

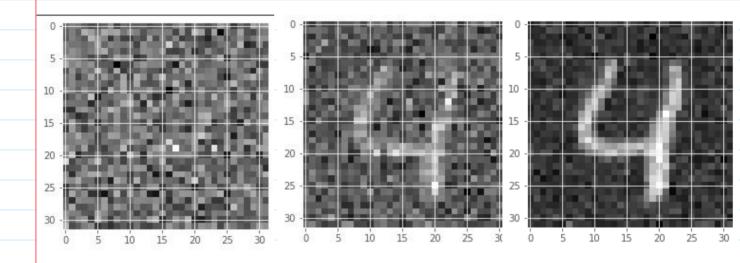
Horizontal flip loss: 4.001473947074086, Accuracy: 37.2%
Vertical flip loss: 4.031508159713623, Accuracy: 39.07%
The flip operation has decreased the accuracy significantly. This is because that our model do not handle any change of images at all, so some symmetric numbers like 1 and 8 might not be influenced, but flip of other numbers can

completely change the image and the model is not able to recognize them (the model judges based on the value of each pixel, and flip of image can change the value).

ii. Gaussian noise with variance 0.01 loss: 0.03470910963717059, Accuracy: 99.0099999999999

Gaussian noise with variance 0.1 loss: 0.5267047533830895, Accuracy: 84.03% Gaussian noise with variance 1 loss: 2.886542671023847, Accuracy: 21.6% High variance noise significantly decrease the accuracy, while low variance noise did not affect that much (still decreased). High variance means more blur in the image, and if the image is highly blurred, it will be hard to recognize since the model purely rely on the value of each pixel.

Below are sample images with noise variance from 1, 0.1, and 0.01.



D)

I used three different augmentations, each on a dataset.

The first dataset is transformed by random horizontal flip with a probability of 0.4.

The second dataset it transformed by random vertical flip with a probability of 0.4.

The third dataset is transformed by adding Gaussian noise to each pixel with a variance of 0.1

Then I concatenate the three datasets, then do a random shuffle, and train the model with the new combined and shuffled dataset.

Horizontal flip loss: 0.0698643539418145, Accuracy: 98.0%

Vertical flip loss: 0.0729027034169191, Accuracy: 97.8500000000001%

Gaussian noise with variance 0.01 loss: 0.041942079610283525, Accuracy: 98.7299999999999

Gaussian noise with variance 0.1 loss: 0.05091885066535971, Accuracy: 98.49%

