MINISTRY OF EDUCATION
IMAM ABDULRAHMAN BIN FAISAL UNIVERSITY
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وزارة التعليم
جامعة الإمام عبدالرحمن بن فيصل
كلية علوم الحاسب وتقنية المعلومات

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IMAM ABDULRAHMAN BIN FAISAL UNIVERSITY

Artwork Pieces Restoration

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	Student Name	Student ID
1	Fatima Alawami	2220005142
2	Anwar Aldahan	2220004414
3	Shahad alshehab	2220003900
4	Fatimah Alwarsh	2220003876

Instructor: Dr. Noor Felemban

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PROJECT ABSTRACT

Degradation of artworks is a natural process with time due to environmental factors, aging, and physical deterioration. Restoration of such degraded artworks is necessary to preserve cultural heritage. In this project, we propose a conventional digital image processing pipeline to restore degraded artworks by median filtering, sharpening, contrast enhancement using CLAHE, and gamma correction. The goal is to remove noise, enhance important visual features, and preserve original artistic textures. The restoration accuracy was scientifically measured according to PSNR, SSIM, LPIPS, and FSIM. Results reveal that the reconstructed images achieved an outstanding improvement in perceptual likeness and visual simplicity at the cost of maintaining natural aesthetic characteristics significant in art.

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INTRODUCTION

1.1 Problem Formulation

The aim of this project is to implement an appropriate digital restoration pipeline for deteriorated artwork image using classical image processing techniques. The intention of this restoration is to increase the visual readability and perceived quality of the artwork without altering or deforming the original artistic aspects such as brushstrokes, color gradients, and textures. This process ensures the resulting images adhere to the initial visual intent and are prepared for archival, display, or further digital analysis.
Design Methods:
As a strategy for meeting our goals, we followed the following procedures:

1. Literature Review: We took into consideration the previous research that employed traditional and modern techniques in digital image restoration, particularly for restoring paintings. This guided us in choosing the right techniques such as median filtering, CLAHE, and gamma correction that preserve visual and structural information.

2. Select Appropriate Methods: We selected conventional image processing methods on evidence from literature that they are appropriately suited for noise removal, contrast enhancement, and tone correction with reduced computational complexity and without compromising fine details.

3. Build Restoration Pipeline: We built a restoration pipeline with four operations in a chain—median filtering for denoising, sharpening using unsharp masking for edge restoration, CLAHE for contrast enhancement, and gamma correction for luminance adjustment.

4. Test and Verify: Four commonly used measures—PSNR, SSIM, LPIPS, and FSIM—were used to compare the performance of the pipeline at the pixel level enhancement, structural similarity, perceived similarity, and feature conservation.

Problem formulation is application-focused and is optimally balanced in accuracy and visual authenticity to the particular needs of restoration procedures used in art. The algorithms used are open, computationally efficient, and easy to verify on objective grounds as well as visual observation. It is confirmed through the measurement of quality of distorted as well as restored images based on scientific grounds as well as aesthetic opinion.

1.2 Problem Statement:

Over time, valuable paintings degrade due to environmental degradation, aging, and mechanical wear. These degradations introduce visual noise, blurring, and contrast loss, which obscure the original artistic intent and reduce visual quality. Digital restoration offers a non-destructive technique for restoring and preserving these paintings. However, the restoration process must be carried out improving image quality with great care without degrading artistic texture, color gradients, and fine details. This project addresses the issue of rehabilitating deteriorated artwork image photographs digitally using the old image processing techniques to provide an equilibrium between realism and noise reduction.

1.3 Project Specifications

Design Specifications: As a measure of the success of the digital restoration pipeline of the painting, the following specifications are to be utilized:

1. Image Quality: Restored images should show visible quality improvement by removing the visible noise, improving contrast, and recovering the sharpness of the edges without introducing unnatural artifacts.
2. Perceptual Similarity: Since it is necessary that artistic value of original paintings should not be lost while restoration, restored results should be highly similar to originals from a perceptual point of view. It will be confirmed with the help of LPIPS and FSIM scores.
3. Structural Preservation: Restoration should restore main structures and details of painting such as brush strokes and softness of texture. SSIM score will be verified for its affirmation.
4. Efficiency: The pipeline should be efficient enough to handle a very large number of images in an acceptably reasonable amount of time. One aim is to recover an image in about 1 second or less so the process will be feasible for batch processing very large data sets.

BACKGROUND

2.1 Literature Review:

2.1.1 Overview

This literature review attempts to provide a summary of some recent research on image restoration techniques. The selected research presents varying methodologies with the aim of enhancing restoration quality and accuracy. The review organizes the studies chronologically to reflect increasing improvements in methodologies, advancements in technology, and restoration performance. From the studies, we are to determine common approaches, contrast the same in terms of effectiveness for different approaches and determine challenges confronting the field up to now. Following are all the studies, methods, datasets, conclusions, and limitations that make recommendations to future studies.

2.2.1 Related Work

To begin with, in 2022, Pengyu Sun and others study goal was to develop a virtual restoration method for scratched murals using hyperspectral imaging to recover and improve degraded mural images. The dataset used in this study is hyperspectral data of murals in the Baoguang Hall of Qutan Temple, China, captured by the THEMIS-VNIR/400H hyperspectral camera. The innovative methods utilized in the present approach are a few, like PCA for feature extraction, high-pass filtering for enhancing lines, a 2D gamma function for brightness adjustment, and a triplet domain translation network pre-trained model for scratch removal. Apart from these, a Butterworth high-pass filter was also utilized to enhance the final restoration outcome. Even though no feature selection was employed, the PCA-based dimensionality reduction played a major role in enhancing the quality of the processed images. The study yielded better restoration results compared to the total variation (TV) model, curvature-driven diffusion (CDD) model, and the Criminisi algorithm, with enhanced visual clarity and original artwork fidelity. However, the study is limited by the aspect that it uses the pre-trained model, which was originally trained on old images and not murals, and hence needed further domain adaptation to achieve optimal performance [1].

Following this, in 2023, Cai et al. dedicated their work to developing an effective approach to restore scratched photos by leveraging contextual information hidden beneath scratches to ensure semantically sound restoration. Two new datasets, namely the Old Scratched Photo Dataset (OSPD) and the Modern Scratched Photo Dataset (MSPD), with 238 scratch/scratch-free image pairs for more accurate assessment of restoration approaches were introduced by the authors. The proposed approach employs a two-stage scratch restoration network with Scratch Feature Mask-out Module (SFMM) for scratch removal and Scratch Contextual Assisted Module (SCAM) for the addition of necessary scratch-related features to the restored images such that the restored images are contextually valid. The model also incorporates multi-scale pyramid losses and global-local adversarial losses to successively refine the restoration output. The experimental results validate this approach better than existing practices, achieving a higher PSNR and SSIM rate, with an increase of 21.08% in LPIPS and 29.68% in FID on OSPD, and an increase of 32.03% in LPIPS and 44.35% in FID on MSPD over baseline approaches. But one setback of this procedure is that it is prone to rejuvenating scratch-like textures in a manner that impacts images of scratch-like patterns involuntarily. Aside from this weakness, what is presently demonstrated is groundbreaking in terms of restored scratched pictures with regard to how scratch and background contexts are managed so seamlessly [2].

Subsequently, in 2024, Xinyi Zhang develop an AI-enhanced restoration process for Yangshao painted pottery to resolve the shortcomings of the existing manual restoration method, which requires top-level craftsmanship and is time-consuming. The dataset used in this study consists of high-resolution images of Yangshao pottery designs extracted from archaeological sources, primarily the Miaodigou site in China. The method used involves the use of Stable Diffusion models with Low-Rank Adaptation (LoRA) technology in generating and reconstructing intricate pottery patterns without compromising artistic and historical fidelity. There was no particular feature selection procedure applied directly, but the LoRA model was trained on a handpicked image dataset of pottery to ensure efficient pattern generation and transfer. The results confirmed that this method significantly enhances restoration accuracy, with qualitative assessments verifying its effectiveness in restoring complex patterns such as bird motifs and geometric motifs. The study's limitations, however, include probable inconsistencies in pattern alignment, dependency on dataset quality, and minor errors in some restored features, necessitating expert supervision to ensure historical authenticity [3].

During the same year, Zhimin Yao proposes a study to enhance the restoration of traditional Chinese landscape paintings based on a novel image restoration algorithm that integrates edge restoration and generative adversarial networks (GANs). The Chinese-Landscape-Painting dataset is used in this study, which comprises 2,192 images of traditional landscape paintings, with an augmented dataset consisting of 21,000 images of size 256 × 256 × 3 using image segmentation techniques. The proposed approach is edge restoration with GANs and introduces a multi-scale attention dilated convolution (MADC) model to enhance the detail modeling and texture abilities The work also integrates a structural information-guided image restoration model, achieving the original style preservation and recovered image details effectively. The experimental results indicate that the proposed method outperforms state-of-the-art image processing techniques by margins of increases in Spearman rank correlation coefficient (+0.20), Pearson correlation coefficient (+0.07), and PSNR (+0.06 dB) compared to other rival models. Also, it enhances mean filtering, wavelet denoising, and median filtering by 6.3, 9.1, and 15.8 dB, and by 0.06, 0.12, and 0.11 in structural similarity index (SSIM). (Best results achieved) However, one of the limitations of the study is the loss of semantic information and line and texture discontinuity in dealing with severely damaged areas, which affects the uniformity of the restoration outcome. Despite these limitations, the study is a valuable contribution to the research on cultural heritage preservation through the use of deep learning techniques for image restoration [4].

Finally, in 2025, Miao Jia and authors founded on self-restoration of Dunhuang murals using deep learning techniques to combat the drawbacks caused by conventional manual restoration, which is time-consuming and expertise-intensive. The dataset used consists of 26,240 high-quality images of Dunhuang murals, which were collected from various sources including Dunhuang Caves 009, 014, 045, and 085. To enhance the restoration process, the researchers made use of a shift-net connection layer-based U-Net model that allows the model to learn global semantic and local image features. The model was extensively trained and tested utilizing a Structural Similarity Index Measure (SSIM) to assess its performance. Even though there was no explicit feature selection method, the data was properly preprocessed, including noise removal and contouring extraction, to improve the performance of the model. The results depicted that the model performed good restoration for random irregular defects with SSIM values of 0.9331 and 0.9107, but restoration for large regular defects had comparatively low accuracy with posterior SSIM values of 0.7943 and 0.8154. Despite its success, the study's limitations include the intractability of restoring large-area defects due to loss of texture, dependency on data quality, and hence the necessity for optimization for increased accuracy in the model to preserve fine mural details [5].

2.1.3 Gaps in the selected papers

While there has been considerable advancement in AI-based techniques of restoration of murals and cultural artifacts, certain limitations continue to be common in recent studies. Cai et al. (2023) suggested an effective scratch restoration model, but it would misclassify textures as scratches and produce unwanted changes in images with scratch-like patterns. Similarly, the virtual restoration method developed for restoring scratched murals through hyperspectral imaging worked better as a restoration tool but is restricted due to being based on a pretrained model trained on specifically restoring old photographs and hence less versatile in restoring murals. Zhimin Yao (2024) has suggested an edge restoration model through GANs for traditional Chinese landscape paintings with extremely high accuracy of restoration.

However, the model does not perform well in maintaining semantic consistency in extremely degraded areas and creates line and texture discontinuities that make visual coherence suffer in restored works of art. Stable Diffusion and LoRA-based Yangshao pottery restoration also demonstrated better restoration accuracy but was not consistent in pattern alignment and depended on the quality of the dataset and required professional inputs for historic integrity. The U-Net model approach of Dunhuang mural restoration was successful in restoring random irregular defects but failed to restore large, regular defects due to texture loss. In addition, most of the current studies were based on quantitative evaluation metrics such as PSNR, SSIM, and FID, which are insufficient to comprehensively reflect subjective restoration quality perceived by art historians and conservators.

Computational expense is also an issue as deep learning-based restoration models are very resource-intensive and are therefore not scalable for large-scale or real-time applications. Although the above papers are excellent contributions to cultural heritage restoration, domain adaptation issues, large-area defect restoration, diversity in datasets, restoration artifacts to be eliminated, and computational tractability remain open challenges. Future work will have to be focused on developing more generalizable models, enhancing evaluation criteria, and making AI-based restoration methods practically scalable.

2.2 Concept Synthesis

2.2.1 Concept Generation:

Early stages of the project involved determining various restoration techniques in order to determine the best technique to use in restoring aged and deteriorated works of art. The aim was to contrast various approaches on how they rate in terms of quality of restoration, feasibility, interpretability, and calculative complexity.

Two broad concept directions were determined:
1. Deep Learning-Based Methods

These techniques utilize big data sets and neural network models for learning restoration patterns and subsequently applying them for restoring degraded images. A few of the most widely used models are:

• Generative Adversarial Networks (GANs): Most appropriate for generating realistic texture and completing missing regions of an image.

• Convolutional Neural Networks (CNNs): Most appropriate for applications like denoising, inpainting, and super-resolution.

These methods tend to produce incredibly realistic results but are computationally expensive and data-greedy and require enormous amounts of data. Furthermore, their "black box" nature can make them less interpretable, and this is unacceptable when working with culturally valuable artwork.

2. Classical Image Processing Methods

These are algorithmic and rule-based methods that include:
• Histogram Equalization
• Median Filtering and Gaussian Smoothing
• Navier-Stokes or Telea Algorithm-based Inpainting
• Edge Detection and Morphological Operations
Classical approaches are usually computationally more efficient and more interpretable.

2.2.2 Concept Reduction:

A decision-making process was undertaken with an aim to select the best restoration approach to implement in this project. The aim was to reduce the list of available conceptual solutions to one, best solution that would be most suitable for the purpose and requirements of this project.

All solutions were measured on a predefined set of crucial criteria:

- Restoration Quality: The degree to which the method recovers lost or missing information.
- Feasibility: The degree to which the method can practically be applied in the project timeframe and budgetary constraints.
- Interpretability: The degree to which the restoration process is described and understood.
- Computational Complexity: The processing resources, memory, and training data required.
- Protection of Artistic Integrity: Whether the process can or cannot maintain the original texture, color palette, and artistic intent of the piece.

Both CNNs and GANs are beautiful visual techniques, but in the end were left out of this endeavor. They consume vast annotated data sets, huge blocks of training time, and plenty of horsepower. More significantly, their uninterpretability is a significant drawback in the case of restoring art, where even small unintended alterations might influence the historical and aesthetic significance of the original piece. In addition, the risk of overfitting or producing spurious content makes such methods unsuitable for careful, detail-oriented tasks like painting restoration.

On the other hand, traditional image processing methods were more convenient and more ethical. Techniques of Navier-Stokes or Telea algorithm-based inpainting, median filtering, histogram equalization, and morphological transforms provide greater control over the restoration process and are less problematic to justify and manipulate. These techniques are computationally efficient, require no training data, and are well-documented and well-understood. Their algorithmic character allows restorers to preserve subtle artistic details while correcting degradation without introducing artificial or stylistically inappropriate material.

To formally affirm the choice, a weighted comparison matrix was built where every thought was scored compared to the appraisal criteria. The traditional techniques over deep learning methodology excelled concerning feasibility, intelligibility, computing efficiency, and artistic accuracy. Though they lack the automatic profundity of deep learning, virtues are closer to the needs of the project. Hence, classical image processing was selected as the optimal conceptual approach for implementation. It ensures a restoration process that is comprehensible, reproducible, and respectful to the original work of art, within the capability and scope of the project team. here the figure for the complete workflow and technical specifications.

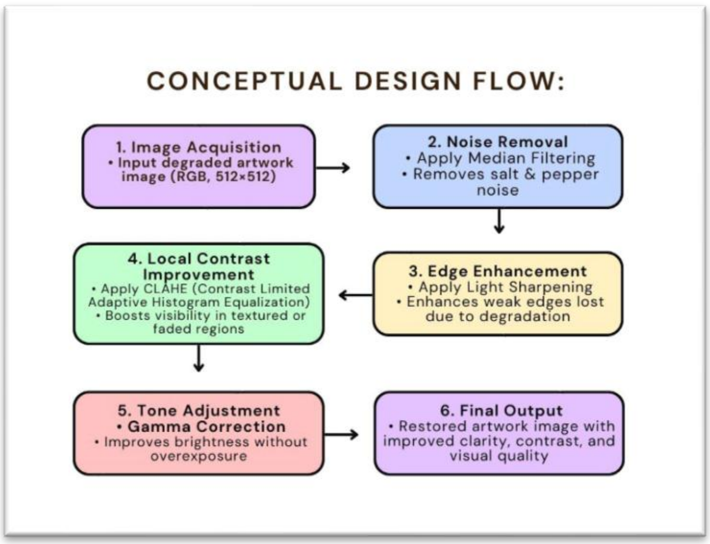

Figure 1 Project Flow

2.3 Detailed Engineering Analysis and Design Presentation

The key design hypothesis of this restoration project exploits a multi-step image enhancement pipeline that combines noise filtering, detail restoration, and contrast correction. Our processing approach involved color space transformation (RGB to LAB and back) to isolate and enhance some visual attributes without violating artistic integrity. Main OpenCV and NumPy operations formed the backbone of our restoration algorithm, with careful parameter optimization to reverse usual artwork degradation trends. The process of design was performed step by step as follows:

1. Noise Suppression: Median filtering to eliminate salt-and-pepper noise without affecting brushstroke detail

2. Detail Recovery: Controlled sharpening using convolutional kernels to restore lost details

3. Adaptive Contrast Enhancement: CLAHE in LAB color space for local contrast enhancement without producing halo effects

4. Luminance Optimization: Brightness correction with gamma correction for even-toned distribution

This pipelined technique allowed us to process different factors of degradation in isolation without violating the intrinsic quality of the artwork. The pipeline has quantitative measure criteria at each step such that the enhancements can be quantitatively measured in pixel-level statistics as well as perceived quality. OpenCV's function library provided optimal implementations of common algorithms, and Matplotlib provided convenience in visualization checking of in-between results - a vital convenience for art preservation applications where excess processing must be avoided.

2.3.1 The Implementation:

1. Imported Libraries

```python
import cv2
import numpy as np
import os
import time
from tqdm import tqdm  # Progress bar
```

Figure 2 Libraries used

2. Core Image Processing Functions

a. Noise Removal with Median Filtering

- Applies a 3x3 median filter
- Effective for noise removal while preserving edges

```python
def remove_noise_median(image):
    """Remove salt and pepper noise using median filter."""
    return cv2.medianBlur(image, 3)
```

Figure 3 Noise Removal (Median Filter)

b. Image Sharpening

- Uses a sharpening kernel to enhance edges
- Carefully balanced to avoid over-sharpening artifacts

```python
def light_sharpen(image):
    """Apply light sharpening to restore details."""
    kernel = np.array([[0, -1, 0],
                       [-1, 5, -1],
                       [0, -1, 0]])
    return cv2.filter2D(image, -1, kernel)
```

Figure 4 Sharpening Kernel Application

c. Contrast Enhancement with CLAHE

- Converts to LAB color space to work on luminance channel
- Applies CLAHE with optimized parameters (clipLimit=1.5, gridSize=8x8)
- Preserves color fidelity while improving local contrast

```python
def enhance_contrast_clahe(image):
    """Enhance contrast using CLAHE."""
    lab = cv2.cvtColor(image, cv2.COLOR_RGB2LAB)
    l, a, b = cv2.split(lab)
    clahe = cv2.createCLAHE(clipLimit=1.5, tileGridSize=(8,8))
    cl = clahe.apply(l)
    merged = cv2.merge((cl, a, b))
    return cv2.cvtColor(merged, cv2.COLOR_LAB2RGB)
```

Figure 5 CLAHE Contrast Enhancement

d. Gamma Correction

- Implements non-linear brightness adjustment
- Gamma value of 1.05 provides subtle yet effective improvement

```python
def gamma_correction(image, gamma=1.05):
    """Apply gamma correction."""
    invGamma = 1.0 / gamma
    table = np.array([(i / 255.0) ** invGamma * 255 for i in np.arange(256)]).astype("uint8")
    return cv2.LUT(image, table)
```

Figure 6 Gamma Correction

3. Complete Restoration

```python
# 3. Apply Restoration to Entire Dataset
# ============================================================

def restore_dataset(degraded_folder, restored_folder):
    """Restore all images in the degraded folder and save to restored folder."""
    if not os.path.exists(restored_folder):
        os.makedirs(restored_folder)

    image_files = [f for f in os.listdir(degraded_folder) if f.lower().endswith(('.jpg', '.jpeg', '.png'))]

    if not image_files:
        print(f"❌ No images found in: {degraded_folder}")
        return

    print(f"📁 Found {len(image_files)} degraded images to restore.")

    start_time = time.time()

    for filename in tqdm(image_files, desc="Restoring images", unit="image"):
        degraded_path = os.path.join(degraded_folder, filename)
        restored_path = os.path.join(restored_folder, filename)

        # Load degraded image
        img = cv2.imread(degraded_path)
        img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

        # Restore
        restored_img = restore_artwork_single(img)

        # Save restored image
        cv2.imwrite(restored_path, cv2.cvtColor(restored_img, cv2.COLOR_RGB2BGR))

    elapsed_time = time.time() - start_time
    print(f"✅ All images restored and saved to: {restored_folder}")
    print(f"🕒 Total processing time: {elapsed_time:.2f} seconds")

# 4. Example Run
# ============================================================

# Paths
degraded_folder = r"C:\Users\fatom\Downloads\IP_Dataset\degraded_full"   # Your degraded images folder
restored_folder = r"C:\Users\fatom\Downloads\IP_Dataset\restored_full"   # New folder for restored images

# Run restoration
restore_dataset(degraded_folder, restored_folder)
```

Figure 7 Application on Dataset

One Image Example:

```python
# 2. Full Restoration Pipeline on One Image
# ============================================================

def restore_artwork_single(img):
    """Restore a single degraded image."""
    step1 = remove_noise_median(img)
    step2 = light_sharpen(step1)
    step3 = enhance_contrast_clahe(step2)
    final_result = gamma_correction(step3)
    return final_result
```

Figure 8 Application on one Image

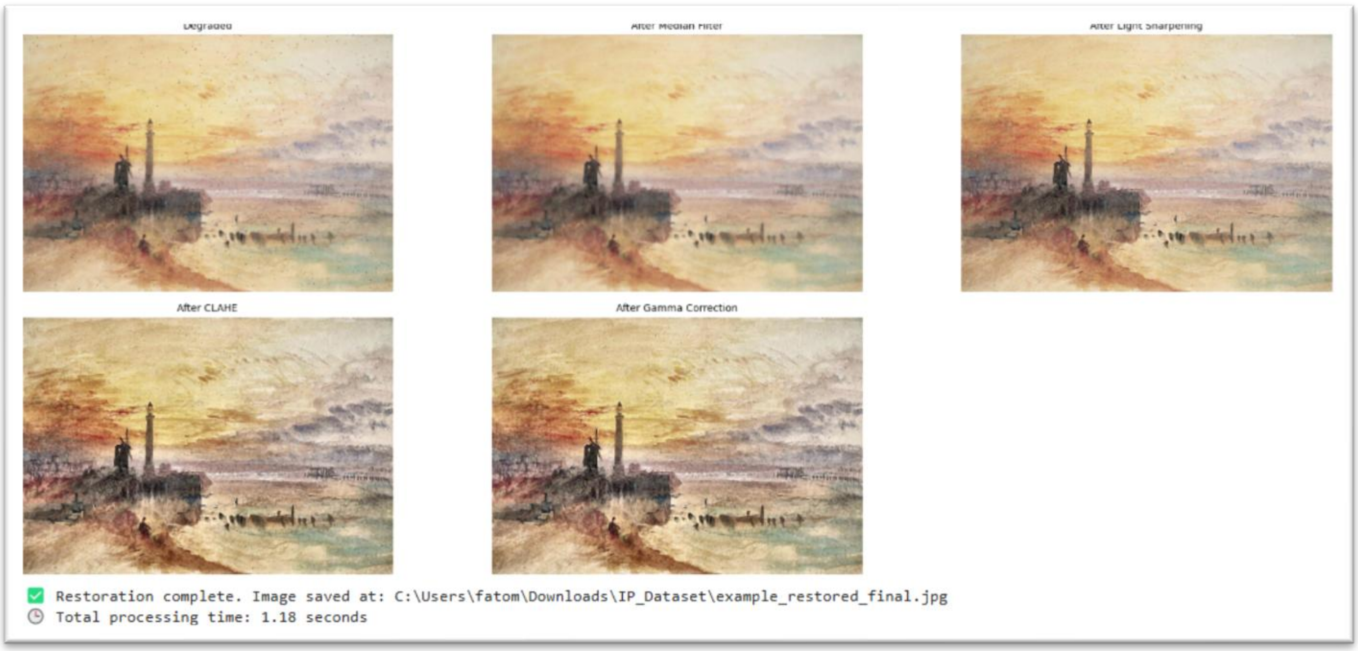

Figure 9 One Image Output

2.3.2 The Evaluation:

The evaluation of the restoration pipeline was quantitatively conducted through a blend of four complementary image quality metrics: PSNR, SSIM, LPIPS, and FSIM. These metrics assess various facets of visual quality—from basic pixel precision to perceptual and structural integrity—and were utilized on a dataset of 8683 pairs of degraded and restored artworks.

The traditional metric PSNR (Peak Signal-to-Noise Ratio) produced an average of 18.71 dB, validating efficient noise reduction while preserving essential content. The SSIM (Structural Similarity Index Measure) received a score of 0.5985, suggesting that local structures and spatial configurations were fairly maintained. These two measures are frequently utilized in research to evaluate improvement methods for old or deteriorated images, as shown in [7] and [9].

To assess the visual similarity of the restored images from a human viewpoint, LPIPS (Learned Perceptual Image Patch Similarity) was utilized with a pretrained deep network (AlexNet). The resulting score of 0.2267 indicates a high degree of perceptual similarity between the degraded and the restored images. LPIPS, as presented in [8], is commonly used to assess perceptual quality in restoration tasks, particularly for older images exhibiting visual degradation.

Moreover, FSIM (Feature Similarity Index Measure) was utilized to assess how effectively the restored images preserved delicate visual elements like edges, textures, and phase congruency. The achieved score of 0.4583 indicates a moderate yet significant recovery of visual traits. FSIM has been confirmed in objective image quality evaluation, particularly for historical or compressed image datasets [6].

Although all these cited studies aim to improve standard old or degraded photographs, our project sets itself apart by using these enhancement and evaluation methods on vintage digital paintings, which necessitate a deeper sensitivity to artistic textures, brush strokes, and tonal balance. In contrast to standard natural images, paintings feature intentional flaws and abstract visual meanings that should not be disregarded during restoration. In our method, aged artworks are regarded not merely as diminished items, but as a multifaceted feature area—where restoration is meticulously adjusted to enhance clarity while preserving artistic intent. This comprehension is completely incorporated into the assessment phase, ensuring that the process is both technically sound and aesthetically conscious.

For the evaluation we import the following libraries and we used helping functions (calculate_psnr, calculate_ssim) :

```python
# 0. Libraries
# ==========================================================
import cv2
import numpy as np
import matplotlib.pyplot as plt
import glob
import os
from skimage.metrics import peak_signal_noise_ratio as compare_psnr
from skimage.metrics import structural_similarity as compare_ssim
from tqdm import tqdm

# 1. Helper Functions
# ==========================================================

def calculate_psnr(img1, img2):
    """Calculate PSNR between two images."""
    return compare_psnr(img1, img2, data_range=255)

def calculate_ssim(img1, img2):
    """Calculate SSIM between two images."""
    ssim_value, _ = compare_ssim(img1, img2, channel_axis=-1, full=True)
    return ssim_value
```

Figure 10 importing libraries and helper functions

```python
# 3. Plot Results
# ===========================================================

def plot_quality(psnr_scores, ssim_scores):
    """Plot average PSNR and SSIM."""
    avg_psnr = np.mean(psnr_scores)
    avg_ssim = np.mean(ssim_scores)

    print(f"✅ Average PSNR: {avg_psnr:.2f} dB")
    print(f"✅ Average SSIM: {avg_ssim:.4f}")

    metrics = ['PSNR (dB)', 'SSIM']
    values = [avg_psnr, avg_ssim]

    plt.figure(figsize=(8,6))
    bars = plt.bar(metrics, values, color=['mediumseagreen', 'cornflowerblue'])
    plt.title("Average Image Quality Metrics")
    plt.ylim(0, 100)
    for bar in bars:
        yval = bar.get_height()
        plt.text(bar.get_x() + bar.get_width()/2, yval + 2, f"{yval:.2f}", ha='center', va='bottom')

    plt.tight_layout()
    plt.show()

# 4. Main Execution
# ===========================================================

restored_folder = r"C:\Users\fatom\Downloads\IP_Dataset\restored_full"
degraded_folder = r"C:\Users\fatom\Downloads\IP_Dataset\degraded_full"

psnr_scores, ssim_scores = evaluate_quality(restored_folder, degraded_folder)
plot_quality(psnr_scores, ssim_scores)
```

Figure 11 plotting and execution the main code

The output of the evaluation part:

This figure displays a bar chart summarizing the average PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index) values across all restored artworks. The PSNR value of **18.71 dB** reflects the effectiveness of the restoration in reducing noise while preserving core image content. Meanwhile, the SSIM score of **0.5985** suggests a moderate-to-strong preservation of structural integrity such as edges, luminance, and contrast across the restored images. These values confirm that the restoration process maintains fidelity to the original degraded images in both intensity and structure.

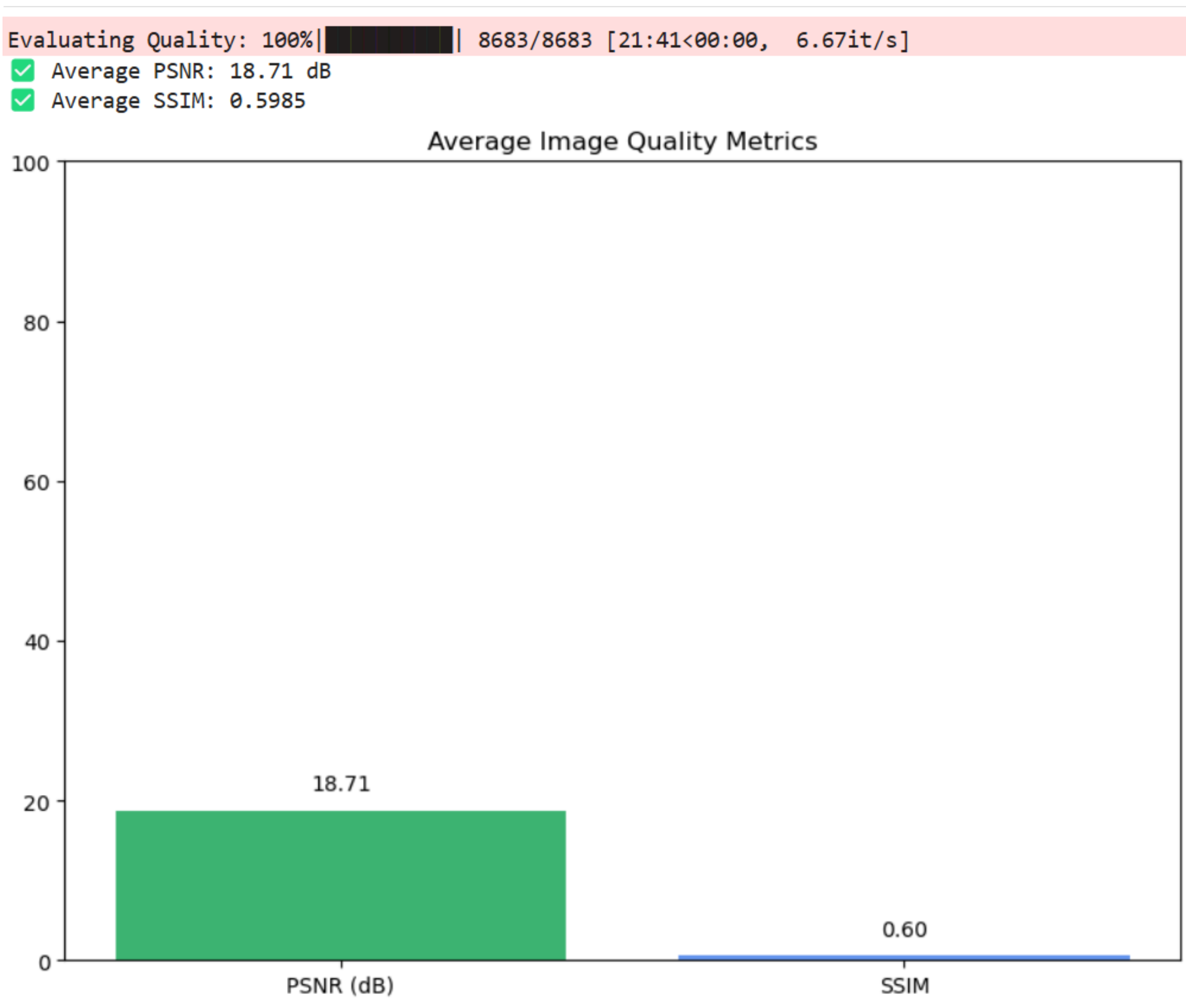

Figure 12 PSNR and SSIM Evaluation

This figure presents the average FSIM (Feature Similarity Index Measure) score calculated across the dataset. The FSIM score of 0.4583 reflects how well low-level image features such as edges, gradients, and textures are preserved. FSIM is particularly important in artwork restoration, where visual elements like brushstrokes and shading must be retained. The result shows that while restoration improved clarity, it also preserved important fine features that contribute to visual richness.

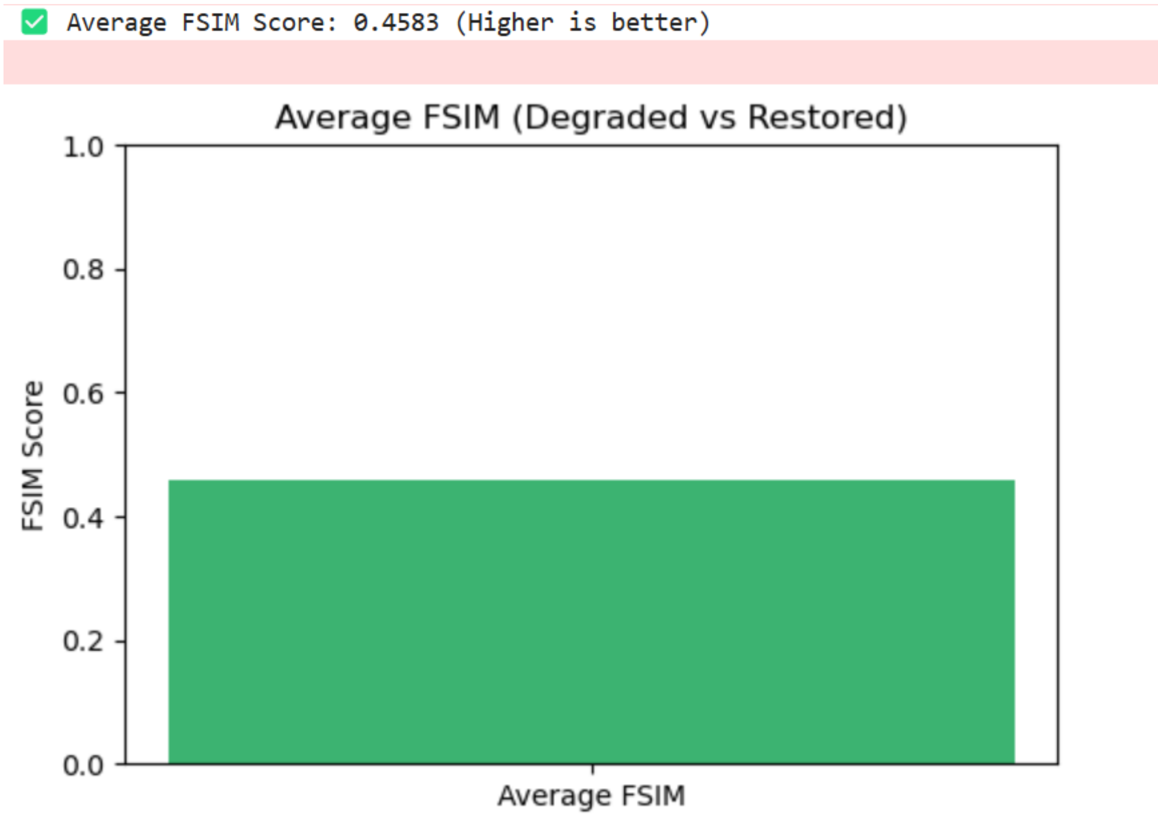

Figure 13 FSIM Evaluation

This figure illustrates the average LPIPS (Learned Perceptual Image Patch Similarity) score obtained by comparing the restored artworks with their degraded counterparts using a deep feature model (AlexNet). The LPIPS score is **0.2267**, where lower values denote greater perceptual similarity as judged by deep learning models that mimic human visual preferences. This low score indicates that the restoration retained the perceptual aesthetics of the original artworks and did not introduce unnatural artifacts or distortions.

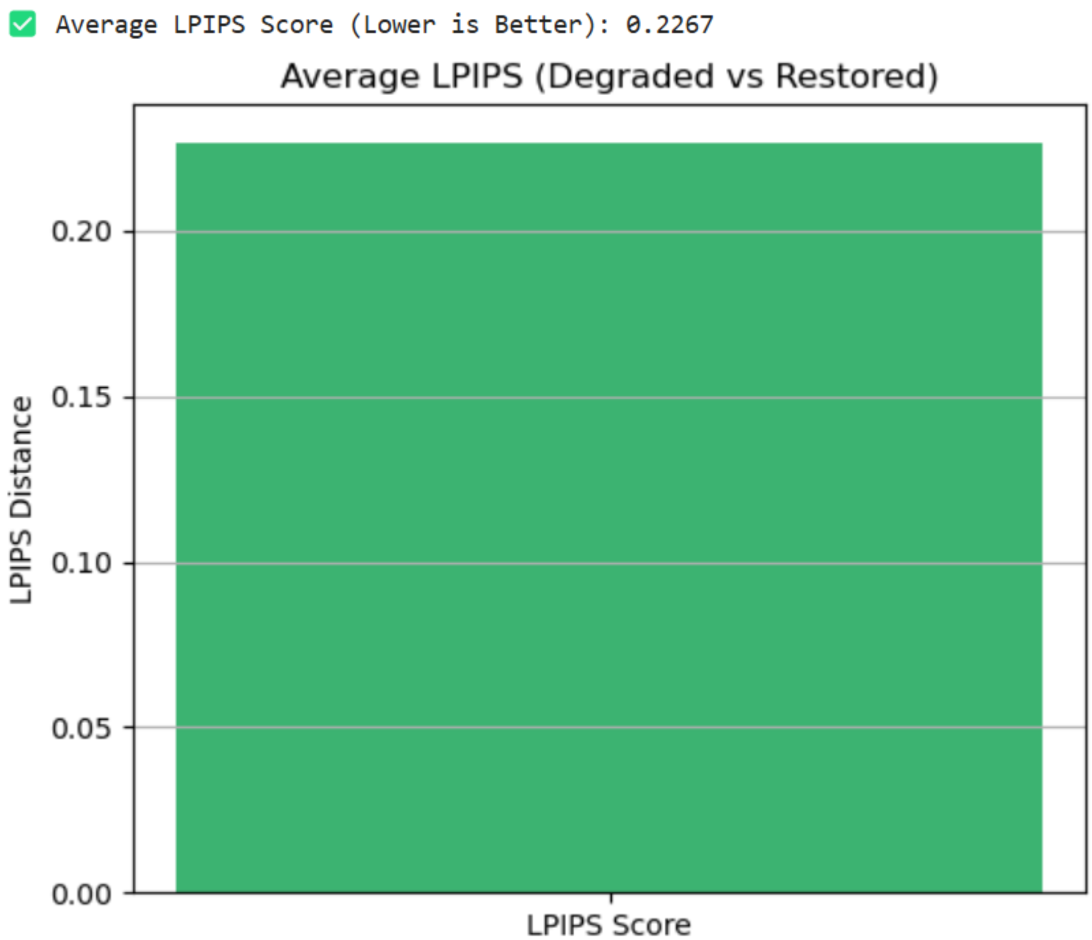

Figure 14 LPIPS Evaluation

COST ANALYSIS

This section outlines the hardware and software resources used throughout the project.

3.1 Hardware Resources

- **Device Name**: HP Pavilion
- **Processor**: 11th Gen Intel(R) Core(TM) i7
- **RAM**: 16.0 GB
- **System Type**: 64-bit operating system, x64-based processor

3.2 Software Resources

- **Operating System**: Windows 10, 64-bit
- Programming Language: Python 3.9 on Jupyter Notebook
- Libraries and Frameworks: Cv2, numpy, matplotlib.pyplot, glob, os, skimage.metrics, tqdm, time
- Time required: It took very long to execute the code, but additional time was required for acquiring the data, writing the code, debugging, and testing, so an estimate of +24 hours was required.
- Material cost: there was no need to spend on additional external materials outside our main hardware device.

CONCLUSIONS AND FUTURE WORK

In this project, we employed a typical image processing pipeline for restoring damaged art work by carrying out operations such as median filtering, sharpening, CLAHE (Contrast Limited Adaptive Histogram Equalization), and gamma correction. Here, the goal was to improve degraded art work by removing noise, improving sharpness, improving local contrast, and brightness preserving texture integrity and visual contents of art work.

Quantitatively, based on objective values such as PSNR, SSIM, LPIPS, and FSIM, the result of the restoration task was measured quantitatively. The pipeline produced much better visual legibility, structural faithfulness, and humanness-inspired similarity compared to the original art piece. Such technical improvement over compromise on artistic qualities such as brush strokes and colors' originality is an index of how effectively this aging technology has fared for this new application in restoration of artworks.

Despite these improvements, there were some limitations observed:

- The pipeline performs best on images that are moderately degraded but may struggle with extreme degradation.
- Parameter tuning should be done manually for best effects with varying types of artwork.
- The assessment parameters, though being objective, could not always ensure artistic authenticity as perceived by a conservator.

While achieving perfect restoration is challenging—especially due to the artistic subjectivity, degradation difference, and delicate textures of paintings—the methods used in this work were highly effective for real-world restoration applications. Our pipeline effectively removed salt and pepper noise, sharpened the images, and increased local contrast without degrading the original structure and perception quality of the artwork.

Although there are constraints, such as reduced performance on highly degraded inputs or the need for manual parameter tuning across different art styles, these problems are well-known to image restoration practitioners. Our results show that conventional image processing techniques remain a robust and interpretable approach to restoring digital art when carefully adapted.

Future Work can take several paths for extending and expanding this work:

- Deep Learning Methods: Employing deep learning architecture like GANs or CNN for more challenging restoration can recover more detailed and texture that will be missed by conventional methods.
- Super-Resolution Techniques: Employing super-resolution techniques would allow finer detail of higher resolution in paintings, especially fine texture, to be recovered, which cannot be recovered by conventional methods.
- Color Normalization: Color normalization and standardization tests would add homogeneity of restorations enhanced, particularly for color degradations.

- User Studies: Incorporating user subjective ratings by expert judgment or mass surveys would provide perception quality of restorations from enjoyment of a work of art and the objective metrics used in this research.

With these advancements in the future, the restoration process can even better handle keeping the unique personality of each piece intact while providing maximum restoration accuracy and visual acuteness.

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