Project Title: Clothing Item Classification Using CNN and Spark



By: Feven Tefera Mihret Kemal

Goal

- Classify clothing items into 10 categories using Fashion MNIST
- Address challenges:
 - Overfitting with drop out and early stopping
 - Computational efficiency with Spark

Real World Application

- Online clothing stores like Amazon, and Zara can use the model to classify product images into categories
- Visual search capabilities where users can find visually similar items based on images (Google, Pinterest)
- Amazon or eBay could use automated captions for product descriptions based on images

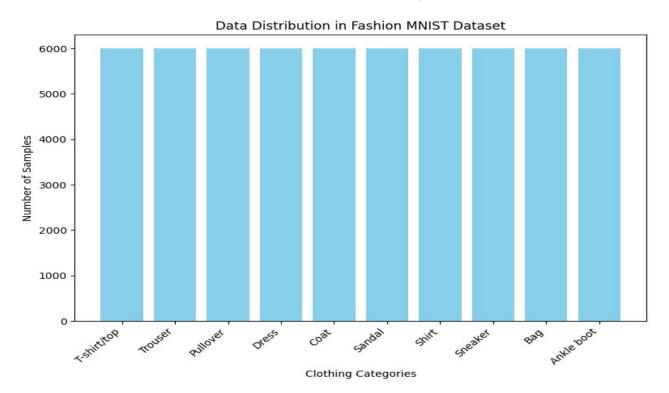
Dataset Overview

- Dataset: <u>Fashion MNIST</u>
- Categories: T-shirt/top, Trouser, Pullover, Dress, Coat, Sandal,
 Shirt, Sneaker, Bag, Ankle Boot
- Sample Size:
 - 60,000 training images
 - 10,000 test images

Data split: 90% - training set, and 10% validation set

Data Distribution

Equal distribution across 10 categories.



Implementation Tools

- Libraries: PySpark, TensorFlow, Keras, NumPy, Sklearn,
 MatplotLib
- Processing:
 - Spark for distributed data handling
 - Keras for CNN design and training

CNN Model Architecture

Model Architecture: Model: "sequential_25"

Layer (type)	Output Shape	Param #
conv2d_50 (Conv2D)	(None, 26, 26, 32)	320
max_pooling2d_50 (MaxPooling2D)	(None, 13, 13, 32)	0
conv2d_51 (Conv2D)	(None, 11, 11, 64)	18,496
max_pooling2d_51 (MaxPooling2D)	(None, 5, 5, 64)	0
dropout_50 (Dropout)	(None, 5, 5, 64)	0
flatten_25 (Flatten)	(None, 1600)	0
dense_50 (Dense)	(None, 128)	204,928
dropout_51 (Dropout)	(None, 128)	0
dense_51 (Dense)	(None, 10)	1,290

Total params: 225,034 (879.04 KB) Trainable params: 225,034 (879.04 KB) Non-trainable params: 0 (0.00 B)

Tuning Hyperparameters

- Learning rate: {0.01, 0.001}
- Batch size: {64,32}
- Dropout: {0.3,0.5}
- We used Grid search with 3 fold cv for hyperparameter tuning

Best Hyperparameters

Learning rate: 0.001

Batch size: 32

Dropout: 0.3

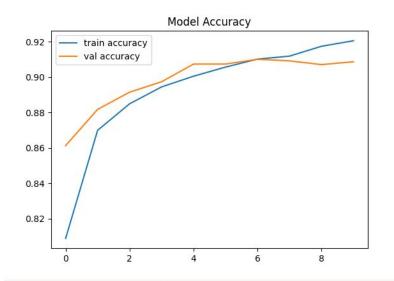
```
Best parameters: {'batch_size': 32, 'model__dropout_rate': 0.3, 'model__learning_rate': 0.001}
Best accuracy: 0.9096000000000001
```

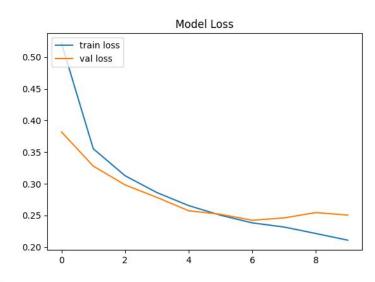
```
Epoch 1/10
                              156s 82ms/step - accuracy: 0.7414 - loss: 0.7043 - val_accuracy: 0.8612 - val_loss: 0.3818
1875/1875
Epoch 2/10
1875/1875
                               202s 82ms/step - accuracy: 0.8646 - loss: 0.3694 - val accuracy: 0.8817 - val loss: 0.3280
Epoch 3/10
1875/1875
                               207s 85ms/step - accuracy: 0.8862 - loss: 0.3123 - val accuracy: 0.8914 - val loss: 0.2983
Epoch 4/10
                              171s 68ms/step - accuracy: 0.8938 - loss: 0.2844 - val_accuracy: 0.8973 - val_loss: 0.2786
1875/1875
Epoch 5/10
                               144s 70ms/step - accuracy: 0.9005 - loss: 0.2667 - val accuracy: 0.9073 - val loss: 0.2575
1875/1875
Epoch 6/10
1875/1875
                               141s 69ms/step - accuracy: 0.9059 - loss: 0.2501 - val_accuracy: 0.9073 - val_loss: 0.2519
Epoch 7/10
1875/1875
                               142s 69ms/step - accuracy: 0.9084 - loss: 0.2409 - val_accuracy: 0.9100 - val_loss: 0.2425
Epoch 8/10
                               141s 69ms/step - accuracy: 0.9122 - loss: 0.2280 - val_accuracy: 0.9091 - val_loss: 0.2462
1875/1875
Epoch 9/10
1875/1875
                               141s 68ms/step - accuracy: 0.9185 - loss: 0.2196 - val_accuracy: 0.9070 - val_loss: 0.2547
Epoch 10/10
1875/1875
                              142s 68ms/step - accuracy: 0.9214 - loss: 0.2065 - val accuracy: 0.9086 - val loss: 0.2506
```

Performance Metrics

• **Test Accuracy**: 0.908599

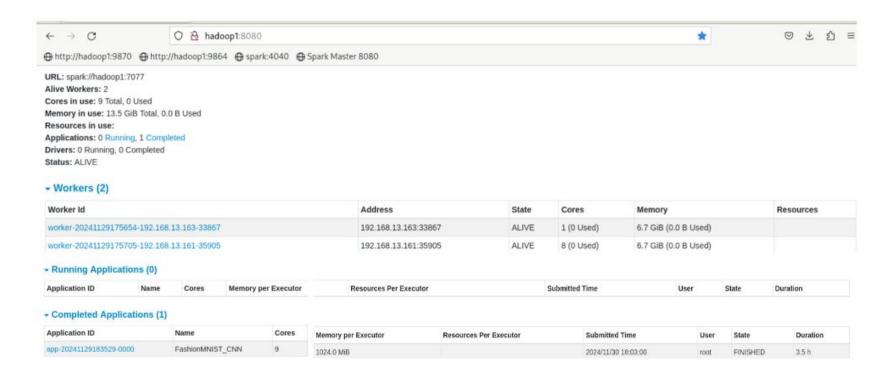
• **Test Loss**: 0.2506





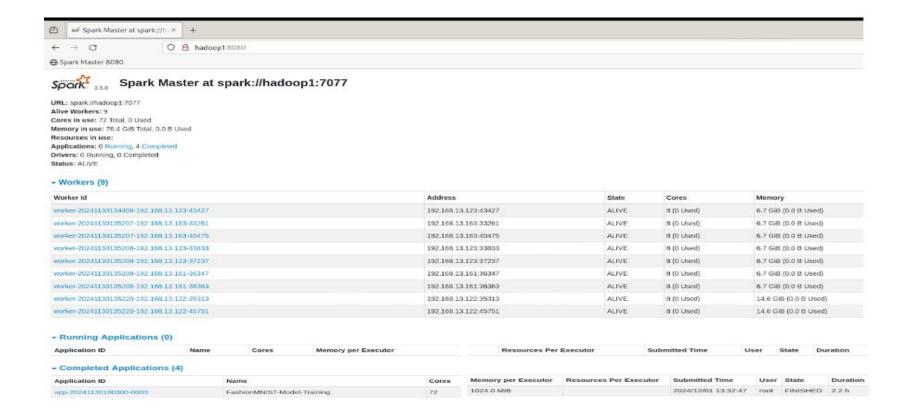
Model Performance on Two VMs

Time: 3.5 hours



Combined Performance of Four VMs:

Time: 2.2 hours



Challenges and Solutions

Challenges:

- Preventing overfitting
- Computational resource constraints

Solutions:

- Dropout layers and early stopping(patience = 3)
- Efficient training using Spark

Thank you! Any Questions?