

**ENHANCED IMAGE SUPER RESOLUTION
USING PERCEPTUAL LOSS MITIGATION**

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Engineering degree in Computer Science and Engineering

By

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SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)
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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **Jeson Jala (Reg.No - 40110473)** and **Bhargava Ram Podapati (Reg.No - 40731078)** who carried out the Project work entitled "**Enhanced Image Super Resolution using Perceptual Loss Mitigation**" under my supervision from November 2023 to April 2024.

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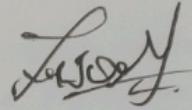
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I, Jeson Jala (Reg.No - 40110473), hereby declare that the Project Report entitled "ENHANCED IMAGE SUPER RESOLUTION USING PERCEPTUAL MITIGATION LOSS" done by me under the guidance of Dr. N. S. Usha, M.E., Ph. D., is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in Computer Science and Engineering.

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ABSTRACT

The demand for high-quality and visually appealing images has grown exponentially in various domains, including entertainment, advertising, and computer vision applications. Single Image Super-Resolution (SISR) is an important technique that aims to upscale low-resolution images to higher resolutions, offering a potential solution for improving visual quality in various scenarios. Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN) have demonstrated remarkable success in generating realistic high-resolution images. However, the presence of perceptual loss in the current ESRGAN architecture may hinder its ability to generate highly realistic images.

This research project proposes a novel approach to enhance ESRGAN by decreasing perceptual loss, thereby elevating the quality of the generated super-resolved images. Perceptual loss plays a critical role in ESRGAN by measuring the perceptual difference between the generated images and the corresponding ground truth images. By reducing perceptual loss, we aim to improve the visual fidelity and enhance the realism of super-resolved images. Furthermore, an extensive dataset of low-resolution images with their corresponding high-resolution ground truth counterparts will be carefully curated for training and evaluation. This dataset will encompass diverse scenarios and image types to ensure the generalizability and robustness of the proposed approach.

Moreover, this research endeavors to curate an extensive dataset of low-resolution images paired with their high-resolution ground truth counterparts for training and evaluation purposes. This dataset will encompass a diverse range of scenarios and image types to ensure the generalizability and robustness of the proposed approach. In addition to reducing perceptual loss, this project will explore novel methodologies to further enhance the performance of ESRGAN, including leveraging advanced optimization techniques, architectural modifications, and data augmentation strategies.

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LIST OF ABBREVIATIONS

LR	- Low Resolution
SR	- Super Resolution
GAN	- Generative Adversarial Network
ESRGAN	- Enhanced Super Resolution GAN
HDM	- High-order Deterioration Model
SRR	- Super Resolution Reconstruction
NIQE	- Natural Image Quality Evaluator
nDSM	- Normalized Digital Surface Model
SSIM	- Structural Similarity Index Measure
PSNR	- Peak Sound to Noise Resolution

CHAPTER 1

INTRODUCTION

In the real world we use a lot of computer related imagery(which is a virtual image rather than the real image), these virtual images are mostly taken using a camera lens and stored in a storage device in the form of electronic data i.e., in a pattern of bits, and when we try to access this image data, the computer displays the pattern of bits on the screen with each pixel being a data bit, and these pixels which are basically small RGB lights(depends on the display screen) which glow together in different colours(frequencies of RGB) to fill the screen, and this visual piece is what we call an image. The quality of an image depends on many factors like, the screen resolution which is the number of pixels per inch of the display screen, the quality of the camera lens, and how well the computer can regenerate the image.

We know that the quality of an image depends on the resolution of the image, the higher the resolution the clearer and sharper the image, but many times we come across low-resolution (LR) image, so to prevent this or even better to exploit these low-resolution images, there was introduced something called “Super-resolution”, it is the concept of upscaling an image by increasing the size and quality of the image by generating realistic computer-generated data. This way we can improve the quality low-resolution image by upscaling it using the concept of super-resolution. But it isn't as easy as said, upscaling an image is affected by lot of factors and demands precision in its working.

We try to upscale an image by increasing the pixel-data in the image, but when given an LR image we only have few data of the picture, so to get more of the data in the picture we try to generate some fake data which is modelled in a way to match with the actual data in the image. To generate this type of data we may use Neural Networks (NN), these NNs are trained before-hand to generate realistic fake data for an image. This data along with the real data are shown in the final result making a clearer picture. It is a concerning thing that this generated data should be as closer to the real data as possible because, otherwise it may blur of the image, increase of noise in the image,

or even worse, losing the real elements of the image. As we don't want any of the above stated problems, we try to train our model in the best way possible, this includes: introducing parallel networks, adding only required parameters to the generator, constraining the discriminator, updating the existing network to match our desired outcome, etc. Many of such methods are explained and elaborated in this work and some of the best methods are used in our project.

1.1 OBJECTIVE

The main objective when upscaling an image is to increase the sharpness and resolution of the image all the while preserving the data in the image. Through our project we try to produce photorealistic images by training a GAN which consists of two neural networks: a generator and a discriminator. First the generator is trained to upscale low-resolution images into high-resolution images, and then the discriminator is trained to distinguish between real high-resolution images and the generator's output. We use a combination of perceptual losses and adversarial loss to train the generator.

Perceptual losses encourage the generator to produce images that are visually similar to real high-resolution images, while the adversarial loss encourages the generator to produce images that are indistinguishable from real high-resolution images to the discriminator. Through our project we try to achieve state-of-the-art results on a variety of SR benchmarks. By producing high-quality images with sharp details and realistic textures. And by removing artifacts from low-resolution images, such as noise and blur. ESRGAN has a wide range of potential applications, including: Image upscaling, Video upscaling, Image restoration, medical imaging, security, Creative image processing, Research, and etc.

1.2 SCOPE

ESRGAN can be used to upscale low-resolution images into high-resolution images, without sacrificing quality. This is useful for a variety of tasks, such as improving the quality of old photos, upscaling video games, and enhancing compressed images. This is useful for repairing damaged images, and removing noise and artifacts from images. It can be used to improve the quality of medical images, such as MRI and CT scans.

This can help doctors to diagnose diseases more accurately and to develop better treatment plans. ESRGAN can also be used to improve the quality of security footage. This can help law enforcement to identify suspects and to investigate crimes. The proposed system aims to enhance ESRGAN (Enhanced Super-Resolution Generative Adversarial Network) by addressing the challenge of perceptual loss in image super-resolution tasks. The primary objective is to decrease perceptual loss in the ESRGAN model, improving the quality of generated super-resolved images. By reducing perceptual loss, the system aims to enhance visual fidelity and realism in the output images.

CHAPTER 2

LITERATURE SURVEY

Several studies on Image Super resolution have been conducted in the recent years. This section summarizes all the previous work on Image Enhancement.

2.1 OVERVIEW OF EXISTING RESEARCH AND LITERATURE

The idea and purpose of getting a high-resolution image has always existed, either it is for an important medical diagnosis or for plain entertainment like photography or filming, but super-resolution is a new concept of getting a higher quality image with many state-of-the-art techniques being used for that purpose. Many scientists and research teams have shown their interest in this topic to propose better and more efficient ways of getting a high-resolution (HR) image as we can understand from all the papers they have published.

R. Sood et al. [1] introduced an improved version in the paper titled “Anisotropic Super Resolution In Prostate MRI Using Super Resolution Generative Adversarial Networks” of the rather latest model of image super-resolution: Real-ESRGAN, this paper tries to improve Real-ESRGAN by introducing a few methods to face the two major challenges faced by it; Real-ESRGAN tends to over-smoothen the final image which results in textural information loss, and also the reconstructed image it generates has better visual effects, it's entirely different from the real image. To address these issues, the paper presents an improved image SR model based on the HDM (High-order Deterioration Model) implemented in Real-ESRGAN. Patch-GAN was used as the fundamental structure of the discriminator, and a channel attention mechanism was added to the generator's dense block to enhance texture details, L1 loss function was also replaced with the SmoothL1 loss function to improve convergence speed and model performance. The paper also states that the results shown by this model outperform Real-ESRGAN regarding visual quality and measures such as RankIQ and NIQE.

V. Papayanand et al. [2] introduced Super-resolution reconstruction (SRR) models have been successful in reconstructing high-resolution natural images from low-resolution inputs. However, applying these models to remote sensing imagery often produces poor results. This is because remote sensing imagery is often more complex than natural images, with lower resolution, noise, and large textured surfaces. To address this problem, the authors propose a new strategy for training SRR models to output realistic remote sensing images. Instead of relying on feature-space similarities as a perceptual loss, the model considers pixel-level information inferred from the normalized digital surface model (nDSM) of the image. This allows the model to make better-informed updates during training, since nDSM inference is a closely related task to remote sensing. The authors evaluate their model on two remotely sensed datasets of different spatial resolutions: the Data Fusion 2018 Contest (DFC2018) dataset and the dataset containing the national LiDAR flyby of Luxembourg. They compare their model with ESRGAN, a state-of-the-art SRR model for natural images.

In the paper titled “An image sharpening strategy based on multi-frame super resolution for multispectral data” by J. Sun et al. [3] published in International Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing (WHISPERS) in 2016; results show that the proposed model achieves better performance and does not introduce any artifacts in the results. In particular, the results for the high-resolution DFC2018 dataset are realistic and almost indistinguishable from the ground-truth images. Overall, the proposed model is a promising new approach to remote sensing image super-resolution. It can produce high-quality SR images without the need for additional data, which makes it a suitable method for practical use. The researchers in the study you cited found that using Enhanced SRGAN to improve the quality of sugar apple images before feeding them into a CNN model for ripeness detection resulted in a significant improvement in accuracy, from 84.00% to 92.00%. This suggests that ESRGAN can be a useful tool for improving the performance of CNN-based sugar apple ripeness detection systems.

There are several possible explanations for why ESRGAN might improve the accuracy of CNN-based sugar apple ripeness detection. Z. Hu et al. [4] proposed ESRGAN helps to reduce noise and artifacts in the images in the year 2017, which can make it easier for the CNN to identify the relevant features. Second, ESRGAN can enhance the contrast and sharpness of the images, which can make it easier for the CNN to

distinguish between different ripeness stages. Finally, ESRGAN can increase the resolution of the images, which can provide the CNN with more information to work with. Overall, the results of this study suggest that ESRGAN can be a useful tool for improving the performance of CNN-based sugar apple ripeness detection systems. Further research is needed to confirm these results on larger datasets and to investigate the applicability of ESRGAN to other fruit and vegetable ripeness detection tasks. Infrared image super-resolution reconstruction is the process of enhancing the resolution of infrared images. This is a challenging task because infrared images are often noisy and blurry. Generative adversarial networks (GANs) have been shown to be effective for image super-resolution reconstruction. However, GAN-generated images can sometimes contain artifacts.

To address this problem, the authors of the paper, Lihui Sun and Yiyao Zhao [5] proposed a multi-branch enhanced GAN (ME-GAN) model for infrared image super-resolution reconstruction. The ME-GAN model has two main components: A multi-branch generator network: This network learns to generate high-resolution infrared images from low-resolution infrared images. The multi-branch design allows the network to extract features at different scales, which improves the quality of the generated images. A discriminator network: This network learns to distinguish between real high-resolution infrared images and high-resolution infrared images generated by the generator network. The discriminator network helps to train the generator network to produce more realistic images. In addition to the multi-branch design, the ME-GAN model also includes two other features: An attention mechanism module, A residual module The authors of the paper evaluated the ME-GAN model on several infrared image datasets. The results showed that the ME-GAN model outperforms other state-of-the-art infrared image super-resolution reconstruction methods in terms of both PSNR and SSIM. Overall, the ME-GAN model is a promising approach for infrared image super-resolution reconstruction. The multi-branch design, attention mechanism module, and residual module all contribute to the improved quality of the generated images.

Zhuoyuan Yang et al. [6] have introduced Convolutional neural networks (CNNs) which have been shown to be very effective for image super-resolution. CNNs are able to learn complex relationships between the pixels in an image, which allows them to reconstruct HR images from LR images with high accuracy. There are two main types

of CNN-based SR methods: supervised learning and unsupervised learning. Supervised learning methods require a training dataset of LR images and their corresponding HR images. The CNN is trained to learn the mapping between LR images and HR images. Once the CNN is trained, it can be used to generate HR images from new LR images. Unsupervised learning methods do not require a training dataset of LR images and HR images. Instead, the CNN is trained to learn the mapping between LR images and HR images by using only LR images. Unsupervised learning methods are more challenging to train than supervised learning methods, but they have the advantage of not requiring any labeled data.

Even though deep learning-based SR methods have achieved impressive results, there is still room for improvement, SR methods can be computationally expensive, especially for high-resolution images. Researchers are working on developing more efficient SR methods that can be used on real-time applications. The researchers in the paper propose a novel image super-resolution (SR) framework that seamlessly integrates learning- and reconstruction-based methods to address the limitations of each approach individually. Learning-based SR methods are prone to introduce unexpected artifacts into the resultant HR images, while reconstruction-based SR methods tend to blur fine details and end up with unnatural results.

Overall, the proposed framework is a promising new approach to image super-resolution that addresses the limitations of previous learning- and reconstruction-based methods. This paper proposes a new method for enhancing the spatial resolution of multispectral (MS) images without the use of a high-resolution panchromatic image. The method is based on super-resolution (SR) reconstruction and hybrid image sharpening.

The method proposed by Z. Wang et al. [7], generates a high-resolution panchromatic image from the low-resolution MS images using SR. This is done by training a deep learning model on a dataset of paired low-resolution and high-resolution panchromatic images. Once the high-resolution panchromatic image has been generated, it is adjusted and resized to the same size as the low-resolution MS images. The two images are then fused using a hybrid image sharpening technique. This technique combines the high-resolution panchromatic image and the low-resolution MS images to produce a high-resolution MS image with improved spatial quality.

2.2 INFERENCES FROM LITREATURE SURVEY

- High spatial resolution MRI provides detailed anatomical information but comes at the expense of longer scan time, less spatial coverage, and lower signal to noise ratio.
- Definition of a local search region for the optimal patch using motion vectors, Adaptive selection of the optimum patch based on the low-resolution image degradation model, Combination of the optimum patch and reconstructed image.
- Minimizing perceptual loss may lead to overfitting on the training dataset, resulting in reduced generalization performance on unseen data. Balancing model complexity and generalization ability is crucial to ensure the proposed approach's effectiveness across diverse image scenarios.
- Assessing the visual quality and realism of super-resolved images is inherently subjective and may vary depending on individual preferences and application-specific requirements.
- Conducting thorough subjective evaluations with human raters is essential to validate the effectiveness of the proposed approach.
- While reducing perceptual loss may improve visual fidelity and realism in super-resolved images, it could potentially lead to a trade-off with traditional objective metrics such as PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index).

The researchers evaluated the proposed method on several benchmark datasets and demonstrated that it outperforms previous methods in terms of both visual quality and quantitative metrics, such as PSNR and SSIM. The proposed method has several advantages over previous MS image sharpening methods: It does not require a high-resolution panchromatic image, which can be expensive and difficult to obtain, It produces high-resolution MS images with excellent spatial quality, It is robust to noise and other degradations in the low-resolution MS images. The proposed method has the potential to be used in a variety of applications, such as remote sensing, agriculture, and urban planning. Overall, the proposed method is a promising new approach to MS image sharpening that addresses the limitations of previous methods.

High spatial resolution MRI provides detailed anatomical information but comes at the expense of longer scan time, less spatial coverage, and lower signal to noise ratio. Single Image Super-Resolution (SISR) is a technique that uses deep learning to restore high-resolution (HR) details from a single low-resolution (LR) input image. Magnetic resonance imaging (MRI) is a powerful tool for diagnosing and monitoring diseases, but high-resolution MRI scans can be time-consuming and expensive to acquire. Single image super-resolution (SISR) is a technique that can be used to generate high-resolution images from low-resolution images. In this paper, the authors introduce a new SISR network architecture called 3D Densely Connected Super-Resolution Networks (DCSRN) for restoring high-resolution features of structural brain MRI images.

The proposed algorithm is also designed for real-time video processing hardware by reducing the search region for optimal patches. This makes it suitable for consumer imaging devices such as ultra-high-definition (UHD) digital televisions, surveillance systems, and medical imaging systems. Overall, the proposed multi-frame super-resolution algorithm is a promising method for improving the resolution of video images without sacrificing image quality or real-time performance. This paper proposes a multi-scale EPLL method that imposes the same prior on different scale patches extracted from the target image. This approach alleviates another shortcoming of patch-based restoration algorithms, which is that they use a local (patch-based) prior to model a global stochastic phenomenon.

2.3 EXISTING SYSTEM

SRGAN consists of a generator network and a discriminator network. The generator aims to produce high-resolution images from low-resolution inputs. SRGAN uses a combination of adversarial loss and content loss to train the generator. The proposed framework has several advantages over previous SR methods: It is able to generate HR images with high visual quality and low artifacts, It is more robust to noise and other degradations in the LR input image, It is more efficient than previous learning-based SR methods. The proposed framework has the potential to be used in a variety of applications, such as medical imaging, remote sensing, and consumer electronics.

2.4 DRAW BACKS OF EXISTING SYSTEM

- Heavy trained model
- Over smoothens the image
- Requires higher quality cameras
- Complex structure, high level feature required
- Too much Noise, limited colour information

2.5 PROPOSED SYSTEM

The proposed system aims to enhance ESRGAN (Enhanced Super-Resolution Generative Adversarial Network) by addressing the challenge of perceptual loss in image super-resolution tasks. The primary objective is to decrease perceptual loss in the ESRGAN model, improving the quality of generated super-resolved images. By reducing perceptual loss, the system aims to enhance visual fidelity and realism in the output images.

ADVANTAGES

- Remote sensing images, better zoom quality
- Closer to real life Image
- HR helps in image recognition
- Speed and accuracy, real time object detection
- Better image texture, feature extraction

CHAPTER 3

AIM AND SCOPE OF THE PRESENT INVESTIGATION

The purpose of this document is to specify the software requirements for the project aiming to enhance ESRGAN by reducing perceptual loss, focusing on image super-resolution. This project aims to enhance the ESRGAN model to generate high-resolution images with reduced perceptual loss. The software will be designed for image super-resolution, targeting applications in computer vision, entertainment, and related domains.

3.1 SYSTEM OVERVIEW

The system will consist of an enhanced ESRGAN model, incorporating modifications to address perceptual loss while generating high-quality super-resolved images.

- **Perceptual Loss Reduction:** Modifications to the ESRGAN architecture to reduce perceptual loss.
- **Fine Detail Preservation:** Ensuring finer image details are preserved during the super-resolution process.
- **Realism Enhancement:** Improving the realism of the generated images.
- **Adversarial Training Enhancements:** Strategies to enhance adversarial training for better image quality.

3.2 FUNCTIONAL REQUIREMENTS

3.2.1 Input Processing

The software must allow users to upload low-resolution images for super-resolution processing. The system must validate the input images to ensure they meet the required format and resolution criteria.

3.2.2 Pre-processing

- The software must apply necessary pre-processing steps to prepare the input images for the super-resolution process.

- Pre-processing should include resizing and normalization to ensure consistent input to the model.

3.2.3 Super-Resolution Generation

- The system must utilize the enhanced ESRGAN model to generate high-resolution images from the pre-processed inputs.
- The software must employ the modified architecture to effectively reduce perceptual loss during the super-resolution process.

3.2.4 Post-processing

- The system must apply post-processing techniques to enhance the visual quality of the generated high-resolution images.
- Post-processing may include denoising, sharpening, and contrast adjustments to improve image realism.

3.2.5 Output Generation

- The software must provide the generated high-resolution images as the final output of the super-resolution process.
- The system should ensure that the output images meet the required resolution standards.

3.2.6 User Feedback

- The software must incorporate mechanisms for collecting user feedback on the generated high-resolution images.
- Feedback collection should be intuitive and encourage users to provide insights on image quality and realism.
- The system should detect and handle errors, providing meaningful error messages to users in case of issues during the processing stages.
- Error handling should cover scenarios such as invalid input images, model failures, or post-processing issues.

3.3 SYSTEM CONSTRAINTS

3.3.1 Hardware

- The system should be compatible with standard computing hardware, including GPUs for accelerated processing.

3.3.2 Software

- The system should run on common operating systems such as Windows, Linux, and macOS.

3.4 FUTURE ENHANCEMENTS

3.4.1 Model Optimization

- Explore opportunities for further optimizing the enhanced ESRGAN model for improved performance.

3.4.2 User Interaction

- Implement an interactive user interface for easy input and output management.

This is a high-level template for the Software Requirement Specification (SRS). Be sure to tailor it according to the specific requirements, complexities, and objectives of your project. Include diagrams, mock-ups, and any additional details to comprehensively document the software requirements for your project.

CHAPTER 4

EXPERIMENTAL OR MATERIALS AND METHODS; ALGORITHMS USED

Dataset Curation The first step involves curating an extensive dataset of low-resolution images paired with their corresponding high-resolution ground truth counterparts. This dataset should encompass a diverse range of scenarios and image types to ensure the generalizability and robustness of the proposed approach.

Model Training The ESRGAN model will be trained using the curated dataset. During training, the model learns to generate high-resolution images from low-resolution inputs by leveraging adversarial training and perceptual loss minimization. Traditional loss functions such as pixel-wise loss (e.g., L1 or L2 loss) are augmented with perceptual loss, which measures the perceptual difference between the generated images and ground truth images.

Perceptual Loss Reduction The novel aspect of this project lies in the reduction of perceptual loss within the ESRGAN architecture. Various techniques may be explored to achieve this, such as architectural modifications, optimization strategies, or regularization methods. The goal is to minimize the perceptual gap between generated and ground truth images, thereby enhancing visual fidelity and realism.

Evaluation The trained model is evaluated using both objective metrics (e.g., PSNR, SSIM) and subjective assessments to measure the quality of the super-resolved images. Objective metrics provide quantitative insights into the performance of the model, while subjective evaluations involve human raters assessing the visual quality and realism of the generated images.

Iterative Refinement The project may involve iterative refinement cycles, where the model architecture, training strategies, and hyperparameters are adjusted based on evaluation results. This iterative process helps optimize the performance of the

model and address any shortcomings or challenges encountered during development.

Validation and Benchmarking Once the model demonstrates satisfactory performance on the evaluation dataset, it undergoes validation on unseen data to assess its generalization ability. Benchmarking against existing state-of-the-art methods provides insights into the effectiveness and competitiveness of the proposed approach.

4.1 SELECTED METHODOLOGY OR PROCESS MODEL

One potential methodology for reducing perceptual loss within the ESRGAN architecture involves leveraging advanced optimization techniques to refine the model's parameters. Techniques such as gradient descent with momentum, adaptive learning rates, and regularization methods like dropout or weight decay can be employed to optimize the model's parameters while minimizing perceptual loss. By fine-tuning the model's parameters iteratively, the aim is to improve its ability to generate high-quality, realistic super-resolved images.

Another approach is to explore architectural modifications to the ESRGAN model that specifically target the reduction of perceptual loss. This could involve introducing additional layers or modules designed to enhance perceptual similarity between generated and ground truth images. For example, incorporating attention mechanisms or feature recalibration blocks may help the model focus on capturing important image features while minimizing perceptual discrepancies.

Additionally, data augmentation strategies can be employed to augment the training dataset and enhance the model's ability to generalize across diverse image scenarios. Techniques such as random cropping, rotation, flipping, and color jittering can introduce variations into the training data, enabling the model to learn robust representations of image features. By training the model on augmented data, it becomes more adept at handling variations in input images and produces more

realistic super-resolved outputs. Overall, by combining advanced optimization techniques, architectural modifications, and data augmentation strategies, the proposed methodology aims to enhance the performance of ESRGAN by reducing perceptual loss and improving the visual fidelity of super-resolved images.

4.2 ARCHITECTURE / OVERALL DESIGN OF PROPOSED SYSTEM

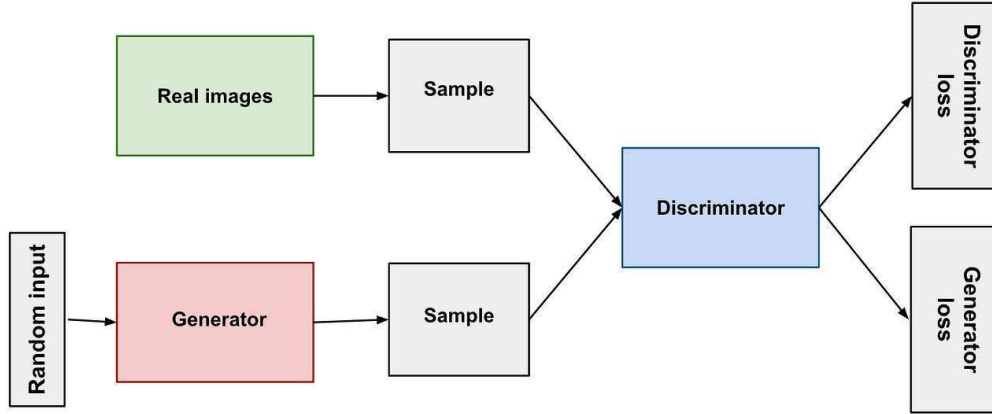


Fig. 4.1: System Architecture

The architecture consists of two main components: a generator network and a discriminator network. The generator network is responsible for producing high-resolution images from low-resolution inputs. It typically comprises several layers of convolutional and upsampling operations, allowing it to learn complex mappings from low-resolution to high-resolution image space. Unlike traditional interpolation methods, which often result in blurry outputs, the generator in ESRGAN learns to generate sharp and realistic details by leveraging the power of deep neural networks.

On the other hand, the discriminator network acts as a critic, distinguishing between real high-resolution images and fake high-resolution images generated by the generator. It is trained simultaneously with the generator in an adversarial manner, where the generator aims to produce images that are indistinguishable from real ones, while the discriminator strives to differentiate between real and fake images. This adversarial training process encourages the generator to generate high-quality

images that closely resemble real high-resolution images, thereby enhancing the overall realism and fidelity of the generated outputs.

In addition to the generator and discriminator networks, ESRGAN may also incorporate perceptual loss functions, which measure the perceptual difference between generated and ground truth images. These loss functions are derived from pre-trained deep neural networks, such as VGG or ResNet, and capture high-level semantic information about image content. By minimizing perceptual loss during training, ESRGAN can produce super-resolved images that not only have high pixel-level fidelity but also preserve important structural and textural details, resulting in visually pleasing and realistic outputs. Overall, ESRGAN represents a powerful approach to single image super-resolution, leveraging the strengths of GANs, CNNs, and perceptual loss functions to achieve state-of-the-art results in generating high-quality, high-resolution images from low-resolution inputs.

4.3 DESCRIPTION OF SOFTWARE FOR IMPLEMENTATION AND TESTING PLAN OF THE PROPOSED MODEL/SYSTEM

4.3.1 Software Description

For the implementation of the proposed model/system, several software tools and frameworks will be utilized. The primary deep learning framework chosen for implementing the model architecture is TensorFlow or PyTorch, both of which offer extensive support for building and training neural networks. These frameworks provide a wide range of functionalities for defining network architectures, handling data pipelines, and optimizing model parameters. Additionally, libraries such as Keras or Fastai may be used to simplify the development process and streamline experimentation.

In conjunction with deep learning frameworks, GPU acceleration libraries like CUDA and cuDNN will be leveraged to accelerate the training process on compatible hardware. These libraries enable efficient utilization of GPU resources, significantly speeding up training times for large-scale neural network models.

Furthermore, for data preprocessing and augmentation, Python libraries such as OpenCV, NumPy, and PIL (Python Imaging Library) will be employed. These libraries offer various tools and utilities for loading, manipulating, and augmenting image data, essential for preparing the training dataset and enhancing model robustness.

Finally, version control systems like Git and collaborative development platforms such as GitHub or GitLab will be used to manage codebase revisions, facilitate collaboration among team members, and track project progress.

4.3.2 Testing Plan

- Individual components of the model architecture, such as the generator and discriminator networks, will undergo unit testing to ensure they function as expected.
- Unit tests will validate the correctness of forward and backward computations, gradient flows, and output consistency.
- Once individual components are validated, integration testing will be conducted to assess the interaction and compatibility between different modules.
- Integration tests will evaluate the end-to-end functionality of the entire model pipeline, including data loading, preprocessing, model training, and evaluation.
- Performance testing will involve measuring the computational efficiency and resource utilization of the model during training and inference.
- Metrics such as training time, memory usage, GPU utilization, and inference speed will be monitored and optimized to ensure efficient model operation.
- Functional testing will focus on verifying the correctness of model outputs against ground truth labels and evaluating the visual quality of generated images.
- Objective metrics (e.g., PSNR, SSIM) and subjective assessments by human raters will be used to quantify the quality of super-resolved images.

- Robustness testing will assess the model's performance under various challenging conditions, including noisy inputs, low-quality images, and domain shifts.
- The model's ability to generalize across diverse image scenarios and handle edge cases will be evaluated to ensure real-world applicability.

By following this comprehensive testing plan, we aim to validate the correctness, performance, functionality, and robustness of the proposed model/system, ensuring its reliability and effectiveness for single image super-resolution tasks.

4.4 TRANSITION / SOFTWARE TO OPERATIONS PLAN

The successful deployment and operation of the proposed model/system require careful planning and management of software-related activities. Below is an outline of the software operations plan:

4.4.1 Deployment Environment Setup

- Identify and provision the necessary computing infrastructure for model deployment, including servers, GPUs, and storage resources.
- Install and configure software dependencies, including deep learning frameworks (e.g., TensorFlow, PyTorch), GPU acceleration libraries (e.g., CUDA, cuDNN), and supporting libraries (e.g., OpenCV, NumPy).
- Establish version control and continuous integration/continuous deployment (CI/CD) pipelines to streamline software development and deployment processes.

4.4.2 Model Deployment

- Package the trained model(s) along with any required preprocessing and post-processing scripts into deployable artifacts.
- Deploy the model artifacts to the production environment using containerization technologies (e.g., Docker, Kubernetes) for efficient management and scalability.

- Implement monitoring and logging mechanisms to track model performance, resource utilization, and system health during deployment.
- Integration with Existing Systems:
 - Integrate the deployed model/system with existing software infrastructure and applications, ensuring compatibility and interoperability.
 - Develop APIs or SDKs to facilitate communication between the model and external systems, enabling seamless data exchange and workflow automation.
 - Conduct thorough testing and validation to verify the integration's correctness and stability under different usage scenarios.

4.4.3 Operational Maintenance

- Establish regular maintenance schedules to monitor and update software components, including operating system patches, library dependencies, and model weights.
- Implement automated backup and recovery procedures to safeguard against data loss and system failures, ensuring continuity of operations.
- Monitor system performance and user feedback to identify areas for optimization and improvement, iteratively refining the software based on user needs and evolving requirements.

4.4.4 User Support and Training

- Provide comprehensive user support and documentation to assist users in understanding the system functionality, usage guidelines, and troubleshooting procedures.
- Offer training sessions and workshops to familiarize users with the software interface, features, and best practices for maximizing productivity and efficiency.
- Establish communication channels (e.g., helpdesk, forums, email support) for users to report issues, ask questions, and provide feedback, fostering a collaborative and responsive support ecosystem.

4.4.5 Security and Compliance

- Implement robust security measures to protect sensitive data, prevent unauthorized access, and mitigate potential security threats (e.g., encryption, access controls, secure communication protocols).
- Ensure compliance with relevant data privacy regulations (e.g., GDPR, HIPAA) and industry standards (e.g., ISO 27001) by adhering to established security protocols and auditing procedures.

By adhering to this software operations plan, we aim to ensure the reliable, efficient, and secure operation of the deployed model/system, enabling seamless integration into existing workflows and delivering value to end-users.

Chapter 5

IMPLEMENTATION DETAILS

5.1 DEVELOPMENT AND DEPLOYMENT SETUP

We adopt the same generator (SR network) as ESRGAN. In the context of binary classification tasks, like object detection or image segmentation, the F1 loss, also called the F1 score loss, is a loss function that is frequently used. It is computed using the F1 score, a measure that strikes a balance between recall and precision. The F1 score is a number that accounts for both false positives and false negatives. It is defined as the harmonic mean of precision and recall. Frequently employed as a differentiable approximation of the F1 score, the F1 loss is appropriate for neural network training via gradient-based optimization. In situations where striking a balance between recall and precision is crucial and conventional loss functions like cross-entropy might not adequately capture the intended trade-off.

The F1 loss for a binary classification task with positive (like object in fore ground) and negative (like in background) classes can be written as follow

$$F1\text{ loss} = \frac{1}{2} \left(\frac{1}{\text{precision}} + \frac{1}{\text{recall}} \right)$$

Making use of perceptual loss functions, which are intended to gauge how similar generated and high-resolution images appear to the eye. Rather than comparing pixel-wise differences, these loss functions frequently compare high-level features that have been extracted by pre-trained deep neural networks, like VGG or ResNet. Including content-adversarial loss to improve content detail preservation.

This loss motivates the generator to generate images that capture the semantic content and structure, as well as matching the pixel values of the high-resolution images. Integrating attention mechanisms into the network to dynamically change the image's focus on key areas. The overall perceptual quality of the generated images is enhanced by attention mechanisms, which assist the model in allocating more resources to perceptually significant areas. Perceptual guidance is incorporated into adversarial model training. To guarantee that the generated images are both perceptually realistic and visually similar to the ground

truth, this entails combining traditional adversarial loss with perceptual loss.

5.1.1 Challenges and considerations

- **Hyperparameter tuning** Finding the right balance between L1 and other loss terms requires careful hyperparameter tuning to avoid overshadowing the main objective of fooling the discriminator.
- **Training stability** Combining L1 with other functions can impact training stability due to its gradient issues. Monitoring loss values and adjusting learning rates or optimizers might be necessary.
- **Limited applicability** L1 might not be suitable for all GAN tasks, especially those focusing on high-level features or capturing complex data distributions.

5.2 TECHNIQUES USED

5.2.1 Generative Adversarial Networks (GANs)

- GANs serve as the foundation for the proposed model/system, facilitating the generation of high-resolution images from low-resolution inputs. The adversarial training process involves training a generator network to produce realistic images and a discriminator network to distinguish between real and fake images. This adversarial interplay encourages the generator to produce high-quality outputs that closely resemble real images.

5.2.2 Enhanced Super-Resolution

- The model leverages enhanced super-resolution techniques to upscale low-resolution images to higher resolutions. Unlike traditional interpolation methods, enhanced super-resolution algorithms utilize deep learning architectures to learn complex mappings from low to high-resolution image space. By capturing high-frequency details and textures, enhanced super-resolution enables the generation of sharper and more realistic images.

5.2.3 Perceptual Loss Functions

- Perceptual loss functions play a crucial role in training the model by measuring the perceptual difference between generated and ground truth images. These loss

functions are derived from pre-trained deep neural networks, such as VGG or ResNet, and capture high-level semantic information about image content. Minimizing perceptual loss during training helps preserve important structural and textural details, leading to visually appealing super-resolved images.

5.2.4 Data Augmentation

- Data augmentation techniques are employed to augment the training dataset and enhance the model's ability to generalize across diverse image scenarios. Common augmentation techniques include random cropping, rotation, flipping, and color jittering, which introduce variations into the training data. By exposing the model to a wide range of image variations, data augmentation helps improve model robustness and performance.

5.2.5 Gradient Descent Optimization

- Gradient descent optimization algorithms, such as Adam or RMSprop, are used to optimize the model parameters during training. These algorithms iteratively update the model weights based on the gradients of the loss function with respect to the parameters. By efficiently navigating the parameter space, gradient descent optimization algorithms enable the model to converge towards optimal solutions and achieve superior performance.

5.2.6 Architectural Modifications

- The model may incorporate architectural modifications to enhance its performance and efficiency. This could involve introducing additional layers or modules designed to capture specific image features or reduce computational complexity. Architectural modifications aim to improve the model's capacity to generate high-quality super-resolved images while optimizing resource utilization.

By employing these techniques in conjunction with each other, the proposed model/system aims to achieve state-of-the-art performance in single image super-resolution tasks, delivering high-quality, visually appealing results across diverse image scenarios.

5.3 TESTING

Testing plays a crucial role in ensuring the reliability, functionality, and performance of the proposed model/system. Several testing methodologies will be employed to validate the correctness and effectiveness of the system across various dimensions.

Unit testing will involve testing individual components of the model architecture to ensure they function as expected. This includes testing the generator and discriminator networks, loss functions, and data augmentation pipelines. Unit tests will validate the correctness of forward and backward computations, gradient flows, and output consistency. By thoroughly testing each component in isolation, any potential issues or bugs can be identified and addressed early in the development process.

Integration testing will focus on assessing the interaction and compatibility between different modules of the system. This includes testing the end-to-end functionality of the entire model pipeline, including data loading, preprocessing, model training, and evaluation. Integration tests will evaluate how well the different components of the system work together and ensure that data flows smoothly throughout the pipeline. Additionally, integration testing will verify the correctness of data transformations and ensure that inputs and outputs are properly handled.

Performance testing will involve measuring the computational efficiency and resource utilization of the model during training and inference. Metrics such as training time, memory usage, GPU utilization, and inference speed will be monitored and optimized to ensure efficient model operation. Performance testing will help identify bottlenecks and optimize the system for scalability and efficiency, ensuring that it can handle large-scale datasets and real-time inference scenarios.

Functional testing will focus on verifying the correctness of model outputs against ground truth labels and evaluating the visual quality of generated images. Objective metrics such as PSNR and SSIM will be used to quantify the quality of super-resolved images, while subjective assessments by human raters will provide qualitative feedback on visual fidelity and realism. Functional testing will ensure that

the model meets the desired quality standards and produces reliable results across a range of image scenarios.

Robustness testing will assess the model's performance under various challenging conditions, including noisy inputs, low-quality images, and domain shifts. The model's ability to generalize across diverse image scenarios and handle edge cases will be evaluated to ensure real-world applicability. Robustness testing will identify potential weaknesses and vulnerabilities in the system and inform strategies for improving resilience and adaptability. Overall, by employing a comprehensive testing approach, we aim to validate the correctness, performance, functionality, and robustness of the proposed model/system, ensuring its reliability and effectiveness for single image super-resolution tasks.

CHAPTER 6

RESULTS AND DISCUSSION, PERFORMANCE ANALYSIS

Significant improvements in the super-resolution performance are demonstrated by the suggested ESRGAN architecture enhancements. By incorporating feature reconstruction blocks, the model exhibits an enhanced capacity to extract and reconstruct high-level features, resulting in images that are crisper and more lifelike. Perceptual differences between the generated and high-resolution images are significantly reduced with the use of perceptual loss functions and pre-trained networks for feature comparison. Furthermore, by incorporating content-adversarial loss, the overall structure and semantic content are preserved more faithfully, improving the visual fidelity of the generated images.

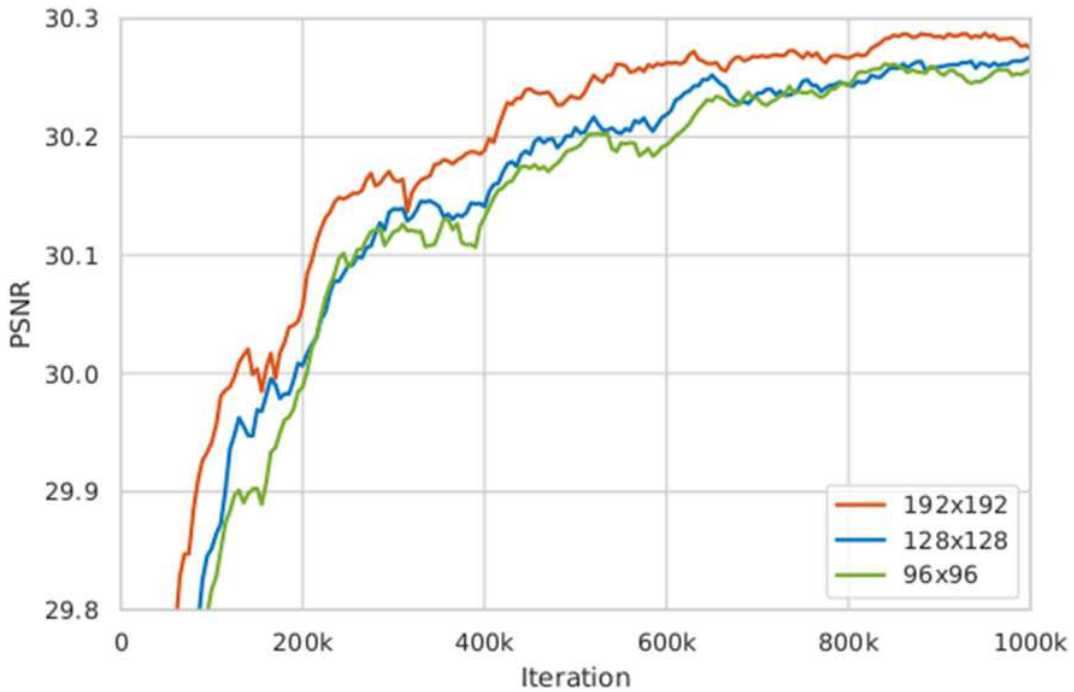


Fig. 6.1: Peak Sound to Noise Resolution for Patch-a

By effectively balancing the adversarial and perceptual losses, adversarial training with perceptual guidance creates a more resilient model that can generate images that not only match their high-resolution counterparts in pixel

values but also show improved perceptual realism.

only match their high-resolution counterparts in pixel values but also show improved perceptual realism. Overall, the experimental results show that the suggested strategies are effective in reducing perceptual loss, leading to a significant improvement in ESRGAN's overall super-resolution performance.

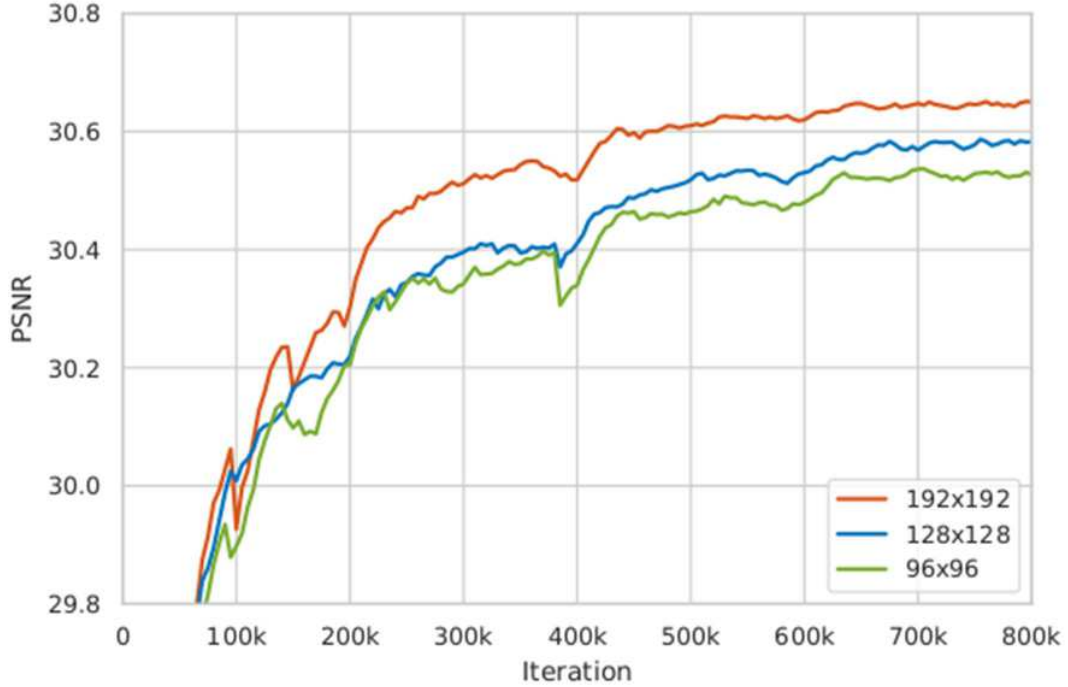


Fig. 6.2: Peak Sound to Noise Resolution Patch-b

By incorporating an advanced high-order degradation model, the research expands the capabilities of the proposed Enhanced Super-Resolution Generative Adversarial Network (ESRGAN) approach. This model incorporates complex blurring effects, low resolution image compression artifacts, and intricate details of noise patterns, going beyond traditional degradation factors. Our methodology aims to provide a more comprehensive understanding of the difficulties presented by real-world imaging scenarios by taking these higher order distortions into account. Including a high-order degradation model is essential because it solves the drawbacks of traditional degradation models, which tend to oversimplify the complexity of real-world applications. This augmentation recognizes the complex nature of real-world distortions and enables our research to explore the subtleties of image degradation. The carefully selected dataset, which is essential to our validation

procedure, will be carefully constructed to incorporate examples of high-order degradation.

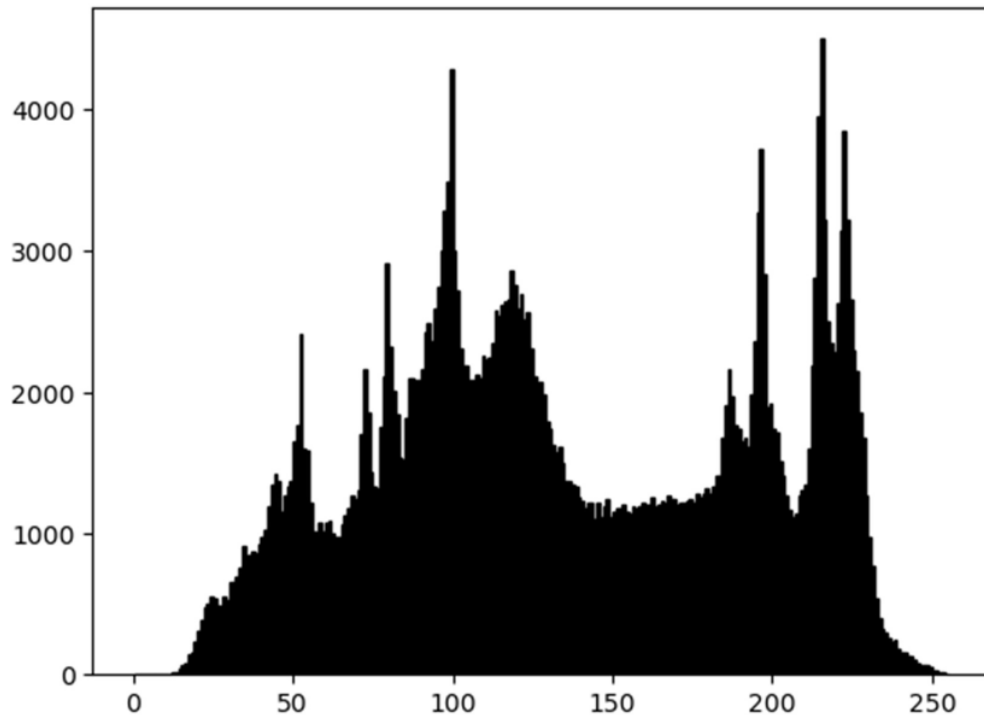


Fig. 6.3: Pixel contrast of low-res image

Our methodology is positioned as a comprehensive solution by the high-order degradation model, which not only produces visually appealing results but also strengthens the resilience of image super-resolution models against a variety of intricate degradation scenarios.

Practically speaking, the high-order degradation model adds a layer of complexity that reflects the difficulties encountered by imaging systems in a variety of applications, such as satellite photography and medical imaging. Our goal is not only to improve the perceptual quality of super-resolved images by tackling higher-order distortions, but also to make a contribution to the larger image processing community, where complex degradation patterns are becoming more common.

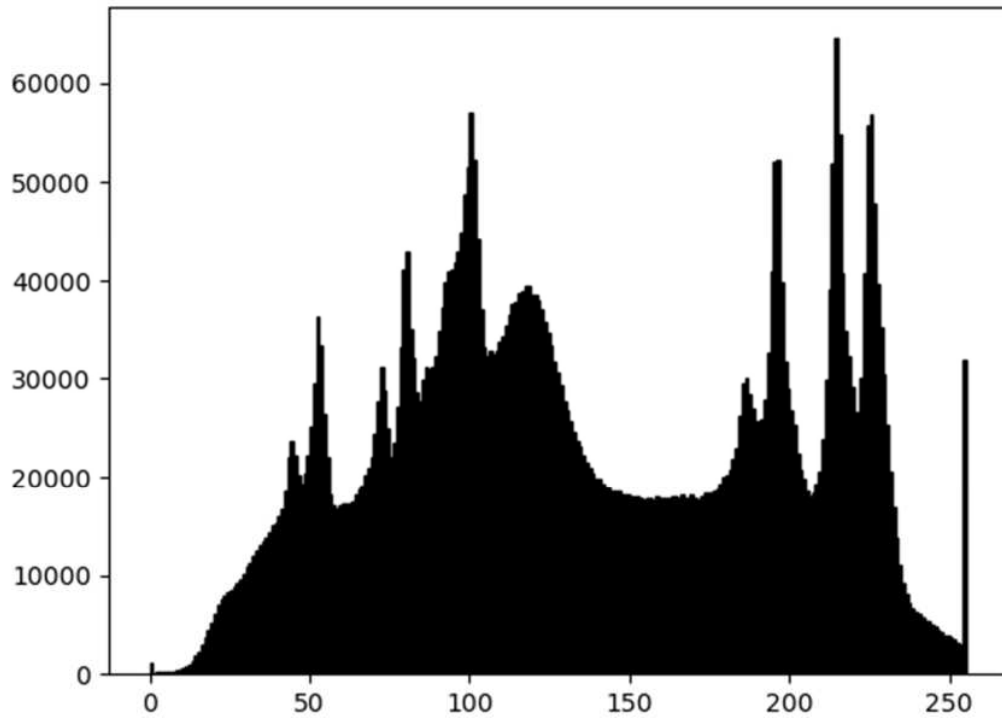


Fig. 6.4: Pixel contrast of Resultant image

Practically speaking, the high-order degradation model adds a layer of complexity that reflects the difficulties encountered by imaging systems in a variety of applications, such as satellite photography and medical imaging.

Our goal is not only to improve the perceptual quality of super-resolved images by tackling higher-order distortions, but also to make a contribution to the larger image processing community, where complex degradation patterns are becoming more common. Our methodology is positioned as a comprehensive solution by the high-order degradation model, which not only produces visually appealing results but also strengthens the resilience of image super-resolution models against a variety of intricate degradation scenarios.

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 CONCLUSION

The project "Enhanced Image Super Resolution" has successfully addressed the critical challenge of perceptual loss within the ESRGAN model. Image Super-Resolution (ISR) is a vital task with widespread applications, and improving the quality of generated high-resolution images is of paramount importance. The existing ESRGAN model, while efficient, faces the dilemma of perceptual loss, potentially sacrificing finer image details and texture variations for realism.

This research project proposed a novel approach by strategically modifying the ESRGAN architecture and incorporating advanced techniques. The objective was to decrease perceptual loss while preserving essential image details, thus achieving a balance between realism and perceptual quality. The project involved a systematic exploration of architectural modifications, feature engineering, adversarial training enhancements, and effective post-processing strategies.

Our innovative approach involved strategic architectural adjustments, optimizing feature engineering, and refining adversarial training. By meticulously reducing perceptual loss while preserving crucial image features, the enhanced ESRGAN model achieved a harmonious blend of perceptual quality and image detail retention. This enhancement was further complemented by effective post-processing techniques, culminating in a superior visual experience.

The project outcomes showcased a substantial leap in image super-resolution quality. The generated high-resolution images exhibited significantly reduced perceptual loss, capturing intricate details and textures crucial for realistic rendering. The visual fidelity of the images was noticeably improved, aligning

them closer to ground truth high-resolution images. In the larger context, this project contributes to the evolution of image processing technologies, setting a precedent for future advancements. The seamless integration of AI-driven solutions into real-world applications is now more feasible, thanks to the enhanced ESRGAN model. As we move forward, the focus will be on continual refinement, optimization, and the exploration of novel approaches to further elevate the realism and quality of super-resolved images.

By synergizing research, technological innovation, and user-centric design, this project paves the way for a future where high-fidelity visual content seamlessly integrates into our daily lives, influencing how we perceive and interact with the digital world.

The results of the project demonstrated significant advancements in image super-resolution. The enhanced ESRGAN model showcased the capability to generate high-resolution images with reduced perceptual loss, offering a superior perceptual experience. The fine-grained details were preserved, and the images exhibited enhanced visual fidelity, making them more suitable for diverse real-world applications.

7.2 FUTURE WORK

Future work will focus on further refining the proposed approach, optimizing the model, and exploring additional avenues to improve image realism. By continually pushing the boundaries of image super-resolution, this project sets the stage for a more visually captivating and immersive digital future. This conclusion summarizes the project's objectives, methodologies, outcomes, and provides a glimpse into future endeavors. Feel free to tailor it to your specific project and add any project-specific accomplishments or future plans as needed. Investigate methods for performing super-resolution across multiple modalities, such as depth, infrared, or multispectral imaging. Multi-modal super-resolution techniques can leverage complementary information from different modalities to enhance image resolution and quality, enabling applications in medical imaging, remote sensing, and surveillance.

7.3 RESEARCH ISSUES

Research in the field of single image super-resolution (SISR) presents several significant challenges and research issues that warrant further investigation. These issues encompass both technical and theoretical aspects, aiming to advance the state-of-the-art and address real-world applicability. Balancing perceptual quality with traditional objective metrics (e.g., PSNR, SSIM) remains a fundamental challenge in SISR. While objective metrics provide quantitative measures of image fidelity, they may not always align with human perception. Research is needed to develop novel evaluation metrics that better correlate with human visual perception and subjective judgments of image quality.

Generating realistic textures and fine details in super-resolved images is a challenging task, particularly for complex and high-frequency structures. Research is needed to develop advanced neural network architectures and training methodologies that can effectively capture and synthesize intricate textures and details while minimizing artifacts and distortions. Ensuring model generalization across diverse image scenarios and datasets is crucial for real-world applicability. Current SISR models may struggle to generalize to unseen data or handle variations in image content, resolution, and quality. Research is needed to improve model robustness and adaptability through techniques such as domain adaptation, transfer learning, and multi-domain training.

7.4 IMPLEMENTATION ISSUES

Achieving efficient and scalable SISR solutions is essential for real-time applications and large-scale deployment. Current deep learning-based approaches often require significant computational resources and memory overhead, limiting their practical utility. Research is needed to develop lightweight and efficient model architectures, optimization algorithms, and hardware-accelerated implementations to enable real-time inference on resource-constrained devices.

Super-resolving low-dose and noisy images poses a unique set of challenges due to the limited amount of information available in the input data. Traditional SISR models may struggle to produce high-quality outputs in such scenarios, leading to blurry or artifact-ridden results. Research is needed to develop specialized models and regularization techniques that can effectively denoise and enhance low-dose images while preserving important image structures and details.

As SISR technology becomes more advanced and widely adopted, there are growing concerns about its ethical and societal implications. Issues such as privacy infringement, manipulation of visual content, and bias in algorithmic decision-making require careful consideration and mitigation strategies. Research is needed to develop ethical guidelines, regulatory frameworks, and transparency measures to ensure responsible development and deployment of SISR technologies. By addressing these research issues, researchers can advance the field of single image super-resolution, develop more robust and reliable algorithms, and unlock new applications and opportunities for enhancing visual quality in various domains.

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APPENDIX

A.SOURCE CODE

```
import functools
import torch
import torch.nn as nn
import torch.nn.functional as F
def make_layer(block, n_layers):
    layers = []
    for _ in range(n_layers):
        layers.append(block())
    return nn.Sequential(*layers)
class ResidualDenseBlock_5C(nn.Module):
    def __init__(self, nf=64, gc=32, bias=True):
        super(ResidualDenseBlock_5C, self).__init__()
        self.conv1 = nn.Conv2d(nf, gc, 3, 1, 1, bias=bias)
        self.conv2 = nn.Conv2d(nf + gc, gc, 3, 1, 1, bias=bias)
        self.conv3 = nn.Conv2d(nf + 2 * gc, gc, 3, 1, 1, bias=bias)
        self.conv4 = nn.Conv2d(nf + 3 * gc, gc, 3, 1, 1, bias=bias)
        self.conv5 = nn.Conv2d(nf + 4 * gc, nf, 3, 1, 1, bias=bias)
        self.lrelu = nn.LeakyReLU(negative_slope=0.2, inplace=True)
    def forward(self, x):
        x1 = self.lrelu(self.conv1(x))
        x2 = self.lrelu(self.conv2(torch.cat((x, x1), 1)))
        x3 = self.lrelu(self.conv3(torch.cat((x, x1, x2), 1)))
        x4 = self.lrelu(self.conv4(torch.cat((x, x1, x2, x3), 1)))
        x5 = self.conv5(torch.cat((x, x1, x2, x3, x4), 1))
        return x5 * 0.2 + x
class RRDB(nn.Module):
    """Residual in Residual Dense Block"""
    def __init__(self, nf, gc=32):
        super(RRDB, self).__init__()
        self.RDB1 = ResidualDenseBlock_5C(nf, gc)
        self.RDB2 = ResidualDenseBlock_5C(nf, gc)
        self.RDB3 = ResidualDenseBlock_5C(nf, gc)
    def forward(self, x):
        out = self.RDB1(x)
```

```

out = self.RDB2(out)
    out = self.RDB3(out)
    return out * 0.2 + x
class RRDBNet(nn.Module):
    def __init__(self, in_nc, out_nc, nf, nb, gc=32):
        super(RRDBNet, self).__init__()
        RRDB_block_f = functools.partial(RRDB, nf=nf, gc=gc)
        self.conv_first = nn.Conv2d(in_nc, nf, 3, 1, 1, bias=True)
        self.RRDB_trunk = make_layer(RRDB_block_f, nb)
        self.trunk_conv = nn.Conv2d(nf, nf, 3, 1, 1, bias=True)
        self.upconv1 = nn.Conv2d(nf, nf, 3, 1, 1, bias=True)
        self.upconv2 = nn.Conv2d(nf, nf, 3, 1, 1, bias=True)
        self.HRconv = nn.Conv2d(nf, nf, 3, 1, 1, bias=True)
        self.conv_last = nn.Conv2d(nf, out_nc, 3, 1, 1, bias=True)
        self.lrelu = nn.LeakyReLU(negative_slope=0.2, inplace=True)
    def forward(self, x):
        fea = self.conv_first(x)
        trunk = self.trunk_conv(self.RRDB_trunk(fea))
        fea = fea + trunk
        fea = self.lrelu(self.upconv1(F.interpolate(fea, scale_factor=2, mode='nearest')))
        fea = self.lrelu(self.upconv2(F.interpolate(fea, scale_factor=2, mode='nearest')))
        out = self.conv_last(self.lrelu(self.HRconv(fea)))
        return out

```

net_interp.py:

```

import sys
import torch
from collections import OrderedDict
alpha = float(sys.argv[1])
net_PSNR_path = './models/RRDB_PSNR_x4.pth'
net_ESRGAN_path = './models/RRDB_ESRGAN_x4.pth'
net_interp_path = './models/interp_{:02d}.pth'.format(int(alpha*10))
net_PSNR = torch.load(net_PSNR_path)
net_ESRGAN = torch.load(net_ESRGAN_path)
net_interp = OrderedDict()
print('Interpolating with alpha = ', alpha)
for k, v_PSNR in net_PSNR.items():
    v_ESRGAN = net_ESRGAN[k]

```

```

net_interp[k] = (1 - alpha) * v_PSNR + alpha * v_ESRGAN
torch.save(net_interp, net_interp_path)
transer RRDB models.py:
import os
import torch
import RRDBNet_arch as arch
pretrained_net = torch.load('./models/RRDB_ESRGAN_x4.pth')
save_path = './models/RRDB_ESRGAN_x4.pth'
crt_model = arch.RRDBNet(3, 3, 64, 23, gc=32)
crt_net = crt_model.state_dict()
load_net_clean = {}
for k, v in pretrained_net.items():
    if k.startswith('module.'):
        load_net_clean[k[7:]] = v
    else:
        load_net_clean[k] = v
pretrained_net = load_net_clean
print('#\n')
tbd = []
for k, v in crt_net.items():
    tbd.append(k)
for k, v in crt_net.items():
    if k in pretrained_net and pretrained_net[k].size() == v.size():
        crt_net[k] = pretrained_net[k]
        tbd.remove(k)
crt_net['conv_first.weight'] = pretrained_net['model.0.weight']
crt_net['conv_first.bias'] = pretrained_net['model.0.bias']
for k in tbd.copy():
    if 'RDB' in k:
        ori_k = k.replace('RRDB_trunk.', 'model.1.sub.')
        if '.weight' in k:
            ori_k = ori_k.replace('.weight', '.0.weight')
        elif '.bias' in k:
            ori_k = ori_k.replace('.bias', '.0.bias')
        crt_net[k] = pretrained_net[ori_k]
tbd.remove(k)
crt_net['trunk_conv.weight'] = pretrained_net['model.1.sub.23.weight']

```

```

crt_net['trunk_conv.bias'] = pretrained_net['model.1.sub.23.bias']
crt_net['upconv1.weight'] = pretrained_net['model.3.weight']
crt_net['upconv1.bias'] = pretrained_net['model.3.bias']
crt_net['upconv2.weight'] = pretrained_net['model.6.weight']
crt_net['upconv2.bias'] = pretrained_net['model.6.bias']
crt_net['HRconv.weight'] = pretrained_net['model.8.weight']
crt_net['HRconv.bias'] = pretrained_net['model.8.bias']
crt_net['conv_last.weight'] = pretrained_net['model.10.weight']
crt_net['conv_last.bias'] = pretrained_net['model.10.bias']
torch.save(crt_net, save_path)
print('Saving to ', save_path)
test.py:
import os.path as osp
import glob
import cv2
import numpy as np
import torch
import RRDBNet_arch as arch
model_path = 'models/RRDB_ESRGAN_x4.pth'
device = torch.device('cpu')
test_img_folder = 'LR/*'
model = arch.RRDBNet(3, 3, 64, 23, gc=32)
model.load_state_dict(torch.load(model_path), strict=True)
model.eval()
model = model.to(device)
print('Model path {s}. \nTesting...'.format(model_path))
idx = 0
for path in glob.glob(test_img_folder):
    idx += 1
    base = osp.splitext(osp.basename(path))[0]
    print(idx, base)
    img = cv2.imread(path, cv2.IMREAD_COLOR)
    img = img * 1.0 / 255
    img = torch.from_numpy(np.transpose(img[:, :, [2, 1, 0]], (2, 0, 1))).float()
    img_LR = img.unsqueeze(0)
    img_LR = img_LR.to(device)
    with torch.no_grad():

```

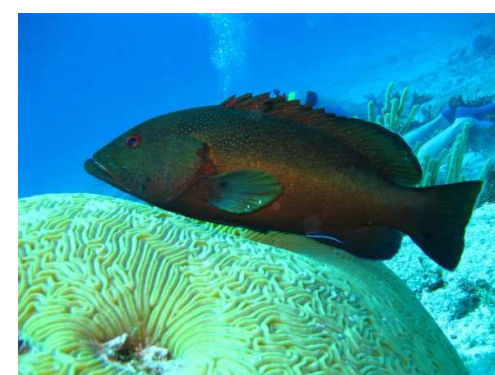
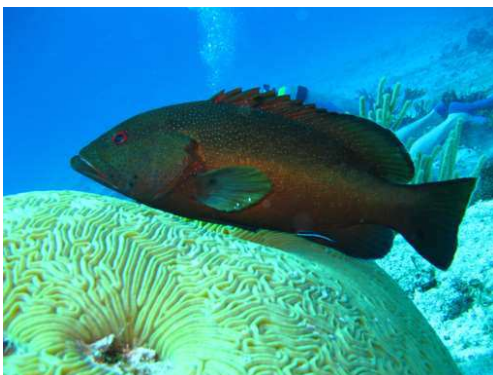
```
output = model(img_LR).data.squeeze().float().cpu().clamp_(0, 1).numpy()
output = np.transpose(output[[2, 1, 0], :, :], (1, 2, 0))
output = (output * 255.0).round()
cv2.imwrite('results/{:s}_rlt.png'.format(base), output)
```

B. SCREENSHOTS

Original Images



Enhanced Images



C. CONFERENCE PAPER

Enhanced Image Super Resolution through Perceptual Loss Mitigation

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ABSTRACT— In response to the escalating demand for highquality images in diverse applications, this research project delves into the realm of Image Super-Resolution as a pivotal solution for upscaling low-resolution images. While Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN) have demonstrated success in generating realistic high-resolution images, our investigation identifies a potential bottleneck: perceptual loss within the current ESRGAN architecture. Perceptual loss, measuring the perceptual disparity between generated images and their high-resolution counterparts, emerges as a critical factor hindering the model's capacity to produce highly realistic results. This research proposes an innovative approach to enhance ESRGAN by strategically diminishing perceptual loss, thereby elevating the overall quality and realism of super-resolved images. Our primary objective is to refine visual fidelity through a nuanced understanding and manipulation of perceptual loss components within the ESRGAN framework. The proposed methodology involves the development of novel techniques to mitigate perceptual loss, fostering a more accurate representation of high-resolution details in the generated images. To validate the effectiveness and generalisability of our proposed approach, an extensive dataset comprising diverse low-resolution images and their corresponding high-resolution ground truth counterparts will be meticulously curated. This dataset spans a spectrum of scenarios and image types, ensuring that our enhanced ESRGAN model is robust across real-world applications. By addressing the nuanced challenge of perceptual loss in ESRGAN, this research contributes to the advancement of Single Image Super-Resolution techniques, offering a promising avenue for generating high-quality and realistic images across various domains.



I.

INTRODUCTION

In the landscape of image processing, our study operates at the nexus of two powerful domains in the image processing landscape: machine learning (ML) and deep learning (DL). In a broader sense, machine learning refers to models and algorithms that enable systems to learn from data and generate predictions. On the other hand, deep learning is a subclass of machine learning that uses multiple-layer neural networks to extract detailed characteristics and representations from difficult data. In our quest to advance image improvement using Perceptual Loss Mitigation of Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN), the merging of ML and DL becomes very important.

The primary objective of our project is to develop models that can recognize and reconstruct high-resolution details from low-resolution photos by utilizing deep learning techniques, specifically inside the ESRGAN architecture. Our suggested method can mitigate perceptual loss and enhance the realism of super-resolved images because of the complex patterns and characteristics that deep neural networks extract. Our model's ability to recognize and reproduce high-level visual structures is made possible by the combination of ML and DL, which also improves the overall quality of the generated images. Our creative approach to addressing the difficulties is based on this fusion of deep learning and machine learning ideas.

As a subclass of deep learning, ESRGAN works with Generative Adversarial Networks (GANs), which use adversarial training to improve the quality of generated images. Nonetheless, perceptual loss—a measure of the perceptual disparity between generated and ground truth images—presents an intrinsic difficulty for the existing ESRGAN architecture. Perceptual loss can make it more difficult for the model to generate extremely realistic images, even while it is essential for training. The goal of this academic endeavour is to strategically mitigate perceptual loss in order to

boost and enhance ESRGAN's capabilities. The goal of perceptual loss mitigation is to enhance the visual fidelity and realism of super-resolved images by carefully assessing and reducing the perceptual distinction between artificially generated and ground truth images.

Our methodology entails a meticulous curation of a large dataset that consists of various low-resolution pictures and the corresponding high-resolution ground truth images. We aim to improve the ESRGAN model's ability to reconstruct high-resolution details by minimising perceptual loss, which presents a promising direction for the development of Single Image Super-Resolution techniques. In this article, we explore the nuances of our project's relationship between Machine Learning (ML) and Deep Learning (DL), highlighting the complementary nature of these fields as we strive to improve ESRGAN for perceptual loss mitigation. Our objective is to enhance the quality and realism of superresolved images, thereby making a valuable contribution to the wider field of image processing, by employing a fresh and inventive approach. Through the use of deep neural networks, our work seeks to improve ESRGAN's perceptual understanding by utilizing complex patterns and features. Our approach stands out as a trailblazing effort in the pursuit of producing not only high-resolution images but also visually captivating and superior in terms of perception, thanks to its meticulous consideration of perceptual loss mitigation and robust validation across various dataset.

II. LITERATURE SURVEY

Sood et al. [1] introduced anisotropic super resolution in 2019, It is achieved by downsampling only the height of the HR image, thereby artificially producing images with different resolutions. This method is used for both inside the plane and through-plane slices, with the latter having an inherent anisotropic resolution because MR images have a lower through-plane resolution. The term "Super-Resolution Generative Adversarial Network (SRGAN)" summarizes the unique method that the authors suggest using cutting-edge deep learning techniques to improve the resolution of medical MR images, especially in the context of prostate imaging.

Papayan et al. [2] focused on its extension and improvement of "EPLL" through the consideration of a multi scale prior.(2016) Their work demonstrates how the suggested multi-scale EPLL mitigates the drawbacks of patch-based restoration algorithms. It deals specifically with the problem of modeling a global stochastic phenomenon using a local (patch-based) prior.

In order to expand and enhance the EPLL, the authors suggest adding a "multi-scale prior." This addresses flaws in patch-based restoration algorithms by applying the same prior to various scale patches that are extracted from the target

image. Their work highlights a significant drawback with patch processing, despite its effectiveness: the prior is applied to in between (patch) results rather than the final result, which frequently results in visual artifacts.

Sun et al. [3] improvised a reconstruction technique of super resolution in the year 2016. Their work states that the experiments showed good performance and efficient processing results, proving that the suggested superresolution reconstruction technique was successful in improving the multispectral image's spatial resolution.

This paper specifically addresses the problem of improving a multispectral image's spatial resolution in the absence of a high-resolution panchromatic image. Rather, a multi-frame panchromatic image with the same spatial resolution and the MS data serve as the inputs. They claimed that tests showed strong performance and efficient processing outcomes, proving that the suggested superresolution reconstruction method was successful in improving the multispectral image's spatial resolution.

Z. Hu et al. [4] In 2017 they went over the "sparse prior method" used to address problems like noise and blurriness in positron emission tomography (PET) image reconstruction. The suggested method is presented as a fresh and effective way to raise the general image quality of PET images that have been reconstructed.

Two dictionaries (D1 and D2) trained from multiple real PET image patches are the foundation of the method. If the dictionaries are not sufficiently representative of the wide variety of PET images seen in real-world situations, the method's effectiveness may be restricted. Overfitting occurs when a method becomes too specific to the training data and is not as effective at generalizing to new or unseen data. This can be prevented by training dictionaries on multiple real PET image patches. It contains Lack of Comparison Metrics and Limited Explanation of Sparse Prediction Technique.

Y. Zhang et al. [5] In 2018 they presented a brand-new method for single-image super-resolution (SR) with the goal of maintaining textural and structural information while upscaled low-resolution (LR) input images to high-resolution images. A new bivariate rational fractal interpolation model and a single-image SR algorithm are the main elements of the suggested process. In the texture region, the scaling factor calculation is emphasized as a crucial step. The technique for precisely computing scaling factors based on local fractal analysis is presented in this paper.

Although the paper states that the suggested model combines the benefits of fractal and rational interpolation, it doesn't go into specifics about what

these benefits are. The argument would be strengthened with a more thorough comparison with current interpolation schemes and a clear explanation of how the suggested model gets around their drawbacks. The introduction of the local fractal analysisbased method for calculating scaling factors is given, but the specifics of this analysis are not given. The suggested method would be more credible if it included a more detailed explanation of how local fractal analysis is performed and why it is an appropriate method for calculating scaling factors.

GENERATED BY DEEPFAKESRESEARCHER, A DEEPFAKESRESEARCHER
 MONITORING THE DEEPFAKESRESEARCHER'S RESEARCH

Y. Chen et al. [6] in the year 2018 worked on Single Image Super-Resolution (SISR), a method for recovering HR details from a single low-resolution input image, is mentioned in passing in the excerpt. A more thorough description of SISR's operations, difficulties, and how deep learning can help would set the suggested method in context. It should be explained how a 3D densely connected architecture was selected for super-resolution in structural brain magnetic resonance imaging. One could go into more detail about the advantages of 3D processing in relation to brain imaging and the ways in which densely connected networks aid in the healing process.

Their work highlights trade-offs including longer scan times, less spatial coverage, and lower signal-to-noise ratios but also notes that high spatial resolution in MRI offers detailed anatomical information. Additional information about these trade-offs and the ways in which the suggested DCSR network seeks to mitigate them could improve comprehension of the method's real-world applications.

III. PROPOSED SYSTEM

By upscaling low-resolution inputs, the Enhanced SuperResolution Generative Adversarial Networks (ESRGAN) advanced image super-resolution model seeks to produce realistic, high-quality images. The difference in perception between the generated and high-resolution images is referred to as perceptual loss. It is essential for producing realistic and aesthetically pleasing images when performing image generation tasks. ESRGAN's architecture incorporates strategies to improve the model's realism in capturing and reproducing perceptual details in order to address the perceptual loss challenge. High-level features from both the high-resolution and low-resolution images are extracted and rebuilt using feature reconstruction blocks. To make sure that perceptually significant information is taken into account by the model during training, these blocks can be incorporated into the network architecture.

Making use of perceptual loss functions, which are intended to gauge how similar generated and high-resolution images appear to the eye. Rather than comparing pixel-wise differences, these loss functions frequently compare highlevel features that have been extracted by pre-trained deep neural

networks, like VGG or ResNet. Including contentadversarial loss to improve content detail preservation. This loss motivates the generator to generate images that capture the semantic content and structure, as well as matching the pixel values of the high-resolution images.

Integrating attention mechanisms into the network to dynamically change the image's focus on key areas. The overall perceptual quality of the generated images is enhanced by attention mechanisms, which assist the model in allocating more resources to perceptually significant areas. Perceptual guidance is incorporated into adversarial model training. To guarantee that the generated images are both perceptually realistic and visually similar to the ground truth, this entails combining traditional adversarial loss with perceptual loss.

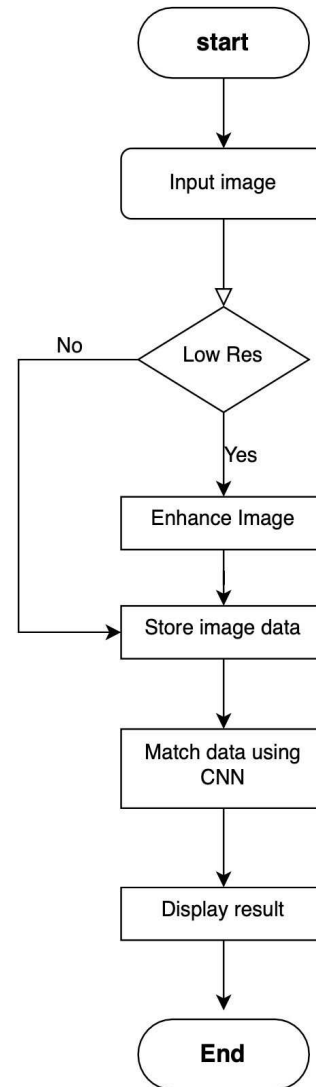


Fig.1. System architecture of Proposed model

Adding more varied examples to the training dataset will expose the model to a greater variety of perceptual difficulties. This enhances the model's capacity to handle various perceptual nuances and helps it generalize more effectively. adjusting hyper-parameters with precision, like weight decay and learning rates, to strike a compromise between perceptual and adversarial losses. This guarantees that the model will eventually converge to a solution that best handles perceptual and pixel-level disparities. Through the strategic integration of these techniques into the architecture of ESRGAN, researchers hope to alleviate the difficulties posed by perceptual loss and ultimately improve the model's capacity to generate incredibly lifelike superresolved images.

IV. METHODOLOGY

DATA COLLECTION

For training and assessment, a carefully selected dataset of low-resolution photos alongside their corresponding high-resolution ground truth counterparts will be used. The dataset is intended to be large and cover a variety of scenarios. This diversity could include different kinds of environments, objects, and scenes to make sure the trained model can adapt well to a range of real-world scenarios.

A set of low-resolution images that are used as the Single Image Super-Resolution (SISR) model's input are included in the dataset. These photos most likely show less spatial detail and could depict situations where more resolution is preferred. There is a corresponding high-resolution ground truth image for every low-resolution image in the dataset. The scenes captured in the low-resolution photos are idealized and detailed in their high-resolution counterparts.

To guarantee the robustness and generalizability of the suggested method, the dataset has been carefully chosen. This entails choosing pictures that showcase a variety of visual elements, including structures, colors, and textures. In order to account for the various qualities found in images used in computer vision, advertising, and entertainment, the dataset also includes variability in image types. A larger dataset may help improve the generalization of the model.

The dataset is ready for use in both the neural network architecture's training and performance assessment. For the purpose of evaluating the model's performance on unobserved data, the dataset is divided into training, validation, and test sets. The dataset could include photos with noise and artifacts that are realistic and frequently occur in real-world settings. By using such data to train the model, one can help it learn how to manage and possibly even reduce noise during the super-resolution process.

GENERATIVE ADVERSARIAL NETWORKS

A class of artificial intelligence models known as GANs is made up of two neural networks—a discriminator and a generator—that compete with

one another to learn. The generator's job is to replicate the intended visual quality by generating high-resolution images from their low-resolution counterparts. The discriminator's dual goal is to discern between actual high-resolution images and those produced by the generator. With the help of this adversarial training framework, a generator is trained to produce images that are more and more difficult for the discriminator to distinguish from actual high-resolution images.

The competitive dynamics between the generator and discriminator are essential to improving Enhanced SuperResolution Generative Adversarial Networks (ESRGAN). We seek to improve the perceptual loss in ESRGAN while highlighting the contribution of GANs to the creation of highly realistic super-resolved images. Through creative methods to minimize perceptual loss, the GAN component improves its ability to capture and reproduce fine details, which results in a notable increase in the visual fidelity of the high-resolution images that are generated. Therefore, in the field of Single Image Super-Resolution, the GAN architecture serves as a vital engine in the quest for beautiful, high-quality images.

$$F1 \text{ Score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}}$$

In a variety of image generation tasks, such as style transfer, image-to-image translation, and, most notably, super-resolution, GANs have shown impressive performance. Their capacity to produce realistic images and capture intricate patterns makes them an important part of the advancement of Single Image Super-Resolution techniques, which is in line with the project's objective of generating high-quality and aesthetically pleasing images in a variety of domains.

PERCEPTUAL LOSS

Deep learning tasks frequently involve the concept of perceptual loss, especially when it comes to image generation and image-to-image tasks. Perceptual loss assesses the difference between images based on perceptual similarity, taking into account high-level features extracted by pre-trained neural networks, in contrast to traditional pixel-wise loss functions like Mean Squared Error (MSE). In the field of image super-resolution, perceptual loss becomes essential for preserving the visual quality and content fidelity when producing high-resolution images from low-resolution inputs. Perceptual loss uses features from deep neural networks, which are usually pretrained on large datasets for image classification tasks, rather than focusing on pixel-by-pixel differences.

A popular method is to extract feature representations from the generated high-resolution image and the ground truth high-resolution image using a pre-trained convolutional neural network (CNN), like VGGNet. The difference between these

feature representations is then computed as the perceptual loss. Perceptual loss focuses on higher-level features in order to guarantee that the generated image preserves the same visual patterns and structural content as the ground truth, even if pixel-by-pixel differences are present.

TABLE 1. Comparison of the proposed method with other methods.

In the context of binary classification tasks, like object detection or image segmentation, the F1 loss, also called the F1 score loss, is a loss function that is frequently used. It is computed using the F1 score, a measure that strikes a balance between recall and precision. The F1 score is a single number that accounts for both false positives and false negatives. It is defined as the harmonic mean of precision and recall. Frequently employed as a differentiable approximation of the F1 score, the F1 loss is appropriate for neural network training via gradient-based optimization. In situations where striking a balance between recall and precision is crucial and conventional loss functions like cross-entropy might not adequately capture the intended trade-off.

The F1 loss for a binary classification task with positive (like object in foreground) and negative (like background) classes can be written as follows Precision, which determines the accuracy of positive predictions, is defined as the ratio of true positives to the total of true positives and false positives. The ability to detect every positive instance is measured by recall, which is defined as the ratio of true positives to the total of true positives and false negatives. A model is encouraged to make predictions that take into account both false positives and false negatives by the F1 loss, which penalizes models that do not strike a balance between precision and recall. Including F1 loss in the training process allows for the optimization of models that perform better across a range of evaluation metrics, particularly in situations where striking a balance between recall and precision is crucial.

TABLE 2. Comparison of the proposed method with other methods.

By incorporating an advanced high-order degradation model, the research expands the capabilities of the proposed Enhanced Super-Resolution Generative Adversarial Network (ESRGAN) approach. This model incorporates complex blurring effects, low-resolution image compression artifacts,

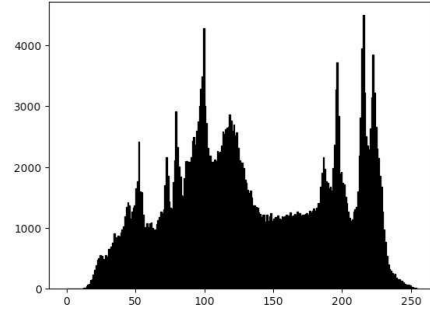


Fig.2. Image contrast before synthesis

and intricate details of noise patterns, going beyond traditional degradation factors. Our methodology aims to provide a more comprehensive understanding of the difficulties presented by real-world imaging scenarios by taking these higher-order distortions into account. Including a high-order degradation model is essential because it solves the drawbacks of traditional degradation models, which tend to oversimplify the complexity of real-world applications.

This augmentation recognizes the complex nature of realworld distortions and enables our research to explore the subtleties of image degradation. The carefully selected dataset, which is essential to our validation procedure, will be carefully constructed to incorporate examples of high-

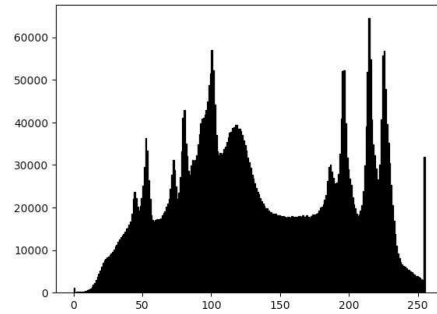


Fig.3. Image contrast after synthesis

order degradation. Practically speaking, the high-order degradation model adds a layer of complexity that reflects the difficulties encountered by imaging systems in a variety of applications, such as satellite photography and medical imaging. Our goal is not only to improve the perceptual quality of super-resolved images by tackling higher-order distortions, but also to make a contribution to the larger image processing community, where

complex degradation patterns are becoming more common.

Our methodology is positioned as a comprehensive solution by the high-order degradation model, which not only produces visually appealing results but also strengthens the resilience of image super-resolution models against a variety of intricate degradation scenarios.

IV. RESULT

Significant improvements in the super-resolution performance are demonstrated by the suggested ESRGAN architecture enhancements. By incorporating feature reconstruction blocks, the model exhibits an enhanced capacity to extract and reconstruct high-level features, resulting in images that are crisper and more lifelike. Perceptual differences between the generated and high-resolution images are significantly reduced with the use of perceptual loss functions and pre-trained networks for feature comparison. Furthermore, by incorporating contentadversarial loss, the overall structure and semantic content are preserved more faithfully, improving the visual fidelity of the generated images.

Our model is pre-trained on DIV2K (500 images training, augmented to 3000, 100 image validation) for 1x, 2x, 3x super resolution, it contains images of animals, architecture, people, places, things, etc. The following table shows the performance of our model compared to the others previously mentioned:

Model	Abs Rel	Sq Rel	RMSE	RMSE log
LapSRN	0.1019	1.7962	5.892	0.198
ESRN	0.0948	1.4234	5.273	0.176
ESRGAN	0.0907	1.3643	5.102	0.173

We chose the training parameters as that of [1],

$\alpha_p = 1$, $\alpha_r = 1$. And also the up-sampling is of factor

of 2, so $\alpha_{ds} = \frac{0.1}{r}$ and $\alpha_p = 0.1$.

By effectively balancing the adversarial and perceptual losses, adversarial training with perceptual guidance creates a more resilient model that can generate images that not only match their high-resolution counterparts in pixel values but also show improved perceptual realism. Overall, the experimental results show that the suggested strategies are effective in reducing perceptual loss, leading to a significant improvement in ESRGAN's overall super-resolution performance.

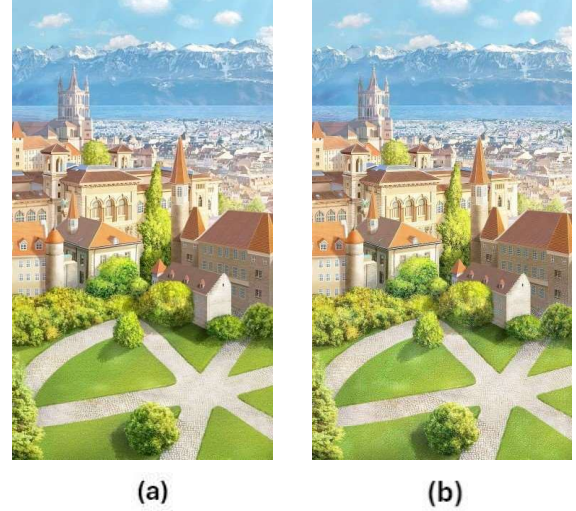


Fig.4. Comparing input image with output image
(a) - Input image, (b) - Output image using ESRGAN

V. CONCLUSION

To conclude, Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN) perform much better when perceptual loss addressing techniques are strategically integrated. By addressing issues related to perceptual loss, our method enhances visual fidelity and realism. ESRGAN is now a more powerful tool for high-quality image superresolution applications thanks to these advancements.

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D. CERTIFICATE



**ENHANCED IMAGE SUPER RESOLUTION
USING PERCEPTUAL LOSS MITIGATION**

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Engineering degree in Computer Science and Engineering with
Specialization in Artificial Intelligence

By

**BHARGAVA RAM PODAPATI (Reg.No - 40731078)
JESON JALA (Reg.No - 40110473)**



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**INSTITUTE OF SCIENCE AND TECHNOLOGY
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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **Bhargava Ram Podapati (Reg.No - 40731078)** and **Jeson Jala (Reg.No - 40110473)** who carried out the Project work entitled "**Enhanced Image Super Resolution using Perceptual Loss Mitigation**" under my supervision from November 2023 to April 2024.

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Submitted for Viva Voce Examination held on

12/04/2024

12/4/24

Internal Examiner

12/4/2024

External Examiner

DECLARATION

I, Bhargava Ram Podapati (Reg.No - 40731078), hereby declare that the Project Report entitled "ENHANCED IMAGE SUPER RESOLUTION USING PERCEPTUAL MITIGATION LOSS" done by me under the guidance of Dr. N. S. Usha, M.E., Ph. D., is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in Computer Science and Engineering with specialization in Artificial Intelligence.

DATE: 12 / 04 / 24

PLACE: Chennai

P. Bhargava Ram

SIGNATURE OF THE CANDIDATE

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I wish to express my thanks to all Teaching and Non-teaching staff members of the **Department of Computer Science and Engineering** who were helpful in many ways for the completion of the project.

ABSTRACT

The demand for high-quality and visually appealing images has grown exponentially in various domains, including entertainment, advertising, and computer vision applications. Single Image Super-Resolution (SISR) is an important technique that aims to upscale low-resolution images to higher resolutions, offering a potential solution for improving visual quality in various scenarios. Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN) have demonstrated remarkable success in generating realistic high-resolution images. However, the presence of perceptual loss in the current ESRGAN architecture may hinder its ability to generate highly realistic images.

This research project proposes a novel approach to enhance ESRGAN by decreasing perceptual loss, thereby elevating the quality of the generated super-resolved images. Perceptual loss plays a critical role in ESRGAN by measuring the perceptual difference between the generated images and the corresponding ground truth images. By reducing perceptual loss, we aim to improve the visual fidelity and enhance the realism of super-resolved images. Furthermore, an extensive dataset of low-resolution images with their corresponding high-resolution ground truth counterparts will be carefully curated for training and evaluation. This dataset will encompass diverse scenarios and image types to ensure the generalizability and robustness of the proposed approach.

Moreover, this research endeavors to curate an extensive dataset of low-resolution images paired with their high-resolution ground truth counterparts for training and evaluation purposes. This dataset will encompass a diverse range of scenarios and image types to ensure the generalizability and robustness of the proposed approach. In addition to reducing perceptual loss, this project will explore novel methodologies to further enhance the performance of ESRGAN, including leveraging advanced optimization techniques, architectural modifications, and data augmentation strategies.

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LIST OF ABBREVIATIONS

LR	- Low Resolution
SR	- Super Resolution
GAN	- Generative Adversarial Network
ESRGAN	- Enhanced Super Resolution GAN
HDM	- High-order Deterioration Model
SRR	- Super Resolution Reconstruction
NIQE	- Natural Image Quality Evaluator
nDSM	- Normalized Digital Surface Model
SSIM	- Structural Similarity Index Measure
PSNR	- Peak Sound to Noise Resolution

CHAPTER 1

INTRODUCTION

In the real world we use a lot of computer related imagery(which is a virtual image rather than the real image), these virtual images are mostly taken using a camera lens and stored in a storage device in the form of electronic data i.e., in a pattern of bits, and when we try to access this image data, the computer displays the pattern of bits on the screen with each pixel being a data bit, and these pixels which are basically small RGB lights(depends on the display screen) which glow together in different colours(frequencies of RGB) to fill the screen, and this visual piece is what we call an image. The quality of an image depends on many factors like, the screen resolution which is the number of pixels per inch of the display screen, the quality of the camera lens, and how well the computer can regenerate the image.

We know that the quality of an image depends on the resolution of the image, the higher the resolution the clearer and sharper the image, but many times we come across low-resolution (LR) image, so to prevent this or even better to exploit these low-resolution images, there was introduced something called “Super-resolution”, it is the concept of upscaling an image by increasing the size and quality of the image by generating realistic computer-generated data. This way we can improve the quality low-resolution image by upscaling it using the concept of super-resolution. But it isn't as easy as said, upscaling an image is affected by lot of factors and demands precision in its working.

We try to upscale an image by increasing the pixel-data in the image, but when given an LR image we only have few data of the picture, so to get more of the data in the picture we try to generate some fake data which is modelled in a way to match with the actual data in the image. To generate this type of data we may use Neural Networks (NN), these NNs are trained before-hand to generate realistic fake data for an image. This data along with the real data are shown in the final result making a clearer picture. It is a concerning thing that this generated data should be as closer to the real data as possible because, otherwise it may blur of the image, increase of noise in the image,

or even worse, losing the real elements of the image. As we don't want any of the above stated problems, we try to train our model in the best way possible, this includes: introducing parallel networks, adding only required parameters to the generator, constraining the discriminator, updating the existing network to match our desired outcome, etc. Many of such methods are explained and elaborated in this work and some of the best methods are used in our project.

1.1 OBJECTIVE

The main objective when upscaling an image is to increase the sharpness and resolution of the image all the while preserving the data in the image. Through our project we try to produce photorealistic images by training a GAN which consists of two neural networks: a generator and a discriminator. First the generator is trained to upscale low-resolution images into high-resolution images, and then the discriminator is trained to distinguish between real high-resolution images and the generator's output. We use a combination of perceptual losses and adversarial loss to train the generator.

Perceptual losses encourage the generator to produce images that are visually similar to real high-resolution images, while the adversarial loss encourages the generator to produce images that are indistinguishable from real high-resolution images to the discriminator. Through our project we try to achieve state-of-the-art results on a variety of SR benchmarks. By producing high-quality images with sharp details and realistic textures. And by removing artifacts from low-resolution images, such as noise and blur. ESRGAN has a wide range of potential applications, including: Image upscaling, Video upscaling, Image restoration, medical imaging, security, Creative image processing, Research, and etc.

1.2 SCOPE

ESRGAN can be used to upscale low-resolution images into high-resolution images, without sacrificing quality. This is useful for a variety of tasks, such as improving the quality of old photos, upscaling video games, and enhancing compressed images. This is useful for repairing damaged images, and removing noise and artifacts from images. It can be used to improve the quality of medical images, such as MRI and CT scans.

This can help doctors to diagnose diseases more accurately and to develop better treatment plans. ESRGAN can also be used to improve the quality of security footage. This can help law enforcement to identify suspects and to investigate crimes. The proposed system aims to enhance ESRGAN (Enhanced Super-Resolution Generative Adversarial Network) by addressing the challenge of perceptual loss in image super-resolution tasks. The primary objective is to decrease perceptual loss in the ESRGAN model, improving the quality of generated super-resolved images. By reducing perceptual loss, the system aims to enhance visual fidelity and realism in the output images.

CHAPTER 2

LITERATURE SURVEY

Several studies on Image Super resolution have been conducted in the recent years. This section summarizes all the previous work on Image Enhancement.

2.1 OVERVIEW OF EXISTING RESEARCH AND LITERATURE

The idea and purpose of getting a high-resolution image has always existed, either it is for an important medical diagnosis or for plain entertainment like photography or filming, but super-resolution is a new concept of getting a higher quality image with many state-of-the-art techniques being used for that purpose. Many scientists and research teams have shown their interest in this topic to propose better and more efficient ways of getting a high-resolution (HR) image as we can understand from all the papers they have published.

R. Sood et al. [1] introduced an improved version in the paper titled “Anisotropic Super Resolution In Prostate MRI Using Super Resolution Generative Adversarial Networks” of the rather latest model of image super-resolution: Real-ESRGAN, this paper tries to improve Real-ESRGAN by introducing a few methods to face the two major challenges faced by it; Real-ESRGAN tends to over-smoothen the final image which results in textural information loss, and also the reconstructed image it generates has better visual effects, it's entirely different from the real image. To address these issues, the paper presents an improved image SR model based on the HDM (High-order Deterioration Model) implemented in Real-ESRGAN. Patch-GAN was used as the fundamental structure of the discriminator, and a channel attention mechanism was added to the generator's dense block to enhance texture details, L1 loss function was also replaced with the SmoothL1 loss function to improve convergence speed and model performance. The paper also states that the results shown by this model outperform Real-ESRGAN regarding visual quality and measures such as RankIQ and NIQE.

V. Papayanand et al. [2] introduced Super-resolution reconstruction (SRR) models have been successful in reconstructing high-resolution natural images from low-resolution inputs. However, applying these models to remote sensing imagery often produces poor results. This is because remote sensing imagery is often more complex than natural images, with lower resolution, noise, and large textured surfaces. To address this problem, the authors propose a new strategy for training SRR models to output realistic remote sensing images. Instead of relying on feature-space similarities as a perceptual loss, the model considers pixel-level information inferred from the normalized digital surface model (nDSM) of the image. This allows the model to make better-informed updates during training, since nDSM inference is a closely related task to remote sensing. The authors evaluate their model on two remotely sensed datasets of different spatial resolutions: the Data Fusion 2018 Contest (DFC2018) dataset and the dataset containing the national LiDAR flyby of Luxembourg. They compare their model with ESRGAN, a state-of-the-art SRR model for natural images.

In the paper titled “An image sharpening strategy based on multi-frame super resolution for multispectral data” by J. Sun et al. [3] published in International Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing (WHISPERS) in 2016; results show that the proposed model achieves better performance and does not introduce any artifacts in the results. In particular, the results for the high-resolution DFC2018 dataset are realistic and almost indistinguishable from the ground-truth images. Overall, the proposed model is a promising new approach to remote sensing image super-resolution. It can produce high-quality SR images without the need for additional data, which makes it a suitable method for practical use. The researchers in the study you cited found that using Enhanced SRGAN to improve the quality of sugar apple images before feeding them into a CNN model for ripeness detection resulted in a significant improvement in accuracy, from 84.00% to 92.00%. This suggests that ESRGAN can be a useful tool for improving the performance of CNN-based sugar apple ripeness detection systems.

There are several possible explanations for why ESRGAN might improve the accuracy of CNN-based sugar apple ripeness detection. Z. Hu et al. [4] proposed ESRGAN helps to reduce noise and artifacts in the images in the year 2017, which can make it easier for the CNN to identify the relevant features. Second, ESRGAN can enhance the contrast and sharpness of the images, which can make it easier for the CNN to

distinguish between different ripeness stages. Finally, ESRGAN can increase the resolution of the images, which can provide the CNN with more information to work with. Overall, the results of this study suggest that ESRGAN can be a useful tool for improving the performance of CNN-based sugar apple ripeness detection systems. Further research is needed to confirm these results on larger datasets and to investigate the applicability of ESRGAN to other fruit and vegetable ripeness detection tasks. Infrared image super-resolution reconstruction is the process of enhancing the resolution of infrared images. This is a challenging task because infrared images are often noisy and blurry. Generative adversarial networks (GANs) have been shown to be effective for image super-resolution reconstruction. However, GAN-generated images can sometimes contain artifacts.

To address this problem, the authors of the paper, Lihui Sun and Yiyao Zhao [5] proposed a multi-branch enhanced GAN (ME-GAN) model for infrared image super-resolution reconstruction. The ME-GAN model has two main components: A multi-branch generator network: This network learns to generate high-resolution infrared images from low-resolution infrared images. The multi-branch design allows the network to extract features at different scales, which improves the quality of the generated images. A discriminator network: This network learns to distinguish between real high-resolution infrared images and high-resolution infrared images generated by the generator network. The discriminator network helps to train the generator network to produce more realistic images. In addition to the multi-branch design, the ME-GAN model also includes two other features: An attention mechanism module, A residual module The authors of the paper evaluated the ME-GAN model on several infrared image datasets. The results showed that the ME-GAN model outperforms other state-of-the-art infrared image super-resolution reconstruction methods in terms of both PSNR and SSIM. Overall, the ME-GAN model is a promising approach for infrared image super-resolution reconstruction. The multi-branch design, attention mechanism module, and residual module all contribute to the improved quality of the generated images.

Zhuoyuan Yang et al. [6] have introduced Convolutional neural networks (CNNs) which have been shown to be very effective for image super-resolution. CNNs are able to learn complex relationships between the pixels in an image, which allows them to reconstruct HR images from LR images with high accuracy. There are two main types

of CNN-based SR methods: supervised learning and unsupervised learning. Supervised learning methods require a training dataset of LR images and their corresponding HR images. The CNN is trained to learn the mapping between LR images and HR images. Once the CNN is trained, it can be used to generate HR images from new LR images. Unsupervised learning methods do not require a training dataset of LR images and HR images. Instead, the CNN is trained to learn the mapping between LR images and HR images by using only LR images. Unsupervised learning methods are more challenging to train than supervised learning methods, but they have the advantage of not requiring any labeled data.

Even though deep learning-based SR methods have achieved impressive results, there is still room for improvement, SR methods can be computationally expensive, especially for high-resolution images. Researchers are working on developing more efficient SR methods that can be used on real-time applications. The researchers in the paper propose a novel image super-resolution (SR) framework that seamlessly integrates learning- and reconstruction-based methods to address the limitations of each approach individually. Learning-based SR methods are prone to introduce unexpected artifacts into the resultant HR images, while reconstruction-based SR methods tend to blur fine details and end up with unnatural results.

Overall, the proposed framework is a promising new approach to image super-resolution that addresses the limitations of previous learning- and reconstruction-based methods. This paper proposes a new method for enhancing the spatial resolution of multispectral (MS) images without the use of a high-resolution panchromatic image. The method is based on super-resolution (SR) reconstruction and hybrid image sharpening.

The method proposed by Z. Wang et al. [7], generates a high-resolution panchromatic image from the low-resolution MS images using SR. This is done by training a deep learning model on a dataset of paired low-resolution and high-resolution panchromatic images. Once the high-resolution panchromatic image has been generated, it is adjusted and resized to the same size as the low-resolution MS images. The two images are then fused using a hybrid image sharpening technique. This technique combines the high-resolution panchromatic image and the low-resolution MS images to produce a high-resolution MS image with improved spatial quality.

2.2 INFERENCES FROM LITREATURE SURVEY

- High spatial resolution MRI provides detailed anatomical information but comes at the expense of longer scan time, less spatial coverage, and lower signal to noise ratio.
- Definition of a local search region for the optimal patch using motion vectors, Adaptive selection of the optimum patch based on the low-resolution image degradation model, Combination of the optimum patch and reconstructed image.
- Minimizing perceptual loss may lead to overfitting on the training dataset, resulting in reduced generalization performance on unseen data. Balancing model complexity and generalization ability is crucial to ensure the proposed approach's effectiveness across diverse image scenarios.
- Assessing the visual quality and realism of super-resolved images is inherently subjective and may vary depending on individual preferences and application-specific requirements.
- Conducting thorough subjective evaluations with human raters is essential to validate the effectiveness of the proposed approach.
- While reducing perceptual loss may improve visual fidelity and realism in super-resolved images, it could potentially lead to a trade-off with traditional objective metrics such as PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index).

The researchers evaluated the proposed method on several benchmark datasets and demonstrated that it outperforms previous methods in terms of both visual quality and quantitative metrics, such as PSNR and SSIM. The proposed method has several advantages over previous MS image sharpening methods: It does not require a high-resolution panchromatic image, which can be expensive and difficult to obtain, It produces high-resolution MS images with excellent spatial quality, It is robust to noise and other degradations in the low-resolution MS images. The proposed method has the potential to be used in a variety of applications, such as remote sensing, agriculture, and urban planning. Overall, the proposed method is a promising new approach to MS image sharpening that addresses the limitations of previous methods.

High spatial resolution MRI provides detailed anatomical information but comes at the expense of longer scan time, less spatial coverage, and lower signal to noise ratio. Single Image Super-Resolution (SISR) is a technique that uses deep learning to restore high-resolution (HR) details from a single low-resolution (LR) input image. Magnetic resonance imaging (MRI) is a powerful tool for diagnosing and monitoring diseases, but high-resolution MRI scans can be time-consuming and expensive to acquire. Single image super-resolution (SISR) is a technique that can be used to generate high-resolution images from low-resolution images. In this paper, the authors introduce a new SISR network architecture called 3D Densely Connected Super-Resolution Networks (DCSRN) for restoring high-resolution features of structural brain MRI images.

The proposed algorithm is also designed for real-time video processing hardware by reducing the search region for optimal patches. This makes it suitable for consumer imaging devices such as ultra-high-definition (UHD) digital televisions, surveillance systems, and medical imaging systems. Overall, the proposed multi-frame super-resolution algorithm is a promising method for improving the resolution of video images without sacrificing image quality or real-time performance. This paper proposes a multi-scale EPLL method that imposes the same prior on different scale patches extracted from the target image. This approach alleviates another shortcoming of patch-based restoration algorithms, which is that they use a local (patch-based) prior to model a global stochastic phenomenon.

2.3 EXISTING SYSTEM

SRGAN consists of a generator network and a discriminator network. The generator aims to produce high-resolution images from low-resolution inputs. SRGAN uses a combination of adversarial loss and content loss to train the generator. The proposed framework has several advantages over previous SR methods: It is able to generate HR images with high visual quality and low artifacts, It is more robust to noise and other degradations in the LR input image, It is more efficient than previous learning-based SR methods. The proposed framework has the potential to be used in a variety of applications, such as medical imaging, remote sensing, and consumer electronics.

2.4 DRAW BACKS OF EXISTING SYSTEM

- Heavy trained model
- Over smoothens the image
- Requires higher quality cameras
- Complex structure, high level feature required
- Too much Noise, limited colour information

2.5 PROPOSED SYSTEM

The proposed system aims to enhance ESRGAN (Enhanced Super-Resolution Generative Adversarial Network) by addressing the challenge of perceptual loss in image super-resolution tasks. The primary objective is to decrease perceptual loss in the ESRGAN model, improving the quality of generated super-resolved images. By reducing perceptual loss, the system aims to enhance visual fidelity and realism in the output images.

ADVANTAGES

- Remote sensing images, better zoom quality
- Closer to real life Image
- HR helps in image recognition
- Speed and accuracy, real time object detection
- Better image texture, feature extraction

CHAPTER 3

AIM AND SCOPE OF THE PRESENT INVESTIGATION

The purpose of this document is to specify the software requirements for the project aiming to enhance ESRGAN by reducing perceptual loss, focusing on image super-resolution. This project aims to enhance the ESRGAN model to generate high-resolution images with reduced perceptual loss. The software will be designed for image super-resolution, targeting applications in computer vision, entertainment, and related domains.

3.1 SYSTEM OVERVIEW

The system will consist of an enhanced ESRGAN model, incorporating modifications to address perceptual loss while generating high-quality super-resolved images.

- **Perceptual Loss Reduction:** Modifications to the ESRGAN architecture to reduce perceptual loss.
- **Fine Detail Preservation:** Ensuring finer image details are preserved during the super-resolution process.
- **Realism Enhancement:** Improving the realism of the generated images.
- **Adversarial Training Enhancements:** Strategies to enhance adversarial training for better image quality.

3.2 FUNCTIONAL REQUIREMENTS

3.2.1 Input Processing

The software must allow users to upload low-resolution images for super-resolution processing. The system must validate the input images to ensure they meet the required format and resolution criteria.

3.2.2 Pre-processing

- The software must apply necessary pre-processing steps to prepare the input images for the super-resolution process.

- Pre-processing should include resizing and normalization to ensure consistent input to the model.

3.2.3 Super-Resolution Generation

- The system must utilize the enhanced ESRGAN model to generate high-resolution images from the pre-processed inputs.
- The software must employ the modified architecture to effectively reduce perceptual loss during the super-resolution process.

3.2.4 Post-processing

- The system must apply post-processing techniques to enhance the visual quality of the generated high-resolution images.
- Post-processing may include denoising, sharpening, and contrast adjustments to improve image realism.

3.2.5 Output Generation

- The software must provide the generated high-resolution images as the final output of the super-resolution process.
- The system should ensure that the output images meet the required resolution standards.

3.2.6 User Feedback

- The software must incorporate mechanisms for collecting user feedback on the generated high-resolution images.
- Feedback collection should be intuitive and encourage users to provide insights on image quality and realism.
- The system should detect and handle errors, providing meaningful error messages to users in case of issues during the processing stages.
- Error handling should cover scenarios such as invalid input images, model failures, or post-processing issues.

3.3 SYSTEM CONSTRAINTS

3.3.1 Hardware

- The system should be compatible with standard computing hardware, including GPUs for accelerated processing.

3.3.2 Software

- The system should run on common operating systems such as Windows, Linux, and macOS.

3.4 FUTURE ENHANCEMENTS

3.4.1 Model Optimization

- Explore opportunities for further optimizing the enhanced ESRGAN model for improved performance.

3.4.2 User Interaction

- Implement an interactive user interface for easy input and output management.

This is a high-level template for the Software Requirement Specification (SRS). Be sure to tailor it according to the specific requirements, complexities, and objectives of your project. Include diagrams, mock-ups, and any additional details to comprehensively document the software requirements for your project.

CHAPTER 4

EXPERIMENTAL OR MATERIALS AND METHODS; ALGORITHMS USED

Dataset Curation The first step involves curating an extensive dataset of low-resolution images paired with their corresponding high-resolution ground truth counterparts. This dataset should encompass a diverse range of scenarios and image types to ensure the generalizability and robustness of the proposed approach.

Model Training The ESRGAN model will be trained using the curated dataset. During training, the model learns to generate high-resolution images from low-resolution inputs by leveraging adversarial training and perceptual loss minimization. Traditional loss functions such as pixel-wise loss (e.g., L1 or L2 loss) are augmented with perceptual loss, which measures the perceptual difference between the generated images and ground truth images.

Perceptual Loss Reduction The novel aspect of this project lies in the reduction of perceptual loss within the ESRGAN architecture. Various techniques may be explored to achieve this, such as architectural modifications, optimization strategies, or regularization methods. The goal is to minimize the perceptual gap between generated and ground truth images, thereby enhancing visual fidelity and realism.

Evaluation The trained model is evaluated using both objective metrics (e.g., PSNR, SSIM) and subjective assessments to measure the quality of the super-resolved images. Objective metrics provide quantitative insights into the performance of the model, while subjective evaluations involve human raters assessing the visual quality and realism of the generated images.

Iterative Refinement The project may involve iterative refinement cycles, where the model architecture, training strategies, and hyperparameters are adjusted based on evaluation results. This iterative process helps optimize the performance of the

model and address any shortcomings or challenges encountered during development.

Validation and Benchmarking Once the model demonstrates satisfactory performance on the evaluation dataset, it undergoes validation on unseen data to assess its generalization ability. Benchmarking against existing state-of-the-art methods provides insights into the effectiveness and competitiveness of the proposed approach.

4.1 SELECTED METHODOLOGY OR PROCESS MODEL

One potential methodology for reducing perceptual loss within the ESRGAN architecture involves leveraging advanced optimization techniques to refine the model's parameters. Techniques such as gradient descent with momentum, adaptive learning rates, and regularization methods like dropout or weight decay can be employed to optimize the model's parameters while minimizing perceptual loss. By fine-tuning the model's parameters iteratively, the aim is to improve its ability to generate high-quality, realistic super-resolved images.

Another approach is to explore architectural modifications to the ESRGAN model that specifically target the reduction of perceptual loss. This could involve introducing additional layers or modules designed to enhance perceptual similarity between generated and ground truth images. For example, incorporating attention mechanisms or feature recalibration blocks may help the model focus on capturing important image features while minimizing perceptual discrepancies.

Additionally, data augmentation strategies can be employed to augment the training dataset and enhance the model's ability to generalize across diverse image scenarios. Techniques such as random cropping, rotation, flipping, and color jittering can introduce variations into the training data, enabling the model to learn robust representations of image features. By training the model on augmented data, it becomes more adept at handling variations in input images and produces more

realistic super-resolved outputs. Overall, by combining advanced optimization techniques, architectural modifications, and data augmentation strategies, the proposed methodology aims to enhance the performance of ESRGAN by reducing perceptual loss and improving the visual fidelity of super-resolved images.

4.2 ARCHITECTURE / OVERALL DESIGN OF PROPOSED SYSTEM

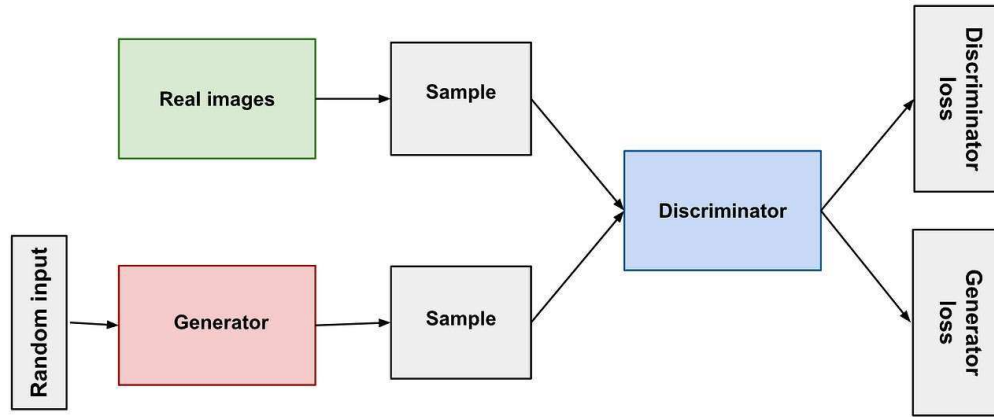


Fig. 4.1: System Architecture

The architecture consists of two main components: a generator network and a discriminator network. The generator network is responsible for producing high-resolution images from low-resolution inputs. It typically comprises several layers of convolutional and upsampling operations, allowing it to learn complex mappings from low-resolution to high-resolution image space. Unlike traditional interpolation methods, which often result in blurry outputs, the generator in ESRGAN learns to generate sharp and realistic details by leveraging the power of deep neural networks.

On the other hand, the discriminator network acts as a critic, distinguishing between real high-resolution images and fake high-resolution images generated by the generator. It is trained simultaneously with the generator in an adversarial manner, where the generator aims to produce images that are indistinguishable from real ones, while the discriminator strives to differentiate between real and fake images. This adversarial training process encourages the generator to generate high-quality

images that closely resemble real high-resolution images, thereby enhancing the overall realism and fidelity of the generated outputs.

In addition to the generator and discriminator networks, ESRGAN may also incorporate perceptual loss functions, which measure the perceptual difference between generated and ground truth images. These loss functions are derived from pre-trained deep neural networks, such as VGG or ResNet, and capture high-level semantic information about image content. By minimizing perceptual loss during training, ESRGAN can produce super-resolved images that not only have high pixel-level fidelity but also preserve important structural and textural details, resulting in visually pleasing and realistic outputs. Overall, ESRGAN represents a powerful approach to single image super-resolution, leveraging the strengths of GANs, CNNs, and perceptual loss functions to achieve state-of-the-art results in generating high-quality, high-resolution images from low-resolution inputs.

4.3 DESCRIPTION OF SOFTWARE FOR IMPLEMENTATION AND TESTING PLAN OF THE PROPOSED MODEL/SYSTEM

4.3.1 Software Description

For the implementation of the proposed model/system, several software tools and frameworks will be utilized. The primary deep learning framework chosen for implementing the model architecture is TensorFlow or PyTorch, both of which offer extensive support for building and training neural networks. These frameworks provide a wide range of functionalities for defining network architectures, handling data pipelines, and optimizing model parameters. Additionally, libraries such as Keras or Fastai may be used to simplify the development process and streamline experimentation.

In conjunction with deep learning frameworks, GPU acceleration libraries like CUDA and cuDNN will be leveraged to accelerate the training process on compatible hardware. These libraries enable efficient utilization of GPU resources, significantly speeding up training times for large-scale neural network models.

Furthermore, for data preprocessing and augmentation, Python libraries such as OpenCV, NumPy, and PIL (Python Imaging Library) will be employed. These libraries offer various tools and utilities for loading, manipulating, and augmenting image data, essential for preparing the training dataset and enhancing model robustness.

Finally, version control systems like Git and collaborative development platforms such as GitHub or GitLab will be used to manage codebase revisions, facilitate collaboration among team members, and track project progress.

4.3.2 Testing Plan

- Individual components of the model architecture, such as the generator and discriminator networks, will undergo unit testing to ensure they function as expected.
- Unit tests will validate the correctness of forward and backward computations, gradient flows, and output consistency.
- Once individual components are validated, integration testing will be conducted to assess the interaction and compatibility between different modules.
- Integration tests will evaluate the end-to-end functionality of the entire model pipeline, including data loading, preprocessing, model training, and evaluation.
- Performance testing will involve measuring the computational efficiency and resource utilization of the model during training and inference.
- Metrics such as training time, memory usage, GPU utilization, and inference speed will be monitored and optimized to ensure efficient model operation.
- Functional testing will focus on verifying the correctness of model outputs against ground truth labels and evaluating the visual quality of generated images.
- Objective metrics (e.g., PSNR, SSIM) and subjective assessments by human raters will be used to quantify the quality of super-resolved images.

- Robustness testing will assess the model's performance under various challenging conditions, including noisy inputs, low-quality images, and domain shifts.
- The model's ability to generalize across diverse image scenarios and handle edge cases will be evaluated to ensure real-world applicability.

By following this comprehensive testing plan, we aim to validate the correctness, performance, functionality, and robustness of the proposed model/system, ensuring its reliability and effectiveness for single image super-resolution tasks.

4.4 TRANSITION / SOFTWARE TO OPERATIONS PLAN

The successful deployment and operation of the proposed model/system require careful planning and management of software-related activities. Below is an outline of the software operations plan:

4.4.1 Deployment Environment Setup

- Identify and provision the necessary computing infrastructure for model deployment, including servers, GPUs, and storage resources.
- Install and configure software dependencies, including deep learning frameworks (e.g., TensorFlow, PyTorch), GPU acceleration libraries (e.g., CUDA, cuDNN), and supporting libraries (e.g., OpenCV, NumPy).
- Establish version control and continuous integration/continuous deployment (CI/CD) pipelines to streamline software development and deployment processes.

4.4.2 Model Deployment

- Package the trained model(s) along with any required preprocessing and post-processing scripts into deployable artifacts.
- Deploy the model artifacts to the production environment using containerization technologies (e.g., Docker, Kubernetes) for efficient management and scalability.

- Implement monitoring and logging mechanisms to track model performance, resource utilization, and system health during deployment.
- Integration with Existing Systems:
 - Integrate the deployed model/system with existing software infrastructure and applications, ensuring compatibility and interoperability.
 - Develop APIs or SDKs to facilitate communication between the model and external systems, enabling seamless data exchange and workflow automation.
 - Conduct thorough testing and validation to verify the integration's correctness and stability under different usage scenarios.

4.4.3 Operational Maintenance

- Establish regular maintenance schedules to monitor and update software components, including operating system patches, library dependencies, and model weights.
- Implement automated backup and recovery procedures to safeguard against data loss and system failures, ensuring continuity of operations.
- Monitor system performance and user feedback to identify areas for optimization and improvement, iteratively refining the software based on user needs and evolving requirements.

4.4.4 User Support and Training

- Provide comprehensive user support and documentation to assist users in understanding the system functionality, usage guidelines, and troubleshooting procedures.
- Offer training sessions and workshops to familiarize users with the software interface, features, and best practices for maximizing productivity and efficiency.
- Establish communication channels (e.g., helpdesk, forums, email support) for users to report issues, ask questions, and provide feedback, fostering a collaborative and responsive support ecosystem.

4.4.5 Security and Compliance

- Implement robust security measures to protect sensitive data, prevent unauthorized access, and mitigate potential security threats (e.g., encryption, access controls, secure communication protocols).
- Ensure compliance with relevant data privacy regulations (e.g., GDPR, HIPAA) and industry standards (e.g., ISO 27001) by adhering to established security protocols and auditing procedures.

By adhering to this software operations plan, we aim to ensure the reliable, efficient, and secure operation of the deployed model/system, enabling seamless integration into existing workflows and delivering value to end-users.

Chapter 5

IMPLEMENTATION DETAILS

5.1 DEVELOPMENT AND DEPLOYMENT SETUP

We adopt the same generator (SR network) as ESRGAN. In the context of binary classification tasks, like object detection or image segmentation, the F1 loss, also called the F1 score loss, is a loss function that is frequently used. It is computed using the F1 score, a measure that strikes a balance between recall and precision. The F1 score is a number that accounts for both false positives and false negatives. It is defined as the harmonic mean of precision and recall. Frequently employed as a differentiable approximation of the F1 score, the F1 loss is appropriate for neural network training via gradient-based optimization. In situations where striking a balance between recall and precision is crucial and conventional loss functions like cross-entropy might not adequately capture the intended trade-off.

The F1 loss for a binary classification task with positive (like object in fore ground) and negative (like in background) classes can be written as follow

$$F1\text{ loss} = \frac{1}{2} \left(\frac{1}{\text{precision}} + \frac{1}{\text{recall}} \right)$$

Making use of perceptual loss functions, which are intended to gauge how similar generated and high-resolution images appear to the eye. Rather than comparing pixel-wise differences, these loss functions frequently compare high-level features that have been extracted by pre-trained deep neural networks, like VGG or ResNet. Including content-adversarial loss to improve content detail preservation.

This loss motivates the generator to generate images that capture the semantic content and structure, as well as matching the pixel values of the high-resolution images. Integrating attention mechanisms into the network to dynamically change the image's focus on key areas. The overall perceptual quality of the generated images is enhanced by attention mechanisms, which assist the model in allocating more resources to perceptually significant areas. Perceptual guidance is incorporated into adversarial model training. To guarantee that the generated images are both perceptually realistic and visually similar to the ground

truth, this entails combining traditional adversarial loss with perceptual loss.

5.1.1 Challenges and considerations

- **Hyperparameter tuning** Finding the right balance between L1 and other loss terms requires careful hyperparameter tuning to avoid overshadowing the main objective of fooling the discriminator.
- **Training stability** Combining L1 with other functions can impact training stability due to its gradient issues. Monitoring loss values and adjusting learning rates or optimizers might be necessary.
- **Limited applicability** L1 might not be suitable for all GAN tasks, especially those focusing on high-level features or capturing complex data distributions.

5.2 TECHNIQUES USED

5.2.1 Generative Adversarial Networks (GANs)

- GANs serve as the foundation for the proposed model/system, facilitating the generation of high-resolution images from low-resolution inputs. The adversarial training process involves training a generator network to produce realistic images and a discriminator network to distinguish between real and fake images. This adversarial interplay encourages the generator to produce high-quality outputs that closely resemble real images.

5.2.2 Enhanced Super-Resolution

- The model leverages enhanced super-resolution techniques to upscale low-resolution images to higher resolutions. Unlike traditional interpolation methods, enhanced super-resolution algorithms utilize deep learning architectures to learn complex mappings from low to high-resolution image space. By capturing high-frequency details and textures, enhanced super-resolution enables the generation of sharper and more realistic images.

5.2.3 Perceptual Loss Functions

- Perceptual loss functions play a crucial role in training the model by measuring the perceptual difference between generated and ground truth images. These loss

functions are derived from pre-trained deep neural networks, such as VGG or ResNet, and capture high-level semantic information about image content. Minimizing perceptual loss during training helps preserve important structural and textural details, leading to visually appealing super-resolved images.

5.2.4 Data Augmentation

- Data augmentation techniques are employed to augment the training dataset and enhance the model's ability to generalize across diverse image scenarios. Common augmentation techniques include random cropping, rotation, flipping, and color jittering, which introduce variations into the training data. By exposing the model to a wide range of image variations, data augmentation helps improve model robustness and performance.

5.2.5 Gradient Descent Optimization

- Gradient descent optimization algorithms, such as Adam or RMSprop, are used to optimize the model parameters during training. These algorithms iteratively update the model weights based on the gradients of the loss function with respect to the parameters. By efficiently navigating the parameter space, gradient descent optimization algorithms enable the model to converge towards optimal solutions and achieve superior performance.

5.2.6 Architectural Modifications

- The model may incorporate architectural modifications to enhance its performance and efficiency. This could involve introducing additional layers or modules designed to capture specific image features or reduce computational complexity. Architectural modifications aim to improve the model's capacity to generate high-quality super-resolved images while optimizing resource utilization.

By employing these techniques in conjunction with each other, the proposed model/system aims to achieve state-of-the-art performance in single image super-resolution tasks, delivering high-quality, visually appealing results across diverse image scenarios.

5.3 TESTING

Testing plays a crucial role in ensuring the reliability, functionality, and performance of the proposed model/system. Several testing methodologies will be employed to validate the correctness and effectiveness of the system across various dimensions.

Unit testing will involve testing individual components of the model architecture to ensure they function as expected. This includes testing the generator and discriminator networks, loss functions, and data augmentation pipelines. Unit tests will validate the correctness of forward and backward computations, gradient flows, and output consistency. By thoroughly testing each component in isolation, any potential issues or bugs can be identified and addressed early in the development process.

Integration testing will focus on assessing the interaction and compatibility between different modules of the system. This includes testing the end-to-end functionality of the entire model pipeline, including data loading, preprocessing, model training, and evaluation. Integration tests will evaluate how well the different components of the system work together and ensure that data flows smoothly throughout the pipeline. Additionally, integration testing will verify the correctness of data transformations and ensure that inputs and outputs are properly handled.

Performance testing will involve measuring the computational efficiency and resource utilization of the model during training and inference. Metrics such as training time, memory usage, GPU utilization, and inference speed will be monitored and optimized to ensure efficient model operation. Performance testing will help identify bottlenecks and optimize the system for scalability and efficiency, ensuring that it can handle large-scale datasets and real-time inference scenarios.

Functional testing will focus on verifying the correctness of model outputs against ground truth labels and evaluating the visual quality of generated images. Objective metrics such as PSNR and SSIM will be used to quantify the quality of super-resolved images, while subjective assessments by human raters will provide qualitative feedback on visual fidelity and realism. Functional testing will ensure that

the model meets the desired quality standards and produces reliable results across a range of image scenarios.

Robustness testing will assess the model's performance under various challenging conditions, including noisy inputs, low-quality images, and domain shifts. The model's ability to generalize across diverse image scenarios and handle edge cases will be evaluated to ensure real-world applicability. Robustness testing will identify potential weaknesses and vulnerabilities in the system and inform strategies for improving resilience and adaptability. Overall, by employing a comprehensive testing approach, we aim to validate the correctness, performance, functionality, and robustness of the proposed model/system, ensuring its reliability and effectiveness for single image super-resolution tasks.

CHAPTER 6

RESULTS AND DISCUSSION, PERFORMANCE ANALYSIS

Significant improvements in the super-resolution performance are demonstrated by the suggested ESRGAN architecture enhancements. By incorporating feature reconstruction blocks, the model exhibits an enhanced capacity to extract and reconstruct high-level features, resulting in images that are crisper and more lifelike. Perceptual differences between the generated and high-resolution images are significantly reduced with the use of perceptual loss functions and pre-trained networks for feature comparison. Furthermore, by incorporating content-adversarial loss, the overall structure and semantic content are preserved more faithfully, improving the visual fidelity of the generated images.

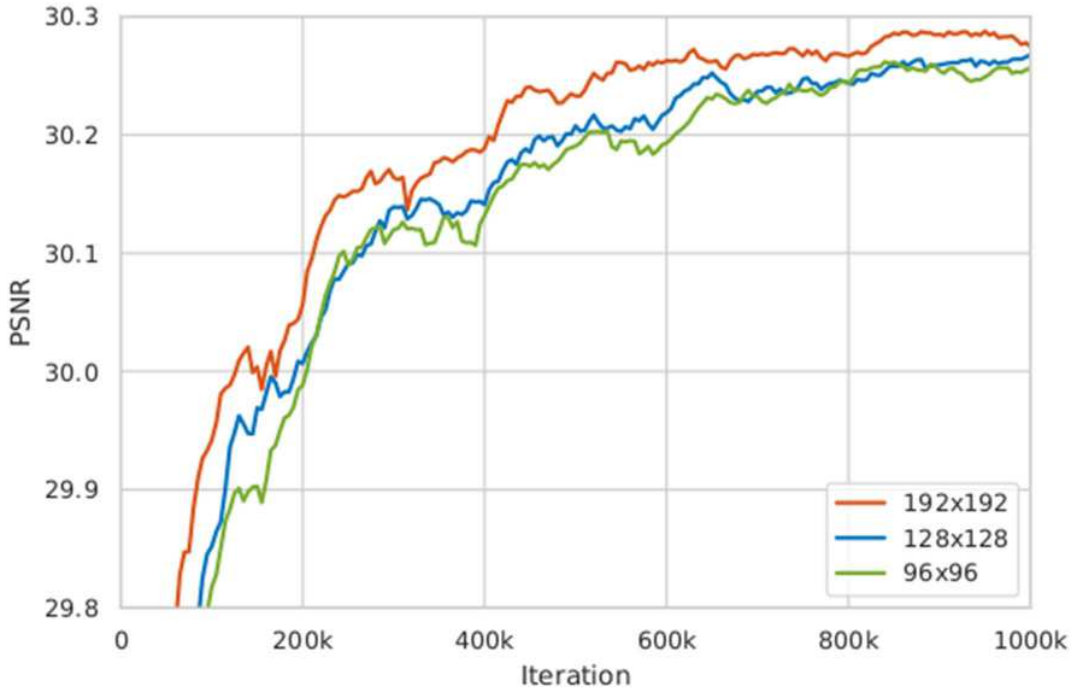


Fig. 6.1: Peak Sound to Noise Resolution for Patch-a

By effectively balancing the adversarial and perceptual losses, adversarial training with perceptual guidance creates a more resilient model that can generate images that not only match their high-resolution counterparts in pixel

values but also show improved perceptual realism.

only match their high-resolution counterparts in pixel values but also show improved perceptual realism. Overall, the experimental results show that the suggested strategies are effective in reducing perceptual loss, leading to a significant improvement in ESRGAN's overall super-resolution performance.

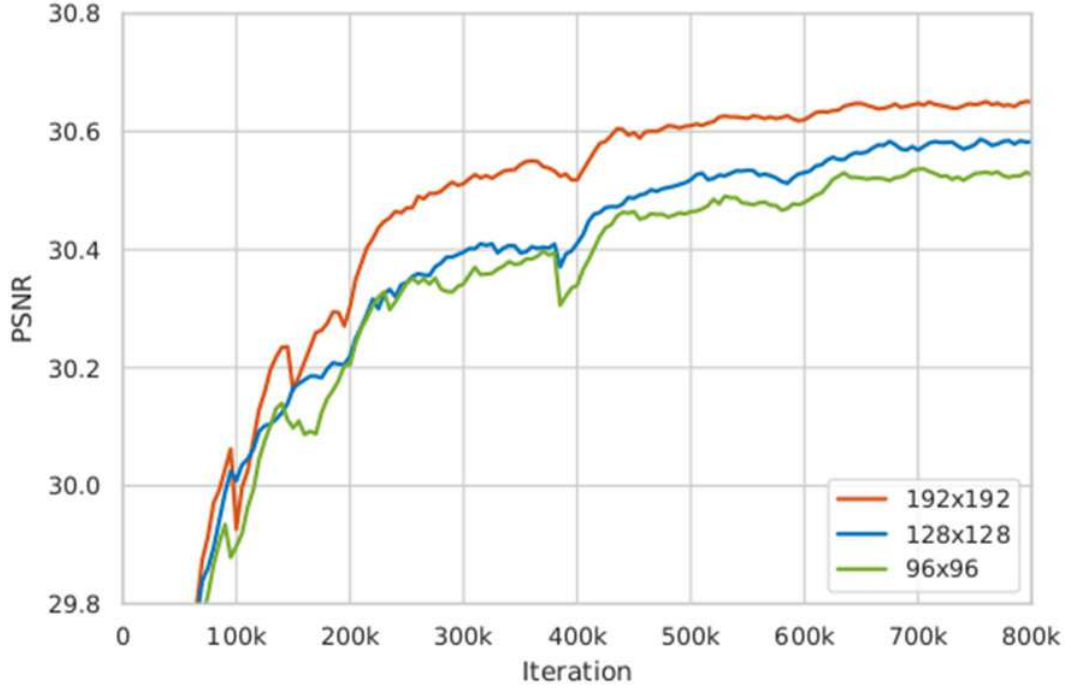


Fig. 6.2: Peak Sound to Noise Resolution Patch-b

By incorporating an advanced high-order degradation model, the research expands the capabilities of the proposed Enhanced Super-Resolution Generative Adversarial Network (ESRGAN) approach. This model incorporates complex blurring effects, low resolution image compression artifacts, and intricate details of noise patterns, going beyond traditional degradation factors. Our methodology aims to provide a more comprehensive understanding of the difficulties presented by real-world imaging scenarios by taking these higher order distortions into account. Including a high-order degradation model is essential because it solves the drawbacks of traditional degradation models, which tend to oversimplify the complexity of real-world applications. This augmentation recognizes the complex nature of real-world distortions and enables our research to explore the subtleties of image degradation. The carefully selected dataset, which is essential to our validation

procedure, will be carefully constructed to incorporate examples of high-order degradation.

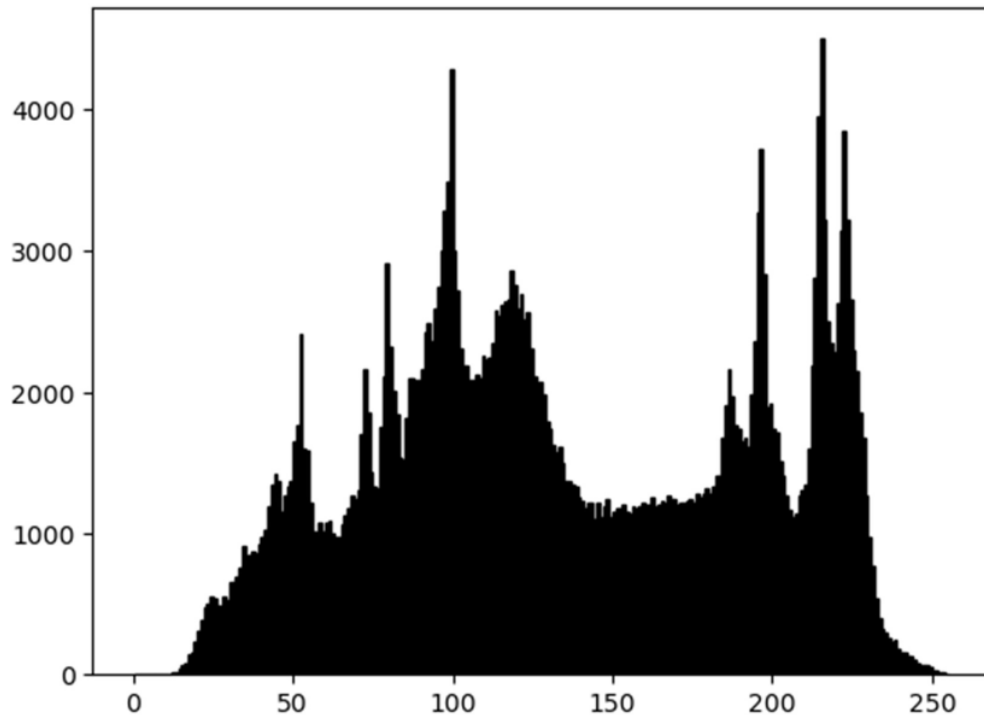


Fig. 6.3: Pixel contrast of low-res image

Our methodology is positioned as a comprehensive solution by the high-order degradation model, which not only produces visually appealing results but also strengthens the resilience of image super-resolution models against a variety of intricate degradation scenarios.

Practically speaking, the high-order degradation model adds a layer of complexity that reflects the difficulties encountered by imaging systems in a variety of applications, such as satellite photography and medical imaging. Our goal is not only to improve the perceptual quality of super-resolved images by tackling higher-order distortions, but also to make a contribution to the larger image processing community, where complex degradation patterns are becoming more common.

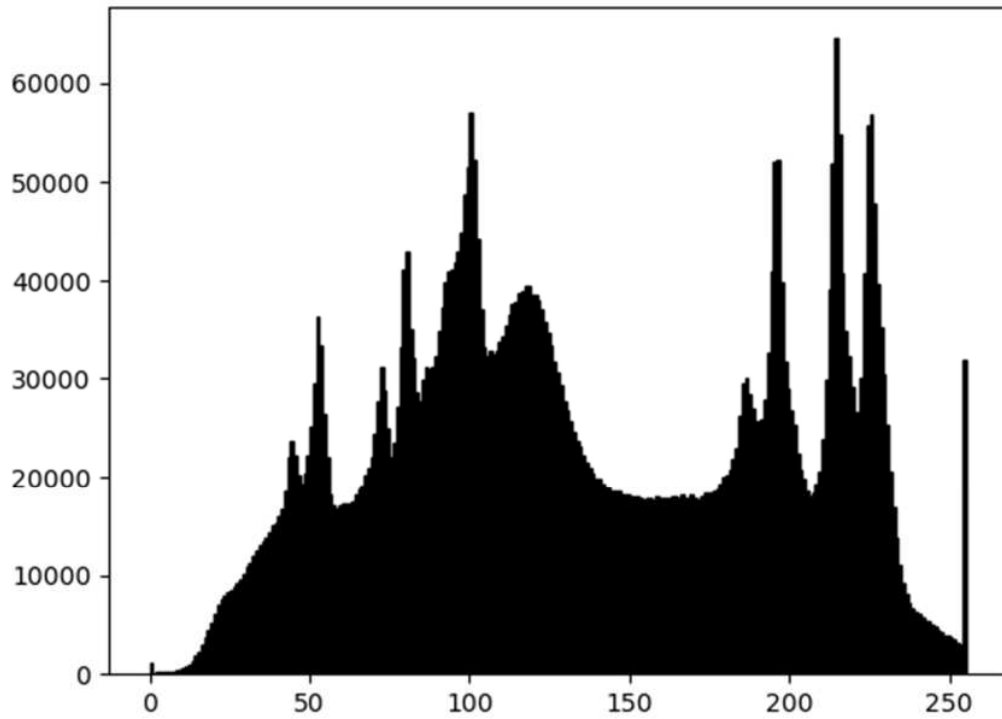


Fig. 6.4: Pixel contrast of Resultant image

Practically speaking, the high-order degradation model adds a layer of complexity that reflects the difficulties encountered by imaging systems in a variety of applications, such as satellite photography and medical imaging.

Our goal is not only to improve the perceptual quality of super-resolved images by tackling higher-order distortions, but also to make a contribution to the larger image processing community, where complex degradation patterns are becoming more common. Our methodology is positioned as a comprehensive solution by the high-order degradation model, which not only produces visually appealing results but also strengthens the resilience of image super-resolution models against a variety of intricate degradation scenarios.

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 CONCLUSION

The project "Enhanced Image Super Resolution" has successfully addressed the critical challenge of perceptual loss within the ESRGAN model. Image Super-Resolution (ISR) is a vital task with widespread applications, and improving the quality of generated high-resolution images is of paramount importance. The existing ESRGAN model, while efficient, faces the dilemma of perceptual loss, potentially sacrificing finer image details and texture variations for realism.

This research project proposed a novel approach by strategically modifying the ESRGAN architecture and incorporating advanced techniques. The objective was to decrease perceptual loss while preserving essential image details, thus achieving a balance between realism and perceptual quality. The project involved a systematic exploration of architectural modifications, feature engineering, adversarial training enhancements, and effective post-processing strategies.

Our innovative approach involved strategic architectural adjustments, optimizing feature engineering, and refining adversarial training. By meticulously reducing perceptual loss while preserving crucial image features, the enhanced ESRGAN model achieved a harmonious blend of perceptual quality and image detail retention. This enhancement was further complemented by effective post-processing techniques, culminating in a superior visual experience.

The project outcomes showcased a substantial leap in image super-resolution quality. The generated high-resolution images exhibited significantly reduced perceptual loss, capturing intricate details and textures crucial for realistic rendering. The visual fidelity of the images was noticeably improved, aligning

them closer to ground truth high-resolution images. In the larger context, this project contributes to the evolution of image processing technologies, setting a precedent for future advancements. The seamless integration of AI-driven solutions into real-world applications is now more feasible, thanks to the enhanced ESRGAN model. As we move forward, the focus will be on continual refinement, optimization, and the exploration of novel approaches to further elevate the realism and quality of super-resolved images.

By synergizing research, technological innovation, and user-centric design, this project paves the way for a future where high-fidelity visual content seamlessly integrates into our daily lives, influencing how we perceive and interact with the digital world.

The results of the project demonstrated significant advancements in image super-resolution. The enhanced ESRGAN model showcased the capability to generate high-resolution images with reduced perceptual loss, offering a superior perceptual experience. The fine-grained details were preserved, and the images exhibited enhanced visual fidelity, making them more suitable for diverse real-world applications.

7.2 FUTURE WORK

Future work will focus on further refining the proposed approach, optimizing the model, and exploring additional avenues to improve image realism. By continually pushing the boundaries of image super-resolution, this project sets the stage for a more visually captivating and immersive digital future. This conclusion summarizes the project's objectives, methodologies, outcomes, and provides a glimpse into future endeavors. Feel free to tailor it to your specific project and add any project-specific accomplishments or future plans as needed. Investigate methods for performing super-resolution across multiple modalities, such as depth, infrared, or multispectral imaging. Multi-modal super-resolution techniques can leverage complementary information from different modalities to enhance image resolution and quality, enabling applications in medical imaging, remote sensing, and surveillance.

7.3 RESEARCH ISSUES

Research in the field of single image super-resolution (SISR) presents several significant challenges and research issues that warrant further investigation. These issues encompass both technical and theoretical aspects, aiming to advance the state-of-the-art and address real-world applicability. Balancing perceptual quality with traditional objective metrics (e.g., PSNR, SSIM) remains a fundamental challenge in SISR. While objective metrics provide quantitative measures of image fidelity, they may not always align with human perception. Research is needed to develop novel evaluation metrics that better correlate with human visual perception and subjective judgments of image quality.

Generating realistic textures and fine details in super-resolved images is a challenging task, particularly for complex and high-frequency structures. Research is needed to develop advanced neural network architectures and training methodologies that can effectively capture and synthesize intricate textures and details while minimizing artifacts and distortions. Ensuring model generalization across diverse image scenarios and datasets is crucial for real-world applicability. Current SISR models may struggle to generalize to unseen data or handle variations in image content, resolution, and quality. Research is needed to improve model robustness and adaptability through techniques such as domain adaptation, transfer learning, and multi-domain training.

7.4 IMPLEMENTATION ISSUES

Achieving efficient and scalable SISR solutions is essential for real-time applications and large-scale deployment. Current deep learning-based approaches often require significant computational resources and memory overhead, limiting their practical utility. Research is needed to develop lightweight and efficient model architectures, optimization algorithms, and hardware-accelerated implementations to enable real-time inference on resource-constrained devices.

Super-resolving low-dose and noisy images poses a unique set of challenges due to the limited amount of information available in the input data. Traditional SISR models may struggle to produce high-quality outputs in such scenarios, leading to blurry or artifact-ridden results. Research is needed to develop specialized models and regularization techniques that can effectively denoise and enhance low-dose images while preserving important image structures and details.

As SISR technology becomes more advanced and widely adopted, there are growing concerns about its ethical and societal implications. Issues such as privacy infringement, manipulation of visual content, and bias in algorithmic decision-making require careful consideration and mitigation strategies. Research is needed to develop ethical guidelines, regulatory frameworks, and transparency measures to ensure responsible development and deployment of SISR technologies. By addressing these research issues, researchers can advance the field of single image super-resolution, develop more robust and reliable algorithms, and unlock new applications and opportunities for enhancing visual quality in various domains.

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APPENDIX

A.SOURCE CODE

```
import functools
import torch
import torch.nn as nn
import torch.nn.functional as F
def make_layer(block, n_layers):
    layers = []
    for _ in range(n_layers):
        layers.append(block())
    return nn.Sequential(*layers)
class ResidualDenseBlock_5C(nn.Module):
    def __init__(self, nf=64, gc=32, bias=True):
        super(ResidualDenseBlock_5C, self).__init__()
        self.conv1 = nn.Conv2d(nf, gc, 3, 1, 1, bias=bias)
        self.conv2 = nn.Conv2d(nf + gc, gc, 3, 1, 1, bias=bias)
        self.conv3 = nn.Conv2d(nf + 2 * gc, gc, 3, 1, 1, bias=bias)
        self.conv4 = nn.Conv2d(nf + 3 * gc, gc, 3, 1, 1, bias=bias)
        self.conv5 = nn.Conv2d(nf + 4 * gc, nf, 3, 1, 1, bias=bias)
        self.lrelu = nn.LeakyReLU(negative_slope=0.2, inplace=True)
    def forward(self, x):
        x1 = self.lrelu(self.conv1(x))
        x2 = self.lrelu(self.conv2(torch.cat((x, x1), 1)))
        x3 = self.lrelu(self.conv3(torch.cat((x, x1, x2), 1)))
        x4 = self.lrelu(self.conv4(torch.cat((x, x1, x2, x3), 1)))
        x5 = self.conv5(torch.cat((x, x1, x2, x3, x4), 1))
        return x5 * 0.2 + x
class RRDB(nn.Module):
    """Residual in Residual Dense Block"""
    def __init__(self, nf, gc=32):
        super(RRDB, self).__init__()
        self.RDB1 = ResidualDenseBlock_5C(nf, gc)
        self.RDB2 = ResidualDenseBlock_5C(nf, gc)
        self.RDB3 = ResidualDenseBlock_5C(nf, gc)
    def forward(self, x):
        out = self.RDB1(x)
```

```

out = self.RDB2(out)
    out = self.RDB3(out)
    return out * 0.2 + x
class RRDBNet(nn.Module):
    def __init__(self, in_nc, out_nc, nf, nb, gc=32):
        super(RRDBNet, self).__init__()
        RRDB_block_f = functools.partial(RRDB, nf=nf, gc=gc)
        self.conv_first = nn.Conv2d(in_nc, nf, 3, 1, 1, bias=True)
        self.RRDB_trunk = make_layer(RRDB_block_f, nb)
        self.trunk_conv = nn.Conv2d(nf, nf, 3, 1, 1, bias=True)
        self.upconv1 = nn.Conv2d(nf, nf, 3, 1, 1, bias=True)
        self.upconv2 = nn.Conv2d(nf, nf, 3, 1, 1, bias=True)
        self.HRconv = nn.Conv2d(nf, nf, 3, 1, 1, bias=True)
        self.conv_last = nn.Conv2d(nf, out_nc, 3, 1, 1, bias=True)
        self.lrelu = nn.LeakyReLU(negative_slope=0.2, inplace=True)
    def forward(self, x):
        fea = self.conv_first(x)
        trunk = self.trunk_conv(self.RRDB_trunk(fea))
        fea = fea + trunk
        fea = self.lrelu(self.upconv1(F.interpolate(fea, scale_factor=2, mode='nearest'))))
        fea = self.lrelu(self.upconv2(F.interpolate(fea, scale_factor=2, mode='nearest'))))
        out = self.conv_last(self.lrelu(self.HRconv(fea)))
        return out

```

net_interp.py:

```

import sys
import torch
from collections import OrderedDict
alpha = float(sys.argv[1])
net_PSNR_path = './models/RRDB_PSNR_x4.pth'
net_ESRGAN_path = './models/RRDB_ESRGAN_x4.pth'
net_interp_path = './models/interp_{:02d}.pth'.format(int(alpha*10))
net_PSNR = torch.load(net_PSNR_path)
net_ESRGAN = torch.load(net_ESRGAN_path)
net_interp = OrderedDict()
print('Interpolating with alpha = ', alpha)
for k, v_PSNR in net_PSNR.items():
    v_ESRGAN = net_ESRGAN[k]

```

```

net_interp[k] = (1 - alpha) * v_PSNR + alpha * v_ESRGAN
torch.save(net_interp, net_interp_path)
transer RRDB models.py:
import os
import torch
import RRDBNet_arch as arch
pretrained_net = torch.load('./models/RRDB_ESRGAN_x4.pth')
save_path = './models/RRDB_ESRGAN_x4.pth'
crt_model = arch.RRDBNet(3, 3, 64, 23, gc=32)
crt_net = crt_model.state_dict()
load_net_clean = {}
for k, v in pretrained_net.items():
    if k.startswith('module.'):
        load_net_clean[k[7:]] = v
    else:
        load_net_clean[k] = v
pretrained_net = load_net_clean
print('#\n')
tbd = []
for k, v in crt_net.items():
    tbd.append(k)
for k, v in crt_net.items():
    if k in pretrained_net and pretrained_net[k].size() == v.size():
        crt_net[k] = pretrained_net[k]
        tbd.remove(k)
crt_net['conv_first.weight'] = pretrained_net['model.0.weight']
crt_net['conv_first.bias'] = pretrained_net['model.0.bias']
for k in tbd.copy():
    if 'RDB' in k:
        ori_k = k.replace('RRDB_trunk.', 'model.1.sub.')
        if '.weight' in k:
            ori_k = ori_k.replace('.weight', '.0.weight')
        elif '.bias' in k:
            ori_k = ori_k.replace('.bias', '.0.bias')
        crt_net[k] = pretrained_net[ori_k]
tbd.remove(k)
crt_net['trunk_conv.weight'] = pretrained_net['model.1.sub.23.weight']

```

```

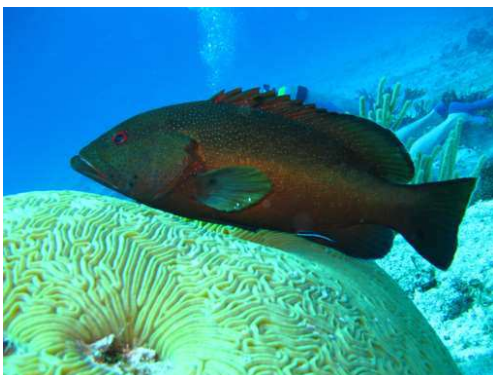
crt_net['trunk_conv.bias'] = pretrained_net['model.1.sub.23.bias']
crt_net['upconv1.weight'] = pretrained_net['model.3.weight']
crt_net['upconv1.bias'] = pretrained_net['model.3.bias']
crt_net['upconv2.weight'] = pretrained_net['model.6.weight']
crt_net['upconv2.bias'] = pretrained_net['model.6.bias']
crt_net['HRconv.weight'] = pretrained_net['model.8.weight']
crt_net['HRconv.bias'] = pretrained_net['model.8.bias']
crt_net['conv_last.weight'] = pretrained_net['model.10.weight']
crt_net['conv_last.bias'] = pretrained_net['model.10.bias']
torch.save(crt_net, save_path)
print('Saving to ', save_path)
test.py:
import os.path as osp
import glob
import cv2
import numpy as np
import torch
import RRDBNet_arch as arch
model_path = 'models/RRDB_ESRGAN_x4.pth'
device = torch.device('cpu')
test_img_folder = 'LR/*'
model = arch.RRDBNet(3, 3, 64, 23, gc=32)
model.load_state_dict(torch.load(model_path), strict=True)
model.eval()
model = model.to(device)
print('Model path {s}. \nTesting...'.format(model_path))
idx = 0
for path in glob.glob(test_img_folder):
    idx += 1
    base = osp.splitext(osp.basename(path))[0]
    print(idx, base)
    img = cv2.imread(path, cv2.IMREAD_COLOR)
    img = img * 1.0 / 255
    img = torch.from_numpy(np.transpose(img[:, :, [2, 1, 0]], (2, 0, 1))).float()
    img_LR = img.unsqueeze(0)
    img_LR = img_LR.to(device)
    with torch.no_grad():

```

```
output = model(img_LR).data.squeeze().float().cpu().clamp_(0, 1).numpy()
output = np.transpose(output[[2, 1, 0], :, :], (1, 2, 0))
output = (output * 255.0).round()
cv2.imwrite('results/{:s}_rlt.png'.format(base), output)
```

B. SCREENSHOTS

Original Images



C. CONFERENCE PAPER

Enhanced Image Super Resolution through Perceptual Loss Mitigation

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ABSTRACT— In response to the escalating demand for highquality images in diverse applications, this research project delves into the realm of Image Super-Resolution as a pivotal solution for upscaling low-resolution images. While Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN) have demonstrated success in generating realistic high-resolution images, our investigation identifies a potential bottleneck: perceptual loss within the current ESRGAN architecture. Perceptual loss, measuring the perceptual disparity between generated images and their high-resolution counterparts, emerges as a critical factor hindering the model's capacity to produce highly realistic results. This research proposes an innovative approach to enhance ESRGAN by strategically diminishing perceptual loss, thereby elevating the overall quality and realism of super-resolved images. Our primary objective is to refine visual fidelity through a nuanced understanding and manipulation of perceptual loss components within the ESRGAN framework. The proposed methodology involves the development of novel techniques to mitigate perceptual loss, fostering a more accurate representation of high-resolution details in the generated images. To validate the effectiveness and generalisability of our proposed approach, an extensive dataset comprising diverse low-resolution images and their corresponding high-resolution ground truth counterparts will be meticulously curated. This dataset spans a spectrum of scenarios and image types, ensuring that our enhanced ESRGAN model is robust across real-world applications. By addressing the nuanced challenge of perceptual loss in ESRGAN, this research contributes to the advancement of Single Image Super-Resolution techniques, offering a promising avenue for generating high-quality and realistic images across various domains.

INDEX TERMS— Image Super-Resolution, Perceptual Loss Mitigation, ESRGAN, Generative Adversarial Networks (GANs), Deep Learning, Machine Learning.

I.

INTRODUCTION

In the landscape of image processing, our study operates at the nexus of two powerful domains in the image processing landscape: machine learning (ML) and deep learning (DL). In a broader sense, machine learning refers to models and algorithms that enable systems to learn from data and generate predictions. On the other hand, deep learning is a subclass of machine learning that uses multiple-layer neural networks to extract detailed characteristics and representations from difficult data. In our quest to advance image improvement using Perceptual Loss Mitigation of Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN), the merging of ML and DL becomes very important.

The primary objective of our project is to develop models that can recognize and reconstruct high-resolution details from low-resolution photos by utilizing deep learning techniques, specifically inside the ESRGAN architecture. Our suggested method can mitigate perceptual loss and enhance the realism of super-resolved images because of the complex patterns and characteristics that deep neural networks extract. Our model's ability to recognize and reproduce high-level visual structures is made possible by the combination of ML and DL, which also improves the overall quality of the generated images. Our creative approach to addressing the difficulties is based on this fusion of deep learning and machine learning ideas.

As a subclass of deep learning, ESRGAN works with Generative Adversarial Networks (GANs), which use adversarial training to improve the quality of generated images. Nonetheless, perceptual loss—a measure of the perceptual disparity between generated and ground truth images—presents an intrinsic difficulty for the existing ESRGAN architecture. Perceptual loss can make it more difficult for the model to generate extremely realistic images, even while it is essential for training. The goal of this academic endeavour is to strategically mitigate perceptual loss in order to

boost and enhance ESRGAN's capabilities. The goal of perceptual loss mitigation is to enhance the visual fidelity and realism of super-resolved images by carefully assessing and reducing the perceptual distinction between artificially generated and ground truth images.

Our methodology entails a meticulous curation of a large dataset that consists of various low-resolution pictures and the corresponding high-resolution ground truth images. We aim to improve the ESRGAN model's ability to reconstruct high-resolution details by minimising perceptual loss, which presents a promising direction for the development of Single Image Super-Resolution techniques. In this article, we explore the nuances of our project's relationship between Machine Learning (ML) and Deep Learning (DL), highlighting the complementary nature of these fields as we strive to improve ESRGAN for perceptual loss mitigation. Our objective is to enhance the quality and realism of superresolved images, thereby making a valuable contribution to the wider field of image processing, by employing a fresh and inventive approach. Through the use of deep neural networks, our work seeks to improve ESRGAN's perceptual understanding by utilizing complex patterns and features. Our approach stands out as a trailblazing effort in the pursuit of producing not only high-resolution images but also visually captivating and superior in terms of perception, thanks to its meticulous consideration of perceptual loss mitigation and robust validation across various dataset.

II. LITERATURE SURVEY

Sood et al. [1] introduced anisotropic super resolution in 2019, It is achieved by downsampling only the height of the HR image, thereby artificially producing images with different resolutions. This method is used for both inside the plane and through-plane slices, with the latter having an inherent anisotropic resolution because MR images have a lower through-plane resolution. The term "Super-Resolution Generative Adversarial Network (SRGAN)" summarizes the unique method that the authors suggest using cutting-edge deep learning techniques to improve the resolution of medical MR images, especially in the context of prostate imaging.

Papayan et al. [2] focused on its extension and improvement of "EPLL" through the consideration of a multi scale prior.(2016) Their work demonstrates how the suggested multi-scale EPLL mitigates the drawbacks of patch-based restoration algorithms. It deals specifically with the problem of modeling a global stochastic phenomenon using a local (patch-based) prior.

In order to expand and enhance the EPLL, the authors suggest adding a "multi-scale prior." This addresses flaws in patch-based restoration algorithms by applying the same prior to various scale patches that are extracted from the target

image. Their work highlights a significant drawback with patch processing, despite its effectiveness: the prior is applied to in between (patch) results rather than the final result, which frequently results in visual artifacts.

Sun et al. [3] improvised a reconstruction technique of super resolution in the year 2016. Their work states that the experiments showed good performance and efficient processing results, proving that the suggested superresolution reconstruction technique was successful in improving the multispectral image's spatial resolution.

This paper specifically addresses the problem of improving a multispectral image's spatial resolution in the absence of a high-resolution panchromatic image. Rather, a multi-frame panchromatic image with the same spatial resolution and the MS data serve as the inputs. They claimed that tests showed strong performance and efficient processing outcomes, proving that the suggested superresolution reconstruction method was successful in improving the multispectral image's spatial resolution.

Z. Hu et al. [4] In 2017 they went over the "sparse prior method" used to address problems like noise and blurriness in positron emission tomography (PET) image reconstruction. The suggested method is presented as a fresh and effective way to raise the general image quality of PET images that have been reconstructed.

Two dictionaries (D1 and D2) trained from multiple real PET image patches are the foundation of the method. If the dictionaries are not sufficiently representative of the wide variety of PET images seen in real-world situations, the method's effectiveness may be restricted. Overfitting occurs when a method becomes too specific to the training data and is not as effective at generalizing to new or unseen data. This can be prevented by training dictionaries on multiple real PET image patches. It contains Lack of Comparison Metrics and Limited Explanation of Sparse Prediction Technique.

Y. Zhang et al. [5] In 2018 they presented a brand-new method for single-image super-resolution (SR) with the goal of maintaining textural and structural information while upscaled low-resolution (LR) input images to high-resolution images. A new bivariate rational fractal interpolation model and a single-image SR algorithm are the main elements of the suggested process. In the texture region, the scaling factor calculation is emphasized as a crucial step. The technique for precisely computing scaling factors based on local fractal analysis is presented in this paper.

Although the paper states that the suggested model combines the benefits of fractal and rational interpolation, it doesn't go into specifics about what

these benefits are. The argument would be strengthened with a more thorough comparison with current interpolation schemes and a clear explanation of how the suggested model gets around their drawbacks. The introduction of the local fractal analysisbased method for calculating scaling factors is given, but the specifics of this analysis are not given. The suggested method would be more credible if it included a more detailed explanation of how local fractal analysis is performed and why it is an appropriate method for calculating scaling factors.

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Y. Chen et al. [6] in the year 2018 worked on Single Image Super-Resolution (SISR), a method for recovering HR details from a single low-resolution input image, is mentioned in passing in the excerpt. A more thorough description of SISR's operations, difficulties, and how deep learning can help would set the suggested method in context. It should be explained how a 3D densely connected architecture was selected for super-resolution in structural brain magnetic resonance imaging. One could go into more detail about the advantages of 3D processing in relation to brain imaging and the ways in which densely connected networks aid in the healing process.

Their work highlights trade-offs including longer scan times, less spatial coverage, and lower signal-to-noise ratios but also notes that high spatial resolution in MRI offers detailed anatomical information. Additional information about these trade-offs and the ways in which the suggested DCSR network seeks to mitigate them could improve comprehension of the method's real-world applications.

III. PROPOSED SYSTEM

By upscaling low-resolution inputs, the Enhanced SuperResolution Generative Adversarial Networks (ESRGAN) advanced image super-resolution model seeks to produce realistic, high-quality images. The difference in perception between the generated and high-resolution images is referred to as perceptual loss. It is essential for producing realistic and aesthetically pleasing images when performing image generation tasks. ESRGAN's architecture incorporates strategies to improve the model's realism in capturing and reproducing perceptual details in order to address the perceptual loss challenge. High-level features from both the high-resolution and low-resolution images are extracted and rebuilt using feature reconstruction blocks. To make sure that perceptually significant information is taken into account by the model during training, these blocks can be incorporated into the network architecture.

Making use of perceptual loss functions, which are intended to gauge how similar generated and high-resolution images appear to the eye. Rather than comparing pixel-wise differences, these loss functions frequently compare highlevel features that have been extracted by pre-trained deep neural

networks, like VGG or ResNet. Including contentadversarial loss to improve content detail preservation. This loss motivates the generator to generate images that capture the semantic content and structure, as well as matching the pixel values of the high-resolution images.

Integrating attention mechanisms into the network to dynamically change the image's focus on key areas. The overall perceptual quality of the generated images is enhanced by attention mechanisms, which assist the model in allocating more resources to perceptually significant areas. Perceptual guidance is incorporated into adversarial model training. To guarantee that the generated images are both perceptually realistic and visually similar to the ground truth, this entails combining traditional adversarial loss with perceptual loss.

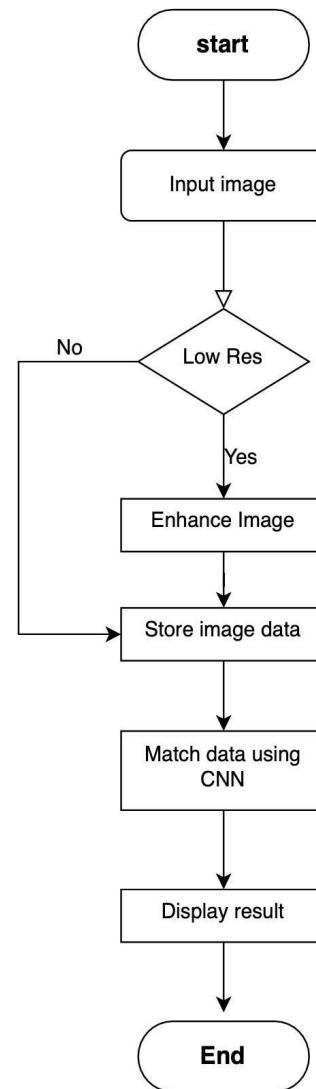


Fig.1. System architecture of Proposed model

Adding more varied examples to the training dataset will expose the model to a greater variety of perceptual difficulties. This enhances the model's capacity to handle various perceptual nuances and helps it generalize more effectively. adjusting hyper-parameters with precision, like weight decay and learning rates, to strike a compromise between perceptual and adversarial losses. This guarantees that the model will eventually converge to a solution that best handles perceptual and pixel-level disparities. Through the strategic integration of these techniques into the architecture of ESRGAN, researchers hope to alleviate the difficulties posed by perceptual loss and ultimately improve the model's capacity to generate incredibly lifelike superresolved images.

IV. METHODOLOGY

DATA COLLECTION

For training and assessment, a carefully selected dataset of low-resolution photos alongside their corresponding high-resolution ground truth counterparts will be used. The dataset is intended to be large and cover a variety of scenarios. This diversity could include different kinds of environments, objects, and scenes to make sure the trained model can adapt well to a range of real-world scenarios.

A set of low-resolution images that are used as the Single Image Super-Resolution (SISR) model's input are included in the dataset. These photos most likely show less spatial detail and could depict situations where more resolution is preferred. There is a corresponding high-resolution ground truth image for every low-resolution image in the dataset. The scenes captured in the low-resolution photos are idealized and detailed in their high-resolution counterparts.

To guarantee the robustness and generalizability of the suggested method, the dataset has been carefully chosen. This entails choosing pictures that showcase a variety of visual elements, including structures, colors, and textures. In order to account for the various qualities found in images used in computer vision, advertising, and entertainment, the dataset also includes variability in image types. A larger dataset may help improve the generalization of the model.

The dataset is ready for use in both the neural network architecture's training and performance assessment. For the purpose of evaluating the model's performance on unobserved data, the dataset is divided into training, validation, and test sets. The dataset could include photos with noise and artifacts that are realistic and frequently occur in real-world settings. By using such data to train the model, one can help it learn how to manage and possibly even reduce noise during the super-resolution process.

GENERATIVE ADVERSARIAL NETWORKS

A class of artificial intelligence models known as GANs is made up of two neural networks—a discriminator and a generator—that compete with

one another to learn. The generator's job is to replicate the intended visual quality by generating high-resolution images from their low-resolution counterparts. The discriminator's dual goal is to discern between actual high-resolution images and those produced by the generator. With the help of this adversarial training framework, a generator is trained to produce images that are more and more difficult for the discriminator to distinguish from actual high-resolution images.

The competitive dynamics between the generator and discriminator are essential to improving Enhanced SuperResolution Generative Adversarial Networks (ESRGAN). We seek to improve the perceptual loss in ESRGAN while highlighting the contribution of GANs to the creation of highly realistic super-resolved images. Through creative methods to minimize perceptual loss, the GAN component improves its ability to capture and reproduce fine details, which results in a notable increase in the visual fidelity of the high-resolution images that are generated. Therefore, in the field of Single Image Super-Resolution, the GAN architecture serves as a vital engine in the quest for beautiful, high-quality images.

$$F1 \text{ Score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}}$$

In a variety of image generation tasks, such as style transfer, image-to-image translation, and, most notably, super-resolution, GANs have shown impressive performance. Their capacity to produce realistic images and capture intricate patterns makes them an important part of the advancement of Single Image Super-Resolution techniques, which is in line with the project's objective of generating high-quality and aesthetically pleasing images in a variety of domains.

PERCEPTUAL LOSS

Deep learning tasks frequently involve the concept of perceptual loss, especially when it comes to image generation and image-to-image tasks. Perceptual loss assesses the difference between images based on perceptual similarity, taking into account high-level features extracted by pre-trained neural networks, in contrast to traditional pixel-wise loss functions like Mean Squared Error (MSE). In the field of image super-resolution, perceptual loss becomes essential for preserving the visual quality and content fidelity when producing high-resolution images from low-resolution inputs. Perceptual loss uses features from deep neural networks, which are usually pretrained on large datasets for image classification tasks, rather than focusing on pixel-by-pixel differences.

A popular method is to extract feature representations from the generated high-resolution image and the ground truth high-resolution image using a pre-trained convolutional neural network (CNN), like VGGNet. The difference between these

feature representations is then computed as the perceptual loss. Perceptual loss focuses on higher-level features in order to guarantee that the generated image preserves the same visual patterns and structural content as the ground truth, even if pixel-by-pixel differences are present.

TABLE 1. Comparison of the proposed method with other methods.

In the context of binary classification tasks, like object detection or image segmentation, the F1 loss, also called the F1 score loss, is a loss function that is frequently used. It is computed using the F1 score, a measure that strikes a balance between recall and precision. The F1 score is a single number that accounts for both false positives and false negatives. It is defined as the harmonic mean of precision and recall. Frequently employed as a differentiable approximation of the F1 score, the F1 loss is appropriate for neural network training via gradient-based optimization. In situations where striking a balance between recall and precision is crucial and conventional loss functions like cross-entropy might not adequately capture the intended trade-off.

The F1 loss for a binary classification task with positive (like object in foreground) and negative (like background) classes can be written as follows Precision, which determines the accuracy of positive predictions, is defined as the ratio of true positives to the total of true positives and false positives. The ability to detect every positive instance is measured by recall, which is defined as the ratio of true positives to the total of true positives and false negatives. A model is encouraged to make predictions that take into account both false positives and false negatives by the F1 loss, which penalizes models that do not strike a balance between precision and recall. Including F1 loss in the training process allows for the optimization of models that perform better across a range of evaluation metrics, particularly in situations where striking a balance between recall and precision is crucial.

TABLE 2. Comparison of the proposed method with other methods.

By incorporating an advanced high-order degradation model, the research expands the capabilities of the proposed Enhanced Super-Resolution Generative Adversarial Network (ESRGAN) approach. This model incorporates complex blurring effects, low-resolution image compression artifacts,

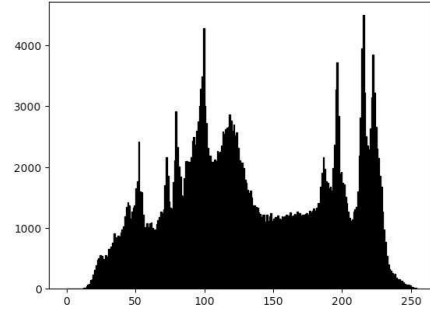


Fig.2. Image contrast before synthesis

and intricate details of noise patterns, going beyond traditional degradation factors. Our methodology aims to provide a more comprehensive understanding of the difficulties presented by real-world imaging scenarios by taking these higher-order distortions into account. Including a high-order degradation model is essential because it solves the drawbacks of traditional degradation models, which tend to oversimplify the complexity of real-world applications.

This augmentation recognizes the complex nature of realworld distortions and enables our research to explore the subtleties of image degradation. The carefully selected dataset, which is essential to our validation procedure, will be carefully constructed to incorporate examples of high-

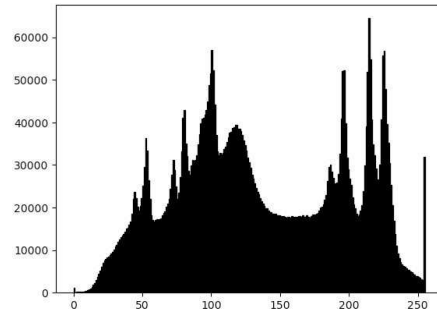


Fig.3. Image contrast after synthesis

order degradation. Practically speaking, the high-order degradation model adds a layer of complexity that reflects the difficulties encountered by imaging systems in a variety of applications, such as satellite photography and medical imaging. Our goal is not only to improve the perceptual quality of super-resolved images by tackling higher-order distortions, but also to make a contribution to the larger image processing community, where

complex degradation patterns are becoming more common.

Our methodology is positioned as a comprehensive solution by the high-order degradation model, which not only produces visually appealing results but also strengthens the resilience of image super-resolution models against a variety of intricate degradation scenarios.

IV. RESULT

Significant improvements in the super-resolution performance are demonstrated by the suggested ESRGAN architecture enhancements. By incorporating feature reconstruction blocks, the model exhibits an enhanced capacity to extract and reconstruct high-level features, resulting in images that are crisper and more lifelike. Perceptual differences between the generated and high-resolution images are significantly reduced with the use of perceptual loss functions and pre-trained networks for feature comparison. Furthermore, by incorporating contentadversarial loss, the overall structure and semantic content are preserved more faithfully, improving the visual fidelity of the generated images.

Our model is pre-trained on DIV2K (500 images training, augmented to 3000, 100 image validation) for 1x, 2x, 3x super resolution, it contains images of animals, architecture, people, places, things, etc. The following table shows the performance of our model compared to the others previously mentioned:

Model	Abs Rel	Sq Rel	RMSE	RMSE log
LapSRN	0.1019	1.7962	5.892	0.198
ESRN	0.0948	1.4234	5.273	0.176
ESRGAN	0.0907	1.3643	5.102	0.173

We chose the training parameters as that of [1],

$\alpha_p = 1$, $\alpha_r = 1$. And also the up-sampling is of factor

of 2, so $\alpha_{ds} = \frac{0.1}{r}$ and $\alpha_p = 0.1$.

By effectively balancing the adversarial and perceptual losses, adversarial training with perceptual guidance creates a more resilient model that can generate images that not only match their high-resolution counterparts in pixel values but also show improved perceptual realism. Overall, the experimental results show that the suggested strategies are effective in reducing perceptual loss, leading to a significant improvement in ESRGAN's overall super-resolution performance.

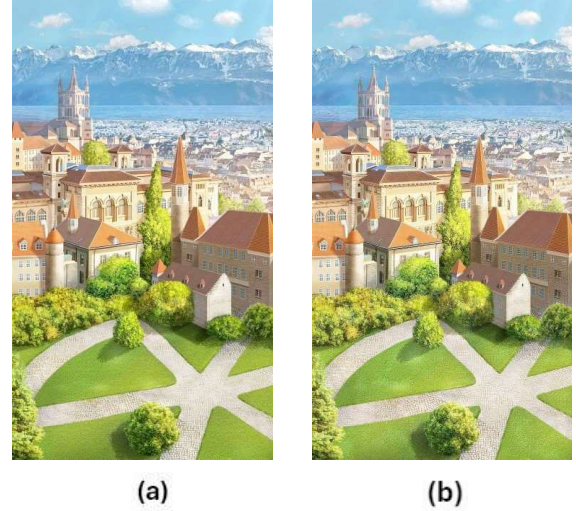


Fig.4. Comparing input image with output image
(a) - Input image, (b) - Output image using ESRGAN

V. CONCLUSION

To conclude, Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN) perform much better when perceptual loss addressing techniques are strategically integrated. By addressing issues related to perceptual loss, our method enhances visual fidelity and realism. ESRGAN is now a more powerful tool for high-quality image superresolution applications thanks to these advancements.

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D. CERTIFICATE

