Slovak University of Technology in Bratislava
Faculty of Informatics and Information Technologies

FIIT-100241-116700

Artur Kozubov

Photo Restoration using Artificial Intelligence

Bachelor's Thesis

Thesis Supervisor: doc. Ing. Giang Nguyen Thu, PhD.

May 2025

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Study Programme:	Informatics
Study Field:	Computer Science
Training Workplace:	Bratislava, Slovakia
Thesis Supervisor:	doc. Ing. Giang Nguyen Thu, PhD.

May 2025

Čestne vyhlasujem, že som túto prácu vypracoval samostatne, na základe konzultácií a s použitím uvedenej literatúry.

I declare in my honor that I have prepared this work independently, on the basis of consultations and using the mentioned literature.

In Bratislava, May 2025 Artur Kozubov

Annotation

Slovak University of Technology in Bratislava
Faculty of Informatics and Information Technologies
Study Programme: Informatics
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Author: Artur Kozubov
Master's Thesis: Photo Restoration using Artificial Intelligence
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May 2025

Photo restoration, as a computer vision field, has always required intensive manual labor in traditional restoration tasks, never satisfying scalability in modern applications. In recent years, with the rapid development of AI, especially the invention of deep learning methods such as CNN and GAN, the quality of the whole restoration process has gone to a new level and enabled automated processing.

The objective of this bachelor's work is to develop an advanced photo restoration system employing the advantages of CNNs and GANs for the enhancement of quality. It also designs and implements a unified model for image upscaling with the correction of several defects like noise, blur, and compression artifacts. Powerful computation resources provided by Google Colab will give efficient training and experimentation capabilities. Implementation involves modern deep learning frameworks: PyTorch.

The core idea of this work is to thoroughly prepare and augment data to create a representative dataset, including scraping images from various sources, their preprocessing for consistency, and augmenting with the goal of enhancing the generalization capability of the model.

This project aims at designing a high-performance photo restoration model that will not only enhance the visual quality of degraded images but also achieve great efficiency towards practical applications. By incorporating state-of-the-art deep learning techniques with optimization in quality and speed, the project attempts to achieve an advancement in automatic photo restoration. It will be expected that the robust and versatile model will be able to handle a wide range of tasks of image degradation and lay the foundation for further research in restoration tool developments.

Keywords: Photo Restoration, Deep Learning, Convolutional Neural Networks

Anotácia

Slovenská technická univerzita v Bratislave
Fakulta informatiky a informačných technológií
Študijný program: Informatika
Študijný odbor: Informatika

Autor: Artur Kozubov
Bakalárska práca: Photo Restoration using Artificial Intelligence
Vedúci diplomového projektu: doc. Ing. Giang Nguyen Thu, PhD.
Máj 2025

Obnova fotografií ako oblasť počítačového videnia si vždy vyžadovala intenzívnu manuálnu prácu pri tradičných úlohách obnovy a nikdy nevyhovovala škálovateľnosti v moderných aplikáciách. V posledných rokoch sa s rýchlym rozvojom umelej inteligencie, najmä s vynálezom metód hlbokého učenia, ako sú CNN a GAN, kvalita celého procesu obnovy posunula na novú úroveň a umožnila automatizované spracovanie.

Cieľom tejto bakalárskej práce je vyvinúť pokročilý systém obnovy fotografií využívajúci výhody CNN a GAN na zvýšenie kvality. Navrhuje a implementuje tiež jednotný model na zvýšenie kvality obrazu s korekciou viacerých chýb, ako sú šum, rozmazanie a kompresné artefakty. Výkonné výpočtové zdroje, ktoré poskytuje Google Colab, poskytnú efektívne možnosti trénovania a experimentovania. Implementácia zahŕňa moderné rámce hlbokého učenia: PyTorch.

Hlavnou myšlienkou tejto práce je dôkladná príprava a rozšírenie údajov s cieľom vytvoriť reprezentatívny súbor údajov vrátane vyškrabania obrázkov z rôznych zdrojov, ich predspracovania na konzistenciu a rozšírenia s cieľom zvýšiť schopnosť modelu zovšeobecňovať.

Cieľom tohto projektu je navrhnúť vysoko výkonný model obnovy fotografií, ktorý nielen zvýši vizuálnu kvalitu degradovaných obrázkov, ale dosiahne aj veľkú účinnosť smerom k praktickým aplikáciám. Začlenením najmodernejších techník hlbokého učenia s optimalizáciou kvality a rýchlosti sa projekt pokúša dosiahnuť pokrok v automatickej obnove fotografií. Očakáva sa, že robustný a všestranný model bude schopný zvládnuť širokú škálu úloh degradácie obrazu a položí základ pre ďalší výskum v oblasti vývoja nástrojov na obnovu.

Oblasť problematiky: Reštaurovanie fotografií, Hlboké učenie, Konvolučné neurónové siete

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Fakulta informatiky a informačných
technológií
2024/2025

ZADANIE BAKALÁRSKEJ PRÁCE

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Názov práce:	**Reštaurovanie obrazov pomocou umelej inteligencie**
Jazyk, v ktorom sa práca vypracuje:	slovenský jazyk
Špecifikácia zadania:	Reštaurovanie obrazov je úloha počítačového videnia, ktorá zahŕňa vrátenie poškodených obrazov do pôvodného stavu. Umelá inteligencia, konkrétne neurónové siete v poslednom čase priniesli revolúciu v tejto oblasti tým, že poskytujú moderné výsledky pri rôznych úlohách obnovy, napríklad denoizáciu obrazu založenú na hlbokom učení alebo vysokom rozlíšení. Tieto metódy majú schopnosť, ktorá sa dá využiť v mnohých aplikáciách s tým, že sú vytrénované na súbore údajov alebo bez nich. Analyzujte súčasný stav reštaurovania obrazov (angl. photo restoration) smerom k praktickému používaniu a v kontexte umelej inteligencie. Navrhnite a implementujte základný modul ako jadro inteligentnej aplikácie na spracovanie a obnovenie obrazov. Ako praktickú ukážku vývoja softvéru, vytvorte docker kontajner pre Vašu aplikáciu. Zvoľte vhodné metriky na meranie výsledkov a ich vyhodnoťte.
Rozsah práce:	40
Termín odovzdania práce:	12. 05. 2025

Contents

Chapter 1

Introduction

Photo restoration has always been a difficult task that demanded considerable efforts from experts to restore damaged or lost image details. These days, after neural networks became commonly used with deep learning techniques, new horizons opened for this area and at once great advance was achieved. Modern deep learning-based approaches[1], [2] can be fully automated and, hence, they present high-quality results and huge savings on processing time.

Today, such approaches are already in use or are planned to be deployed in many areas where the demands on image reconstruction accuracy and speed are high. Medical imaging is one of the areas where AI-based image restoration methods are applied to clean medical images[3][4], allowing better diagnosis and treatment planning. For space and aerial images, superior algorithms mean sharper and more detailed views of the Earth's surface for mapping, environmental monitoring, and other military applications[5]. Image restoration technologies in the forensic and security areas help improve facial recognition[6][7] and evidence analysis, increasing the efficiency of the investigation. Enhanced AI will be able to be used to create more powerful visual systems for autonomous vehicles[8][9][10], which will give more reliable recognition of objects[11] and traffic conditions[12].

Image resolution enhancement technologies allow for more realistic and detailed game visuals[13][14], elaboration for games coming from the entertainment and media industry, which really pushes the user's experience further. In such a way, the elaboration of artificial intelligence-based photo restoration methods solved for the authors not only a problem of image restoration but also opened wide perspectives.

Chapter 2

Overview - State-of-the-art

Before moving next we need to clarify what is an example of an image restoration and where is it applied. Photo restoration simple aims to remove all possible defects to make the image look as good as possible.

Defects, in fact, might be of various types, such as noise, blur, compression artifacts, color distortion, etc. But additionally each of their defects also differs: Gaussian, Poisson, Masked, High-frequency, Impulse, Quantization noise, and many many more. In addition, images might combine these defects, which makes the problem even more challenging. So in the end, we face the problem of solving the equation with thousands of unknown variables and multiple constraints.

But, in contrast to those vague facts, most of this defect does not appear in real world life. So, following the studies[15], researches[16][17] and statistics, we can identify the most common defects and focus on them.

- Noise
- Blur
- Compression Artifacts
- Color Distortion
  - This also includes improper image contrast, brightness, and saturation.
- Low-Light Artifacts

Corresponding to those defects, we will omit methods, information and studies that are not related to those defects.

2.1 Background

Technically speaking, photo restoration represents a collection of mathematical and computational methods to cope with issues like noise reduction, artifact removal, color correction, enhancement of resolution, and other defects. The basic problem can be modeled as an inverse problem, recovering the original image HQ (High-Quality) from its degraded version, LQ (Low-Quality):

$$LQ = H(HQ) + N \tag{2.1}$$

where:

- LQ is the degraded image,
- H is the degradation operator (which can include blurring, compression artifacts, etc.),
- N represents noise or other forms of corruption.

The restoration process aims to estimate HQ given LQ, often by applying techniques that can inverse or somehow reverse the effects of H and N.

2.1.1 Traditional Digital Image Restoration Methods

In some time before, before applying neural networks, the most common methods for image restoration were based on traditional signal processing techniques, which can be broadly summarized under two major methods: **spatial domain** and **frequency domain** methods.

2.1.1.1 Spatial Domain Methods

Spatial domain techniques work directly on pixels. The given image can be visualized as a 2D matrix of the pixel values, whereby operations have to be performed directly on the values.

Filtering Noise and other unwanted artifacts could be removed using linear or non-linear filters. A very common example is the Gaussian filter, which, though smoothing the image, reduces high-frequency noise through simple averaging of pixel values with their neighbors.

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{2.2}$$

where $G(x, y)$ is the Gaussian kernel, and σ controls the amount of smoothing.

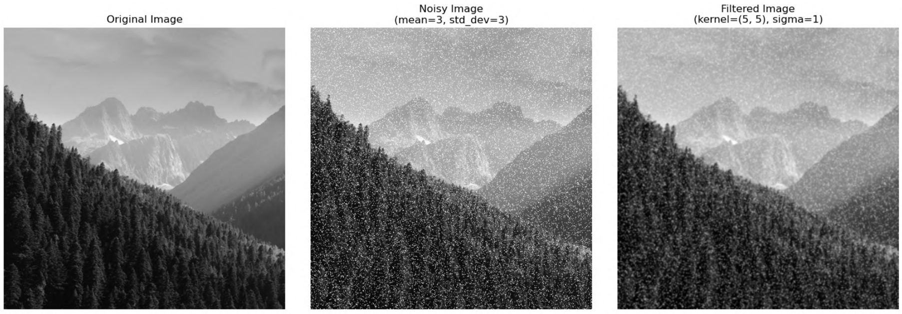

Figure 2.1: Applying a Gaussian filter to an image.

As seen in Figure 2.1 above, the Gaussian filter effectively removes high-frequency noise but unfortunately also significantly blurs the image, which is always not desirable and which causes loss of important and many details of the image.

Interpolation In other words, interpolation using estimation of unknown pixel values in an image based on the values of surrounding pixels. It is crucial in image restoration tasks, such as resizing, repairing damaged areas, and filling in missing or corrupted pixel data.

Bilinear Interpolation Bilinear interpolation uses the four closest pixel values to calculate a weighted average. The formula for bilinear interpolation is:

$$I(x,y) = (1-u)(1-v)I_{00} + u(1-v)I_{10} + (1-u)vI_{01} + uvI_{11} \tag{2.3}$$

where $I(x,y)$ is the interpolated pixel value, $I_{00}, I_{10}, I_{01}, I_{11}$ are the intensities of the surrounding pixels and $u = x - \lfloor x \rfloor$, $v = y - \lfloor y \rfloor$ are the fractional parts of the coordinates.

Bicubic Interpolation Bicubic interpolation uses 16 neighboring pixels and uses cubic polynomials for smoother results. The interpolated value is given by:

$$I(x,y) = \sum_{i=-1}^{2} \sum_{j=-1}^{2} w(i,u)w(j,v)I_{i,j} \tag{2.4}$$

where $w(k,t)$ is a cubic weight function, often defined as:

$$w(k,t) = \begin{cases} (a+2)|t|^3 - (a+3)|t|^2 + 1, & |t| \leq 1 \\ a|t|^3 - 5a|t|^2 + 8a|t| - 4a, & 1 < |t| \leq 2 \\ 0, & |t| > 2 \end{cases} \tag{2.5}$$

where a is a constant, typically -0.5.

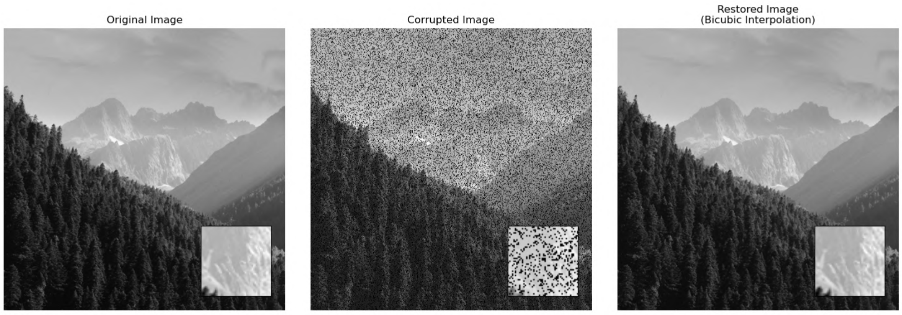

Figure 2.2: Applying a Bicubic interpolation to an image with missing pixels.

As seen in Figure 2.2 above, bicubic interpolation provides a smooth and more visually appealing result, but in some cases it may introduce artifacts or distortions or would lead to loss of image details.

2.1.1.2 Frequency Domain Methods

Frequency domain methods transfer the image into the frequency space by making use of tools such as the Fourier transform. These methods are very good at bringing out and then manipulating specific frequency components corresponding to various noises and/or artifacts.

Fourier Transform To selectively perform attenuation or amplification on some frequencies, first transform the image from the spatial to the frequency domain.

$$F(u,v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) e^{-j2\pi\left(\frac{ux}{M} + \frac{vy}{N}\right)} \tag{2.6}$$

where $F(u,v)$ is the Fourier transform of the image $f(x,y)$, and M and N are the dimensions of the image.

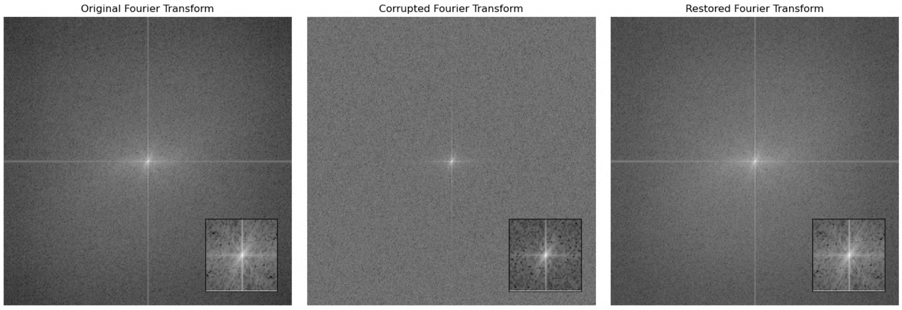

Figure 2.3: Using Fourier transform to convert an image to frequency domain.

As seen in Figure 2.3 above, the Fourier transform helps to visualize the frequency components of the image, which can be selectively manipulated to remove noise or other artifacts, but not as good as bilinear or bicubic interpolation.

Wiener Filtering The statistical approach is to minimize the mean squared error between the estimated and true images. This shows a trade between the balance of noise suppression and the preservation of the signal,

$$H_{\text{Wiener}}(u,v) = \frac{|H(u,v)|^2}{|H(u,v)|^2 + \frac{S_N(u,v)}{S_I(u,v)}} \tag{2.7}$$

where $H(u,v)$ is the frequency domain degradation function, $S_N(u,v)$ denotes the power spectral density of noise, and $S_I(u,v)$ shows the power spectral density of the original image.

2.1.2 Neural Networks for Image Restoration

While this introduction of machine learning, and more precisely deep learning, has been able to enable restorers to learn complex patterns[18][19] from large datasets in much better quality and efficiency compared to traditional approaches.

2.1.2.1 Autoencoders

Autoencoders[20] are a type of neural network that can learn to compress data and then reconstruct it. It consists of two parts: an encoder E that maps the input x to a latent space representation z and a decoder D that reconstructs $\hat{x}$ from z:

$$z = E(x), \quad \hat{x} = D(z) \tag{2.8}$$

The loss function used for reconstruction is commonly the Mean Squared Error (MSE):

$$\mathcal{L}_{\text{reconstruction}} = \frac{1}{n}\sum_{i=1}^{n} \|x_i - \hat{x}_i\|^2 \tag{2.9}$$

Autoencoders are good starting points for image restoration tasks, as they can learn about a wide range of image defects and can be used for various tasks. However, they are limited in terms of the quality of the restored images, as they tend to produce blurry results[20].

2.1.2.2 Convolutional Neural Networks (CNNs)

CNN is a more advanced type of neural network that is widely used for spatially aware tasks in image restoration, leveraging convolutional layers to extract hierarchical features. The convolution operation is given by:

$$y[i,j] = \sum_{m}\sum_{n} x[i+m, j+n] \cdot k[m,n] \tag{2.10}$$

where x is the input, k is the kernel, and y is the output. CNNs excel in tasks such as super-resolution[21], where the network learns to map low-resolution inputs to high-resolution outputs[22], but can also be used to denoize, deblur and other restoration tasks.

2.1.2.3 Generative Adversarial Networks (GANs)

GAN is a type of neural network that consists of two models: a generator G that generates samples, and a discriminator D that distinguishes between real and generated samples. The objective function of GANs is:

$$\min_G \max_D \mathbb{E}_{x\sim p_{\text{data}}}[\log D(x)] + \mathbb{E}_{z\sim p_z}[\log(1 - D(G(z)))] \tag{2.11}$$

GANs are particularly effective for image restoration tasks, as the generator learns to create visually plausible images from corrupted input, while the discriminator ensures realism.

2.1.2.4 Transformers for Image Restoration

Transformers, originally developed for natural language processing, have been adapted for image restoration due to their ability to model long-range dependencies, making them suitable for tasks such as inpainting and super-resolution[23]. The attention mechanism on the transformers allows the model to focus on the relevant parts of the image, allowing for high-quality restoration. And this core mechanism is the self-attention:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) \tag{2.12}$$

where Q, K, and V are the query, key, and value matrices, respectively. Transformers excel in handling global context, making them effective for high-level restoration tasks.

2.1.2.5 Complex and Combined Networks

Different architectures have been combined and proved to be effective for image restoration. For example, auto-encoders can serve as pre-processors for GAN inputs, while CNNs may work as feature extractors for transformers. The joint loss function may look like the sum of reconstruction, adversarial, and perceptual terms:

$$\mathcal{L}_{\text{total}} = \lambda_1 \mathcal{L}_{\text{reconstruction}} + \lambda_2 \mathcal{L}_{\text{adversarial}} + \lambda_3 \mathcal{L}_{\text{perceptual}} \tag{2.13}$$

where λ_1, λ_2, and λ_3 control the weight of each term.

These advanced architectures and their combinations have enabled recognizable progress in the field of image restoration, making it possible to recover details even from severely degraded images[24].

2.2 Related Work

The field of image restoration has seen significant advancements in recent years, with a focus on developing deep learning models that can effectively and qualitatively restore images. Here are some notable works that have contributed to the state-of-the-art in image restoration.

2.2.1 Deep Image Prior (DIP)

Deep Image Prior[25] considers a convolutional neural network for image restoration tasks without the use of training data. The basic idea of DIP is that the structure of the network itself acts as a priori inherent in the structure of convolution neural networks (2.1.2.2), thus enabling them to learn the underlying image distribution with a single corrupted input image and concentrate on minimizing some form of reconstruction loss, for example, Mean Squared Error (2.1.2.1), in between the output and the corrupted image. In other words, by optimizing the weights of the network to be able to reduce the reconstruction error, DIP is effective in the denoising, deblurring, and inpainting of images when no ground-truth data are available.

This unsupervised strategy has opened new avenues for image restoration tasks where labeled training data is not available or collection of labels is not possible, such as medical imaging or satellite imagery.

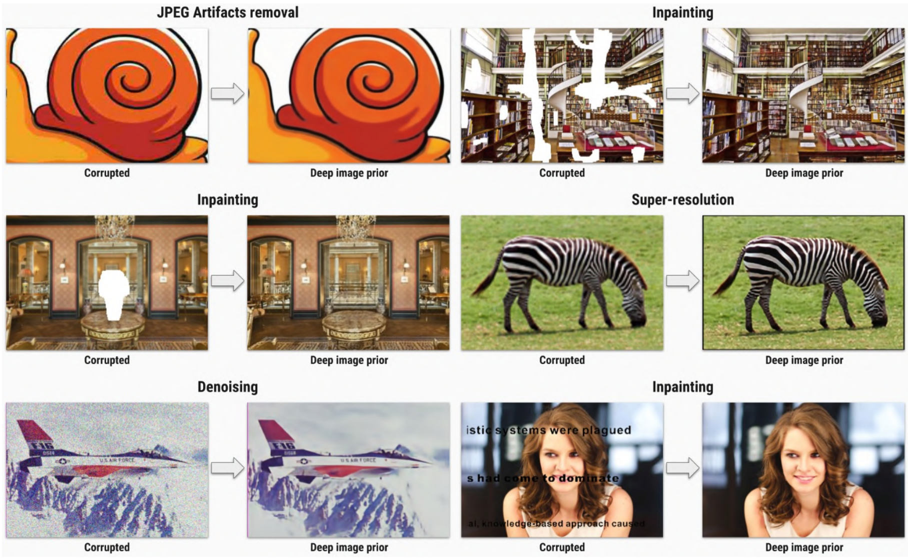

Figure 2.4: Example of image restoration using Deep Image Prior.

On the other hand, DIP has several limitations besides all the benefits. For example, DIP cannot deal with complex image degradation and produce good quality results. Also, the optimization procedure may be very time-consuming and computationally expensive; therefore, in several real-time applications, it may not be practical.

2.2.2 Blind Image Restoration (InstantIR)

InstantIR[26] is a new single image restoration model designed to restore degraded images with the help of a diffusion-based approach with instant generative reference. It has pre-trained vision encoder to get image features into one representation, capturing structure and semantic information. In a processing pipeline, a Previewer module generates restoration previews at each step, serving as instant generative references. These references guide the Aggregator in refining the image, excelently addressing unknown degradations faced during inference.

Figure 2.5: Example of image restoration using InstantIR.

Due to diffuise-based approach, which involves iterative processing, computations of this model are intensive and are not suitable for real-world application. Also, the model is not capable of handling multiple restoration tasks simultaneously, which limits its flexibility.

2.2.3 Flexible Blind Convolutional Neural Network (FBCNN)

FBCNN[27] represents a convolutional neural network for the removal of blind JPEG artifacts. Predicts variable quality factors for balancing the elimination of artifacts and the retention of details. This network comprises a decoupler module aimed at decomposition of the input JPEG image to extract its quality factor, and a reconstructor module that uses this factor for restoration.

Unfortunately, FBCNN is specialized for JPEG artifacts removal and may not be suitable for other types of image degradations. Also, the model's performance may vary depending on the quality of the input image, making it less robust in real-world scenarios.

2.3 Summary and Starting Points

Image restoration is a traditional and well-known problem that has been solved and is still being solved by many different methods, approaches, and ideas, including traditional methods of filtering and interpolation and advanced deep learning models. During the time when those approaches have been developed and improved, and still are, by new proposals and ideas such as the latest InstantIR model (2.2.2).

The models and methods proposed so far excel in many restoration tasks, though some others suffer from one problem or another. Therefore, developing efficient high-performance all-in-one models to cope with several restoration tasks for combating various kinds of image degradations remains one major tendency of image restoration[**swinir**][28][27].

There is also room for such improvements to develop increasingly efficient and effective models of image restoration tasks.

2.3.1 Identified Gaps

Among the recent advances in image restoration, in the models of different type and range, the most noticeable gaps might be summarized to:

- **Task Specialization** Many existing models and methods (2.1.1,2.2.3) are optimized for specific restoration tasks and lack the flexibility to handle multiple types of image defects simultaneously.
- **Computational Efficiency** Complex models that address multiple defects tend to be computationally intensive (2.2.1), limiting their practicality for real-time or resource-constrained applications.
- **Data Dependency** Advanced models often require large paired data sets for training, such as diffusion data sets (2.5), which may not be readily available for all types of image degradation.
- **Scalability** Existing models may struggle to scale effectively to high-resolution images or adapt to diverse and unpredictable degradation patterns encountered in real-world scenarios[29].

2.3.2 Starting Points

To minimize the identified gaps, the project will focus on the following key areas.

- **Model Development** Designing an all-in-one CNN-based framework capable of handling multiple restoration tasks such as upscaling, denoising, deblurring, and artifact removal within a single unified model. This will give an opportunity to minimize storage requirements and would cover a wide range of user requests.

- **Data Preparation and Scraping** A dataset could be collected and prepared that has diversity in the types of degradations, which would include supporting scraping images from different sources, proper annotations, and data augmentation that helps the model to be robust.
- **Model Performance** This could take several forms, from quantization, where the model size gets compressed for improved inference speed, to transfer learning, which would look at exploring reusing pre-trained models in such a way as to generalize better.
- **Evaluation Metrics** Utilize comprehensive evaluation frameworks and methods to evaluate the performance of the model in various restoration tasks. This will involve using quantitative metrics such as PSNR (3.3.1) and SSIM (3.3.2), as well as blind image quality assessment to ensure the effectiveness of the model in real-world scenarios.

Chapter 3

Objectives and Methodology

3.1 Objectives

The project targets to develop a complete application for photo restoration with help of use of CNN and optionally GAN neural network. Following Chapter 2 the goals of this thesis are focused on selected objectives to try to solve the following challenges:

Create a Dataset Pipeline

- Develop a robust pipeline capable of loading images from different sources, such as online repositories, local directories, and cloud storage.
- Implement mapping and preprocessing steps including normalization and augmentation to prepare the data for training.
- Handle image effects applying transformations to simulate real-world conditions.

Develop an Architecture for Enhancing Image Quality

- Attempt to design an all-in-one CNN-based architecture that addresses common image defects encountered in real-world scenarios.
- Focus primarily on image upscaling while incorporating modules for noise reduction, blur removal, and artifact correction.
- Ensure that the architecture is efficient to handle large volumes of images continuously and can be deployed on various devices.

Pack the Solution

- Pack solution to be deployed on several devices by using, for example, Docker containers technology.
- Create the lightweight API to serve the model and provide a user-friendly interface for interacting with the system.
- Implement a web-based application to demonstrate the capabilities of the system.

3.2 Methodology

The following steps have been chosen for the design and development of the proposed solution:

- Step 1. Create a data set pipeline to load, preprocess, and augment images from diverse sources.
- Step 2. Design an efficient architecture for enhancing image quality while maintaining a wide range of image defects.
- Step 3. Train the model on the prepared dataset and evaluate its performance and results with various metrics, including PSNR, SSIM, and visual inspection.
- Step 4. Create a lightweight API to serve the model and provide a user-friendly interface for interacting with the system. Including a web-based application to demonstrate the capabilities of the system.
- Step 5. Pack the solution using Docker containers technology.

3.3 Evaluation metrics

The proposed all-in-one photo restoration model will be thoroughly tested using a set of metrics. These metrics are very important in evaluating various performance aspects of image restoration in terms of quality and realism, along with computational efficiency. We will combine them into one score to holistically evaluate the model, inspiring a challenge of image enhancement[30]. Metrics would be normalized by their maximum and minimal scores and then combined into one score.

$$\text{Overall Score} = w_{\text{PSNR}} \cdot \text{PSNR}_{\text{norm}} + w_{\text{SSIM}} \cdot \text{SSIM}_{\text{norm}} + w_{\text{Other}} \cdot \text{Other}_{\text{norm}},$$

where:

- $w_{\text{PSNR}}, w_{\text{SSIM}}, w_{\text{LPIPS}}, w_{\text{BIQA}}, w_{\text{Inference Time}}, w_{\text{Resource Usage}}, w_{\text{Other}}$ are the weights assigned to each metric.
- $\text{PSNR}_{\text{norm}}$, $\text{SSIM}_{\text{norm}}, \text{LPIPS}_{\text{norm}}, \text{BIQA}_{\text{norm}}$ are the normalized values of PSNR, SSIM, LPIPS, and BIQA, respectively.

But also watching all distinct metrics evaluation values to ensure that the model is performing well in all aspects. The following metrics will be used to evaluate the model: Peak signal-to-noise ratio (PSNR), structural similarity index measure (SSIM), learned perceptual image patch similarity (LPIPS) and inference time, as well as Blind Image Quality Assessment (BIQA) metrics. Performance time and resource usage will also be evaluated and included.

3.3.1 Peak Signal-to-Noise Ratio (PSNR)

PNSR was one of the existing objective metrics for measuring the quality of reconstructed images in relation to the originals. The PSNR has been defined as the ratio between the maximum possible power of a signal and the power of corrupting noise influencing its representation fidelity.

$$\text{PSNR} = 20 \cdot \log_{10} \left(\frac{\text{MAX}_I}{\sqrt{\text{MSE}}} \right) \tag{3.1}$$

where:

- MAX_I is the maximum possible pixel value of the image (e.g., 255 for an 8-bit image).
- MSE is the Mean Squared Error between the restored image I_{restored} and the ground truth image I_{original}:

$$\text{MSE} = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} \left(I_{\text{original}}(i,j) - I_{\text{restored}}(i,j) \right)^2$$

PSNR gives the reconstruction accuracy in quantitative terms. Its larger value accounts for better fidelity to the original. However, PSNR does not sometimes show good correspondence with perceived visual quality sometimes; hence, it is complemented by other metrics.

3.3.2 Structural Similarity Index Measure (SSIM)

SSIM has been designed to outperform traditional metrics such as PSNR. It is sensitive to changes with respect to structural information, luminance, and contrast.

The SSIM between two images x and y is calculated as:

$$\text{SSIM}(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{3.2}$$

where:

- μ_x and μ_y are the mean luminance of x and y, respectively.
- σ_x^2 and σ_y^2 are the variance of x and y.
- σ_{xy} is the covariance of x and y.
- C_1 and C_2 are stabilization constants to avoid division by zero.

Actually, SSIM was proposed to measure the similarity between two given images based on these factors important for perception. Second, SSIM is in concert with human perception of vision, since it places greater emphasis on structural information. This metric allows for a more accurate visual quality assessment than PSNR. So, SSIM is the metric relevant for the image restoration performance test.

3.3.3 Blind Image Quality Assessment (Blind)

In fact, it's assessment metrics for any given image without the availability of a reference or ground truth image. Indeed, the underlying approaches reviewed in this paper are of particular importance when the original is not available, for instance, in real-world applications where images may suffer from a host of unknown degradations.

Common BIQA Metrics:

- **NIQE (Naturalness Image Quality Evaluator)**: Measures the deviation of image statistics from natural scene statistics.
- **BRISQUE (Blind/Referenceless Image Spatial Quality Evaluator)**: Assesses image quality based on spatial statistics of the natural environment.
- **PIQE (Perception-based Image Quality Evaluator)**: Evaluates perceptual image quality using patch-based methods.

BIQA can solve the image quality assessment problem with more flexibility and practically, especially in real-world applications where the availability of reference images is not possible. The weight assigned to BIQA will be high, at 40%, since it contributes a lot to the evaluation of the overall perceptual quality of the restoration model and its applicability in diverse environments.

3.3.4 Inference Time

Time inference characterizes computational efficiency by the time it takes for an image to be processed by the restoration model. This metric will be important in determining applicability for real-time usage and scalability in terms of the number of images to be processed.

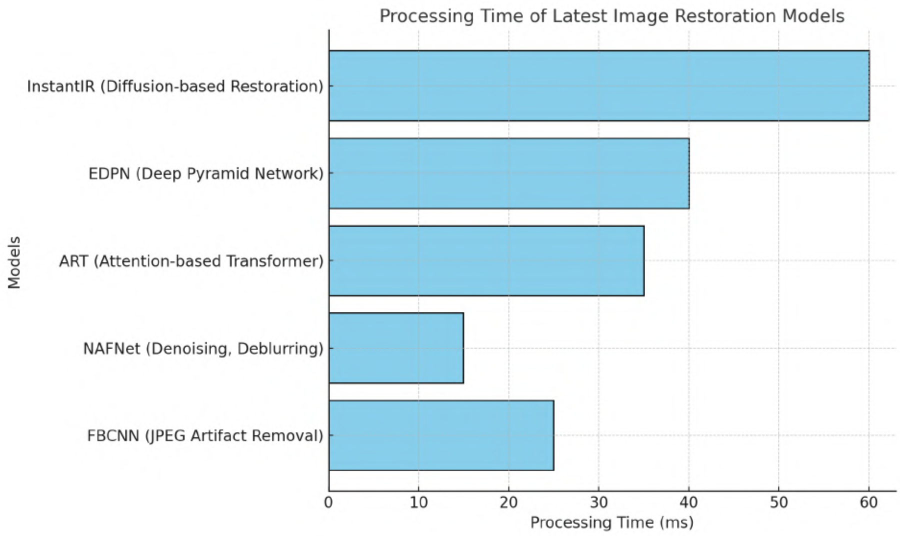

Figure 3.1: Example of processing time for different models[31][32][33][34].

Chapter 4

Design

The design encompasses the overall architecture of the system, the dataset loading mechanisms, the detailed model architecture using pseudocode, and the deployment strategy to provide end-user access.

4.1 Architecture Overview

The overall architecture is designed to facilitate efficient data ingestion, model training, evaluation, and deployment. The system is divided into four main components:

Figure 4.1 illustrates the flow of data and processes within the system, structured into four primary subgraphs:

1. **Data Ingestion & Local Buffer**: Handles the collection and initial preprocessing of raw images from various sources.
2. **Datasets & Data Loaders**: Manages the organization and loading of datasets for training and validation.
3. **Model Training & Evaluation**: Encompasses the training routines, loss computations, and performance evaluations of the restoration model.
4. **Deployment**: Focuses on serving the trained model to end users through a web application.

4.1.1 Data Preprocessing

4.1.1.1 Data Ingestion & Local Buffer

Data are sourced from multiple external channels. Raw images are ingested and stored in a local buffer where they undergo initial preprocessing steps such as cropping and

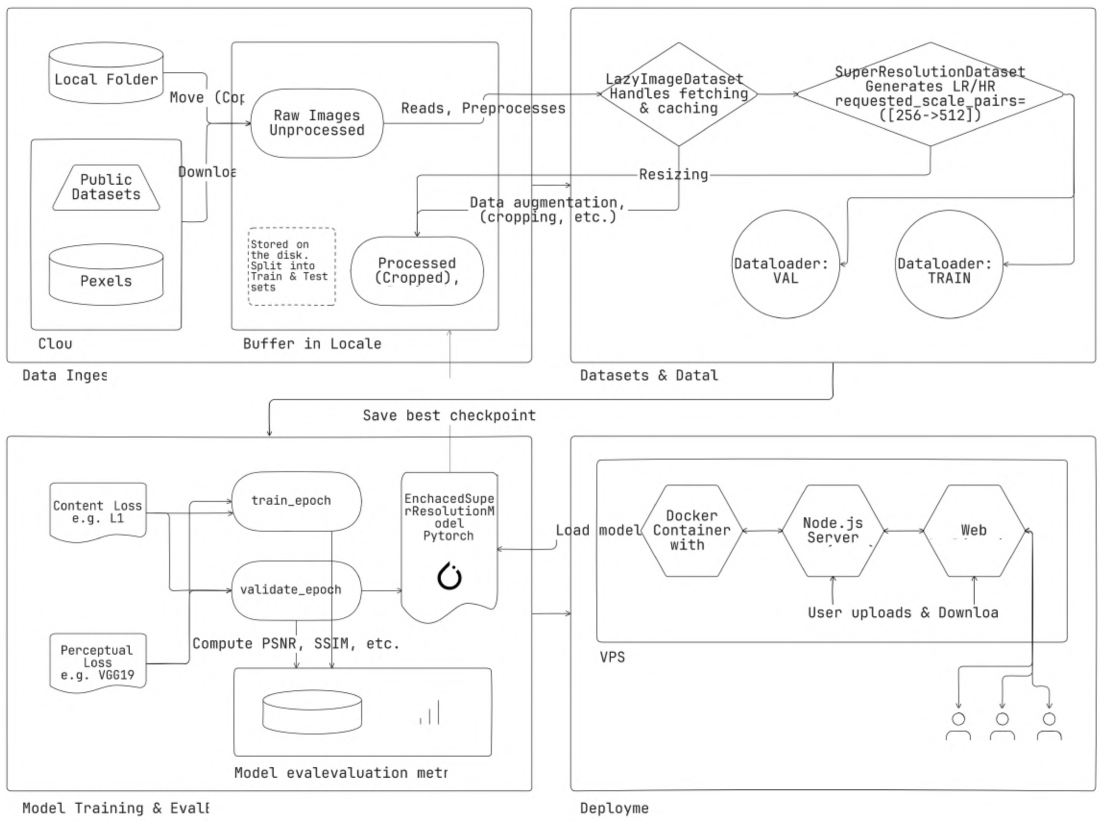

Figure 4.1: Architecture of whole designed workflow of application

resizing, adding distortion effect, such as noise, blur, etc. The processed images are then split into training and testing sets to facilitate model development.

4.1.1.2 Datasets & Data Loaders

Two data sets (data loaders) were designed. First, it handles lazy loading and caching images by storing them in buffer from different, configured, and integrated external sources, also, making initial preparation like cropping, resizing to one size, and normalization.

Second, it generates low-resolution (LR) and high-resolution (HR) requested image pairs required for training the model. Data loaders are used to efficiently batch and shuffle data during the training and validation phases.

The data set is then split into training and validation sets, ensuring that the model is evaluated on unseen data to gauge its performance accurately.

4.1.2 Model Architecture

The photo restoration model is designed to handle multiple restoration tasks, such as upscaling, denoising, deblurring, and artifact removal, all in one, as described in the Object and Methodology chapter (3). The architecture leverages CNN (2.1.2.2) with residual and up-sampling blocks to achieve high-quality restorations. The following tables provide a detailed overview of each component within the model.

4.1.2.1 Residual Block

The `residual block` is a fundamental building block of the model, allowing the network to learn residual mappings. This facilitates the training of deeper networks by mitigating the vanishing gradient problem.

Layer Type	Parameters
Conv2d	in_channels = 64, out_channels = 64, kernel_size = 3, padding = 1
BatchNorm2d	num_features = 64
PReLU	Activation function with learnable parameters
Conv2d	in_channels = 64, out_channels = 64, kernel_size = 3, padding = 1
BatchNorm2d	num_features = 64
Skip Connection	Add input tensor to the output of the second BatchNorm layer

Table 4.1: Residual Block Architecture

4.1.2.2 Upsample Block

The `Upsample Blocks` are responsible for increasing the spatial resolution of feature maps, enabling the model to generate high resolution outputs from low resolution inputs.

Layer Type	Parameters
Conv2d	in_channels = 64, out_channels = 256 (for upscale_factor = 2), kernel_size = 3, padding = 1
PixelShuffle	upscale_factor = 2, rearranges elements to increase spatial resolution
PReLU	Activation function with learnable parameters

Table 4.2: Upsample Block Architecture

4.1.2.3 Enhanced Super Resolution Model

The model integrates multiple residual blocks and upsample blocks to perform a comprehensive image restoration. The model architecture is designed to capture both local and global image features, ensuring detailed and accurate restorations.

Layer Type	**Parameters**
Conv2d	in_channels = 3, out_channels = 64, kernel_size = 9, padding = 4
PReLU	Activation function with learnable parameters
Residual Layers (16 Residual Blocks)	
ResidualBlock	Refer to Table 4.1
Conv2d	in_channels = 64, out_channels = 64, kernel_size = 3, padding = 1
BatchNorm2d	num_features = 64
Skip Connection	Add output of residual layers to the current tensor
Upsampling Layers	
UpsampleBlock	Refer to Table 4.2
Conv2d	in_channels = 64, out_channels = 3, kernel_size = 9, padding = 4

Table 4.3: Enhanced Super Resolution Model Architecture

4.1.2.4 Perceptual Loss

To enhance the perceptual quality of the restored images, the `Perceptual Loss` class computes the loss based on feature maps extracted from a pre-trained VGG19[35] network. This approach ensures that the restored images maintain high-level semantic features and textures similar to the ground-truth images.

Component	**Description**
VGG19 Feature Extractor	Pre-trained on ImageNet, extracts feature maps up to the 35th layer
Forward Pass	Pass both super-resolved (SR) and high-resolution (HR) images through the VGG19 feature extractor
Loss Computation	Compute L1 loss between the extracted features of SR and HR images

Table 4.4: Perceptual Loss Components

4.1.3 Serving and Deployment

To provide end-users with access to the trained photo restoration model, we propose a robust and scalable deployment strategy. This strategy ensures that the model is accessible, efficient, and user-friendly, facilitating seamless interaction between the back-end restoration processes and the front-end user interface.

4.1.3.1 Model Deployment

The trained *Enhanced Super Resolution Model* is deployed in a production environment that ensures high availability and reliability. The deployment process involves the following.

- **Model Hosting**: The restoration model is hosted on a scalable server infrastructure capable of handling multiple concurrent requests. This setup ensures that the model can process numerous image restoration tasks simultaneously without significant delays.
- **API Integration**: An application programming interface (API) is developed to facilitate communication between the front-end user interface and the back-end model. The API handles image upload requests, processes them through the restoration model, and returns the restored images to the user.
- **Scalability and Load Balancing**: To accommodate varying loads and ensure consistent performance, the deployment architecture incorporates scalability measures and load balancing mechanisms. This approach allows the system to dynamically allocate resources based on demand, maintaining optimal performance during peak usage times.

4.1.3.2 Web Interface

A user-friendly web application serves as the primary interface for interacting with the photo-restoration model. The Web interface is designed with the following features:

- **Intuitive Design**: The front-end is developed using modern web technologies to create an intuitive and responsive user experience. Users can easily navigate the application, upload images, and view restoration results.
- **Image Upload and Management**: Users are provided with straightforward options to upload images from their local devices. The application supports various image formats and ensures the secure handling of user data during the upload process.
- **Real-Time Processing Feedback**: The Web interface includes real-time feedback mechanisms that inform users about the status of their restoration requests. Progress indicators and notifications improve the user experience by keeping users

informed about the processing stages.
- **Result Display and Download**: After processing, the restored images are displayed alongside the original uploads, allowing users to compare and evaluate the quality of the restoration. Users can download the restored images directly from the interface for personal use or further processing.
- **Accessibility and Responsiveness**: The Web application is optimized for accessibility, ensuring compatibility between various devices and screen sizes. Responsive design principles are applied to provide a consistent experience on desktops, tablets, and mobile devices.

4.1.3.3 Security and Privacy

Ensuring the security and privacy of user data is paramount in the deployment strategy.
- **Data Encryption**: All data transmissions between the user interface and the backend servers are encrypted using industry-standard protocols (e.g., HTTPS) to protect user images and restoration results from unauthorized access.
- **Secure Storage**: Uploaded images and restored output are stored securely, adhering to best practices for data protection and compliance with relevant privacy regulations.
- **Access Control**: Strict access control measures are implemented to restrict unauthorized access to the model and user data. Authentication and authorization mechanisms ensure that only legitimate requests are processed.

4.1.3.4 End-to-End Workflow

The end-to-end workflow of the deployment process is designed to ensure efficiency and reliability:
1. **User Interaction**: The user accesses the web application and uploads a degraded image through the intuitive interface.
2. **Request Handling**: The web application sends the uploaded image to the backend server via the established API.
3. **Model Inference**: The backend server receives the image, processes it through the *EnhancedSuperResolutionModel*, and generates a restored high-resolution version of the image.
4. **Result Delivery**: The restored image is sent back to the web application, where it is displayed to the user alongside the original upload.
5. **User Feedback**: Users can download the restored image or initiate additional restoration requests as needed, continuing the interaction seamlessly.

This strategy here should be to create a deployment in which access to photo-restoration capabilities will be easy, efficient, safe, and friendly for users. By abstracting the underlying technologies, the focus will remain on the delivery of top-notch restoration experiences, not exposing complexity in the back-end infrastructure.

Chapter 5

Experiments and Evaluation

5.1 Setup

5.1.0.1 Hardware

All experiments were carried out using Google Colab, a cloud-based platform that provides access to computational resources. The specific hardware configurations used in expirements are:

- **Processor:** Intel Xeon CPU @ 2.30 GHz (a multicore processor with 2-4 cores).
- **Graphics Processing Unit (GPU):** NVIDIA Tesla T4. This GPU is well-suited for deep learning tasks, offering 16 GB of memory and efficient parallel processing capabilities.
- **Memory:** 52 GB of RAM, sufficient for handling large datasets and complex model architectures.
- **Storage:** Provided storage with a capacity of 100 GB, which is utilized to store data sets, model checkpoints, and intermediate results during training and evaluation.

5.2 Case Study - Experiment 01

5.2.1 Data Obtaining and Preprocessing

For this experiment, we used the Pexels[36] platform as the primary source of high-quality free-to-use images in training process. A total of 5000 images were lazy downloaded from the platform, with a variety of scenes, objects, and lighting conditions, and query-based on the following keywords: *mountain, nature, landscape*.

The dataset was preprocessed by resizing all images to a resolution of 512 pixels High-Quality (HQ) and to 256x256 Low-Quality (LQ). The images were then split into training and validation sets, with 80% of the images used for training and the remaining 20% used for validation.

5.2.2 Training Process

The initial training process was made with next parameters:

Parameter	Value
Number of Images	5000
Batch Size	16
Number of Epochs	20
Loss Functions	L1 Content Loss, Perceptual Loss (VGG19)
Optimizer	Adam (learning rate: 1e-4)
Learning Rate Scheduler	StepLR (step size: 20, gamma: 0.5)
Device	CUDA A-100 GPU

Table 5.1: Training parameters

5.2.3 Results

Extensive experiments were conducted to validate the performance of the proposed photo restoration model. In the process of training, the training loss and validation loss consistently decreased within 20 epochs using 5,000 images, reflecting good learning and generalization ability. PSNR and SSIM increased steadily during this process, which means the quality and structure of images would be gradually improved during training.

Figure 5.1 illustrates the increasing metric values for the PSNR and SSIM metrics over the course of the training process. The model's performance improved significantly after the first 13 epochs, with the PSNR and SSIM values reaching 25.5 dB and 0.85, respectively. The model's performance continued to improve until the 20th epoch, with the PSNR and SSIM values reaching 31.8 dB and 0.86, respectively.

In addition to PSNR and SSIM, the Blind Image Quality Assessment (NIQE) scores further highlight the model's effectiveness. Sample #1 recorded a NIQE of 4.13, while Samples #2 and #3 achieved higher scores of 5.44 and 7.41, respectively. These NIQE scores suggest that the restored images possess enhanced perceptual quality, with higher values indicating better naturalness and reduced artifacts. Furthermore, the inference times for all samples were exceptionally low, ranging from 0.45 to 0.51 milliseconds, underscoring the model's computational efficiency and suitability for real-time applications.

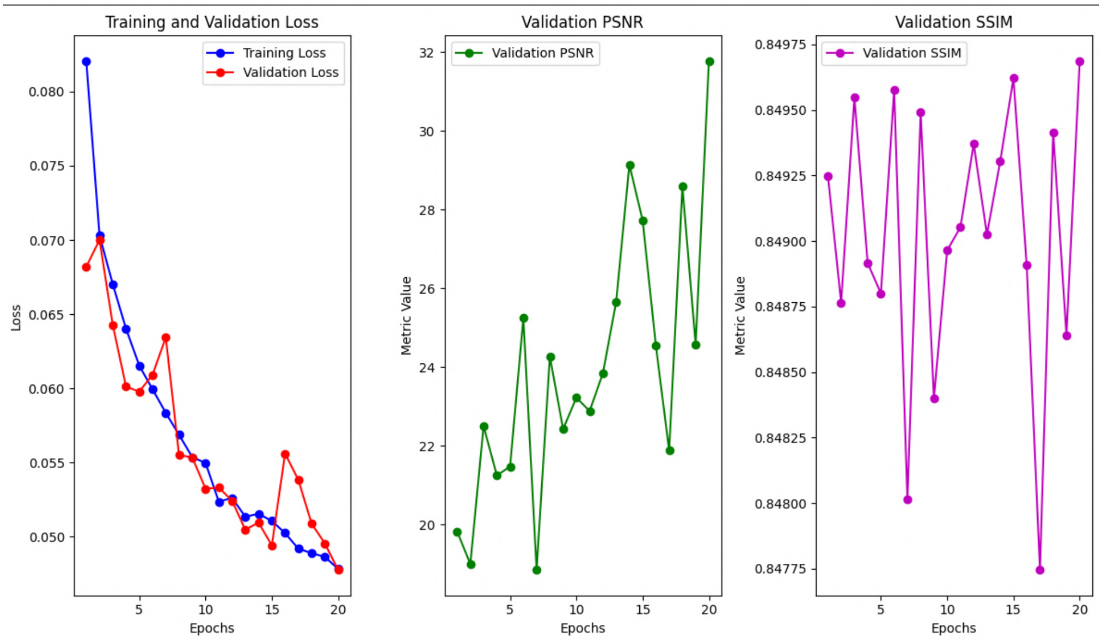

Figure 5.1: Loss and metric values through epochs

Figure 5.2 showcases the evaluation results for three sample images. Each row displays one image in several variants: Low-Quality (LQ), Super-Quality (SQ) (Restored), and High-Quality (HQ).

Note that the model was trained on unrevised data, with a subset of images unrelated to the restoration queries or with extra elements. With all these imperfections in the data and a really short training period of only 20 epochs, the model manages to produce very remarkable results. High values of PSNR and SSIM, together with a low inference time, mean the model learns to restore images, even when exposed to rather noisy and diverse data. All these very encouraging results indicate that this network, with more training and cleaning of the dataset, could achieve even higher levels of performance and extend the applicability and strength of real photo restoration tasks.

Figure 5.2: Evaluation results for a few samples

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Appendix A

Work Schedule

A.1 Work Schedule for BP1

1. **Weeks 1-2: Research and Familiarization**
    - Understand the basics of photo restoration and AI techniques.
    - Explore the current trends and challenges in the field.
2. **Weeks 3-4: Literature Review**
    - Conduct a comprehensive review of related work.
    - Identify key models and methodologies used in photo restoration.
3. **Weeks 5-6: Problem Definition and Goal Setting**
    - Define specific problems to address within photo restoration.
    - Set clear and measurable project goals.
4. **Weeks 7-8: Data Collection and Preparation**
    - Gather diverse datasets relevant to photo restoration.
    - Make up scraping additional images if necessary and preprocess the data.
5. **Weeks 9-10: Model Development**
    - Design and implement the CNN-based restoration model.
    - Implement to be possible to handle continuos super-resolution.
    - Optionally explore GAN-based approaches for comparison.
6. **Weeks 11-12: Training and Optimization**
    - Train and evaluate the restoration model.
7. **Weeks 13-14: Experimentation and Evaluation**
    - Conduct experiments to evaluate the model's performance.

Self-Evaluation of Work Schedule for BP1: Due to the enormous problems and the novelty of the topic to the stident there were delays in the planned plan, but by the end it turned out to be successful to stick to the plan and overall outcomes.