

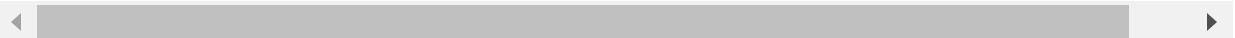
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Dataset taken from Kaggle

<https://www.kaggle.com/datasets/clorichel/boat-types-recognition>

**Dataset created by taking three classes:
Boats, Gondola and Ship**



Acessing Google Drive

```
In [ ]: from google.colab import drive  
drive.mount('/content/drive')
```

Mounted at /content/drive

DATASET LOADING AND SPLITTING

```
In [ ]: import tensorflow as tf  
import tensorflow_datasets as tfds
```

```
In [ ]: dataset = tf.keras.preprocessing.image_dataset_from_directory("/content/drive/MyDrive/  
  
ds_train = tf.keras.preprocessing.image_dataset_from_directory(  
    directory = "/content/drive/MyDrive/SEM 6/Deep Learning/usecase1" ,  
    validation_split=0.2,  
    subset="training",  
    seed=123  
)  
ds_test = tf.keras.preprocessing.image_dataset_from_directory(  
    directory = "/content/drive/MyDrive/SEM 6/Deep Learning/usecase1",  
    validation_split=0.2,  
    subset="validation",  
    seed=123)
```

```
Found 610 files belonging to 3 classes.  
Found 610 files belonging to 3 classes.  
Using 488 files for training.  
Found 610 files belonging to 3 classes.  
Using 122 files for validation.
```

```
In [ ]: batch_size = 128  
dataset_name = dataset  
class_name = dataset.class_names  
class_name
```

```
Out[ ]: ['Boat', 'Gondala', 'Ship']
```

IMAGE PREPROCESSING

```
In [ ]: size = (224,224)  
ds_train = ds_train.map(lambda image , label : (tf.image.resize(image,size),label))  
ds_test = ds_test.map(lambda image , label : (tf.image.resize(image,size),label))
```

```
In [ ]: import matplotlib.pyplot as plt  
  
plt.figure(figsize = (10,10))  
for images, labels in ds_train.take(1):  
    for i in range(9):  
        ax = plt.subplot(3,3,i+1)  
        plt.imshow(images[i].numpy().astype("uint8"))  
        plt.title(class_name[labels[i]])  
        plt.axis("off")
```



```
In [ ]: from tensorflow.keras.models import Sequential
from tensorflow.keras import layers

image = Sequential(
    [
        layers.RandomFlip("horizontal"),
        layers.RandomRotation(0.1),
        layers.RandomZoom(height_factor = (-0.2,-0.3),interpolation = "bilinear"),
        layers.RandomContrast(factor=0.1),
        layers.RandomTranslation(height_factor=0.1,width_factor = 0.1),
    ],
    name = "image"
)
```

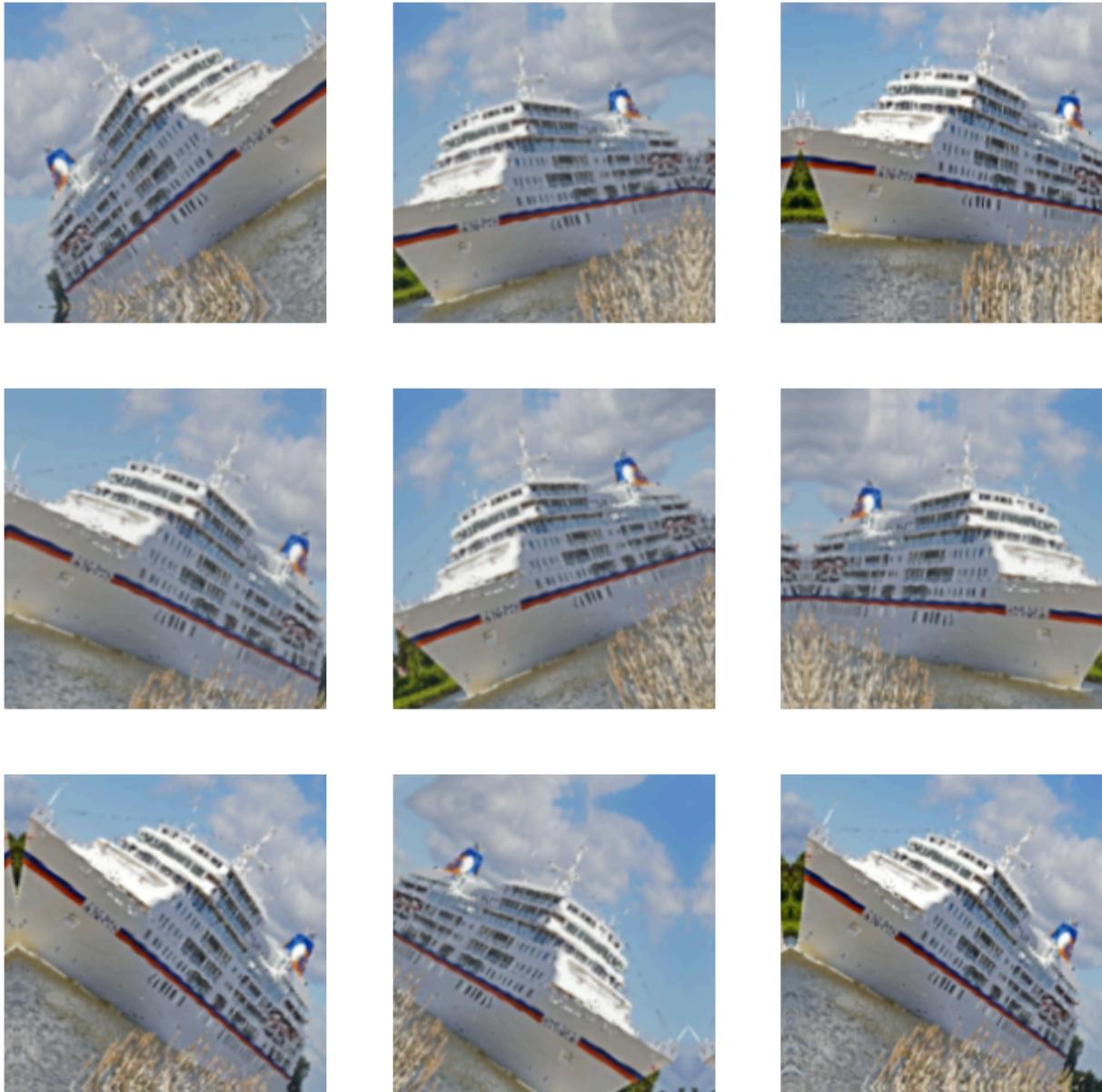
```
In [ ]: import numpy as np

for images,label in ds_train.take(1):
    plt.figure(figsize = (10,10))
    first_image= images[0]
```

```

def f(x):
    return np.int(x)
f2 = np.vectorize(f)
for i in range(9):
    ax = plt.subplot(3,3,i+1)
    augmented_image = image(tf.expand_dims(first_image,0),training = True)
    plt.imshow(augmented_image[0].numpy().astype("int32"))
    plt.axis("off")

```



In []:

```

import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf

for images, labels in ds_train.take(1):
    plt.figure(figsize=(10, 10))

    #Creating random index to choose any image from the folder
    random_index = np.random.randint(0, len(images))

    # Selecting a random image
    selected_image = images[random_index]

```

```

# Function for image augmentation
def image_augmentation(image):
    # Some augmentation operations as needed
    augmented_image = tf.image.random_flip_left_right(image)
    augmented_image = tf.image.random_flip_up_down(augmented_image)
    augmented_image = tf.image.random_brightness(augmented_image, max_delta=0.2)
    augmented_image = tf.image.random_contrast(augmented_image, lower=0.5, upper=1)

    return augmented_image

# Apply augmentation to the selected image
augmented_image = image_augmentation(selected_image)

# Displaying both original and augmented images for finding difference
plt.subplot(1, 2, 1)
plt.imshow(selected_image.numpy().astype("int32"))
plt.title('Original Image')
plt.axis('off')

plt.subplot(1, 2, 2)
plt.imshow(augmented_image.numpy().astype("int32"))
plt.title('Augmented Image')
plt.axis('off')

plt.show()

```

WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).

Original Image



Augmented Image



In []:

```

for images, labels in ds_train.take(1):
    plt.figure(figsize=(15, 10))

    # Choosing 5-7 random indices
    num_images = min(7, len(images))
    random_indices = np.random.choice(len(images), size=num_images, replace=False)

    # Function for image augmentation
    def image_augmentation(image):
        # Some augmentation operations

```

```

augmented_image = tf.image.random_flip_left_right(image)
augmented_image = tf.image.random_flip_up_down(augmented_image)
augmented_image = tf.image.random_brightness(augmented_image, max_delta=0.2)
augmented_image = tf.image.random_contrast(augmented_image, lower=0.5, upper=1

return augmented_image

# Displaying both original and augmented images for finding difference
for i, random_index in enumerate(random_indices):
    plt.subplot(2, num_images, i + 1)
    selected_image = images[random_index]
    augmented_image = image_augmentation(selected_image)

    plt.imshow(selected_image.numpy().astype("int32"))
    plt.title('Original')
    plt.axis('off')

    plt.subplot(2, num_images, i + num_images + 1)
    plt.imshow(augmented_image.numpy().astype("int32"))
    plt.title('Augmented')
    plt.axis('off')

plt.show()

```

WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
 WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
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 WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).



MOBILENET MODEL

```
In [ ]: !pip install split-folders
```

```
Collecting split-folders
  Downloading split_folders-0.5.1-py3-none-any.whl (8.4 kB)
Installing collected packages: split-folders
Successfully installed split-folders-0.5.1
```

Splitting the data into train,test and validation set using splitfolders

```
In [ ]: import splitfolders
```

```
splitfolders.ratio("/content/drive/MyDrive/SEM 6/Deep Learning/usecase1", output="/cor
```

```
Copying files: 610 files [00:56, 10.79 files/s]
```

```
In [ ]: from tensorflow.keras.preprocessing import image
from tensorflow.keras.preprocessing.image import ImageDataGenerator, load_img
```

```
In [ ]: datagen = ImageDataGenerator()
```

```
#TRAIN SET
```

```
train_generator = datagen.flow_from_directory(
    directory="/content/drive/MyDrive/SEM 6/Deep Learning/usecase1_split/train",
    classes = class_name,
    target_size=(200, 200),
    batch_size=32,
    class_mode="binary",
)
```

```
#VALIDATION SET
```

```
valid_generator = datagen.flow_from_directory(
    directory="/content/drive/MyDrive/SEM 6/Deep Learning/usecase1_split/val",
    classes = class_name,
    target_size=(224, 224),
    batch_size=32,
    class_mode="binary",
)
```

```
#TEST SET
```

```
test_generator = datagen.flow_from_directory(
    directory="/content/drive/MyDrive/SEM 6/Deep Learning/usecase1_split/test",
    classes = class_name,
    target_size=(224, 224),
    batch_size=32,
    class_mode="binary",
)
```

```
Found 427 images belonging to 3 classes.
```

```
Found 122 images belonging to 3 classes.
```

```
Found 61 images belonging to 3 classes.
```

MOBILENET Model

```
In [ ]: import tensorflow as tf
```

```
from tensorflow.keras.applications import MobileNet
from tensorflow.keras import layers, models
```

```
In [ ]: #MobileNet base model
base_model = MobileNet(input_shape=(224, 224, 3), include_top=False)

# Freeze the layers of the base model
for layer in base_model.layers:
    layer.trainable = False

# Creating layers for classification
x = layers.GlobalAveragePooling2D()(base_model.output)
x = layers.Dense(128, activation='relu')(x)
x = layers.Dropout(0.5)(x)
output = layers.Dense(len(class_name), activation='softmax')(x)

#Final model
model = models.Model(inputs=base_model.input, outputs=output)

#Compilation of the model
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accu

# Display Model summary
model.summary()
```

Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/mobilenet/mobilenet_1_0_224_tf_no_top.h5

17225924/17225924 [=====] - 0s 0us/step

Model: "model"

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 224, 224, 3)]	0
conv1 (Conv2D)	(None, 112, 112, 32)	864
conv1_bn (BatchNormalizati on)	(None, 112, 112, 32)	128
conv1_relu (ReLU)	(None, 112, 112, 32)	0
conv_dw_1 (DepthwiseConv2D)	(None, 112, 112, 32)	288
conv_dw_1_bn (BatchNormali zation)	(None, 112, 112, 32)	128
conv_dw_1_relu (ReLU)	(None, 112, 112, 32)	0
conv_pw_1 (Conv2D)	(None, 112, 112, 64)	2048
conv_pw_1_bn (BatchNormali zation)	(None, 112, 112, 64)	256
conv_pw_1_relu (ReLU)	(None, 112, 112, 64)	0
conv_pad_2 (ZeroPadding2D)	(None, 113, 113, 64)	0
conv_dw_2 (DepthwiseConv2D)	(None, 56, 56, 64)	576
conv_dw_2_bn (BatchNormali zation)	(None, 56, 56, 64)	256
conv_dw_2_relu (ReLU)	(None, 56, 56, 64)	0
conv_pw_2 (Conv2D)	(None, 56, 56, 128)	8192
conv_pw_2_bn (BatchNormali zation)	(None, 56, 56, 128)	512
conv_pw_2_relu (ReLU)	(None, 56, 56, 128)	0
conv_dw_3 (DepthwiseConv2D)	(None, 56, 56, 128)	1152
conv_dw_3_bn (BatchNormali zation)	(None, 56, 56, 128)	512
conv_dw_3_relu (ReLU)	(None, 56, 56, 128)	0
conv_pw_3 (Conv2D)	(None, 56, 56, 128)	16384
conv_pw_3_bn (BatchNormali zation)	(None, 56, 56, 128)	512

conv_pw_3_relu (ReLU)	(None, 56, 56, 128)	0
conv_pad_4 (ZeroPadding2D)	(None, 57, 57, 128)	0
conv_dw_4 (DepthwiseConv2D)	(None, 28, 28, 128)	1152
conv_dw_4_bn (BatchNormali zation)	(None, 28, 28, 128)	512
conv_dw_4_relu (ReLU)	(None, 28, 28, 128)	0
conv_pw_4 (Conv2D)	(None, 28, 28, 256)	32768
conv_pw_4_bn (BatchNormali zation)	(None, 28, 28, 256)	1024
conv_pw_4_relu (ReLU)	(None, 28, 28, 256)	0
conv_dw_5 (DepthwiseConv2D)	(None, 28, 28, 256)	2304
conv_dw_5_bn (BatchNormali zation)	(None, 28, 28, 256)	1024
conv_dw_5_relu (ReLU)	(None, 28, 28, 256)	0
conv_pw_5 (Conv2D)	(None, 28, 28, 256)	65536
conv_pw_5_bn (BatchNormali zation)	(None, 28, 28, 256)	1024
conv_pw_5_relu (ReLU)	(None, 28, 28, 256)	0
conv_pad_6 (ZeroPadding2D)	(None, 29, 29, 256)	0
conv_dw_6 (DepthwiseConv2D)	(None, 14, 14, 256)	2304
conv_dw_6_bn (BatchNormali zation)	(None, 14, 14, 256)	1024
conv_dw_6_relu (ReLU)	(None, 14, 14, 256)	0
conv_pw_6 (Conv2D)	(None, 14, 14, 512)	131072
conv_pw_6_bn (BatchNormali zation)	(None, 14, 14, 512)	2048
conv_pw_6_relu (ReLU)	(None, 14, 14, 512)	0
conv_dw_7 (DepthwiseConv2D)	(None, 14, 14, 512)	4608
conv_dw_7_bn (BatchNormali zation)	(None, 14, 14, 512)	2048
conv_dw_7_relu (ReLU)	(None, 14, 14, 512)	0

conv_pw_7 (Conv2D)	(None, 14, 14, 512)	262144
conv_pw_7_bn (BatchNormalization)	(None, 14, 14, 512)	2048
conv_pw_7_relu (ReLU)	(None, 14, 14, 512)	0
conv_dw_8 (DepthwiseConv2D)	(None, 14, 14, 512)	4608
conv_dw_8_bn (BatchNormalization)	(None, 14, 14, 512)	2048
conv_dw_8_relu (ReLU)	(None, 14, 14, 512)	0
conv_pw_8 (Conv2D)	(None, 14, 14, 512)	262144
conv_pw_8_bn (BatchNormalization)	(None, 14, 14, 512)	2048
conv_pw_8_relu (ReLU)	(None, 14, 14, 512)	0
conv_dw_9 (DepthwiseConv2D)	(None, 14, 14, 512)	4608
conv_dw_9_bn (BatchNormalization)	(None, 14, 14, 512)	2048
conv_dw_9_relu (ReLU)	(None, 14, 14, 512)	0
conv_pw_9 (Conv2D)	(None, 14, 14, 512)	262144
conv_pw_9_bn (BatchNormalization)	(None, 14, 14, 512)	2048
conv_pw_9_relu (ReLU)	(None, 14, 14, 512)	0
conv_dw_10 (DepthwiseConv2D)	(None, 14, 14, 512)	4608
conv_dw_10_bn (BatchNormalization)	(None, 14, 14, 512)	2048
conv_dw_10_relu (ReLU)	(None, 14, 14, 512)	0
conv_pw_10 (Conv2D)	(None, 14, 14, 512)	262144
conv_pw_10_bn (BatchNormalization)	(None, 14, 14, 512)	2048
conv_pw_10_relu (ReLU)	(None, 14, 14, 512)	0
conv_dw_11 (DepthwiseConv2D)	(None, 14, 14, 512)	4608
conv_dw_11_bn (BatchNormalization)	(None, 14, 14, 512)	2048
conv_dw_11_relu (ReLU)	(None, 14, 14, 512)	0

conv_pw_11 (Conv2D)	(None, 14, 14, 512)	262144
conv_pw_11_bn (BatchNormal ization)	(None, 14, 14, 512)	2048
conv_pw_11_relu (ReLU)	(None, 14, 14, 512)	0
conv_pad_12 (ZeroPadding2D)	(None, 15, 15, 512)	0
conv_dw_12 (DepthwiseConv2 D)	(None, 7, 7, 512)	4608
conv_dw_12_bn (BatchNormal ization)	(None, 7, 7, 512)	2048
conv_dw_12_relu (ReLU)	(None, 7, 7, 512)	0
conv_pw_12 (Conv2D)	(None, 7, 7, 1024)	524288
conv_pw_12_bn (BatchNormal ization)	(None, 7, 7, 1024)	4096
conv_pw_12_relu (ReLU)	(None, 7, 7, 1024)	0
conv_dw_13 (DepthwiseConv2 D)	(None, 7, 7, 1024)	9216
conv_dw_13_bn (BatchNormal ization)	(None, 7, 7, 1024)	4096
conv_dw_13_relu (ReLU)	(None, 7, 7, 1024)	0
conv_pw_13 (Conv2D)	(None, 7, 7, 1024)	1048576
conv_pw_13_bn (BatchNormal ization)	(None, 7, 7, 1024)	4096
conv_pw_13_relu (ReLU)	(None, 7, 7, 1024)	0
global_average_pooling2d (GlobalAveragePooling2D)	(None, 1024)	0
dense (Dense)	(None, 128)	131200
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 3)	387
<hr/>		
Total params: 3360451 (12.82 MB)		
Trainable params: 131587 (514.01 KB)		
Non-trainable params: 3228864 (12.32 MB)		

In []: epochs = 10
history = model.fit(train_generator, epochs=epochs, validation_data=valid_generator, ba

```

Epoch 1/10
14/14 [=====] - 15s 684ms/step - loss: 1.4756 - accuracy: 0.
4309 - val_loss: 0.6791 - val_accuracy: 0.7049
Epoch 2/10
14/14 [=====] - 8s 557ms/step - loss: 0.7587 - accuracy: 0.6
768 - val_loss: 0.6235 - val_accuracy: 0.7541
Epoch 3/10
14/14 [=====] - 7s 482ms/step - loss: 0.6431 - accuracy: 0.7
283 - val_loss: 0.5617 - val_accuracy: 0.8033
Epoch 4/10
14/14 [=====] - 8s 573ms/step - loss: 0.5363 - accuracy: 0.7
822 - val_loss: 0.5315 - val_accuracy: 0.8033
Epoch 5/10
14/14 [=====] - 7s 477ms/step - loss: 0.4918 - accuracy: 0.8
126 - val_loss: 0.5106 - val_accuracy: 0.8115
Epoch 6/10
14/14 [=====] - 8s 590ms/step - loss: 0.4527 - accuracy: 0.8
478 - val_loss: 0.5080 - val_accuracy: 0.8033
Epoch 7/10
14/14 [=====] - 7s 483ms/step - loss: 0.4341 - accuracy: 0.8
454 - val_loss: 0.4869 - val_accuracy: 0.8443
Epoch 8/10
14/14 [=====] - 8s 580ms/step - loss: 0.3667 - accuracy: 0.8
689 - val_loss: 0.4762 - val_accuracy: 0.8525
Epoch 9/10
14/14 [=====] - 8s 562ms/step - loss: 0.3451 - accuracy: 0.8
735 - val_loss: 0.4705 - val_accuracy: 0.8443
Epoch 10/10
14/14 [=====] - 7s 492ms/step - loss: 0.3240 - accuracy: 0.8
829 - val_loss: 0.4593 - val_accuracy: 0.8361

```

```
In [ ]: test_loss, test_acc = model.evaluate(test_generator)
print("The test loss is: ", test_loss)
print("The best accuracy is: ", test_acc*100)
```

```
2/2 [=====] - 2s 1s/step - loss: 0.5064 - accuracy: 0.8033
The test loss is: 0.5064443349838257
The best accuracy is: 80.32786846160889
```

```
In [ ]: Labels = ["Boat", "Gondala", "Ship"]
```

```
In [ ]: def preprocess_image(image):
    img_array = tf.keras.preprocessing.image.img_to_array(image)
    img_array = tf.expand_dims(img_array, 0)
    img_array = tf.keras.applications.mobilenet.preprocess_input(img_array)
    return img_array

#Predictions for images in TEST DATA
for batch in ds_test.take(5): # Take the first 5 batches
    # Extract images and labels from the batch
    images, labels = batch

    # Preprocess the images for prediction
    preprocessed_images = tf.map_fn(preprocess_image, images)

    # Reshaping the input tensor to match the MobileNet model's input shape
    preprocessed_images = tf.reshape(preprocessed_images, (-1, 224, 224, 3))

    #Making predictions
    predictions = model.predict(preprocessed_images)
```

```
class_labels = Labels #Category's names
predicted_classes = np.argmax(predictions, axis=1)

# Displaying each test image along with the original and predicted class
for i in range(images.shape[0]):
    plt.imshow(tf.keras.preprocessing.image.array_to_img(images[i]))
    plt.title(f"Original Class: {class_labels[labels[i]]}\nPredicted Class: {class_
    plt.axis("off")
    plt.show()
```

1/1 [=====] - 0s 29ms/step

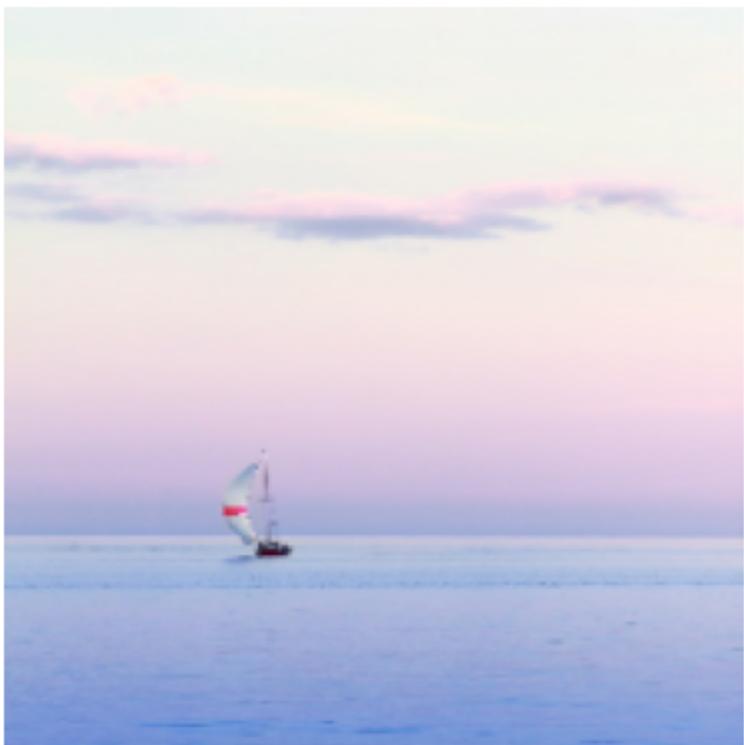
Original Class: Ship
Predicted Class: Ship



Original Class: Ship
Predicted Class: Ship



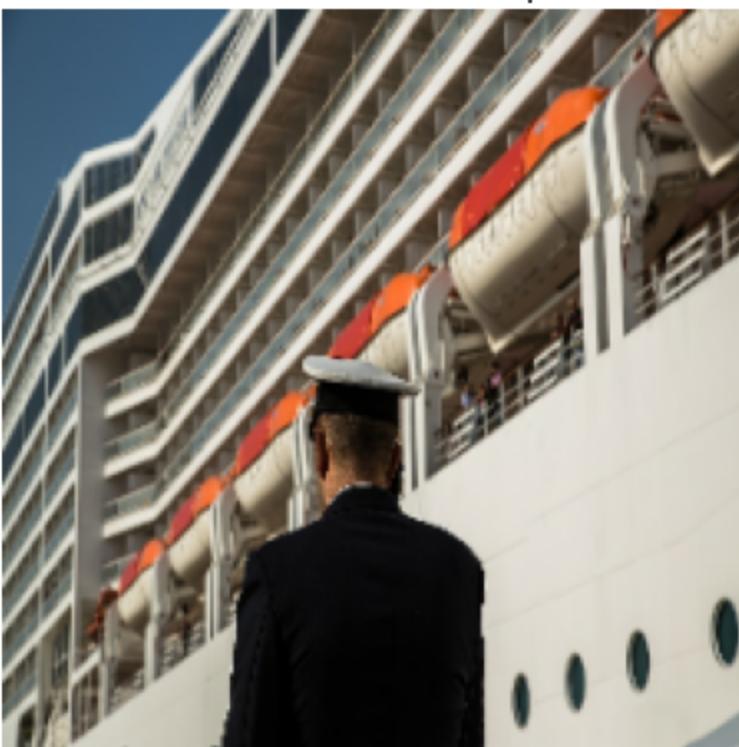
Original Class: Boat
Predicted Class: Boat



Original Class: Gondola
Predicted Class: Gondola



Original Class: Ship
Predicted Class: Ship



Original Class: Boat
Predicted Class: Boat



Original Class: Ship
Predicted Class: Ship



Original Class: Boat
Predicted Class: Ship



Original Class: Ship
Predicted Class: Ship



Original Class: Ship
Predicted Class: Ship



Original Class: Boat
Predicted Class: Boat



Original Class: Boat
Predicted Class: Boat



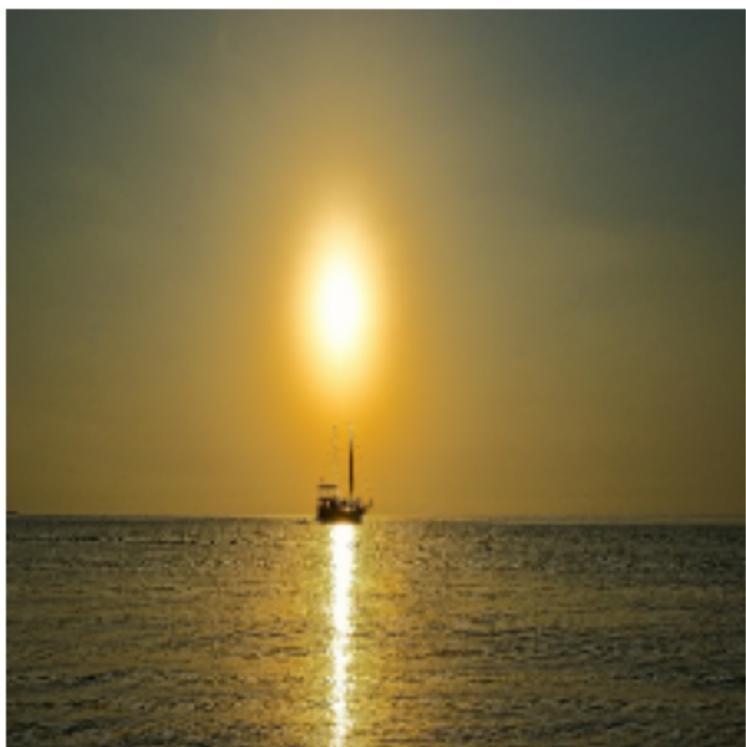
Original Class: Gondola
Predicted Class: Gondola



Original Class: Gondola
Predicted Class: Gondola



Original Class: Boat
Predicted Class: Boat



Original Class: Gondola
Predicted Class: Boat



Original Class: Gondola
Predicted Class: Gondola



Original Class: Ship
Predicted Class: Ship



Original Class: Ship
Predicted Class: Ship



Original Class: Gondola
Predicted Class: Gondola



Original Class: Gondola
Predicted Class: Ship



Original Class: Gondola
Predicted Class: Gondola



Original Class: Ship
Predicted Class: Ship



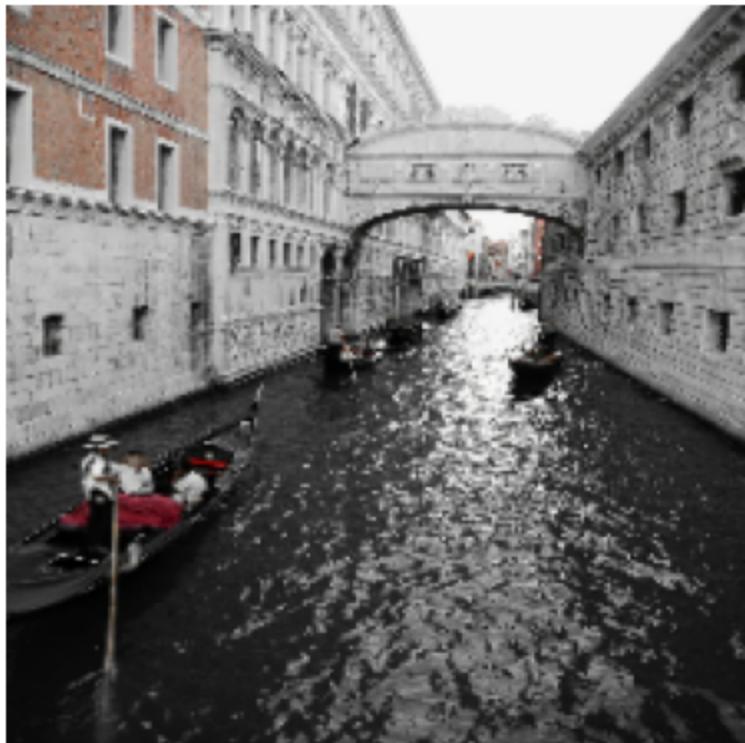
Original Class: Boat
Predicted Class: Boat



Original Class: Boat
Predicted Class: Boat



Original Class: Gondola
Predicted Class: Ship



Original Class: Ship
Predicted Class: Ship



Original Class: Ship
Predicted Class: Ship



Original Class: Gondola
Predicted Class: Ship



Original Class: Ship
Predicted Class: Ship



Original Class: Boat
Predicted Class: Ship



Original Class: Gondola
Predicted Class: Gondola



1/1 [=====] - 0s 53ms/step

Original Class: Ship
Predicted Class: Ship



Original Class: Ship
Predicted Class: Ship



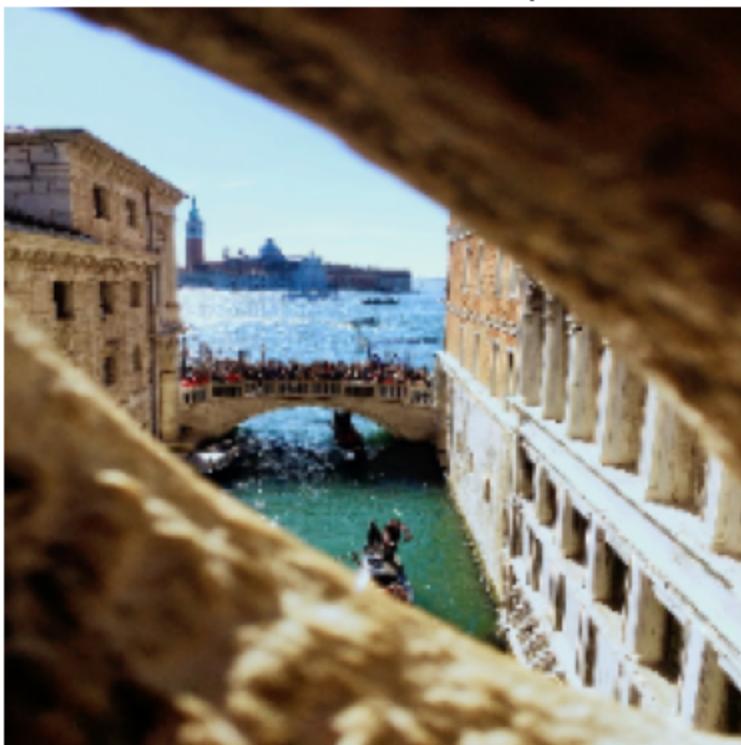
Original Class: Ship
Predicted Class: Ship



Original Class: Ship
Predicted Class: Ship



Original Class: Gondola
Predicted Class: Ship



Original Class: Ship
Predicted Class: Ship



Original Class: Ship
Predicted Class: Ship



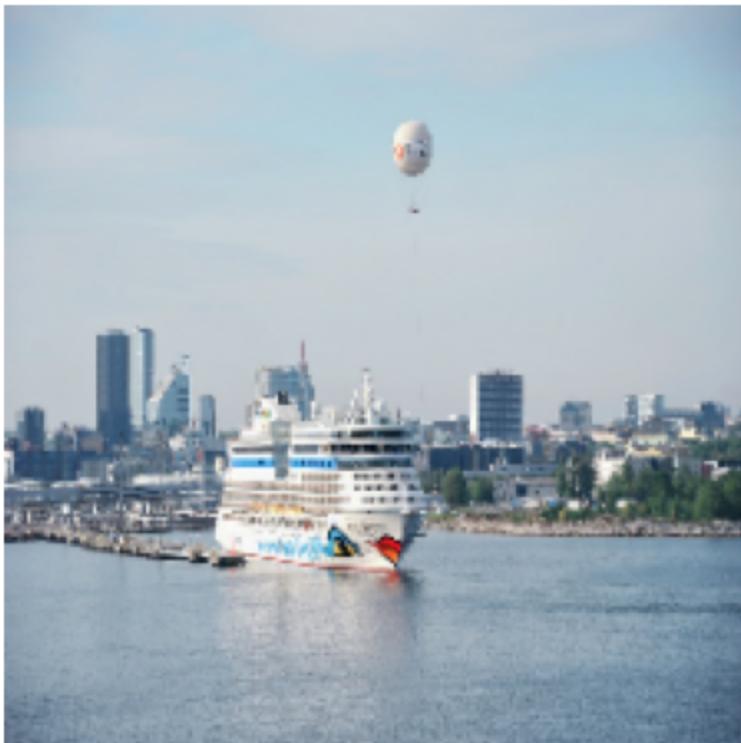
Original Class: Boat
Predicted Class: Boat



Original Class: Gondola
Predicted Class: Gondola



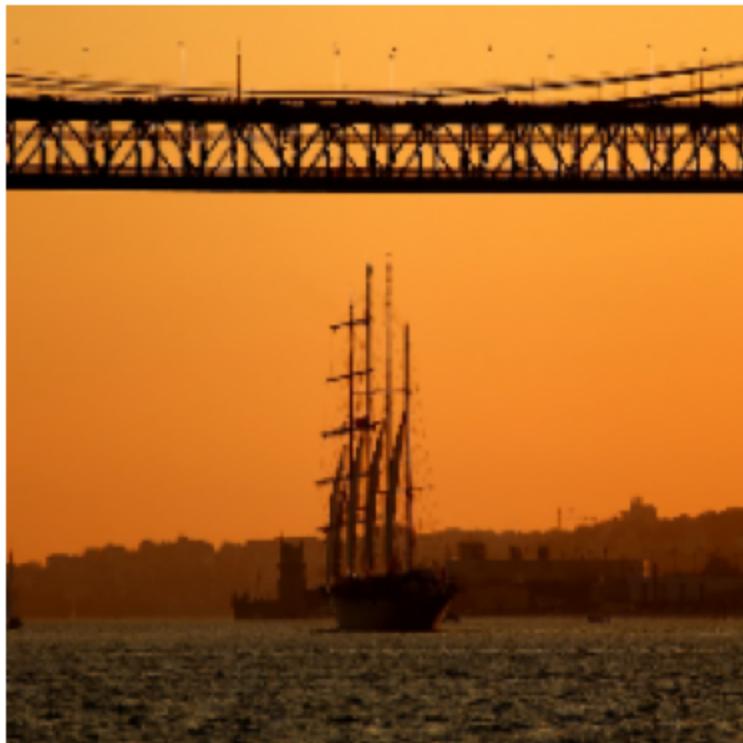
Original Class: Ship
Predicted Class: Ship



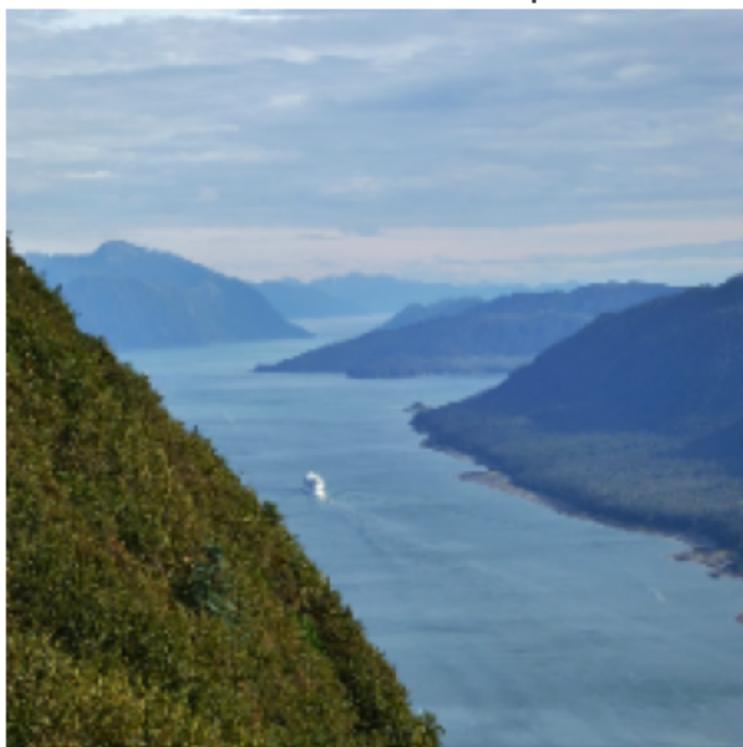
Original Class: Boat
Predicted Class: Boat



Original Class: Boat
Predicted Class: Boat



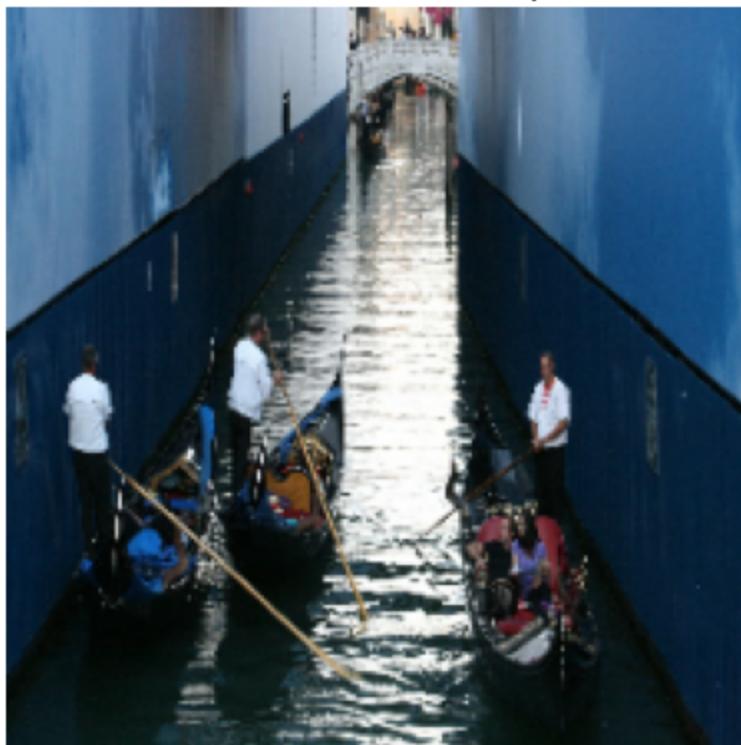
Original Class: Ship
Predicted Class: Ship



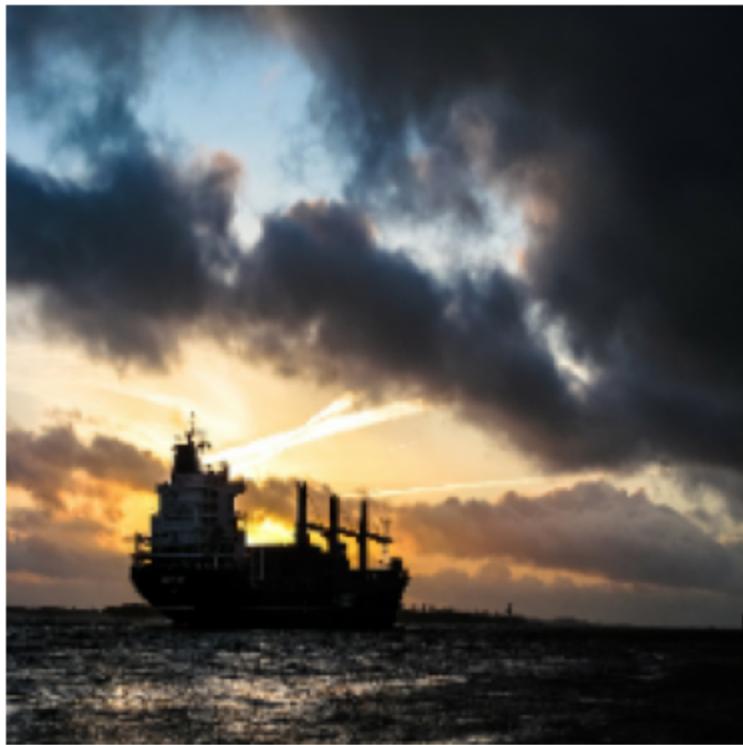
Original Class: Gondola
Predicted Class: Gondola



Original Class: Gondola
Predicted Class: Ship



Original Class: Ship
Predicted Class: Ship



Original Class: Ship
Predicted Class: Ship



Original Class: Ship
Predicted Class: Ship



Original Class: Boat
Predicted Class: Ship



Original Class: Ship
Predicted Class: Ship



Original Class: Gondola
Predicted Class: Gondola



Original Class: Boat
Predicted Class: Ship



Original Class: Boat
Predicted Class: Ship



Original Class: Gondola
Predicted Class: Gondola



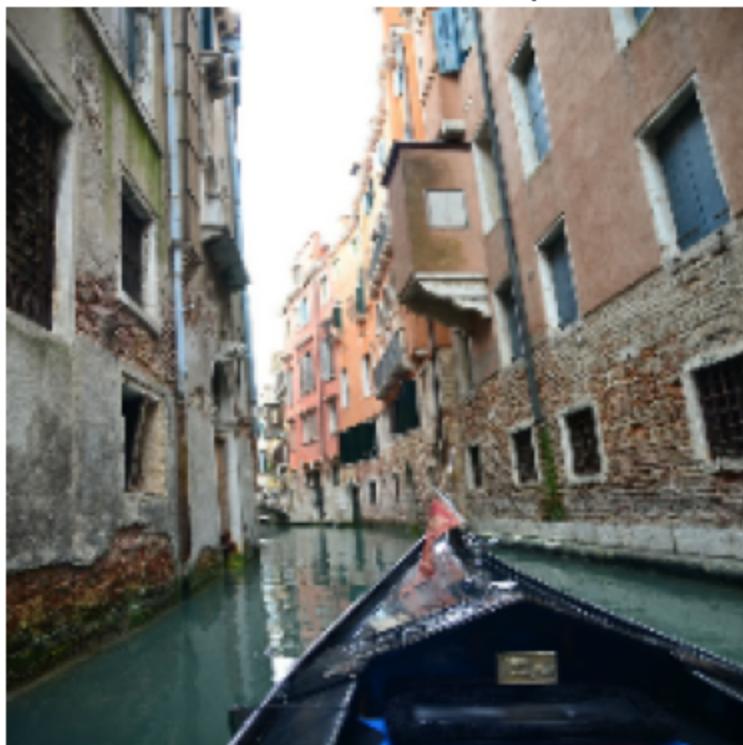
Original Class: Boat
Predicted Class: Boat



Original Class: Boat
Predicted Class: Boat



Original Class: Gondola
Predicted Class: Ship



Original Class: Gondola
Predicted Class: Gondola



Original Class: Gondola
Predicted Class: Gondola



Original Class: Boat
Predicted Class: Boat



Original Class: Boat
Predicted Class: Ship



Original Class: Boat
Predicted Class: Boat

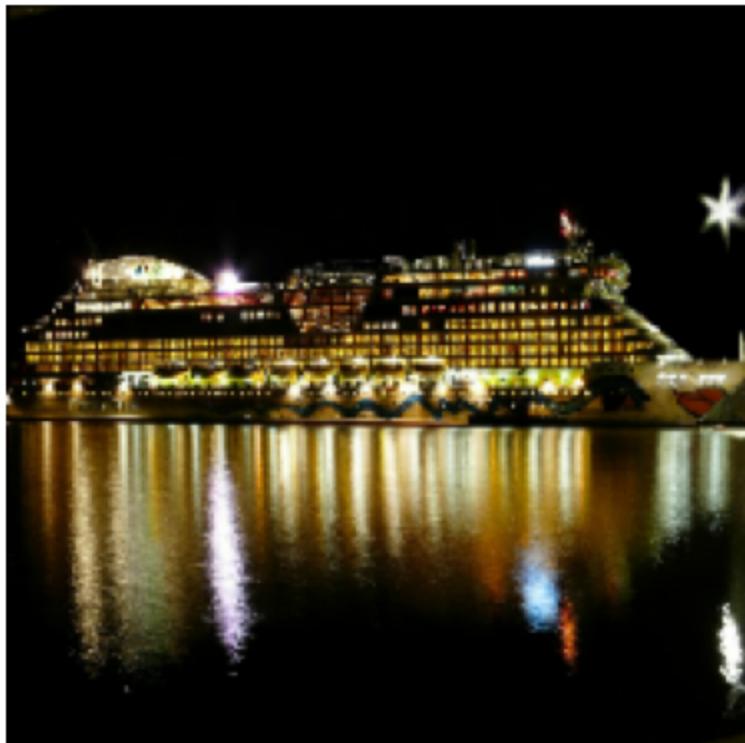


1/1 [=====] - 0s 40ms/step

Original Class: Ship
Predicted Class: Ship



Original Class: Ship
Predicted Class: Ship



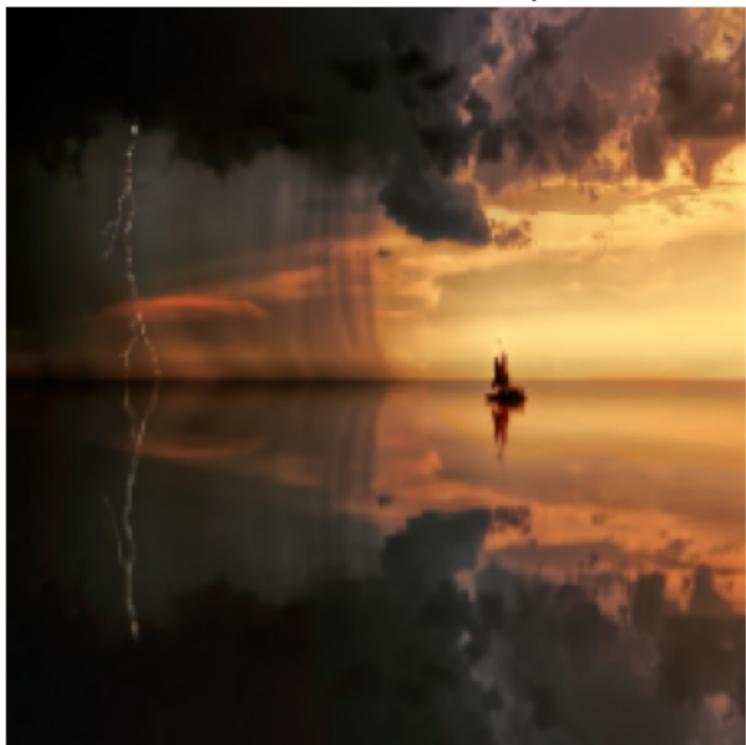
Original Class: Gondola
Predicted Class: Gondola



Original Class: Gondola
Predicted Class: Ship



Original Class: Boat
Predicted Class: Ship



Original Class: Boat
Predicted Class: Ship



Original Class: Ship
Predicted Class: Ship



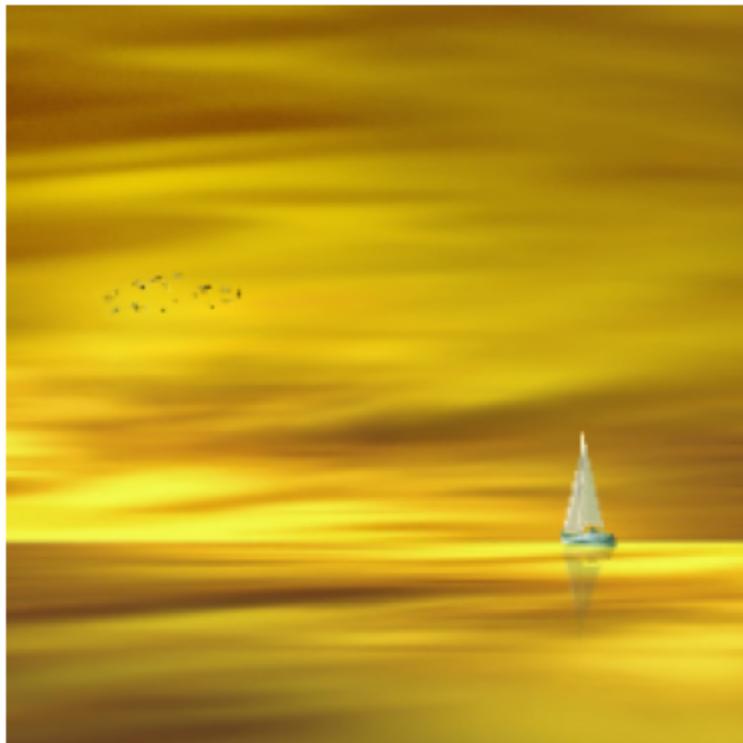
Original Class: Gondola
Predicted Class: Gondola



Original Class: Gondola
Predicted Class: Gondola



Original Class: Boat
Predicted Class: Boat



Original Class: Gondola
Predicted Class: Gondola



Original Class: Boat
Predicted Class: Boat



Original Class: Ship
Predicted Class: Ship



Original Class: Ship
Predicted Class: Ship



Original Class: Ship
Predicted Class: Ship



Original Class: Boat
Predicted Class: Boat



Original Class: Gondola
Predicted Class: Gondola



Original Class: Boat
Predicted Class: Boat



Original Class: Ship
Predicted Class: Ship



Original Class: Boat
Predicted Class: Boat



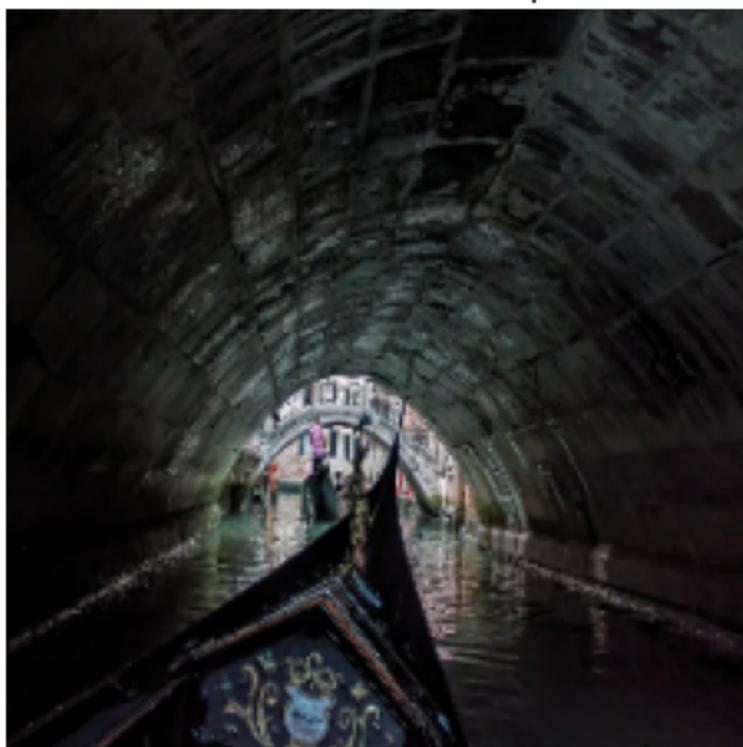
Original Class: Gondola
Predicted Class: Gondola



Original Class: Ship
Predicted Class: Boat



Original Class: Gondola
Predicted Class: Ship



Original Class: Ship
Predicted Class: Ship



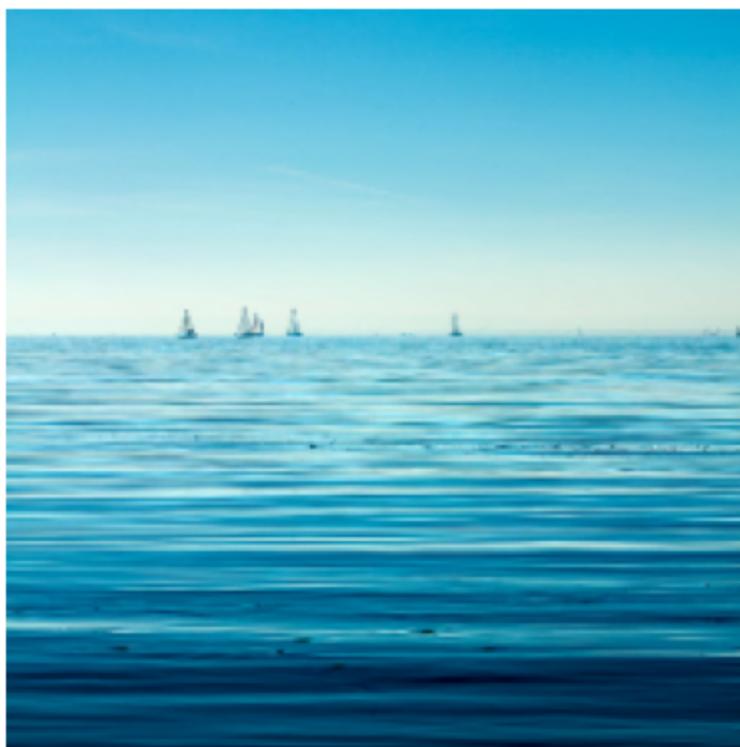
Original Class: Gondola
Predicted Class: Ship



Original Class: Gondola
Predicted Class: Gondola



Original Class: Boat
Predicted Class: Boat



Original Class: Gondola

Predicted Class: Ship



Original Class: Gondola

Predicted Class: Gondola



Original Class: Boat
Predicted Class: Boat



Original Class: Boat
Predicted Class: Ship



Original Class: Ship
Predicted Class: Ship



1/1 [=====] - 0s 47ms/step

Original Class: Gondola
Predicted Class: Ship



Original Class: Gondola
Predicted Class: Gondola



Original Class: Boat
Predicted Class: Boat



Original Class: Boat
Predicted Class: Boat

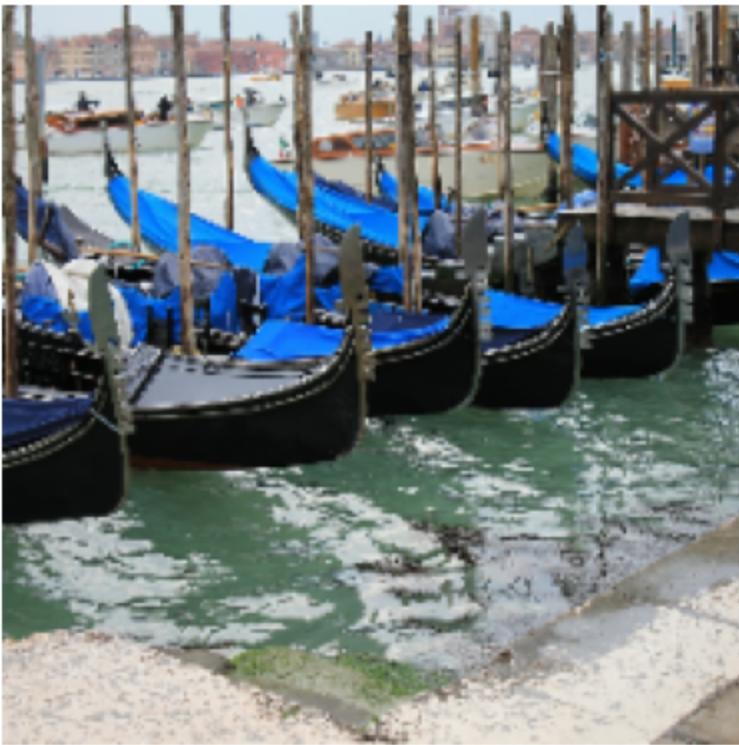


Original Class: Boat
Predicted Class: Boat



Original Class: Gondola

Predicted Class: Gondola



Original Class: Boat

Predicted Class: Boat



Original Class: Gondola
Predicted Class: Gondola



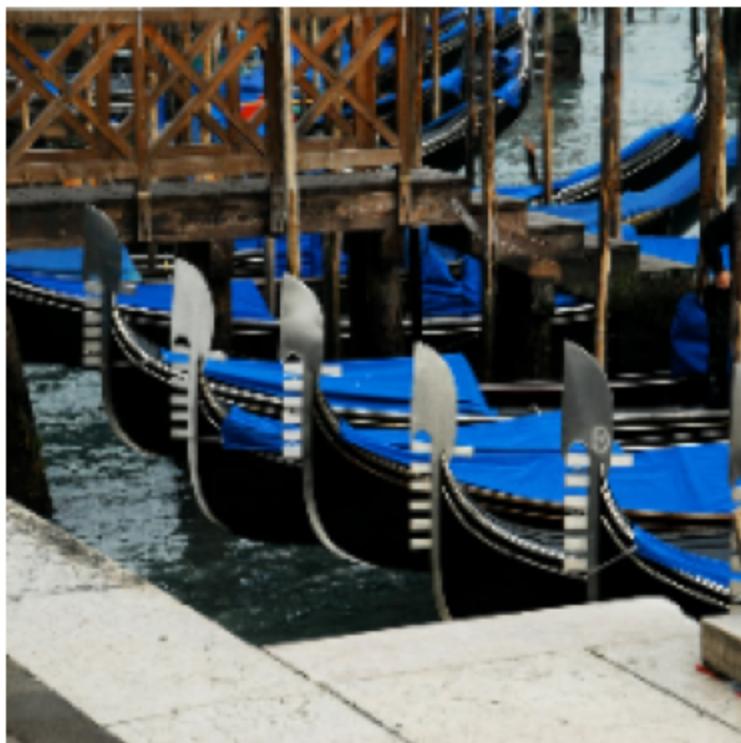
Original Class: Gondola
Predicted Class: Ship



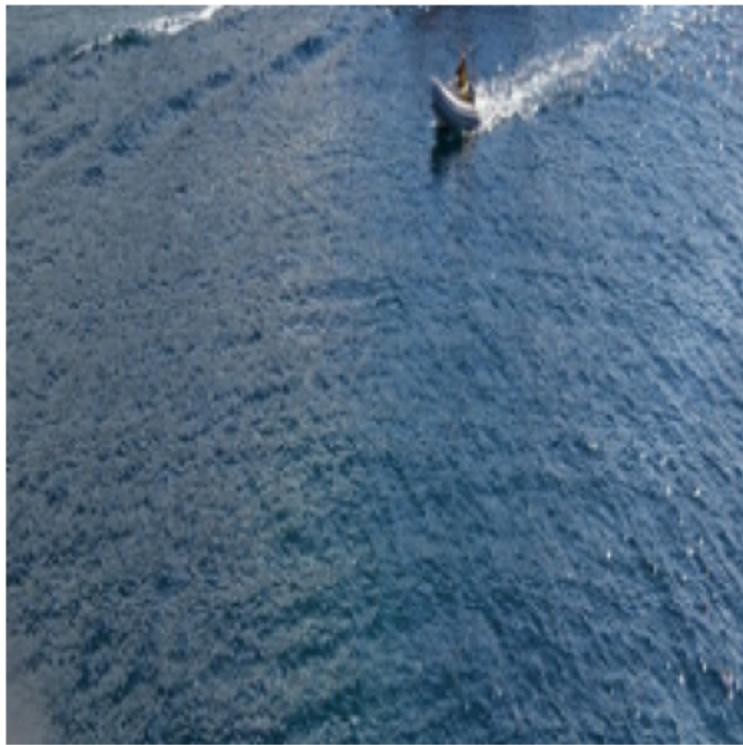
Original Class: Gondola
Predicted Class: Gondola



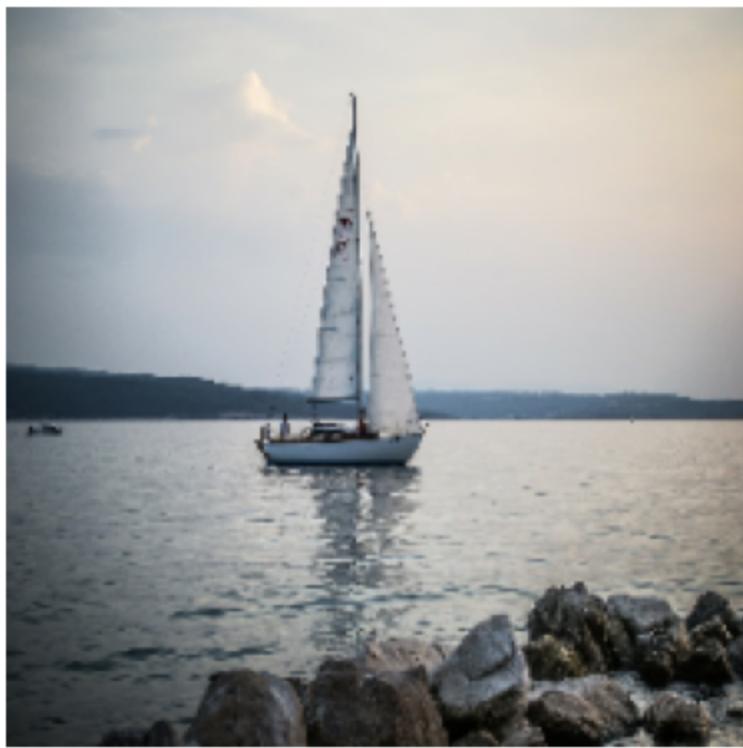
Original Class: Gondola
Predicted Class: Gondola



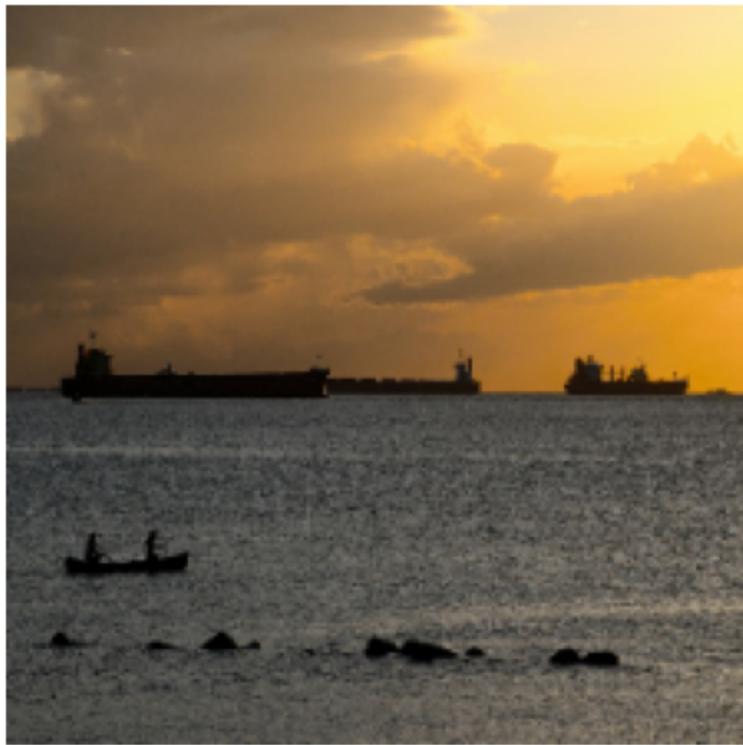
Original Class: Boat
Predicted Class: Boat



Original Class: Boat
Predicted Class: Boat



Original Class: Ship
Predicted Class: Ship



Original Class: Boat
Predicted Class: Boat



Original Class: Ship
Predicted Class: Ship



Original Class: Gondola
Predicted Class: Gondola



Original Class: Gondola
Predicted Class: Gondola



Original Class: Ship
Predicted Class: Ship



Original Class: Boat
Predicted Class: Boat



Original Class: Gondola
Predicted Class: Gondola



Original Class: Ship
Predicted Class: Ship



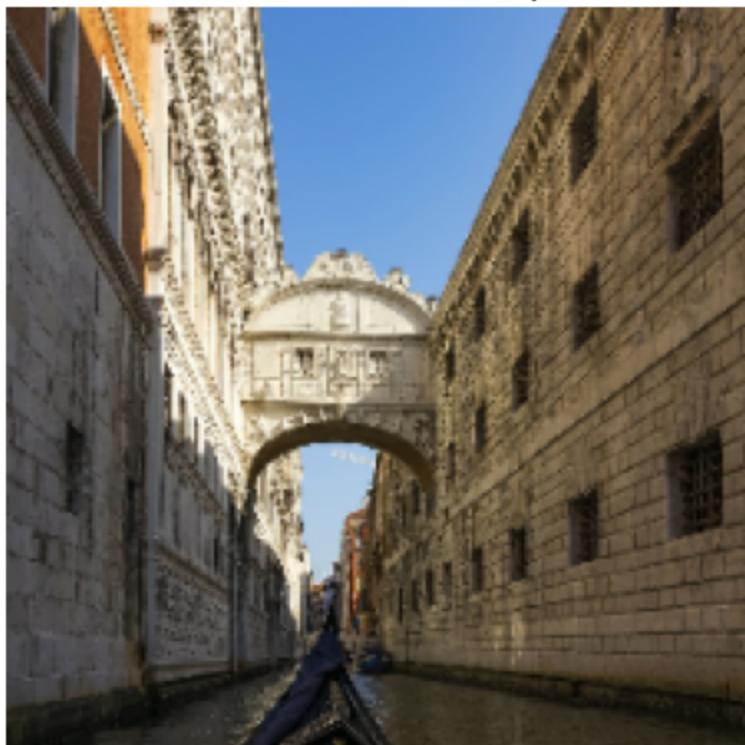
Original Class: Gondola
Predicted Class: Gondola



Original Class: Ship
Predicted Class: Ship



Original Class: Gondola
Predicted Class: Ship



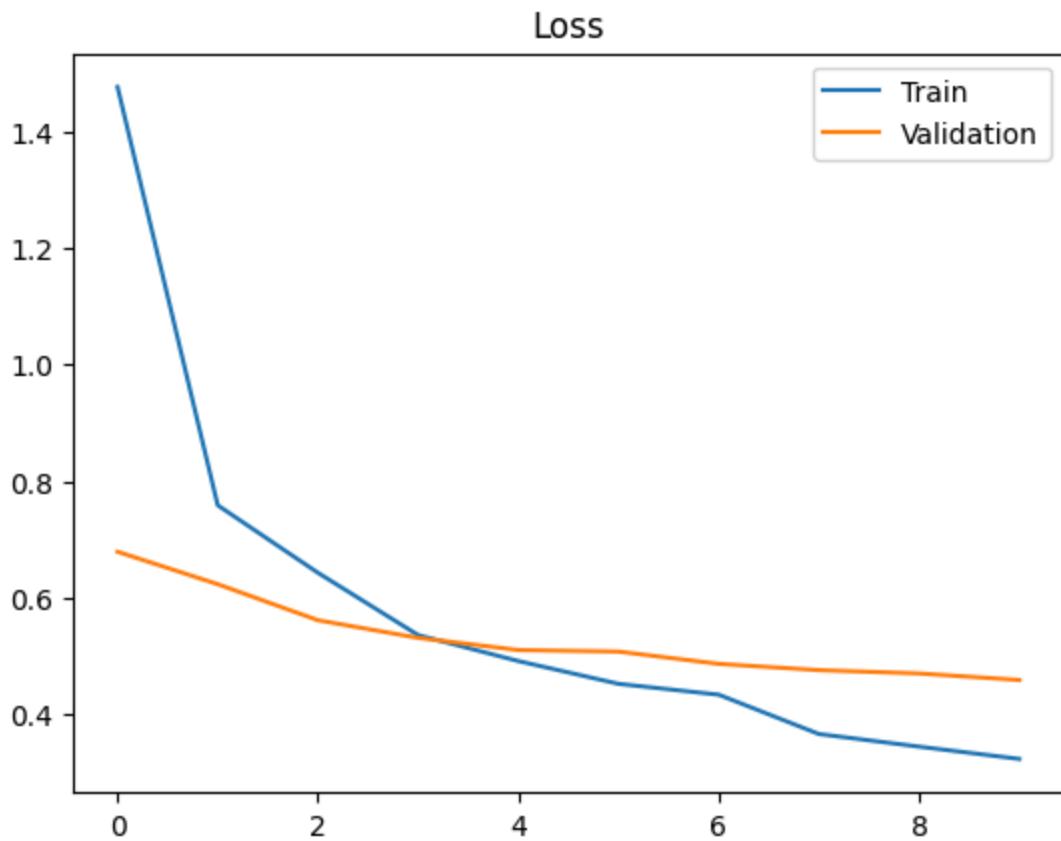
Original Class: Gondola

Predicted Class: Gondola

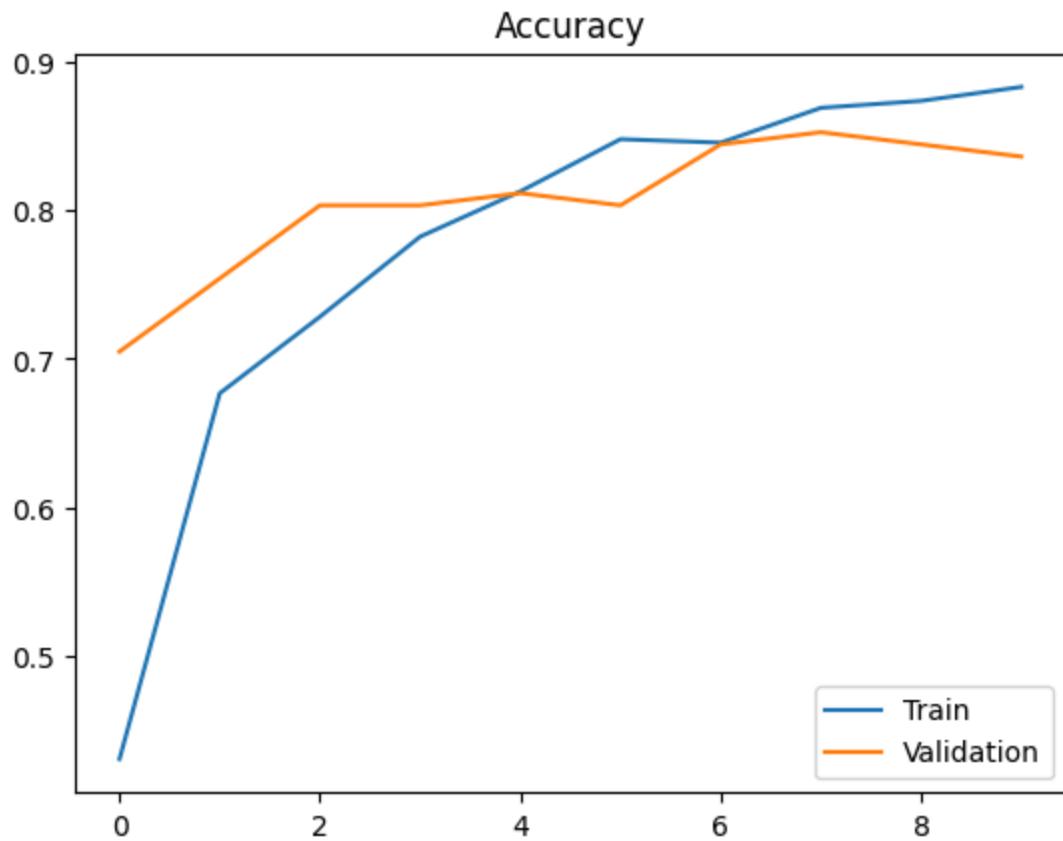


Performance Metrics

```
In [ ]: loss_train_curve = history.history["loss"]
loss_val_curve = history.history["val_loss"]
plt.plot(loss_train_curve, label = "Train")
plt.plot(loss_val_curve, label = "Validation")
plt.legend(loc = 'upper right')
plt.title("Loss")
plt.show()
```



```
In [ ]: acc_train_curve = history.history["accuracy"]
acc_val_curve = history.history["val_accuracy"]
plt.plot(acc_train_curve, label = "Train")
plt.plot(acc_val_curve, label = "Validation")
plt.legend(loc = 'lower right')
plt.title("Accuracy")
plt.show()
```



```
In [ ]: from sklearn.metrics import confusion_matrix, classification_report
import seaborn as sns

# Empty lists to store true labels and predicted labels
true_labels = []
predicted_labels = []

# Make predictions for images in TEST DATA
for batch in ds_test:
    # Extract images and Labels from the batch
    images, labels = batch

    # Preprocess the images for prediction
    preprocessed_images = tf.map_fn(preprocess_image, images)

    # Reshape the input tensor to match the MobileNet model's input shape
    preprocessed_images = tf.reshape(preprocessed_images, (-1, 224, 224, 3))

    # Making predictions
    predictions = model.predict(preprocessed_images)

    predicted_classes = np.argmax(predictions, axis=1)

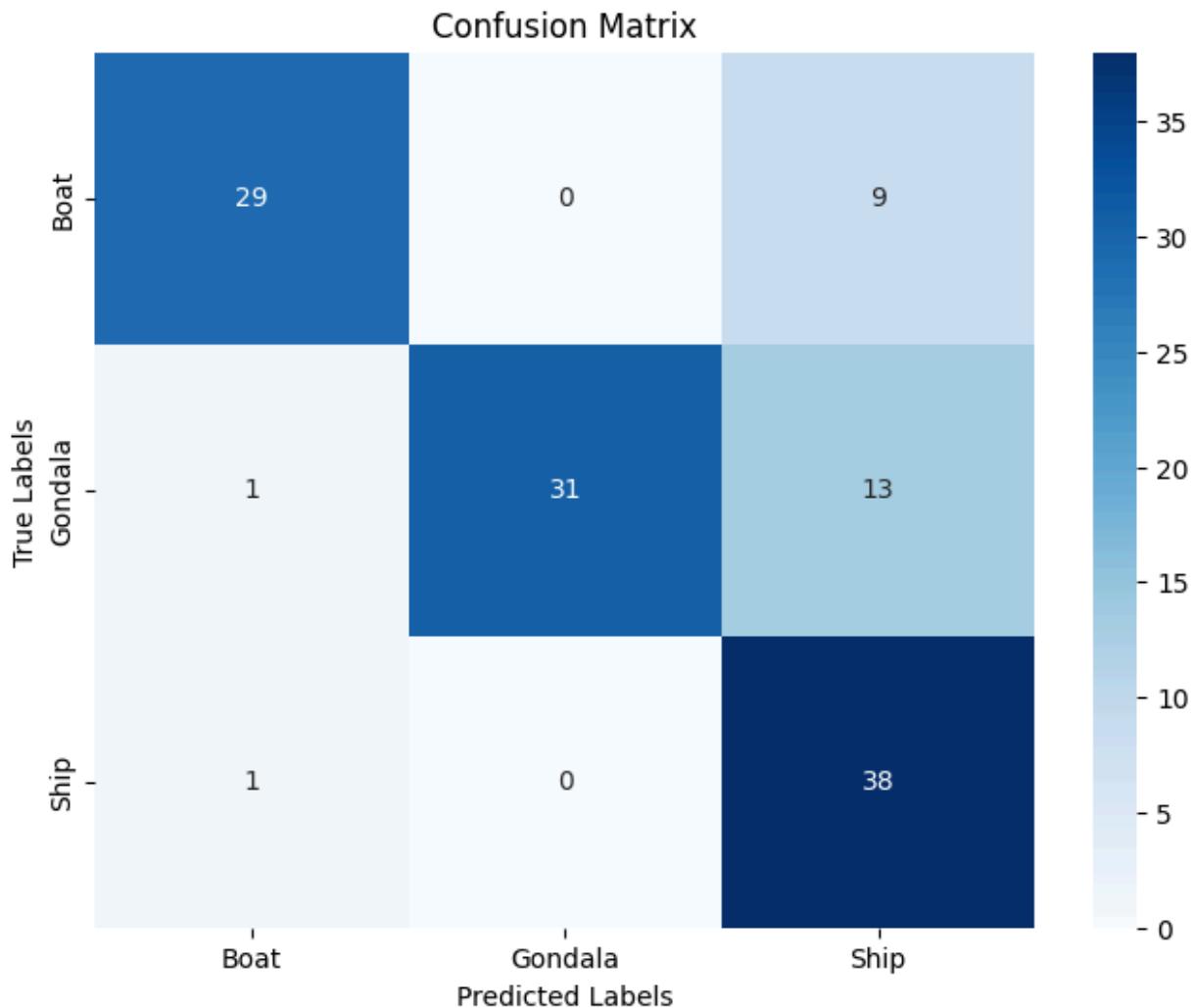
    # Append true and predicted labels to the lists
    true_labels.extend(labels.numpy())
    predicted_labels.extend(predicted_classes)

# Create a confusion matrix
conf_matrix = confusion_matrix(true_labels, predicted_labels)

# Displaying the confusion matrix using Seaborn
```

```
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=class_labels,
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.title('Confusion Matrix')
plt.show()
```

```
1/1 [=====] - 0s 28ms/step
1/1 [=====] - 0s 37ms/step
1/1 [=====] - 0s 28ms/step
1/1 [=====] - 0s 27ms/step
```



RESNET MODEL

```
In [ ]: from tensorflow.keras import layers
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.applications import ResNet50
from tensorflow.keras.applications.resnet50 import preprocess_input
```

```
In [ ]: resnet_50 = ResNet50(include_top=False, weights='imagenet', input_shape=(224,224,3))
for layer in resnet_50.layers:
    layer.trainable = False
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/re  
snet/resnet50_weights_tf_dim_ordering_tf_kernels_notop.h5  
94765736/94765736 [=====] - 1s 0us/step
```

```
In [ ]: X = resnet_50.output  
X = layers.GlobalAveragePooling2D()(X)  
X = layers.Dense(512, activation='relu')(X)  
X = layers.Dropout(0.5)(X)  
X = layers.Dense(256, activation='relu')(X)  
X = layers.Dropout(0.5)(X)  
X = layers.Dense(128, activation='relu')(X)  
X = layers.Dropout(0.5)(X)  
X = layers.Dense(64, activation='relu')(X)  
X = layers.Dropout(0.5)(X)  
predictions = layers.Dense(3, activation='softmax')(X)  
model = Model(inputs = resnet_50.input, outputs = predictions)
```

```
In [ ]: model.compile(optimizer="adam", loss="sparse_categorical_crossentropy", metrics=["accu  
model.summary()
```

Model: "model_1"

Layer (type)	Output Shape	Param #	Connected to
<hr/>			
input_2 (InputLayer)	[None, 224, 224, 3]	0	[]
conv1_pad (ZeroPadding2D)	(None, 230, 230, 3)	0	['input_2[0][0]']
conv1_conv (Conv2D)	(None, 112, 112, 64)	9472	['conv1_pad[0][0]']
conv1_bn (BatchNormalizati on)	(None, 112, 112, 64)	256	['conv1_conv[0][0]']
conv1_relu (Activation)	(None, 112, 112, 64)	0	['conv1_bn[0][0]']
pool1_pad (ZeroPadding2D)	(None, 114, 114, 64)	0	['conv1_relu[0][0]']
pool1_pool (MaxPooling2D)	(None, 56, 56, 64)	0	['pool1_pad[0][0]']
conv2_block1_1_conv (Conv2 D)	(None, 56, 56, 64)	4160	['pool1_pool[0][0]']
conv2_block1_1_bn (BatchNo rnalization)	(None, 56, 56, 64)	256	['conv2_block1_1_
conv2_block1_1_relu (Activ ation)	(None, 56, 56, 64)	0	['conv2_block1_1_
conv2_block1_2_conv (Conv2 D)	(None, 56, 56, 64)	36928	['conv2_block1_1_
conv2_block1_2_bn (BatchNo rnalization)	(None, 56, 56, 64)	256	['conv2_block1_2_
conv2_block1_2_relu (Activ ation)	(None, 56, 56, 64)	0	['conv2_block1_2_
conv2_block1_0_conv (Conv2 D)	(None, 56, 56, 256)	16640	['pool1_pool[0][0]']
conv2_block1_3_conv (Conv2 D)	(None, 56, 56, 256)	16640	['conv2_block1_2_
conv2_block1_0_bn (BatchNo rnalization)	(None, 56, 56, 256)	1024	['conv2_block1_0_

rnalization)			
conv2_block1_3_bn (BatchNo (None, 56, 56, 256) conv[0][0]') rnalization)	1024	['conv2_block1_3_	
conv2_block1_add (Add) (None, 56, 56, 256) bn[0][0]', bn[0][0]']	0	['conv2_block1_0_	'conv2_block1_3_
conv2_block1_out (Activati (None, 56, 56, 256) d[0][0]') on)	0	['conv2_block1_ad	
conv2_block2_1_conv (Conv2 (None, 56, 56, 64) t[0][0]') D)	16448	['conv2_block1_ou	
conv2_block2_1_bn (BatchNo (None, 56, 56, 64) conv[0][0]') rnalization)	256	['conv2_block2_1_	
conv2_block2_1_relu (Activ (None, 56, 56, 64) bn[0][0]') ation)	0	['conv2_block2_1_	
conv2_block2_2_conv (Conv2 (None, 56, 56, 64) relu[0][0]') D)	36928	['conv2_block2_1_	
conv2_block2_2_bn (BatchNo (None, 56, 56, 64) conv[0][0]') rnalization)	256	['conv2_block2_2_	
conv2_block2_2_relu (Activ (None, 56, 56, 64) bn[0][0]') ation)	0	['conv2_block2_2_	
conv2_block2_3_conv (Conv2 (None, 56, 56, 256) relu[0][0]') D)	16640	['conv2_block2_2_	
conv2_block2_3_bn (BatchNo (None, 56, 56, 256) conv[0][0]') rnalization)	1024	['conv2_block2_3_	
conv2_block2_add (Add) (None, 56, 56, 256) t[0][0]', bn[0][0]']	0	['conv2_block1_ou	'conv2_block2_3_
conv2_block2_out (Activati (None, 56, 56, 256) d[0][0]') on)	0	['conv2_block2_ad	
conv2_block3_1_conv (Conv2 (None, 56, 56, 64) t[0][0]') D)	16448	['conv2_block2_ou	

conv2_block3_1_bn (BatchNo conv[0][0]') rnalization)	256	['conv2_block3_1_
conv2_block3_1_relu (Activ bn[0][0]') ation)	0	['conv2_block3_1_
conv2_block3_2_conv (Conv2 relu[0][0]') D)	36928	['conv2_block3_1_
conv2_block3_2_bn (BatchNo conv[0][0]') rnalization)	256	['conv2_block3_2_
conv2_block3_2_relu (Activ bn[0][0]') ation)	0	['conv2_block3_2_
conv2_block3_3_conv (Conv2 relu[0][0]') D)	16640	['conv2_block3_2_
conv2_block3_3_bn (BatchNo conv[0][0]') rnalization)	1024	['conv2_block3_3_
conv2_block3_add (Add) t[0][0]', bn[0][0]']	0	['conv2_block2_ou 'conv2_block3_3_
conv2_block3_out (Activati d[0][0]') on)	0	['conv2_block3_ad
conv3_block1_1_conv (Conv2 t[0][0]') D)	32896	['conv2_block3_ou
conv3_block1_1_bn (BatchNo conv[0][0]') rnalization)	512	['conv3_block1_1_
conv3_block1_1_relu (Activ bn[0][0]') ation)	0	['conv3_block1_1_
conv3_block1_2_conv (Conv2 relu[0][0]') D)	147584	['conv3_block1_1_
conv3_block1_2_bn (BatchNo conv[0][0]') rnalization)	512	['conv3_block1_2_
conv3_block1_2_relu (Activ bn[0][0]') ation)	0	['conv3_block1_2_

conv3_block1_0_conv (Conv2 (None, 28, 28, 512) t[0][0]')	D)	131584	['conv2_block3_out']
conv3_block1_3_conv (Conv2 (None, 28, 28, 512) relu[0][0]')	D)	66048	['conv3_block1_2_out']
conv3_block1_0_bn (BatchNorm (None, 28, 28, 512) conv[0][0]')	rnmalization)	2048	['conv3_block1_0_out']
conv3_block1_3_bn (BatchNorm (None, 28, 28, 512) conv[0][0]')	rnmalization)	2048	['conv3_block1_3_out']
conv3_block1_add (Add) bn[0][0]', bn[0][0]'	(None, 28, 28, 512)	0	['conv3_block1_0_out'] ['conv3_block1_3_out']
conv3_block1_out (Activation (None, 28, 28, 512) d[0][0]')	on)	0	['conv3_block1_activation']
conv3_block2_1_conv (Conv2 (None, 28, 28, 128) t[0][0]')	D)	65664	['conv3_block1_out']
conv3_block2_1_bn (BatchNorm (None, 28, 28, 128) conv[0][0]')	rnmalization)	512	['conv3_block2_1_out']
conv3_block2_1_relu (Activation (None, 28, 28, 128) bn[0][0]')	ation)	0	['conv3_block2_1_out']
conv3_block2_2_conv (Conv2 (None, 28, 28, 128) relu[0][0]')	D)	147584	['conv3_block2_1_out']
conv3_block2_2_bn (BatchNorm (None, 28, 28, 128) conv[0][0]')	rnmalization)	512	['conv3_block2_2_out']
conv3_block2_2_relu (Activation (None, 28, 28, 128) bn[0][0]')	ation)	0	['conv3_block2_2_out']
conv3_block2_3_conv (Conv2 (None, 28, 28, 512) relu[0][0]')	D)	66048	['conv3_block2_2_out']
conv3_block2_3_bn (BatchNorm (None, 28, 28, 512) conv[0][0]')	rnmalization)	2048	['conv3_block2_3_out']
conv3_block2_add (Add) t[0][0]'	(None, 28, 28, 512)	0	['conv3_block1_out']

bn[0][0]']		'conv3_block2_3_
conv3_block2_out (Activati (None, 28, 28, 512) d[0][0]' on)	0	['conv3_block2_ad
conv3_block3_1_conv (Conv2 (None, 28, 28, 128) t[0][0]')	65664	['conv3_block2_ou
D)		D)
conv3_block3_1_bn (BatchNo (None, 28, 28, 128) conv[0][0]' rmalization)	512	['conv3_block3_1_
bn[0][0]']		rnmalization)
conv3_block3_1_relu (Activ (None, 28, 28, 128) bn[0][0]' ation)	0	['conv3_block3_1_
bn[0][0]']		rnmalization)
conv3_block3_2_conv (Conv2 (None, 28, 28, 128) relu[0][0]')	147584	['conv3_block3_1_
D)		rnmalization)
conv3_block3_2_bn (BatchNo (None, 28, 28, 128) conv[0][0]' rmalization)	512	['conv3_block3_2_
bn[0][0]']		rnmalization)
conv3_block3_2_relu (Activ (None, 28, 28, 128) bn[0][0]' ation)	0	['conv3_block3_2_
bn[0][0]']		rnmalization)
conv3_block3_3_conv (Conv2 (None, 28, 28, 512) relu[0][0]')	66048	['conv3_block3_2_
D)		rnmalization)
conv3_block3_3_bn (BatchNo (None, 28, 28, 512) conv[0][0]' rmalization)	2048	['conv3_block3_3_
bn[0][0]']		rnmalization)
conv3_block3_add (Add) (None, 28, 28, 512) t[0][0]', bn[0][0]'	0	['conv3_block2_ou
		'conv3_block3_3_
bn[0][0]']		rnmalization)
conv3_block3_out (Activati (None, 28, 28, 512) d[0][0]' on)	0	['conv3_block3_ad
		on)
conv3_block4_1_conv (Conv2 (None, 28, 28, 128) t[0][0]')	65664	['conv3_block3_ou
D)		D)
conv3_block4_1_bn (BatchNo (None, 28, 28, 128) conv[0][0]' rmalization)	512	['conv3_block4_1_
bn[0][0]']		rnmalization)
conv3_block4_1_relu (Activ (None, 28, 28, 128) bn[0][0]' ation)	0	['conv3_block4_1_
bn[0][0]']		rnmalization)

conv3_block4_2_conv (Conv2 (None, 28, 28, 128) relu[0][0]') D)	147584	['conv3_block4_1_
conv3_block4_2_bn (BatchNo (None, 28, 28, 128) conv[0][0]') rnmalization)	512	['conv3_block4_2_
conv3_block4_2_relu (Activ (None, 28, 28, 128) bn[0][0]') ation)	0	['conv3_block4_2_
conv3_block4_3_conv (Conv2 (None, 28, 28, 512) relu[0][0]') D)	66048	['conv3_block4_2_
conv3_block4_3_bn (BatchNo (None, 28, 28, 512) conv[0][0]') rnmalization)	2048	['conv3_block4_3_
conv3_block4_add (Add) t[0][0]', bn[0][0]']	0	['conv3_block3_ou 'conv3_block4_3_
conv3_block4_out (Activati (None, 28, 28, 512) d[0][0]') on)	0	['conv3_block4_ad
conv4_block1_1_conv (Conv2 (None, 14, 14, 256) t[0][0]') D)	131328	['conv3_block4_ou
conv4_block1_1_bn (BatchNo (None, 14, 14, 256) conv[0][0]') rnmalization)	1024	['conv4_block1_1_
conv4_block1_1_relu (Activ (None, 14, 14, 256) bn[0][0]') ation)	0	['conv4_block1_1_
conv4_block1_2_conv (Conv2 (None, 14, 14, 256) relu[0][0]') D)	590080	['conv4_block1_1_
conv4_block1_2_bn (BatchNo (None, 14, 14, 256) conv[0][0]') rnmalization)	1024	['conv4_block1_2_
conv4_block1_2_relu (Activ (None, 14, 14, 256) bn[0][0]') ation)	0	['conv4_block1_2_
conv4_block1_0_conv (Conv2 (None, 14, 14, 1024) t[0][0]') D)	525312	['conv3_block4_ou
conv4_block1_3_conv (Conv2 (None, 14, 14, 1024) relu[0][0]') D)	263168	['conv4_block1_2_

conv4_block1_0_bn (BatchNo conv[0][0]' rmalization)	(None, 14, 14, 1024)	4096	['conv4_block1_0_
conv4_block1_3_bn (BatchNo conv[0][0]' rmalization)	(None, 14, 14, 1024)	4096	['conv4_block1_3_
conv4_block1_add (Add) bn[0][0]', bn[0][0]'	(None, 14, 14, 1024)	0	['conv4_block1_0_ 'conv4_block1_3_
conv4_block1_out (Activati d[0][0]' on)	(None, 14, 14, 1024)	0	['conv4_block1_ad
conv4_block2_1_conv (Conv2 t[0][0]')	(None, 14, 14, 256)	262400	['conv4_block1_ou
conv4_block2_1_bn (BatchNo conv[0][0]' rmalization)	(None, 14, 14, 256)	1024	['conv4_block2_1_
conv4_block2_1_relu (Activ bn[0][0]'	(None, 14, 14, 256)	0	['conv4_block2_1_
conv4_block2_2_conv (Conv2 relu[0][0]')	(None, 14, 14, 256)	590080	['conv4_block2_1_
conv4_block2_2_bn (BatchNo conv[0][0]'	(None, 14, 14, 256)	1024	['conv4_block2_2_
conv4_block2_2_relu (Activ bn[0][0]'	(None, 14, 14, 256)	0	['conv4_block2_2_
conv4_block2_3_conv (Conv2 relu[0][0]')	(None, 14, 14, 1024)	263168	['conv4_block2_2_
conv4_block2_3_bn (BatchNo conv[0][0]'	(None, 14, 14, 1024)	4096	['conv4_block2_3_
conv4_block2_add (Add) t[0][0]', bn[0][0]'	(None, 14, 14, 1024)	0	['conv4_block1_ou 'conv4_block2_3_
conv4_block2_out (Activati d[0][0]' on)	(None, 14, 14, 1024)	0	['conv4_block2_ad
conv4_block3_1_conv (Conv2 None, 14, 14, 256)	(None, 14, 14, 256)	262400	['conv4_block2_ou

t[0][0]'] D)			
conv4_block3_1_bn (BatchNo (None, 14, 14, 256) conv[0][0]' rnalization)	1024	['conv4_block3_1_	
conv4_block3_1_relu (Activ (None, 14, 14, 256) bn[0][0]' ation)	0	['conv4_block3_1_	
conv4_block3_2_conv (Conv2 (None, 14, 14, 256) relu[0][0]' D)	590080	['conv4_block3_1_	
conv4_block3_2_bn (BatchNo (None, 14, 14, 256) conv[0][0]' rnalization)	1024	['conv4_block3_2_	
conv4_block3_2_relu (Activ (None, 14, 14, 256) bn[0][0]' ation)	0	['conv4_block3_2_	
conv4_block3_3_conv (Conv2 (None, 14, 14, 1024) relu[0][0]' D)	263168	['conv4_block3_2_	
conv4_block3_3_bn (BatchNo (None, 14, 14, 1024) conv[0][0]' rnalization)	4096	['conv4_block3_3_	
conv4_block3_add (Add) (None, 14, 14, 1024) t[0][0]', bn[0][0]']	0	['conv4_block2_ou 'conv4_block3_3_	
conv4_block3_out (Activati (None, 14, 14, 1024) d[0][0]' on)	0	['conv4_block3_ad	
conv4_block4_1_conv (Conv2 (None, 14, 14, 256) t[0][0]')	262400	['conv4_block3_ou	
conv4_block4_1_bn (BatchNo (None, 14, 14, 256) conv[0][0]' rnalization)	1024	['conv4_block4_1_	
conv4_block4_1_relu (Activ (None, 14, 14, 256) bn[0][0]' ation)	0	['conv4_block4_1_	
conv4_block4_2_conv (Conv2 (None, 14, 14, 256) relu[0][0]'	590080	['conv4_block4_1_	
conv4_block4_2_bn (BatchNo (None, 14, 14, 256) conv[0][0]' rnalization)	1024	['conv4_block4_2_	

conv4_block4_2_relu (Activ ation)	(None, 14, 14, 256) bn[0][0]'	0	['conv4_block4_2_
conv4_block4_3_conv (Conv2 D)	(None, 14, 14, 1024) relu[0][0]'	263168	['conv4_block4_2_
conv4_block4_3_bn (BatchNo rnalization)	(None, 14, 14, 1024) conv[0][0]'	4096	['conv4_block4_3_
conv4_block4_add (Add)	(None, 14, 14, 1024) t[0][0]', bn[0][0]'	0	['conv4_block3_ou ' conv4_block4_3_
conv4_block4_out (Activati on)	(None, 14, 14, 1024) d[0][0]'	0	['conv4_block4_ad
conv4_block5_1_conv (Conv2 D)	(None, 14, 14, 256) t[0][0]'	262400	['conv4_block4_ou
conv4_block5_1_bn (BatchNo rnalization)	(None, 14, 14, 256) conv[0][0]'	1024	['conv4_block5_1_
conv4_block5_1_relu (Activ ation)	(None, 14, 14, 256) bn[0][0]'	0	['conv4_block5_1_
conv4_block5_2_conv (Conv2 D)	(None, 14, 14, 256) relu[0][0]'	590080	['conv4_block5_1_
conv4_block5_2_bn (BatchNo rnalization)	(None, 14, 14, 256) conv[0][0]'	1024	['conv4_block5_2_
conv4_block5_2_relu (Activ ation)	(None, 14, 14, 256) bn[0][0]'	0	['conv4_block5_2_
conv4_block5_3_conv (Conv2 D)	(None, 14, 14, 1024) relu[0][0]'	263168	['conv4_block5_2_
conv4_block5_3_bn (BatchNo rnalization)	(None, 14, 14, 1024) conv[0][0]'	4096	['conv4_block5_3_
conv4_block5_add (Add)	(None, 14, 14, 1024) t[0][0]', bn[0][0]'	0	['conv4_block4_ou ' conv4_block5_3_
conv4_block5_out (Activati on)	(None, 14, 14, 1024) d[0][0]'	0	['conv4_block5_ad

on)			
conv4_block6_1_conv (Conv2 (None, 14, 14, 256) t[0][0]')	262400	['conv4_block5_out']	D)
conv4_block6_1_bn (BatchNo (None, 14, 14, 256) conv[0][0]') rnalization)	1024	['conv4_block6_1_	
conv4_block6_1_relu (Activ (None, 14, 14, 256) bn[0][0]') ation)	0	['conv4_block6_1_	
conv4_block6_2_conv (Conv2 (None, 14, 14, 256) relu[0][0]')	590080	['conv4_block6_1_	D)
conv4_block6_2_bn (BatchNo (None, 14, 14, 256) conv[0][0]') rnalization)	1024	['conv4_block6_2_	
conv4_block6_2_relu (Activ (None, 14, 14, 256) bn[0][0]') ation)	0	['conv4_block6_2_	
conv4_block6_3_conv (Conv2 (None, 14, 14, 1024) relu[0][0]')	263168	['conv4_block6_2_	D)
conv4_block6_3_bn (BatchNo (None, 14, 14, 1024) conv[0][0]') rnalization)	4096	['conv4_block6_3_	
conv4_block6_add (Add) (None, 14, 14, 1024) t[0][0]', bn[0][0]']	0	['conv4_block5_out']	'conv4_block6_3_
conv4_block6_out (Activati (None, 14, 14, 1024) d[0][0]') on)	0	['conv4_block6_ad	
conv5_block1_1_conv (Conv2 (None, 7, 7, 512) t[0][0]')	524800	['conv4_block6_out']	D)
conv5_block1_1_bn (BatchNo (None, 7, 7, 512) conv[0][0]') rnalization)	2048	['conv5_block1_1_	
conv5_block1_1_relu (Activ (None, 7, 7, 512) bn[0][0]') ation)	0	['conv5_block1_1_	
conv5_block1_2_conv (Conv2 (None, 7, 7, 512) relu[0][0]')	2359808	['conv5_block1_1_	D)
conv5_block1_2_bn (BatchNo (None, 7, 7, 512)	2048	['conv5_block1_2_	

conv[0][0]'] rmalization)			
conv5_block1_2_relu (Activ (None, 7, 7, 512) bn[0][0]'] ation)	0		['conv5_block1_2_
conv5_block1_0_conv (Conv2 (None, 7, 7, 2048) t[0][0]'] D)	2099200		['conv4_block6_ou
conv5_block1_3_conv (Conv2 (None, 7, 7, 2048) relu[0][0]'] D)	1050624		['conv5_block1_2_
conv5_block1_0_bn (BatchNo (None, 7, 7, 2048) conv[0][0]'] rmalization)	8192		['conv5_block1_0_
conv5_block1_3_bn (BatchNo (None, 7, 7, 2048) conv[0][0]'] rmalization)	8192		['conv5_block1_3_
conv5_block1_add (Add) (None, 7, 7, 2048) bn[0][0]', bn[0][0]']	0		['conv5_block1_0_
conv5_block1_out (Activati (None, 7, 7, 2048) d[0][0]'] on)	0		['conv5_block1_ad
conv5_block2_1_conv (Conv2 (None, 7, 7, 512) t[0][0]'] D)	1049088		['conv5_block1_ou
conv5_block2_1_bn (BatchNo (None, 7, 7, 512) conv[0][0]'] rmalization)	2048		['conv5_block2_1_
conv5_block2_1_relu (Activ (None, 7, 7, 512) bn[0][0]'] ation)	0		['conv5_block2_1_
conv5_block2_2_conv (Conv2 (None, 7, 7, 512) relu[0][0]'] D)	2359808		['conv5_block2_1_
conv5_block2_2_bn (BatchNo (None, 7, 7, 512) conv[0][0]'] rmalization)	2048		['conv5_block2_2_
conv5_block2_2_relu (Activ (None, 7, 7, 512) bn[0][0]'] ation)	0		['conv5_block2_2_
conv5_block2_3_conv (Conv2 (None, 7, 7, 2048) relu[0][0]'] D)	1050624		['conv5_block2_2_

conv5_block2_3_bn (BatchNo conv[0][0]' rnalization)	(None, 7, 7, 2048)	8192	['conv5_block2_3_
conv5_block2_add (Add) t[0][0]',	(None, 7, 7, 2048)	0	['conv5_block1_ou 'conv5_block2_3_
bn[0][0]']			
conv5_block2_out (Activati d[0][0]' on)	(None, 7, 7, 2048)	0	['conv5_block2_ad
conv5_block3_1_conv (Conv2 t[0][0]'	(None, 7, 7, 512)	1049088	['conv5_block2_ou
D)			
conv5_block3_1_bn (BatchNo conv[0][0]' rnalization)	(None, 7, 7, 512)	2048	['conv5_block3_1_
bn[0][0]']			
conv5_block3_1_relu (Activ bn[0][0]' ation)	(None, 7, 7, 512)	0	['conv5_block3_1_
relu[0][0]']			
D)			
conv5_block3_2_conv (Conv2 relu[0][0]'	(None, 7, 7, 512)	2359808	['conv5_block3_1_
D)			
conv5_block3_2_bn (BatchNo conv[0][0]' rnalization)	(None, 7, 7, 512)	2048	['conv5_block3_2_
bn[0][0]']			
conv5_block3_2_relu (Activ bn[0][0]' ation)	(None, 7, 7, 512)	0	['conv5_block3_2_
relu[0][0]']			
D)			
conv5_block3_3_conv (Conv2 relu[0][0]'	(None, 7, 7, 2048)	1050624	['conv5_block3_2_
D)			
conv5_block3_3_bn (BatchNo conv[0][0]' rnalization)	(None, 7, 7, 2048)	8192	['conv5_block3_3_
bn[0][0]']			
conv5_block3_add (Add) t[0][0]',	(None, 7, 7, 2048)	0	['conv5_block2_ou 'conv5_block3_3_
bn[0][0]']			
conv5_block3_out (Activati d[0][0]' on)	(None, 7, 7, 2048)	0	['conv5_block3_ad
global_average_pooling2d_1 t[0][0]'	(None, 2048)	0	['conv5_block3_ou
(GlobalAveragePooling2D)			
dense_2 (Dense) pooling2d_1[0]	(None, 512)	1049088	['global_average_

][0]']

dropout_1 (Dropout)	(None, 512)	0	['dense_2[0][0]']
dense_3 (Dense)[0]']	(None, 256)	131328	['dropout_1[0]
dropout_2 (Dropout)	(None, 256)	0	['dense_3[0][0]']
dense_4 (Dense)[0]']	(None, 128)	32896	['dropout_2[0]
dropout_3 (Dropout)	(None, 128)	0	['dense_4[0][0]']
dense_5 (Dense)[0]']	(None, 64)	8256	['dropout_3[0]
dropout_4 (Dropout)	(None, 64)	0	['dense_5[0][0]']
dense_6 (Dense)[0]']	(None, 3)	195	['dropout_4[0]

=====

=====

Total params: 24809475 (94.64 MB)

Trainable params: 1221763 (4.66 MB)

Non-trainable params: 23587712 (89.98 MB)

```
In [ ]: batch_size = 128
epochs = 15
Resnet_Model = model.fit(train_generator, validation_data=valid_generator, epochs=epoch)
```

```

Epoch 1/15
14/14 [=====] - 9s 650ms/step - loss: 0.4570 - accuracy: 0.8
407 - val_loss: 0.3061 - val_accuracy: 0.9098
Epoch 2/15
14/14 [=====] - 8s 565ms/step - loss: 0.4829 - accuracy: 0.8
056 - val_loss: 0.2512 - val_accuracy: 0.9180
Epoch 3/15
14/14 [=====] - 7s 513ms/step - loss: 0.4267 - accuracy: 0.8
548 - val_loss: 0.3693 - val_accuracy: 0.9016
Epoch 4/15
14/14 [=====] - 8s 589ms/step - loss: 0.4173 - accuracy: 0.8
290 - val_loss: 0.2621 - val_accuracy: 0.9098
Epoch 5/15
14/14 [=====] - 7s 501ms/step - loss: 0.3194 - accuracy: 0.8
759 - val_loss: 0.3481 - val_accuracy: 0.9098
Epoch 6/15
14/14 [=====] - 8s 576ms/step - loss: 0.3437 - accuracy: 0.8
735 - val_loss: 0.2640 - val_accuracy: 0.9344
Epoch 7/15
14/14 [=====] - 7s 491ms/step - loss: 0.2256 - accuracy: 0.9
133 - val_loss: 0.2727 - val_accuracy: 0.9016
Epoch 8/15
14/14 [=====] - 7s 489ms/step - loss: 0.2465 - accuracy: 0.9
251 - val_loss: 0.3428 - val_accuracy: 0.9098
Epoch 9/15
14/14 [=====] - 8s 564ms/step - loss: 0.1997 - accuracy: 0.9
297 - val_loss: 0.2522 - val_accuracy: 0.9262
Epoch 10/15
14/14 [=====] - 7s 511ms/step - loss: 0.1745 - accuracy: 0.9
485 - val_loss: 0.3747 - val_accuracy: 0.9098
Epoch 11/15
14/14 [=====] - 8s 588ms/step - loss: 0.1627 - accuracy: 0.9
321 - val_loss: 0.3608 - val_accuracy: 0.9262
Epoch 12/15
14/14 [=====] - 7s 489ms/step - loss: 0.1299 - accuracy: 0.9
602 - val_loss: 0.3561 - val_accuracy: 0.9180
Epoch 13/15
14/14 [=====] - 8s 594ms/step - loss: 0.1641 - accuracy: 0.9
555 - val_loss: 0.3297 - val_accuracy: 0.9180
Epoch 14/15
14/14 [=====] - 7s 520ms/step - loss: 0.1212 - accuracy: 0.9
578 - val_loss: 0.3680 - val_accuracy: 0.9180
Epoch 15/15
14/14 [=====] - 7s 519ms/step - loss: 0.0923 - accuracy: 0.9
766 - val_loss: 0.4453 - val_accuracy: 0.9262

```

```
In [ ]: test_loss, test_acc = model.evaluate(test_generator)
print("The test loss is: ", test_loss)
print("The best accuracy is: ", test_acc*100)
```

```
2/2 [=====] - 3s 2s/step - loss: 0.3804 - accuracy: 0.9344
The test loss is: 0.38037899136543274
The best accuracy is: 93.44262480735779
```

```
In [ ]: def preprocess_image(image):
    image = tf.image.resize(image, (224, 224))
    img_array = tf.keras.preprocessing.image.img_to_array(image)
    img_array = tf.expand_dims(img_array, 0)
    img_array = tf.keras.applications.resnet.preprocess_input(img_array)
    return img_array
```

```
# Make predictions for images in Whole Dataset
for batch in dataset.take(1): # Take the first 1 batch
    # Extract images and labels from the batch
    images, labels = batch

    # Preprocess the images for prediction
    preprocessed_images = tf.map_fn(preprocess_image, images)

    # Reshape the input tensor to match the ResNet model's input shape
    preprocessed_images = tf.reshape(preprocessed_images, (-1, 224, 224, 3))

    # Making predictions
    predictions = model.predict(preprocessed_images)

    class_labels = Labels #Category's names
    predicted_classes = np.argmax(predictions, axis=1)

    # Displaying each test image along with the original and predicted class
    for i in range(images.shape[0]):
        plt.imshow(tf.keras.preprocessing.image.array_to_img(images[i]))
        plt.title(f"Original Class: {class_labels[labels[i]]}\nPredicted Class: {class_labels[predicted_classes[i]]}")
        plt.axis("off")
        plt.show()
```

1/1 [=====] - 0s 34ms/step

Original Class: Ship
Predicted Class: Ship



Original Class: Ship
Predicted Class: Ship



Original Class: Gondola
Predicted Class: Gondola



Original Class: Boat
Predicted Class: Boat



Original Class: Ship
Predicted Class: Ship

