# Low-Signal to Noise Astronomical Image Upscaling via Deep Learning

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## ABSTRACT

Often when photographing objects in deep space, astronomers are limited by the amount of light that can be collected from these distant, often extremely dim objects. This results in images with low a signal-to-noise ratio, making it difficult to analyze the morphology, or shape, of these objects. Similarly, as technology improves, previous cutting edge survey data becomes outdated, and images taken with older instruments are often of lower resolution and quality compared to modern images. Being able to enhance these low signal-to-noise, low-resolution images to higher signal-to-noise, higher-resolution images is extremely valuable for astronomers, as it gives even more information for an extremely data hungry field, and allows for more data to be extracted from telescopes in the same amount of time. In this paper, I explore the use of deep learning techniques to enhance low signal-to-noise, low-resolution images of galaxies to higher signal-to-noise, higher-resolution images. I find that deep learning-based image upscaling methods significantly outperform traditional interpolation methods such as Nearest Neighbor, Bilinear, Bicubic, and Lanczos resampling, scoring an average of 85% classification accuracy on morphological classification tasks, compared to 80% for the best traditional method.

*Keywords:* Galaxy Morphology, Deep Learning, Image Upscaling, Super-Resolution, Astronomy

## 1. INTRODUCTION

Astronomy is unique among the sciences in that it is almost entirely observational; unlike other sciences, astronomers often cannot conduct controlled experiments to test hypotheses. Outside of the few objects in our solar system, for all intents and purposes, astronomers are limited to observing distant objects from Earth. With the technological advancments over the past few centuries, however, we have been able to capture a massive amount of data about the universe, particularly in the form of images taken by telescopes.

By studying these images, we can learn more about the formation and evolution of various celestial objects, such as galaxies, nebulae, and star clusters. However, this incredible amount of data is also a curse; with so many images to analyze, it is impossible for human astronomers to manually classify and study each object. Machine Learning techniques have been increasingly used in recent years to help automate the process of classifying and analyzing astronomical images.

Astronomers have strong incentives to take advantage of every bit of recorded data, as telescope time is extremely limited and expensive. Thus, being able to enhance low-quality images that have already been taken is exteremely valuable. This project explores the use of deep learning techniques to enhance low signal-to-noise, low-resolution images of Deep Space Objects (DSOs), specifically galaxies, to higher signal-to-noise, higher-resolution images that can be more easily analyzed and classified.

In this project, I evaluate the performance of various image upscaling methods at supporting morphological classification of galaxies, using labels from the GalaxyZoo dataset. In addition, I train a Convolutional Neural Network (CNN) based on the Enhanced Deep Super-Resolution (EDSR) architecture to perform image upscaling, and compare its performance to traditional interpolation methods such as Nearest Neighbor, Bilinear, Bicubic, and Lanczos resampling. Finally, I evaluate the performance of these methods on both artificially generated low signal-to-noise images and real world low signal-to-noise images from the Digitized Sky Survey (DSS).

The rest of this paper is organized as follows: Section 2 defines the problem being addressed in this project. Section 3 describes the various algorithms used in this project. Section 4 describes the datasets used for training and evaluation. Section 5 presents the results of the experiments conducted. Section 7 discusses related work in this area. Finally, Section 8 concludes the paper and suggests future work.

## 2. PROBLEM DEFINITION

When photographing Deep Space Objects (DSOs) such as galaxies, nebulae, and star clusters, astronomers often face the challenge that, from Earth, these objects are relatively dim and small. This results in images with low signal-to-noise ratios and low resolution, making it difficult to analyze the morphology of these objects. Signal-to-noise ratio is a metric measuring the strength of the desired signal (in this case, the object being photographed) relative to the noise from background or instrucmental sources. Increasing the signal-to-noise ratio and resolution of these images is crucial for accurate classification and study of DSOs.

Traditionally, there are three main methods for increasing the signal-to-noise ratio of images:

- **Using Larger Apetures**: By using telescopes with larger apertures, more light from the DSO can be collected, overpowering random noise. However, this method is often limited by the availability and cost of larger telescopes, and modern telescopes are reaching the phyiscal limit of lens manufacturing.

- **Longer Exposure Times:** By increasing the exposure time of the camera, more light from the DSO is collected, reducing the impact of noise. However, this method is limited by factors such as Earth's rotation, atmospheric conditions, and the availability of telescope time. Ground-based telescopes also face challenges relating to airplane traffic, weather conditions, and satellite interference.

- **Stacking Multiple Images:** Taking multiple shorter-exposure images and stacking them can also improve the signal-to-noise ratio. This method averages out random noise while preserving the signal from the DSO. However, it requires precise alignment of images, is computationally intensive, and still requires significant telescope time.

This project is intended to explore using deep learning techniques to take low signal-to-noise, low-resolution images of DSOs and upscale them to higher signal-to-noise, higher-resolution images. This is a very active area of research, and astronomy is particularly well-suited to benefit from these techniques due to the large amount of image data available from various sky surveys.

## 3. ALGORITHM DEFINITIONS

This section will define the various algorithms used or referenced in other sections of this paper.

### 3.1. *Traditional Image Upscaling Methods*

Traditional image upscaling methods are techniques that transform a low-resolution image into a higher-resolution image using only the information contained in the image itself; there is no training dataset or machine learning involved.

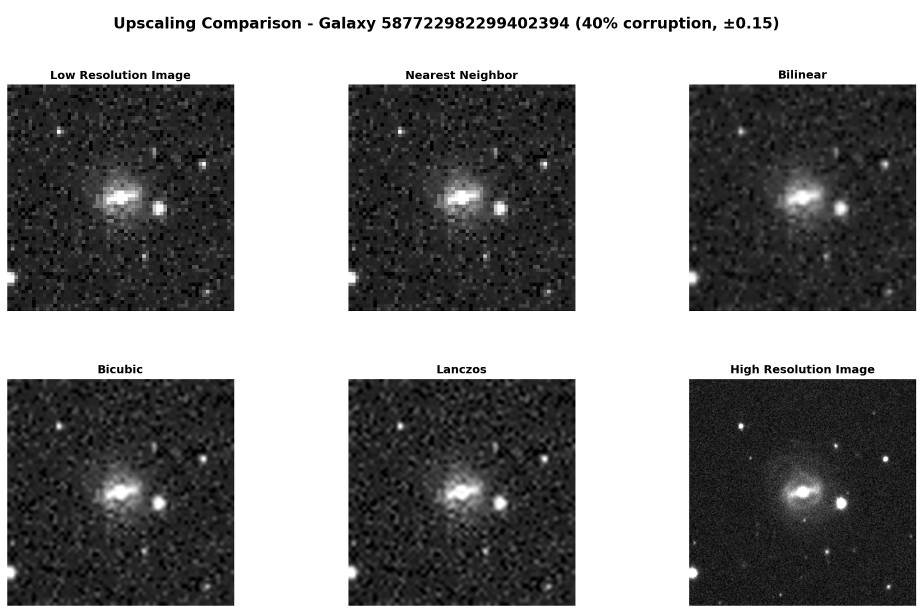


**Figure 1.** A comparison of different traditional upscaling methods on an image of a galaxy.

#### 3.1.1. *Nearest Neighbor Interpolation*

**Nearest Neighbor Interpolation** is arguably the simplest image upscaling method, where each pixel in the high-resolution image is assigned the value of the pixel nearest to its position in the low-resolution image. A 4x image upscaling would effectively turn each pixel in the low-resolution image into 4 pixels in the high-resolution image(R. C. Gonzalez & R. E. Woods 2018).

Nearest Neighbor is exteremely fast and simple, but it produces blocky, low-quality images that are not suitable for most applications.

### 3.1.2. *Bilinear Interpolation*

**Bilinear Interpolation** improves on Nearest Neighbor by averaging the values of the nearest pixels in the low-resolution image to determine the value of their corresponding pixels in the high-resolution image. Specifically, for each pixel in the high-resolution image, the four nearest pixels in the low-resolution image are identified, and their values are weighted based on their distance to the target pixel. The resulting weighted average is then assigned to the target pixel(R. C. Gonzalez & R. E. Woods 2018).

This results in smoother images compared to Nearest Neighbor, but harsh edges and fine details are often oversmoothed and lost.

### 3.1.3. *Bicubic Interpolation*

**Bicubic Interpolation** is very similar to Bilinear Interpolation, but instead of using the four nearest pixels, it uses the sixteen nearest pixels to calculate the value of each pixel in the high-resolution image. This further improves the smoothness and quality of the upscaled image, preserving more details and reducing artifacts compared to Bilinear Interpolation (R. Keys 1981).

However, it is also more computationally intensive than Bilinear Interpolation, and still often fails to recover fine details in images with complex textures.

### 3.1.4. *Lanczos Resampling*

**Lanczos Resampling** is a more advanced interpolation method that uses a sinc function to weight the contributions of surrounding pixels when calculating the value of each pixel in the high-resolution image. Lanczos Resampling generally produces higher-quality images compared to Bicubic Interpolation, particularly for images with sharp edges and fine details. However, it is also even more computationally intensive C. Lanczos (1938).

For this project, Lanczos resampling is potentially the best traditional method to compare against, as it generally produces the highest quality images among traditional interpolation methods. It also acts as edge-enhancement, which is useful for morphological classification of galaxies.

## 3.2. *Deep Learning*

Deep Learning has been used extensively in image processing tasks, and super-resolution (image upscaling)/denoising is a well-studied application of deep learning techniques.

#### 3.2.1. *Convolutional Neural Networks*

For this project, the deep learning method used is a **Convolutional Neural Network** (CNN). CNNs differ from typical neural network in that they include convolutional layers, where nodes only receive input from a subset of the nodes in the previous layer, as defined by a kernel. This allows CNNs to capture information relating to the relative proximity of pixels/features in an image, which is extremely useful for image processing tasks (Y. LeCun et al. 1989).

In particular, the CNN used in this project is based on the **Enhanced Deep Super-Resolution** (EDSR) (B. Lim et al. 2017) architecture, which has been shown to perform very well on image super-resolution tasks. EDSR is characterized by its use of residual blocks, where the model learns the difference between the input and output images, then adds this difference to the input image to produce the final output.

The specific architecture used in this project is:

- The input image is copied and upscaled using Bilinear Interpolation to the target resolution (4x), and the copy is put aside.
- Inital Convolutional Layer: 64 nodes with a kernel size of 5, meaning each node receives input from a 5x5 pixel area of the previous layer. A ReLu activation function is applied.
- 12 Residual Blocks: Each block contains two convolutional layers with 64 nodes and a kernel size of 3, with ReLu activation functions applied after each layer.
- After the residual blocks, a skip connection adds the output of the inital convolutional layer to the output of the residual blocks.
- Upscaling Layer: A convolutional layer that takes 64 node from the previous layer, and outputs 256 nodes, with a kernel size of 3.
- PixelShuffle Layer: This layer rearranges the output of the previous layer to increase the spatial resolution by a factor of 4, using the PixelShuffle technique (W. Shi et al. 2016).
- Convolutional Layer: A convolutional layer that takes 64 nodes from the previous layer, and outputs 32 nodes, with a kernel size of 3 and a ReLu activation function.
- Convolutional Layer: A convolutional layer that takes 32 nodes from the previous layer, and outputs 16 node with a kernel size of 3 and ReLu activation function.
- Output Layer: A final convolutional layer that takes 16 nodes from the previous layer, and outputs a single channel image with a kernel size of 3. The result it combined with the bicubic upscaled input image to produce the final output.

For the loss function, a combination of Mean Squared Error and L1 loss was used, to balance between minimizing large errors and preserving fine details. Initally, only Mean Squared Error was used, but the models tended to produce uniform gray images, rather than learning the features of the images. Adding L1 loss helped encourage the model to preserve more details.

$$F_{loss}(x) = 0.6 * l1 + 0.4 * MSE$$

I also experimented with Perceptual Loss, using a pre-trained VGG network to compute the loss based on high-level features, but this did not significantly improve performance. I suspect that this is due to the fact that VGG is trained on images of everyday objects, and presumably galaxies do not share many features with these objects.

### 3.3. *Classification*

The end goal of this project is to support classification of galaxies based on their morphology, using labels from the GalaxyZoo dataset.

For this project, a **Random Forest** classifier is used. Random Forest was chosen due to its relative simplicity and strong performance for image classification tasks, and because it is less computationally intensive than deep learning-based classifiers (L. Breiman 2001).

## 4. DATA

The data used in this project is sourced from three main datasets:

- **GalaxyZoo Dataset:** The GalaxyZoo dataset contains morphological information on over a million galaxies, classified by thousands of volunteer scientists. This dataset provides coordinates and labels for galaxies that can be cross-referenced with other datasets.

- **Sloan Digital Sky Survey (SDSS):** The SDSS provides a massive repository of astronomical images, taken from ground-based telescopes. The SDSS images can be queried through their SkyServer API using coordinates from the GalaxyZoo dataset to obtain images of the galaxies in different wavelengths of light. For the purposes of this project, these images served as the high signal-to-noise, high-resolution ground truth images.

- **Digitized Sky Survey (DSS):** The DSS is an older sky survey from the 1950s, which was photographed using physical plates. The DSS images are generally lower quality than the SDSS images, and thus serve as the real world low signal-to-noise, low-resolution input images for this project. The DSS data is exteremely low quality, so this serves more as a proof of concept, while artificially generated low signal-to-noise images were also used for training.

### 4.1. *GalaxyZoo*

The GalaxyZoo dataset provides, among other information, the celestial coordinates (Right Ascension and Declination) and morphological classifications for over a million galaxies, as labeled by volunteer scientists. The data was recorded via an online decision tree, where volunteers were shown images of galaxies and asked a series of questions about their morphology. The responses were aggregated to construct probabilistic labels for each galaxy, based on the fraction of volunteers who selected each option (C. J. Lintott et al. 2008).

### 4.2. *Sloan Digital Sky Survey (SDSS)*

The Sloan Digital Sky Survey (SDSS) is a major astronomical survey, operating in New Mexico since 2000, that has imaged about 35% of the sky (visible from the Northern Hemisphere). The SDSS captures images in various wavelengths, from ultraviolet to near-infrared, using a massive ground-based telescope. The SDSS images are of relatively high quality, with good resolution and signal-to-noise ratios, particularly when compared to DSS (D. G. York et al. 2000).

The GalaxyZoo project used SDSS images as the data given to volunteers for classification, so it makes sense to use SDSS images as the high-quality ground truth images for this project. The SDSS images are made available through the SkyServer API, which allows querying for images based on celestial coordinates. For this project, I used the AstroQuery [2] Python package to download SDSS images corresponding to the galaxies in the GalaxyZoo dataset, based on their Right Ascension and Declination coordinates. The images were downloaded in FITS format, which is a common format for astronomical images.

### 4.3. *Digital Sky Survey (DSS)*

The Digitized Sky Survey (DSS) is an older astronomical survey that was conducted using photographic plates in the 1950s as part of the National Geographic Society - Palomar Observatory Sky Survey (NGS-POSS). These images were digitized in 1994 to create the DSS. In particular, the DSS1 survey used light-sensitive photographic plates, which are of lower quality compared to modern CCD images. Future DSS releases contain much higher quality images, but for the purposes of this project, DSS1 images were used as a source of real world low signal-to-noise, low-resolution images (B. M. Lasker et al. 1990).

To collect DSS images for this project, I used NASA's SkyView service[3], which allows querying for images based on celestial coordinates. As with the SDSS images, DSS images were downloaded in FITS format.

[2] https://astroquery.readthedocs.io/en/latest/sdss/sdss.html
[3] https://skyview.gsfc.nasa.gov/current/cgi/titlepage.pl

### 4.4. *Artifical Low Signal-to-Noise Images*

Due to the limited availability of DSS images, and extreme low quality of the DSS1 images in general, this project also used artificially generated low signal-to-noise images. These images were created by taking SDSS images and applying Gaussian noise and downsampling to simulate images taken with lower quality instruments.

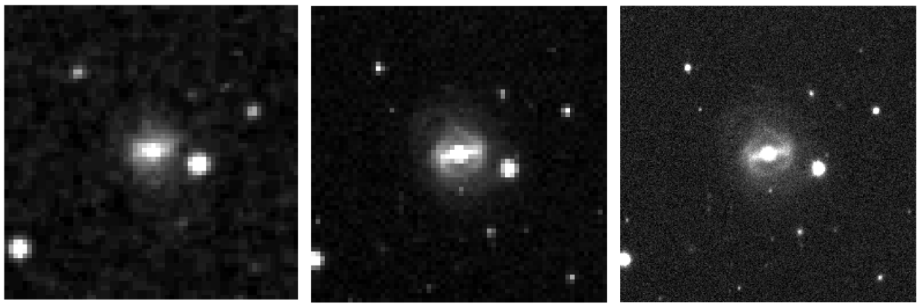

**Figure 2.** Image of a galaxy from the DSS (left), an artificially downsampled SDSS image (middle), and the original SDSS image (right). The DSS image is significantly lower quality, with much more noise.

### 4.5. *Data Preprocessing*

To prepare the data for training and evaluation, there were a few preprocessing steps that were needed.

Starting with the GalaxyZoo dataset, I chose o nly a subset of the features available, specifically the unique id for each galaxy, its celestial coordinates, and the labels related to its morphology (Elliptical vs Spiral/Bar), whether it is edge-on or facing Earth, and whether it had spiral arms. Since the GalaxyZoo dataset gives percentage-based labels, I filtered the dataset to only include galaxies where at least 80% of volunteers agreed on a label.

I then converted the probabilistic labels into discrete, binary labels, to make classification easier. For practicality, only a subset of these galaxies were downloaded, about 50,000 total, as downloading the full dataset would have been infeasible given time and resource constraints. Depending on the specific labels bein used, this dataset may be further filtered to ensure a balanced distribution of classes.

Next, I downloaded the corresponding SDSS and DSS images for each galaxy using their celestial coordinates. Each image was a cutout of a larger plate, centered on the galaxy of interest. For the high-resolution SDSS images, the cutouts were 256x256 pixels, while for the low-resolution DSS images, the cutouts were 64x64 pixels. Both datasets include multiple wavelengths, but the different wavelengths have different qualitys, so only red channel images were used. Red light is commonly used for structural classification of galaxies, as it is less affected by dust and gas.

Since the SDSS and DSS images are not consistently oriented the same way, I apply a rotation on each image using OpenCV's phase correlation method to align the images based on their features. Finally, I normalized the pixel values of the images to be between 0 and 1, to make training the deep learning model easier. The images were also converted to NumPy arrays for easier manipulation during training.

Due to the significant noise in the DSS images, I also used OpenCV to artifically downscale and add Gaussian noise to the SDSS images to create additional low signal-to-noise, low-resolution images for training.

### 4.6. *Morphology Labels*

For the purposes of this project, I focused on two main morphological classification tasks.

First, classifying galaxies as Elliptical vs Spiral/Bar (”Features”). Elliptical galaxies are generally smooth and featureless, while Spiral/Bar galaxies have distinct structures such as spiral arms or bars. In general, galaxies with features are more prevalent, making up approximately 70% of the galaxies in the GalaxyZoo dataset. This means automated classification can help find the relatively rare Elliptical galaxies.

Second, classifying galaxies as Edge-on vs Face-on. Edge-on galaxies are viewed from the side, while Face-on galaxies are viewed from above or below. This classification is important because a galaxy viewed edge-on provides valuable information about its rotation, via Doppler shifting of light from different parts of the galaxy. This method is how astronomers first found evidence for dark matter, by observing that the outer parts of galaxies were rotating faster than expected based on visible matter alone V. C. Rubin et al. (1980). Edge-on galaxies are much, much rarer than Face-on galaxies, numbering only about 5,000 in the GalaxyZoo dataset, compared to over 100,000s of Face-on galaxies (that met confidence thresholds).

Since both of these classification tasks are heavily imbalanced, each dataset was balanced by undersampling the majority class to ensure that the classifier would not be biased towards the more common class.

## 5. RESULTS

The key metric for evaluating the performance of the image upscaling methods in this project is the (balanced) classification accuracy achieved when using the upscaled images in a Random Forest classifier.

The control for this experiement is the classification accuracy and PSNR from the SDSS images directly, with the inital assumption that any upscaling method will not be able to outperform the original with less information. Running Random Forest classification on the SDSS images for the morphological labels resulted in accuracies of approximately 86% for Elliptical vs Spiral/Bar and 89% for Edge-on vs Face-on, on datasets of  10,000 images.

Then, the dataset was downsampled to create a low quality version of the images. OpenCV was used to downscale the images to 64x64 pixels, using effectively a reversed version of Bilinear Interpolation. Since these downscaled images still had relatively high signal-to-noise ratios, Gaussian noise was added to simulate low signal-to-noise images. After building this low-quality dataset, Random Forest classification resulted in accuracies of approximately 78% for Elliptical vs Spiral/Bar and 76% for Edge-on vs Face-on.

To compare the simulated low quality images to real world low quality images, I also ran classification on the DSS images. The DSS images resulted in accuracies of approximately 78% for Elliptical vs Spiral/Bar and 75% for Edge-on vs Face-on, which is surprisingly close to the simulated images. Visually, the DSS images seem much less clear than the simulated images, and there are clearer differences after upscaling, but for classification with low resolution data, the results are similar.

Training the CNN model took approximately 6 hours for 50 epochs on a dataset of 50,000 image pairs. Two models were trained, one on the artificially generated low-quality images, and one on the DSS images.

Next, I applied the various upscaling methods to the low-quality images, and evaluated their performance using classification accuracy. First, the artifically downscaled dataset, which the results for are summarized in Table 1.

| **Upscaling Method** | **Morphology Accuracy** | **Edge-on Accuracy** |
|---|---|---|
| SDSS | **86%** | **89%** |
| Downsampled | 78% | 76% |
| Nearest Neighbor | 78% | 80% |
| Bilinear Interpolation | 79% | 83% |
| Bicubic Interpolation | 78% | 81% |
| Lanczos Resampling | 78% | 81% |
| CNN | **82%** | **87%** |

**Table 1.** Classification accuracies for different upscaling methods on low signal-to-noise images (artificially generated).

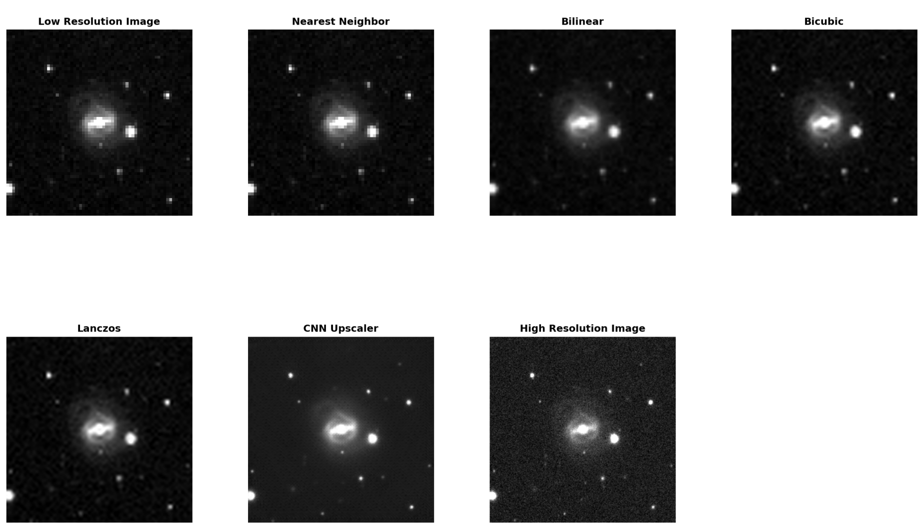


**Figure 3.** A comparison of different upscaling methods, including the CNN, on an image of a galaxy.

The obvious takeaway from these results is that the CNN significantly outperforms traditional upscaling methods for both classification tasks, only slightly underperforming the original SDSS images. For the morphology classification, all the traditional methods performed essentially the same, but for the edge-on classification, Bilinear Interpolation performed noticeably better than the other traditional methods. Visually, the CNN clearly produces the best quality images, as shown in Figure 3, with sharper edges and more defined features.

The model trained on DSS images has a different spread of results, summarized in Table 2.

| **Upscaling Method** | **Morphology Accuracy** | **Edge-on Accuracy** |
|---|---|---|
| SDSS | **86%** | **89%** |
| DSS | 77% | 78% |
| Nearest Neighbor | **89%** | **90%** |
| Bilinear Interpolation | 88% | **90%** |
| Bicubic Interpolation | **89%** | 89% |
| Lanczos Resampling | 88% | **90%** |
| CNN | **89%** | **90%** |

**Table 2.** Classification accuracies for different upscaling methods on low signal-to-noise images (DSS).

Here, the CNN is arguably the best performing model, and even outperforming the original SDSS images for both tasks. However, the traditional methods also performed significantly better than on the simulated dataset, with Nearest Neighbor and Bicubic Interpolation both achieving 89% accuracy for morphology classification. This suggests that the DSS images may have some artifacts or features that the traditional methods are able to exploit for classification, skewing the results. Visually, the CNN clearly does not produce clear images, as shown in Figure 4, likely due to the extreme noise and low quality of the DSS images.

One possible explaination for unusually effective classification in the DSS images is that there is some error in how the data was collected or preprocessed, resulting in the model learning to classify based on meta features rather than the images themselves. The fact that even Nearest Neighbor interpolation is able to achieve such high accuracy suggests that there may be some underlying issue with the dataset, as it effectively just magnifies the low-resolution image without adding any new information.

## 6. FUTURE WORK

There are several avenues for future work in this area. First, experimenting with different deep learning architectures, such as Generative Adversarial Networks (GANs) or Transformer-based models, could potentially yield better results. The CNN architecture used in this project is relatively simple, and couldn't be trained much longer

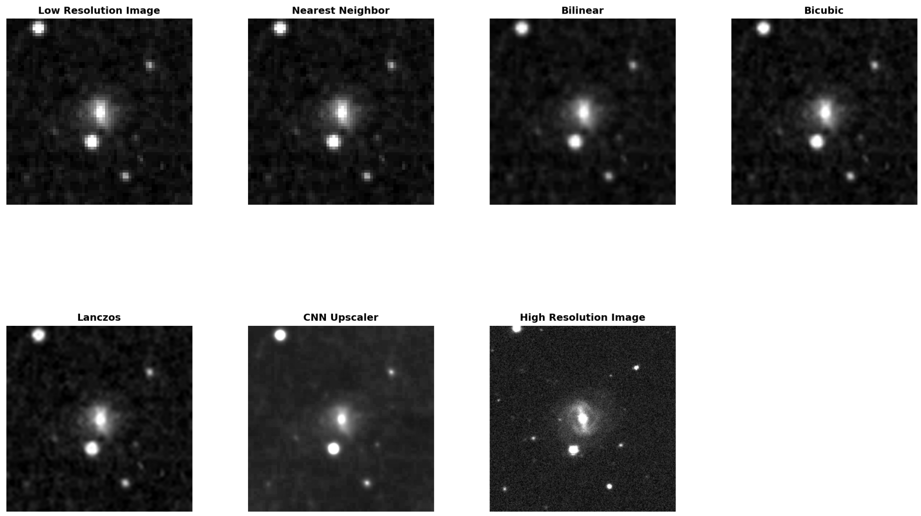


**Figure 4.** A comparison of different upscaling methods, including the CNN trained on DSS images, on an image of a galaxy. Clearly the CNN is not able to produce a clear image from the extremely noisy DSS input.

than a single night due to hardware constraints. More data could also be collected, as this project only used a small subset of a small subset of the GalaxyZoo dataset.

In addition, SDSS images themselves are relatively low quality compared to images taken by space-based telescopes such as the Hubble Space Telescope. Using higher quality images as ground truth could potentially yield better results, although that would also require much stronger hardware to upscale on. This would both potentially allow for better performance, as well as be more relavant for real world application. A different downstream task would need to be explored, however, as galaxy morphology is relatively simple for classification tasks, and more complex tasks such as identifying gravitational lenses or merging galaxies could be more interesting.

Finally, further investigation into the results from the DSS images is needed to understand why traditional methods performed so well, and whether there are any issues with the dataset or preprocessing steps that need to be addressed. It feels intuitive that the CNN should be able to outperform traditional methods even on the DSS images, given enough training time and data. The unexpected results strongly imply that there is some underlying issue that needs to be resolved.

## 7. RELATED WORK

There has been a lot of significant work in the area of image super-resolution and denoising using deep learning techniques. One of the most notable works is the Enhanced Deep Super-Resolution (EDSR) architecture proposed by Lim et al. (2017), which I used as the (general) structure of the CNN in this project. EDSR has been shown to outperform previous state-of-the-art methods on various benchmark datasets, and is particularly effective at preserving fine details in images. Another notable work is the Super-Resolution Generative Adversarial Network (SRGAN)(C. Ledig et al. 2017), which uses a GAN architecture to generate high-resolution images from low-resolution inputs. SRGAN has been shown to produce visually appealing results, particularly for images with complex textures and details.

This specific project idea has been explored in prior work as well. For example, (S. Dieleman et al. 2015) applied CNNs to the Galaxy Zoo dataset, achieving greater than 99% accuracy on classifications. This focused on classification directly, rather than image upscaling, but clearly relates to this project. Another relevant work is by (K. Schawinski et al. 2017), who used GANs to generate high-resolution images of galaxies from low-resolution inputs, demonstrating the potential of deep learning for enhancing astronomical images. Their work focused on generating images themselves rather than downstream tasks, but is still relevant to this project. The major difference is that this project focused on single image upscaling, which is fundementally different from GANs, which generate images from random noise, which provides more information but also introduces a much higher risk of hallucinating features that are not present in the original image.

## 8. CONCLUSION

In this project, I explored the use of various image upscaling techniques to aid in classification of galaxy morphology from low signal-to-noise, low-resolution images. Deep learning-based methods, specifically a CNN based on the EDSR architecture, significantly outperformed traditional interpolation methods such as Nearest Neighbor, Bilinear, Bicubic, and Lanczos resampling. The CNN was able to nearly match the classification accuracy of the original high-quality images, and produced visually superior images compared to traditional methods.

I also explored the use of real world low-quality images from the Digitized Sky Survey (DSS), but the results were less conclusive, with traditional methods performing suspisiously well. This is likely due to some underlying issue with the dataset or preprocessing steps, and not a fundamental limitation of the CNN approach.

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