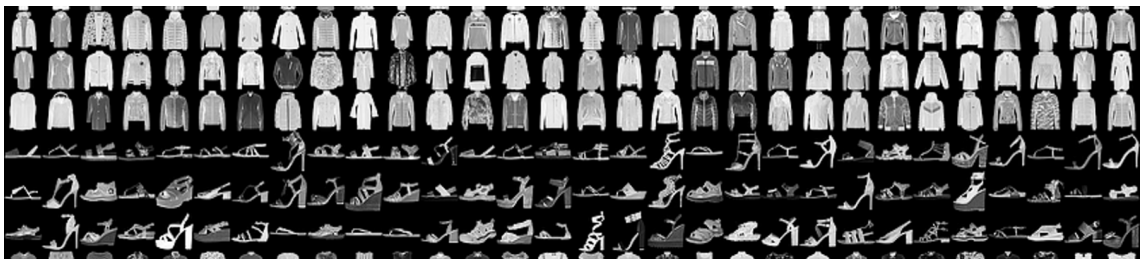

Zalando Clothing Classificaton

January 2, 2023

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1 Introduction

Lorem Ipsum is simply dummy text of the printing and typesetting industry. Lorem Ipsum has been the industry's standard dummy text ever since the 1500s, when an unknown printer took a galley of type and scrambled it to make a type specimen book. It has survived not only five centuries, but also the leap into electronic typesetting, remaining essentially unchanged. It was popularised in the 1960s with the release of Letraset sheets

2 Data and Preprocessing

2.1 Dataset

The Fashion-MNIST is a dataset of Zalando article images, consisting of a training set of 60,000 samples and 10,000 test samples. The dataset used here is a small portion of the original dataset, 10,000 training and 5,000 test samples. Each sample is a 28x28 pixels gray-scale image with a label indicating the type of clothing item associated with each.

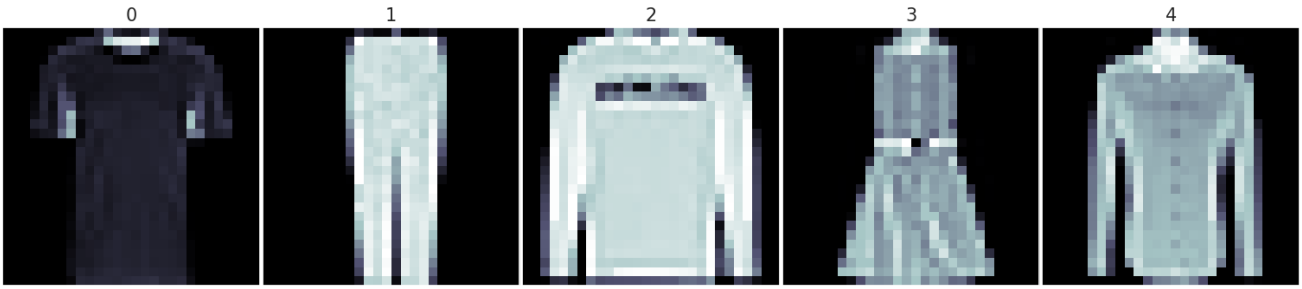

Figure 1: One sample from each class

2.1.1 Naming Conventions

Table 1 shows the translation from class labels to clothing type. The clothing type will be used instead of the labels in the report for better readability

Label	0	1	2	3	4
Type of clothing	T-shirt/Top	Trousers	Pullover	Dress	Shirt

Table 1: Mapping from class-labels to clothing type

2.2 Data Cleaning

The dataset provided was already in a cleaned state, which was verified by checking for missing values, and checking that the pixel values were no greater than 255 and no smaller than 0.

2.3 Preprocessing

The pixels values were in the range $[0, 255]$. This range was normalized to $[0, 1]$ by dividing each pixel by 255. This was done to improve training time and make it easier for neural networks to work with the data, as smaller numbers are slightly faster to compute and are preferred by neural networks

2.4 Class Distribution

Whether or not a machine learning model can learn to predict classes well depends to a high degree on how those classes are distributed within our training and training dataset. Both the datasets are extremely balanced, with the test being fully balanced (1000 of each class). This is illustrated on the plots below

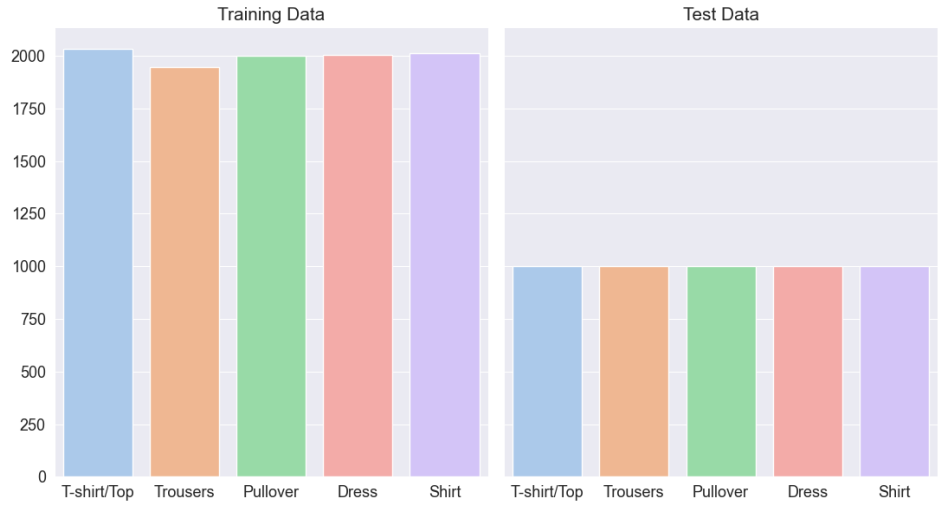

Figure 2: Distribution of clothing items in our training and test dataset

3 Exploratory Data Analysis

One effective way to understand and explore a dataset is through visualization of the feature distribution for each class. However, when the number of features is high, such as 728 in this case, this method may not be practical or informative. In these situations, alternative approaches for visualizing the dataset can be utilized to extract useful insights.

3.1 Principal Component Analysis

One way to gain insights from a large dataset that may be difficult to visualize is through the use of principal component analysis (PCA). PCA is a technique that reduces the number of features in a dataset while preserving the most important information. It does this by transforming the original variables into a new set of variables called principal components, which are uncorrelated and capture the maximum amount of variance in the data. In the following analysis, we will investigate the relationships between the first three principal components.

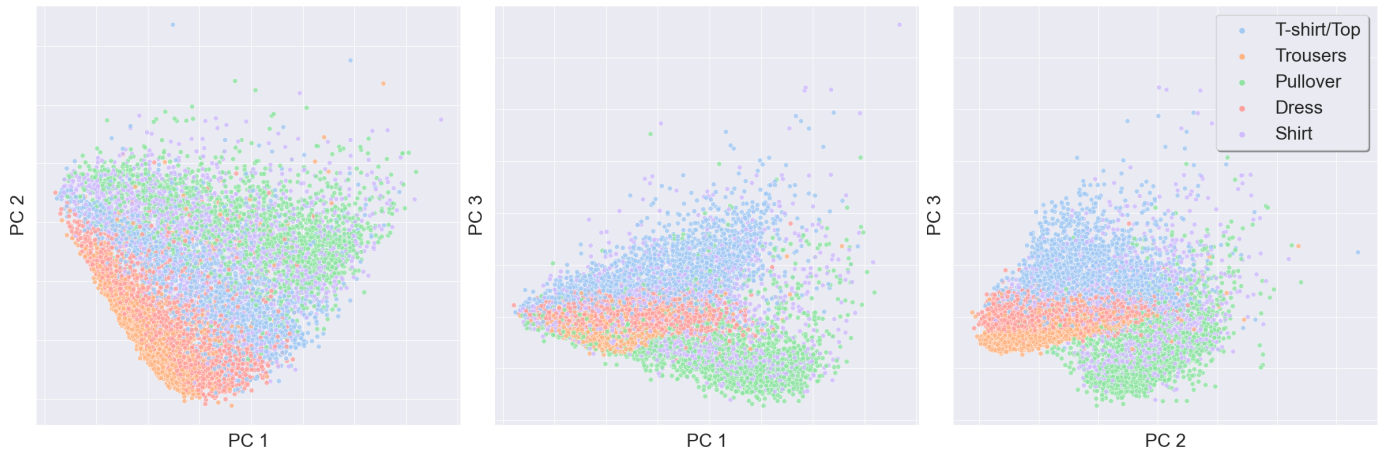

Figure 3: Visualizing relationships between the first 3 principal components

The first 3 principal components explain 42.7% variance, and it requires 61 principal components to explain above 90% variance. The pca plots are a useful tool to visualize how well the classes are seperated and gives a general idea of which classes might be easier and harder to classify correctly.

4 Decision Tree

In this section, we will discuss how the `DecisionTreeClassifier()` model is implemented and how the hyperparameters are chosen, as well as the results of using this model.

A decision tree is a supervised machine learning model that can be used for classification or regression tasks. It works by building a tree-like structure, where at each internal node, the algorithm evaluates all the available features and selects the split that maximizes the purity of the resulting splits. This process is repeated until a stopping condition is reached, such as a maximum depth or no further improvement in purity. The resulting leaf nodes are also known as decision regions, and the prediction for a sample is made by traversing the tree to find the correct decision region and then predicting the most common class in that region. Decision trees are popular because they are easy to understand and interpret due to their tree-like structure, and they can handle different types of data and decision boundaries. However, during training, the algorithm only considers the best split for each internal node without considering the potential negative effects on future splits, which is known as a greedy approach, and can potentially lead to sub-optimal trees for some datasets.

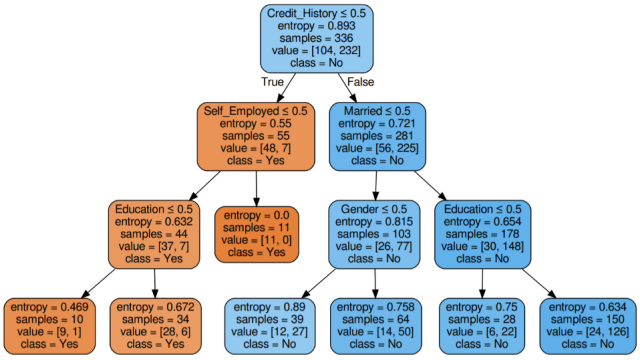

Figure 4: Simple Decision Tree

4.1 Implementation

As this project is focused on classification rather than regression a classification tree was implemented. It was done in Python using two classes:

1. `Node()`
2. `DecisionTreeClassifier()`

4.1.1 Node()

The `Node()` class represents the internal and leaf nodes that make up the decision tree. The `Node()` has the most responsibility of the two classes. It holds the data and passes it down the tree constantly splitting itself into more nodes with the `_split()` method. This is done by finding the best split with the `_get_best_split()` method based on either the gini or entropy impurity measure. The term 'best split' refers to the process of selecting the feature and value that will result in the highest increase in the purity of the resulting nodes when splitting a node in the tree. The best split of a given `Node()` can then be used to create two new nodes `self.left` and `self.right`.

4.1.2 DecisionTreeClassifier()

The `DecisionTreeClassifier()` is the classifier class. which has the `fit()` and `predict()` methods and two additional methods `get_depth()` and `get_n_leaves()`, that can be called after the model has been fitted, to get the depth and number of leaf nodes of the resulting decision tree. The `fit(X, y)` method takes the following two parameters, a feature matrix `(X)` and class labels `(y)` This data fed into the first node in the tree (the root). The purity of the node is then found and if a split can improve the purity and all split criteria (`max_depth` and `min_samples_split`) are fulfilled the node calls `_split()` on itself. This happens recursively and is how the tree-structure is created. The `predict(X)` method takes an array of samples or a single sample, and predicts the corresponding label. It works by traversing down the tree until a leaf node is reached, and then predicting the most frequent class in that node. The constructor take the following 4 parameters.

- `max_depth` - (An integer - the maximum depth to which the tree can grow)

- `min_samples_split` - (An integer - minimum number of samples in a node before for it to split)
- `criterion` - (A string - impurity measure (gini or entropy))
- `random_state` - (An integer - set the random seed for reproducible results)

4.2 Correctness

To validate the correctness of our implementation a thorough comparison with the Scikit-learn version was done. First a comparison of 200 Scikit-learn models and 200 of our models accuracy score was done using the `load_digits()` dataset from `Scikit-learn.datasets`, with a training and test size of 80% and 20% respectively.

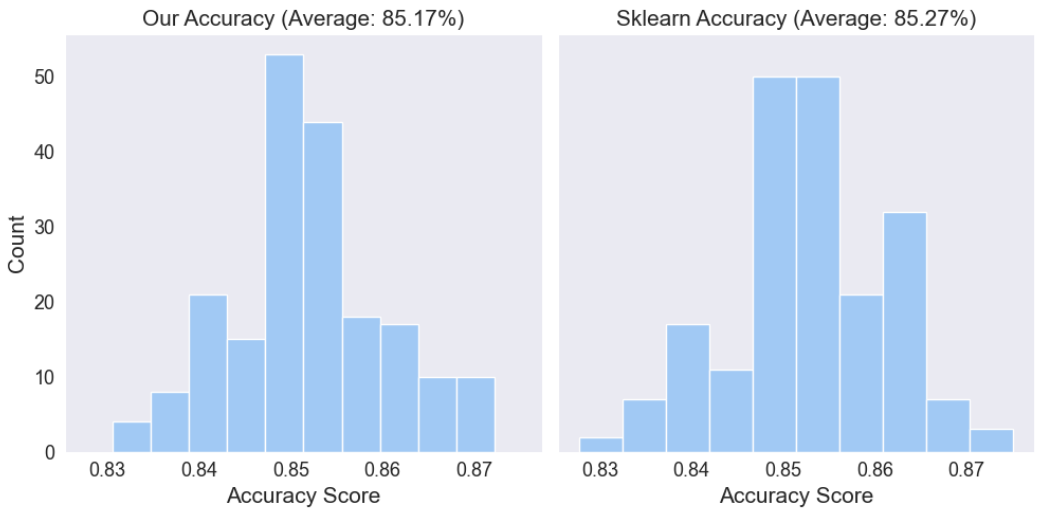

Figure 5: Accuracy distribution from 200 models

Each decision tree used in Figure 5 is fitted with the default parameters of both the Scikit-learn and our model. This means that the `max_depth` is not restricted and the `min_samples_split` is set to 2. A decision tree has randomness involved in the training process. This is because if two splits yield the same purity gain, one of them is chosen at random. This means the models might perform slightly different based on a single evaluation but very similar on average as seen in Figure 5.

The resulting tree depths and number of leaves were also compared and showed that the decision trees in both implementations grow to the same depth and with the same number of leaf nodes.

Lastly a comparison of **some** of the actual splits (best feature and cutoff) were done to assert correctness and as a sanity check, and the two implementations also agreed on this.

4.3 Hyperparameters

A decision tree is extremely prone to overfitting to the training data. This is especially the case if the max depth or other early stopping to the growth is not controlled. This can lead to a very high training accuracy but might struggle with unseen data. Another way to solve this is using post-pruning where

the tree is first grown fully, and then afterwards its size is reduced. Post-pruning was not implemented, instead, we focused on identifying an optimal combination of `max_depth`, `min_samples_split`, and `criterion` (gini or entropy). This was done using 5-fold cross-validation through the Scikit-learn class `GridSearchCV()`. The following parameter grid was specified and passed to the `GridSearchCV()` instance.

- `max_depth`: [None, 5, 7, 9, 11, 12]
- `min_samples_split`: [2, 4, 8, 10]
- `criterion`: [gini, entropy]

This led to the following combination of hyperparameters

```
max_depth=9   min_samples_split=4   criterion=gini
```

These values were selected due to their ability to effectively prevent overfitting, due to achieving the highest validation accuracy score.

4.4 Results

Evaluation Metric	Accuracy Score
Training Accuracy	89.83%
Test Accuracy	79.32%

Class	Precision	Recall	F1-Score
T-shirt/Top	0.76	0.75	0.75
Trousers	0.97	0.92	0.95
Pullover	0.80	0.83	0.81
Dress	0.82	0.88	0.85
Shirt	0.61	0.60	0.60

Table 2: Decision Tree Performance

The results reported in table 2 are results of our implementation of the `DecisionTreeClassifier()` with the hyperparameters specified in section **4.3**. To reproduce these exact results it should additionally be initialized with `random_state=42`, to eliminate the randomness.

4.4.1 Discussing Results

5 Feed-Forward Neural Network

In this section, we will discuss how the `NeuralNetworkClassifier()` model is implemented and how the hyperparameters are chosen, as well as the results of using this model.

A feedforward neural network is a type of artificial neural network that consists of an input layer, one or more hidden layers, and an output layer. Each layer consists of a set of neurons, which are connected to the neurons in the next layer via weights. The input layer receives input data and passes it through the network to the output layer, where the output is produced.

The hidden layers process the input data and transform it into a form that can be used by the output layer to produce the desired output. The weights of the connections between neurons are adjusted during the training process to minimize the difference between the predicted output and the actual output, a process known as backpropagation.

Feedforward neural networks can be used for a wide range of tasks, including image and speech recognition, natural language processing, and predicting outcomes in complex systems. They are a popular choice for machine learning tasks due to their ability to learn and generalize from data. Typically neural networks require significantly more training-data than the traditional machine learning methods to produce desirable results.

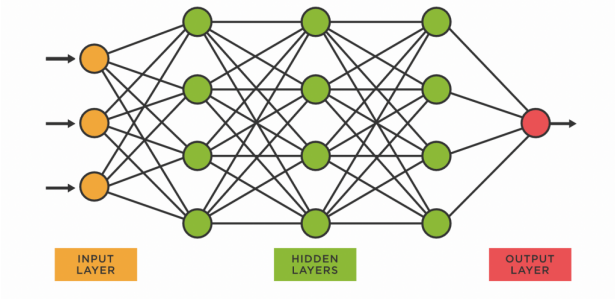

Figure 6: Simple Neural Network Architecture

5.1 Implementation

The implementation of the Feed-Forward Neural Network (FNN) was in Python using two classes.

1. `DenseLayer()`
2. `NeuralNetworkClassifier()`

5.1.1 DenseLayer()

The `DenseLayer()` represents the hidden-layers and the output layer that make up the FNN. It should be initialized with a `layer_size` and an `activation`. The `layer_size` represents the number of neurons in the layer, for example if you have a multiclass classification with 3 classes the output layer should have `layer_size=3`. The `activation` parameter is the activation function to be applied to the output of the layer. The current implemented activation-functions are Sigmoid, ReLU and Softmax, where Softmax can only be applied to the output layer.

The `DenseLayer()` has two primary methods `forward()` and `backward()`. The `forward(x, weights, bias)` method performs a forward pass through the layer, given the input data (`x`), weights (`weights`), and bias (`bias`). It calculates the dot product of the inputs and weights, adds the bias, and applies the activation function to the result to produce the output of the layer. It returns pre-activated output of the layer, and the activation of the layer. The `backward(dA_curr, W_curr, Z_curr, A_prev)` method performs the backward pass through the layer, given the gradient of the cost with respect to the current layer's activations `(dA_curr)`, the current layer's weights `(W_curr)`, the current layer's pre-activation values `(Z_curr)`, and the previous layer's activations (`A_prev`). It calculates the gradients of the cost with respect to the weights (`dW`), bias (`db`), and previous layer's activations (`dA`) using the chain rule. The return values of both the `forward()` and the `backward()` method are needed for backpropagation which happens in the `NeuralNetworkClassifier()`.

5.1.2 NeuralNetworkClassifier()

The `NeuralNetworkClassifier()` is the classifier class. It's primary methods are `fit()` and `predict()`. Additionally, it includes a lot of helper methods that all have different responsibilities. These include initializing and updating weights and biases based on the layer sizes and input data dimensions specified. The constructor take the following 4 parameters:

- `layers` - (A list of DenseLayer objects - the layers in the network)
- `learning_rate` - (A float - how fast the weights update after each mini-batch)
- `epochs` - (An integer - the number of epochs to train the neural network for)
- `random_state` - (A integer - set the random seed for reproducible results)

The `fit(x, y, batch_size, validation_size)` method is used to train the model, and takes 4 parameters: The training data (`x`) and labels (`y`), the `batch_size` (an integer indicating the number of samples to use in each mini-batch during training). Lastly `validation_size` (a float indicating the proportion of the training data to use for validation). To keep it short the `fit()` method does the following: For each mini-batch, the model makes predictions using the `_forward()` method, computes the loss using the `delta_cross_entropy()` function, then performs backpropagation with the `_backward()` method and finally updates weights and biases using the gradients calculated with `_backward()` with the `_update_trainable_params()` method. This process is performed as many times as specified in the constructor of the class.

5.2 Correctness

For the scope of this project the correctness of our implementation was done primarily visually. The training accuracy and training loss was compared to a similar model from the Tensorflow library. The models used here has two ReLU activated hidden layers with 128 and 64 neurons respectively, a softmax activated output layer with 5 neurons (one for each clothing item), a learning rate of 0.01, and lastly for reproduction of these exact graph `random_state=42`, and `tf.random.set_seed(42)` was used.

Figure 7: Comparing Accuracy and Loss with Tensorflow

As seen in Figure 7 the trend in accuracy and loss is very similar same however Tensorflow's model is obviously far better optimized so the curves are much smoother. Based on Figure 7 our model was considered correctly implemented.

5.3 Hyperparameters

Neural Networks are excellent at learning from data. This however can often lead to overfitting, when the number of epochs or learning rate is too high. We restricted ourselves to just look at the number of epochs while keeping all the other fixed, meaning, using the same hidden layers as in section **5.2** and the following parameters `learning_rate=0.01`, `batch_size=32`, `random_state=42`. This meant a number of epochs that gave a high validation accuracy while still keeping the validation loss low was optimal. Figure 8 shows the models performance during training and was used to choose 70 as the number of epochs. These parameters was then used to train an instance of the `NeuralNetworkClassifier()` and the results are reported in the following section.

Figure 8: Performance during training

Evaluation Metric	Accuracy Score
Training Accuracy	94.29%
Test Accuracy	85.16%

Class	Precision	Recall	F1-Score
T-shirt/Top	0.81	0.80	0.81
Trousers	0.97	0.97	0.97
Pullover	0.86	0.87	0.86
Dress	0.90	0.89	0.90
Shirt	0.72	0.73	0.72

Table 3: Neural Network Performance

5.4 Results

5.4.1 Discussing Results

6 Random Forest

The last classifier used is the `RandomForestClassifier()` from `sklearn.ensemble`. A random forest is a type of ensemble learning method. An ensemble method is a machine learning technique that combines the predictions of multiple models to make more accurate predictions than any individual model. In a Random Forest, a set of decision trees are typically trained on a subset of the original dataset, however in some cases each tree can be trained on the entire data set. The predicted class of an input sample is a vote by the trees in the forest, weighted by their probability estimates. That is, the predicted class is the one with highest mean probability estimate across the trees. This means that a random forest is not as prone to overfitting as a single decision tree, since this voting process helps to reduce the variance of the model.

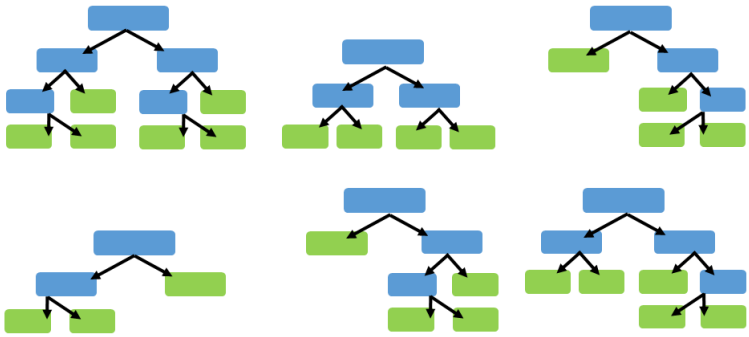

Figure 9: Random forest illustration

6.1 Hyperparameters

The hyperparameters was chosen similar to the `DecisionTreeClassifier()`. One additional parameter was looked at, `bootstrap`. Boostrap refers to whether to use the entire dataset or sample from when building the trees. The parameter grid used was the following:

- `max_depth`: [None, 10, 15, 20, 21, 22, 23]
- `min_samples_split`: [2, 4, 8]
- `criterion`: [gini, entropy]
- `bootstrap`: [True, False]

which gave the best combination as:

```
max_depth=21   min_samples_split=4   criterion=gini   boostrap=False
```

Using the entire dataset did not cause overfitting for this particular dataset, so `boostrap` was set to false. These values were selected due to their ability to effectively prevent overfitting and improve the accuracy of the model, just like the decision tree parameters. Then an instance of the `RandomForestClassifier()` was trained, with the parameters, while keeping all others at their default values. Additionally `random_state=42` was again used, and will lead to the reproduction of the results reported in the next section.

6.2 Results

Evaluation Metric	Accuracy Score
Training Accuracy	100%
Test Accuracy	85.54%

Class	Precision	Recall	F1-Score
T-shirt/Top	0.82	0.86	0.84
Trousers	0.99	0.96	0.97
Pullover	0.83	0.89	0.86
Dress	0.89	0.93	0.91
Shirt	0.74	0.64	0.69

Table 4: Random Forest Performance

6.3 Discussing Results