Image Restoration using Super Resolution Generative Adversarial Network

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***Abstract*— It can be challenging to extract valuable information from photographs taken with low-resolution cameras or images that have been deteriorated by noise, blur, or other factors. The ability of conventional image restoration methods to return photos to their original quality is constrained. Thus, there is a need for more sophisticated methods that can improve the quality of restored photos. The goal of this project is to create an image restoration model that can improve low-resolution or degraded photos utilizing post-processing methods along with SRGAN. The project's objective is to build the SRGAN model followed by post-processing methods for image restoration. This project will also investigate how various characteristics, like the size of the training dataset, the number of layers in the network, and the post-processing methods employed, affect the performance of the model. The initiative will aid in the creation of more sophisticated picture restoration methods that may be applied to a variety of situations, including surveillance, remote sensing, and medical imaging.**

SRGAN with two models, where these two separate models are pitted against each other simultaneously during training: a generator and discriminator model both attempt to outsmart one another. The Generator takes input data containing a low-resolution version of an image, then up samples it which outputs a high-resolution image. The Discriminator attempts to distinguish between real/fake output generated by G so as D's success rate progresses more accurate results are achieved through feedback loops affecting G till desired accuracy goals have been set. During the training, A high-resolution image (HR) is down sampled to a low-resolution image (LR). A GAN generator up samples LR images to super-resolution images (SR). We use a discriminator to distinguish the HR images and backpropagate the GAN loss to train the discriminator and the generator. This advanced Machine Learning technique uses both generators and discriminators and also uses the pre trained weights called as VGG19 in order to discern between high-resolution original photos and their generated counterparts. As opposed to simply upscaling blurred photos often seen with conventional methods like nearest neighbour interpolation, these AI models produce results that are much closer to the quality as perceived by humans making them perfect for applications such as picture enhancement or dealing with poor digital zoom performance due lack of details produced when enlarging digital images artificially.

Keywords—SRGAN, Image restoration, SRCNN, Generator, Discriminator, VGG19, Unsharp masking, Contrast stretching.

I. Introduction

Image restoration is the process of removing noise, blurring and other types of distortion from a degraded digital image and returning it to a near-original quality. The most common type of noise that affects images is Gaussian noise, which can be removed with filter convolution operations such as those implemented in Wiener filters or Wiener deconvolution algorithms. Using SRGAN, a generative adversarial network for single image super-resolution, is one of the most recent developments in image restoration. An adversarial loss and a content loss make up the perceptual loss function used by SRGAN. Through the use of a discriminator network that has been trained to distinguish between super-resolved images and actual high-resolution images, the adversarial loss drives the solution to the natural image manifold. The perceptual loss quantifies the difference in feature space between the high-resolution image and the super-resolved image. It is also possible to employ post-processing methods to enhance the quality of the restored image. For instance, with surveillance photographs, the entire image can be compressed and then made to pass through SRGAN and passed the super-resolved images into post processing techniques to drive a new colorful image.

II. Literature Survey

A. *Working of GAN and its implications*

Image restoration involves removing the blurry and damaged image and replacing it with a healthy image. "Restoring the Imagery" is implied by its literal meaning. According to its descriptor meaning, we consider it a useful discipline that developed from photo alteration to restore the lost feel of photographs. There are many different sorts of corruption, including blur, smear, ruined edges, and camera focus issues. By highlighting the point source in the image, the blurring process of the image is reversed throughout the photo restoration process. The Point Spread Function is what it is named[1].

Due to its significant practical importance in numerous low-level vision applications, image restoration (IR) has been a long-standing issue. Denoising, deblurring, and super-resolution are IR issues. IR's main objective is to extract the latent clean picture from its degraded observation. An

important service to recover your digital images and other assets is image restoration[2]. Numerous and diverse features can reinvent your encounters and prevent them from deteriorating in any way. Images can become dull and lifeless over time, much like jewellery, due to numerous variables like age, dampness, and dust. Amazing quality software allows for the restoration of all damaged areas in photos, giving the impression that the image was never harmed[3].

As one of the most fundamental issues in image processing, picture denoising has received a lot of research. Numerous neural-network-based attempts were attempted to complete this job as deep learning emerged over the previous ten years. These produced cutting-edge results in frequently used full reference distortion measurements, like Mean-Squared-Error (MSE), which calculates the difference between the denoised image and its original, clean source. The majority of DL solutions for this issue have opted to concentrate on the design of the denoiser while increasing distortion performance. However, distortion-driven approaches produce hazy outcomes with poor perceptual quality, particularly in situations with excessive noise[4]. The research paper "High Perceptual Quality Image Denoising with a Posterior Sampling" proposes a method to denoised images nearest to their source images. The goal was to achieve high perceptual quality with acceptable distortion. They sampled from the posterior distribution while willing to compromise up to 3dB in PSNR performance rather than attempting to strike a balance between perceptual quality and distortion performance. [5] The model took advantage of the fact that any stochastic denoiser that takes samples from such a distribution must also agree with it in expectation in order to regularise the proposed sampling. Training of the Posterior Sampling CGAN (PSCGAN) is performed to get ideal outputs. They relied on perceptual quality and guaranteed distortion and CGAN based training of the dataset is basis of the work.

Super-resolution is used to upscale the images, in simple terms it means to increase the clarity or resolution of the images. Deep learning is being used relied on more these days, which has encouraged the development of SR models that perform remarkably well on standard SR criteria while maintaining a high level of fidelity. When tested in real-world settings, models developed from clean, matched datasets typically perform poorly. [6] Adversarial Attacks can be used to evaluate how well a model is able to withstand invisible noise. These attacks are based on adversarial examples, which are small-scale changes made to the input image with the express purpose of leading the model to fail. Adversarial examples have shown improvements in the generalization of models to noise for a variety of tasks, including object detection, semantic segmentation, and classification. Models become more human-perception-aligned through robust training, becoming invariant to noise. In "Generalized Real-World Super-Resolution through Adversarial Robustness" an RSR method that is robust was proposed to generalize well across various datasets without re-training for specific noise priors. It included using a GAN-based model that was previously trained on clear LR pictures, we deploy SR. Then using a noise optimization procedure. Finally, extensive training of the GAN robust using the adversarial cases as LR inputs was done. The results showed that it worked well when compared to real-world SR datasets and in most cases better than other models.

[7] The authors of "Graph2Pix: A Graph-Based Image to Image Translation Framework" paper used the popular creativity platform Art breeder to generate an image-to-image translation framework based on graphs to generate images. This topic can help me understand how we get a clear image if numerous defective or different images are given as input to the model, which is in fact known as Graph2Pix, and a popular model for such creations and utilization is the GAN model. This innovative method of creating new images results in a tree-like structure that allows one to monitor historical information regarding the creation of a certain image. [8]A generalized image-to-image translation method was proposed by the authors that take in multiple images and their respective lineage structure and derives the target image as output. The framework constituted of a graph structure and considers the tree structure of lineage data as a sub-case as both are the necessary parameters to arrive at the output. The proposed approach was not restricted to producing pictures from Art breeder. Their method can be used in any situation where numerous photos need to be combined into one because of the adaptability of the graph structure, such as multi-source human image synthesis. The results of their experiments showed that the application of a tree-based graph structure improved the performance when deeper lineage structures were given as input. But there were some failures as well as the algorithm sometimes failed to capture the details of the lineage properly if the given input lineages were very different in nature and one of the main disadvantage to this model is that it requires tree-based structure for it to function.

The authors of "Underwater Image Processing: State of the Art of Restoration and Image Enhancement Methods" discuss various ways to improve the image processing quality of the images taken undersea, this is useful in studies of marine biology, marine ecosystem, underwater archaeological exploration, etc. Considering the fundamental physics of light propagation in the water medium is the first thing we must do in order to deal with underwater picture processing. Degradation effects brought on by the medium's physical characteristics are not seen in typical air-based photographs. Because light is rapidly attenuated as it moves through the water, underwater photos are fundamentally defined by their poor visibility, which leaves the scenes with weak contrast and haze. The total effectiveness of underwater imaging systems is influenced by the processes of light absorption and scattering in water. When explicit information of the degradation function h(x, y) and the noise characteristics are given, image restoration attempts to reconstruct the original image f (x, y) from the given input image g(x, y). The system reaction from the imaging system itself and the impacts of the medium are both included in the degradation function h(x, y) which is water here. Various algorithms related to image restoration, image enhancement and color correction methods were discussed in detail. Their conclusion is that even while there are many methods and algorithms for improving images, most of them are only applicable to regular images, and only a few methods have been created especially for underwater images. They outlined the techniques for image restoration and enhancement that are now accessible, concentrating on the circumstances under which each algorithm was first created. They have also emphasized in their work the process for assessing the effectiveness of the algorithms, highlighting the works that make use of a quantitative quality metric.

The paper " SwinIR: Image Restoration Using Swin Transformer " analyzed the baseline SwinIR model for image restoration based on the Swin Transformer. It consists of three parts to its application, they are shallow feature extraction, deep feature extraction, and high-quality image reconstruction. The experiment was based on the processes of image super-resolution, grayscale and color image denoising, and JPEG compression artifact reduction as these help in the reconstruction of clean images with high quality. While the performance of most CNN-based methods, such as residual learning and dense connections, is much better than that of conventional model-based methods, they typically have two fundamental issues that originate from the fundamental building block. Transformer methods create a self-attention mechanism to collect contextual global interactions and have demonstrated promising results in a number of vision-related issues. Vision Transformers for picture restoration, however, often break the input image into small, uniform patches and

process each patch separately. While Swin Transformer is a hybrid of both CNN and transformer designs and it essentially brings together the best of both models. The proposed SwinIR is compared with the CNN-based model RCAN to analyze the difference between Transformer-based and CNN-based models. The proposed model was able to demonstrate effectiveness and easy generalization.

Image fusion is the process of combining data from various image sources into a single, condensed representation of an image. Compared to a single source image, the fused image has more data. As in most cases the images contain varied information, such as different colors, brightness levels, and features, image fusion from several sensory modalities is significantly more difficult. There are articles on various algorithms to combine these images while removing the noises in the images. The research paper "A System for Fusing Color and Near-Infrared Images in Radiance Domain" focuses on the fusing of color images with Near-Infrared images (NIR) the goal of it being to increase the color image detail using the extra details provided by NIR all the while preserving brightness and color of the image. Image-enhancing enhancing techniques like denoising and dehazing are among the most promising uses of RGB-NIR fusion. One of its uses is to fix the issue of image improvement in hazy weather. This paper was focused on designing a system to overcome image quality issues and rise the range of fusion images to obtain High Dynamic Range (HDR) images. Here using a guided image filter, the RGB and NIR components were adjusted individually and choose how much NIR should be added to the RGB to prevent see-through clothes. The decomposed details of the fusion image are then added back in after the fusion image has been deconstructed once again and swapped into the base of the decomposed RGB. This aids in preserving the original RGB color while adding all the NIR features. The next step is to identify the haze zones and modify the pixels' saturation for dehazing if there is any haze present in the scene. The resultant system was able to control the details such as colors, seethrough effect prevention, and dehazing in the image.

The process of restoring a clear image from a damaged one is known as image restoration. Deterioration commonly takes the form of noise, blur, rain, haze, etc. The problem is extremely poorly phrased because there are countless workable answers. Existing restoration algorithms explicitly use images prior that are created with empirical observations to limit the solution space to valid/natural images. However, creating such priors is a difficult operation that is frequently not generalizable. Convolutional neural networks (CNNs), which learn more general priors by capturing natural picture statistics from enormous amounts of data, are now being used in state-of-the-art methods to address this problem. The model design of CNN-based approaches is principally responsible for their superior performance compared to the others. Recursive residual learning, dilated convolutions, attention mechanisms, dense connections, encoder-decoders, and generative models are only a few of the network modules and functional units that have been developed for picture restoration. However, almost all of these models for simple visual issues are built using a single stage. On the other hand, it is demonstrated that multi-stage networks outperform their single-stage counterparts on high-level vision issues like posture estimation, scene parsing, and action segmentation. "Multi-Stage Progressive Image Restoration" aims to design a multi-stage architecture that gradually learns restoration algorithms for the degraded inputs, dividing the total recovery effort into more manageable parts. A novel per-pixel adaptive design that uses in-situ supervised attention to reweight the local features was added at each stage. Information flow between several stages is a crucial component of this multi-stage system. To achieve this, they suggested a two-pronged strategy in which, in addition to information being transferred sequentially from early to late stages, lateral connections across feature processing blocks are also present in order to prevent information loss. On various benchmark datasets, the proposed model exhibits significant performance improvements. Additionally, the proposed model is small in terms of model size and quick to operate, both of which are important for devices with constrained resources.

Convolutional neural networks and other deep learning approaches have drawn a lot of attention in practically all fields of image processing, particularly picture categorization. Image restoration, however, is a fundamental and difficult problem that is important to image processing, comprehension, and representation. The methodologies and mechanisms used by deep learning techniques for image restoration differ significantly. Discriminative learningbased approaches can successfully address the challenges of establishing a restoration mapping function, and methods based on optimization models can improve performance even further under certain learning constraints. One of the common techniques is to train machine - learning computational models to learn picture priors or kernels. It is more beneficial to acquire priors from machine learning computational models, as efficient normalisation concepts for the illposed issues, than sophisticated hand-crafted picture priors, and requires less labour to extract such priors. The training goal function involves numerous loss components, hence it is necessary to simultaneously minimise many losses. Although linear combination is the simplest method, the cumulative losses after weighing and addition could not be convex, making it challenging to find the best solution by gradient descent. Due of the ill-posed nature of image restoration, it is a difficult image processing operation. The deterioration methods and distortion models are built using traditional methods, which rely on handcrafted models. In reality, noise models and degradation mechanisms are rarely homogeneous and overly simple.

[17]. In recent decades, the field of image processing has seen intense study on the single image super-resolution (SISR), which tries to rebuild a high resolution (HR) image from a low-resolution (LR) observation. Deep learning based super-resolution (SR) techniques in particular have received a lot of attention and have significantly enhanced the reconstruction performance on artificial data. Recent research demonstrates that the ability to mega real-world images is typically overestimated by simulated data on synthetic data. Researchers are devoting more and more of their time in this area to creating SR methods for realistic photos. This essay seeks to provide a thorough analysis of actual single-image super resolution (RSISR). The four primary categories of RSISR methods—degradation modeling-based RSISR, image pairs-based RSISR, domain translation-based RSISR, and self-learning-based RSISR—as well as the essential publicly accessible datasets and evaluation criteria are covered in more detail. On benchmark datasets, comparisons are also done between representative RSISR approaches in terms of the accuracy of the reconstruction and the computing efficiency. In addition, we cover RSISR research problems and hot themes. The super-resolution of real-world photographs has drawn more attention in recent years. This article provides a brief overview of new super-resolution techniques for realistic photos, including algorithms based on deterioration modelling, image pairings, domain translation, and self-learning. In the interim, we list the most popular datasets and evaluation criteria for RSISR model training and evaluation. Furthermore, even though RSISR has made some progress in recent years, there are still issues that need to be resolved, such as the need for realistic datasets for model testing and training, as well as specific models for assessing the effectiveness of real-world image super-resolution and reconstruction. These open issues also point to intriguing areas for further investigation.

[15]. Extending a trained network to new conditional generation tasks without forgetting earlier tasks, while assuming access to the training data for the current task only, is known as the lifelong learning challenge for generative models. This research proposes a more general framework for continuous learning of generative models under various conditional image creation conditions as opposed to state-of-the-art memory replay based techniques, which are restricted to label-conditioned image generation tasks. To transfer learned knowledge from older networks to the current one, the lifelong GAN uses knowledge distillation. As a result, image-conditioned generating tasks can be completed in a lifelong learning environment. In order to demonstrate the generality and efficacy of Lifelong GAN, we validate it for both label conditioned and image-conditioned generation tasks. We investigate the challenge of continuous learning for generative networks and present a distillation-based framework that allows a single system to be expanded to new tasks without forgetting past jobs while requiring only supervision for the current task. We use knowledge distillation to transport learned information from past networks to the new network, in contrast to prior techniques that used memory replay to create images from prior tasks as training data. In contrast to memory replay-based approaches, our generic architecture supports a wider range of generating tasks, including picture to image translation. Both qualitative and quantitative findings demonstrate the versatility and efficacy of our technique, and we validate Lifelong GAN for image-conditioned and label conditioned generation tasks.

III. Theory

A. *VGG-19 Model*

The VGG-19 model is a convolutional neural network (CNN) model and is widely used in various computer vision tasks. It is an extension of the VGG-16 model, which has 16 layers, but it has a deeper architecture with 19 layers. The architecture of VGG-19 comprises of 16 convolutional layers that are responsible for learning spatial features from the input image, 5 max-pooling layers for reducing the spatial dimensions and the 3 fully connected layers for classification. The input to the network is a 224 x 224 x 3 RGB image, where 224 x 224 is the size of the input image, and 3 represents the three-color channels (red, green, and blue).

The first 16 layers of the network consist of convolutional layers with 3x3 filters and a stride of 1. Each convolutional layer is followed by a ReLU activation function, to introduce non-linearity, and a 2x2 max-pooling layer with a stride of 2. The output of the 16th convolutional layer is flattened and passed on to the fully connected layers.

Each of the first 2 fully connected layers have 4096 units and are followed by a ReLU activation function. Meanwhile, the 3rd fully connected layer has 1000 units, corresponding to the number of classes in the ImageNet dataset, i.e., the dataset it was pre-trained on, and is followed by a softmax layer that produces a probability distribution over the classes. The output of the softmax layer and the network represents the probability that the input image belongs to each of the 1000 classes in the ImageNet dataset.

The VGG19 model is used in SRGAN for the interpretation of the perceptual loss that is used for the model. The VGG19 model is used to calculate the content loss, which measures the difference between the high-resolution image and the generated image. The content loss is used to ensure that the generated image has the same content as the high-resolution image.

B. *Loss Functions*

The loss function in SRGAN is used to optimize the generator network during training to minimize the difference between the generated and reference images, while also encouraging the generated images to have high perceptual quality. The loss function is a weighted sum of a content loss and an adversarial loss component. The content loss is typically calculated using a pre-trained VGG network, and the adversarial loss is calculated using a discriminator network.

The content loss is calculated as the mean squared error (MSE) between the feature maps of the pre-trained VGG network for the generated and reference images. The adversarial loss is calculated using the binary cross-entropy loss between the discriminator's predictions for the generated and reference images.

The perceptual loss function combines the content loss and the adversarial loss at a ratio of 1000:1 to encourage the generator to find solutions that lie within the probability density function of natural images without overly conditioning the network to reproduce rather than generate new images.

The loss function in SRGAN is a weighted sum of a content loss and an adversarial loss component. The content loss is typically calculated using a pre-trained VGG network, and the adversarial loss is calculated using a discriminator network.

The loss function can be written as follows:

l_SR = l_XSR + 10^-3 * l_GenSR

where l_XSR is the content loss, l_GenSR is the adversarial loss, and 10^-3 is a weighting factor.

The content loss is calculated as the mean squared error (MSE) between the feature maps of the pre-trained VGG network for the generated and reference images. The adversarial loss is calculated using the binary cross-entropy loss between the discriminator's predictions for the generated and reference images.

The final loss function is optimized during training to minimize the difference between the generated and reference images, while also encouraging the generated images to have high perceptual quality.

IV. Proposed Structure

A. *SRGAN network*

While performing image restoration tasks like image super-resolution, the SRGAN (Super-Resolution Generative Adversarial Network) model is used. A generator and a discriminator network are its two major parts. An outline of the SRGAN model's operation is provided below:

To create an output image with a greater resolution, the input image is first sent through the generator network.

Generators:

The low-resolution input image is transformed into a high-resolution output image by the generator network, a deep neural network. The mapping from low-resolution to high-resolution images is learned by the generator network, which consists of a number of convolutional layers and residual blocks. The generator network produces a higher-resolution image as its output.

Discriminator:

Deep neural networks used in the discriminator network attempt to discriminate between pairs of high- and low-resolution images. In order to distinguish between authentic high-resolution photos and artificial high-resolution images, the discriminator network is trained. The generator network is encouraged by the discriminator network to create more lifelike images.

Adversarial Training:

A procedure known as adversarial training is used by the SRGAN model to simultaneously train the generator and discriminator networks. Although the discriminator network tries to tell the difference between the real and generated

images, the generator network seeks to create images that are identical to the real high-resolution photos. High-quality images are produced as a result of the rivalry between the generator and discriminator networks.

Loss Function:

The SRGAN model employs a loss function with two parts: an adversarial loss and a content loss. The adversarial loss measures the difference between the distribution of generated images and the distribution of real images, whereas the content loss measures the similarity between the generated high-resolution image and the real high-resolution image.

The loss function of the SRGAN model can be written as:

Loss = content_loss + adversarial_loss

where the adversarial loss is determined using the adversarial loss function of the discriminator network, and the content loss is calculated as the mean squared error between the generated high-resolution image and the original high-resolution image.

Overall, the SRGAN model creates high-quality images with higher resolutions than the input images by combining deep neural networks, adversarial training, and loss functions.

B. Unsharp Masking

Unsharp masking is a linear image processing technique that is used to sharpen an image by enhancing its edges and details. The technique involves subtracting a blurred version of the image from itself, scaling the difference, and adding it back to the original image. The blurred version of the image is obtained by convolving the original image with a Gaussian low-pass filter. The unsharp mask filter can be represented mathematically as follows:

Output (x, y) = input (x, y) + amount * (input (x, y) – Blurred (x, y))

where input(x, y) is the pixel value of the original image at position (x, y), blurred(x, y) is the pixel value of the blurred image at position (x, y), amount is a scaling factor that controls the strength of the sharpening effect, and output(x, y) is the pixel value of the sharpened image at position (x, y). The blurred image can be obtained by convolving the original image with a Gaussian kernel G (x, y) as follows:

Blurred (x, y) = (input * G) (x, y) = $\sum\sum$ input (i, j) * G (x-i, y-j)

where G(x, y) is the two-dimensional Gaussian function defined as follows:

G(x, y) = (1 / (2πσ^2)) * e^(-(x^2 + y^2) / (2σ^2))

where σ is the standard deviation of the Gaussian distribution.

Unsharp masking can be used to increase the contrast along the edges of objects in a photo, making them appear sharper. It can also be used to enhance the details in an image, such as the texture of a surface or the fine lines in a drawing. Unsharp masking is commonly used in image processing applications, such as photo editing software, to improve the visual quality of images.

C. Contrast Streching

Contrast stretching is an image enhancement technique that tries to improve the contrast by stretching the intensity values of an image to fill the entire dynamic range[1]. The transformation function used is always linear and monotonically increasing.

The contrast stretching equation is given by:

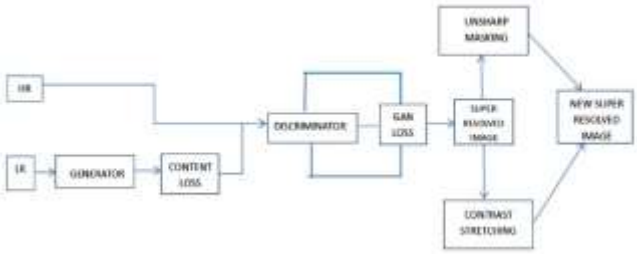
s = (r - r_min) * (s_max - s_min) / (r_max - r_min) + s_min

where, s is the output pixel value, r is the input pixel value, r_min and r_max are the minimum and maximum pixel values in the input image, and s_min and s_max are the minimum and maximum pixel values in the output image.

Contrast stretching can be applied to color images by first converting the color model from RGB to HSV. It is not recommended to apply scalar contrast stretching to the red, green, and blue channels independently.

Contrast stretching can be used to stretch the contrast over the entire range of intensities or over a small range of intensities. The goal of contrast stretching is to make the images use the entire range of values available to them.

Contrast stretching maps the minimum intensity in the image to the minimum value in the range and maps the maximum intensity in the image to the maximum value in the range. Contrast stretching is unreliable if there exist only two pixels with 0 and 255 Intensity.



V. RESULTS

The results must be evaluated subjectively. For the purposes of this evaluation, the focus would be on the input image and how that input image changes over the course of the implementation of the proposed methodology. The input image used for this purpose was that of a high-resolution image. High resolution image is used to generate low resolution image which acts as input for the generator. Then the high-resolution image is sent through discriminator. We then backpropagate the GAN loss to train the discriminator and the generator.

Image 1: Unsharp Masking

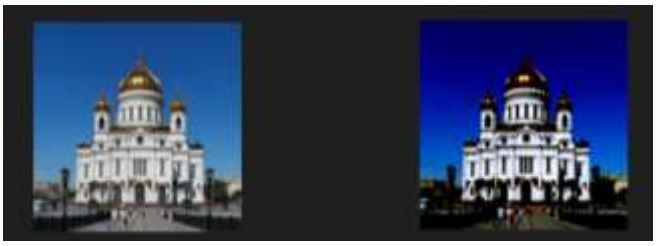


Image 2: Contrast stretching

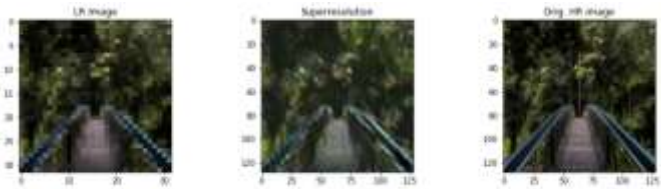


Image 3: Comparison between low resolved, and super resolved(SRGAN) and original images

VI. Conclusion

Depending on your image state, Image Restoration offers a wide range of options. As an example, portrait restoration, digital photo enhancement, old photograph reproduction, water and light damage photo restoration, antique picture restoration, and many more. All of these categories are effective in removing imperfections and inaccuracies at the most ingrained level.

There are various models and algorithms to overcome each of the distortion or noise in the image, each of them having its own advantages and disadvantages based on the scenario they are applied it. Ultimately it is the development of AI and machine learning that are improving the scope of the models of image restoration and processing. Thus, increasing the future scope of development and improvement in this domain.

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