



# Fashion Mnist Using Machine Learning

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## Abstract

We present Fashion-MNIST, another dataset including  $28 \times 28$  grayscale pictures of 70,000 design items from 10 classifications, with 7,000 pictures for every class. The preparation set has 60,000 pictures and the test set has 10,000 pictures. Style MNIST is planned to fill in as a direct dropin swap for the first MNIST dataset for benchmarking AI calculations, as it has a similar picture size, information design and the construction of preparing and testing parts.

## Introduction

In this changing world, information technology is going to play important role in our life. The main purpose of our project (Fashion Mnist using machine learning) that it provides provision to reduce the human effort in garment industries. The current system is offline system and very time taken. Our project aim to provide accurate and relevant information regarding garments. Our project provides all the required facilities in garment industries.

This work is important for my trials with Fashion-MNIST dataset utilizing different Machine Learning calculations/models. The goal is to distinguish (anticipate) distinctive design items from the given pictures utilizing different most ideal Machine Learning Models (Algorithms) and analyse their outcomes (execution measures/scores) to show up at the best ML model. We have likewise explored different avenues regarding 'dimensionality decrease' strategy for this issue.

The MNIST dataset including 10-class manually written digits, was first presented by LeCun et al. [1998] in 1998. Around then one couldn't have anticipated the heavenly ascent of profound learning procedures and their exhibition. Notwithstanding the way that today profound learning can accomplish such a great deal the straightforward MNIST dataset has become the most generally utilized testbed in profound getting the hang of, outperforming CIFAR10 [Krizhevsky and Hinton, 2009] and ImageNet [Deng et al., 2009] in its ubiquity through Google patterns. Notwithstanding its effortlessness its utilization doesn't appear to be diminishing in spite of calls for it in the profound learning local area.

## Literature Survey

Many researches have been done on Machine Learning related projects. Earlier projects have included less number of layers namely Flatten layer and Dense layer. But as the concept of Deep Learning evolved, many new layers such as Convolution layer and MaxPooling layer have come into effect. The main advantage of these layers is that they are time efficient as well as highly accurate. Earlier this project was designed in Octave in 2010.

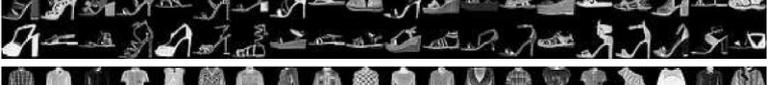
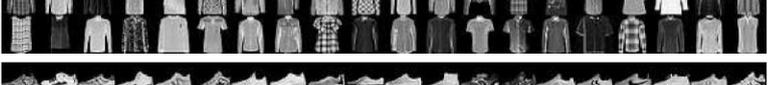
In 2014 there were less number of labels due to which the accuracy of the model was less, but in present time large number of labels are included which makes our model more accurate.

## Classes in Dataset

This dataset is taken from a package called TensorFlow. TensorFlow is an end to end open source machine learning platform that help us to develop and train various machine learning model. It has a flexible ecosystem that lets researchers push the state of the art in machine learning and developers easily build and deploy ML powered models. TensorFlow also helps many high level APIs like keras to run that makes model formation much easier.

The dataset in TensorFlow consist of training set that consist of 60,000 images and a test set that contains 10,000 images. The grayscale size of each image is 28\*28. There are 10 labels in this dataset that are as follows:

Table 2: Class names and example images in Fashion-MNIST dataset.

Label	Description	Examples
0	T-Shirt/Top	
1	Trouser	
2	Pullover	
3	Dress	
4	Coat	
5	Sandals	
6	Shirt	
7	Sneaker	
8	Bag	
9	Ankle boots	

## Summary of the model

Following are the layers and functions used to build our model:

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 26, 26, 64)	640
max_pooling2d (MaxPooling2D)	(None, 13, 13, 64)	0
conv2d_1 (Conv2D)	(None, 11, 11, 64)	36928
max_pooling2d_1 (MaxPooling2D)	(None, 5, 5, 64)	0
flatten (Flatten)	(None, 1600)	0
dense (Dense)	(None, 128)	204928
dense_1 (Dense)	(None, 128)	16512
dense_2 (Dense)	(None, 10)	1290
Total params: 260,298		
Trainable params: 260,298		
Non-trainable params: 0		

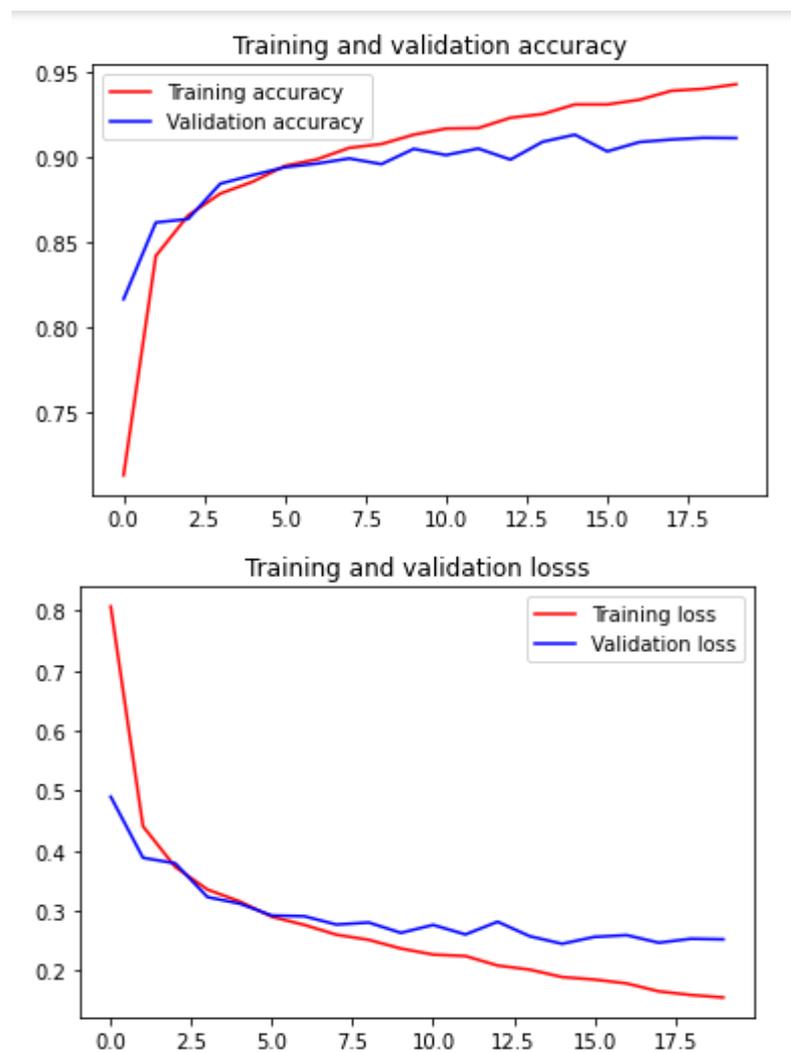
## Accuracy and loss metrics

The model is trained upto 20 epochs, and the value of training accuracy and validation accuracy are as follows:

```
Epoch 1/20
106/106 [=====] - 5s 20ms/step - loss: 0.8071 - accuracy: 0.7128 - val_loss: 0.4900 - val_accuracy: 0.8165
Epoch 2/20
106/106 [=====] - 2s 16ms/step - loss: 0.4407 - accuracy: 0.8420 - val_loss: 0.3881 - val_accuracy: 0.8617
Epoch 3/20
106/106 [=====] - 2s 15ms/step - loss: 0.3729 - accuracy: 0.8658 - val_loss: 0.3789 - val_accuracy: 0.8637
Epoch 4/20
106/106 [=====] - 2s 15ms/step - loss: 0.3352 - accuracy: 0.8786 - val_loss: 0.3227 - val_accuracy: 0.8845
Epoch 5/20
106/106 [=====] - 2s 15ms/step - loss: 0.3153 - accuracy: 0.8856 - val_loss: 0.3117 - val_accuracy: 0.8895
Epoch 6/20
106/106 [=====] - 2s 16ms/step - loss: 0.2897 - accuracy: 0.8949 - val_loss: 0.2918 - val_accuracy: 0.8942
Epoch 7/20
106/106 [=====] - 2s 16ms/step - loss: 0.2763 - accuracy: 0.8988 - val_loss: 0.2907 - val_accuracy: 0.8963
Epoch 8/20
106/106 [=====] - 2s 15ms/step - loss: 0.2599 - accuracy: 0.9056 - val_loss: 0.2768 - val_accuracy: 0.8993
Epoch 9/20
106/106 [=====] - 2s 16ms/step - loss: 0.2514 - accuracy: 0.9078 - val_loss: 0.2802 - val_accuracy: 0.8960
Epoch 10/20
106/106 [=====] - 2s 16ms/step - loss: 0.2368 - accuracy: 0.9133 - val_loss: 0.2630 - val_accuracy: 0.9050
Epoch 11/20
106/106 [=====] - 2s 16ms/step - loss: 0.2268 - accuracy: 0.9169 - val_loss: 0.2762 - val_accuracy: 0.9013
Epoch 12/20
106/106 [=====] - 2s 16ms/step - loss: 0.2243 - accuracy: 0.9172 - val_loss: 0.2603 - val_accuracy: 0.9052
Epoch 13/20
106/106 [=====] - 2s 16ms/step - loss: 0.2086 - accuracy: 0.9233 - val_loss: 0.2815 - val_accuracy: 0.8987
Epoch 14/20
106/106 [=====] - 2s 16ms/step - loss: 0.2016 - accuracy: 0.9255 - val_loss: 0.2573 - val_accuracy: 0.9092
Epoch 15/20
106/106 [=====] - 2s 16ms/step - loss: 0.1893 - accuracy: 0.9311 - val_loss: 0.2448 - val_accuracy: 0.9133
Epoch 16/20
106/106 [=====] - 2s 16ms/step - loss: 0.1852 - accuracy: 0.9311 - val_loss: 0.2562 - val_accuracy: 0.9035
Epoch 17/20
106/106 [=====] - 2s 16ms/step - loss: 0.1787 - accuracy: 0.9339 - val_loss: 0.2592 - val_accuracy: 0.9090
Epoch 18/20
106/106 [=====] - 2s 16ms/step - loss: 0.1654 - accuracy: 0.9392 - val_loss: 0.2465 - val_accuracy: 0.9105
Epoch 19/20
106/106 [=====] - 2s 16ms/step - loss: 0.1594 - accuracy: 0.9404 - val_loss: 0.2532 - val_accuracy: 0.9115
Epoch 20/20
106/106 [=====] - 2s 16ms/step - loss: 0.1553 - accuracy: 0.9430 - val_loss: 0.2522 - val_accuracy: 0.9113
```

As from the above analysis training accuracy is 94.30% and validation accuracy is 91.13%.

The accuracy and loss metrics of training as well as validation sets are shown in the following graphs:



## Conclusion

This paper presented Fashion-MNIST, a design item pictures dataset planned to be a dropin substitution of MNIST and while giving a really provoking option in contrast to benchmarking AI calculation. The pictures in Fashion-MNIST are changed over to an organization that coordinates with that of the MNIST dataset, making it quickly viable with any AI bundle fit for working with the first MNIST dataset.

## References

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