CNN on Mnist

In [0]:
```
# Credits: https://github.com/keras-team/keras/blob/master/examples/mnist_cnn.
py

from __future__ import print_function
import keras
from keras.datasets import mnist
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten
from keras.layers import Conv2D, MaxPooling2D
from keras import backend as K
import matplotlib.pyplot as plt


batch_size = 128
num_classes = 10
epochs = 20

# input image dimensions
img_rows, img_cols = 28, 28

# the data, split between train and test sets
(x_train, y_train), (x_test, y_test) = mnist.load_data()

if K.image_data_format() == 'channels_first':
    x_train = x_train.reshape(x_train.shape[0], 1, img_rows, img_cols)
    x_test = x_test.reshape(x_test.shape[0], 1, img_rows, img_cols)
    input_shape = (1, img_rows, img_cols)
else:
    x_train = x_train.reshape(x_train.shape[0], img_rows, img_cols, 1)
    x_test = x_test.reshape(x_test.shape[0], img_rows, img_cols, 1)
    input_shape = (img_rows, img_cols, 1)
```

```
Using TensorFlow backend.

Downloading data from https://s3.amazonaws.com/img-datasets/mnist.npz
11493376/11490434 [==============================] - 0s 0us/step
```

Data Normalization

here we normalize the data using X => (X - Xmin)/(Xmax-Xmin) = X/256

In [0]:
```
x_train = x_train.astype('float32')
x_test = x_test.astype('float32')
x_train /= 255
x_test /= 255
print('x_train shape:', x_train.shape)
print(x_train.shape[0], 'train samples')
print(x_test.shape[0], 'test samples')

# convert class vectors to binary class matrices
y_train = keras.utils.to_categorical(y_train, num_classes)
y_test = keras.utils.to_categorical(y_test, num_classes)
```

```
x_train shape: (60000, 28, 28, 1)
60000 train samples
10000 test samples
```

Building model

kernel_size 3*3

1. Three Convolution layer with kernel_size 3*3 and layers with activation- ReLU and optimizer-Adam

In [0]:
```
model_1 = Sequential()

# first set of CONV => RELU
model_1.add(Conv2D(32, kernel_size=(3, 3),padding='same',activation='relu',inp
ut_shape=input_shape))

# second set of CONV => RELU => POOL
model_1.add(Conv2D(64, (3, 3), activation='relu'))
model_1.add(MaxPooling2D(pool_size=(2, 2)))

# Third set of CONV => RELU => POOL
model_1.add(Conv2D(128, (3, 3), activation='relu'))
model_1.add(MaxPooling2D(pool_size=(2, 2)))

model_1.add(Dropout(0.25))
model_1.add(Flatten())

#Hidden layer 1
model_1.add(Dense(128, activation='relu'))
# Dropout
model_1.add(Dropout(0.5))
#Hidden layer 2
model_1.add(Dense(64,activation='relu'))

#Output layer
model_1.add(Dense(num_classes, activation='softmax'))

model_1.compile(loss=keras.losses.categorical_crossentropy,optimizer=keras.opt
imizers.Adadelta(),metrics=['accuracy'])

history1=model_1.fit(x_train, y_train,batch_size=batch_size,epochs=epochs,verb
ose=1,validation_data=(x_test, y_test))
```

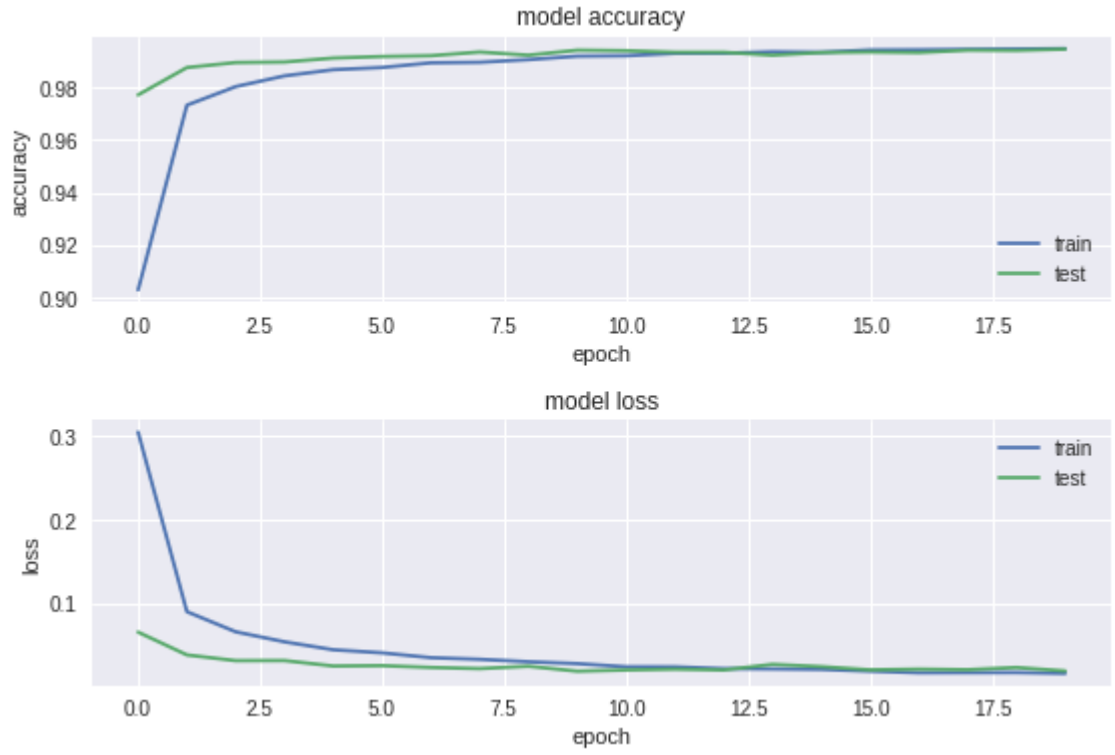
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 260s 4ms/step - loss: 0.3053 -
acc: 0.9031 - val_loss: 0.0662 - val_acc: 0.9772
Epoch 2/20
60000/60000 [==============================] - 260s 4ms/step - loss: 0.0906 -
acc: 0.9733 - val_loss: 0.0389 - val_acc: 0.9876
Epoch 3/20
60000/60000 [==============================] - 260s 4ms/step - loss: 0.0665 -
acc: 0.9803 - val_loss: 0.0320 - val_acc: 0.9895
Epoch 4/20
60000/60000 [==============================] - 259s 4ms/step - loss: 0.0546 -
acc: 0.9844 - val_loss: 0.0321 - val_acc: 0.9897
Epoch 5/20
60000/60000 [==============================] - 260s 4ms/step - loss: 0.0450 -
acc: 0.9868 - val_loss: 0.0256 - val_acc: 0.9912
Epoch 6/20
60000/60000 [==============================] - 260s 4ms/step - loss: 0.0414 -
acc: 0.9876 - val_loss: 0.0261 - val_acc: 0.9918
Epoch 7/20
60000/60000 [==============================] - 260s 4ms/step - loss: 0.0356 -
acc: 0.9894 - val_loss: 0.0239 - val_acc: 0.9921
Epoch 8/20
60000/60000 [==============================] - 261s 4ms/step - loss: 0.0337 -
acc: 0.9896 - val_loss: 0.0225 - val_acc: 0.9935
Epoch 9/20
60000/60000 [==============================] - 260s 4ms/step - loss: 0.0307 -
acc: 0.9906 - val_loss: 0.0253 - val_acc: 0.9923
Epoch 10/20
60000/60000 [==============================] - 259s 4ms/step - loss: 0.0285 -
acc: 0.9919 - val_loss: 0.0194 - val_acc: 0.9942
Epoch 11/20
60000/60000 [==============================] - 260s 4ms/step - loss: 0.0247 -
acc: 0.9921 - val_loss: 0.0209 - val_acc: 0.9940
Epoch 12/20
60000/60000 [==============================] - 259s 4ms/step - loss: 0.0246 -
acc: 0.9930 - val_loss: 0.0218 - val_acc: 0.9934
Epoch 13/20
60000/60000 [==============================] - 259s 4ms/step - loss: 0.0225 -
acc: 0.9930 - val_loss: 0.0209 - val_acc: 0.9934
Epoch 14/20
60000/60000 [==============================] - 259s 4ms/step - loss: 0.0221 -
acc: 0.9936 - val_loss: 0.0276 - val_acc: 0.9923
Epoch 15/20
60000/60000 [==============================] - 257s 4ms/step - loss: 0.0216 -
acc: 0.9934 - val_loss: 0.0249 - val_acc: 0.9933
Epoch 16/20
60000/60000 [==============================] - 260s 4ms/step - loss: 0.0194 -
acc: 0.9943 - val_loss: 0.0211 - val_acc: 0.9935
Epoch 17/20
60000/60000 [==============================] - 259s 4ms/step - loss: 0.0176 -
acc: 0.9943 - val_loss: 0.0219 - val_acc: 0.9933
Epoch 18/20
60000/60000 [==============================] - 260s 4ms/step - loss: 0.0177 -
acc: 0.9945 - val_loss: 0.0212 - val_acc: 0.9942
Epoch 19/20
60000/60000 [==============================] - 259s 4ms/step - loss: 0.0178 -
```

```
acc: 0.9947 - val_loss: 0.0239 - val_acc: 0.9941
Epoch 20/20
60000/60000 [==============================] - 258s 4ms/step - loss: 0.0168 -
acc: 0.9948 - val_loss: 0.0197 - val_acc: 0.9946
```

In [0]:
```
score = model_1.evaluate(x_test, y_test, verbose=1)
print('Test error:', score[0])
print('Test accuracy:', score[1])


# Credits: https://towardsdatascience.com/a-simple-2d-cnn-for-mnist-digit-recognition-a998dbc1e79a
import os
# plotting the metrics
fig = plt.figure()
plt.subplot(2,1,1)
plt.plot(model_1.history.history['acc'])
plt.plot(model_1.history.history['val_acc'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='lower right')
plt.subplot(2,1,2)
plt.plot(model_1.history.history['loss'])
plt.plot(model_1.history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper right')
plt.tight_layout()
#fig
```

```
10000/10000 [==============================] - 13s 1ms/step
Test error: 0.019698028537289382
Test accuracy: 0.9946
```



With 3 hidden layer

In [0]:
```
model_2 = Sequential()

# first set of CONV => RELU
model_2.add(Conv2D(32, kernel_size=(3, 3),padding='same',activation='relu',inp
ut_shape=input_shape))

# second set of CONV => RELU => POOL
model_2.add(Conv2D(64, (3, 3), activation='relu'))
model_2.add(MaxPooling2D(pool_size=(2, 2)))

# Third set of CONV => RELU => POOL
model_2.add(Conv2D(128, (3, 3), activation='relu'))
model_2.add(MaxPooling2D(pool_size=(2, 2)))

model_2.add(Dropout(0.25))
model_2.add(Flatten())


#Hidden layer 1
model_2.add(Dense(256, activation='relu'))
# Dropout
model_2.add(Dropout(0.5))
#Hidden layer 2
model_2.add(Dense(128,activation='relu'))
#Hidden layer 3
model_2.add(Dense(64,activation='relu'))
#Output layer
model_2.add(Dense(num_classes, activation='softmax'))

model_2.compile(loss=keras.losses.categorical_crossentropy,optimizer=keras.opt
imizers.Adadelta(),metrics=['accuracy'])

history2=model_2.fit(x_train, y_train,batch_size=batch_size,epochs=epochs,verb
ose=1,validation_data=(x_test, y_test))
```

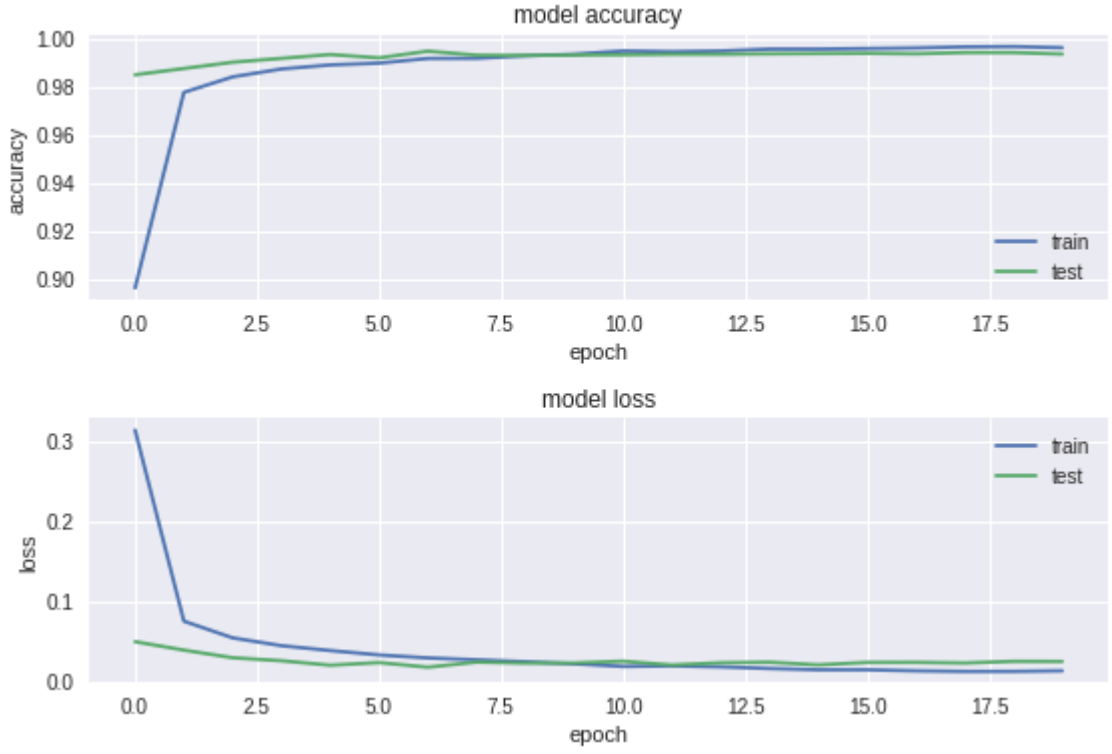
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 265s 4ms/step - loss: 0.3144 -
acc: 0.8964 - val_loss: 0.0492 - val_acc: 0.9848
Epoch 2/20
60000/60000 [==============================] - 262s 4ms/step - loss: 0.0749 -
acc: 0.9775 - val_loss: 0.0386 - val_acc: 0.9874
Epoch 3/20
60000/60000 [==============================] - 262s 4ms/step - loss: 0.0539 -
acc: 0.9839 - val_loss: 0.0290 - val_acc: 0.9900
Epoch 4/20
60000/60000 [==============================] - 263s 4ms/step - loss: 0.0441 -
acc: 0.9872 - val_loss: 0.0253 - val_acc: 0.9916
Epoch 5/20
60000/60000 [==============================] - 264s 4ms/step - loss: 0.0380 -
acc: 0.9889 - val_loss: 0.0197 - val_acc: 0.9932
Epoch 6/20
60000/60000 [==============================] - 262s 4ms/step - loss: 0.0325 -
acc: 0.9896 - val_loss: 0.0230 - val_acc: 0.9918
Epoch 7/20
60000/60000 [==============================] - 262s 4ms/step - loss: 0.0288 -
acc: 0.9916 - val_loss: 0.0172 - val_acc: 0.9946
Epoch 8/20
60000/60000 [==============================] - 263s 4ms/step - loss: 0.0264 -
acc: 0.9916 - val_loss: 0.0235 - val_acc: 0.9929
Epoch 9/20
60000/60000 [==============================] - 262s 4ms/step - loss: 0.0240 -
acc: 0.9926 - val_loss: 0.0222 - val_acc: 0.9928
Epoch 10/20
60000/60000 [==============================] - 261s 4ms/step - loss: 0.0214 -
acc: 0.9933 - val_loss: 0.0224 - val_acc: 0.9930
Epoch 11/20
60000/60000 [==============================] - 265s 4ms/step - loss: 0.0181 -
acc: 0.9947 - val_loss: 0.0247 - val_acc: 0.9931
Epoch 12/20
60000/60000 [==============================] - 263s 4ms/step - loss: 0.0188 -
acc: 0.9944 - val_loss: 0.0199 - val_acc: 0.9933
Epoch 13/20
60000/60000 [==============================] - 266s 4ms/step - loss: 0.0176 -
acc: 0.9947 - val_loss: 0.0227 - val_acc: 0.9933
Epoch 14/20
60000/60000 [==============================] - 265s 4ms/step - loss: 0.0155 -
acc: 0.9954 - val_loss: 0.0234 - val_acc: 0.9935
Epoch 15/20
60000/60000 [==============================] - 267s 4ms/step - loss: 0.0139 -
acc: 0.9954 - val_loss: 0.0201 - val_acc: 0.9936
Epoch 16/20
60000/60000 [==============================] - 264s 4ms/step - loss: 0.0139 -
acc: 0.9957 - val_loss: 0.0231 - val_acc: 0.9937
Epoch 17/20
60000/60000 [==============================] - 265s 4ms/step - loss: 0.0126 -
acc: 0.9959 - val_loss: 0.0232 - val_acc: 0.9935
Epoch 18/20
60000/60000 [==============================] - 266s 4ms/step - loss: 0.0119 -
acc: 0.9964 - val_loss: 0.0224 - val_acc: 0.9940
Epoch 19/20
60000/60000 [==============================] - 264s 4ms/step - loss: 0.0119 -
```

```
acc: 0.9965 - val_loss: 0.0245 - val_acc: 0.9940
Epoch 20/20
60000/60000 [==============================] - 266s 4ms/step - loss: 0.0127 -
acc: 0.9960 - val_loss: 0.0244 - val_acc: 0.9934
```

In [0]:
```
score = model_2.evaluate(x_test, y_test, verbose=1)
print('Test error:', score[0])
print('Test accuracy:', score[1])

# plotting the metrics
fig = plt.figure()
plt.subplot(2,1,1)
plt.plot(model_2.history.history['acc'])
plt.plot(model_2.history.history['val_acc'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='lower right')
plt.subplot(2,1,2)
plt.plot(model_2.history.history['loss'])
plt.plot(model_2.history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper right')
plt.tight_layout()
```

```
10000/10000 [==============================] - 13s 1ms/step
Test error: 0.024354995393209948
Test accuracy: 0.9934
```



5 layer

In [0]:
```
model_3 = Sequential()

# first set of CONV => RELU
model_3.add(Conv2D(32, kernel_size=(3, 3),padding='same',activation='relu',inp
ut_shape=input_shape))

# second set of CONV => RELU => POOL
model_3.add(Conv2D(64, (3, 3), activation='relu'))
model_3.add(MaxPooling2D(pool_size=(2, 2)))

# Third set of CONV => RELU => POOL
model_3.add(Conv2D(128, (3, 3), activation='relu'))
model_3.add(MaxPooling2D(pool_size=(2, 2)))

model_3.add(Dropout(0.25))
model_3.add(Flatten())


#Hidden layer 1
model_3.add(Dense(512, activation='relu'))
# Dropout
model_3.add(Dropout(0.5))
#Hidden layer 2
model_3.add(Dense(256,activation='relu'))
#Hidden layer 3
model_3.add(Dense(128,activation='relu'))
#Hidden layer 4
model_3.add(Dense(64,activation='relu'))
#Hidden layer 5
model_3.add(Dense(32,activation='relu'))
#Output layer
model_3.add(Dense(num_classes, activation='softmax'))

model_3.compile(loss=keras.losses.categorical_crossentropy,optimizer=keras.opt
imizers.Adadelta(),metrics=['accuracy'])

history3=model_3.fit(x_train, y_train,batch_size=batch_size,epochs=epochs,verb
ose=1,validation_data=(x_test, y_test))
```

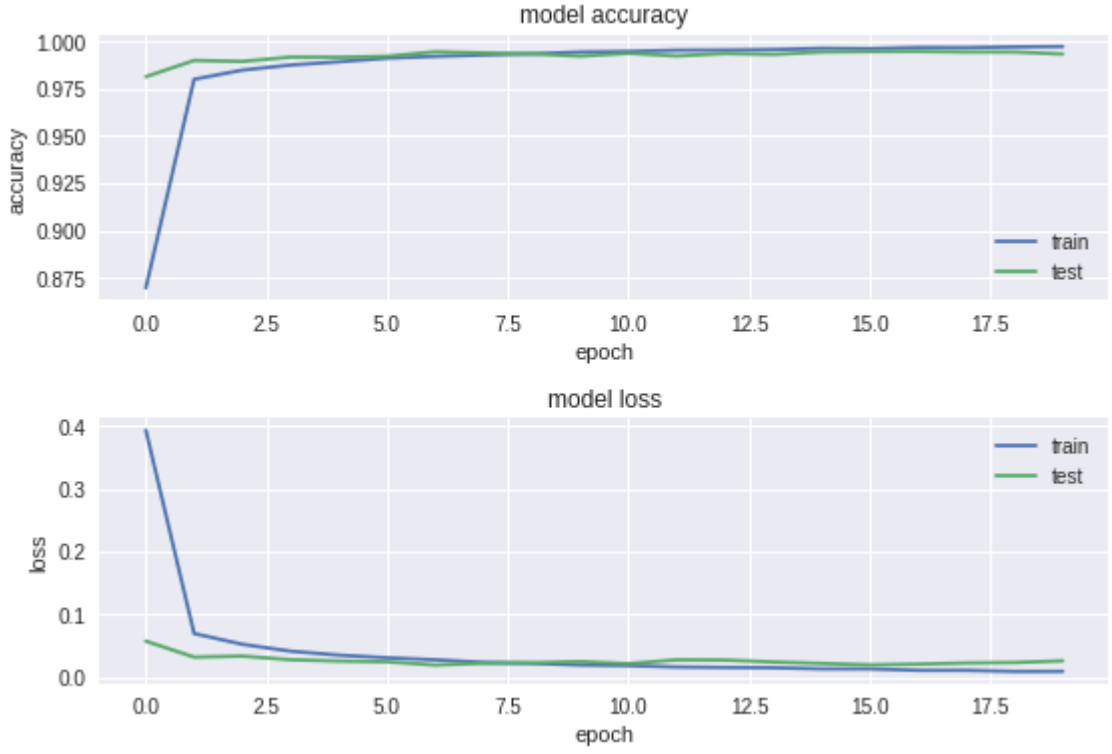
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 285s 5ms/step - loss: 0.3936 -
acc: 0.8696 - val_loss: 0.0571 - val_acc: 0.9814
Epoch 2/20
60000/60000 [==============================] - 283s 5ms/step - loss: 0.0692 -
acc: 0.9800 - val_loss: 0.0315 - val_acc: 0.9900
Epoch 3/20
60000/60000 [==============================] - 291s 5ms/step - loss: 0.0520 -
acc: 0.9849 - val_loss: 0.0332 - val_acc: 0.9895
Epoch 4/20
60000/60000 [==============================] - 287s 5ms/step - loss: 0.0410 -
acc: 0.9876 - val_loss: 0.0274 - val_acc: 0.9918
Epoch 5/20
60000/60000 [==============================] - 288s 5ms/step - loss: 0.0347 -
acc: 0.9893 - val_loss: 0.0252 - val_acc: 0.9917
Epoch 6/20
60000/60000 [==============================] - 282s 5ms/step - loss: 0.0305 -
acc: 0.9912 - val_loss: 0.0241 - val_acc: 0.9922
Epoch 7/20
60000/60000 [==============================] - 287s 5ms/step - loss: 0.0273 -
acc: 0.9922 - val_loss: 0.0190 - val_acc: 0.9946
Epoch 8/20
60000/60000 [==============================] - 293s 5ms/step - loss: 0.0231 -
acc: 0.9929 - val_loss: 0.0217 - val_acc: 0.9940
Epoch 9/20
60000/60000 [==============================] - 291s 5ms/step - loss: 0.0217 -
acc: 0.9935 - val_loss: 0.0225 - val_acc: 0.9935
Epoch 10/20
60000/60000 [==============================] - 294s 5ms/step - loss: 0.0189 -
acc: 0.9944 - val_loss: 0.0244 - val_acc: 0.9923
Epoch 11/20
60000/60000 [==============================] - 298s 5ms/step - loss: 0.0180 -
acc: 0.9948 - val_loss: 0.0210 - val_acc: 0.9938
Epoch 12/20
60000/60000 [==============================] - 299s 5ms/step - loss: 0.0157 -
acc: 0.9954 - val_loss: 0.0272 - val_acc: 0.9924
Epoch 13/20
60000/60000 [==============================] - 299s 5ms/step - loss: 0.0150 -
acc: 0.9955 - val_loss: 0.0269 - val_acc: 0.9937
Epoch 14/20
60000/60000 [==============================] - 300s 5ms/step - loss: 0.0146 -
acc: 0.9958 - val_loss: 0.0238 - val_acc: 0.9932
Epoch 15/20
60000/60000 [==============================] - 297s 5ms/step - loss: 0.0127 -
acc: 0.9964 - val_loss: 0.0214 - val_acc: 0.9945
Epoch 16/20
60000/60000 [==============================] - 299s 5ms/step - loss: 0.0127 -
acc: 0.9962 - val_loss: 0.0192 - val_acc: 0.9947
Epoch 17/20
60000/60000 [==============================] - 298s 5ms/step - loss: 0.0105 -
acc: 0.9968 - val_loss: 0.0204 - val_acc: 0.9948
Epoch 18/20
60000/60000 [==============================] - 299s 5ms/step - loss: 0.0104 -
acc: 0.9968 - val_loss: 0.0221 - val_acc: 0.9945
Epoch 19/20
60000/60000 [==============================] - 298s 5ms/step - loss: 0.0087 -
```

```
acc: 0.9972 - val_loss: 0.0229 - val_acc: 0.9945
Epoch 20/20
60000/60000 [==============================] - 296s 5ms/step - loss: 0.0089 -
acc: 0.9974 - val_loss: 0.0256 - val_acc: 0.9934
```

In [0]:
```
score = model_3.evaluate(x_test, y_test, verbose=1)
print('Test error:', score[0])
print('Test accuracy:', score[1])

# plotting the metrics
fig = plt.figure()
plt.subplot(2,1,1)
plt.plot(model_3.history.history['acc'])
plt.plot(model_3.history.history['val_acc'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='lower right')
plt.subplot(2,1,2)
plt.plot(model_3.history.history['loss'])
plt.plot(model_3.history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper right')
plt.tight_layout()
```

```
10000/10000 [==============================] - 14s 1ms/step
Test error: 0.025622119065406106
Test accuracy: 0.9934
```



kernel_size 5*5

1. Three Convolution layer with kernel_size 5*5 and layers with activation- ReLU and optimizer-Adam

In [0]:
```
model_4 = Sequential()

# first set of CONV => RELU
model_4.add(Conv2D(32, kernel_size=(5, 5),padding='same',activation='relu',inp
ut_shape=input_shape))

# second set of CONV => RELU => POOL
model_4.add(Conv2D(64, (5, 5), activation='relu'))
model_4.add(MaxPooling2D(pool_size=(2, 2)))

model_4.add(Dropout(0.25))
model_4.add(Flatten())

#Hidden layer 1
model_4.add(Dense(128, activation='relu'))
# Dropout
model_4.add(Dropout(0.5))
#Hidden layer 2
model_4.add(Dense(64,activation='relu'))
#Output layer
model_4.add(Dense(num_classes, activation='softmax'))

model_4.compile(loss=keras.losses.categorical_crossentropy,optimizer=keras.opt
imizers.Adadelta(),metrics=['accuracy'])

history4=model_4.fit(x_train, y_train,batch_size=batch_size,epochs=epochs,verb
ose=1,validation_data=(x_test, y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 365s 6ms/step - loss: 0.2698 -
acc: 0.9155 - val_loss: 0.0482 - val_acc: 0.9840
Epoch 2/20
60000/60000 [==============================] - 367s 6ms/step - loss: 0.0813 -
acc: 0.9756 - val_loss: 0.0322 - val_acc: 0.9884
Epoch 3/20
60000/60000 [==============================] - 365s 6ms/step - loss: 0.0595 -
acc: 0.9826 - val_loss: 0.0300 - val_acc: 0.9905
Epoch 4/20
60000/60000 [==============================] - 366s 6ms/step - loss: 0.0482 -
acc: 0.9856 - val_loss: 0.0279 - val_acc: 0.9901
Epoch 5/20
60000/60000 [==============================] - 364s 6ms/step - loss: 0.0407 -
acc: 0.9878 - val_loss: 0.0329 - val_acc: 0.9898
Epoch 6/20
60000/60000 [==============================] - 366s 6ms/step - loss: 0.0383 -
acc: 0.9891 - val_loss: 0.0230 - val_acc: 0.9923
Epoch 7/20
60000/60000 [==============================] - 364s 6ms/step - loss: 0.0329 -
acc: 0.9901 - val_loss: 0.0218 - val_acc: 0.9931
Epoch 8/20
60000/60000 [==============================] - 363s 6ms/step - loss: 0.0299 -
acc: 0.9911 - val_loss: 0.0209 - val_acc: 0.9934
Epoch 9/20
60000/60000 [==============================] - 365s 6ms/step - loss: 0.0257 -
acc: 0.9921 - val_loss: 0.0236 - val_acc: 0.9928
Epoch 10/20
60000/60000 [==============================] - 363s 6ms/step - loss: 0.0249 -
acc: 0.9930 - val_loss: 0.0221 - val_acc: 0.9936
Epoch 11/20
60000/60000 [==============================] - 362s 6ms/step - loss: 0.0215 -
acc: 0.9934 - val_loss: 0.0218 - val_acc: 0.9936
Epoch 12/20
60000/60000 [==============================] - 362s 6ms/step - loss: 0.0206 -
acc: 0.9937 - val_loss: 0.0258 - val_acc: 0.9923
Epoch 13/20
60000/60000 [==============================] - 362s 6ms/step - loss: 0.0199 -
acc: 0.9938 - val_loss: 0.0194 - val_acc: 0.9948
Epoch 14/20
60000/60000 [==============================] - 361s 6ms/step - loss: 0.0183 -
acc: 0.9943 - val_loss: 0.0185 - val_acc: 0.9945
Epoch 15/20
60000/60000 [==============================] - 360s 6ms/step - loss: 0.0162 -
acc: 0.9951 - val_loss: 0.0213 - val_acc: 0.9931
Epoch 16/20
60000/60000 [==============================] - 363s 6ms/step - loss: 0.0165 -
acc: 0.9950 - val_loss: 0.0232 - val_acc: 0.9932
Epoch 17/20
60000/60000 [==============================] - 365s 6ms/step - loss: 0.0152 -
acc: 0.9959 - val_loss: 0.0237 - val_acc: 0.9939
Epoch 18/20
60000/60000 [==============================] - 363s 6ms/step - loss: 0.0147 -
acc: 0.9954 - val_loss: 0.0221 - val_acc: 0.9933
Epoch 19/20
60000/60000 [==============================] - 365s 6ms/step - loss: 0.0144 -
```

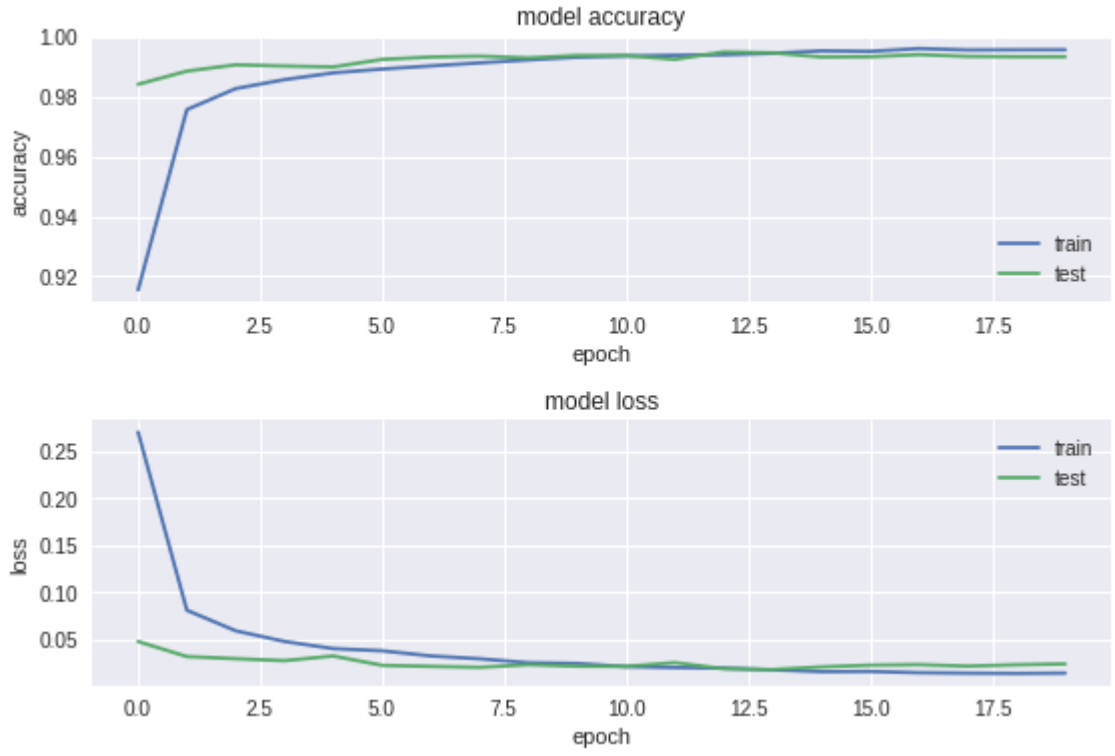
```
acc: 0.9955 - val_loss: 0.0236 - val_acc: 0.9932
Epoch 20/20
60000/60000 [==============================] - 362s 6ms/step - loss: 0.0147 -
acc: 0.9955 - val_loss: 0.0245 - val_acc: 0.9932
```

In [0]:
```
import matplotlib.pyplot as plt

score = model_4.evaluate(x_test, y_test, verbose=1)
print('Test error:', score[0])
print('Test accuracy:', score[1])


# Credits: https://towardsdatascience.com/a-simple-2d-cnn-for-mnist-digit-recognition-a998dbc1e79a
import os
# plotting the metrics
fig = plt.figure()
plt.subplot(2,1,1)
plt.plot(model_4.history.history['acc'])
plt.plot(model_4.history.history['val_acc'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='lower right')
plt.subplot(2,1,2)
plt.plot(model_4.history.history['loss'])
plt.plot(model_4.history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper right')
plt.tight_layout()
#fig
```

```
10000/10000 [==============================] - 18s 2ms/step
Test error: 0.024457520741859844
Test accuracy: 0.9932
```



With 3 hidden layer

In [0]:
```
model_5 = Sequential()

# first set of CONV => RELU
model_5.add(Conv2D(32, kernel_size=(5, 5),padding='same',activation='relu',inp
ut_shape=input_shape))

# second set of CONV => RELU => POOL
model_5.add(Conv2D(64, (5, 5), activation='relu'))
model_5.add(MaxPooling2D(pool_size=(2, 2)))


model_5.add(Dropout(0.25))
model_5.add(Flatten())


#Hidden layer 1
model_5.add(Dense(256, activation='relu'))
# Dropout
model_5.add(Dropout(0.5))
#Hidden layer 2
model_5.add(Dense(128,activation='relu'))
#Hidden layer 3
model_5.add(Dense(64,activation='relu'))
#Output layer
model_5.add(Dense(num_classes, activation='softmax'))

model_5.compile(loss=keras.losses.categorical_crossentropy,optimizer=keras.opt
imizers.Adadelta(),metrics=['accuracy'])

history5=model_5.fit(x_train, y_train,batch_size=batch_size,epochs=epochs,verb
ose=1,validation_data=(x_test, y_test))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 396s 7ms/step - loss: 0.2587 -
acc: 0.9187 - val_loss: 0.0593 - val_acc: 0.9797
Epoch 2/20
60000/60000 [==============================] - 396s 7ms/step - loss: 0.0699 -
acc: 0.9793 - val_loss: 0.0368 - val_acc: 0.9880
Epoch 3/20
60000/60000 [==============================] - 390s 6ms/step - loss: 0.0522 -
acc: 0.9845 - val_loss: 0.0303 - val_acc: 0.9899
Epoch 4/20
60000/60000 [==============================] - 390s 7ms/step - loss: 0.0400 -
acc: 0.9879 - val_loss: 0.0254 - val_acc: 0.9914
Epoch 5/20
60000/60000 [==============================] - 389s 6ms/step - loss: 0.0350 -
acc: 0.9898 - val_loss: 0.0239 - val_acc: 0.9919
Epoch 6/20
60000/60000 [==============================] - 387s 6ms/step - loss: 0.0298 -
acc: 0.9906 - val_loss: 0.0252 - val_acc: 0.9917
Epoch 7/20
60000/60000 [==============================] - 386s 6ms/step - loss: 0.0263 -
acc: 0.9920 - val_loss: 0.0210 - val_acc: 0.9939
Epoch 8/20
60000/60000 [==============================] - 385s 6ms/step - loss: 0.0224 -
acc: 0.9931 - val_loss: 0.0234 - val_acc: 0.9930
Epoch 9/20
60000/60000 [==============================] - 387s 6ms/step - loss: 0.0204 -
acc: 0.9936 - val_loss: 0.0270 - val_acc: 0.9924
Epoch 10/20
60000/60000 [==============================] - 385s 6ms/step - loss: 0.0181 -
acc: 0.9942 - val_loss: 0.0239 - val_acc: 0.9936
Epoch 11/20
60000/60000 [==============================] - 384s 6ms/step - loss: 0.0158 -
acc: 0.9952 - val_loss: 0.0252 - val_acc: 0.9926
Epoch 12/20
60000/60000 [==============================] - 386s 6ms/step - loss: 0.0141 -
acc: 0.9955 - val_loss: 0.0218 - val_acc: 0.9940
Epoch 13/20
60000/60000 [==============================] - 385s 6ms/step - loss: 0.0137 -
acc: 0.9956 - val_loss: 0.0259 - val_acc: 0.9930
Epoch 14/20
60000/60000 [==============================] - 386s 6ms/step - loss: 0.0120 -
acc: 0.9963 - val_loss: 0.0237 - val_acc: 0.9938
Epoch 15/20
60000/60000 [==============================] - 387s 6ms/step - loss: 0.0123 -
acc: 0.9962 - val_loss: 0.0224 - val_acc: 0.9941
Epoch 16/20
60000/60000 [==============================] - 385s 6ms/step - loss: 0.0101 -
acc: 0.9969 - val_loss: 0.0220 - val_acc: 0.9939
Epoch 17/20
60000/60000 [==============================] - 384s 6ms/step - loss: 0.0088 -
acc: 0.9972 - val_loss: 0.0244 - val_acc: 0.9936
Epoch 18/20
60000/60000 [==============================] - 383s 6ms/step - loss: 0.0094 -
acc: 0.9970 - val_loss: 0.0256 - val_acc: 0.9937
Epoch 19/20
60000/60000 [==============================] - 384s 6ms/step - loss: 0.0088 -
```

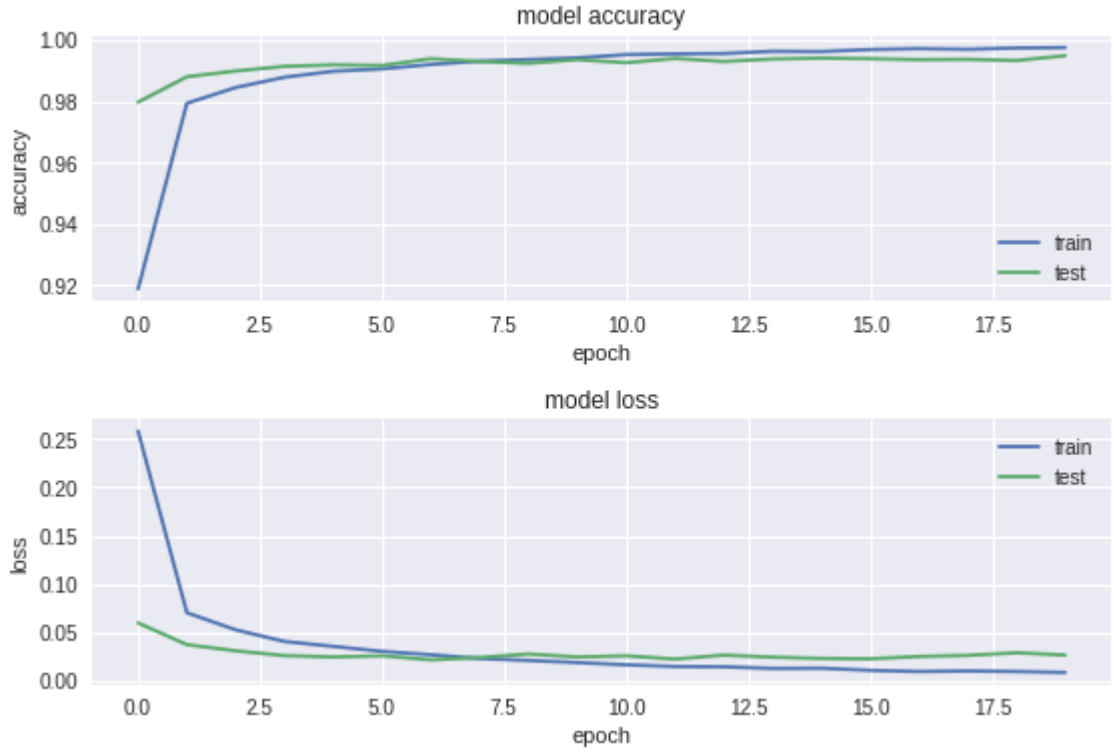
```
acc: 0.9974 - val_loss: 0.0283 - val_acc: 0.9933
Epoch 20/20
60000/60000 [==============================] - 384s 6ms/step - loss: 0.0079 -
acc: 0.9975 - val_loss: 0.0259 - val_acc: 0.9949
```

In [0]:
```
import matplotlib.pyplot as plt

score = model_5.evaluate(x_test, y_test, verbose=1)
print('Test error:', score[0])
print('Test accuracy:', score[1])

# plotting the metrics
fig = plt.figure()
plt.subplot(2,1,1)
plt.plot(model_5.history.history['acc'])
plt.plot(model_5.history.history['val_acc'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='lower right')
plt.subplot(2,1,2)
plt.plot(model_5.history.history['loss'])
plt.plot(model_5.history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper right')
plt.tight_layout()
```

```
10000/10000 [==============================] - 19s 2ms/step
Test error: 0.025942582759580363
Test accuracy: 0.9949
```



5 layer

In [0]:
```
model_6 = Sequential()

# first set of CONV => RELU
model_6.add(Conv2D(32, kernel_size=(5, 5),padding='same',activation='relu',inp
ut_shape=input_shape))

# second set of CONV => RELU => POOL
model_6.add(Conv2D(64, (5, 5), activation='relu'))
model_6.add(MaxPooling2D(pool_size=(2, 2)))


model_6.add(Dropout(0.25))
model_6.add(Flatten())


#Hidden layer 1
model_6.add(Dense(512, activation='relu'))
# Dropout
model_6.add(Dropout(0.5))
#Hidden layer 2
model_6.add(Dense(256,activation='relu'))
#Hidden layer 3
model_6.add(Dense(128,activation='relu'))
#Hidden layer 4
model_6.add(Dense(64,activation='relu'))
#Hidden layer 5
model_6.add(Dense(32,activation='relu'))
#Output layer
model_6.add(Dense(num_classes, activation='softmax'))

model_6.compile(loss=keras.losses.categorical_crossentropy,optimizer=keras.opt
imizers.Adadelta(),metrics=['accuracy'])

history6=model_6.fit(x_train, y_train,batch_size=batch_size,epochs=epochs,verb
ose=1,validation_data=(x_test, y_test))
```

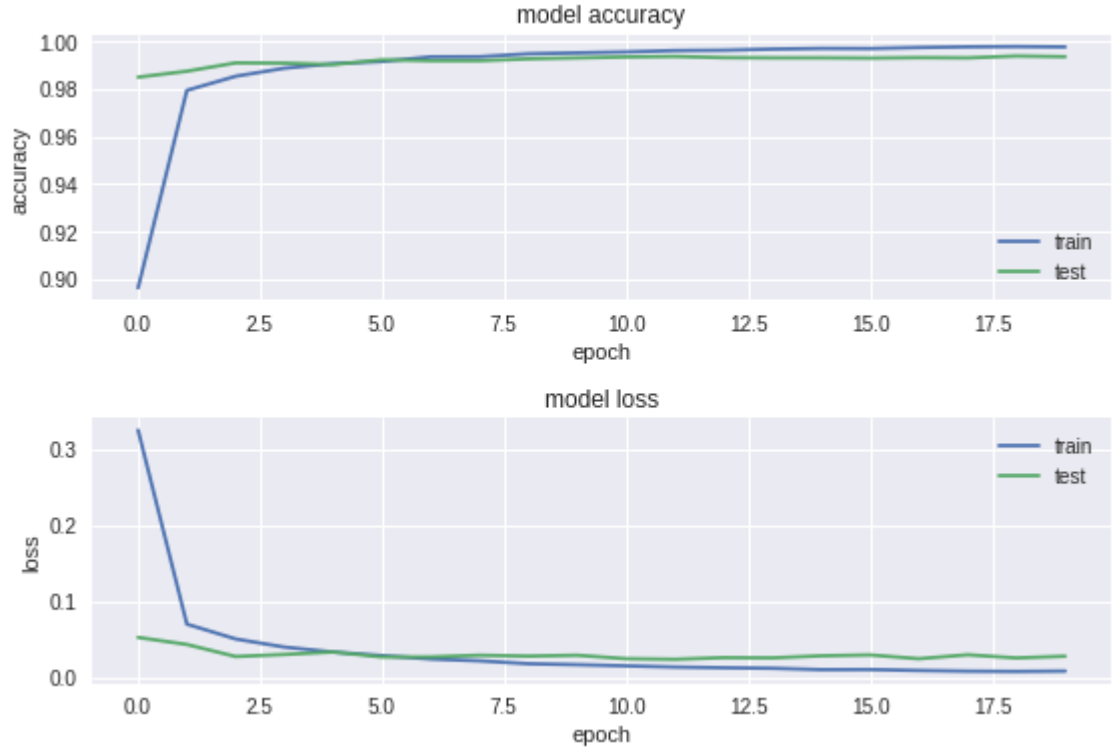
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 421s 7ms/step - loss: 0.3252 -
acc: 0.8964 - val_loss: 0.0520 - val_acc: 0.9850
Epoch 2/20
60000/60000 [==============================] - 421s 7ms/step - loss: 0.0695 -
acc: 0.9794 - val_loss: 0.0427 - val_acc: 0.9875
Epoch 3/20
60000/60000 [==============================] - 422s 7ms/step - loss: 0.0500 -
acc: 0.9854 - val_loss: 0.0269 - val_acc: 0.9910
Epoch 4/20
60000/60000 [==============================] - 420s 7ms/step - loss: 0.0393 -
acc: 0.9888 - val_loss: 0.0296 - val_acc: 0.9909
Epoch 5/20
60000/60000 [==============================] - 417s 7ms/step - loss: 0.0327 -
acc: 0.9907 - val_loss: 0.0328 - val_acc: 0.9903
Epoch 6/20
60000/60000 [==============================] - 379s 6ms/step - loss: 0.0281 -
acc: 0.9916 - val_loss: 0.0262 - val_acc: 0.9923
Epoch 7/20
60000/60000 [==============================] - 414s 7ms/step - loss: 0.0236 -
acc: 0.9935 - val_loss: 0.0263 - val_acc: 0.9919
Epoch 8/20
60000/60000 [==============================] - 414s 7ms/step - loss: 0.0212 -
acc: 0.9936 - val_loss: 0.0285 - val_acc: 0.9919
Epoch 9/20
60000/60000 [==============================] - 416s 7ms/step - loss: 0.0174 -
acc: 0.9948 - val_loss: 0.0274 - val_acc: 0.9927
Epoch 10/20
60000/60000 [==============================] - 414s 7ms/step - loss: 0.0161 -
acc: 0.9952 - val_loss: 0.0285 - val_acc: 0.9931
Epoch 11/20
60000/60000 [==============================] - 418s 7ms/step - loss: 0.0146 -
acc: 0.9956 - val_loss: 0.0240 - val_acc: 0.9935
Epoch 12/20
60000/60000 [==============================] - 435s 7ms/step - loss: 0.0130 -
acc: 0.9962 - val_loss: 0.0232 - val_acc: 0.9937
Epoch 13/20
60000/60000 [==============================] - 433s 7ms/step - loss: 0.0120 -
acc: 0.9963 - val_loss: 0.0254 - val_acc: 0.9932
Epoch 14/20
60000/60000 [==============================] - 433s 7ms/step - loss: 0.0114 -
acc: 0.9968 - val_loss: 0.0251 - val_acc: 0.9931
Epoch 15/20
60000/60000 [==============================] - 438s 7ms/step - loss: 0.0096 -
acc: 0.9971 - val_loss: 0.0278 - val_acc: 0.9931
Epoch 16/20
60000/60000 [==============================] - 431s 7ms/step - loss: 0.0097 -
acc: 0.9970 - val_loss: 0.0289 - val_acc: 0.9930
Epoch 17/20
60000/60000 [==============================] - 430s 7ms/step - loss: 0.0085 -
acc: 0.9975 - val_loss: 0.0239 - val_acc: 0.9932
Epoch 18/20
60000/60000 [==============================] - 436s 7ms/step - loss: 0.0076 -
acc: 0.9978 - val_loss: 0.0292 - val_acc: 0.9931
Epoch 19/20
60000/60000 [==============================] - 432s 7ms/step - loss: 0.0072 -
```

```
acc: 0.9979 - val_loss: 0.0250 - val_acc: 0.9939
Epoch 20/20
60000/60000 [==============================] - 434s 7ms/step - loss: 0.0077 -
acc: 0.9977 - val_loss: 0.0273 - val_acc: 0.9936
```

In [0]:
```
score = model_6.evaluate(x_test, y_test, verbose=1)
print('Test error:', score[0])
print('Test accuracy:', score[1])

# plotting the metrics
fig = plt.figure()
plt.subplot(2,1,1)
plt.plot(model_6.history.history['acc'])
plt.plot(model_6.history.history['val_acc'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='lower right')
plt.subplot(2,1,2)
plt.plot(model_6.history.history['loss'])
plt.plot(model_6.history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper right')
plt.tight_layout()
```

```
10000/10000 [==============================] - 20s 2ms/step
Test error: 0.027272584022387945
Test accuracy: 0.9936
```



kernel_size 2*2

1. Three Convolution layer with kernel_size 2*2 and layers with activation- ReLU and optimizer-Adam

In [0]:
```
model_7 = Sequential()

# first set of CONV => RELU => POOL
model_7.add(Conv2D(128, kernel_size=(2,2),padding='same',activation='relu',inp
ut_shape=input_shape))
model_7.add(MaxPooling2D(pool_size=(2, 2)))

# second set of CONV => RELU => POOL
model_7.add(Conv2D(64, (2, 2), activation='relu'))
model_7.add(MaxPooling2D(pool_size=(2, 2)))

# Third set of CONV => RELU => POOL
model_7.add(Conv2D(32, (2, 2), activation='relu'))
model_7.add(MaxPooling2D(pool_size=(2, 2)))

model_7.add(Dropout(0.25))
model_7.add(Flatten())

#Hidden layer 1
model_7.add(Dense(128, activation='relu'))
# Dropout
model_7.add(Dropout(0.5))
#Hidden layer 2
model_7.add(Dense(64,activation='relu'))

#Output layer
model_7.add(Dense(num_classes, activation='softmax'))

model_7.compile(loss=keras.losses.categorical_crossentropy,optimizer=keras.opt
imizers.Adadelta(),metrics=['accuracy'])

history7=model_7.fit(x_train, y_train,batch_size=batch_size,epochs=epochs,verb
ose=1,validation_data=(x_test, y_test))
```

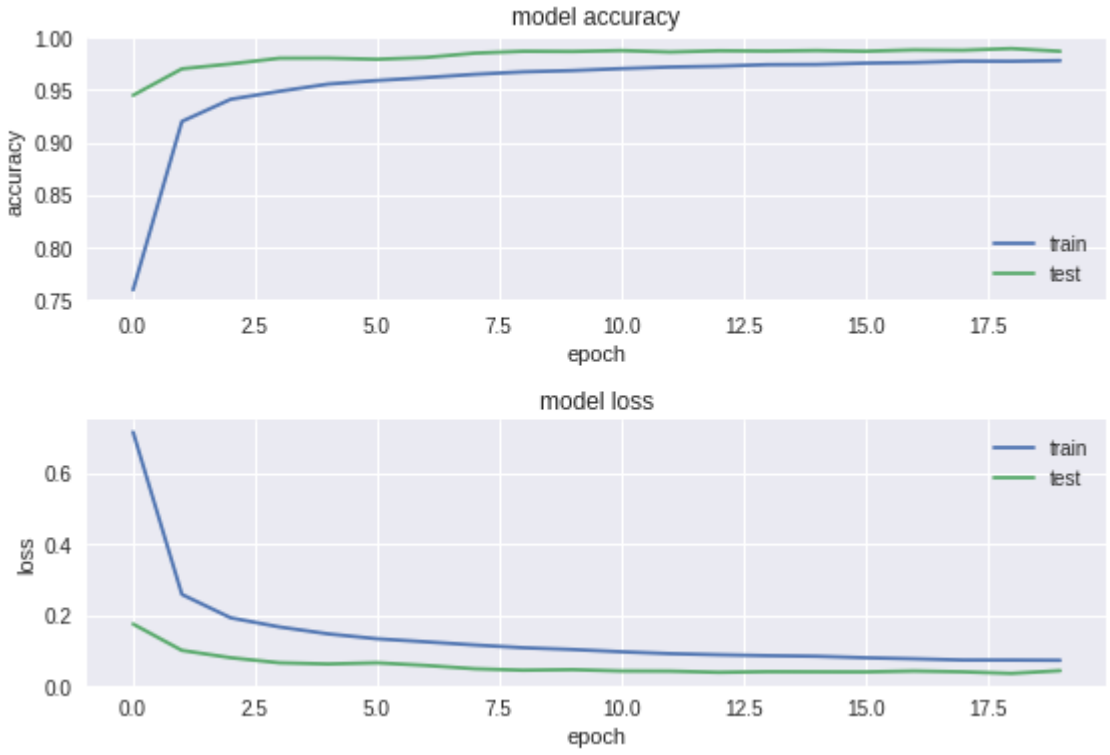
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 186s 3ms/step - loss: 0.7171 -
acc: 0.7596 - val_loss: 0.1759 - val_acc: 0.9450
Epoch 2/20
60000/60000 [==============================] - 185s 3ms/step - loss: 0.2594 -
acc: 0.9200 - val_loss: 0.1015 - val_acc: 0.9702
Epoch 3/20
60000/60000 [==============================] - 188s 3ms/step - loss: 0.1933 -
acc: 0.9412 - val_loss: 0.0808 - val_acc: 0.9749
Epoch 4/20
60000/60000 [==============================] - 186s 3ms/step - loss: 0.1676 -
acc: 0.9488 - val_loss: 0.0664 - val_acc: 0.9803
Epoch 5/20
60000/60000 [==============================] - 186s 3ms/step - loss: 0.1480 -
acc: 0.9557 - val_loss: 0.0632 - val_acc: 0.9804
Epoch 6/20
60000/60000 [==============================] - 186s 3ms/step - loss: 0.1342 -
acc: 0.9591 - val_loss: 0.0664 - val_acc: 0.9793
Epoch 7/20
60000/60000 [==============================] - 189s 3ms/step - loss: 0.1256 -
acc: 0.9619 - val_loss: 0.0591 - val_acc: 0.9810
Epoch 8/20
60000/60000 [==============================] - 192s 3ms/step - loss: 0.1168 -
acc: 0.9649 - val_loss: 0.0496 - val_acc: 0.9851
Epoch 9/20
60000/60000 [==============================] - 192s 3ms/step - loss: 0.1090 -
acc: 0.9673 - val_loss: 0.0456 - val_acc: 0.9869
Epoch 10/20
60000/60000 [==============================] - 192s 3ms/step - loss: 0.1040 -
acc: 0.9685 - val_loss: 0.0472 - val_acc: 0.9867
Epoch 11/20
60000/60000 [==============================] - 192s 3ms/step - loss: 0.0976 -
acc: 0.9704 - val_loss: 0.0433 - val_acc: 0.9876
Epoch 12/20
60000/60000 [==============================] - 191s 3ms/step - loss: 0.0923 -
acc: 0.9719 - val_loss: 0.0430 - val_acc: 0.9862
Epoch 13/20
60000/60000 [==============================] - 192s 3ms/step - loss: 0.0892 -
acc: 0.9727 - val_loss: 0.0396 - val_acc: 0.9874
Epoch 14/20
60000/60000 [==============================] - 192s 3ms/step - loss: 0.0866 -
acc: 0.9742 - val_loss: 0.0414 - val_acc: 0.9871
Epoch 15/20
60000/60000 [==============================] - 192s 3ms/step - loss: 0.0849 -
acc: 0.9744 - val_loss: 0.0411 - val_acc: 0.9876
Epoch 16/20
60000/60000 [==============================] - 191s 3ms/step - loss: 0.0807 -
acc: 0.9756 - val_loss: 0.0408 - val_acc: 0.9869
Epoch 17/20
60000/60000 [==============================] - 190s 3ms/step - loss: 0.0778 -
acc: 0.9762 - val_loss: 0.0433 - val_acc: 0.9882
Epoch 18/20
60000/60000 [==============================] - 187s 3ms/step - loss: 0.0743 -
acc: 0.9775 - val_loss: 0.0411 - val_acc: 0.9879
Epoch 19/20
60000/60000 [==============================] - 186s 3ms/step - loss: 0.0741 -
```

```
acc: 0.9774 - val_loss: 0.0365 - val_acc: 0.9895
Epoch 20/20
60000/60000 [==============================] - 186s 3ms/step - loss: 0.0735 -
acc: 0.9780 - val_loss: 0.0443 - val_acc: 0.9869
```

In [0]:
```
score = model_7.evaluate(x_test, y_test, verbose=1)
print('Test error:', score[0])
print('Test accuracy:', score[1])


# Credits: https://towardsdatascience.com/a-simple-2d-cnn-for-mnist-digit-recognition-a998dbc1e79a
import os
# plotting the metrics
fig = plt.figure()
plt.subplot(2,1,1)
plt.plot(model_7.history.history['acc'])
plt.plot(model_7.history.history['val_acc'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='lower right')
plt.subplot(2,1,2)
plt.plot(model_7.history.history['loss'])
plt.plot(model_7.history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper right')
plt.tight_layout()
#fig
```

```
10000/10000 [==============================] - 7s 673us/step
Test error: 0.04430655418855604
Test accuracy: 0.9869
```



With 3 hidden layer

In [0]:
```
model_8 = Sequential()

# first set of CONV => RELU
model_8.add(Conv2D(32, kernel_size=(2, 2),padding='same',activation='relu',inp
ut_shape=input_shape))

# second set of CONV => RELU => POOL
model_8.add(Conv2D(64, (2, 2), activation='relu'))
model_8.add(MaxPooling2D(pool_size=(2, 2)))


model_8.add(Dropout(0.25))
model_8.add(Flatten())


#Hidden layer 1
model_8.add(Dense(256, activation='relu'))
# Dropout
model_8.add(Dropout(0.5))
#Hidden layer 2
model_8.add(Dense(128,activation='relu'))
#Hidden layer 3
model_8.add(Dense(64,activation='relu'))
#Output layer
model_8.add(Dense(num_classes, activation='softmax'))

model_8.compile(loss=keras.losses.categorical_crossentropy,optimizer=keras.opt
imizers.Adadelta(),metrics=['accuracy'])

history8=model_8.fit(x_train, y_train,batch_size=batch_size,epochs=epochs,verb
ose=1,validation_data=(x_test, y_test))
```

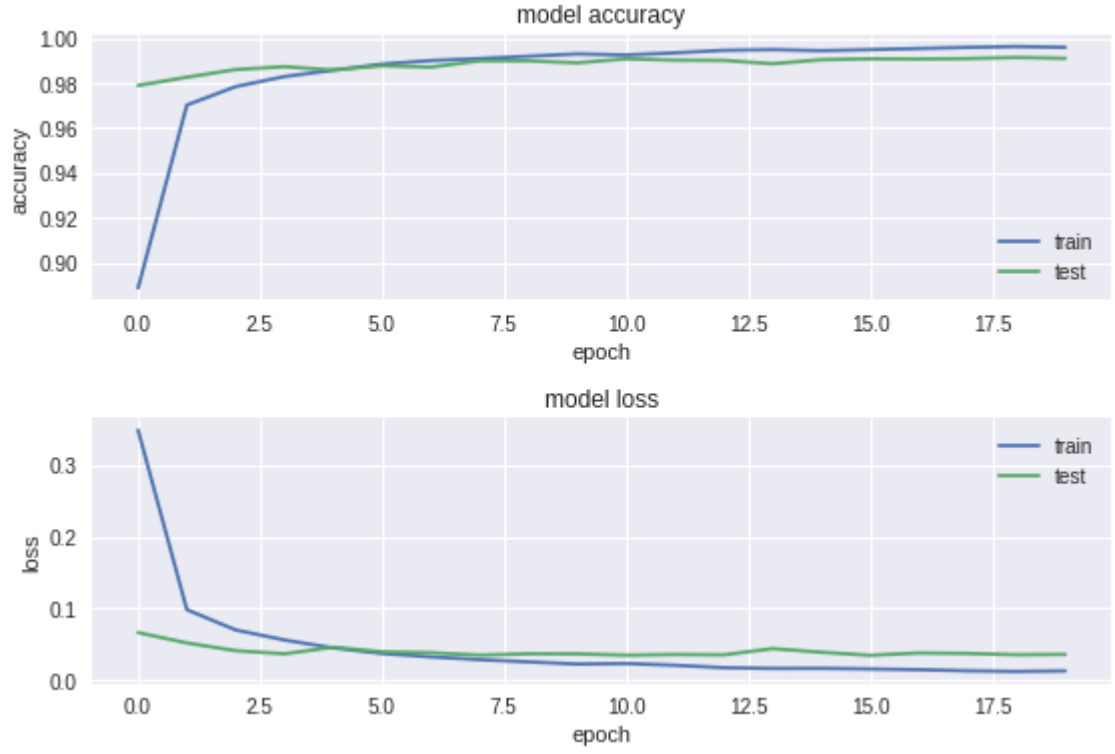
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 172s 3ms/step - loss: 0.3498 -
acc: 0.8887 - val_loss: 0.0664 - val_acc: 0.9790
Epoch 2/20
60000/60000 [==============================] - 170s 3ms/step - loss: 0.0983 -
acc: 0.9703 - val_loss: 0.0518 - val_acc: 0.9827
Epoch 3/20
60000/60000 [==============================] - 171s 3ms/step - loss: 0.0700 -
acc: 0.9785 - val_loss: 0.0410 - val_acc: 0.9861
Epoch 4/20
60000/60000 [==============================] - 170s 3ms/step - loss: 0.0559 -
acc: 0.9830 - val_loss: 0.0365 - val_acc: 0.9874
Epoch 5/20
60000/60000 [==============================] - 170s 3ms/step - loss: 0.0448 -
acc: 0.9858 - val_loss: 0.0458 - val_acc: 0.9859
Epoch 6/20
60000/60000 [==============================] - 171s 3ms/step - loss: 0.0370 -
acc: 0.9885 - val_loss: 0.0394 - val_acc: 0.9878
Epoch 7/20
60000/60000 [==============================] - 170s 3ms/step - loss: 0.0323 -
acc: 0.9901 - val_loss: 0.0381 - val_acc: 0.9872
Epoch 8/20
60000/60000 [==============================] - 169s 3ms/step - loss: 0.0284 -
acc: 0.9910 - val_loss: 0.0347 - val_acc: 0.9900
Epoch 9/20
60000/60000 [==============================] - 168s 3ms/step - loss: 0.0253 -
acc: 0.9920 - val_loss: 0.0366 - val_acc: 0.9900
Epoch 10/20
60000/60000 [==============================] - 170s 3ms/step - loss: 0.0222 -
acc: 0.9931 - val_loss: 0.0365 - val_acc: 0.9891
Epoch 11/20
60000/60000 [==============================] - 169s 3ms/step - loss: 0.0230 -
acc: 0.9926 - val_loss: 0.0346 - val_acc: 0.9909
Epoch 12/20
60000/60000 [==============================] - 173s 3ms/step - loss: 0.0206 -
acc: 0.9935 - val_loss: 0.0356 - val_acc: 0.9903
Epoch 13/20
60000/60000 [==============================] - 173s 3ms/step - loss: 0.0172 -
acc: 0.9947 - val_loss: 0.0351 - val_acc: 0.9902
Epoch 14/20
60000/60000 [==============================] - 176s 3ms/step - loss: 0.0161 -
acc: 0.9950 - val_loss: 0.0438 - val_acc: 0.9887
Epoch 15/20
60000/60000 [==============================] - 176s 3ms/step - loss: 0.0162 -
acc: 0.9945 - val_loss: 0.0388 - val_acc: 0.9905
Epoch 16/20
60000/60000 [==============================] - 175s 3ms/step - loss: 0.0154 -
acc: 0.9950 - val_loss: 0.0345 - val_acc: 0.9909
Epoch 17/20
60000/60000 [==============================] - 176s 3ms/step - loss: 0.0144 -
acc: 0.9955 - val_loss: 0.0377 - val_acc: 0.9908
Epoch 18/20
60000/60000 [==============================] - 176s 3ms/step - loss: 0.0128 -
acc: 0.9960 - val_loss: 0.0371 - val_acc: 0.9910
Epoch 19/20
60000/60000 [==============================] - 177s 3ms/step - loss: 0.0119 -
```

```
acc: 0.9964 - val_loss: 0.0352 - val_acc: 0.9915
Epoch 20/20
60000/60000 [==============================] - 173s 3ms/step - loss: 0.0127 -
acc: 0.9960 - val_loss: 0.0358 - val_acc: 0.9911
```

In [0]:
```
score = model_8.evaluate(x_test, y_test, verbose=1)
print('Test error:', score[0])
print('Test accuracy:', score[1])

# plotting the metrics
fig = plt.figure()
plt.subplot(2,1,1)
plt.plot(model_8.history.history['acc'])
plt.plot(model_8.history.history['val_acc'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='lower right')
plt.subplot(2,1,2)
plt.plot(model_8.history.history['loss'])
plt.plot(model_8.history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper right')
plt.tight_layout()
```

```
10000/10000 [==============================] - 7s 748us/step
Test error: 0.03578541702437269
Test accuracy: 0.9911
```



5 layer

In [0]:
```
model_9 = Sequential()

# first set of CONV => RELU
model_9.add(Conv2D(32, kernel_size=(2, 2),padding='same',activation='relu',inp
ut_shape=input_shape))

# second set of CONV => RELU => POOL
model_9.add(Conv2D(64, (2, 2), activation='relu'))
model_9.add(MaxPooling2D(pool_size=(2, 2)))

# Third set of CONV => RELU => POOL
model_9.add(Conv2D(128, (2, 2), activation='relu'))
model_9.add(MaxPooling2D(pool_size=(2, 2)))

model_9.add(Dropout(0.25))
model_9.add(Flatten())


#Hidden layer 1
model_9.add(Dense(512, activation='relu'))
# Dropout
model_9.add(Dropout(0.5))
#Hidden layer 2
model_9.add(Dense(256,activation='relu'))
#Hidden layer 3
model_9.add(Dense(128,activation='relu'))
#Hidden layer 4
model_9.add(Dense(64,activation='relu'))
#Hidden layer 5
model_9.add(Dense(32,activation='relu'))
#Output layer
model_9.add(Dense(num_classes, activation='softmax'))

model_9.compile(loss=keras.losses.categorical_crossentropy,optimizer=keras.opt
imizers.Adadelta(),metrics=['accuracy'])

history9=model_9.fit(x_train, y_train,batch_size=batch_size,epochs=epochs,verb
ose=1,validation_data=(x_test, y_test))
```

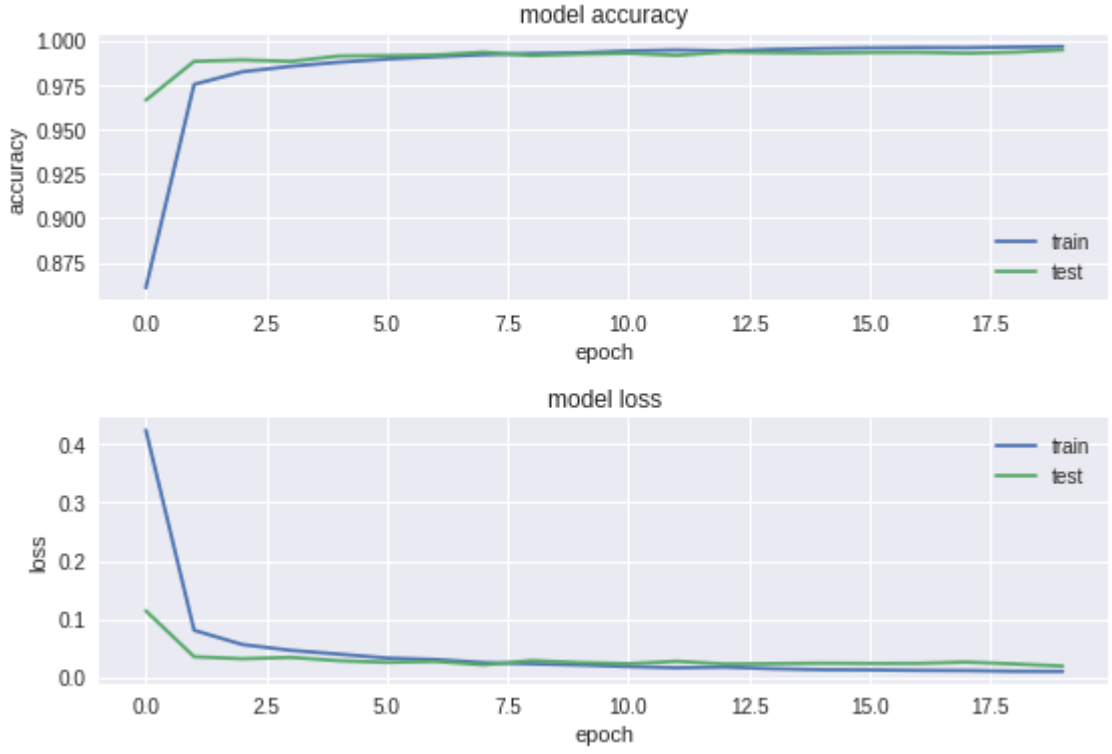
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 209s 3ms/step - loss: 0.4240 -
acc: 0.8606 - val_loss: 0.1145 - val_acc: 0.9666
Epoch 2/20
60000/60000 [==============================] - 209s 3ms/step - loss: 0.0811 -
acc: 0.9755 - val_loss: 0.0358 - val_acc: 0.9885
Epoch 3/20
60000/60000 [==============================] - 206s 3ms/step - loss: 0.0567 -
acc: 0.9826 - val_loss: 0.0323 - val_acc: 0.9893
Epoch 4/20
60000/60000 [==============================] - 208s 3ms/step - loss: 0.0468 -
acc: 0.9857 - val_loss: 0.0347 - val_acc: 0.9885
Epoch 5/20
60000/60000 [==============================] - 213s 4ms/step - loss: 0.0402 -
acc: 0.9880 - val_loss: 0.0289 - val_acc: 0.9915
Epoch 6/20
60000/60000 [==============================] - 210s 3ms/step - loss: 0.0335 -
acc: 0.9898 - val_loss: 0.0261 - val_acc: 0.9917
Epoch 7/20
60000/60000 [==============================] - 210s 4ms/step - loss: 0.0310 -
acc: 0.9911 - val_loss: 0.0277 - val_acc: 0.9921
Epoch 8/20
60000/60000 [==============================] - 210s 3ms/step - loss: 0.0257 -
acc: 0.9923 - val_loss: 0.0219 - val_acc: 0.9937
Epoch 9/20
60000/60000 [==============================] - 209s 3ms/step - loss: 0.0236 -
acc: 0.9929 - val_loss: 0.0292 - val_acc: 0.9918
Epoch 10/20
60000/60000 [==============================] - 210s 4ms/step - loss: 0.0216 -
acc: 0.9933 - val_loss: 0.0256 - val_acc: 0.9926
Epoch 11/20
60000/60000 [==============================] - 212s 4ms/step - loss: 0.0189 -
acc: 0.9944 - val_loss: 0.0238 - val_acc: 0.9931
Epoch 12/20
60000/60000 [==============================] - 214s 4ms/step - loss: 0.0168 -
acc: 0.9949 - val_loss: 0.0280 - val_acc: 0.9919
Epoch 13/20
60000/60000 [==============================] - 215s 4ms/step - loss: 0.0180 -
acc: 0.9944 - val_loss: 0.0233 - val_acc: 0.9938
Epoch 14/20
60000/60000 [==============================] - 216s 4ms/step - loss: 0.0152 -
acc: 0.9953 - val_loss: 0.0240 - val_acc: 0.9934
Epoch 15/20
60000/60000 [==============================] - 217s 4ms/step - loss: 0.0135 -
acc: 0.9958 - val_loss: 0.0246 - val_acc: 0.9932
Epoch 16/20
60000/60000 [==============================] - 218s 4ms/step - loss: 0.0132 -
acc: 0.9961 - val_loss: 0.0242 - val_acc: 0.9935
Epoch 17/20
60000/60000 [==============================] - 216s 4ms/step - loss: 0.0123 -
acc: 0.9963 - val_loss: 0.0244 - val_acc: 0.9936
Epoch 18/20
60000/60000 [==============================] - 215s 4ms/step - loss: 0.0120 -
acc: 0.9962 - val_loss: 0.0266 - val_acc: 0.9931
Epoch 19/20
60000/60000 [==============================] - 215s 4ms/step - loss: 0.0108 -
```

```
acc: 0.9966 - val_loss: 0.0234 - val_acc: 0.9937
Epoch 20/20
60000/60000 [==============================] - 217s 4ms/step - loss: 0.0106 -
acc: 0.9969 - val_loss: 0.0198 - val_acc: 0.9950
```

In [0]:
```
score = model_9.evaluate(x_test, y_test, verbose=1)
print('Test error:', score[0])
print('Test accuracy:', score[1])

# plotting the metrics
fig = plt.figure()
plt.subplot(2,1,1)
plt.plot(model_9.history.history['acc'])
plt.plot(model_9.history.history['val_acc'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='lower right')
plt.subplot(2,1,2)
plt.plot(model_9.history.history['loss'])
plt.plot(model_9.history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper right')
plt.tight_layout()
```

```
10000/10000 [==============================] - 10s 1ms/step
Test error: 0.019771983769868166
Test accuracy: 0.995
```



2 Hidden Layer

kernel_size 2* 2

In [4]:
```
model_10 = Sequential()

# first set of CONV => RELU
model_10.add(Conv2D(32, kernel_size=(2, 2),activation='relu',input_shape=input
_shape))

# second set of CONV => RELU => POOL
model_10.add(Conv2D(64, (2, 2), activation='relu'))
model_10.add(MaxPooling2D(pool_size=(2, 2)))

model_10.add(Dropout(0.25))
model_10.add(Flatten())



#Hidden layer 1
model_10.add(Dense(64,activation='relu'))
#Hidden layer 2
model_10.add(Dense(32,activation='relu'))
#Output layer
model_10.add(Dense(num_classes, activation='softmax'))

model_10.compile(loss=keras.losses.categorical_crossentropy,optimizer=keras.op
timizers.Adadelta(),metrics=['accuracy'])

history10=model_10.fit(x_train, y_train,batch_size=batch_size,epochs=epochs,ve
rbose=1,validation_data=(x_test, y_test))
```

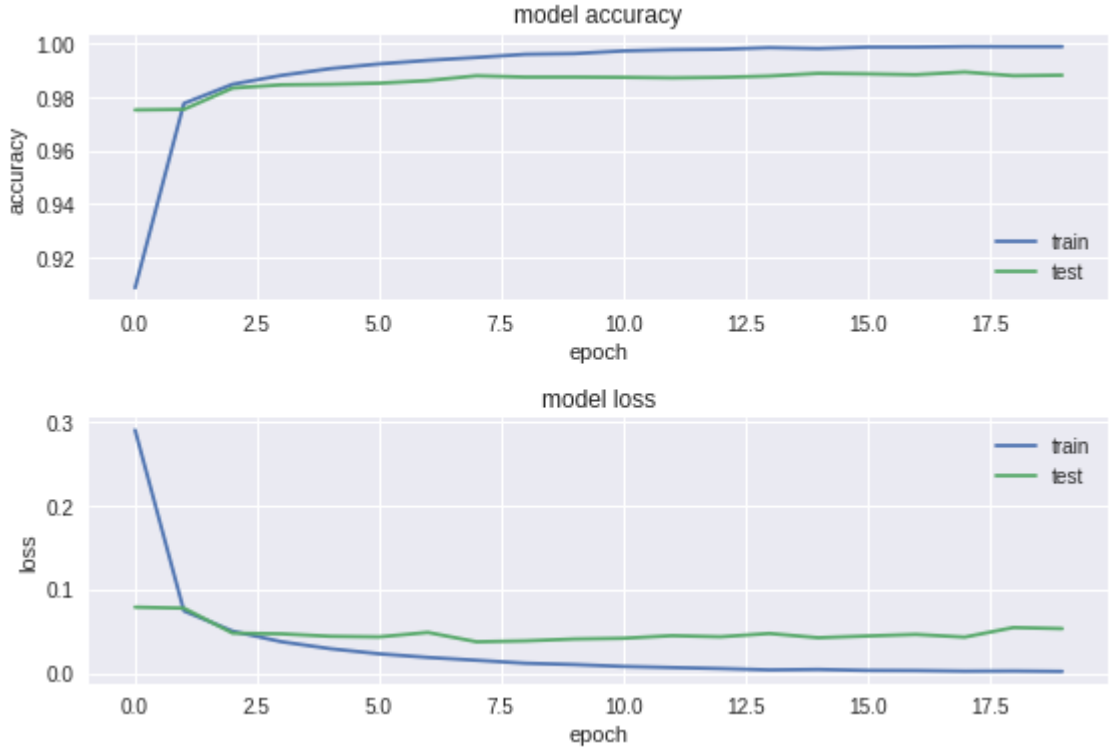
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 122s 2ms/step - loss: 0.2902 -
acc: 0.9086 - val_loss: 0.0793 - val_acc: 0.9753
Epoch 2/20
60000/60000 [==============================] - 129s 2ms/step - loss: 0.0748 -
acc: 0.9777 - val_loss: 0.0781 - val_acc: 0.9755
Epoch 3/20
60000/60000 [==============================] - 122s 2ms/step - loss: 0.0506 -
acc: 0.9849 - val_loss: 0.0483 - val_acc: 0.9835
Epoch 4/20
60000/60000 [==============================] - 122s 2ms/step - loss: 0.0380 -
acc: 0.9882 - val_loss: 0.0475 - val_acc: 0.9847
Epoch 5/20
60000/60000 [==============================] - 122s 2ms/step - loss: 0.0297 -
acc: 0.9908 - val_loss: 0.0445 - val_acc: 0.9849
Epoch 6/20
60000/60000 [==============================] - 122s 2ms/step - loss: 0.0237 -
acc: 0.9925 - val_loss: 0.0438 - val_acc: 0.9853
Epoch 7/20
60000/60000 [==============================] - 121s 2ms/step - loss: 0.0194 -
acc: 0.9939 - val_loss: 0.0491 - val_acc: 0.9863
Epoch 8/20
60000/60000 [==============================] - 122s 2ms/step - loss: 0.0160 -
acc: 0.9950 - val_loss: 0.0379 - val_acc: 0.9881
Epoch 9/20
60000/60000 [==============================] - 122s 2ms/step - loss: 0.0124 -
acc: 0.9961 - val_loss: 0.0391 - val_acc: 0.9876
Epoch 10/20
60000/60000 [==============================] - 123s 2ms/step - loss: 0.0109 -
acc: 0.9964 - val_loss: 0.0413 - val_acc: 0.9876
Epoch 11/20
60000/60000 [==============================] - 122s 2ms/step - loss: 0.0086 -
acc: 0.9974 - val_loss: 0.0421 - val_acc: 0.9875
Epoch 12/20
60000/60000 [==============================] - 122s 2ms/step - loss: 0.0073 -
acc: 0.9978 - val_loss: 0.0453 - val_acc: 0.9873
Epoch 13/20
60000/60000 [==============================] - 126s 2ms/step - loss: 0.0061 -
acc: 0.9980 - val_loss: 0.0439 - val_acc: 0.9875
Epoch 14/20
60000/60000 [==============================] - 125s 2ms/step - loss: 0.0045 -
acc: 0.9986 - val_loss: 0.0479 - val_acc: 0.9880
Epoch 15/20
60000/60000 [==============================] - 125s 2ms/step - loss: 0.0050 -
acc: 0.9983 - val_loss: 0.0428 - val_acc: 0.9890
Epoch 16/20
60000/60000 [==============================] - 126s 2ms/step - loss: 0.0038 -
acc: 0.9988 - val_loss: 0.0449 - val_acc: 0.9888
Epoch 17/20
60000/60000 [==============================] - 124s 2ms/step - loss: 0.0037 -
acc: 0.9989 - val_loss: 0.0468 - val_acc: 0.9885
Epoch 18/20
60000/60000 [==============================] - 123s 2ms/step - loss: 0.0030 -
acc: 0.9990 - val_loss: 0.0435 - val_acc: 0.9895
Epoch 19/20
60000/60000 [==============================] - 124s 2ms/step - loss: 0.0032 -
```

```
acc: 0.9990 - val_loss: 0.0549 - val_acc: 0.9881
Epoch 20/20
60000/60000 [==============================] - 124s 2ms/step - loss: 0.0027 -
acc: 0.9990 - val_loss: 0.0537 - val_acc: 0.9883
```

In [5]:
```
score = model_10.evaluate(x_test, y_test, verbose=1)
print('Test error:', score[0])
print('Test accuracy:', score[1])

# plotting the metrics
fig = plt.figure()
plt.subplot(2,1,1)
plt.plot(model_10.history.history['acc'])
plt.plot(model_10.history.history['val_acc'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='lower right')
plt.subplot(2,1,2)
plt.plot(model_10.history.history['loss'])
plt.plot(model_10.history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper right')
plt.tight_layout()
```

```
10000/10000 [==============================] - 5s 509us/step
Test error: 0.05367055785792263
Test accuracy: 0.9883
```



kernel_size 5 *5

In [6]:
```
model_11 = Sequential()

# first set of CONV => RELU
model_11.add(Conv2D(32, kernel_size=(5, 5),activation='relu',input_shape=input
_shape))

# second set of CONV => RELU => POOL
model_11.add(Conv2D(64, (5, 5), activation='relu'))
model_11.add(MaxPooling2D(pool_size=(2, 2)))

model_11.add(Dropout(0.25))
model_11.add(Flatten())



#Hidden layer 1
model_11.add(Dense(64,activation='relu'))
#Hidden layer 2
model_11.add(Dense(32,activation='relu'))
#Output layer
model_11.add(Dense(num_classes, activation='softmax'))

model_11.compile(loss=keras.losses.categorical_crossentropy,optimizer=keras.op
timizers.Adadelta(),metrics=['accuracy'])

history11=model_11.fit(x_train, y_train,batch_size=batch_size,epochs=epochs,ve
rbose=1,validation_data=(x_test, y_test))
```

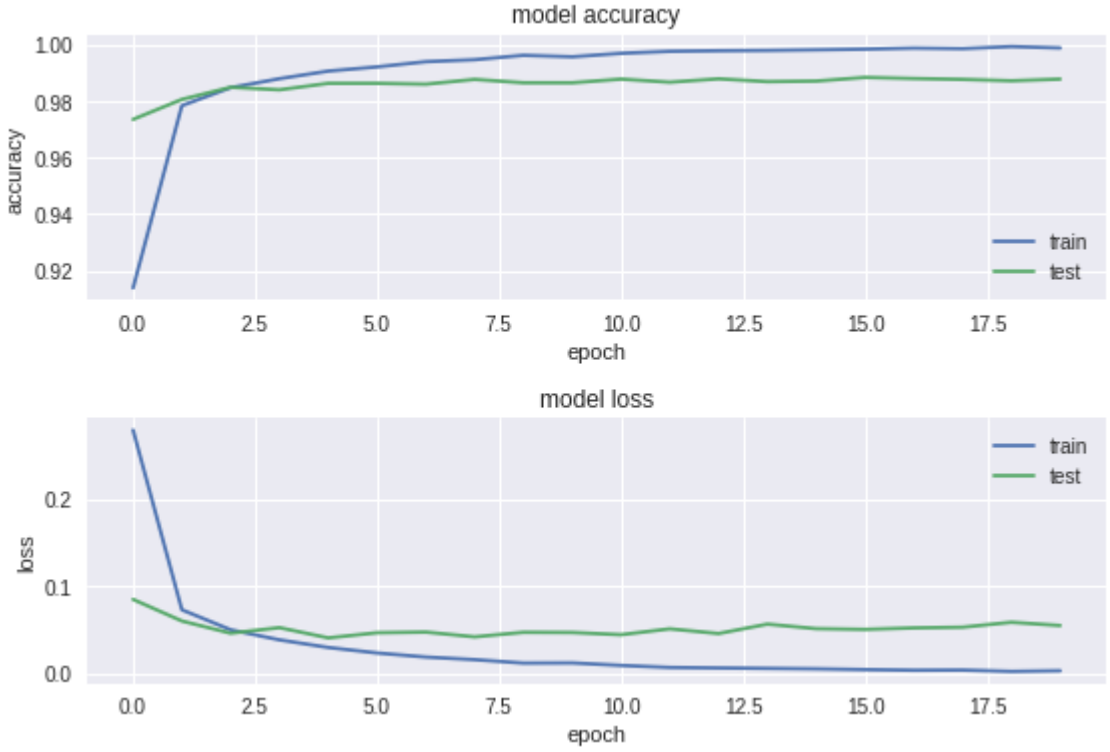
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 129s 2ms/step - loss: 0.2795 -
acc: 0.9138 - val_loss: 0.0851 - val_acc: 0.9736
Epoch 2/20
60000/60000 [==============================] - 126s 2ms/step - loss: 0.0732 -
acc: 0.9785 - val_loss: 0.0603 - val_acc: 0.9807
Epoch 3/20
60000/60000 [==============================] - 125s 2ms/step - loss: 0.0501 -
acc: 0.9849 - val_loss: 0.0462 - val_acc: 0.9850
Epoch 4/20
60000/60000 [==============================] - 124s 2ms/step - loss: 0.0386 -
acc: 0.9880 - val_loss: 0.0526 - val_acc: 0.9841
Epoch 5/20
60000/60000 [==============================] - 124s 2ms/step - loss: 0.0298 -
acc: 0.9908 - val_loss: 0.0409 - val_acc: 0.9864
Epoch 6/20
60000/60000 [==============================] - 124s 2ms/step - loss: 0.0235 -
acc: 0.9922 - val_loss: 0.0467 - val_acc: 0.9864
Epoch 7/20
60000/60000 [==============================] - 125s 2ms/step - loss: 0.0189 -
acc: 0.9941 - val_loss: 0.0475 - val_acc: 0.9861
Epoch 8/20
60000/60000 [==============================] - 127s 2ms/step - loss: 0.0159 -
acc: 0.9948 - val_loss: 0.0421 - val_acc: 0.9878
Epoch 9/20
60000/60000 [==============================] - 126s 2ms/step - loss: 0.0119 -
acc: 0.9963 - val_loss: 0.0473 - val_acc: 0.9866
Epoch 10/20
60000/60000 [==============================] - 124s 2ms/step - loss: 0.0121 -
acc: 0.9958 - val_loss: 0.0470 - val_acc: 0.9866
Epoch 11/20
60000/60000 [==============================] - 124s 2ms/step - loss: 0.0093 -
acc: 0.9971 - val_loss: 0.0445 - val_acc: 0.9879
Epoch 12/20
60000/60000 [==============================] - 124s 2ms/step - loss: 0.0069 -
acc: 0.9978 - val_loss: 0.0513 - val_acc: 0.9868
Epoch 13/20
60000/60000 [==============================] - 127s 2ms/step - loss: 0.0063 -
acc: 0.9980 - val_loss: 0.0459 - val_acc: 0.9880
Epoch 14/20
60000/60000 [==============================] - 127s 2ms/step - loss: 0.0059 -
acc: 0.9981 - val_loss: 0.0567 - val_acc: 0.9870
Epoch 15/20
60000/60000 [==============================] - 129s 2ms/step - loss: 0.0053 -
acc: 0.9983 - val_loss: 0.0514 - val_acc: 0.9872
Epoch 16/20
60000/60000 [==============================] - 129s 2ms/step - loss: 0.0045 -
acc: 0.9985 - val_loss: 0.0506 - val_acc: 0.9885
Epoch 17/20
60000/60000 [==============================] - 130s 2ms/step - loss: 0.0037 -
acc: 0.9989 - val_loss: 0.0523 - val_acc: 0.9881
Epoch 18/20
60000/60000 [==============================] - 129s 2ms/step - loss: 0.0039 -
acc: 0.9987 - val_loss: 0.0531 - val_acc: 0.9878
Epoch 19/20
60000/60000 [==============================] - 128s 2ms/step - loss: 0.0024 -
```

```
acc: 0.9995 - val_loss: 0.0588 - val_acc: 0.9873
Epoch 20/20
60000/60000 [==============================] - 129s 2ms/step - loss: 0.0031 -
acc: 0.9990 - val_loss: 0.0551 - val_acc: 0.9879
```

In [7]:
```
score = model_11.evaluate(x_test, y_test, verbose=1)
print('Test error:', score[0])
print('Test accuracy:', score[1])

# plotting the metrics
fig = plt.figure()
plt.subplot(2,1,1)
plt.plot(model_11.history.history['acc'])
plt.plot(model_11.history.history['val_acc'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='lower right')
plt.subplot(2,1,2)
plt.plot(model_11.history.history['loss'])
plt.plot(model_11.history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper right')
plt.tight_layout()
```

```
10000/10000 [==============================] - 6s 563us/step
Test error: 0.055056300737153105
Test accuracy: 0.9879
```



kernel_size 3*3

In [9]:
```
model_12 = Sequential()

# first set of CONV => RELU
model_12.add(Conv2D(32, kernel_size=(3, 3),activation='relu',input_shape=input
_shape))

# second set of CONV => RELU => POOL
model_12.add(Conv2D(64, (3, 3), activation='relu'))
model_12.add(MaxPooling2D(pool_size=(2, 2)))

model_12.add(Dropout(0.25))
model_12.add(Flatten())



#Hidden layer 1
model_12.add(Dense(64,activation='relu'))
#Hidden layer 2
model_12.add(Dense(32,activation='relu'))
#Output layer
model_12.add(Dense(num_classes, activation='softmax'))

model_12.compile(loss=keras.losses.categorical_crossentropy,optimizer=keras.op
timizers.Adadelta(),metrics=['accuracy'])

history11=model_12.fit(x_train, y_train,batch_size=batch_size,epochs=epochs,ve
rbose=1,validation_data=(x_test, y_test))
```

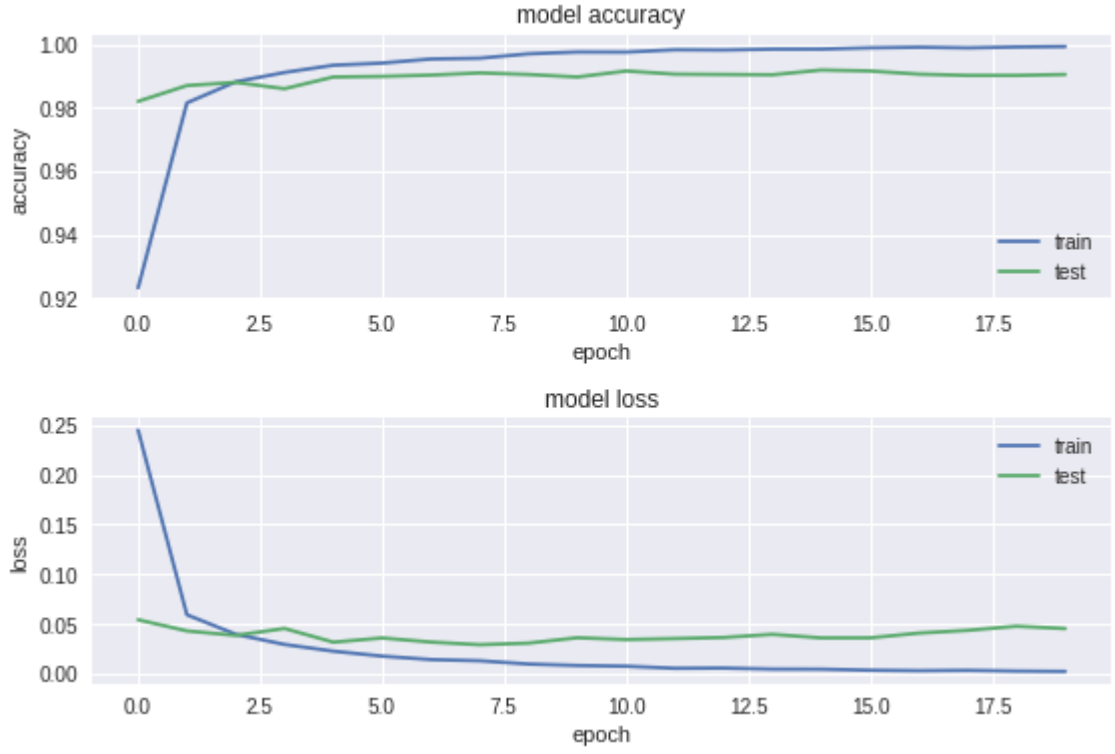
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 161s 3ms/step - loss: 0.2450 -
acc: 0.9231 - val_loss: 0.0543 - val_acc: 0.9820
Epoch 2/20
60000/60000 [==============================] - 160s 3ms/step - loss: 0.0593 -
acc: 0.9815 - val_loss: 0.0431 - val_acc: 0.9870
Epoch 3/20
60000/60000 [==============================] - 159s 3ms/step - loss: 0.0397 -
acc: 0.9882 - val_loss: 0.0385 - val_acc: 0.9880
Epoch 4/20
60000/60000 [==============================] - 160s 3ms/step - loss: 0.0295 -
acc: 0.9911 - val_loss: 0.0455 - val_acc: 0.9860
Epoch 5/20
60000/60000 [==============================] - 160s 3ms/step - loss: 0.0227 -
acc: 0.9934 - val_loss: 0.0318 - val_acc: 0.9897
Epoch 6/20
60000/60000 [==============================] - 159s 3ms/step - loss: 0.0177 -
acc: 0.9941 - val_loss: 0.0360 - val_acc: 0.9899
Epoch 7/20
60000/60000 [==============================] - 159s 3ms/step - loss: 0.0143 -
acc: 0.9954 - val_loss: 0.0319 - val_acc: 0.9903
Epoch 8/20
60000/60000 [==============================] - 157s 3ms/step - loss: 0.0131 -
acc: 0.9956 - val_loss: 0.0292 - val_acc: 0.9910
Epoch 9/20
60000/60000 [==============================] - 156s 3ms/step - loss: 0.0098 -
acc: 0.9970 - val_loss: 0.0308 - val_acc: 0.9905
Epoch 10/20
60000/60000 [==============================] - 156s 3ms/step - loss: 0.0083 -
acc: 0.9976 - val_loss: 0.0362 - val_acc: 0.9897
Epoch 11/20
60000/60000 [==============================] - 156s 3ms/step - loss: 0.0076 -
acc: 0.9976 - val_loss: 0.0344 - val_acc: 0.9916
Epoch 12/20
60000/60000 [==============================] - 155s 3ms/step - loss: 0.0055 -
acc: 0.9983 - val_loss: 0.0354 - val_acc: 0.9906
Epoch 13/20
60000/60000 [==============================] - 156s 3ms/step - loss: 0.0057 -
acc: 0.9982 - val_loss: 0.0365 - val_acc: 0.9905
Epoch 14/20
60000/60000 [==============================] - 156s 3ms/step - loss: 0.0047 -
acc: 0.9985 - val_loss: 0.0396 - val_acc: 0.9904
Epoch 15/20
60000/60000 [==============================] - 157s 3ms/step - loss: 0.0046 -
acc: 0.9985 - val_loss: 0.0361 - val_acc: 0.9919
Epoch 16/20
60000/60000 [==============================] - 157s 3ms/step - loss: 0.0035 -
acc: 0.9989 - val_loss: 0.0361 - val_acc: 0.9916
Epoch 17/20
60000/60000 [==============================] - 157s 3ms/step - loss: 0.0031 -
acc: 0.9991 - val_loss: 0.0409 - val_acc: 0.9906
Epoch 18/20
60000/60000 [==============================] - 156s 3ms/step - loss: 0.0034 -
acc: 0.9989 - val_loss: 0.0436 - val_acc: 0.9902
Epoch 19/20
60000/60000 [==============================] - 156s 3ms/step - loss: 0.0027 -
```

```
acc: 0.9992 - val_loss: 0.0478 - val_acc: 0.9902
Epoch 20/20
60000/60000 [==============================] - 155s 3ms/step - loss: 0.0024 -
acc: 0.9993 - val_loss: 0.0454 - val_acc: 0.9905
```

In [10]:
```
score = model_12.evaluate(x_test, y_test, verbose=1)
print('Test error:', score[0])
print('Test accuracy:', score[1])

# plotting the metrics
fig = plt.figure()
plt.subplot(2,1,1)
plt.plot(model_12.history.history['acc'])
plt.plot(model_12.history.history['val_acc'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='lower right')
plt.subplot(2,1,2)
plt.plot(model_12.history.history['loss'])
plt.plot(model_12.history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper right')
plt.tight_layout()
```

```
10000/10000 [==============================] - 7s 727us/step
Test error: 0.045423888562876436
Test accuracy: 0.9905
```



* With padding

kernel_size 3*3	Test Error	Test Accuracy
2 Layer	0.01969	0.9946
3 Layer	0.02435	0.9934
5 Layer	0.02562	0.9934

kernel_size 5*5	Test Error	Test Accuracy
2 Layer	0.02445	0.9932
3 Layer	0.02594	0.9949
5 Layer	0.02727	0.9936

kernel_size 2*2	Test Error	Test Accuracy
2 Layer	0.04430	0.9869
3 Layer	0.03578	0.9911
5 Layer	0.01977	0.9550

* Without padding

2layer	Test Error	Test Accuracy
kernel_size 2*2	0.05367	0.9883
kernel_size 3*3	0.04542	0.9905
kernel_size 5*5	0.05505	0.9879

Conclusion

* Conv2D with padding perform better than Conv2D without padding.
* As we increase number of Conv2D layer it may incerse accuracy.
* As we increase number of layer it may increase accuracy.
* As we increase number of neurons in layer it may increase accuracy.