ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)

Vol 9, Issue 7, July 2022

Restoring Deteriorated Images using Deep Learning Techniques: Region Filling, Median Filter

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Abstract— ***Image restoration is a technique for recovering images from corrupted images that have blur and noise, lowering the image's quality. Motion blur, low resolution, moisture in the atmosphere, and other factors can all contribute to image noise. For noise removal, there are a variety of restoration techniques and a spatial domain filter. To eliminate blur and scratches in deteriorated photographs, an image restoration method has been developed. Deep learning has gained popularity as a method for image restoration during the last few years. Denoising and other image restoration operations are necessary steps in many image processing applications. Image fusion using the stacked median operator, low resolution detail improvement using guided super sampling, and repeated visual consistency assessment and refining are the three processes in the restoration process. Two VAEs (Variational Autoencoders) are trained in this model to translate old and clean pictures into two latent spaces, respectively. This is due to the fact that they are all using supervised learning, which is a difficulty created by the domain gap between the original image and the ones synthesized for training. The suggested project offers a cost-effective solution that can deal with noise, picture rotations, and occlusions.`.***

Index Terms—About four key words or phrases in alphabetical order, separated by commas

I. INTRODUCTION

Photography has come a long way in its relatively short history. In roughly 200 years, the camera has progressed from a rudimentary box that took fuzzy photos to the high-tech minicomputers seen in today's DSLRs and smartphones. Photographs have a way of bringing our own experiences together and presenting our story in a unique way. Photographs allow us to express our specific and distinct viewpoints on a particular event. A photograph does not tell a single tale; each of us[19] projects our own interpretations based on memories of a certain sensation experienced at the time the photograph was taken.

All silver-based photographic materials deteriorate with time. The silver particles that make up the image are prone to oxidation, which causes the image to yellow and fade. Image degradation can also occur as a result of poor processing. Different print developers will [21] have done a better or worse job with new or old chemicals, resulting in certain prints deteriorating more quickly. In all cases, the print's age is crucial. A clear image from the 1920s with high contrast now appears washed out and lacking in detail.

Colour prints from the 1960s and 1980s have a high rate of deterioration due to the fact that this was a new technique at the time. In reality, while black-and-white images from the 1950s may have held their image better, colour was the way to go. High-quality cameras became the standard after the 1980s, and colour [16]development improved as a result. The prints are still deteriorating, but it is less noticeable than it was with the early colour images. The prints from the 1980s lack the precise focus that your fantastic new SLR camera supplied. It's important remembering that these prints were created over 30 years ago and have a finite lifespan.

The term "image restoration" refers to the process of restoring a deteriorated image. The atmospheric disturbances are the source of image noise. Visually, the noise adds dirty grains to the photograph with varying intensities, which can drastically diminish visual enjoyment and image details in some situations. Several attempts were made prior to the deep learning era to restore images[20] by automatically recognising localised flaws such as scratches and blemishes and filling up the damaged regions with inpainting techniques. When compared to modern photographic images, restored photos still appear ancient since none of these approaches can cure spatially consistent flaws like film grain, sepia effect, colour fading, or other spatially uniform defects. Gaussian noise, Poisson noise, salt and pepper noise, and so on are all examples of noise. Gaussian noise, such as sensor noise caused by low illumination, emerges when a digital image is taken. Dark pixels will appear in bright areas and bright pixels will appear in dark areas in an image with salt and pepper noise. A-to-D converter problems, transmission bit mistakes, and other factors can all contribute to this type of noise. The median filter can almost completely eradicate it. The method of using[18] background information to repair and reconstruct deleted areas of an image is known as image inpainting.

II. LITERATURE REVIEW

Modelling of the deterioration function and application of the inverse process are part of the survey [1]. There are two domains in which this is processed: frequency domain and spatial domain. Blur, noise, illuminations, geometrical degradations, and other sorts of degradations can be found in nature. This picture restoration study began in the[22] 1950s with astronomical imaging, when scientists from the United States and the Soviet Union collaborated to create photos of the Earth and solar system.

Resolution, an important technical indicator, can be used to define the level of picture observation. Image resolution [2] refers to the density at which pixels are shown. More pixels are presented per inch of screen or paper with high resolution (HR). HR pictures are reconstructed using super-resolution (SR) reconstruction from single-frame or multi-frame data. Signal processing techniques are used to create low-resolution (LR) images.

The documentation is about image inpainting and enhancement. It also comes with a suite of dataset generating tools and image transformations. Through the ability to generate almost endless training samples, it is also possible to switch from a Generative Adversarial Network to a problem tailored loss function [3]. The review is divided into two parts. They are the fundamentals of picture generation and digital image restoration.

Deep Learning, an artificial intelligence field, has a vast range of network architectures. Deep Learning gathers the most useful features of massive data automatically. Deep learning has a variety of applications [4]. A few examples are computer vision, natural language processing, video or audio recognition, finance and banking, and so on. Because of limitations in [24] computer memory, CPU, and GPU, the deep learning technique faces a number of obstacles in the early stages of computer vision development. There are a number of computer vision applications that can be built to address these issues. The methods used are K-means, Nave Bayes, Decision Tree, Boosting, Random Forest, Haar classifier, Expectation Maximization, K-Nearest Neighbor, and Support Vector Machine.

The process of converting an image to a digital format and then performing operations on it to improve the image or extract pertinent data is known as image processing. Images are typically incorporated as a two-dimensional signal in image processing systems, and signal processing algorithms that have already been described are used [5]. We called the process of restoring a degraded/distorted image to its original data and quality image restoration. The restoration's major goal is to raise the quality of digital photos that have been harmed by various types of noise and overlaid blur. The damage photo was repaired with an airbrush, and the repair mostly consisted of painting the damage.

The technique of converting a low-resolution image to a high-resolution image is known as single-picture super-resolution. From security and surveillance imaging to medical imaging, it covers a wide spectrum of computer vision applications [6]. The computer vision field has looked into a number of other single-picture super-resolution approaches. Bicubic interpolation and Lanczos resampling were previously employed as interpolation algorithms. These methods are now being used to express a patch mapping from low to high resolution. Neighbour embedding is utilised for things like patch subspace interpolation. To boost accuracy, random forest and convolutional neural networks have been used.

Image restoration improves the image's appearance. By reducing the noise in the deteriorated image, Image Restoration algorithms produce the highest quality image. This technique aims to estimate an uncorrupted image from a degraded one. Restoration process is divided into two steps [7]. There are two phases: deterioration and repair. The degradation phase happens when image degradation begins as a result of blurring and additional noise.[15] During the restoration step, the deteriorated image is filtered and an image for the original image is produced as an output. There are two types of restoration phases. There are two classes: blind and non-blind.

Prior to the deep learning era, several attempts were attempted to repair photos by automatically detecting localised imperfections like scratches and blemishes and filling up the damaged areas with inpainting techniques. However, [23] because none of these methods can correct spatially homogeneous issues such film grain, sepia effect, colour fading, and so on, the restored photos still appear ancient when compared to modern photographic images [8]. Convolutional neural networks' excellent representation capability may now be used to handle a variety of low-level picture restoration difficulties thanks to the arrival of deep learning.

Most of the basic theories underlying physics and engineering are modelled using partial differential equations. The Laplace equations are discussed in this study as part of the strategy image inpainting [9]. Inpainting is a computer technique for reassembling historical photographs by filling in the missing areas in a logical and consistent manner. By executing multiple iterations of the formulation, we may replace the corrupted pixels in the picture matrix using a numerical method for discretizing the Laplace equation.

For Gaussian independent and identically distributed linear inverse problems, many modern techniques have proven effective [10]. Because Poisson noise is signal dependent, the noise variance at each pixel is proportional to the strength of the underlying signal, these methods are not relevant to Poisson inverse situations. As a result, the deconvolution techniques developed to address this issue are very important and crucial. Due to the ill-posedness of the Poisson inverse issue, the linear operator that relates Poisson's observations to prospective intensities is either conditional or unique. After then, a number of objective function-based optimisation algorithms were presented. [11]

ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)

Vol 9, Issue 7, July 2022

III. SYSTEM DESIGN

A. Problem Formulation

The organization neglects to sum up in light of the fact that true photograph debasement is convoluted, and the space hole among engineered and certifiable old photographs makes the organization fizzle. [12] Therefore, we've fostered another trio area interpretation network that works with both genuine and manufactured picture matches. Two variational autoencoders (VAEs) are prepared to decipher old and clean pictures into two distinct dormant spaces. The interpretation between these two inactive regions is gotten the hang of utilizing manufactured matched information.

B. Objectives

The objectives of the proposed work are:

- Detection of scratch in the photographs and reduce it.
- Refine the face regions and facial features enhancement.
- Reduce photo degradation and enhance the quality of the image.

C. Proposed Design

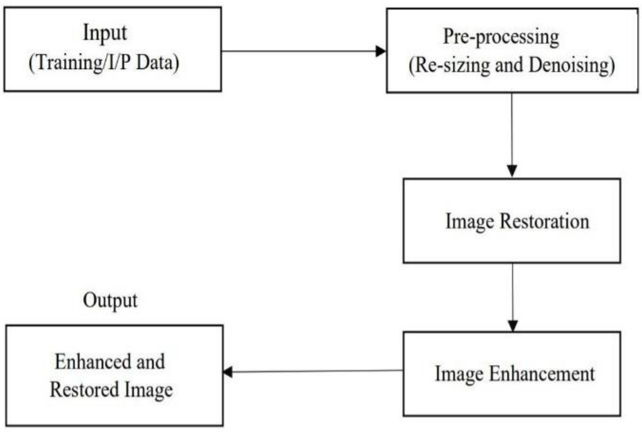

Fig. 1. Block Diagram of Proposed Design

The proposed design is shown in figure 1.

- Input Module: The training dataset will be loaded into the project dictionary, and the input image will be provided for restoration.
- Pre-processing: The input image will be handled using the median filter algorithm to remove salt and pepper noise and deblur the image during pre-processing.
- Image Restoration: The image will be rebuilt with fresh pixel values to replace the corrupted ones. Without utilising an explicit model, the network can learn the colour of each pixel reliably given a significant amount of training data. [14]
- Image Enhancement: The enhanced image will then be forwarded to the region filling feature, which will fill the bounded region with colour or image.

IV. METHODOLOGY

The system is built with the Python programming language and the Spyder IDE. The data for the input comes from a standard dataset. The suggested joint framework can eliminate noise, restore an occluded image, and recognise objects. This combined structure unites the restoration and recognition duties by providing [13] common, restoration, and categorisation layers. The categorisation and restoration losses are combined in the total loss function.

The suggested solution uses an end-to-end mapping trained on image pairings with and without reflections to distinguish and isolate sounds from the input image. The presence of a representative and suitably big collection of training data is critical to the effectiveness.

A. Median Filter

Step 1: Consider an image f(x,y) of value 4*4 and an empty image mask h(x,y) of value 3*3.

Step 2: To convolve this image there are two methods. They are Pixel Replication and Zero Padding.

1. Pixel replication involves replication of the specified columns.
   a. *For the given image f(x,y), replicate their end rows and columns*
   b. *Convolve the empty mask h(x,y) over the image f(x,y).*
   c. *While convolving arrange the matrix under the mask h(x,y) in an increasing order and find the median 'M'.*
   d. *The preceding median is replaced with the new median 'M'.*
   e. *Move the mask h(x,y) to the right by one column each time and cover the image f(x,y) by moving one at a time.*
   f. *Final f `(x,y) with the modified value is the resultant.*
2. In zero padding, zero is padded at the sides all over.
   a. *Remaining steps 1(a)-(f) as in Pixel Replication.*

B. Region Filling

Step 1: Consider black pixels as 1 which is the object, and white as 0 which is the background

Step 2: Let p be a pixel in a region surrounded by an 8 connected boundary as A, assign X_0=p

Step 3: Evaluate X_k= (X_{k-1} XOR B)

Where, X_k→ image used for next iteration

X_{k-1}→image which is achieved in previous expression

B→cross shaped structuring element

Step 4: Output from previous step and the intersection with complement of the original image

X_k = (X_{k-1} XOR B) AND A`

Where A`→ complement of original image

Step 5: if X_k = $X_{k-1,}$ Repeat till K^{th} iteration

IFERP
ISSN (Online) 2394-2320
International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)
Vol 9, Issue 7, July 2022

V. RESULT AND DISSCUSION

Deep Learning algorithms can be used for both image denoising and image restoration since they extract picture features from groups of images. This technology takes advantage of huge data and the autonomous learning process to surpass classic image restoration techniques. Using an end-to-end mapping trained on image pairs with and without reflections, this method restores severely degraded old photos and recognises and separates noises from the input image. The availability of a representative and suitably big collection of training data is critical to the effectiveness.

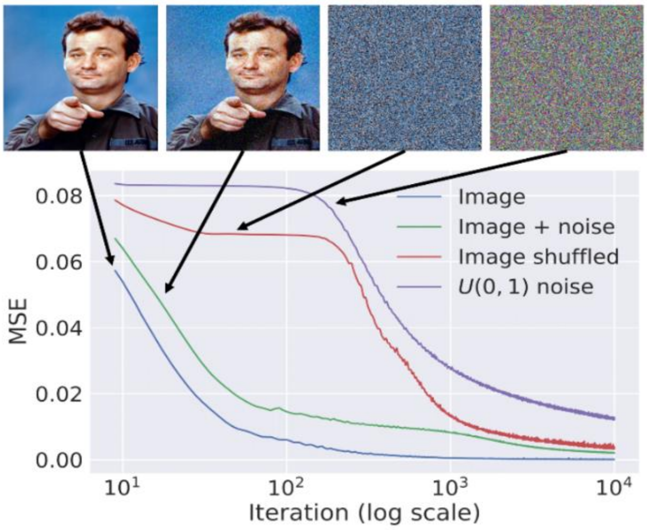

Fig. 2. Analysis of noise in image

The study and results are based on the standard test image, Lena, as illustrated in Figure 3. Figure 4 demonstrates the addition of additive Gaussian noise with a mean of 0 and a standard deviation of 0.05. Figures 5 and 6 demonstrate the outcomes of the Median filter and the proposed image enhancement filter, respectively.

The Median Filter is shown to be ineffective at removing Gaussian noise and only works in edge regions, leaving blur effects in continuous regions. The image enhancement filter was successful in removing Gaussian noise in both edge and continuous regions.

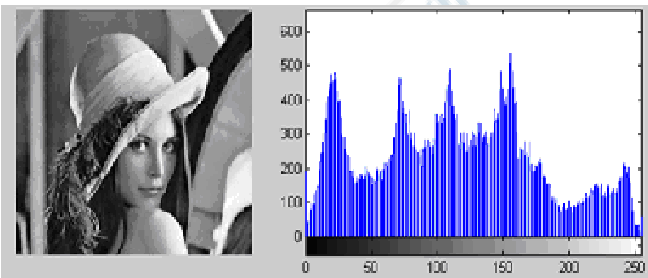

Fig. 3. Actual image with histogram

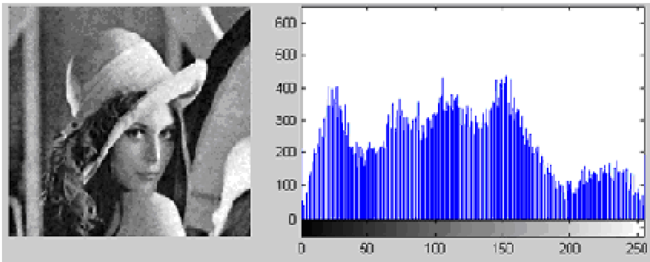

Fig. 4. Restored image using Median filter with histogram

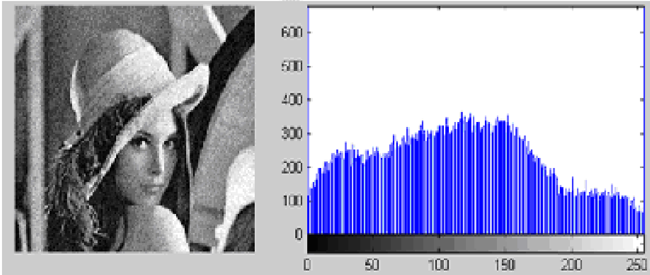

Fig. 5. Salt and Pepper noise added image with histogram

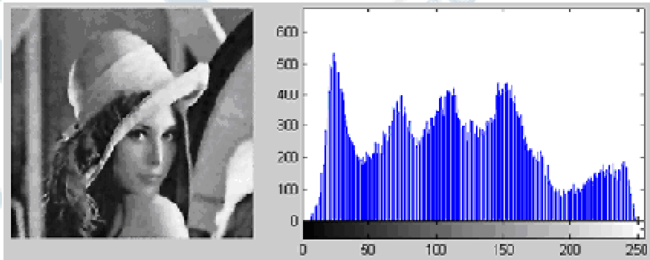

Fig. 6. Restored image using Image enhancement filter with histogram.

VI. CONCLUSION

Deep Learning techniques extract visual features from groups of pictures, allowing for image denoising and restoration. To overcome traditional picture restoration approaches, this system uses large amounts of data and an autonomous learning process. This method has been found to rescue highly degraded antique photographs. Image denoising, inpainting, and colorization will all benefit from network inversion in the future. We may state that this approach is promising based on the deblurring results, but other picture degradations or combinations of image degradations require more research.

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