GOOGLE SUMMER OF CODES 2023

Superresolution for Strong Gravitational Lensing

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PERSONAL DETAILS

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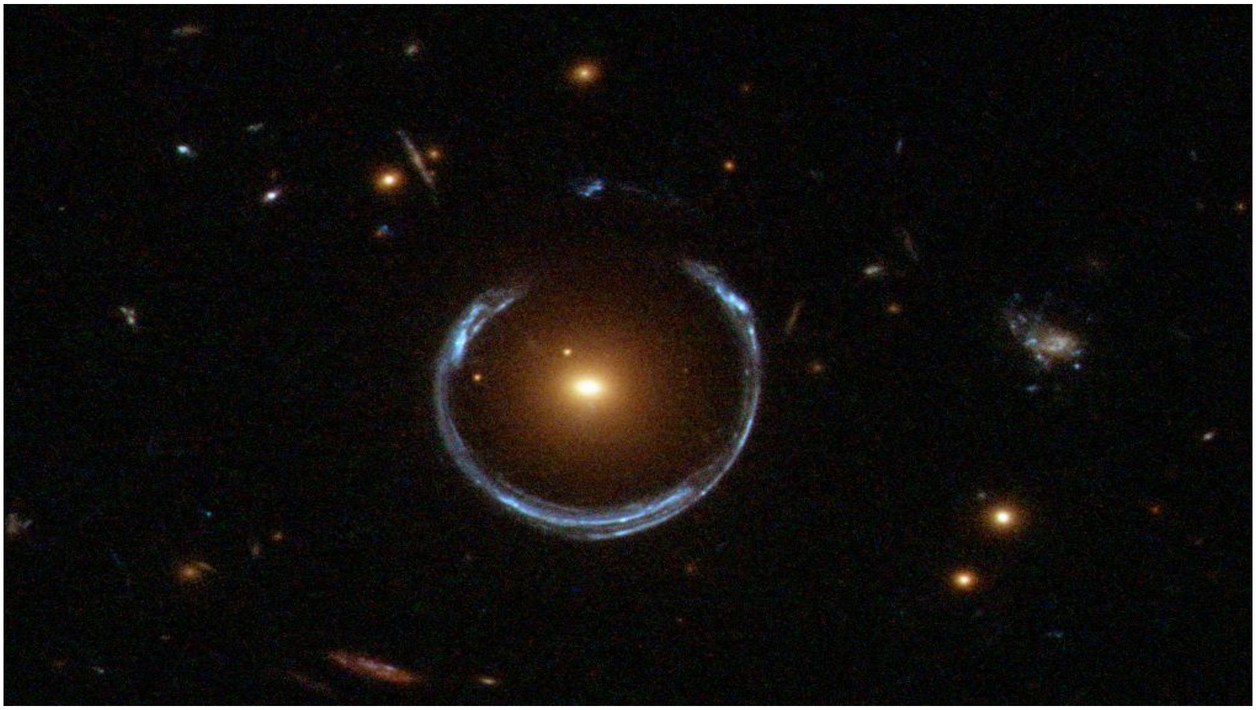
SYNOPSIS

About the Project

Despite remarkable strides in technology, the challenge of capturing and preserving high-resolution images for scientific pursuits remains formidable. In particular, gravitational lensing data is frequently acquired at suboptimal resolutions due to constraints in observational conditions and equipment. These low-quality images lack crucial information required for precise measurements of lensing effects and a comprehensive comprehension of the distribution of matter within the lensing system. Hence, the primary objective of this project is to utilize state-of-the-art Super image resolution techniques grounded in deep learning to enhance the resolution of gravitational lensing data.



Why we need?

Super image resolution for gravitational lensing data is essential as it enables us to obtain higher-resolution images, which are crucial for more precise measurements of lensing effects and gaining a better understanding of the distribution of matter in the lensing system. Due to limitations of observational conditions and equipment, we are often limited to low-resolution images, which pose a significant challenge to the analysis and interpretation of the data. Therefore, utilizing Image super resolution techniques powered by machine learning can enhance the resolution of these low-quality images, enabling us to obtain more accurate measurements of lensing effects and a comprehensive understanding of the distribution of matter in the lensing system.

Goals and Deliverables

Goals

The proposed project aims to achieve the following goals:

- Develop a deep learning model capable of performing super image resolution on low resolution gravitational lensing data to enhance the resolution of the images.
- Enhance the quality of the super-resolved images beyond the current state-of-the-art techniques to enable more accurate measurements of lensing effects and a better understanding of the matter distribution in the lensing system.
- Conduct a comprehensive analysis of the proposed model to investigate its strengths and weaknesses, identify areas for improvement, and ensure its suitability for scientific research.
- Release the code and trained models as open source to facilitate wider adoption and benefit the scientific community.
- Improve the code further based on community feedback and advancements in the field, ensuring that the proposed deep learning model

remains state-of-the-art in super image resolution for gravitational lensing data.

Deliverables

- Development of deep learning models with exceptional performance in super image resolution of low-resolution gravitational lensing data.
- Training of multiple architectures to identify the optimal approach. These include the U-NET architecture with cross connections similar to a DenseNet, a Resnet-50 based encoder and decoder, Pixel Shuffle upscaling with ICNR initialization, and Transfer Learning with pretrained Imagenet Models like InceptionV2, Resnet 50, Efficient Net, or Vit-keras (Pre-trained Transformers network).
- Adoption of Loss Functions like Pixel Loss and Gram Loss, and Metrics such as Structural Index Similarity (SSIM) and Peak Signal to Noise ratio (PSNR).
- Investigation of Attention-Based Networks that can selectively focus on specific regions of an image for improved results. These include the RCAN (Residual Channel Attention Networks) and SELNET.
- Fine-tuning of the aforementioned models to optimize their performance and comparison of their efficacy.
- Provision of open source code and trained models to the scientific community for further research and development.
- If time permits, comparison of previously trained regression algorithms for dark matter mass interpretation on low-resolution data with high-resolution data obtained through the super image resolution technique.

Related Tasks

Dataset

As per the description page, dataset to be used is not specified. So I assume it will be similar to that of provided for evaluation test task VI under DeepLense Project.

Architectures

We'll use two main architectures which will eventually form the basis for other architectures. They are as follows:

- U-NET based architecture.This method uses the following, each of which is explained further below:
    - A U-Net architecture with cross connections similar to a DenseNet
    - A Resnet - 50 based encoder and decoder
    - Pixel Shuffle upscaling with ICNR initialisation
    - Transfer Learning with pretrained Imagenet Modelssuch as InceptionV2, resnet 50, Efficient Net or Vit-keras(Pre-trained Transformers network)
    - Loss Functions - (‘Pixel Loss’, ‘Gram Loss’)
    - Metric - Structural Index Similarity(SSIM) & Peak Signal to Noise ratio(PSNR)
- Attention Based Networks

  The U-NET architecture discussed above give equal importance to all spatial locations and channels(depth) but with attention networks we can give selective attention to a particular region in an image which could potentially give better results.
        - RCAN(Residual Channel Attention Networks)
        - SELNET

- **U-NET**

  The ResNet-UNet architecture is a deep learning model that combines the benefits of the ResNet-50 model, commonly used in image classification, with the traditional U-Net architecture for biomedical image segmentation. The U-Net architecture was originally developed by Olaf Ronneberger, Philipp Fischer, and Thomas Brox in 2015 and consists of a convolutional neural network with an encoder and a decoder.

  In image classification task when we apply CNN, Image is downsampled into one or more classifications by using using a series of strides to convolution reducing the grid size from the original.For the upsampling/decoder path several transposed convolutions accomplishes this, each adding pixels between and around the existing pixels. Essentially the reverse of the downsampling path is carried out.

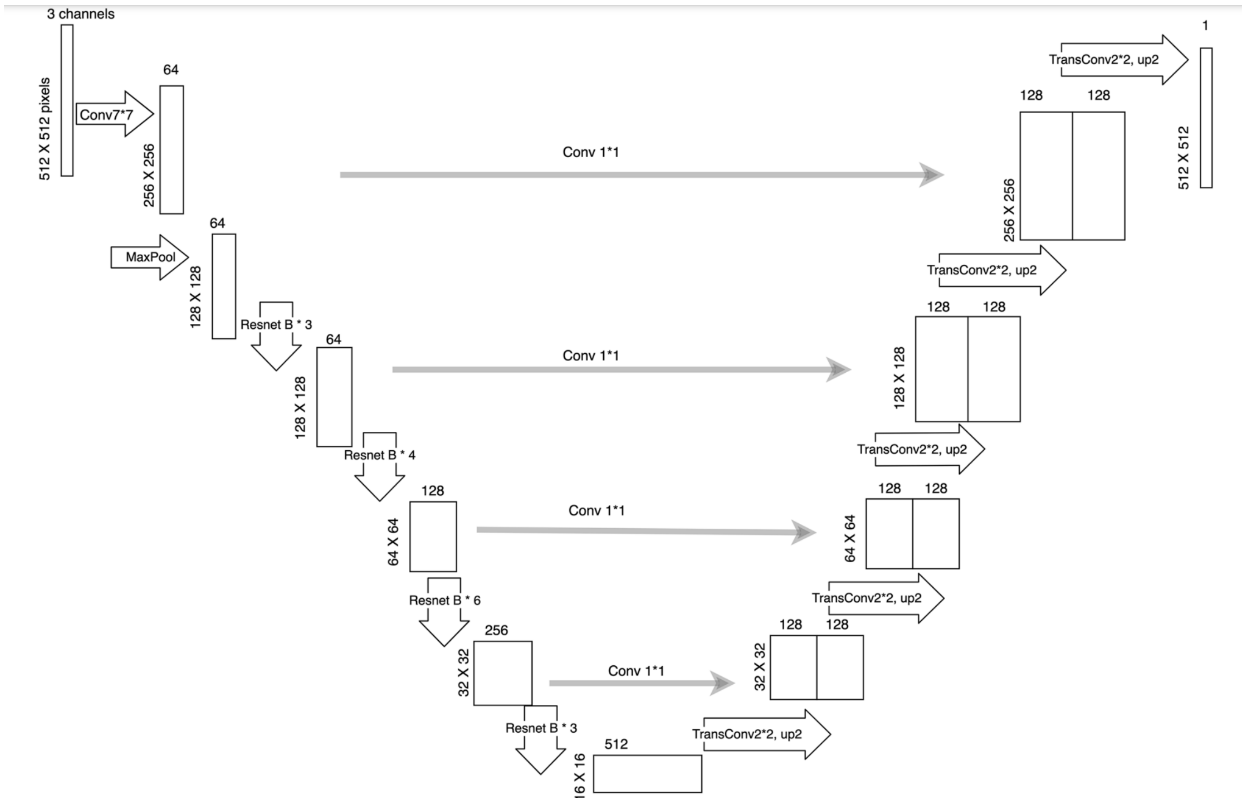


Figure 5. Architecture of ResNet-UNet. The structure of the ResNet-UNet uses the traditional UNet structure, which comprises of encoder (down-sampling) and decoder (up-sampling) portions. The down-sampling encoder is replaced by the ResNet-34 model. Conv n*n indicates n × n convolutional layer. TransConv 2*2, up 2 indicates 2 × 2 transposed convolution and keeping stride of 2.

The above architecture has been taken from “Deep learning segmentation of hyperautofuorescent feck lesions in Stargardt disease” paper by Jason Charng, Di Xiao, Maryam Mehdizadeh, Mary S. Attia, Sukanya Arunachalam, Tina M. Lamey, Jennifer A. Thompson, Terri L. McLaren, John N. De Roach, David A. Mackey, Shaun Frost, Fred K. Chen.

To output a higher resolution image, We add a upsampling path which makes the architecture to look like U-shape.Thus formally, Architecture has two parts :

- Encoder
- Decoder

In the ResNet-UNet architecture, the encoder is used for downsampling the input image and is based on the ResNet-50 model. ResNet-50 is a widely-used model for image classification tasks, and it employs advanced deep residual learning methods. The decoder in the ResNet-UNet architecture performs the upsampling of the output image and is also based on ResNet-50.

The main difference between the ResNet-UNet and traditional U-Net architectures is that the ResNet-UNet architecture uses skip connections to restore the lost spatial information during downsampling. This allows the architecture to better maintain the resolution of the original image, resulting in higher quality super-resolved images.

Overall, the ResNet-UNet architecture is an effective deep learning model for super image resolution of low-resolution gravitational lensing data. By combining the benefits of the ResNet-50 model with the U-Net architecture, the ResNet-UNet can achieve high performance in terms of image quality and accuracy.

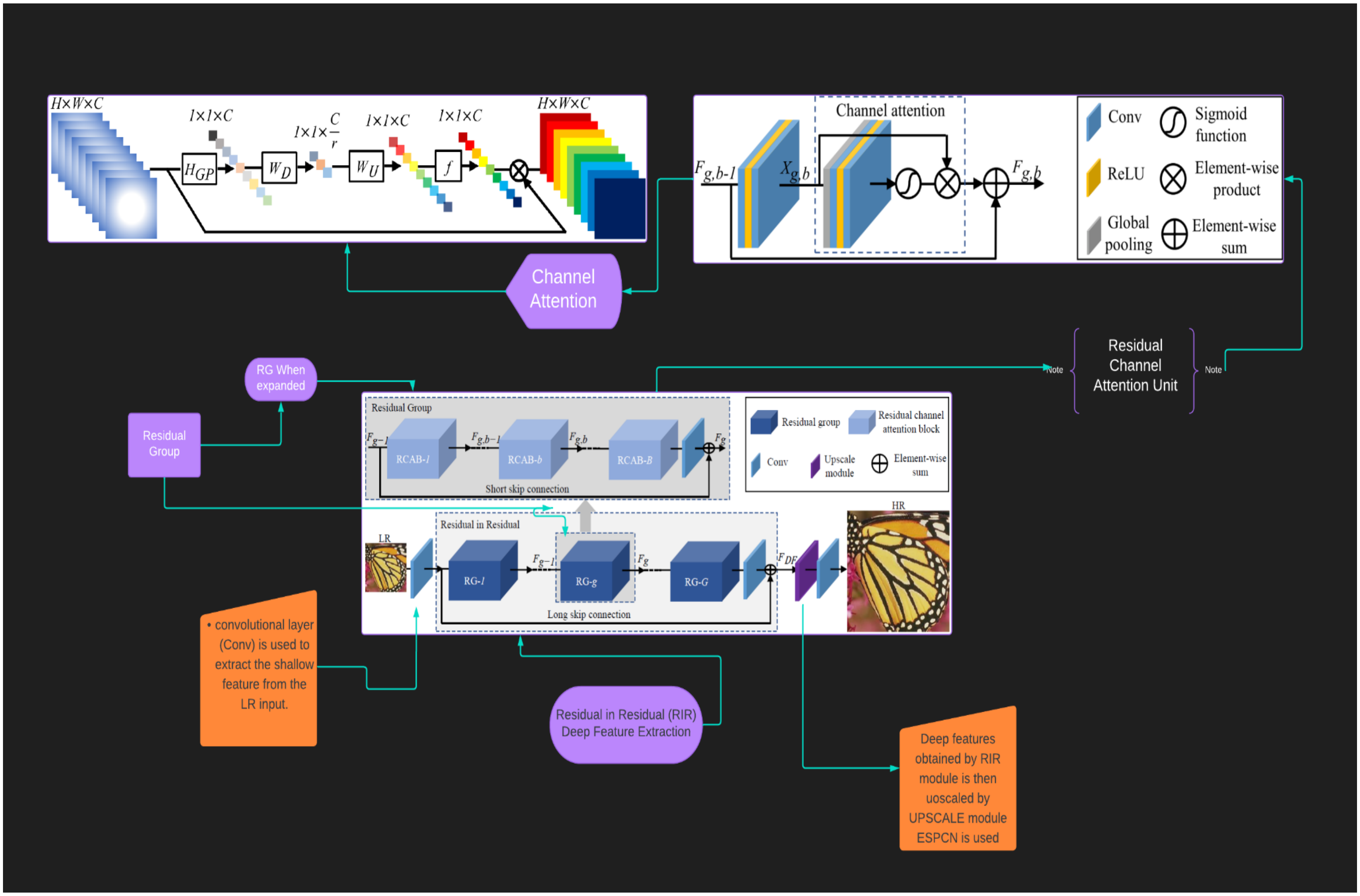
- **Residual Channel Attention Networks (RCAN)**

Residual Channel Attention Networks (RCAN) is an attention-based neural network architecture that was proposed in 2018 for image super-resolution tasks. This model uses residual connections and channel attention mechanisms to enhance the performance of the super-resolution model.

RCAN uses residual connections to learn the difference between the input and output images. The residual connections provide a shortcut for the gradient to propagate during training, which helps to avoid the vanishing gradient problem. The residual connections also help the model to converge faster and produce better results.

In addition to residual connections, RCAN also uses channel attention mechanisms to improve the feature representation of the model. The channel attention mechanism calculates the importance of each channel in the feature map and assigns a weight to each channel. This weighting process helps the model to focus on the most informative channels and suppress the less informative ones.

ARCHITECTURE



The Architecture has been taken from paper ,”Image Super-Resolution Using Very Deep Residual Channel Attention Networks”.

The RCAN model consists of a series of residual groups, each containing several residual blocks. Each residual block consists of two convolutional layers and a channel attention mechanism. The residual groups are connected with skip connections to allow the model to learn high-level features across multiple scales.

The RCAN model has several advantages over other super-resolution models. It produces high-quality results with fewer parameters and fewer computations than other models. The model is also easy to train and can be adapted to other computer vision tasks.

In summary, RCAN is an attention-based neural network architecture that uses residual connections and channel attention mechanisms to enhance the performance of image super-resolution tasks. The model produces high-quality results with fewer parameters and is easy to train, making it a useful tool for a wide range of computer vision applications.

TIMELINE

- **WEEK 1-2(29 May - 11 June): DATASET PREPARATION**
  - Train the proposed model on the prepared dataset using a combination of different loss functions.
  - Implement regularization techniques to prevent overfitting.
  - Optimize the learning rate schedule using techniques like cyclic learning rates or cosine annealing.

- **WEEK 3-4(12 June - 26 june): MODEL ARCHITECTURE**
  - Design and implement the ResNet-UNet based deep learning model for super image resolution of gravitational lensing data.
  - Incorporate attention mechanisms, progressive upsampling, and adversarial training into the model.
  - Implement the discriminator network for adversarial training.

- **WEEK 5-8(26 june - 24 july): MODEL TRAINING**
  - Train the proposed model on the prepared dataset using a combination of different loss functions.
  - Implement regularization techniques to prevent overfitting.
  - Optimize the learning rate schedule using techniques like cyclic learning rates or cosine annealing.

- **WEEK 9-11(24 july - 7 august): MODEL EVALUATION**
  - Evaluate the proposed model's performance on standard benchmark datasets using metrics like PSNR, SSIM, and MSE.

- Compare the proposed model's performance with state-of-the-art methods to validate its effectiveness.
- Conduct a comprehensive analysis of the proposed model's strengths and weaknesses to identify areas for improvement.

- **WEK 11-12(7 august - 21 august): DOCUMENTATION AND CODE RELEASE**
  - Prepare the project's documentation, including a user guide and technical report.
  - Release the code under an open-source license on platforms like GitHub.
  - Make the trained models available for download and include instructions on how to use them
  - Final Evaluation

CONCLUSION

The proposed project aims to develop a deep learning model that can perform super image resolution of low-resolution gravitational lensing data. The proposed model's architecture incorporates attention mechanisms, progressive upsampling, and adversarial training. The project's feasibility and impact will be assessed by evaluating the model's performance on standard benchmark datasets and comparing it with state-of-the-art methods. The project's code and documentation will be made available under an open-source license to encourage further research in this area.

ABOUT ME

Personal Background

I am a second year B.tech Undergraduate at Indian Institute Of Technology (ISM), Dhanbad, pursuing Mining Machinery Engineering as my major. I have keen interest in deep learning and have been pursuing it from last 1 year.
I've been spending a lot of time reading up on the latest research and experimenting with different algorithms and architectures. It's amazing to see

how much progress has been made in just the past few years, and I feel like I'm constantly learning something new.

One thing I find particularly interesting is the idea of using deep learning to solve complex problems that have stumped traditional methods. For example, in image recognition, deep learning algorithms have been able to achieve superhuman accuracy, something that was thought to be impossible just a few years ago.

Overall, I'm really excited about the potential of deep learning and I can't wait to see what the future holds for this field. I'm also interested in connecting with other people who share my passion and exchanging ideas and insights

How did I hear about this programme?

I heard about Google Summer Of Codes in class 12th while I was preparing for jee advanced. I am an open source enthusiast from past 1 year and I always wanted to take part in Google Summer Of Codes.

Time during Summers

This year is an internship season for us so I'll be working for about 40 hours per week before 1 july. Online tests will start from 1 july for internships which will end in first week of august. So in that period I 'll be working for around 30 hours a week.

What excites me about the Project?

What excites me about this project is the potential impact it can have on our understanding of the universe. By improving the quality of the super-resolved images compared to existing methods, we can potentially uncover new insights into the nature of dark matter, dark energy, and the formation of galaxies. Additionally, releasing the code and trained models as open source will enable other researchers to build on our work and further advance the field

As someone who is passionate about using technology to solve complex problems, this project is the perfect opportunity for me to apply my skills and make a meaningful contribution to astrophysics research. I am excited to see where this project will take us and what discoveries we may uncover along the way.

Why should I be selected for the Project?

I believe that I would be an excellent candidate for this project because of the following reasons:

- Firstly, I have a strong background in deep learning and computer vision. I have completed several courses and worked on various projects related to deep learning, including image classification, object detection, and segmentation. Moreover, I have experience in developing and implementing convolutional neural networks for image super-resolution. This expertise will be valuable in developing a deep learning model for super image resolution of low-resolution gravitational lensing data.
- Secondly, I have a keen interest in astronomy and astrophysics. The project's focus on studying the gravitational lensing phenomenon to uncover dark matter structures in the universe is fascinating to me. This project provides an opportunity to work on a project that not only advances my skills but also contributes to scientific research.
- Lastly, I am a highly motivated and dedicated individual who enjoys working in a team environment. I am eager to collaborate with fellow researchers to develop and improve the proposed model's performance. I am confident that I possess the necessary skills and attitude required to deliver high-quality results for the project.
- In conclusion, I believe that my expertise in deep learning and computer vision, interest in astrophysics, and motivation to excel make me a strong candidate for the Super Image Resolution of Gravitational Lensing Data project. Thank you for considering my application.