
Fashion-MNIST: a Novel Image Dataset for Benchmarking Machine Learning Algorithms

Han Xiao

Zalando Research
Mühlenstraße 25, 10243 Berlin
han.xiao@zalando.de

Kashif Rasul

Zalando Research
Mühlenstraße 25, 10243 Berlin
kashif.rasul@zalando.de

Roland Vollgraf

Zalando Research
Mühlenstraße 25, 10243 Berlin
roland.vollgraf@zalando.de

Abstract

We present Fashion-MNIST, a new dataset comprising of 28×28 grayscale images of 70,000 fashion products from 10 categories, with 7,000 images per category. The training set has 60,000 images and the test set has 10,000 images. Fashion-MNIST is intended to serve as a direct drop-in replacement for the original MNIST dataset for benchmarking machine learning algorithms, as it shares the same image size, data format and the structure of training and testing splits. The dataset is freely available at <https://github.com/zalando-research/fashion-mnist>.

1 Introduction

The MNIST dataset comprising of 10-class handwritten digits, was first introduced by LeCun et al. [1998] in 1998. At that time one could not have foreseen the stellar rise of deep learning techniques and their performance. Despite the fact that today deep learning can do so much the simple MNIST dataset has become the most widely used testbed in deep learning, surpassing CIFAR-10 [Krizhevsky and Hinton, 2009] and ImageNet [Deng et al., 2009] in its popularity via Google trends¹. Despite its simplicity its usage does not seem to be decreasing despite calls for it in the deep learning community.

The reason MNIST is so popular has to do with its size, allowing deep learning researchers to quickly check and prototype their algorithms. This is also complemented by the fact that all machine learning libraries (e.g. scikit-learn) and deep learning frameworks (e.g. Tensorflow, Pytorch) provide helper functions and convenient examples that use MNIST out of the box.

Our aim with this work is to create a good benchmark dataset which has all the accessibility of MNIST, namely its small size, straightforward encoding and permissive license. We took the approach of sticking to the 10 classes 70,000 grayscale images in the size of 28×28 as in the original MNIST. In fact, the only change one needs to use this dataset is to change the URL from where the MNIST dataset is fetched. Moreover, Fashion-MNIST poses a more challenging classification task than the simple MNIST digits data, whereas the latter has been trained to accuracies above 99.7% as reported in Wan et al. [2013], Ciregan et al. [2012].

We also looked at the EMNIST dataset provided by Cohen et al. [2017], an extended version of MNIST that extends the number of classes by introducing uppercase and lowercase characters. How-

¹<https://trends.google.com/trends/explore?date=all&q=mnist,CIFAR,ImageNet>

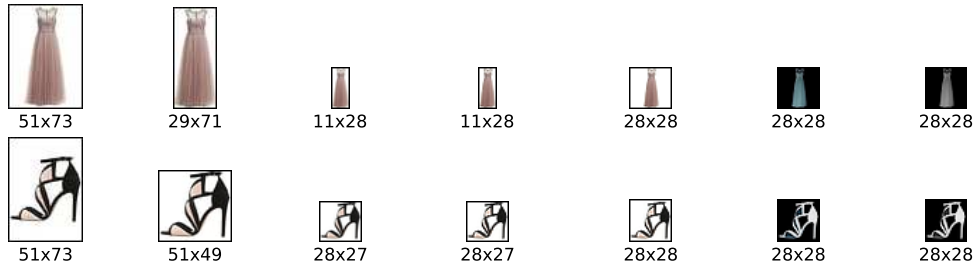
ever, to be able to use it seamlessly one needs to not only extend the deep learning framework’s MNIST helpers, but also change the underlying deep neural network to classify these extra classes.

2 Fashion-MNIST Dataset

Fashion-MNIST is based on the assortment on Zalando’s website². Every fashion product on Zalando has a set of pictures shot by professional photographers, demonstrating different aspects of the product, i.e. front and back looks, details, looks with model and in an outfit. The original picture has a light-gray background (hexadecimal color: #fdfdfd) and stored in 762×1000 JPEG format. For efficiently serving different frontend components, the original picture is resampled with multiple resolutions, e.g. large, medium, small, thumbnail and tiny.

We use the front look thumbnail images of 70,000 unique products to build Fashion-MNIST. Those products come from different gender groups: men, women, kids and neutral. In particular, white-color products are not included in the dataset as they have low contrast to the background. The thumbnails (51×73) are then fed into the following conversion pipeline, which is visualized in Figure 1.

1. Converting the input to a PNG image.
2. Trimming any edges that are close to the color of the corner pixels. The “closeness” is defined by the distance within 5% of the maximum possible intensity in RGB space.
3. Resizing the longest edge of the image to 28 by subsampling the pixels, i.e. some rows and columns are skipped over.
4. Sharpening pixels using a Gaussian operator of the radius and standard deviation of 1.0, with increasing effect near outlines.
5. Extending the shortest edge to 28 and put the image to the center of the canvas.
6. Negating the intensities of the image.
7. Converting the image to 8-bit grayscale pixels.



(1) PNG image (2) Trimming (3) Resizing (4) Sharpening (5) Extending (6) Negating (7) Grayscale

Figure 1: Diagram of the conversion process used to generate Fashion-MNIST dataset. Two examples from dress and sandals categories are depicted, respectively. Each column represents a step described in section 2.

Table 1: Files contained in the Fashion-MNIST dataset.

Name	Description	# Examples	Size
train-images-idx3-ubyte.gz	Training set images	60,000	25 MBytes
train-labels-idx1-ubyte.gz	Training set labels	60,000	140 Bytes
t10k-images-idx3-ubyte.gz	Test set images	10,000	4.2 MBytes
t10k-labels-idx1-ubyte.gz	Test set labels	10,000	92 Bytes

For the class labels, we use the silhouette code of the product. The silhouette code is manually labeled by the in-house fashion experts and reviewed by a separate team at Zalando. Each product

²Zalando is the Europe’s largest online fashion platform. <http://www.zalando.com>

contains only one silhouette code. Table 2 gives a summary of all class labels in Fashion-MNIST with examples for each class.

Finally, the dataset is divided into a training and a test set. The training set receives a randomly-selected 6,000 examples from each class. Images and labels are stored in the same file format as the MNIST data set, which is designed for storing vectors and multidimensional matrices. The result files are listed in Table 1. We sort examples by their labels while storing, resulting in smaller label files after compression comparing to the MNIST. It is also easier to retrieve examples with a certain class label. The data shuffling job is therefore left to the algorithm developer.

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	

3 Experiments

We provide some classification results in Table 3 to form a benchmark on this data set. All algorithms are repeated 5 times by shuffling the training data and the average accuracy on the test set is reported. The benchmark on the MNIST dataset is also included for a side-by-side comparison. A more comprehensive table with explanations on the algorithms can be found on <https://github.com/zalandoresearch/fashion-mnist>.

Table 3: Benchmark on Fashion-MNIST (Fashion) and MNIST.

Classifier	Parameter	Test Accuracy	
		Fashion	MNIST
DecisionTreeClassifier	criterion=entropy max_depth=10 splitter=best	0.798	0.873
	criterion=entropy max_depth=10 splitter=random	0.792	0.861
	criterion=entropy max_depth=50 splitter=best	0.789	0.886

Continued on next page

Table 3 – continued from previous page

Classifier	Parameter	Test Accuracy	
		Fashion	MNIST
	criterion=entropy max_depth=100 splitter=best	0.789	0.886
	criterion=gini max_depth=10 splitter=best	0.788	0.866
	criterion=entropy max_depth=50 splitter=random	0.787	0.883
	criterion=entropy max_depth=100 splitter=random	0.787	0.881
	criterion=gini max_depth=100 splitter=best	0.785	0.879
	criterion=gini max_depth=50 splitter=best	0.783	0.877
	criterion=gini max_depth=10 splitter=random	0.783	0.853
	criterion=gini max_depth=50 splitter=random	0.779	0.873
	criterion=gini max_depth=100 splitter=random	0.777	0.875
ExtraTreeClassifier	criterion=gini max_depth=10 splitter=best	0.775	0.806
	criterion=entropy max_depth=100 splitter=best	0.775	0.847
	criterion=entropy max_depth=10 splitter=best	0.772	0.810
	criterion=entropy max_depth=50 splitter=best	0.772	0.847
	criterion=gini max_depth=100 splitter=best	0.769	0.843
	criterion=gini max_depth=50 splitter=best	0.768	0.845
	criterion=entropy max_depth=50 splitter=random	0.752	0.826
	criterion=entropy max_depth=100 splitter=random	0.752	0.828
	criterion=gini max_depth=50 splitter=random	0.748	0.824
	criterion=gini max_depth=100 splitter=random	0.745	0.820
	criterion=gini max_depth=10 splitter=random	0.739	0.737
	criterion=entropy max_depth=10 splitter=random	0.737	0.745
GaussianNB	priors=[0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1]	0.511	0.524
GradientBoostingClassifier	n_estimators=100 loss=deviance max_depth=10	0.880	0.969
	n_estimators=50 loss=deviance max_depth=10	0.872	0.964
	n_estimators=100 loss=deviance max_depth=3	0.862	0.949
	n_estimators=10 loss=deviance max_depth=10	0.849	0.933
	n_estimators=50 loss=deviance max_depth=3	0.840	0.926
	n_estimators=10 loss=deviance max_depth=50	0.795	0.888
	n_estimators=10 loss=deviance max_depth=3	0.782	0.846
KNeighborsClassifier	weights=distance n_neighbors=5 p=1	0.854	0.959
	weights=distance n_neighbors=9 p=1	0.854	0.955
	weights=uniform n_neighbors=9 p=1	0.853	0.955
	weights=uniform n_neighbors=5 p=1	0.852	0.957
	weights=distance n_neighbors=5 p=2	0.852	0.945
	weights=distance n_neighbors=9 p=2	0.849	0.944
	weights=uniform n_neighbors=5 p=2	0.849	0.944
	weights=uniform n_neighbors=9 p=2	0.847	0.943
	weights=distance n_neighbors=1 p=2	0.839	0.943
	weights=uniform n_neighbors=1 p=2	0.839	0.943
	weights=uniform n_neighbors=1 p=1	0.838	0.955
	weights=distance n_neighbors=1 p=1	0.838	0.955
LinearSVC	loss=hinge C=1 multi_class=ovr penalty=12	0.836	0.917
	loss=hinge C=1 multi_class=crammer_singer penalty=12	0.835	0.919
	loss=squared_hinge C=1 multi_class=crammer_singer penalty=12	0.834	0.919
	loss=squared_hinge C=1 multi_class=crammer_singer penalty=11	0.833	0.919
	loss=hinge C=1 multi_class=crammer_singer penalty=11	0.833	0.919
	loss=squared_hinge C=1 multi_class=ovr penalty=12	0.820	0.912
	loss=squared_hinge C=10 multi_class=ovr penalty=12	0.779	0.885
	loss=squared_hinge C=100 multi_class=ovr penalty=12	0.776	0.873
	loss=hinge C=10 multi_class=ovr penalty=12	0.764	0.879
	loss=hinge C=100 multi_class=ovr penalty=12	0.758	0.872

Continued on next page

Table 3 – continued from previous page

Classifier	Parameter	Test Accuracy	
		Fashion	MNIST
	loss=HINGE C=10 multi_class=crammer_singer penalty=11	0.751	0.783
	loss=HINGE C=10 multi_class=crammer_singer penalty=12	0.749	0.816
	loss=squared_hinge C=10 multi_class=crammer_singer penalty=12	0.748	0.829
	loss=squared_hinge C=10 multi_class=crammer_singer penalty=11	0.736	0.829
	loss=HINGE C=100 multi_class=crammer_singer penalty=11	0.516	0.759
	loss=HINGE C=100 multi_class=crammer_singer penalty=12	0.496	0.753
	loss=squared_hinge C=100 multi_class=crammer_singer penalty=11	0.492	0.746
	loss=squared_hinge C=100 multi_class=crammer_singer penalty=12	0.484	0.737
LogisticRegression	C=1 multi_class=ovr penalty=11	0.842	0.917
	C=1 multi_class=ovr penalty=12	0.841	0.917
	C=10 multi_class=ovr penalty=12	0.839	0.916
	C=10 multi_class=ovr penalty=11	0.839	0.909
	C=100 multi_class=ovr penalty=12	0.836	0.916
MLPClassifier	activation=relu hidden_layer_sizes=[100]	0.871	0.972
	activation=relu hidden_layer_sizes=[100, 10]	0.870	0.972
	activation=tanh hidden_layer_sizes=[100]	0.868	0.962
	activation=tanh hidden_layer_sizes=[100, 10]	0.863	0.957
	activation=relu hidden_layer_sizes=[10, 10]	0.850	0.936
	activation=relu hidden_layer_sizes=[10]	0.848	0.933
	activation=tanh hidden_layer_sizes=[10, 10]	0.841	0.921
	activation=tanh hidden_layer_sizes=[10]	0.840	0.921
PassiveAggressiveClassifier	C=1	0.776	0.877
	C=100	0.775	0.875
	C=10	0.773	0.880
Perceptron	penalty=l1	0.782	0.887
	penalty=l2	0.754	0.845
	penalty=elasticnet	0.726	0.845
RandomForestClassifier	n_estimators=100 criterion=entropy max_depth=100	0.873	0.970
	n_estimators=100 criterion=gini max_depth=100	0.872	0.970
	n_estimators=50 criterion=entropy max_depth=100	0.872	0.968
	n_estimators=100 criterion=entropy max_depth=50	0.872	0.969
	n_estimators=50 criterion=entropy max_depth=50	0.871	0.967
	n_estimators=100 criterion=gini max_depth=50	0.871	0.971
	n_estimators=50 criterion=gini max_depth=50	0.870	0.968
	n_estimators=50 criterion=gini max_depth=100	0.869	0.967
	n_estimators=10 criterion=entropy max_depth=50	0.853	0.949
	n_estimators=10 criterion=entropy max_depth=100	0.852	0.949
	n_estimators=10 criterion=gini max_depth=50	0.848	0.948
	n_estimators=10 criterion=gini max_depth=100	0.847	0.948
	n_estimators=50 criterion=entropy max_depth=10	0.838	0.947
	n_estimators=100 criterion=entropy max_depth=10	0.838	0.950
	n_estimators=100 criterion=gini max_depth=10	0.835	0.949
	n_estimators=50 criterion=gini max_depth=10	0.834	0.945
	n_estimators=10 criterion=entropy max_depth=10	0.828	0.933
	n_estimators=10 criterion=gini max_depth=10	0.825	0.930
SGDClassifier	loss=HINGE penalty=12	0.819	0.914
	loss=perceptron penalty=11	0.818	0.912
	loss=modified_huber penalty=11	0.817	0.910
	loss=modified_huber penalty=12	0.816	0.913
	loss=log penalty=elasticnet	0.816	0.912
	loss=HINGE penalty=elasticnet	0.816	0.913

Continued on next page

Table 3 – continued from previous page

Classifier	Parameter	Test Accuracy	
		Fashion	MNIST
	loss=squared_hinge penalty=elasticnet	0.815	0.914
	loss=hinge penalty=l1	0.815	0.911
	loss=log penalty=l1	0.815	0.910
	loss=perceptron penalty=12	0.814	0.913
	loss=perceptron penalty=elasticnet	0.814	0.912
	loss=squared_hinge penalty=12	0.814	0.912
	loss=modified_huber penalty=elasticnet	0.813	0.914
	loss=log penalty=12	0.813	0.913
	loss=squared_hinge penalty=11	0.813	0.911
SVC	C=10 kernel=rbf	0.897	0.973
	C=10 kernel=poly	0.891	0.976
	C=100 kernel=poly	0.890	0.978
	C=100 kernel=rbf	0.890	0.972
	C=1 kernel=rbf	0.879	0.966
	C=1 kernel=poly	0.873	0.957
	C=1 kernel=linear	0.839	0.929
	C=10 kernel=linear	0.829	0.927
	C=100 kernel=linear	0.827	0.926
	C=1 kernel=sigmoid	0.678	0.898
	C=10 kernel=sigmoid	0.671	0.873
	C=100 kernel=sigmoid	0.664	0.868

4 Conclusions

This paper introduced Fashion-MNIST, a fashion product images dataset intended to be a drop-in replacement of MNIST and whilst providing a more challenging alternative for benchmarking machine learning algorithm. The images in Fashion-MNIST are converted to a format that matches that of the MNIST dataset, making it immediately compatible with any machine learning package capable of working with the original MNIST dataset.

References

- D. Ciregan, U. Meier, and J. Schmidhuber. Multi-column deep neural networks for image classification. In *Computer Vision and Pattern Recognition (CVPR), 2012 IEEE Conference on*, pages 3642–3649. IEEE, 2012.
- G. Cohen, S. Afshar, J. Tapson, and A. van Schaik. Emnist: an extension of mnist to handwritten letters. *arXiv preprint arXiv:1702.05373*, 2017.
- J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei. Imagenet: A large-scale hierarchical image database. In *Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on*, pages 248–255. IEEE, 2009.
- A. Krizhevsky and G. Hinton. Learning multiple layers of features from tiny images. 2009.
- Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324, 1998.
- L. Wan, M. Zeiler, S. Zhang, Y. L. Cun, and R. Fergus. Regularization of neural networks using dropconnect. In *Proceedings of the 30th international conference on machine learning (ICML-13)*, pages 1058–1066, 2013.