We have used **div2k datasets** for training algorithms. It consists of high-definition high-resolution images that are divided into training, validation, and testing sets. The training data starts with 800 high-resolution images, which are used to obtain corresponding low-resolution images for training purposes. The dataset provides both high and low-resolution images for downscaling factors of 2, 3, and 4. The validation data includes 100 high-resolution images used to generate low-resolution corresponding images for feedback during the challenge. The testing data comprises 100 diverse images used to create low-resolution images for evaluation.

The developed SR algorithms underwent testing using data sets from recent literature, specifically Set5, and Set14, as outlined in Table 3.1. And 3.2 respectively in addition to the set1and set2 datasets [38][39][40].

Table 3.1 Set5 Datasets

Image set	Resolution
Baby	(512x512)
Bird	(288x288)
Butterfly	(256x256)
Head	(280x280)
Woman	(228x344)

Table 3.2 Set14 Datasets

Image set	Resolution
Baboon	(500x480)
Barbara	(720x576)
Bridge	(512x512)
Coastguard	(352x288)
Comic	(250x361)
Face	(276x276)
Flowers	(500x362)
Foreman	(352x288)
Lenna	(512x512)
Man	(512x512)
Monarch	(768x512)
Pepper	(512x512)
Ppt3	(529x656)
Zebra	(586x391)

We have presented the input data in Figure 3.1 and Figure 3.2 respectively

Figure 3.1 Set5 datasets

Figure 3.2 Set14 datasets

3.4 Convolutional methods

Figure 3.3 outlines the key steps of our implementation process. Initially, we generate low-resolution images (LR) from the high-resolution (HR) ones by down sampling Bicubic interpolation. Next, we apply interpolation algorithms to enhance them into our new super-resolution images. Subsequently, we upload it to MATLAB for calculating SSIM and PSNR values.

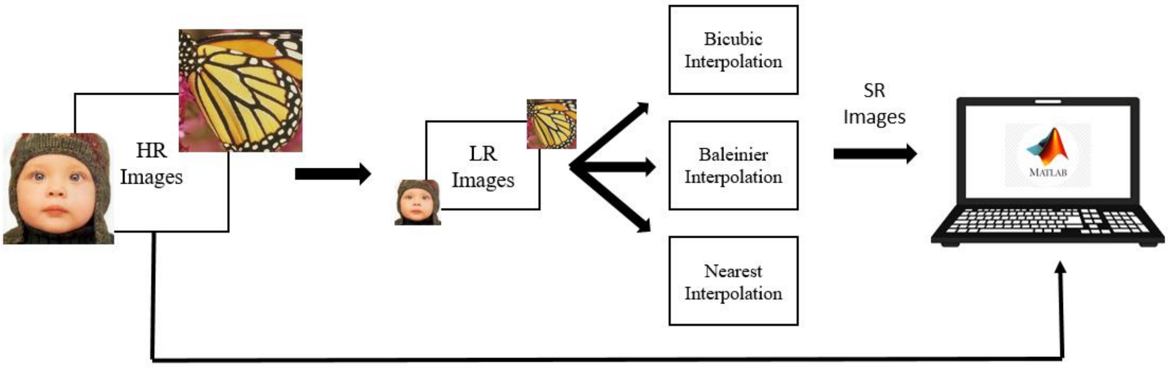

Figure 3.3 key steps of the implementation conventional SR process

3.4.1 Discussion of the first experiment

The obtained results of the tow criteria PSNR (dB) and SSIM are surmised in the following tables for Set5 and Set14 datasets (3.3-3.4)

Table 3.3 PSNR and SSIM of Classical methods (Bicubic, Bilinear and Nearest) interpolation on Set5 Datasets

	Bicubic		**Bilinear**		**Nearest**	
Image set	**PSNR**(dB)	**SSIM**	**PSNR**(dB)	**SSIM**	**PSNR**(dB)	**SSIM**
Baby	30.3052	0.90038	29.7149	0.89538	27.3863	0.86525
Bird	28.1471	0.9475	27.3112	0.93957	24.8975	0.90488
Butterfly	20.6742	0.85721	20.2167	0.85074	18.3545	0.80519
Head	28.5914	0.79383	28.5653	0.79238	27.2477	0.76411
Woman	25.0258	0.91719	24.492	0.91137	22.4795	0.87701

Table 3.4 PSNR and SSIM of Classical methods (Bicubic, Bilinear and Nearest) interpolation on Set14 Datasets

	Bicubic		**Bilinear**		**Nearest**	
Image set	**PSNR**(dB)	**SSIM**	**PSNR**(dB)	**SSIM**	**PSNR**(dB)	**SSIM**
Baboon	19.302	0.6194	19.6663	0.61937	18.4774	0.5902
Barbara	21.6903	0.68995	22.0363	0.69099	20.4919	0.64974
Bridge	22.444	0.44182	22.4906	0.40966	21.4078	0.39817
Coastguard	26.5924	0.66498	26.3841	0.63306	24.8006	0.60386
Comic	23.2181	0.84374	22.6818	0.81722	19.9596	0.74238
Face	30.8267	0.87325	30.6623	0.86666	28.4937	0.82355
Flowers	24.2703	0.83509	24.0904	0.8275	21.8012	0.77805
Foreman	29.8337	0.94095	28.9754	0.93195	26.046	0.89485
Lenna	28.0658	0.96214	27.7954	0.96049	26.0702	0.94724
Man	23.9549	0.45427	23.8895	0.42057	22.5399	0.39625
Monarch	24.3737	0.94147	24.0775	0.93944	22.1964	0.91437
Pepper	26.5483	0.96046	26.3027	0.95786	24.7942	0.94165
Ppt3	19.0296	0.73171	18.9986	0.72628	17.2529	0.69239
Zebra	23.099	0.88707	22.4656	0.87061	19.6613	0.81481

3.4.2 Comparative study

Presenting the average results of PSNR (dB) and SSIM on (Tables 3.5- 3.6)

Table 3.5 The average results of PSNR (dB), SSIM on the Set5 dataset

	Bicubic	Bilinear	Nearest
PSNR (dB)	**26.5487**	26.0600	24.0731
SSIM	**0.8832**	0.8779	0.8433

Table 3.6 The average results of PSNR (dB), SSIM on the Set14 dataset

	Bicubic	Bilinear	Nearest
PSNR (dB)	**24.5178**	24.3226	22.4281
SSIM	**0.7747**	0.7623	0.7277

We provides a visual demonstration of how convolutional methods can be applied to enhance the quality of images from the Set5 (baby, butterfly and woman) in **Figure 3.4** and Set14 (baboon, man and comic) datasets in **Figure 3.5**. The ground truth images (**GT**) serve as a reference for evaluating the effectiveness of the convolutional methods.

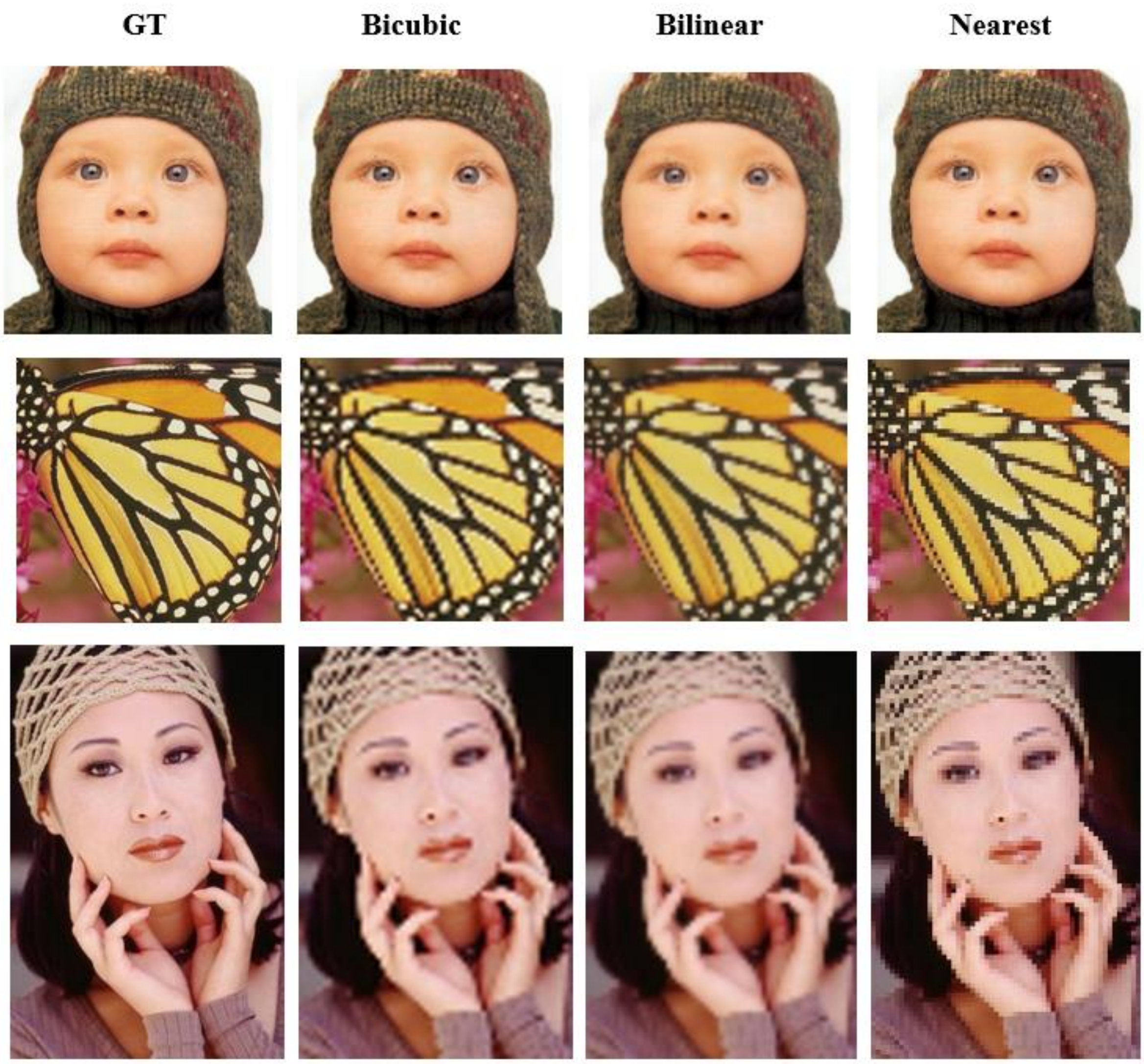

Figure 3.4 ground truth (GT), Bicubic interpolation, Bilinear interpolation and Nearest interpolation results for Set5 Datasets

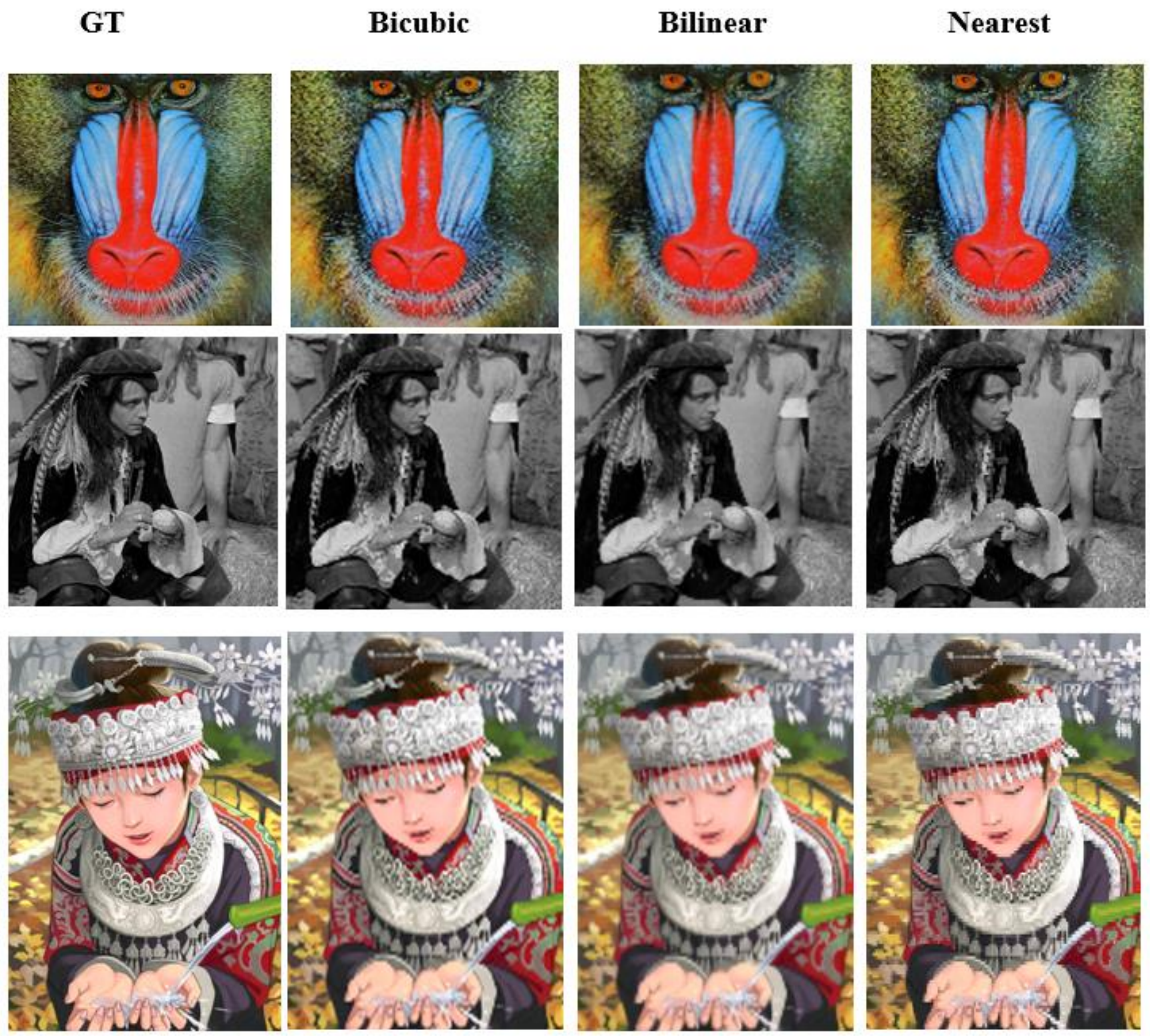

Figure 3.5 ground truth (GT), Bicubic interpolation, Bilinear interpolation and Nearest interpolation results for Set14 Datasets

After the convolutional methods are applied to the low-resolution images, we achieve enhanced versions that closely resemble the ground truth images. These improved images display heightened sharpness, clarity, and detail in comparison to their low-resolution counterparts. Nonetheless, it's crucial to acknowledge that while these methods can elevate the visual quality of images, they might introduce artifacts or distortions, especially in areas containing high-frequency details.

3.5 Deep Learning SR methods Based on CNN

VDSR (Very Deep Super Resolution) and EDSR (Enhanced Deep Super Resolution) are both deep learning methods for single-image super-resolution (SR) tasks based on convolutional neural networks (CNNs)

3.5.1 Very Deep Super Resolution (VDSR)

The flowchart shown in Figure 3.6 summarizes the main steps of the implementation of VDSR process. After preparing the input data (LR) by downsampling the original images, the process begins with feature extraction. Here, the LR input image undergoes feature extraction via a deep convolutional neural network (CNN). Then, the network learns to predict the residual image, which represents the difference between the low-resolution input and its corresponding high-resolution ground truth. Finally, the network upscales the low-resolution input by adding the predicted residual to it, resulting in the generation of a super-resolution output.

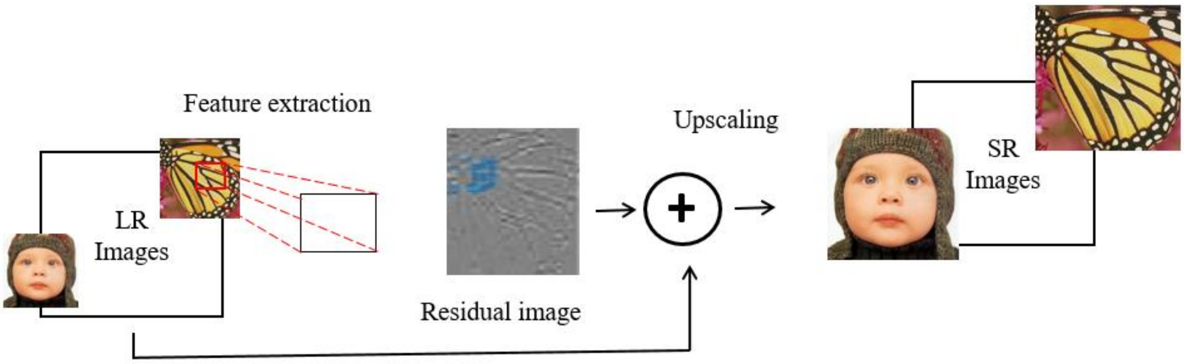

Figure 3.6 key steps of the implementation VDSR process

3.5.2 Enhanced Deep Super Resolution (EDSR)

We apply convolutional layers to extract features from the LR input. Then we use a series of residual blocks to learn complex features. After that we Apply convolutional layers to reconstruct the features to upscale the features to a high-resolution HR image, this method allows the EDSR model to efficiently learn and reconstruct HR images from LR inputs. This process is surmised in the following flowchart Figure 3.7.

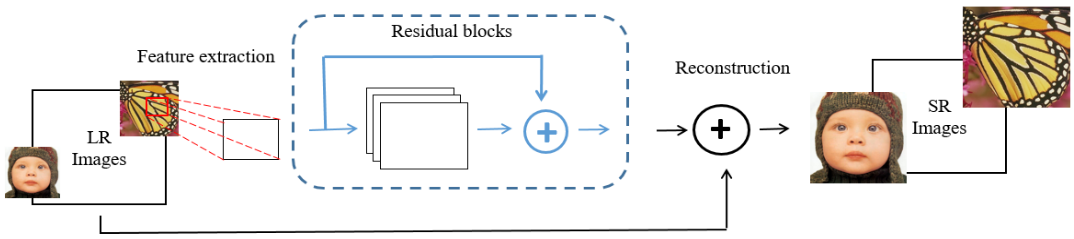

Figure 3.7 key steps of the implementation EDSR process

3.5.3 Discussion of the second experiment

The results for the two evaluation criteria, PSNR (dB) and SSIM, are summarized in the tables below for the Set5 and Set14 datasets (see Tables 3.7-3.10).

Table 3.7 PSNR and SSIM of SR Deep Learning methods based on CNN (VDSR, EDSR) on Set5 Datasets

	VDSR		EDSR	
Image set	**PSNR**(dB)	**SSIM**	**PSNR**(dB)	**SSIM**
Baby	31.582	0.90772	42.1036	0.98286
Bird	29.9299	0.94885	42.766	0.99482
Butterfly	25.3008	0.9401	30.2485	0.97679
Head	29.4086	0.77438	32.5598	0.90757
Woman	27.9475	0.94171	37.8052	0.9922
Average	28.8338	0.9026	37.0966	0.9708

Table 3.8 PSNR and SSIM of SR Deep Learning methods based on CNN (VDSR, EDSR) on Set14 Datasets

	VDSR		EDSR	
Image set	**PSNR**(dB)	**SSIM**	**PSNR**(dB)	**SSIM**
Baboon	19.2458	0.58771	24.9463	0.87726
Barbara	25.6463	0.8	31.5599	0.95839
Bridge	18.2981	0.07835	29.2052	0.79146
Coastguard	22.744	0.31411	37.1828	0.93525
Comic	15.2072	0.45965	28.2757	0.90767
Face	30.6273	0.81305	32.573	0.90805
Flowers	18.3177	0.63385	32.4208	0.95764
Foreman	23.6336	0.85522	33.9618	0.96549
Lenna	19.6851	0.89051	36.3184	0.99285
Man	17.9388	0.088933	28.8014	0.73955
Monarch	19.3494	0.87822	36.2772	0.99369
Pepper	18.7083	0.85894	32.6692	0.98652
Ppt3	16.0994	0.43851	28.7718	0.56145
Zebra	14.7964	0.64741	36.3612	0.9791
Average	20.0212	0.5960	32.0946	0.8967

3.5.4 Comparative study

We present a visual demonstration of how SR deep learning based on CNNs can enhance image quality for the Set5 (baby, butterfly, and woman) and Set14 (baboon, man, and comic) datasets in Figures 3.8 and 3.9, respectively. The ground truth images (GT) serve as references for evaluating the effectiveness of the VDSR and EDSR methods.

Figure 3.8 ground truth (GT), VDSR and EDSR results for Set5 Datasets

Figure 3.9 ground truth (GT), VDSR EDSR results for Set14 Datasets

Visually we can note that VDSR images typically appear slightly softer, with good enhancement but some visible noise and minor artifacts. In contrast, EDSR images are clearer and sharper, with more defined edges and minimal artifacts, resulting in a more photorealistic appearance.

3.6 Deep Learning SR methods Based on GAN

3.6.1 Enhanced Super-Resolution Generative Adversarial Network (ESRGAN)

We start with feature extraction from the low-resolution input images. Then, we apply a series of Residual-in-Residual Dense Blocks (RRDBs) to these features, enhancing their representation through deeper and more complex learning. After that, convolutional layers are used to refine the features in the reconstruction phase. Finally, an upscaling phase is applied to convert the refined features into a high-resolution output image.as it is shown on Figure 3.10

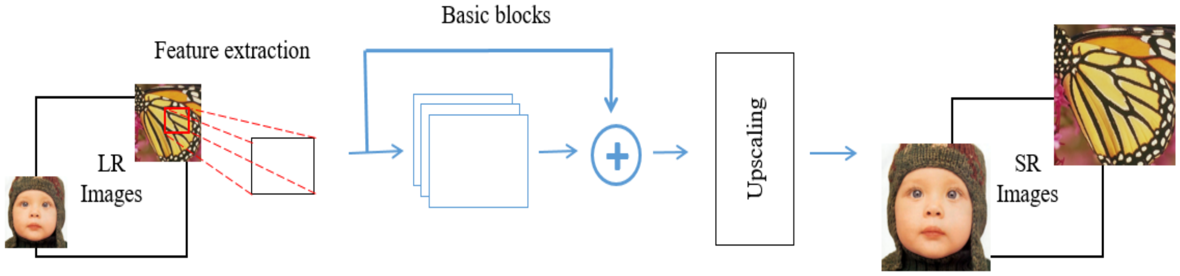

Figure 3.10 key steps of the implementation ESRGAN process

3.6.2 Discussion of the third experiment

Figure 3.11 and **Figure 3.12**, represents examples from data5 and data14 respectively for ESRGAN process.

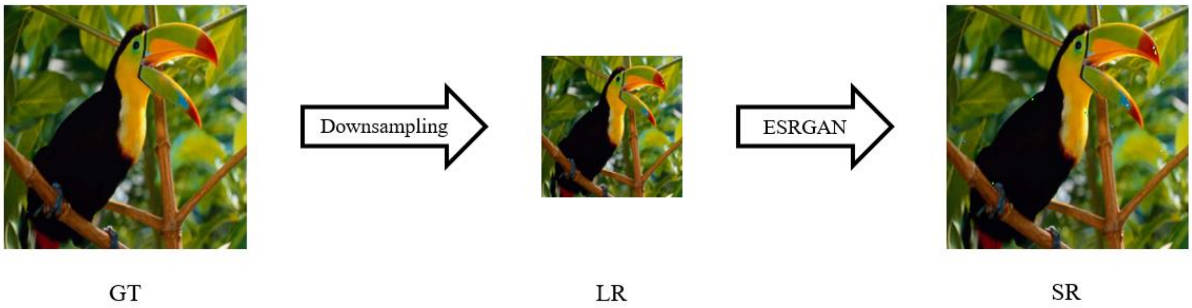

Figure 3.11 Bird by ESRGAN process

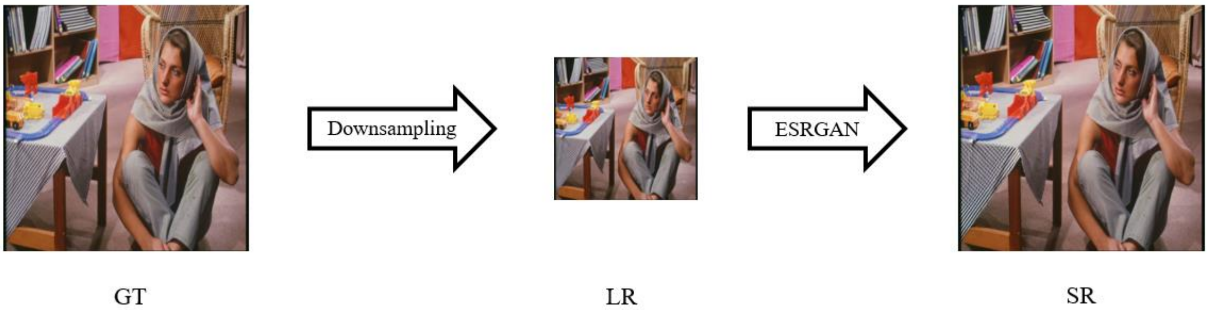

Figure 3.12 Barbara by ESRGAN process

The tables below (3.11-3.12) summarize the results for the two evaluation criteria, PSNR (dB) and SSIM, for the Set5 and Set14 datasets. Also represents the average PSNR and SSIM

Table 3.9 PSNR and SSIM of SR Deep Learning methods based on GAN (ESRGAN) on Set5 Datasets

	ESRGAN	
Image set	**PSNR**(dB)	**SSIM**
Baby	29.1986	0.84057
Bird	31.403	0.96898
Butterfly	30.0391	0.96814
Head	28.5411	0.79741
Woman	28.5081	0.94964
Average	29.5380	0.9049

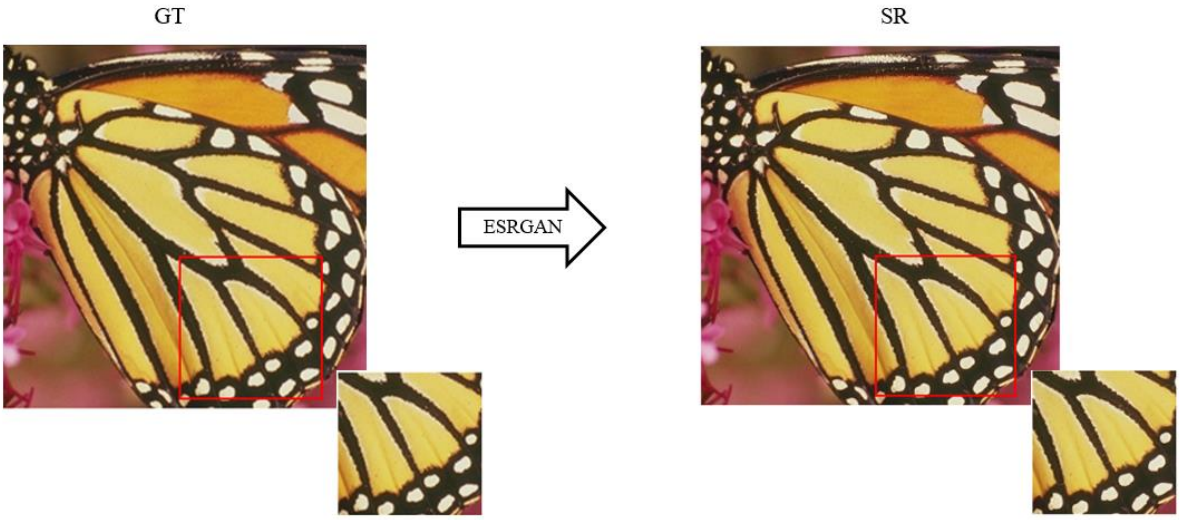

Figure 3.13 Qualitative results of ESRGAN on Butterfly image

Table 3.10 PSNR and SSIM of SR Deep Learning methods based on GAN (ESRGAN) on Set14 Datasets

	ESRGAN	
Image set	**PSNR**(dB)	**SSIM**
Baboon	19.3921	0.63313
Barbara	23.9224	0.78102
Bridge	19.0077	0.33722
Coastguard	17.3378	0.26895
Comic	18.5262	0.70181
Face	28.2252	0.79635
Flowers	21.4437	0.8097
Foreman	26.2932	0.91511
Lenna	27.2488	0.95577
Man	17.421	0.3008
Monarch	28.9775	0.97622
Pepper	19.1367	0.89541
Ppt3	10.3132	0.3531
Zebra	14.9173	0.72328
Average	20.8688	0.6748

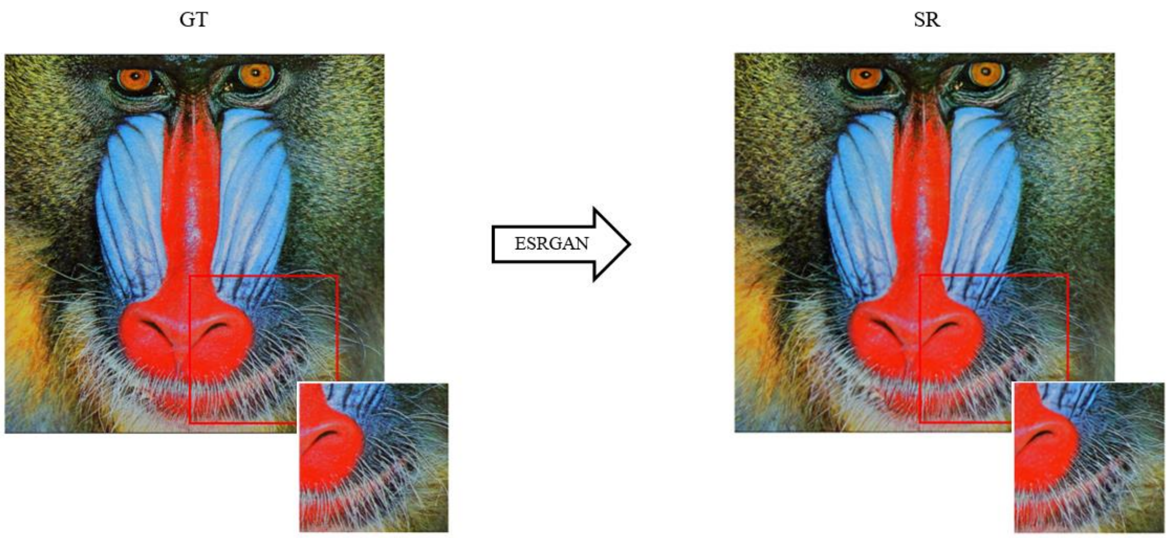

Figure 3.14 Qualitative results of ESRGAN on Baboon image

The images appear significantly sharper with enhanced textures, more realistic and natural details, and minimal artifacts, it could be observed in **(Figures 3.13)**, **(Figure 3.14)**

3.7 Global qualitative and quantitative comparative study

We compare our final models VDSR, EDSR ESRGAN and classical methods (Bicubic, Bilinear and Nearest) on several public benchmark datasets by average PSNR and SSIM presented in (**Table 3.11)** including. Since there is no effective and standard metric for perceptual quality, we present some representative qualitative results in Figures (3.15- 3.18**)**

Table 3.11 The average results of PSNR and SSIM on the Set5 and Set14 Datasets

Dataset	*Metric*	*Bicubic*	*Bilinear*	*Nearest*	*VDSR*	*EDSR*	*ESRGAN*
Set5	**PSNR**	26.5487	26.0600	24.0731	28.8338	37.0966	29.5380
	SSIM	0.8832	0.8779	0.8433	0.9026	0.9708	0.9049
Set14	**PSNR**	24.5178	24.3226	22.4281	20.0212	32.0946	29.5380
	SSIM	0.7747	0.7623	0.7277	0.5960	0.8967	0.9049

From (**Table 3.11)** we can surmise that the VDSR offers a solid balance between performance and speed, achieving respectable PSNR and SSIM values. EDSR improves upon these metrics, attaining higher PSNR and SSIM scores than VDSR, primarily due to its deeper architecture and the elimination of batch normalization. Although ESRGAN may not always reach the highest PSNR, it frequently scores high on SSIM and excels in visual quality, thanks to its use of adversarial and perceptual losses.

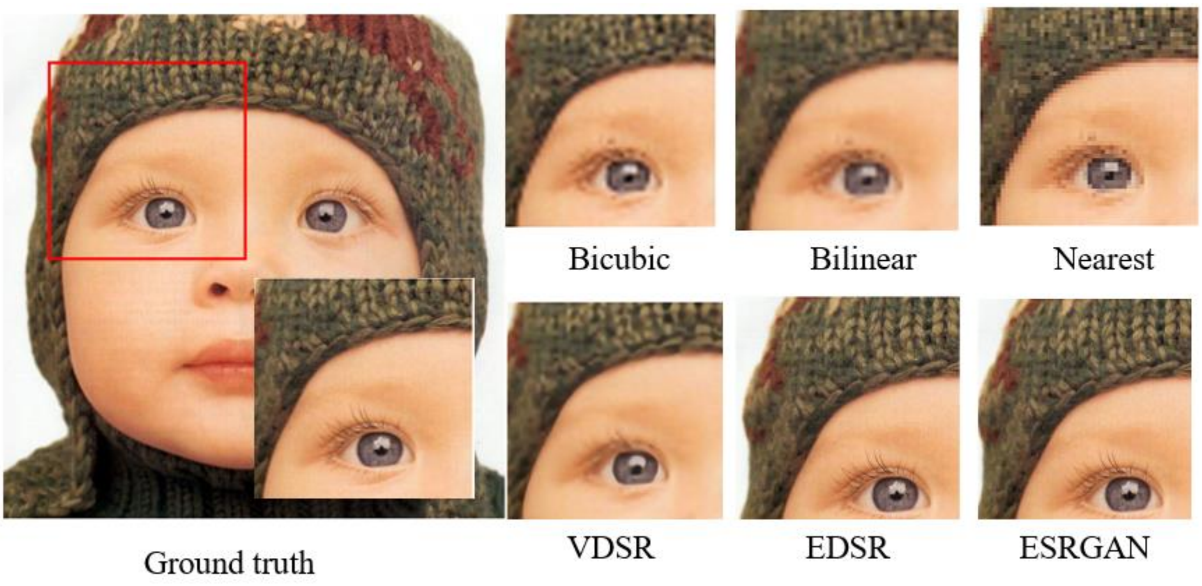

Figure 3.15 Qualitative results on Baby image from Set5

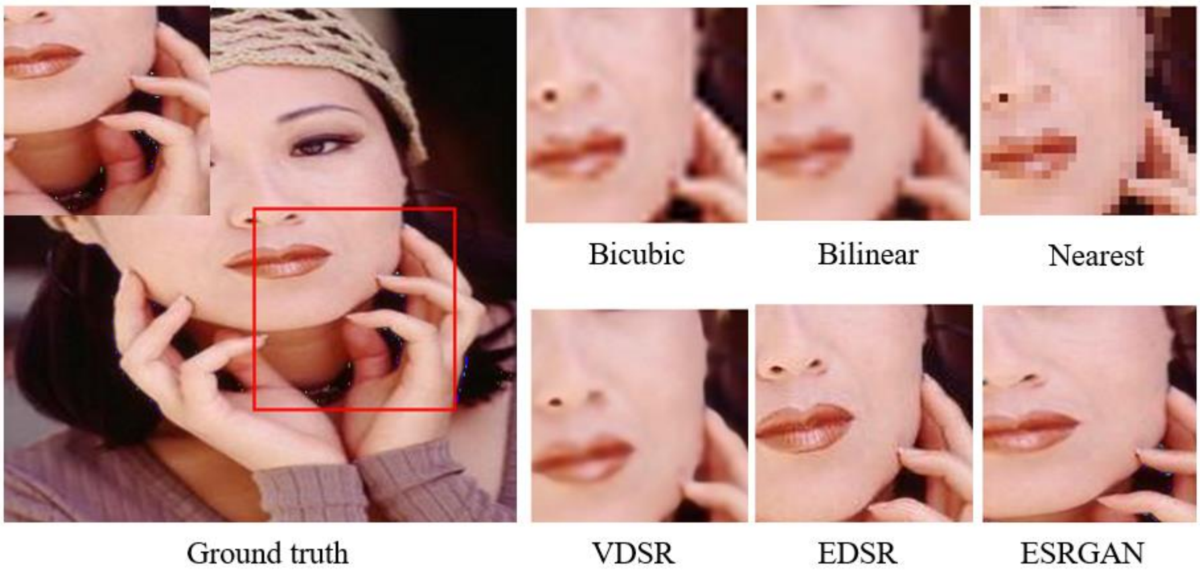

Figure 3.16 Qualitative results on Woman image from Set5

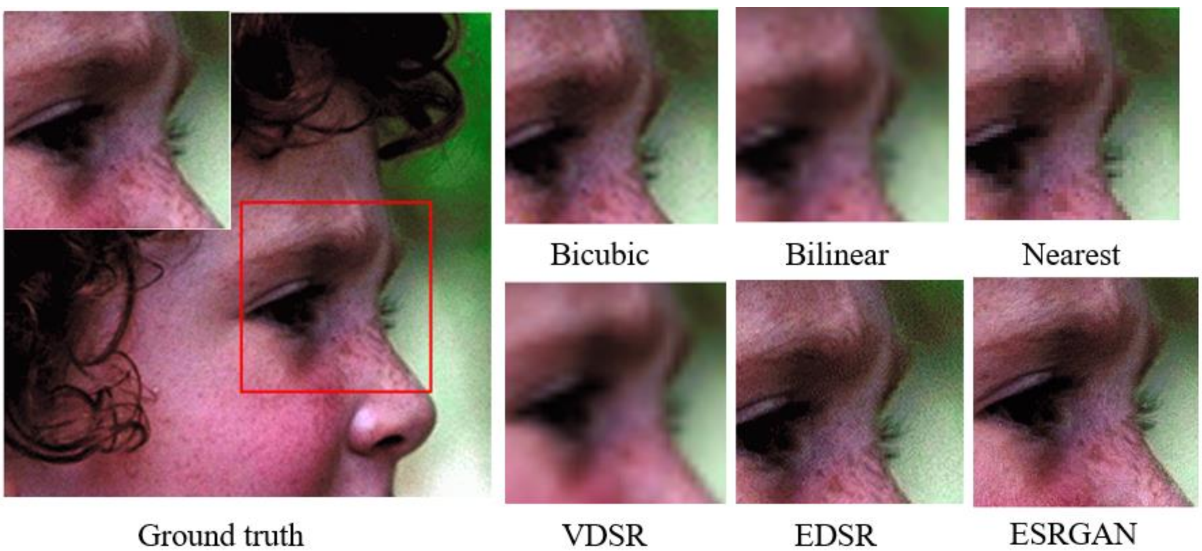

Figure 3.17 Qualitative results on Face image from Set14

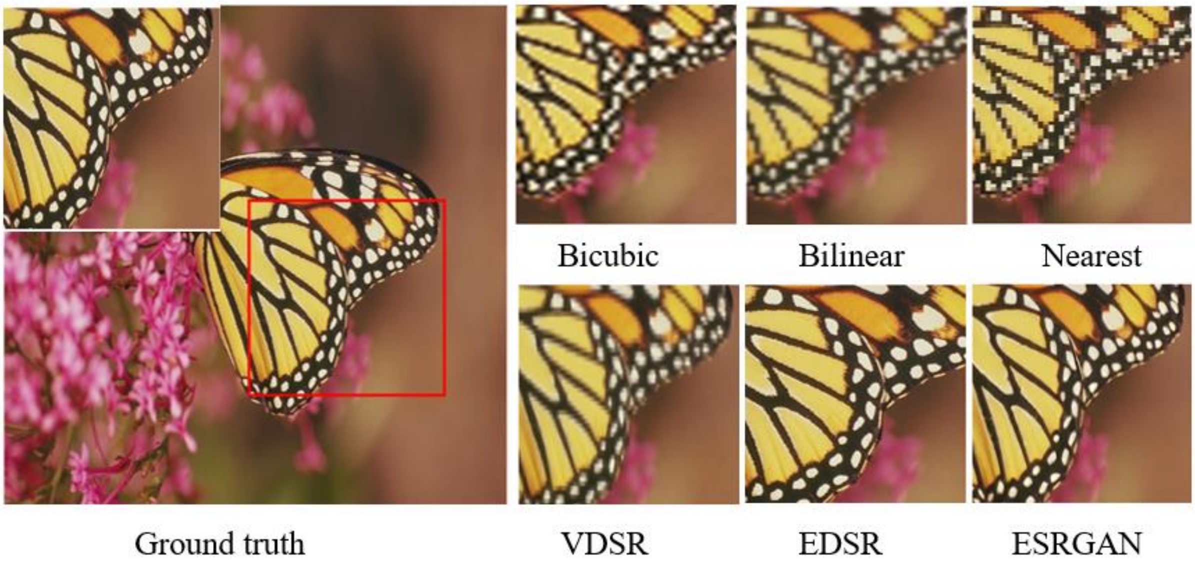

Figure 3.18 Qualitative results on Monarch image from Set14

We compare our final models VDSR, EDSR and ESRGAN on set1 and set2 datasets (medical datasets) by average PSNR and SSIM presented in (Table 3.12) including. Since there is no effective and standard metric for perceptual quality, we present some representative qualitative results in Figures (3.15- 3.14**)**

Table 3.12 The average results of PSNR and SSIM on the Set1 and Set2 Datasets

Dataset	***Metric***	*VDSR*	*EDSR*	*ESRGAN*
Set1	**PSNR**	11.4051	22.4454	26.5267
	SSIM	0.0072	0.3682	0.4869
Set2	**PSNR**	10.1653	31.3146	30.6207
	SSIM	0.0335	0.5007	0.5025

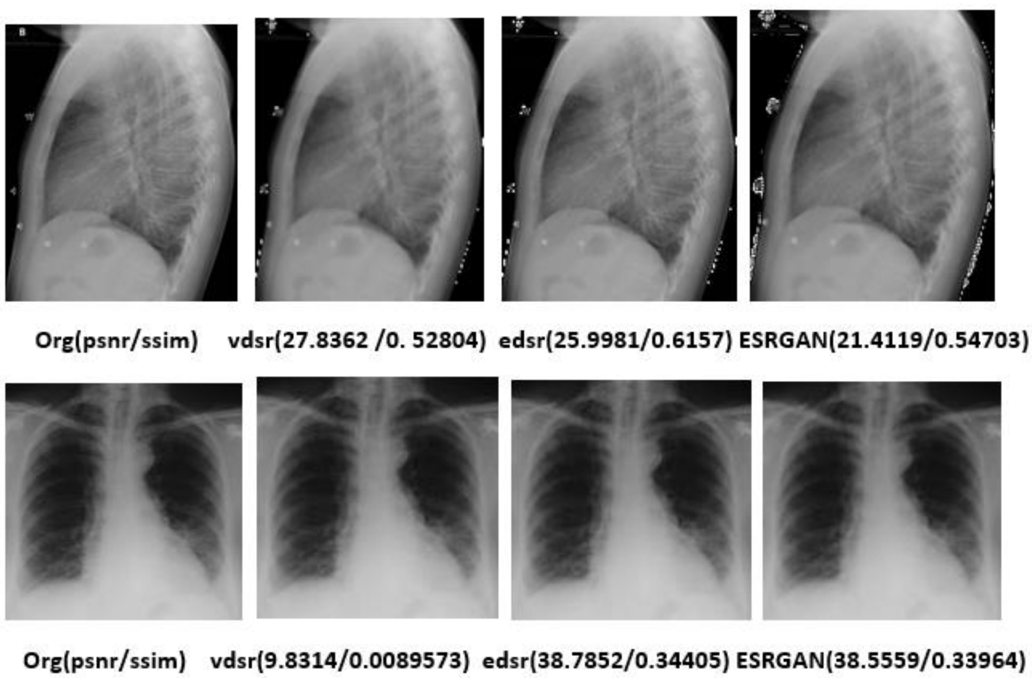

Figure 3.19 original image (org), VDSR and EDSR results for Set1 Datasets

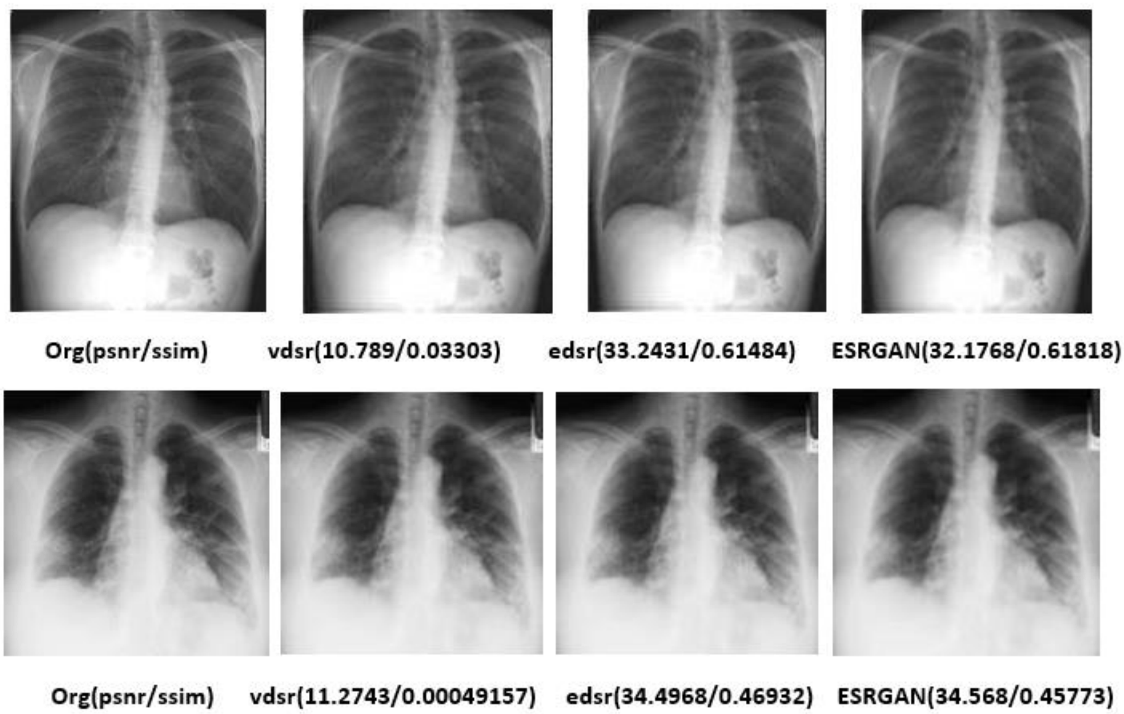

Figure 3.20 original image (org), VDSR and EDSR results for Set2 Datasets

The qualitative analysis of images produced by different upscaling methods (Bicubic, Bilinear, Nearest Neighbor, VDSR, EDSR, and ESRGAN) reveals on differences in visual quality which we will surmise it in follow

- Bicubic Interpolation produces relatively smooth images but often lacks sharpness and detail. Also Fine textures may appear blurry.
- Nearest Neighbor produces images with noticeable pixilation and jagged edges. Lacks smooth transitions between pixels.
- Bilinear Interpolation results in smoother images than Nearest Neighbor but tends to blur details more significantly than Bicubic.
- VDSR delivers a good balance of sharpness and detail, significantly improving over traditional interpolation methods.
- EDSR outperforms VDSR in terms of sharpness and detail, with more natural and crisp results. Reduced artifacts and better preservation of textures.
- ESRGAN excels in visual quality with high detail and sharpness, often producing images with a more natural and visually appealing texture. Although it may not always achieve the highest PSNR, its SSIM scores are commendable, reflecting better perceptual quality.

3.8 Future work

Future research can provide a deeper understanding of the strengths and limitations of current super-resolution techniques by including other Quality Metrics, like LPIPS (Learned Perceptual Image Patch Similarity) to better capture perceptual quality and similarity. And Testing the algorithms on a wider range of datasets, including diverse scenes such as medical images, and satellite imagery, to evaluate their generalizability and robustness.to pave the way for more advanced, efficient, and versatile image enhancement solutions, Which enables us to develop hybrid models that combine the strengths of different algorithms.

3.9 Conclusion

In this chapter, we thoroughly compared various upscaling methods, through both qualitative and quantitative analyses for Bicubic, Bilinear, Nearest Neighbor, VDSR, EDSR, and ESRGAN algorithms. Where we identified distinct differences in performance and visual quality among these techniques.

Bicubic and Bilinear interpolation methods, while fast and straightforward, often fall short in delivering sharpness and detail, producing images that can appear blurry or pixelated. Nearest Neighbor, though simple, introduces significant artifacts and is generally unsuitable for high-quality applications.

Deep learning-based approaches, namely VDSR, EDSR, and ESRGAN, demonstrated substantial improvements over traditional methods. VDSR provides a balanced enhancement in quality, making it a suitable choice for general use. EDSR, with its deeper architecture and removal of batch normalization, achieves higher PSNR and SSIM scores, offering superior sharpness and detail preservation.

ESRGAN stands out for its exceptional visual quality, leveraging adversarial and perceptual losses to produce images with high detail and natural textures. Although it may not always achieve the highest PSNR, its SSIM scores and qualitative performance indicate a strong ability to maintain perceptual quality.

Our findings highlight the importance of choosing the appropriate upscaling method based on specific application requirements. For tasks requiring high visual fidelity, EDSR and ESRGAN are the preferred choices, whereas VDSR offers a good balance between quality and computational efficiency.

General Conclusion

This comprehensive study has delved into the advancements and methodologies in the field of single image super-resolution (SISR), charting the evolution from traditional approaches to cutting-edge deep learning techniques. We began by framing the SISR problem, outlining key performance assessment criteria, and reviewing conventional SR algorithms. This foundational knowledge paved the way for a deeper exploration of machine learning and deep learning concepts, particularly focusing on Neural Networks (NNs) and Convolutional Neural Networks (CNNs).

This study explored key super-resolution (SR) models, beginning with the Super Resolution Convolutional Neural Network (SRCNN) and advancing through the Very Deep Super Resolution (VDSR) and the Enhanced Deep Super-Resolution Network (EDSR), all of which significantly improved image quality and detail preservation. Additionally, we highlighted the transformative impact of Generative Adversarial Networks (GANs) on SR technology. The focus was particularly on ESRGAN, which demonstrated how adversarial training can produce highly realistic and visually appealing images, setting new benchmarks for image quality.

We have implemented the considered SR algorithms and conduct several simulation experiments to obtain the SR images from LR ones and to highlight the benefit of the deep learning SR algorithms.

Our detailed comparative analyses of CNN and GAN based methods underscored the strengths and limitations of each approach, providing valuable insights into their performance. The experimental results reinforced the potential of these advanced models in achieving superior super-resolution outcomes.

Ultimately, this work aimed to pave the way for the development of a new hybrid approach that integrates the strengths of existing SR techniques to create a more robust and effective solution. The continuous advancements in this field hold promise for further innovations, with significant implications for various applications such as digital photography, medical imaging, and satellite imagery.

The last chapter concludes by outlining potential directions for future work, including the exploration of additional evaluation metrics, broader dataset usage, and algorithmic improvements. These avenues hold promise for advancing the field of single image super-resolution, ultimately leading to more versatile and robust solutions.

In conclusion, the dynamic and evolving nature of image super-resolution research continues to push the boundaries of what is possible, offering exciting opportunities for future exploration and development. This study provides a solid foundation for ongoing research and highlights the potential for hybrid methods to drive further advancements in the quest for ever-better image quality and resolution.

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