

Image Super-resolution and Deblurring Model



**ME781 COURSE PROJECT
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GROUP 19

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Problem Definition Description

The application developed will take any input low-resolution image and upscale it to high-resolution. We will also explore how we could add more functionalities of deblurring and denoising to the same. It can be used for any kind of people who click photos digitally, from beginners to professional photographers. Upscaling of resolution is provided by applications like Photoshop which are usually paid and require a professional to work with it. This AI-based super-resolution technique will provide free-of-cost automatic super-resolution options, which literally anybody can find handy.

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Technology Landscape Assessment

Published Literature/ Papers:

- Deep Learning for Image Super-resolution: Zhihao Wang, Jian Chen, Steven C.H. Hoi, Fellow, IEEE
- Super-resolution reconstruction of a digital elevation model based on a deep residual network: Donglai Jiao, Dajiang Wang, Haiyang Lv and Yang Peng
- Deep Wavelet Prediction for Image Super-resolution: Tiantong Guo, Hojjat Seyed Mousavi, Tiep Huu Vu, Vishal Monga

- Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network: Christian Ledig, Lucas Theis, Ferenc Huszar, Jose Caballero, Andrew Cunningham, Alejandro Acosta, Andrew Aitken, Alykhan Tejani, Johannes Totz Patents:
 - Increasing object resolutions from a motion-blurred image (<https://patents.google.com/patent/US7639289>)
 - Reconstructing Blurred High-Resolution Images (<https://patents.justia.com/patent/20080002909>)

Note: These patents use different DL/ML Methods or Technologies for Super-Resolution than our proposal.

Open Source Libraries:

- NumPy, matplotlib, pandas, Keras, Tensorflow, pywt (Pywavelet)

Project Planning

Project Task Breakdown & Project Timeline

- 15 Oct - 24 Oct: Literature Survey and Establishing objective for the Project. Collection and organization of a quality dataset relevant to the Project and basic dataset exploration.
- 24 Oct - 31 Oct: Exploratory Data Analysis - Cleaning and preparing the dataset. Data labeling is an important function within this step.
- 31 Oct - 10 Nov: Proper labeling provides the neural network with the ‘ground truth’ that it needs to learn.
- 10 Nov - 20 Nov: Model selection and training.
- 20 Nov - 25 Nov: Testing and measuring performance.

Basic Chart Link:

<https://docs.google.com/spreadsheets/d/17OhhgVyYyMYT-b4Ce0UP0GI8a6yU348BDpldTQvEdg/edit?usp=sharing>

Conceptual Design

For DL methods like Super Resolution, Denoising etc:

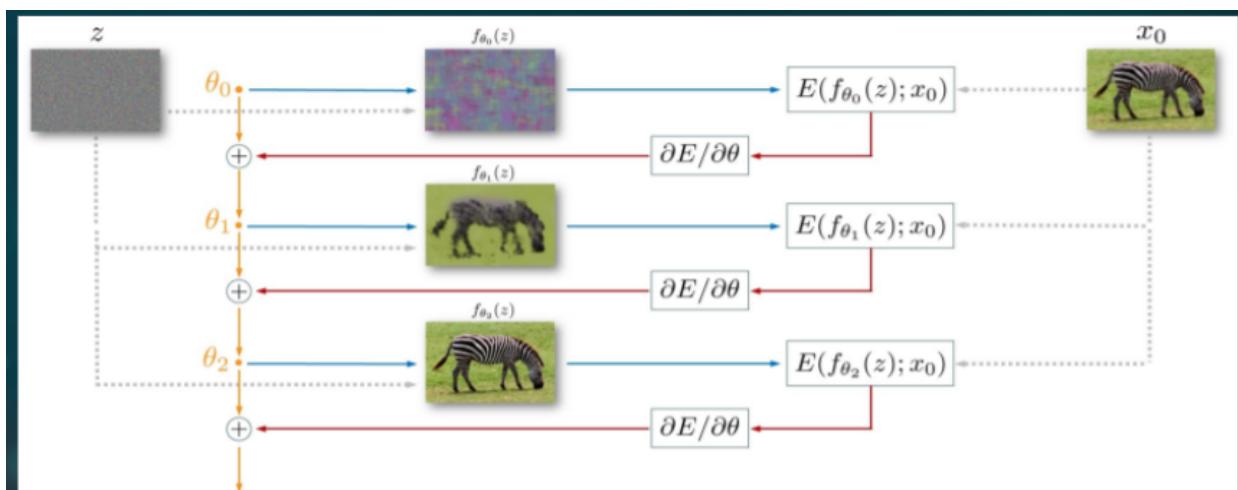
PROPOSED METHOD

Deep networks are applied to image generation by learning generator/decoder networks $x = f_{\theta}(z)$ that map a random code vector z to an image x .

Our aim is to investigate the prior implicitly captured by the choice of a particular generator network structure, before any of its parameters are learned

Parametrization $x = f_{\theta}(z)$ of an image $x \in \mathbb{R}^{3 \times H \times W}$

Most of our experiments are performed using a U-Net type “hourglass” architecture with skip-connections, where z and x have the same spatial size.



To demonstrate the power of this parametrization, we consider inverse tasks such as denoising, super-resolution and inpainting.

$$x^* = \min_x E(x; x_0) + R(x),$$

where $E(x; x_0)$ is a task-dependent data term, x_0 the noisy/low-resolution/occluded image, and $R(x)$ a regulariser

In this work, we replace the regularizer $R(x)$ with the implicit prior captured by the neural network, as follows:

$$\theta^* = \operatorname{argmin}_{\theta} E(f_{\theta}(z); x_0), \quad x^* = f_{\theta^*}(z).$$

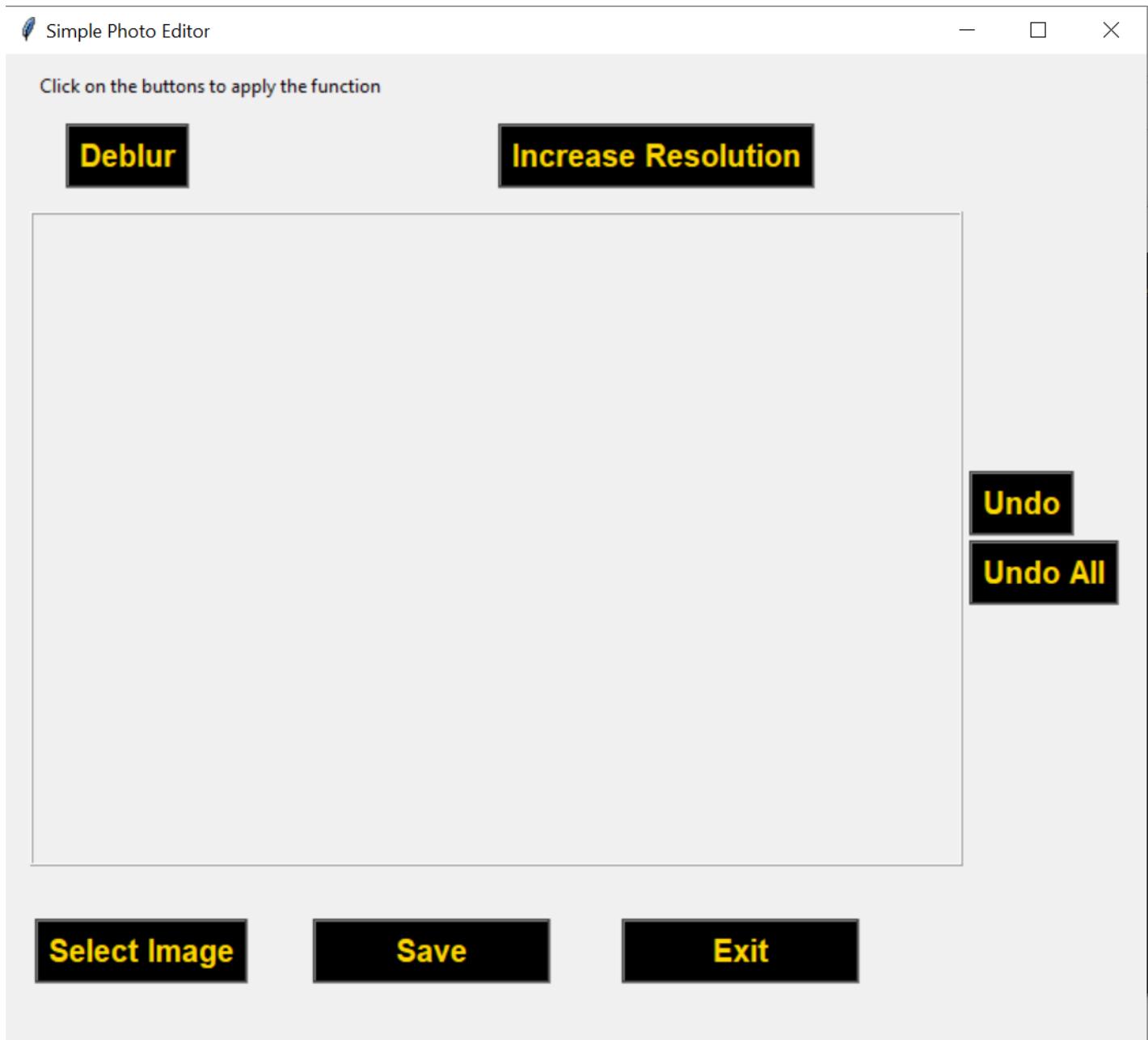
For ML models like deblurring:

PROPOSED METHOD

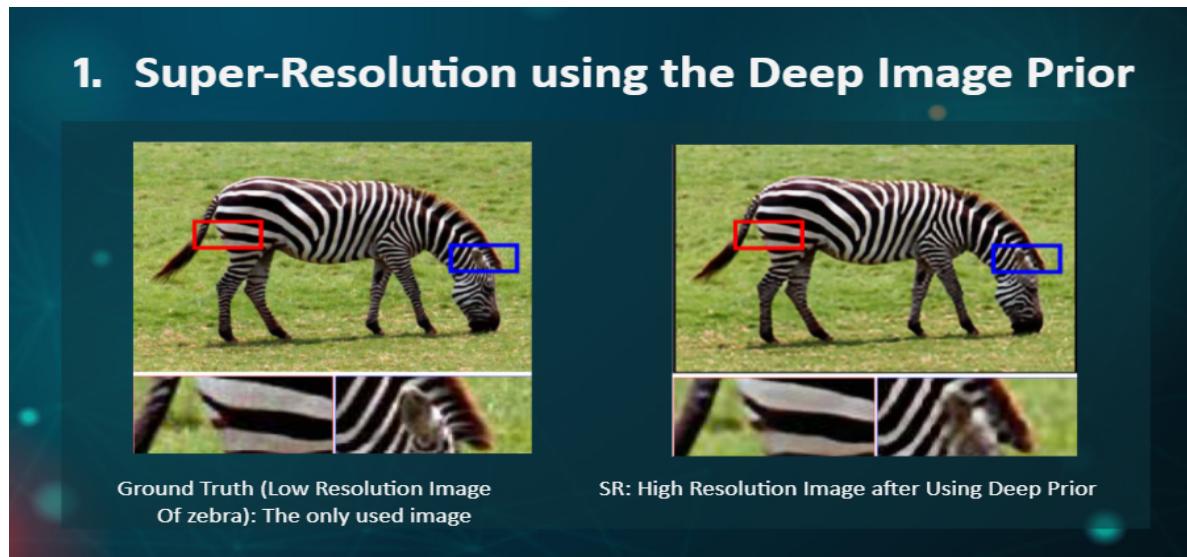
- Three models have been tried out:
 - SVR Regression on HSV
 - SVR Regression on RGB channels separately
 - Random Forest Regression on HSV
- These models are less complicated than Neural Network models.
- Tried these models for patch width ranging from 11 to 71
- Anything smaller than 11 would have been too small to analyse accurately.
- Anything larger than 71 would have been too much to extract a local pixel intensity value and would have overfit the model

Screenshots Of User Interface And Output Visualization

User GUI Interface:



Output Examples:



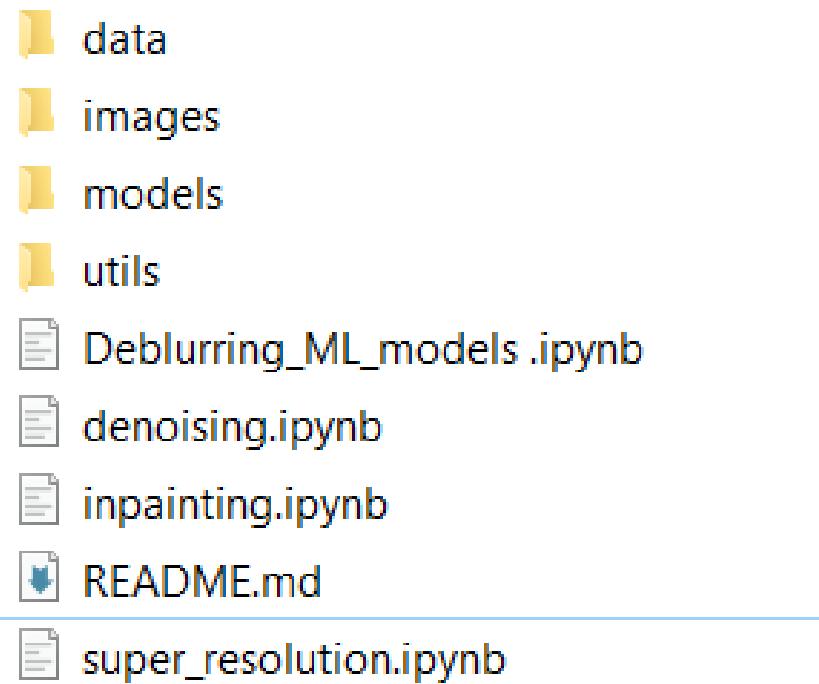
(Deblurring using Random Forest Regression)



Unit Testing Report

We have run our code on Google Colab and have done the development on that platform. We have 4 types of technologies in our company at present i.e. Super-Resolution, Denoising, Impainting and Deblurring. We have made different code for each. We have a corresponding dataset and other supplementary code available to support these .py files. As code is developed and run over Google Colab, it will run over any platform supporting it.

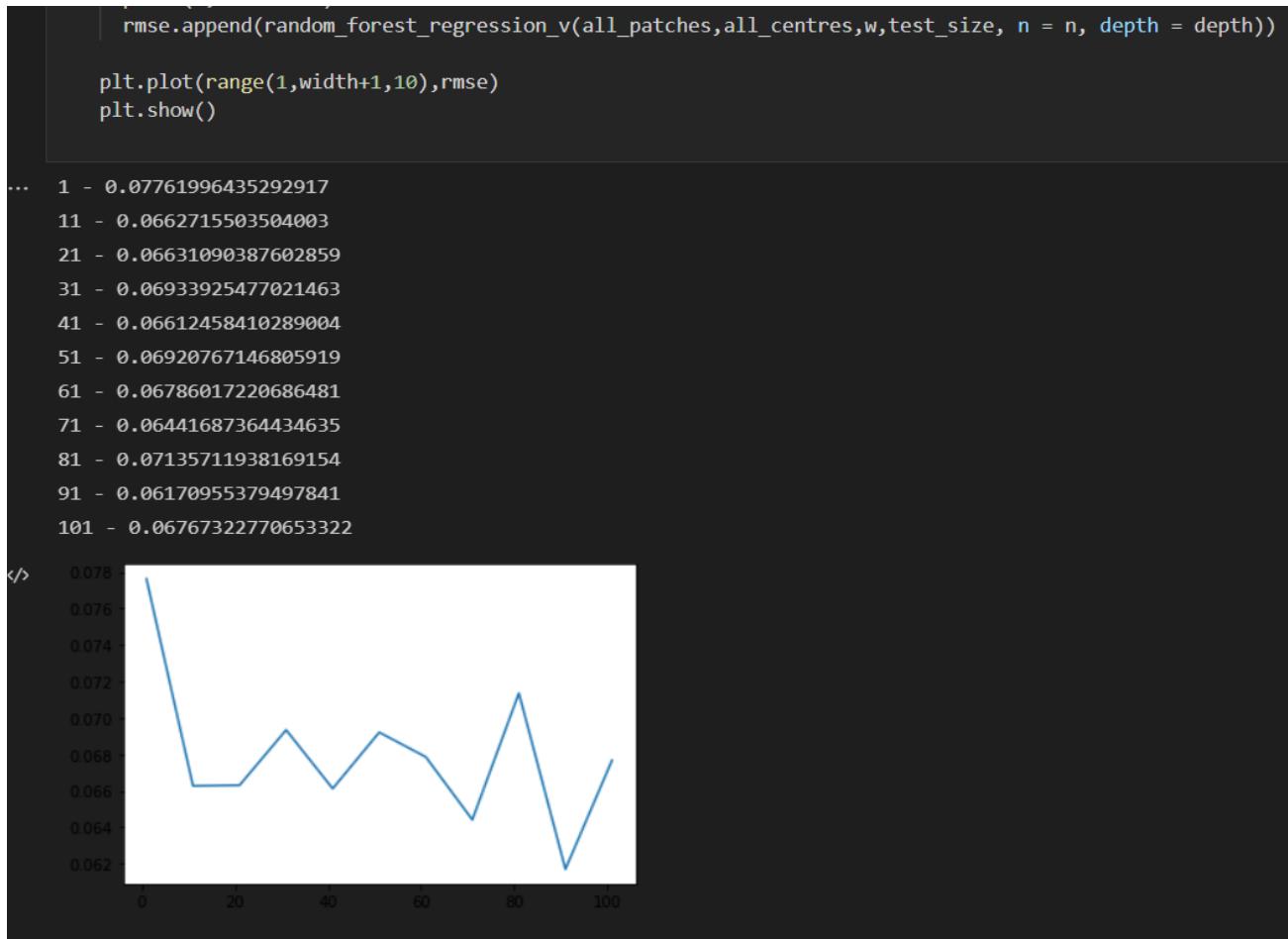
Here is a sample of our directory:



We have also provided a readme file to tell user how to run our code.

Model Training And Testing Report

Here are some samples when our ML models were being trained and best parameters were chosen:



For DL models, we have used the metric of PSNR (Peak Signal-to-Noise Ratio)

Results

- In case of Super Resolution and Denoising, evaluation is done using denoising approach on the standard dataset which consists of 9 colored images with noise strength of $\sigma = 25$.
- A PSNR of 29.22 after 1800 optimization steps is achieved. The score is improved up to 30.43 if we additionally average the restored images obtained in the last iterations (using exponential sliding window).
- The deep image prior is tested with different network architectures and a 35.05 PSNR is achieved for UNet and a 31.95 PSNR for ResNet.
- Random Forest Regression performs better than the Support Vector Regression in deblurring the images.

Implementation of SR

- Downsampling is done using operator $d()$ that resizes an image by a factor t given by $d(\cdot) : R(3 \times tH \times tW) \rightarrow R(3 \times H \times W)$
- Next, Regularizing the problem (given in method section) is done by considering the re-parametrization $x = f\theta(z)$ and optimizing the resulting energy w.r.t. θ . Optimization which uses gradient descent

PSNR Comparisons with other methods

1. 4X Super-Resolution

IMAGE	DEEP PRIOR	BEST
LR Zebra	25.71	26.98 (LapSRN)

2. 8X Super-Resolution

IMAGE	DEEP PRIOR	BEST
LR Zebra	20.62	20.62 (DEEP PRIOR)

User Manual

- Product description:

The application developed will take any input low-resolution image and upscale it to high-resolution. We will also explore how we could add more functionalities of deblurring and denoising to the same.

- Intended use:

This application can be used for any kind of people who click photos digitally, from beginners to professional photographers.

- Features/accessories:

- These models are less complicated than Neural Network models.
- Tried these models for patch width ranging from 11 to 71
- Anything smaller than 11 would have been too small to analyze accurately.
- Anything larger than 71 would have been too much to extract a local pixel intensity value and would have overfitted the model

- Description of the user interface:

After logging in to the software you will be able to see your user id on the top right of the interface. In the top panel, you will see Home, About Us, Result/Report, Collaborate, Blog and Contact Us.

- Home: Your main page just after login
- About Us: Details of our team, background story and more.

- Results: Enhanced higher resolution image corresponding to a low-resolution image input. Contains past results and reports.
- Steps to use the app:
 1. Log in with your details.
 2. Once you have logged in you will be able to see the ‘Results’ button in the top right corner. Click on it to view the previous records.
 3. Choose a previously existing image or upload a new picture.
 4. After uploading the image, our model will give you an enhanced higher resolution image.
 - Repair information: If you face any problem, try restarting the app. If it doesn’t help, check out our self-help videos. If the problem stays, do contact our technical team for assistance.
 - Data Privacy Concerns: Privacy is our most important concern.
 - Contact details: For technical assistance contact us at techsupport@superreso.com or reach out to our team.