₹

```
!pip install -q kaggle
from google.colab import files
files.upload()
Choose Files No file chosen
                                            Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to
     enable.
     Saving kaggle (2).json to kaggle (2).json
     {\kaggle (2) ison\\ h\{\"username\\"crazyhurg\" \kay\\\"a2h356a8d172h567d86528de0d43e8a6\\\\}\}
!mkdir -p ~/.kaggle
!cp kaggle.json ~/.kaggle/
!chmod 600 ~/.kaggle/kaggle.json
⇒ cp: cannot stat 'kaggle.json': No such file or directory
      chmod: cannot access '/root/.kaggle/kaggle.json': No such file or directory
!kaggle datasets download -d rhammell/ships-in-satellite-imagery
Dataset URL: <a href="https://www.kaggle.com/datasets/rhammell/ships-in-satellite-imagery">https://www.kaggle.com/datasets/rhammell/ships-in-satellite-imagery</a>
     License(s): CC-BY-SA-4.0
     Downloading ships-in-satellite-imagery.zip to /content
     96% 178M/185M [00:01<00:00, 125MB/s]
100% 185M/185M [00:01<00:00, 130MB/s]
!unzip ships-in-satellite-imagery.zip
```

inflating: shinsnet/shinsnet/0 20161218 180844 0e26 -122 43570635251734 37 81780153646771 nng

```
inflating: shipsnet/shipsnet/0_20161218_180844_0e26__-122.43818561434492_37.88189597797097.png
        inflating: shipsnet/shipsnet/0_20161218_180844_0e26_ -122.44292051246497_37.86017914204665.png inflating: shipsnet/shipsnet/0_20161218_180844_0e26_ -122.4796958662502_37.829549813389136.png inflating: shipsnet/shipsnet/0_20161218_180844_0e26_ -122.47984174489888_37.83790556670464.png
        inflating: shipsnet/shipsnet/0_20161218_180844_0e26__-122.48871932039954_37.84589395485927.png
!1s
     'kaggle (2).json'
                              scenes
                                                                       shipsnet
       sample_data
                              ships-in-satellite-imagery.zip
                                                                       shipsnet.json
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix
import tensorflow as tf
from tensorflow.keras import layers, models
from tensorflow.keras.utils import to_categorical
!ls /content
      'kaggle (2).json'
                                                                       shipsnet
       sample_data
                              ships-in-satellite-imagery.zip
                                                                       shipsnet.json
```

!unzip /content/ships-in-satellite-imagery.zip -d /content/ships-in-satellite-imagery



```
inflating: /content/ships-in-satellite-imagery/shipsnet/shipsnet/0_20161102_180658_0e26__-122.23122736968294_37.75239959943399.png ▲
       inflating: /content/ships-in-satellite-imagery/shipsnet/shipsnet/0_20161102_180658_0e26__-122.28126318568829_37.769020038003475.pn
       inflating: /content/ships-in-satellite-imagery/shipsnet/shipsnet/0_20161102_180658_0e26__-122.31527680074582_37.79277375149748.png
       inflating: /content/ships-in-satellite-imagery/shipsnet/shipsnet/0__20161102_180658_0e26__-122.32843644745485_37.73923054907409.png
       inflating: /content/ships-in-satellite-imagery/shipsnet/shipsnet/0_20161102_180658_0e26__-122.34040514248915_37.748761931300486.pn
!ls /content/ships-in-satellite-imagery

→ scenes shipsnet shipsnet.json

dataset_path = "/content/ships-in-satellite-imagery/shipsnet"
import os
import numpy as np
from tensorflow.keras.preprocessing.image import load_img, img_to_array
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
# Path to the dataset (update this if necessary)
dataset_path = "/content/ships-in-satellite-imagery"
# Verify the dataset path
if not os.path.exists(dataset_path):
    # Debug: Print available directories
    print("Available directories in /content:")
    print(os.listdir("/content"))
    raise FileNotFoundError(f"The dataset path '{dataset_path}' does not exist. Please check the path.")
# Debug: Print contents of the dataset directory
print("Contents of the dataset directory:")
print(os.listdir(dataset_path))
# Load images and labels
images = []
labels = []
# Recursively search for .png files
for root, dirs, files in os.walk(dataset_path):
    for filename in files:
        if filename.endswith(".png"): # Ensure only PNG files are processed
            # Load image
            img_path = os.path.join(root, filename)
            img = load_img(img_path, target_size=(80, 80)) # Resize images to 80x80
            img = img_to_array(img) / 255.0 # Normalize pixel values to [0, 1]
            images.append(img)
            # Extract label from filename (e.g., "ship_1.png" -> "ship")
            label = filename.split("_")[0] # Adjust based on filename structure
            labels.append(label)
# Check if any images were loaded
if len(images) == 0:
    raise ValueError("No images were loaded. Check the dataset path and file structure.")
# Convert to numpy arrays
images = np.array(images)
labels = np.array(labels)
# Encode labels to integers
label_encoder = LabelEncoder()
labels_encoded = label_encoder.fit_transform(labels)
# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(images, labels_encoded, test_size=0.2, random_state=42)
print(f"Loaded {len(images)} images and {len(labels)} labels.")
print(f"Unique labels: {np.unique(labels)}")
print(f"Training data shape: {X_train.shape}, Testing data shape: {X_test.shape}")

→ Contents of the dataset directory:
     ['shipsnet.json', 'shipsnet', 'scenes']
     Loaded 4008 images and 4008 labels.
     Unique labels: ['0' '1' 'lb' 'sfbay']
     Training data shape: (3206, 80, 80, 3), Testing data shape: (802, 80, 80, 3)
```

```
import os
import numpy as np
from tensorflow.keras.preprocessing.image import load_img, img_to_array
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
dataset_path = "/content/ships-in-satellite-imagery"
if not os.path.exists(dataset path):
    raise FileNotFoundError(f"The dataset path '{dataset_path}' does not exist. Please check the path.")
images = []
labels = []
for filename in os.listdir(dataset_path):
    if filename.endswith(".png"): # Ensure only PNG files are processed
        # Load image
        img_path = os.path.join(dataset_path, filename)
        img = load_img(img_path, target_size=(80, 80)) # Resize images to 80x80
        img = img_to_array(img) / 255.0 # Normalize pixel values to [0, 1]
        images.append(img)
        # Extract label from filename (e.g., "ship_1.png" -> "ship")
        label = filename.split("_")[0] # Adjust based on filename structure
        labels.append(label)
images = np.array(images)
labels = np.array(labels)
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout
# Define the CNN model
model = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(80, 80, 3)), # First convolutional layer
    MaxPooling2D((2, 2)), # First max-pooling layer
    Conv2D(64, (3, 3), activation='relu'), # Second convolutional layer
    MaxPooling2D((2, 2)), # Second max-pooling layer
    Conv2D(128, (3, 3), activation='relu'), # Third convolutional layer
    MaxPooling2D((2, 2)), # Third max-pooling layer
    Flatten(), # Flatten the output for dense layers
    Dense(128, activation='relu'), # Fully connected layer
    Dropout(0.5), # Dropout to prevent overfitting
    Dense(len(label_encoder.classes_), activation='softmax') # Output layer
])
# Compile the model
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
# Print model summary
model.summary()
```

/usr/local/lib/python3.11/dist-packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass an `input_shape`/`inpusuper().__init__(activity_regularizer=activity_regularizer, **kwargs)

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 78, 78, 32)	896
max_pooling2d (MaxPooling2D)	(None, 39, 39, 32)	0
conv2d_1 (Conv2D)	(None, 37, 37, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 18, 18, 64)	0
conv2d_2 (Conv2D)	(None, 16, 16, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 8, 8, 128)	0
flatten (Flatten)	(None, 8192)	0
dense (Dense)	(None, 128)	1,048,704
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 4)	516

Total params: 1,142,468 (4.36 MB)
Trainable params: 1,142,468 (4.36 MB)

```
from tensorflow.keras.callbacks import EarlyStopping
# Data Augmentation
from tensorflow.keras.preprocessing.image import ImageDataGenerator
datagen = ImageDataGenerator(
    rotation_range=20,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    {\tt fill\_mode='nearest'}
)
# Fit the data generator to the training data
datagen.fit(X_train)
# Early stopping to prevent overfitting
early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=True)
# Train the model
history = model.fit(
    datagen.flow(X_train, y_train, batch_size=32),
    validation_data=(X_test, y_test),
    callbacks=[early_stopping]
)
🚁 /usr/local/lib/python3.11/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121: UserWarning: Your `PyDataset` cla 🍨
       self._warn_if_super_not_called()
     Epoch 1/50
     101/101 -
                                 – 63s 596ms/step - accuracy: 0.7100 - loss: 0.6549 - val_accuracy: 0.8890 - val_loss: 0.3661
     Epoch 2/50
     101/101 -
                                 - 57s 556ms/step - accuracy: 0.8127 - loss: 0.4288 - val_accuracy: 0.9015 - val_loss: 0.3398
     Epoch 3/50
     101/101
                                 - 60s 591ms/step - accuracy: 0.8301 - loss: 0.4136 - val_accuracy: 0.8878 - val_loss: 0.3486
     Epoch 4/50
     101/101
                                  · 60s 599ms/step - accuracy: 0.8408 - loss: 0.3879 - val_accuracy: 0.9052 - val_loss: 0.3225
     Fnoch 5/50
     101/101
                                 - 75s 527ms/step - accuracy: 0.8452 - loss: 0.3505 - val_accuracy: 0.8791 - val_loss: 0.3148
     Epoch 6/50
     101/101
                                 - 59s 588ms/step - accuracy: 0.8443 - loss: 0.3523 - val accuracy: 0.8940 - val loss: 0.3188
     Epoch 7/50
     101/101 -
                                 - 61s 605ms/step - accuracy: 0.8412 - loss: 0.3459 - val_accuracy: 0.8853 - val_loss: 0.3211
     Epoch 8/50
     101/101
                                 - 55s 543ms/step - accuracy: 0.8463 - loss: 0.3343 - val_accuracy: 0.8990 - val_loss: 0.3080
     Epoch 9/50
     101/101
                                  · 81s 538ms/step - accuracy: 0.8575 - loss: 0.3300 - val_accuracy: 0.8853 - val_loss: 0.3085
     Epoch 10/50
     101/101
                                 - 58s 578ms/step - accuracy: 0.8574 - loss: 0.3141 - val_accuracy: 0.8990 - val_loss: 0.2949
```

plt.show()

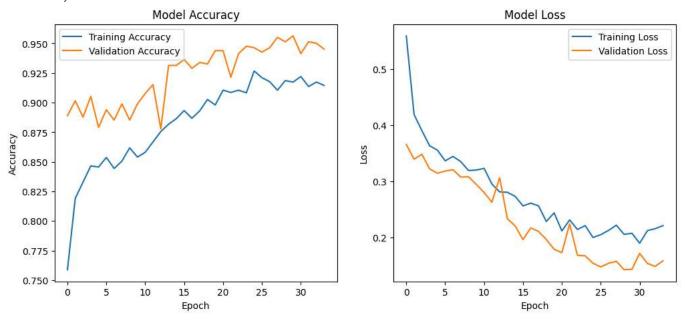
```
Epoch 11/50
                            • 53s 524ms/step - accuracy: 0.8610 - loss: 0.3108 - val_accuracy: 0.9077 - val_loss: 0.2806
101/101
Epoch 12/50
101/101
                            - 59s 585ms/step - accuracy: 0.8614 - loss: 0.2963 - val_accuracy: 0.9152 - val_loss: 0.2631
Epoch 13/50
101/101 -
                            - 53s 529ms/step - accuracy: 0.8816 - loss: 0.2730 - val_accuracy: 0.8778 - val_loss: 0.3068
Epoch 14/50
                            - 62s 612ms/step - accuracy: 0.8861 - loss: 0.2747 - val_accuracy: 0.9314 - val_loss: 0.2335
101/101
Epoch 15/50
101/101
                            · 57s 566ms/step - accuracy: 0.8913 - loss: 0.2592 - val_accuracy: 0.9314 - val_loss: 0.2207
Fnoch 16/50
101/101
                            - 57s 564ms/step - accuracy: 0.8921 - loss: 0.2490 - val_accuracy: 0.9364 - val_loss: 0.1966
Epoch 17/50
101/101 -
                            - 62s 619ms/step - accuracy: 0.8986 - loss: 0.2350 - val_accuracy: 0.9289 - val_loss: 0.2175
Epoch 18/50
101/101 -
                            - 78s 577ms/step - accuracy: 0.8833 - loss: 0.2706 - val_accuracy: 0.9339 - val_loss: 0.2110
Epoch 19/50
101/101 -
                            - 55s 549ms/step - accuracy: 0.8962 - loss: 0.2408 - val_accuracy: 0.9327 - val_loss: 0.1968
Epoch 20/50
101/101
                            - 57s 557ms/step - accuracy: 0.8983 - loss: 0.2476 - val_accuracy: 0.9439 - val_loss: 0.1793
Epoch 21/50
101/101
                            - 57s 563ms/step - accuracy: 0.9123 - loss: 0.2022 - val_accuracy: 0.9439 - val_loss: 0.1733
Epoch 22/50
101/101
                            - 56s 551ms/step - accuracy: 0.9016 - loss: 0.2376 - val_accuracy: 0.9214 - val_loss: 0.2247
Epoch 23/50
101/101
                            - 56s 558ms/step - accuracy: 0.9090 - loss: 0.2281 - val_accuracy: 0.9414 - val_loss: 0.1686
Epoch 24/50
101/101 -
                            - 56s 560ms/step - accuracy: 0.9040 - loss: 0.2263 - val_accuracy: 0.9476 - val_loss: 0.1676
Epoch 25/50
101/101 -
                            - 57s 566ms/step - accuracy: 0.9264 - loss: 0.2086 - val_accuracy: 0.9464 - val_loss: 0.1543
Epoch 26/50
101/101
                            - 55s 545ms/step - accuracy: 0.9128 - loss: 0.2122 - val_accuracy: 0.9426 - val_loss: 0.1479
Epoch 27/50
101/101 -
                            - 56s 556ms/step - accuracy: 0.9081 - loss: 0.2285 - val_accuracy: 0.9464 - val_loss: 0.1544
```

```
# Evaluate the model on the test set
test_loss, test_accuracy = model.evaluate(X_test, y_test)
print(f"Test Accuracy: {test_accuracy * 100:.2f}%")
# Plot training and validation accuracy and loss
import matplotlib.pyplot as plt
plt.figure(figsize=(12, 5))
# Plot accuracy
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
# Plot loss
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val loss'], label='Validation Loss')
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
```

Epoch 9/20 101/101 —

Epoch 10/20

```
26/26 2s 89ms/step - accuracy: 0.9565 - loss: 0.1425 Test Accuracy: 95.14%
```



```
from tensorflow.keras.applications import VGG16
from tensorflow.keras.layers import GlobalAveragePooling2D
# Load pre-trained VGG16 model (without the top layers)
base_model = VGG16(weights='imagenet', include_top=False, input_shape=(80, 80, 3))
# Freeze the base model layers
base_model.trainable = False
# Add custom layers on top of the base model
model = Sequential([
        base_model,
        GlobalAveragePooling2D(),
        Dense(128, activation='relu'),
        Dropout(0.5).
        Dense(len(label_encoder.classes_), activation='softmax')
])
# Compile the model
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
# Train the model
history = model.fit(
        datagen.flow(X_train, y_train, batch_size=32),
        epochs=20,
        validation_data=(X_test, y_test),
        callbacks=[early_stopping]
)
         Downloading data from <a href="https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg16/vgg1
          58889256/58889256
                                                                                           0s Ous/step
          Epoch 1/20
          101/101
                                                                      397s 4s/step - accuracy: 0.7243 - loss: 0.6724 - val_accuracy: 0.9152 - val_loss: 0.2355
          Epoch 2/20
          101/101 -
                                                                      393s 4s/step - accuracy: 0.8917 - loss: 0.2642 - val accuracy: 0.9352 - val loss: 0.1930
          Epoch 3/20
          101/101
                                                                      391s 4s/step - accuracy: 0.9156 - loss: 0.2034 - val_accuracy: 0.9426 - val_loss: 0.1740
          Epoch 4/20
          101/101
                                                                      394s 4s/step - accuracy: 0.9190 - loss: 0.2010 - val_accuracy: 0.9352 - val_loss: 0.1874
          Epoch 5/20
          101/101
                                                                      394s 4s/step - accuracy: 0.9256 - loss: 0.1849 - val_accuracy: 0.9401 - val_loss: 0.1757
          Epoch 6/20
          101/101
                                                                      392s 4s/step - accuracy: 0.9407 - loss: 0.1592 - val_accuracy: 0.9514 - val_loss: 0.1464
          Epoch 7/20
          101/101
                                                                      386s 4s/step - accuracy: 0.9389 - loss: 0.1502 - val_accuracy: 0.9564 - val_loss: 0.1387
          Epoch 8/20
          101/101
                                                                      395s 4s/step - accuracy: 0.9320 - loss: 0.1689 - val_accuracy: 0.9489 - val_loss: 0.1484
```

- 386s 4s/step - accuracy: 0.9414 - loss: 0.1560 - val_accuracy: 0.9551 - val_loss: 0.1465

101/101 — 394s 4s/step - accuracy: 0.9355 - loss: 0.1532 - val_accuracy: 0.9626 - val_loss: 0.1168