

# Fashion MNIST Report

## Problem Statement

[Fashion-MNIST](#) is a small dataset for fashion product classification consisting of 60,000 training images and 10,000 test images. All images are grayscale 28x28 pixels and there are 10 classes of clothing.

The following document discusses ideas and presents some models for the classification of these images.

## Idea and approach

The base idea is that this dataset is not much more complex than the traditional MNIST dataset. With that assumption, we will try using some network architectures that are known to perform well on the MNIST dataset. Also, I tried training the model with just one part of the dataset for faster training (10,000 train images) and also with the whole dataset.

I tried running the models without data augmentation and the results were much worse. When doing data augmentation I used zooming, rotation, shifting, and shear.

As for the loss function, all models use Categorical-Crossentropy

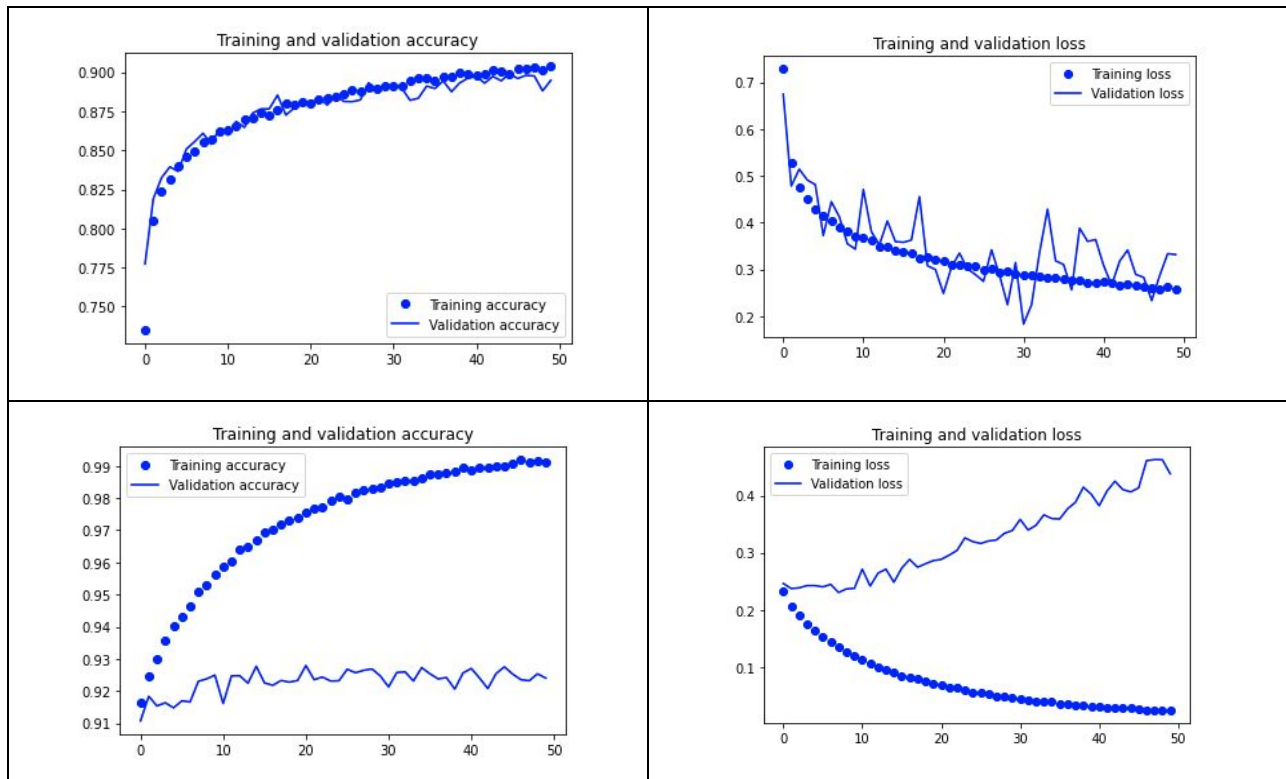
## 1 Layer CNN

The first approach is a simple neural network with one convolutional layer that has 693,932 trainable parameters. The following image represents the network architecture.

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 26, 26, 32)	320
max_pooling2d_1 (MaxPooling2	(None, 13, 13, 32)	0
dropout_1 (Dropout)	(None, 13, 13, 32)	0
flatten_1 (Flatten)	(None, 5408)	0
dense_1 (Dense)	(None, 128)	692352
dense_2 (Dense)	(None, 10)	1290

Total params: 693,962  
Trainable params: 693,962  
Non-trainable params: 0

This architecture works surprisingly well given its simplicity. Here, we have 91.39% accuracy on the validation dataset. Training this network on Google Colab with GPU acceleration took ~15min.

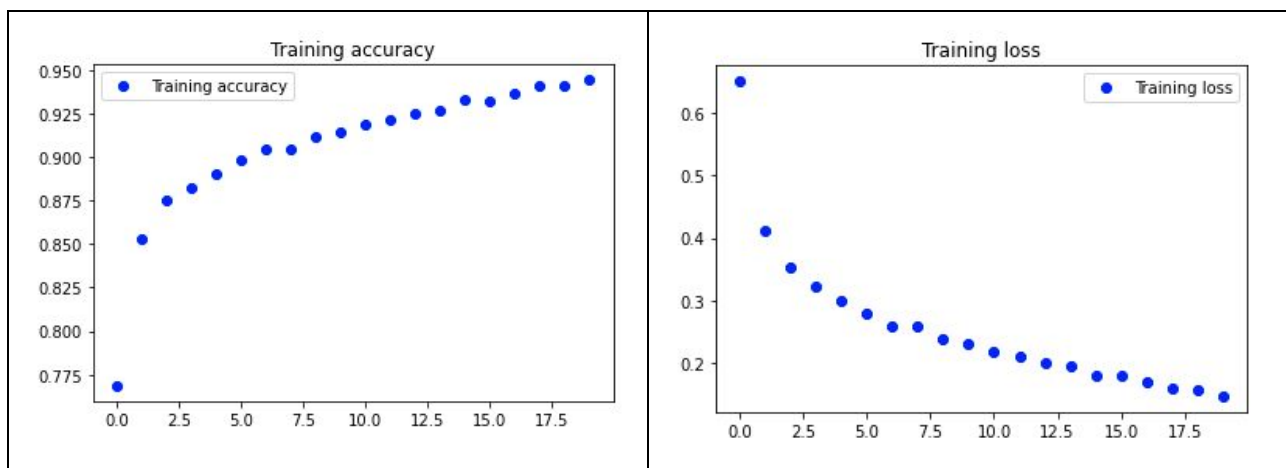


## LeNet-5

For the second approach, I chose LeNet-5, an old CNN architecture proven to be reliable for simple image classification tasks, especially on small resolution images. Here we have 136,586 parameters and training doesn't take more than 15 minutes.

With LeNet-5 the training accuracy is 95.28% and validation accuracy is 92.11%.

Layer (type)	Output Shape	Param #
conv2d_10 (Conv2D)	(None, 32, 32, 6)	156
max_pooling2d_10 (MaxPooling)	(None, 16, 16, 6)	0
conv2d_11 (Conv2D)	(None, 16, 16, 16)	2416
max_pooling2d_11 (MaxPooling)	(None, 8, 8, 16)	0
flatten_6 (Flatten)	(None, 1024)	0
dense_16 (Dense)	(None, 120)	123000
dense_17 (Dense)	(None, 84)	10164
dense_18 (Dense)	(None, 10)	850
Total params: 136,586		
Trainable params: 136,586		
Non-trainable params: 0		

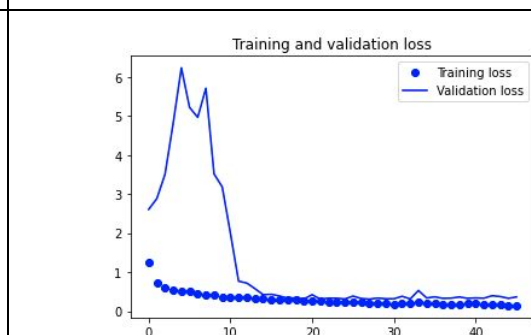
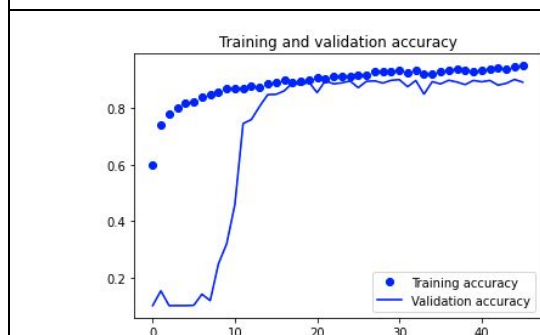
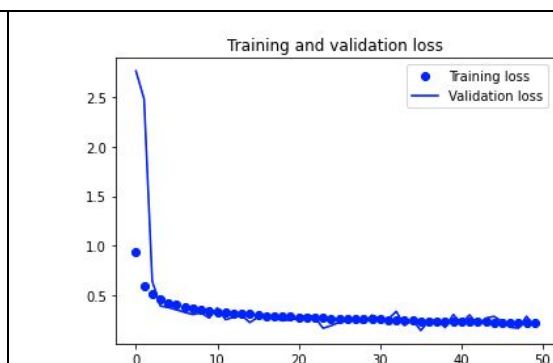
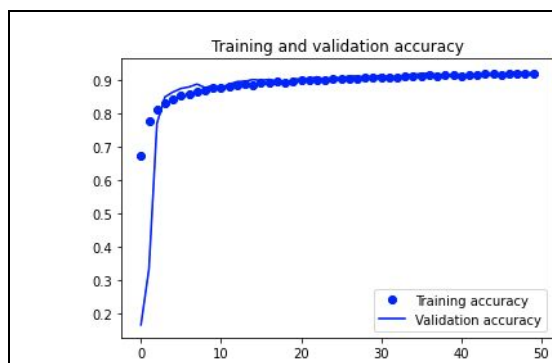


## 4 Layer CNN

The second approach was simply to stack more layers. Here we have a neural network with 4 convolutional layers that has 1,221,546 parameters. After adding padding we get 3 times more parameters. This model gave the best results, 92.51%.

Layer (type)	Output Shape	Param #
conv2d_5 (Conv2D)	(None, 26, 26, 32)	320
batch_normalization_7 (Batch Normalization)	(None, 26, 26, 32)	128
conv2d_6 (Conv2D)	(None, 24, 24, 32)	9248
batch_normalization_8 (Batch Normalization)	(None, 24, 24, 32)	128
max_pooling2d_3 (MaxPooling2D)	(None, 12, 12, 32)	0
dropout_6 (Dropout)	(None, 12, 12, 32)	0
conv2d_7 (Conv2D)	(None, 10, 10, 64)	18496
batch_normalization_9 (Batch Normalization)	(None, 10, 10, 64)	256
dropout_7 (Dropout)	(None, 10, 10, 64)	0
conv2d_8 (Conv2D)	(None, 8, 8, 128)	73856
batch_normalization_10 (Batch Normalization)	(None, 8, 8, 128)	512
max_pooling2d_4 (MaxPooling2D)	(None, 4, 4, 128)	0
dropout_8 (Dropout)	(None, 4, 4, 128)	0
flatten_2 (Flatten)	(None, 2048)	0
dense_4 (Dense)	(None, 512)	1049088
batch_normalization_11 (Batch Normalization)	(None, 512)	2048
dropout_9 (Dropout)	(None, 512)	0
dense_5 (Dense)	(None, 128)	65664
batch_normalization_12 (Batch Normalization)	(None, 128)	512
dropout_10 (Dropout)	(None, 128)	0
dense_6 (Dense)	(None, 10)	1290
Total params: 1,221,546		
Trainable params: 1,219,754		
Non-trainable params: 1,792		

Layer (type)	Output Shape	Param #
conv2d_15 (Conv2D)	(None, 28, 28, 32)	320
batch_normalization_12 (Batch Normalization)	(None, 28, 28, 32)	128
conv2d_16 (Conv2D)	(None, 28, 28, 32)	9248
batch_normalization_13 (Batch Normalization)	(None, 28, 28, 32)	128
max_pooling2d_11 (MaxPooling2D)	(None, 14, 14, 32)	0
dropout_11 (Dropout)	(None, 14, 14, 32)	0
conv2d_17 (Conv2D)	(None, 14, 14, 64)	18496
batch_normalization_14 (Batch Normalization)	(None, 14, 14, 64)	256
dropout_12 (Dropout)	(None, 14, 14, 64)	0
conv2d_18 (Conv2D)	(None, 14, 14, 128)	73856
batch_normalization_15 (Batch Normalization)	(None, 14, 14, 128)	512
max_pooling2d_12 (MaxPooling2D)	(None, 7, 7, 128)	0
dropout_13 (Dropout)	(None, 7, 7, 128)	0
flatten_6 (Flatten)	(None, 6272)	0
dense_17 (Dense)	(None, 512)	3211776
batch_normalization_16 (Batch Normalization)	(None, 512)	2048
dropout_14 (Dropout)	(None, 512)	0
dense_18 (Dense)	(None, 128)	65664
batch_normalization_17 (Batch Normalization)	(None, 128)	512
dropout_15 (Dropout)	(None, 128)	0
dense_19 (Dense)	(None, 10)	1290
Total params: 3,384,234		
Trainable params: 3,382,442		
Non-trainable params: 1,792		



## Results

In the following table, you can see the results for different model architectures, data preparation, hyperparameters, and more.

Validation is done on 10,000 images from the Fashion-MNIST dataset which are normalized and augmented the same way as the training images.

	1 Layer CNN	1 Layer CNN	4 Layer CNN	4 Layer CNN	LeNet-5
<b>Data</b>	1 fold	Full dataset	1 fold	Full dataset	Full dataset
<b>Augmentation</b>	Normalization	Normalization, rotation, zoom, shear, shift	Normalization	Normalization, rotation, zoom, shear, shift	Normalization
<b>Loss function</b>	Categorical Crossentropy	Categorical Crossentropy	Categorical Crossentropy	Categorical Crossentropy	Sparse Categorical Crossentropy
<b># of parameters</b>	693,932	693,932	1,219,754	1,219,754	136,586
<b>Hyperparameters</b>	Batch size: 256 Epochs: 100	Batch size: 256 Epochs: 50	Batch size: 256 Epochs: 100	Batch size: 256 Epochs: 50	Batch size: 32 Epochs: 20
<b>Training accuracy</b>	99.13%	90.30%	95.23%	91.19%	95.28%
<b>Validation accuracy</b>	91.97%	90.29%	89.92%	92.51%	92.11%

## Future improvements

- RMSprop and Adam for each model
- Data augmentation methods
  - Rescale
  - Horizontal flip
  - Vertical flip
- Different batch sizes and epochs