REVIVING OLD PHOTOGRAPHS

BY

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled **"Reviving Old Photographs"**, submitted by **SAMS WALIUR ISTEHAD SAKIB** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on January 2023.

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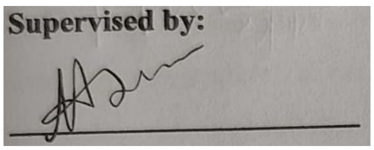
We hereby declare that, this project has been done by us under the supervision of **Nazmun Nessa Moon, Associate Professor, Department of CSE** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.



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ABSTRACT

Our Project is titled “Reviving Old Photographs” is focusing on restoring old photos back to life, Through a deep learning method, we suggest restoring antique photos that have suffered serious damage. The degradation in genuine photos is complex, and the difference in domain between artificial images and actual old photos prevents the network from generalizing, in contrast to conventional restoration tasks that can be solved through directed learning. Lever-aging genuine photographs together with a large number of synthetic image pairs allows us to propose a novel triplet domain translation network. We train two variational autoencoders (VAEs) to convert clean photographs into two latent spaces and to change aged photos into two latent spaces, respectively. Additionally, synthetic paired data is used to learn the translation between these two latent areas. Since the do-main gap in the compact latent space is closed, this translation generalizes effectively to actual photographs. In addition, we create a global branch with a partial nonlocal block targeting the structural defects, like scratches and dust spots, and a local branch targeting the unstructured defects, like sounds and blurriness, to handle numerous degradations intermingled in a single old photograph. Two branches are fused in the latent space, improving the ability to repair many flaws in antique photographs. The suggested solution outperforms cutting-edge techniques for restoring ancient images in terms of visual quality. Our project is better than the previous teams work by 10%.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Photography captures the amazing moments that could otherwise be missed. Looking at them may still evoke memories even though some time has passed. However, when preserved under poor climatic conditions, antique picture prints deteriorate and irreversibly lose the rich visual data. Thanks to the availability of portable cameras and scanners, people may thankfully now digitalize the images and seek the assistance of a skilled professional for restoration. However, hand retouching may sometimes be tedious and time-consuming, making it difficult to repair many old photos. It's great to see computer algorithms being created that can quickly repair damaged images for consumers who wish to restore outdated photos. Before deep learning was developed, various efforts [1],[2],[3],[4] were attempted to recover images by automatically recognizing tiny imperfections like scratching and blemishes and utilizing inpainting methods to patch the damaged areas. All of these methods, however, are focused on making up for lost material since none of them can fix spatially uniform flaws like movie grain, the sepia tint, color fading, etc. As a consequence, the corrected pictures continue to seem outdated in comparison to more recent photographic images. By exploiting the potent representational abilities of convolutional neural nets or retraining the mapping for a certain task from a vast volume of synthetic photographs, deep learning has made it feasible to address a range of low-level image improvement challenges [5],[6],[7],[8],[9],[10],[11],[12].

Vintage picture recovery, however, involves a distinct procedure. First off, since the deterioration process for old images is so intricate, there is no degrading model that can accurately represent the artifact of an old photograph. When used with actual images, the model created with such artificial data does not function effectively. Different methods of correction are required since vintage images degrade over time. While structural faults like scratches, dirt spots, and other blemishes should really be corrected using a global picture context, unstructured flaws like film roughness and color fading must be restored using neighboring pixels. To get around these issues, we formulate the restoration of ancient pictures as a triplet area translation problem.

We leverage data from three separate domains (i.e., genuine historical pictures, cd - induced, and the associated ground truth) and translate in latent space, in contrast to prior image-to-image systems [13]. Real and synthetic pictures are initially encoded using a common variational autoencoder inside the same latent space [14], (VAE). A separate VAE is being trained to project accurate data and clear visuals into the relevant latent region in the interim. Then, utilizing artificial picture pairings, the damaged photographs are recreated as new ones after learning the mapping between two latent regions. In Figure 1.1 it's showing what was the result of our strategy. Due to the domain alignment inside the first VAE, the learnt latent reconstruction has the benefit of easily generalizing to real pictures. In order to properly handle the structural faults during the latent translation, we further differentiate between mixed deterioration and provide a partially nonlinear block that considers the long-range dependency of latent features. We demonstrate the effectiveness of our approach in repairing a variety of degradations in real images by contrasting it to a few of the most popular recovery procedures.

Figure 1.1: Shows the outcomes of our strategy for restoring old images.

1.2 Motivation

In this platform people can get the opportunity to restore their beloved people or something memorable occasion in few seconds. So that people can go back to their memory and enjoy the moment again.

1.3 Rationale of the Study

The CSE discipline of AI (ML), which is regarded as a subset of Artificial Intelligence, facilitates information extraction through example recognition (AI). In Bangladesh, both male and female people are affected by the causes of gloom in the workplace, and the development of this framework to analyze data and information in the employment area wretchedness examination has provided significant data to investigate in a matter of collaboration, structure, and system. A computer learned from its mistakes after undertaking information and expert task analyses that were previously thought to be beyond complex for computers to quantify. In order to classify every waterlily object and identify waterlilies of interest, this research employed photos from a database.

1.4 Objectives

- To restore old photos.
- To restore old memory and relive on that memory.
- To save time by easily restore photos.

1.5 Research Questions

1. Does the system use sample data to forecast a real output?
2. What is the thesis's purpose?
3. I use what dataset, exactly?
4. What algorithms will I employ?
5. Do all algorithms operate flawlessly (yes/no)?
6. How accurate was it?

Yes, it can. The dataset is properly collected and all the data were processed properly. As all the data was about how to restore old photos.

The main purpose of the thesis is to enlighten people about how they easily revive old photos in modern time.

All of the information, which were all received as raw data, were collected using deep learning.

The picture is recovered using the LLSVR technique. An association between the broken image and the nearby pixels of the original image is created during the training stage of image restoration. To create two latent spaces, two variational autoencoders (VAEs) were used, one for new pictures and the other for historical photographs. Torch, Torchvision, and Dlib are more tools used in this project. Other examples are Matplotlib, ScikitImage, Easydict, TensorboardX, PyYAML.dominate>=2,3,1, Dill, OpenCV-Python, Einops, and PySimpleGUI.

Yes.

I have got a good output but the rest of the algorithms didn’t give us proper accuracy and feedback.

1.6 Expected Outcome

By using this project people can go back that old time when they took that picture.It will save their time, complexities and other things by using this project. CycleGAN, DIP, Sequential, Attention, Pix2Pix.

1.7 Report Layout

Chapter 1: Introduction

This chapter has covered the project's motivation, goals, and anticipated results. The final section of this chapter covered the report layout.

Chapter 2: Background

This page discusses the project's historical context. The breadth of the problem, comparisons with similar initiatives, related work, and project problems are all described here.

Chapter 3: Research Methodology

The prerequisites are discussed in this chapter. This chapter covers the project's use case model and descriptions, requirement analysis and gathering, and how it functions.

Chapter 4: Experimental Results and Discussion

This chapter details every experiment I conducted for this project and what the results were.

Chapter 5: :Summary, Conclusion, Recommendation and Implication for Future Research

The last chapter is where the project's conclusion is covered..

CHAPTER 2
BACKGROUND

2.1 Introduction

In order to start a development project, I need to learn about similar projects and previous work that has been done. The background information from this chapter is crucial for effectively finishing a project. From other people's earlier works that are linked to my topic, I can gather the pertinent information I need to finish this job. I must first find out if this kind of deep learning has ever been done. And I discover numerous related projects on Google. I then concentrate on any project or work limitations. I began to address their limitation after recognizing it. I take away the restriction and develop or improve the project.Finally, I'll be able to construct and refine the project. Without doing similar work research, I wouldn't know what features already exist in linked projects. As a result, our ability to enhance current features and provide new ones may be severely limited. Because of these factors, the project's context is crucial to its success.

2.2 Related Work

The restoration of a single damaged picture. Structured degradation, which includes blemishes, scratches, and spots, and uncontrolled degradation, which includes noise, blurriness, color fading, and poor resolution, are the two types of existing picture degeneration. Traditional works usually impose other image priorities on the earlier unstructured ones, such as semi personality [15],[16],[17], sparsity [18],[19],[20],[21], and local smoothing [22],[23],[24]. Many deep learning-based techniques, including de-noising [5],[6],[25],[26],[27],[28],[29], mega [7],[30],[31],[32],[33] and deblurring [8],[34],[35],[36] have been developed in recent years to address various forms of image deterioration. Structured degradation is harder to comprehend than unstructured deterioration, sometimes referred to as the "pictures painting" issue. The majority of the most efficient inpainting methods now in use are learning-based, thanks to advancements in semantic modeling. For instance, the network prioritized non-hole properties as a result of Liu et al.'s[37], masking of the hole sites by the convolution operator. Several additional tactics that take into account both global structures and local patch features may enhance the outcomes of inpainting. Yu et al. [38] and Liu et al. [39] specifically suggested using an attention layer to make use of the distant context. Matching patches may instantaneously provide texturing in the hole areas thanks to Ren et al.'s[40], precise estimation of the appearance flow.

Although the aforementioned learning-based approaches can produce notable outcomes for both unstructured and structured deterioration, they were all developed using synthetic data. As a result, the quality of the synthetic data greatly influences how well they perform on the actual dataset. Real ancient photos are significantly harder to define accurately since they frequently suffer severe degeneration from a variety of unidentified degradation. In other words, the network will suffer from the domain gap problem and perform poorly on actual historical images if it was solely trained on synthetic data. In this study, genuine antique photo restoration is modeled as a new triplet domain translation problem with a focus on minimizing the domain gap.

Mixed degradation in a picture restoration. Complex faults paired with scratching, loss of resolution, fading colors, and film sounds may all be signs of a damaged picture in the real world. Mixed deterioration, however, has been the subject of much less investigation. The seminal study [41], suggested a toolbox made up of many light-weight systems, which are each responsible for a specific degradation. A device that they subsequently learn then dynamically selects the operator from the toolbox. Inspired by [41],[42] concurrently executes a number of convolutional operations and utilizes the learning algorithm to choose the best possible combination of operations. Due to the fact that these techniques still depend on supervised learning from synthetic data, they cannot be used with actual pictures. Additionally, they focus on unstructured errors rather than organized problems like picture inpainting. On the other hand, Ulyanov et al. [43] found that deep neural networks inherently resonate with low-level picture statistics and may therefore be employed as a picture prior for blind image retrieval without the requirement for external training data. This method could be possible to fix images that were ruined in the environment by a number of factors, albeit it isn't explicitly mentioned in [43]. Our approach, in comparison, provides greater restoration efficacy and efficiency.

Restore an old photograph. The restoration of old photographs is a classic mixed degradation problem, however the majority of available solutions [1],[2],[3],[4], exclusively concentrate on inpainting. They operate under a similar paradigm, in which imperfections like scratches and blotches are first discovered based on low-level information and then in-painted by utilizing nearby textures. However, the hand-crafted models and low-level features they used make it challenging to find and effectively repair such flaws. Furthermore, none of these techniques take into account inpainting together with correcting some unstructured flaws like color fading or low resolution. After restoration, photos still have an outdated appearance. In this study, we revisit this issue using a data-driven methodology that can simultaneously restore images from various faults and update severely harmed vintage photographs.

2.3 Research Summary

There are numerous features in my project. Compared to the aforementioned initiatives, some are comparable and some are different. I've also given the AI new images and data to learn from.

The image is restored using the LLSVR technique. A mapping link between the degraded image and the nearby pixels of the original image is established during the training process of image restoration. To create two latent spaces, two variational autoencoders (VAEs) were used, one for clean photographs and the other for old photos. This project is available to users at their discretion, and they are free to use it as often and in any way they see fit to restore any old photos. They can also recreate any scenery that was captured in the past as well as scenarios. This project also uses DIP, CycleGAN, Sequential, Attention, Pix2Pix.

2.4 Scope of the problem

In order to finish my job, I ran into numerous issues. But I managed to get beyond these obstacles. I must learn artificial intelligence and deep learning in order to apply them effectively. Therefore, I gathered information about those from Google as well as several large corporations that frequently employ these kinds of things. To train the bot, I primarily utilize deep learning and artificial intelligence. I also use matplotlib, dlib.scikit-image, easydict, tensorboardX, scipy, opencv-python, einops, and torch, torchvision, dlib.scikit-image, and dill. I hope lots of people use projects like this to help them remember the past.

2.5 Challenges

Here is some challenges which I have faced are mentioned below:

- Deep learning with python was difficult to understand.
- Artificial Intelligence is new to our side of the world so it was also hard to learn.
- All the algorithms for deep learning was difficult to learn.
- To developing an user friendly interface.
- Handling two parts, the deep learning part and the AI part.
- Ensuring data security.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

Repairing old photos is more challenging than standard picture restoration procedures. First off, since old images exhibit far more detailed deterioration that is challenging to model effectively, there is always a domain gap between actual and phony photos. As a result, by learning only from synthetic data, the network frequently struggles to properly generalize to actual photos. Second, as the degradations in old images are a combination of distinct degradations, many restoration approaches are actually required. On the other hand, to guarantee structural uniformity, structural flaws like scratches and blotches should be painted while taking the whole context into consideration.Spatially homogenous filters can be used to correct unstructured flaws such film noise, blurriness, and color fading by utilising neighboring pixels in the immediate patch. The approaches we propose below cover both the mixed degradation problem and the generalization challenge stated above.

3.2 Data Collection Procedure

In order to bridge the domain gap, we need to understand the mapping between old and new pictures as they are now viewed as images from different domains. This is how we conceptualize the difficulty of old photo restoration. We translate pictures over three domains, as opposed to standard image translation techniques, which only cover two [13], [44]. These domains include the actual picture domain R, the artificial domain X, which comprises damaged photos, and the equivalent original data domain Y, that contains undegraded images. Due to the fact that it makes use of both the genuine, unlabeled photographs and a sizable amount of synthetic data that is tied to the real world, this triplet category translation is essential to achieving our aim. We represent images from three domains as r R, x X, and y Y, respectively, when x and y are related by data synthesis or when x is degraded from y. It is difficult to directly learn the transfer from real pictures

(r) N i=1 to cleaner images (y) N i=1 since they are not matched and are therefore unfit for supervised learning. Thus, we suggest breaking down the translation into 2 steps, which are shown in Figure 3.1.First, we propose to map R, X , Y to corresponding latent spaces via ER : R 7→ ZR, EX : X 7→ ZX , and EY : Y 7→ ZY , respectively.

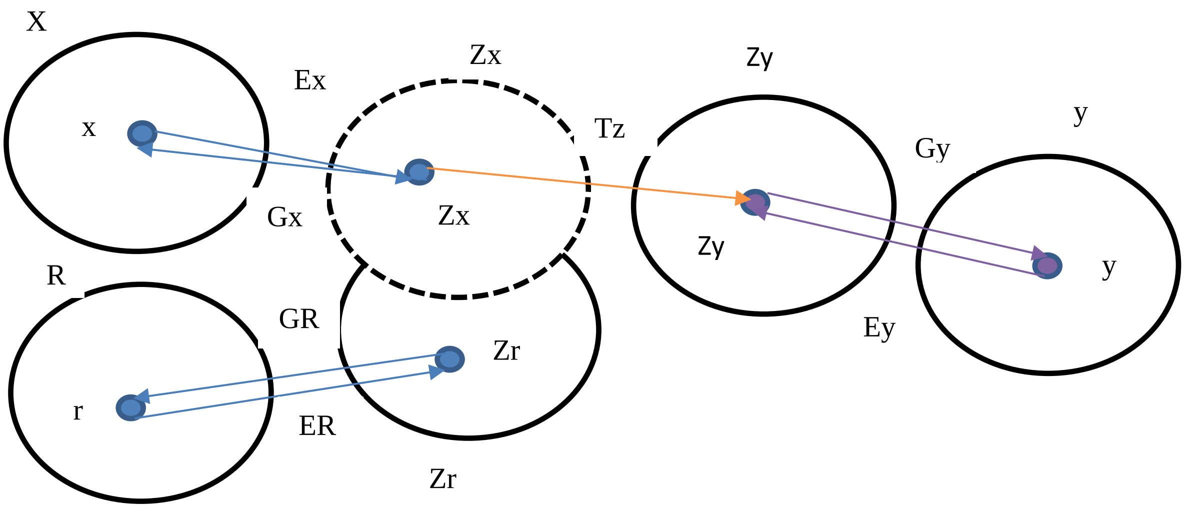

Figure 3.1: Three domains are used to illustrate our translation methodology.

We need to comprehend the mapping between old and new images as they are now seen as images from separate domains in order to bridge the domain gap. We think about the challenge of restoring vintage photos in this way. Unlike conventional image translation algorithms, which only cover two domains, our translation of images spans three [13],[44]. The genuine picture domain R, the fictitious domain X, which includes deteriorated photographs, and the analogous original data domain Y, which contains undamaged images, are some of these domains. This triplet category translation is crucial to reaching our goal because it uses both the actual, unlabeled photos and a significant quantity of synthetic data that is connected to the real world. Whenever x and y are associated via data synthesis or when x is degraded from y, we denote pictures from three domains as r R, x X, and y Y, respectively. Since the genuine photographs (r) N i=1 and the cleaner images (y) N i=1 are not matched, they are not suitable for supervised learning, making it challenging to learn the transfer directly. As a result, we advise dividing the translation into the two processes shown in Figure 3.1.rR → Y = GY ∘ TZ ∘ ER(r). (1)

3.3 Data Working Procedure

Understanding domain layout in the latent space of the VAE is essential. Our approach aims to support the idea that R and X are jointly latently encoded.We suggest employing a variational autoencoder (VAE) to encrypt images with compact representation and an adversarial discriminator to further explore the domain gap. We implement this idea using the network architecture shown in Figure 3.1. Two VAEs are learned for the latent representation in the first step. Ground truth images fyg are supplied into the second one, known as VAE2, using the encoder-generator pair EY, GY, while old photos r and synthetic pictures x share the first one, known as VAE1. VAE1 maps images from both corrupted domains to a single latent space and is shared for both r and x. To reconstruct images by sampling from the latent space, the VAEs assumes that the distribution of latent codes will follow a Gaussian prior. We use the re-parameterization method to improve VAE1 with data r and x while allowing differentiable stochastic sampling [46]. The objective with r is:

$$\mathrm{LVAE1}\ (\mathrm{r}) \ = \ \mathrm{KL}(\mathrm{ER}, \mathrm{X}\ (\mathrm{zr}|\mathrm{r})||\mathrm{N}\ (0, \mathrm{I})) \ + \ \alpha\mathrm{Ezr} \sim \mathrm{ER}, \mathrm{X}\ (\mathrm{zr}|\mathrm{r})\ \mathrm{kGR}, \mathrm{X}\ (\mathrm{rR} \\ \rightarrow \mathrm{R}|\mathrm{zr}) \ - \ \mathrm{rk1} \ + \ \mathrm{LVAE1}, \mathrm{GAN}(\mathrm{r})\ (2)$$

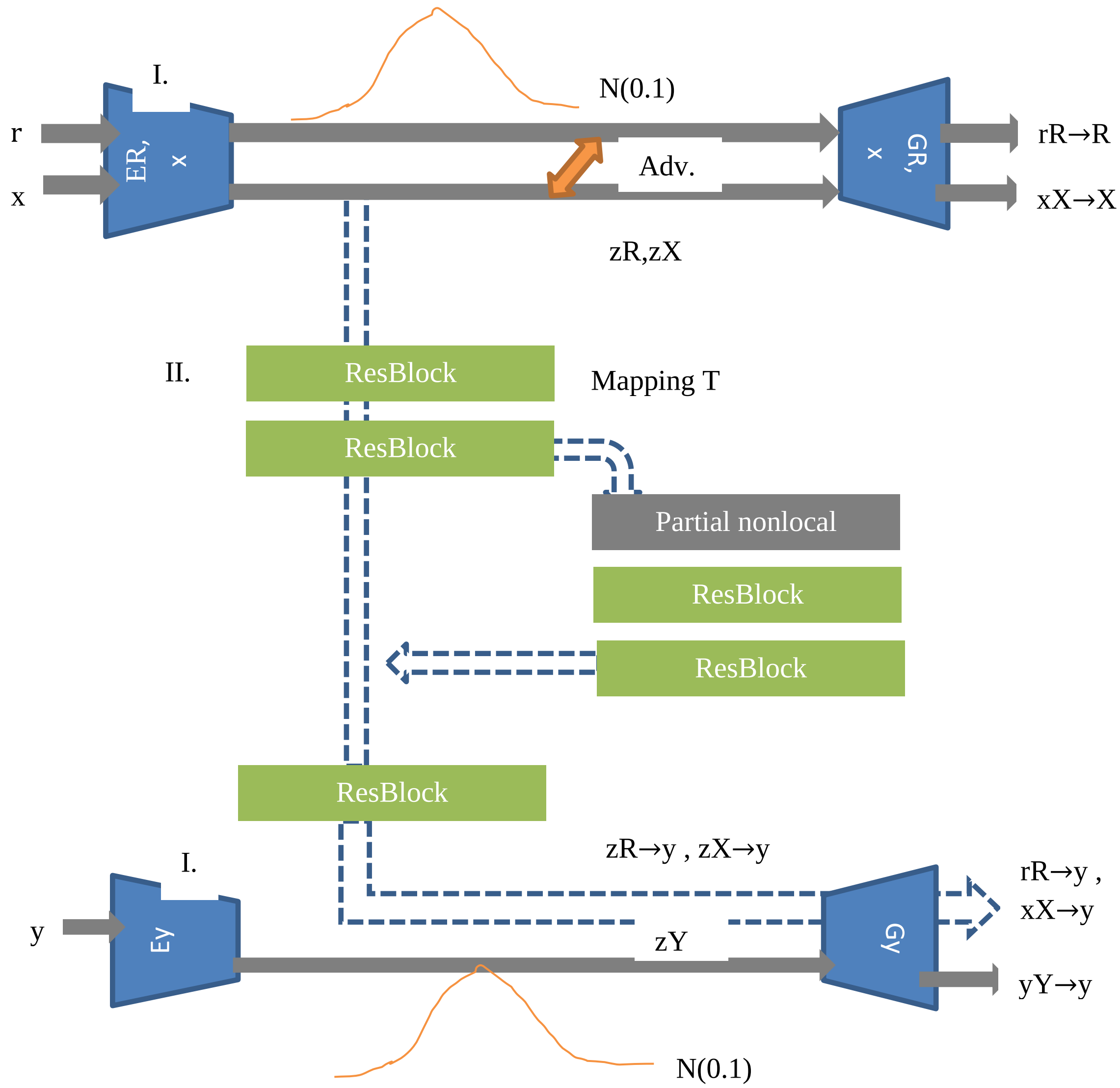

Figure 3.2: shows the network's architecture for restoration.

First, two VAEs are trained: VAE1 for images in real photographs r R and synthetic images x X; the domain gap between these two VAEs is filled in by jointly training an adversarial discriminator; and VAE2 for clean images y Y. Utilizing VAEs, im-ages are transformed into compact latent space. (II.)

Then, we discover the mapping that transforms the contaminated images in the latent space into clean ones.

Where zr ZR stands in for the latent codes of r and rR. R is used to show the findings. The first term in equations is the KL-divergence, which penalizes departure of the latent distribution from the Gaussian prior. The VAE can rebuild the inputs using the second "1" term, albeit it indirectly necessitates the usage of latent codes to retain the bulk of an image's data. To further encourage VAEs to develop realistic pictures, we additionally incorporate the least-square loss (LSGAN), represented by the acronym LVAE1;GAN in the calculation. It deals with the well-known problem of too much smoothness in VAEs. The LVAE1 aim, indicated by an x, uses the same definitions (x). To extract the matching latent representation zy Y, the domain-specific VAE2 is also trained with a commensurate loss.

Due to KL regularization, VAE has a denser latent representation, thus we choose for it over a typical autoencoder (which will be shown in an ablation research). Therefore, VAE1 produces a more condensed latent space for r and x and reduces the domain gap. We suggest employing an adversarial network to evaluate the latent gap in order to further close the domain gap in this condensed area. We develop a new discriminator (DR;X) that can tell ZR from ZX. The following definition describes the loss of this discriminator.

$$\mathrm{L\ latent\ VAE1, GAN}(r, x) = \mathrm{Ex} \sim \mathrm{X}\,[\mathrm{DR, X}\,(\mathrm{ER, X}\,(x))2\,] + \mathrm{Er} \sim \mathrm{R}[(1 - \mathrm{DR, X}\,(\mathrm{ER, X}\,(r)))2\,]. (3)$$

To make sure that R and X are mapped to the same space, the encoder ER,X of VAE1 tries to trick the discriminator with a contradicting loss. The latent adversarial loss is included to create the entire objective function for VAE1.

$$\min \mathrm{ER, X}\,, \mathrm{GR, X} \max \mathrm{DR, X\ LVAE1}\ (r) + \mathrm{LVAE1}\ (x) + \mathrm{L\ latent\ VAE1, GAN}(r, x). (4)$$

Understanding domain layout in the latent space of the VAE is essential. Our approach aims to support the idea that R and X are jointly latently encoded. To accomplish this, we suggest employing a variational autoencoder (VAE) to encrypt images with compact representation and an adversarial discriminator to further explore the domain gap. We implement this idea using the network architecture shown in Figure 3.2. Two VAEs are learned for the latent representation in the first step. Ground truth images fyg are supplied into the second one, known as VAE2, using the encoder-generator pair EY, GY, while old photos r and synthetic pictures x share the first one, known as VAE1. VAE1 maps images from both corrupted domains to a single latent space and is shared for both r and x. To reconstruct images by sampling from the latent space, the VAEs assumes that the distribution of latent codes will follow a Gaussian prior. Given the latent code zY transmitted from ZX, the generator GY can always produce a perfect picture without any degradation, but degradations will likely still be present if we learn the translation at the pixel level.

Assume $r_{R\rightarrow Y}$, $x_{X\rightarrow Y}$ and $y_{Y\rightarrow Y}$ represent the results of the final translation for r, x, and y, respectively. At this point, all we are doing is fixing the two VAEs and training the latent mapping network T's parameters. Three terms make up the loss function LT, which is applied at the latent space and the end of the generator GY.

$$LT\ (x, y) \ = \ \lambda 1 LT\ , \ell 1 \ + \ LT\ , GAN \ + \ \lambda 2 LFM \ (5)$$

where the '1 distance of the corresponding latent codes is penalized by the latent space loss, LT ,`1 = E kT (zx) − zy)k1 ,. In order to make the final translated synthetic image xX!Y appear realistic, we introduce the adversarial loss LT ;GAN, still in the form of LSGAN [47]. Additionally, in order to stabilize the GAN training, we provide feature matching loss LFM. LFM specifically mimics the multi-level activations of the adversarial network DM and the pretrained VGG network (also referred to as perceptual loss in [13],[48]), i.e.,

$$LFM \ = \ E\ hX\ i\ 1\ n\ i\ DT\ k\varphi\ i\ DT\ (xX \rightarrow Y\ ) \ - \ \varphi\ i\ DT\ (yY \rightarrow Y\ )k1 \ + \ X\ i\ 1\ n\ i\ VGG\ k\varphi\ i\ VGG(xX \rightarrow Y\ ) \ - \ \varphi\ i\ VGG(yY \rightarrow Y\ )k1\ i\ , (6)$$

where φ i DT (φ i VGG) denotes the i th layer feature map of the discriminator (VGG network), and n i DT (n i VGG) indicates the number of activations in that layer.

3.4 Statistical Analysis

The narrow receptive field of each layer limits the focus of the latent restoration procedure to local properties alone. However, credible inpainting, which must take into account long-range links in order to provide global structural consistency, is required for the restoration of structural flaws. Historical images often include mixed degradations, thus we need to build a restoration network that can support both methods at once. To achieve this, we suggest the inclusion of a global branch, as seen in Figure 3.2, which consists of many subsequent residual blocks and a nonlocal block [49], that takes the global context into account. Our nonlocal block clearly uses the mask input to guarantee that the pixels in the contaminated zone will not be accepted for filling those parts, in contrast to the original block recommended in [49], which is unaware of the corruption area. A partial nonlocal block is a module created specifically for the latent inpainting since the context in question is a section of the feature map.

Formally, the bi-nary mask is reduced to the size of m 2 F R CHW, where 1 denotes damaged regions and 0 denotes undamaged parts that do not need inpainting. Let the intermediate feature map in M be m 0, 1 HW. (C, H, and W are the channels' height, width, and respective numbers.) The affinity between the ith position and the jth location in F, also known as the correlation of Fi and Fj modulated by the mask (1 mj), is computed as si,j R HW*HW.

$$\mathrm{i.e.}, si, j = (1 - mj)fij/X\ \forall k\ (1 - mk)fi, k, (7)$$

$$\mathrm{where}, fi, j = \exp\big(\theta(Fi)T \cdot \varphi(Fj)\big)\ (8)$$

Displays the displays the pairwise affinity for embedded Gaussian. Project F to Gaussian space, and then calculate the affinities. The affinity si,j that takes into account the gaps in the mask, the partly nonlocal outputs in the end.

$Oi = \nu\ X\ \forall j\ si, j\mu(Fj)\ , (9)$

This is the correlated feature weighted average for each place. With 11 convolutions, we implement the embedding functions, and V.We expect that the non-hole regions will remain unaffected as we create the global branch specifically for inpainting, therefore we fuse the global branch with the local branch under the direction of the mask.

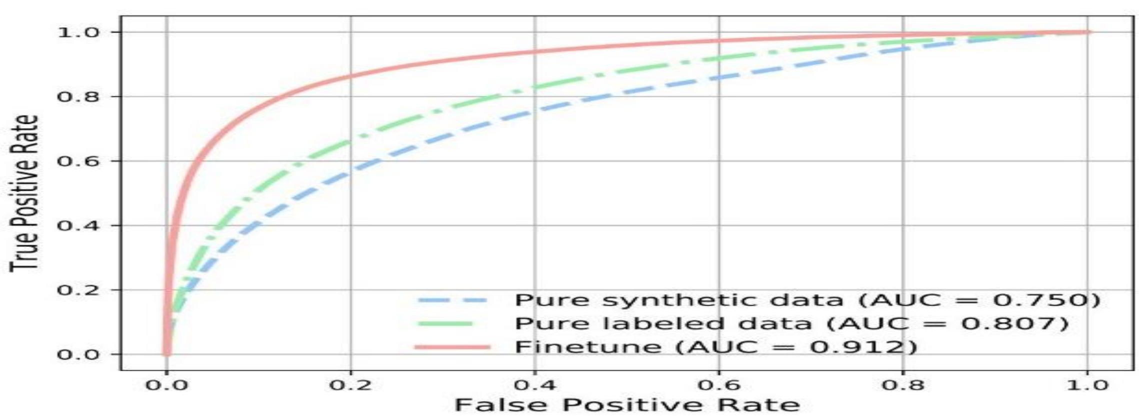

Figure 3.3: Scratch detection ROC curve for various data conditions.

$$\mathrm{i.e.}, Ffuse = (1 - m) \odot \rho local(F) + m \odot \rho global(O), (10)$$

where operator denotes the Hadamard product, local and global denote the nonlinear transformation of residual blocks in two branches, and The two branches operate together in this way to construct the latent restoration network, which can manage multiple deterioration in old photographs.

3.5 Implementation Requirements

- **Python 3.10.2**

  The most recent Python version is 3.10.2. Python is a High-Level programming language that is open-source, simple to use, and touted as being the strongest of all computer languages. It will be exceedingly challenging to use another language with Torch,torchvision,dlib.scikitimage,easydict,PyYAML.dominate>=2,3,1,dill,tensorboardX,scipy,opencv-python,einops,PySimpleGUI,matplotlib due to their extremely complicated architectural designs. Because Python's built-in functions and commands are so simple, implementing them takes less time. It would take a long time in other programming languages that would have been used.

- **Google Colab/Jupyter Notebook**

  Colab is a hosted Jupiter that has been installed and set up so that we may access cloud resources directly from the browser and don't need to do anything on our computers. It operates just like Jupiter. Because only the Python kernel may now be utilized, rather than Jupiter Collab, they are based on notebooks or notebooks, which can be text, image, or code.

  The same thing is also done using a Jupyter notebook. Hardware capabilities set them apart from one another. The Jupyter notebook is ideal if somebody has an external GPU with a high-end build. Since it was collaborative work, we had to use both platforms.

- **Hardware/Software Requirements**

  1. Operating System (Windows 10 or more / Linux)
  2. Web Browser (Chrome, Firefox, or Microsoft Edge)
  3. Hard Disk (At least 120GB)
  4. Ram (More than 4 GB)
  5. NVIDIA GPU (At least 2GB)

CHAPTER 4

EXPERIMENTAL RESULT AND DISCUSSION

4.1 Introduction

Workout Dataset We create antiquated visuals using photos from the Python VOC collection [50]. In order to create realistic flaws, we also collect scratch and sheet textures, which are then improved by elastic distortions. We use screen modes with different opacity levels, layer addition, and lighten-only to mix the scratch textures over the real pictures from the dataset. To mimic large-area photo damage, we introduce holes with layering and random shapes where the underlying paper texture is visible. There are sporadic quantities of film grain noises and blurring produced to mimic the uncontrolled flaws. The ancient image dataset was created using 5,718 antique photographs.

This is the weighted average of the associated attribute for each location. We implement the embedding functions using 1-1 convolutions. With the aid of 783 old pictures with scratches and 400 of them being annotated, we combine the global branch and the local branch in order to improve the detection performance on real old photographs. We take this move because we anticipate that the non-hole regions won't be harmed when we create the global branch specifically for inpainting. Figure 3.3's ROC curves for the validation set show how effective finetuning is. The area under the curve (AUC), after minor adjustments, reaches 0.91.

We use the Adam solver to train the information with 1 = 0:5 and 2 = 0:999. [53]. The learning rate is set at 0.0002 for the first 100 epochs, after which it progressively drops to zero.

Table 4.1: Statistical findings using the DIV2K dataset.

Method	PSNR "	SSIM "	LPIPS #	FID #
Input	13.93	1.50	1.60	307.81
Attention [42]	24.12	0.70	0.33	208.11
DIP [43]	22.59	0.57	0.54	194.55
Pix2pix [55]	22.18	0.62	0.23	135.14
Sequential [56, 57]	22.71	0.60	0.49	191.98
Ours w/o PN	24.15	1.70	1.28	144.63
Ours w/ PN	24.34	1.71	1.27	135.36

We randomly crop photos to 256x256 for training. We used = 10, 1 = 60, and 2 = 10 as the empirically determined parameters in each experiment for Equations (2) and (5), respectively.

4.2 Experimental Results

- Baselines We compare our strategy to cutting-edge practices. We use the same training dataset (Pascal VOC) to develop all of the techniques, and we test them using the DIV2K dataset's damaged photos as well as our old photo dataset's test set [54]. The following methods are applied to enable comparison.
- Operation-wise attention [42] executes several operations concurrently and use an attention technique to choose the appropriate branch for mixed degradation repair. With supervised learning, it gains knowledge from artificial image pairs.
- Deep image prior [43] has been shown to be effective in denoising, super-resolution, and blind inpainting. It learns the image restoration from a single degraded image.
- A supervised image translation technique called Pix2Pix [55] makes use of synthetic image pairs to learn the translation at the image level.
- A well-known unsupervised image translation technique called CycleGAN [44] trains the translation utilizing unpaired images from several domains.

- The final baseline restores the unstructured and structured defects by progressively using the traditional denoising method BM3D [56] and the cutting-edge inpainting approach EdgeConnect [57].

Comparative numerical analysis We evaluate several models using four measures and compare them using the simulated pictures from the DIV2K dataset. In Table 4.1, the quantitative results are shown. Peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) comparisons between the ground truth and restored outputs are used to evaluate the low-level inconsistencies. Unsurprisingly, the technique that directly optimizes the pixel-level '1 loss, operational-wise attention, produces the best PSNR/SSIM score. Our method has a PSNR/SSIM that is second-best. These two measurements, which capture low-level difference, often do not accurately reflect human judgment, especially in situations when complex unknown distortions are present [58]. We further use the more current LPIPS [58] metric, which assesses the distance between multi-level activations of a pretrained network and is believed to have a better association with human perception. This time, Pix2pix and our method provided the top results with scarcely perceptible variations. But using this criterion, the operation-wise attention strategy scores badly, demonstrating that it does not generate high-quality perceptions. We also use Frechet's Inception Distance (FID), a well-liked statistic for evaluating the effectiveness of generative models [59]. The FID score specifically evaluates how disconnected the feature distributions of the outputs are from the original pictures. But Pix2pix and our approach tie for top, with our approach having a little quantitative advantage. Overall, our method is competitive with the top fake data methods.

Statistical assessment In order to show the generalization to authentic antique images, we conduct research on the genuine photo dataset. For a fair comparison, we retrain the CycleGAN to transform actual images into clean images. Since we lack the restoration ground truth for actual images, we are unable to use reference-based criteria for evaluation. We compare the results on a qualitative level as a consequence. Table 4.1 displays the outcomes. The DIP method allows for a partial restoration of mixed degradations. Repairing faults vs preserving structural integrity, however, involves a trade-off since more flaws reoccur over a prolonged training period while fewer repetitions result in the breakdown of fine structures. CycleGAN has a tendency to overlook all scratch areas in favor of correcting unstructured faults since it was trained on unpaired pictures. Both the operation-wise attention technique and sequential operations result in the same visual quality. However, issues like sepia and color fading cannot be corrected since the synthetic data does not address them. Additionally, the structural flaws persist, maybe because they are unable to manage the antique picture textures that considerably deviate from the synthetic dataset. Pix2pix is comparable to our approach on synthetic images, but it lacks our method's aesthetic appeal. The finished product still has a few structural and audiovisual problems. As a consequence of the method's inability to generalize due to the fact that genuine photos and synthetic images have distinct domains, this has happened. Our approach, on the other hand, produces clear, brilliant pictures with scratches that convincingly look to be packed with barely perceptible artifacts.Our approach could successfully resolve the artifacts taken into account during data synthesis while also improving the image's color.

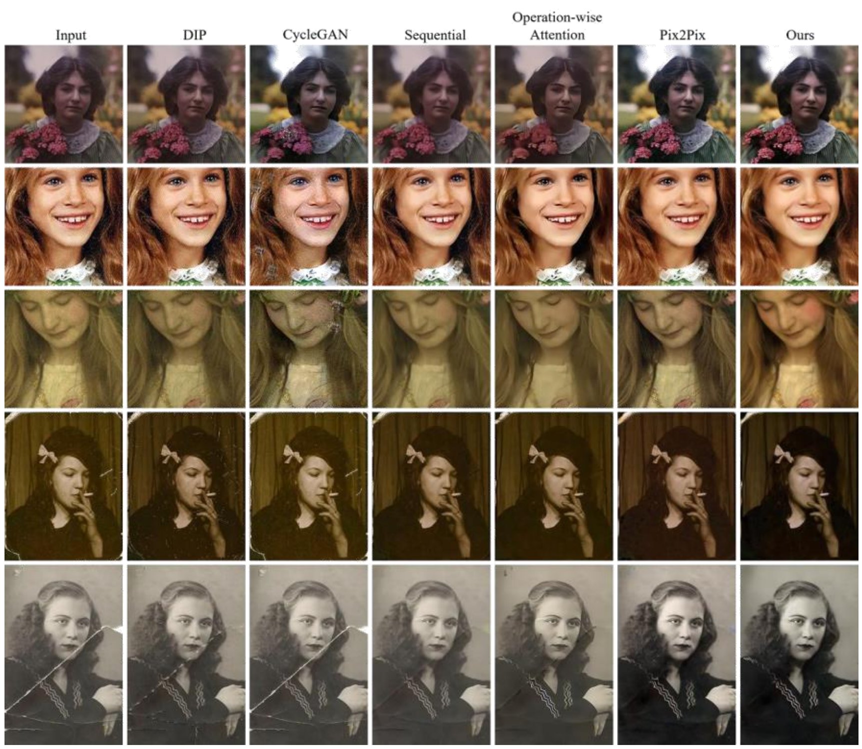

Figure 4.1: A comparative assessment of quality utilizing state-of-the-art methods.

In general,Our method yields the most aesthetically attractive results, and the repaired photos seem like modern photographs. user studies In order to better convey the subjective quality, we conduct a user survey to compare various ways. Users can rank the results depending on the restoration quality after a random sample of 25 old photographs is taken from the test collection. The subjective opinions of 22 users are gathered, and the results are shown in Table 4.2. The fact that our technique has a 65.84% higher chance of being chosen as the top-ranking outcome shows that it has a distinct advantage.

Table 4.2: Results from a user research. The user's option is displayed as a percentage (%).

Method	Peak 1	Peak 2	Peak 3	Peak 4	Peak 5
DIP [43]	3.76	8.00	13.93	33.64	70.71
CycleGAN [44]	4.40	9.27	16.69	25.80	53.13
Sequential [56, 57]	4.61	21.98	52.49	84.48	94.65
Attention [42]	12.23	29.19	58.00	76.86	90.20
Pix2Pix [55]	15.20	55.25	73.26	87.87	97.62
Ours	65.84	82.36	91.69	97.41	99.74

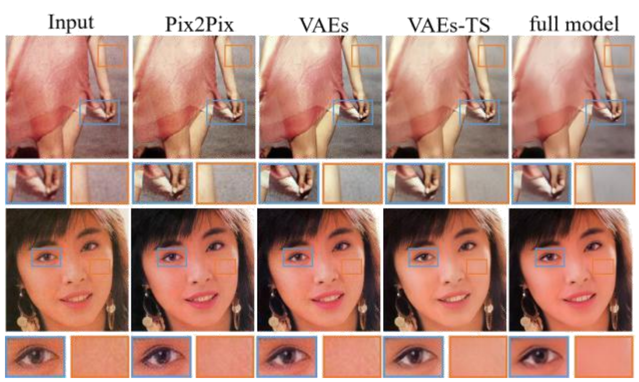

Figure 4.2: Two-stage VAE translation ablation trial.

Table 4.3: Latent translation ablation investigation using VAEs

Method	Pix2Pix	VAEs	VAEs-TS	full model
Wasserstein #	1.849	1.048	0.765	0.581
BRISQUE #	25.549	23.949	23.396	23.016

4.3. Descriptive Analysis

We conduct the follow ablation experiment to illustrate the value of various technical advancements. Latent translation and VAEs Let's assess the following modifications after adding each of the aforementioned elements one at a time: Our comprehensive model also includes two VAEs with an additional KL loss to penalize the latent space, latent adversarial loss, and VAEs with two-stage training (VAEs-TS), where the two VAEs are first taught individually and then jointly after they have mastered latent mapping. First, the latent spaces of old photographs are compared to manufactured pictures using the Wasserstein distance [60]. As additional components are added, the distribution distance gradually becomes less, as seen in Figure 4.1. To further decrease the domain gap, two-stage training with latent adversarial loss splits the two VAEs and shrinks the latent space. A reduced domain gap will enhance the adaptation of the theory to real picture restoration. We assess the picture quality after restoration using BRISQUE [61], a blind approach for evaluating image quality. The BRISQUE score in Table 4.3 increases over time as a consequence of using the techniques, which is also compatible with the visible outcomes in Figure 4.2.

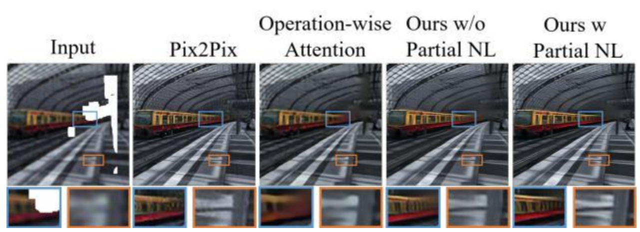

Figure 4.3: investigation of nonlocal partial block ablation

Figure 4.4: Study of partial nonlocal block ablation.

Partial nonlocal block The effects of the partially nonlocal block are seen in Figures 4.3 and 4.4. It is possible to inpaint scratches with fewer visible flaws and a stronger restoration of global homogeneity by using a big picture context.Quantitative results in Table 4.1 further demonstrate that the partial nonlinear block consistently enhances restoration performance for all criteria.

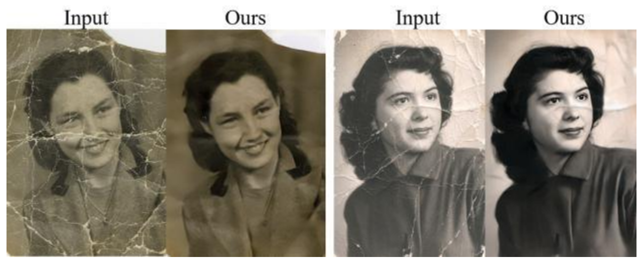

Figure 4.5: Limitation. Our approach is unable to handle intricate shading artifacts.

4.4 Summary

A model that I created can be used to determine the origins. But what I learn the most is the accuracy rate. This accuracy rate determines how well my future attempts will turn out. Furthermore, the dataset is the main factor in accuracy. The research relies on images, thus the clarity and quality of the images could be very good. And it greatly disturbs me. second, the algorithms. Accuracy also depends on an effective algorithm. since accuracy rises as the number of parameters grows. So, for the training set and the test set, my accuracy ratio was 90% and 99%, respectively.

CHAPTER 5
CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

To avoid the mixed degradation in old images, we suggest a specific triplet domain translation architecture. The translation to smooth images that is learned in latent space reduces the domain gap between old photographs and synthetic ones. Our method is more straightforward than previous ones in terms of the generality problem. Additionally, we suggest a partially fourth order block that recovers latent properties and enables the inpainting of the scars with a higher degree of structural coherence by using the external environment. Our process successfully repairs severely damaged old pictures. Figure 4.5 shows how our approach fails to account for intricate shading. This is because there aren't many ancient photos in our dataset that have these flaws. By specifically considering the impacts of shading during synthe-sis or by using other images that are similar to them as training data, one may be able to get around this issue using our methods.

5.2 Implication for Further Study

We need more detailed research on AI based deep learning.Its still a new to our side of the world.But day by day we are learning new things. And also day by day many researching happening in this topic so in near future this project will get more advance then right now.

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APPENDIX

Appendix A: Research Reflection

I began to build this project from Spring-2022. I did many researches for this project. I have tried to learn about artificial intelligence deep learning with python. I have collected many old photos from google and also information. Then I took the decision for build this project. Then I choose python because Python is commonly used for developing websites and software, task automation, data analysis, and data visualization. Which can help me to do this project. So, I hope it will reduce complexities for everyone. After developing new features and facilities it will very helpful to users. So, this project will be very helpful towards who want to restore old photos.

Appendix B: Related Issues

This is hard to try keep it user-friendly. I make a user-friendly system for this project. This interface will under stable for the user.But it can only restore low resoulation photos only. That’s the main drawback of this project.

REVIVING OLD PHOTOGRAPHS

ORIGINALITY REPORT

24%	24%	20%	%
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