Image Resampling and Super-Resolution using Multi Discriminator Generative Adversarial Networks

Project Mid Report Summary

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In this work, we aim at exploiting this area of artificial intelligence to solve the problem of Image Resampling and Super Resolution. The problem is an easy one to understand, but a tricky one to solve. It states, for any low resolution, low-quality image, convert it into a high resolution, high quality one. The tricky part is the fact that doing such a thing requires bringing back lost information, which is physically impossible. So we propose a deep learning algorithm, built upon the ever-popular Generative Adversarial Networks, proposed by Ian Goodfellow et al. 2014.

Motivation

The fact that a high-resolution image can be more than just a technical achievement. It can be the difference between an innocent being caught and let free, the difference between the discovery of a new star or identifying it as a fluke, and this is our primary motivator for this project where we aim to exploit the vast potential of deep neural networks, to create high-resolution images, from previously low-resolution ones.

Type of Project

This project is a combination of Development cum Research Project. It aims to research on the most technical factors of a CNN to generate a network capable of photo-realistic super resolution. It also leads to development as work has previously been done on this problem by various famous and non famous people and it aims to make life easier through technology.

Literature Survey

Interpolation Techniques in Image Resampling - Manjunatha et. al.

Manjunatha et. al. demonstrate that resampling establishes a regular interrelationship between pixels by interpolation. The authors presented the comparative study of Interpolating methods for Image resampling.

Deep Learning for Super-Resolution

One pioneering work by Chao et al. is the Super-Resolution Convolutional Neural Network (SRCNN)]. It implicitly learns a mapping between LR and HR images using a fully convolutional network.

Convolutional Neural Networks (CNN) Yann LeCun et al 1998

Convolutional Neural Networks (CNNs) are analogous to traditional ANNs in that they are comprised of neurons that self-optimise through learning. Each neuron will still receive input and operate (such as a scalar product followed by a nonlinear function) - the basis of countless ANNs.

Generative Adversarial Networks - Goodfellow et al. 2014

It comprises of two neural networks - Generator and Discriminator. The generator creates images and the discriminator labels them as fake and this goes on until the generator becomes so good that the discriminator can't identify the images as fake anymore.

Sub Pixel Convolutional Neural Networks-Wenghe Shi et al.

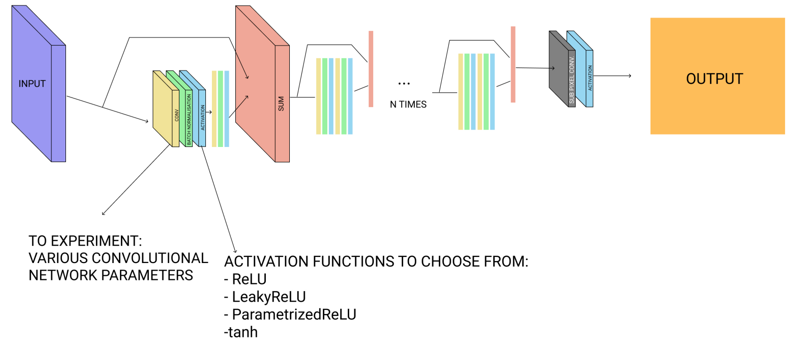
This process is also known as Pixel shuffling. Pixel shuffling rearranges the tensor of shape (N,C,H,W) into (N,C/r*r,H*r,W*r) where r is the shuffling factor.

Design of Project

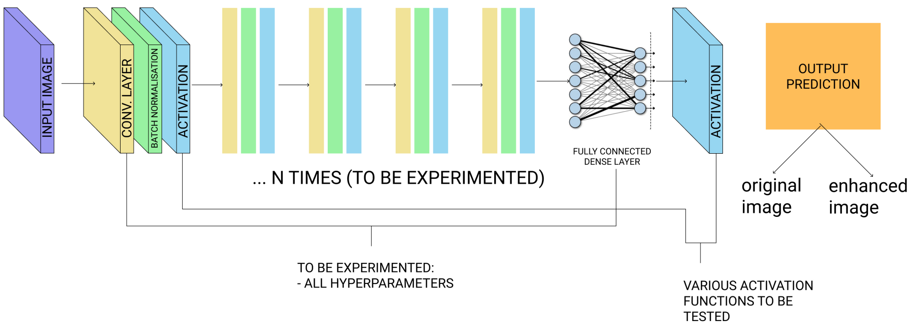
The following image shows the idea of the Generative Adversarial network isolated by taking into account various papers.These ideas were isolated as to divert from general Generative Adversarial Networks and CNN's:

1. Use of Deep Residual learning - Xiangyu et al. 2015
2. Use of Sub-Pixel Convolutional 2D networks - Wenzhe Shi et al. 2016
3. Expanding the channels while reducing the kernel matrix in successive CNN's.
4. Using Multi Discriminatory networks.

GENERATOR NETWORK



DISCRIMINATOR NETWORK:



Work Done + Libraries

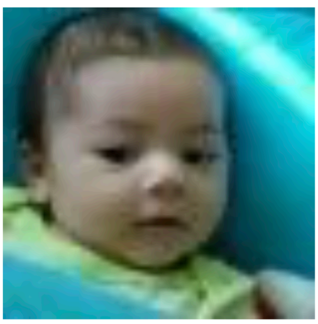
A sample image was taken and simple mathematical upscaling techniques were applied to them, to judge what general methods amount to, what they are capable of, and what our approach stands against. Here we show a sample where we use the nearest neighbour interpolation technique to generate a 4x upscaled image using a previously 4x downscaled image (using state of the art Anti-Aliasing technique).

Languages Used:

Python, along with numpy, and matplotlib

Original Image

256 px x 256 px



Downscaled @ 4x

64px x 64 px

Upscaled by a factor of 4

256px x 256px

Method : Nearest Neighbor