1. Use exactly the same architectures (both densely connected layers and from convolutional layers) as the above MNIST e.g., replace the dataset. Save the Jupyter Notebook in its original format and output a PDF file after training, testing, and validation. Make sure to write down how do they perform (training accuracy, testing accuracy). Densely connected layers In [1]: import tensorflow as tf from tensorflow.keras import layers from tensorflow.keras import models import numpy as np import tensorflow.keras as keras import matplotlib.pyplot as plt from tensorflow.keras.utils import to\_categorical # loading dataset (train\_mnist\_fash\_img, train\_mnist\_fash\_label), (test\_mnist\_fash\_img, test\_mnist\_fash\_label) = keras.datasets.fashion\_mnist.load\_data() In [2]: # recreating model model\_densly = models.Sequential() model\_densly.add(layers.Dense(512, activation='relu', input\_shape=(28 \* 28,))) model\_densly.add(layers.Dense(10, activation='softmax')) model\_densly.compile(optimizer='rmsprop', loss='mean\_squared\_error', metrics=['accuracy']) In [3]: # normalazing and flattening images train\_mnist\_fash\_img\_flat = train\_mnist\_fash\_img.reshape((60000, 28 \* 28)) train\_mnist\_fash\_img\_flat = train\_mnist\_fash\_img\_flat.astype('float32') / 255 test\_mnist\_fash\_img\_flat = test\_mnist\_fash\_img.reshape((10000, 28 \* 28)) test\_mnist\_fash\_img\_flat = test\_mnist\_fash\_img\_flat.astype('float32') / 255 # compiling model model\_densly.compile(optimizer='rmsprop', loss='categorical\_crossentropy', metrics=['accuracy']) # making image labels categorical train\_mnist\_fash\_label = to\_categorical(train\_mnist\_fash\_label) test\_mnist\_fash\_label = to\_categorical(test\_mnist\_fash\_label) In [4]: # training model model\_densly.fit(train\_mnist\_fash\_img\_flat, train\_mnist\_fash\_label, epochs=5, batch\_size=128) Epoch 1/5 Epoch 2/5 Epoch 3/5 Epoch 4/5 Epoch 5/5 Out[4]: <tensorflow.python.keras.callbacks.History at 0x7fc2a2ed8210> train\_model\_loss, train\_model\_acc = model\_densly.evaluate(train\_mnist\_fash\_img\_flat, train\_mnist\_fash\_label) test\_model\_loss, test\_model\_acc = model\_densly.evaluate(test\_mnist\_fash\_img\_flat, test\_mnist\_fash\_label) print(f'Train model accuracy: {round(train\_model\_acc, 3)}') print(f'Test model accuracy: {round(test\_model\_acc, 3)}') Train model accuracy: 0.881 Test model accuracy: 0.853 In [6]: predictions = model\_densly.predict(test\_mnist\_fash\_img\_flat[:10])  $img_num = 6$ print(test\_mnist\_fash\_label[img\_num]) plt.imshow(test\_mnist\_fash\_img[img\_num], cmap=plt.get\_cmap('gray')) plt.show() [0. 0. 0. 0. 1. 0. 0. 0. 0. 0.] As you can see model classified coat as a coat Convolutional layers In [7]: # making model model\_conv = models.Sequential() model\_conv.add(layers.Conv2D(32, (3, 3), activation='relu', input\_shape=(28, 28, 1))) model\_conv.add(layers.MaxPooling2D((2, 2))) model\_conv.add(layers.Conv2D(64, (3, 3), activation='relu')) model\_conv.add(layers.MaxPooling2D((2, 2))) model\_conv.add(layers.Conv2D(64, (3, 3), activation='relu')) model\_conv.add(layers.Flatten()) model\_conv.add(layers.Dense(64, activation='relu')) model\_conv.add(layers.Dense(10, activation='softmax')) # normalazing, flattening and reshaping images train\_mnist\_fash\_img\_conv = train\_mnist\_fash\_img.reshape((60000, 28, 28, 1)) train\_mnist\_fash\_img\_conv = train\_mnist\_fash\_img\_conv.astype('float32') / 255 test\_mnist\_fash\_img\_conv = test\_mnist\_fash\_img.reshape((10000, 28, 28, 1)) test\_mnist\_fash\_img\_conv = test\_mnist\_fash\_img\_conv.astype('float32') / 255 model\_conv.compile(optimizer='rmsprop', loss='categorical\_crossentropy', metrics=['accuracy']) model\_conv.fit(train\_mnist\_fash\_img\_conv, train\_mnist\_fash\_label, epochs=10, batch\_size=64) Epoch 1/10 Epoch 3/10 Epoch 4/10 Epoch 5/10 Epoch 7/10 Epoch 8/10 Epoch 9/10 Out[10]: <tensorflow.python.keras.callbacks.History at 0x7fc23e5a8c90> In [11]: train\_model\_conv\_loss, train\_model\_conv\_acc = model\_conv.evaluate(train\_mnist\_fash\_img\_conv, train\_mnist\_fash\_label) test\_model\_conv\_loss, test\_model\_conv\_acc = model\_conv.evaluate(test\_mnist\_fash\_img\_conv, test\_mnist\_fash\_label) print(f'Train model conv accuracy: {round(train\_model\_conv\_acc, 3)}') print(f'Test model conv accuracy: {round(test\_model\_conv\_acc, 3)}') print(f'Train model accuracy: {round(train\_model\_acc, 3)}') print(f'Test model accuracy: {round(test\_model\_acc, 3)}') Train model conv accuracy: 0.952 Test model conv accuracy: 0.91 Train model accuracy: 0.881 Test model accuracy: 0.853 2. Improve the architecture. Experiment with different numbers of layers, size of layers, number of filters, size of filters. You are required to make those adjustment to get the highest accuracy. Watch out for overfitting -- we want the highest testing accuracy! Please provide a PDF file of the result, the best test accuracy and the architecture (different numbers of layers, size of layers, number of filters, size of filters) In [12]: **from** tensorflow.keras.callbacks **import** EarlyStopping model\_stop = models.Sequential() model\_stop.add(layers.Conv2D(32, (3, 3), activation='relu', input\_shape=(28, 28, 1))) model\_stop.add(layers.MaxPooling2D((2, 2))) model\_stop.add(layers.Conv2D(64, (3, 3), activation='relu')) model\_stop.add(layers.Flatten()) model\_stop.add(layers.Dense(64, activation='relu')) model\_stop.add(layers.Dense(10, activation='softmax')) model\_stop.summary(line\_length=None, positions=None, print\_fn=None) model\_stop.compile(loss='categorical\_crossentropy', optimizer='adam', metrics=['accuracy']) epochs = 30 batch\_size = 128 trained\_model\_stop = model\_stop.fit(train\_mnist\_fash\_img\_conv, train\_mnist\_fash\_label, epochs=epochs, batch\_size=batch\_size, validation\_data=(test\_mnist\_fash\_img\_conv, test\_mnist\_fash\_label), callbacks = [EarlyStopping(monitor='val\_accuracy', patience=2)]) model\_history = trained\_model\_stop # Model acc plot plt.plot(model\_history.history['accuracy']) plt.plot(model\_history.history['val\_accuracy']) plt.title('Model acc') plt.ylabel('Acc') plt.xlabel('epochs') plt.legend(['train', 'test'], loc='upper left') plt.show() # Loss function plot plt.plot(model\_history.history['loss']) plt.plot(model\_history.history['val\_loss']) plt.title('Model loss func') plt.ylabel('Loss func') plt.xlabel('epochs') plt.legend(['train', 'test'], loc='upper left') plt.show() Model: "sequential\_2" Output Shape Param # \_\_\_\_\_\_ conv2d\_3 (Conv2D) (None, 26, 26, 32) .8759 .8912

max_pooling2d_2 (MaxPooli	ng2 (None, 13	3, 13,	32)	0						
conv2d_4 (Conv2D)	(None, 1	1, 11,	64)	18496						
flatten_1 (Flatten)	(None, 7	744)		0						
dense_4 (Dense)	(None, 64	4)		495680						
dense_5 (Dense)	(None, 10	9)		650						
Total params: 515,146 Trainable params: 515,146 Non-trainable params: 0										
Epoch 1/30 469/469 [====================================	========	==] -	3s 6ms/ste	p - loss:	0.6688	- accuracy:	0.7669 - val_loss:	0.3591 -	val_accuracy:	0.8759
469/469 [========= Epoch 3/30	========	==] -	2s 5ms/ste	p - loss:	0.3176	- accuracy:	0.8869 - val_loss:	0.3025 -	val_accuracy:	0.8912
469/469 [========= Epoch 4/30	========	==] -	2s 5ms/ste	p - loss:	0.2594	- accuracy:	0.9070 - val_loss:	0.2683 -	val_accuracy:	0.9025
469/469 [========= Epoch 5/30	========	==] -	2s 5ms/ste	p - loss:	0.2305	- accuracy:	0.9157 - val_loss:	0.2506 -	val_accuracy:	0.9114
469/469 [========= Epoch 6/30	========	==] -	2s 5ms/ste	p - loss:	0.2035	- accuracy:	0.9254 - val_loss:	0.2374 -	val_accuracy:	0.9161
469/469 [========= Epoch 7/30	========	==] -	2s 5ms/ste	p - loss:	0.1760	- accuracy:	0.9359 - val_loss:	0.2354 -	val_accuracy:	0.9148
469/469 [======== Epoch 8/30	========	==] -	2s 5ms/ste	p - loss:	0.1631	- accuracy:	0.9393 - val_loss:	0.2268 -	val_accuracy:	0.9185
469/469 [========= Epoch 9/30	========	==] -	2s 5ms/ste	p - loss:	0.1433	- accuracy:	0.9484 - val_loss:	0.2371 -	val_accuracy:	0.9173
469/469 [=========		==] -	2s 5ms/ste	p - loss:	0.1259	- accuracy:	0.9548 - val_loss:	0.2324 -	val_accuracy:	0.9160
M	adal acc									

```
Model acc
       train
      test
0.90
0.88
0.86
        1 2 3 4 5 6 7 8
                  Model loss func
0.45 -
0.40 -
0.35
0.30
0.20
0.15
```

```
train_model_early_loss, train_model_early_acc = model_stop.evaluate(train_mnist_fash_img_conv, train_mnist_fash_label)
 test_model_early_loss, test_model_early_acc = model_stop.evaluate(test_mnist_fash_img_conv, test_mnist_fash_label)
print(f'Train model accuracy: {round(train_model_acc, 3)}')
print(f'Test model accuracy: {round(test_model_acc, 3)}')
print(f'Train model conv accuracy: {round(train_model_conv_acc, 3)}')
print(f'Test model conv accuracy: {round(test_model_conv_acc, 3)}')
 print(f'My new model train accuracy: {round(train_model_early_acc, 3)}')
print(f'My new model test accuracy: {round(test_model_early_acc, 3)}')
```

Train model accuracy: 0.881 Test model accuracy: 0.853 Train model conv accuracy: 0.952 Test model conv accuracy: 0.91 My new model train accuracy: 0.963 My new model test accuracy: 0.916

print(f'My models is {round(test\_model\_early\_acc-test\_model\_conv\_acc, 4)} more/less accurate on test dataset')

My models is 0.0055 more accurate on test dataset By deleting 2 layers from the initial CNN and applying early stopping I was able to create a more accurate model that performs better on test dataset