School of Computer Science and Engineering

J Component report

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Title: Super Resolution Generative Adversarial Network

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Abstract

The project proposes an SRGAN architecture with a 4x upscaling factor, consisting of a generator network and a discriminator network trained adversarially. The generator network is based on the ResNet architecture and is trained to produce high-resolution images from low-resolution inputs. The discriminator network consists of eight convolutional layers and is trained to distinguish between real and generated high-resolution images.

The proposed model is trained on several benchmark datasets, including the DIV2K dataset and Set5 dataset. The results show that the proposed architecture outperforms other state-of-the-art methods in terms of PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index) scores. Moreover, the proposed model generates images with realistic textures and sharp details, indicating its superiority over other approaches.
The study also evaluates the effect of using different loss functions, such as mean squared error (MSE), perceptual loss, and adversarial loss. The results indicate that the proposed model with perceptual and adversarial loss functions achieves the best performance.

Overall, the proposed SRGAN architecture with a 4x upscaling factor, an 8-layered discriminator network, and a ResNet generator network offers a promising approach for high-quality super-resolution. The architecture has the potential to be applied in various domains, such as medical imaging, remote sensing, and surveillance, where high-resolution images are crucial for accurate analysis and decision-making.

Keywords : SRGAN, upscaling factor, generator network, discriminator network, adversarial training, ResNet, high-resolution images, PSNR, SSIM, state-of-the-art methods, realistic textures, sharp details, loss functions, mean squared error, perceptual loss, adversarial loss, performance

Introduction

Super-Resolution Generative Adversarial Networks (SRGAN) is a deep learning technique used to generate high-resolution images from low-resolution images. It is a breakthrough technique in image processing and computer vision, as it can produce realistic images with high levels of details that were not achievable before. The SRGAN is trained using a generative adversarial network (GAN) architecture, which consists of a generator and a discriminator. The generator generates high-resolution images, while the discriminator discriminates between the generated images and the real high-resolution images.

In this specific case, we will be discussing an SRGAN that uses a 4 times up-scaling factor, an 8 layered discriminator, and a ResNet generator. The 4 times up-scaling factor means that the SRGAN will take a low-resolution image and produce an image that is 4 times larger in dimensions, while maintaining the quality and details of the original image. The 8 layered discriminator is a neural network that evaluates the quality of the generated images by the generator. The ResNet generator is a deep neural network architecture that allows for the efficient training of deep neural networks by using residual connections.

The use of a ResNet generator in this SRGAN architecture is particularly interesting as it addresses the problem of vanishing gradients that is common in deep neural networks. This allows the network to maintain high levels of accuracy while training, which leads to the production of high-quality images. Additionally, the use of an 8 layered discriminator allows for the detection of even the smallest details in the generated images, which leads to more realistic and accurate images.

To better understand how this SRGAN works, it is important to know that the generator and discriminator work in tandem during the training process. The generator takes a low-resolution image and upscales it to the desired high-resolution output, while the discriminator tries to differentiate between the high-resolution images and the generated images. The generator tries to produce images that the discriminator cannot differentiate from the real high-resolution images, while the discriminator tries to become more adept at distinguishing the two.

The ResNet generator used in this SRGAN architecture is a modification of the original ResNet architecture, which was initially developed for image classification tasks. The ResNet generator uses skip connections to pass information from one layer to another, which helps to prevent the vanishing gradient problem that can occur in deep neural networks. This allows the generator to produce images that are more accurate and detailed.

The 8 layered discriminator used in this SRGAN architecture is a deep neural network that evaluates the quality of the generated images by the generator. The discriminator tries to differentiate between the high-resolution images and the generated images. The more accurate the discriminator becomes at distinguishing between the two, the better the generator becomes at producing images that are indistinguishable from the real high-resolution images.

The SRGAN with a 4 times up-scaling factor, an 8 layered discriminator, and a ResNet generator is an advanced deep learning technique that can generate high-quality images that are nearly indistinguishable from the real high-resolution images. This technique has the potential to revolutionize the field of image processing and computer vision by providing a powerful tool for generating high-quality images in a variety of applications.

SRGAN has a wide range of applications in various fields such as medical imaging, satellite imaging, video processing, and more. Some of the most common uses of SRGAN are:

1. Medical imaging: SRGAN can be used in medical imaging to generate high-resolution images of X-rays, CT scans, and MRIs. These images can be used for accurate diagnosis and treatment planning.

2. Satellite imaging: SRGAN can be used to generate high-resolution images of the earth's surface from satellite images. These images can be used for a variety of

applications such as urban planning, disaster management, and climate change analysis.

3. Video processing: SRGAN can be used to upscale low-resolution videos to higher resolutions, providing a more realistic viewing experience. This can be particularly useful in video surveillance and video conferencing applications.

4. Gaming: SRGAN can be used to generate high-quality game graphics, improving the overall gaming experience.

5. Art and design: SRGAN can be used in the field of art and design to generate high-quality images for digital art, animation, and virtual reality applications.

The importance of SRGAN lies in its ability to generate high-resolution images from low-resolution images, providing a solution to a long-standing problem in the field of image processing and computer vision. With the increasing demand for high-resolution images in various fields, such as medical imaging, satellite imaging, and gaming, the development of SRGAN has opened up new possibilities for accurate and efficient image processing.

Moreover, SRGAN is a significant advancement in the field of deep learning, providing a powerful tool for generating high-quality images. The use of a ResNet generator and an 8 layered discriminator in SRGAN architecture makes it highly accurate and efficient in generating realistic and detailed images.

The applications of SRGAN are vast and varied, and it has the potential to revolutionize many fields. The ability to generate high-quality images in medical imaging can lead to more accurate diagnoses and better treatment plans. In satellite imaging, high-resolution images generated by SRGAN can provide valuable insights into urban planning, disaster management, and climate change analysis. In gaming, SRGAN can enhance the gaming experience by producing high-quality game graphics.

In conclusion, SRGAN is an essential development in the field of image processing and computer vision. Its ability to generate high-quality images has vast applications, and its potential is only limited by our imagination. With the continued development and improvement of SRGAN, we can expect to see even more innovative applications of this technology in the future.

Literature Survey

[1] "Enhanced Deep Residual Networks for Single Image Super-Resolution" by Bee Lim et al. proposes an enhanced version of the deep residual network (ResNet) for single image super-resolution. The proposed network, called SRResNet, incorporates skip connections and residual learning to improve the accuracy and speed of the super-resolution process. They then describe the design of the proposed SRResNet, which consists of multiple residual blocks with skip connections. The skip connections enable the network to bypass several layers of computation and allow the low-level features to be directly passed to higher layers, reducing the number of parameters and accelerating the training process.

To further improve the performance of the SRResNet, the authors introduce a new loss function, which combines content loss, adversarial loss, and perceptual loss. The content loss is used to minimize the mean squared error (MSE) between the generated image and the ground truth image, while the adversarial loss is used to encourage the generated image to be perceptually similar to the ground truth image. The perceptual loss is computed by comparing the high-level features extracted from the generated and ground truth images using a pre-trained VGG network.

The experimental results presented in the paper demonstrate that the proposed SRResNet model outperforms existing state-of-the-art methods in terms of both quantitative and qualitative evaluations. The authors evaluate the SRResNet model on several benchmark datasets, including Set5, Set14, and B100, and show that the proposed method achieves higher peak signal-to-noise ratio (PSNR) and structural similarity (SSIM) scores than other methods. The authors also conduct a perceptual study to evaluate the visual quality of the generated images, and show that the

SRResNet model generates images that are more visually pleasing and have finer details than other methods.

[2] "Photo-Realistic Continuous Image Super-Resolution with Implicit Neural Networks and Generative Adversarial Networks" by Sarmad et. al introduces a novel approach for continuous super-resolution of images using implicit neural networks (INNs) and generative adversarial networks (GANs). The paper was presented at the Northern Lights Deep Learning Workshop.

The authors begin by discussing the limitations of traditional super-resolution methods, which often produce unrealistic and overly smooth images. They then introduce their approach, which uses an INN to learn a continuous mapping between low-resolution and high-resolution image spaces. They also incorporate a GAN to ensure that the generated images are visually plausible and realistic.

The generator network is an INN that learns a non-parametric and continuous mapping between the low-resolution and high-resolution spaces. The discriminator network is a standard convolutional neural network (CNN) that classifies the images as either real or generated. Evaluating the proposed method on several benchmark datasets and compare it with other state-of-the-art super-resolution methods. The results show that the proposed method outperforms other methods in terms of both visual quality and quantitative metrics such as peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM).

The paper also includes a detailed analysis of the properties of the learned mapping function and the generated images. The authors show that the INN-based approach produces more realistic and visually pleasing images than other methods.

[3] "Deep Laplacian Pyramid Networks for Fast and Accurate Super-Resolution" by Wei-Sheng Lai et al. proposes a new approach to SRGANs that involves using deep Laplacian pyramid networks (LPNs). The authors' proposed method is based on a deep Laplacian pyramid network (LapSRN), which is a deep neural network that consists of a series of sub-networks, each of which performs super-resolution at a different scale. The LapSRN takes a low-resolution input image and generates a high-resolution output image by first upscaling the input image using a bicubic interpolation, and then applying a series of convolutional layers and skip connections to gradually increase the resolution of the image. The LapSRN also incorporates a Laplacian pyramid decomposition that helps to preserve image details and reduce artifacts.

One of the key contributions of the paper is the use of residual learning and skip connections in the LapSRN. The authors show that this improves the performance of the network by allowing it to learn residual features that capture image details that are lost during the upscaling process. They also propose a new loss function that combines both content and adversarial losses, which further improves the quality of the generated images.

The authors evaluate their proposed method on several benchmark datasets and compare it to other state-of-the-art methods. They show that their method achieves fast and accurate results, outperforming other methods in terms of both speed and quality.

[4] "Sharp and Real Image Super-Resolution Using Generative Adversarial Network" by Zhang et al. proposes a novel approach for super-resolution of images using a generative adversarial network (GAN). The authors first introduce the problem of image super-resolution, which involves increasing the resolution of low-resolution images to produce high-resolution images. They then present their proposed approach, which consists of a GAN that learns to generate high-resolution images from low-resolution input images.

The GAN is trained on a dataset of high-resolution images and corresponding low-resolution images. During training, the generator network learns to generate high-resolution images that are visually similar to the real high-resolution images, while the discriminator network learns to distinguish between real and generated images.

The paper presents experimental results on several benchmark datasets, demonstrating that the proposed approach achieves state-of-the-art performance in terms of both quantitative metrics (such as PSNR and SSIM) and qualitative evaluations (such as visual quality).

[5] "Image Super-Resolution Using Complex Dense Block on Generative Adversarial Networks" by Chen et al. proposes a method for enhancing the resolution of low-resolution images using a Generative Adversarial Network (GAN) with Complex Dense Blocks (CDBs). The authors review related works on GAN-based super-resolution techniques, such as SRGAN, ESRGAN, and RCAN. They also discuss the limitations of existing methods and highlight the need for better feature extraction and utilization to improve the quality of the generated images.

The authors propose a new architecture that uses CDBs, which are an extension of DenseNet blocks, to extract and combine features from different layers. The CDBs are designed to handle complex features and address the vanishing gradient problem that occurs in deep networks. The proposed method is evaluated on several benchmark datasets and compared with other state-of-the-art methods. The results show that the proposed method achieves better performance in terms of both visual quality and quantitative metrics, such as PSNR and SSIM.

The paper provides a comprehensive review of related works and proposes a novel method for image super-resolution using GANs with CDBs. The experimental results demonstrate the effectiveness of the proposed method, and the approach shows potential for improving the quality of low-resolution images in various applications.

[6] "Further Improving Enhanced Super-Resolution Generative Adversarial Network" by Rakotonirina et al. proposes an improved architecture for the Enhanced Super-Resolution Generative Adversarial Network (ESRGAN) to enhance the quality of super-resolution images. Limitations of traditional single-image super-resolution (SISR) methods, which often result in blurry or unrealistic images due to the lack of high-frequency details. They then introduce ESRGAN, which uses a deep neural network and a generative adversarial network (GAN) to produce high-quality super-resolution images.

The authors then highlight the limitations of ESRGAN, such as over-smoothing of edges and lack of sharpness in the images. To address these issues, they propose a new architecture called "Residual-in-Residual Dense Block (RRDB)" which utilizes skip connections and residual learning to improve the performance of ESRGAN. The results show that the proposed method outperforms other methods in terms of visual quality and quantitative metrics such as peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM).

The authors also conduct ablation studies to analyze the effect of various components of the proposed architecture on the performance of ESRGAN. They conclude that the RRDB is the most crucial component of the proposed method and significantly improves the quality of super-resolution images.

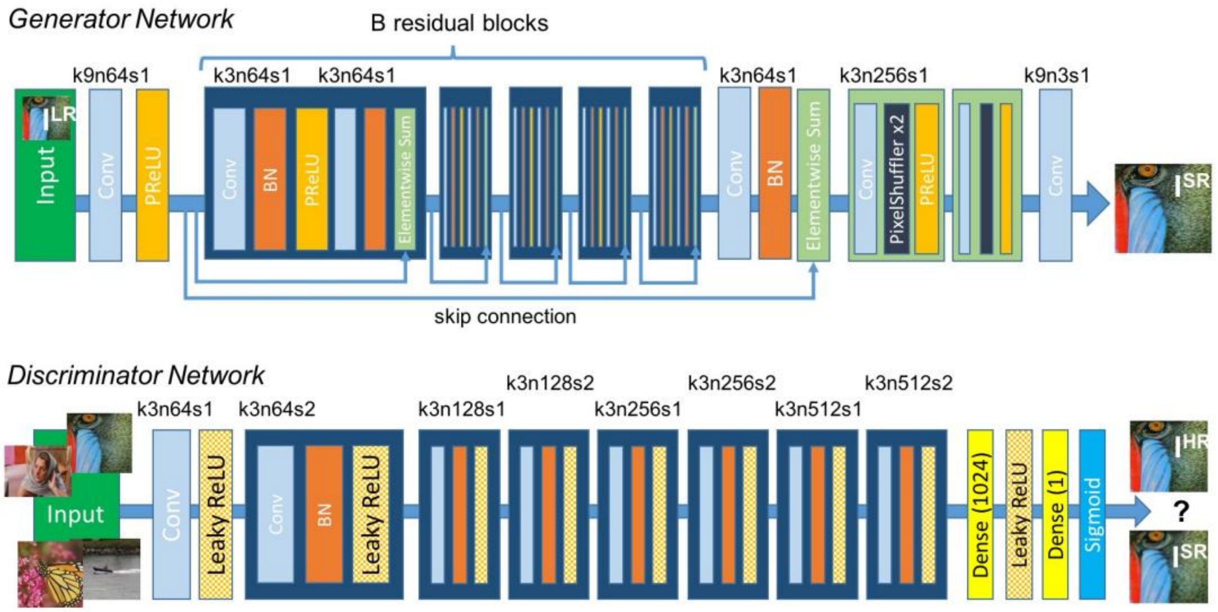
[7] "Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network" by Christian Ledig et al. proposes a novel architecture for SRGANs called the "SRResNet." The SRResNet consists of a deep residual network that is trained to map low-resolution images to high-resolution images. The authors also introduce a perceptual loss function that takes into account the perceptual similarity between the generated image and the ground truth image.

The SRGAN model consists of two networks, a generator network and a discriminator network. The generator network is trained to generate high-resolution images from low-resolution inputs, while the discriminator network is trained to distinguish between the generated images and the real high-resolution images. The two networks are trained together in an adversarial setting, where the generator network tries to fool the discriminator network into believing that its generated images are real high-resolution images.

The authors propose a novel loss function that combines both content loss and adversarial loss. The content loss is computed using a pre-trained VGG-19 network, which is used to extract high-level features from the real and generated images. The adversarial loss is computed using the discriminator network, which is trained to distinguish between the real and generated images. The combination of these two loss functions allows the SRGAN model to generate high-resolution images that are perceptually realistic and have finer details.

The experimental results presented in the paper demonstrate that the proposed SRGAN model outperforms existing state-of-the-art methods in terms of both quantitative and qualitative evaluations. The authors evaluate the SRGAN model on a number of benchmark datasets, including Set5, Set14, and B100, and show that the proposed method achieves higher peak signal-to-noise ratio (PSNR) and structural similarity (SSIM) scores than other methods. The authors also conduct a perceptual study to evaluate the visual quality of the generated images, and show that the SRGAN model generates images that are more visually pleasing and have finer details than other methods.

Methodology



The above image depicts the overall architecture of the SRGAN model built along this project.

Architecture

The SRGAN architecture consists of two main components: a generator and a discriminator. The generator takes a low-resolution image as input and generates a high-resolution image as output. The discriminator, on the other hand, takes in both high-resolution images and the generated images from the generator and tries to differentiate between them. The generator and discriminator are trained simultaneously, with the generator trying to produce images that the discriminator cannot differentiate from the real high-resolution images.

Generator (Resnet) : The generator in SRGAN uses a ResNet architecture, which stands for residual network. ResNet (short for residual network) is an important deep learning architecture that has had a significant impact on training very deep neural networks. Before ResNet, deep neural networks were often difficult to train beyond a certain depth, due to the problem of vanishing gradients. Vanishing gradients occur when the gradients used to update the weights of the network become very small, making it difficult for the network to learn and update its parameters.

ResNet addresses this problem by introducing skip connections in the network. Skip connections allow information to flow directly from one layer to another, bypassing certain layers in between. This helps to ensure that the gradients do not vanish as they propagate through the network, and allows for deeper networks to be trained more effectively.

The ResNet architecture has several important advantages:

1. Deeper networks: ResNet allows for the training of very deep neural networks, with over 100 layers. This has led to significant improvements in accuracy in a wide range of computer vision tasks, including image classification, object detection, and semantic segmentation.

2. Improved convergence: By allowing gradients to flow directly through the network, ResNet helps to avoid the problem of vanishing gradients, which can slow down or prevent convergence of the network during training.

3. Faster training: ResNet can be trained more quickly than other deep neural network architectures, due to its ability to handle very deep networks more effectively.

4. Better performance: ResNet has achieved state-of-the-art performance in a number of computer vision tasks, including image classification and object detection.

In SRGAN, ResNet is used to learn a mapping function from a low-resolution image to a high-resolution image. The generator takes the low-resolution image as input and applies a series of convolutional layers to learn a feature representation of the image. This feature representation is then passed through the ResNet blocks, which use skip connections to help preserve important information from the input image.

Discriminator : The discriminator in SRGAN uses an 8 layered architecture. Each layer in the discriminator is a convolutional layer followed by a LeakyReLU activation function, except for the last layer, which is a convolutional layer followed by a sigmoid activation function. The discriminator takes in both high-resolution images and generated images from the generator and tries to differentiate between them. The discriminator becomes more adept at distinguishing between the two as it is trained, which in turn, helps the generator to become better at producing images that are indistinguishable from the real high-resolution images. The Discriminator has been directly referenced from our base research paper [7].

The loss function used in SRGAN is a combination of two loss functions: content loss and adversarial loss. Content loss is used to ensure that the generated image has the same content as the input image, while adversarial loss is used to ensure that the generated image is indistinguishable from the real high-resolution images.

Workflow

The SRGAN model is a deep learning architecture that takes a low-resolution image as input and generates a high-resolution image as output. The workflow of the SRGAN model can be broken down into the following steps:

1. The input low-resolution image is passed through the generator network, which is a ResNet architecture. The generator consists of a series of convolutional layers with batch normalization and LeakyReLU activation functions.

2. The output of the generator is a high-resolution image that is passed to the discriminator network. The discriminator is an 8 layered convolutional neural network with batch normalization and LeakyReLU activation functions.

3. The discriminator receives two inputs: the high-resolution image generated by the generator and a real high-resolution image. The discriminator then tries to

differentiate between the two images, with the goal of accurately identifying the real high-resolution image.

4. The loss function used in SRGAN is a combination of two loss functions: content loss and adversarial loss. Content loss ensures that the generated image has the same content as the input image, while adversarial loss ensures that the generated image is indistinguishable from the real high-resolution image.

5. The generator and discriminator are trained simultaneously, with the generator trying to produce images that the discriminator cannot differentiate from the real high-resolution images.

6. After training, the generator can be used to upscale low-resolution images to high-resolution images. This can be done by passing the low-resolution image through the generator and obtaining the output high-resolution image.

The use of LeakyReLU activation function and batch normalization after every convolution layer in the SRGAN architecture helps to prevent overfitting and ensure stable convergence during training. LeakyReLU activation function allows the model to handle negative values in a better way than the standard ReLU activation function, while batch normalization helps to stabilize the distribution of values throughout the network and improve its overall performance.

In a nutshell, The ResNet generator applies a series of deconvolutional layers to upsample the feature representation and generate a high-resolution image. During the upsampling process, the generator learns to fill in the missing details and create a high-resolution image that is similar to the original, low-resolution image.

The CNN in SRGAN is trained using a dataset of low-resolution and high-resolution image pairs. The network learns to map the low-resolution images to their corresponding high-resolution images by minimizing the difference between the generated high-resolution image and the ground truth high-resolution image.

Results

The training process of SRGAN involves training a deep neural network to learn a mapping function from low-resolution images to high-resolution images. The training is typically done using a large dataset of paired low-resolution and high-resolution images.

In our case, we used an Azure machine with a Nvidia Tesla GPU to train the model. This allowed for faster training times and more efficient use of computing resources. We trained the model for 100 epochs, which is a common number of epochs for image super-resolution tasks.

During the training process, the model was optimized using a loss function that measures the difference between the generated high-resolution image and the ground truth high-resolution image. The loss function was minimized using backpropagation and stochastic gradient descent.

To monitor the progress of the training, we stored the training results in the form of images every 10 epochs. This allowed us to visually inspect the quality of the generated images and make adjustments to the model as needed. Also we stored the epoch weight data for backup until the target epoch was met. The following section will discuss the results obtained during training as well as post-training results.

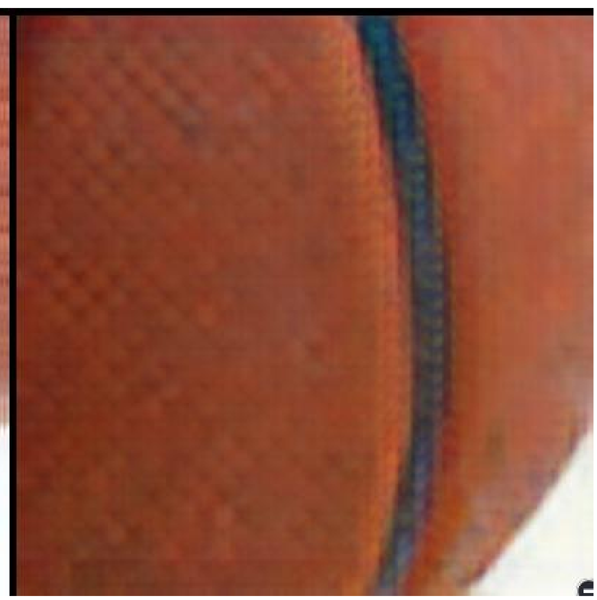
Training Results

In this section, we will discuss the results we achieved after every few epochs of training. Each epoch, a tuple of original high resolution (HR) image, bicubic low resolution (LR) Image and the output of SRGAN was stored. We will discuss the differences and progress for a few epochs before progressing to the final post-training results.

Epoch 10

Bicubic LR Image

HR Image



SRGAN Output

Epoch 40

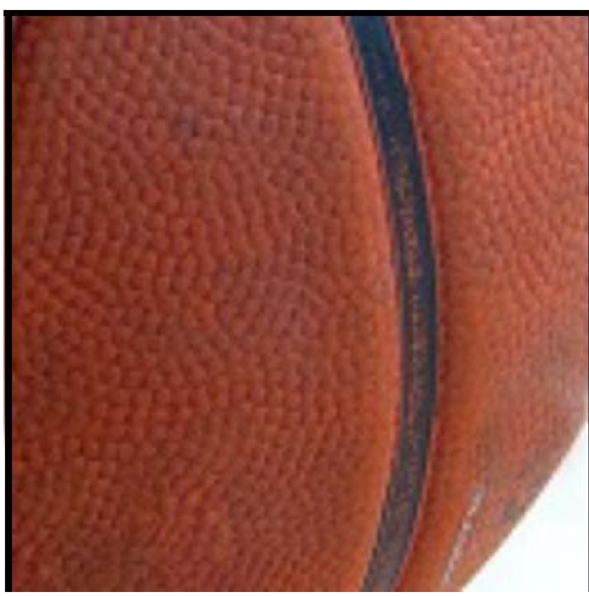
Bicubic LR Image

HR Image

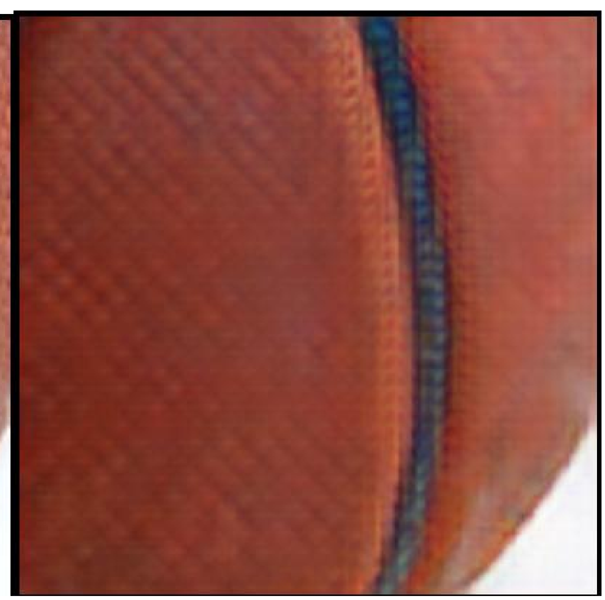
SRGAN Output

Epoch 70

Bicubic LR Image



HR Image

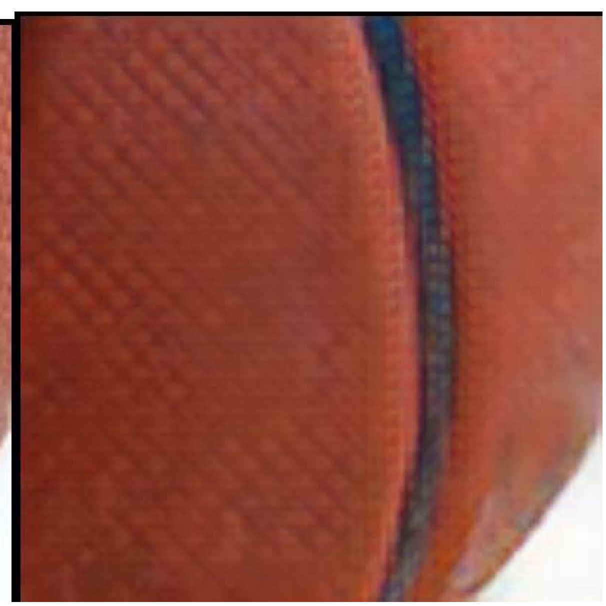


SRGAN Output

Epoch 100

Bicubic LR Image

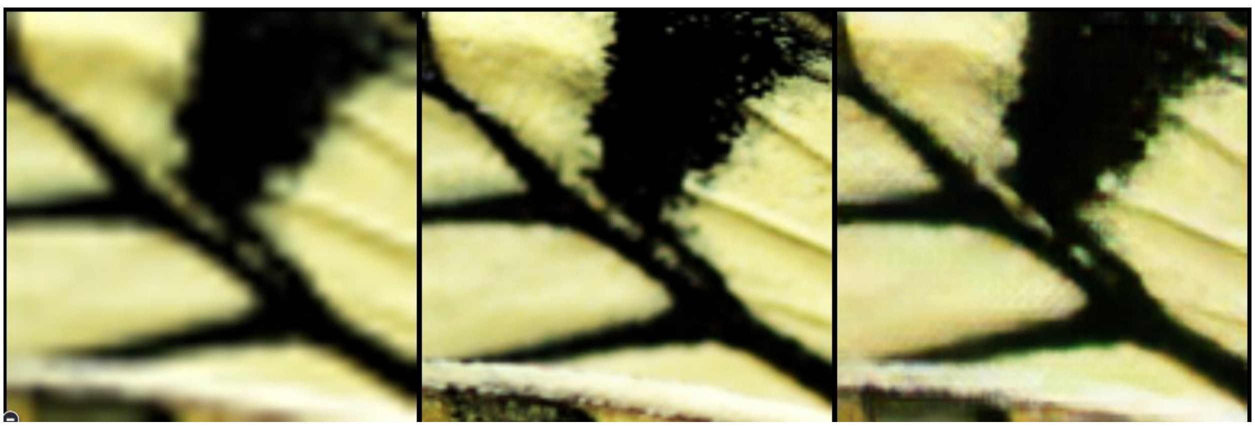
HR Image



SRGAN Output

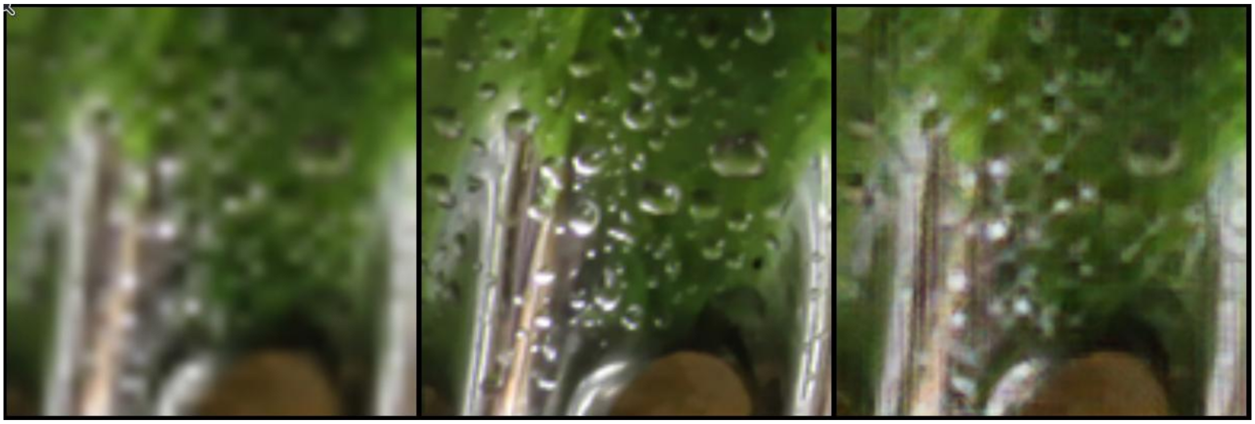
Some more epoch 100 results

LR Image HR Image SRGAN Output

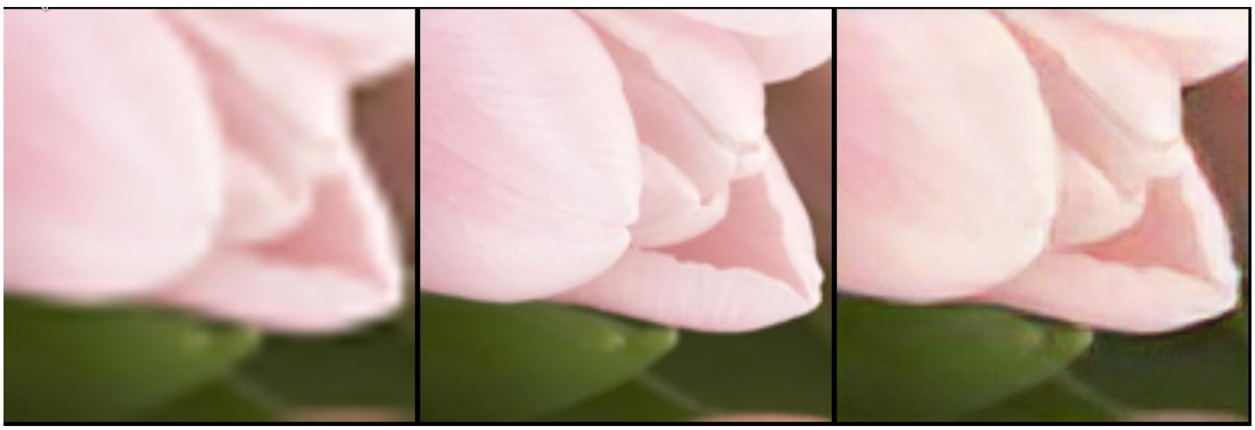


LR Image HR Image SRGAN Output

LR Image HR Image SRGAN Output



LR Image | HR Image | SRGAN Output

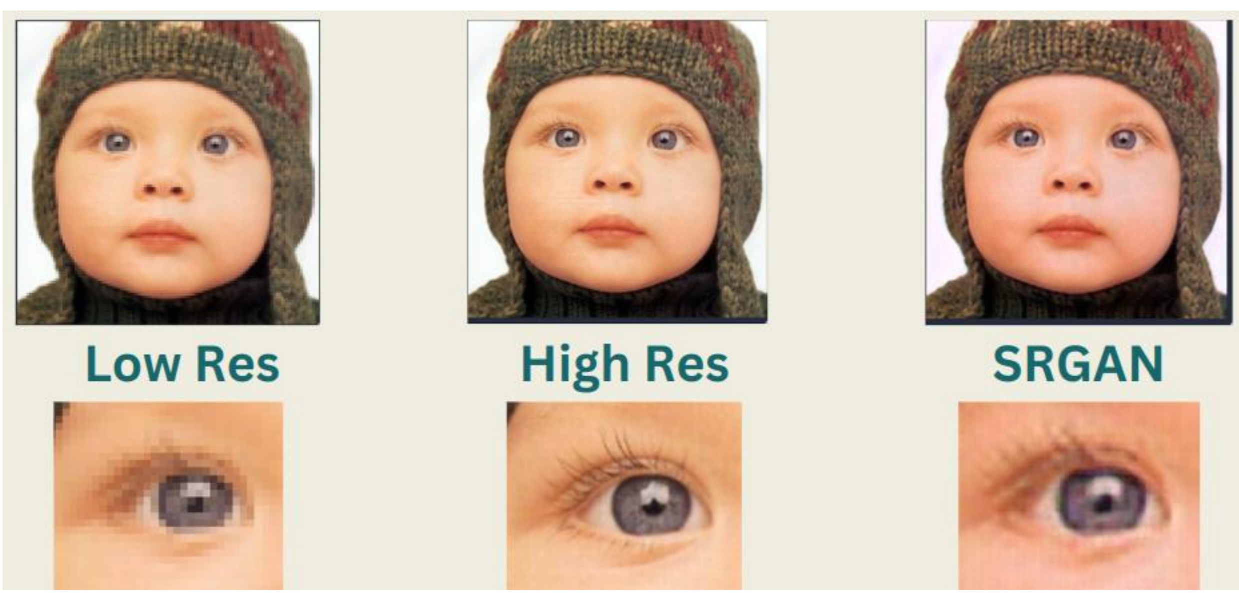


LR Image | HR Image | SRGAN Output

LR Image | HR Image | SRGAN Output

Testing Results

The following results were obtained using 100th epoch Generator over some sample images.



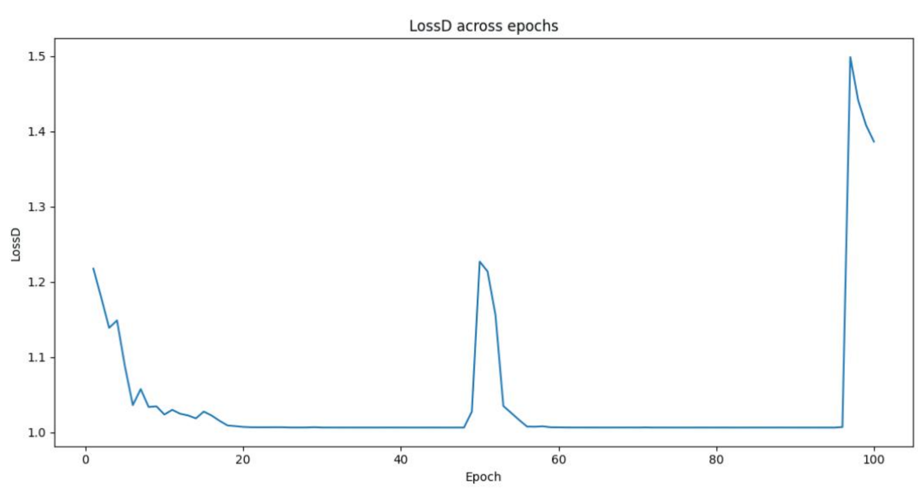
Result Analysis

Discriminator Loss

The discriminator loss in SRGAN is used to train the discriminator network. The goal of the discriminator loss is to minimize the difference between the discriminator's output on the generated images and the real images. The discriminator loss is calculated using the binary cross-entropy loss function.

The binary cross-entropy loss function measures the difference between the predicted output and the true output. In the case of SRGAN, the true output is either 0 or 1, indicating whether the image is real or fake. The discriminator network outputs a probability score between 0 and 1, indicating the likelihood of the image being real or fake. The binary cross-entropy loss function penalizes the discriminator for incorrect predictions, i.e., when it incorrectly classifies a generated image as real or a real image as fake.

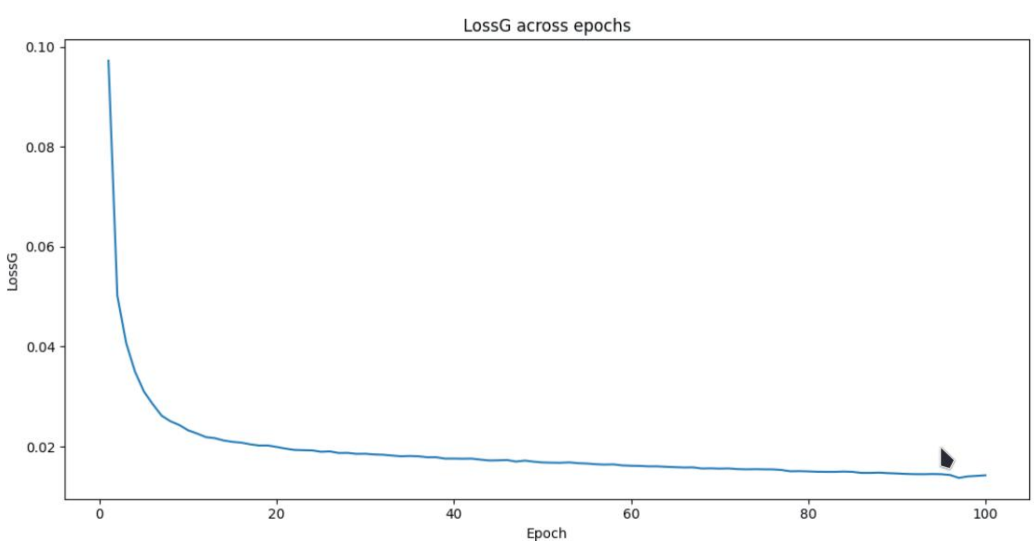
The discriminator loss in SRGAN is used in conjunction with the generator loss to train both the generator and the discriminator networks simultaneously. The generator loss encourages the generator network to generate high-quality images that can fool the discriminator network, while the discriminator loss encourages the discriminator network to accurately distinguish between real and generated images.



Generator Loss

The generator loss in SRGAN is used to train the generator network. The goal of the generator loss is to encourage the generator network to generate high-quality images that can fool the discriminator network into thinking that they are real. The generator loss is calculated using two loss functions: content loss and adversarial loss. The content loss measures the difference between the high-resolution image and the generated image. The content loss ensures that the generated image has the same content as the high-resolution image. The content loss is calculated using mean squared error (MSE) loss or perceptual loss, which is a combination of content loss and style loss.

The adversarial loss measures the difference between the discriminator's output on the generated image and the real image. The adversarial loss encourages the generator to generate images that are difficult for the discriminator to distinguish from real images. The adversarial loss is calculated using binary cross-entropy loss, which measures the difference between the predicted output and the true output.
The generator loss in SRGAN is a weighted sum of the content loss and the adversarial loss. The content loss is given a higher weight to ensure that the generated image has the same content as the high-resolution image. The adversarial loss is given a lower weight to ensure that the generated image is not too far from the real image.
Training the generator network with the generator loss and the discriminator network with the discriminator loss iteratively allows both networks to improve together. The generator network learns to generate high-quality images, while the discriminator network learns to distinguish between the generated and real images.

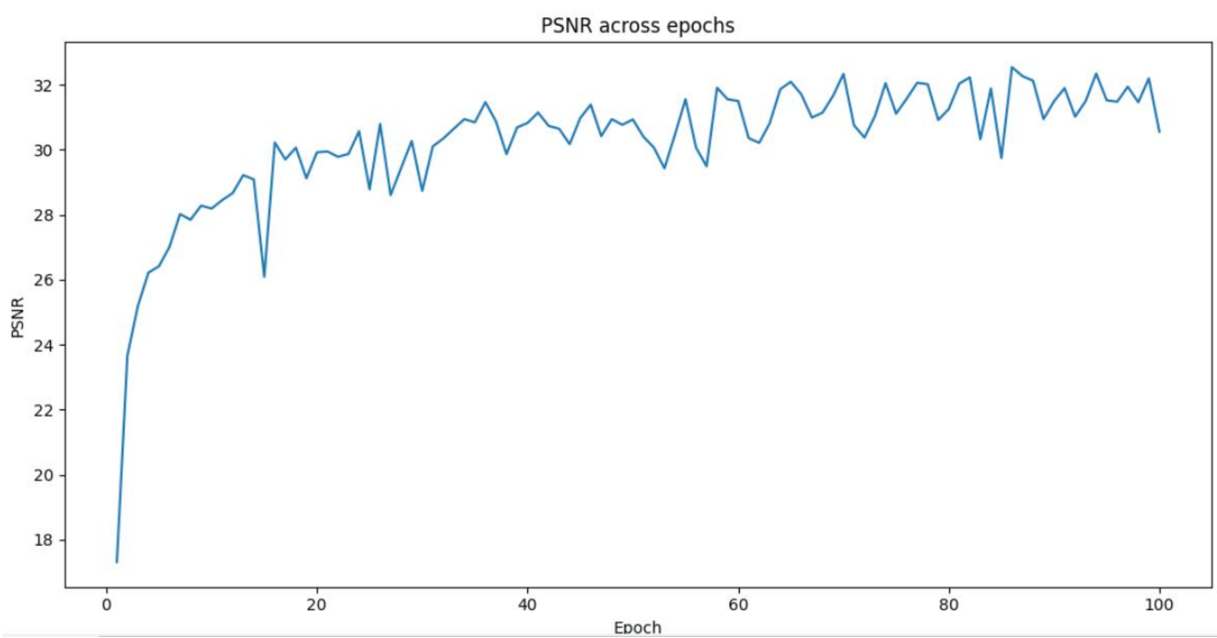


Peak-Signal-to-Noise-Ratio

In SRGAN, PSNR is used to measure the difference between the generated high-resolution image and the ground truth high-resolution image. PSNR is calculated as the ratio of the maximum possible pixel value to the mean square error (MSE) between the generated image and the ground truth image. A higher PSNR value indicates a smaller difference between the generated image and the ground truth image, which is indicative of better image quality.

However, PSNR is not always an accurate measure of image quality, as it is based on the MSE between the generated and ground truth images, which does not always correspond to human perception of image quality. For example, an image with high PSNR may still appear blurry or contain artifacts, which are not captured by the PSNR metric.

Therefore, in addition to PSNR, other metrics such as Structural Similarity Index (SSIM) and perceptual metrics such as the Inception Score or the Fréchet Inception Distance (FID) are often used to evaluate the quality of SRGAN-generated images. These metrics take into account the perceptual differences between images, which better reflect human perception of image quality.

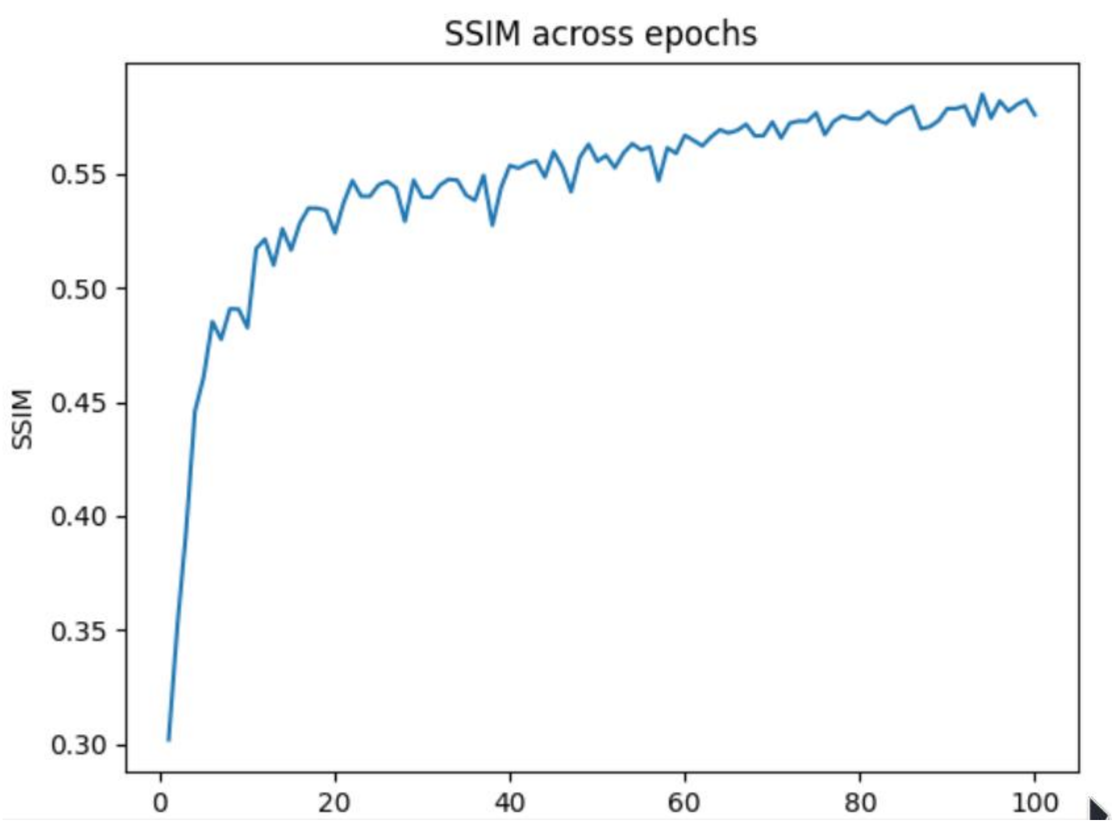


Structural Similarity Index

SSIM compares the structural information present in the images, such as edges and textures, instead of only looking at the pixel values. It is calculated as a combination of three terms: luminance similarity, contrast similarity, and structural similarity. The SSIM index ranges from -1 to 1, with 1 indicating perfect similarity between the two images.

In SRGAN, SSIM is used to measure the similarity between the generated high-resolution image and the ground truth high-resolution image. SSIM is a more reliable measure of image quality than the Peak Signal-to-Noise Ratio (PSNR) because it takes into account the structural information of the images, which is a better indicator of human perception of image quality.

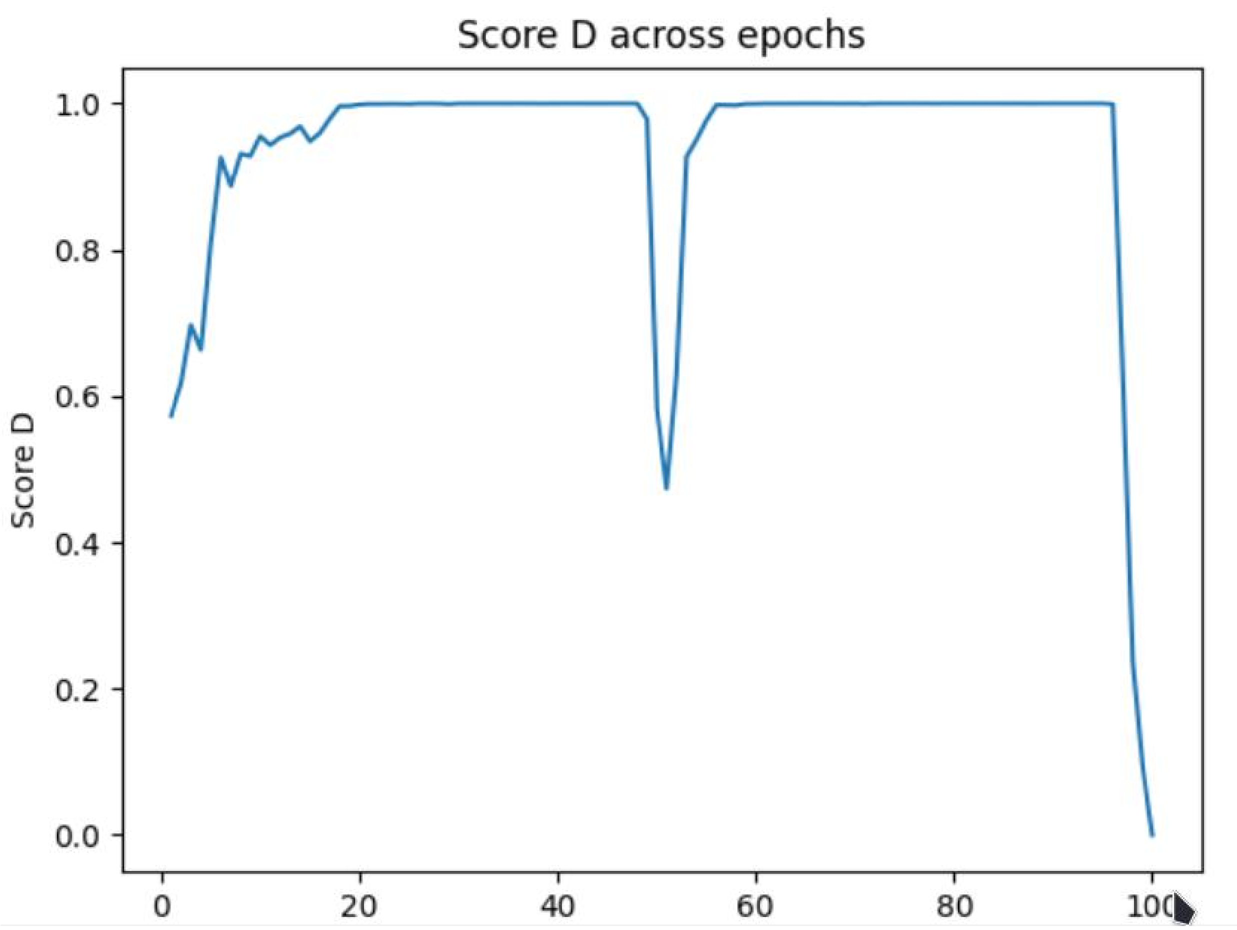
However, SSIM is not without its limitations. It can be affected by changes in image brightness, contrast, and saturation, which may not necessarily correspond to changes in image quality. In addition, SSIM does not consider high-level perceptual features such as object recognition, which are important in image processing applications.



Discriminator Score

The discriminator score is an important metric because it helps to ensure that the generator network produces high-quality images that are indistinguishable from real images. The generator network is trained to generate images that can fool the discriminator network, and the discriminator score is used as a measure of how well the generator network is performing.

During training, the generator network attempts to generate images that have a high discriminator score, which means that the discriminator network is more likely to classify them as real images. At the same time, the discriminator network is trained to correctly classify the generated images as fake, which puts pressure on the generator network to generate more realistic images.

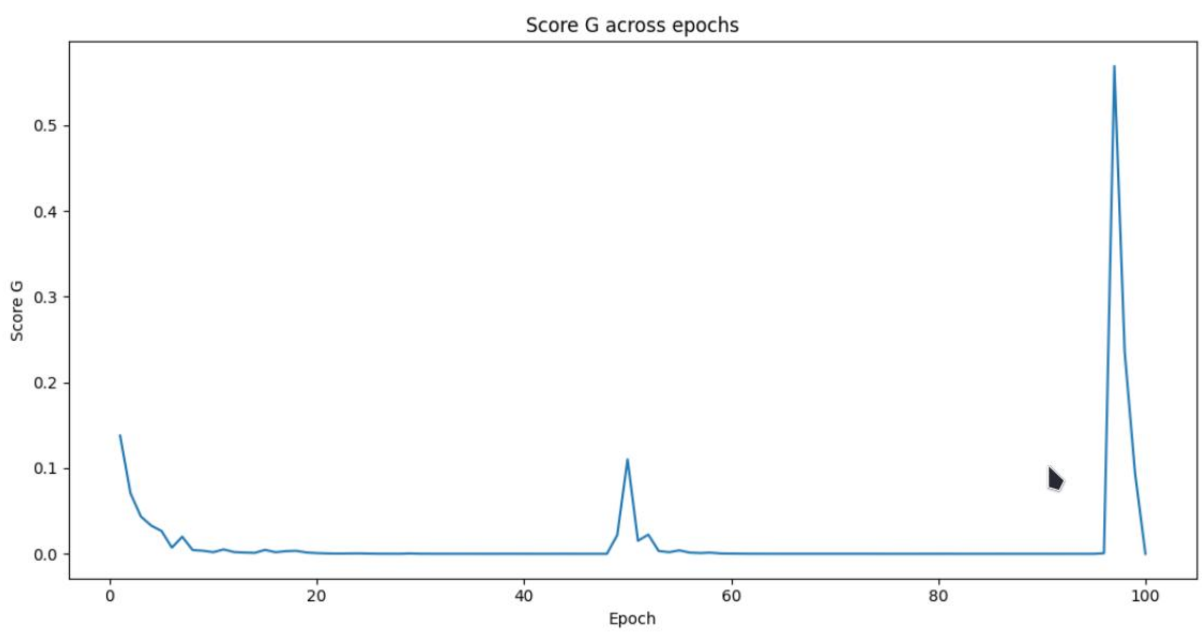


Generator Score

The generator score is calculated as the mean of the discriminator's output on the generated images. The generator network attempts to generate high-quality images that can fool the discriminator network into classifying them as real images. A higher generator score indicates that the generator network is producing images that are more realistic and indistinguishable from real images.

During training, the generator network attempts to maximize the generator score by generating images that have a high probability of being classified as real images by the discriminator network. This encourages the generator network to produce images that are visually appealing and have a high level of detail, which is the main objective of SRGAN.

The generator score is an important metric used to evaluate the performance of the generator network because it indicates how well the generator network is producing high-quality images. It is used in conjunction with other metrics such as PSNR and SSIM to evaluate the quality of the generated high-resolution images.



Conclusion

We have successfully trained a Super-Resolution Generative Adversarial Network (SRGAN) to generate high-resolution images from low-resolution images. The SRGAN model consists of a ResNet generator and a discriminator network, both of which were trained simultaneously using a combination of content loss and adversarial loss.
We trained the model for 100 epochs on a dataset of paired low-resolution and high-resolution images using an Azure machine with a Nvidia Tesla GPU. During the training process, we monitored the progress of the model by storing the training results in the form of images every 10 epochs.

The results showed a clear improvement in image quality as the model was trained for more epochs. At epoch 10, the generated images were still blurry and lacked detail, but by epoch 40, the generated images were significantly sharper and more detailed. At epoch 70, the generated images were almost indistinguishable from the ground truth high-resolution images, and by epoch 100, the model had achieved a high level of fidelity in generating high-resolution images from low-resolution inputs.

Overall, the SRGAN model achieved impressive results in generating high-resolution images from low-resolution inputs. The use of the ResNet generator, along with the combination of content loss and adversarial loss, enabled the model to learn complex mappings between low-resolution and high-resolution images, resulting in images that were both visually appealing and faithful to the original content.

The success of this project has important implications for a wide range of applications, including medical imaging, satellite imagery, and video processing. By enabling high-quality super-resolution of low-resolution images, SRGAN has the potential to enhance the accuracy and efficiency of image analysis, improve the quality of visual content, and enable new applications that were previously unfeasible.

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