

Image Classification with Intel Dataset

Authors

Muhammad Zaid, and Jiarui Zhao

The dataset I am using for this assignment is the [Intel Image Classification Dataset] (<https://www.kaggle.com/datasets/puneet6060/intel-image-classification%7D>) found on kaggle. This dataset contains 25,000 images of 6 different classes: buildings, forest, glacier, mountain, sea, and street.

In the next few code blocks I will showcase the properties of the dataset, especially the number of images per class, the size of the images, and the number of images in the training and test sets.

Install All Necessary Packages

```
In [ ]: %pip install "tensorflow-cpu"
```

Requirement already satisfied: tensorflow-cpu in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (2.12.0)
Requirement already satisfied: tensorflow-intel==2.12.0 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from tensorflow-cpu) (2.12.0)
Requirement already satisfied: absl-py>=1.0.0 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from tensorflow-intel==2.12.0->tensorflow-cpu) (1.4.0)
Requirement already satisfied: astunparse>=1.6.0 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from tensorflow-intel==2.12.0->tensorflow-cpu) (1.6.3)
Requirement already satisfied: flatbuffers>=2.0 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from tensorflow-intel==2.12.0->tensorflow-cpu) (23.3.3)
Requirement already satisfied: gast<=0.4.0,>=0.2.1 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from tensorflow-intel==2.12.0->tensorflow-cpu) (0.4.0)
Requirement already satisfied: google-pasta>=0.1.1 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from tensorflow-intel==2.12.0->tensorflow-cpu) (0.2.0)
Requirement already satisfied: h5py>=2.9.0 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from tensorflow-intel==2.12.0->tensorflow-cpu) (3.8.0)
Requirement already satisfied: jax>=0.3.15 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from tensorflow-intel==2.12.0->tensorflow-cpu) (0.4.8)
Requirement already satisfied: libclang>=13.0.0 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from tensorflow-intel==2.12.0->tensorflow-cpu) (16.0.0)
Requirement already satisfied: numpy<1.24,>=1.22 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from tensorflow-intel==2.12.0->tensorflow-cpu) (1.23.5)
Requirement already satisfied: opt-einsum>=2.3.2 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from tensorflow-intel==2.12.0->tensorflow-cpu) (3.3.0)
Requirement already satisfied: packaging in c:\users\muzai\appdata\roaming\python\python311\site-packages (from tensorflow-intel==2.12.0->tensorflow-cpu) (23.0)
Requirement already satisfied: protobuf!=4.21.0,!>=4.21.1,!>=4.21.2,!>=4.21.3,!>=4.21.4,!>=4.21.5,<5.0.0dev,>=3.20.3 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from tensorflow-intel==2.12.0->tensorflow-cpu) (4.22.3)
Requirement already satisfied: setuptools in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from tensorflow-intel==2.12.0->tensorflow-cpu) (65.5.0)
Requirement already satisfied: six>=1.12.0 in c:\users\muzai\appdata\roaming\python\python311\site-packages (from tensorflow-intel==2.12.0->tensorflow-cpu) (1.16.0)
Requirement already satisfied: termcolor>=1.1.0 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from tensorflow-intel==2.12.0->tensorflow-cpu) (2.2.0)
Requirement already satisfied: typing-extensions>=3.6.6 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from tensorflow-intel==2.12.0->tensorflow-cpu) (4.5.0)
Requirement already satisfied: wrapt<1.15,>=1.11.0 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from tensorflow-intel==2.12.0->tensorflow-cpu) (1.14.1)
Requirement already satisfied: grpcio<2.0,>=1.24.3 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from tensorflow-intel==2.12.0->tensorflow-cpu) (1.54.0)

```
Requirement already satisfied: tensorboard<2.13,>=2.12 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from tensorflow-intel==2.12.0->tensorflow-cpu) (2.12.2)
Requirement already satisfied: tensorflow-estimator<2.13,>=2.12.0 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from tensorflow-intel==2.12.0->tensorflow-cpu) (2.12.0)
Requirement already satisfied: keras<2.13,>=2.12.0 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from tensorflow-intel==2.12.0->tensorflow-cpu) (2.12.0)
Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from tensorflow-intel==2.12.0->tensorflow-cpu) (0.31.0)
Requirement already satisfied: wheel<1.0,>=0.23.0 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from astunparse>=1.6.0->tensorflow-intel==2.12.0->tensorflow-cpu) (0.40.0)
Requirement already satisfied: ml-dtypes>=0.0.3 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from jax>=0.3.15->tensorflow-intel==2.12.0->tensorflow-cpu) (0.1.0)
Requirement already satisfied: scipy>=1.7 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from jax>=0.3.15->tensorflow-intel==2.12.0->tensorflow-cpu) (1.10.1)
Requirement already satisfied: google-auth<3,>=1.6.3 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from tensorboard<2.13,>=2.12->tensorflow-intel==2.12.0->tensorflow-cpu) (2.17.3)
Requirement already satisfied: google-auth-oauthlib<1.1,>=0.5 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from tensorboard<2.13,>=2.12->tensorflow-intel==2.12.0->tensorflow-cpu) (1.0.0)
Requirement already satisfied: markdown>=2.6.8 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from tensorboard<2.13,>=2.12->tensorflow-intel==2.12.0->tensorflow-cpu) (3.4.3)
Requirement already satisfied: requests<3,>=2.21.0 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from tensorboard<2.13,>=2.12->tensorflow-intel==2.12.0->tensorflow-cpu) (2.28.2)
Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from tensorboard<2.13,>=2.12->tensorflow-intel==2.12.0->tensorflow-cpu) (0.7.0)
Requirement already satisfied: tensorboard-plugin-wit>=1.6.0 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from tensorboard<2.13,>=2.12->tensorflow-intel==2.12.0->tensorflow-cpu) (1.8.1)
Requirement already satisfied: werkzeug>=1.0.1 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from tensorboard<2.13,>=2.12->tensorflow-intel==2.12.0->tensorflow-cpu) (2.2.3)
Requirement already satisfied: cachetools<6.0,>=2.0.0 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from google-auth<3,>=1.6.3->tensorboard<2.13,>=2.12->tensorflow-intel==2.12.0->tensorflow-cpu) (5.3.0)
Requirement already satisfied: pyasn1-modules>=0.2.1 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from google-auth<3,>=1.6.3->tensorboard<2.13,>=2.12->tensorflow-intel==2.12.0->tensorflow-cpu) (0.3.0)
Requirement already satisfied: rsa<5,>=3.1.4 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from google-auth<3,>=1.6.3->tensorboard<2.13,>=2.12->tensorflow-intel==2.12.0->tensorflow-cpu) (4.9)
Requirement already satisfied: requests-oauthlib>=0.7.0 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from google-auth-oauthlib<1.1,>=0.5->tensorboard<2.13,>=2.12->tensorflow-intel==2.12.0->tensorflow-cpu) (1.3.1)
Requirement already satisfied: charset-normalizer<4,>=2 in c:\users\muzai\appdata\local\programs\python\python311\lib\site-packages (from requests<3,>=2.21.0->tensorboard<2.13,>=2.12->tensorflow-intel==2.12.0->tensorflow-cpu) (4.0.2)
```

```

rd<2.13,>=2.12->tensorflow-intel==2.12.0->tensorflow-cpu) (3.1.0)
Requirement already satisfied: idna<4,>=2.5 in c:\users\muzai\appdata\local\programs
\python\python311\lib\site-packages (from requests<3,>=2.21.0->tensorboard<2.13,>=2.
12->tensorflow-intel==2.12.0->tensorflow-cpu) (3.4)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in c:\users\muzai\appdata\local
\programs\python\python311\lib\site-packages (from requests<3,>=2.21.0->tensorboard<
2.13,>=2.12->tensorflow-intel==2.12.0->tensorflow-cpu) (1.26.15)
Requirement already satisfied: certifi>=2017.4.17 in c:\users\muzai\appdata\local\pr
ograms\python\python311\lib\site-packages (from requests<3,>=2.21.0->tensorboard<2.1
3,>=2.12->tensorflow-intel==2.12.0->tensorflow-cpu) (2022.12.7)
Requirement already satisfied: MarkupSafe>=2.1.1 in c:\users\muzai\appdata\local\pro
grams\python\python311\lib\site-packages (from werkzeug>=1.0.1->tensorboard<2.13,>=
2.12->tensorflow-intel==2.12.0->tensorflow-cpu) (2.1.2)
Requirement already satisfied: pyasn1<0.6.0,>=0.4.6 in c:\users\muzai\appdata\local
\programs\python\python311\lib\site-packages (from pyasn1-modules>=0.2.1->google-aut
h<3,>=1.6.3->tensorboard<2.13,>=2.12->tensorflow-intel==2.12.0->tensorflow-cpu) (0.
5.0)
Requirement already satisfied: oauthlib>=3.0.0 in c:\users\muzai\appdata\local\progr
ams\python\python311\lib\site-packages (from requests-oauthlib>=0.7.0->google-auth-o
authlib<1.1,>=0.5->tensorboard<2.13,>=2.12->tensorflow-intel==2.12.0->tensorflow-cp
u) (3.2.2)
Note: you may need to restart the kernel to use updated packages.

[notice] A new release of pip is available: 23.0.1 -> 23.1.1
[notice] To update, run: python.exe -m pip install --upgrade pip

```

Data Loading And Exploration

```

In [ ]: from PIL import Image

import numpy as np
import os

image = Image.open(os.getcwd()+'\\archive\\seg_train\\seg_train\\forest\\8.jpg')

print("Image Size of Images in Dataset: ", image.size)
print("Image Mode of Images in Dataset: ", image.mode)
imageCount:int = 0
classNum:list = []

for dirname, _, filenames in os.walk(os.getcwd()+'\\archive\\seg_train\\seg_train'):
    for filename in filenames:
        imageCount += 1

    classNum.append((imageCount, dirname.split('\\')[-1]))
    imageCount = 0

classNum.pop(0)

print("Number of Images in Dataset: ", sum([i[0] for i in classNum]))
print("Number of Classes in Dataset: ", len(classNum))
print("Number of Images in each Class: ", classNum)

```

```
Image Size of Images in Dataset: (150, 150)
Image Mode of Images in Dataset: RGB
Number of Images in Dataset: 14034
Number of Classes in Dataset: 6
Number of Images in each Class: [(2191, 'buildings'), (2271, 'forest'), (2404, 'gla
cier'), (2512, 'mountain'), (2274, 'sea'), (2382, 'street')]
```

As can be see in the ouput above the following is true:

- There are 6 classes of images
- Each class has an almosrt equal number of images
- The image size of each image is 150x150 pixels
- All images are in the RGB format

Now to display the distribution of the dataset

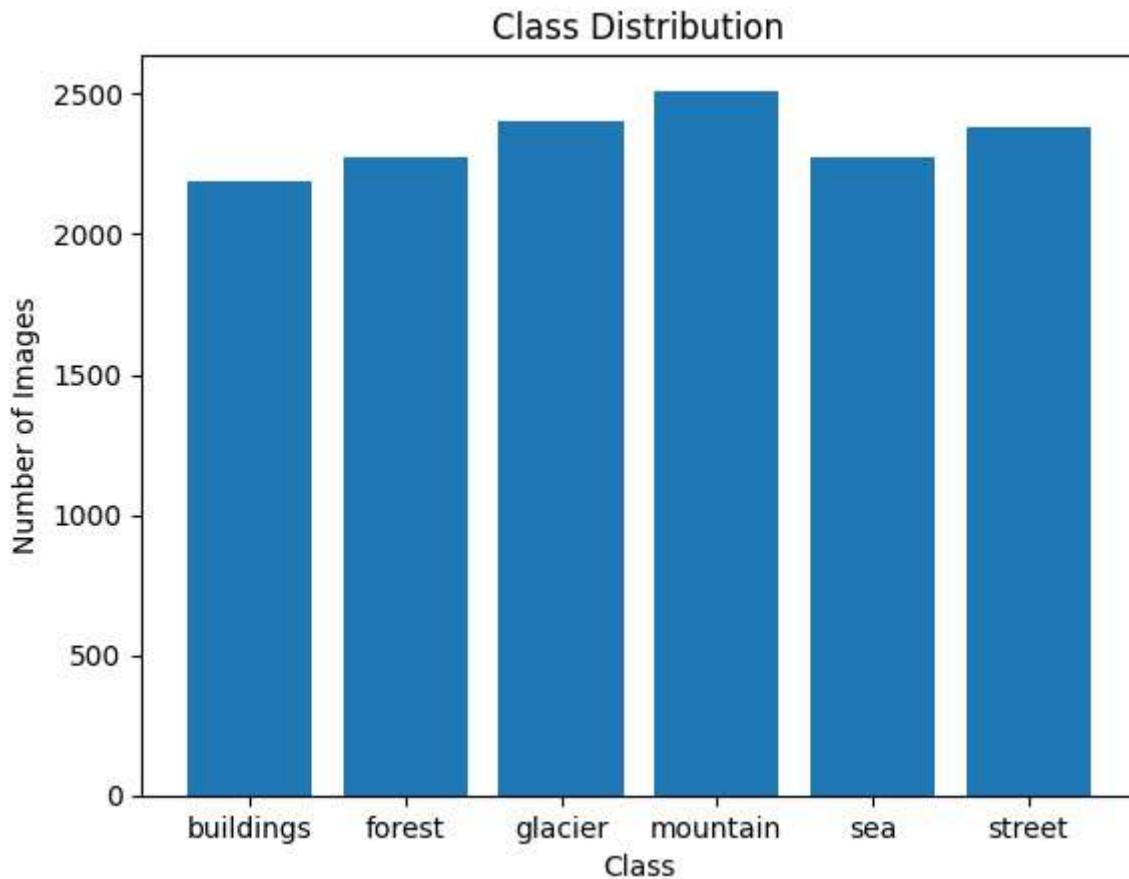
```
In [ ]: import matplotlib.pyplot as plt

# Extract the class names and values into separate lists
classes = [d[1] for d in classNum]
values = [d[0] for d in classNum]

# Create a bar chart of the values for each class
plt.bar(classes, values)

# Set the chart title and axis Labels
plt.title('Class Distribution')
plt.xlabel('Class')
plt.ylabel('Number of Images')

# Show the chart
plt.show()
```



Since we have an equal distribution of images per class, we can hope for high recall and precision for each class.

The dataset with its six different classes can employ a multi class classification cnn model. So we would be predicting based on the images in the testing set which class the image belongs to.

The dataset is split into a training, testing, and prediction set. The prediction set does not have any class labels.

Lets show a image from each class, so that there is a visual representation of the classes.

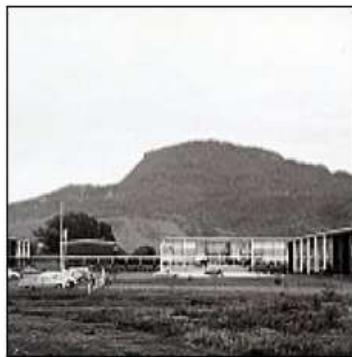
```
In [ ]: import glob

cwd = os.getcwd() + "\\archive\\seg_train\\seg_train\\"
subdirs = [f.path for f in os.scandir(cwd) if f.is_dir()]

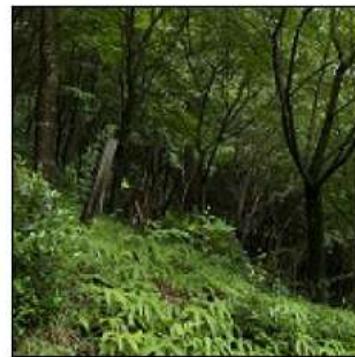
listOfFiles:list = []

# Iterate over each subdirectory and find the first file
for subdir in subdirs:
    classname = os.path.basename(subdir)
    # Get a List of all files in the subdirectory
    files = glob.glob(subdir + '/*')
    if len(files) > 0:
        # Print the first file in the subdirectory
        listOfFiles.append((classname, files[0]))
```

```
plt.figure(figsize=(10,10))
for i in range(listOfFiles.__len__()):
    img = np.array(Image.open(listOfFiles[i][1]))
    plt.subplot(3,3,i+1)
    plt.xticks([])
    plt.yticks([])
    plt.grid(False)
    plt.imshow(img)
    plt.xlabel(listOfFiles[i][0])
plt.show()
```



buildings



forest



glacier



mountain



sea



street

Now I need to preprocess the image to convert all images into numpy arrays and then normalize the images. This way I can directly feed the images into the model.

I also need to make sure that the dataset has a 80 to 20 split for training and testing.

I will evaluate the results for two different models with and without color in the model.

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

train_url = os.getcwd() + "\\archive\\seg_train\\seg_train\\"
test_url = os.getcwd() + "\\archive\\seg_test\\seg_test\\"

datagen = ImageDataGenerator(
    rescale=1./255, # rescale pixel values to be between 0 and 1
    rotation_range=10, # randomly rotate images by up to 20 degrees
    horizontal_flip=True) # randomly flip images horizontally
```

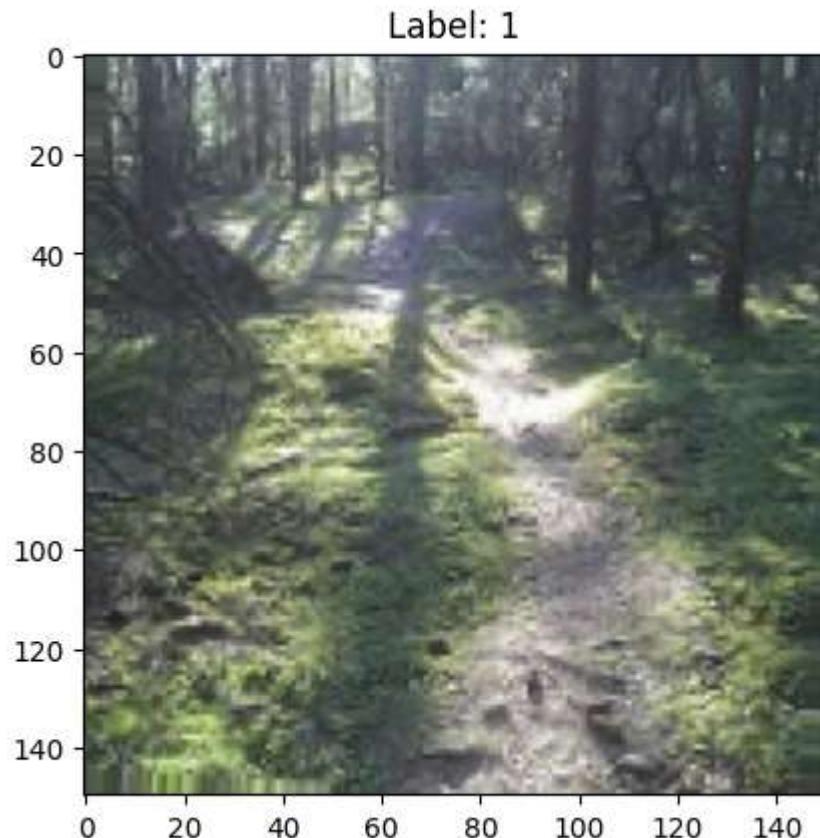
```
train = datagen.flow_from_directory(train_url, target_size=(150, 150), batch_size=2
test = datagen.flow_from_directory(test_url, target_size=(150, 150), batch_size=256

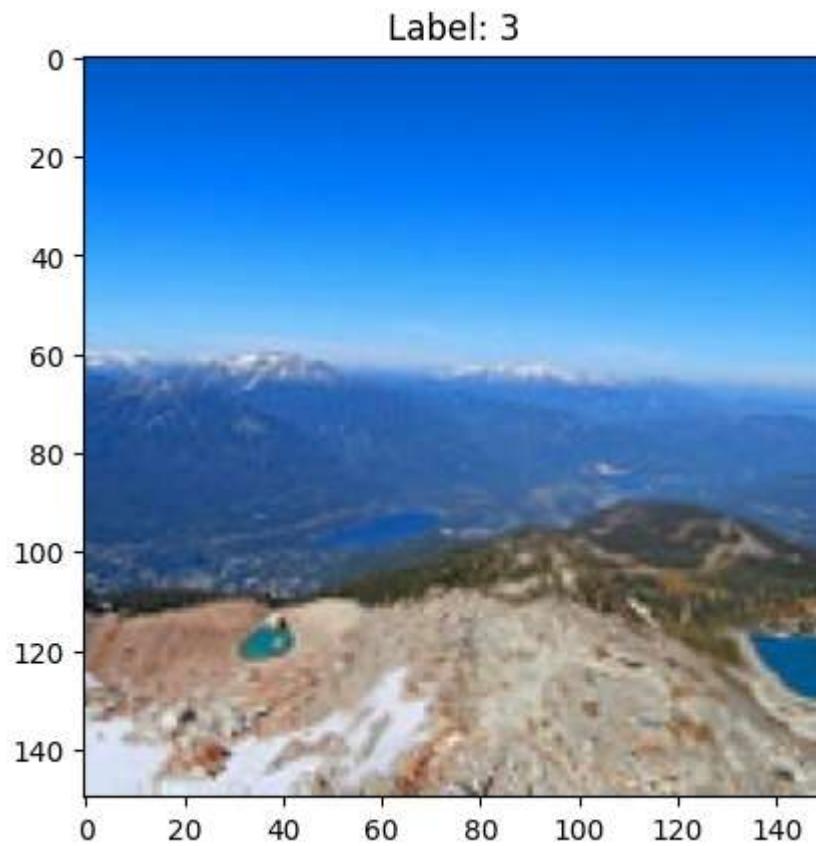
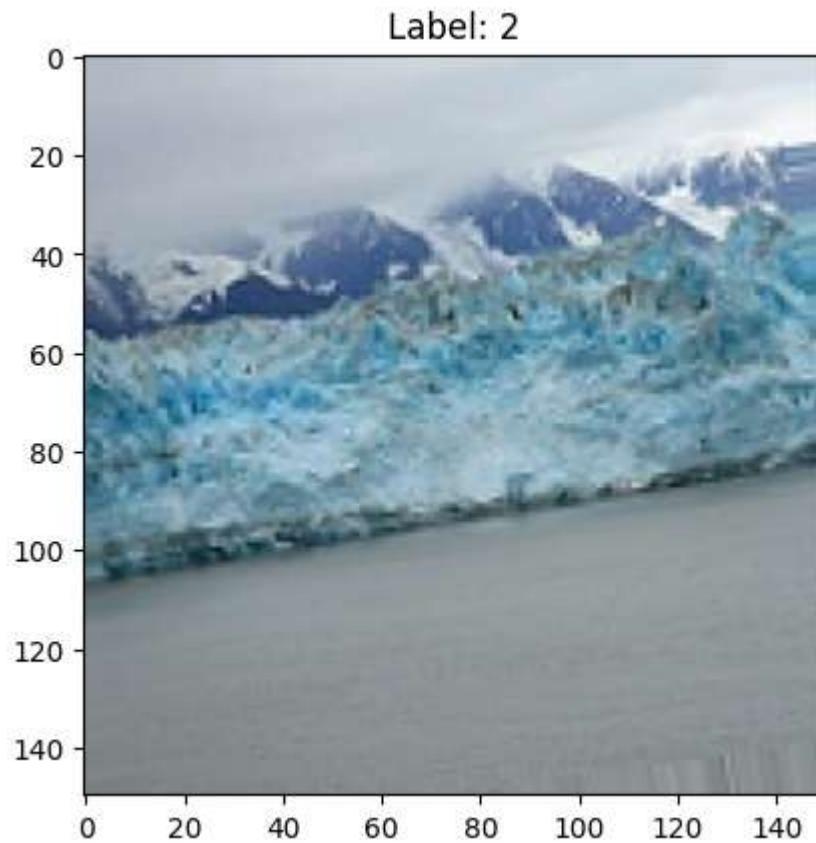
images, labels = next(train)

# Display the properties of the first few images
for i in range(3):
    plt.imshow(images[i])
    plt.title('Label: {}'.format(np.argmax(labels[i])))
    plt.show()
```

Found 14034 images belonging to 6 classes.

Found 3000 images belonging to 6 classes.





The Labels for each image indicate a number from 0 to 5, representing a class. This datagen is for images with color.

And as can be seen by the number of images for each train and test, the split is roughly around 80 to 20.

Model Building

First, I will build a CNN based model for color images.

The model will have 4 convolutional layers, 4 max pooling layers, a flatten layer, 2 dense layers, and a dropout layer.

Second, I will build a CNN based model for grayscaler images.

Third, I will build a CNN based model for color images with a different architecture.

The model will have 3 convolutional layers, 3 max pooling layers, a flatten layer, 2 dense layers, and a dropout layer.

I want to see how decreasing the convolutional layers affects the model.

Fourth, I will use transfer learning to train a pretrained model on my dataset, could use RestNet or Yolo.

I will then evaluate all the results for the models, to see which of these performed the best.

```
In [ ]: import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout

model = Sequential()
model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(150, 150, 3)))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(128, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(128, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(256, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Flatten())
model.add(Dense(512, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(6, activation='softmax'))

model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
<hr/>		
conv2d (Conv2D)	(None, 148, 148, 32)	896
max_pooling2d (MaxPooling2D)	(None, 74, 74, 32)	0
conv2d_1 (Conv2D)	(None, 72, 72, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 36, 36, 64)	0
conv2d_2 (Conv2D)	(None, 34, 34, 128)	73856
max_pooling2d_2 (MaxPooling2D)	(None, 17, 17, 128)	0
conv2d_3 (Conv2D)	(None, 15, 15, 128)	147584
max_pooling2d_3 (MaxPooling2D)	(None, 7, 7, 128)	0
conv2d_4 (Conv2D)	(None, 5, 5, 256)	295168
max_pooling2d_4 (MaxPooling2D)	(None, 2, 2, 256)	0
<hr/>		
Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 148, 148, 32)	896
max_pooling2d (MaxPooling2D)	(None, 74, 74, 32)	0
conv2d_1 (Conv2D)	(None, 72, 72, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 36, 36, 64)	0
conv2d_2 (Conv2D)	(None, 34, 34, 128)	73856
max_pooling2d_2 (MaxPooling2D)	(None, 17, 17, 128)	0
conv2d_3 (Conv2D)	(None, 15, 15, 128)	147584
max_pooling2d_3 (MaxPooling2D)	(None, 7, 7, 128)	0
conv2d_4 (Conv2D)	(None, 5, 5, 256)	295168
max_pooling2d_4 (MaxPooling2D)	(None, 2, 2, 256)	0
flatten (Flatten)	(None, 1024)	0

dense (Dense)	(None, 512)	524800
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 6)	3078
<hr/>		
Total params: 1,063,878		
Trainable params: 1,063,878		
Non-trainable params: 0		

```
In [ ]: from tensorflow import keras

optimizer = keras.optimizers.Adam(learning_rate=0.001)

if os.path.exists('models/image_classification_model_2.h5'):
    model = keras.models.load_model('models/image_classification_model_1.h5')
else:
    model.compile(optimizer=optimizer, loss='categorical_crossentropy', metrics=['a

fitted = model.fit(train, steps_per_epoch = 50 ,batch_size=128, epochs=10, vali
```

```
In [ ]: import random
from tensorflow.keras.preprocessing import image

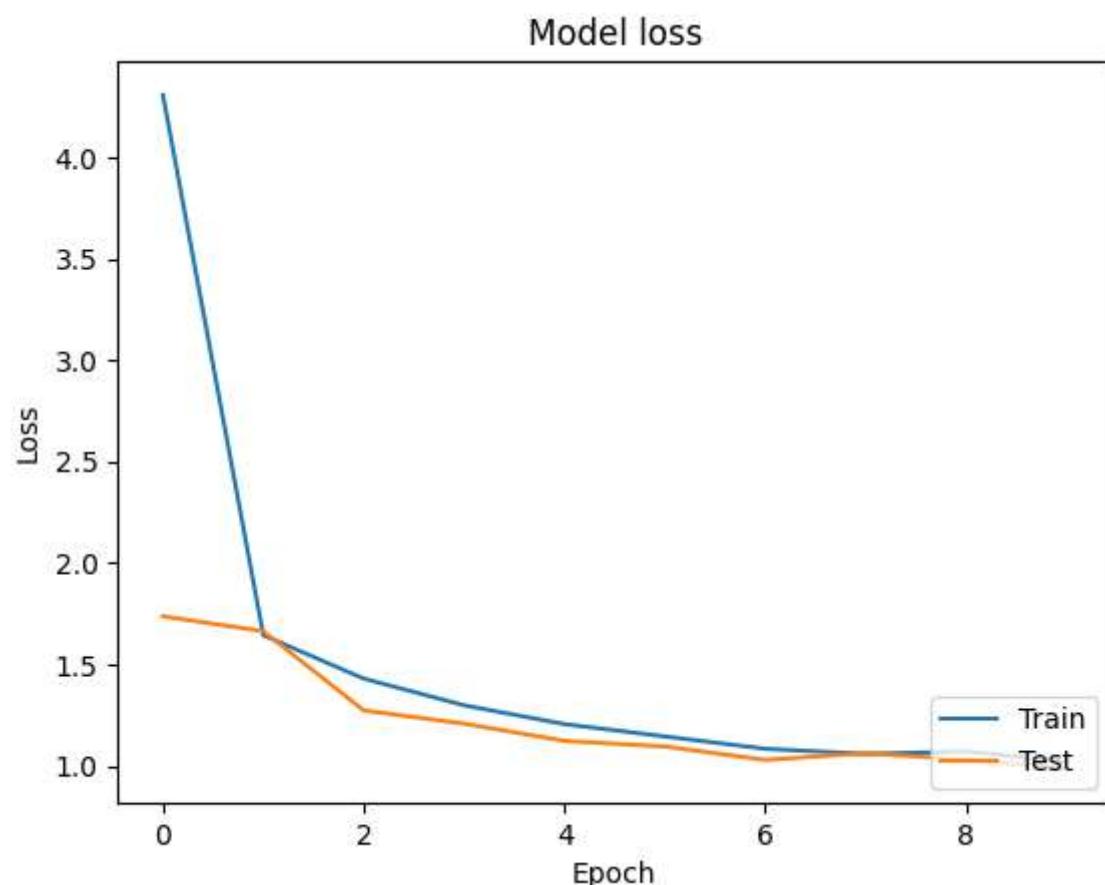
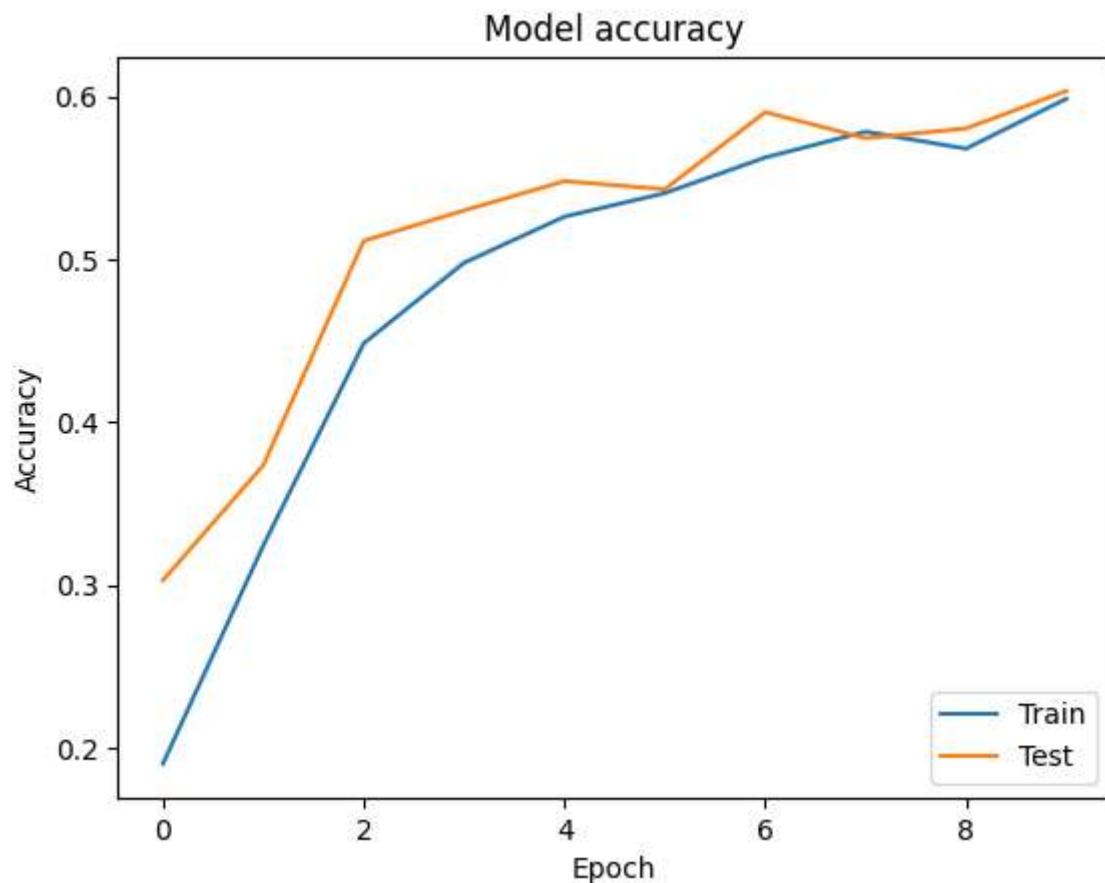
model.save('models/image_classification_model_1.h5')

plt.plot(fitted.history['accuracy'])
plt.plot(fitted.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='lower right')
plt.show()

plt.plot(fitted.history['loss'])
plt.plot(fitted.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='lower right')
plt.show()

cwd = os.getcwd() + "\\archive\\seg_pred\\seg_pred\\"
img_names = os.listdir(cwd)
random_img_names = random.sample(img_names, 5)

class_dict = {0: 'buildings', 1: 'forest', 2: 'glacier', 3: 'mountain', 4: 'sea', 5
```



```
In [ ]: pred_url = os.getcwd() + "\\archive\\seg_pred"

datagen = ImageDataGenerator(
    rescale=1./255, # rescale pixel values to be between 0 and 1
    rotation_range=10, # randomly rotate images by up to 20 degrees
    horizontal_flip=True) # randomly flip images horizontally

pred = datagen.flow_from_directory(pred_url, target_size=(150, 150), batch_size=256)

import matplotlib.pyplot as plt
import numpy as np

# get the class labels
class_labels = list(train.class_indices.keys())

# get a batch of images and their predictions
x, _ = next(pred)
y_pred = model.predict(x)

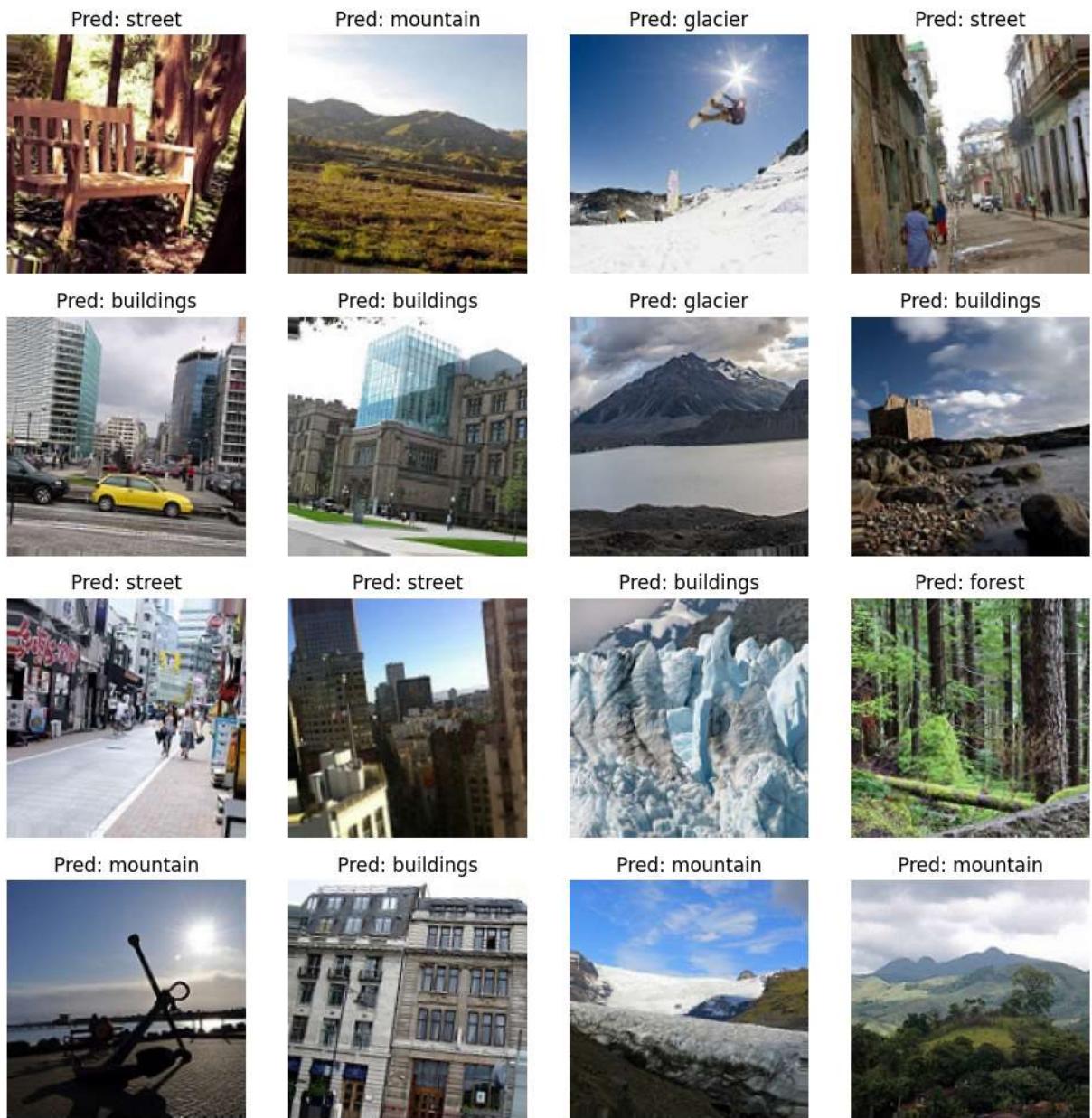
# display the images and their predictions
fig, axs = plt.subplots(4, 4, figsize=(10, 10))
for i, ax in enumerate(axs.flatten()):
    # show the image
    ax.imshow(x[i])
    ax.axis('off')

    # show the predicted label
    pred_label = class_labels[np.argmax(y_pred[i])]
    ax.set_title(f'Pred: {pred_label}')

plt.tight_layout()
plt.show()
```

Found 7301 images belonging to 1 classes.

8/8 [=====] - 1s 71ms/step



First model done with the color images.

Now to train the same model with the grayscale images.

And then to train the same model with the color images but with a different architecture.

And then finally transfer learning.

```
In [ ]: train_url = os.getcwd() + "\\archive\\seg_train\\seg_train\\"
test_url = os.getcwd() + "\\archive\\seg_test\\seg_test\\"

datagen = ImageDataGenerator(
    rescale=1./255, # rescale pixel values to be between 0 and 1
    rotation_range=10, # randomly rotate images by up to 20 degrees
    horizontal_flip=True) # randomly flip images horizontally

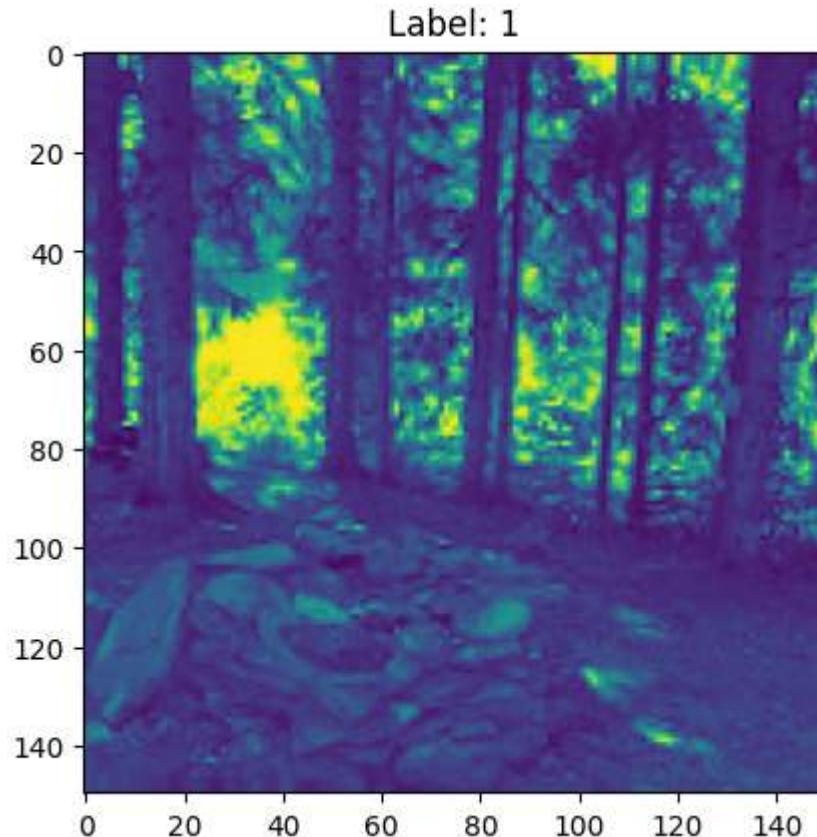
train_gs = datagen.flow_from_directory(train_url, target_size=(150, 150), batch_size=
test_gs = datagen.flow_from_directory(test_url, target_size=(150, 150), batch_size=
```

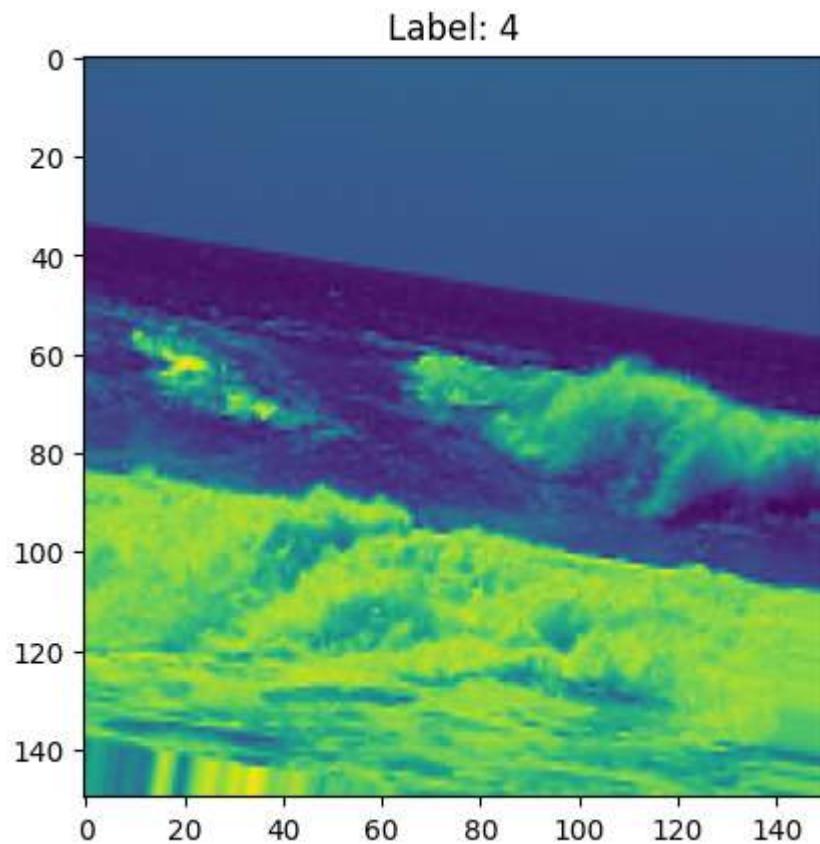
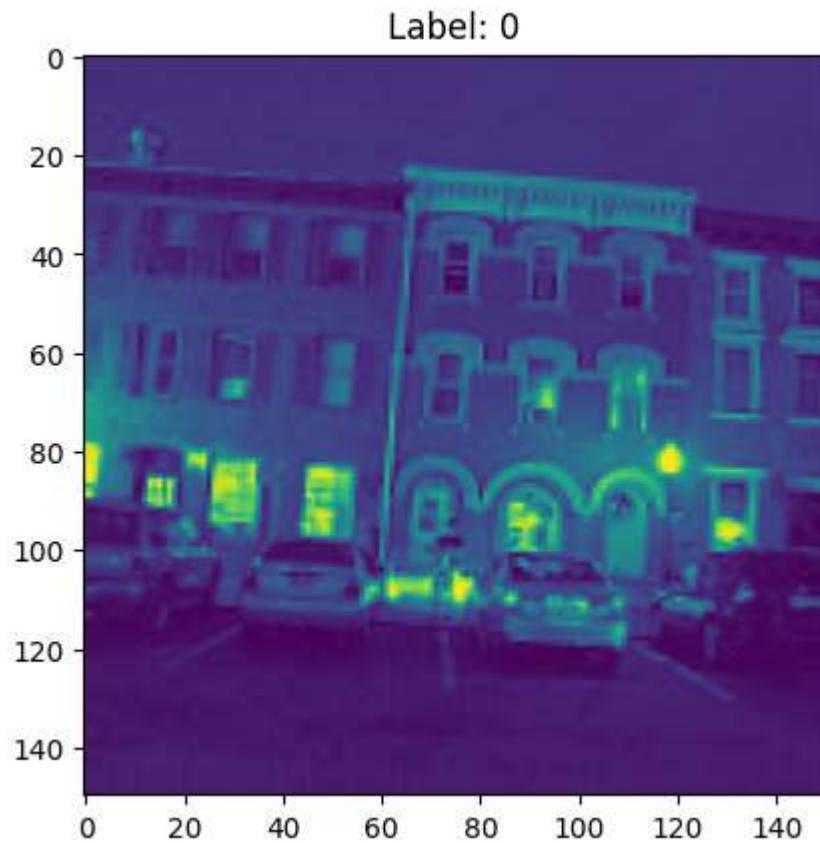
```
images, labels = next(train_gs)

# Display the properties of the first few images
for i in range(3):
    plt.imshow(images[i])
    plt.title('Label: {}'.format(np.argmax(labels[i])))
    plt.show()
```

Found 14034 images belonging to 6 classes.

Found 3000 images belonging to 6 classes.





```
In [ ]: model = Sequential()  
model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(150, 150, 1)))  
model.add(MaxPooling2D((2, 2)))
```

```
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(128, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(128, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(256, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Flatten())
model.add(Dense(512, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(6, activation='softmax'))

model.summary()
```

Model: "sequential_9"

Layer (type)	Output Shape	Param #
<hr/>		
conv2d_44 (Conv2D)	(None, 148, 148, 32)	320
max_pooling2d_44 (MaxPooling2D)	(None, 74, 74, 32)	0
conv2d_45 (Conv2D)	(None, 72, 72, 64)	18496
max_pooling2d_45 (MaxPooling2D)	(None, 36, 36, 64)	0
conv2d_46 (Conv2D)	(None, 34, 34, 128)	73856
max_pooling2d_46 (MaxPooling2D)	(None, 17, 17, 128)	0
conv2d_47 (Conv2D)	(None, 15, 15, 128)	147584
max_pooling2d_47 (MaxPooling2D)	(None, 7, 7, 128)	0
conv2d_48 (Conv2D)	(None, 5, 5, 256)	295168
max_pooling2d_48 (MaxPooling2D)	(None, 2, 2, 256)	0
flatten_9 (Flatten)	(None, 1024)	0
dense_28 (Dense)	(None, 512)	524800
dropout_9 (Dropout)	(None, 512)	0
dense_29 (Dense)	(None, 6)	3078
<hr/>		
Total params:	1,063,302	
Trainable params:	1,063,302	
Non-trainable params:	0	

In []: `from tensorflow import keras`

```
optimizer = keras.optimizers.Adam(learning_rate=0.001)

if os.path.exists('models/image_classification_model_2.h5'):
    model = keras.load_model('models/image_classification_model_2.h5')
else:
    model.compile(optimizer=optimizer, loss='categorical_crossentropy', metrics=['accuracy'])
    cnn_gray = model.fit(train_gs, steps_per_epoch=50, batch_size=128, epochs=10, validation_data=val_gs)
    model.save('models/image_classification_model_2.h5')
```

```
Epoch 1/10
50/50 [=====] - 73s 1s/step - loss: 1.5865 - accuracy: 0.31
55 - val_loss: 1.3255 - val_accuracy: 0.4690
Epoch 2/10
50/50 [=====] - 70s 1s/step - loss: 1.2530 - accuracy: 0.48
96 - val_loss: 1.1159 - val_accuracy: 0.5637
Epoch 3/10
50/50 [=====] - 73s 1s/step - loss: 1.1027 - accuracy: 0.55
98 - val_loss: 1.0181 - val_accuracy: 0.6030
Epoch 4/10
50/50 [=====] - 74s 1s/step - loss: 1.0196 - accuracy: 0.60
92 - val_loss: 0.9071 - val_accuracy: 0.6487
Epoch 5/10
50/50 [=====] - 72s 1s/step - loss: 0.9427 - accuracy: 0.63
88 - val_loss: 0.8662 - val_accuracy: 0.6697
Epoch 6/10
50/50 [=====] - 72s 1s/step - loss: 0.8936 - accuracy: 0.65
87 - val_loss: 0.8102 - val_accuracy: 0.6920
Epoch 7/10
50/50 [=====] - 72s 1s/step - loss: 0.8247 - accuracy: 0.68
37 - val_loss: 0.8457 - val_accuracy: 0.6713
Epoch 8/10
50/50 [=====] - 72s 1s/step - loss: 0.7991 - accuracy: 0.69
78 - val_loss: 0.7893 - val_accuracy: 0.6897
Epoch 9/10
50/50 [=====] - 73s 1s/step - loss: 0.7515 - accuracy: 0.71
27 - val_loss: 0.7040 - val_accuracy: 0.7337
Epoch 10/10
50/50 [=====] - 72s 1s/step - loss: 0.7249 - accuracy: 0.72
84 - val_loss: 0.7532 - val_accuracy: 0.7243
```

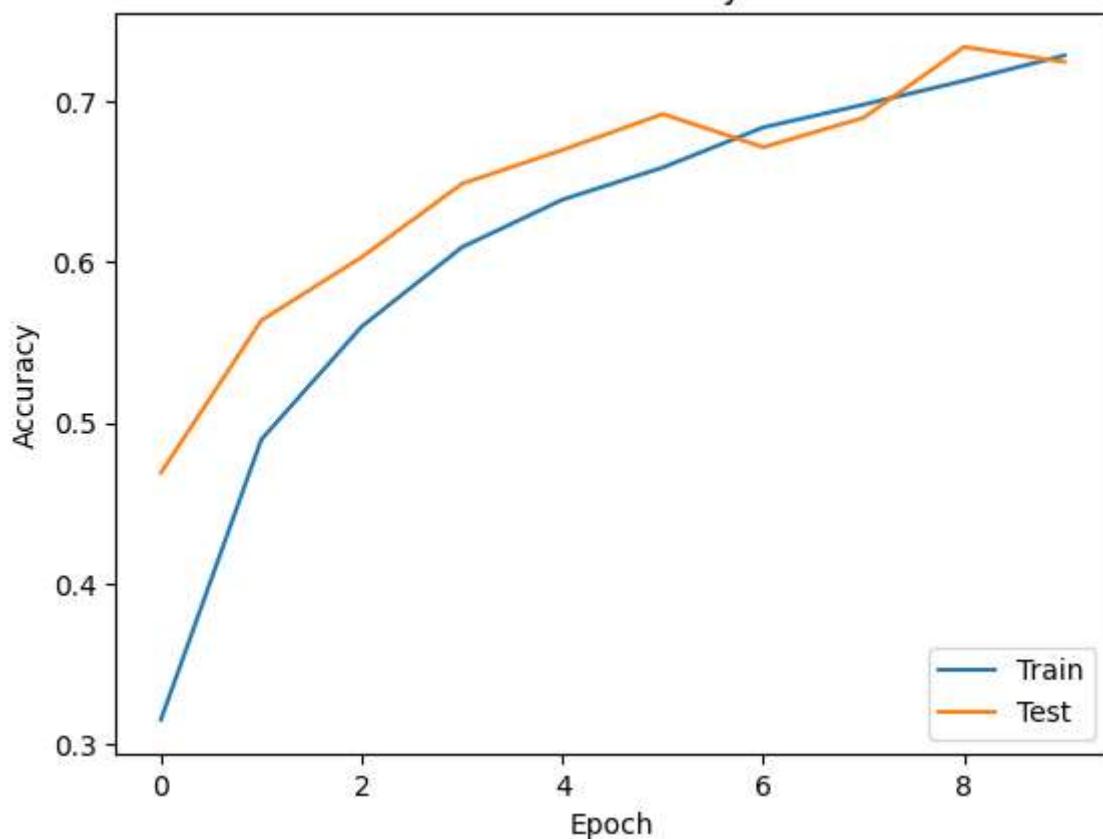
```
In [ ]: plt.plot(cnn_gray.history['accuracy'])
plt.plot(cnn_gray.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='lower right')
plt.show()

plt.plot(cnn_gray.history['loss'])
plt.plot(cnn_gray.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='lower right')
plt.show()

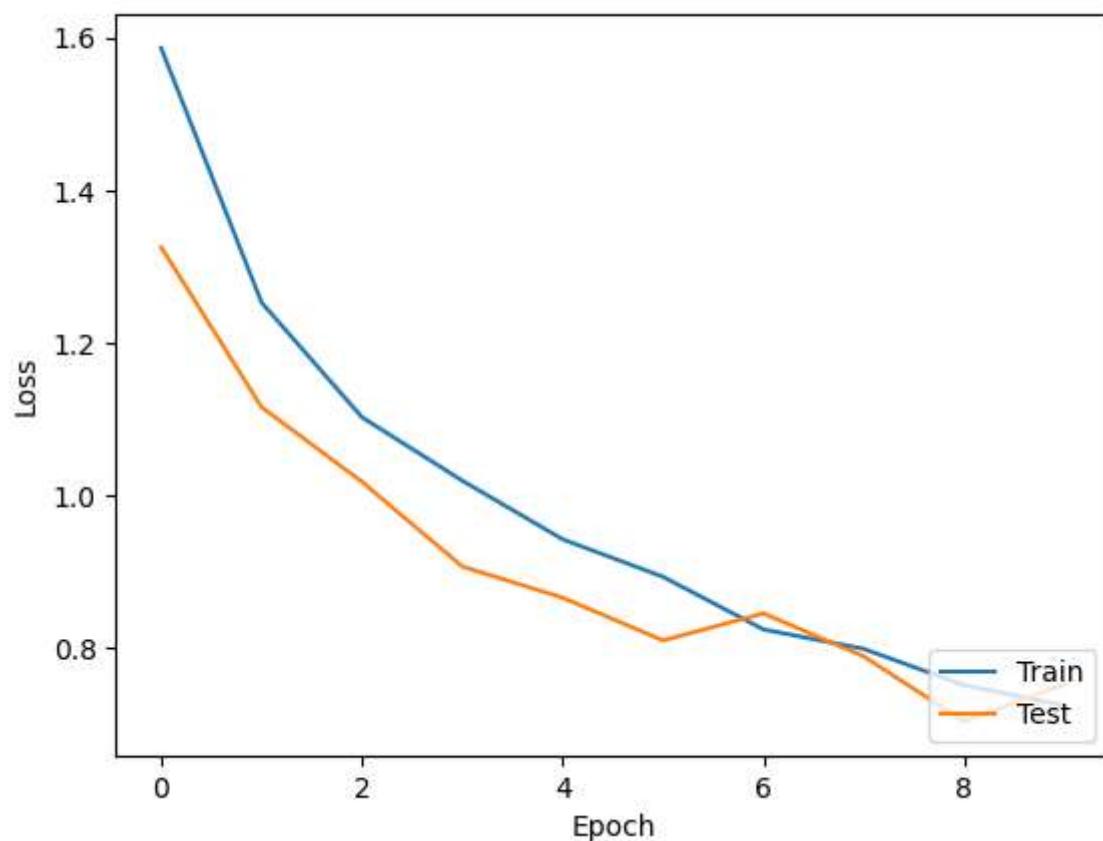
cwd = os.getcwd() + "\\archive\\seg_pred\\seg_pred\\"
img_names = os.listdir(cwd)
random_img_names = random.sample(img_names, 5)

class_dict = {0: 'buildings', 1: 'forest', 2: 'glacier', 3: 'mountain', 4: 'sea', 5:
```

Model accuracy



Model loss



```
In [ ]: pred_url = os.getcwd() + "\\archive\\seg_pred"

datagen = ImageDataGenerator(
    rescale=1./255, # rescale pixel values to be between 0 and 1
    rotation_range=10, # randomly rotate images by up to 20 degrees
    horizontal_flip=True) # randomly flip images horizontally

pred = datagen.flow_from_directory(pred_url, target_size=(150, 150), batch_size=256)

import matplotlib.pyplot as plt
import numpy as np

# get the class labels
class_labels = list(train.class_indices.keys())

# get a batch of images and their predictions
x, _ = next(pred)
y_pred = model.predict(x)

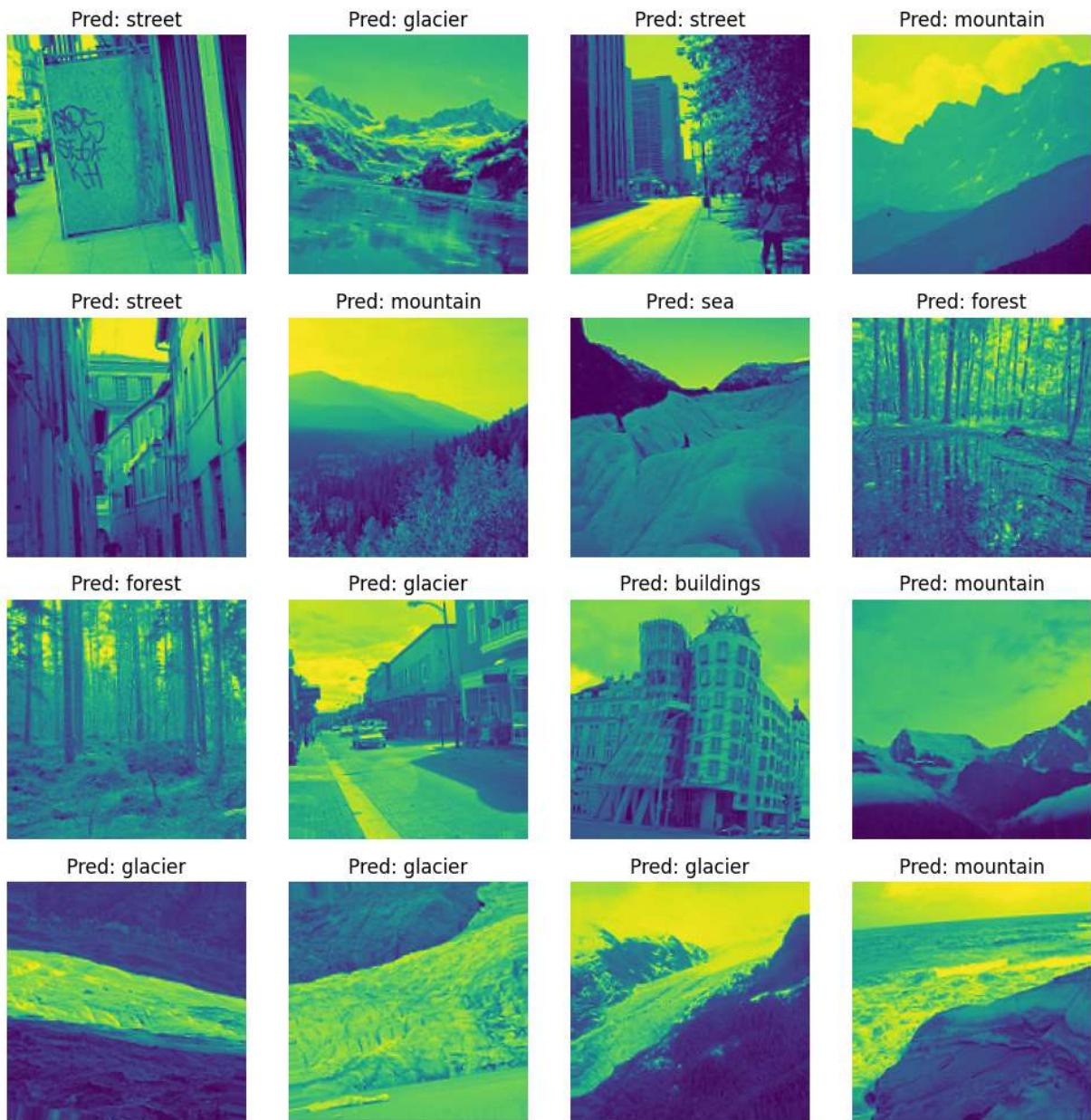
# display the images and their predictions
fig, axs = plt.subplots(4, 4, figsize=(10, 10))
for i, ax in enumerate(axs.flatten()):
    # show the image
    ax.imshow(x[i])
    ax.axis('off')

    # show the predicted label
    pred_label = class_labels[np.argmax(y_pred[i])]
    ax.set_title(f'Pred: {pred_label}')

plt.tight_layout()
plt.show()
```

Found 7301 images belonging to 1 classes.

8/8 [=====] - 1s 74ms/step



Now to train with a different architecture.

```
In [ ]: model = Sequential()
model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(150, 150, 3)))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(128, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(128, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Flatten())
model.add(Dense(512, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(6, activation='softmax'))

model.summary()
```

Model: "sequential_8"

Layer (type)	Output Shape	Param #
<hr/>		
conv2d_40 (Conv2D)	(None, 148, 148, 32)	896
max_pooling2d_40 (MaxPooling2D)	(None, 74, 74, 32)	0
conv2d_41 (Conv2D)	(None, 72, 72, 64)	18496
max_pooling2d_41 (MaxPooling2D)	(None, 36, 36, 64)	0
conv2d_42 (Conv2D)	(None, 34, 34, 128)	73856
max_pooling2d_42 (MaxPooling2D)	(None, 17, 17, 128)	0
conv2d_43 (Conv2D)	(None, 15, 15, 128)	147584
max_pooling2d_43 (MaxPooling2D)	(None, 7, 7, 128)	0
flatten_8 (Flatten)	(None, 6272)	0
dense_16 (Dense)	(None, 512)	3211776
dropout_8 (Dropout)	(None, 512)	0
dense_17 (Dense)	(None, 6)	3078
<hr/>		
Total params: 3,455,686		
Trainable params: 3,455,686		
Non-trainable params: 0		

```
In [ ]: from tensorflow import keras

optimizer = keras.optimizers.Adam(learning_rate=0.001)

if os.path.exists('models/image_classification_model_3.h5'):
    model = keras.load_model('models/image_classification_model_3.h5')

else:
    model.compile(optimizer=optimizer, loss='categorical_crossentropy', metrics=['accuracy'])
    cnn = model.fit_generator(generator=train, steps_per_epoch=50, epochs=10, validation_data=test, verbose=1)
    model.save('models/image_classification_model_3.h5')
```

C:\Users\muzai\AppData\Local\Temp\ipykernel_11832\884340771.py:7: UserWarning: `Model.fit_generator` is deprecated and will be removed in a future version. Please use `Model.fit`, which supports generators.
 cnn = model.fit_generator(generator=train, steps_per_epoch=50, epochs=10, validation_data=test, verbose=1)

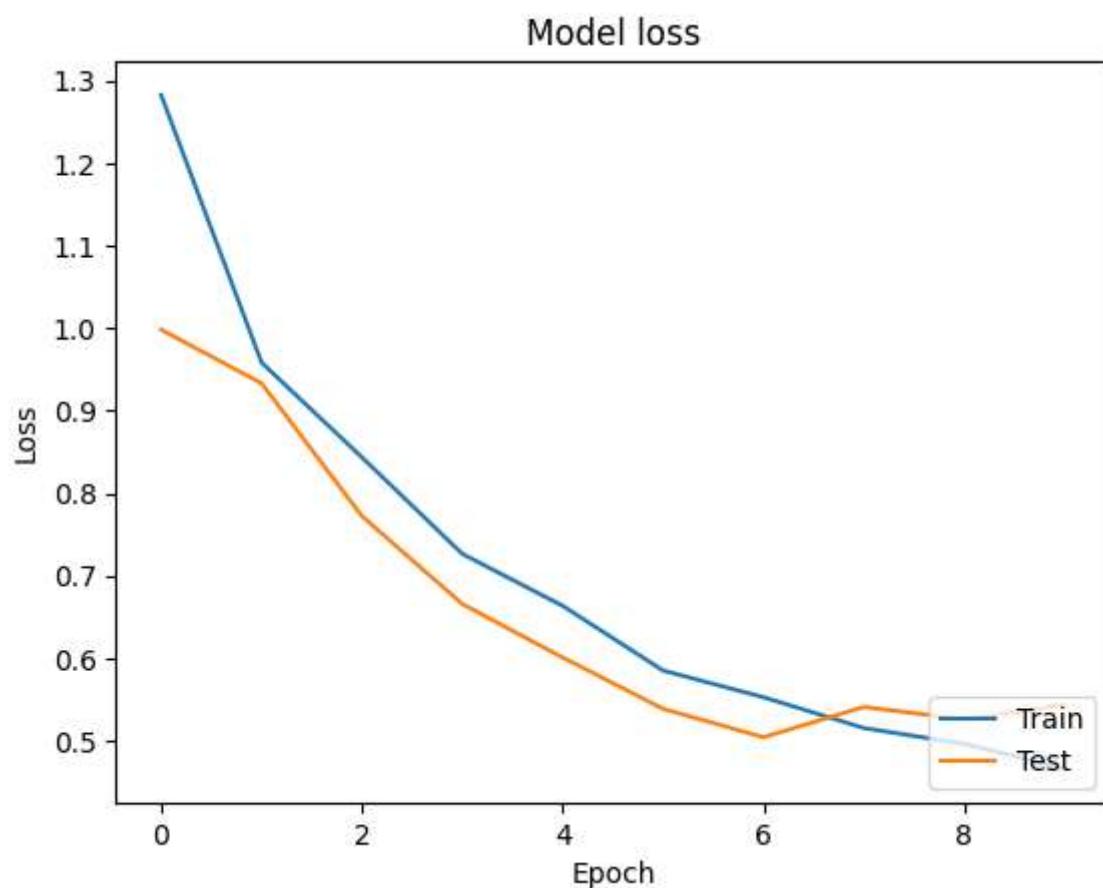
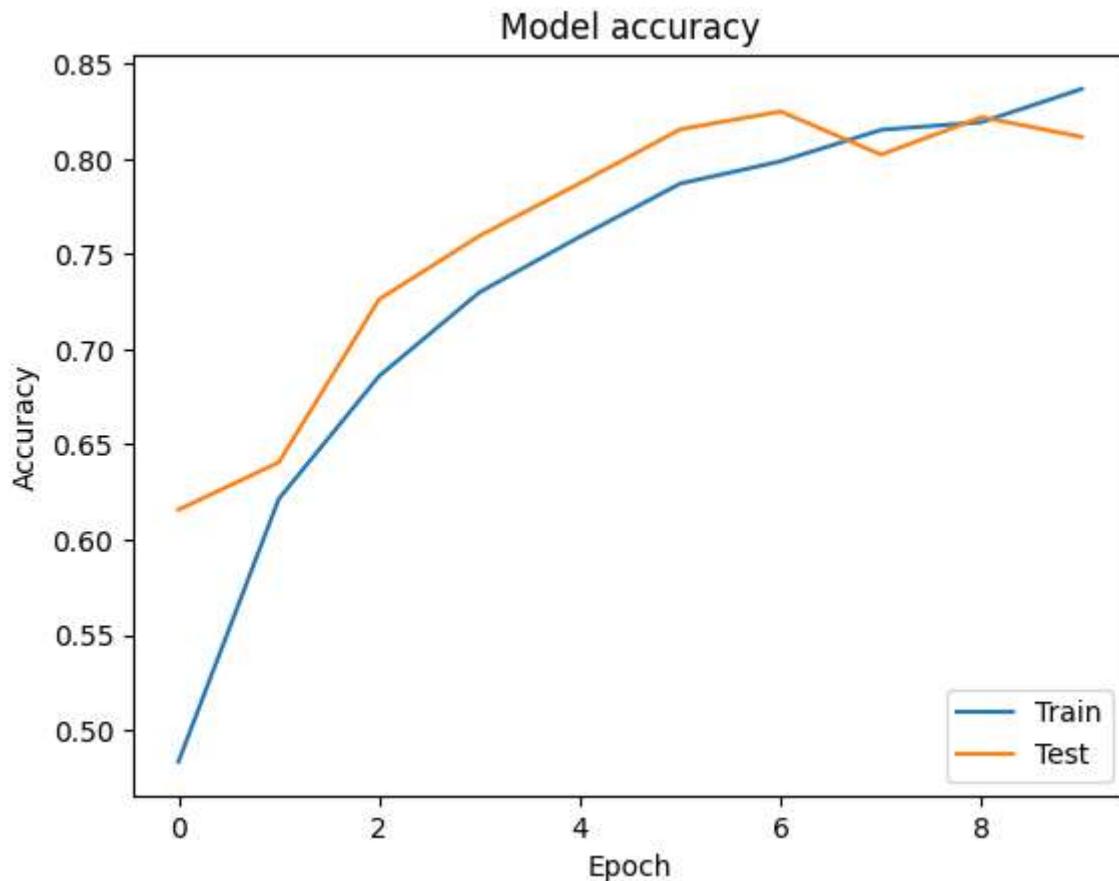
```
Epoch 1/10
50/50 [=====] - 138s 3s/step - loss: 1.2823 - accuracy: 0.4
833 - val_loss: 0.9981 - val_accuracy: 0.6157
Epoch 2/10
50/50 [=====] - 140s 3s/step - loss: 0.9582 - accuracy: 0.6
215 - val_loss: 0.9331 - val_accuracy: 0.6407
Epoch 3/10
50/50 [=====] - 133s 3s/step - loss: 0.8433 - accuracy: 0.6
860 - val_loss: 0.7722 - val_accuracy: 0.7263
Epoch 4/10
50/50 [=====] - 140s 3s/step - loss: 0.7264 - accuracy: 0.7
300 - val_loss: 0.6657 - val_accuracy: 0.7597
Epoch 5/10
50/50 [=====] - 143s 3s/step - loss: 0.6635 - accuracy: 0.7
592 - val_loss: 0.6009 - val_accuracy: 0.7873
Epoch 6/10
50/50 [=====] - 132s 3s/step - loss: 0.5851 - accuracy: 0.7
871 - val_loss: 0.5387 - val_accuracy: 0.8157
Epoch 7/10
50/50 [=====] - 135s 3s/step - loss: 0.5527 - accuracy: 0.7
988 - val_loss: 0.5043 - val_accuracy: 0.8250
Epoch 8/10
50/50 [=====] - 138s 3s/step - loss: 0.5154 - accuracy: 0.8
154 - val_loss: 0.5409 - val_accuracy: 0.8023
Epoch 9/10
50/50 [=====] - 135s 3s/step - loss: 0.4963 - accuracy: 0.8
194 - val_loss: 0.5260 - val_accuracy: 0.8220
Epoch 10/10
50/50 [=====] - 131s 3s/step - loss: 0.4664 - accuracy: 0.8
368 - val_loss: 0.5435 - val_accuracy: 0.8117
```

```
In [ ]: plt.plot(cnn.history['accuracy'])
plt.plot(cnn.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='lower right')
plt.show()

plt.plot(cnn.history['loss'])
plt.plot(cnn.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='lower right')
plt.show()

cwd = os.getcwd() + "\\archive\\seg_pred\\seg_pred\\"
img_names = os.listdir(cwd)
random_img_names = random.sample(img_names, 5)

class_dict = {0: 'buildings', 1: 'forest', 2: 'glacier', 3: 'mountain', 4: 'sea', 5:
```



```
In [ ]: pred_url = os.getcwd() + "\\archive\\seg_pred"

datagen = ImageDataGenerator(
    rescale=1./255, # rescale pixel values to be between 0 and 1
    rotation_range=10, # randomly rotate images by up to 20 degrees
    horizontal_flip=True) # randomly flip images horizontally

pred = datagen.flow_from_directory(pred_url, target_size=(150, 150), batch_size=256)

import matplotlib.pyplot as plt
import numpy as np

# get the class labels
class_labels = list(train.class_indices.keys())

# get a batch of images and their predictions
x, _ = next(pred)
y_pred = model.predict(x)

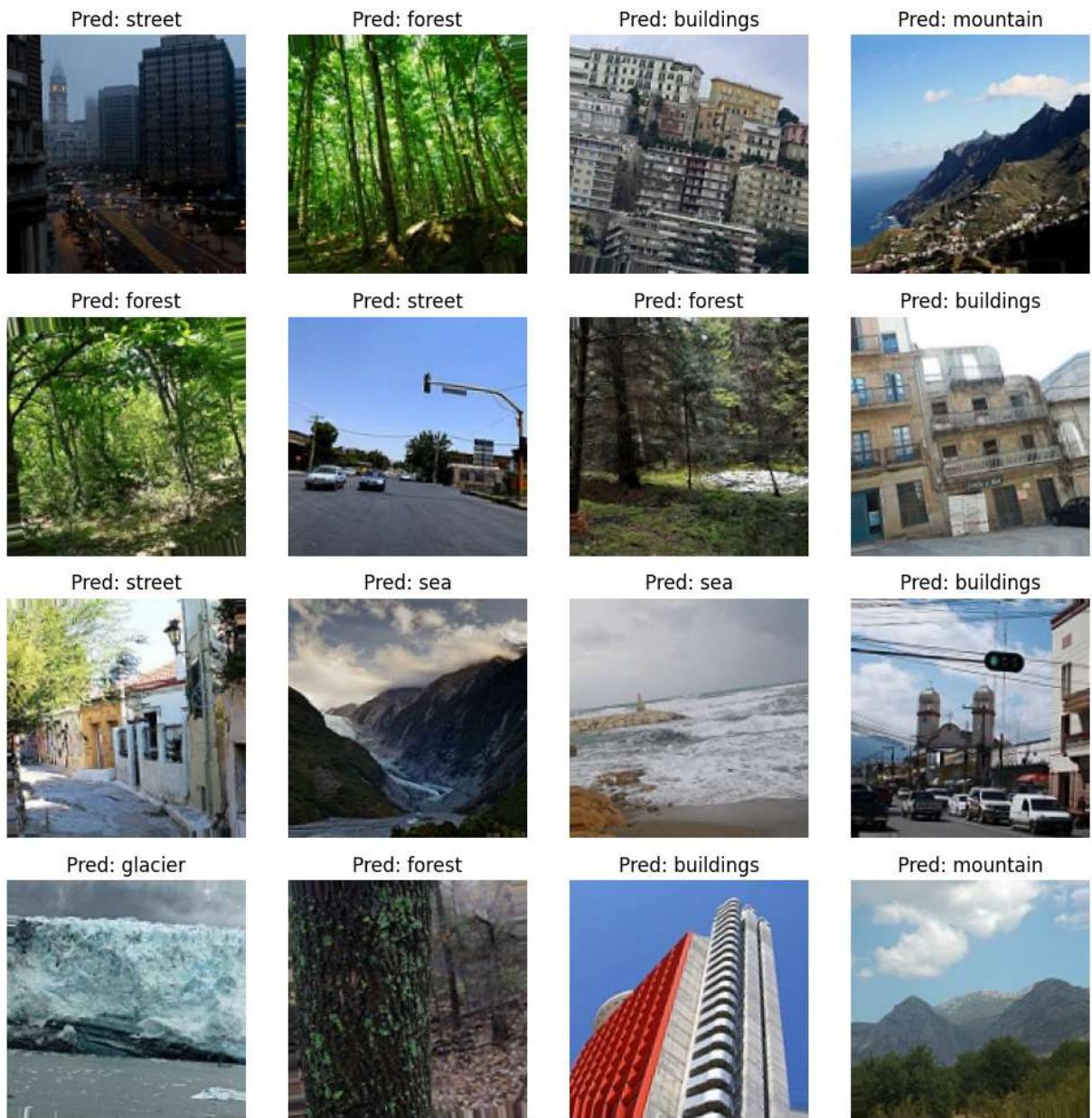
# display the images and their predictions
fig, axs = plt.subplots(4, 4, figsize=(10, 10))
for i, ax in enumerate(axs.flatten()):
    # show the image
    ax.imshow(x[i])
    ax.axis('off')

    # show the predicted label
    pred_label = class_labels[np.argmax(y_pred[i])]
    ax.set_title(f'Pred: {pred_label}')

plt.tight_layout()
plt.show()
```

Found 7301 images belonging to 1 classes.

8/8 [=====] - 1s 75ms/step



Now to use transfer learning.

```
In [ ]: import tensorflow as tf

base_model = tf.keras.applications.ResNet50(weights='imagenet', include_top = False)

x = base_model.output
x = tf.keras.layers.GlobalAveragePooling2D()(x)
x = tf.keras.layers.Dense(1024, activation='relu')(x)
x = tf.keras.layers.Dropout(0.5)(x)
x = tf.keras.layers.Dense(1024, activation='relu')(x)
x = tf.keras.layers.Dropout(0.5)(x)
x = tf.keras.layers.Dense(1024, activation='relu')(x)
x = tf.keras.layers.Dropout(0.5)(x)
x = tf.keras.layers.Dense(512, activation='relu')(x)
x = tf.keras.layers.Dropout(0.5)(x)
preds = tf.keras.layers.Dense(6, activation ='softmax')(x)
```

```
model = tf.keras.models.Model(inputs=base_model.input, outputs=preds)
print(model.summary())
```

Model: "model_2"

Layer (type)	Output Shape	Param #	Connected to
<hr/>			
input_4 (InputLayer)	[(None, None, None, 3)]	0	[]
conv1_pad (ZeroPadding2D)	(None, None, None, 3)	0	['input_4[0][0]']
conv1_conv (Conv2D)	(None, None, None, 64)	9472	['conv1_pad[0][0]']
conv1_bn (BatchNormalization)	(None, None, None, 64)	256	['conv1_conv[0][0]']
conv1_relu (Activation)	(None, None, None, 64)	0	['conv1_bn[0][0]']
pool1_pad (ZeroPadding2D)	(None, None, None, 64)	0	['conv1_relu[0][0]']
pool1_pool (MaxPooling2D)	(None, None, None, 64)	0	['pool1_pad[0][0]']
conv2_block1_1_conv (Conv2D)	(None, None, None, 64)	4160	['pool1_pool[0][0]']
conv2_block1_1_bn (BatchNormalizat	(None, None, None, 64)	256	['conv2_block1_1_co
ization)			nization]
conv2_block1_1_relu (Activatio	(None, None, None, 64)	0	['conv2_block1_1_bn
n)			n]
conv2_block1_2_conv (Conv2D)	(None, None, None, 64)	36928	['conv2_block1_1_re
lu[0][0]']			lu[0][0]']
conv2_block1_2_bn (BatchNormalizat	(None, None, None, 64)	256	['conv2_block1_2_co
ization)			nization]
conv2_block1_2_relu (Activatio	(None, None, None, 64)	0	['conv2_block1_2_bn
n)			n]
conv2_block1_0_conv (Conv2D)	(None, None, None, 256)	16640	['pool1_pool[0][0]']
[0]']			

conv2_block1_3_conv (Conv2D) lu[0][0]'	(None, None, None, 256)	16640	['conv2_block1_2_re lu[0][0]']
conv2_block1_0_bn (BatchNormal nv[0][0]' ization)	(None, None, None, 256)	1024	['conv2_block1_0_co nv[0][0]']
conv2_block1_3_bn (BatchNormal nv[0][0]' ization)	(None, None, None, 256)	1024	['conv2_block1_3_co nv[0][0]']
conv2_block1_add (Add) [0][0]', [0][0]'	(None, None, None, 256)	0	['conv2_block1_0_bn 'conv2_block1_3_bn
conv2_block1_out (Activation) [0][0]'	(None, None, None, 256)	0	['conv2_block1_add [0][0]']
conv2_block2_1_conv (Conv2D) lu[0][0]'	(None, None, None, 64)	16448	['conv2_block1_out [0][0]']
conv2_block2_1_bn (BatchNormal nv[0][0]' ization)	(None, None, None, 64)	256	['conv2_block2_1_co nv[0][0]']
conv2_block2_1_relu (Activatio n)[0][0]'	(None, None, None, 64)	0	['conv2_block2_1_bn n]
conv2_block2_2_conv (Conv2D) lu[0][0]'	(None, None, None, 64)	36928	['conv2_block2_1_re lu[0][0]']
conv2_block2_2_bn (BatchNormal nv[0][0]' ization)	(None, None, None, 64)	256	['conv2_block2_2_co nv[0][0]']
conv2_block2_2_relu (Activatio n)[0][0]'	(None, None, None, 64)	0	['conv2_block2_2_bn n]
conv2_block2_3_conv (Conv2D) lu[0][0]'	(None, None, None, 256)	16640	['conv2_block2_2_re lu[0][0]']
conv2_block2_3_bn (BatchNormal nv[0][0]' ization)	(None, None, None, 256)	1024	['conv2_block2_3_co nv[0][0]']
conv2_block2_add (Add) [0][0]',	(None, None, None, 0)	0	['conv2_block1_out [0][0]']

[0][0]']	256)	'conv2_block2_3_bn
conv2_block2_out (Activation) [0][0]'	(None, None, None, 0 256)	['conv2_block2_add
conv2_block3_1_conv (Conv2D) [0][0]'	(None, None, None, 16448 64)	['conv2_block2_out
conv2_block3_1_bn (BatchNormal nv[0][0]' ization)	(None, None, None, 256 64)	['conv2_block3_1_co
conv2_block3_1_relu (Activatio n) [0][0]'	(None, None, None, 0 64)	['conv2_block3_1_bn
conv2_block3_2_conv (Conv2D) lu[0][0]'	(None, None, None, 36928 64)	['conv2_block3_1_re
conv2_block3_2_bn (BatchNormal nv[0][0]' ization)	(None, None, None, 256 64)	['conv2_block3_2_co
conv2_block3_2_relu (Activatio n) [0][0]'	(None, None, None, 0 64)	['conv2_block3_2_bn
conv2_block3_3_conv (Conv2D) lu[0][0]'	(None, None, None, 16640 256)	['conv2_block3_2_re
conv2_block3_3_bn (BatchNormal nv[0][0]' ization)	(None, None, None, 1024 256)	['conv2_block3_3_co
conv2_block3_add (Add) [0][0]', [0][0]'	(None, None, None, 0 256)	['conv2_block2_out 'conv2_block3_3_bn
conv2_block3_out (Activation) [0][0]'	(None, None, None, 0 256)	['conv2_block3_add
conv3_block1_1_conv (Conv2D) [0][0]'	(None, None, None, 32896 128)	['conv2_block3_out
conv3_block1_1_bn (BatchNormal nv[0][0]' ization)	(None, None, None, 512 128)	['conv3_block1_1_co

conv3_block1_1_relu (Activation)	(None, None, None, 0 [0][0])	n)	128)	['conv3_block1_1_bn
conv3_block1_2_conv (Conv2D)	(None, None, None, 147584 lu[0][0])		128)	['conv3_block1_1_re
conv3_block1_2_bn (BatchNormal nv[0][0])	(None, None, None, ization)	128)	512	['conv3_block1_2_co
conv3_block1_2_relu (Activatio n[0][0])	(None, None, None, 0 n)	128)	512)	['conv3_block1_2_bn
conv3_block1_0_conv (Conv2D)	(None, None, None, 131584 [0][0])		512)	['conv2_block3_out
conv3_block1_3_conv (Conv2D)	(None, None, None, 66048 lu[0][0])		512)	['conv3_block1_2_re
conv3_block1_0_bn (BatchNormal nv[0][0])	(None, None, None, ization)	512)	2048	['conv3_block1_0_co
conv3_block1_3_bn (BatchNormal nv[0][0])	(None, None, None, ization)	512)	2048	['conv3_block1_3_co
conv3_block1_add (Add)	(None, None, None, 0 [0][0], [0][0])	512)	512)	['conv3_block1_0_bn 'conv3_block1_3_bn
conv3_block1_out (Activation)	(None, None, None, 0 [0][0])		512)	['conv3_block1_add
conv3_block2_1_conv (Conv2D)	(None, None, None, 65664 [0][0])		128)	['conv3_block1_out
conv3_block2_1_bn (BatchNormal nv[0][0])	(None, None, None, ization)	128)	512	['conv3_block2_1_co
conv3_block2_1_relu (Activatio n[0][0])	(None, None, None, 0 n)	128)	512)	['conv3_block2_1_bn
conv3_block2_2_conv (Conv2D)	(None, None, None, 147584 lu[0][0])		128)	['conv3_block2_1_re

conv3_block2_2_bn (BatchNormal nv[0][0]) ization)	(None, None, None, 128)	512	['conv3_block2_2_co nv[0][0]']
conv3_block2_2_relu (Activatio n[0][0]) n)	(None, None, None, 128)	0	['conv3_block2_2_bn lu[0][0]']
conv3_block2_3_conv (Conv2D) lu[0][0])	(None, None, None, 512)	66048	['conv3_block2_2_re lu[0][0]']
conv3_block2_3_bn (BatchNormal nv[0][0]) ization)	(None, None, None, 512)	2048	['conv3_block2_3_co nv[0][0]']
conv3_block2_add (Add) [0][0]', [0][0])	(None, None, None, 512)	0	['conv3_block1_out 'conv3_block2_3.bn [0][0]']
conv3_block2_out (Activation) [0][0])	(None, None, None, 512)	0	['conv3_block2_add [0][0]']
conv3_block3_1_conv (Conv2D) lu[0][0])	(None, None, None, 128)	65664	['conv3_block2_out [0][0]']
conv3_block3_1_bn (BatchNormal nv[0][0]) ization)	(None, None, None, 128)	512	['conv3_block3_1_co nv[0][0]']
conv3_block3_1_relu (Activatio n[0][0]) n)	(None, None, None, 128)	0	['conv3_block3_1.bn [0][0]']
conv3_block3_2_conv (Conv2D) lu[0][0])	(None, None, None, 128)	147584	['conv3_block3_1_re lu[0][0]']
conv3_block3_2_bn (BatchNormal nv[0][0]) ization)	(None, None, None, 128)	512	['conv3_block3_2_co nv[0][0]']
conv3_block3_2_relu (Activatio n[0][0]) n)	(None, None, None, 128)	0	['conv3_block3_2.bn [0][0]']
conv3_block3_3_conv (Conv2D) lu[0][0])	(None, None, None, 512)	66048	['conv3_block3_2_re lu[0][0]']
conv3_block3_3_bn (BatchNormal nv[0][0]) ization)	(None, None, None, 2048)	2048	['conv3_block3_3.co nv[0][0]']

ization)	512)		
conv3_block3_add (Add) [0][0]', [0][0]']	(None, None, None, 0 512)		['conv3_block2_out 'conv3_block3_3_bn
conv3_block3_out (Activation) [0][0]']	(None, None, None, 0 512)		['conv3_block3_add
conv3_block4_1_conv (Conv2D) [0][0]']	(None, None, None, 65664 128)		['conv3_block3_out
conv3_block4_1_bn (BatchNormal nv[0][0]' ization)	(None, None, None, 512 128)		['conv3_block4_1_co
conv3_block4_1_relu (Activatio n)[0][0]']	(None, None, None, 0 128)		['conv3_block4_1_bn
conv3_block4_2_conv (Conv2D) lu[0][0]']	(None, None, None, 147584 128)		['conv3_block4_1_re
conv3_block4_2_bn (BatchNormal nv[0][0]' ization)	(None, None, None, 512 128)		['conv3_block4_2_co
conv3_block4_2_relu (Activatio n)[0][0]']	(None, None, None, 0 128)		['conv3_block4_2_bn
conv3_block4_3_conv (Conv2D) lu[0][0]']	(None, None, None, 66048 512)		['conv3_block4_2_re
conv3_block4_3_bn (BatchNormal nv[0][0]' ization)	(None, None, None, 2048 512)		['conv3_block4_3_co
conv3_block4_add (Add) [0][0]', [0][0]']	(None, None, None, 0 512)		['conv3_block3_out 'conv3_block4_3_bn
conv3_block4_out (Activation) [0][0]']	(None, None, None, 0 512)		['conv3_block4_add
conv4_block1_1_conv (Conv2D) [0][0]']	(None, None, None, 131328 256)		['conv3_block4_out

conv4_block1_1_bn (BatchNormal nv[0][0]) ization)	(None, None, None, 256)	1024	['conv4_block1_1_co nvolution']
conv4_block1_1_relu (Activatio n[0][0]) n)	(None, None, None, 256)	0	['conv4_block1_1_bn ReLU']
conv4_block1_2_conv (Conv2D) lu[0][0])	(None, None, None, 256)	590080	['conv4_block1_1_re lu']
conv4_block1_2_bn (BatchNormal nv[0][0]) ization)	(None, None, None, 256)	1024	['conv4_block1_2_co nvolution']
conv4_block1_2_relu (Activatio n[0][0]) n)	(None, None, None, 256)	0	['conv4_block1_2_bn ReLU']
conv4_block1_0_conv (Conv2D) [0][0])	(None, None, None, 1024)	525312	['conv3_block4_out ']
conv4_block1_3_conv (Conv2D) lu[0][0])	(None, None, None, 1024)	263168	['conv4_block1_2_re lu']
conv4_block1_0_bn (BatchNormal nv[0][0]) ization)	(None, None, None, 1024)	4096	['conv4_block1_0_co nvolution']
conv4_block1_3_bn (BatchNormal nv[0][0]) ization)	(None, None, None, 1024)	4096	['conv4_block1_3_co nvolution']
conv4_block1_add (Add) [0][0], [0][0])	(None, None, None, 1024)	0	['conv4_block1_0_bn ', 'conv4_block1_3_bn ']
conv4_block1_out (Activation) [0][0])	(None, None, None, 1024)	0	['conv4_block1_add ']
conv4_block2_1_conv (Conv2D) [0][0])	(None, None, None, 256)	262400	['conv4_block1_out ']
conv4_block2_1_bn (BatchNormal nv[0][0]) ization)	(None, None, None, 256)	1024	['conv4_block2_1_co nvolution']
conv4_block2_1_relu (Activatio n[0][0]) n)	(None, None, None, 256)	0	['conv4_block2_1_bn ReLU']

conv4_block2_2_conv (Conv2D) (None, None, None, lu[0][0])	590080	['conv4_block2_1_relu[0][0]']
256)		
conv4_block2_2_bn (BatchNormal (None, None, None, nv[0][0]) ization)	1024	['conv4_block2_2_co nization]
256)		
conv4_block2_2_relu (Activatio [0][0]) n)	0	['conv4_block2_2_bn 256)
conv4_block2_3_conv (Conv2D) (None, None, None, lu[0][0])	263168	['conv4_block2_2_re lu[0][0]']
1024)		
conv4_block2_3_bn (BatchNormal (None, None, None, nv[0][0]) ization)	4096	['conv4_block2_3_co 1024)
conv4_block2_add (Add) (None, None, None, [0][0], 1024) [0][0])	0	['conv4_block1_out 'conv4_block2_3_bn [0][0]']
conv4_block2_out (Activation) (None, None, None, [0][0])	0	['conv4_block2_add 1024)
conv4_block3_1_conv (Conv2D) (None, None, None, [0][0])	262400	['conv4_block2_out 256)
conv4_block3_1_bn (BatchNormal (None, None, None, nv[0][0]) ization)	1024	['conv4_block3_1_co 256)
conv4_block3_1_relu (Activatio [0][0]) n)	0	['conv4_block3_1_bn 256)
conv4_block3_2_conv (Conv2D) (None, None, None, lu[0][0])	590080	['conv4_block3_1_re lu[0][0]']
256)		
conv4_block3_2_bn (BatchNormal (None, None, None, nv[0][0]) ization)	1024	['conv4_block3_2_co 256)
conv4_block3_2_relu (Activatio [0][0]) n)	0	['conv4_block3_2_bn 256)
conv4_block3_3_conv (Conv2D) (None, None, None, lu[0][0])	263168	['conv4_block3_2_re lu[0][0]']

1024)

conv4_block3_3_bn (BatchNormal nv[0][0]') ization)	(None, None, None, 1024)	4096	['conv4_block3_3_co v4_block3_3_bn']
conv4_block3_add (Add) [0][0]', [0][0]']	(None, None, None, 1024)	0	['conv4_block2_out 'conv4_block3_3_bn [0][0]']
conv4_block3_out (Activation) [0][0]']	(None, None, None, 1024)	0	['conv4_block3_add [0][0]']
conv4_block4_1_conv (Conv2D) [0][0]']	(None, None, None, 256)	262400	['conv4_block3_out [0][0]']
conv4_block4_1_bn (BatchNormal nv[0][0]') ization)	(None, None, None, 256)	1024	['conv4_block4_1_co v4_block4_1_bn [0][0]']
conv4_block4_1_relu (Activatio n)	(None, None, None, 256)	0	['conv4_block4_1_bn [0][0]']
conv4_block4_2_conv (Conv2D) lu[0][0]']	(None, None, None, 256)	590080	['conv4_block4_1_re lu[0][0]']
conv4_block4_2_bn (BatchNormal nv[0][0]') ization)	(None, None, None, 256)	1024	['conv4_block4_2_co v4_block4_2_bn [0][0]']
conv4_block4_2_relu (Activatio n)	(None, None, None, 256)	0	['conv4_block4_2_bn [0][0]']
conv4_block4_3_conv (Conv2D) lu[0][0]']	(None, None, None, 1024)	263168	['conv4_block4_2_re lu[0][0]']
conv4_block4_3_bn (BatchNormal nv[0][0]') ization)	(None, None, None, 1024)	4096	['conv4_block4_3_co v4_block4_3_bn [0][0]']
conv4_block4_add (Add) [0][0]', [0][0]']	(None, None, None, 1024)	0	['conv4_block3_out 'conv4_block4_3_bn [0][0]']
conv4_block4_out (Activation) [0][0]']	(None, None, None, 1024)	0	['conv4_block4_add [0][0]']

conv4_block5_1_conv (Conv2D) [0][0]'	(None, None, None, 262400 256)		['conv4_block4_out
conv4_block5_1_bn (BatchNormal nv[0][0]' ization)	(None, None, None, 1024 256)		['conv4_block5_1_co
conv4_block5_1_relu (Activatio n[0][0]'	(None, None, None, 0 256)		['conv4_block5_1_bn
conv4_block5_2_conv (Conv2D) lu[0][0]'	(None, None, None, 590080 256)		['conv4_block5_1_re
conv4_block5_2_bn (BatchNormal nv[0][0]' ization)	(None, None, None, 1024 256)		['conv4_block5_2_co
conv4_block5_2_relu (Activatio n[0][0]'	(None, None, None, 0 256)		['conv4_block5_2_bn
conv4_block5_3_conv (Conv2D) lu[0][0]'	(None, None, None, 263168 1024)		['conv4_block5_2_re
conv4_block5_3_bn (BatchNormal nv[0][0]' ization)	(None, None, None, 4096 1024)		['conv4_block5_3_co
conv4_block5_add (Add) [0][0]', [0][0]'	(None, None, None, 0 1024)		['conv4_block4_out 'conv4_block5_3_bn
conv4_block5_out (Activation) [0][0]'	(None, None, None, 0 1024)		['conv4_block5_add [0][0]']
conv4_block6_1_conv (Conv2D) [0][0]'	(None, None, None, 262400 256)		['conv4_block5_out
conv4_block6_1_bn (BatchNormal nv[0][0]' ization)	(None, None, None, 1024 256)		['conv4_block6_1_co
conv4_block6_1_relu (Activatio n[0][0]'	(None, None, None, 0 256)		['conv4_block6_1_bn
conv4_block6_2_conv (Conv2D) lu[0][0]'	(None, None, None, 590080 256)		['conv4_block6_1_re

conv4_block6_2_bn (BatchNormal [0][0]) ization)	(None, None, None, 256)	1024	['conv4_block6_2_co nv[0][0]']
conv4_block6_2_relu (Activatio n[0][0]) n)	(None, None, None, 256)	0	['conv4_block6_2_bn lu[0][0]']
conv4_block6_3_conv (Conv2D) lu[0][0])	(None, None, None, 1024)	263168	['conv4_block6_2_re lu[0][0]']
conv4_block6_3_bn (BatchNormal [0][0]) ization)	(None, None, None, 1024)	4096	['conv4_block6_3_co nv[0][0]']
conv4_block6_add (Add) [0][0]', [0][0])	(None, None, None, 1024)	0	['conv4_block5_out 'conv4_block6_3.bn [0][0]']
conv4_block6_out (Activation) [0][0])	(None, None, None, 1024)	0	['conv4_block6_add [0][0]']
conv5_block1_1_conv (Conv2D) [0][0])	(None, None, None, 512)	524800	['conv4_block6_out [0][0]']
conv5_block1_1_bn (BatchNormal [0][0]) ization)	(None, None, None, 512)	2048	['conv5_block1_1_co nv[0][0]']
conv5_block1_1_relu (Activatio n[0][0]) n)	(None, None, None, 512)	0	['conv5_block1_1.bn [0][0]']
conv5_block1_2_conv (Conv2D) lu[0][0])	(None, None, None, 512)	2359808	['conv5_block1_1_re lu[0][0]']
conv5_block1_2_bn (BatchNormal [0][0]) ization)	(None, None, None, 512)	2048	['conv5_block1_2_co nv[0][0]']
conv5_block1_2_relu (Activatio n[0][0]) n)	(None, None, None, 512)	0	['conv5_block1_2.bn [0][0]']
conv5_block1_0_conv (Conv2D) [0][0])	(None, None, None, 2048)	2099200	['conv4_block6_out [0][0]']
conv5_block1_3_conv (Conv2D) lu[0][0])	(None, None, None, 1050624)	1050624	['conv5_block1_2.re lu[0][0]']

2048)

conv5_block1_0_bn (BatchNormal nv[0][0]') ization)	(None, None, None, 2048)	8192	['conv5_block1_0_co nv[0][0]']
conv5_block1_3_bn (BatchNormal nv[0][0]') ization)	(None, None, None, 2048)	8192	['conv5_block1_3_co nv[0][0]']
conv5_block1_add (Add) [0][0]', [0][0]']	(None, None, None, 2048)	0	['conv5_block1_0_bn 'conv5_block1_3_bn [0][0]']
conv5_block1_out (Activation) [0][0]']	(None, None, None, 2048)	0	['conv5_block1_add [0][0]']
conv5_block2_1_conv (Conv2D) [0][0]']	(None, None, None, 512)	1049088	['conv5_block1_out [0][0]']
conv5_block2_1_bn (BatchNormal nv[0][0]') ization)	(None, None, None, 512)	2048	['conv5_block2_1_co nv[0][0]']
conv5_block2_1_relu (Activatio n)	(None, None, None, 512)	0	['conv5_block2_1_bn [0][0]']
conv5_block2_2_conv (Conv2D) lu[0][0]']	(None, None, None, 512)	2359808	['conv5_block2_1_re lu[0][0]']
conv5_block2_2_bn (BatchNormal nv[0][0]') ization)	(None, None, None, 512)	2048	['conv5_block2_2_co nv[0][0]']
conv5_block2_2_relu (Activatio n)	(None, None, None, 512)	0	['conv5_block2_2_bn [0][0]']
conv5_block2_3_conv (Conv2D) lu[0][0]']	(None, None, None, 2048)	1050624	['conv5_block2_2_re lu[0][0]']
conv5_block2_3_bn (BatchNormal nv[0][0]') ization)	(None, None, None, 2048)	8192	['conv5_block2_3_co nv[0][0]']
conv5_block2_add (Add) [0][0]', [0][0]']	(None, None, None, 2048)	0	['conv5_block1_out 'conv5_block2_3_bn [0][0]']

conv5_block2_out (Activation) [0][0]'	(None, None, None, 0 2048)		['conv5_block2_add
conv5_block3_1_conv (Conv2D) [0][0]'	(None, None, None, 1049088 512)		['conv5_block2_out
conv5_block3_1_bn (BatchNormal nv[0][0]' ization)	(None, None, None, 2048 512)		['conv5_block3_1_co
conv5_block3_1_relu (Activatio n)[0][0]'	(None, None, None, 0 512)		['conv5_block3_1_bn
conv5_block3_2_conv (Conv2D) lu[0][0]'	(None, None, None, 2359808 512)		['conv5_block3_1_re
conv5_block3_2_bn (BatchNormal nv[0][0]' ization)	(None, None, None, 2048 512)		['conv5_block3_2_co
conv5_block3_2_relu (Activatio n)[0][0]'	(None, None, None, 0 512)		['conv5_block3_2_bn
conv5_block3_3_conv (Conv2D) lu[0][0]'	(None, None, None, 1050624 2048)		['conv5_block3_2_re
conv5_block3_3_bn (BatchNormal nv[0][0]' ization)	(None, None, None, 8192 2048)		['conv5_block3_3_co
conv5_block3_add (Add) [0][0]', [0][0]'	(None, None, None, 0 2048)		['conv5_block2_out 'conv5_block3_3.bn
conv5_block3_out (Activation) [0][0]'	(None, None, None, 0 2048)		['conv5_block3_add
global_average_pooling2d_3 (Gl obalAveragePooling2D) [0][0]'	(None, 2048)	0	['conv5_block3_out
dense_35 (Dense) ooling2d_3[0][0]	(None, 1024)	2098176	['global_average_po ']]
dropout_14 (Dropout)	(None, 1024)	0	['dense_35[0][0]']
dense_36 (Dense)	(None, 1024)	1049600	['dropout_14[0]

```
[0]']

dropout_15 (Dropout)      (None, 1024)      0      ['dense_36[0][0]']

dense_37 (Dense)          (None, 1024)      1049600  ['dropout_15[0]

[0]']

dropout_16 (Dropout)      (None, 1024)      0      ['dense_37[0][0]']

dense_38 (Dense)          (None, 512)       524800   ['dropout_16[0

[0]']

dropout_17 (Dropout)      (None, 512)       0      ['dense_38[0][0]']

dense_39 (Dense)          (None, 6)        3078    ['dropout_17[0

[0]']

=====
=====

Total params: 28,312,966
Trainable params: 28,259,846
Non-trainable params: 53,120
```

None

```
In [ ]: datagen = ImageDataGenerator(
    rescale=1./255, # rescale pixel values to be between 0 and 1
    rotation_range=10, # randomly rotate images by up to 20 degrees
    horizontal_flip=True) # randomly flip images horizontally

train = datagen.flow_from_directory(train_url, target_size=(150, 150), batch_size=1
test = datagen.flow_from_directory(test_url, target_size=(150, 150), batch_size=128

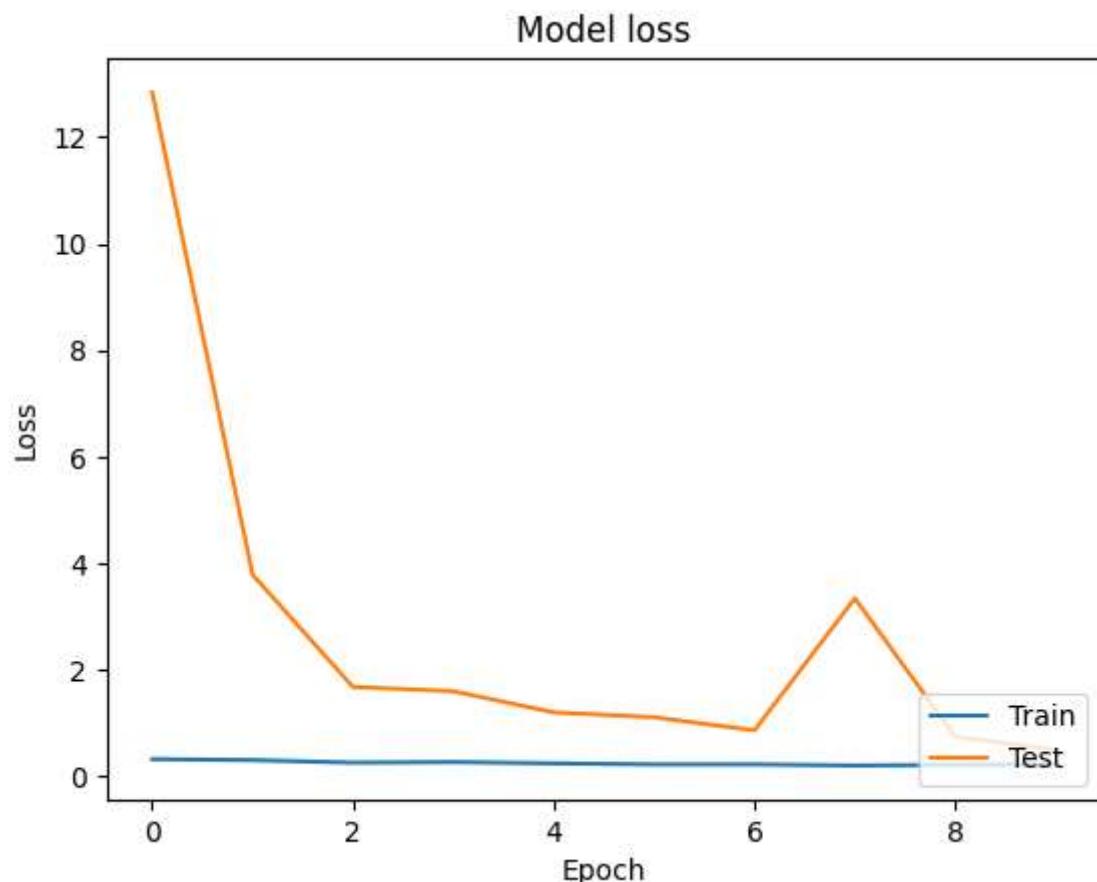
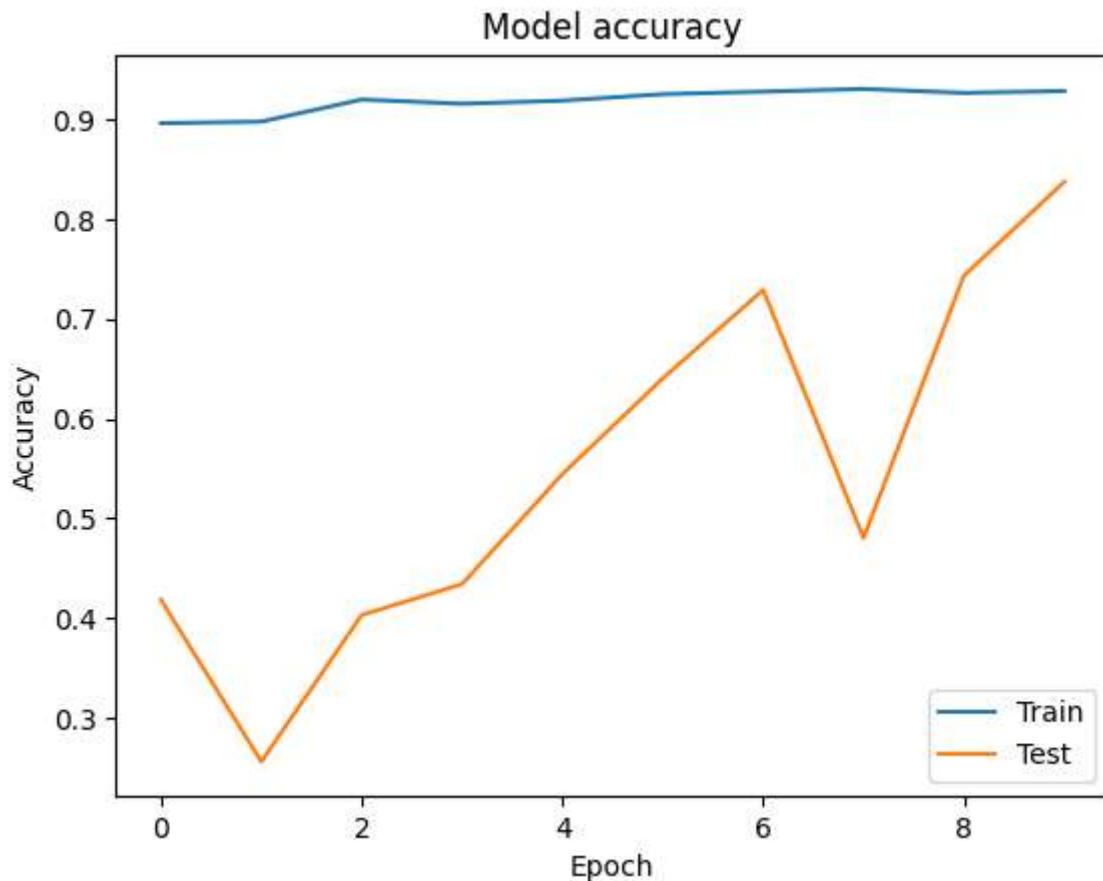
callback = tf.keras.callbacks.EarlyStopping(monitor='val_loss', patience=3)

if os.path.exists('models/image_classification_model_5.h5'):
    model = tf.keras.models.load_model('models/image_classification_model_4.h5')

else:
    model.compile(optimizer='Adam', loss='categorical_crossentropy', metrics=['accu
cnn = model.fit(train, steps_per_epoch=50, epochs = 10, validation_data=test, v
model.save('models/image_classification_model_4.h5')
```

```
Found 14034 images belonging to 6 classes.  
Found 3000 images belonging to 6 classes.  
Epoch 1/10  
50/50 [=====] - 661s 13s/step - loss: 0.3220 - accuracy: 0.  
8961 - val_loss: 12.8451 - val_accuracy: 0.4183  
Epoch 2/10  
50/50 [=====] - 694s 14s/step - loss: 0.3035 - accuracy: 0.  
8977 - val_loss: 3.7855 - val_accuracy: 0.2560  
Epoch 3/10  
50/50 [=====] - 632s 13s/step - loss: 0.2555 - accuracy: 0.  
9198 - val_loss: 1.6775 - val_accuracy: 0.4030  
Epoch 4/10  
50/50 [=====] - 653s 13s/step - loss: 0.2665 - accuracy: 0.  
9156 - val_loss: 1.5976 - val_accuracy: 0.4340  
Epoch 5/10  
50/50 [=====] - 690s 14s/step - loss: 0.2424 - accuracy: 0.  
9187 - val_loss: 1.1986 - val_accuracy: 0.5443  
Epoch 6/10  
50/50 [=====] - 599s 12s/step - loss: 0.2225 - accuracy: 0.  
9252 - val_loss: 1.1079 - val_accuracy: 0.6403  
Epoch 7/10  
50/50 [=====] - 568s 11s/step - loss: 0.2231 - accuracy: 0.  
9278 - val_loss: 0.8623 - val_accuracy: 0.7290  
Epoch 8/10  
50/50 [=====] - 597s 12s/step - loss: 0.2018 - accuracy: 0.  
9305 - val_loss: 3.3420 - val_accuracy: 0.4803  
Epoch 9/10  
50/50 [=====] - 573s 11s/step - loss: 0.2140 - accuracy: 0.  
9265 - val_loss: 0.7422 - val_accuracy: 0.7433  
Epoch 10/10  
50/50 [=====] - 581s 12s/step - loss: 0.2206 - accuracy: 0.  
9284 - val_loss: 0.4969 - val_accuracy: 0.8373
```

```
In [ ]: plt.plot(cnn.history['accuracy'])  
plt.plot(cnn.history['val_accuracy'])  
plt.title('Model accuracy')  
plt.ylabel('Accuracy')  
plt.xlabel('Epoch')  
plt.legend(['Train', 'Test'], loc='lower right')  
plt.show()  
  
plt.plot(cnn.history['loss'])  
plt.plot(cnn.history['val_loss'])  
plt.title('Model loss')  
plt.ylabel('Loss')  
plt.xlabel('Epoch')  
plt.legend(['Train', 'Test'], loc='lower right')  
plt.show()
```



```
In [ ]: pred_url = os.getcwd() + "\\archive\\seg_pred"

datagen = ImageDataGenerator(
    rescale=1./255, # rescale pixel values to be between 0 and 1
    rotation_range=10, # randomly rotate images by up to 20 degrees
    horizontal_flip=True) # randomly flip images horizontally

pred = datagen.flow_from_directory(pred_url, target_size=(150, 150), batch_size=256)

import matplotlib.pyplot as plt
import numpy as np

# get the class labels
class_labels = list(train.class_indices.keys())

# get a batch of images and their predictions
x, _ = next(pred)
y_pred = model.predict(x)

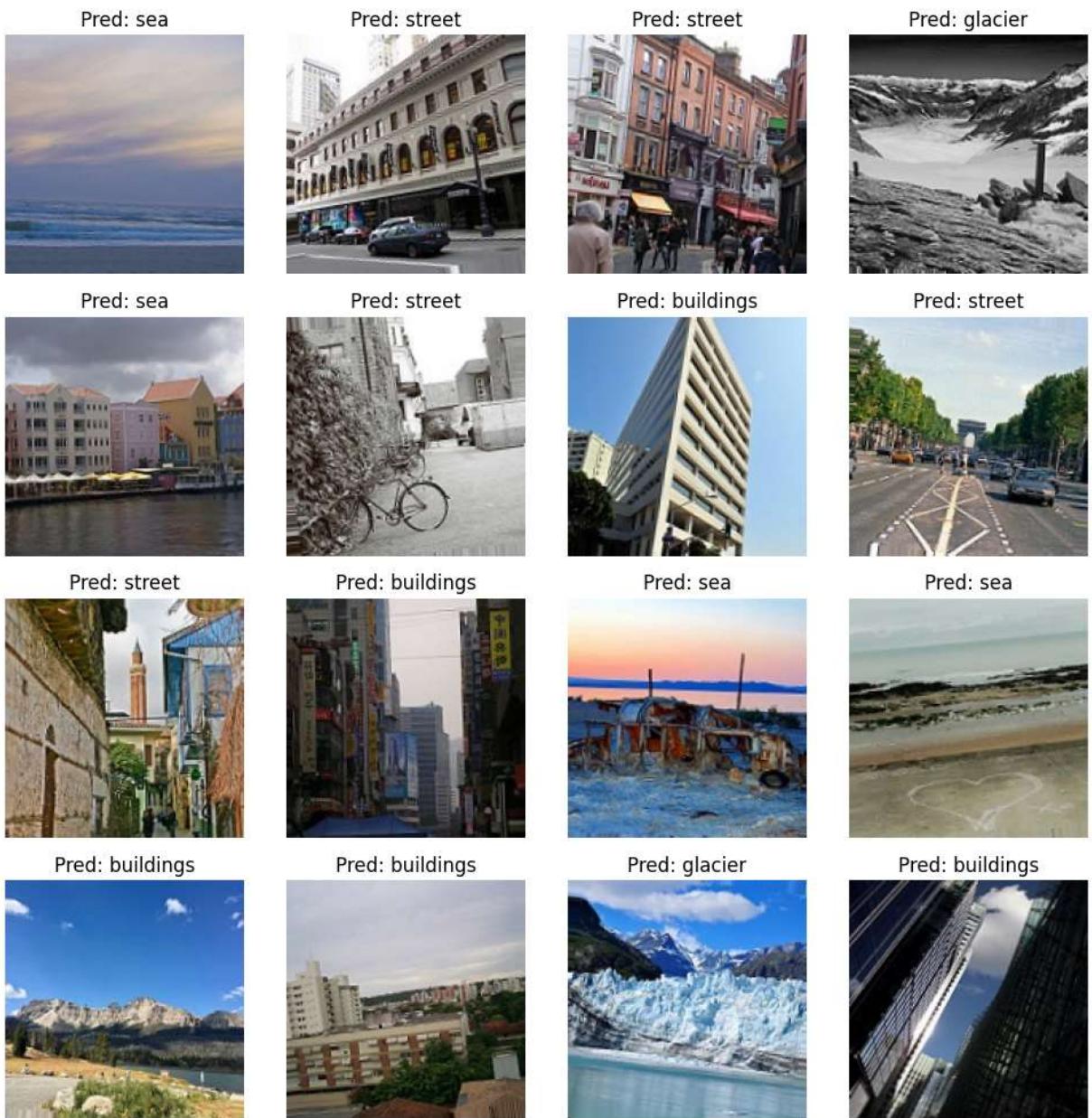
# display the images and their predictions
fig, axs = plt.subplots(4, 4, figsize=(10, 10))
for i, ax in enumerate(axs.flatten()):
    # show the image
    ax.imshow(x[i])
    ax.axis('off')

    # show the predicted label
    pred_label = class_labels[np.argmax(y_pred[i])]
    ax.set_title(f'Pred: {pred_label}')

plt.tight_layout()
plt.show()
```

Found 7301 images belonging to 1 classes.

8/8 [=====] - 5s 559ms/step



Model Evaluation

As can be seen in all the models above, the accuracy for the sequential model with color images and 4 conv2d layers has the lowest accuracy.

With just a simple change in using grayscale images, the accuracy jumps 10% with it going from 50 to 62.

The deep learning model seems to work better with less layers since the accuracy for the 3 conv2d layer model was around 65%, far higher than the 4conv2d layer model. Note that there were no other changes made to original architecture, even the color input was kept the same.

The amount of learning parameters as well as the number of images quite affected the training time of these models. It took an hour each to train most of them, especially because some used to stall out for some reason.

The model that performed best was the transfer learning model, with an accuracy of 86%. I could not let it run for longer because of problems with time, since every epoch seemed to take around 10 minutes, and I could not let it run continuously external problems. Otherwise I think it would have definitely performed better than what is seen here.