

# Can a Convolutional Neural Network implement histogram equalization in image analysis?

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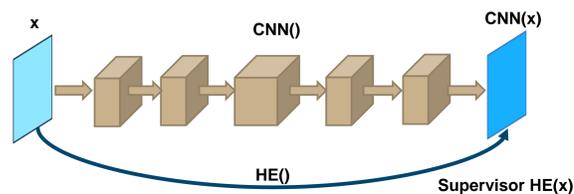
## Motivation

The Convolutional Neural Network (CNN) as a typical deep learning technique has been widely used in many image processing applications and achieved remarkable success. The benefit of pre-processing is natural in traditional image processing, but it is questionable in deep learning. For instance, the Histogram Equalization (HE) is a global operation to images but convolutional operations in CNN are localized, and thus we hypothesize that a CNN may inherently be unable to perform HE on images. This study aims to examine this hypothesis.

## CNN Architecture

We built a CNN having several layers and its input and output are same size images.

- Input: image  $x$
- Output: supervised by  $HE(x)$

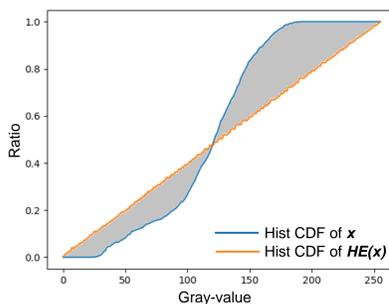


## Evaluation Method

Since HE is a operation on histogram, we evaluate the differences between two histograms (Hists) via the Wasserstein distance (W-dist).

$$W_1(p, q) = \inf_{\gamma \in \Pi(p, q)} \iint \gamma(x, y) d(x, y) dx dy = \int |P - Q|$$

- For two 1-D distributions and  $d(x, y) = |x - y|$
- $P, Q$  are the respective CDFs of histogram  $p$  and  $q$



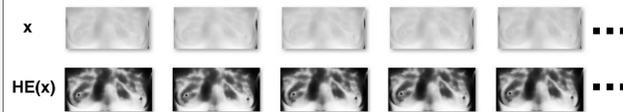
The  $W$ -dist of this example is 34.92 (the gray area).

The max-value for  $W$ -dist is 255.

## Experiment 1

### Test 1

- Train on 10 IR breast images (same patient).

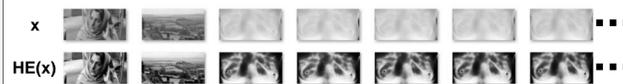


- Validate on 50 IR breast images (including different patients), barbara, goldhill and lenna.

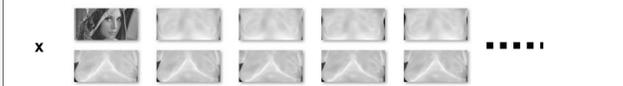


### Test 2

- Train on 10 IR breast images (same patient), barbara and goldhill (more categories).

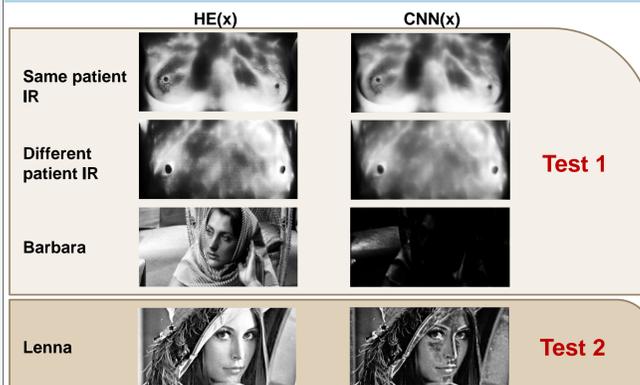


- Validate on 50 IR breast images (including different patients), and lenna.



## Results of Experiment 1

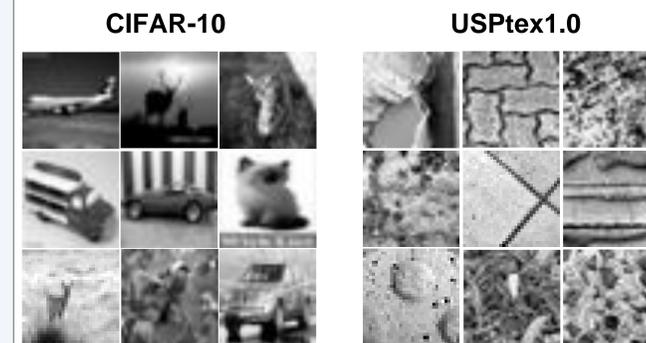
For Test 1, when  $x$  is from the same patient in training set,  $CNN(x)$  looks very close to  $HE(x)$ . To  $x$  is from different patients,  $CNN(x)$  looks similar to  $HE(x)$ . If  $x$  is not IR image,  $CNN(x)$  looks very different to  $HE(x)$ . But for Test 2, when  $x$  is not IR image,  $CNN(x)$  looks similar to  $HE(x)$ . These results are also reflected on  $W$ -dist values (smaller is better).



Test 1	Average W-dist	Test 2	Average W-dist
Other Categories	<b>109.73</b>	lenna	<b>49.28</b>
Same patient IR	<b>6.86</b>	Same patient IR	<b>9.14</b>
Other patient IR 1	31.75	Other patient IR 1	35.05
Other patient IR 2	52.58	Other patient IR 2	48.51
Other patient IR 3	39.88	Other patient IR 3	38.10

## Experiment 2

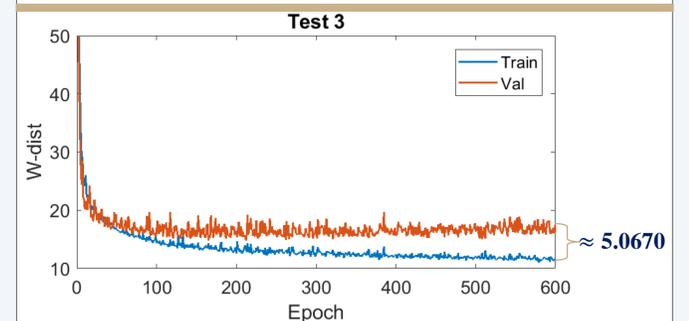
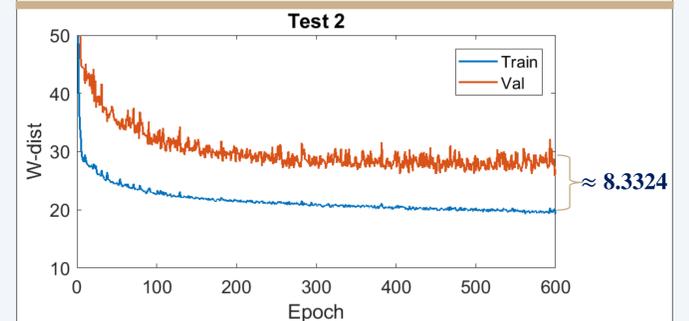
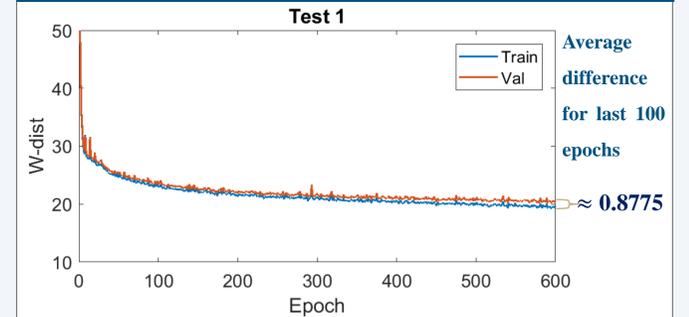
We used two open-source image databases (CIFAR-10 and USPtex1.0) to examine our hypothesis by more images. The CIFAR-10 has 60,000 images of animals and transporters and USPtex1.0 has 2,292 texture images. Their contents are very different.



We randomly selected images from the two databases to build 3 tests. For each test, 1,000 images were used to train the CNN and 1,000 images were for validation. After every epoch of training, average  $W$ -dists between histograms of  $CNN(x)$  and  $HE(x)$  for training and validation images were computed. In this experiment, we had much more images to train the CNN to obtain reliable results. And since the  $W$ -dist were verified as an effective method to measure the similarity of two images in experiment 1, we evaluate outcomes by the  $W$ -dists instead of comparing images by looking. Although training process is conducted by MSE, we only show the  $W$ -dists.

Test	Data for training	Validation
1	1000 from CIFAR	1000 from CIFAR
2	1000 from CIFAR	1000 from USPtex
3	1000 from USPtex	1000 from CIFAR

## Results of Experiment 2



## Conclusions

- Such results demonstrate CNN does not well learn HE but somewhat image style transformation to a certain category. Otherwise, the  $W$ -dist difference between two categories would be zero. Because once HE is learned, it should be implemented as needed for any kind of images.
- CNN performs better in Test 3 because USPtex1.0 contains more similar and simpler images than CIFAR-10. CNN might learn the key transformation easier.
- Such results imply that image pre-processing such as HE might be needed to apply in CNN applications to improve their performance because CNN cannot implement then automatically.