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Real Image Super Resolution using GAN Algorithm

Project Proposal Presentation

by

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Project Guide

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1. Introduction

A **real image**, in the context of computer vision and image processing, refers to an image that is captured from the real world using a camera or other imaging device. These images represent the physical world as seen by the human eye or a camera sensor. Real images can be photographs, video frames, or any digital representation of scenes or objects from the physical environment.

- **Super resolution** refers to the process of enhancing the resolution and quality of an image or video beyond its original resolution.
- The goal of super resolution techniques is to generate high-resolution images or videos with more details, sharpness, and clarity than the original low-resolution versions.
- Enhancing the quality of low-resolution images in photography, medical imaging, satellite imaging, and surveillance.
- Upscaling images and videos for display on high-resolution screens or devices.
- Enhancing the visual quality of old or degraded images and videos.

2. SDG Goals

SDG 3: Good Health and Well-being

SDG 9: Industry, Innovation, and Infrastructure

SDG 11: Sustainable Cities and Communities

SDG 13: Climate Action

SDG 17: Partnerships for the Goals

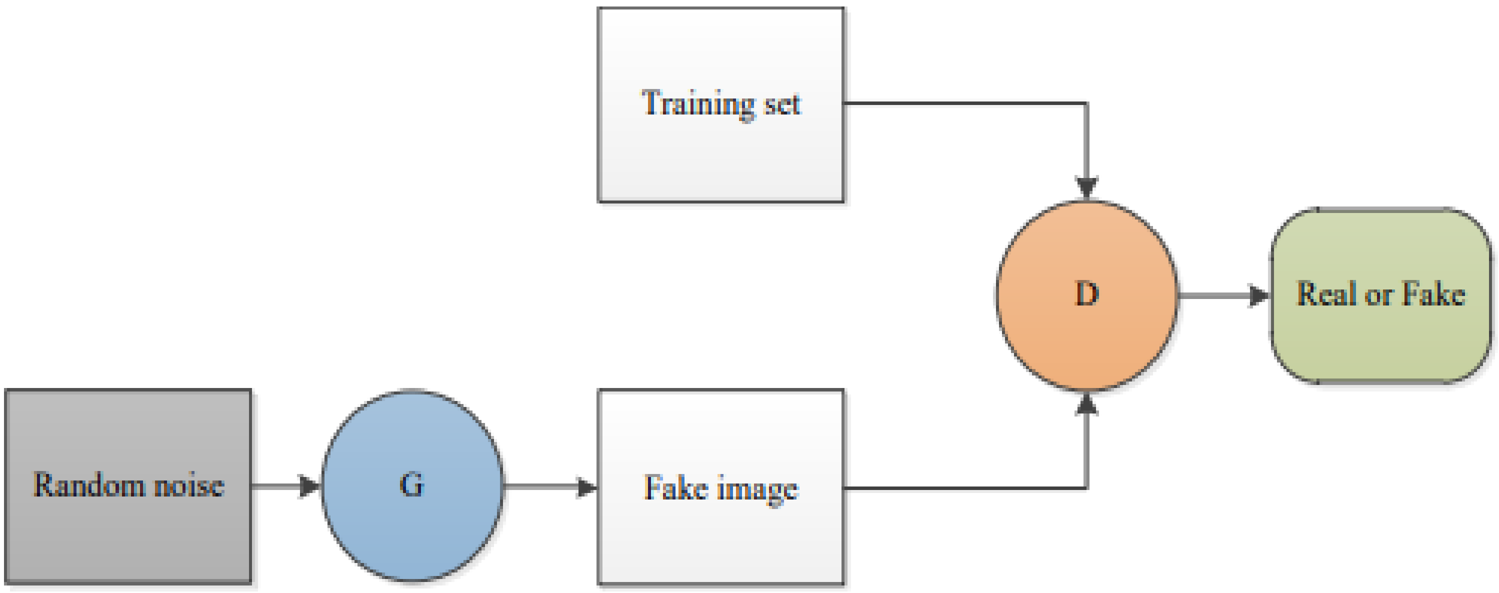
3. Existing System

- **Training Data Dependency:** Require large amounts of high-resolution training data.
- **Complexity and Computational Cost:** Computationally intensive, limiting real-time or resource-constrained deployment.
- **Quality and Stability:** Prone to training instability and mode collapse, affecting image quality.
- **Generalization and Adaptability:** Difficulty generalizing across diverse imaging conditions.
- **Lack of Interpretability:** Lack of interpretability, complicates control and trust in critical applications.
- **Limited Upscaling Factors:** struggle with achieving significant upscaling factors without sacrificing quality or introducing artifacts.

4. Proposed System

Functional Description:

The proposed system aims to enhance the resolution of real-world images using Generative Adversarial Networks (GANs). It addresses the limitations of existing methods by providing a robust framework capable of effectively handling various image degradations and producing high-quality super-resolved images.



Architecture of Generative Adversarial Networks

Proposed Solution Architecture:

- **Residual block:** residual blocks play a crucial role in improving the training stability and enhancing the quality of generated high-resolution images.
- **Generator Network:** The generator network in SRGAN (Super-Resolution Generative Adversarial Network) is responsible for transforming low-resolution images into high-resolution counterparts.
- **Discriminator Network:** A network that discriminates between real and generated images, providing feedback to the generator for improving image quality. It may incorporate techniques such as conditional GANs or second-order channel attention mechanisms to enhance the discrimination process.
- **Loss Functions:** Various loss functions are utilized to train the generator network effectively, which are adversarial loss and perceptual loss. These loss functions ensure that the generated images are visually appealing and maintain consistency with ground-truth high-resolution images.

Proposed Solution Architecture:

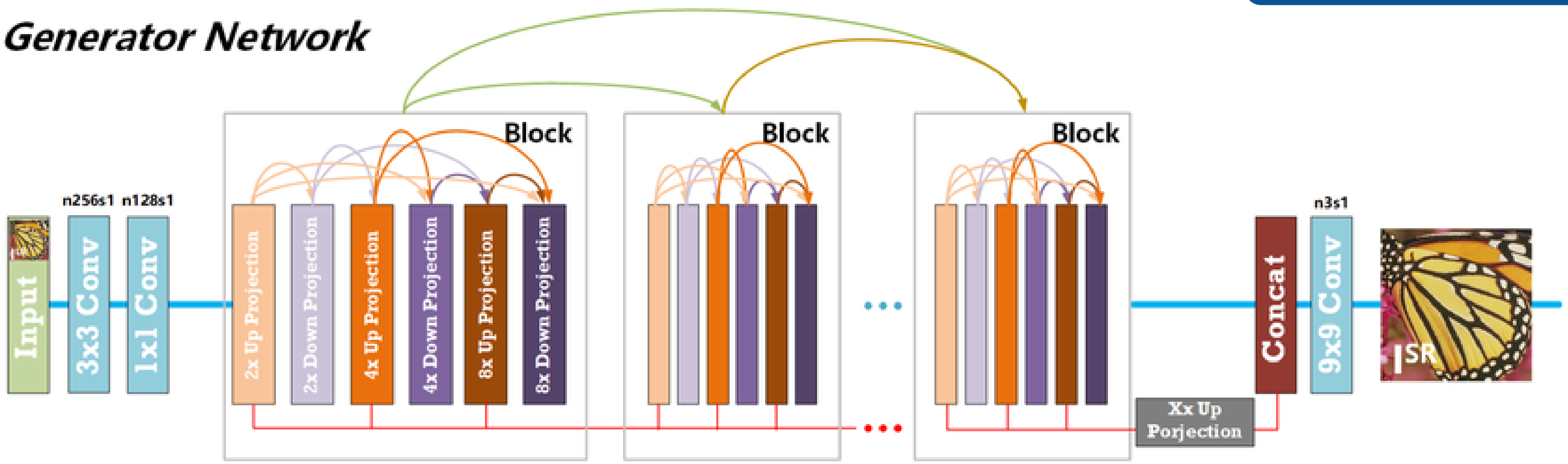
- **VGG19 :** VGG19 is used to extract high-level features (e.g., textures, structures, edges) from both the generated high-resolution images and the ground truth high-resolution images. Residual blocks play a crucial role in improving the training stability and enhancing the quality of generated high-resolution images.

- **Adversarial Network :** The adversarial network in SRGAN (Super-Resolution Generative Adversarial Network) is used to improve the quality and realism of generated high-resolution images.

- **GAN:** In SRGAN (Super-Resolution Generative Adversarial Network), GAN (Generative Adversarial Network) is used to improve the quality of super-resolved images.

- **PSNR (Peak Signal-to-Noise Ratio):** value can be used as a metric to evaluate the quality of generated images.

Generator Network



Discriminator Network

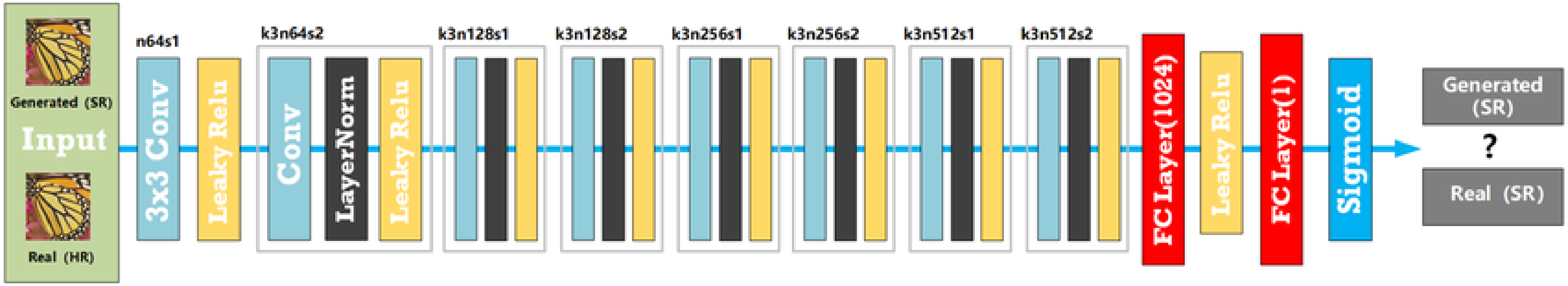


Image enhancement using SRGAN model

Software & Hardware Requirements:

- Deep Learning Frameworks
- Python Programming Environment
- Development Environment
- Storage
- Memory
- Network Connectivity

5. Feasibility Analysis

- Time: Training GAN-based super-resolution models can be time-consuming due to the complexity of the architecture and the need for large datasets. However, inference time for generating high-resolution images is generally faster once the model is trained.

- Cost: The cost associated with GAN-based super-resolution primarily involves computational resources for training and inference, including high-performance GPUs or TPUs and potentially cloud computing services

- Implementation Issues: Implementing GAN-based super-resolution techniques requires expertise in deep learning, particularly GAN architectures. Addressing training stability issues, mode collapse, and hyperparameter tuning are common challenges during implementation.

- Data Availability: Access to high-quality, diverse training data is crucial for training effective GAN-based super-resolution models. Acquiring or preparing such datasets may be challenging and may require significant effort and resources.

- Generalization: Ensuring that trained models generalize well across different imaging conditions and datasets is essential. Techniques such as data augmentation and transfer learning can help improve generalization but require careful implementation and validation.

- Quality Evaluation: Evaluating the quality of super-resolved images is subjective and often relies on metrics like PSNR(Peak Signal-to-Noise Ratio). Ensuring consistent and reliable evaluation methodologies is important for assessing the effectiveness of GAN-based super-resolution techniques.

- Ethical Considerations: Ethical considerations regarding the use of GAN-generated images, particularly in sensitive domains like medical imaging or surveillance, should be addressed. Ensuring fairness, transparency, and privacy protection in model development and deployment is essential.

6. Benefits of Proposed

Achieve superior image quality and resolution through innovative GAN-based techniques, surpassing traditional methods and addressing real-world image degradation challenges.

7. Anticipated Outcomes

Enhanced image resolution and quality surpassing traditional methods, achieved through applying GAN-based super-resolution techniques, facilitating improved analysis and decision-making in various domains.

8. Plan of Work

Develop a comprehensive methodology integrating GAN-based super-resolution techniques, including data acquisition, preprocessing, model training, and evaluation, with a timeline spanning from dataset preparation to model deployment and refinement.

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