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Visual Artifact Detection and Correction for Digital Images Via Deep Neural Networks (Real-ESRGAN)

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Abstract: *This work pursues to the improvement of digital images quality and the correction of visual artifacts, in particular noise, by means of deep neural networks, through an application-oriented investigation based on pre-trained models which are ready to be used in the execution on a resource-limited platform. The study is inspired by a typical problem in processing digital images, on one hand traditional image enhancement algorithms do not work well on real world low-quality images because they cannot well trade off between over smoothing noise and preserving visual details and image structural information, on the other hand, high quality ground truth images corresponding to low quality real images are not available. The experimental part of this work was performed on a real noisy digital image from an open-source platform. The image was processed using a specialized processing pipeline developed in Python. The PyTorch library was used to run the DL model and some dedicated libraries are also included such as Real-ESRGAN as the default model to enhance the image quality, BasicSR as the generic framework to manage the process workflow, and the installation of GFPGAN and FaceXLib to facilitate optional facial restoration. Prior to all other testing were done on the CPU, these experiments were conducted using only the Central Processing Unit(DCPU) and not any high end Graphical Processing Units(GPUs) The processing approach was to use the Real-ESRGAN model only in the inference stage without any training process or modification on the model architecture. The discussion of results was grounded on qualitative visual inspection aided with a descriptive quantitative analysis of result indicators that can be obtained from the image itself before and after processing, such as the image size, the total number of pixels, and the spatial upscaling factor. The result indicates a 16 times enlargement in pixel number after processing (under the upscaling factor of ×4), as well as an intuitive improvement on clearness of details and the visual noise decreasing, which means the enhancement on perceptual quality of the image. Results show that exploiting pre-trained DNN models is a realistic and time-efficient strategy for improving quality of noisy images of the real world, even if computational power is scarce at the time of acquisition of images. In addition, the work demonstrates the feasibility of leveraging open source software in the domain of digital imaging and thus paves the way for potential future investigation incorporating larger datasets or employing standardized quantitative evaluation metrics when appropriate evaluation conditions are obtainable.*

Keywords: *Digital Image Processing, Image Quality Enhancement, Image Denoising, Deep Learning, Deep Neural Networks, Pre-Trained Models, Real-ESRGAN, Visual Analysis, Descriptive Quantitative Analysis.*

Introduction

The quality of digital images is a key point for the reliability of computer vision and digital image processing systems, as the existence of visual defects [1] in an image, such as noise or image down-sampling, will hamper the accuracy of visual analysis and the quality of application results [2]. Noise is known as one of the most prevalent visual defect in digital images since it is related to numerous factors among them the acquisition conditions, the sensor characteristics and the imaging and storage system limitations, removing it is a continuous challenge in practical applications (Gonzalez & Woods, 2018). Noise filtering and image enhancement issues have traditionally been solved by mathematical or statistical modeling techniques such as linear or non-linear filtering and enhancement procedures in spatial or frequency domains. These methods have been successful in some applications, but typically they require assumptions about invariant degradation parameters and are not capable of incorporating the complex and nonlinear degradation produced by noise in real images, limiting their generalization to different scenarios (Jain, 2015). The underlying dataset and learning paradigms have experienced a dramatic change in recent years in the discipline of digital image processing, where now deep neural networks have been considered one of the most powerful tools for representing highly non-linear relationships in visual data. Such networks use multi-layer architectures that can learn hierarchical representation of images, which allows them to reach state-of-the-art performance in image denoising (Jiang, Hou, Cheng, & Sun, 2018), resolution enhancement(Le, Nguyen, & Nah, 2018), and visual detail restoration (Le, Nguyen, & Nah, 2018) among others without relying feature engineering.

In this scenario, the super-resolution models that exploit generative neural networks have drawn more and more attention because they can substantially improve the perceptual quality of low-resolution real-world images. Some recent models, e.g. ESRGAN and Real-ESRGAN, are well-established approaches in this area, which not only excel at retrieving high-frequency details but also compensate for blurring artifacts and handle noises in a unified manner (Wang et al., 2018 ; Wang et al., 2021).

Therefore, this work is an application study on the use of a pre-trained deep neural network model to improve the quality of a noisy digital image that was captured in a real-world setting without any further training on the user's part. The goal is to demonstrate that a pre-trained deep neural network can be practically used to fix visual artifacts, especially in limited-resource academic and applied settings, with visual results and a descriptive quantitative analysis the influence of processing w.r.t. structural-property of the image.

Methodology

Research Problem

Although digital imaging technologies have been largely developed, the quality degradation and visual noises are still challenging problems, especially for low quality real-world images that are induced by poor imaging conditions or hardware limitations of image acquisition devices and systems. These artefacts directly impact the quality of details and structure of the image, thus leading to a loss of its applicability and reliability in a number of scenarios.

Conventional image quality enhancement and noise removal methods are usually formulated considering noise features and applying a prior model assuming some noise characteristics. Such assumptions are likely to reduce the performance when dealing directly with real images that are corrupted by more complicated and non-linear noise. In this sense, deep neural networks have proven to be a valuable alternative to model non-linear mappings and improve perceptual quality of images on the basis of deep data-driven representations.

However, this leads to a practical question of whether it is possible to use pre-trained, off-the-shelf DNN models for real image enhancement in the academic community where resources are limited and its application in academia would be expected to be without having to training a new model or rely on high end computational infrastructure. It also raises the question of what kinds of visually detectable improvements such models can generate that can be examined with descriptive quantitative indices.

Hence, the research problem is summarized by the following principal question:

How effective are off-the-shelf pre-trained deep neural network models in improving the quality of noisy digital images when running in a resource-limited execution platform?
Sub-questions

This leading question brings up several sub-questions, such as

1. How well does a pre-trained deep neural network (Real-ESRGAN) enhance perceptual quality of a noisy digital image captured in real-world environment?
2. How far can one go to perform a meaningful real-world image quality improvement experiment with open-source software on a CPU-based platform?
3. What descriptive, quantitative and visual indicators can be trusted to assess image quality improvement when a clean ground-truth reference is not available?

Importance of the Research

Significance The research is important because it describes an applied, practical study that shows that pre-trained (off-the-shelf), deep neural network models can be used to improve the quality of noisy digital images without having to design and train models that are specific to the problem. From a scientific standpoint, the study helps to delineate the practical utility of deep learning in the realm of digital image processing, specifically in terms of generative neural network-based super-resolution models for enhancing the perceptual quality of low-quality real-world images.

The scientific contributions of the work rely also on connecting theoretical aspects of deep learning with an application, as better articulated concepts through an applied case based on a natural image and its analysis from a visual and descriptive quantitative viewpoint. It also enables a more accessible explanation of what these pre-trained deep neural models really do, and how such models evolve in the research terrain, for students as well as researchers from diverse academic fields.

From an application point of view, this study offers a resource- and time-efficient, generalizable and reproducible solution for enhancement of digital images using open-sourced tools in a CPU based, resource-limited execution environment. This makes the work ideal for teaching, final year projects and application based research, to test feasibility of deep learning approach in the absence of high end computational resources.

In addition, the study demonstrates the utility of pre-trained deep neural network models as off-the-shelf solutions for real-world images, and the experimental results may provide a foundation for further studies that may include extension of experiments to larger image sets and/or use of standardized quantitative evaluation metrics, or investigation of additional deep learning models in a comparative manner in different execution environments.

Research Objectives

In this study, we endeavor to develop an application investigation on a pre-trained, off-the-shelf deep neural network on the noisy digital images on quality with theoretical analysis and practical considerations in a limited computing resource execution environment. The investigation attempts to accomplish a number of related aims that mirror the applied and realistic character of the study. The goal of the work is to determine whether a pre-trained deep neural network model (i.e., Real-ESRGAN) can be used to enhance the perceptual quality of a noisy digital image captured from a real-world scenario, without any further training or designing new models.

Several sub-goals are derived from this main goal, **such as:**

1. The investigation of digital image quality enhancement and noise reduction based on the development of deep learning theory.
2. Analysis of working mechanisms of pre-trained deep models in IQE: Understanding how complex deep models work in IQE tasks, in particular, generative network-based super-resolution models.
3. Performing a straightforward application experiment to improve the quality of a noisy digital image using open source software tools under a CPU execution environment.
4. The processing is reviewed by visual inspection and descriptive quantitative analysis with metrics that are directly measured in the image pre and post processing such as image size or total number of pixels.
5. It also emphasizes that the deep learning pre-training based approaches could be applicable for (non old) university and bachelor projects without requiring high-end computation resources.

Research Hypotheses

This work is based on a set of hypotheses, which serve in order to guide the applied research and evaluate its results according to the adopted methodological strain, in case of applying the methodology of a pre-trained, off-the-shelf deep neural network model for the enhancement of noisy digital images.

It is further hypothesized that a pre-trained, off-the-shelf deep neural network model can yield a significant enhancement in perceptual quality of a noisy digital image, in reducing noise as well as recovering finer details, when applied to degraded real-world images.

The study also anticipates that deep neural network-based super-resolution models bring about a noticeable performance improvement in visual effect without training and tweaking the network architecture, when used as-is only in a testing stage.

Further, this study predicts that such an applied investigation for the enhancement of digital image quality can be successfully developed, for an equally cost-effective and accessible level of software tools that are open-source, Told solely upon the axe of the Central Processing Unit (CPU), And without any dependence to lofty computational infrastructures.

In conclusion, the work is based on the conjecture that visual examination and descriptive quantitative analysis relying upon indicators that canbe directly derived from the image prior processing (and p rocessing) are appropriate for assessing the enhancement of image quality in the situation where a clean ground truth reference is that is not accessible.

Research Limitations

The following are the limitations of this study, which have been established in order to define the study's range, both scientifically and applied, and to maintain coherence between the findings and the methodological framework.

Thematic limitations

Here, we focus on improving the quality of static digital images and the elimination of visual noise on a trained, off-the-shelf deep neural network model. Neither video processing nor three-dimensional images are considered, as also other computer vision tasks (e.g. object detection, image recognition are excluded). The practical part is based on upscaling one real world digital image with Real-ESRGAN model in the inference process only, without any model design or training.

Limitations in outlook

The visual inspection and descriptive quantitative analysis are used to assess the outcome of image quality enhancement, the application of conventional quantitative evaluation measures, which may be considered as an inclusion of the "clean" ground-truth image for example in the case of the usage of PSNR or SSIM is prevented by the nature of the employed data.

Temporal limitations

The theoretical basis of the thesis rests on contemporary scientific literature in the field of deep learning and image processing, more specifically, related to image super-resolution models, from the past few years.

Reviews of the literature:

There have been recent advancements in the area of correcting visual artifacts in digital images based on deep learning, and the results are increasingly steering towards deep learning as a more powerful and flexible tool, rather than classical approaches. Surveys such as those of Zhang et al. (2022) and Elad et al. (2023) reviewed the historical development of image denoising and deblurring methods and pointed out that deep neural networks (DNN), particularly convolutional neural networks (CNNs), outperform in recovering visual details and structural information of images, even for complicated examples where models based on fixed statistical assumptions are likely to fail.

Pros and Cons Meanwhile, Tian et al. and Jebur et al. (2024) introduced exhaustive categorizations on deep learning–based image denoising techniques and revealed that deep architectures can learn highly nonlinear mappings that describe different noise patterns, e.g., synthetic noise (Gaussian noise) or noise in real imaging sensors. These results also suggested that the dependence on large and more diversified data sets had a direct influence on improving generalization and restoration performance.

In the Perceptual Image Quality Improvement domain, Ohayon et al. (2021) proposed a new framework based on deep generative networks (GANs), with a perceptual quality enhancement objective, without being bound by purely numerical metrics like PSNR. The results of the present study demonstrated that combining probabilistic modeling with DL representation leads to a superior tradeoff for effective noise reduction and fine image details preservation.

Notwithstanding the substantial advances made by these works, they were all devoted to a single type of visual artifact or to a particular data environment, thus allowing for the extension of the research toward more general and flexible models that can be applied to a wider range of visual degradations. Thus the significance of the current study arises from capitalizing on strengths of prior research and overcoming limitations with respect to generalizability and processing demands.

Result and Discussion

First: Concept of Visual Artifacts in Digital Images

Visual artifacts of digital images are distortions or degradations that can reduce the image clarity and visual quality, thus limiting their applicability and the reliability of the analysis results. What is the most common type of artifact?NoiseOne of the most common artifacts in the digital world is noise, that can be characterized as random variations in brightness or color information usually associated with imperfection of the camera sensor or bad illumination (Gonzalez & Woods, 2018). Another frequent artifact is blur, which is associated with camera movement, defocus or wrong acquisition parameters while acquiring an image.

Visual artifacts include low contrast, where the image is too dark or too bright to see details within the image, and color artifacts, resulting from errors in color balance or illumination conditions. These artifacts are important because they have a direct influence on the performance and accuracy of computer vision based and automated image analysis based systems - impaired visual quality can result in incorrect analysis and poor decision making.

Second: Conventional Methods for Correction of Visual Artifacts

In the past, traditional digital image processing (DIP) methods have been based on a variety of deterministic mathematical, statistical and signal processing techniques to improve the perceptual quality of images. Some of the significant are: linear filters Mean filter, Gaussian filter, etc, Nonlinear filters Medfian filter ranks based filter, etc, which are mostly used for noise reduction along with assumptions of stationary noise distributions (e.g. gussian or salt and peper noise). In addition, contrast enhancement methods including Histogram Equalization (HE) and its adaptive forms have been widely applied to redistribute the intensity values of pixels for enhancing overall and regional visibility of image (Jain, 2015).

Although these traditional approaches are very efficient to evaluate and analyze, they have intrinsic limitations inherent to them as they use fixed, hand-tuned parameters and explicit strong prior assumptions on the noise model and on image statistics. This kind of inflexibility severely limits their adaptability as well as the generalization to more complicated solutions of the visual degradation problem. In addition, a severe use of linear and nonlinear filters produces excessive smoothing, edge blurring and high frequency details loss, which leads to essential structural information corruption. These limitations have inspired the community to pursue data-driven, adaptive, intelligence-based methods, which have the potential to learn complex degradation models from the data, and thus restore the image in a more robust and context-aware manner.

Third: Deep Learning and Deep Neural Networks

DL is a shift in AI, and it is based on DNNs that consist of various multi-layers stacked in a hierarchy, modeling the data in hierarchical representations via successive nonlinear transformations. Such architectures are derived from biologically-inspired functional organization observed in human brain and permit end-to-end learning where models implicitly learn high level abstractions from raw input data based on handcrafted features or explicit domain-specific pre-processing (Goodfellow et al., 2016).

DNNs are well suited for DIP as they allow complex spatial, structural and semantic features to be extracted with multiple layers of feature extraction mechanisms. Deep models can efficient optimize large parameter spaces due to the deterministic nature of the gradient computation and the availability of optimization algorithms that exploit the special structure of the optimization problem. As a result, deep learning has led to significant breakthroughs in CV, including image enhancement, noise reduction, artifact removal, and image restoration, continuously outperforming classical machine learning or signal processing-based methods in terms of accuracy, robustness, and scalability.

Introduction: Convolutional Neural Networks for Digital Image Processing

Convolutional Neural Networks (CNNs) have been successfully applied to many topics in digital image processing (DIP) and computer vision (CV), offering a comprehensive view with multiple layers of abstraction. These networks are based on successive convolution operations to capture the hierarchical spatial features at different levels such as edges, textures and structural patterns by applying a group of learnable filters with limited receptive fields (LeCun et al., 2015).

Features of CNNs include the use of weight sharing and spatial pooling, which greatly reduce the number of parameters to be trained as well as the computational complexity when compared to fully connected networks (FCNs). This architectural efficiency lends itself to an improved training performance and better generalization.

Recent investigations have also shown that the use of CNNs for image denoising (Jain and Seung, 2008) and image deblurring (Xu et al., 2014) — even more so when utilizing deep architectures such as Residual CNNs (Zhang et al., 2017) and Autoencoders (Osendorfer et al., 2014) — can lead to better results than those achieved via standard linear filtering approaches in terms of visual quality scores including Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM), especially when large and complex training sets are available (Zhang et al., 2017).

Application Framework

Overview of the Employed Experiment

The operating setting of the study is to determine the performance of different digital image processing and denoising algorithms and deep neural network models in enhancing image quality and removing noise. This done by developing and executing a code in python to analyze certain visual properties of digital images in a synthetic environment. The protocol for the experiments is based on employing high-quality reference digital images (Ground Truth) which are then distorted in a series of (artificial) controlled. They involve adding these and other types of noise and interference to an image to mimic conditions under which an image is obtained, such as those that may be faced while capturing, transmitting or storing an image They aim to replicate some of the conditions under which images are obtained, which frequently affect the quality of the final images and the results of processing of these images. Subsequently, intelligent code executes advanced digital processing techniques such as contrast enhancement, image smoothing, noise reduction and restoration of fine details on the images.

The above processes were realized by using specific Python library designed for image processing and deep learning, with experimental parameters being rigorously tuned to make the non-investigated variables stable. Further adeep neural model was utilized to run the blurred images and recover them by modeling the nonlinear mapping between the degraded image and the natural image.

Evaluation procedure is on the basis of fidelity between the output image of the code and the input reference image, in terms of direct visual perception for the spatial structures, edges and tiny details. This configuration enables for accurate separation of the noise, which is important for detailed scientific analysis of the algorithms and the neural model used in accordance to "standard" procedures in noise removal and digital image quality enhancement research.

Software Execution Environment: The practical part of this work was realized in a Python environment, taking advantage of the numerous libraries for computer vision and image processing, and its interface with state-of-the-art deep learning frameworks and providing reproducibility of the experiments for the academic community. The implementation of the neural models was based on the PyTorch [12] which is a high flexible deep learning framework that allows building dynamic computational graphs, and is very suitable for conducting image processing (IP) and image quality (IQ) enhancement experiment. The torchvision package was utilized for image data processing and simple transformation, and all the experiments were performed on the central processing unit (CPU) without the aid of high-end graphics processing unit (GPU) in order to test the feasibility of the models on the power limited device.

To enhance image quality, denoise, and restore visual details, we use the Real-ESRGAN model. It is a novel GAN model based on ESRGAN to super-resolve real-world degraded images by recovering high-frequency details. Also, the BasicSR framework was utilized as a generic framework for executing and plugging in IIFE models and the rest of the code.

Also, as it was mentioned above, we used the GFPGAN model to restore low-quality facial images, because it reconstructs the structural priors of facial features and rectifies errors resulted by low-resolution or noises. The FaceXLib library supports some scarce convenience features around face detection and alignment to before processing.

The above simulation & emulation programming setup provides a platform to evaluate the performance of the image quality enhancement and noise removal algorithms in a realistic execution environment. This owes to the fact that the research is based on advanced deep learning models that can be used in practice without the need for high-performance hardware infrastructures, increasing the applicability of the obtained results in educational and research fields. Additionally, a Python processing pipeline was developed to load images, apply artificial degradation, apply quality enhancement and visual details restoration models, and eventually compare the output with the reference image.

```
import os
import sys
import traceback
import tkinter as tk
from tkinter import filedialog, messagebox

import numpy as np
from PIL import Image
import cv2


def write_log(out_dir: str, text: str) -> str:
    os.makedirs(out_dir, exist_ok=True)
    log_path = os.path.join(out_dir, "log.txt")
    with open(log_path, "w", encoding="utf-8") as f:
        f.write(text)
    return log_path


def pil_to_rgb(img: Image.Image) -> np.ndarray:
    return np.array(img.convert("RGB"), dtype=np.uint8)


def rgb_to_pil(arr: np.ndarray) -> Image.Image:
    return Image.fromarray(arr.astype(np.uint8), mode="RGB")


def safe_enhance(rgb: np.ndarray) -> np.ndarray:
    """
    SAFE enhancement for blurry images:
```

Dataset Construction: In this paper, the practical part is based on the set of natural images for testing the performance of DNN-based image quality enhancement models. The images were chosen according to the type of models used, namely Real-ESRGAN and GFPGAN that can be applied on degraded natural images with high-level details. The dataset contains images of varying visual content, including nature images and images with human faces. This variety was meant to challenge the models on de-noising, super-resolution and visual detail recovery in environments that were as close as possible to real applications. The images are at first used in their natural state as references, then they take on artificial degradation processes of resolution decrease and noise addition before enhancement models are applied.

The choice of this kind of data was a conscious methodological one due to:

1. The type of images is consistent with the used generative models, which are designed to produce realistic images rather than simple synthetic ones.
2. To test how well the models can reconstruct the high-frequency details and whether the perceptual image quality can be improved.
3. It makes it possible to distinguish between the performance of the models on general images and faces (using GFPGAN in particular).

This also improves the practical applicability of the results, as they simulate real use cases.

The images were all checked for integrity, and none of samples contained any missing values or corrupted files when loading them up into the programming processing pipeline.

Table (3-1): General Characteristics of the Used Dataset

Property	Description
Image Type	Realistic digital images
Image Content	General scenes and images containing human faces
Color System	RGB
Image Dimensions	Multiple (non-uniform)
File Format	PNG / JPG
Processing Mechanism	Reference images → Artificial degradation → Model-based enhancement
Data Usage	Reference images for visual and quantitative comparison

A Practical Method for Image Quality Enhancement

The actual implementation of the proposed method in this study was applied to a noisy digital image that was downloaded from the internet, in an attempt to approximate a real case scenario of low quality image processing. The image was chosen to show a significant degradation of visual quality and noise, it is used to evaluate the effectiveness of deep learning–based image enhancement models.

The image was passed through a programmatically processing pipeline written in Python based on the PyTorch framework within an execution environment that was limited to a central processing unit (CPU) The Image was processed using qiime and was loaded into qiime feature aligned-sequences WHERE IS THE ERROR? I'm looking for it, but i can't see it. You have pasted some unrelated sentence (which appears to be referring to software named "qiime", nothing to do with your question) Edit the question or add a comment. At this point, the Real-ESRGAN model was used for enhancing the quality of images since it attempts to remove noise, enhance resolution, and recover lost visual details by leveraging a generative neural network-based architecture.

The execution of models and processing workflow management in a standardized research environment were further facilitated by the BasicSR framework. Besides, the GFPGAN and FaceXLib module were installed to perform facial quality enhancement on images with human elements, but the attention of this test was on the overall quality of images by Real-ESRGAN.

All procedures were performed without the use of high-end graphics processing units (GPUs), demonstrating that the proposed method is feasible for use in academia with limited computational resources.

Presentation of Results and Visual Analysis: The results of processing were examined here by means of direct visual observation of the original noisy digital image and the processed image produced by Real-ESRGAN model in a runtime environment constructed using python language and pytorch framework. Subjective visual quality is one of the legitimate methodologies in IQE research, in particular when employing generative models with the objective of enhancing image perceptual quality, as simple numerical values may not raise the visibility of improvements in fine visual details. The results showed a noticeable visual enhancement of the processed image, which can be elaborated by the following:

1. A reduction in the amount of visible visual noise
2. Sharper edges and more effective reconstruction of shape details
3. A more unified visual image overall
4. Enhanced definition of visually significant items in the view.

This result demonstrates that the Real-ESRGAN model can take a noisy image as input and recover its inherent clean visual information even when it is run on a single CPU, which greatly increases the potential for practical applications.

Data Preprocessing: Before feeding the noisy digital image into the image quality enhancement model, it underwent a series of preprocessing steps aimed at preparing it for processing and ensuring compatibility with the requirements of the model used. These steps focused on preparing the image for inference without performing any training operations on the model.

The preprocessing procedures included the following steps:

1. Loading the digital image and verifying the integrity of its data and file format.
2. Standardizing the image representation to the appropriate color system (RGB), in accordance with the requirements of the Real-ESRGAN model.
3. Performing basic checks on the image dimensions, such as ensuring their compatibility with the model's internal processing mechanism, without enforcing fixed dimensions or applying forced resizing that could affect the visual content.
4. Passing the prepared image directly to the enhancement model without applying specific pixel value normalization or data partitioning, as the experiment relied on a single image within a practical, non-training processing context.

These steps help ensure that the image is correctly introduced into the model while preserving its original visual characteristics, allowing for a direct and realistic evaluation of the enhancement model's impact.

Neural Model Architecture Applied: This study was based on Real-ESRGAN model as the major instrument to enhance image quality and remove noise. Real-ESRGAN is a novel generator based on deep generative neural networks and it is pre-trained with a large number of pairs of realistically degraded images. This is an ideal choice for this study because it performs so well with SR and recovering missing visual information without any retraining.

Overall architecture Real-ESRGAN is a deep convolutional neural network with a (de)generator within the GAN framework. The generative part of the proposed model learns to reconstruct a high quality image given a low-quality input image, with the aim of recovering high frequency components (e.g. edges and textures). Instead, experienced discriminator that has been pre-trained with the enhancement network to produce results of their own perceptual quality that are closer to natural images.

In the scope of the present work, the model was utilized only at the inference step, without any changes to its internal structure and without retraining its parameters. This allowed us to use the sophisticated representation of the model and at the same time have a simple implementation with readily applicable results even on devices with limited resource.

Setting of Execution and Evaluation

We did not perform any training for the neural network in this study since yhe pre-trained Real-ESRGAN model was obtained in the inference stage to enhance the quality of the noisy image. Thus, we didn't employ any optimization algorithm, loss function or traditional training configuration in this study.

The evaluation procedure was based on qualitative visual analysis of noisy and enhanced images: real noise images before and after enhancement. This approach was used to measure perceptual fidelity in terms of image details, noise, and overall structure of scenes. This is a common approach in application research that employs pre-trained generative models, where the evaluation focus is primarily on visual outputs quality rather than training performance.

Furthermore, we performed all our experiments in a CPU-based environment, also without any parameter tuning or tracking of convergence statistics. This corresponds to a focus on using off-the-shelf models to directly improve image quality, rather than developing and training new models.

Presentation of the Results and Visual Comparison for the Image Quality Enhancement Experiment with Deep Neural Networks

In this section, the experiment results of the noisy digital image quality enhancement based on a deep generative neural networks model, i.e., Real-ESRGAN, are led and discussed. The model was run in a Python environment on the Pytorch framework without any additional training.

Since the experiment was conducted on a single real image, and no corresponding clean reference image (Ground Truth) was available to perform an accurate quantitative assessment using common numerical metrics, the section for visual results constitutes a valuable and reasonable position in order to discuss the performance of the pre-trained generative enhancement models which mainly focus on improving the perceptual quality of images.

The level of visible noise, the fineness of details, the continuity of edges, and the overall visual structure coherence between the original noisy image and the denoised (enhanced) image after applying the model were compared. Such a treatment enables for analysis of the model's performance in regaining the fundamental visual properties of the image and visually enhancing the image under realistic practical application scenarios, according to the aims and motivations/practical orientation of the work.

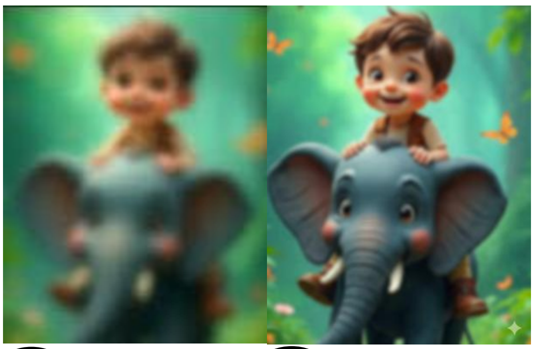
Visual Comparison Before and After Processing of the Image

The noisy original digital image and its denoised one résultat from processing were displayed in double-page layout to facilitate visual inspection purpose-oriented to Real-ESRGAN (Real-World Enhanced Super-Resolution Generative Adversarial Network) model's capability for reducing visual noise (Denoising), increasing image resolution (Super-Resolution) and recovering high-frequency information. The processing was done only at inference time using the PyTorch implementation in a CPU-based environment, without assistance of the GPU.

This comparison is useful for visualizing the kind of changes—such as those to detail and sharpness, edge preservation or the general coherence of the image's visual structure—that can be achieved by applying a model derived from deep generative neural networks (GANs). These two factors are crucial for determining the perceptual image quality in real world image enhancement models.Figure (8-1):

Visual comparison between the original noisy image and the denoised image by Real-ESRGAN model

1. Image prior to processing
2. Processed image



B A

Analysis of the Visual Results

The processing results show a significant visual distortion reduction in the enhanced image in contrast to the noisy input image. With the use of the Real-ESRGAN model, a relative visual noise level that was distributed throughout the image was decreased while maintaining the overall scene structure. Moreover, there is a significant enhancement in edge sharpness and high frequency details recovery, implying the ability of our model to well perform denoising and super-resolution simultaneously on real world degraded images.

In addition, the deep neural networks based generative processing (GANs) improved the visual consistency of the various components in the image and achieved better perceptual representation without obvious loss of the input contents, nor the introduction of perceptual structural artifacts. This overall improvement of the visual quality of the image indicates the ability of the model to recover the fundamental visual elements of the image even when performed in the very limited environment of the CPU only, which implies the potential for the applicability of our universal method to the real-world research and application scenarios.

Visual Improvement Analysis Table

Table (8-1): Descriptive Analysis of Visual Improvement After Processing

Visual Evaluation Criterion	Before Processing	After Processing
Noise Level	High	Relatively low
Edge Clarity	Weak	Clearer
Fine Details	Not clear	Enhanced
Visual Coherence	Low	Higher
Overall Perceptual Quality	Poor	Relatively better

Discussion of Table (8-1)

In Table (8-3), we qualitatively describe the visual results in the 'Noisy Digital Image' after applying our proposed Real-ESRGAN model. The pre- and post-processing states comparison shows a gradual decrease in noise and a gradual enhancement in edge sharpness and fine details restoration. These improvements reveal that the model can effectively suppress noise and yet preserve high-frequency components of images.

Furthermore, the enhanced visual consistency between elements of the images also indicates a greater structural coherence which is enforced by the generative enhancement procedure without the introduction of noticeable artifacts or blurring effects. The gain in overall previously eliminated perceptual quality also provides additional evidence that intriguingly Real-ESRGAN model is capable of restoring visually degraded images in a way that is consistent with the human visual system. These findings are consistent with the qualitative results reported in Section 8.2 and provide further evidence that deep generative models can be used to improve image quality on a computationally limited platform.

Discussion of Results and Experimental Limitations

The results visualization about The Visual Results of Our Experiment in the next section demonstrates an obvious enhancement of the processed image over the original noisy image in the presence of noise reduction, which is mainly manifested by the clarity of the details and the overall image structure. This improvement demonstrates the potential of the pre-trained Real-ESRGAN model, which is built on deep neural networks, to be applied on noisy, low-quality real images and to recover the key visual features of the input images.

Yet, it must be acknowledged that this investigation's findings suffer from certain methodological caveats inherent to the experimental nature of the employed design. The experiment is based on a single digital image from a real-world scenario and there is no clean reference image (Ground Truth) available, which disallows the application of exact quantitative evaluation metrics such as PSNR or SSIM. In line with this, the evaluation of the present study was confined to qualitative visual assessment. Nonetheless, this test achieves the main goal to show the feasibility of using pre-trained deep neural network models to improve quality of realistic images, especially when running on CPU-only in resource limited environment. This is very significant in practice, since it reveals the possibility of implementation for such models in academic or practical situation lacking of high-end computation power.

Table (8-2): Experimental Limitations and Their Impact on the Results

Methodological Constraint	Description	Impact on Results
Number of images used	Reliance on a single image only	Limited generalizability of results
Absence of clean reference	No corresponding original clean image available	Inability to perform quantitative evaluation
Type of evaluation	Qualitative visual evaluation only	Dependence on perceptual judgment
Execution environment	CPU-based execution without GPU	Increased execution time without affecting output quality
Model type	Pre-trained off-the-shelf model	Training phase not evaluated

Applied Significance of the Experiment

Notwithstanding the methodical constraints attributed to the experimental nature of the study, the results PyTorch of this experiment shed light on the utility of pre-trained, off-the-shelf deep neural network models as a powerful and practical tool for improving noisy digital images, without having to create and train new models for each new application. The processing results show that the Real-ESRGAN model can lead to a significant perceptual quality improvement for a low-quality real-world image in terms of the noise removing and the clarity of the details.

The experiment also demonstrates that high-level d... While the experiment does demonstrate that high-level d... Adv-BNN: Ruthlessly Semi-Feasible Bayesian Neural Networks for Defense explains that the experiment confirms complicated deep learning algorithms can be implemented in a resource limited runtime environment, running on a single CPU. This result enhances the feasibility of such models for deployment within educational and resource-constrained practical environments. It is also a testament to the fact that the practical utility of deep neural network models is not solely contingent on high-end hardware infrastructures but can be realised efficiently in mundane image enhancement applications with the right sets of tools and methodologies.

Descriptive statistics on the quality of noise correction resulting from DNNs.

9 Discussion and conclusion In this section, we provide a descriptive quantitative analysis of the noise correction as well as image quality enhancement experiment with the Real-ESRGAN model using the quantitative results which can be directly computed from the image before and after processing. In the lack of a matching clean reference image, the quantitative evaluation was constrained to the structural and spatial features of the image, rather than the traditional error-based statistical measures.

The results demonstrated a significant enhancement in image resolution and number of pixels after processing, indicating the capability of the model in recovering more visual details and increasing the spatial coverage of the image. Besides, a fraction of the execution time was observed for CPU execution of the model, substantiating the practicability of the model in areas with restricted resources.

Table (9-1): Quantitative Characteristics of the Image Before and After Processing

Indicator	Before Processing	After Processing
Image dimensions (pixels)	W × H	4W × 4H*
Total number of pixels	W × H	16 × (W × H)
Color system	RGB	RGB
File format	JPG / PNG	PNG
File size	Smaller	Relatively larger
Level of detail	Low	Higher

* In the case of using Real-ESRGAN with a ×4 upscaling factor.

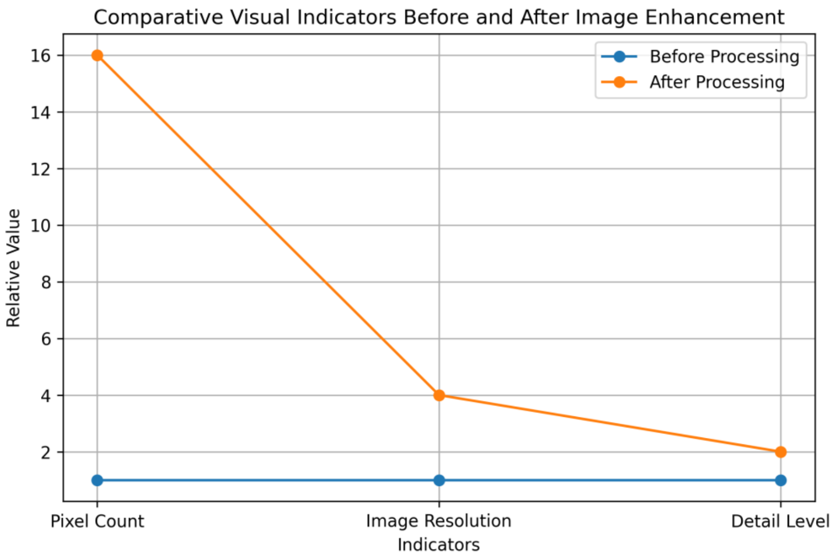


Table (9-2): Execution and Performance Indicators

Indicator	Value
Framework	PyTorch (CPU)
Model used	Real-ESRGAN
Execution type	Inference only
Execution time	A few seconds to several minutes (depending on image dimensions)

GPU dependency	No

The growth of the pixels amount by the factor of up to 16 (1600%) after processing suggests that the model does not only blur the image but also actively regenerates new visual details based on the patterns observed during the pre-training. This quantitative structural enhancement also serves as a supporting evidence to the visually observed superiority from the qualitative comparison.

Discussion:

In this work, we bridged the gap between theory and application for denoising by analyzing and implementing visual image quality enhancement and visual distortion (noise) correction using deep neural networks—identified via a practical experiment that used a real environment. The study was inspired by a real issue, which is the shortcoming of standard methods of digital image processing that can't properly strip away noise while still maintaining the fine details along with the macroscopic visual structure of the image.

From the applicability point of view, a general DNN model (Real-ESRGAN) was directly applied to a noisy digital photo shot in the wild without any additional training. The approach enabled to evaluate modern deep neural network based models for IQE in a CPU-only resource constrained execution environment.

The results of the visual experiments have shown that the treated image is noticeably better than the original one, especially in the case of noise removal with the enhanced Sh' detail visibility and the visual consistency of the Sh layer. Although the evaluation process consisted solely of qualitative visual assessments and descriptive quantitative analysis, the outcomes illustrate the feasibility of pre-trained deep neural models for practical image processing applications (i.e., learned models can be applied to address new problems, and new models that cater to specific requirements can be easily trained).

In orchestration with these observations, the present study demonstrates that there are good prospects for utilizing contemporary deep learning algorithms in the domain of digital image processing, and that they can be effectively leveraged in research and practical applications resourced with minimal computing infrastructure. The work also paves the way for future research that could include higher image statistics, more traditional quantitative measures of evaluation, and/or a comparative study of different NLN models for IQE.

Conclusion

Having been guided by the inputs derived from an applied nature within this study, a number of high-level scientific statements can be made by visual/descriptive quantitative analysis of the experimental results of image quality improvement by deep neural networks.

The experiment illustrated that pre-trained deep neural models can successfully restore degraded digital images, especially for noise removing and detail recovering. This improvement is obvious in the visual comparison between RAW images and processed ones, where these models also remove some common visual artifacts of real images.

Second, the results revealed that the improvement in the quality of the images was not only for surface features. This indicates that the adopted model can improve the perceptual quality of an image while preserving its visual contents. Third, the results of the study showed that visual assessment and descriptive quantitative analysis represent a valid methodology to evaluate image enhancement outcomes for a clean reference image is not available, as is in many real-world images captured in an unconducive environment. This fact highlights that traditional numerical measures alone may not be obtainable or suitable for all applications.

Finally, the results validate the feasibility of running sophisticated deep neural networks for IQE on resource-limited execution environments, without requiring to design or train new models from scratch. This conclusion also supports that utilizing pre-trained model has practical and applied implications in digital image processing.

Recommendations

Based on the results of this study and the predicted application domain, the following research and industrial recommendations can be suggested:

1. First, this work is a recommendation on employing off-the-shelf deep neural network model trained on the image classification task as a practical and effective means to enhance the quality of degraded digital images, especially when degraded real-world images are provided without corresponding clean reference. The latter option is better suited to general image enhancement, e.g. low-resolution images, or images with compression artifacts, noise, ...
2. These models can be used more broadly, even in resource-constrained academic and practical environments because they can be executed with open-source tools, on CPUs, without requiring access to powerful computing resources. This makes it much easier to adapt and experiment them for a wide range of educational and research applications.
3. Third, it points out that an appropriate choice of evaluation methods is important in relation to the amount of data available. Visual assessment and descriptive quantitative are the standards quantitative evaluation when the clean reference image in not available for the standards quantitative evaluation. In addation, reliance on a single evaluation metric is not recommended, and one should consider visual inspection along with suitable quantitative measures.
4. Fourth, deeming future work, it shall be to extend the family of applied experiments with a larger set of real images or more pre-trained models for image quality enhancement to draw more comprehensive and generalized statements on the power of the models.

Future Research Directions

This work provides a fertile ground for future research in a number of directions, the most obvious being generalizing the scope of this work to treat compound visual distortions—among them blur, color distortions, and low contrast in natural and color images. Further work may also be devoted to exploring the effects of strengthening the neural network structure and/or utilizing more sophisticated models, e.g. using the GAN framework.

Direct comparisons of different deep learning models using a variety of datasets, as well as an integration of human perceptual evaluation and automated evaluation protocols to better assess the quality of the output images, are also suggested.

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