Super Resolution of Wind And Solar Data Using Generative Adversarial Networks

Major Project Report Part 1 / Part 2

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CERTIFICATE

*This is to certify that the major project report entitled "**Super Resolution of Wind And Solar Data Using Generative Adversarial Networks**" is a bonafide record of the Project done by **Vijay Krishna Varkolu** (B200994EC), **Pranith Kumar Boge** (B201032EC), **Shanmuga Sundaram Hemanth Kumar(B201019EC)** under our supervision, in partial fulfillment of the requirements for the award of the degree of **Bachelor of Technology in Electronics and Communication Engineering** from **National Institute of Technology Calicut**, and this work has not been submitted elsewhere for the award of a degree.*

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ABSTRACT

This report proposes a method to enhance the resolution of low-resolution (LR) wind velocity data using Generative Adversarial Network (GAN) techniques. GANs have demonstrated better performance in improving image resolution compared to other deep learning models like Convolutional Neural Networks (CNN). Our approach involves implementing a GAN based on a customized version of the SRGAN, specifically made for wind data, known as the PhIREGAN network. Additionally, we have refined the training process by integrating The Kolmogorov Law of Turbulence into the loss function. The results from our modified training approach have shown significant improvements, particularly in Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Metric (SSIM), and Energy Spectral characteristics.

In addition to our current methodology, we have incorporated Wasserstein Generative Adversarial Network (WPGAN) into our approach and observed promising results. The integration of WPGAN has further optimized the training process, resulting in enhanced resolution of wind velocity data. WPGAN's training algorithms have successfully captured intricate features of wind data, leading to more accurate and detailed results. This advancement marks a significant step forward in renewable energy resource assessment and planning, contributing to the ongoing efforts towards a sustainable energy future

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List of Abbreviations

GCM	Global Climate Model
CNN	Convolutional Neural Network
LR	Low Resolution
HR	High Resolution
SR	Super Resolution
PSNR	Peak-Signal-to-Noise Ratio
SSIM	Structural Similarity Index Metrix
SRCNN	Super Resolution Using CNN
EDSR	Enhanced Deep Super-Resolution
GAN	Generative Adversarial Network
ESRGAN	Enhanced Super-Resolution GAN
PhIREGAN	Physics Informed Resolution Enhancing GAN
WGAN-GP	Wasserstein Generative Adversarial Networks with Gradient Penalty
NREL	National Renewable Energy Laboratory
NSRDB	National Solar Radiation Database
DNI	Direct Normal Irradiance
DHI	Diffused Horizontal Irradiance
SISR	Single Image Super-Resolution
ReLU	Rectified Linear Unit

CHAPTER 1

Introduction

Predicting future weather and environmental conditions, which are crucial for various sectors like energy, transportation, and agriculture is a big challenge. But this task becomes even more complex when we are trying to anticipate how climate change will affect renewable energy resources like wind and solar power.

To meet this challenge, we are employing advanced computer techniques, specifically machine learning methods. We are focusing on enhancing the resolution of climate data, particularly data related to wind and solar energy, obtained from Global Climate Models (GCMs) [1][3]. These models simulate the Earth's climate and provide us with valuable insights into future climate scenarios.

We are utilizing deep learning techniques, such as super-resolution, to refine this climate data even further. Essentially, we are using artificial intelligence to enhance the detail and accuracy of the information we have. This allows us to better understand how wind patterns and sunlight distribution might change in different regions as the climate evolves.

By generating high-resolution climate data that preserves essential physical characteristics, we're aiming to improve our ability to forecast the impact of climate change on renewable energy generation. This means we can better predict how much energy we can harness from wind and solar sources in specific locations, aiding in the planning and integration of renewable energy systems into local power grids. Ultimately, this research helps us adapt to a changing climate while maximizing the potential of renewable energy resources.

CHAPTER 2

Project Overview

2.1 Problem Statement

The resolution of climate data obtained from Global Climate Models (GCMs) is typically coarse, with a resolution around 1^o or approximately 100 kilometers. However, this level of resolution is not enough for accurately assessing renewable energy resources, which require finer resolutions, ideally below 10 kilometers and preferably around 2 kilometers. Consequently, there exists a critical need for methods that can enhance the resolution of GCM output to better study the impact of energy on various climatic conditions.

To address this challenge, various Machine Learning (ML) techniques have been integrated into GCMs. Among these techniques, the deep learning model, PhIREGAN[1] (Physics Informed Resolution Enhancing GAN), has been utilized to generate high-resolution (HR) climate data. PhIREGAN is designed to learn the spatial characteristics of the data and produce outputs that closely resemble actual data while preserving physically relevant characteristics.

The primary objective is to produce high-quality images through adversarial training that not only learn from the existing data but also preserve key physical features essential for accurately assessing renewable energy resources. Thus, the focus is on bridging the resolution gap between GCM output and the requirements for optimal resource planning, enabling more precise predictions of energy generation under different climatic conditions.

2.2 Background

2.2.1 Global Climate Model

A Global Climate Model (GCM)[1], also known as a General Circulation Model, is a computer-based simulation tool used to predict climate patterns and changes over large geographic areas. These models incorporate complex mathematical equations to simulate interactions between the atmosphere, oceans, land surface, and ice. By inputting various factors such as greenhouse gas concentrations, solar radiation, and land use changes, GCMs can project future climate conditions under different scenarios. They are crucial for understanding the Earth's climate system, assessing the impacts of human activities on climate, and informing policymaking related to climate change mitigation and adaptation.

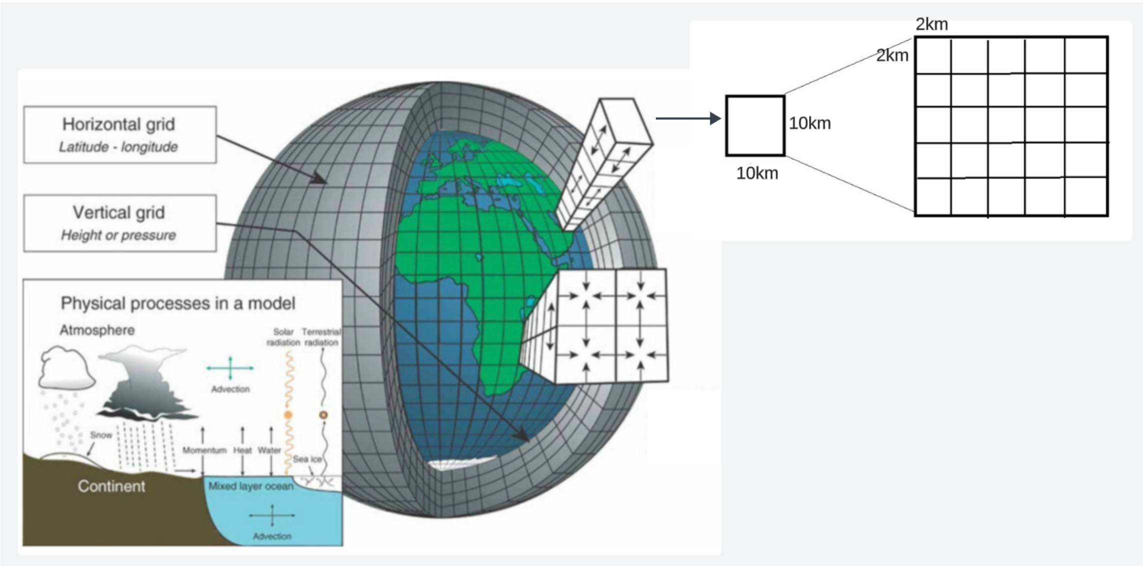

Figure 2.1: Global Climate Model

2.2.2 Image Super-Resolution

Image Super-Resolution[1] is a machine learning task where the goal is to increase the resolution of an image, often by a factor of 4x or more, while maintaining its content and details as much as possible. The end result is a high-resolution version of the original image. This task can be used for various applications such as improving image quality, enhancing visual detail, and increasing the accuracy of computer vision

algorithms.
Some methods through which Super Resolution is achieved are:

- Bicubic Interpolation
- SR CNN
- EDSR
- ESR GAN
- PhIRE GAN

2.2.3 Bicubic interpolation

Bicubic interpolation is a method commonly used for image upscaling or super resolution. When you zoom in on a digital image, the pixels become more apparent, leading to a loss of detail. Bicubic interpolation helps in recreating a higher-resolution version of the image by estimating the color values of the new pixels based on the surrounding pixels in the original image.

2.2.4 Super Resolution Using Convolutional Neural Network (SRCNN)

SRCNN is trained using a large dataset of paired low-resolution and high-resolution images[2]. During training, the model learns to minimize the difference between the predicted high-resolution images and the ground truth high-resolution images. This is typically done using mean squared error (MSE) or other loss functions.

2.2.5 Enhanced Deep Super-Resolution (EDSR)

Enhanced Deep Super-Resolution (EDSR) enhances low-resolution images by extracting features through convolutional layers and residual blocks with skip connections to retain crucial details. Non-linear mapping within these blocks allows the network to learn complex relationships between low and high-resolution representations, aided by residual scaling to fine-tune corrections. Upsampling techniques increase feature map resolution, followed by reconstruction through additional convolutional layers.

Trained on paired low and high-resolution images, EDSR minimizes differences between predicted and ground truth high-resolution images, achieving state-of-the-art performance in single-image super-resolution tasks.

2.2.6 Generative Adversarial Network (GAN)

Generative Adversarial Networks (GANs) [3]consist of two neural networks, the generator and the discriminator, engaged in a competitive game-like scenario. The generator creates synthetic data, such as images, while the discriminator's task is to distinguish between real and fake data. During training, the generator aims to produce data that is indistinguishable from real data, while the discriminator strives to improve its ability to differentiate between real and fake data. As training progresses, the generator learns to generate increasingly realistic data by receiving feedback from the discriminator. Meanwhile, the discriminator becomes better at distinguishing between real and fake data. Through this adversarial process, GANs are capable of generating highly realistic synthetic data, making them valuable for various applications in image generation.

2.2.7 Enhanced Super-Resolution Generative Adversarial Network (ESRGAN)

Enhanced Super-Resolution Generative Adversarial Network, is a deep learning model which builds upon the traditional GAN architecture by incorporating a novel generator network that employs residual blocks and dense connections to capture intricate details in the high-resolution images. During training, the generator learns to produce high-resolution images from low-resolution inputs by minimizing the perceptual loss, which measures the difference between the generated images and their corresponding ground truth high-resolution images. Additionally, ESRGAN introduces a feature extractor network, known as the perceptual loss network, to improve the perceptual quality of the generated images by aligning them with the features extracted from pre-trained deep neural networks.

2.2.8 Physics Informed Resolution Enhancing GAN

The network has a similar architecture that is based off of the state-of-the-art Super Resolution Generative Adversarial Network (SRGAN)[1] with several modifications. Each network is a deep fully convolutional neural net with 16 residual blocks with skip connections. All convolutional kernels are 3×3 and are followed by rectified linear unit activation functions. Experimentation on subsets of the training data uncovered the need to remove batch normalization layers from the Ledig et al. architecture, which were found to hinder the network's ability to transfer to data coming from different models. Other differences in the proposed network include adapting the SR layers to accommodate the larger-resolution jumps being performed and adjusting the network input layers to consist of two data channels corresponding to either (u, v) wind velocity components or (DNI, DHI) solar irradiance components. This is in contrast to the three RGB channels typically used for image processing. Finally, we note that since the networks are fully convolutional, they are agnostic to the size of the input data—a property that enables training on smaller patches of the data while running on larger fields in deployment.

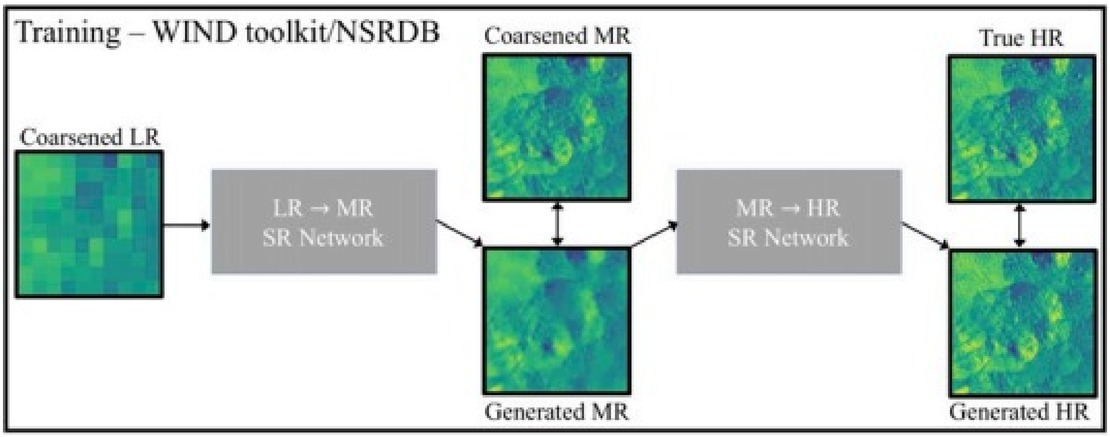

Figure 2.2: Two step Training Process

2.2.9 Semivariogram

A semivariogram is a statistical tool used in spatial analysis and geostatistics to quantify spatial variability or spatial dependence in a dataset. It's particularly useful in fields like environmental science, agriculture, and natural resource management where understanding spatial patterns and variability is crucial.[5]

The semivariogram measures the variability between pairs of sample points as a function of the distance separating them. It quantifies how the values of a variable change with respect to distance, providing insights into the spatial structure and correlation within the dataset.

2.2.10 Data Set

Wind data

Wind data for ML training is derived from NREL's wtk-us.h5 dataset. It includes wind speed and direction at 100 meters above the US. High resolution (HR) grids are extracted per time step, and low resolution (LR) grids are created by subsampling HR data. LR and HR wind components are organized into smaller grids, generating PNG images for training. Data is then converted into tensorflow TFRecord format for efficient processing during training.

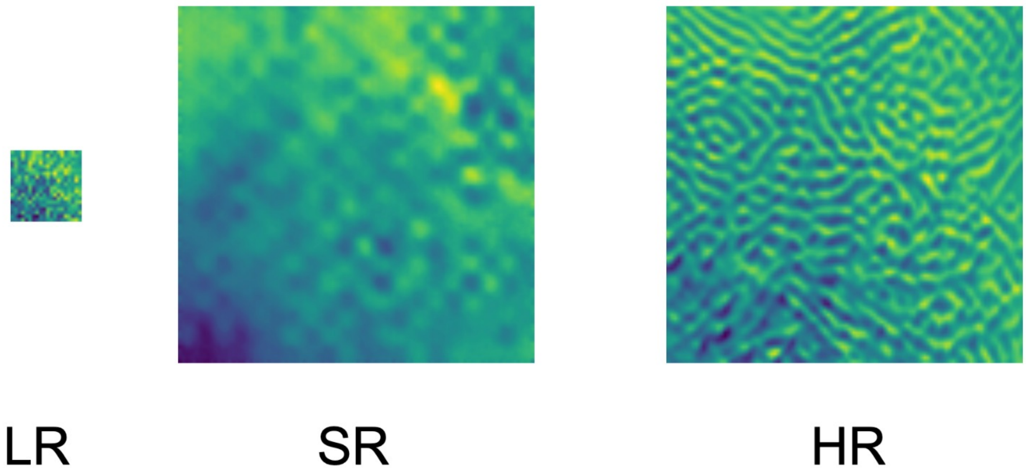

Figure 2.3: Wind Data ,Low Resolution ; Super Resolution ; High Resolution

Solar data

We consider solar irradiance data from the NSRDB in terms of direct normal irradiance (DNI) and diffused horizontal irradiance (DHI) at an approximately 4km$\times$1/2hr spatiotemporal resolution. The solar dataset produced for this work samples data at an hourly temporal resolution from 6 am to 6 pm for the years 2007 to 2013.

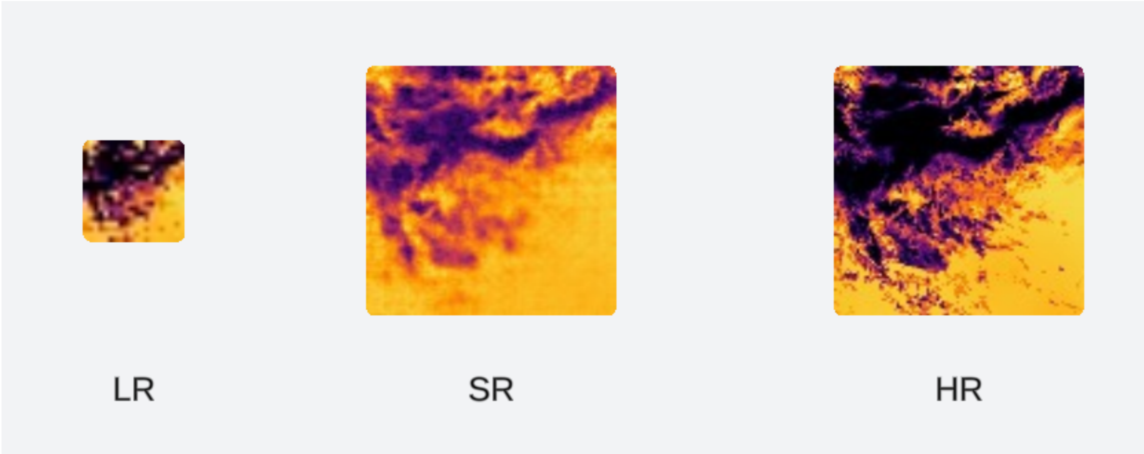

Figure 2.4: Solar Data , Low Resolution ; Super Resolution ; High Resolution

2.2.11 Loss Functions

The standard GAN loss function, also known as the min-max loss is given by

$$\min_G \max_D E[\log(D(y))] + E[\log(1 - D(G(x)))]...[1]$$

[1] The generator tries to minimize this function while the discriminator tries to maximize it. Looking at it as a min-max game, this formulation of the loss seemed effective.

1) Generator Loss: The loss function of the generator is designed considering three aspects: first, the adversarial process between the generator and discriminator, second, the features contained in the SR image, and third, the Kolmogorov loss.

While the generator is trained, it samples random noise and produces an output from that noise. The output then goes through the discriminator and gets classified as either "Real" or "Fake" based on the ability of the discriminator to tell one from the other.

The generator loss is then calculated from the discriminator's classification – it gets rewarded if it successfully fools the discriminator, and gets penalized otherwise.

Generator Loss function is as follows:

$$G_{Loss} = L_{Adv} + (\alpha)L_{Content} + (\beta)L_{Kol}$$

where L_{Adv} represents the adversarial loss[1] between the generator and discriminator , $\alpha = 0.01$ and $\beta = 0.1$. It is defined as:

$$L_{Adv} = E[\log(1 - D(G(x)))] \sim -\log(D(y))$$

[1] The content loss[1] is a way of measuring how closely the generated high-resolution image matches the actual high-resolution image. It is done by calculating the average squared difference between corresponding pixels in the two images and is given by:

$$L_{Content} = ||y - G(x)||_2^2$$

[1] *2) Discriminator Loss:*
While the discriminator is trained, it classifies both the real data and the fake data from the generator.
It penalizes itself for misclassifying a real instance as fake, or a fake instance (created by the generator) as real, by maximizing the below function.
It is given by:

$$L_D(x, y) = -\log(D(y)) - \log(D(G(x)))...[1]$$

2.3 Objective

- **Reviewing Super-Resolution Techniques:** We'll explore various methods for improving the quality of wind and solar data, focusing on advanced techniques like deep learning. By understanding these methods better, we aim to see how they can enhance the resolution of our renewable energy datasets.

- **Analyzing Key Research Papers:** We'll closely examine three important studies that have explored ways to enhance wind and solar data resolution. These papers provide valuable insights into what works best and what challenges exist in improving the clarity of this crucial renewable energy information.

- **Testing Methodologies:** We'll put these techniques to the test to see how effective they are at actually improving the resolution of wind and solar data while ensuring that the results remain accurate and reliable. This rigorous evaluation will help us understand which methods are most practical for real-world applications.

- **Exploring Impact:** We'll explore the benefits and implications of having higher-resolution wind and solar data. This clearer information could improvise how we plan and implement renewable energy projects, leading to better decision-making, more efficient resource allocation, and advancements in renewable energy technology.

2.4 Motivation

Our report is all about making renewable energy, like wind and solar power, easier to understand and use. Right now, the data we have isn't detailed enough, which makes it hard to plan things well.
We're looking into super-resolution techniques to fix this problem for a few reasons:

- **Helping People Decide Better:** By giving people in the renewable energy business clearer information, they can make smarter choices. This means they can spend money and resources in the right places.

- **Making Renewable Energy Fit In:** With better data, we can make it simpler to add renewable energy to our current systems. This could mean making our power grids better or planning where to put things like solar panels more efficiently.

- **Moving Renewable Tech Forward:** We're also trying to push renewable energy technology ahead. By using new techniques like deep learning, we can solve problems faster and get closer to using renewable energy everywhere.

2.5 Proposed Plan

2.5.1 Integrating Physics Principles for Enhanced Super Resolution

Our proposed plan aims to enhance the **PHIREGAN** model by incorporating the Kolmogorov loss into its training process. This addition will enable the model to better adhere to the fundamental laws governing fluid dynamics, such as the Kolmogorov law.

By integrating the Kolmogorov loss, we'll guide the model to produce super-resolved wind and solar data that more accurately reflect the behaviors expected from fluids. This adjustment strengthens the model's grasp of physics principles, ensuring that its outputs align more closely with real-world phenomena.

Ultimately, our goal is to deliver super-resolution results that not only exhibit heightened clarity but also maintain fidelity to the underlying physical laws.

Optimising the training process:

Wasserstein Generative Adversarial Networks with Gradient Penalty (WGAN-GP) provide notable advantages over traditional GANs. They offer improved stability during training, leading to smoother dynamics and mitigating issues like mode collapse. WGAN-GP promotes faster convergence, encouraging the generator to learn more efficiently and produce higher quality samples that closely match real data distributions. Additionally, WGAN-GP is less sensitive to architecture choices and hyperparameters, simplifying training and reducing mode collapse occurrences. The gradient penalty in WGAN-GP enforces a Lipschitz continuity constraint on the discriminator, enhancing stability by penalizing erratic gradients and encouraging a smoother decision boundary.

2.5.2 The Kolmogorov Law of Turbulence

Kolmogorov -5/3 law : The 5/3's law states that, in some inertial range [k1,k2], the energy density of the flow E(k) behaves like $Ck^{-5/3}$,where k denotes the current wave number.

$$E \propto k^{-5/3}$$

$$E = Ck^{-5/3}$$

$$\log(E) = \log(C) - \frac{5}{3}\log(k)$$

$$\frac{dE}{dk} = -\frac{5}{3}\frac{E}{k}$$

2.5.3 Calculation of Energy Spectrum

Image Preparation

- **Reading and Converting the Image:** Start by loading the image using **Image.open(imgpath).convert('L')**, which opens the image from a specified path and converts it to grayscale. This step ensures that the image analysis is based solely on luminance data, discarding color information which isn't necessary for frequency analysis.

- **Saving the Grayscale Image:** The grayscale image is saved and reloaded to ensure it is handled correctly in subsequent steps. This also aids in debugging by providing a checkpoint to examine the modified image.

Rescaling the Image Data

- **Linear Rescaling:** Utilize the **rescalelinear** function to adjust the pixel values of the image so that they span a specified range given by **newmin** and **newmax**. This normalization step is critical because it standardizes the image data, facilitating more consistent analysis.

Fourier Transform

- **Computing Fourier Transform:** The Fourier transform of the image is computed using **np.fft.fftn(image)**. This transform converts the spatial representation of the image into a frequency domain representation. Each point in this frequency domain represents a particular frequency contained in the spatial domain image.

- **Amplitude Spectrum:** The squared magnitudes of the Fourier transform coefficients are calculated to obtain the power spectrum (often referred to as the amplitude spectrum in the context of image processing). This spectrum represents the energy contribution from each spatial frequency component.

Radial Averaging

- **Frequency Binning:** Spatial frequencies are represented in a 2D grid (due to the 2D nature of images). To analyze the distribution of energy, we convert these 2D frequencies into a 1D radial frequency variable **knrm**, which is the radial distance from the origin of the frequency domain.

- **Histogram Binning:** The squared amplitudes are then averaged over annular (ring-shaped) bins in the frequency domain. This averaging is performed radially to ensure that all frequencies with the same radial distance are treated equivalently, providing a 1D profile of energy as a function of spatial frequency. This binning process involves grouping the squared amplitudes based on their radial distances and averaging within these groups.

- **Area Scaling:** Since higher radial frequencies cover a larger area in the 2D frequency space, it is necessary to scale the binned averages by the area of the **annuli (determined by the radii of the bins)**. This scaling compensates for the increasing **"sampling"** area at higher frequencies and ensures that the spectrum represents a true density rather than merely a sum over a larger number of points.

2.5.4 Wasserstein GAN

GANs can produce very visually appealing samples, but are often hard to train. Standard GANs often struggle with two main issues:

- Mode collapse: The generator might only learn to produce a limited variety of samples, ignoring the full diversity of the training data.

- Vanishing gradients: Training can become unstable, especially when the discriminator gets too good at distinguishing real from fake, making it hard for the generator to learn.

If the discriminator is trained to optimality before each generator parameter update, then minimizing the value function amounts to minimizing the Jensen-Shannon divergence between Pr and Pg, but doing so often leads to vanishing gradients as the discriminator saturates.

- Wasserstein GAN (WGAN) proposes a new cost function using Wasserstein distance that has a smoother gradient everywhere. WGAN learns no matter the generator is performing or not. The diagram below repeats a similar plot on the value of D(X) for both GAN and WGAN. For GAN (the red line), it fills with areas with diminishing or exploding gradients. For WGAN (the blue line), the gradient is smoother everywhere and learns better even the generator is not producing good images.

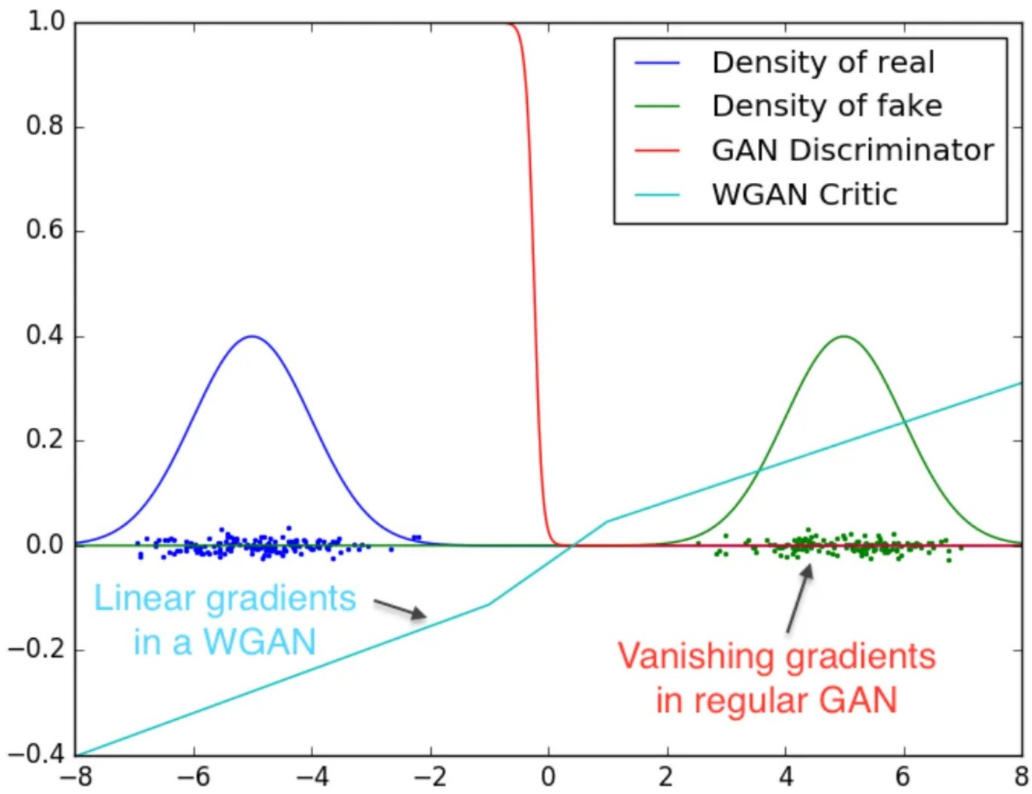

Figure 2.5: Optimal discriminator and critic when learning to differentiate two Gaussians.

The WGAN value function is constructed using the Kantorovich-Rubinstein duality to obtain

$$\min_{G} \max_{D \in D} E_{x \sim P_r}[D(x)] - E_{\bar{x} \sim P_g}[D(\bar{x})]$$

where D is the set of 1-Lipschitz functions and Pg is once again the model distribution implicitly defined by $\bar{x}$ = G(z), z $\sim$ p(z). In that case, under an optimal discriminator (called a critic in the paper, since it's not trained to classify), minimizing the value function with respect to the generator parameters minimizes W(Pr, Pg).

- The WGAN value function results in a critic function whose gradient with respect to its input is better behaved than its GAN counterpart, making optimization of the generator easier. Empirically, it was also observed that the WGAN value function appears to correlate with sample quality, which is not the case for GANs.

2.5.5 Gradient Penalty

A differentiable function is 1-Lipschtiz if and only if it has gradients with norm at most 1 everywhere, so we consider directly constraining the gradient norm of the critic's output with respect to its input. To circumvent tractability issues, we enforce a soft version of the constraint with a penalty on the gradient norm for random samples x $\sim$ Px.

$$L = E_{x^{\sim} \sim P_g}[D(x^{\sim})] - E_{x \sim P_r}[D(x)] + \lambda E_{\hat{x} \sim P_{\hat{x}}}[(||\nabla \hat{x} D(\hat{x})||_2 - 1)^2]$$

Gradient penalty is a regularization technique commonly used in the context of training generative adversarial networks to improve stability and convergence. It was introduced as a way to enforce the Lipschitz constraint on the discriminator function. The Lipschitz constraint ensures that the gradient of the discriminator does not grow too large, which can help prevent mode collapse and other training instabilities in GANs.

In the context of GANs, the gradient penalty is typically applied to the discriminator loss function. It involves computing the gradient of the discriminator's output with respect to its input, and penalizing the magnitude of this gradient.

The gradient penalty term is added to the discriminator loss function as follows:

Discriminator Loss + λ

Gradient Penalty

Where:

λ is a hyperparameter that controls the strength of the penalty. The gradient penalty is calculated based on the gradients of the discriminator's output with respect to its input, typically measured using the L2 norm.

The formulation of the gradient penalty term often involves interpolating between real and generated samples to ensure that the gradient is penalized along straight paths between these samples.

CHAPTER 3

Literature Survey

→ The paper **"Adversarial Super-Resolution of Climatological Wind and Solar Data"** presents a innovative approach utilizing adversarial learning to enhance the resolution of wind and solar data derived from global climate models.

Research Area Overview:

- **Super-resolution Techniques:** Super-resolution methods aim to increase the spatial or temporal resolution of data, commonly applied in image processing. These techniques are crucial in climate science for enhancing the resolution of climate model outputs to better capture local-scale phenomena.

- **Generative Adversarial Networks (GANs):** GANs are a class of deep learning architectures consisting of two neural networks – a generator and a discriminator – engaged in a adversarial game. GANs have demonstrated remarkable success in generating high-quality synthetic data and have found applications in various domains, including image generation, text-to-image synthesis, and data augmentation.

- **Climate Modeling:** Climate modeling involves simulating Earth's climate system using mathematical models to understand past, present, and future climate conditions. Global climate models (GCMs) provide valuable insights into climate dynamics, but they often produce data at coarse resolutions, necessitating downscaling techniques for finer-scale analyses.

Relevant Research:

- **Traditional Climate Downscaling:** Traditional downscaling methods, such as statistical downscaling and dynamical downscaling, have been employed to refine coarse-resolution climate model outputs. However, these approaches are often computationally intensive and may lack the ability to capture fine-scale features accurately.

- **Deep Learning for Super-Resolution:** Deep learning techniques, particularly convolutional neural networks (CNNs), have shown promise in enhancing the resolution of images and other data types. Recent advancements in deep learning have spurred interest in applying these methods to climate data, offering potential solutions to the challenges of climate downscaling.

- **Understanding the Paper's Contribution:** "Adversarial Super-Resolution of Climatological Wind and Solar Data" is notable for using GANs in a new way to improve the resolution of wind and solar data from global climate models. This could make renewable energy assessments more accurate and help us better understand climate patterns. The study demonstrates the efficacy of GAN-based super-resolution in significantly increasing data resolution while preserving physical consistency, thus advancing the state-of-the-art in climate data analysis.

Conclusion:
"Adversarial Super-Resolution of Climatological Wind and Solar Data" represents a significant advancement in the field of climate modeling and renewable energy research. By pioneering the use of GANs for climate data super-resolution, the paper opens avenues for further exploration and refinement of deep learning techniques in addressing the challenges of climate downscaling.

→ Super-resolution techniques have attained significant attention in recent years, particularly in the context of improving the resolution of weather-related data such as wind and solar measurements. The paper **"WiSoSuper: Benchmarking Super-Resolution Methods on Wind and Solar Data"** focuses on exploring the advancements in super-resolution techniques for wind and solar data, their applications in renewable energy systems optimization, and the associated challenges and opportunities.
Relevant Research:

- **Traditional Downscaling Methods:** Historically, conventional downscaling techniques for enhancing weather data resolution have predominantly relied on interpolation or complex physical models. However, these methods often suffer from limitations such as computational intensity and lack of accuracy, especially when dealing with complex spatiotemporal patterns inherent in wind and solar data.
- **Machine Learning for Weather Forecasting:** With the emergence of machine learning approaches, particularly deep learning, there has been a paradigm shift towards data-driven methodologies for weather forecasting and super-resolution tasks. These approaches leverage the capacity of neural networks to learn complex relationships directly from data, offering promising alternatives to traditional methods.
- **Renewable Energy Integration:** The optimization of renewable energy systems heavily relies on accurate weather forecasting, including high-resolution wind and solar data. Super-resolution techniques play a crucial role in improving the granularity and fidelity of weather data, thereby enhancing the performance and efficiency of renewable energy generation and integration strategies.
- **How WiSoSuper Fits In:** The "WiSoSuper" paper contributes significantly to the field by providing a comprehensive benchmarking framework for evaluating leading super-resolution methods for wind and solar data. By comparing and analyzing deep learning-based approaches, the study sheds light on the strengths and limitations of different methodologies, thereby guiding future research directions and practical applications in renewable energy optimization.

→ The paper "Single Image Super-Resolution Using Wasserstein Generative Adversarial Network with Gradient Penalty" by tackles the task of enhancing image resolution using a specific type of Generative Adversarial Network i.e., WGAN.
Research Area:

- **Single Image Super-Resolution (SISR):** This field focuses on enhancing the resolution of a single low-resolution image, crucial for various applications like image restoration, surveillance, and medical imaging.

Relevant Research:

- **Traditional Interpolation Methods:** Historically, SISR methods relied heavily on interpolation techniques like bicubic or nearest neighbour. However, these methods often produce blurry results and fail to preserve fine details.

- **Deep Learning-based SISR:** With the advent of deep learning, Convolutional Neural Networks (CNNs) have emerged as powerful tools for SISR. These models can learn complex mappings from low-resolution to high-resolution images, capturing intricate details and textures.

- **Understanding the Paper's Focus:** This paper addresses a critical issue in GAN-based SISR: **training instability**. Traditional GANs may suffer from mode collapse or oscillatory behavior during training, leading to suboptimal results. To mitigate this, the paper proposes employing a Wasserstein Generative Adversarial Network with Gradient Penalty (WGAN-GP) for SISR. WGAN-GP offers improved stability by introducing a gradient penalty term into the loss function, encouraging smoothness in the learned distribution. The study investigates the efficacy of WGAN-GP in generating high-quality, high-resolution images while preserving important visual characteristics and details.

- **Alternative Approaches for Improving GAN Training Stability:** Beyond WGAN-GP, other techniques have been proposed to enhance the stability of GAN training. These include spectral normalization, feature matching, and various regularization methods. Investigating these approaches could provide insights into alternative strategies for robust SISR.

- **Additional Considerations:** Architectural Innovations in CNNs for SISR: Recent advancements in CNN architectures have led to improved performance and efficiency in SISR. Techniques such as residual learning, attention mechanisms, and progressive growing of GANs have shown promise in generating high-quality super-resolved images.

  Conclusion: In summary, this literature survey provides a comprehensive overview of the research landscape surrounding SISR and GANs, contextualizing the paper's contribution within this broader framework. By exploring recent advancements, alternative approaches, and evaluation methodologies, researchers can gain a deeper understanding of the challenges and opportunities in this exciting field.

CHAPTER 4

Results and Discussion

Results Of Modified PhIREGAN for Wind Data:

MODEL	Mean PSNR	SSIM
PhIREGAN	28.6	0.3178
Modified PhIREGAN	**28.8**	**0.34**

Table 4.1: Summary of average metric values for Solar Data

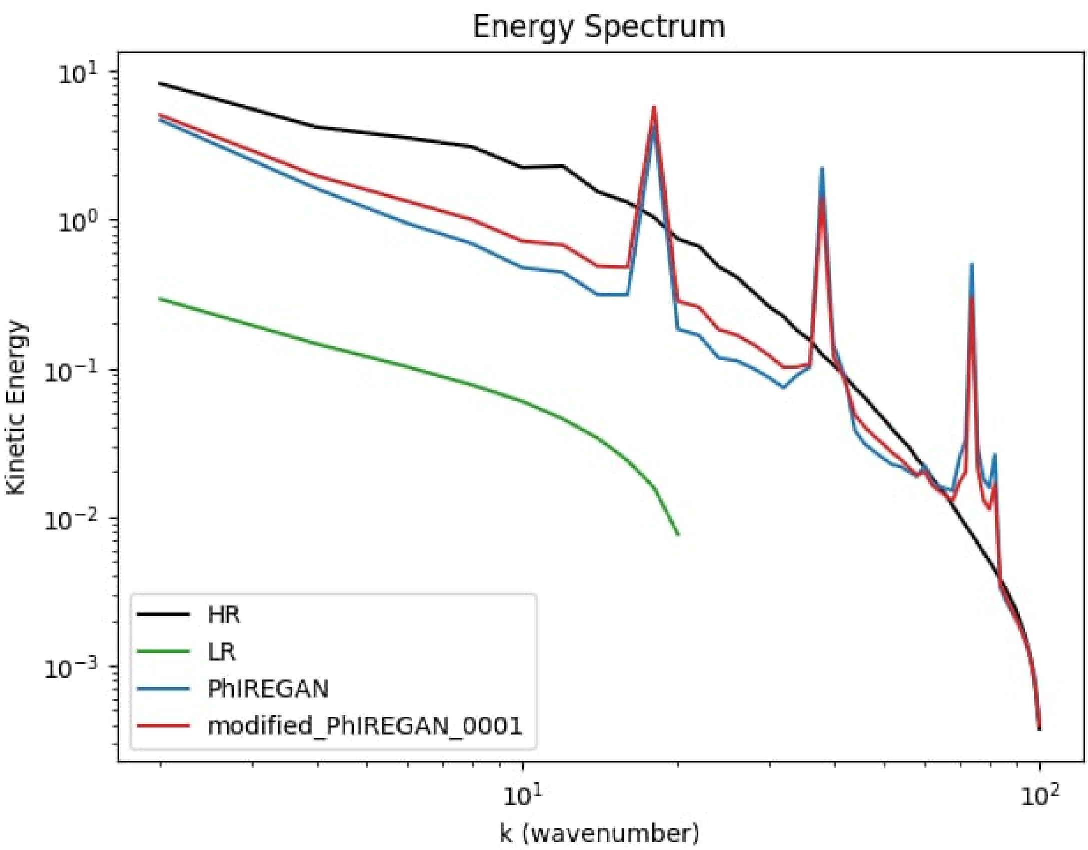

Figure 4.1: Energy Spectrum of Modified PhIRE GAN.

Results Of PhIREGAN for Solar Data:

MODEL	Mean PSNR	SSIM
PhIREGAN	28.251	0.3178

Table 4.2: Summary of average metric values for Solar Data

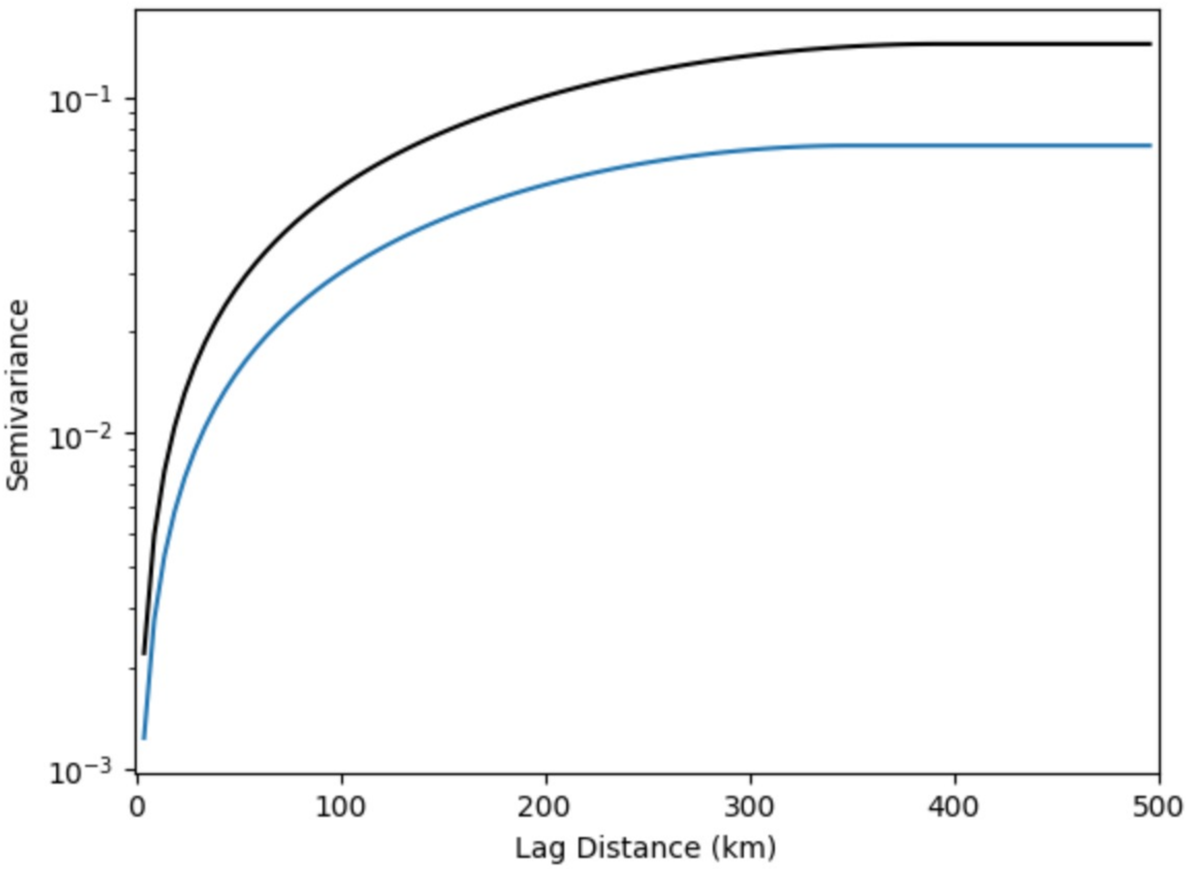

Figure 4.2: Semivariogram for Solar data.

Results of WPGAN:

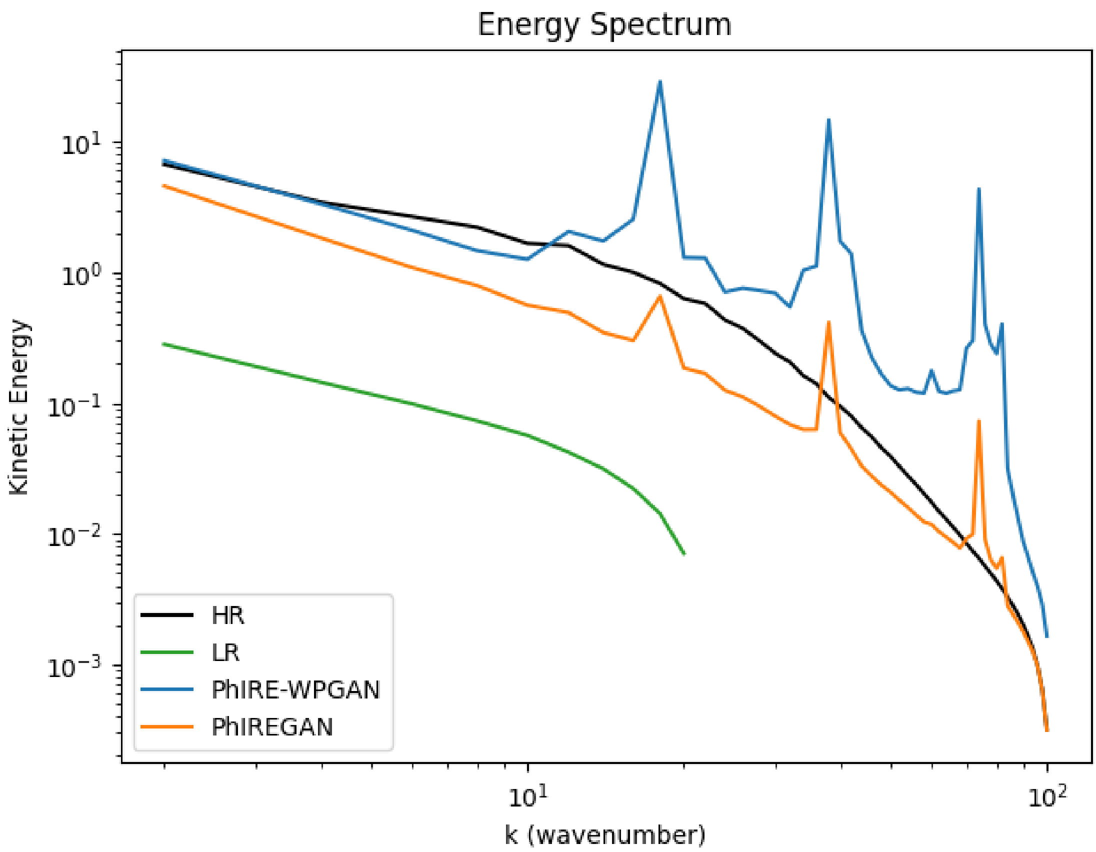

Figure 4.3: Energy Spectrum of WPGAN.

Parameters and Hyper Parameters	Values
Train data set	25600 Images
Test data set	6400 images
LR dimensions	10 x 10
MR dimensions	20 x 20
HR dimensions	100 x 100
Learning Rate	0.001
Batch size	16
Epochs	50
Estimated processing time	40 hours
Optimiser	Adam

Table 4.3: Parameters and Hyper Parameters

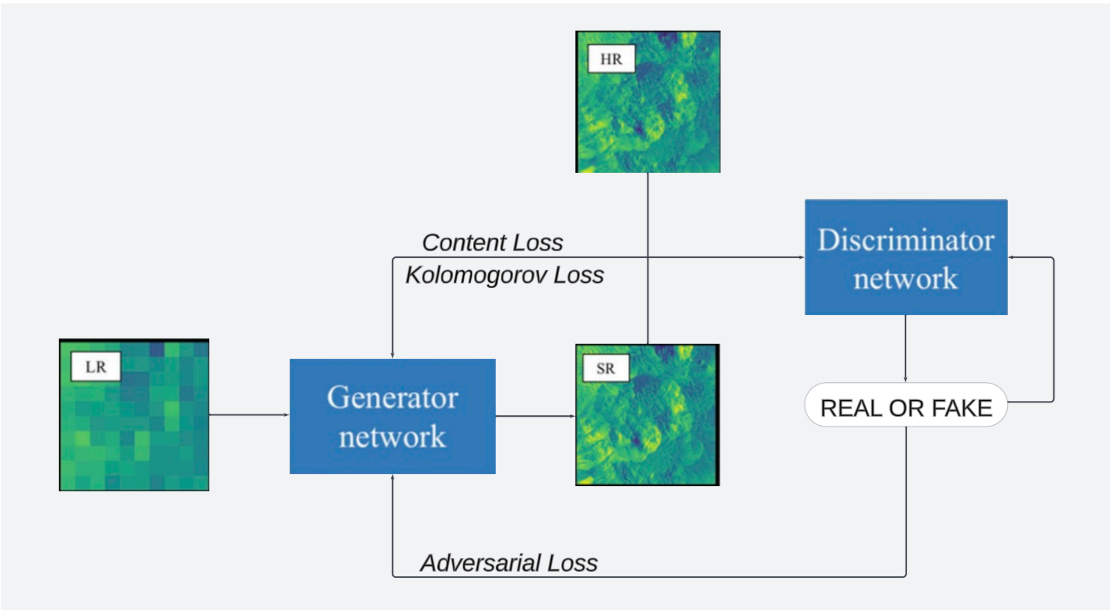

Figure 4.4: Schematic of GANs for Super Resolution

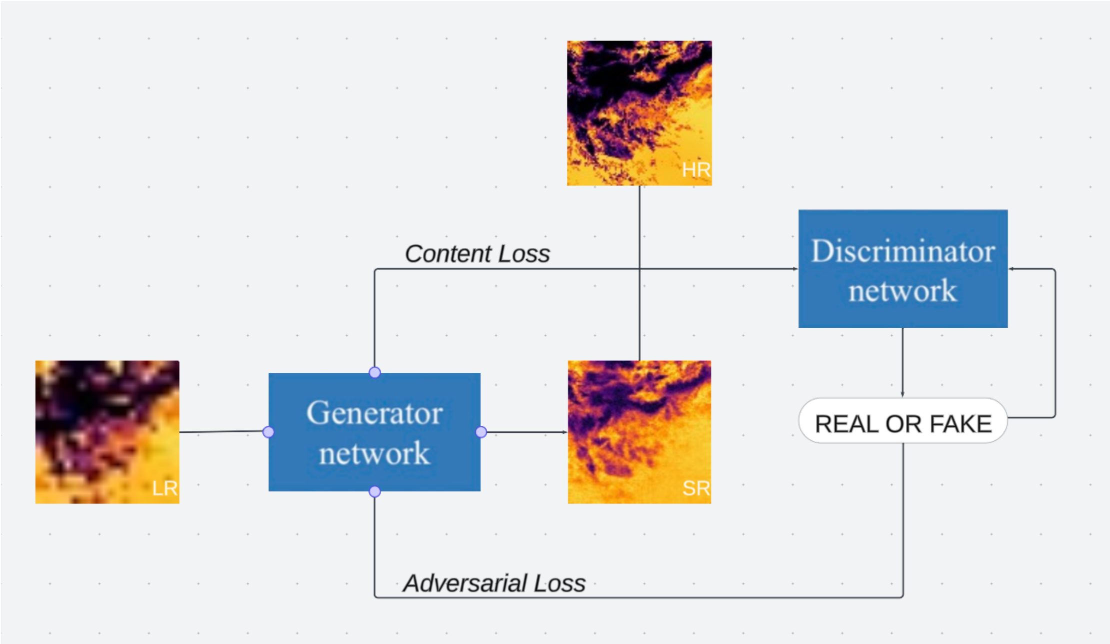

Figure 4.5: Schematic of GANs for Super Resolution of Solar data

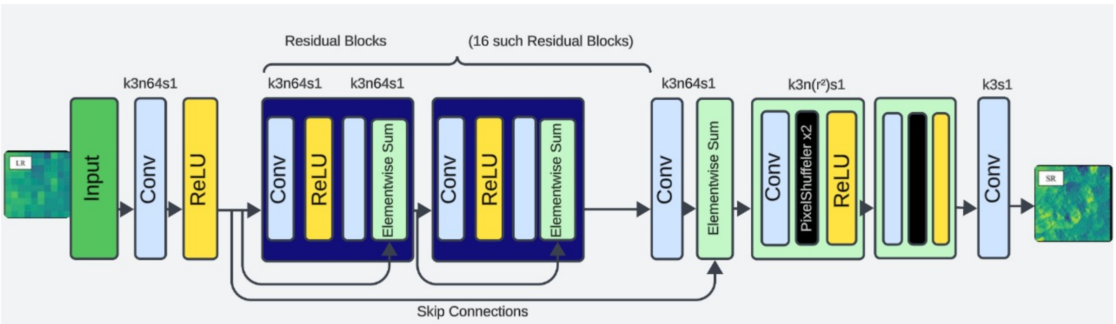

Figure 4.6: Architecture of the generator.

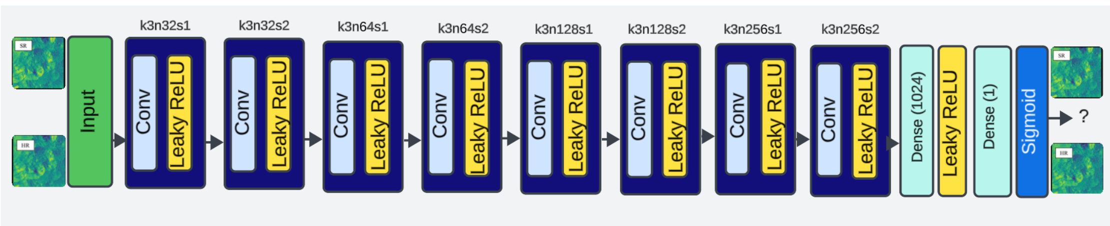

Figure 4.7: Architecture of the discriminator.

CHAPTER 5

Conclusion

In conclusion, the modifications made to our GAN model have yielded significant improvements in its performance, particularly evident in the analysis of the energy spectrum. The incorporation of the Kolmogorov loss into the loss function and the implementation of WGAN-GP have both demonstrated notable enhancements in the energy spectrum. These results indicate the effectiveness of these modifications in improving the model's ability to generate high-quality data with more favorable energy distributions. Moving forward, further exploration and refinement of these techniques could lead to even greater advancements in GAN-based data generation and synthesis.

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