

## Introduction

The goal of this project is to clean up noisy image and predict the digits from the noisy datas

## Implementation

Imported and divided datasets into train and valid sets

```
21 ###
22 from sklearn.model_selection import train_test_split
23 #X_train, X_test = train_test_split(X_train, test_size=0.2, random_state=42)
24 X_train, X_valid= X_train_in[:-5000], X_train_in[-5000:]
25 X_train_set = X_train
26 X_valid_set = X_valid
27
28 y_train, y_valid= y_train_in[:-5000], y_train_in[-5000:]
29 y_train_set = y_train
30 y_valid_set = y_valid
31 print(X_train_set.shape)
32 print(y_train_set.shape)
```

A simple for loop was used to compute binary\_accuracy value for different hyperparameters and calculate the average accuracy for each combination. The highest value belongs to [Adelta, relu, binary\_accuracy]

1	<b>SGD</b>	<b>relu</b>	<b>binary_accuracy</b>			<b>average value</b>
2	0.8084	0.8082	0.8095	0.8102	0.8105	0.80936
3	<b>SGD</b>	<b>softmax</b>	<b>binary_accuracy</b>			<b>average value</b>
4	NAN	NAN	NAN	NAN	NAN	NAN
5	<b>Adadelata</b>	<b>softmax</b>	<b>binary_accuracy</b>			<b>average value</b>
6	0.8088	0.8088	0.8075	0.8089	0.8089	0.80858
7	<b>Adadelata</b>	<b>relu</b>	<b>binary_accuracy</b>			<b>average value</b>
8	0.8133	0.8143	0.8101	0.8127	0.8143	0.81294

This program uses CNN autoencoder. There are 2 layers with filters of size 12 and 14, and 1 pooling layer of size 2.

```
34 ###
35 import tensorflow.keras as keras
36 conv_encoder = keras.models.Sequential([
37     keras.layers.Reshape([28, 28, 1], input_shape=[28, 28]),
38     keras.layers.Conv2D(12, kernel_size=3, padding="SAME", activation="relu"),
39     keras.layers.MaxPool2D(pool_size=2),
40     keras.layers.Conv2D(14, kernel_size=3, padding="SAME", activation="relu"),
41 ])
42 conv_encoder.summary()
```

To restore the compressed representation, a decoder with 2 layer was used.

```
44 conv_decoder = keras.models.Sequential([
45     keras.layers.Conv2DTranspose(12, kernel_size=3, strides=2,
46                                   padding="SAME", activation="relu", input_shape=[7, 7, 14]),
47     keras.layers.Conv2DTranspose(1, kernel_size=3, strides=1,
48                                   padding="SAME", activation="sigmoid"),
49     keras.layers.Reshape([28, 28])
50 ])
51 conv_decoder.summary()
```

The final model has a total of 3279 parameters

```
In [272]: conv_ae = keras.models.Sequential([conv_encoder, conv_decoder])
...: conv_ae.summary()
```

Layer (type)	Output Shape	Param #
=====		
sequential_91 (Sequential)	(None, 14, 14, 14)	1646
=====		
sequential_94 (Sequential)	(None, 28, 28)	1633
=====		
Total params: 3,279		
Trainable params: 3,279		
Non-trainable params: 0		
=====		

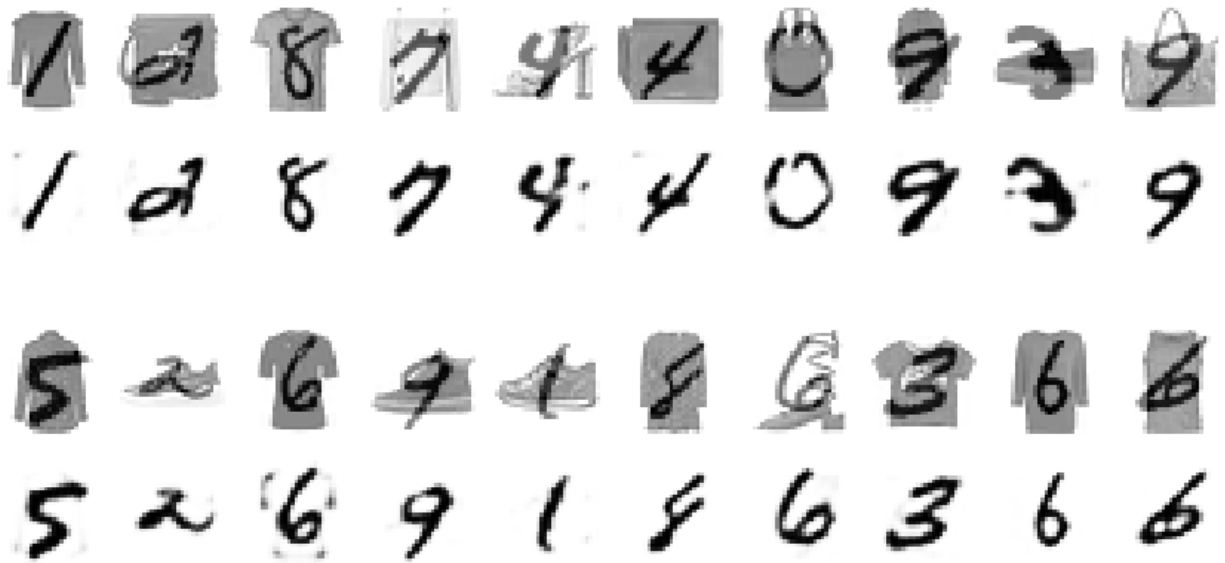
The results are reasonably good for a small number of training parameters with the highest accuracy = 0.8130 (full results on last page)

```
In [273]: conv_ae.compile(loss="binary_crossentropy", optimizer="Adadelta", metrics=["binary_accuracy"])
...: history = conv_ae.fit(X_train_set, y_train_set, epochs=10, validation_data=(X_valid_set,
y_valid_set))
Train on 55000 samples, validate on 5000 samples
Epoch 1/10

- - - - -
Epoch 10/10
55000/55000 [=====] - 8s 153us/sample - loss: 0.0958 - binary_accuracy: 0.8130 -
val_loss: 0.0957 - val_binary_accuracy: 0.8129
```

## Discussion

The reconstructed images were plotted (textbook functions) to confirm that they can be identified correctly by human eyes. Top row is the original noisy image and the bottom is the denoised ones



The model could perform better with more training parameters and deeper layers in the autoencoder. However, within the scope of this project, the model does reasonably well in reconstructing denoised images

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Report 4

Train on 55000 samples, validate on 5000 samples

Epoch 1/10

55000/55000 [=====] - 10s 188us/sample - loss: 0.1275 -  
binary\_accuracy: 0.8110 - val\_loss: 0.1050 - val\_binary\_accuracy: 0.8117

Epoch 2/10

55000/55000 [=====] - 9s 162us/sample - loss: 0.1036 - binary\_accuracy:  
0.8119 - val\_loss: 0.1032 - val\_binary\_accuracy: 0.8127

Epoch 3/10

55000/55000 [=====] - 8s 152us/sample - loss: 0.1021 - binary\_accuracy:  
0.8122 - val\_loss: 0.1018 - val\_binary\_accuracy: 0.8120

Epoch 4/10

55000/55000 [=====] - 8s 150us/sample - loss: 0.1009 - binary\_accuracy:  
0.8123 - val\_loss: 0.1006 - val\_binary\_accuracy: 0.8124

Epoch 5/10

55000/55000 [=====] - 8s 150us/sample - loss: 0.0999 - binary\_accuracy:  
0.8125 - val\_loss: 0.1038 - val\_binary\_accuracy: 0.8103

Epoch 6/10

55000/55000 [=====] - 8s 150us/sample - loss: 0.0990 - binary\_accuracy:  
0.8126 - val\_loss: 0.0999 - val\_binary\_accuracy: 0.8136

Epoch 7/10

55000/55000 [=====] - 8s 150us/sample - loss: 0.0982 - binary\_accuracy:  
0.8127 - val\_loss: 0.0995 - val\_binary\_accuracy: 0.8138

Epoch 8/10

55000/55000 [=====] - 8s 151us/sample - loss: 0.0974 - binary\_accuracy:  
0.8128 - val\_loss: 0.0975 - val\_binary\_accuracy: 0.8135

Epoch 9/10

55000/55000 [=====] - 8s 154us/sample - loss: 0.0966 - binary\_accuracy:  
0.8129 - val\_loss: 0.0964 - val\_binary\_accuracy: 0.8128

Epoch 10/10

55000/55000 [=====] - 8s 153us/sample - loss: 0.0958 - binary\_accuracy:  
0.8130 - val\_loss: 0.0957 - val\_binary\_accuracy: 0.8129