In [2]:
```python
import numpy as np

import tensorflow as tf
from tensorflow.keras.datasets import mnist
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.layers import Activation, Dense,Input

import matplotlib.pyplot as plt
%matplotlib inline
```

In [3]:
```python
(x_train, y_train), (x_test, y_test) = mnist.load_data()
```

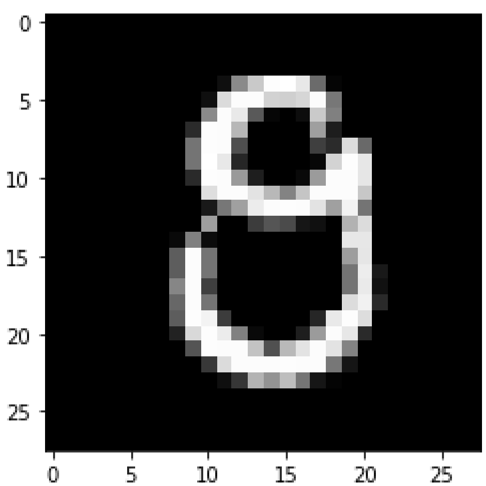
In [4]:
```python
x_train.shape
```

Out[4]:
```
(60000, 28, 28)
```

In [7]:
```python
print("Actual Lable :", y_train[80])
plt.imshow(x_train[80], cmap="gray")
```

```
Actual Lable : 9
```

Out[7]:
```
<matplotlib.image.AxesImage at 0x2017e0f1240>
```



Create model

In [8]:
```python
def create_model_1():
    model = Sequential()  # MLP Model
    model.add(Dense(20, activation="sigmoid", input_shape=(28*28,)))
    model.add(Dense(32, activation="sigmoid"))
    model.add(Dense(10, activation="softmax"))
    model.compile(loss='categorical_crossentropy', optimizer='SGD', metrics=["accuracy"])
    model.summary()
    return model

model_1 = create_model_1()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_3 (Dense)              (None, 20)                15700
_________________________________________________________________
dense_4 (Dense)              (None, 32)                672
_________________________________________________________________
dense_5 (Dense)              (None, 10)                330
=================================================================
Total params: 16,702
Trainable params: 16,702
Non-trainable params: 0
_________________________________________________________________
```

In [9]:
```python
y_train.shape
```

Out[9]:
```
(60000,)
```

Covert lables to one-hot vectors for MLP model training

In [11]:
```python
from tensorflow.keras.utils import to_categorical
```

In [12]:
```python
y_train_vecs = to_categorical(y_train, num_classes=10)
y_test_vecs = to_categorical(y_test,num_classes=10 )
print(y_train_vecs.shape, y_test_vecs.shape)
```

```
(60000, 10) (10000, 10)
```

In [13]:
```
# Inspect vectors
y_test_vecs[0], y_test[0]
```

Out[13]:
```
(array([0., 0., 0., 0., 0., 0., 0., 1., 0., 0.], dtype=float32), 7)
```

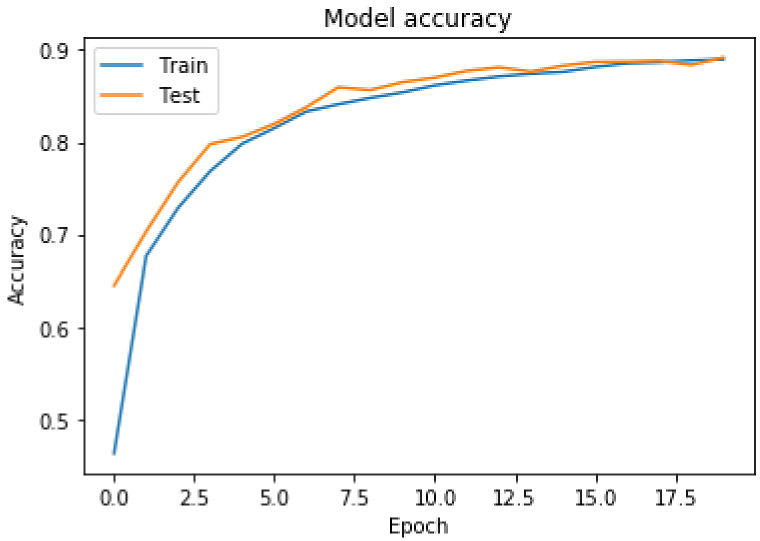
Let's train the model

In [14]:
```python
history = model_1.fit(x=x_train.reshape((60000, 28*28)),
          y=y_train_vecs,
          batch_size=64,
          epochs=20,
          verbose=1,
         validation_data=(x_test.reshape((10000, 28*28)), y_test_vecs))
```

```
Train on 60000 samples, validate on 10000 samples
WARNING:tensorflow:From C:\Users\subhendu_mishra\AppData\Local\Continuum\anaconda3\lib\site-packages\tensorflo
w\python\ops\math_ops.py:3066: to_int32 (from tensorflow.python.ops.math_ops) is deprecated and will be remove
d in a future version.
Instructions for updating:
Use tf.cast instead.
Epoch 1/20
60000/60000 [==============================] - 5s 78us/sample - loss: 2.0916 - acc: 0.4632 - val_loss: 1.8798
- val_acc: 0.6449
Epoch 2/20
60000/60000 [==============================] - 5s 80us/sample - loss: 1.6939 - acc: 0.6765 - val_loss: 1.5100
- val_acc: 0.7030
Epoch 3/20
60000/60000 [==============================] - 4s 71us/sample - loss: 1.3540 - acc: 0.7287 - val_loss: 1.2133
- val_acc: 0.7566
Epoch 4/20
60000/60000 [==============================] - 4s 62us/sample - loss: 1.1145 - acc: 0.7684 - val_loss: 1.0179
- val_acc: 0.7978
Epoch 5/20
60000/60000 [==============================] - 4s 65us/sample - loss: 0.9464 - acc: 0.7982 - val_loss: 0.8974
- val_acc: 0.8056
Epoch 6/20
60000/60000 [==============================] - 5s 78us/sample - loss: 0.8337 - acc: 0.8151 - val_loss: 0.7927
- val_acc: 0.8197
Epoch 7/20
60000/60000 [==============================] - 4s 66us/sample - loss: 0.7437 - acc: 0.8331 - val_loss: 0.7059
- val_acc: 0.8378
Epoch 8/20
60000/60000 [==============================] - 5s 78us/sample - loss: 0.6803 - acc: 0.8409 - val_loss: 0.6451
- val_acc: 0.8594
Epoch 9/20
60000/60000 [==============================] - 4s 75us/sample - loss: 0.6319 - acc: 0.8479 - val_loss: 0.6003
- val_acc: 0.8564
Epoch 10/20
60000/60000 [==============================] - 3s 58us/sample - loss: 0.5896 - acc: 0.8539 - val_loss: 0.5707
- val_acc: 0.8650
```

```
Epoch 11/20
60000/60000 [==============================] - 4s 65us/sample - loss: 0.5598 - acc: 0.8615 - val_loss: 0.5428
- val_acc: 0.8699
Epoch 12/20
60000/60000 [==============================] - 4s 61us/sample - loss: 0.5270 - acc: 0.8666 - val_loss: 0.5002
- val_acc: 0.8772
Epoch 13/20
60000/60000 [==============================] - 4s 68us/sample - loss: 0.5020 - acc: 0.8711 - val_loss: 0.4835
- val_acc: 0.8810
Epoch 14/20
60000/60000 [==============================] - 3s 53us/sample - loss: 0.4807 - acc: 0.8740 - val_loss: 0.4748
- val_acc: 0.8764
Epoch 15/20
60000/60000 [==============================] - 3s 56us/sample - loss: 0.4715 - acc: 0.8761 - val_loss: 0.4647
- val_acc: 0.8828
Epoch 16/20
60000/60000 [==============================] - 4s 61us/sample - loss: 0.4504 - acc: 0.8814 - val_loss: 0.4375
- val_acc: 0.8869
Epoch 17/20
60000/60000 [==============================] - 3s 57us/sample - loss: 0.4378 - acc: 0.8854 - val_loss: 0.4430
- val_acc: 0.8872
Epoch 18/20
60000/60000 [==============================] - 4s 66us/sample - loss: 0.4322 - acc: 0.8865 - val_loss: 0.4360
- val_acc: 0.8881
Epoch 19/20
60000/60000 [==============================] - 4s 66us/sample - loss: 0.4200 - acc: 0.8884 - val_loss: 0.4168
- val_acc: 0.8837
Epoch 20/20
60000/60000 [==============================] - 4s 70us/sample - loss: 0.4066 - acc: 0.8897 - val_loss: 0.4167
- val_acc: 0.8916
```

In [15]:
```python
# Plot training & validation accuracy values
def plot_keras_history(h):
    plt.plot(h.history['acc'])
    plt.plot(h.history['val_acc'])
    plt.title('Model accuracy')
    plt.ylabel('Accuracy')
    plt.xlabel('Epoch')
    plt.legend(['Train', 'Test'], loc='upper left')
    plt.show()

plot_keras_history(history)
```



Let's examine few good and bad cases for which our model works and doesn't work

In [16]:
```
y_pred = model_1.predict_classes(x_test.reshape((10000,28*28)))  ## predict_classes can directly give us predict
print(y_pred.shape)
```

```
(10000,)
```

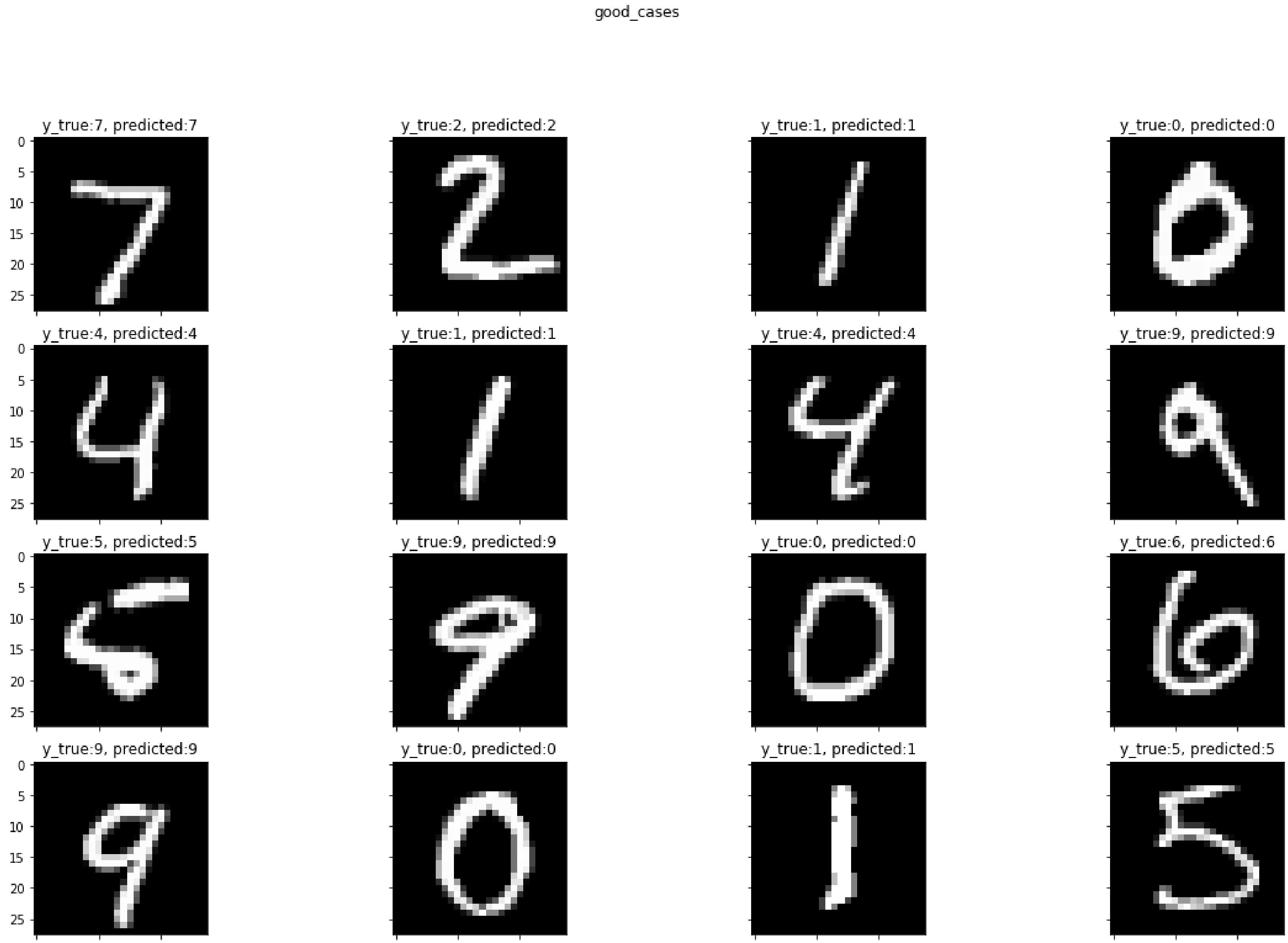
In [18]:
```
## First 20 examples
n = 20
i = 0
good_cases = []
for y_hat , y in zip(y_pred, y_test):
    if y_hat == y:
        good_cases.append(i)
        if len(good_cases) == n:
            break
    i += 1

i = 0
bad_cases = []
for y_hat , y in zip(y_pred, y_test):
    if y_hat != y:
        bad_cases.append(i)
        if len(bad_cases) == n:
            break
    i += 1

print(good_cases ,"\n", bad_cases)
```

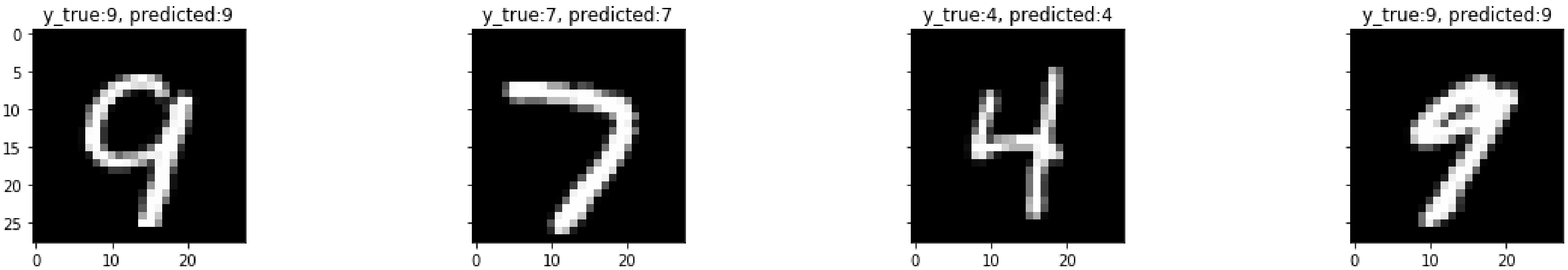
```
[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 19, 20]
 [18, 33, 62, 77, 87, 92, 104, 124, 125, 149, 150, 151, 172, 185, 187, 195, 217, 233, 235, 241]
```

Now Let's visualize them

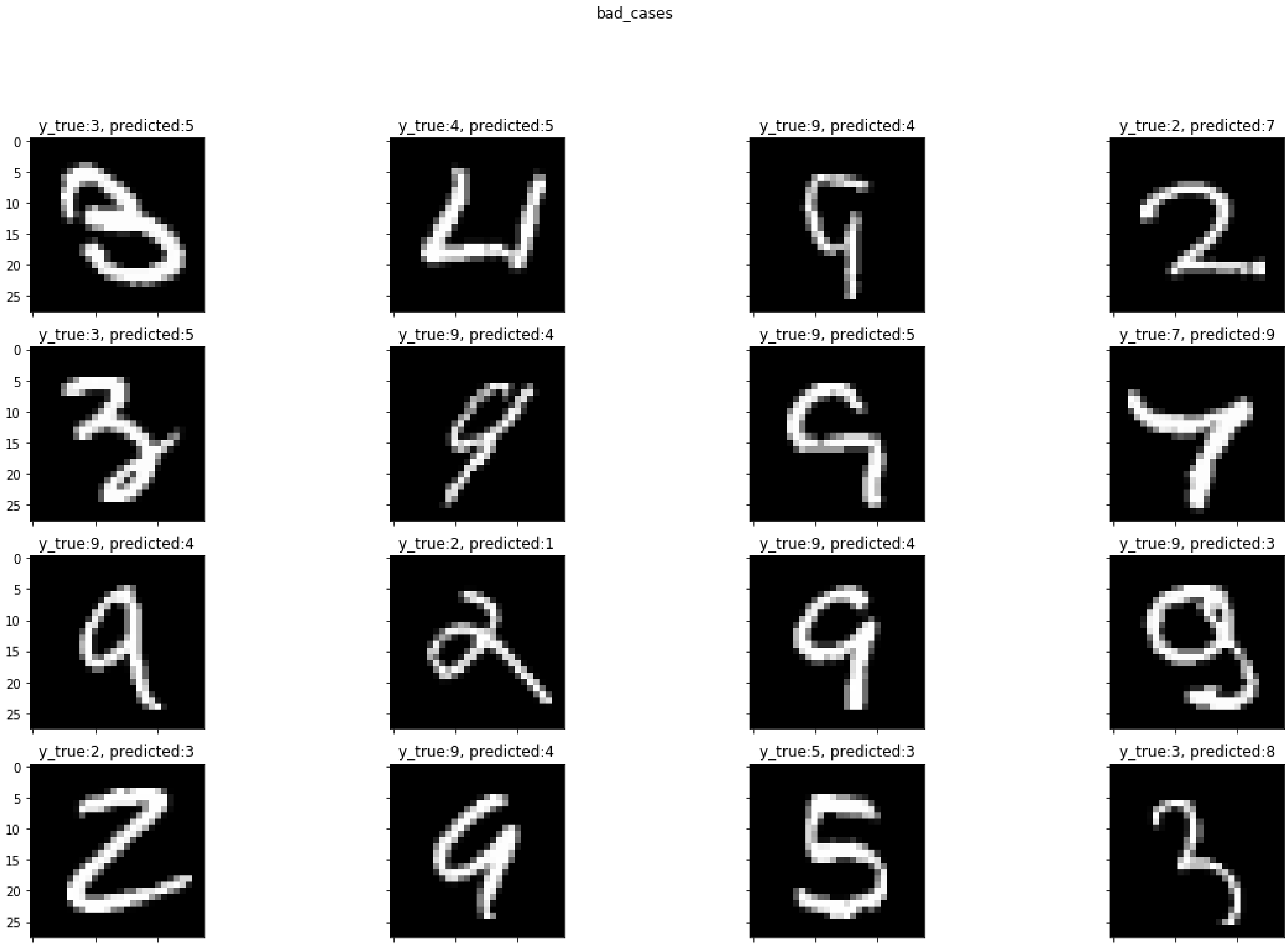
In [35]:
```
def show_mnist(data, y_pred, y_true, n_rows=0, n_cols=0, title=""):
    n = len(data)
    assert n==n_rows*n_cols , "n_rows*n_cols should be equal to nun of samples"

    fig, axs = plt.subplots(n_rows, n_cols, sharex=True, sharey=True, squeeze=False, figsize=(20,15))

    fig.suptitle(title)

    for i in range(n_rows):
        for j in range(n_cols):
            m = i*n_cols + j
            img = data[m]
            sub_title = "y_true:{}, predicted:{}".format(y_true[m], y_pred[m])
            axs[i,j].imshow(img, cmap="gray")
            axs[i,j].title.set_text(sub_title)
```

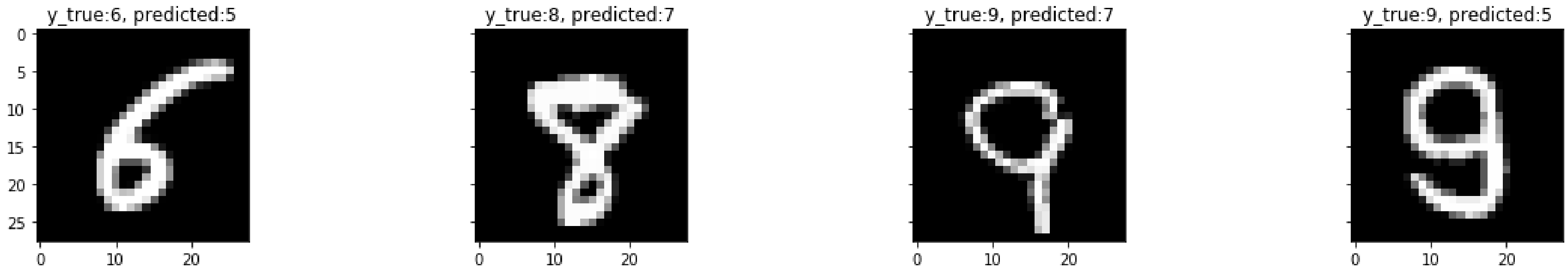
In [36]:
```
show_mnist(x_test[good_cases],
           y_pred[good_cases],
           y_test[good_cases],
           n_rows=5, n_cols=4,
           title= "good_cases")
```




y_true:9, predicted:9
y_true:7, predicted:7
y_true:4, predicted:4
y_true:9, predicted:9

In [37]:
```
show_mnist(x_test[bad_cases],
           y_pred[bad_cases],
           y_test[bad_cases],
           n_rows=5, n_cols=4,
           title= "bad_cases")
```





Second Try

Let's do a second try to improve the performance of this model

Let's examine the data once again

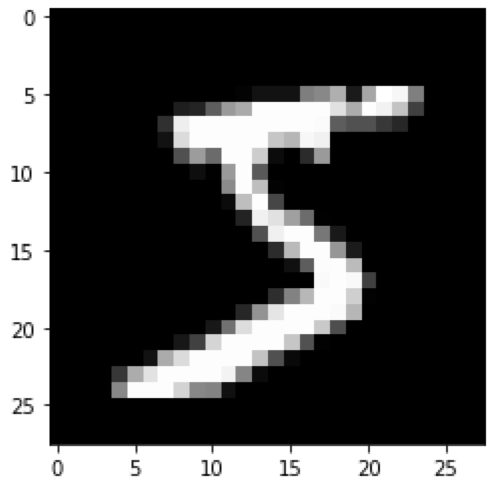
In [39]:
```
np.max(x_train) , np.max(x_test)
```

Out[39]:
```
(255, 255)
```

- As shown above the image contains gray scale values in integer format
- let's scale them back to -1 to +1 range and try again

In [46]:
```
x_train_new = x_train / 255
x_test_new = x_test / 255
```

In [47]:
```
plt.imshow(x_train_new[0] , cmap="gray")
```
Out[47]: <matplotlib.image.AxesImage at 0x20137e13278>



In [48]:
```
## Use a special layer called dropout to avoid over fitting
from tensorflow.keras.layers import Dropout
```

In [49]:
```
def create_model_2():
    model = Sequential()  # MLP Model
    model.add(Dense(64, activation="relu", input_shape=(28*28,)))
    model.add(Dropout(0.25))
    model.add(Dense(64, activation="relu"))
    model.add(Dropout(0.25))
    model.add(Dense(10, activation="softmax"))
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=["accuracy"])
    model.summary()
    return model

model_2 = create_model_2()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_10 (Dense)             (None, 64)                50240     
_________________________________________________________________
dropout_2 (Dropout)          (None, 64)                0         
_________________________________________________________________
dense_11 (Dense)             (None, 64)                4160      
_________________________________________________________________
dropout_3 (Dropout)          (None, 64)                0         
_________________________________________________________________
dense_12 (Dense)             (None, 10)                650       
=================================================================
Total params: 55,050
Trainable params: 55,050
Non-trainable params: 0
_________________________________________________________________
```

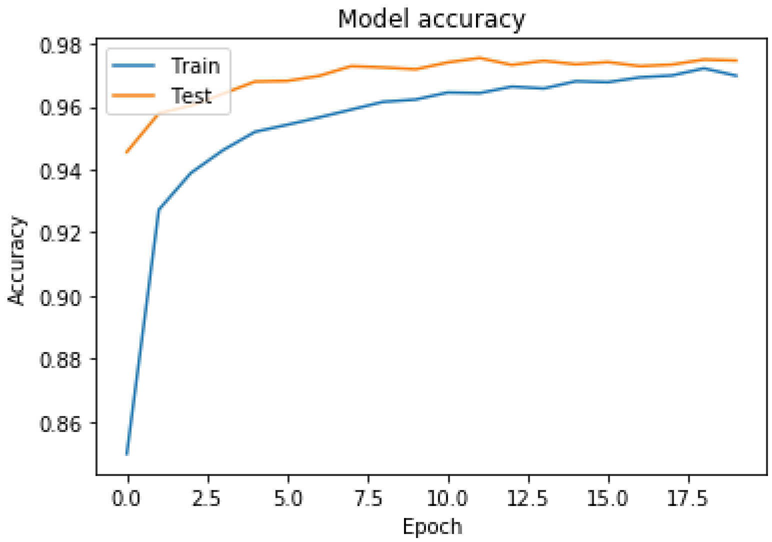
Let's train Model 2

In [50]:
```python
# Make sure to use the new rescaled datasets x_train_new and x_test_new
history_2 = model_2.fit(x=x_train_new.reshape((60000, 28*28)),
          y=y_train_vecs,
          batch_size=64,
          epochs=20,
          verbose=1,
         validation_data=(x_test_new.reshape((10000, 28*28)), y_test_vecs))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 7s 118us/sample - loss: 0.4971 - acc: 0.8497 - val_loss: 0.1815
- val_acc: 0.9456
Epoch 2/20
60000/60000 [==============================] - 5s 90us/sample - loss: 0.2454 - acc: 0.9272 - val_loss: 0.1391
- val_acc: 0.9579
Epoch 3/20
60000/60000 [==============================] - 5s 87us/sample - loss: 0.2024 - acc: 0.9389 - val_loss: 0.1274
- val_acc: 0.9603
Epoch 4/20
60000/60000 [==============================] - 5s 91us/sample - loss: 0.1808 - acc: 0.9462 - val_loss: 0.1241
- val_acc: 0.9641
Epoch 5/20
60000/60000 [==============================] - 5s 83us/sample - loss: 0.1629 - acc: 0.9520 - val_loss: 0.1098
- val_acc: 0.9680
Epoch 6/20
60000/60000 [==============================] - 6s 96us/sample - loss: 0.1507 - acc: 0.9542 - val_loss: 0.1064
- val_acc: 0.9682
Epoch 7/20
60000/60000 [==============================] - 6s 92us/sample - loss: 0.1411 - acc: 0.9566 - val_loss: 0.1006
- val_acc: 0.9698
Epoch 8/20
60000/60000 [==============================] - 5s 83us/sample - loss: 0.1355 - acc: 0.9591 - val_loss: 0.0942
- val_acc: 0.9729
Epoch 9/20
60000/60000 [==============================] - 5s 88us/sample - loss: 0.1268 - acc: 0.9615 - val_loss: 0.0932
- val_acc: 0.9725
Epoch 10/20
60000/60000 [==============================] - 5s 85us/sample - loss: 0.1223 - acc: 0.9623 - val_loss: 0.0958
- val_acc: 0.9719
Epoch 11/20
60000/60000 [==============================] - 5s 82us/sample - loss: 0.1150 - acc: 0.9645 - val_loss: 0.0890
- val_acc: 0.9741
Epoch 12/20
```

```
60000/60000 [==============================] - 5s 87us/sample - loss: 0.1142 - acc: 0.9643 - val_loss: 0.0852
- val_acc: 0.9755
Epoch 13/20
60000/60000 [==============================] - 5s 84us/sample - loss: 0.1099 - acc: 0.9664 - val_loss: 0.0902
- val_acc: 0.9733
Epoch 14/20
60000/60000 [==============================] - 5s 87us/sample - loss: 0.1074 - acc: 0.9658 - val_loss: 0.0863
- val_acc: 0.9746
Epoch 15/20
60000/60000 [==============================] - 5s 86us/sample - loss: 0.1043 - acc: 0.9681 - val_loss: 0.0928
- val_acc: 0.9735
Epoch 16/20
60000/60000 [==============================] - 5s 89us/sample - loss: 0.1019 - acc: 0.9678 - val_loss: 0.0868
- val_acc: 0.9742
Epoch 17/20
60000/60000 [==============================] - 5s 89us/sample - loss: 0.0996 - acc: 0.9693 - val_loss: 0.0880
- val_acc: 0.9729
Epoch 18/20
60000/60000 [==============================] - 6s 107us/sample - loss: 0.0952 - acc: 0.9699 - val_loss: 0.0905
- val_acc: 0.9734
Epoch 19/20
60000/60000 [==============================] - 5s 91us/sample - loss: 0.0911 - acc: 0.9722 - val_loss: 0.0853
- val_acc: 0.9750
Epoch 20/20
60000/60000 [==============================] - 5s 87us/sample - loss: 0.0936 - acc: 0.9699 - val_loss: 0.0876
- val_acc: 0.9747
```

In [52]:
```
plot_keras_history(history_2)
```



WOW ! 97.5% accuracy in validation

- Now with these changes we have got 97.5% accuracy . **But still we missed 2.5%** . We would examine them latter
- Model_2 inorporated following changes
    - Activation function of layes chnaged to "relu"
    - Layer dims increased to 64

- Dropout added to avoid overfitting
- Data rescaled

Let's examine bad cases for which even our updtaed model doesn't work

In [54]:
```
y_pred_2 = model_2.predict_classes(x_test_new.reshape((10000,28*28)))
print("y_pred_2 : ", y_pred_2.shape)
```

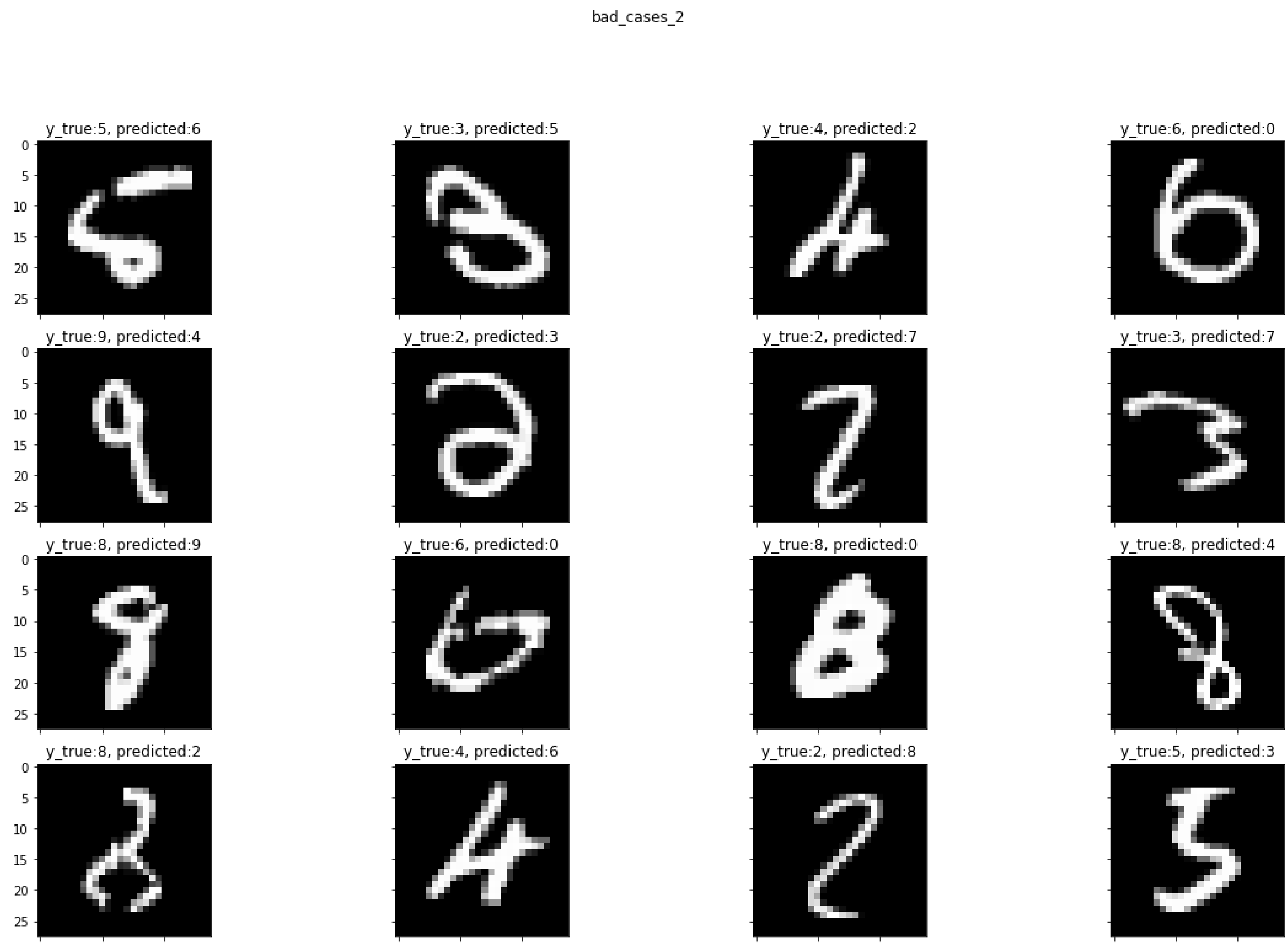
```
y_pred_2 :  (10000,)
```

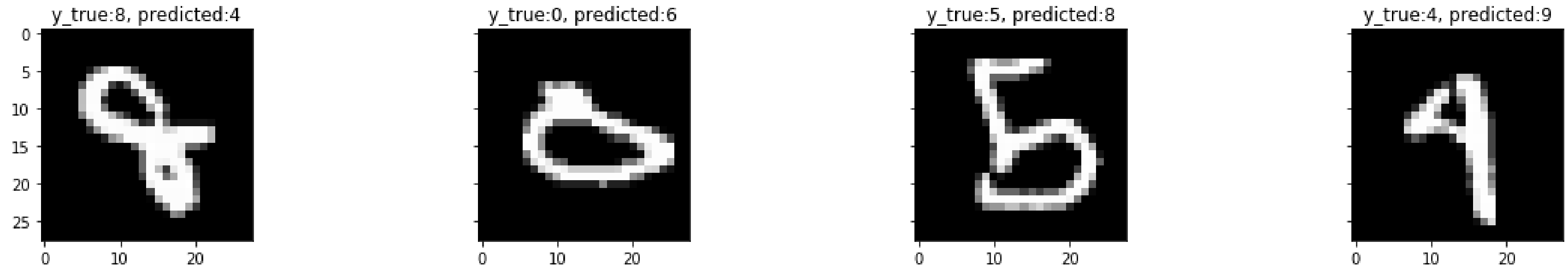
In [56]:
```
## First 20 bad examples
n = 20
i = 0
bad_cases_2 = []
for y_hat , y in zip(y_pred_2, y_test):
    if y_hat != y:
        bad_cases_2.append(i)
        if len(bad_cases_2) == n:
            break
    i += 1

print(bad_cases_2)
```

```
[8, 18, 247, 259, 264, 318, 321, 381, 435, 445, 495, 543, 582, 610, 613, 674, 691, 717, 720, 740]
```

In [58]:

```
show_mnist(x_test[bad_cases_2],
           y_pred_2[bad_cases_2],
           y_test[bad_cases_2],
           n_rows=5, n_cols=4,
           title= "bad_cases_2")
```





Those are really tough .. but we can achive > 99% accuracy with CNNs !

Done !