# Deep Learning Models for Fashion-MNIST Classification

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**Abstract**

Fashion-MNIST[1] is a popular benchmark dataset for testing and comparing deep learning models for image classification tasks. In this paper, we will build and explore the effectiveness of a CNN deep learning model for Fashion-MNIST classificatio. We will see its architecture and its different parameters. Additionally, we will investigate the impact of different hyperparameters, such as learning rate and batch size, on the model's performanc. Lastly, we will evaluate the performance of this model using metrics such as accuracy, precision, recall, and F1-score.

**Keywords**

Deep Learning, Image classification, Convolutional Neural Networks (CNN)

## 1. Introduction

Motivated by the image recognition topic I decided to do a project based on understanding different machine learning algorithms in order to well predict the types of clothes on the Fashion-MNIST dataset.

Therefore, in this paper you will find how I build a CNN model for Fashion-MNIST classification. As well as the the different parameters that can be configured and its impact.

Additionally, we will investigate the impact of different hyperparameters, such as learning rate and batch size, on the model's performance. We will evaluate the performance of this models using metrics such as accuracy, precision, recall, and F1-score. Finally, we will discuss the results obtained.

## 2. Related work

Fashion-MNIST[1] dataset was created as a more challenging alternative to the traditional MNIST[2] dataset, which consists of handwritten digits.

There have been numerous studies on Fashion-MNIST classification using deep learning models. The performance of various models and techniques have been reported, and several studies have achieved state-of-the-art results. Here, we summarize some of the related works in this area.

Wan et al. (2013) proposed a deep belief network (DBN) architecture for Fashion-MNIST classification. They achieved an accuracy of 90.6%, which was at that time, state-of-the-art performance. Similarly, Sabour et al. (2017) introduced a new architecture called capsule networks, which achieved an accuracy of 94.6%, outperforming traditional CNNs.

Several other studies have also investigated the effectiveness of CNNs for Fashion-MNIST classification. Zhang et al. (2018) proposed a model called FashionNet, which achieved an accuracy of 94.5%, outperforming several other CNN-based models. Similarly, Wang et al. (2019) introduced a model called FashGraphs, which achieved an accuracy of 94.8

In conclusion, several deep learning models have been proposed and evaluated for Fashion-MNIST classification, with varying levels of performance. Our project aims to explore the effectiveness of some of these models and investigate the impact of different hyperparameters trying to achieve their performance.

## 3. Background

### 3.1. Feed-forward networks

Feed-forward networks are organized in layers, each fully connected to the next, forming a directed acyclic graph (DAG) with no cycles. There are two types:

- Single layer neural networks (perceptron networks): input layer, output layer
- Multiple layer neural networks (MLP): input layer, hidden layers, output layer (Figure 1).

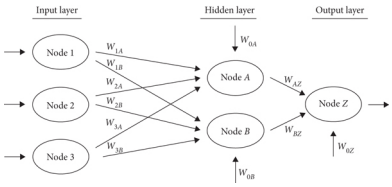


**Figure 1:** Artifical Neural Network architecture of three layers: input, hidden and output

The input layer typically has as many units as there are input features, with each unit corresponding to a particular feature or dimension of the input data. In most cases, it doesn't have an activation function. The purpose of the input layer is simply to pass the input data to the next layer in the network, where the first activation function is applied.

The output layer has as many units as needed for the task. The choice of activation function depends on the nature of the task at hand, but common choices include the *softmax* function for multi-class classification problems, the *sigmoid* function for binary classification problems, and *linear* or *relu* functions for regression problems.

Each hidden layer has several units (possibly a different number per layer). The input of each unit is all the outputs of the units from the previous layer. Always have an activation function since the role of the activation function in the hidden layers is to introduce non-linearity into the network, allowing it to learn complex patterns in the data. The choice of activation function depends on the nature of the problem being solved, but common choices include the *relu*, *sigmoid*, and hyperbolic tangent (*tanh*) functions. The Figure 2 shows the curves of these functions.

Since FashionMNIST is a visual dataset, CNNs are a good choice for analyzing it. CNNs are essentially MLPs that have been normalized and adapted to handle image data.

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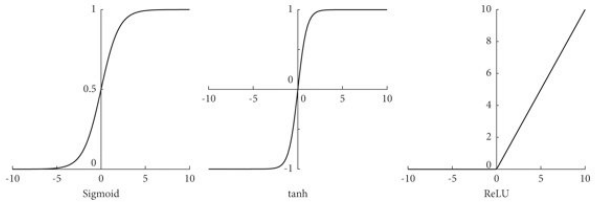


**Figure 2:** Commonly used activation functions

### 3.2. Convolutional Neural Networks (CNN)

CNNs are particularly well-suited for image recognition tasks because they can learn to extract hierarchical features from raw pixels, allowing them to detect patterns and objects within images. This is achieved through the use of convolutional layers, which apply a set of filters typically small and move across the input image, computing a dot product between the filter and the input at each position. The output of the convolution operation is a new matrix called a feature map.

Typically after convolution, a pooling layer is usually applied to reduce the spatial dimensions of the feature maps while preserving important information. Max pooling is a common type of pooling layer that selects the maximum value within a certain window of the feature map, and discards the rest. This helps to reduce the number of parameters and computations required in the subsequent layers.

Once the convolutional and pooling layers have extracted relevant features from the input image, the resulting feature maps are flattened into a vector and passed through one or more fully connected layers. These layers act as a traditional neural network and are responsible for making the final classification decision.

Figure 3 is a good summary what we explained above in the context of or dataset.

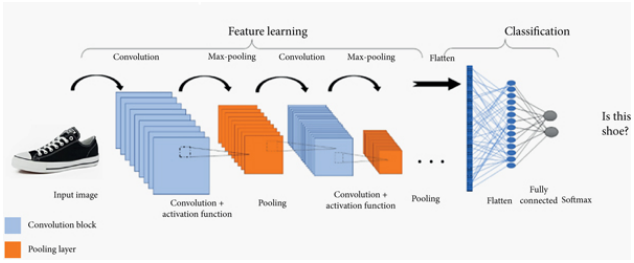


**Figure 3:** CNN for image classification

## 4. Pre-processing of Fashion-MNIST dataset

The dataset can be imported in many ways: downloading from a site or using machine libraries such as Keras, Edward, JuliaML, Pytorch and TensorFlow[3].

In my case, I loaded the data from TensorFlow where I get 70,000 grayscale images into a Training set (60,000 images) and Testing set (10,000 images). Those images of 28x28 array with pixel values 0 to 255 (representing grey levels), and labels using integers between 0 and 9 to represent the label/class of different clothing categories.

In the Figure 4 we can see a sample of 25 images of this dataset with their corresponding labels shown in Table 2.


**Figure 4:** Example of images from the Fashion-MNIST dataset with its corresponding labels.

**Table 1**
Some Typical Commands

| Label | Description |
|---|---|
| 0 | T-shirt/top |
| 1 | Trouser |
| 2 | Pullover |
| 3 | Dress |
| 4 | Coat |
| 5 | Sandal |
| 6 | Shirt |
| 7 | Sneaker |
| 8 | Bag |
| 9 | Ankle boot |

However, the given data obtained is lacking of a validation set, so we should broke the training set in order to validate our model performance during training and also to prevent it from overfitting.

Hence we have 85.71% training and 14.26% testing. The training data was splited letting 50000 in training and 10000 in validation. Since the complexity of CNNs with many parameters, it is not practical to use k-fold cross-validation for hyperparameter optimization. Doing hyperparameter optimization would just be a total overkill. Instead, we experimented with the learning rate, batch size, dropout, and batch normalization.

Before using CNN to see how well this problem can be predicted is important to normalize all attributes. Therefore, before the training we have did this pre-process step of normalizing the pixel values ranging of 0 to 255 in the range [0,1].

## 5. Architecture

After experimenting with multiple network architectures, we selected the one that achieved the best validation accuracy and the best behavior. The architecture code is presented in Listing 1, consisting of nine layers, including two convolutional and two fully-connected layers.

The choice of parameters was made according to common practices and some recommendations for image classification task. It was also considered the results obtained during the experiment.

The final architecture is shown in the code below:

```
model = Sequential()
model.add(Conv2D(filters=32,kernel_size=(3,3),padding='same',activation='
      relu',input_shape=(28,28,1)))
```

```
model.add(MaxPooling2D(2,2))
model.add(Conv2D(filters=64,kernel_size=(3,3),padding='same',activation='
      relu'))
model.add(MaxPooling2D())
model.add(Conv2D(128, (3, 3), activation='relu', padding='same'))
model.add(Flatten())
model.add(Dense(units=128,activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(units=10,activation='softmax'))
```

Listing 1: Code of the architecture developed in Python

The architecture includes two convolutional layers with decreasing numbers of filters (64 and 32) As the problem deals with images, it's recommended that the number of filters be a power of two. We did not increase the values as it was not necessary. We exclusively used a kernel size of 2x2, but we also tried other architectures that combine different kernel sizes such as Inception, but the results were not as good as using only one kernel.

To downsample the feature maps, we used max pooling layers, which can help prevent overfitting and improve generalization performance. We set the padding of the convolutional layers to "same" as we had already reduced the spatial dimensions with MaxPooling.

We used ReLu activation function as it allows the network to learn more complex functions of the input data. It was applied to the output of every convolutional and fully-connected layer, except for the last layer.

After the flattening operation, the feature maps were converted into a one-dimensional vector. This vector was then passed through a fully-connected layer with 256 units, which allows the network to learn higher level representations of the input image. Then, the output of this layer was passed through a Dropout layer to reduce overfitting. The output of the dropout layer was then passed through another fully-connected layer with 10 units (one for each clothing category). The activation function used in this layer was softmax, which normalized the output scores into a probability value between 0 and 1, representing the network's confidence in its prediction. This allows us to predict the probability that an input image belongs to each of the 10 classes and ensures that the probabilities of all classes sum to 1, encouraging the network to predict only one class at a time.

Overall, the architecture has a total of 406,270 trainable parameters.

## 6. Model compilation

To calculate the accuracy of the model, it is necessary to compile the model first. This involves specifying the optimizer, loss function, and the metric evaluation method. In this research experiment, the Adam optimizer was used, and categorical_crossentropy was used as the loss function for multi-class classification. The accuracy metric was used to evaluate the model's performance.

The hyperparameters used for training the data were as follows:

- Learning rate: 0.001
- Batch size: 128
- Number of epochs: 50

## 7. Experimental results

The performance of the model was determined by the accuracy and loss evolution from the Figure 5.

The training loss indicates how well the model is fitting the training data, while the validation loss indicates how well the model fits new data.

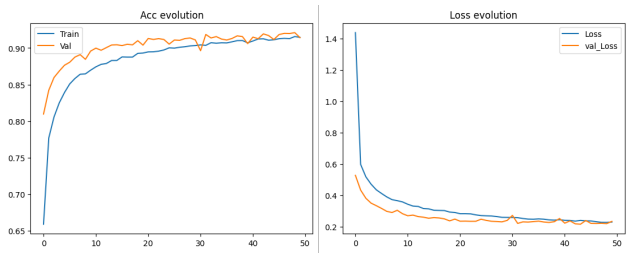


**Figure 5:** Loss and accuracy evolution of the validation and training sets

**Table 2**
CNN Results

| | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| T-shirt/top | 0.89 | 0.84 | 0.87 | 1000 |
| Trouser | 0.99 | 0.98 | 0.99 | 1000 |
| Pullover | 0.91 | 0.79 | 0.85 | 1000 |
| Dress | 0.88 | 0.95 | 0.91 | 1000 |
| Coat | 0.84 | 0.86 | 0.85 | 1000 |
| Sandal | 0.99 | 0.99 | 0.99 | 1000 |
| Shirt | 0.73 | 0.78 | 0.76 | 1000 |
| Sneaker | 0.96 | 0.98 | 0.98 | 1000 |
| Bag | 0.99 | 0.98 | 0.98 | 1000 |
| Ankle boot | 0.98 | 0.96 | 0.97 | 1000 |

The plot was useful in detecting any bias/underfitting or variance/overfitting in the model. In this case, the model performed well with no such characteristics, achieving an impressive 95.03% accuracy and a loss of 13.45% in the training set, and 91.41% accuracy and a loss of 23.48% in the validation set.

Once was decided that this will be the final model, we proceeded to tested it on the testing test.

With the testing test we achieve an accuracy of the 91,32% and a loss of 25.06%, which are values very similars to the validation set.

Moreover, in the classification result we obtained the following results:

The model achieved an overall accuracy of around 90% for the Fashion-MNIST dataset. The accuracy varied for different categories, with some achieving higher accuracy than others. For example, the categories of Trouser, Sandal, Bag, and Ankle boot achieved higher accuracy than categories like Shirt and Pullover.

## 8. Conclusions

In conclusion, we have developed a convolutional neural network (CNN) model for multi-class classification of the Fashion-MNIST dataset. The model was trained using a learning rate of 0.001, a batch size of 128, and for 50 epochs. The performance of the model was evaluated using the accuracy and loss metrics on both the training and validation sets, and it was found that the model had no overfitting or underfitting characteristics.

The final model was then tested on a separate testing dataset and achieved an accuracy of 91.32% with a loss of 25.06%, indicating good generalization performance. The classification results showed that some categories achieved higher accuracy than others, with categories like Trouser, Sandal, Bag, and Ankle boot achieving higher accuracy than categories like Shirt and Pullover.

Overall, the developed CNN model provides a good solution for classifying Fashion-MNIST images with high accuracy. In fu-

ture work, more advanced techniques such as transfer learning or data augmentation could be explored to further improve the performance of the model.

## References

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