Section 2: CIFAR-10 Image Classification with Transfer Learning

Loading Model

Transfer learning will be used with Google's vit-base-patch16-224 which can be found here: https://huggingface.co/google/vit-base-patch16-224?library=transformers. The model uses 224x224 images but has its own processor to deal with resizing and other transformations. The result of that processing is a dictionary that includes a 3x224x224 tensor.

```
from transformers import TFViTModel

# Load model (without output layer)
print('Loading from Hugging Face ...')
base_model = TFViTModel.from_pretrained('google/vit-base-patch16-224')
base_model.save_pretrained('baseline_vit_model')
```

```
/apps/tensorflow/2.18/lib/python3.11/site-packages/tqdm/auto.py:21:
TqdmWarning: IProgress not found. Please update jupyter and
ipywidgets. See
https://ipywidgets.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
2025-04-16 00:58:23.975804: E
external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:467] Unable to
register cuFFT factory: Attempting to register factory for plugin
cuFFT when one has already been registered
WARNING: All log messages before absl::InitializeLog() is called are
written to STDERR
E0000 00:00:1744779503.999351 2308149 cuda_dnn.cc:8579] Unable to
register cuDNN factory: Attempting to register factory for plugin
cuDNN when one has already been registered
E0000 00:00:1744779504.006655 2308149 cuda_blas.cc:1407] Unable to
register cuBLAS factory: Attempting to register factory for plugin
cuBLAS when one has already been registered
W0000 00:00:1744779504.025828 2308149 computation_placer.cc:177]
computation placer already registered. Please check linkage and avoid
linking the same target more than once.
W0000 00:00:1744779504.025843 2308149 computation_placer.cc:177]
computation placer already registered. Please check linkage and avoid
linking the same target more than once.
W0000 00:00:1744779504.025845 2308149 computation_placer.cc:177]
computation placer already registered. Please check linkage and avoid
linking the same target more than once.
W0000 00:00:1744779504.025847 2308149 computation_placer.cc:177]
computation placer already registered. Please check linkage and avoid
linking the same target more than once.
```

```
2025-04-16 00:58:24.032003: I
tensorflow/core/platform/cpu_feature_guard.cc:210] This TensorFlow
binary is optimized to use available CPU instructions in performance-
critical operations.
To enable the following instructions: AVX2 FMA, in other operations,
rebuild TensorFlow with the appropriate compiler flags.

Loading from Hugging Face ...

2025-04-16 00:58:31.971284: E
external/local_xla/xla/stream_executor/cuda/cuda_platform.cc:51]
failed call to cuInit: INTERNAL: CUDA error: Failed call to cuInit:
UNKNOWN ERROR (303)
Some weights of the PyTorch model were not used when initializing the
TF 2.0 model TFViTModel: ['classifier.bias', 'classifier.weight']
- This IS expected if you are initializing TFViTModel from a PyTorch
model trained on another task or with another architecture (e.g.
initializing a TFBertForSequenceClassification model from a
BertForPreTraining model).
- This IS NOT expected if you are initializing TFViTModel from a
PyTorch model that you expect to be exactly identical (e.g.
initializing a TFBertForSequenceClassification model from a
BertForSequenceClassification model).
Some weights or buffers of the TF 2.0 model TFViTModel were not
initialized from the PyTorch model and are newly initialized:
['vit.pooler.dense.weight', 'vit.pooler.dense.bias']
You should probably TRAIN this model on a down-stream task to be able
to use it for predictions and inference.
```

```python
# Show layers
print('Original Layers')
print('------------------')

for layer in base_model.layers:
    print(layer)
```

```
Original Layers
------------------
<transformers.models.vit.modeling_tf_vit.TFViTMainLayer object at
0x14e1813640d0>
```

Loading Data

The data will be loaded (processing will be done later with training).

```python
import numpy as np
from tensorflow.keras.datasets import cifar10

# Load data
(X_train, y_train), (X_test, y_test) = cifar10.load_data()
```

```
X_train = X_train
X_test = X_test
y_train = y_train
y_test = y_test
```

Initial Training

The main layers will be frozen, but the output layer will be replaced to allow for 10 classes. It is very minimalistic so that there can be a baseline.

```
from tensorflow.keras.layers import Input, Dense, Layer
from tensorflow.keras.models import Sequential
from transformers import TFViTModel
from sklearn.model_selection import train_test_split, StratifiedKFold
from tensorflow.keras.callbacks import EarlyStopping
import tensorflow as tf
import keras
import time

# Wrapper to convert to Keras layer
class ViTLayer(Layer):
    def __init__(self, vit_model=None, model_name='google/vit-base-
patch16-224', **kwargs):
        super(ViTLayer, self).__init__(**kwargs)
        # Load vit_model
        self.vit_model = vit_model if vit_model is not None else
TFViTModel.from_pretrained('baseline_vit_model')
        # Store model name for serialization (needed for
saving/loading)
        self.model_name = model_name

    def call(self, inputs):
        outputs = self.vit_model(inputs)
        return outputs.pooler_output

    def get_config(self):
        config = super(ViTLayer, self).get_config()
        config.update({
            'model_name': self.model_name
        })
        return config

    @classmethod
    def from_config(cls, config):
        # Get model_name and remove it from config to avoid passing to
init
        model_name = config.pop('model_name')
        # Create instance without vit_model (will be loaded in init)
```

```
        return cls(model_name=model_name, **config)

# Form new model
model = Sequential([
    Input(shape=(3, 224, 224)),
    ViTLayer(base_model, model_name='google/vit-base-patch16-224'),
    Dense(10, activation='softmax', name='classifier')
])

# Show layers
print(f'Layers: {model.layers}')

# Freeze everything except output layer
model.layers[0].trainable = False

# Compile
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

# Print model summary
print(model.summary())
```

```
Layers: [<ViTLayer name=vi_t_layer, built=True>, <Dense
name=classifier, built=True>]

Model: "sequential"

┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━
━━━━━┓
┃ Layer (type)                     ┃ Output Shape           ┃
Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━
━━━━━┩
│ vi_t_layer (ViTLayer)            │ (None, 768)            │
0 │
├──────────────────────────────────┼────────────────────────┼──────────
─────┤
│ classifier (Dense)               │ (None, 10)             │
7,690 │
└──────────────────────────────────┴────────────────────────┴──────────
─────┘

 Total params: 7,690 (30.04 KB)

 Trainable params: 7,690 (30.04 KB)

 Non-trainable params: 0 (0.00 B)

None
```

Start training (using K-Fold Cross Validation). Due to time constraints, only half of the training data will be used for fitting but it will be shuffled and randomly chosen to avoid sample bias.

```
from transformers import AutoImageProcessor

# Tracking metrics
start_time = time.time()
train_accuracy = []
val_accuracy = []
train_loss = []
val_loss = []

# Process in batches and each batch with KFold cross validation
num_batches = 50
num_kfolds = 4
batch_kf = StratifiedKFold(n_splits=num_batches, shuffle=True,
random_state=42)
val_kf = StratifiedKFold(n_splits=num_kfolds, shuffle=True,
random_state=42)
batch_num = 1

for _, batch_index in batch_kf.split(X_train, y_train):

    print('-------------------------------------')
    print(f'Working on Batch {batch_num} ...')
    print('-------------------------------------')
    X_train_batch = X_train[batch_index]
    y_train_batch = y_train[batch_index]
    fold_num = 1

    for train_index, val_index in val_kf.split(X_train_batch,
y_train_batch):

        print(f'Working on Fold {fold_num} ...')
        X_train_split = X_train_batch[train_index]
        y_train_split = y_train_batch[train_index]
        X_val_split = X_train_batch[val_index]
        y_val_split = y_train_batch[val_index]

        processor = AutoImageProcessor.from_pretrained('google/vit-
base-patch16-224')
        X_train_split = processor(images=X_train_split,
return_tensors='tf')['pixel_values']
        X_val_split = processor(images=X_val_split,
return_tensors='tf')['pixel_values']

        history = model.fit(X_train_split, y_train_split,
validation_data=(X_val_split, y_val_split), epochs=1)
        train_accuracy += history.history['accuracy']
        val_accuracy += history.history['val_accuracy']
```

```python
        train_loss += history.history['loss']
        val_loss += history.history['val_loss']
        fold_num += 1

    # Train on half of the training set
    if batch_num == int(round(num_batches/2)):
        break

    batch_num += 1

# Print time it took to train
end_time = time.time()
train_time_secs = end_time - start_time
train_time_mins = train_time_secs / 60
print(f'Training Time: {train_time_mins} mins')
```

```
-------------------------------------
Working on Batch 1 ...
-------------------------------------
Working on Fold 1 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 108s 4s/step - accuracy: 0.2956 - loss:
2.0610 - val_accuracy: 0.8520 - val_loss: 1.0355
Working on Fold 2 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9112 - loss:
0.8060 - val_accuracy: 0.9280 - val_loss: 0.4957
Working on Fold 3 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9510 - loss:
0.4174 - val_accuracy: 0.9440 - val_loss: 0.3472
Working on Fold 4 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9544 - loss:
0.3138 - val_accuracy: 0.9760 - val_loss: 0.2084
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Working on Batch 2 ...
-------------------------------------
Working on Fold 1 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 94s 4s/step - accuracy: 0.9581 - loss:
0.2600 - val_accuracy: 0.9560 - val_loss: 0.2498
Working on Fold 2 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9640 - loss:
0.2217 - val_accuracy: 0.9560 - val_loss: 0.2246
Working on Fold 3 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9740 - loss:
0.1885 - val_accuracy: 0.9560 - val_loss: 0.1928
Working on Fold 4 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 94s 4s/step - accuracy: 0.9730 - loss:
0.1598 - val_accuracy: 0.9920 - val_loss: 0.0923
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Working on Batch 3 ...
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Working on Fold 1 ...
```

```
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9454 - loss:
0.2124 - val_accuracy: 0.9440 - val_loss: 0.2014
Working on Fold 2 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9611 - loss:
0.1809 - val_accuracy: 0.9440 - val_loss: 0.1978
Working on Fold 3 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9543 - loss:
0.1735 - val_accuracy: 0.9680 - val_loss: 0.1393
Working on Fold 4 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 94s 4s/step - accuracy: 0.9627 - loss:
0.1573 - val_accuracy: 0.9720 - val_loss: 0.1318
-------------------------------------
Working on Batch 4 ...
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Working on Fold 1 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9346 - loss:
0.2073 - val_accuracy: 0.9640 - val_loss: 0.1291
Working on Fold 2 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 94s 4s/step - accuracy: 0.9492 - loss:
0.1600 - val_accuracy: 0.9520 - val_loss: 0.1659
Working on Fold 3 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 94s 4s/step - accuracy: 0.9600 - loss:
0.1527 - val_accuracy: 0.9440 - val_loss: 0.1506
Working on Fold 4 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 94s 4s/step - accuracy: 0.9611 - loss:
0.1351 - val_accuracy: 0.9720 - val_loss: 0.1233
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Working on Batch 5 ...
-------------------------------------
Working on Fold 1 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 94s 4s/step - accuracy: 0.9529 - loss:
0.1739 - val_accuracy: 0.9520 - val_loss: 0.1865
Working on Fold 2 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9620 - loss:
0.1414 - val_accuracy: 0.9800 - val_loss: 0.1212
Working on Fold 3 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 96s 4s/step - accuracy: 0.9740 - loss:
0.1186 - val_accuracy: 0.9720 - val_loss: 0.1166
Working on Fold 4 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9668 - loss:
0.1274 - val_accuracy: 0.9800 - val_loss: 0.0837
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Working on Batch 6 ...
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Working on Fold 1 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9634 - loss:
0.1310 - val_accuracy: 0.9480 - val_loss: 0.1355
Working on Fold 2 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9568 - loss:
```

```
0.1365 - val_accuracy: 0.9760 - val_loss: 0.1007
Working on Fold 3 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9593 - loss:
0.1188 - val_accuracy: 0.9800 - val_loss: 0.1180
Working on Fold 4 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9742 - loss:
0.0853 - val_accuracy: 0.9760 - val_loss: 0.0839
-------------------------------------
Working on Batch 7 ...
-------------------------------------
Working on Fold 1 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9685 - loss:
0.1243 - val_accuracy: 0.9720 - val_loss: 0.1007
Working on Fold 2 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9742 - loss:
0.0971 - val_accuracy: 0.9840 - val_loss: 0.0729
Working on Fold 3 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 96s 4s/step - accuracy: 0.9750 - loss:
0.0959 - val_accuracy: 0.9680 - val_loss: 0.0983
Working on Fold 4 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9869 - loss:
0.0731 - val_accuracy: 0.9760 - val_loss: 0.1033
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Working on Batch 8 ...
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Working on Fold 1 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9536 - loss:
0.1147 - val_accuracy: 0.9880 - val_loss: 0.0736
Working on Fold 2 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9774 - loss:
0.0902 - val_accuracy: 0.9640 - val_loss: 0.1207
Working on Fold 3 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9852 - loss:
0.0871 - val_accuracy: 0.9760 - val_loss: 0.0711
Working on Fold 4 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9784 - loss:
0.0719 - val_accuracy: 1.0000 - val_loss: 0.0548
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Working on Batch 9 ...
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Working on Fold 1 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9625 - loss:
0.1143 - val_accuracy: 0.9360 - val_loss: 0.1721
Working on Fold 2 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 94s 4s/step - accuracy: 0.9648 - loss:
0.1247 - val_accuracy: 0.9720 - val_loss: 0.1021
Working on Fold 3 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 94s 4s/step - accuracy: 0.9721 - loss:
0.0998 - val_accuracy: 0.9560 - val_loss: 0.1129
```

```
Working on Fold 4 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9702 - loss:
0.0916 - val_accuracy: 0.9880 - val_loss: 0.0544
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Working on Batch 10 ...
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Working on Fold 1 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 94s 4s/step - accuracy: 0.9662 - loss:
0.1008 - val_accuracy: 0.9680 - val_loss: 0.1262
Working on Fold 2 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 94s 4s/step - accuracy: 0.9744 - loss:
0.1065 - val_accuracy: 0.9800 - val_loss: 0.0838
Working on Fold 3 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9770 - loss:
0.1030 - val_accuracy: 0.9920 - val_loss: 0.0674
Working on Fold 4 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9813 - loss:
0.0813 - val_accuracy: 0.9960 - val_loss: 0.0632
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Working on Batch 11 ...
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Working on Fold 1 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9477 - loss:
0.1428 - val_accuracy: 0.9680 - val_loss: 0.1093
Working on Fold 2 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9699 - loss:
0.1068 - val_accuracy: 0.9640 - val_loss: 0.0982
Working on Fold 3 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 94s 4s/step - accuracy: 0.9764 - loss:
0.0929 - val_accuracy: 0.9760 - val_loss: 0.0878
Working on Fold 4 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 94s 4s/step - accuracy: 0.9677 - loss:
0.0848 - val_accuracy: 0.9840 - val_loss: 0.0671
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Working on Batch 12 ...
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Working on Fold 1 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 94s 4s/step - accuracy: 0.9548 - loss:
0.1278 - val_accuracy: 0.9520 - val_loss: 0.1434
Working on Fold 2 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9720 - loss:
0.0959 - val_accuracy: 0.9600 - val_loss: 0.0988
Working on Fold 3 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9710 - loss:
0.0916 - val_accuracy: 0.9840 - val_loss: 0.0793
Working on Fold 4 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9784 - loss:
0.0827 - val_accuracy: 0.9920 - val_loss: 0.0477
-------------------------------------
```

```
Working on Batch 13 ...
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Working on Fold 1 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9410 - loss:
0.1608 - val_accuracy: 0.9520 - val_loss: 0.1487
Working on Fold 2 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9606 - loss:
0.1300 - val_accuracy: 0.9520 - val_loss: 0.1346
Working on Fold 3 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9549 - loss:
0.1181 - val_accuracy: 0.9840 - val_loss: 0.0713
Working on Fold 4 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9647 - loss:
0.1027 - val_accuracy: 0.9600 - val_loss: 0.0925
-------------------------------------
Working on Batch 14 ...
-------------------------------------
Working on Fold 1 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9630 - loss:
0.1165 - val_accuracy: 0.9520 - val_loss: 0.1183
Working on Fold 2 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9603 - loss:
0.1042 - val_accuracy: 0.9760 - val_loss: 0.0786
Working on Fold 3 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9586 - loss:
0.0927 - val_accuracy: 0.9680 - val_loss: 0.0895
Working on Fold 4 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9752 - loss:
0.0712 - val_accuracy: 0.9840 - val_loss: 0.0523
-------------------------------------
Working on Batch 15 ...
-------------------------------------
Working on Fold 1 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9580 - loss:
0.1240 - val_accuracy: 0.9520 - val_loss: 0.1417
Working on Fold 2 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9589 - loss:
0.1118 - val_accuracy: 0.9520 - val_loss: 0.1118
Working on Fold 3 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 96s 4s/step - accuracy: 0.9713 - loss:
0.1004 - val_accuracy: 0.9720 - val_loss: 0.0837
Working on Fold 4 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9767 - loss:
0.0825 - val_accuracy: 0.9680 - val_loss: 0.0739
-------------------------------------
Working on Batch 16 ...
-------------------------------------
Working on Fold 1 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9764 - loss:
```

```
0.1078 - val_accuracy: 0.9640 - val_loss: 0.1019
Working on Fold 2 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9745 - loss:
0.0889 - val_accuracy: 0.9720 - val_loss: 0.1150
Working on Fold 3 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 94s 4s/step - accuracy: 0.9683 - loss:
0.0924 - val_accuracy: 0.9800 - val_loss: 0.0611
Working on Fold 4 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9813 - loss:
0.0699 - val_accuracy: 0.9920 - val_loss: 0.0570
-------------------------------------
Working on Batch 17 ...
-------------------------------------
Working on Fold 1 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9677 - loss:
0.1196 - val_accuracy: 0.9720 - val_loss: 0.0830
Working on Fold 2 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 96s 4s/step - accuracy: 0.9646 - loss:
0.1291 - val_accuracy: 0.9680 - val_loss: 0.1107
Working on Fold 3 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9765 - loss:
0.0906 - val_accuracy: 0.9920 - val_loss: 0.0461
Working on Fold 4 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9805 - loss:
0.0688 - val_accuracy: 0.9800 - val_loss: 0.0937
-------------------------------------
Working on Batch 18 ...
-------------------------------------
Working on Fold 1 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9445 - loss:
0.1514 - val_accuracy: 0.9680 - val_loss: 0.0960
Working on Fold 2 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9624 - loss:
0.1067 - val_accuracy: 0.9600 - val_loss: 0.1367
Working on Fold 3 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9702 - loss:
0.0843 - val_accuracy: 0.9720 - val_loss: 0.0875
Working on Fold 4 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9734 - loss:
0.0776 - val_accuracy: 0.9840 - val_loss: 0.0495
-------------------------------------
Working on Batch 19 ...
-------------------------------------
Working on Fold 1 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 96s 4s/step - accuracy: 0.9594 - loss:
0.1319 - val_accuracy: 0.9760 - val_loss: 0.0543
Working on Fold 2 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9726 - loss:
0.1068 - val_accuracy: 0.9680 - val_loss: 0.1318
```

```
Working on Fold 3 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9712 - loss:
0.1009 - val_accuracy: 0.9720 - val_loss: 0.0970
Working on Fold 4 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9820 - loss:
0.0707 - val_accuracy: 0.9920 - val_loss: 0.0439
-------------------------------------
Working on Batch 20 ...
-------------------------------------
Working on Fold 1 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9874 - loss:
0.0608 - val_accuracy: 0.9760 - val_loss: 0.0953
Working on Fold 2 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 94s 4s/step - accuracy: 0.9806 - loss:
0.0558 - val_accuracy: 0.9800 - val_loss: 0.0732
Working on Fold 3 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 94s 4s/step - accuracy: 0.9811 - loss:
0.0830 - val_accuracy: 0.9880 - val_loss: 0.0592
Working on Fold 4 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9894 - loss:
0.0519 - val_accuracy: 0.9880 - val_loss: 0.0466
-------------------------------------
Working on Batch 21 ...
-------------------------------------
Working on Fold 1 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9821 - loss:
0.0745 - val_accuracy: 0.9760 - val_loss: 0.0835
Working on Fold 2 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9742 - loss:
0.0864 - val_accuracy: 0.9880 - val_loss: 0.0523
Working on Fold 3 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9803 - loss:
0.0589 - val_accuracy: 0.9880 - val_loss: 0.0531
Working on Fold 4 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9863 - loss:
0.0473 - val_accuracy: 0.9960 - val_loss: 0.0365
-------------------------------------
Working on Batch 22 ...
-------------------------------------
Working on Fold 1 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9730 - loss:
0.0714 - val_accuracy: 0.9640 - val_loss: 0.1494
Working on Fold 2 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 96s 4s/step - accuracy: 0.9798 - loss:
0.0726 - val_accuracy: 0.9600 - val_loss: 0.1148
Working on Fold 3 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9678 - loss:
0.1080 - val_accuracy: 0.9840 - val_loss: 0.0462
Working on Fold 4 ...
```

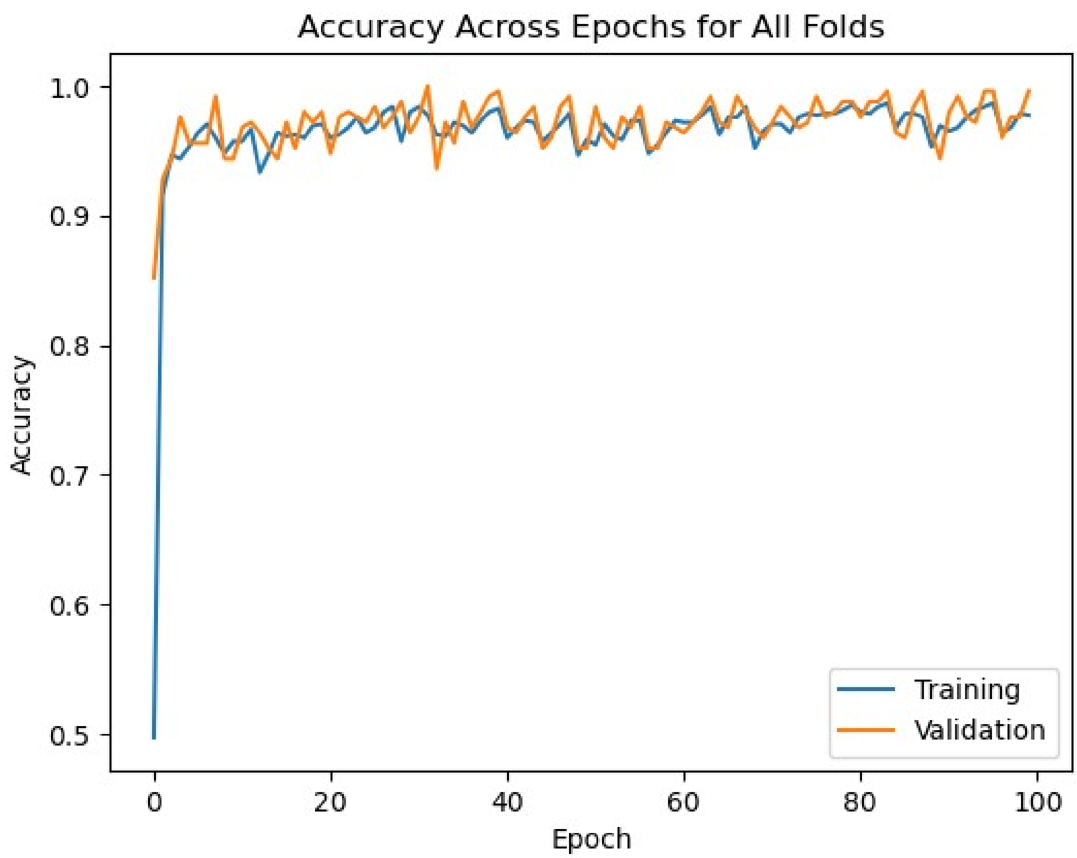
```
24/24 ━━━━━━━━━━━━━━━━━━━━ 96s 4s/step - accuracy: 0.9785 - loss:
0.0743 - val_accuracy: 0.9960 - val_loss: 0.0297
-------------------------------------
Working on Batch 23 ...
-------------------------------------
Working on Fold 1 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 96s 4s/step - accuracy: 0.9538 - loss:
0.1415 - val_accuracy: 0.9640 - val_loss: 0.1016
Working on Fold 2 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9842 - loss:
0.0591 - val_accuracy: 0.9440 - val_loss: 0.1534
Working on Fold 3 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 96s 4s/step - accuracy: 0.9637 - loss:
0.1202 - val_accuracy: 0.9800 - val_loss: 0.0490
Working on Fold 4 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9701 - loss:
0.0729 - val_accuracy: 0.9920 - val_loss: 0.0773
-------------------------------------
Working on Batch 24 ...
-------------------------------------
Working on Fold 1 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9737 - loss:
0.1186 - val_accuracy: 0.9760 - val_loss: 0.0712
Working on Fold 2 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9794 - loss:
0.0696 - val_accuracy: 0.9720 - val_loss: 0.1365
Working on Fold 3 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9832 - loss:
0.0955 - val_accuracy: 0.9960 - val_loss: 0.0423
Working on Fold 4 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 94s 4s/step - accuracy: 0.9871 - loss:
0.0687 - val_accuracy: 0.9960 - val_loss: 0.0555
-------------------------------------
Working on Batch 25 ...
-------------------------------------
Working on Fold 1 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9604 - loss:
0.0900 - val_accuracy: 0.9600 - val_loss: 0.1376
Working on Fold 2 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9685 - loss:
0.1031 - val_accuracy: 0.9760 - val_loss: 0.0638
Working on Fold 3 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 95s 4s/step - accuracy: 0.9713 - loss:
0.0760 - val_accuracy: 0.9760 - val_loss: 0.0784
Working on Fold 4 ...
24/24 ━━━━━━━━━━━━━━━━━━━━ 96s 4s/step - accuracy: 0.9817 - loss:
0.0673 - val_accuracy: 0.9960 - val_loss: 0.0318
Training Time: 186.46512285073598 mins
```

```python
from tensorflow.keras.models import load_model

# Save model
model.save('baseline_transfer_model.keras')
```

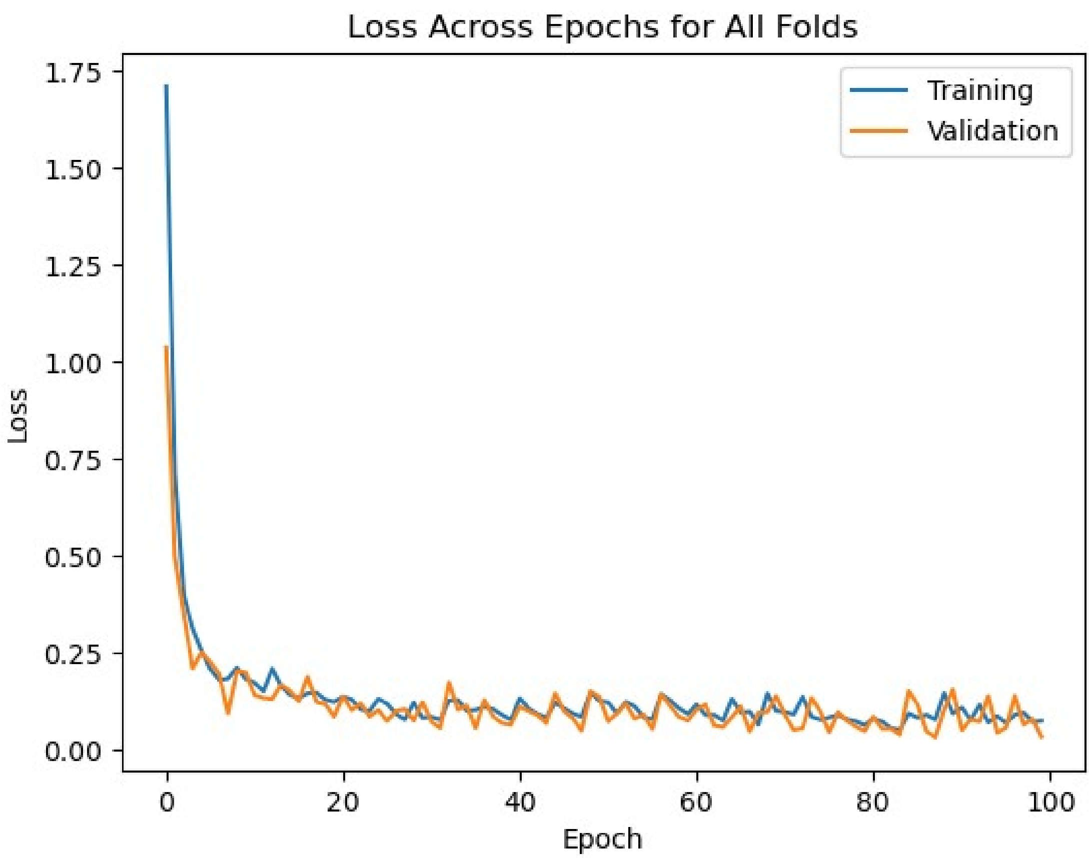
Some preliminary metrics will be shown ...

```python
import matplotlib.pyplot as plt
import numpy as np

# Print accuracies across all epochs and folds
print(f'Best Training Accuracy: {max(train_accuracy)}')
print(f'Best Validation Accuracy: {max(val_accuracy)}')
print(f'Average Training Accuracy: {np.mean(train_accuracy)}')
print(f'Average Validation Accuracy: {np.mean(val_accuracy)}')
print(f'Last Training Accuracy: {train_accuracy[-1]}')
print(f'Last Validation Accuracy: {val_accuracy[-1]}')

# Plot accuracy
num_total_epochs = len(train_accuracy)
plt.plot(range(num_total_epochs), train_accuracy, label='Training')
plt.plot(range(num_total_epochs), val_accuracy, label='Validation')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.title('Accuracy Across Epochs for All Folds')
plt.legend()
plt.show()

# Plot loss
num_total_epochs = len(train_loss)
plt.plot(range(num_total_epochs), train_loss, label='Training')
plt.plot(range(num_total_epochs), val_loss, label='Validation')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Loss Across Epochs for All Folds')
plt.legend()
plt.show()
```

```
Best Training Accuracy: 0.9866666793823242
Best Validation Accuracy: 1.0
Average Training Accuracy: 0.9634400016069412
Average Validation Accuracy: 0.9707600003480912
Last Training Accuracy: 0.9773333072662354
Last Validation Accuracy: 0.9959999918937683
```



Accuracy Across Epochs for All Folds
Accuracy
Epoch
Training
Validation

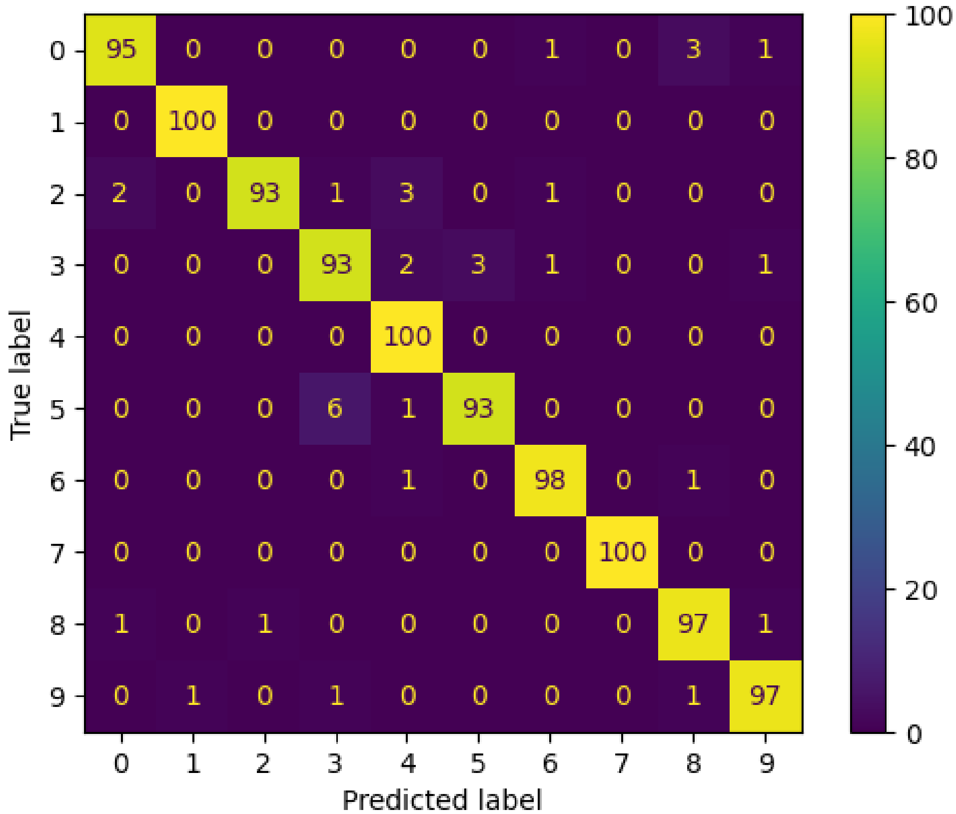



```
from sklearn.metrics import classification_report, confusion_matrix,
ConfusionMatrixDisplay, roc_curve, auc
import matplotlib.pyplot as plt
import time
from sklearn.model_selection import StratifiedKFold, train_test_split

# Function to evaluate performance
def evaluate(model, X_true, y_true):

    """ Evaluate Model Performance """

    # List class names in order
    class_names = [
    "airplane", "automobile", "bird", "cat", "deer",
    "dog", "frog", "horse", "ship", "truck"]

    # Make predictions
    start_time = time.time()
    y_pred = model.predict(X_true)
    y_pred = np.argmax(y_pred, axis=-1)
    end_time = time.time()
    pred_time_secs = end_time - start_time
    print(f'Time to Predict: {pred_time_secs} secs')
```

```
    print()

    # Precision, Recall, F1-score
    print('Classification Report')
    print(classification_report(y_true, y_pred))
    print()

    # Confusion Matrix
    cm = confusion_matrix(y_true, y_pred)
    print('Confusion Matrix')
    disp = ConfusionMatrixDisplay(confusion_matrix=cm)
    disp.plot()
    plt.show()

# Show performance on first batch and last batch
batch_kf = StratifiedKFold(n_splits=num_batches, shuffle=True,
random_state=42)
batch_num = 1

for _, batch_index in batch_kf.split(X_train, y_train):

    if batch_num == 1 or batch_num == int(round(num_batches/2)):
        print(f'Training Performance for Batch {batch_num}')
        print('-----------------------------------------------')
        X_train_batch = X_train[batch_index]
        y_train_batch = y_train[batch_index]
        processor = AutoImageProcessor.from_pretrained('google/vit-
base-patch16-224')
        X_train_batch = processor(images=X_train_batch,
return_tensors='tf')['pixel_values']
        evaluate(model, X_train_batch, y_train_batch)
        print()

    batch_num += 1
```

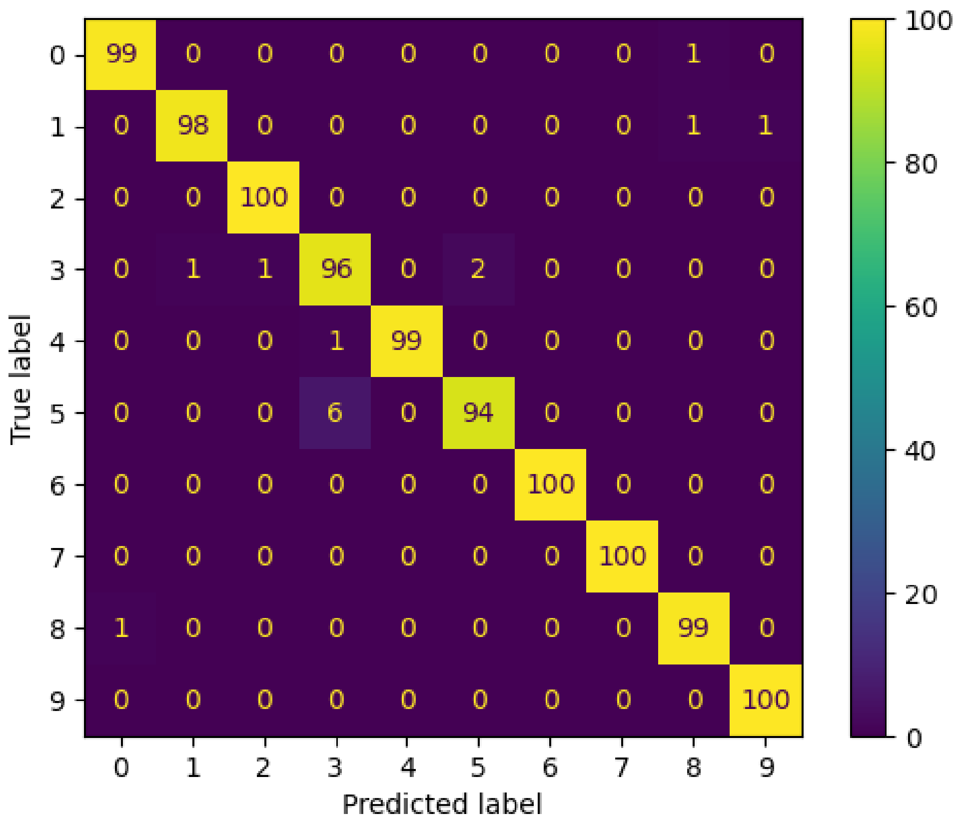
```
Training Performance for Batch 1
----------------------------------------------
32/32 ━━━━━━━━━━━━━━━━━━━━ 95s 3s/step
Time to Predict: 94.90864443778992 secs

Classification Report
              precision    recall  f1-score   support

           0       0.97      0.95      0.96       100
           1       0.99      1.00      1.00       100
           2       0.99      0.93      0.96       100
           3       0.92      0.93      0.93       100
           4       0.93      1.00      0.97       100
           5       0.97      0.93      0.95       100
           6       0.97      0.98      0.98       100
```

```
              7       1.00      1.00      1.00       100
              8       0.95      0.97      0.96       100
              9       0.97      0.97      0.97       100

    accuracy                           0.97      1000
   macro avg       0.97      0.97      0.97      1000
weighted avg       0.97      0.97      0.97      1000


Confusion Matrix
```




```

Training Performance for Batch 25
----------------------------------------------------
32/32 ━━━━━━━━━━━━━━━━━━━━ 94s 3s/step
Time to Predict: 94.51385283470154 secs

Classification Report
              precision    recall  f1-score   support

           0       0.99      0.99      0.99       100
           1       0.99      0.98      0.98       100
           2       0.99      1.00      1.00       100
           3       0.93      0.96      0.95       100
```

```
           4       1.00      0.99      0.99       100
           5       0.98      0.94      0.96       100
           6       1.00      1.00      1.00       100
           7       1.00      1.00      1.00       100
           8       0.98      0.99      0.99       100
           9       0.99      1.00      1.00       100

    accuracy                           0.98      1000
   macro avg       0.99      0.98      0.99      1000
weighted avg       0.99      0.98      0.99      1000


Confusion Matrix
```




```


"""
-------------------------------------------------
Example of Loading Model for Future Reference
-------------------------------------------------

# Wrapper to convert to Keras layer
class ViTLayer(Layer):
    def __init__(self, vit_model=None, model_name='google/vit-base-
```

```
patch16-224', **kwargs):
        super(ViTLayer, self).__init__(**kwargs)
        # Load vit_model
        self.vit_model = vit_model if vit_model is not None else
TFViTModel.from_pretrained('baseline_vit_model')
        # Store model name for serialization (needed for
saving/loading)
        self.model_name = model_name

    def call(self, inputs):
        outputs = self.vit_model(inputs)
        return outputs.pooler_output

    def get_config(self):
        config = super(ViTLayer, self).get_config()
        config.update({
            'model_name': self.model_name
        })
        return config

    @classmethod
    def from_config(cls, config):
        # Get model_name and remove it from config to avoid passing to
init
        model_name = config.pop('model_name')
        # Create instance without vit_model (will be loaded in init)
        return cls(model_name=model_name, **config)

# Load model
loaded_model = load_model('baseline_transfer_model.keras',
custom_objects={'ViTLayer': ViTLayer})

# Make predictions
y_true = y_train
X_true = X_train
y_pred = loaded_model.predict(X_true)
y_pred = np.argmax(y_pred, axis=-1)
print('Classification Report')
print(classification_report(y_true, y_pred))
"""
```

```
"\n-----------------------------------------------\nExample of
Loading Model for Future Reference\
n----------------------------------------------\n\n# Wrapper to
convert to Keras layer\nclass ViTLayer(Layer):\n    def __init__(self,
vit_model=None, model_name='google/vit-base-patch16-224', **kwargs):\n
super(ViTLayer, self).__init__(**kwargs)\n        # Load vit_model\n
self.vit_model = vit_model if vit_model is not None else
TFViTModel.from_pretrained('baseline_vit_model')\n        # Store
model name for serialization (needed for saving/loading)\n
```

```
self.model_name = model_name\n    \n    def call(self, inputs):\n
outputs = self.vit_model(inputs)\n        return
outputs.pooler_output\n    \n    def get_config(self):\n        config
= super(ViTLayer, self).get_config()\n        config.update({\n
'model_name': self.model_name\n        })\n        return config\
n    \n    @classmethod\n    def from_config(cls, config):\n        #
Get model_name and remove it from config to avoid passing to init\n
model_name = config.pop('model_name')\n        # Create instance
without vit_model (will be loaded in init)\n        return
cls(model_name=model_name, **config)\n\n# Load model\nloaded_model =
load_model('baseline_transfer_model.keras',
custom_objects={'ViTLayer': ViTLayer})\n    \n# Make predictions\
ny_true = y_train\nX_true = X_train\ny_pred =
loaded_model.predict(X_true)\ny_pred = np.argmax(y_pred, axis=-1)\
nprint('Classification Report')\nprint(classification_report(y_true,
y_pred))\n"
```