

# Handwritten Digit Classifier Using the MNIST Dataset

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CAP 6619 - Deep Learning | Project 1 | Summer 2022 - Dr. Marques | Matthew Acs



*This project will create and evaluate a handwritten digit classifier based on the MNIST dataset*

## References and Sources

The following links contain useful resources that provide information relating to this project. Some of the sources provide background information while others answer questions specifically relating to the implementation of the classifier.

- 
- <https://www.tensorflow.org/datasets/catalog/mnist>

Background information on the MNIST dataset

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- [https://en.wikipedia.org/wiki/MNIST\\_database](https://en.wikipedia.org/wiki/MNIST_database)

Background information on the MNIST dataset

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- [https://keras.io/examples/vision/mnist\\_convnet/](https://keras.io/examples/vision/mnist_convnet/)

An example CNN classifier for the MNIST dataset

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- [https://github.com/the-deep-learners/deep-learning-illustrated/blob/master/notebooks/shallow\\_net\\_in\\_keras.ipynb](https://github.com/the-deep-learners/deep-learning-illustrated/blob/master/notebooks/shallow_net_in_keras.ipynb)

An example shallow classifier for the MNIST dataset

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- <https://stackoverflow.com/questions/68836551/keras-attributeerror-sequential-object-has-no-attribute-predict-classes>

How to get an array of the predictions from a Keras classifier

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- <https://scikit-learn.org/stable/modules/generated/sklearn.metrics.ConfusionMatrixDisplay.html#sklearn.metrics.C>

Scikit-learn documentation to create a confusion matrix

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- [https://scikit-learn.org/stable/auto\\_examples/classification/plot\\_digits\\_classification.html](https://scikit-learn.org/stable/auto_examples/classification/plot_digits_classification.html)

Scikit-learn documentation example of a confusion matrix for a digit classifier

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## Setup

```
In [1]: from tensorflow import keras
        from keras.datasets import mnist
        from keras.models import Sequential
        from keras.layers import Dense
        from tensorflow.keras.optimizers import SGD
        from sklearn import metrics
        from tensorflow.keras import layers
        from matplotlib import pyplot as plt
        import numpy as np
```

## Load and prepare the data

```
In [2]: # Model / data parameters
        num_classes = 10
        input_shape = (28, 28, 1)

        # the data, split between train and validation sets
        (X_train, y_train), (X_valid, y_valid) = mnist.load_data()
```

Downloading data from <https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz>

11493376/11490434 [=====] - 0s 0us/step

11501568/11490434 [=====] - 0s 0us/step

```
In [3]: X_train.shape
```

Out[3]: (60000, 28, 28)

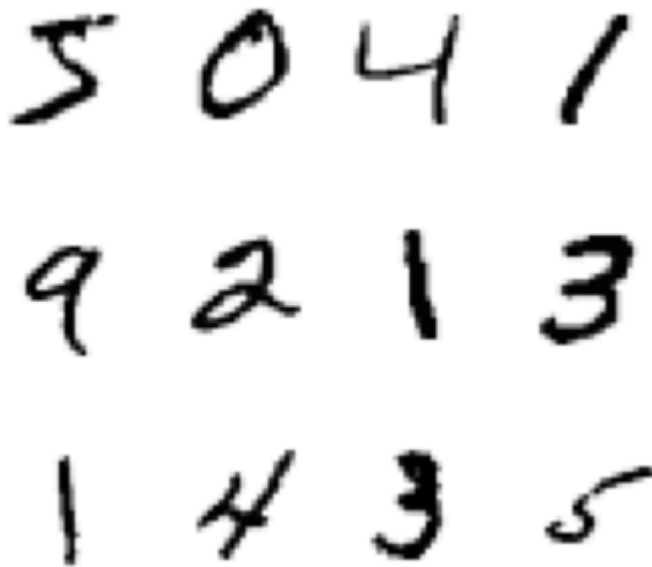
```
In [4]: y_train.shape
```

Out[4]: (60000,)

```
In [5]: y_train[0:12]
```

Out[5]: array([5, 0, 4, 1, 9, 2, 1, 3, 1, 4, 3, 5], dtype=uint8)

```
In [6]: plt.figure(figsize=(5,5))
for k in range(12):
    plt.subplot(3, 4, k+1)
    plt.imshow(X_train[k], cmap='Greys')
    plt.axis('off')
plt.tight_layout()
plt.show()
```



```
In [7]: X_valid.shape
```

Out[7]: (10000, 28, 28)

```
In [8]: y_valid.shape
```

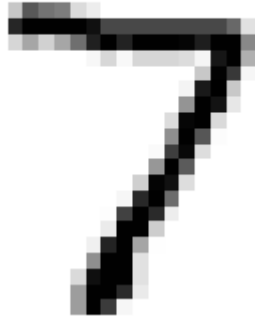
Out[8]: (10000,)

```
In [9]: y_valid[0]
```

Out[9]: 7

```
In [10]: plt.imshow(X_valid[0], cmap='Greys')
```

```
plt.axis('off')
plt.show()
```



```
In [11]: # Reshape (flatten) images
X_train_resaped = X_train.reshape(60000, 784).astype('float32')
X_valid_resaped = X_valid.reshape(10000, 784).astype('float32')

# Scale images to the [0, 1] range
X_train_scaled_resaped = X_train_resaped / 255
X_valid_scaled_resaped = X_valid_resaped / 255

# Renaming for conciseness
X_training = X_train_scaled_resaped
X_validation = X_valid_scaled_resaped

print("X_training shape (after reshaping + scaling):", X_training.shape)
print(X_training.shape[0], "train samples")
print("X_validation shape (after reshaping + scaling):", X_validation.shape)
print(X_validation.shape[0], "validation samples")
```

```
X_training shape (after reshaping + scaling): (60000, 784)
60000 train samples
X_validation shape (after reshaping + scaling): (10000, 784)
10000 validation samples
```

```
In [12]: # convert class vectors to binary class matrices
y_training = keras.utils.to_categorical(y_train, num_classes)
y_validation = keras.utils.to_categorical(y_valid, num_classes)
```

```
In [13]: print(y_valid[0])
print(y_validation[0])
```

```
7
[0. 0. 0. 0. 0. 0. 0. 1. 0. 0.]
```

## Question 1

Explain the meaning and contents of X\_training, y\_training, X\_validation, and y\_validation

---

X\_training is a tensor that contains the data for training the model while y\_training is a tensor that contains the labels for the training data. X\_validation is a tensor that contains the data for validating the model while y\_validation is a tensor that contains the labels for the validation data. All four tensors are rank-2 tensors because they are arrays of arrays. The labels are represented in an array such that there are ten elements in each array and a 1 is present at the index that corresponds to the label. For example, the label 2 is represented by [0, 0, 1, 0, 0, 0, 0, 0, 0, 0]. The data is represented in an array that was created by flattening a 28 by 28 pixel grid into an array of 784 elements. Each element in the array represents a greyscale pixel with a value in the range of 0 to 1 with 1 being black and 0 being white.

As an example, X\_training [0] would give you an array of 784 numbers in the range 0-1 that represents the first digit in the dataset. y\_training [0] would give you an array of 10 numbers with a 1 in the index that represents the label of the first digit in the dataset. X\_training [1] and y\_training [1] would give you the data and label for the second digit in the dataset and so on.

## PART 1 - Shallow neural network architecture

```
In [14]: model = Sequential()
model.add(Dense(64, activation='sigmoid', input_shape=(784,)))
model.add(Dense(10, activation='softmax'))
```

```
In [15]: model.summary()
```

Model: "sequential"

| Layer (type)             | Output Shape | Param # |
|--------------------------|--------------|---------|
| dense (Dense)            | (None, 64)   | 50240   |
| dense_1 (Dense)          | (None, 10)   | 650     |
| Total params: 50,890     |              |         |
| Trainable params: 50,890 |              |         |
| Non-trainable params: 0  |              |         |

### Question 2

Explain the meaning of the results you get when you run model.summary()

When you run model.summary(), the output shows the structure of the neural network's architecture. It displays the Keras model type along with the layers and the information associated with each layer. The summary shows us that the model type is sequential and that there are two layers in the model. The first layer has an output shape of 64 and contains 50,240 parameters. This output shape refers to the fact that the output of the first layer will be a rank-2 tensor with the innermost array having 64 elements in it. The 50,240 parameters are the weights and biases that the model updates in order to train the model. There are 64 outputs and 784 inputs and there is one

weight for each connection from the input to the layer, so there are  $784 \times 64 = 50,176$  weights. Each output also has a bias so there are  $50,176 + 64 = 50,240$  total trainable parameters. The second layer has an output shape of 10 and contains 650 parameters. This means that the output of the layer will be a rank-2 tensor with the innermost array containing 10 elements. This is the output layer of the model, so the 10 elements refer to the probability that the input is in one of the 10 classes. It contains 650 parameters because 64 inputs are each connected to 10 outputs with a weight for each connection, thus totaling  $64 \times 10 = 640$  weights. Adding the 10 biases for each output makes  $640 + 10 = 650$  trainable parameters for the second layer. Thus, adding all of the parameters you get 50,890. The bottom section then shows us that there are a total of 50,890 total parameters and trainable parameters.

```
In [16]: (64*784)
```

```
Out[16]: 50176
```

```
In [17]: (64*784)+64
```

```
Out[17]: 50240
```

```
In [18]: (10*64)+10
```

```
Out[18]: 650
```

## Configure model

The following two configurations will configure the model using different loss functions and optimizers. The second configuration with a loss function of mean\_squared\_error had about a 90% accuracy while the first configuration with a loss function of poisson had an accuracy of about 82%. After experimentation, it can be seen that the choice of loss function and optimizer has a significant impact on the performance of the model. The configuration is currently set to the original with a loss function of mean\_squared\_error.

```
In [19]: x = 0

if x == 1:
    model.compile(
        loss='poisson',
        optimizer='adadelta',
        metrics=['accuracy']
    )
else:
    model.compile(
        loss='mean_squared_error',
        optimizer=SGD(learning_rate=0.01),
        metrics=['accuracy']
    )
```

# Train!

In [20]:

```
batch_size=128
epochs=500

history = model.fit(
    X_training, # training data
    y_training, # training targets
    epochs=epochs,
    batch_size=batch_size,
    verbose=1,
    validation_data=(X_validation, y_validation)
)
```

Epoch 1/500

469/469 [=====] - 4s 4ms/step - loss: 0.0936 - accuracy: 0.0971  
- val\_loss: 0.0927 - val\_accuracy: 0.0924

Epoch 2/500

469/469 [=====] - 2s 3ms/step - loss: 0.0921 - accuracy: 0.0870  
- val\_loss: 0.0916 - val\_accuracy: 0.0809

Epoch 3/500

469/469 [=====] - 2s 3ms/step - loss: 0.0912 - accuracy: 0.0864  
- val\_loss: 0.0909 - val\_accuracy: 0.0854

Epoch 4/500

469/469 [=====] - 1s 3ms/step - loss: 0.0906 - accuracy: 0.0939  
- val\_loss: 0.0903 - val\_accuracy: 0.0920

Epoch 5/500

469/469 [=====] - 1s 3ms/step - loss: 0.0901 - accuracy: 0.1046  
- val\_loss: 0.0899 - val\_accuracy: 0.1051

Epoch 6/500

469/469 [=====] - 1s 3ms/step - loss: 0.0897 - accuracy: 0.1178  
- val\_loss: 0.0895 - val\_accuracy: 0.1195

Epoch 7/500

469/469 [=====] - 1s 3ms/step - loss: 0.0893 - accuracy: 0.1402  
- val\_loss: 0.0891 - val\_accuracy: 0.1527

Epoch 8/500

469/469 [=====] - 1s 3ms/step - loss: 0.0890 - accuracy: 0.1825  
- val\_loss: 0.0888 - val\_accuracy: 0.2047

Epoch 9/500

469/469 [=====] - 1s 3ms/step - loss: 0.0887 - accuracy: 0.2304  
- val\_loss: 0.0885 - val\_accuracy: 0.2533

Epoch 10/500

469/469 [=====] - 2s 4ms/step - loss: 0.0884 - accuracy: 0.2587  
- val\_loss: 0.0882 - val\_accuracy: 0.2765

Epoch 11/500

469/469 [=====] - 1s 3ms/step - loss: 0.0881 - accuracy: 0.2734  
- val\_loss: 0.0880 - val\_accuracy: 0.2867

Epoch 12/500

469/469 [=====] - 1s 3ms/step - loss: 0.0879 - accuracy: 0.2830  
- val\_loss: 0.0877 - val\_accuracy: 0.2926

Epoch 13/500

469/469 [=====] - 1s 3ms/step - loss: 0.0876 - accuracy: 0.2912  
- val\_loss: 0.0874 - val\_accuracy: 0.3009

Epoch 14/500

469/469 [=====] - 1s 3ms/step - loss: 0.0873 - accuracy: 0.3012  
- val\_loss: 0.0871 - val\_accuracy: 0.3163

Epoch 15/500

469/469 [=====] - 1s 3ms/step - loss: 0.0870 - accuracy: 0.3158  
- val\_loss: 0.0868 - val\_accuracy: 0.3313

Epoch 16/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0867 - accuracy: 0.3324  
- val\_loss: 0.0865 - val\_accuracy: 0.3510  
Epoch 17/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0865 - accuracy: 0.3491  
- val\_loss: 0.0862 - val\_accuracy: 0.3671  
Epoch 18/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0862 - accuracy: 0.3647  
- val\_loss: 0.0859 - val\_accuracy: 0.3786  
Epoch 19/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0859 - accuracy: 0.3791  
- val\_loss: 0.0856 - val\_accuracy: 0.3893  
Epoch 20/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0856 - accuracy: 0.3903  
- val\_loss: 0.0853 - val\_accuracy: 0.3996  
Epoch 21/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0852 - accuracy: 0.4028  
- val\_loss: 0.0850 - val\_accuracy: 0.4079  
Epoch 22/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0849 - accuracy: 0.4098  
- val\_loss: 0.0847 - val\_accuracy: 0.4156  
Epoch 23/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0846 - accuracy: 0.4168  
- val\_loss: 0.0843 - val\_accuracy: 0.4245  
Epoch 24/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0843 - accuracy: 0.4227  
- val\_loss: 0.0840 - val\_accuracy: 0.4330  
Epoch 25/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0839 - accuracy: 0.4302  
- val\_loss: 0.0836 - val\_accuracy: 0.4396  
Epoch 26/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0836 - accuracy: 0.4347  
- val\_loss: 0.0833 - val\_accuracy: 0.4468  
Epoch 27/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0832 - accuracy: 0.4412  
- val\_loss: 0.0829 - val\_accuracy: 0.4542  
Epoch 28/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0828 - accuracy: 0.4480  
- val\_loss: 0.0825 - val\_accuracy: 0.4592  
Epoch 29/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0824 - accuracy: 0.4525  
- val\_loss: 0.0821 - val\_accuracy: 0.4634  
Epoch 30/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0821 - accuracy: 0.4567  
- val\_loss: 0.0817 - val\_accuracy: 0.4681  
Epoch 31/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0817 - accuracy: 0.4629  
- val\_loss: 0.0813 - val\_accuracy: 0.4742  
Epoch 32/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0813 - accuracy: 0.4692  
- val\_loss: 0.0809 - val\_accuracy: 0.4794  
Epoch 33/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0808 - accuracy: 0.4747  
- val\_loss: 0.0805 - val\_accuracy: 0.4847  
Epoch 34/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0804 - accuracy: 0.4790  
- val\_loss: 0.0800 - val\_accuracy: 0.4903  
Epoch 35/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0800 - accuracy: 0.4855  
- val\_loss: 0.0796 - val\_accuracy: 0.4961



Epoch 36/500  
469/469 [=====] - 2s 5ms/step - loss: 0.0796 - accuracy: 0.4903  
- val\_loss: 0.0791 - val\_accuracy: 0.5009  
Epoch 37/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0791 - accuracy: 0.4958  
- val\_loss: 0.0787 - val\_accuracy: 0.5065  
Epoch 38/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0787 - accuracy: 0.5018  
- val\_loss: 0.0782 - val\_accuracy: 0.5127  
Epoch 39/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0782 - accuracy: 0.5083  
- val\_loss: 0.0778 - val\_accuracy: 0.5166  
Epoch 40/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0778 - accuracy: 0.5128  
- val\_loss: 0.0773 - val\_accuracy: 0.5228  
Epoch 41/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0773 - accuracy: 0.5188  
- val\_loss: 0.0768 - val\_accuracy: 0.5280  
Epoch 42/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0768 - accuracy: 0.5239  
- val\_loss: 0.0763 - val\_accuracy: 0.5325  
Epoch 43/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0763 - accuracy: 0.5284  
- val\_loss: 0.0759 - val\_accuracy: 0.5381  
Epoch 44/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0759 - accuracy: 0.5342  
- val\_loss: 0.0754 - val\_accuracy: 0.5425  
Epoch 45/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0754 - accuracy: 0.5383  
- val\_loss: 0.0749 - val\_accuracy: 0.5474  
Epoch 46/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0749 - accuracy: 0.5436  
- val\_loss: 0.0744 - val\_accuracy: 0.5529  
Epoch 47/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0744 - accuracy: 0.5487  
- val\_loss: 0.0739 - val\_accuracy: 0.5570  
Epoch 48/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0739 - accuracy: 0.5534  
- val\_loss: 0.0734 - val\_accuracy: 0.5608  
Epoch 49/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0734 - accuracy: 0.5582  
- val\_loss: 0.0729 - val\_accuracy: 0.5650  
Epoch 50/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0729 - accuracy: 0.5621  
- val\_loss: 0.0724 - val\_accuracy: 0.5692  
Epoch 51/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0724 - accuracy: 0.5667  
- val\_loss: 0.0719 - val\_accuracy: 0.5722  
Epoch 52/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0719 - accuracy: 0.5704  
- val\_loss: 0.0714 - val\_accuracy: 0.5766  
Epoch 53/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0714 - accuracy: 0.5743  
- val\_loss: 0.0708 - val\_accuracy: 0.5800  
Epoch 54/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0709 - accuracy: 0.5783  
- val\_loss: 0.0703 - val\_accuracy: 0.5834  
Epoch 55/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0704 - accuracy: 0.5826  
- val\_loss: 0.0698 - val\_accuracy: 0.5867

Epoch 56/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0699 - accuracy: 0.5859  
- val\_loss: 0.0693 - val\_accuracy: 0.5896  
Epoch 57/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0694 - accuracy: 0.5891  
- val\_loss: 0.0688 - val\_accuracy: 0.5922  
Epoch 58/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0689 - accuracy: 0.5921  
- val\_loss: 0.0683 - val\_accuracy: 0.5959  
Epoch 59/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0684 - accuracy: 0.5948  
- val\_loss: 0.0678 - val\_accuracy: 0.5998  
Epoch 60/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0679 - accuracy: 0.5982  
- val\_loss: 0.0672 - val\_accuracy: 0.6026  
Epoch 61/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0674 - accuracy: 0.6008  
- val\_loss: 0.0667 - val\_accuracy: 0.6048  
Epoch 62/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0668 - accuracy: 0.6032  
- val\_loss: 0.0662 - val\_accuracy: 0.6061  
Epoch 63/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0663 - accuracy: 0.6059  
- val\_loss: 0.0657 - val\_accuracy: 0.6084  
Epoch 64/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0658 - accuracy: 0.6082  
- val\_loss: 0.0652 - val\_accuracy: 0.6117  
Epoch 65/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0653 - accuracy: 0.6113  
- val\_loss: 0.0647 - val\_accuracy: 0.6144  
Epoch 66/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0648 - accuracy: 0.6136  
- val\_loss: 0.0642 - val\_accuracy: 0.6159  
Epoch 67/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0643 - accuracy: 0.6160  
- val\_loss: 0.0637 - val\_accuracy: 0.6186  
Epoch 68/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0638 - accuracy: 0.6183  
- val\_loss: 0.0632 - val\_accuracy: 0.6209  
Epoch 69/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0633 - accuracy: 0.6210  
- val\_loss: 0.0627 - val\_accuracy: 0.6225  
Epoch 70/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0629 - accuracy: 0.6228  
- val\_loss: 0.0622 - val\_accuracy: 0.6244  
Epoch 71/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0624 - accuracy: 0.6251  
- val\_loss: 0.0617 - val\_accuracy: 0.6277  
Epoch 72/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0619 - accuracy: 0.6277  
- val\_loss: 0.0612 - val\_accuracy: 0.6302  
Epoch 73/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0614 - accuracy: 0.6298  
- val\_loss: 0.0607 - val\_accuracy: 0.6319  
Epoch 74/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0609 - accuracy: 0.6324  
- val\_loss: 0.0603 - val\_accuracy: 0.6345  
Epoch 75/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0605 - accuracy: 0.6346  
- val\_loss: 0.0598 - val\_accuracy: 0.6362

Epoch 76/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0600 - accuracy: 0.6369  
- val\_loss: 0.0593 - val\_accuracy: 0.6388  
Epoch 77/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0595 - accuracy: 0.6395  
- val\_loss: 0.0588 - val\_accuracy: 0.6410  
Epoch 78/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0591 - accuracy: 0.6416  
- val\_loss: 0.0584 - val\_accuracy: 0.6436  
Epoch 79/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0586 - accuracy: 0.6440  
- val\_loss: 0.0579 - val\_accuracy: 0.6452  
Epoch 80/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0582 - accuracy: 0.6464  
- val\_loss: 0.0575 - val\_accuracy: 0.6475  
Epoch 81/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0577 - accuracy: 0.6484  
- val\_loss: 0.0570 - val\_accuracy: 0.6498  
Epoch 82/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0573 - accuracy: 0.6506  
- val\_loss: 0.0566 - val\_accuracy: 0.6522  
Epoch 83/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0568 - accuracy: 0.6528  
- val\_loss: 0.0561 - val\_accuracy: 0.6557  
Epoch 84/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0564 - accuracy: 0.6550  
- val\_loss: 0.0557 - val\_accuracy: 0.6578  
Epoch 85/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0560 - accuracy: 0.6576  
- val\_loss: 0.0553 - val\_accuracy: 0.6597  
Epoch 86/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0555 - accuracy: 0.6594  
- val\_loss: 0.0548 - val\_accuracy: 0.6610  
Epoch 87/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0551 - accuracy: 0.6622  
- val\_loss: 0.0544 - val\_accuracy: 0.6640  
Epoch 88/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0547 - accuracy: 0.6647  
- val\_loss: 0.0540 - val\_accuracy: 0.6661  
Epoch 89/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0543 - accuracy: 0.6674  
- val\_loss: 0.0536 - val\_accuracy: 0.6686  
Epoch 90/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0539 - accuracy: 0.6699  
- val\_loss: 0.0532 - val\_accuracy: 0.6718  
Epoch 91/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0535 - accuracy: 0.6728  
- val\_loss: 0.0528 - val\_accuracy: 0.6749  
Epoch 92/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0531 - accuracy: 0.6750  
- val\_loss: 0.0524 - val\_accuracy: 0.6780  
Epoch 93/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0527 - accuracy: 0.6775  
- val\_loss: 0.0520 - val\_accuracy: 0.6810  
Epoch 94/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0523 - accuracy: 0.6806  
- val\_loss: 0.0516 - val\_accuracy: 0.6844  
Epoch 95/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0519 - accuracy: 0.6830  
- val\_loss: 0.0512 - val\_accuracy: 0.6870

Epoch 96/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0516 - accuracy: 0.6857  
- val\_loss: 0.0508 - val\_accuracy: 0.6897  
Epoch 97/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0512 - accuracy: 0.6882  
- val\_loss: 0.0505 - val\_accuracy: 0.6928  
Epoch 98/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0508 - accuracy: 0.6903  
- val\_loss: 0.0501 - val\_accuracy: 0.6953  
Epoch 99/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0505 - accuracy: 0.6929  
- val\_loss: 0.0497 - val\_accuracy: 0.6982  
Epoch 100/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0501 - accuracy: 0.6957  
- val\_loss: 0.0494 - val\_accuracy: 0.7017  
Epoch 101/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0497 - accuracy: 0.6982  
- val\_loss: 0.0490 - val\_accuracy: 0.7049  
Epoch 102/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0494 - accuracy: 0.7009  
- val\_loss: 0.0487 - val\_accuracy: 0.7090  
Epoch 103/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0490 - accuracy: 0.7039  
- val\_loss: 0.0483 - val\_accuracy: 0.7124  
Epoch 104/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0487 - accuracy: 0.7064  
- val\_loss: 0.0480 - val\_accuracy: 0.7159  
Epoch 105/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0484 - accuracy: 0.7094  
- val\_loss: 0.0476 - val\_accuracy: 0.7191  
Epoch 106/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0480 - accuracy: 0.7124  
- val\_loss: 0.0473 - val\_accuracy: 0.7217  
Epoch 107/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0477 - accuracy: 0.7148  
- val\_loss: 0.0470 - val\_accuracy: 0.7245  
Epoch 108/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0474 - accuracy: 0.7171  
- val\_loss: 0.0466 - val\_accuracy: 0.7269  
Epoch 109/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0470 - accuracy: 0.7196  
- val\_loss: 0.0463 - val\_accuracy: 0.7299  
Epoch 110/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0467 - accuracy: 0.7222  
- val\_loss: 0.0460 - val\_accuracy: 0.7327  
Epoch 111/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0464 - accuracy: 0.7247  
- val\_loss: 0.0457 - val\_accuracy: 0.7349  
Epoch 112/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0461 - accuracy: 0.7272  
- val\_loss: 0.0454 - val\_accuracy: 0.7372  
Epoch 113/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0458 - accuracy: 0.7298  
- val\_loss: 0.0450 - val\_accuracy: 0.7405  
Epoch 114/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0455 - accuracy: 0.7326  
- val\_loss: 0.0447 - val\_accuracy: 0.7427  
Epoch 115/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0452 - accuracy: 0.7355  
- val\_loss: 0.0444 - val\_accuracy: 0.7448

Epoch 116/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0449 - accuracy: 0.7380  
- val\_loss: 0.0441 - val\_accuracy: 0.7481  
Epoch 117/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0446 - accuracy: 0.7407  
- val\_loss: 0.0438 - val\_accuracy: 0.7519  
Epoch 118/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0443 - accuracy: 0.7433  
- val\_loss: 0.0435 - val\_accuracy: 0.7545  
Epoch 119/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0440 - accuracy: 0.7469  
- val\_loss: 0.0433 - val\_accuracy: 0.7580  
Epoch 120/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0437 - accuracy: 0.7496  
- val\_loss: 0.0430 - val\_accuracy: 0.7609  
Epoch 121/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0434 - accuracy: 0.7528  
- val\_loss: 0.0427 - val\_accuracy: 0.7636  
Epoch 122/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0432 - accuracy: 0.7554  
- val\_loss: 0.0424 - val\_accuracy: 0.7660  
Epoch 123/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0429 - accuracy: 0.7580  
- val\_loss: 0.0421 - val\_accuracy: 0.7688  
Epoch 124/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0426 - accuracy: 0.7609  
- val\_loss: 0.0418 - val\_accuracy: 0.7713  
Epoch 125/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0423 - accuracy: 0.7640  
- val\_loss: 0.0416 - val\_accuracy: 0.7744  
Epoch 126/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0421 - accuracy: 0.7668  
- val\_loss: 0.0413 - val\_accuracy: 0.7775  
Epoch 127/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0418 - accuracy: 0.7701  
- val\_loss: 0.0410 - val\_accuracy: 0.7802  
Epoch 128/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0416 - accuracy: 0.7724  
- val\_loss: 0.0408 - val\_accuracy: 0.7827  
Epoch 129/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0413 - accuracy: 0.7753  
- val\_loss: 0.0405 - val\_accuracy: 0.7857  
Epoch 130/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0410 - accuracy: 0.7785  
- val\_loss: 0.0403 - val\_accuracy: 0.7886  
Epoch 131/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0408 - accuracy: 0.7810  
- val\_loss: 0.0400 - val\_accuracy: 0.7920  
Epoch 132/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0405 - accuracy: 0.7833  
- val\_loss: 0.0398 - val\_accuracy: 0.7949  
Epoch 133/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0403 - accuracy: 0.7855  
- val\_loss: 0.0395 - val\_accuracy: 0.7981  
Epoch 134/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0401 - accuracy: 0.7894  
- val\_loss: 0.0393 - val\_accuracy: 0.8008  
Epoch 135/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0398 - accuracy: 0.7917  
- val\_loss: 0.0390 - val\_accuracy: 0.8034

Epoch 136/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0396 - accuracy: 0.7941  
- val\_loss: 0.0388 - val\_accuracy: 0.8059  
Epoch 137/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0393 - accuracy: 0.7961  
- val\_loss: 0.0386 - val\_accuracy: 0.8090  
Epoch 138/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0391 - accuracy: 0.7985  
- val\_loss: 0.0383 - val\_accuracy: 0.8108  
Epoch 139/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0389 - accuracy: 0.8013  
- val\_loss: 0.0381 - val\_accuracy: 0.8133  
Epoch 140/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0387 - accuracy: 0.8032  
- val\_loss: 0.0379 - val\_accuracy: 0.8157  
Epoch 141/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0384 - accuracy: 0.8052  
- val\_loss: 0.0376 - val\_accuracy: 0.8166  
Epoch 142/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0382 - accuracy: 0.8078  
- val\_loss: 0.0374 - val\_accuracy: 0.8192  
Epoch 143/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0380 - accuracy: 0.8094  
- val\_loss: 0.0372 - val\_accuracy: 0.8213  
Epoch 144/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0378 - accuracy: 0.8115  
- val\_loss: 0.0370 - val\_accuracy: 0.8229  
Epoch 145/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0376 - accuracy: 0.8136  
- val\_loss: 0.0368 - val\_accuracy: 0.8244  
Epoch 146/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0374 - accuracy: 0.8154  
- val\_loss: 0.0365 - val\_accuracy: 0.8254  
Epoch 147/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0371 - accuracy: 0.8167  
- val\_loss: 0.0363 - val\_accuracy: 0.8271  
Epoch 148/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0369 - accuracy: 0.8183  
- val\_loss: 0.0361 - val\_accuracy: 0.8286  
Epoch 149/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0367 - accuracy: 0.8200  
- val\_loss: 0.0359 - val\_accuracy: 0.8297  
Epoch 150/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0365 - accuracy: 0.8210  
- val\_loss: 0.0357 - val\_accuracy: 0.8317  
Epoch 151/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0363 - accuracy: 0.8231  
- val\_loss: 0.0355 - val\_accuracy: 0.8330  
Epoch 152/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0361 - accuracy: 0.8242  
- val\_loss: 0.0353 - val\_accuracy: 0.8344  
Epoch 153/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0359 - accuracy: 0.8252  
- val\_loss: 0.0351 - val\_accuracy: 0.8351  
Epoch 154/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0357 - accuracy: 0.8263  
- val\_loss: 0.0349 - val\_accuracy: 0.8356  
Epoch 155/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0356 - accuracy: 0.8278  
- val\_loss: 0.0347 - val\_accuracy: 0.8362

Epoch 156/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0354 - accuracy: 0.8288  
- val\_loss: 0.0345 - val\_accuracy: 0.8372  
Epoch 157/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0352 - accuracy: 0.8300  
- val\_loss: 0.0343 - val\_accuracy: 0.8379  
Epoch 158/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0350 - accuracy: 0.8308  
- val\_loss: 0.0342 - val\_accuracy: 0.8390  
Epoch 159/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0348 - accuracy: 0.8316  
- val\_loss: 0.0340 - val\_accuracy: 0.8404  
Epoch 160/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0346 - accuracy: 0.8327  
- val\_loss: 0.0338 - val\_accuracy: 0.8408  
Epoch 161/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0345 - accuracy: 0.8340  
- val\_loss: 0.0336 - val\_accuracy: 0.8419  
Epoch 162/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0343 - accuracy: 0.8353  
- val\_loss: 0.0334 - val\_accuracy: 0.8425  
Epoch 163/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0341 - accuracy: 0.8363  
- val\_loss: 0.0333 - val\_accuracy: 0.8438  
Epoch 164/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0339 - accuracy: 0.8372  
- val\_loss: 0.0331 - val\_accuracy: 0.8443  
Epoch 165/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0338 - accuracy: 0.8380  
- val\_loss: 0.0329 - val\_accuracy: 0.8448  
Epoch 166/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0336 - accuracy: 0.8390  
- val\_loss: 0.0327 - val\_accuracy: 0.8461  
Epoch 167/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0334 - accuracy: 0.8399  
- val\_loss: 0.0326 - val\_accuracy: 0.8466  
Epoch 168/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0333 - accuracy: 0.8406  
- val\_loss: 0.0324 - val\_accuracy: 0.8475  
Epoch 169/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0331 - accuracy: 0.8414  
- val\_loss: 0.0322 - val\_accuracy: 0.8477  
Epoch 170/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0329 - accuracy: 0.8422  
- val\_loss: 0.0321 - val\_accuracy: 0.8485  
Epoch 171/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0328 - accuracy: 0.8430  
- val\_loss: 0.0319 - val\_accuracy: 0.8492  
Epoch 172/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0326 - accuracy: 0.8434  
- val\_loss: 0.0318 - val\_accuracy: 0.8505  
Epoch 173/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0325 - accuracy: 0.8441  
- val\_loss: 0.0316 - val\_accuracy: 0.8510  
Epoch 174/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0323 - accuracy: 0.8446  
- val\_loss: 0.0315 - val\_accuracy: 0.8521  
Epoch 175/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0322 - accuracy: 0.8456  
- val\_loss: 0.0313 - val\_accuracy: 0.8529

Epoch 176/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0320 - accuracy: 0.8463  
- val\_loss: 0.0312 - val\_accuracy: 0.8536  
Epoch 177/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0319 - accuracy: 0.8468  
- val\_loss: 0.0310 - val\_accuracy: 0.8541  
Epoch 178/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0317 - accuracy: 0.8475  
- val\_loss: 0.0309 - val\_accuracy: 0.8547  
Epoch 179/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0316 - accuracy: 0.8480  
- val\_loss: 0.0307 - val\_accuracy: 0.8554  
Epoch 180/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0314 - accuracy: 0.8490  
- val\_loss: 0.0306 - val\_accuracy: 0.8561  
Epoch 181/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0313 - accuracy: 0.8493  
- val\_loss: 0.0304 - val\_accuracy: 0.8574  
Epoch 182/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0312 - accuracy: 0.8498  
- val\_loss: 0.0303 - val\_accuracy: 0.8579  
Epoch 183/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0310 - accuracy: 0.8505  
- val\_loss: 0.0301 - val\_accuracy: 0.8588  
Epoch 184/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0309 - accuracy: 0.8509  
- val\_loss: 0.0300 - val\_accuracy: 0.8594  
Epoch 185/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0307 - accuracy: 0.8513  
- val\_loss: 0.0299 - val\_accuracy: 0.8598  
Epoch 186/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0306 - accuracy: 0.8517  
- val\_loss: 0.0297 - val\_accuracy: 0.8601  
Epoch 187/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0305 - accuracy: 0.8522  
- val\_loss: 0.0296 - val\_accuracy: 0.8605  
Epoch 188/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0304 - accuracy: 0.8526  
- val\_loss: 0.0295 - val\_accuracy: 0.8613  
Epoch 189/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0302 - accuracy: 0.8532  
- val\_loss: 0.0293 - val\_accuracy: 0.8619  
Epoch 190/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0301 - accuracy: 0.8536  
- val\_loss: 0.0292 - val\_accuracy: 0.8623  
Epoch 191/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0300 - accuracy: 0.8540  
- val\_loss: 0.0291 - val\_accuracy: 0.8628  
Epoch 192/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0298 - accuracy: 0.8544  
- val\_loss: 0.0290 - val\_accuracy: 0.8631  
Epoch 193/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0297 - accuracy: 0.8549  
- val\_loss: 0.0288 - val\_accuracy: 0.8634  
Epoch 194/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0296 - accuracy: 0.8554  
- val\_loss: 0.0287 - val\_accuracy: 0.8639  
Epoch 195/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0295 - accuracy: 0.8557  
- val\_loss: 0.0286 - val\_accuracy: 0.8642



Epoch 196/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0294 - accuracy: 0.8564  
- val\_loss: 0.0285 - val\_accuracy: 0.8646  
Epoch 197/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0292 - accuracy: 0.8565  
- val\_loss: 0.0284 - val\_accuracy: 0.8651  
Epoch 198/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0291 - accuracy: 0.8570  
- val\_loss: 0.0282 - val\_accuracy: 0.8655  
Epoch 199/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0290 - accuracy: 0.8574  
- val\_loss: 0.0281 - val\_accuracy: 0.8661  
Epoch 200/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0289 - accuracy: 0.8578  
- val\_loss: 0.0280 - val\_accuracy: 0.8667  
Epoch 201/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0288 - accuracy: 0.8582  
- val\_loss: 0.0279 - val\_accuracy: 0.8670  
Epoch 202/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0287 - accuracy: 0.8585  
- val\_loss: 0.0278 - val\_accuracy: 0.8675  
Epoch 203/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0286 - accuracy: 0.8589  
- val\_loss: 0.0277 - val\_accuracy: 0.8681  
Epoch 204/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0285 - accuracy: 0.8591  
- val\_loss: 0.0276 - val\_accuracy: 0.8684  
Epoch 205/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0284 - accuracy: 0.8594  
- val\_loss: 0.0274 - val\_accuracy: 0.8688  
Epoch 206/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0282 - accuracy: 0.8598  
- val\_loss: 0.0273 - val\_accuracy: 0.8695  
Epoch 207/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0281 - accuracy: 0.8602  
- val\_loss: 0.0272 - val\_accuracy: 0.8696  
Epoch 208/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0280 - accuracy: 0.8605  
- val\_loss: 0.0271 - val\_accuracy: 0.8702  
Epoch 209/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0279 - accuracy: 0.8608  
- val\_loss: 0.0270 - val\_accuracy: 0.8702  
Epoch 210/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0278 - accuracy: 0.8612  
- val\_loss: 0.0269 - val\_accuracy: 0.8703  
Epoch 211/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0277 - accuracy: 0.8616  
- val\_loss: 0.0268 - val\_accuracy: 0.8705  
Epoch 212/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0276 - accuracy: 0.8619  
- val\_loss: 0.0267 - val\_accuracy: 0.8708  
Epoch 213/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0275 - accuracy: 0.8622  
- val\_loss: 0.0266 - val\_accuracy: 0.8710  
Epoch 214/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0274 - accuracy: 0.8626  
- val\_loss: 0.0265 - val\_accuracy: 0.8716  
Epoch 215/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0273 - accuracy: 0.8627  
- val\_loss: 0.0264 - val\_accuracy: 0.8719

Epoch 216/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0272 - accuracy: 0.8630  
- val\_loss: 0.0263 - val\_accuracy: 0.8720  
Epoch 217/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0271 - accuracy: 0.8632  
- val\_loss: 0.0262 - val\_accuracy: 0.8721  
Epoch 218/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0271 - accuracy: 0.8637  
- val\_loss: 0.0261 - val\_accuracy: 0.8724  
Epoch 219/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0270 - accuracy: 0.8640  
- val\_loss: 0.0260 - val\_accuracy: 0.8729  
Epoch 220/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0269 - accuracy: 0.8641  
- val\_loss: 0.0260 - val\_accuracy: 0.8729  
Epoch 221/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0268 - accuracy: 0.8645  
- val\_loss: 0.0259 - val\_accuracy: 0.8729  
Epoch 222/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0267 - accuracy: 0.8648  
- val\_loss: 0.0258 - val\_accuracy: 0.8731  
Epoch 223/500  
469/469 [=====] - 1s 3ms/step - loss: 0.0266 - accuracy: 0.8651  
- val\_loss: 0.0257 - val\_accuracy: 0.8735  
Epoch 224/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0265 - accuracy: 0.8653  
- val\_loss: 0.0256 - val\_accuracy: 0.8737  
Epoch 225/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0264 - accuracy: 0.8657  
- val\_loss: 0.0255 - val\_accuracy: 0.8738  
Epoch 226/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0263 - accuracy: 0.8659  
- val\_loss: 0.0254 - val\_accuracy: 0.8739  
Epoch 227/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0263 - accuracy: 0.8663  
- val\_loss: 0.0253 - val\_accuracy: 0.8741  
Epoch 228/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0262 - accuracy: 0.8665  
- val\_loss: 0.0253 - val\_accuracy: 0.8741  
Epoch 229/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0261 - accuracy: 0.8668  
- val\_loss: 0.0252 - val\_accuracy: 0.8741  
Epoch 230/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0260 - accuracy: 0.8670  
- val\_loss: 0.0251 - val\_accuracy: 0.8743  
Epoch 231/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0259 - accuracy: 0.8672  
- val\_loss: 0.0250 - val\_accuracy: 0.8744  
Epoch 232/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0258 - accuracy: 0.8675  
- val\_loss: 0.0249 - val\_accuracy: 0.8749  
Epoch 233/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0258 - accuracy: 0.8678  
- val\_loss: 0.0248 - val\_accuracy: 0.8751  
Epoch 234/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0257 - accuracy: 0.8679  
- val\_loss: 0.0248 - val\_accuracy: 0.8755  
Epoch 235/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0256 - accuracy: 0.8680  
- val\_loss: 0.0247 - val\_accuracy: 0.8755

Epoch 236/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0255 - accuracy: 0.8685  
- val\_loss: 0.0246 - val\_accuracy: 0.8757  
Epoch 237/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0255 - accuracy: 0.8686  
- val\_loss: 0.0245 - val\_accuracy: 0.8760  
Epoch 238/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0254 - accuracy: 0.8691  
- val\_loss: 0.0245 - val\_accuracy: 0.8761  
Epoch 239/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0253 - accuracy: 0.8692  
- val\_loss: 0.0244 - val\_accuracy: 0.8764  
Epoch 240/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0252 - accuracy: 0.8694  
- val\_loss: 0.0243 - val\_accuracy: 0.8767  
Epoch 241/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0252 - accuracy: 0.8696  
- val\_loss: 0.0242 - val\_accuracy: 0.8770  
Epoch 242/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0251 - accuracy: 0.8696  
- val\_loss: 0.0242 - val\_accuracy: 0.8774  
Epoch 243/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0250 - accuracy: 0.8698  
- val\_loss: 0.0241 - val\_accuracy: 0.8774  
Epoch 244/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0249 - accuracy: 0.8702  
- val\_loss: 0.0240 - val\_accuracy: 0.8777  
Epoch 245/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0249 - accuracy: 0.8704  
- val\_loss: 0.0239 - val\_accuracy: 0.8779  
Epoch 246/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0248 - accuracy: 0.8706  
- val\_loss: 0.0239 - val\_accuracy: 0.8781  
Epoch 247/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0247 - accuracy: 0.8708  
- val\_loss: 0.0238 - val\_accuracy: 0.8782  
Epoch 248/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0247 - accuracy: 0.8710  
- val\_loss: 0.0237 - val\_accuracy: 0.8782  
Epoch 249/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0246 - accuracy: 0.8712  
- val\_loss: 0.0237 - val\_accuracy: 0.8785  
Epoch 250/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0245 - accuracy: 0.8714  
- val\_loss: 0.0236 - val\_accuracy: 0.8784  
Epoch 251/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0245 - accuracy: 0.8717  
- val\_loss: 0.0235 - val\_accuracy: 0.8787  
Epoch 252/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0244 - accuracy: 0.8719  
- val\_loss: 0.0235 - val\_accuracy: 0.8789  
Epoch 253/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0243 - accuracy: 0.8722  
- val\_loss: 0.0234 - val\_accuracy: 0.8794  
Epoch 254/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0243 - accuracy: 0.8724  
- val\_loss: 0.0233 - val\_accuracy: 0.8795  
Epoch 255/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0242 - accuracy: 0.8725  
- val\_loss: 0.0233 - val\_accuracy: 0.8795

Epoch 256/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0241 - accuracy: 0.8726  
- val\_loss: 0.0232 - val\_accuracy: 0.8796  
Epoch 257/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0241 - accuracy: 0.8729  
- val\_loss: 0.0231 - val\_accuracy: 0.8799  
Epoch 258/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0240 - accuracy: 0.8730  
- val\_loss: 0.0231 - val\_accuracy: 0.8800  
Epoch 259/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0239 - accuracy: 0.8735  
- val\_loss: 0.0230 - val\_accuracy: 0.8803  
Epoch 260/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0239 - accuracy: 0.8737  
- val\_loss: 0.0230 - val\_accuracy: 0.8805  
Epoch 261/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0238 - accuracy: 0.8740  
- val\_loss: 0.0229 - val\_accuracy: 0.8809  
Epoch 262/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0238 - accuracy: 0.8741  
- val\_loss: 0.0228 - val\_accuracy: 0.8813  
Epoch 263/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0237 - accuracy: 0.8743  
- val\_loss: 0.0228 - val\_accuracy: 0.8816  
Epoch 264/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0236 - accuracy: 0.8744  
- val\_loss: 0.0227 - val\_accuracy: 0.8817  
Epoch 265/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0236 - accuracy: 0.8744  
- val\_loss: 0.0227 - val\_accuracy: 0.8822  
Epoch 266/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0235 - accuracy: 0.8747  
- val\_loss: 0.0226 - val\_accuracy: 0.8824  
Epoch 267/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0235 - accuracy: 0.8750  
- val\_loss: 0.0225 - val\_accuracy: 0.8825  
Epoch 268/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0234 - accuracy: 0.8754  
- val\_loss: 0.0225 - val\_accuracy: 0.8828  
Epoch 269/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0234 - accuracy: 0.8756  
- val\_loss: 0.0224 - val\_accuracy: 0.8829  
Epoch 270/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0233 - accuracy: 0.8759  
- val\_loss: 0.0224 - val\_accuracy: 0.8831  
Epoch 271/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0232 - accuracy: 0.8762  
- val\_loss: 0.0223 - val\_accuracy: 0.8832  
Epoch 272/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0232 - accuracy: 0.8763  
- val\_loss: 0.0223 - val\_accuracy: 0.8834  
Epoch 273/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0231 - accuracy: 0.8765  
- val\_loss: 0.0222 - val\_accuracy: 0.8838  
Epoch 274/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0231 - accuracy: 0.8766  
- val\_loss: 0.0221 - val\_accuracy: 0.8839  
Epoch 275/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0230 - accuracy: 0.8768  
- val\_loss: 0.0221 - val\_accuracy: 0.8838

Epoch 276/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0230 - accuracy: 0.8770  
- val\_loss: 0.0220 - val\_accuracy: 0.8840  
Epoch 277/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0229 - accuracy: 0.8771  
- val\_loss: 0.0220 - val\_accuracy: 0.8839  
Epoch 278/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0229 - accuracy: 0.8773  
- val\_loss: 0.0219 - val\_accuracy: 0.8840  
Epoch 279/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0228 - accuracy: 0.8775  
- val\_loss: 0.0219 - val\_accuracy: 0.8839  
Epoch 280/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0228 - accuracy: 0.8777  
- val\_loss: 0.0218 - val\_accuracy: 0.8842  
Epoch 281/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0227 - accuracy: 0.8779  
- val\_loss: 0.0218 - val\_accuracy: 0.8842  
Epoch 282/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0227 - accuracy: 0.8781  
- val\_loss: 0.0217 - val\_accuracy: 0.8846  
Epoch 283/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0226 - accuracy: 0.8784  
- val\_loss: 0.0217 - val\_accuracy: 0.8848  
Epoch 284/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0226 - accuracy: 0.8785  
- val\_loss: 0.0216 - val\_accuracy: 0.8848  
Epoch 285/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0225 - accuracy: 0.8787  
- val\_loss: 0.0216 - val\_accuracy: 0.8852  
Epoch 286/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0225 - accuracy: 0.8788  
- val\_loss: 0.0215 - val\_accuracy: 0.8854  
Epoch 287/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0224 - accuracy: 0.8789  
- val\_loss: 0.0215 - val\_accuracy: 0.8855  
Epoch 288/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0224 - accuracy: 0.8790  
- val\_loss: 0.0214 - val\_accuracy: 0.8858  
Epoch 289/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0223 - accuracy: 0.8792  
- val\_loss: 0.0214 - val\_accuracy: 0.8859  
Epoch 290/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0223 - accuracy: 0.8794  
- val\_loss: 0.0213 - val\_accuracy: 0.8860  
Epoch 291/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0222 - accuracy: 0.8796  
- val\_loss: 0.0213 - val\_accuracy: 0.8863  
Epoch 292/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0222 - accuracy: 0.8799  
- val\_loss: 0.0213 - val\_accuracy: 0.8867  
Epoch 293/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0221 - accuracy: 0.8800  
- val\_loss: 0.0212 - val\_accuracy: 0.8870  
Epoch 294/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0221 - accuracy: 0.8801  
- val\_loss: 0.0212 - val\_accuracy: 0.8871  
Epoch 295/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0220 - accuracy: 0.8804  
- val\_loss: 0.0211 - val\_accuracy: 0.8873

Epoch 296/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0220 - accuracy: 0.8805  
- val\_loss: 0.0211 - val\_accuracy: 0.8876  
Epoch 297/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0220 - accuracy: 0.8806  
- val\_loss: 0.0210 - val\_accuracy: 0.8876  
Epoch 298/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0219 - accuracy: 0.8807  
- val\_loss: 0.0210 - val\_accuracy: 0.8878  
Epoch 299/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0219 - accuracy: 0.8810  
- val\_loss: 0.0209 - val\_accuracy: 0.8880  
Epoch 300/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0218 - accuracy: 0.8811  
- val\_loss: 0.0209 - val\_accuracy: 0.8882  
Epoch 301/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0218 - accuracy: 0.8812  
- val\_loss: 0.0209 - val\_accuracy: 0.8883  
Epoch 302/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0217 - accuracy: 0.8813  
- val\_loss: 0.0208 - val\_accuracy: 0.8885  
Epoch 303/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0217 - accuracy: 0.8813  
- val\_loss: 0.0208 - val\_accuracy: 0.8885  
Epoch 304/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0217 - accuracy: 0.8815  
- val\_loss: 0.0207 - val\_accuracy: 0.8890  
Epoch 305/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0216 - accuracy: 0.8816  
- val\_loss: 0.0207 - val\_accuracy: 0.8892  
Epoch 306/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0216 - accuracy: 0.8817  
- val\_loss: 0.0206 - val\_accuracy: 0.8895  
Epoch 307/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0215 - accuracy: 0.8819  
- val\_loss: 0.0206 - val\_accuracy: 0.8895  
Epoch 308/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0215 - accuracy: 0.8821  
- val\_loss: 0.0206 - val\_accuracy: 0.8895  
Epoch 309/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0214 - accuracy: 0.8823  
- val\_loss: 0.0205 - val\_accuracy: 0.8900  
Epoch 310/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0214 - accuracy: 0.8824  
- val\_loss: 0.0205 - val\_accuracy: 0.8901  
Epoch 311/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0214 - accuracy: 0.8824  
- val\_loss: 0.0204 - val\_accuracy: 0.8903  
Epoch 312/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0213 - accuracy: 0.8826  
- val\_loss: 0.0204 - val\_accuracy: 0.8903  
Epoch 313/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0213 - accuracy: 0.8827  
- val\_loss: 0.0204 - val\_accuracy: 0.8906  
Epoch 314/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0212 - accuracy: 0.8827  
- val\_loss: 0.0203 - val\_accuracy: 0.8908  
Epoch 315/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0212 - accuracy: 0.8828  
- val\_loss: 0.0203 - val\_accuracy: 0.8910

Epoch 316/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0212 - accuracy: 0.8831  
- val\_loss: 0.0203 - val\_accuracy: 0.8911  
Epoch 317/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0211 - accuracy: 0.8831  
- val\_loss: 0.0202 - val\_accuracy: 0.8911  
Epoch 318/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0211 - accuracy: 0.8832  
- val\_loss: 0.0202 - val\_accuracy: 0.8913  
Epoch 319/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0211 - accuracy: 0.8833  
- val\_loss: 0.0201 - val\_accuracy: 0.8914  
Epoch 320/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0210 - accuracy: 0.8834  
- val\_loss: 0.0201 - val\_accuracy: 0.8917  
Epoch 321/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0210 - accuracy: 0.8836  
- val\_loss: 0.0201 - val\_accuracy: 0.8917  
Epoch 322/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0209 - accuracy: 0.8838  
- val\_loss: 0.0200 - val\_accuracy: 0.8918  
Epoch 323/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0209 - accuracy: 0.8838  
- val\_loss: 0.0200 - val\_accuracy: 0.8918  
Epoch 324/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0209 - accuracy: 0.8841  
- val\_loss: 0.0200 - val\_accuracy: 0.8918  
Epoch 325/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0208 - accuracy: 0.8842  
- val\_loss: 0.0199 - val\_accuracy: 0.8919  
Epoch 326/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0208 - accuracy: 0.8842  
- val\_loss: 0.0199 - val\_accuracy: 0.8921  
Epoch 327/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0208 - accuracy: 0.8844  
- val\_loss: 0.0199 - val\_accuracy: 0.8923  
Epoch 328/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0207 - accuracy: 0.8845  
- val\_loss: 0.0198 - val\_accuracy: 0.8923  
Epoch 329/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0207 - accuracy: 0.8847  
- val\_loss: 0.0198 - val\_accuracy: 0.8924  
Epoch 330/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0207 - accuracy: 0.8848  
- val\_loss: 0.0198 - val\_accuracy: 0.8925  
Epoch 331/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0206 - accuracy: 0.8850  
- val\_loss: 0.0197 - val\_accuracy: 0.8928  
Epoch 332/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0206 - accuracy: 0.8850  
- val\_loss: 0.0197 - val\_accuracy: 0.8928  
Epoch 333/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0206 - accuracy: 0.8852  
- val\_loss: 0.0197 - val\_accuracy: 0.8928  
Epoch 334/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0205 - accuracy: 0.8853  
- val\_loss: 0.0196 - val\_accuracy: 0.8928  
Epoch 335/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0205 - accuracy: 0.8855  
- val\_loss: 0.0196 - val\_accuracy: 0.8927

Epoch 336/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0205 - accuracy: 0.8856  
- val\_loss: 0.0196 - val\_accuracy: 0.8932  
Epoch 337/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0204 - accuracy: 0.8857  
- val\_loss: 0.0195 - val\_accuracy: 0.8932  
Epoch 338/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0204 - accuracy: 0.8858  
- val\_loss: 0.0195 - val\_accuracy: 0.8933  
Epoch 339/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0204 - accuracy: 0.8860  
- val\_loss: 0.0195 - val\_accuracy: 0.8935  
Epoch 340/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0203 - accuracy: 0.8860  
- val\_loss: 0.0194 - val\_accuracy: 0.8936  
Epoch 341/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0203 - accuracy: 0.8862  
- val\_loss: 0.0194 - val\_accuracy: 0.8939  
Epoch 342/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0203 - accuracy: 0.8863  
- val\_loss: 0.0194 - val\_accuracy: 0.8944  
Epoch 343/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0202 - accuracy: 0.8864  
- val\_loss: 0.0193 - val\_accuracy: 0.8944  
Epoch 344/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0202 - accuracy: 0.8866  
- val\_loss: 0.0193 - val\_accuracy: 0.8946  
Epoch 345/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0202 - accuracy: 0.8866  
- val\_loss: 0.0193 - val\_accuracy: 0.8947  
Epoch 346/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0201 - accuracy: 0.8867  
- val\_loss: 0.0192 - val\_accuracy: 0.8947  
Epoch 347/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0201 - accuracy: 0.8869  
- val\_loss: 0.0192 - val\_accuracy: 0.8948  
Epoch 348/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0201 - accuracy: 0.8870  
- val\_loss: 0.0192 - val\_accuracy: 0.8948  
Epoch 349/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0201 - accuracy: 0.8872  
- val\_loss: 0.0192 - val\_accuracy: 0.8949  
Epoch 350/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0200 - accuracy: 0.8873  
- val\_loss: 0.0191 - val\_accuracy: 0.8950  
Epoch 351/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0200 - accuracy: 0.8874  
- val\_loss: 0.0191 - val\_accuracy: 0.8952  
Epoch 352/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0200 - accuracy: 0.8875  
- val\_loss: 0.0191 - val\_accuracy: 0.8954  
Epoch 353/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0199 - accuracy: 0.8876  
- val\_loss: 0.0190 - val\_accuracy: 0.8957  
Epoch 354/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0199 - accuracy: 0.8877  
- val\_loss: 0.0190 - val\_accuracy: 0.8957  
Epoch 355/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0199 - accuracy: 0.8878  
- val\_loss: 0.0190 - val\_accuracy: 0.8959



Epoch 356/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0198 - accuracy: 0.8879  
- val\_loss: 0.0190 - val\_accuracy: 0.8960  
Epoch 357/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0198 - accuracy: 0.8881  
- val\_loss: 0.0189 - val\_accuracy: 0.8961  
Epoch 358/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0198 - accuracy: 0.8881  
- val\_loss: 0.0189 - val\_accuracy: 0.8962  
Epoch 359/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0198 - accuracy: 0.8882  
- val\_loss: 0.0189 - val\_accuracy: 0.8961  
Epoch 360/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0197 - accuracy: 0.8882  
- val\_loss: 0.0188 - val\_accuracy: 0.8964  
Epoch 361/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0197 - accuracy: 0.8883  
- val\_loss: 0.0188 - val\_accuracy: 0.8964  
Epoch 362/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0197 - accuracy: 0.8885  
- val\_loss: 0.0188 - val\_accuracy: 0.8964  
Epoch 363/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0197 - accuracy: 0.8886  
- val\_loss: 0.0188 - val\_accuracy: 0.8964  
Epoch 364/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0196 - accuracy: 0.8886  
- val\_loss: 0.0187 - val\_accuracy: 0.8965  
Epoch 365/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0196 - accuracy: 0.8887  
- val\_loss: 0.0187 - val\_accuracy: 0.8964  
Epoch 366/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0196 - accuracy: 0.8889  
- val\_loss: 0.0187 - val\_accuracy: 0.8966  
Epoch 367/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0195 - accuracy: 0.8889  
- val\_loss: 0.0187 - val\_accuracy: 0.8967  
Epoch 368/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0195 - accuracy: 0.8890  
- val\_loss: 0.0186 - val\_accuracy: 0.8969  
Epoch 369/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0195 - accuracy: 0.8891  
- val\_loss: 0.0186 - val\_accuracy: 0.8969  
Epoch 370/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0195 - accuracy: 0.8892  
- val\_loss: 0.0186 - val\_accuracy: 0.8970  
Epoch 371/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0194 - accuracy: 0.8893  
- val\_loss: 0.0186 - val\_accuracy: 0.8971  
Epoch 372/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0194 - accuracy: 0.8895  
- val\_loss: 0.0185 - val\_accuracy: 0.8972  
Epoch 373/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0194 - accuracy: 0.8895  
- val\_loss: 0.0185 - val\_accuracy: 0.8972  
Epoch 374/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0194 - accuracy: 0.8896  
- val\_loss: 0.0185 - val\_accuracy: 0.8973  
Epoch 375/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0193 - accuracy: 0.8896  
- val\_loss: 0.0185 - val\_accuracy: 0.8974

Epoch 376/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0193 - accuracy: 0.8897  
- val\_loss: 0.0184 - val\_accuracy: 0.8974  
Epoch 377/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0193 - accuracy: 0.8898  
- val\_loss: 0.0184 - val\_accuracy: 0.8974  
Epoch 378/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0193 - accuracy: 0.8898  
- val\_loss: 0.0184 - val\_accuracy: 0.8973  
Epoch 379/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0192 - accuracy: 0.8899  
- val\_loss: 0.0184 - val\_accuracy: 0.8975  
Epoch 380/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0192 - accuracy: 0.8900  
- val\_loss: 0.0183 - val\_accuracy: 0.8976  
Epoch 381/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0192 - accuracy: 0.8901  
- val\_loss: 0.0183 - val\_accuracy: 0.8979  
Epoch 382/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0192 - accuracy: 0.8903  
- val\_loss: 0.0183 - val\_accuracy: 0.8977  
Epoch 383/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0191 - accuracy: 0.8902  
- val\_loss: 0.0183 - val\_accuracy: 0.8978  
Epoch 384/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0191 - accuracy: 0.8902  
- val\_loss: 0.0182 - val\_accuracy: 0.8979  
Epoch 385/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0191 - accuracy: 0.8904  
- val\_loss: 0.0182 - val\_accuracy: 0.8979  
Epoch 386/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0191 - accuracy: 0.8904  
- val\_loss: 0.0182 - val\_accuracy: 0.8980  
Epoch 387/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0190 - accuracy: 0.8905  
- val\_loss: 0.0182 - val\_accuracy: 0.8982  
Epoch 388/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0190 - accuracy: 0.8906  
- val\_loss: 0.0181 - val\_accuracy: 0.8981  
Epoch 389/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0190 - accuracy: 0.8907  
- val\_loss: 0.0181 - val\_accuracy: 0.8981  
Epoch 390/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0190 - accuracy: 0.8908  
- val\_loss: 0.0181 - val\_accuracy: 0.8982  
Epoch 391/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0189 - accuracy: 0.8909  
- val\_loss: 0.0181 - val\_accuracy: 0.8984  
Epoch 392/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0189 - accuracy: 0.8910  
- val\_loss: 0.0181 - val\_accuracy: 0.8984  
Epoch 393/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0189 - accuracy: 0.8910  
- val\_loss: 0.0180 - val\_accuracy: 0.8985  
Epoch 394/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0189 - accuracy: 0.8911  
- val\_loss: 0.0180 - val\_accuracy: 0.8985  
Epoch 395/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0189 - accuracy: 0.8913  
- val\_loss: 0.0180 - val\_accuracy: 0.8985

Epoch 396/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0188 - accuracy: 0.8913  
- val\_loss: 0.0180 - val\_accuracy: 0.8986  
Epoch 397/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0188 - accuracy: 0.8914  
- val\_loss: 0.0179 - val\_accuracy: 0.8987  
Epoch 398/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0188 - accuracy: 0.8915  
- val\_loss: 0.0179 - val\_accuracy: 0.8988  
Epoch 399/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0188 - accuracy: 0.8916  
- val\_loss: 0.0179 - val\_accuracy: 0.8989  
Epoch 400/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0187 - accuracy: 0.8918  
- val\_loss: 0.0179 - val\_accuracy: 0.8990  
Epoch 401/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0187 - accuracy: 0.8918  
- val\_loss: 0.0179 - val\_accuracy: 0.8990  
Epoch 402/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0187 - accuracy: 0.8919  
- val\_loss: 0.0178 - val\_accuracy: 0.8991  
Epoch 403/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0187 - accuracy: 0.8920  
- val\_loss: 0.0178 - val\_accuracy: 0.8992  
Epoch 404/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0187 - accuracy: 0.8921  
- val\_loss: 0.0178 - val\_accuracy: 0.8990  
Epoch 405/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0186 - accuracy: 0.8922  
- val\_loss: 0.0178 - val\_accuracy: 0.8992  
Epoch 406/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0186 - accuracy: 0.8923  
- val\_loss: 0.0178 - val\_accuracy: 0.8992  
Epoch 407/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0186 - accuracy: 0.8924  
- val\_loss: 0.0177 - val\_accuracy: 0.8992  
Epoch 408/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0186 - accuracy: 0.8924  
- val\_loss: 0.0177 - val\_accuracy: 0.8994  
Epoch 409/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0186 - accuracy: 0.8925  
- val\_loss: 0.0177 - val\_accuracy: 0.8994  
Epoch 410/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0185 - accuracy: 0.8926  
- val\_loss: 0.0177 - val\_accuracy: 0.8996  
Epoch 411/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0185 - accuracy: 0.8926  
- val\_loss: 0.0176 - val\_accuracy: 0.8999  
Epoch 412/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0185 - accuracy: 0.8927  
- val\_loss: 0.0176 - val\_accuracy: 0.8997  
Epoch 413/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0185 - accuracy: 0.8927  
- val\_loss: 0.0176 - val\_accuracy: 0.9000  
Epoch 414/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0184 - accuracy: 0.8928  
- val\_loss: 0.0176 - val\_accuracy: 0.9000  
Epoch 415/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0184 - accuracy: 0.8928  
- val\_loss: 0.0176 - val\_accuracy: 0.9000

Epoch 416/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0184 - accuracy: 0.8929  
- val\_loss: 0.0175 - val\_accuracy: 0.9000  
Epoch 417/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0184 - accuracy: 0.8930  
- val\_loss: 0.0175 - val\_accuracy: 0.9000  
Epoch 418/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0184 - accuracy: 0.8931  
- val\_loss: 0.0175 - val\_accuracy: 0.9000  
Epoch 419/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0183 - accuracy: 0.8931  
- val\_loss: 0.0175 - val\_accuracy: 0.9000  
Epoch 420/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0183 - accuracy: 0.8932  
- val\_loss: 0.0175 - val\_accuracy: 0.9002  
Epoch 421/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0183 - accuracy: 0.8934  
- val\_loss: 0.0175 - val\_accuracy: 0.9003  
Epoch 422/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0183 - accuracy: 0.8932  
- val\_loss: 0.0174 - val\_accuracy: 0.9003  
Epoch 423/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0183 - accuracy: 0.8934  
- val\_loss: 0.0174 - val\_accuracy: 0.9003  
Epoch 424/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0183 - accuracy: 0.8935  
- val\_loss: 0.0174 - val\_accuracy: 0.9004  
Epoch 425/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0182 - accuracy: 0.8937  
- val\_loss: 0.0174 - val\_accuracy: 0.9004  
Epoch 426/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0182 - accuracy: 0.8937  
- val\_loss: 0.0174 - val\_accuracy: 0.9004  
Epoch 427/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0182 - accuracy: 0.8939  
- val\_loss: 0.0173 - val\_accuracy: 0.9006  
Epoch 428/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0182 - accuracy: 0.8938  
- val\_loss: 0.0173 - val\_accuracy: 0.9008  
Epoch 429/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0182 - accuracy: 0.8941  
- val\_loss: 0.0173 - val\_accuracy: 0.9009  
Epoch 430/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0181 - accuracy: 0.8941  
- val\_loss: 0.0173 - val\_accuracy: 0.9009  
Epoch 431/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0181 - accuracy: 0.8943  
- val\_loss: 0.0173 - val\_accuracy: 0.9009  
Epoch 432/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0181 - accuracy: 0.8943  
- val\_loss: 0.0173 - val\_accuracy: 0.9009  
Epoch 433/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0181 - accuracy: 0.8944  
- val\_loss: 0.0172 - val\_accuracy: 0.9008  
Epoch 434/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0181 - accuracy: 0.8944  
- val\_loss: 0.0172 - val\_accuracy: 0.9009  
Epoch 435/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0180 - accuracy: 0.8946  
- val\_loss: 0.0172 - val\_accuracy: 0.9010

Epoch 436/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0180 - accuracy: 0.8948  
- val\_loss: 0.0172 - val\_accuracy: 0.9009  
Epoch 437/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0180 - accuracy: 0.8948  
- val\_loss: 0.0172 - val\_accuracy: 0.9012  
Epoch 438/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0180 - accuracy: 0.8948  
- val\_loss: 0.0171 - val\_accuracy: 0.9012  
Epoch 439/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0180 - accuracy: 0.8950  
- val\_loss: 0.0171 - val\_accuracy: 0.9012  
Epoch 440/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0180 - accuracy: 0.8950  
- val\_loss: 0.0171 - val\_accuracy: 0.9012  
Epoch 441/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0179 - accuracy: 0.8950  
- val\_loss: 0.0171 - val\_accuracy: 0.9013  
Epoch 442/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0179 - accuracy: 0.8951  
- val\_loss: 0.0171 - val\_accuracy: 0.9013  
Epoch 443/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0179 - accuracy: 0.8952  
- val\_loss: 0.0171 - val\_accuracy: 0.9013  
Epoch 444/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0179 - accuracy: 0.8953  
- val\_loss: 0.0170 - val\_accuracy: 0.9013  
Epoch 445/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0179 - accuracy: 0.8954  
- val\_loss: 0.0170 - val\_accuracy: 0.9012  
Epoch 446/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0178 - accuracy: 0.8954  
- val\_loss: 0.0170 - val\_accuracy: 0.9012  
Epoch 447/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0178 - accuracy: 0.8955  
- val\_loss: 0.0170 - val\_accuracy: 0.9013  
Epoch 448/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0178 - accuracy: 0.8954  
- val\_loss: 0.0170 - val\_accuracy: 0.9014  
Epoch 449/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0178 - accuracy: 0.8956  
- val\_loss: 0.0170 - val\_accuracy: 0.9015  
Epoch 450/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0178 - accuracy: 0.8957  
- val\_loss: 0.0169 - val\_accuracy: 0.9016  
Epoch 451/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0178 - accuracy: 0.8958  
- val\_loss: 0.0169 - val\_accuracy: 0.9016  
Epoch 452/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0177 - accuracy: 0.8959  
- val\_loss: 0.0169 - val\_accuracy: 0.9016  
Epoch 453/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0177 - accuracy: 0.8960  
- val\_loss: 0.0169 - val\_accuracy: 0.9016  
Epoch 454/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0177 - accuracy: 0.8960  
- val\_loss: 0.0169 - val\_accuracy: 0.9017  
Epoch 455/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0177 - accuracy: 0.8961  
- val\_loss: 0.0169 - val\_accuracy: 0.9017

Epoch 456/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0177 - accuracy: 0.8961  
- val\_loss: 0.0168 - val\_accuracy: 0.9018  
Epoch 457/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0177 - accuracy: 0.8961  
- val\_loss: 0.0168 - val\_accuracy: 0.9018  
Epoch 458/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0176 - accuracy: 0.8962  
- val\_loss: 0.0168 - val\_accuracy: 0.9019  
Epoch 459/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0176 - accuracy: 0.8962  
- val\_loss: 0.0168 - val\_accuracy: 0.9019  
Epoch 460/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0176 - accuracy: 0.8963  
- val\_loss: 0.0168 - val\_accuracy: 0.9019  
Epoch 461/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0176 - accuracy: 0.8963  
- val\_loss: 0.0168 - val\_accuracy: 0.9019  
Epoch 462/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0176 - accuracy: 0.8964  
- val\_loss: 0.0168 - val\_accuracy: 0.9021  
Epoch 463/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0176 - accuracy: 0.8965  
- val\_loss: 0.0167 - val\_accuracy: 0.9021  
Epoch 464/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0176 - accuracy: 0.8965  
- val\_loss: 0.0167 - val\_accuracy: 0.9023  
Epoch 465/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0175 - accuracy: 0.8966  
- val\_loss: 0.0167 - val\_accuracy: 0.9024  
Epoch 466/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0175 - accuracy: 0.8967  
- val\_loss: 0.0167 - val\_accuracy: 0.9024  
Epoch 467/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0175 - accuracy: 0.8966  
- val\_loss: 0.0167 - val\_accuracy: 0.9024  
Epoch 468/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0175 - accuracy: 0.8967  
- val\_loss: 0.0167 - val\_accuracy: 0.9026  
Epoch 469/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0175 - accuracy: 0.8968  
- val\_loss: 0.0166 - val\_accuracy: 0.9027  
Epoch 470/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0175 - accuracy: 0.8968  
- val\_loss: 0.0166 - val\_accuracy: 0.9026  
Epoch 471/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0174 - accuracy: 0.8969  
- val\_loss: 0.0166 - val\_accuracy: 0.9026  
Epoch 472/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0174 - accuracy: 0.8969  
- val\_loss: 0.0166 - val\_accuracy: 0.9026  
Epoch 473/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0174 - accuracy: 0.8970  
- val\_loss: 0.0166 - val\_accuracy: 0.9026  
Epoch 474/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0174 - accuracy: 0.8970  
- val\_loss: 0.0166 - val\_accuracy: 0.9028  
Epoch 475/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0174 - accuracy: 0.8971  
- val\_loss: 0.0166 - val\_accuracy: 0.9028

Epoch 476/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0174 - accuracy: 0.8972  
- val\_loss: 0.0165 - val\_accuracy: 0.9029  
Epoch 477/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0174 - accuracy: 0.8972  
- val\_loss: 0.0165 - val\_accuracy: 0.9029  
Epoch 478/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0173 - accuracy: 0.8973  
- val\_loss: 0.0165 - val\_accuracy: 0.9028  
Epoch 479/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0173 - accuracy: 0.8974  
- val\_loss: 0.0165 - val\_accuracy: 0.9028  
Epoch 480/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0173 - accuracy: 0.8974  
- val\_loss: 0.0165 - val\_accuracy: 0.9028  
Epoch 481/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0173 - accuracy: 0.8975  
- val\_loss: 0.0165 - val\_accuracy: 0.9028  
Epoch 482/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0173 - accuracy: 0.8975  
- val\_loss: 0.0165 - val\_accuracy: 0.9030  
Epoch 483/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0173 - accuracy: 0.8975  
- val\_loss: 0.0164 - val\_accuracy: 0.9027  
Epoch 484/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0172 - accuracy: 0.8976  
- val\_loss: 0.0164 - val\_accuracy: 0.9029  
Epoch 485/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0172 - accuracy: 0.8977  
- val\_loss: 0.0164 - val\_accuracy: 0.9030  
Epoch 486/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0172 - accuracy: 0.8978  
- val\_loss: 0.0164 - val\_accuracy: 0.9030  
Epoch 487/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0172 - accuracy: 0.8978  
- val\_loss: 0.0164 - val\_accuracy: 0.9030  
Epoch 488/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0172 - accuracy: 0.8978  
- val\_loss: 0.0164 - val\_accuracy: 0.9032  
Epoch 489/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0172 - accuracy: 0.8979  
- val\_loss: 0.0164 - val\_accuracy: 0.9032  
Epoch 490/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0172 - accuracy: 0.8980  
- val\_loss: 0.0163 - val\_accuracy: 0.9034  
Epoch 491/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0171 - accuracy: 0.8980  
- val\_loss: 0.0163 - val\_accuracy: 0.9034  
Epoch 492/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0171 - accuracy: 0.8980  
- val\_loss: 0.0163 - val\_accuracy: 0.9034  
Epoch 493/500  
469/469 [=====] - 2s 3ms/step - loss: 0.0171 - accuracy: 0.8981  
- val\_loss: 0.0163 - val\_accuracy: 0.9034  
Epoch 494/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0171 - accuracy: 0.8982  
- val\_loss: 0.0163 - val\_accuracy: 0.9034  
Epoch 495/500  
469/469 [=====] - 2s 4ms/step - loss: 0.0171 - accuracy: 0.8982  
- val\_loss: 0.0163 - val\_accuracy: 0.9034

```

Epoch 496/500
469/469 [=====] - 2s 4ms/step - loss: 0.0171 - accuracy: 0.8982
- val_loss: 0.0163 - val_accuracy: 0.9036
Epoch 497/500
469/469 [=====] - 2s 3ms/step - loss: 0.0171 - accuracy: 0.8983
- val_loss: 0.0163 - val_accuracy: 0.9035
Epoch 498/500
469/469 [=====] - 2s 3ms/step - loss: 0.0171 - accuracy: 0.8984
- val_loss: 0.0162 - val_accuracy: 0.9035
Epoch 499/500
469/469 [=====] - 2s 3ms/step - loss: 0.0170 - accuracy: 0.8984
- val_loss: 0.0162 - val_accuracy: 0.9034
Epoch 500/500
469/469 [=====] - 2s 3ms/step - loss: 0.0170 - accuracy: 0.8984
- val_loss: 0.0162 - val_accuracy: 0.9034

```

## Plot learning curves

In [21]:

```

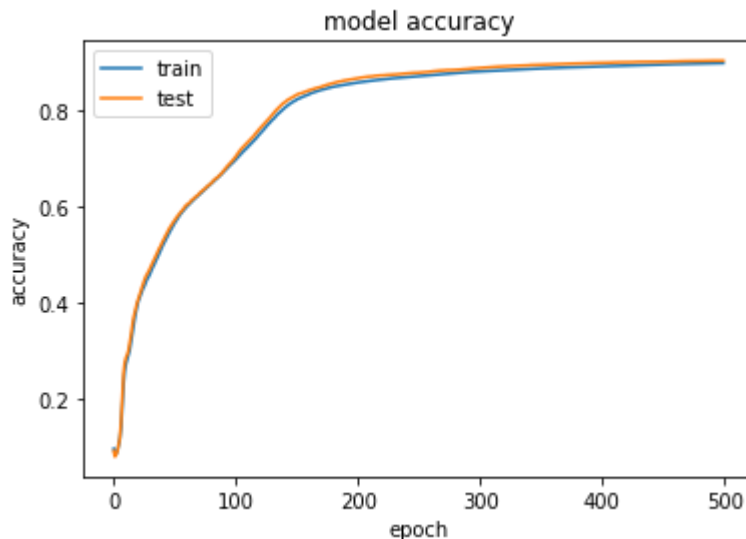
# list all data in history
print(history.history.keys())

# summarize history for accuracy
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()

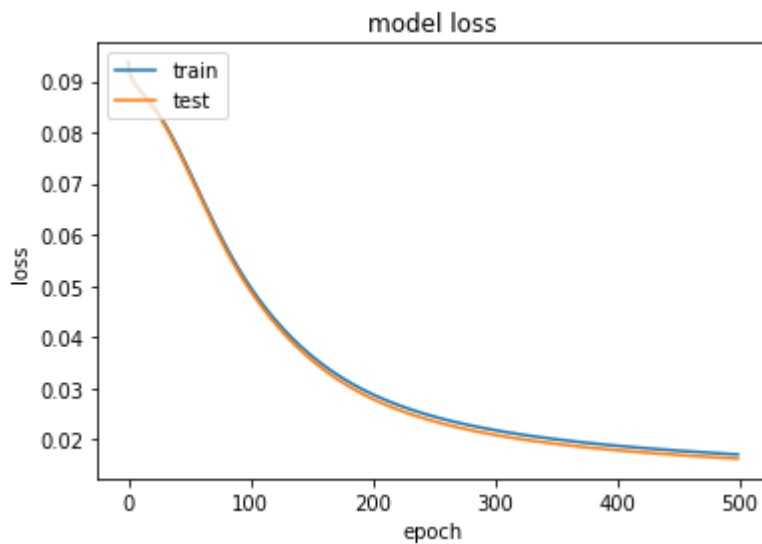
# summarize history for loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()

```

```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```







### Question 3

Does the model show any indication of overfitting? Why (not)?

Overfitting is when the model performs well on the training data but does not perform well on the validation data. In the graphs above, the model is actually shown to be more accurate with the validation data than the training data and the loss for the validation data is also less than the loss for the training data. Additionally, both datasets perform very closely. This indicates that the model does not show any indication of overfitting because the model does not perform better with the training data than with the validation data. This means that the model is not specific to the training data and will perform similarly with data that it has not seen before, which is important if the model will be used to classify outside data.

### Evaluate the model

```
In [22]: model.evaluate(X_validation, y_validation)
```

```
313/313 [=====] - 1s 2ms/step - loss: 0.0162 - accuracy: 0.9034
Out[22]: [0.016211673617362976, 0.9034000039100647]
```

### Confusion Matrix

The confusion matrix below shows the mistakes that the classifier made on the validation data. The matrix shows that the classifier performed reasonably well, but still made a significant number of mistakes. The multi-colored diagonal represents the data that was correctly classified while the purple squares represent the incorrectly classified data. Additionally, many of these mistakes are quite random, such as predicting a 1 to be an 8. While many digits share common features, a 1 and an 8 do not, showing us that the classifier's performance could be improved and that it makes mistakes on non-ambiguous data.

```
In [23]: prediction = model.predict(X_validation)
```

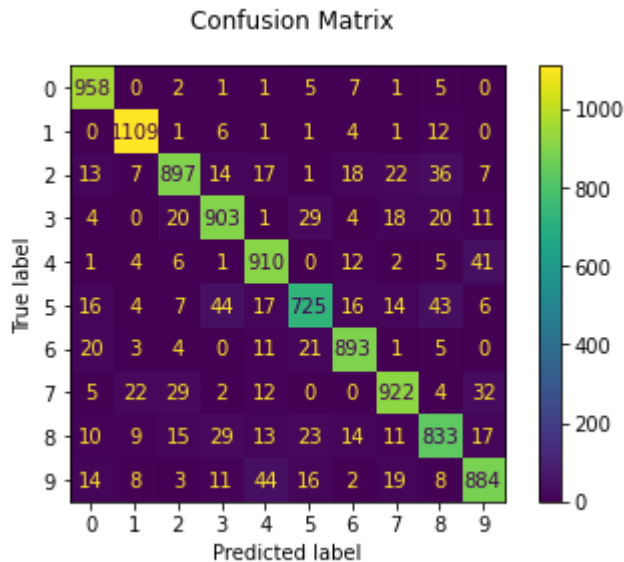
```

prediction_classes = np.argmax(prediction, axis=1)

disp = metrics.ConfusionMatrixDisplay.from_predictions(y_valid, prediction_classes)
disp.figure_.suptitle("Confusion Matrix")

plt.show()

```



## Mistakes

The following ten examples display some of the mistakes that the classifier made. As you can see, some of the samples could be confused with the prediction, but many of them do not share any resemblance between the prediction and the actual class.

```

In [24]: wrong = []
for i in range(len(prediction_classes)):
    if prediction_classes[i] != y_valid[i]:
        wrong.append(i)

print("Number of mistakes made: " + str(len(wrong)))

for i in range(10):
    print("-----")
    plt.imshow(X_valid[wrong[i]], cmap='Greys')
    plt.axis('off')
    plt.show()

    print("Actual class: " + str(y_valid[wrong[i]]))
    print("Predicted class: " + str(prediction_classes[wrong[i]]))
    print("-----")

```

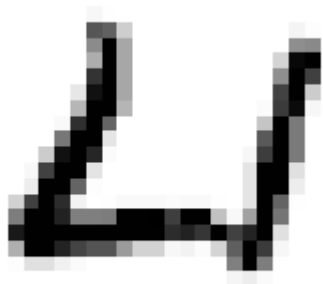
Number of mistakes made: 966

-----



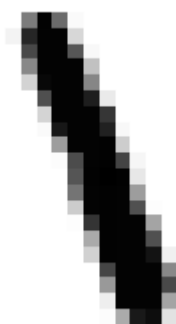
Actual class: 5  
Predicted class: 6

-----



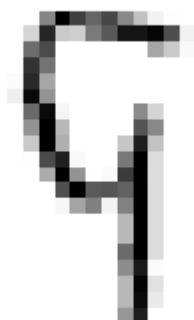
Actual class: 4  
Predicted class: 6

-----



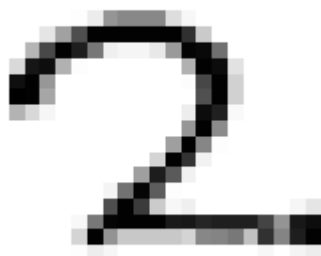
Actual class: 1  
Predicted class: 3

-----



Actual class: 9  
Predicted class: 4

-----



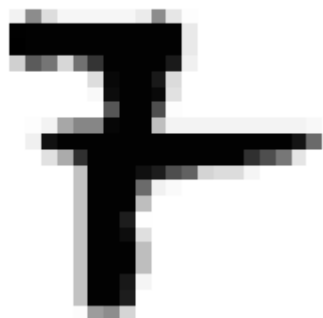
Actual class: 2  
Predicted class: 7

-----



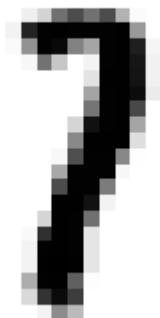
Actual class: 3  
Predicted class: 5

-----



Actual class: 7  
Predicted class: 1

-----



Actual class: 7  
Predicted class: 1

-----



Actual class: 7  
Predicted class: 4

-----



Actual class: 2  
Predicted class: 9

## PART 2 - Convolutional neural network (CNN) architecture

```
In [25]: model_cnn = keras.Sequential(  
    [  
        keras.layers.InputLayer(input_shape),  
        layers.Conv2D(32, kernel_size=(3, 3), activation="relu"),  
        layers.MaxPooling2D(pool_size=(2, 2)),  
        layers.Conv2D(64, kernel_size=(3, 3), activation="relu"),  
        layers.MaxPooling2D(pool_size=(2, 2)),  
        layers.Flatten(),  
        layers.Dropout(0.5),  
        layers.Dense(num_classes, activation="softmax"),  
    ]  
)  
  
model_cnn.summary()
```

Model: "sequential\_1"

| Layer (type)                   | Output Shape       | Param # |
|--------------------------------|--------------------|---------|
| =====                          |                    |         |
| conv2d (Conv2D)                | (None, 26, 26, 32) | 320     |
| max_pooling2d (MaxPooling2D)   | (None, 13, 13, 32) | 0       |
| conv2d_1 (Conv2D)              | (None, 11, 11, 64) | 18496   |
| max_pooling2d_1 (MaxPooling2D) | (None, 5, 5, 64)   | 0       |
| flatten (Flatten)              | (None, 1600)       | 0       |
| dropout (Dropout)              | (None, 1600)       | 0       |
| dense_2 (Dense)                | (None, 10)         | 16010   |
| =====                          |                    |         |

Total params: 34,826  
Trainable params: 34,826  
Non-trainable params: 0

---

## Configure model

```
In [26]: model_cnn.compile(  
        loss="categorical_crossentropy",  
        optimizer="adam",  
        metrics=["accuracy"]  
    )
```

## Prepare the data

The CNN does not expect the images to be flattened.

```
In [27]: # Reload the data, just in case  
(X_train, y_train), (X_valid, y_valid) = mnist.load_data()  
  
# convert class vectors to binary class matrices  
y_training = keras.utils.to_categorical(y_train, num_classes)  
y_validation = keras.utils.to_categorical(y_valid, num_classes)  
  
# Scale images to the [0, 1] range  
X_train_cnn = X_train.astype("float32") / 255  
X_valid_cnn = X_valid.astype("float32") / 255  
  
# Redefine dimension of train/test inputs  
X_train_cnn = np.expand_dims(X_train_cnn, -1)  
X_valid_cnn = np.expand_dims(X_valid_cnn, -1)  
  
# Make sure images have shape (28, 28, 1)  
print("x_train shape:", X_train_cnn.shape)  
print(X_train_cnn.shape[0], "train samples")  
print(X_valid_cnn.shape[0], "test samples")
```

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

## Train!

```
In [28]: batch_size=128  
epochs=15  
  
history = model_cnn.fit(  
    X_train_cnn, # training data  
    y_training, # training targets  
    epochs=epochs,  
    batch_size=batch_size,  
    verbose=1,  
    validation_data=(X_valid_cnn, y_validation)  
)
```

```

Epoch 1/15
469/469 [=====] - 12s 6ms/step - loss: 0.3363 - accuracy: 0.899
0 - val_loss: 0.0794 - val_accuracy: 0.9763
Epoch 2/15
469/469 [=====] - 3s 5ms/step - loss: 0.1018 - accuracy: 0.9691
- val_loss: 0.0521 - val_accuracy: 0.9846
Epoch 3/15
469/469 [=====] - 2s 5ms/step - loss: 0.0755 - accuracy: 0.9767
- val_loss: 0.0430 - val_accuracy: 0.9864
Epoch 4/15
469/469 [=====] - 2s 5ms/step - loss: 0.0639 - accuracy: 0.9807
- val_loss: 0.0381 - val_accuracy: 0.9866
Epoch 5/15
469/469 [=====] - 2s 5ms/step - loss: 0.0567 - accuracy: 0.9824
- val_loss: 0.0333 - val_accuracy: 0.9886
Epoch 6/15
469/469 [=====] - 2s 5ms/step - loss: 0.0521 - accuracy: 0.9837
- val_loss: 0.0304 - val_accuracy: 0.9898
Epoch 7/15
469/469 [=====] - 3s 5ms/step - loss: 0.0465 - accuracy: 0.9850
- val_loss: 0.0280 - val_accuracy: 0.9905
Epoch 8/15
469/469 [=====] - 3s 5ms/step - loss: 0.0440 - accuracy: 0.9862
- val_loss: 0.0256 - val_accuracy: 0.9912
Epoch 9/15
469/469 [=====] - 3s 6ms/step - loss: 0.0414 - accuracy: 0.9868
- val_loss: 0.0253 - val_accuracy: 0.9911
Epoch 10/15
469/469 [=====] - 2s 5ms/step - loss: 0.0381 - accuracy: 0.9883
- val_loss: 0.0237 - val_accuracy: 0.9919
Epoch 11/15
469/469 [=====] - 2s 5ms/step - loss: 0.0365 - accuracy: 0.9882
- val_loss: 0.0252 - val_accuracy: 0.9910
Epoch 12/15
469/469 [=====] - 3s 5ms/step - loss: 0.0345 - accuracy: 0.9894
- val_loss: 0.0250 - val_accuracy: 0.9916
Epoch 13/15
469/469 [=====] - 3s 6ms/step - loss: 0.0343 - accuracy: 0.9892
- val_loss: 0.0239 - val_accuracy: 0.9918
Epoch 14/15
469/469 [=====] - 3s 5ms/step - loss: 0.0323 - accuracy: 0.9898
- val_loss: 0.0223 - val_accuracy: 0.9925
Epoch 15/15
469/469 [=====] - 2s 5ms/step - loss: 0.0292 - accuracy: 0.9905
- val_loss: 0.0224 - val_accuracy: 0.9928

```

## Plot learning curves

In [29]:

```

# list all data in history
print(history.history.keys())

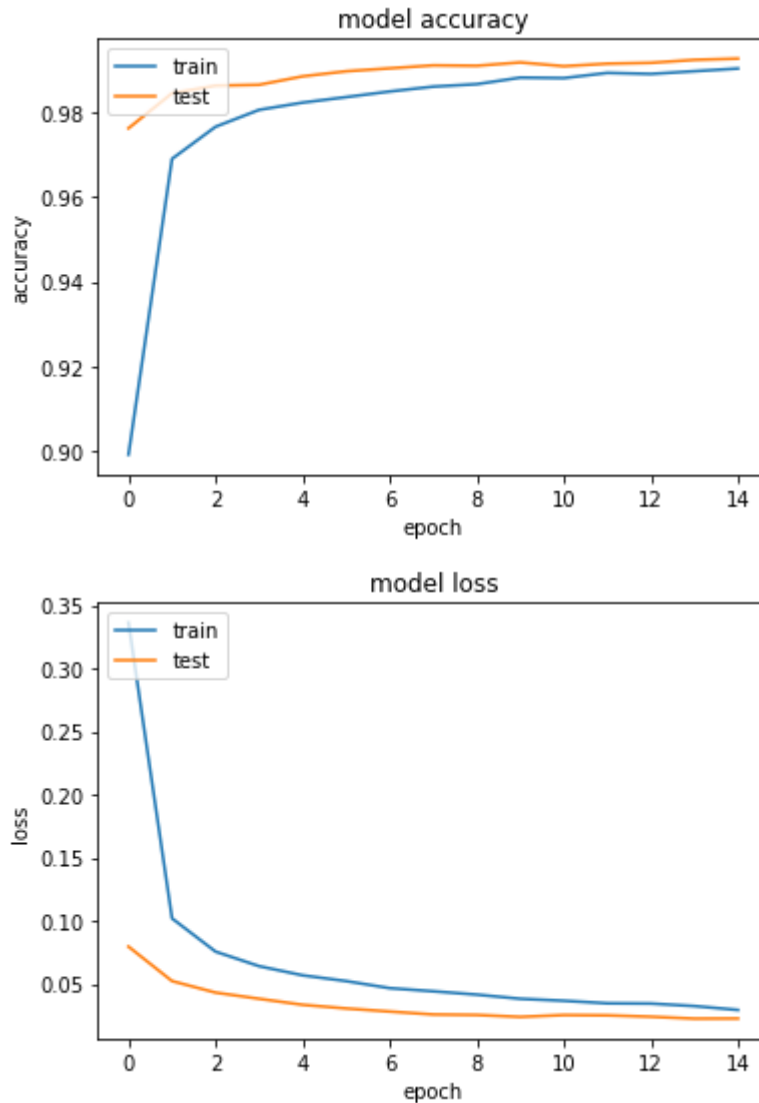
# summarize history for accuracy
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()

```



```
# summarize history for loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```

```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```



## Evaluate the model

```
In [30]: model_cnn.evaluate(X_valid_cnn, y_validation)
```

```
313/313 [=====] - 1s 3ms/step - loss: 0.0224 - accuracy: 0.9928
Out[30]: [0.022425470873713493, 0.9927999973297119]
```

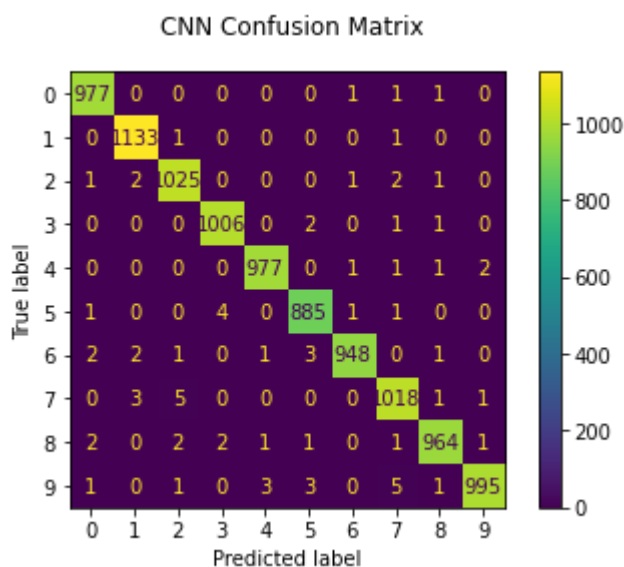
## Confusion Matrix

The following confusion matrix shows the mistakes that the model made. It can clearly be seen that the CNN performed significantly better than the shallow neural network because less data was classified incorrectly as shown by the numbers in the purple squares. Additionally, it can be seen that when the model did make mistakes, it often made mistakes between similar digits such as a 6 and a 5. This suggests that the mistakes that the model makes occur when the data contains ambiguity.

```
In [31]: cnn_prediction = model_cnn.predict(X_valid_cnn)
cnn_prediction_classes = np.argmax(cnn_prediction, axis=1)

disp = metrics.ConfusionMatrixDisplay.from_predictions(y_valid, cnn_prediction_classes)
disp.figure_.suptitle("CNN Confusion Matrix")

plt.show()
```



## Mistakes

The following ten examples display mistakes that the classifier made. As you can see, many of these digits had elements of ambiguity to them that made it difficult for even a person to distinguish them between two similar digits. However, a few examples were still incorrectly classified despite the true classification being clear.

```
In [32]: wrong = []
for i in range(len(cnn_prediction_classes)):
    if cnn_prediction_classes[i] != y_valid[i]:
        wrong.append(i)

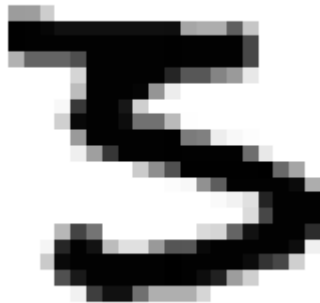
print("Number of mistakes made: " + str(len(wrong)))

for i in range(10):
    print("-----")
    plt.imshow(X_valid[wrong[i]], cmap='Greys')
    plt.axis('off')
    plt.show()
```

```
print("Actual class: " + str(y_valid[wrong[i]]))
print("Predicted class: " + str(cnn_prediction_classes[wrong[i]]))
print("-----")
```

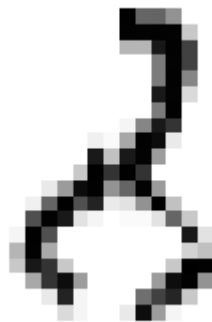
Number of mistakes made: 72

-----



Actual class: 3  
Predicted class: 5

-----



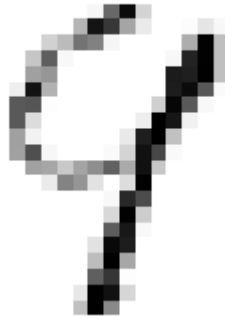
Actual class: 8  
Predicted class: 2

-----



Actual class: 2  
Predicted class: 1

-----



Actual class: 9  
Predicted class: 7

-----



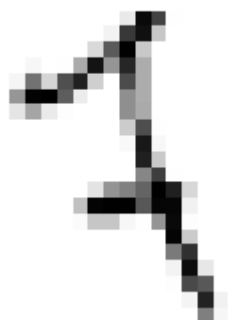
Actual class: 8  
Predicted class: 9

-----



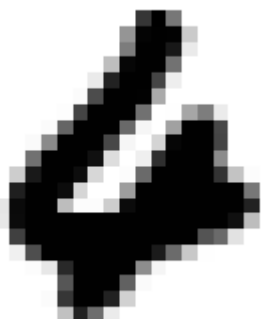
Actual class: 6  
Predicted class: 5

-----



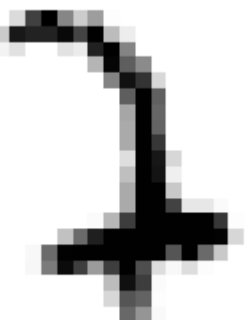
Actual class: 7  
Predicted class: 1

-----



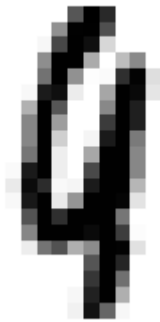
Actual class: 4  
Predicted class: 6

-----



Actual class: 7  
Predicted class: 2

-----



Actual class: 9  
Predicted class: 4

-----

## Question 4

**How do the accuracy and loss compare to the previous model? What can you infer from this comparison?**

---

The accuracy is around 9% greater in the CNN than in the original shallow neural network while the loss values are similar. Additionally, the confusion matrices show that the CNN was significantly more accurate and more often made mistakes between similar digits when compared to the original shallow neural network. The loss value tells us how significant the errors that the neural network made were and the accuracy tells us how many data points were incorrectly classified when the probabilities are converted to discrete predictions. The accuracy is a more useful metric to compare the two classifiers because it is a measure of how useful the model is. A highly accurate model is more useful in classifying data than one with low accuracy because more data points will be correctly classified. Based on the comparison, it can be inferred that the CNN is a better model to classify the MNIST dataset because it was significantly more accurate in classifying the data. The CNN's more complex architecture is better for this classification task than the simpler neural networks architecture. Moreover, the CNN took less time to train and needed fewer epochs than the shallow neural network.

## Discussions and Conclusions

Overall, this assignment introduced Keras by creating a classifier for the MNIST dataset. The two classifiers that were created clearly showed that the simple neural network performed significantly worse at correctly classifying the data compared to the CNN. Through the visualization of the results by using a confusion matrix it also became apparent that the CNN made fewer mistakes and the mistakes that it did make were often between similar digits. Furthermore, the shallow neural network made mistakes in a more random way. This was further supported by viewing a few examples of the mistakes that the classifiers made. The CNN's mistakes were made with data that contained greater ambiguity when compared with the shallow neural network's mistakes. Finally, the shallow neural network took a much longer time to train and had more epochs than the CNN

despite the CNN's superior performance. This suggests that the architecture of the neural network is more important than the number of training iterations.

This project demonstrated the steps involved in creating a classifier from a dataset. The data and labels needed to be prepared in a way that the classifier could use, then the model's architecture needed to be defined and configured. The model was then trained using the training data. Finally, the progress and results of the model were viewed using learning curves and confusion matrixes. The different parameters and steps that this project involved helped me understand what creating and evaluating a deep learning model entails and what the Keras workflow looks like. I now have a greater understanding of how deep learning models are created and how they work. The next steps to increase my level of understanding and proficiency in using Keras for deep learning would be to explore the different types of neural networks and their applications.