Google Summer of Code (GSoC) 2023 Project Proposal
Super-Resolution for Strong Gravitational Lensing

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Abstract

Strong gravitational lensing is a promising probe of the substructure of dark matter to better understand its underlying nature. Deep learning methods have the potential to accurately identify images containing substructure, and differentiate WIMP particle dark matter from other well-motivated models, including axions and axion-like particles, cold dark matter etc. Gravitational lensing data is often collected at low resolution due to limitations of the instruments or observing conditions. Image super-resolution techniques can be used to enhance the resolution of these images with machine learning, allowing for more precise measurements of the lensing effects and a better understanding of the distribution of matter in the lensing system. This can improve our understanding of the mass distribution of the lensing galaxy and its environment, as well as the properties of the background source being lensed. This project will focus on the development of deep learning-based image super-resolution techniques to enhance the resolution of gravitational lensing data. Furthermore, we will also investigate leveraging the super-resolution models for other strong lensing tasks such as regression and lens finding.

Keywords: Dark Matter, Strong Gravitational Lensing, ML in Astrophysics, Deep Learning, Image Super-Resolution

I. INTRODUCTION

Strong gravitational lensing is a highly valuable astrophysical phenomenon that has the potential to provide unique insights into the substructure of dark matter, thereby aiding in the comprehension of its underlying nature [1] [2]. Dark matter, which constitutes around 85% of the total matter in the universe, is a significant enigma in modern astrophysics, as it cannot be directly observed due to its non-interaction with electromagnetic radiation. However, its gravitational effects on visible matter and cosmic background radiation can be inferred, making the study of dark matter crucial to understanding the large-scale structure and evolution of the universe.

As a technique that can reveal information about the distribution of dark matter, strong gravitational lensing has the potential to discriminate between various theoretical models, such as weakly interacting massive particles (WIMPs) [3], axions and axion-like particles [4–6], cold dark matter, and others. Strong gravitational lensing occurs when the light from a distant object, such as a galaxy or quasar, is deflected by the gravitational field of a massive object, like a galaxy cluster or an individual galaxy, lying along the line of sight. This results in the creation of multiple, magnified, and distorted images of the background source, which contain valuable information about the lensing system's mass distribution.

Unfortunately, the quality of the data collected through gravitational lensing is often limited by the resolution of the instruments used or the observing conditions. Consequently, this constraint can hinder the extraction of essential information from the lensing data and limit our understanding of the lensing system's properties. Image super-resolution techniques, which involve the enhancement of image resolution using machine learning algorithms [7], can provide a solution to this challenge. By improving the resolution of gravitational lensing data, these methods can enable more precise measurements of lensing effects and lead to a deeper understanding of the distribution of matter in the lensing system.

Deep learning-based image super-resolution methods [7] have shown great promise in addressing the resolution challenge in various domains, such as medical imaging [8], remote sensing [9], and video enhancement [10]. These techniques leverage the power of artificial neural networks, particularly convolutional neural networks (CNNs), to learn high-level features from low-resolution images and generate high-resolution counterparts that exhibit more precise structural details. The application of deep learning-based super-resolution techniques to gravitational lensing data has the potential to significantly improve our understanding of the lensing system's mass distribution and the properties of the background source being lensed.

This research project aims to develop and employ deep learning-based image super-resolution techniques to enhance the resolution of gravitational lensing data. In addition, we will explore the potential applications of these super-resolution models in other strong lensing tasks, such as regression and lens finding.

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II. RELATED WORK

This literature review explores the history and development of deep learning-based super-resolution techniques, followed by their application in astronomy and cosmology, and finally focuses on specific applications in strong lensing cosmology. Through the analysis of various studies, we also highlight the applications of super-resolution and discuss the potential for advancing our understanding of dark matter and its substructure through strong gravitational lensing.

Super-resolution techniques have been studied since the 1980s, initially focusing on non-learning-based methods like frequency domain-based [11], interpolation [12], iterative back-projection (IBP) [13], and regularization-based methods [14] [15]. These methods provided modest improvements in image resolution but were limited by their assumptions about the underlying image formation process. The introduction of deep learning techniques in super-resolution began with the development of sparse coding-based methods in the early 2000s [16]. Sparse coding uses over-complete dictionaries to represent images as a linear combination of a small number of basis functions. Yang et al. (2010) [17] proposed a method called Sparse Representation for Super-Resolution (ScSR), which used sparse coding to generate high-resolution images from low-resolution counterparts. The first deep learning-based super-resolution technique using convolutional neural networks (CNNs) was proposed by Dong et al. (2014) [18] in their seminal work on Super-Resolution Convolutional Neural Networks (SRCNN). SRCNN demonstrated significant improvements over traditional methods, leading to a surge of research in this area. Ledig et al. (2017) [19] introduced Super-Resolution Generative Adversarial Networks (SRGAN), which combined the power of GANs with CNNs to generate high-resolution images. SRGAN offered improvements in perceptual quality by modelling the high-frequency details of images more effectively than previous techniques.

Deep learning-based super-resolution techniques have been applied to enhance the resolution of astronomical images, particularly those obtained from ground-based telescopes affected by atmospheric turbulence. Schawinski et al. (2017) [20] proposed the use of GANs for image enhancement in astronomy, demonstrating the potential of these techniques to recover high-resolution information from low-resolution images. Li et al (2021) [21] developed super-resolution models to enhance low-resolution dark-matter simulations. Deep learning methods have also been applied to classify galaxy morphologies using high-resolution images. Huertas-Company et al. (2018) [22] utilized CNNs to classify galaxy morphologies, achieving a level of accuracy comparable to that of human experts. Alexander et al. (2019) [23] utilized CNNs to classify dark matter models with disparate substructure morphology. Super-resolution techniques can help improve the classification performance by providing higher-resolution inputs for deep learning models. Brehmer et al. (2018) [24] applied CNNs to model strong gravitational lenses, showing that these models can be trained to learn the properties of dark matter halos and the underlying mass distribution. By improving the resolution of the lensing data, super-resolution techniques can lead to more accurate mass distribution models and a better understanding of the lensing system. Super-resolution techniques can also be used to assist in lens finding and regression tasks in strong lensing cosmology. Jacobs et al. (2017) [25] employed CNNs for lens finding and achieved a high degree of accuracy in detecting strong lensing systems. Super-resolution techniques can be leveraged to enhance the input data for such tasks, potentially leading to improved performance in lens finding and regression.

III. PROPOSED METHODOLOGY

This research aims to develop deep learning-based image super-resolution techniques to enhance the resolution of gravitational lensing data. We will explore convolutional neural network (CNN)-based models, residual learning-based models, equivariant neural networks, and diffusion models.

Image super-resolution is a technique used to enhance the resolution of an image by reconstructing a high-resolution (HR) image from a low-resolution (LR) input. Deep learning-based methods have gained popularity in this field due to their ability to learn complex image features and generate high-quality HR images. Several deep learning architectures have been proposed for image super-resolution, including CNN-based models, residual learning-based models, equivariant neural networks, and diffusion models.

Convolutional neural networks (CNNs) have been widely used for image super-resolution tasks due to their ability to capture local and global features in images. Fast Super-Resolution Convolutional Neural Network (FSRCNN) [26] is a lightweight CNN architecture designed for speed and efficiency while still providing good performance. Super-Resolution Residual Network (SR-ResNet) [19] is another CNN-based model that incorporates residual learning to improve image reconstruction. The Super-Resolution Generative Adversarial Network (SRGAN) [19] combines a generator network with a discriminator network, which compete against each other to generate more realistic HR images.

Residual learning-based models incorporate residual connections to improve the flow of information and gradients during training. Enhanced Deep Super-Resolution (EDSR) [27] is an example of such a model that utilizes residual learning to improve the performance of a CNN-based super-resolution model. Residual Dense Network (RDN) [28] is another example, where the model uses densely connected residual blocks to capture more image features and improve image reconstruction.

Equivariant neural networks (ENNs) [29] are designed to preserve certain symmetries in the input data, which can be beneficial for tasks that involve rotation or reflection invariance. ENN-based models have outperformed CNN-based models in tasks such as classification [30], and ENN-based super-resolution models could prove effective in upsampling low-resolution lensed images.

Diffusion models, such as denoising diffusion probabilistic models [31], have been recently proposed for image synthesis tasks, including image super-resolution. These models iteratively refine an input image by applying a series of noise-corrupted gradient steps and learning to reconstruct the target image from the corrupted one. They have shown potential for generating high-quality HR images in a variety of applications [32].

The models will be implemented using deep learning frameworks such as PyTorch [33] and e2cnn [34]. The models will be trained on the preprocessed dataset, and their performance will be evaluated using suitable metrics, such as peak signal-to-noise ratio (PSNR), structural similarity index (SSIM) [35] [36], and mean squared error (MSE). PSNR is a widely-used metric for measuring the quality of reconstructed images. It compares the original high-resolution image with the super-resolved image in terms of the mean squared error (MSE) between pixel intensities. Higher PSNR values indicate better image quality. SSIM measures the similarity between the original and reconstructed images, taking into account luminance, contrast, and structural information. It evaluates the image quality on a scale of -1 to 1, with higher values indicating better image quality and similarity. MSE is a simple metric that calculates the average squared difference between the pixel intensities of the original and reconstructed images. Lower MSE values indicate better image quality.

Furthermore, the networks will be optimized using various cost functions, such as reconstruction loss, adversarial loss, and content loss [37], and appropriate hyperparameters, such as learning rate, batch size, and the number of epochs.

IV. PRELIMINARY RESULTS

In this section, we present preliminary results obtained using a deep learning-based image super-resolution technique, specifically the Residual Dense Network (RDN) model, for enhancing the resolution of strong gravitational lensing data. We discuss the performance of the RDN model in terms of its ability to upscale low-resolution images. To evaluate the effectiveness of the RDN model, we used a dataset of simulated strong gravitational lensing images with no substructure. The dataset included 10,000 low-resolution (LR) (75x75) and high-resolution (HR) (150x150) pairs, where the LR images were downsampled versions of the HR images. A 90/10 split for training and validation sets was used for training the model, whereas a hidden dataset of 2500 image pairs was used for the calculation of the evaluation metrics. Standard image/data processing and analysis libraries, such as NumPy [38], OpenCV [39], Scikit-learn [40], and Scikit-image [41], were employed for data preprocessing and evaluation metrics.

The Residual Dense Network (RDN) is a deep learning-based SR model that has demonstrated state-of-the-art performance on various benchmark datasets [28]. RDN employs a hierarchical architecture consisting of multiple dense connections and residual learning to effectively capture both local and global image features. The dense connections enable efficient feature reuse, while residual learning facilitates the training of deep networks by alleviating the vanishing gradient problem. The deep learning framework PyTorch was used for the implementation of the model, and the training was performed on a Google Colab notebook [42]. The model has been optimized using an adaptive learning rate optimization algorithm like Adam [43] for 100 epochs using the mean squared error (MSE) loss function. Tables I and II show the complete set of hyperparameters. The Model Specific Hyperparameters for the Residual Dense Network (RDN) include the scale factor, which determines the upscaling ratio for the super-resolution task (in this case, a factor of 2 to upscale 75x75 images to 150x150 images). The number of features (32) represents the feature maps in the shallow feature extraction layer, while the growth rate (32) controls the additional feature maps produced by each convolutional layer within a dense block. The model also has a specified number of residual dense blocks (6), each responsible for extracting local features and learning a residual mapping function. Finally, the number of layers (4) within each residual dense block indicates the convolutional layers responsible for extracting local features. These hyperparameters are crucial for determining the performance and complexity of the RDN model, and careful tuning can lead to improved super-resolution performance on the gravitational lensing dataset. While we have focused solely on the MSE loss, for future implementations, we will also explore more complex loss functions such as the VGG-based content loss.

TABLE I: Hyperparameters

Model	RDN
Training Epochs	100
Learning Rate	2e-4
Optimizer	Adam
Loss Function	MSE
LR Scheduler	Cyclic

TABLE II: Model Specific Hyperparameters

Model	RDN
Scale Factor	2
Num Features	32
Growth Rate	32
Num Blocks	6
Num Layers	4

The performance of the trained RDN model will be evaluated on the testing dataset using quantitative metrics such as peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), and mean squared error (MSE). We will also conduct a qualitative assessment of the super-resolved images by visually comparing them to the ground truth HR images and the results obtained from conventional interpolation methods, such as bilinear interpolation. Our preliminary results showed that the RDN model significantly improved the resolution of the strong gravitational lensing images, achieving higher PSNR, SSIM, and lower MSE values compared to the baseline interpolated images. Figure 1 presents some upsampled images and Table III consists of the evaluation metrics. The upsampled images are visually more detailed, with better-defined arcs, allowing for a more accurate analysis of the lensing system.

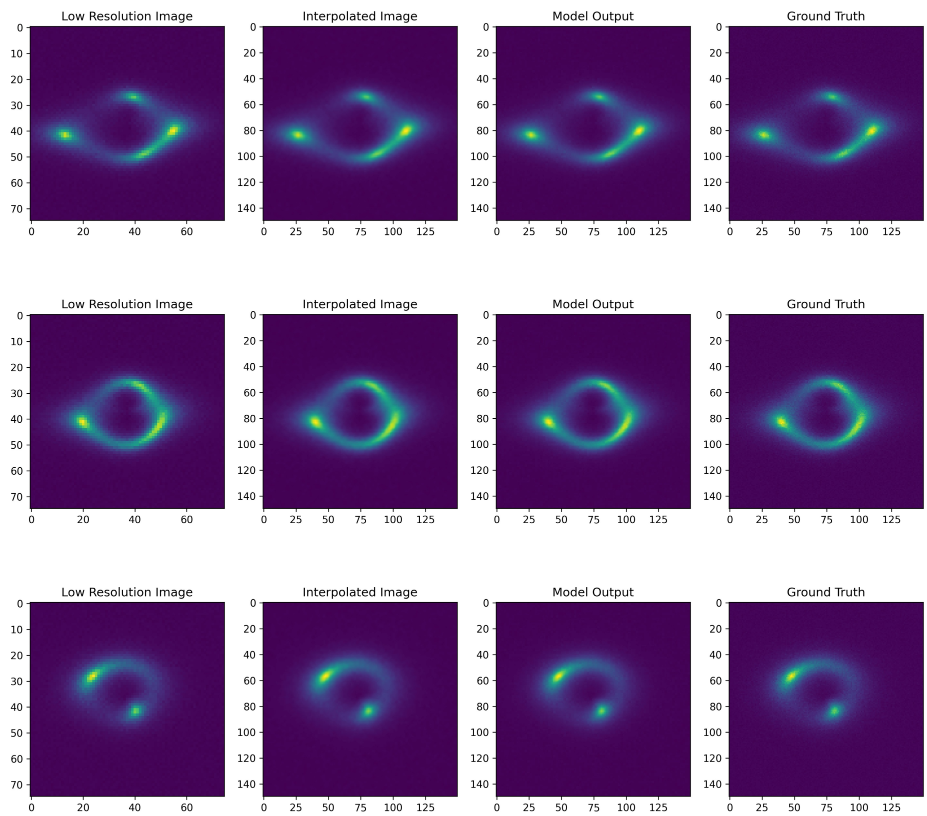

FIG. 1: Selected samples of low resolution images (Column-1), interpolated images (Column-2), RDN model super-resolution outputs (Column-3), and the original ground truth images (Column-4)

TABLE III: Evaluation Metrics

Metric	RDN	Bilinear Interpolation
MSE	0.00006	0.00007
SSIM	0.97678	0.97297
PSNR	42.36252	41.6783

V. TIMELINE

We present a brief project timeline. Tables IV and V in the appendix contains a 12-week project schedule for the summer.

VI. CONCLUSION

Preliminary analysis of the test dataset shows promising results, and the successful completion of this project will result in the development of deep learning-based image super-resolution techniques specifically designed for gravitational lensing data. These techniques are expected to significantly improve the resolution of lensing images, allowing for more precise measurements of the lensing effects and a better understanding of the distribution of matter in the lensing system. Furthermore, the project will investigate the potential applications of the super-resolution models in other strong lensing tasks, such as regression and lens finding. This could lead to improved performance in these tasks, ultimately contributing to a deeper understanding of the properties of dark matter and its distribution in the universe.

In conclusion, this project aims to address the challenges associated with low-resolution gravitational lensing data by developing and applying deep learning-based image super-resolution techniques. The outcomes of this project have the potential to significantly enhance our understanding of the mass distribution of lensing galaxies, their environments, and the properties of the background sources being lensed, ultimately providing valuable insights into the nature of dark matter and the large-scale structure of the universe. Furthermore, this project represents a timely and significant effort to harness the power of deep learning for enhancing the resolution of strong gravitational lensing data, with the potential to advance the state-of-the-art in the field and contribute to a deeper understanding of the fundamental nature of dark matter.

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Appendix A: Timeline

TABLE IV: Project Schedule

Duration	Deliverables
Week 1	**Literature Review and Familiarization** 1. Study previous work on strong gravitational lensing and image super-resolution techniques 2. Review popular deep learning models and architectures for image super-resolution, including FSRCNN, SRResNet, SRGAN, EDSR, RDN, equivariant neural networks, and diffusion models 3. Familiarize with the dataset, tools, and libraries necessary for the project
Week 2	**Dataset Preparation and Preprocessing** 1. Collect and curate gravitational lensing data from various sources 2. Preprocess the dataset: data cleaning, normalization, and augmentation 3. Split the dataset into training, validation, and testing sets
Week 3	**Model Selection and Baseline Models** 1. Choose a suitable CNN-based model as the baseline (e.g., FSRCNN) 2. Implement and train the baseline model on the prepared dataset 3. Evaluate baseline model performance using appropriate metrics (e.g., PSNR, SSIM)
Week 4	**Implementing Advanced Models** 1. Implement and train the SRResNet, SRGAN, EDSR, and RDN models on the dataset 2. Compare their performance with the baseline model 3. Analyze the strengths and weaknesses of each model
Week 5	**Equivariant Neural Networks** 1. Investigate equivariant neural networks for image super-resolution 2. Implement and train the chosen models on the dataset 3. Evaluate their performance and compare them with other models
Week 6	**Diffusion Models** 1. Investigate diffusion models for image super-resolution 2. Implement and train the chosen models on the dataset 3. Evaluate their performance and compare them with other models
Week 7	**Model Optimization and Hyperparameter Tuning** 1. Perform hyperparameter tuning and optimization for the best-performing models 2. Identify and address potential issues related to overfitting, underfitting, or convergence 3. Evaluate the optimized models using the validation set
Week 8	**Model Evaluation and Comparison** 1. Evaluate the performance of all models on the test set 2. Compare the models using appropriate metrics and visualizations 3. Identify the best-performing model for the given dataset and task

TABLE V: Project Schedule (Contd.)

Duration	Deliverables
Week 9	**Leveraging Super-Resolution Models for Other Lensing Tasks** 1. Investigate the potential of using super-resolution models for regression and lens finding tasks in strong gravitational lensing 2. Modify the best-performing super-resolution model to adapt it to the new tasks 3. Train and evaluate the modified model on appropriate datasets for regression and lens finding
Week 10	**Real-World Application** 1. Integrate the best-performing model into a suitable software framework for gravitational lensing analysis 2. Test the integrated model on real-world data and perform any necessary fine-tuning 3. Explore Domain Adaptation if necessary
Week 11	**Documentation and Testing** 1. Write comprehensive documentation for the developed models, including usage instructions, implementation details, and performance metrics 2. Conduct thorough testing to ensure the model's robustness and reliability 3. Address any identified issues or bugs
Week 12	**Finalizing and Submission** 1. Prepare a project presentation highlighting the project's objectives, methods, results, and conclusions 2. Write a detailed project report summarizing the entire project, including methodology, results, and future work 3. Review the entire project, including code, documentation, presentation, and report 4. Address any last-minute issues, improvements, or fixes 5. Submit the final project deliverables to Google Summer of Code (GSoC)