

digit-recognizer

July 16, 2024

```
[1]: import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
from tensorflow.keras import layers, models, Input, regularizers, Model, backend
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.utils import plot_model
from IPython.display import SVG
import IPython.display as display
```

```
[2]: train = pd.read_csv("train.csv")
test = pd.read_csv("test.csv")
```

```
[3]: print(f"Training Data: {train.shape}")
print(f"Testing Data: {test.shape}")
```

Training Data: (42000, 785)

Testing Data: (28000, 784)

```
[4]: x_train = train.iloc[:, 1:].values.reshape(-1, 28, 28, 1)/255.0
y_train = train.iloc[:, 0].values.reshape(-1, 1)
x_test = test.values.reshape(-1, 28, 28, 1)/255.0
print(f"Training Images: {x_train.shape}")
print(f"Label Images: {y_train.shape}")
```

Training Images: (42000, 28, 28, 1)

Label Images: (42000, 1)

```
[5]: print(f"Min: {x_train.min()}")
print(f"Min: {x_train.max()}")
```

Min: 0.0

Min: 1.0

```
[8]: print(f"Training Images Dims: {x_train.shape}, Training Labels Dims: {y_train.
↪shape}")
```

Training Images Dims: (42000, 28, 28, 1), Training Labels Dims: (42000, 1)

```
[9]: label_counts = y_train.flatten()
      vals, counts = np.unique(label_counts, return_counts=True)

      for value, count in zip(vals, counts):
          print(f"{value}: {round(count/len(label_counts)*100, 3)}%")
```

```
0: 9.838%
1: 11.152%
2: 9.945%
3: 10.36%
4: 9.695%
5: 9.036%
6: 9.85%
7: 10.479%
8: 9.674%
9: 9.971%
```

```
[10]: ## ----- Function to print model Summary
      ↪-----
      def print_model_summary(model):
          total_params = model.count_params()
          trainable_params = np.sum([backend.count_params(w) for w in model.
          ↪trainable_weights])
          non_trainable_params = np.sum([backend.count_params(w) for w in model.
          ↪non_trainable_weights])

          print(f'Total params: {total_params:,}')
          print(f'Trainable params: {trainable_params:,}')
          print(f'Non-trainable params: {non_trainable_params:,}')
```

```
[11]: ## ----- Function to Display Model Graphically
      ↪-----
      def display_model(model):
          plot_model(model, to_file='model.png', show_shapes=True,
          ↪show_layer_names=True, dpi=50)
          display.display(display.HTML('<div style="text-align: center;"></div>'))
```

```
[14]: import tensorflow as tf
      from tensorflow.keras import layers, models

      def basic_conv_model():
          model = models.Sequential()
          model.add(layers.Conv2D(32, (5, 5), activation='relu', input_shape=(28, 28,
          ↪1), padding='same'))
          model.add(layers.MaxPool2D((3, 3)))
          model.add(layers.BatchNormalization())
```

```

model.add(layers.Conv2D(64, (5, 5), activation='relu', padding='same'))
model.add(layers.MaxPool2D((2, 2)))
model.add(layers.BatchNormalization())
model.add(layers.Flatten())
model.add(layers.Dense(256, activation='relu'))
model.add(layers.BatchNormalization())
model.add(layers.Dropout(0.25))
model.add(layers.Dense(128, activation='relu'))
model.add(layers.BatchNormalization())
model.add(layers.Dropout(0.25))
model.add(layers.Dense(64, activation='relu'))
model.add(layers.BatchNormalization())
model.add(layers.Dense(10, activation='softmax'))

return model

basic_conv_model = basic_conv_model()
basic_conv_model.summary()

```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_2 (Conv2D)	(None, 28, 28, 32)	832
max_pooling2d_2 (MaxPooling2D)	(None, 9, 9, 32)	0
batch_normalization_5 (BatchNormalization)	(None, 9, 9, 32)	128
conv2d_3 (Conv2D)	(None, 9, 9, 64)	51,264
max_pooling2d_3 (MaxPooling2D)	(None, 4, 4, 64)	0
batch_normalization_6 (BatchNormalization)	(None, 4, 4, 64)	256
flatten_1 (Flatten)	(None, 1024)	0
dense_4 (Dense)	(None, 256)	262,400
batch_normalization_7 (BatchNormalization)	(None, 256)	1,024
dropout_2 (Dropout)	(None, 256)	0

dense_5 (Dense)	(None, 128)	32,896
batch_normalization_8 (BatchNormalization)	(None, 128)	512
dropout_3 (Dropout)	(None, 128)	0
dense_6 (Dense)	(None, 64)	8,256
batch_normalization_9 (BatchNormalization)	(None, 64)	256
dense_7 (Dense)	(None, 10)	650

Total params: 358,474 (1.37 MB)

Trainable params: 357,386 (1.36 MB)

Non-trainable params: 1,088 (4.25 KB)

```
[23]: ## ----- BIGGER CONVOLUTION NETWORK
↳ -----

def big_conv_model():
    model=models.Sequential()
    #
↳ -----
    model.add(layers.Conv2D(64, (5,5), padding='same', input_shape=(28,28,1)))
    model.add(layers.Conv2D(64, (5,5), padding='same'))
    model.add(layers.Activation('relu'))
    model.add(layers.MaxPool2D((3,3)))
    model.add(layers.BatchNormalization())
    #
↳ -----
    model.add(layers.Conv2D(128, (3,3), padding='same'))
    model.add(layers.Conv2D(128, (3,3), padding='same'))
    model.add(layers.Activation('relu'))
    model.add(layers.MaxPool2D((2,2)))
    model.add(layers.BatchNormalization())
    #
↳ -----
    model.add(layers.Flatten(input_shape=(28,28)))
```

```

#
↪
    model.add(layers.Dense(256, activation='relu',
↪kernel_regularizer=regularizers.l2(0.05)))
    model.add(layers.BatchNormalization())
    model.add(layers.Dropout(0.5))
#
↪
    # model.add(layers.Dense(128, activation='relu',
↪kernel_regularizer=regularizers.l2(0.5)))
    # model.add(layers.BatchNormalization())
    # model.add(layers.Dropout(0.3))
#
↪
    model.add(layers.Dense(128, activation='relu',
↪kernel_regularizer=regularizers.l2(0.05)))
    model.add(layers.BatchNormalization())
#
↪
    model.add(layers.Dense(10, activation='softmax'))

return model

```

```

[24]: big_conv_model = big_conv_model()
      print_model_summary(big_conv_model)

```

```

Total params: 886,602
Trainable params: 885,450
Non-trainable params: 1,152

```

```

[26]: ### ----- BASIC RESIDUAL NETWORK -----

def residual_model():
    inputs = Input(shape=(28, 28, 1))
    #
    ↪
    x = layers.Conv2D(32, (5, 5), padding='same')(inputs)
    x = layers.BatchNormalization()(x)
    x = layers.Activation('relu')(x)
    #
    ↪
    skip_connection_1 = layers.Conv2D(64, (3, 3), padding='same')(inputs)
    skip_connection_1 = layers.BatchNormalization()(skip_connection_1)
    ### ----- BASIC RESIDUAL NETWORK
    ↪

```

```

def residual_model():
    inputs = Input(shape=(28, 28, 1))
    #
    ↪
    x = layers.Conv2D(32, (5, 5), padding='same')(inputs)
    x = layers.BatchNormalization()(x)
    x = layers.Activation('relu')(x)
    #
    ↪
    skip_connection_1 = layers.Conv2D(64, (3, 3), padding='same')(inputs)
    skip_connection_1 = layers.BatchNormalization()(skip_connection_1)
    # skip_connection_1 = layers.Activation('relu')(skip_connection_1)
    #
    ↪
    x = layers.Conv2D(64, (3, 3), padding='same')(x)
    x = layers.BatchNormalization()(x)
    # x = layers.Activation('relu')(x)
    #
    ↪
    x = layers.add([x, skip_connection_1])
    x = layers.BatchNormalization()(x)
    x = layers.Activation('relu')(x)
    x = layers.MaxPooling2D((2, 2))(x)
    #
    ↪
    x = layers.Conv2D(128, (3, 3), padding='same')(x)
    x = layers.BatchNormalization()(x)
    x = layers.Activation('relu')(x)
    #
    ↪
    skip_connection_2 = layers.Conv2D(256, (3, 3), padding='same')(x)
    skip_connection_2 = layers.BatchNormalization()(skip_connection_2)
    #
    ↪
    x = layers.Conv2D(256, (3, 3), padding='same')(x)
    x = layers.BatchNormalization()(x)
    #
    ↪
    x = layers.add([x, skip_connection_2])
    x = layers.BatchNormalization()(x)
    x = layers.Activation('relu')(x)
    x = layers.MaxPooling2D((2, 2))(x)
    #
    ↪
    x = layers.Flatten()(x)

```

```

#
↪
x = layers.Dense(128, activation='relu')(x)
x = layers.BatchNormalization()(x)
x = layers.Dropout(0.5)(x)
#
↪
x = layers.Dense(64, activation='relu')(x)
x = layers.BatchNormalization()(x)
x = layers.Dropout(0.25)(x)
#
↪
outputs = layers.Dense(10, activation='softmax')(x)
#
↪
model = Model(inputs=inputs, outputs=outputs, name='conv_model')
return model

residual_model = residual_model()

print_model_summary(residual_model)

```

Total params: 2,304,074
Trainable params: 2,301,450
Non-trainable params: 2,624

```

[27]: ## ----- Function to Train Models -----
def train_model(model):
    model.compile(optimizer='adam', loss='sparse_categorical_crossentropy',
↪metrics=['accuracy'])
    history = model.fit(x_train, y_train, epochs=15, batch_size=30,
↪validation_split=0.2)
    return history

```

```

[28]: ## ----- Function to Summarise Model Performance -----
↪
def plot_model_training(history):
    plt.figure(figsize=(14, 5))

    # Training loss vs Validation loss
    plt.subplot(1, 2, 1)
    plt.plot(history.history['loss'], label='Train Loss')
    plt.plot(history.history['val_loss'], label='Validation Loss')
    plt.title('Loss')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend(loc='upper right')

```

```

plt.grid(True)
# Training vs Validation Accuracy
plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(loc='upper left')
plt.grid(True)

plt.tight_layout()
plt.show()

```

```

[29]: history = train_model(basic_conv_model)
      plot_model_training(history)

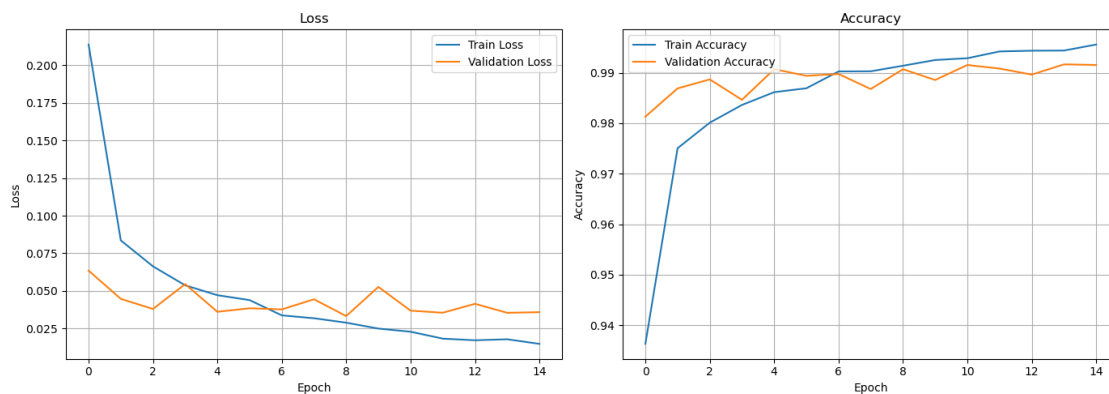
```

```

Epoch 1/15
1120/1120          20s 15ms/step -
accuracy: 0.8725 - loss: 0.4172 - val_accuracy: 0.9813 - val_loss: 0.0635
Epoch 2/15
1120/1120          18s 16ms/step -
accuracy: 0.9743 - loss: 0.0874 - val_accuracy: 0.9869 - val_loss: 0.0448
Epoch 3/15
1120/1120          18s 16ms/step -
accuracy: 0.9806 - loss: 0.0666 - val_accuracy: 0.9887 - val_loss: 0.0380
Epoch 4/15
1120/1120          18s 16ms/step -
accuracy: 0.9831 - loss: 0.0549 - val_accuracy: 0.9846 - val_loss: 0.0546
Epoch 5/15
1120/1120          19s 17ms/step -
accuracy: 0.9869 - loss: 0.0460 - val_accuracy: 0.9907 - val_loss: 0.0362
Epoch 6/15
1120/1120          18s 16ms/step -
accuracy: 0.9869 - loss: 0.0432 - val_accuracy: 0.9894 - val_loss: 0.0385
Epoch 7/15
1120/1120          18s 16ms/step -
accuracy: 0.9904 - loss: 0.0333 - val_accuracy: 0.9898 - val_loss: 0.0377
Epoch 8/15
1120/1120          18s 16ms/step -
accuracy: 0.9901 - loss: 0.0326 - val_accuracy: 0.9868 - val_loss: 0.0445
Epoch 9/15
1120/1120          18s 16ms/step -
accuracy: 0.9925 - loss: 0.0257 - val_accuracy: 0.9907 - val_loss: 0.0333
Epoch 10/15
1120/1120          20s 18ms/step -
accuracy: 0.9929 - loss: 0.0239 - val_accuracy: 0.9886 - val_loss: 0.0527

```


Epoch 11/15
 1120/1120 18s 16ms/step -
 accuracy: 0.9939 - loss: 0.0202 - val_accuracy: 0.9915 - val_loss: 0.0369
 Epoch 12/15
 1120/1120 18s 16ms/step -
 accuracy: 0.9950 - loss: 0.0169 - val_accuracy: 0.9908 - val_loss: 0.0355
 Epoch 13/15
 1120/1120 19s 17ms/step -
 accuracy: 0.9954 - loss: 0.0144 - val_accuracy: 0.9896 - val_loss: 0.0415
 Epoch 14/15
 1120/1120 22s 20ms/step -
 accuracy: 0.9950 - loss: 0.0173 - val_accuracy: 0.9917 - val_loss: 0.0355
 Epoch 15/15
 1120/1120 21s 19ms/step -
 accuracy: 0.9963 - loss: 0.0123 - val_accuracy: 0.9915 - val_loss: 0.0359



```
[30]: history = train_model(big_conv_model)
      plot_model_training(history)
```

Epoch 1/15
 1120/1120 167s 146ms/step
 - accuracy: 0.8814 - loss: 6.8008 - val_accuracy: 0.9386 - val_loss: 0.7786
 Epoch 2/15
 1120/1120 161s 144ms/step
 - accuracy: 0.9516 - loss: 0.6963 - val_accuracy: 0.9661 - val_loss: 0.5711
 Epoch 3/15
 1120/1120 152s 136ms/step
 - accuracy: 0.9587 - loss: 0.5795 - val_accuracy: 0.9527 - val_loss: 0.5744
 Epoch 4/15
 1120/1120 135s 121ms/step
 - accuracy: 0.9622 - loss: 0.5185 - val_accuracy: 0.9781 - val_loss: 0.4383
 Epoch 5/15
 1120/1120 126s 113ms/step
 - accuracy: 0.9669 - loss: 0.4449 - val_accuracy: 0.9549 - val_loss: 0.5094

Epoch 6/15
 1120/1120 134s 120ms/step
 - accuracy: 0.9685 - loss: 0.4289 - val_accuracy: 0.9858 - val_loss: 0.3366

Epoch 7/15
 1120/1120 541s 483ms/step
 - accuracy: 0.9683 - loss: 0.4074 - val_accuracy: 0.9805 - val_loss: 0.3441

Epoch 8/15
 1120/1120 173s 154ms/step
 - accuracy: 0.9720 - loss: 0.3694 - val_accuracy: 0.9818 - val_loss: 0.3527

Epoch 9/15
 1120/1120 157s 140ms/step
 - accuracy: 0.9750 - loss: 0.3482 - val_accuracy: 0.9864 - val_loss: 0.3017

Epoch 10/15
 1120/1120 156s 139ms/step
 - accuracy: 0.9752 - loss: 0.3499 - val_accuracy: 0.9549 - val_loss: 0.4210

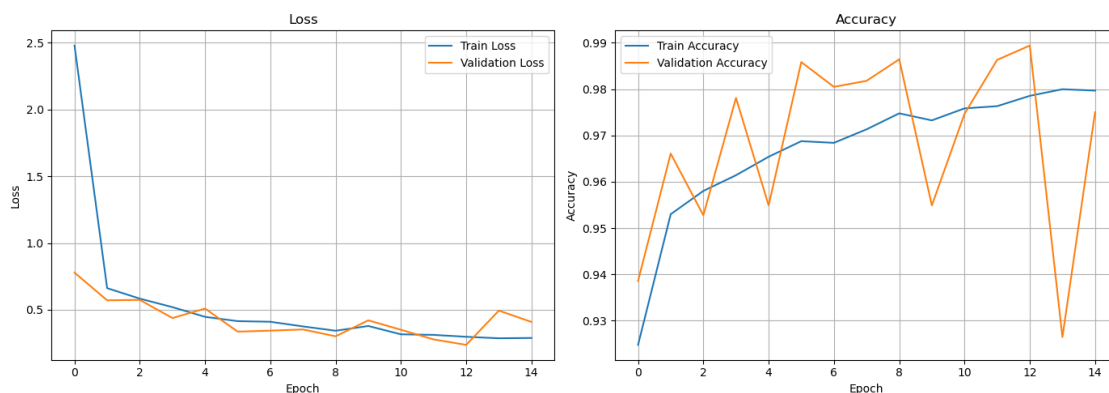
Epoch 11/15
 1120/1120 161s 143ms/step
 - accuracy: 0.9768 - loss: 0.3167 - val_accuracy: 0.9746 - val_loss: 0.3507

Epoch 12/15
 1120/1120 160s 142ms/step
 - accuracy: 0.9777 - loss: 0.3028 - val_accuracy: 0.9863 - val_loss: 0.2782

Epoch 13/15
 1120/1120 162s 145ms/step
 - accuracy: 0.9780 - loss: 0.2960 - val_accuracy: 0.9894 - val_loss: 0.2374

Epoch 14/15
 1120/1120 149s 133ms/step
 - accuracy: 0.9814 - loss: 0.2721 - val_accuracy: 0.9264 - val_loss: 0.4942

Epoch 15/15
 1120/1120 151s 135ms/step
 - accuracy: 0.9807 - loss: 0.2863 - val_accuracy: 0.9750 - val_loss: 0.4090



```
[31]: history = train_model(residual_model)
      plot_model_training(history)
```

Epoch 1/15
1120/1120 355s 311ms/step
- accuracy: 0.8545 - loss: 0.4843 - val_accuracy: 0.9606 - val_loss: 0.1209

Epoch 2/15
1120/1120 353s 315ms/step
- accuracy: 0.9663 - loss: 0.1127 - val_accuracy: 0.9782 - val_loss: 0.0707

Epoch 3/15
1120/1120 340s 304ms/step
- accuracy: 0.9763 - loss: 0.0807 - val_accuracy: 0.9917 - val_loss: 0.0295

Epoch 4/15
1120/1120 338s 301ms/step
- accuracy: 0.9792 - loss: 0.0706 - val_accuracy: 0.9913 - val_loss: 0.0314

Epoch 5/15
1120/1120 291s 260ms/step
- accuracy: 0.9805 - loss: 0.0640 - val_accuracy: 0.9910 - val_loss: 0.0291

Epoch 6/15
1120/1120 47958s 43s/step
- accuracy: 0.9857 - loss: 0.0488 - val_accuracy: 0.9911 - val_loss: 0.0351

Epoch 7/15
1120/1120 389s 347ms/step
- accuracy: 0.9842 - loss: 0.0539 - val_accuracy: 0.9913 - val_loss: 0.0300

Epoch 8/15
1120/1120 360s 321ms/step
- accuracy: 0.9850 - loss: 0.0480 - val_accuracy: 0.9912 - val_loss: 0.0331

Epoch 9/15
1120/1120 341s 305ms/step
- accuracy: 0.9896 - loss: 0.0358 - val_accuracy: 0.9930 - val_loss: 0.0293

Epoch 10/15
1120/1120 319s 285ms/step
- accuracy: 0.9893 - loss: 0.0342 - val_accuracy: 0.9883 - val_loss: 0.0451

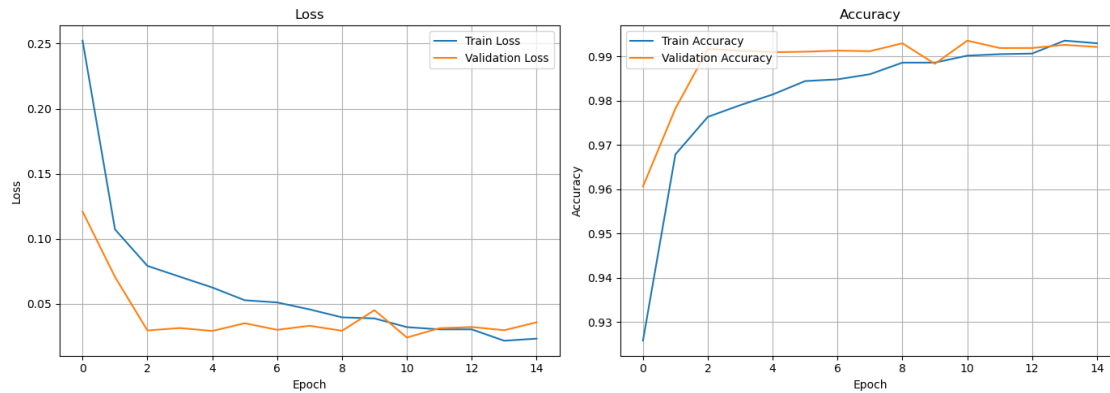
Epoch 11/15
1120/1120 315s 281ms/step
- accuracy: 0.9911 - loss: 0.0299 - val_accuracy: 0.9936 - val_loss: 0.0241

Epoch 12/15
1120/1120 307s 274ms/step
- accuracy: 0.9915 - loss: 0.0276 - val_accuracy: 0.9919 - val_loss: 0.0312

Epoch 13/15
1120/1120 307s 274ms/step
- accuracy: 0.9914 - loss: 0.0287 - val_accuracy: 0.9919 - val_loss: 0.0322

Epoch 14/15
1120/1120 306s 273ms/step
- accuracy: 0.9940 - loss: 0.0204 - val_accuracy: 0.9926 - val_loss: 0.0297

Epoch 15/15
1120/1120 307s 274ms/step
- accuracy: 0.9936 - loss: 0.0227 - val_accuracy: 0.9921 - val_loss: 0.0358



```
[32]: best_model = residual_model
      predictions = np.argmax(best_model.predict(x_test), axis=1)
```

875/875 60s 68ms/step

```
[33]: predictions.shape
```

[33]: (28000,)

```
[34]: ## ----- Function to Show Predictions
      ↪ -----
      def print_predictions(model, x_test, num_predictions=64):
          predictions = model.predict(x_test)

          fig, axes = plt.subplots(8, 8, figsize=(15, 15))

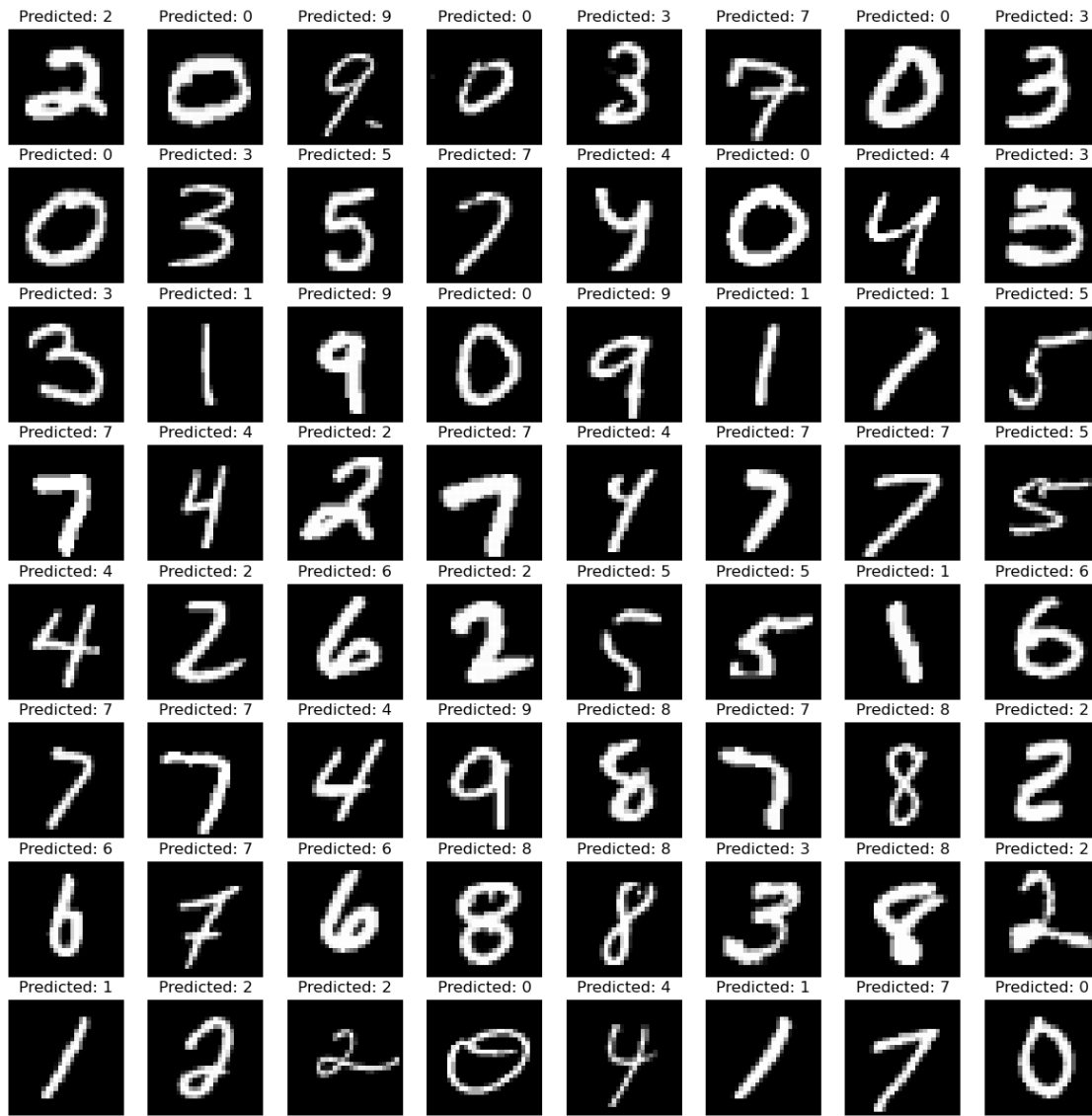
          for i, ax in enumerate(axes.flat):
              prediction = predictions[i]
              predicted_class = np.argmax(prediction)

              ax.imshow(x_test[i].reshape(28, 28), cmap='gray')
              ax.set_title(f"Predicted: {predicted_class}")
              ax.axis('off')

          plt.show()
```

```
[35]: print_predictions(best_model, x_test)
```

875/875 67s 77ms/step



```
[37]: sample = pd.read_csv("sample_submission.csv")
sample.head()
```

```
[37]:
```

	ImageId	Label
0	1	0
1	2	0
2	3	0
3	4	0
4	5	0

```
[39]: submission = pd.DataFrame({'ImageId': np.arange(1, 28001), 'Label':
    ↳ predictions})
```

```
submission.to_csv('submission.csv', index=False)
```

```
[ ]:
```