# Image Super-Resolution Project


**Name：Jonas(Liu Zijun)**

**Supervisor：Dr.Happy Nkanta Monday**

**Chengdu University of Technology Oxford Brookes College**

# Contents

01

# Introduction to Image Super-Resolution

# Definition

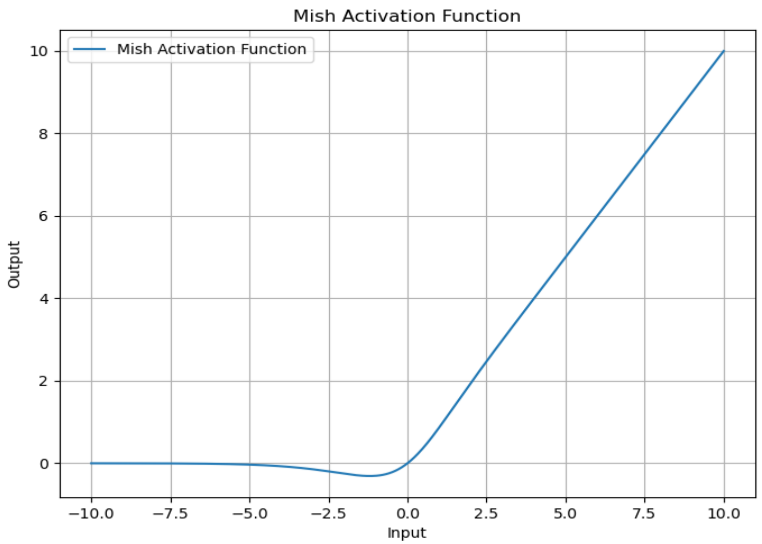
## Definition and Background

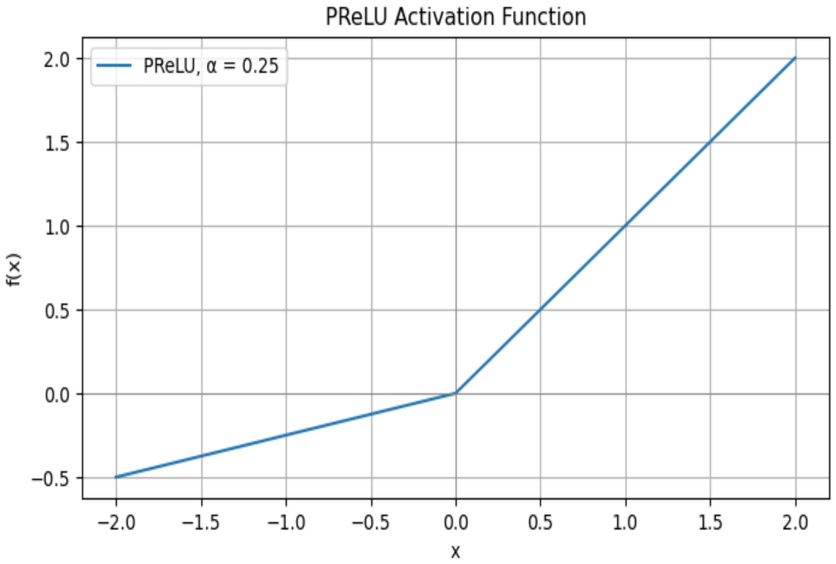
Super-resolution (SR) technology is a set of techniques used to enhance the resolution of an image beyond the capabilities of the original imaging system. This process involves reconstructing a high-resolution (HR) image from one or more low-resolution (LR) images. SR techniques can increase the number of pixels and improve the level of detail, making the image sharper and clearer.

02

# Methodology

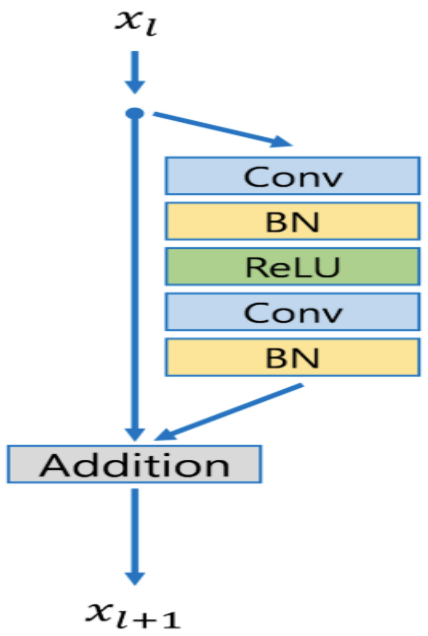
# Activation Function

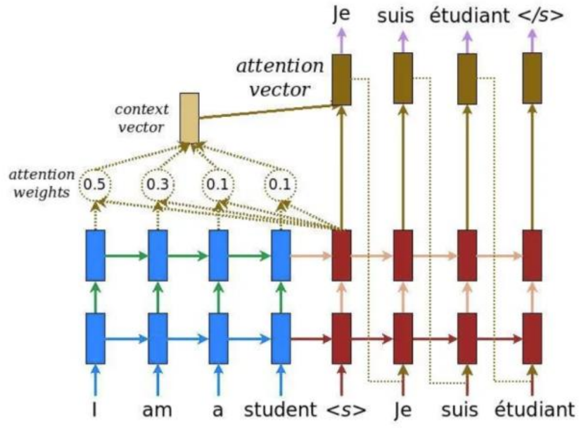



The Mish activation function is smooth and non-saturating, providing better gradient flow and convergence.
PRELU has strong adaptability, effectively mitigating the vanishing gradient problem through learnable parameters but increasing model complexity.

# SRResNet Architecture and Attention Mechanisms



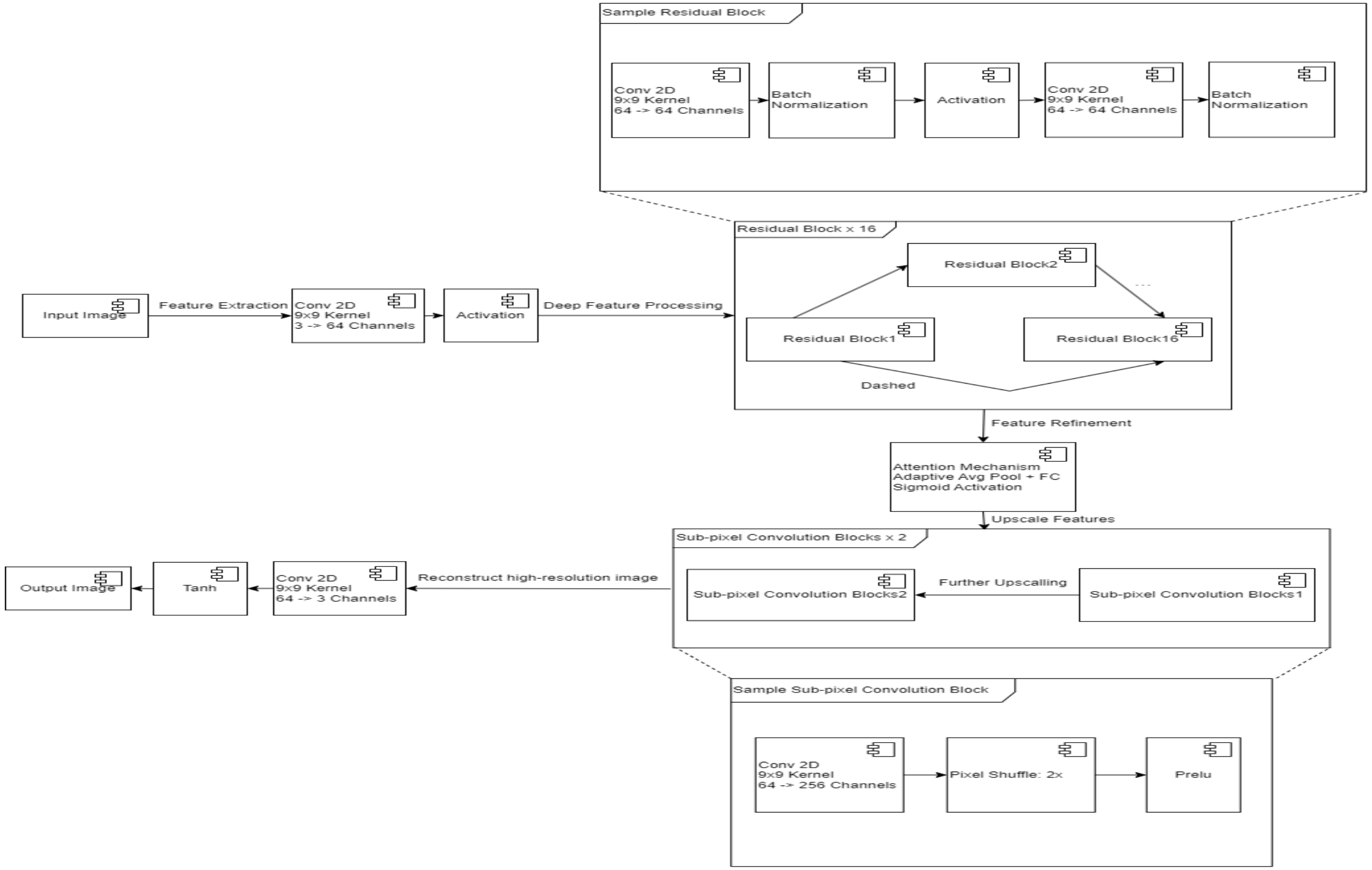

## Overview of SRResNet

Super-resolution network model

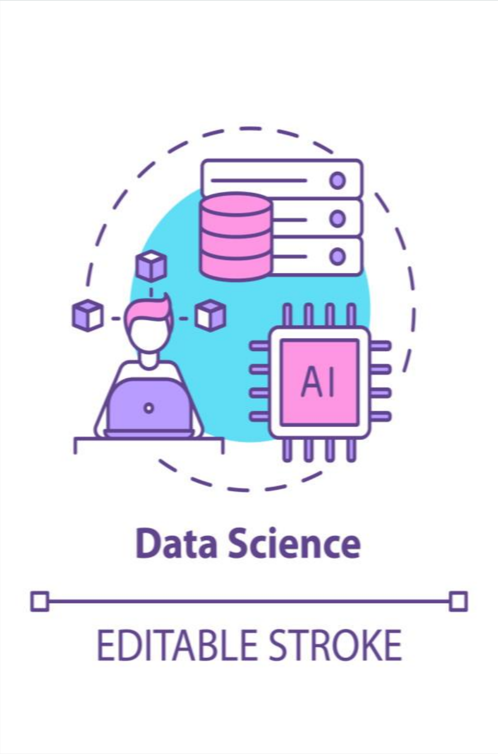
## Attention Mechanisms

Techniques to enhance image detail quality

# Model Structure



# Datasets Used for Training and Testing




## Training Datasets

COCO14, or Common Objects in Context, is a large-scale dataset containing over 200,000 labeled images of everyday scenes.

## Testing Datasets

Set 5, Small dataset for benchmarking SR algorithms.

Set14, Widely used for evaluating SR techniques.

BSDS100,Part of the Berkeley Segmentation Dataset.

# Evaluating and Optimizing Performance

Objective metrics (PSNR, SSIM, MSE).

**Performance Evaluation Methods**

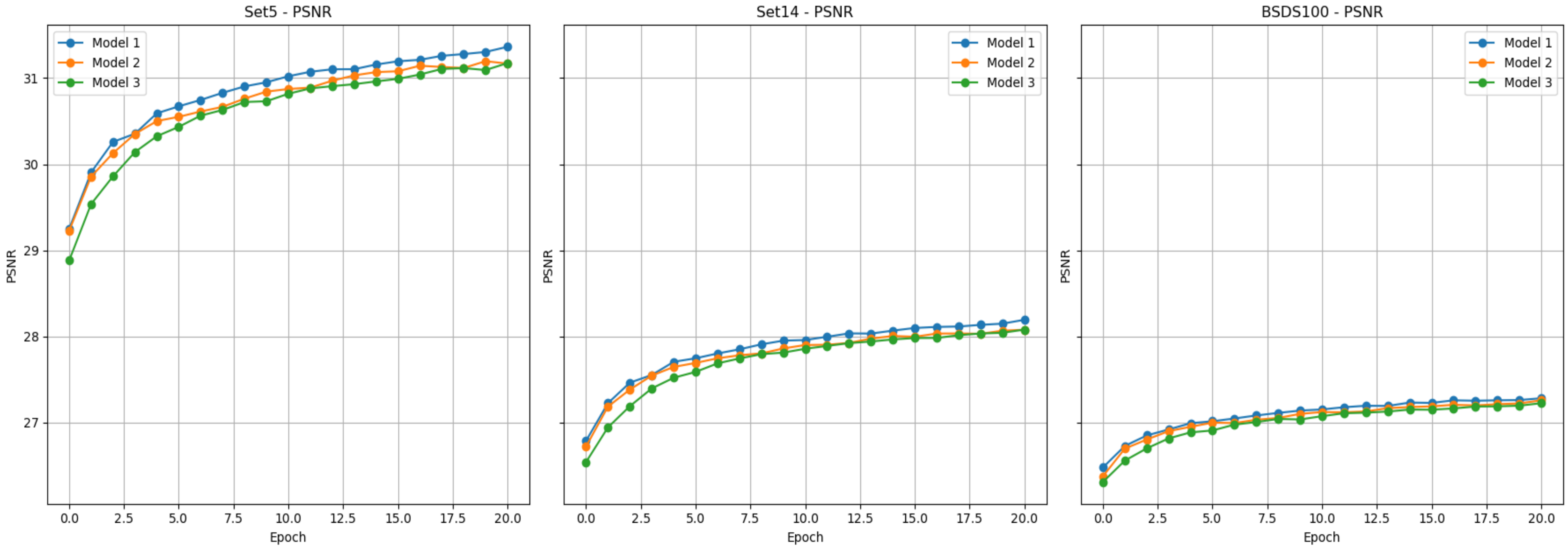
Adjust model parameters and structure.

**Performance Optimization Strategies**

# 03

# Results

# Metrics: PSNR




## Model1

**Crop size:64**

**Batch size: 8**

**Activation: Mish**

## Model 2

**Crop size:64**

**Batch size: 8**

**Activation: Prelu**

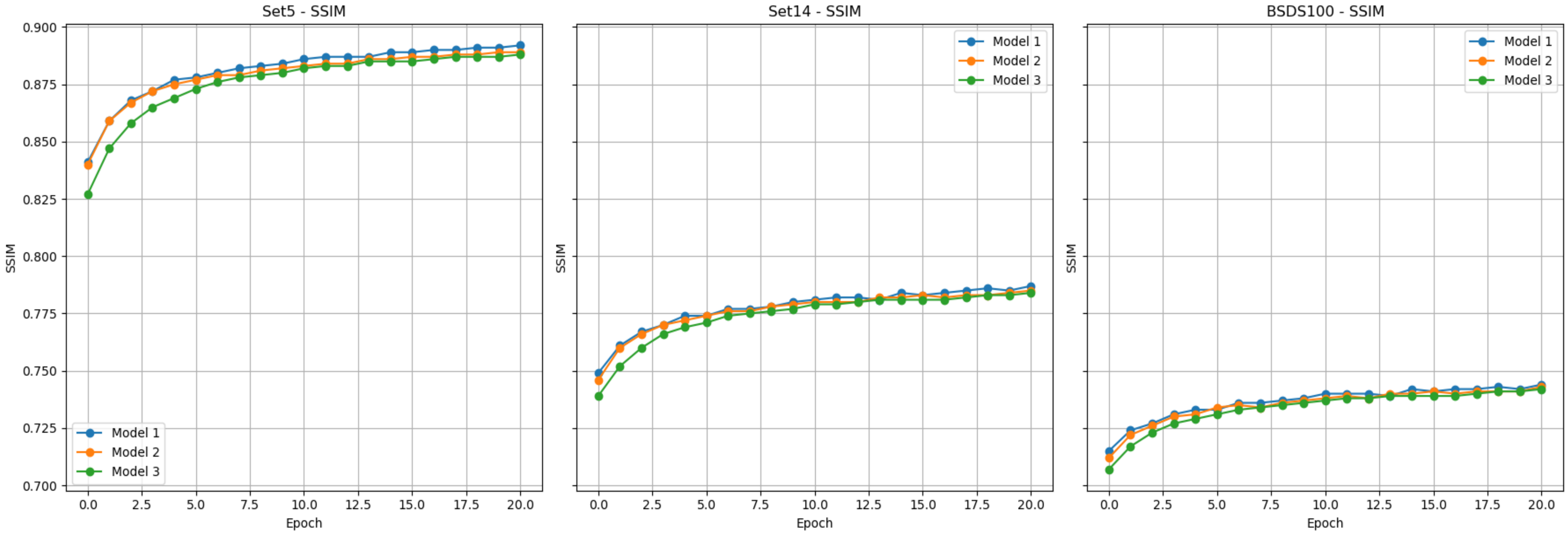
## Model 3

**Crop size: 96**

**Batch size: 16**

**Activation: Prelu**

# Metrics: PSNR




## Model1

**Crop size:64**

**Batch size: 8**

**Activation: Mish**

## Model 2

**Crop size:64**

**Batch size: 8**

**Activation: Prelu**

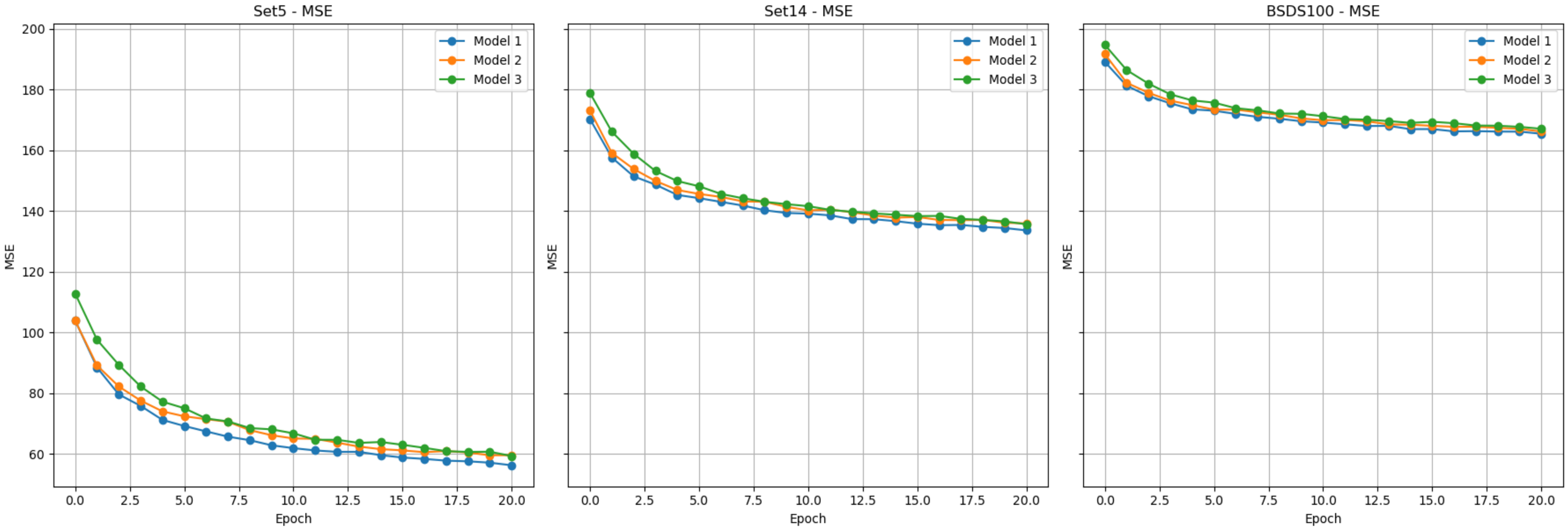
## Model 3

**Crop size: 96**

**Batch size: 16**

**Activation: Prelu**

# Metrics: MSE




## Model1

**Crop size:64**

**Batch size: 8**

**Activation: Mish**

## Model 2

**Crop size:64**

**Batch size: 8**

**Activation: Prelu**

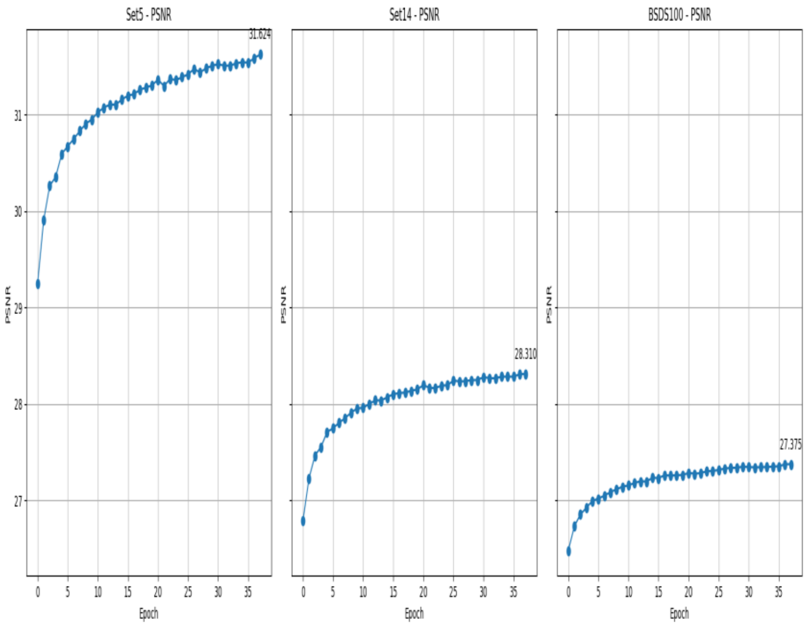
## Model 3

**Crop size: 96**

**Batch size: 16**

**Activation: Prelu**

# Best Parameter

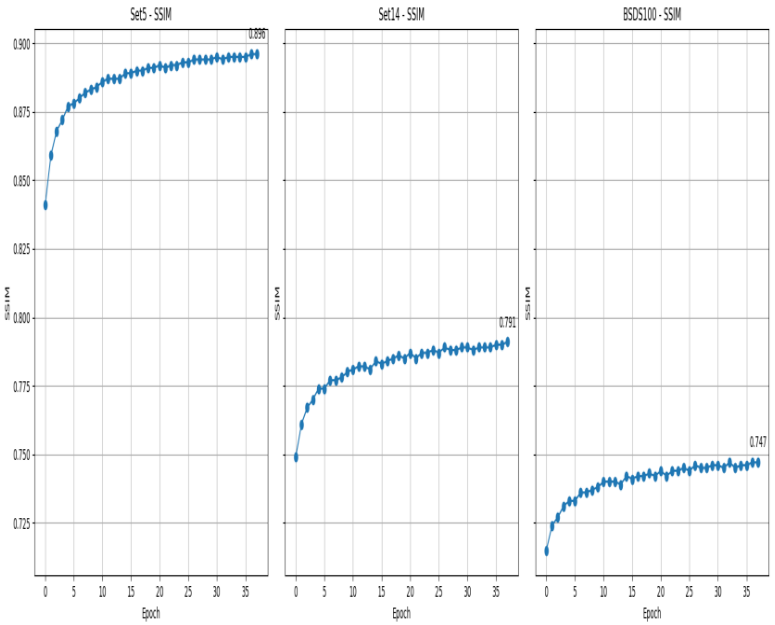



## PSNR (Peak Signal-to-Noise Ratio)

Set 5: 31.624dB

Set 14: 28.310dB

BSDS 100: 27.375dB

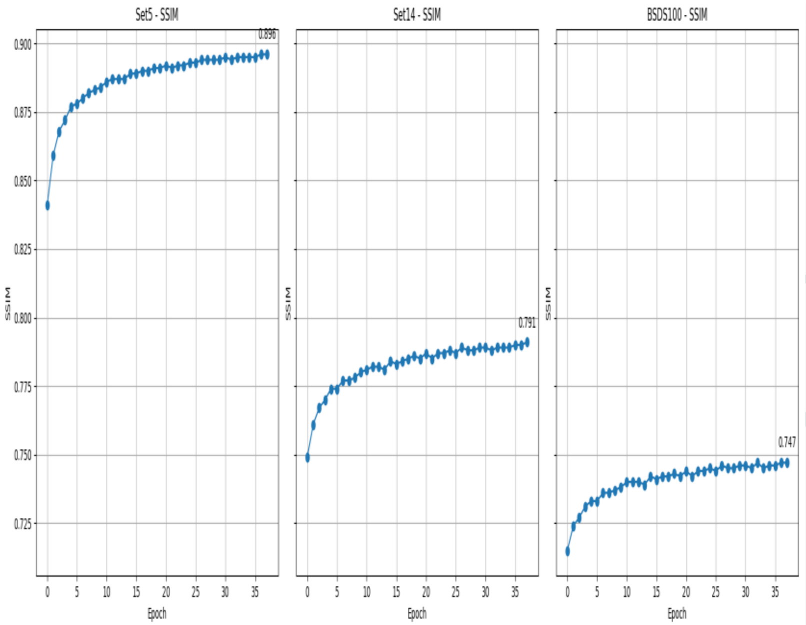



## SSIM (Structural Similarity)

Set 5: 0.896

Set 14: 0.791

BSDS100: 0.747



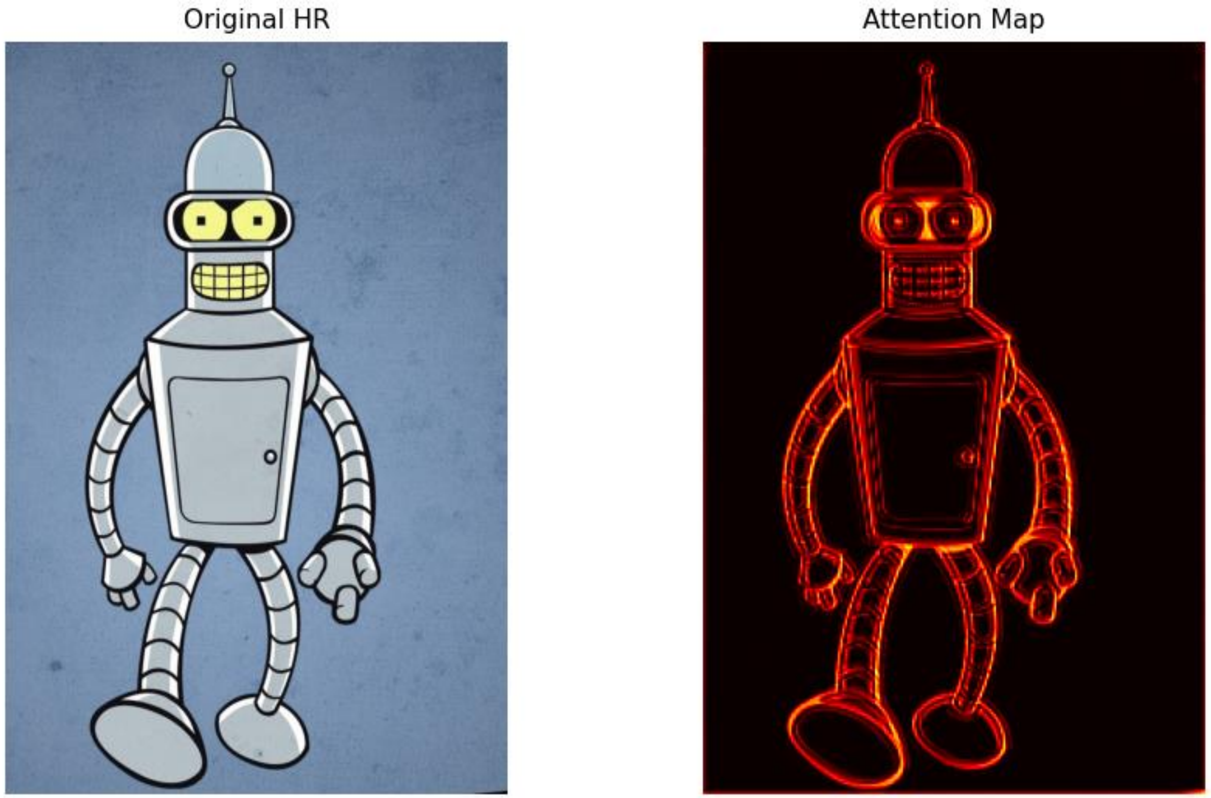

## MSE (Mean Squared Error)

Set 5: 52.860

Set 14: 130.538

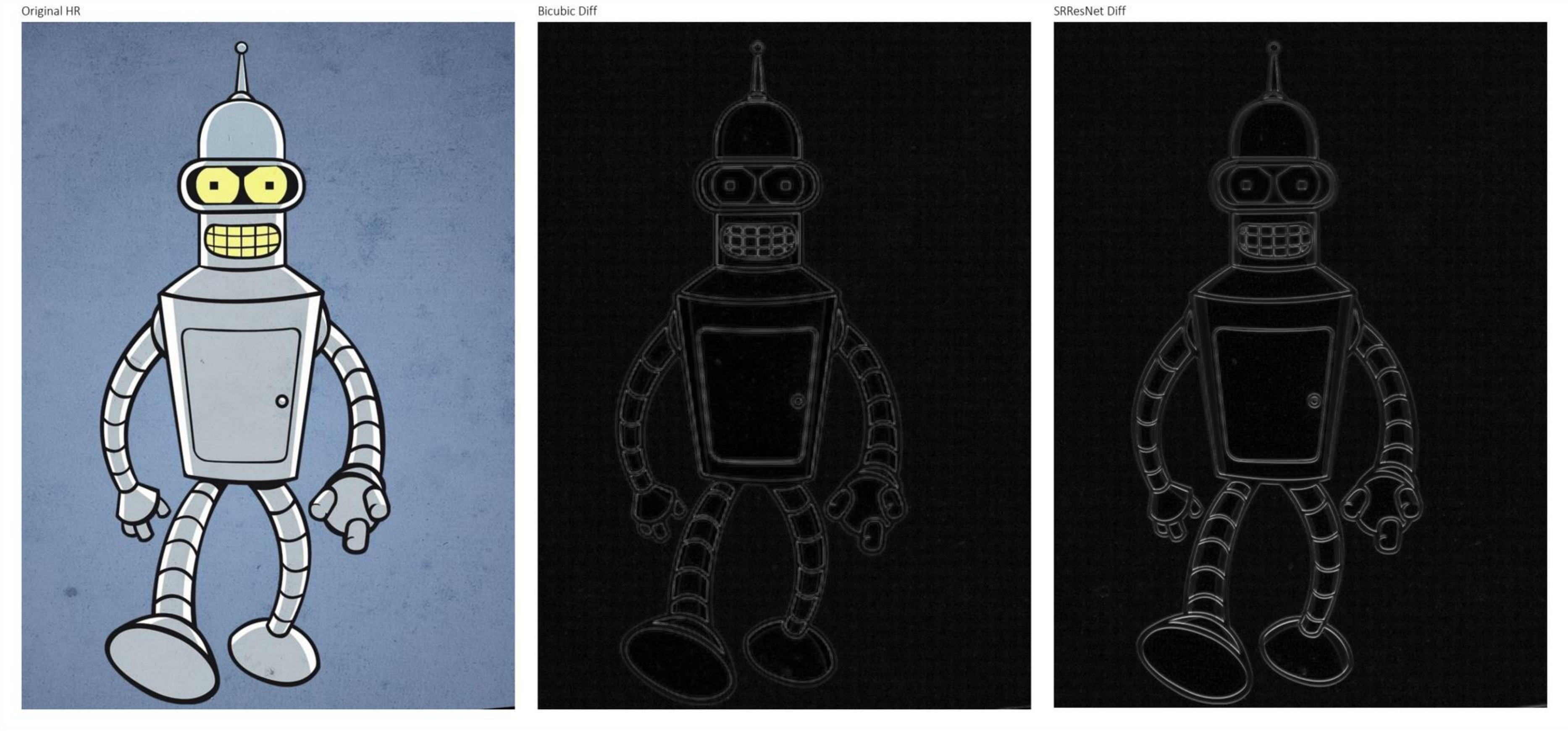
BSDS 100: 162.514

# Attention Map



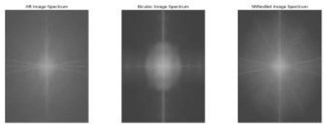

The Attention Map highlights the areas of the image where the model focuses to improve resolution.
It shows which parts of the image the model gives more "attention" to, enhancing the finer details and textures.

# Difference Map



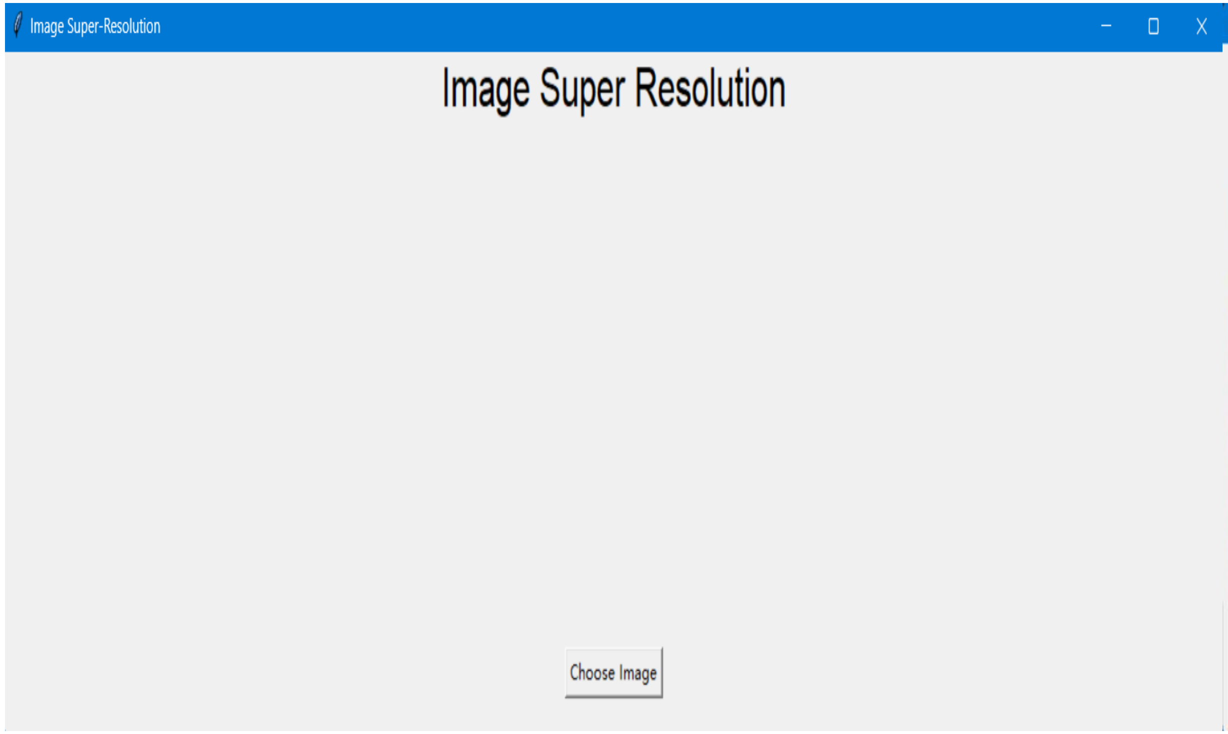

A difference map visually represents the pixel-by-pixel differences between two images. Compared to the bicubic difference map, the SRResNet difference map should have fewer noticeable differences, indicating better performance in preserving the details of the original image.

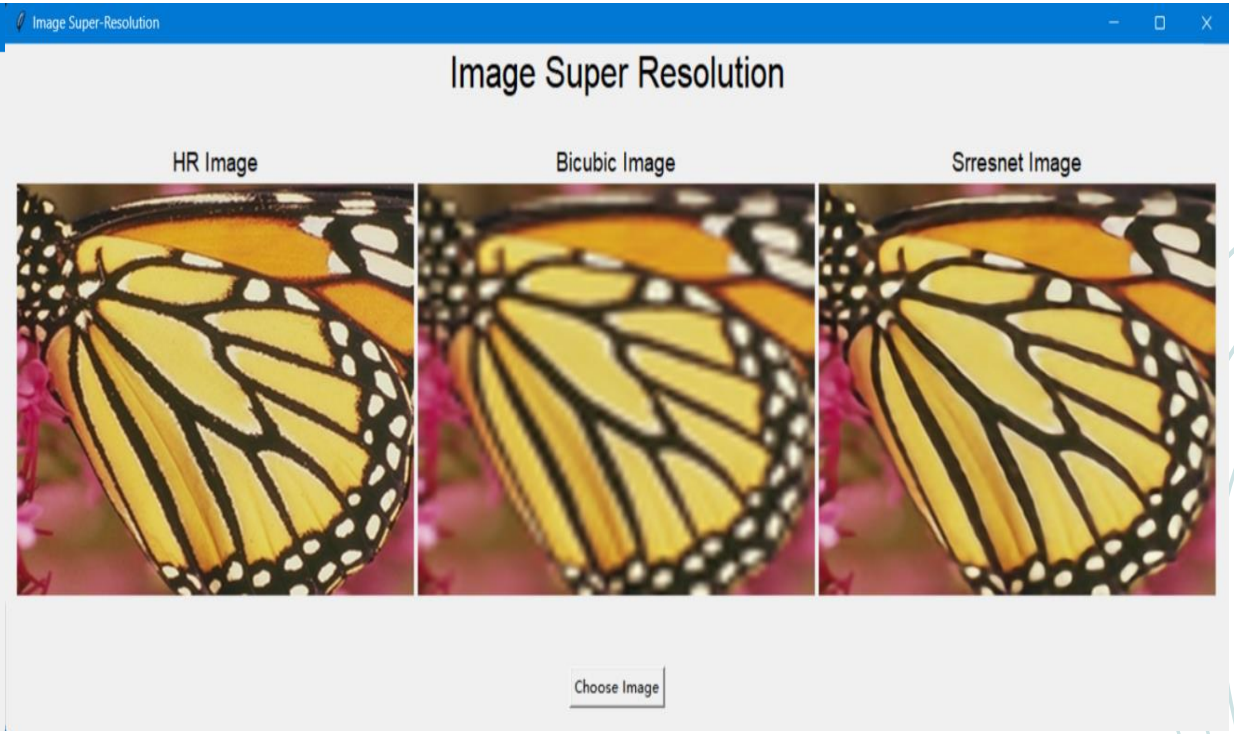
# Spectral Analysis



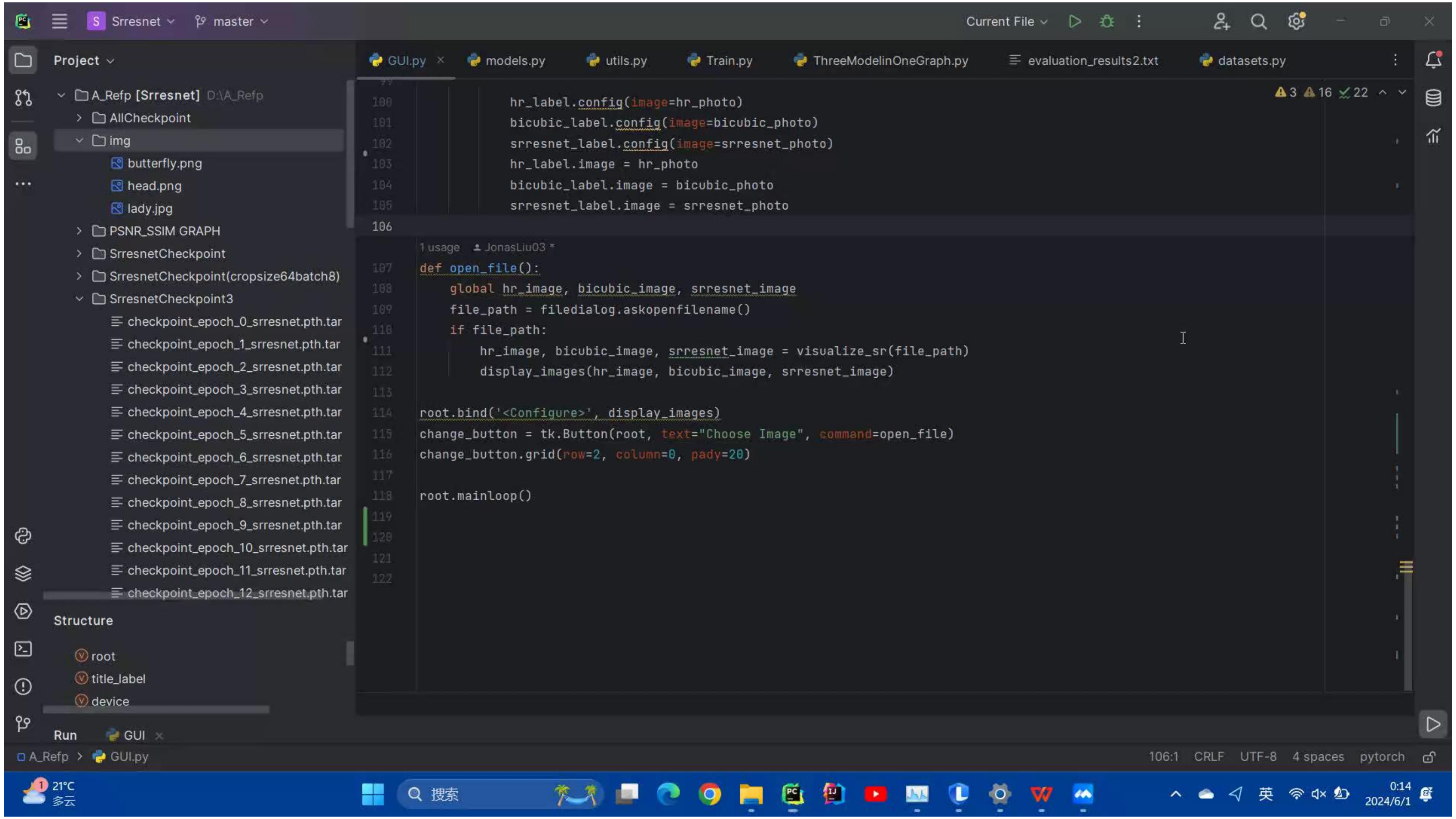

The spectral analysis reveals that SRResNet significantly outperforms bicubic interpolation in image super-resolution. While bicubic interpolation fails to adequately recover high-frequency details, resulting in a blurrier image, SRResNet successfully preserves both low and high-frequency components, closely matching the high-resolution original. This demonstrates SRResNet's superior ability to maintain image details and textures, producing clearer and more detailed super-resolved images.

# GUI Interface



# GUI Interface



# 04

# Conclusion

# Conclusion

The super-resolution model faced challenges in balancing resolution enhancement and artifact risk, generating higher noise levels while improving details, and struggling with high computational demands and complex patterns. Despite these, it outperformed bicubic interpolation in clarity and detail, achieving high PSNR values across datasets like Set5, Set14, and BSD100. Evaluations with MSE, SSIM, and PSNR metrics showed significant advantages. Attention and difference maps highlighted the model's focus on detailed regions, though SSIM scores indicated room for improvement. Spectral analysis showed proficiency in low-frequency detail recovery but challenges with high-frequency noise.

# Thank You