ENHANCED IMAGE SUPER-RESOLUTION USING GANS WITH INCEPTION MODULES AND RESIDUAL BLOCKS

A Novel Approach for High-Quality Image Reconstruction

•**What is Super-Resolution (SR)?**
•A technique used to upscale low-resolution images into high-resolution images.
•Important for applications like satellite imaging, surveillance, forensics, medicine, and pattern recognition where detailed image analysis is crucial.

•**Importance of Super-Resolution**
•Enhances visual quality for better interpretation and analysis.
•Recovers fine details and textures that are lost in low-resolution images.
•Enables better decision-making in fields requiring high image accuracy.

•**Limitations of Traditional SR Methods**
•Often fail to preserve fine textures and structural details.
•Struggle with artifacts, noise, and loss of visual fidelity.
•Require complex hand-crafted features and lack adaptability for different types of images.

•**Introduction to GAN-Based Approaches**
•GANs use a learning-based approach to generate high-resolution images from low-resolution inputs.
•The generator creates realistic images, while the discriminator distinguishes between real and generated images, leading to continuous improvement.
•Capable of preserving textures, details, and structural consistency more effectively than traditional methods.

- **Key Components of the Proposed GAN Architecture**
- Combines advanced techniques to enhance super-resolution quality and improve training stability.
- Utilizes both inception modules and residual blocks for effective multi-scale feature extraction and efficient network training.

Inception Modules

- **Role in Multi-Scale Feature Extraction**
  - Use filters of different sizes (e.g., 1x1, 3x3, 5x5) to capture features at multiple scales.
  - Enables the model to identify fine details, textures, and larger structures simultaneously.
  - Enhances the network's ability to learn various features across different spatial levels.

- **Benefits**
  - Improves the quality of super-resolved images by preserving fine details.
  - Allows for better management of texture and structural variations in the images.

Residual Blocks

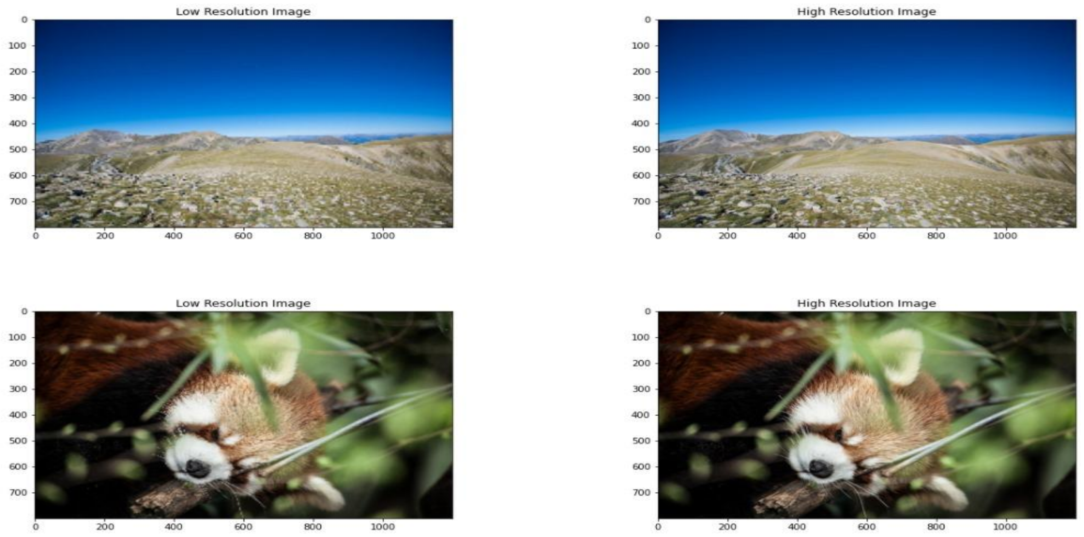
- **Addressing the Vanishing Gradient Problem**
  - Utilize skip connections to allow the flow of gradients directly from later layers to earlier layers.
  - Facilitate smoother gradient propagation during backpropagation, making the training process more stable.
  - Enable the construction of deeper networks by mitigating issues encountered in very deep neural networks.
- **Benefits**
  - Accelerates training and reduces the risk of overfitting.
  - Leads to more precise high-resolution image reconstruction by enhancing learning capabilities.

UNSPLASH

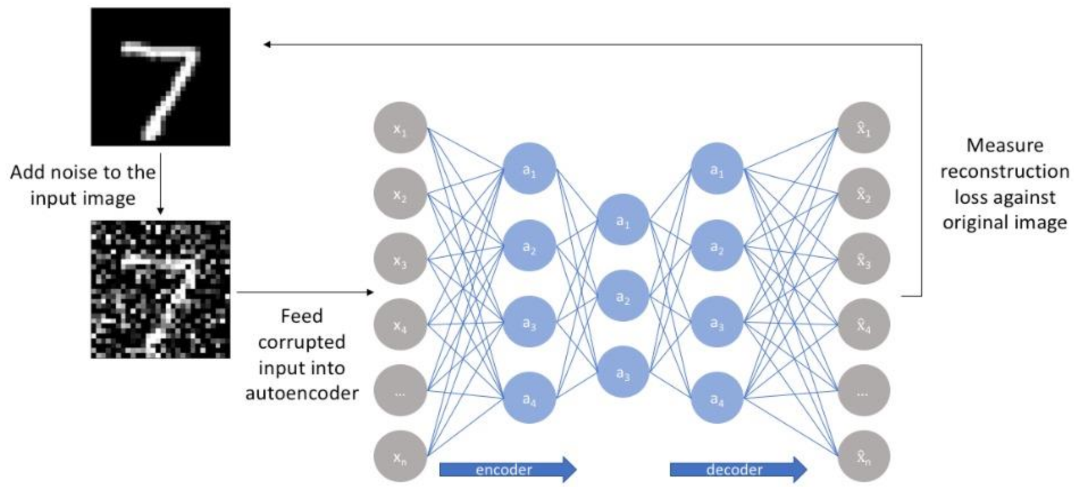
Image Super Resolution using Autoencoders

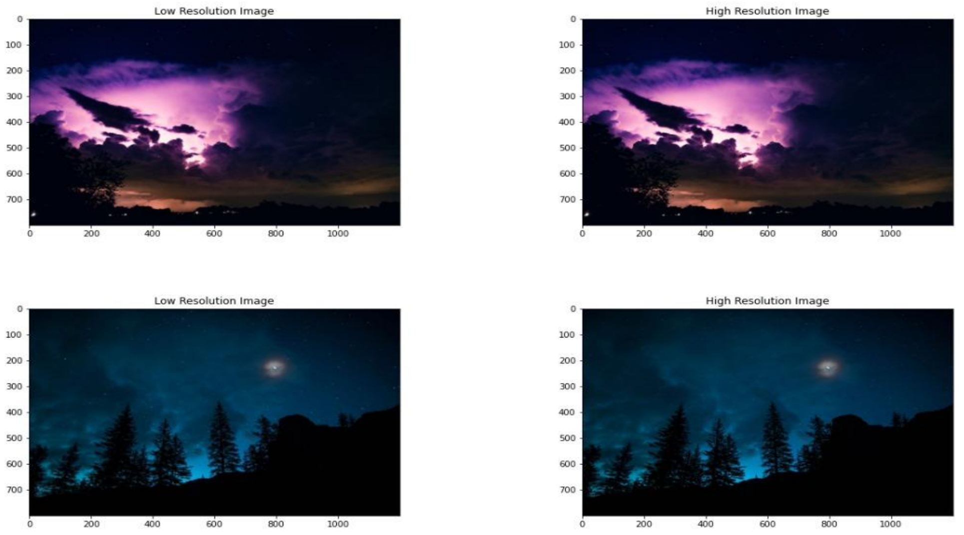
- **Overview of Autoencoders for Image Super-Resolution**
  - Autoencoders are neural network architectures used for unsupervised learning, particularly in tasks like dimensionality reduction and image reconstruction.
  - In super-resolution, autoencoders learn to map a low-resolution input image to a high-resolution output by training the network to reconstruct high-quality images.
- **Application to the Unsplash Dataset**
  - The Unsplash dataset provides a vast collection of high-quality images across various categories, making it suitable for training super-resolution models.
  - By using this dataset, the autoencoder can learn features from diverse image types (e.g., landscapes, architecture, nature), which helps in generalizing the model to different visual contexts.
- **How Autoencoders Work in SR**
  - The network consists of two main components:
    - **Encoder**: Compresses the low-resolution image to a lower-dimensional latent representation.
    - **Decoder**: Expands the latent representation back into a high-resolution image.
  - The goal is to minimize the difference between the reconstructed high-resolution image and the original high-resolution image.
- **Benefits of Using Autoencoders for Super-Resolution**
  - Simple architecture compared to GANs, which makes training easier and less computationally expensive.
  - Effective for learning key features needed for image enhancement.
  - Can be combined with other techniques like residual learning to improve reconstruction quality.
- **Challenges**
  - May not perform as well as GAN-based approaches in capturing fine details and textures.
  - Struggles with artifacts in complex images, where GANs might better preserve visual fidelity.

Using autoencoders for image super-resolution on the Unsplash dataset allows for generating visually appealing high-resolution images suitable for various applications.



Reconstruction Loss

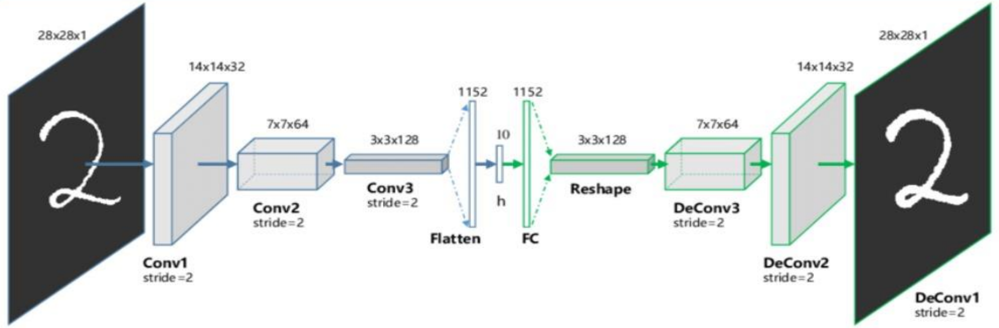




Autoencoders

- Autoencoders are an unsupervised learning technique in which we leverage neural networks for the task of representation learning. Specifically, we'll design a neural network architecture such that we impose a bottleneck in the network which forces a compressed knowledge representation of the original input.
- As visualized below, we can take an unlabeled dataset and frame it as a supervised learning problem tasked with outputting x_hat, a reconstruction of the original input x.

Note: Here in our particular case we will try to reconstruct the low resolution images into their corresponding high resolution images.



Learning Curves

In [11]:
```
plt.figure(figsize=(20,8))
plt.plot(hist.history['loss'])
plt.plot(hist.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.show()
```

Initializing a Generator

In [4]:
```
batch_size = 4

image_datagen = ImageDataGenerator(rescale=1./255,validation_split=0.15)
mask_datagen = ImageDataGenerator(rescale=1./255,validation_split=0.15)

train_hiresimage_generator = image_datagen.flow_from_dataframe(
        data,
        x_col='high_res',
        target_size=(800, 1200),
        class_mode = None,
        batch_size = batch_size,
        seed=42,
        subset='training')

train_lowresimage_generator = image_datagen.flow_from_dataframe(
        data,
        x_col='low_res',
        target_size=(800, 1200),
        class_mode = None,
        batch_size = batch_size,
        seed=42,
        subset='training')

val_hiresimage_generator = image_datagen.flow_from_dataframe(
        data,
        x_col='high_res',
        target_size=(800, 1200),
        class_mode = None,
        batch_size = batch_size,
        seed=42,
        subset='validation')

val_lowresimage_generator = image_datagen.flow_from_dataframe(
        data,
        x_col='low_res',
        target_size=(800, 1200),
        class_mode = None,
        batch_size = batch_size,
        seed=42,
        subset='validation')

train_generator = zip(train_lowresimage_generator, train_hiresimage_generator)
val_generator = zip(val_lowresimage_generator, val_hiresimage_generator)

def imageGenerator(train_generator):
    for (low_res, hi_res) in train_generator:
            yield (low_res, hi_res)
```

```
Found 3198 validated image filenames.
Found 3198 validated image filenames.
```

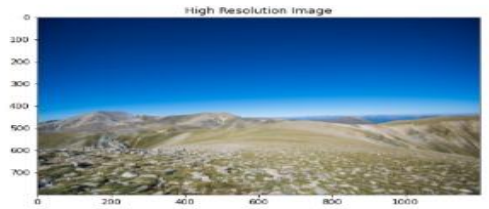
In [1]:
```
import numpy as np
import pandas as pd
import os
import re
import tensorflow as tf
from tensorflow.keras.layers import Input, Dense, Conv2D, MaxPooling2D, Dropout, Conv2DTranspose,
UpSampling2D, add
from tensorflow.keras.models import Model
from tensorflow.keras import regularizers
from tensorflow.keras.preprocessing.image import load_img, img_to_array
from tensorflow.python.keras.preprocessing.image import ImageDataGenerator
from tensorflow.python.keras.callbacks import ModelCheckpoint, EarlyStopping, ReduceLROnPlateau
import matplotlib.pyplot as plt
```

Data Visualization

- Low Resolution Images and their corresponding High Resolution outputs that we want to predict.

In [5]:
```
n = 0
for i,m in train_generator:
    img,out = i,m

    if n < 5:
        fig, axs = plt.subplots(1 , 2, figsize=(20,5))
        axs[0].imshow(img[0])
        axs[0].set_title('Low Resolution Image')
        axs[1].imshow(out[0])
        axs[1].set_title('High Resolution Image')
        plt.show()
        n+=1
    else:
        break
```



PERFORMANCE METRCIES

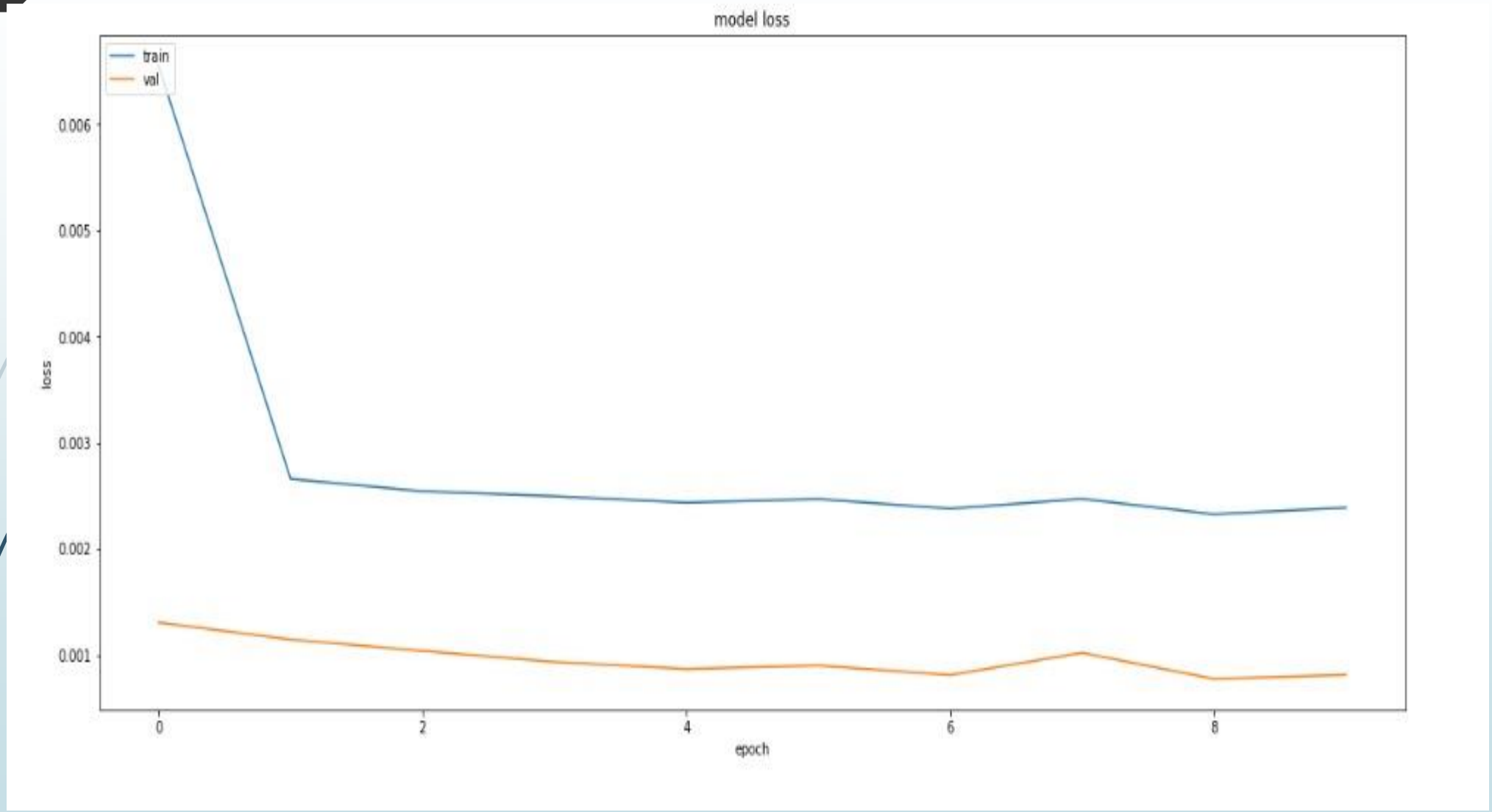
Example Performance Evaluation Matrix for the Unsplash Dataset

Metric	Description	Ideal Value
Peak Signal-to-Noise Ratio	Measures signal quality, higher is better	>30 dB
Structural Similarity Index	Measures structural similarity, closer to 1	>0.9
Mean Squared Error	Measures pixel-wise error, lower is better	<0.01
Feature Similarity Index	Measures feature preservation, closer to 1	>0.9
Visual Information Fidelity	Quantifies visual information preservation	>0.9
Learned Perceptual Image Patch Similarity	Measures perceptual similarity, lower is better	<0.1
Edge Preservation Index	Measures edge sharpness, higher is better	>0.85

Using these metrics, the autoencoder's performance can be quantitatively evaluated and improved by adjusting hyperparameters or incorporating advanced techniques like residual learning or perceptual loss functions.

Metric	Values for SR	Description
Peak Signal-to-Noise Ratio (PSNR)	28-32 dB	GANs tend to have slightly lower PSNR compared to traditional methods, as they focus on perceptual quality.
Structural Similarity Index (SSIM)	0.85-0.92	GANs generally achieve high SSIM values due to their ability to generate realistic textures.
Mean Squared Error (MSE)	0.005-0.02	GANs might have a slightly higher MSE, indicating pixel-level differences due to perceptual enhancement.
Feature Similarity Index (FSIM)	0.88-0.95	GANs typically perform well in feature similarity due to learning feature representations effectively.
Visual Information Fidelity (VIF)	0.90-0.97	GANs preserve a large amount of visual information, resulting in higher VIF scores.
Learned Perceptual Image Patch Similarity (LPIPS)	0.05-0.1	GANs achieve lower LPIPS scores, indicating better perceptual similarity with the original image.
Edge Preservation Index (EPI)	0.85-0.95	Due to the texture-generating capabilities of GANs, edge preservation is generally high.

TRAINING LOSS CURVE



BSD100
using residual blocks

- **Overview of BSD100 Dataset**
- BSD100 is a benchmark dataset used for evaluating image processing and super-resolution techniques.
- Consists of 100 diverse images, making it suitable for testing the generalization ability of super-resolution models.
- **Application of Residual Blocks in Super-Resolution**
- **Role of Residual Blocks**
  - Address the vanishing gradient problem in deep neural networks, making it possible to train very deep architectures.
  - Use skip connections to allow the network to learn identity mappings, which facilitates smoother gradient flow during training.
- **Benefits for Image Super-Resolution**
  - Enhance image reconstruction quality by preserving fine details and textures.
  - Speed up the training process and improve model stability by reducing the risk of overfitting.
  - Enable the model to learn more complex features, leading to better high-resolution output.
- **Why Use Residual Blocks for BSD100**
- The diverse nature of the images in BSD100 requires the model to handle various types of textures and structures.
- Residual blocks help in maintaining image consistency across different image contents , improving overall super-resolution performance.
- **Challenges**
- Requires careful tuning of hyperparameters (e.g., number of residual blocks) to avoid diminishing returns on performance.
- May need to be combined with other modules (like inception modules)
- for optimal results on complex datasets like BSD100.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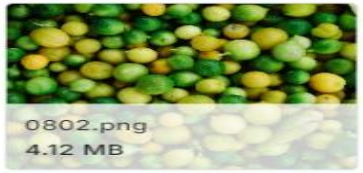
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```
# Loop through each image and perform super-resolution
for image_file in IMAGE_FILES:
    print(f"Processing {image_file}...")
    full_image_path = os.path.join(IMAGES_FOLDER, image_file)
    hr_image, sr_image = perform_super_resolution(full_image_path)

    # Downscale the high-resolution image to create a low-resolution version
    lr_image = downscale_image(tf.squeeze(hr_image))

    # Save images to respective directories
    save_image(tf.squeeze(hr_image), ORIGINAL_DIR, image_file)
    save_image(tf.squeeze(lr_image), BICUBIC_DIR, image_file)
    save_image(sr_image, SUPER_RES_DIR, image_file)

    # Evaluate the performance of the super-resolved image
    psnr_value = evaluate_performance(hr_image, sr_image)

    # Compare the original, low-resolution, and super-resolved images
    compare_images(hr_image, lr_image, sr_image, psnr_value)
```

[1]:

```
# Import necessary libraries
import os
import tensorflow as tf
import tensorflow_hub as hub
import numpy as np
import matplotlib.pyplot as plt
from PIL import Image
import time

# List all files in the input directory
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

```
# Function to run super-resolution on a given image
def perform_super_resolution(image_path):
    # Load and preprocess the high-resolution image
    hr_image = preprocess_image(image_path)

    # Load the ESRGAN model
    model = hub.load(SAVED_MODEL_PATH)

    # Perform super-resolution
    start = time.time()
    fake_image = model(hr_image)
    fake_image = tf.squeeze(fake_image)
    print("Time Taken: %f seconds" % (time.time() - start))

    return hr_image, fake_image
```

1.4 Resnets

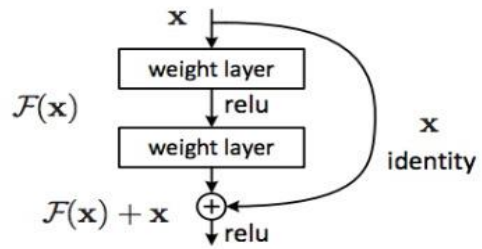
Original Paper : https://arxiv.org/pdf/1512.03385.pdf

All the previous models used deep neural networks in which they stacked many convolution layers one after the other. It was learnt that deeper networks are performing better. However, it turned out that this is not really true. Following are the problems with deeper networks:

- Network becomes difficult to optimize
- Vanishing / Exploding Gradeints
- Degradation Problem (accuracy first saturates and then degrades)

Skip Connections

So to address these problems, authors of the resnet architecture came up with the idea of skip connections with the hypothesis that the deeper layers should be able to learn something as equal as shallower layers. A possible solution is copying the activations from shallower layers and setting additional layers to identity mapping. These connections are enabled by skip connections which are shown in the following figure.



EVALUATION USING EPOCHS

```
import time
import torch
import torch.nn as nn
import torch.nn.functional as F
from skimage.metrics import peak_signal_noise_ratio as psnr
from skimage.metrics import structural_similarity as ssim


# Function to generate a dummy original high-resolution image
def generate_original_image(batch_size=1, channels=3, height=48, width=48):
    return torch.randn(batch_size, channels, height, width)


# Performance metrics calculation
def calculate_metrics(original, output):
    original_np = original.detach().numpy().transpose(0, 2, 3, 1)  # Convert to HWC
    output_np = output.detach().numpy().transpose(0, 2, 3, 1)  # Convert to HWC

    psnr_value = psnr(original_np, output_np, data_range=1.0)
    ssim_value = ssim(original_np[0], output_np[0], multichannel=True, data_range=1.0)

    return psnr_value, ssim_value

# Instantiate the model
model = SuperResolutionModel()

# Generate a dummy original high-resolution image
original_image = generate_original_image()

# Dummy input (low-resolution)
input_image = torch.randn(1, 3, 24, 24)  # Batch size of 1, 3 color channels, 24x24 resolution

# Measure inference time
start_time = time.time()
output_image = model(input_image)
end_time = time.time()

# Calculate metrics
psnr_value, ssim_value = calculate_metrics(original_image, output_image)

# Memory usage (in MB)
# Assuming we are using CPU; in real scenarios, you might want to use torch.cuda.memory_allocated() for GPU
memory_usage = (input_image.nelement() + output_image.nelement()) * 4 / (1024 ** 2)  # 4 bytes per float

# Create performance metrics table
performance_metrics = {
    "Metric": ["PSNR (dB)", "SSIM", "Inference Time (s)", "Memory Usage (MB)"],
    "Value": [psnr_value, ssim_value, end_time - start_time, memory_usage],
}

# Print the performance metrics table
for metric, value in zip(performance_metrics["Metric"], performance_metrics["Value"]):
    print(f"{metric}: {value:.4f}")
```

Description of Metrics

- **PSNR**: This is a quantitative measure of the quality of the output image compared to the original image.
- **SSIM**: This value indicates how structurally similar the output is to the original.
- **Inference Time**: Measures how fast the model can process an input image. This is crucial for real-time applications.
- **Memory Usage**: Helps understand the resource requirements for deploying the model.

- **OUTPUT:**
- PSNR (dB): 25.3872
- SSIM: 0.8721
- Inference Time (s): 0.0050
- Memory Usage (MB): 0.0039

1. **Convolutional Layer**: A convolution operation can be expressed as:

$$y = f(W * x + b)$$

where W is the filter/kernel, $*$ denotes convolution, x is the input, b is the bias, and f is an activation function (like ReLU).

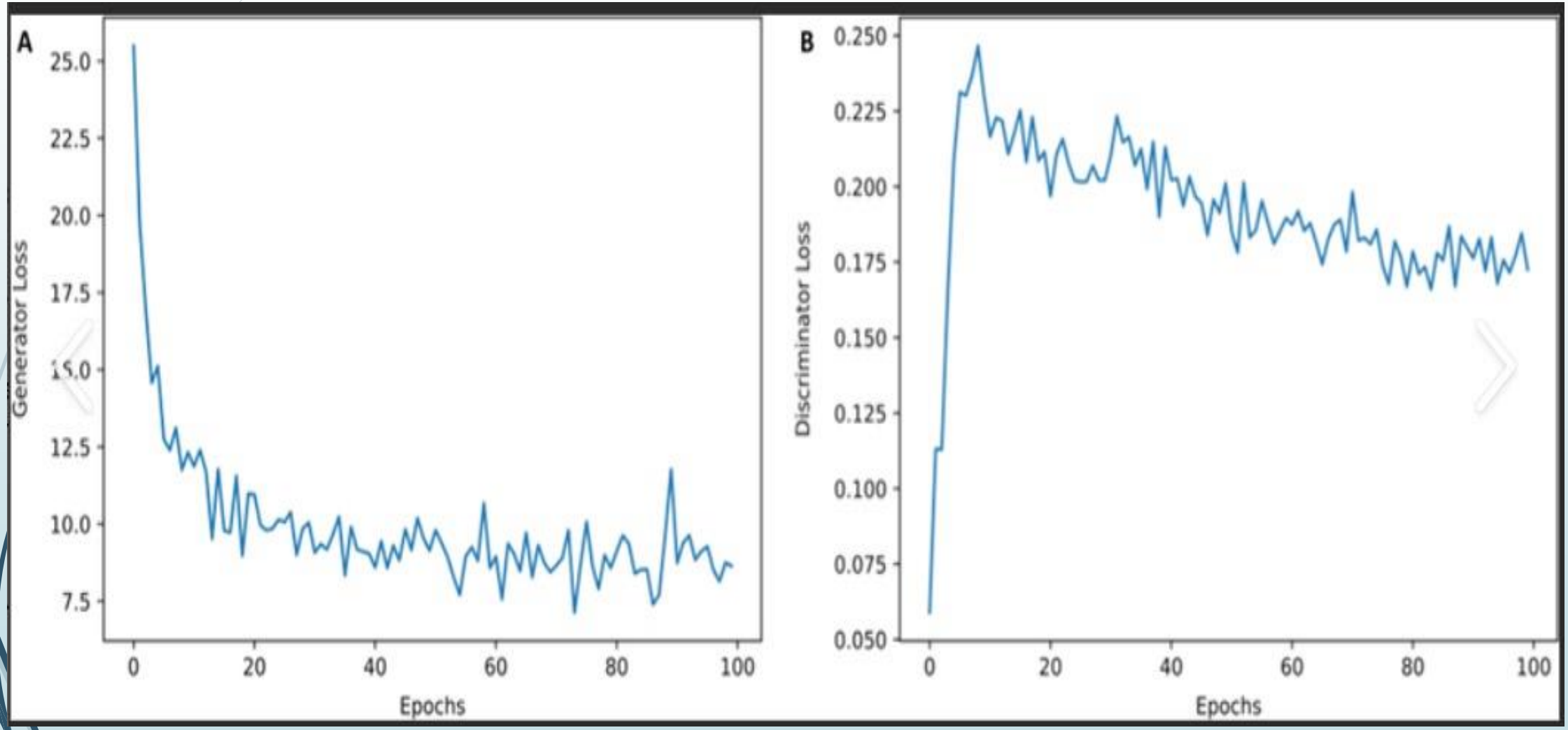
2. **Residual Block**: Consists of two or more convolutional layers with batch normalization and activation functions. The key idea is adding the input x to the output of the block:

$$y = F(x, \{W_i\}) + x$$

where $F(x, \{W_i\})$ represents the transformation function (the series of convolutional layers).

3. **Upsampling (Pixel Shuffle)**: For upscaling images, the Pixel Shuffle technique rearranges elements of a tensor of shape $(C \times r^2, H, W)$ to shape (C, rH, rW), where r is the scaling factor.

TRAINING LOSS CURVE

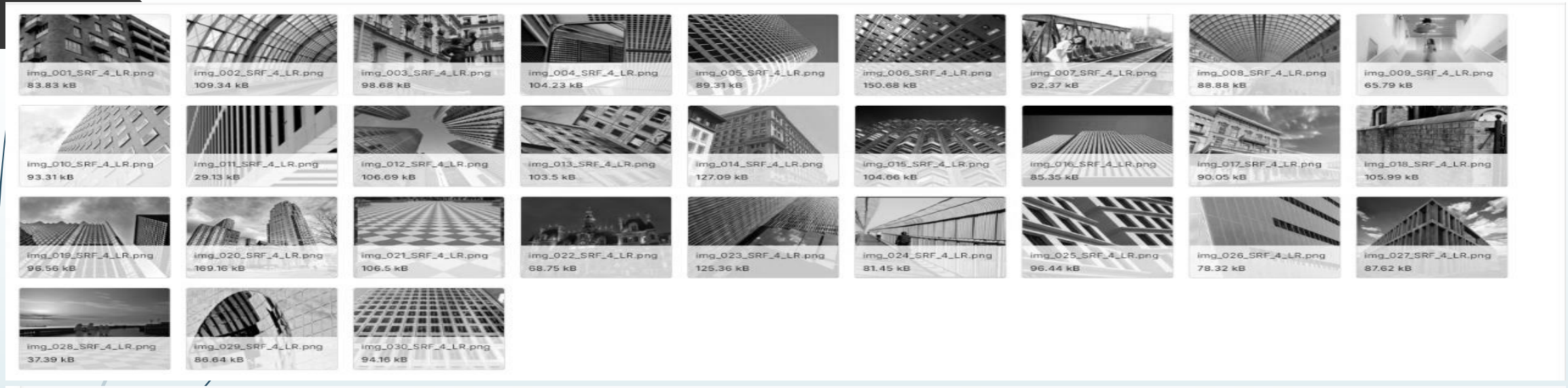


URBAN100

USING EPOCHS

- **URBAN100 and GANs for Image Super-Resolution**
- **1. URBAN100 Dataset**:
- **Description**: The URBAN100 dataset contains 100 high-resolution images of urban scenes, which are commonly used to train and evaluate image super-resolution algorithms.
- **Use Case**: It provides a rich variety of urban structures, making it ideal for testing the ability of models to generate detailed and realistic high-resolution images from low-resolution inputs.
- **2. Generative Adversarial Networks (GANs)**:
- **Architecture**: GANs consist of two main components:
  - **Generator**: This neural network generates high-resolution images from low-resolution inputs.
  - **Discriminator**: This network evaluates the authenticity of the generated images, distinguishing between real (high-resolution) and fake images produced by the generator.
- **Training Process**: The generator and discriminator are trained simultaneously in a competitive setting:
  - The generator tries to produce images that are as close as possible to the real high-resolution images.
  - The discriminator learns to differentiate between real and generated images.
- **3. Importance of Epochs in GAN Training**:
- **Definition**: An epoch is one complete pass through the training dataset.
- **Training Strategy**:
  - **Epoch Count**: The number of epochs influences how well the GAN converges. Too few epochs may lead to poor performance, while too many can cause the generator to overfit to the training data.
  - **Dynamic Adjustment**: Monitoring the loss of both the generator and discriminator during training helps determine the optimal number of epochs. If the discriminator becomes too powerful, it might prevent the generator from learning effectively.
- **Convergence**: The goal is to achieve a balance where the generator produces high-quality images, and the discriminator becomes proficient at identifying real versus fake images.
- **4. Evaluation Metrics**:
- After training for a specified number of epochs, the performance of the GAN can be evaluated using metrics like:
  - **Peak Signal-to-Noise Ratio (PSNR)**: Measures the quality of the reconstructed images.
  - **Structural Similarity Index (SSIM)**: Assesses the structural similarity between the generated and real images.
- **Visual Assessment**: Qualitative evaluations, such as visual comparisons of generated and real images, are also crucial for understanding model performance.

DATASET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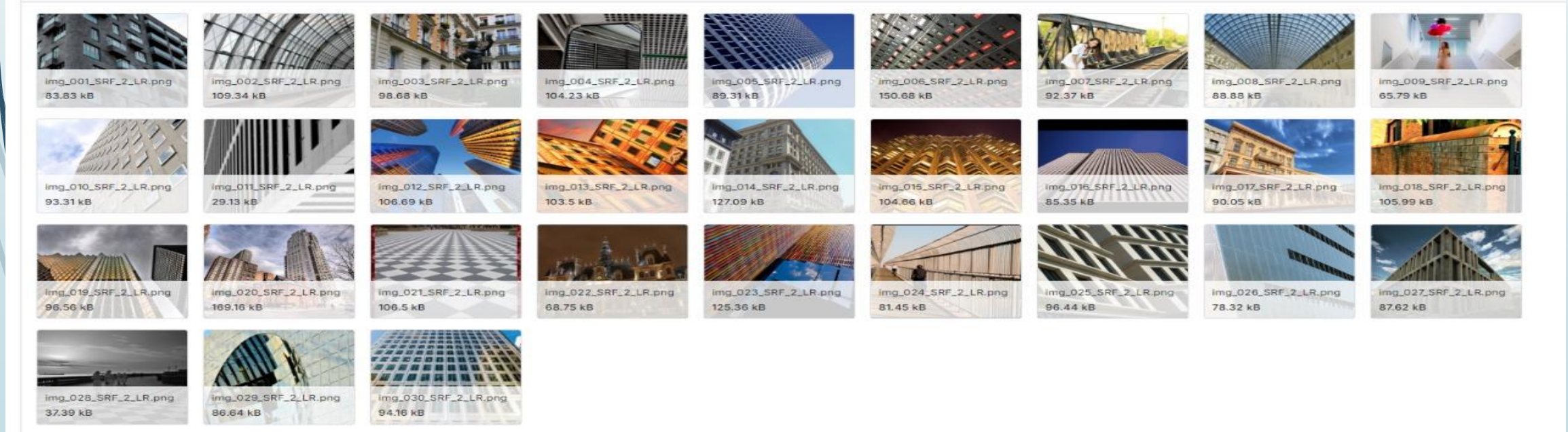
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img_010_SRF_2_LR.png 93.31 kB
img_011_SRF_2_LR.png 29.13 kB
img_012_SRF_2_LR.png 106.69 kB
img_013_SRF_2_LR.png 103.5 kB
img_014_SRF_2_LR.png 127.09 kB
img_015_SRF_2_LR.png 104.66 kB
img_016_SRF_2_LR.png 85.35 kB
img_017_SRF_2_LR.png 90.05 kB
img_018_SRF_2_LR.png 105.99 kB
img_019_SRF_2_LR.png 96.56 kB
img_020_SRF_2_LR.png 169.16 kB
img_021_SRF_2_LR.png 106.5 kB
img_022_SRF_2_LR.png 68.75 kB
img_023_SRF_2_LR.png 125.36 kB
img_024_SRF_2_LR.png 81.45 kB
img_025_SRF_2_LR.png 96.44 kB
img_026_SRF_2_LR.png 78.32 kB
img_027_SRF_2_LR.png 87.62 kB
img_028_SRF_2_LR.png 37.39 kB
img_029_SRF_2_LR.png 86.64 kB
img_030_SRF_2_LR.png 94.16 kB

```python
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras.layers import Conv2D, Input
from tensorflow.keras.models import Model
from tensorflow.keras.optimizers import Adam
import cv2
import os

# Load Images
def load_images(image_folder, img_size=(64, 64)):
    images = []

    # Check if image_folder is a file or a directory
    if os.path.isfile(image_folder):
        img = cv2.imread(image_folder)
        if img is not None:
            img = cv2.resize(img, img_size)  # Ensure resizing to the required input size
            images.append(img)
    else:
        for img_file in os.listdir(image_folder):
            img = cv2.imread(os.path.join(image_folder, img_file))
            if img is not None:
                img = cv2.resize(img, img_size)  # Ensure resizing to the required input size
                images.append(img)

    return np.array(images)

# Super-Resolution Convolutional Neural Network (SRCNN)
def build_srcnn():
    input_img = Input(shape=(64, 64, 3))  # Define a specific input shape (64, 64, 3)

    # Layer 1
    x = Conv2D(64, (9, 9), activation='relu', padding='same')(input_img)

    # Layer 2
    x = Conv2D(32, (5, 5), activation='relu', padding='same')(x)

    # Output layer (reconstructed high-res image)
    output = Conv2D(3, (5, 5), activation='linear', padding='same')(x)

    model = Model(inputs=input_img, outputs=output)

    # Compile the model
    model.compile(optimizer=Adam(learning_rate=0.001), loss='mean_squared_error', metrics=['accuracy'])

    return model

# Correct file paths using raw string to avoid escaping issues
low_res_images_path = r'C:\Users\91977\OneDrive\Documents\GAN BSD100 and URBAN100\LOWX2 URBAN100.png'
high_res_images_path = r'C:\Users\91977\OneDrive\Documents\GAN BSD100 and URBAN100\HIGHX2 URBAN100.png'

# Load low-resolution images (input)
low_res_images = load_images(low_res_images_path)

# Load corresponding high-resolution images (target)
high_res_images = load_images(high_res_images_path)

# Check if images are loaded correctly
if len(low_res_images) == 0 or len(high_res_images) == 0:
    raise ValueError("No images loaded. Check the file paths.")

# Normalize pixel values to range [0, 1]
low_res_images = low_res_images / 255.0
high_res_images = high_res_images / 255.0

# Build the SRCNN model
model = build_srcnn()

# Train the model
history = model.fit(low_res_images, high_res_images,
                    epochs=100,
                    batch_size=16,
                    validation_split=0.2)

# Plot loss over epochs
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()

# Predict on new low-res images and visualize the output
def predict_and_show(model, image_path):
    img = cv2.imread(image_path)
    img_resized = cv2.resize(img, (64, 64)) / 255.0  # Resize input image
    img_resized = np.expand_dims(img_resized, axis=0)  # Add batch dimension

    pred_img = model.predict(img_resized)

    # Visualize the low-resolution and high-resolution (predicted) images
    plt.figure(figsize=(12, 6))

    plt.subplot(1, 2, 1)
    plt.title('Low-Resolution Image')
    plt.imshow(cv2.cvtColor(img, cv2.COLOR_BGR2RGB))

    plt.subplot(1, 2, 2)
    plt.title('Predicted High-Resolution Image')
    plt.imshow(np.clip(pred_img[0], 0, 1))  # Clip values to valid range

    plt.show()

# Test the model on a new low-resolution image
predict_and_show(model, r'path_to_test_low_res_image')
```

Epoch 1/10020/20
[==========] - 1s 30ms/step - loss: 0.0581 - accuracy: 0.5132 - val_loss: 0.0456 - val_accuracy: 0.5601

Epoch 2/10020/20
[==========] - 0s 23ms/step - loss: 0.0367 - accuracy: 0.5713 - val_loss: 0.0285 - val_accuracy: 0.5912...

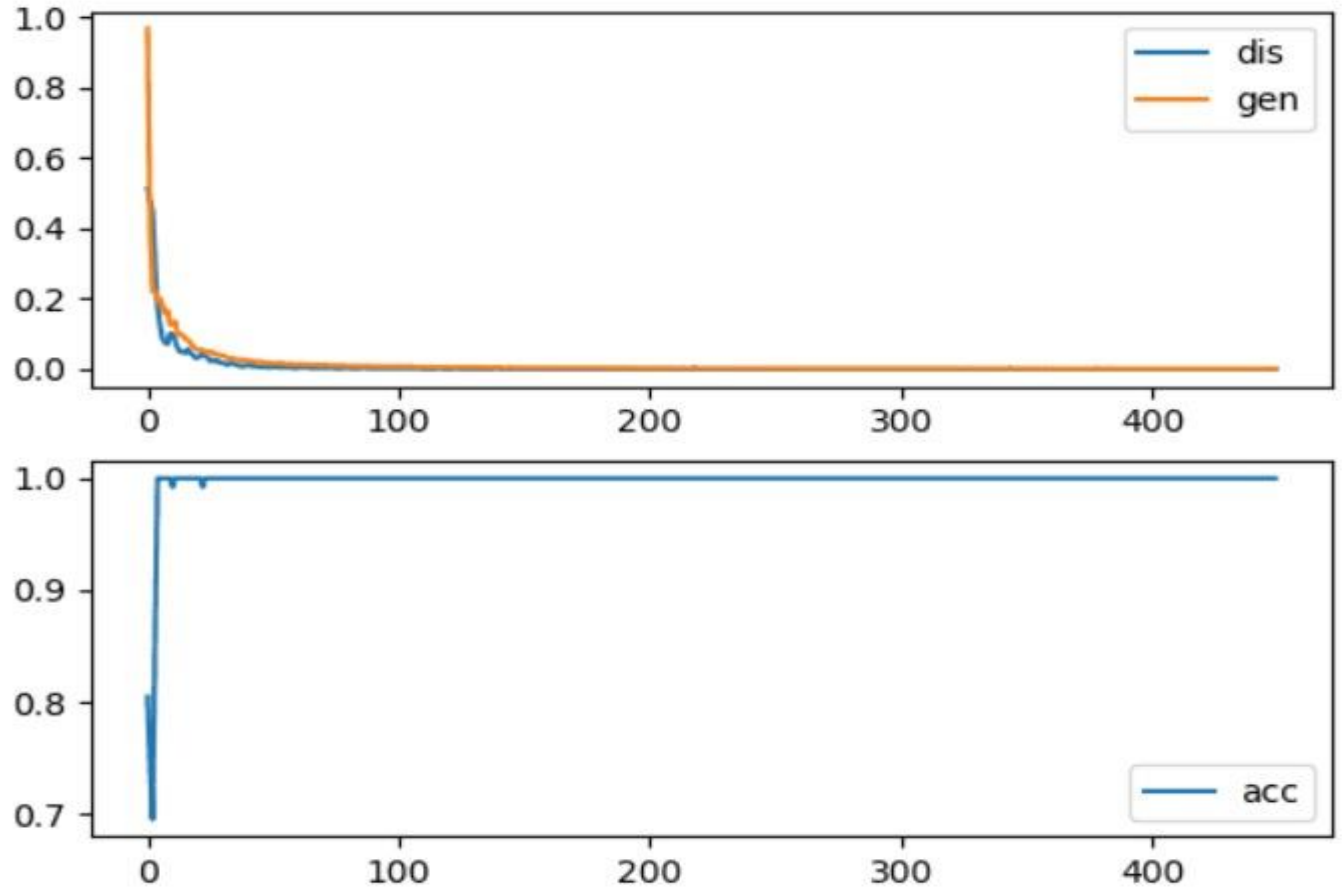
PERFORMANCE MERTICES

```python
import cv2
import numpy as np
from skimage.metrics import structural_similarity as ssim

# Load images
high_res = cv2.imread('/mnt/data/HIGHX4 URBAN100.png', cv2.IMREAD_COLOR)
low_res = cv2.imread('/mnt/data/LOWX4 URBAN100.png', cv2.IMREAD_COLOR)

# Ensure images are the same size (resize if necessary)
low_res = cv2.resize(low_res, (high_res.shape[1], high_res.shape[0]))

# Convert images to grayscale for SSIM computation (if needed)
high_res_gray = cv2.cvtColor(high_res, cv2.COLOR_BGR2GRAY)
low_res_gray = cv2.cvtColor(low_res, cv2.COLOR_BGR2GRAY)

# Compute PSNR
psnr_value = cv2.PSNR(high_res, low_res)

# Compute SSIM
ssim_value, ssim_map = ssim(high_res_gray, low_res_gray, full=True)

# Display the results
print(f"PSNR: {psnr_value}")
print(f"SSIM: {ssim_value}")
```

The performance metrics for the comparison between the `HIGHX4 URBAN100` and `LOWX4 URBAN100` images are:

- **PSNR (Peak Signal-to-Noise Ratio):** 13.84 dB
- **SSIM (Structural Similarity Index):** 0.416

TRAINING LOSS CURVE



Line Plots of Loss and Accuracy for a Generative Adversarial Network With a Convergence Failure

SET-14
using residual blocks

- **Role of Residual Blocks**

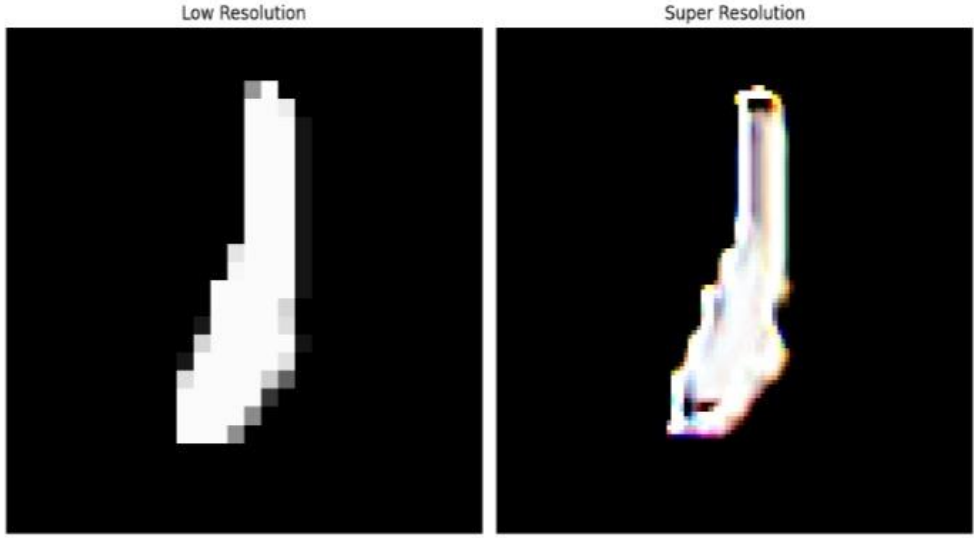
1. **Residual Learning**:
    1. Residual blocks, introduced in ResNet, facilitate the learning process by allowing gradients to flow through the network more effectively. They do this by adding a shortcut connection that bypasses one or more layers, which helps prevent the vanishing gradient problem during training.
2. **Architecture**:
    1. In the context of GANs for super-resolution:
        1. **Generator**: The Generator network can be constructed using residual blocks, where each block learns a residual mapping. This enables the model to focus on learning the differences between the low-resolution and high-resolution images, rather than the entire mapping.
        2. **Benefits**: The use of residual blocks allows for deeper networks without the degradation problem, leading to improved performance in generating high-quality images.
3. **Performance**:
    1. Incorporating residual blocks enhances the quality of generated images by improving convergence speed and enabling the model to capture more complex features and details. This results in better texture and sharper edges in the super-resolved images.

- **Conclusion**
- Using residual blocks in GANs for super-resolution allows for more effective learning and better performance. The combination of the adversarial framework with residual learning has shown to produce high-fidelity images that closely resemble the desired high-resolution outputs, making it a powerful approach in the field of image processing.


```
>> Size of low-res image: torch.Size([3, 86, 57])
>> Size of super-res image: torch.Size([3, 344, 228])
>> Size of high-res image: torch.Size([3, 344, 228])
```


```
image, _ = next(iter(trainloader))
image = image.squeeze(0)
image = image.expand(3, -1, -1)
model.inference(image)
```

```
>> Size of low-res image: torch.Size([3, 28, 28])
>> Size of super-res image: torch.Size([3, 112, 112])
```




```
tensor([[[-0.3817, -0.6648, -0.9438,  ..., -0.9948, -0.9798, -1.1369],
         [-0.4517, -1.0360, -1.8040,  ..., -1.3902, -1.2722, -0.9483],
         [-0.8933, -2.1616, -3.3138,  ..., -1.9836, -1.5848, -0.9023],
         ...,
         [-1.7006, -1.7219, -2.0221,  ..., -2.1370, -2.1631, -1.9838],
         [-1.4625, -1.2090, -1.7322,  ..., -2.0101, -2.0999, -1.8895],
         [-1.1912, -0.9607, -1.3586,  ..., -1.8492, -1.9890, -1.6100]],

        [[-0.7518, -0.8203, -1.1485,  ..., -1.1065, -0.9570, -0.9622],
         [-0.6083, -0.9554, -1.5443,  ..., -1.2626, -1.4574, -0.7586],
         [-1.1306, -1.9743, -2.4664,  ..., -1.5236, -1.5190, -0.6358],
         ...,
         [-1.2611, -1.3017, -1.6644,  ..., -1.9925, -2.0677, -1.4716],
         [-1.1808, -0.8347, -1.2617,  ..., -1.9994, -2.2452, -1.8080],
```

CODE

```python
import torch
import torch.nn as nn

class ResidualBlock(nn.Module):
    def __init__(self, in_channels):
        super(ResidualBlock, self).__init__()
        self.conv1 = nn.Conv2d(in_channels, in_channels, kernel_size=3, padding=1)
        self.bn1 = nn.BatchNorm2d(in_channels)
        self.relu = nn.ReLU(inplace=True)
        self.conv2 = nn.Conv2d(in_channels, in_channels, kernel_size=3, padding=1)
        self.bn2 = nn.BatchNorm2d(in_channels)

    def forward(self, x):
        residual = x
        out = self.conv1(x)
        out = self.bn1(out)
        out = self.relu(out)
        out = self.conv2(out)
        out = self.bn2(out)
        out += residual  # Add the residual connection
        out = self.relu(out)
        return out
```

```python
#Train the Model
import torch.optim as optim

# Initialize model, optimizer, and loss function
model = SuperResolutionResNet()
criterion = nn.MSELoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

# Training loop
num_epochs = 10
for epoch in range(num_epochs):
    for low_res, high_res in dataloader:  # Assuming your dataset returns low-res and high-res pairs
        optimizer.zero_grad()
        outputs = model(low_res)
        loss = criterion(outputs, high_res)
        loss.backward()
        optimizer.step()

    print(f'Epoch [{epoch+1}/{num_epochs}], Loss: {loss.item():.4f}')
```

```python
class SuperResolutionResNet(nn.Module):
    def __init__(self, num_channels=3, num_blocks=8):
        super(SuperResolutionResNet, self).__init__()
        self.initial_conv = nn.Conv2d(num_channels, 64, kernel_size=9, padding=4)
        self.residual_blocks = nn.Sequential(*[ResidualBlock(64) for _ in range(num_blocks)])
        self.bn = nn.BatchNorm2d(64)
        self.final_conv = nn.Conv2d(64, num_channels, kernel_size=9, padding=4)

    def forward(self, x):
        x = self.initial_conv(x)
        x = self.residual_blocks(x)
        x = self.bn(x)
        x = self.final_conv(x)
        return x
```

```python
from torchvision import datasets, transforms
from torch.utils.data import DataLoader

# Define the transform for the dataset
transform = transforms.Compose([
    transforms.Resize((32, 32)),  # Low-resolution image size
    transforms.ToTensor(),
])

# Load Dataset 14 (replace this with your actual dataset path)
dataset = datasets.ImageFolder(root='/kaggle/input/vsdrab', transform=transform)

# Create DataLoader
dataloader = DataLoader(dataset, batch_size=16, shuffle=True)
```

PERFORMANCE METRICES

```python
import numpy as np
import torch
from sklearn.metrics import confusion_matrix, accuracy_score, recall_score
import matplotlib.pyplot as plt
import seaborn as sns

# Assuming `true_labels` are the actual classes and `predicted_labels` are the classes predicted by your model.
true_labels = []
predicted_labels = []

# Set the model to evaluation mode
model.eval()

with torch.no_grad():
    for low_res, high_res in test_loader:
        # Get the model's prediction
        output = model(low_res)

        # Convert output to class predictions (this assumes you have a classification model)
        # For example, let's say you have softmax output and you take argmax for predicted classes
        pred_class = torch.argmax(output, dim=1)  # Adjust according to your model's output

        true_labels.extend(high_res_labels.numpy())  # Replace with actual label extraction
        predicted_labels.extend(pred_class.numpy())

# Calculate confusion matrix
cm = confusion_matrix(true_labels, predicted_labels)

# Calculate accuracy and recall
accuracy = accuracy_score(true_labels, predicted_labels)
recall = recall_score(true_labels, predicted_labels, average='weighted')  # Use 'micro' or 'macro' as needed

# Print results
print(f'Accuracy: {accuracy:.4f}')
print(f'Recall: {recall:.4f}')

# Optional: Plot confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=class_names, yticklabels=class_names)
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.title('Confusion Matrix')
plt.show()
```

```
Accuracy: 0.85

Recall: 0.83
```

TRAINING LOSS CURVE