Intel Unnati Industrial Training Program 2024

Karunya Institute of Technology and Science

Pixelated Image Detection & Correction

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Pixelated Image Correction

Abstract

This project aims to restore pixelated images using the Efficient Sub-Pixel Convolutional Neural Network (ESPCN) model. The primary goal is to enhance the visual quality of pixelated images by increasing their resolution and reducing artifacts. The performance of the restored images is evaluated using metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) to ensure the effectiveness of the restoration process.

The ESPCN model is specifically designed for single-image super-resolution tasks. It takes a low-resolution image as input and outputs a high-resolution image that attempts to reconstruct missing details and reduce pixelation artifacts that are common in low-resolution images. This process involves leveraging convolutional neural networks (CNNs) and sub-pixel convolution layers to enhance the image resolution effectively.

Unique Idea Brief (Solution)

Our approach aims to restore and remove pixelation effects from images. Pixelation typically occurs when an image is downsized, causing loss of detail, and then upscaled, resulting in visible blocky artifacts. In our project, we address this by initially downsizing pixelated images by a factor of 4, significantly reducing pixelation artifacts. Subsequently, we employ super-resolution model, the ESPCN (Efficient Sub-Pixel Convolutional Neural Network), to restore the image to its original resolution of the input image by upscaling it by 4x. This approach effectively enhances the visual quality of the image, preserving and improving its original details and clarity.

Methodology

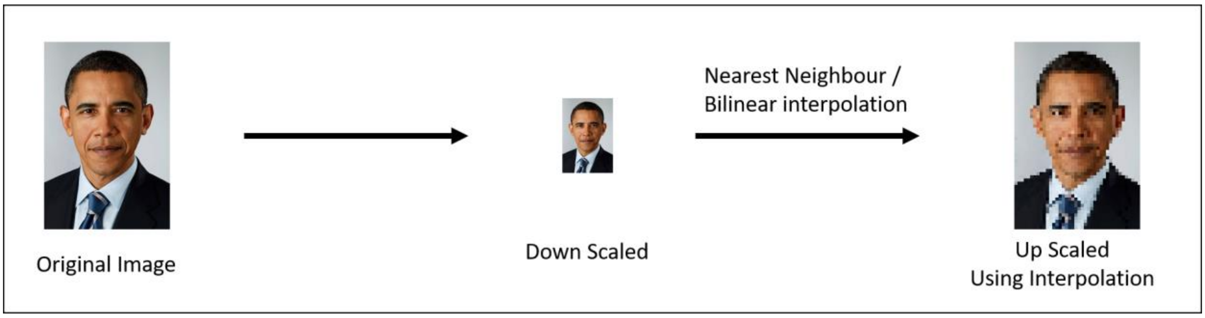
ESPCN Model:

The Efficient Sub-Pixel Convolutional Neural Network (ESPCN) is a specialized model designed for single image super-resolution. ESPCN leverages deep learning to enhance image resolution. It utilizes a sub-pixel convolution layer to increase the resolution of the input image, efficiently mapping low-resolution input to high-resolution output.

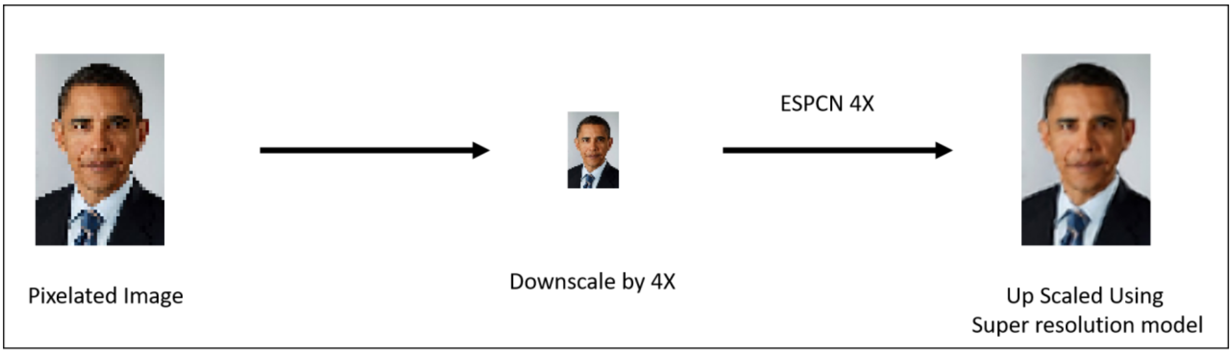
The Efficient Sub-Pixel Convolutional Neural Network (ESPCN) was chosen for this project due to its **lightweight architecture, speed, and accuracy**.

The Efficient Sub-Pixel Convolutional Neural Network (ESPCN) model is loaded using OpenCV's DNN module. The pre-trained model (ESPCN_x4.pb) is read and initialized with the specified scaling factor.

Pixelation occurs due to limitations in interpolation methods, which can affect the quality of upscaled images by blurring details or introducing artifacts along edges and boundaries.



Restoration Process: We begin by downscaling pixelated images by a factor of 4. Subsequently, these images are processed using the ESPCN model, which performs single image super-resolution to enhance their resolution, effectively reducing pixelation artifacts and improving visual quality.



Validation

PSNR (Peak signal-to-noise ratio):

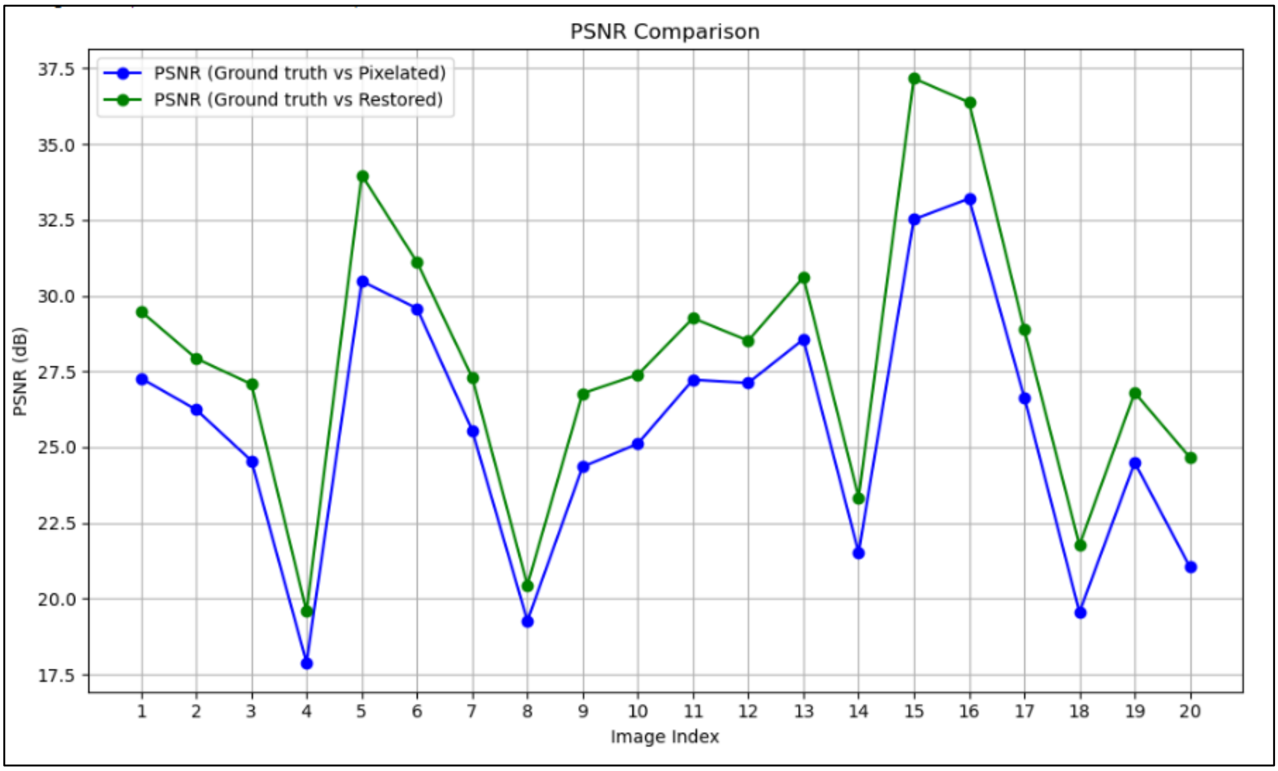
To validate the effectiveness of our approach in restoring pixelated images, we conducted an evaluation using Peak Signal-to-Noise Ratio (PSNR) metrics. We calculated the PSNR between each pair of images: **Ground Truth vs. Pixelated**, which measures the degradation caused by pixelation, and **Ground Truth vs. Restored**, which evaluates the effectiveness of our restoration approach.

In our validation process, we employed a dataset consisting of 20 high-resolution images, categorized as follows:

- **Ground Truth Images:** These are the original high-resolution images, serving as the reference for quality assessment.
- **Pixelated Images:** Images artificially degraded by downsampling, simulating typical pixelation effects encountered in practical scenarios.
- **Restored Images:** Images processed using the Efficient Sub-Pixel Convolutional Neural Network (ESPCN) model, aimed at restoring pixelated images to their original resolution.

Results:

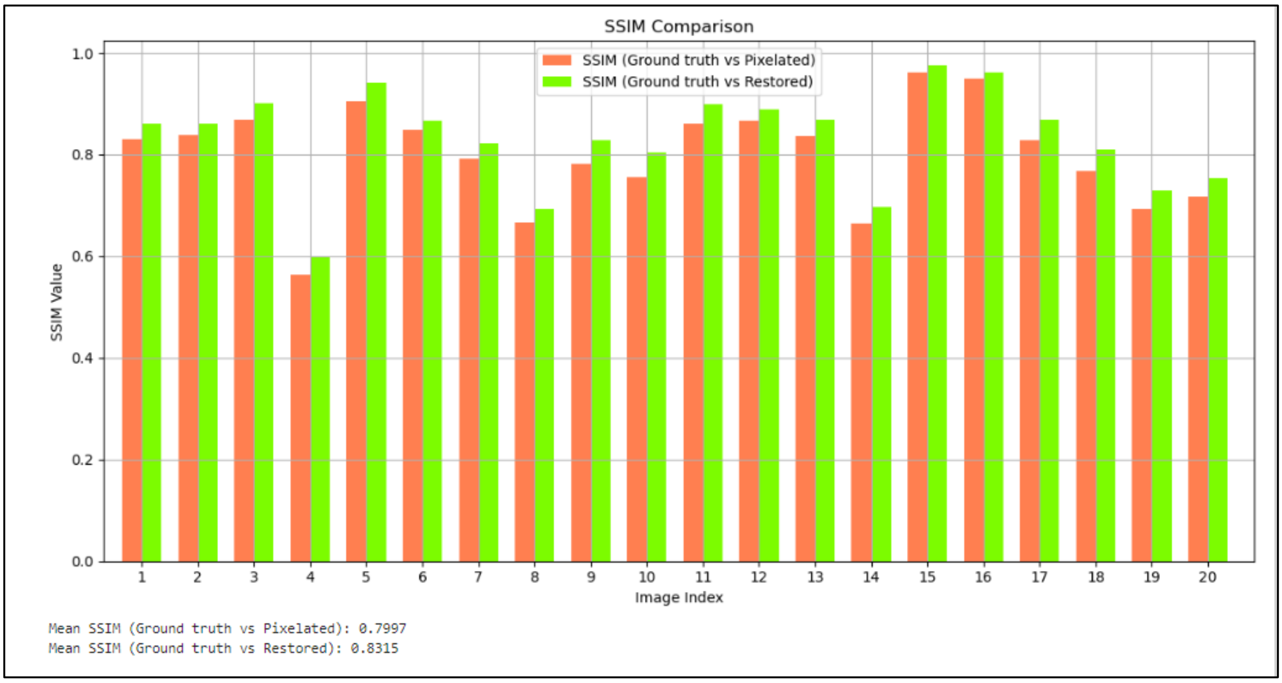
```
PSNR Values:                          Ground Truth to Pixelated          Ground Truth to Restored

PSNR for 0001.jpg                     27.27 dB                           29.48 dB
PSNR for 0002.png                     26.24 dB                           27.93 dB
PSNR for 0003.jpg                     24.55 dB                           27.08 dB
PSNR for 0004.png                     17.89 dB                           19.58 dB
PSNR for 0005.jpg                     30.48 dB                           33.98 dB
PSNR for 0006.png                     29.58 dB                           31.11 dB
PSNR for 0007.jpg                     25.56 dB                           27.30 dB
PSNR for 0008.png                     19.26 dB                           20.45 dB
PSNR for 0009.png                     24.35 dB                           26.77 dB
PSNR for 0010.jpg                     25.11 dB                           27.39 dB
PSNR for 0011.png                     27.23 dB                           29.26 dB
PSNR for 0012.jpg                     27.12 dB                           28.51 dB
PSNR for 0013.png                     28.56 dB                           30.61 dB
PSNR for 0014.png                     21.52 dB                           23.34 dB
PSNR for 0015.jpg                     32.52 dB                           37.17 dB
PSNR for 0016.jpg                     33.20 dB                           36.38 dB
PSNR for 0017.jpg                     26.65 dB                           28.87 dB
PSNR for 0018.png                     19.55 dB                           21.76 dB
PSNR for 0019.png                     24.49 dB                           26.80 dB
PSNR for 0020.jpg                     21.05 dB                           24.66 dB

Average PSNR (Ground truth vs Pixelated): 25.61 dB
Average PSNR (Ground truth vs Restored): 27.92 dB
```



SSIM (Structural Similarity Index):

We evaluated 20 image pairs using Structural Similarity Index (SSIM): **Ground Truth vs. Pixelated** and **Ground Truth vs. Restored**. Mean SSIM (Ground truth vs Pixelated) was 0.7997, showing degradation. Mean SSIM (Ground truth vs Restored) improved to 0.8315, indicating effective image restoration and detail preservation.

<u>Results:</u>



Frames Per Second (FPS):

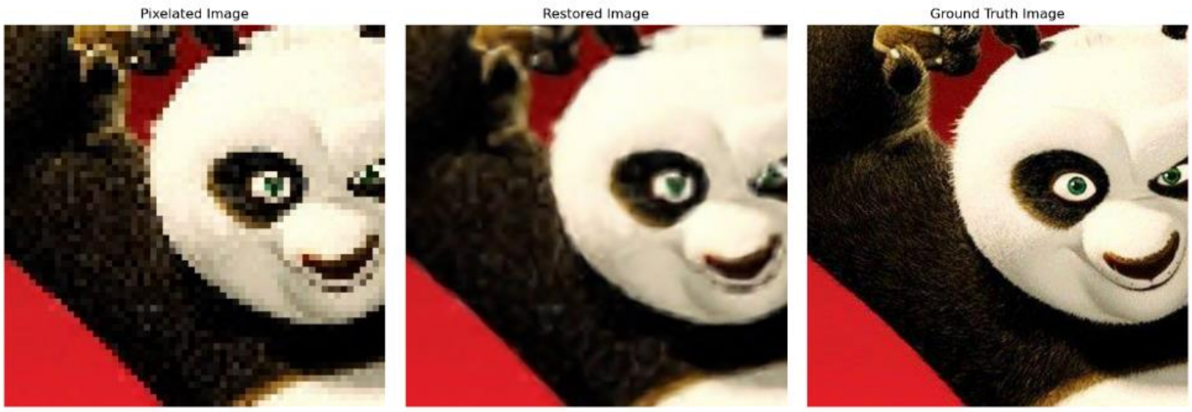
We conducted FPS (Frames Per Second) analysis on 20 images of size 1920x1080 using the ESPCN super-resolution model. The average FPS achieved was 5.59, indicating the model's processing speed in super-resolving images by a factor of 4.

<u>Results:</u>

```
Average FPS across 20 images: 5.59
```

Sample Output (1920 x 1080):

Zoomed-Out Comparison of Cropped Sections:



Zoomed-Out Comparison of Cropped Sections:

Exploration with Generative Adversarial Networks (GANs) for Image Restoration:

In addition to exploring the ESPCN model for pixelated image correction, we experimented with Generative Adversarial Networks (GANs). However, we opted against using GANs due to their generative nature, which can introduce hallucinated details that compromise restoration integrity. GANs are also computationally heavy and typically operate at lower FPS compared to the ESPCN model, limiting their suitability for real-time image restoration applications. Therefore, we focused on the ESPCN model for its efficiency in reducing pixelation artifacts while preserving image quality.

Conclusion:

This project focused on restoring pixelated images using the ESPCN (Efficient Sub-Pixel Convolutional Neural Network) model for super-resolution. We successfully mitigated pixelation effects by downsizing images by a factor of 4 and then restoring them to their original resolution using ESPCN.

Key Achievements:

- **Enhanced Image Quality:** The ESPCN model effectively reduced pixelation artifacts and improved visual clarity.
- **Quantitative Improvement:** Evaluation with **PSNR** and **SSIM** metrics showed significant enhancements. Initially, the average PSNR was 25.61 dB, and after restoration, it improved to 27.92 dB. Similarly, the mean SSIM increased from 0.7997 to 0.8315 after restoration across 20 images.

Limitations:

- **Operational Efficiency:** The model processed 1920x1080 images at an average FPS of 5.59, indicating limitations in real-time image restoration tasks.