Effect of Image Quality on Classification Accuracy

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1. Introduction

Convolution Neural Networks (CNNs) has shown great potential in image classification. Commonly, machine vision systems are trained and tested on high quality image datasets, yet in practical applications the input images cannot be assumed to be of high quality [1]. Image distortion is always a practical challenge in imaging system. So, it is important to characterize the effect of image quality on classification accuracy.

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In imaging system, detector is where image forms and where parameters (e.g. pixel size and color filter) can show great influence in image quality. Many types of image quality distortions from detector have effects on classifications accuracy and we are especially interested in the effect of blur, noise, pixel size, color field and contrast.

Gaussian blur (also known as Gaussian smoothing) is a common type of blur which is the result of blurring an image by a Gaussian kernel. Gaussian noise is also very common which has values that on are Gaussian-distributed. Principal sources of Gaussian noise in digital images arise during acquisition [2]. Pixel size of sensor is also an important factor that cannot be overlooked. An image's resolution can be expressed in terms of the number of pixels [3]. In a given space, the more pixel numbers mean higher resolution. In digital images, color fields are three-dimensional arrangements of color sensations [color space]. Contrast refers to the difference in luminance or color that makes an object (or its representation in an image or display) distinguishable [4].

2. Related Works

Nanne van Noord, Eric Postma [4] investigate in the variations in image resolutions, sizes of objects and patterns depicted, and image scales that hamper CNN training and performance. They successfully build a multi-scale CNN outperformances single-scale CNN.

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Samuel Dodge and Lina Karam [1] provide an evaluation of four CNNs for image classification under quality distortions. They found that the existing networks are susceptible to quality distortions and conclude that more CNN is required.

Sonali Dash, Uma Ranjan Jena [5] try various color spaces like RGB, HSV, Lab, XYZ, YCbCr and YIQ for the same two datasets for color texture classification and reach conclusion that incorporation of various color information improves the performance of texture classification.

how does this related work connect to the current topic?

3. Methods

In our project, we try to provide an evaluation of a VGG16 for image classification under distortions based on CIFAR10 database. The physical layer we optimize is detector's parameters, such as pixel size, color field and contrast.

3.1 Pre-process images

After downloading CIFAR10, we separately pre-process by resizing, adding blur, adding noise, changing color field and enhancing contrast.

how did you do each of these? This is what the methods section is really about, explaining exactly what you did and why. -1

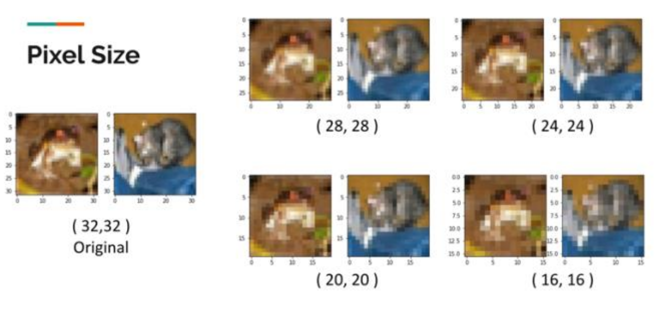

Figure 1. Resize from original (32,32) to four other sizes

what does this simulate? Resizing doesn't actually correspond to a physical effect that would happen during image acquisition

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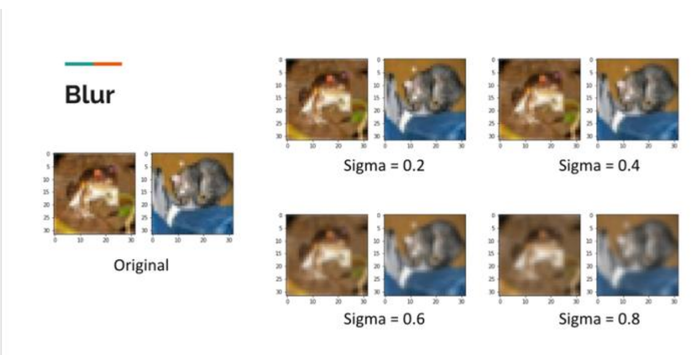


what does the blur mean?

Why Gaussian? There are better blurs to use that mimic a camera blur

Figure 2. Add Gaussian Blur with sigma equal to 0.2, 0.4, 0.6 and 0.8

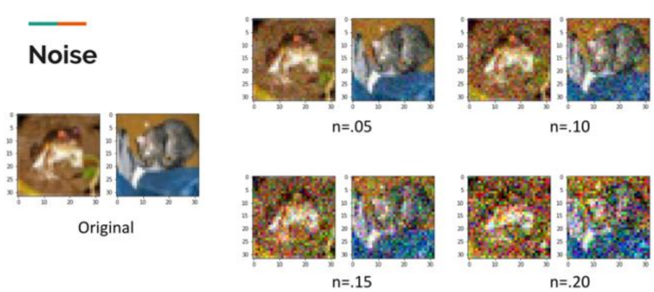
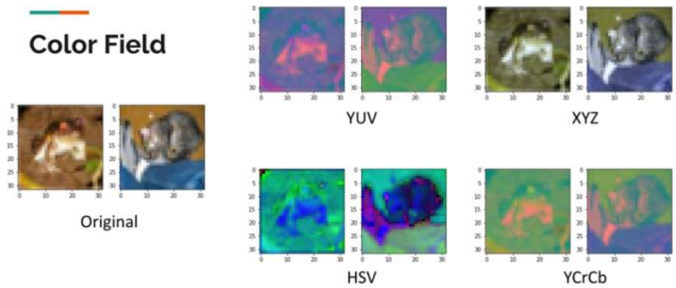


Figure 3. Add Gaussian noise with sigma equal to 0.05, 0.10, 0.15 and 0.20



why would this change the outcome?

This again isn't a physical parameter.

Figure 4. Except original RGB color field, we also try four other color fields

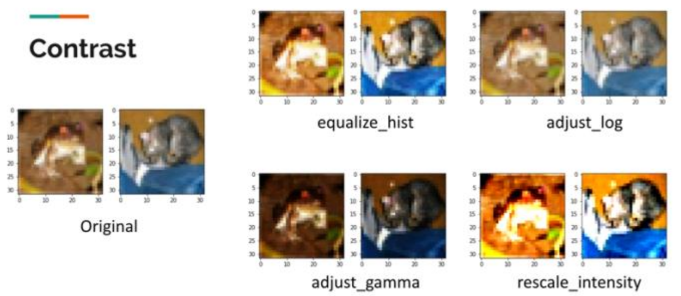
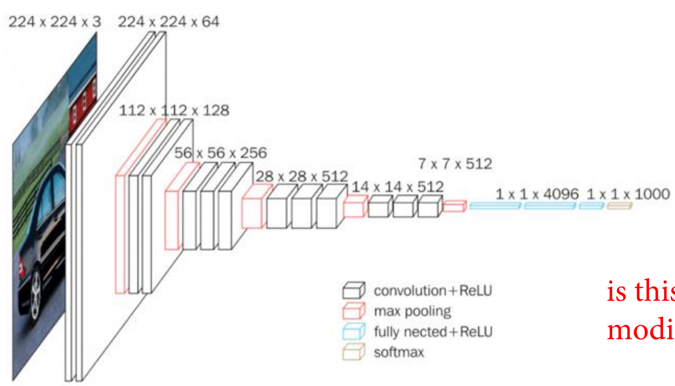


Figure 5. Apply four methods to enhance contrast

3.2 Modify network and Train

We modify VGG16 for benefits, using Batch Normalization and Dropout. With input images prepared, we put them into our modified VGG16 network to train. Batch size used is 64 and epochs are 25. Monitor and store validation accuracy and plot.



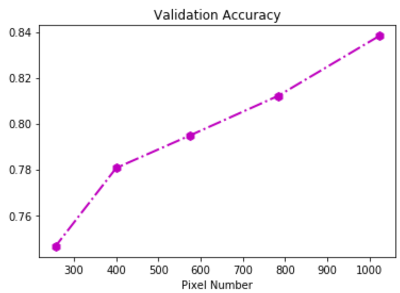
is this the network you used? It says you modified it, where are the modifications?

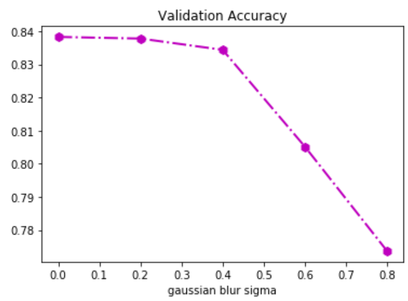
Figure 6. VGG16 network

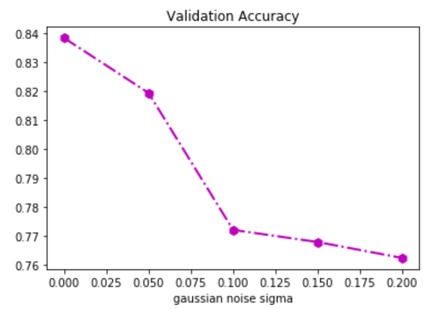
4. Results

The relationship between validation accuracy and pixel numbers, degree of blur, degree of noise, color fields and contrast.

just one sentence about the results?







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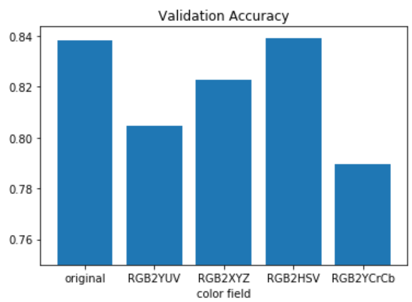
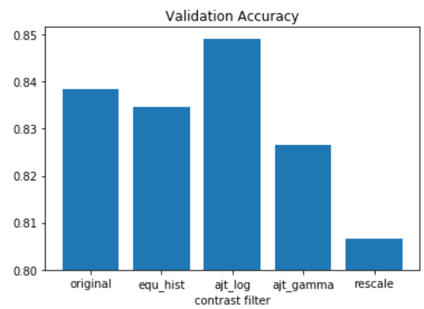
what is pixel number? What does it represent? Same with blur





what is standard deviation?

Did you just run once?

This discussion is very minimal - need to discuss more about the physical parameters and why they are important.

5. Discussion

With the number of pixels decreasing, the validation accuracy also decreases. This is because of information loss. As a result, the feature that can be extracted to do classification is less. Besides, the time costs as well as device requirements are lessened.

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By adding Gaussian blur (or noise) and making image's degree of blur (or noise) more and more heavy, we can see the classification accuracy decreases. In real world we should try to avoid blur and noise in image systems. At the same, deblur technique is required. To make our project more meaningful, future direction is to simulate more realistic blur and noise that occur in real world.

With an aim to improve classification accuracy of color images, we investigate in color field's effect. But we found that except original RBG, only HSV works well. This may because HSV helps to enhance contrast.

References

[1] Samuel Dodge and Lina Karam “Understanding How Image Quality Affects Deep Neural Networks”

[2] Philippe Cattin (2012-04-24). "Image Restoration: Introduction to Signal and Image Processing". MIAC, University of Basel. Retrieved 11 October 2013.

[3] Nanne van Noord, Eric Postma “Learning scale-variant and scale-invariant features for deep image classification”

[4] Arun Kumar et al, / (IJCSIT) International Journal of Computer Science and Information Technologies, Vol. 6 (6), 2015, 4882-4887 “Effect of Image Quality Improvement on the Leaf Image Classification Accuracy”

[5] Sonali Dash et al. / International Journal of Engineering and Technology (IJET) “Texture classification using Laws’ filter in various color spaces”

Figures: 4
References: 3

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