

# Captcha Recognition

## Import Libraries

```
[149]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.image as img
import tensorflow as tf
import keras as k
import os
import cv2
import pickle
from keras.utils import to_categorical
from PIL import Image
from keras.preprocessing.image import img_to_array, ImageDataGenerator
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
from sklearn.model_selection import train_test_split
from keras.models import Sequential
from keras.layers import Activation, MaxPooling2D, Flatten, Conv2D, Dropout, Dense
from keras.callbacks import EarlyStopping
import warnings
warnings.filterwarnings('ignore')
```

## Loading and Preprocessing Data

```
[150]: # Directory containing the images
directory = '/content/drive/MyDrive/CAPTCHA/samples'
```

```
[151]: sample = []

for filename in os.listdir(directory):
    image_path = os.path.join(directory, filename)
    img = Image.open(image_path)
    sample.append((filename, img))
```

```
[152]: sample_images = sample[:4]

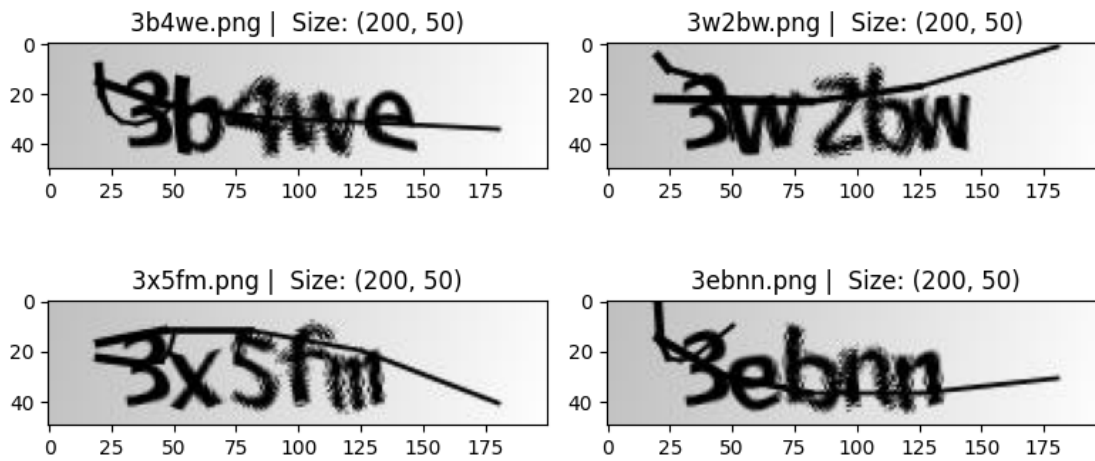
fig, axes = plt.subplots(2, 2, figsize=(8, 4))
```

```

for i in range(len(sample_images)):
    row = i // 2
    col = i % 2
    filename, img = sample_images[i]
    axes[row, col].imshow(img)
    axes[row, col].set_title(f'{filename} | Size: {img.size}')
    axes[row, col].axis()

plt.tight_layout()
plt.show()

```



```

[153]: unique_characters = set()
max_length = 0
total_samples = 0

for filename in os.listdir(directory):
    # Extract characters from the filename
    characters = os.path.splitext(filename)[0]
    # Update unique characters
    unique_characters.update(set(characters))
    # Update maximum length
    max_length = max(max_length, len(characters))
    # Update total samples
    total_samples += 1

characters_present = sorted(list(unique_characters))

print("Number of unique characters in the whole dataset:", len(unique_characters))
print("Maximum length of any captcha:", max_length)
print("Characters present:", characters_present)

```

```
print("Total number of samples in the dataset:", total_samples)
```

Number of unique characters in the whole dataset: 19

Maximum length of any captcha: 5

Characters present: ['2', '3', '4', '5', '6', '7', '8', 'b', 'c', 'd', 'e', 'f', 'g', 'm', 'n', 'p', 'w', 'x', 'y']

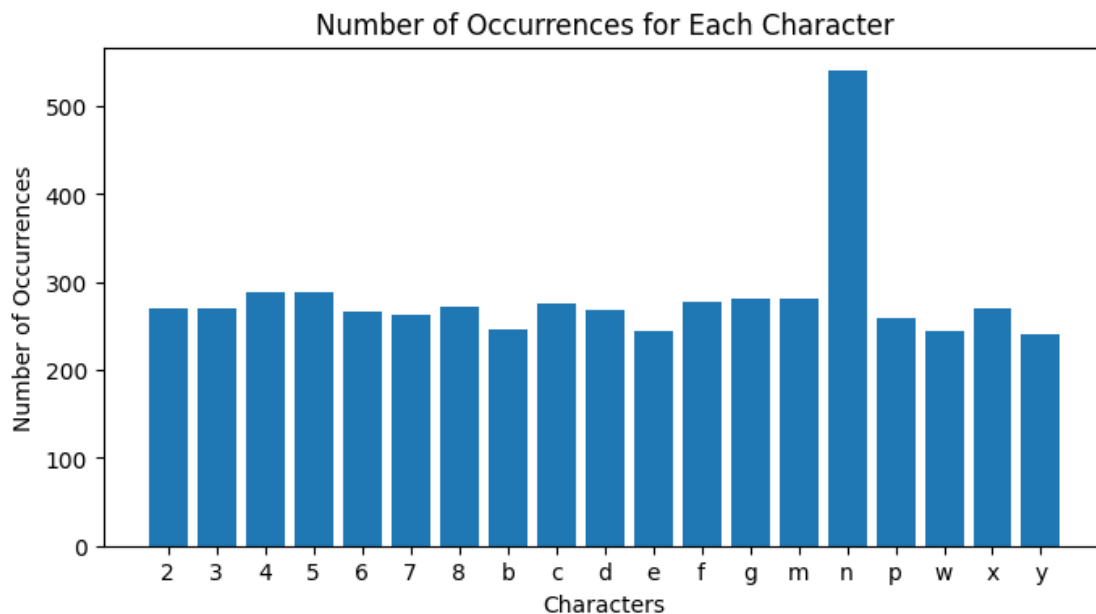
Total number of samples in the dataset: 1070

```
[154]: character_counts = {}

for filename in os.listdir(directory):
    # Extract characters from the filename
    characters = os.path.splitext(filename)[0]
    # Update character counts
    for char in characters:
        character_counts[char] = character_counts.get(char, 0) + 1

characters_present = sorted(character_counts.keys())
counts = [character_counts[char] for char in characters_present]

plt.figure(figsize=(8, 4))
plt.bar(characters_present, counts)
plt.xlabel('Characters')
plt.ylabel('Number of Occurrences')
plt.title('Number of Occurrences for Each Character')
plt.show()
```



## Preprocessing Data

```
[155]: def load_data(data_dir):
        images = []
        labels = []
        for img_name in os.listdir(data_dir):
            img_path = os.path.join(data_dir, img_name)
            label = os.path.splitext(img_name)[0]

            image = cv2.imread(img_path, cv2.IMREAD_GRAYSCALE) # Read image in
            ↪ grayscale
            image = cv2.adaptiveThreshold(image, 255, cv2.
            ↪ ADAPTIVE_THRESH_GAUSSIAN_C, cv2.THRESH_BINARY, 145, 0)
            kernel_close = np.ones((5, 5), np.uint8)
            image = cv2.morphologyEx(image, cv2.MORPH_CLOSE, kernel_close)
            kernel_dilate = np.ones((2, 2), np.uint8)
            image = cv2.dilate(image, kernel_dilate, iterations=1)
            image = cv2.GaussianBlur(image, (5, 5), 0)

            # Split the image into segments
            segments = [image[10:50, 30:50], image[10:50, 50:70],
                        ↪ image[10:50, 70:90], image[10:50, 90:110], image[10:50, 110:
            ↪ 130]]

            for segment, letter in zip(segments, label):
                images.append(segment)
                labels.append(letter)

        return np.array(images), np.array(labels)
```

```
[156]: images, labels = load_data(directory)
```

```
[157]: images=images.astype('float32')
        images/=255
```

```
[158]: labels_le = LabelEncoder().fit_transform(labels)
        labels_ohe = OneHotEncoder(sparse = False).fit_transform(labels_le.
        ↪ reshape(len(labels_le),1))
```

```
[159]: X_train, X_test, y_train, y_test = train_test_split(images, labels_ohe,
        ↪ test_size = 0.2, random_state = 42)
```

```
[160]: row, col = images.shape[1],images.shape[2]
        categories = labels_ohe.shape[1]
        info = {labels_le[i] : labels[i] for i in range(len(labels))}
```

## Training the Model

```
[161]: model = Sequential()

model.add(Conv2D(filters=16, kernel_size=(3,3), padding='same',
    ↪input_shape=(row, col, 1)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2,2)))

model.add(Conv2D(filters=16, kernel_size=(3,3), padding='same'))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2,2)))

model.add(Conv2D(filters=32, kernel_size=(3,3), padding='same'))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2,2)))

model.add(Conv2D(filters=32, kernel_size=(3,3), padding='same'))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2,2)))

model.add(Flatten())
model.add(Dropout(0.4))
model.add(Dense(1500))
model.add(Activation('relu'))
model.add(Dropout(0.2))
model.add(Dense(categories))
model.add(Activation("softmax"))

model.compile(loss='categorical_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
```

```
[162]: model.summary()
```

Model: "sequential\_6"

| Layer (type)                    | Output Shape       | Param # |
|---------------------------------|--------------------|---------|
| conv2d_24 (Conv2D)              | (None, 40, 20, 16) | 160     |
| activation_18 (Activation)      | (None, 40, 20, 16) | 0       |
| max_pooling2d_24 (MaxPooling2D) | (None, 20, 10, 16) | 0       |
| conv2d_25 (Conv2D)              | (None, 20, 10, 16) | 2320    |
| activation_19 (Activation)      | (None, 20, 10, 16) | 0       |

|                                     |                   |       |
|-------------------------------------|-------------------|-------|
| max_pooling2d_25 (MaxPooli<br>ng2D) | (None, 10, 5, 16) | 0     |
| conv2d_26 (Conv2D)                  | (None, 10, 5, 32) | 4640  |
| activation_20 (Activation)          | (None, 10, 5, 32) | 0     |
| max_pooling2d_26 (MaxPooli<br>ng2D) | (None, 5, 2, 32)  | 0     |
| conv2d_27 (Conv2D)                  | (None, 5, 2, 32)  | 9248  |
| activation_21 (Activation)          | (None, 5, 2, 32)  | 0     |
| max_pooling2d_27 (MaxPooli<br>ng2D) | (None, 2, 1, 32)  | 0     |
| flatten_6 (Flatten)                 | (None, 64)        | 0     |
| dropout_12 (Dropout)                | (None, 64)        | 0     |
| dense_12 (Dense)                    | (None, 1500)      | 97500 |
| activation_22 (Activation)          | (None, 1500)      | 0     |
| dropout_13 (Dropout)                | (None, 1500)      | 0     |
| dense_13 (Dense)                    | (None, 19)        | 28519 |
| activation_23 (Activation)          | (None, 19)        | 0     |

```
=====
Total params: 142387 (556.20 KB)
Trainable params: 142387 (556.20 KB)
Non-trainable params: 0 (0.00 Byte)
```

```
[163]: batch_size = 150
epochs = 200

history = model.fit(X_train, y_train,
                    batch_size=batch_size,
                    epochs=epochs,
                    validation_data=(X_test, y_test),
                    shuffle=True)
```

Epoch 1/200

29/29 [=====] - 6s 150ms/step - loss: 2.9157 - accuracy: 0.1009 - val\_loss: 2.8505 - val\_accuracy: 0.0935  
Epoch 2/200  
29/29 [=====] - 2s 83ms/step - loss: 2.4981 - accuracy: 0.2243 - val\_loss: 1.9184 - val\_accuracy: 0.4477  
Epoch 3/200  
29/29 [=====] - 2s 77ms/step - loss: 1.7756 - accuracy: 0.4769 - val\_loss: 1.3503 - val\_accuracy: 0.6308  
Epoch 4/200  
29/29 [=====] - 2s 81ms/step - loss: 1.4178 - accuracy: 0.5871 - val\_loss: 1.1295 - val\_accuracy: 0.6710  
Epoch 5/200  
29/29 [=====] - 2s 82ms/step - loss: 1.2439 - accuracy: 0.6357 - val\_loss: 0.9850 - val\_accuracy: 0.7168  
Epoch 6/200  
29/29 [=====] - 4s 131ms/step - loss: 1.1345 - accuracy: 0.6804 - val\_loss: 0.8832 - val\_accuracy: 0.7514  
Epoch 7/200  
29/29 [=====] - 3s 110ms/step - loss: 1.0300 - accuracy: 0.7072 - val\_loss: 0.8165 - val\_accuracy: 0.7523  
Epoch 8/200  
29/29 [=====] - 2s 76ms/step - loss: 0.9441 - accuracy: 0.7273 - val\_loss: 0.7942 - val\_accuracy: 0.7692  
Epoch 9/200  
29/29 [=====] - 2s 83ms/step - loss: 0.8823 - accuracy: 0.7449 - val\_loss: 0.7092 - val\_accuracy: 0.7869  
Epoch 10/200  
29/29 [=====] - 2s 76ms/step - loss: 0.8450 - accuracy: 0.7528 - val\_loss: 0.6774 - val\_accuracy: 0.7944  
Epoch 11/200  
29/29 [=====] - 3s 90ms/step - loss: 0.7932 - accuracy: 0.7785 - val\_loss: 0.6366 - val\_accuracy: 0.8178  
Epoch 12/200  
29/29 [=====] - 4s 138ms/step - loss: 0.7485 - accuracy: 0.7792 - val\_loss: 0.6026 - val\_accuracy: 0.8224  
Epoch 13/200  
29/29 [=====] - 2s 83ms/step - loss: 0.7059 - accuracy: 0.7991 - val\_loss: 0.6002 - val\_accuracy: 0.8215  
Epoch 14/200  
29/29 [=====] - 2s 77ms/step - loss: 0.7090 - accuracy: 0.7867 - val\_loss: 0.5964 - val\_accuracy: 0.8215  
Epoch 15/200  
29/29 [=====] - 2s 79ms/step - loss: 0.6701 - accuracy: 0.8065 - val\_loss: 0.5793 - val\_accuracy: 0.8355  
Epoch 16/200  
29/29 [=====] - 2s 83ms/step - loss: 0.6395 - accuracy: 0.8096 - val\_loss: 0.5635 - val\_accuracy: 0.8411  
Epoch 17/200

29/29 [=====] - 3s 109ms/step - loss: 0.6174 - accuracy: 0.8147 - val\_loss: 0.5546 - val\_accuracy: 0.8364  
Epoch 18/200  
29/29 [=====] - 4s 130ms/step - loss: 0.6110 - accuracy: 0.8192 - val\_loss: 0.5267 - val\_accuracy: 0.8495  
Epoch 19/200  
29/29 [=====] - 2s 76ms/step - loss: 0.5714 - accuracy: 0.8273 - val\_loss: 0.5171 - val\_accuracy: 0.8467  
Epoch 20/200  
29/29 [=====] - 2s 82ms/step - loss: 0.5685 - accuracy: 0.8315 - val\_loss: 0.5217 - val\_accuracy: 0.8477  
Epoch 21/200  
29/29 [=====] - 2s 77ms/step - loss: 0.5585 - accuracy: 0.8280 - val\_loss: 0.5123 - val\_accuracy: 0.8486  
Epoch 22/200  
29/29 [=====] - 2s 83ms/step - loss: 0.5330 - accuracy: 0.8350 - val\_loss: 0.5236 - val\_accuracy: 0.8533  
Epoch 23/200  
29/29 [=====] - 4s 125ms/step - loss: 0.5363 - accuracy: 0.8357 - val\_loss: 0.5094 - val\_accuracy: 0.8570  
Epoch 24/200  
29/29 [=====] - 3s 112ms/step - loss: 0.5052 - accuracy: 0.8435 - val\_loss: 0.4971 - val\_accuracy: 0.8626  
Epoch 25/200  
29/29 [=====] - 2s 81ms/step - loss: 0.4823 - accuracy: 0.8500 - val\_loss: 0.4710 - val\_accuracy: 0.8626  
Epoch 26/200  
29/29 [=====] - 2s 76ms/step - loss: 0.4716 - accuracy: 0.8521 - val\_loss: 0.4810 - val\_accuracy: 0.8607  
Epoch 27/200  
29/29 [=====] - 2s 78ms/step - loss: 0.4806 - accuracy: 0.8470 - val\_loss: 0.4812 - val\_accuracy: 0.8710  
Epoch 28/200  
29/29 [=====] - 2s 77ms/step - loss: 0.4813 - accuracy: 0.8491 - val\_loss: 0.5058 - val\_accuracy: 0.8617  
Epoch 29/200  
29/29 [=====] - 4s 135ms/step - loss: 0.4719 - accuracy: 0.8509 - val\_loss: 0.4823 - val\_accuracy: 0.8664  
Epoch 30/200  
29/29 [=====] - 3s 97ms/step - loss: 0.4459 - accuracy: 0.8565 - val\_loss: 0.4743 - val\_accuracy: 0.8617  
Epoch 31/200  
29/29 [=====] - 2s 77ms/step - loss: 0.4496 - accuracy: 0.8556 - val\_loss: 0.4952 - val\_accuracy: 0.8692  
Epoch 32/200  
29/29 [=====] - 2s 77ms/step - loss: 0.4420 - accuracy: 0.8572 - val\_loss: 0.4874 - val\_accuracy: 0.8673  
Epoch 33/200



29/29 [=====] - 2s 77ms/step - loss: 0.4241 - accuracy: 0.8626 - val\_loss: 0.4861 - val\_accuracy: 0.8636  
Epoch 34/200  
29/29 [=====] - 3s 99ms/step - loss: 0.4149 - accuracy: 0.8664 - val\_loss: 0.5280 - val\_accuracy: 0.8673  
Epoch 35/200  
29/29 [=====] - 4s 139ms/step - loss: 0.4317 - accuracy: 0.8551 - val\_loss: 0.4878 - val\_accuracy: 0.8589  
Epoch 36/200  
29/29 [=====] - 2s 78ms/step - loss: 0.4007 - accuracy: 0.8706 - val\_loss: 0.4760 - val\_accuracy: 0.8701  
Epoch 37/200  
29/29 [=====] - 2s 82ms/step - loss: 0.4037 - accuracy: 0.8664 - val\_loss: 0.4793 - val\_accuracy: 0.8673  
Epoch 38/200  
29/29 [=====] - 2s 79ms/step - loss: 0.3899 - accuracy: 0.8717 - val\_loss: 0.4723 - val\_accuracy: 0.8720  
Epoch 39/200  
29/29 [=====] - 2s 83ms/step - loss: 0.3950 - accuracy: 0.8701 - val\_loss: 0.4980 - val\_accuracy: 0.8673  
Epoch 40/200  
29/29 [=====] - 3s 120ms/step - loss: 0.3959 - accuracy: 0.8701 - val\_loss: 0.4768 - val\_accuracy: 0.8682  
Epoch 41/200  
29/29 [=====] - 3s 112ms/step - loss: 0.3881 - accuracy: 0.8745 - val\_loss: 0.4916 - val\_accuracy: 0.8682  
Epoch 42/200  
29/29 [=====] - 2s 82ms/step - loss: 0.3789 - accuracy: 0.8762 - val\_loss: 0.5065 - val\_accuracy: 0.8664  
Epoch 43/200  
29/29 [=====] - 2s 84ms/step - loss: 0.3683 - accuracy: 0.8780 - val\_loss: 0.5140 - val\_accuracy: 0.8673  
Epoch 44/200  
29/29 [=====] - 2s 78ms/step - loss: 0.3535 - accuracy: 0.8853 - val\_loss: 0.4890 - val\_accuracy: 0.8729  
Epoch 45/200  
29/29 [=====] - 2s 84ms/step - loss: 0.3468 - accuracy: 0.8804 - val\_loss: 0.4750 - val\_accuracy: 0.8692  
Epoch 46/200  
29/29 [=====] - 4s 140ms/step - loss: 0.3347 - accuracy: 0.8813 - val\_loss: 0.4930 - val\_accuracy: 0.8701  
Epoch 47/200  
29/29 [=====] - 3s 85ms/step - loss: 0.3625 - accuracy: 0.8769 - val\_loss: 0.4972 - val\_accuracy: 0.8645  
Epoch 48/200  
29/29 [=====] - 2s 77ms/step - loss: 0.3511 - accuracy: 0.8778 - val\_loss: 0.5039 - val\_accuracy: 0.8738  
Epoch 49/200

29/29 [=====] - 2s 77ms/step - loss: 0.3502 - accuracy: 0.8797 - val\_loss: 0.4672 - val\_accuracy: 0.8776  
Epoch 50/200  
29/29 [=====] - 2s 78ms/step - loss: 0.3402 - accuracy: 0.8839 - val\_loss: 0.5086 - val\_accuracy: 0.8692  
Epoch 51/200  
29/29 [=====] - 3s 100ms/step - loss: 0.3368 - accuracy: 0.8815 - val\_loss: 0.5172 - val\_accuracy: 0.8682  
Epoch 52/200  
29/29 [=====] - 4s 142ms/step - loss: 0.3223 - accuracy: 0.8893 - val\_loss: 0.4881 - val\_accuracy: 0.8748  
Epoch 53/200  
29/29 [=====] - 2s 76ms/step - loss: 0.3125 - accuracy: 0.8916 - val\_loss: 0.4994 - val\_accuracy: 0.8701  
Epoch 54/200  
29/29 [=====] - 2s 79ms/step - loss: 0.3155 - accuracy: 0.8928 - val\_loss: 0.4950 - val\_accuracy: 0.8692  
Epoch 55/200  
29/29 [=====] - 2s 82ms/step - loss: 0.2991 - accuracy: 0.8986 - val\_loss: 0.5201 - val\_accuracy: 0.8682  
Epoch 56/200  
29/29 [=====] - 2s 79ms/step - loss: 0.3081 - accuracy: 0.8963 - val\_loss: 0.5063 - val\_accuracy: 0.8729  
Epoch 57/200  
29/29 [=====] - 3s 122ms/step - loss: 0.3007 - accuracy: 0.8951 - val\_loss: 0.4988 - val\_accuracy: 0.8748  
Epoch 58/200  
29/29 [=====] - 3s 117ms/step - loss: 0.3108 - accuracy: 0.8916 - val\_loss: 0.5278 - val\_accuracy: 0.8748  
Epoch 59/200  
29/29 [=====] - 2s 79ms/step - loss: 0.3048 - accuracy: 0.8930 - val\_loss: 0.5010 - val\_accuracy: 0.8757  
Epoch 60/200  
29/29 [=====] - 2s 84ms/step - loss: 0.3000 - accuracy: 0.8923 - val\_loss: 0.5176 - val\_accuracy: 0.8785  
Epoch 61/200  
29/29 [=====] - 2s 84ms/step - loss: 0.2987 - accuracy: 0.8958 - val\_loss: 0.5127 - val\_accuracy: 0.8794  
Epoch 62/200  
29/29 [=====] - 2s 85ms/step - loss: 0.3025 - accuracy: 0.8942 - val\_loss: 0.5046 - val\_accuracy: 0.8776  
Epoch 63/200  
29/29 [=====] - 4s 137ms/step - loss: 0.2935 - accuracy: 0.8958 - val\_loss: 0.5473 - val\_accuracy: 0.8692  
Epoch 64/200  
29/29 [=====] - 3s 92ms/step - loss: 0.3031 - accuracy: 0.8986 - val\_loss: 0.5168 - val\_accuracy: 0.8701  
Epoch 65/200

29/29 [=====] - 2s 79ms/step - loss: 0.3088 - accuracy: 0.8911 - val\_loss: 0.5113 - val\_accuracy: 0.8748  
Epoch 66/200  
29/29 [=====] - 2s 76ms/step - loss: 0.2809 - accuracy: 0.9014 - val\_loss: 0.5114 - val\_accuracy: 0.8766  
Epoch 67/200  
29/29 [=====] - 2s 85ms/step - loss: 0.2766 - accuracy: 0.9033 - val\_loss: 0.5454 - val\_accuracy: 0.8720  
Epoch 68/200  
29/29 [=====] - 3s 109ms/step - loss: 0.2850 - accuracy: 0.9007 - val\_loss: 0.4976 - val\_accuracy: 0.8794  
Epoch 69/200  
29/29 [=====] - 4s 132ms/step - loss: 0.2683 - accuracy: 0.9035 - val\_loss: 0.5081 - val\_accuracy: 0.8794  
Epoch 70/200  
29/29 [=====] - 2s 82ms/step - loss: 0.2695 - accuracy: 0.9096 - val\_loss: 0.5190 - val\_accuracy: 0.8710  
Epoch 71/200  
29/29 [=====] - 2s 84ms/step - loss: 0.2795 - accuracy: 0.9033 - val\_loss: 0.5214 - val\_accuracy: 0.8710  
Epoch 72/200  
29/29 [=====] - 2s 87ms/step - loss: 0.2629 - accuracy: 0.9079 - val\_loss: 0.5050 - val\_accuracy: 0.8729  
Epoch 73/200  
29/29 [=====] - 2s 83ms/step - loss: 0.2647 - accuracy: 0.9091 - val\_loss: 0.5151 - val\_accuracy: 0.8860  
Epoch 74/200  
29/29 [=====] - 4s 134ms/step - loss: 0.2699 - accuracy: 0.9035 - val\_loss: 0.5510 - val\_accuracy: 0.8776  
Epoch 75/200  
29/29 [=====] - 3s 92ms/step - loss: 0.2772 - accuracy: 0.9068 - val\_loss: 0.5307 - val\_accuracy: 0.8766  
Epoch 76/200  
29/29 [=====] - 2s 78ms/step - loss: 0.2712 - accuracy: 0.9051 - val\_loss: 0.5259 - val\_accuracy: 0.8757  
Epoch 77/200  
29/29 [=====] - 2s 84ms/step - loss: 0.2456 - accuracy: 0.9105 - val\_loss: 0.5387 - val\_accuracy: 0.8794  
Epoch 78/200  
29/29 [=====] - 2s 77ms/step - loss: 0.2508 - accuracy: 0.9084 - val\_loss: 0.5531 - val\_accuracy: 0.8785  
Epoch 79/200  
29/29 [=====] - 3s 100ms/step - loss: 0.2378 - accuracy: 0.9164 - val\_loss: 0.5456 - val\_accuracy: 0.8776  
Epoch 80/200  
29/29 [=====] - 4s 141ms/step - loss: 0.2475 - accuracy: 0.9112 - val\_loss: 0.5471 - val\_accuracy: 0.8813  
Epoch 81/200

29/29 [=====] - 2s 83ms/step - loss: 0.2747 - accuracy:  
 0.9009 - val\_loss: 0.5597 - val\_accuracy: 0.8813  
 Epoch 82/200  
 29/29 [=====] - 2s 83ms/step - loss: 0.2484 - accuracy:  
 0.9121 - val\_loss: 0.5664 - val\_accuracy: 0.8813  
 Epoch 83/200  
 29/29 [=====] - 2s 82ms/step - loss: 0.2480 - accuracy:  
 0.9140 - val\_loss: 0.5723 - val\_accuracy: 0.8776  
 Epoch 84/200  
 29/29 [=====] - 2s 79ms/step - loss: 0.2391 - accuracy:  
 0.9171 - val\_loss: 0.5603 - val\_accuracy: 0.8804  
 Epoch 85/200  
 29/29 [=====] - 4s 127ms/step - loss: 0.2464 -  
 accuracy: 0.9119 - val\_loss: 0.5511 - val\_accuracy: 0.8804  
 Epoch 86/200  
 29/29 [=====] - 3s 110ms/step - loss: 0.2447 -  
 accuracy: 0.9161 - val\_loss: 0.5771 - val\_accuracy: 0.8794  
 Epoch 87/200  
 29/29 [=====] - 2s 82ms/step - loss: 0.2378 - accuracy:  
 0.9126 - val\_loss: 0.5743 - val\_accuracy: 0.8804  
 Epoch 88/200  
 29/29 [=====] - 2s 77ms/step - loss: 0.2478 - accuracy:  
 0.9114 - val\_loss: 0.5412 - val\_accuracy: 0.8804  
 Epoch 89/200  
 29/29 [=====] - 2s 85ms/step - loss: 0.2515 - accuracy:  
 0.9129 - val\_loss: 0.5584 - val\_accuracy: 0.8710  
 Epoch 90/200  
 29/29 [=====] - 2s 86ms/step - loss: 0.2381 - accuracy:  
 0.9143 - val\_loss: 0.5375 - val\_accuracy: 0.8804  
 Epoch 91/200  
 29/29 [=====] - 4s 137ms/step - loss: 0.2441 -  
 accuracy: 0.9114 - val\_loss: 0.5590 - val\_accuracy: 0.8785  
 Epoch 92/200  
 29/29 [=====] - 3s 89ms/step - loss: 0.2297 - accuracy:  
 0.9140 - val\_loss: 0.5852 - val\_accuracy: 0.8757  
 Epoch 93/200  
 29/29 [=====] - 2s 77ms/step - loss: 0.2262 - accuracy:  
 0.9185 - val\_loss: 0.5775 - val\_accuracy: 0.8804  
 Epoch 94/200  
 29/29 [=====] - 2s 78ms/step - loss: 0.2292 - accuracy:  
 0.9145 - val\_loss: 0.5640 - val\_accuracy: 0.8776  
 Epoch 95/200  
 29/29 [=====] - 2s 83ms/step - loss: 0.2371 - accuracy:  
 0.9124 - val\_loss: 0.5600 - val\_accuracy: 0.8776  
 Epoch 96/200  
 29/29 [=====] - 3s 112ms/step - loss: 0.2434 -  
 accuracy: 0.9112 - val\_loss: 0.5483 - val\_accuracy: 0.8785  
 Epoch 97/200

29/29 [=====] - 4s 128ms/step - loss: 0.2261 - accuracy: 0.9187 - val\_loss: 0.6144 - val\_accuracy: 0.8804  
Epoch 98/200  
29/29 [=====] - 2s 82ms/step - loss: 0.2271 - accuracy: 0.9187 - val\_loss: 0.5562 - val\_accuracy: 0.8804  
Epoch 99/200  
29/29 [=====] - 2s 78ms/step - loss: 0.2019 - accuracy: 0.9276 - val\_loss: 0.5885 - val\_accuracy: 0.8850  
Epoch 100/200  
29/29 [=====] - 2s 85ms/step - loss: 0.2164 - accuracy: 0.9220 - val\_loss: 0.5881 - val\_accuracy: 0.8766  
Epoch 101/200  
29/29 [=====] - 2s 80ms/step - loss: 0.2113 - accuracy: 0.9264 - val\_loss: 0.5932 - val\_accuracy: 0.8748  
Epoch 102/200  
29/29 [=====] - 4s 138ms/step - loss: 0.2037 - accuracy: 0.9255 - val\_loss: 0.6009 - val\_accuracy: 0.8841  
Epoch 103/200  
29/29 [=====] - 3s 104ms/step - loss: 0.2147 - accuracy: 0.9222 - val\_loss: 0.5962 - val\_accuracy: 0.8813  
Epoch 104/200  
29/29 [=====] - 2s 78ms/step - loss: 0.2091 - accuracy: 0.9245 - val\_loss: 0.6055 - val\_accuracy: 0.8813  
Epoch 105/200  
29/29 [=====] - 2s 83ms/step - loss: 0.2098 - accuracy: 0.9229 - val\_loss: 0.5675 - val\_accuracy: 0.8794  
Epoch 106/200  
29/29 [=====] - 2s 78ms/step - loss: 0.2352 - accuracy: 0.9159 - val\_loss: 0.6186 - val\_accuracy: 0.8804  
Epoch 107/200  
29/29 [=====] - 3s 92ms/step - loss: 0.2279 - accuracy: 0.9187 - val\_loss: 0.5702 - val\_accuracy: 0.8804  
Epoch 108/200  
29/29 [=====] - 4s 140ms/step - loss: 0.2247 - accuracy: 0.9175 - val\_loss: 0.5752 - val\_accuracy: 0.8785  
Epoch 109/200  
29/29 [=====] - 2s 81ms/step - loss: 0.2264 - accuracy: 0.9136 - val\_loss: 0.6045 - val\_accuracy: 0.8822  
Epoch 110/200  
29/29 [=====] - 2s 77ms/step - loss: 0.2044 - accuracy: 0.9243 - val\_loss: 0.6087 - val\_accuracy: 0.8738  
Epoch 111/200  
29/29 [=====] - 2s 80ms/step - loss: 0.1987 - accuracy: 0.9255 - val\_loss: 0.5911 - val\_accuracy: 0.8766  
Epoch 112/200  
29/29 [=====] - 2s 78ms/step - loss: 0.1966 - accuracy: 0.9292 - val\_loss: 0.6235 - val\_accuracy: 0.8850  
Epoch 113/200

29/29 [=====] - 3s 109ms/step - loss: 0.2004 -  
accuracy: 0.9294 - val\_loss: 0.6485 - val\_accuracy: 0.8832  
Epoch 114/200  
29/29 [=====] - 4s 124ms/step - loss: 0.1983 -  
accuracy: 0.9264 - val\_loss: 0.6055 - val\_accuracy: 0.8822  
Epoch 115/200  
29/29 [=====] - 2s 83ms/step - loss: 0.2034 - accuracy:  
0.9259 - val\_loss: 0.5973 - val\_accuracy: 0.8813  
Epoch 116/200  
29/29 [=====] - 3s 87ms/step - loss: 0.2077 - accuracy:  
0.9231 - val\_loss: 0.6366 - val\_accuracy: 0.8785  
Epoch 117/200  
29/29 [=====] - 2s 79ms/step - loss: 0.1990 - accuracy:  
0.9280 - val\_loss: 0.5812 - val\_accuracy: 0.8813  
Epoch 118/200  
29/29 [=====] - 2s 77ms/step - loss: 0.2069 - accuracy:  
0.9215 - val\_loss: 0.6163 - val\_accuracy: 0.8785  
Epoch 119/200  
29/29 [=====] - 4s 131ms/step - loss: 0.2124 -  
accuracy: 0.9217 - val\_loss: 0.5937 - val\_accuracy: 0.8804  
Epoch 120/200  
29/29 [=====] - 3s 100ms/step - loss: 0.2057 -  
accuracy: 0.9262 - val\_loss: 0.6263 - val\_accuracy: 0.8766  
Epoch 121/200  
29/29 [=====] - 2s 84ms/step - loss: 0.1949 - accuracy:  
0.9290 - val\_loss: 0.5900 - val\_accuracy: 0.8860  
Epoch 122/200  
29/29 [=====] - 2s 82ms/step - loss: 0.1927 - accuracy:  
0.9285 - val\_loss: 0.5645 - val\_accuracy: 0.8850  
Epoch 123/200  
29/29 [=====] - 2s 83ms/step - loss: 0.2020 - accuracy:  
0.9271 - val\_loss: 0.6094 - val\_accuracy: 0.8822  
Epoch 124/200  
29/29 [=====] - 3s 104ms/step - loss: 0.2017 -  
accuracy: 0.9280 - val\_loss: 0.6184 - val\_accuracy: 0.8776  
Epoch 125/200  
29/29 [=====] - 4s 139ms/step - loss: 0.1894 -  
accuracy: 0.9332 - val\_loss: 0.5911 - val\_accuracy: 0.8879  
Epoch 126/200  
29/29 [=====] - 2s 83ms/step - loss: 0.1952 - accuracy:  
0.9315 - val\_loss: 0.5970 - val\_accuracy: 0.8757  
Epoch 127/200  
29/29 [=====] - 2s 85ms/step - loss: 0.2119 - accuracy:  
0.9229 - val\_loss: 0.5665 - val\_accuracy: 0.8804  
Epoch 128/200  
29/29 [=====] - 2s 79ms/step - loss: 0.2048 - accuracy:  
0.9231 - val\_loss: 0.6208 - val\_accuracy: 0.8813  
Epoch 129/200

29/29 [=====] - 2s 77ms/step - loss: 0.1950 - accuracy: 0.9278 - val\_loss: 0.5850 - val\_accuracy: 0.8822  
Epoch 130/200  
29/29 [=====] - 4s 136ms/step - loss: 0.1919 - accuracy: 0.9290 - val\_loss: 0.5845 - val\_accuracy: 0.8841  
Epoch 131/200  
29/29 [=====] - 3s 106ms/step - loss: 0.1998 - accuracy: 0.9269 - val\_loss: 0.6086 - val\_accuracy: 0.8879  
Epoch 132/200  
29/29 [=====] - 2s 83ms/step - loss: 0.1832 - accuracy: 0.9364 - val\_loss: 0.5795 - val\_accuracy: 0.8822  
Epoch 133/200  
29/29 [=====] - 2s 83ms/step - loss: 0.1948 - accuracy: 0.9273 - val\_loss: 0.5850 - val\_accuracy: 0.8766  
Epoch 134/200  
29/29 [=====] - 2s 78ms/step - loss: 0.1851 - accuracy: 0.9332 - val\_loss: 0.6112 - val\_accuracy: 0.8860  
Epoch 135/200  
29/29 [=====] - 3s 96ms/step - loss: 0.1766 - accuracy: 0.9346 - val\_loss: 0.6588 - val\_accuracy: 0.8813  
Epoch 136/200  
29/29 [=====] - 4s 137ms/step - loss: 0.1797 - accuracy: 0.9334 - val\_loss: 0.5940 - val\_accuracy: 0.8766  
Epoch 137/200  
29/29 [=====] - 2s 82ms/step - loss: 0.1960 - accuracy: 0.9304 - val\_loss: 0.6072 - val\_accuracy: 0.8841  
Epoch 138/200  
29/29 [=====] - 2s 78ms/step - loss: 0.1902 - accuracy: 0.9322 - val\_loss: 0.6227 - val\_accuracy: 0.8785  
Epoch 139/200  
29/29 [=====] - 2s 84ms/step - loss: 0.1811 - accuracy: 0.9357 - val\_loss: 0.6252 - val\_accuracy: 0.8832  
Epoch 140/200  
29/29 [=====] - 2s 79ms/step - loss: 0.1756 - accuracy: 0.9325 - val\_loss: 0.6492 - val\_accuracy: 0.8813  
Epoch 141/200  
29/29 [=====] - 3s 115ms/step - loss: 0.1708 - accuracy: 0.9339 - val\_loss: 0.6425 - val\_accuracy: 0.8822  
Epoch 142/200  
29/29 [=====] - 3s 116ms/step - loss: 0.1679 - accuracy: 0.9393 - val\_loss: 0.6235 - val\_accuracy: 0.8860  
Epoch 143/200  
29/29 [=====] - 2s 77ms/step - loss: 0.1751 - accuracy: 0.9341 - val\_loss: 0.6972 - val\_accuracy: 0.8785  
Epoch 144/200  
29/29 [=====] - 2s 78ms/step - loss: 0.1836 - accuracy: 0.9325 - val\_loss: 0.6603 - val\_accuracy: 0.8832  
Epoch 145/200

29/29 [=====] - 2s 77ms/step - loss: 0.1977 - accuracy:  
 0.9287 - val\_loss: 0.6428 - val\_accuracy: 0.8841  
 Epoch 146/200  
 29/29 [=====] - 2s 78ms/step - loss: 0.1840 - accuracy:  
 0.9311 - val\_loss: 0.6151 - val\_accuracy: 0.8841  
 Epoch 147/200  
 29/29 [=====] - 4s 141ms/step - loss: 0.1805 -  
 accuracy: 0.9327 - val\_loss: 0.6540 - val\_accuracy: 0.8794  
 Epoch 148/200  
 29/29 [=====] - 3s 108ms/step - loss: 0.1755 -  
 accuracy: 0.9362 - val\_loss: 0.6245 - val\_accuracy: 0.8850  
 Epoch 149/200  
 29/29 [=====] - 2s 78ms/step - loss: 0.1841 - accuracy:  
 0.9308 - val\_loss: 0.6744 - val\_accuracy: 0.8841  
 Epoch 150/200  
 29/29 [=====] - 2s 80ms/step - loss: 0.1750 - accuracy:  
 0.9357 - val\_loss: 0.6542 - val\_accuracy: 0.8738  
 Epoch 151/200  
 29/29 [=====] - 2s 82ms/step - loss: 0.1690 - accuracy:  
 0.9397 - val\_loss: 0.6439 - val\_accuracy: 0.8841  
 Epoch 152/200  
 29/29 [=====] - 3s 99ms/step - loss: 0.1641 - accuracy:  
 0.9397 - val\_loss: 0.6341 - val\_accuracy: 0.8860  
 Epoch 153/200  
 29/29 [=====] - 4s 143ms/step - loss: 0.1582 -  
 accuracy: 0.9432 - val\_loss: 0.6370 - val\_accuracy: 0.8832  
 Epoch 154/200  
 29/29 [=====] - 2s 82ms/step - loss: 0.1724 - accuracy:  
 0.9346 - val\_loss: 0.6453 - val\_accuracy: 0.8832  
 Epoch 155/200  
 29/29 [=====] - 2s 77ms/step - loss: 0.1839 - accuracy:  
 0.9322 - val\_loss: 0.6625 - val\_accuracy: 0.8897  
 Epoch 156/200  
 29/29 [=====] - 3s 87ms/step - loss: 0.1677 - accuracy:  
 0.9423 - val\_loss: 0.6181 - val\_accuracy: 0.8879  
 Epoch 157/200  
 29/29 [=====] - 2s 78ms/step - loss: 0.1571 - accuracy:  
 0.9397 - val\_loss: 0.6251 - val\_accuracy: 0.8888  
 Epoch 158/200  
 29/29 [=====] - 4s 130ms/step - loss: 0.1836 -  
 accuracy: 0.9334 - val\_loss: 0.6511 - val\_accuracy: 0.8850  
 Epoch 159/200  
 29/29 [=====] - 3s 113ms/step - loss: 0.1747 -  
 accuracy: 0.9376 - val\_loss: 0.6085 - val\_accuracy: 0.8776  
 Epoch 160/200  
 29/29 [=====] - 2s 79ms/step - loss: 0.1653 - accuracy:  
 0.9425 - val\_loss: 0.6405 - val\_accuracy: 0.8850  
 Epoch 161/200



29/29 [=====] - 2s 80ms/step - loss: 0.1778 - accuracy:  
 0.9329 - val\_loss: 0.6659 - val\_accuracy: 0.8813  
 Epoch 162/200  
 29/29 [=====] - 2s 82ms/step - loss: 0.1761 - accuracy:  
 0.9325 - val\_loss: 0.6526 - val\_accuracy: 0.8841  
 Epoch 163/200  
 29/29 [=====] - 2s 82ms/step - loss: 0.1674 - accuracy:  
 0.9400 - val\_loss: 0.6723 - val\_accuracy: 0.8832  
 Epoch 164/200  
 29/29 [=====] - 4s 134ms/step - loss: 0.1738 -  
 accuracy: 0.9374 - val\_loss: 0.6085 - val\_accuracy: 0.8860  
 Epoch 165/200  
 29/29 [=====] - 3s 100ms/step - loss: 0.1412 -  
 accuracy: 0.9477 - val\_loss: 0.6507 - val\_accuracy: 0.8869  
 Epoch 166/200  
 29/29 [=====] - 2s 79ms/step - loss: 0.1696 - accuracy:  
 0.9381 - val\_loss: 0.7099 - val\_accuracy: 0.8794  
 Epoch 167/200  
 29/29 [=====] - 2s 83ms/step - loss: 0.1703 - accuracy:  
 0.9381 - val\_loss: 0.6719 - val\_accuracy: 0.8841  
 Epoch 168/200  
 29/29 [=====] - 2s 78ms/step - loss: 0.1642 - accuracy:  
 0.9379 - val\_loss: 0.6712 - val\_accuracy: 0.8785  
 Epoch 169/200  
 29/29 [=====] - 3s 102ms/step - loss: 0.1541 -  
 accuracy: 0.9449 - val\_loss: 0.6363 - val\_accuracy: 0.8729  
 Epoch 170/200  
 29/29 [=====] - 4s 140ms/step - loss: 0.1691 -  
 accuracy: 0.9400 - val\_loss: 0.6576 - val\_accuracy: 0.8776  
 Epoch 171/200  
 29/29 [=====] - 2s 79ms/step - loss: 0.1530 - accuracy:  
 0.9416 - val\_loss: 0.6653 - val\_accuracy: 0.8776  
 Epoch 172/200  
 29/29 [=====] - 2s 78ms/step - loss: 0.1582 - accuracy:  
 0.9456 - val\_loss: 0.7024 - val\_accuracy: 0.8720  
 Epoch 173/200  
 29/29 [=====] - 2s 79ms/step - loss: 0.1594 - accuracy:  
 0.9404 - val\_loss: 0.6891 - val\_accuracy: 0.8757  
 Epoch 174/200  
 29/29 [=====] - 2s 80ms/step - loss: 0.1802 - accuracy:  
 0.9350 - val\_loss: 0.6257 - val\_accuracy: 0.8757  
 Epoch 175/200  
 29/29 [=====] - 3s 117ms/step - loss: 0.1590 -  
 accuracy: 0.9411 - val\_loss: 0.6326 - val\_accuracy: 0.8785  
 Epoch 176/200  
 29/29 [=====] - 3s 120ms/step - loss: 0.1699 -  
 accuracy: 0.9379 - val\_loss: 0.6652 - val\_accuracy: 0.8869  
 Epoch 177/200

29/29 [=====] - 2s 77ms/step - loss: 0.1633 - accuracy:  
0.9402 - val\_loss: 0.6451 - val\_accuracy: 0.8888  
Epoch 178/200  
29/29 [=====] - 2s 79ms/step - loss: 0.1658 - accuracy:  
0.9418 - val\_loss: 0.6547 - val\_accuracy: 0.8785  
Epoch 179/200  
29/29 [=====] - 2s 80ms/step - loss: 0.1623 - accuracy:  
0.9409 - val\_loss: 0.6818 - val\_accuracy: 0.8850  
Epoch 180/200  
29/29 [=====] - 2s 86ms/step - loss: 0.1408 - accuracy:  
0.9442 - val\_loss: 0.6535 - val\_accuracy: 0.8860  
Epoch 181/200  
29/29 [=====] - 4s 142ms/step - loss: 0.1497 -  
accuracy: 0.9449 - val\_loss: 0.6990 - val\_accuracy: 0.8832  
Epoch 182/200  
29/29 [=====] - 3s 100ms/step - loss: 0.1514 -  
accuracy: 0.9423 - val\_loss: 0.6823 - val\_accuracy: 0.8832  
Epoch 183/200  
29/29 [=====] - 2s 86ms/step - loss: 0.1748 - accuracy:  
0.9341 - val\_loss: 0.6894 - val\_accuracy: 0.8832  
Epoch 184/200  
29/29 [=====] - 2s 79ms/step - loss: 0.1426 - accuracy:  
0.9465 - val\_loss: 0.7009 - val\_accuracy: 0.8813  
Epoch 185/200  
29/29 [=====] - 2s 83ms/step - loss: 0.1561 - accuracy:  
0.9411 - val\_loss: 0.7164 - val\_accuracy: 0.8766  
Epoch 186/200  
29/29 [=====] - 3s 104ms/step - loss: 0.1589 -  
accuracy: 0.9411 - val\_loss: 0.6466 - val\_accuracy: 0.8850  
Epoch 187/200  
29/29 [=====] - 4s 134ms/step - loss: 0.1497 -  
accuracy: 0.9423 - val\_loss: 0.6888 - val\_accuracy: 0.8841  
Epoch 188/200  
29/29 [=====] - 2s 78ms/step - loss: 0.1568 - accuracy:  
0.9425 - val\_loss: 0.6533 - val\_accuracy: 0.8804  
Epoch 189/200  
29/29 [=====] - 2s 78ms/step - loss: 0.1466 - accuracy:  
0.9451 - val\_loss: 0.7104 - val\_accuracy: 0.8776  
Epoch 190/200  
29/29 [=====] - 3s 109ms/step - loss: 0.1386 -  
accuracy: 0.9479 - val\_loss: 0.6428 - val\_accuracy: 0.8822  
Epoch 191/200  
29/29 [=====] - 5s 181ms/step - loss: 0.1529 -  
accuracy: 0.9437 - val\_loss: 0.6663 - val\_accuracy: 0.8841  
Epoch 192/200  
29/29 [=====] - 4s 147ms/step - loss: 0.1499 -  
accuracy: 0.9437 - val\_loss: 0.6739 - val\_accuracy: 0.8794  
Epoch 193/200

```

29/29 [=====] - 3s 117ms/step - loss: 0.1556 -
accuracy: 0.9393 - val_loss: 0.6530 - val_accuracy: 0.8860
Epoch 194/200
29/29 [=====] - 3s 105ms/step - loss: 0.1561 -
accuracy: 0.9418 - val_loss: 0.6767 - val_accuracy: 0.8766
Epoch 195/200
29/29 [=====] - 3s 101ms/step - loss: 0.1460 -
accuracy: 0.9430 - val_loss: 0.6709 - val_accuracy: 0.8794
Epoch 196/200
29/29 [=====] - 4s 145ms/step - loss: 0.1295 -
accuracy: 0.9502 - val_loss: 0.6718 - val_accuracy: 0.8879
Epoch 197/200
29/29 [=====] - 2s 78ms/step - loss: 0.1546 - accuracy:
0.9411 - val_loss: 0.6356 - val_accuracy: 0.8897
Epoch 198/200
29/29 [=====] - 2s 80ms/step - loss: 0.1318 - accuracy:
0.9521 - val_loss: 0.6903 - val_accuracy: 0.8879
Epoch 199/200
29/29 [=====] - 2s 78ms/step - loss: 0.1480 - accuracy:
0.9465 - val_loss: 0.6562 - val_accuracy: 0.8888
Epoch 200/200
29/29 [=====] - 2s 86ms/step - loss: 0.1460 - accuracy:
0.9470 - val_loss: 0.7013 - val_accuracy: 0.8832

```

### Evaluating the Model performance

```

[164]: scores = model.evaluate(X_test, y_test, verbose=1)
print('Test loss:', scores[0])
print('Test accuracy:', scores[1])

```

```

34/34 [=====] - 0s 7ms/step - loss: 0.7013 - accuracy:
0.8832
Test loss: 0.701292872428894
Test accuracy: 0.8831775784492493

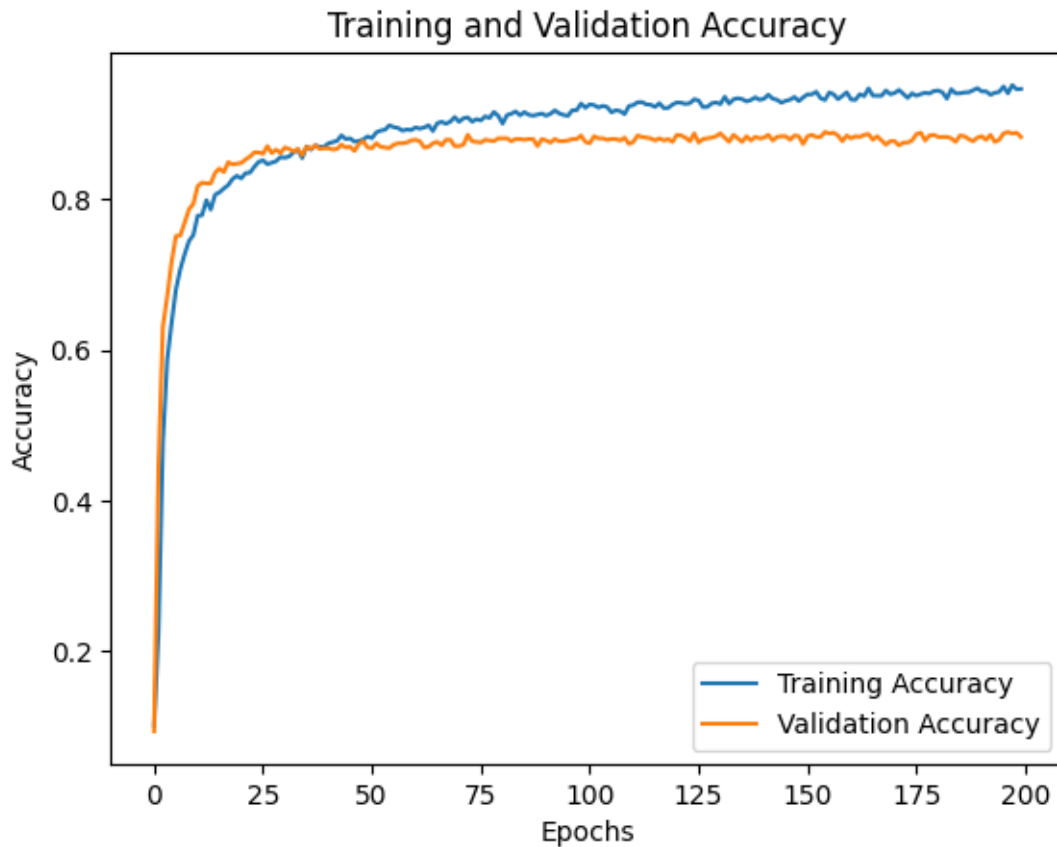
```

### Plot for training and validation accuracy

```

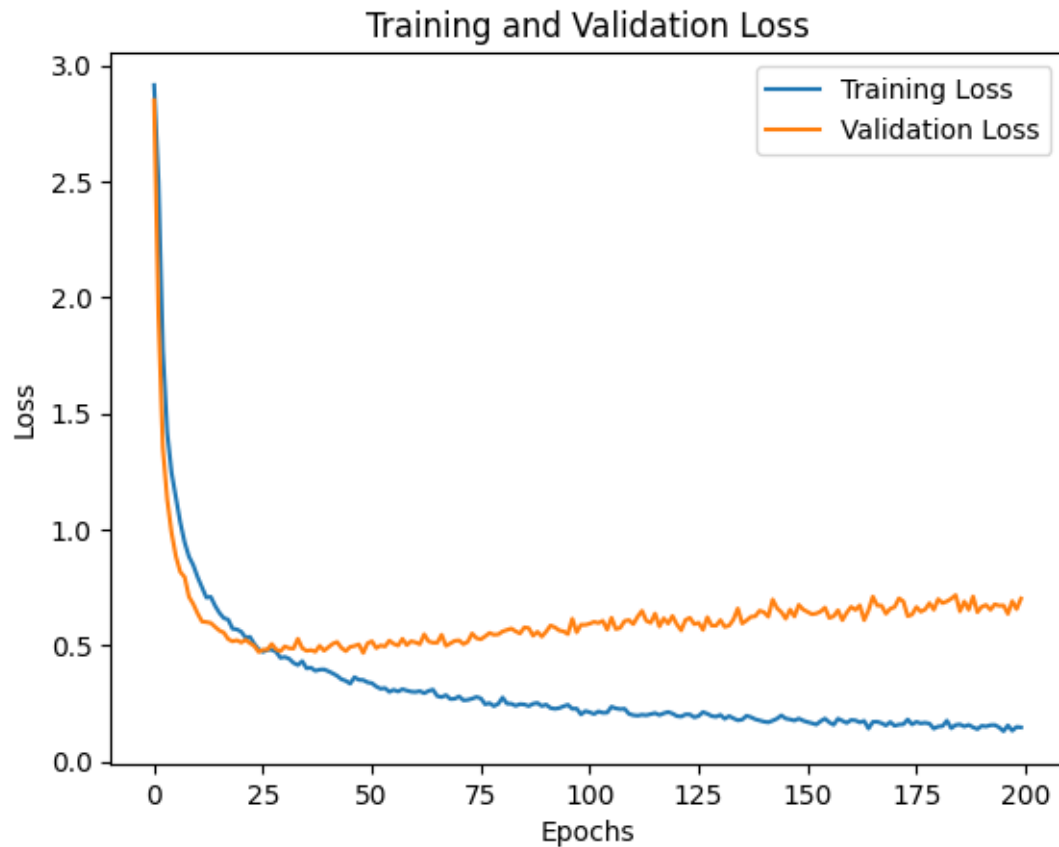
[165]: plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()

```



Plot for training and validation loss

```
[166]: plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



### Predicting with new image

```
[167]: def predict_captcha(img_path) :

    img = cv2.imread(img_path, cv2.IMREAD_GRAYSCALE)

    plt.imshow(img, cmap='gray')
    plt.axis('off')
    plt.show()

    image = cv2.adaptiveThreshold(img, 255, cv2.ADAPTIVE_THRESH_GAUSSIAN_C, cv2.
    ↪THRESH_BINARY, 145, 0)
    image = cv2.adaptiveThreshold(image, 255, cv2.ADAPTIVE_THRESH_GAUSSIAN_C, ↪
    ↪cv2.THRESH_BINARY, 145, 0)
    kernel = np.ones((5,5),np.uint8)
    image = cv2.morphologyEx(image, cv2.MORPH_CLOSE, kernel)
    kernel = np.ones((2,2),np.uint8)
    image = cv2.dilate(image, kernel, iterations = 1)
    image = cv2.GaussianBlur(image, (5,5), 0)
```

```

x = [image[10:50, 30:50], image[10:50, 50:70], image[10:50, 70:90],
      image[10:50, 90:110], image[10:50, 110:130]]

X_pred = []
for i in range(5) :
    X_pred.append(img_to_array(Image.fromarray(x[i])))

X_pred = np.array(X_pred)
X_pred/= 255.0

y_pred = model.predict(X_pred)
y_pred = np.argmax(y_pred, axis = 1)

print('Prediction: ', end='')
for res in y_pred :
    print(info[res], end='')

print('\nActual:      ', img_path[len(img_path)-9:len(img_path)-4])

```

```
[168]: predict_captcha('/content/drive/MyDrive/CAPTCHA/samples/6cm6m.png')
```



```

1/1 [=====] - 0s 156ms/step
Prediction: 6cn6m
Actual:      6cm6m

```

#### Save the model

```
[169]: model.save('cnn_model.h5')

with open('cnn_model.pkl', 'wb') as f:
    pickle.dump(model, f)

print("Model saved successfully!")

```

Model saved successfully!