Classification With Transfer Learning

1 Importing Necessary Libraries

```
[1]: import os
  import numpy as np
  import seaborn as sns
  import tensorflow as tf
  import matplotlib.pyplot as plt
  from tensorflow.keras.utils import plot_model
  from tensorflow.keras.applications import VGG19
  from tensorflow.keras import layers, mixed_precision
  from sklearn.metrics import classification_report, confusion_matrix
```

2 Defining Model Architecture (VGG19) and Data Loading

```
[4]: def cnn(input_shape, num_classes):
    base = VGG19(weights = "imagenet", include_top = False, input_shape = uinput_shape)
    base.trainable = False

model = tf.keras.Sequential([
    base,
    # layers.GlobalAveragePooling2D(),
    layers.Flatten(),

layers.Dense(512, activation = "relu"),
    layers.BatchNormalization(),

layers.Dense(256, activation = "relu"),
    layers.BatchNormalization(),

layers.Dense(128, activation = "relu"),
    layers.BatchNormalization(),

layers.Dense(num_classes, activation = "softmax")
])
```

return model

```
[6]: dir = "../Dataset/Intel/seg_train"

batch_size = 16
img_h, img_w = 150, 150

train_dataset = tf.keras.utils.image_dataset_from_directory(dir, seed = 100, u)
simage_size = (img_h, img_w), batch_size = batch_size, shuffle = True)
```

Found 14034 files belonging to 6 classes.

```
[7]: train_dataset.class_names
```

[7]: ['buildings', 'forest', 'glacier', 'mountain', 'sea', 'street']

3 Model Initialization

3.1 Model Architecture Summary and Visualization

[27]: model.summary()

Model: "sequential_2"

Layer (type)	Output Shape	
vgg19 (Functional)		
flatten_2 (Flatten)	(None, 8192)	0
dense_8 (Dense)	(None, 512)	4194816
<pre>batch_normalization_6 (Batc hNormalization)</pre>	(None, 512)	2048
dense_9 (Dense)	(None, 256)	131328
<pre>batch_normalization_7 (Batch hNormalization)</pre>	(None, 256)	1024
dense_10 (Dense)	(None, 128)	32896
<pre>batch_normalization_8 (Batch hNormalization)</pre>	(None, 128)	512

dense_11 (Dense) (None, 6) 774

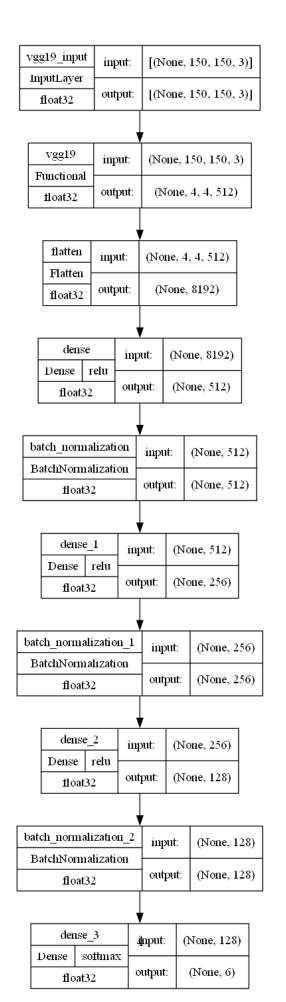
Total params: 24,387,782 Trainable params: 4,361,606

Non-trainable params: 20,026,176

[16]: plot_model(model, show_layer_names = True, show_dtype = True,__

⇒show_layer_activations = True, show_shapes = True)

[16]:



3.2 Training

```
[29]: model.compile(optimizer = "adam", loss = "sparse_categorical_crossentropy", u
     →metrics = ["accuracy"])
[31]: # Ensure GPU Usage (if you want to use CPU, "/CPU:0")
    with tf.device("/GPU:0"):
       history = model.fit(train_dataset, epochs = 20)
    Epoch 1/20
    878/878 [============= ] - 116s 125ms/step - loss: 0.4186 -
    accuracy: 0.8511
    Epoch 2/20
    878/878 [============ ] - 94s 107ms/step - loss: 0.2434 -
    accuracy: 0.9139
    Epoch 3/20
    878/878 [============= ] - 98s 111ms/step - loss: 0.1806 -
    accuracy: 0.9344
    Epoch 4/20
    accuracy: 0.9510
    Epoch 5/20
    878/878 [============ ] - 67s 77ms/step - loss: 0.1153 -
    accuracy: 0.9577
    Epoch 6/20
    878/878 [============ ] - 68s 77ms/step - loss: 0.0973 -
    accuracy: 0.9642
    Epoch 7/20
    878/878 [============ ] - 68s 77ms/step - loss: 0.0766 -
    accuracy: 0.9720
    Epoch 8/20
    878/878 [============= ] - 68s 78ms/step - loss: 0.0631 -
    accuracy: 0.9785
    Epoch 9/20
    accuracy: 0.9803
    Epoch 10/20
    878/878 [============] - 70s 79ms/step - loss: 0.0540 -
    accuracy: 0.9808
    Epoch 11/20
    878/878 [============ ] - 71s 81ms/step - loss: 0.0419 -
    accuracy: 0.9849
    Epoch 12/20
    878/878 [============] - 40s 46ms/step - loss: 0.0417 -
    accuracy: 0.9866
```

```
Epoch 13/20
accuracy: 0.9889
Epoch 14/20
accuracy: 0.9900
Epoch 15/20
accuracy: 0.9885
Epoch 16/20
accuracy: 0.9905
Epoch 17/20
accuracy: 0.9912
Epoch 18/20
accuracy: 0.9911
Epoch 19/20
accuracy: 0.9917
Epoch 20/20
878/878 [================ ] - 43s 49ms/step - loss: 0.0203 -
accuracy: 0.9932
```

4 Saving The Trained Model

```
[179]: model.save("../Models/Intel/Model With Transfer Learning.h5")
```

5 Model Evaluation and Other Metrics

5.1 Loss and Accuracy Graphs

```
[108]: # Plot training accuracy and loss
def plot_loss_accuracy(history):
    acc = history.history['accuracy']
    loss = history.history['loss']

    epochs = range(1, len(acc) + 1)

    plt.figure(figsize=(10, 5)) # Adjust size

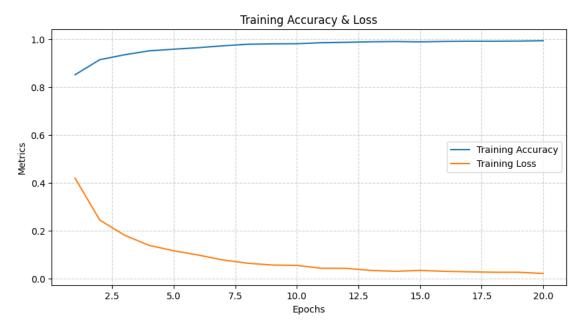
# Plot accuracy and loss on the same graph
    plt.plot(epochs, acc, label='Training Accuracy') # Blue line with circles
    plt.plot(epochs, loss, label='Training Loss') # Red line with triangles
```

```
# Labels & title
plt.xlabel('Epochs')
plt.ylabel('Metrics')
plt.title('Training Accuracy & Loss')

# Grid and legend
plt.grid(True, linestyle='--', alpha=0.6) # Dashed gridlines
plt.legend()

plt.show()

plot_loss_accuracy(history)
```



5.2 Confusion Matrix and Classification Report

Found 3000 files belonging to 6 classes.

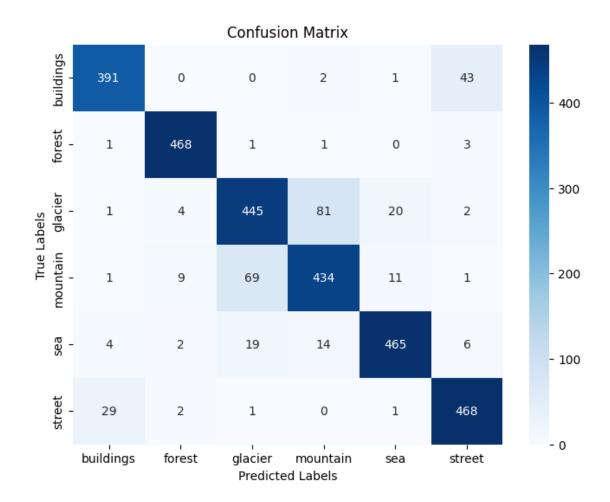
```
[110]: y_true = np.concatenate([labels.numpy() for _, labels in test_dataset])
```

```
# Get model predictions
y_pred = model.predict(test_dataset)
y_pred_classes = np.argmax(y_pred, axis=1)
# Define class names
class_names = test_dataset.class_names
# Generate Classification Report
print(" Classification Report:\n")
print(classification_report(y_true, y_pred_classes, target_names=class_names))
# Generate Confusion Matrix
cm = confusion_matrix(y_true, y_pred_classes)
# Plot Confusion Matrix
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=class_names, ___

yticklabels=class_names)
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.title('Confusion Matrix')
plt.show()
```

188/188 [============] - 8s 41ms/step Classification Report:

	precision	recall	f1-score	support
buildings	0.92	0.89	0.91	437
forest	0.96	0.99	0.98	474
glacier	0.83	0.80	0.82	553
mountain	0.82	0.83	0.82	525
sea	0.93	0.91	0.92	510
street	0.89	0.93	0.91	501
accuracy			0.89	3000
macro avg	0.89	0.89	0.89	3000
weighted avg	0.89	0.89	0.89	3000



6 Inference

6.1 Importing the necessary libraries

```
num_images = len(img_paths)
         grid_rows = math.ceil(num_images / grid_cols) # Calculate number of rows_
       \rightarrowneeded
         plt.figure(figsize=(grid_cols * 4, grid_rows * 4)) # Adjust figure size_
       \rightarrow dynamically
         for i, img_path in enumerate(img_paths):
            img = cv2.imread(img_path)
            # Preprocess image
            img_expanded = np.expand_dims(img, axis=0)
            prediction = model.predict(img_expanded)
            predicted_class = np.argmax(prediction, axis=1)[0]
            predicted_label = class_names[predicted_class]
            # Plot image in a grid
            plt.subplot(grid_rows, grid_cols, i + 1)
            plt.imshow(img)
            plt.axis('off')
            plt.title(f"{predicted_label}", fontsize=12)
         plt.tight_layout() # Adjust layout for better spacing
         plt.show()
[174]: parent_dir = "../Dataset/Intel/seg_pred/"
     num_images = 9  # Number of images to predict
     img_files = random.sample(os.listdir(parent_dir), num_images)
     img_paths = [os.path.join(parent_dir, img) for img_in img_files]
     inference_grid(img_paths, grid_cols = 3)
     1/1 [======] - 0s 21ms/step
     1/1 [======] - 0s 19ms/step
     1/1 [======] - Os 17ms/step
     1/1 [======] - 0s 18ms/step
     1/1 [======] - 0s 18ms/step
     1/1 [=======] - Os 18ms/step
     1/1 [======] - 0s 17ms/step
     1/1 [======== ] - Os 17ms/step
```

