

Exploration Between Image resolutions and Classification

Abstract

- Studies shown the importances of image resolution in convolutional operation [1]. It further implies the need for higher resolutions images. This paper would explore the need of super resolution with Deep Learning methods which would further improve classification performance.

Project Overview

- The reason we chose MSRN is that it has several advantages over traditional approaches. First of all, it is easy to reproduce the experimental results. Unlike most SR models which are sensitive to the subtle network architectural changes and highly rely on the network configuration, MSRN blabla. Secondly, it avoids inadequate of features utilization. It enhances the performance not by blindly increasing the depth of the network. Instead. Last but not lease, it has good scalability. Therefore, this method is easy for us to observe the result and save time of computation.
- Overall, there are 3 training. In the first training, the original images are feed into denseNet directly. And the result will be as the baseline. In the second training, the image is down-scaled and then up-scaled with naive algorithm which results low resolution image. Then feed it into denseNet to do classification. In the third training, we do naïve down-scale on the image too. we feed it into MSRN. And after MSRN, we feed it into denseNet. By comparing second and third training group, we can know how much resolution improved by MSRN. Also, we compared the classification result of first and third training group. So we can compared the classification result to see the differences

Datasets

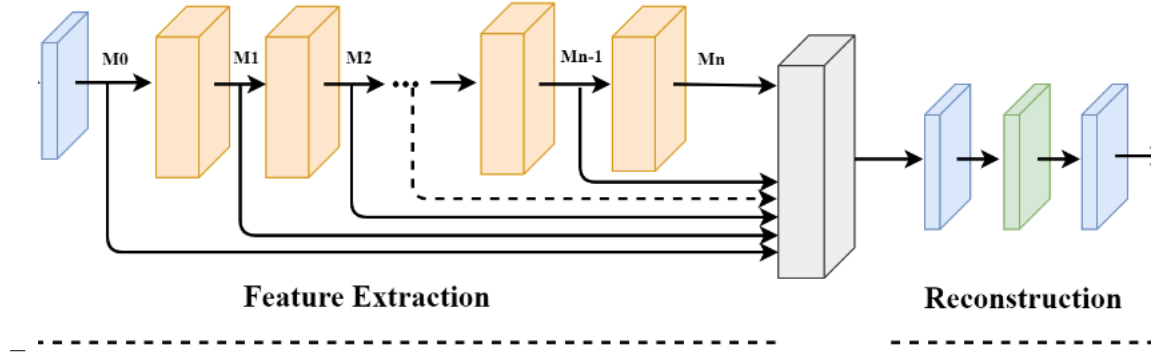
- This paper uses a annoated image dataset known as the CIFAR-10 dataset [2]. It contain ten classes of images. As figure2 as shown, the dataset has classes of airplane, automobile , bird , cat , deer , dog , frog , horse, ship and truck. The CIFAR-10 contains total of 50,000 training images and 10,000 test images. Furthermore, the trainingsets contains exactly 5000 images for each class[2].
- The motivation for choosing this dataset is that each object is clearly distinguishable by other class. It evades the concern of illumination , deformation and occlusion of the image. For example, the important feature points that identifies bird is clearly distinguishable then the key feature points of a truck. The learning curve for training such classifier is less computationally expensive than other datasets.
- Therefore, this experiment conducts on training a identical densenet with two different of inputs, a naive resized images and output images of MSRN. The evaluation metris of the classifiers is the test error and training loss variances. Training loss variance identifies how fast the classifier learn from the inputs relative to labels. Statistically, loss variances implies how distinguishable are the features between classes. In this context, feeding naive and super resolutions images can help this paper to conclude the impact of resolution on classification in terms of test accuracy and training cost.

Details of the Preprocessing

- All of the implmentation and running instruction are in this repository
-

1. MSRN Resized Image preprocessing

- The implementation of this approach is here
- MSRN stands for **Multi-Scale Residual Network**, it is a supervised learning model that learns to upscale the image from low resolution to a higher resolution. This network serves a purpose of scaling an image to a given ratio by perserves the key features such as line and shape.
- MSRN is built by multiple residual network block to perform lower resolution feature extraction on **y** channel of the input which formatted in color space **yCbCr**[3]. Then concatenated all of the filters and feeded to a **Sub-Pixel Convolutional layer** to reconstruct a higher resolution image. Sub-pixeling Convolutional Neural Network is network structure learn to upscale the lower resolution image to a higher resolution output by estimating resolution arangement based on ground truth [4]. This enable MSRN to generate super resolution image based on ground truth.

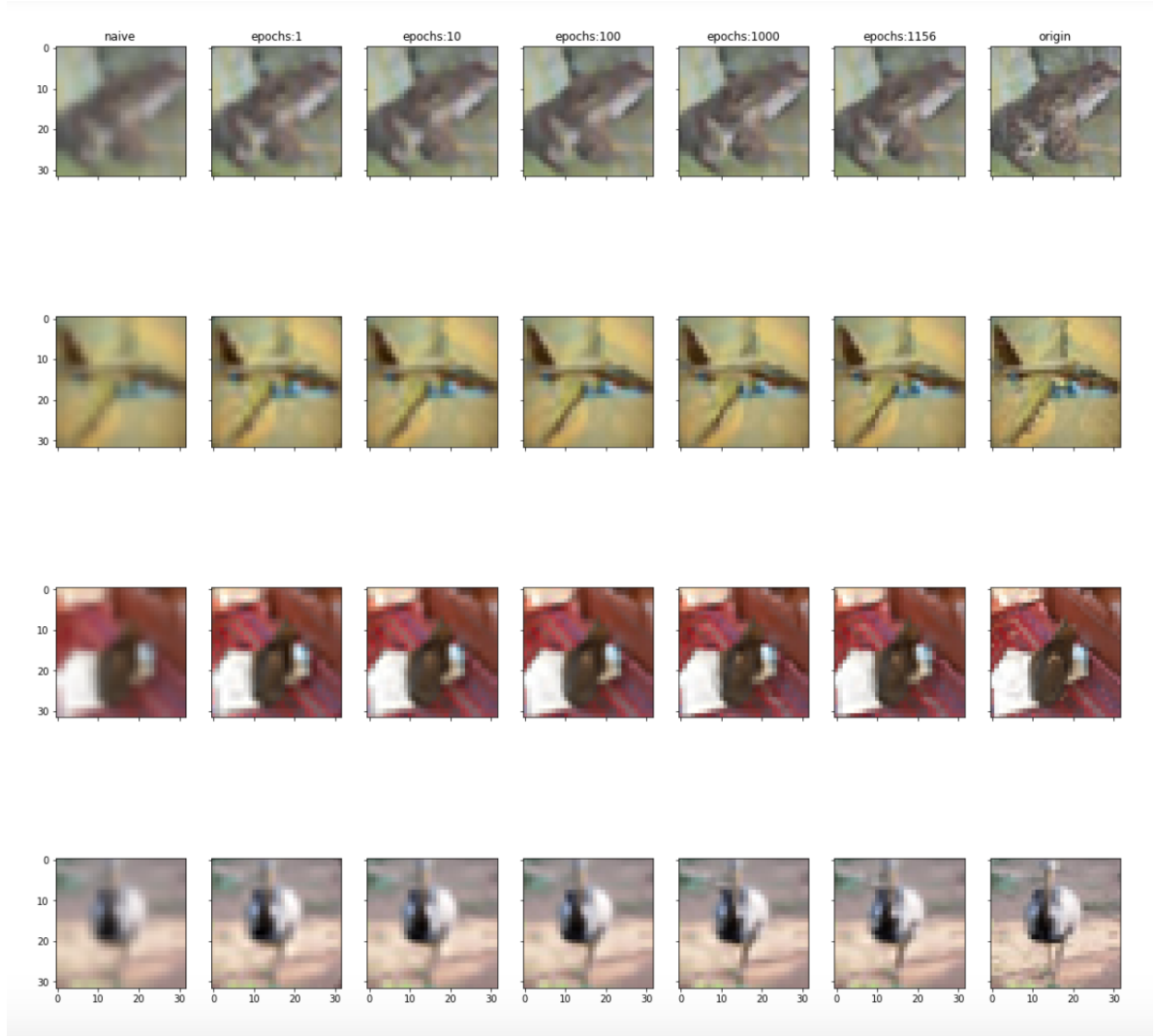


* **figure 1.1**, this show the architecture of MSRN it consists of n block of residual layer and reconstructed by a sub-pixel convolutional layer in reconstruction layer

- The following function L is the cost function of training an MSRN. I_i^{LR} is y channel of naive downsampled images in **yCrCb** colorspace. I_i^{HR} is y channel of the origin image in **yCrCb** and F_θ is the forward pass of the MSRN. This allow the network to evaluate how far are the features between pixle spaces which allow back propagation to derivate gradient to optimizes the network.

$$- (2)L(F_\theta(I_i^{LR}, I_i^{HR})) = ||F_\theta(I_i^{LR} - I_i^{HR})||_1[3]$$

- In this experiment, MSRN is trained with 49,000 training images with 1,000 of test images. With **L1loss** (2) function, MSRN is able generated feature perserving image which further enhanced classification performances.



- — *figures 1.2, this show the learning steepness of MSRN. It show 4 test image that predicted by different epoches.*

2. Naive Resized Image preprocessing

- The implementation of this approach is here
- Naive often refer brute forces to solve the given problem. However, in this given approaches refer as `cv2.resize` API in openCV. The goal is applying different geometric transformation to images like scaling by reprojecting image points on a different plane and perserve its key features like ratios of distances between points.
- The algorithm started with input image X has shape of (h_x, w_x) and output y image is (h_y, w_y) . First compute the scaling factor by computing $(\frac{h_y}{h_x}, \frac{w_y}{w_x})$ and mulitplied the identy matrix I_n obtain the scaling matrix $M = \begin{bmatrix} \frac{h_y}{h_x} & 0 \\ 0 & \frac{w_y}{w_x} \end{bmatrix}$ then computed $f : X \rightarrow Mx \rightarrow y$ to obtain image $Y_{downscale}$ [5].
- In this approach, training and testing images will processed by this algorithm twice. First downscaling the image by half and upscale once to origin sizes which perserves the same input size during classification. This allow this project to explore the result of classification with different scaling preprocessing.



- *figures 2.1: present the resize prprocessing of this approach*

3. Result & Analysis

References

1. Etten Adam Van. Quantifying the Effects of Resolution on Image Classification Accuracy. Medium.com. retrieved from <https://goo.gl/v2xa2T>
2. Alex krizhesky, Vinod N, GEoffrey H. The CIFAR-10 dataset, Univeristy of Toronto. retreived from <https://www.cs.toronto.edu/~kriz/cifar.html>
3. MSRN
4. pixle shuffling
5. Geometric Operations: Affine Transform, R. Fisher, S. Perkins, A. Walker and E. Wolfart.