

Section 2: CIFAR-10 Image Classification with Transfer Learning

Augmentation

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('augment_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 13:09:00.700510: 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 00:00:1744823340.718687 3104857 cuda_dnn.cc:8579] Unable to register cuDNN factory: Attempting to register factory for plugin cuDNN when one has already been registered
E0000 00:00:1744823340.724360 3104857 cuda_blas.cc:1407] Unable to register cuBLAS factory: Attempting to register factory for plugin cuBLAS when one has already been registered
W0000 00:00:1744823340.737807 3104857 computation_placer.cc:177] computation placer already registered. Please check linkage and avoid linking the same target more than once.
W0000 00:00:1744823340.737820 3104857 computation_placer.cc:177] computation placer already registered. Please check linkage and avoid linking the same target more than once.
W0000 00:00:1744823340.737822 3104857 computation_placer.cc:177] computation placer already registered. Please check linkage and avoid

```
linking the same target more than once.
W0000 00:00:1744823340.737823 3104857 computation_placer.cc:177]
computation placer already registered. Please check linkage and avoid
linking the same target more than once.
2025-04-16 13:09:00.742308: 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 13:09:06.746340: 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.
```

```
# 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
0x14e8625c2590>
```

Loading Data

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

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

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

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. Moving forward, about 2/50 or 4/50 of the training dataset will be used since it will allow more options to be explored to possibly improve the previously trained baseline model.

```
from tensorflow.keras.layers import Input, Dense, Layer, Permute,
RandomFlip, RandomRotation, RandomZoom
from tensorflow.keras.models import Sequential
from transformers import TFBViTModel
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
TFBViTModel.from_pretrained('augment_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)),
    Permute((2, 3, 1)),
    RandomFlip('horizontal'),
    RandomRotation(0.2),
    RandomZoom(0.1),
    Permute((3, 1, 2)),
    ViTLayer(base_model, model_name='google/vit-base-patch16-224',
name='base_transformer'),
    Dense(10, activation='softmax', name='classifier')
])

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

# Freeze everything except output layer
model.get_layer(name='base_transformer').trainable = False

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

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

```

```

Layers: [<Permute name=permute, built=True>, <RandomFlip
name=random_flip, built=True>, <RandomRotation name=random_rotation,
built=True>, <RandomZoom name=random_zoom, built=True>, <Permute
name=permute_1, built=True>, <ViTLayer name=base_transformer,
built=True>, <Dense name=classifier, built=True>]

```

```

Model: "sequential"

```

| Layer (type) Param # | Output Shape |
|-------------------------|---------------------|
| permute (Permute) | (None, 224, 224, 3) |

| | | | |
|-------|----------------------------------|---------------------|--|
| 0 | random_flip (RandomFlip) | (None, 224, 224, 3) | |
| 0 | random_rotation (RandomRotation) | (None, 224, 224, 3) | |
| 0 | random_zoom (RandomZoom) | (None, 224, 224, 3) | |
| 0 | permute_1 (Permute) | (None, 3, 224, 224) | |
| 0 | base_transformer (ViTLayer) | (None, 768) | |
| 7,690 | classifier (Dense) | (None, 10) | |

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) ...

```
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
total_batches_to_train = 2

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

        # Train on half of the training set
        if batch_num == total_batches_to_train:
            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 ----- 112s 4s/step - accuracy: 0.2428 - loss:
2.2078 - val_accuracy: 0.5960 - val_loss: 1.5364
Working on Fold 2 ...
24/24 ----- 102s 4s/step - accuracy: 0.5619 - loss:
1.5164 - val_accuracy: 0.8280 - val_loss: 0.9247
Working on Fold 3 ...
24/24 ----- 103s 4s/step - accuracy: 0.6900 - loss:
1.1224 - val_accuracy: 0.9040 - val_loss: 0.7008
Working on Fold 4 ...
24/24 ----- 104s 4s/step - accuracy: 0.7035 - loss:
1.0048 - val_accuracy: 0.9480 - val_loss: 0.4541
-----
Working on Batch 2 ...
-----
Working on Fold 1 ...
24/24 ----- 108s 5s/step - accuracy: 0.7085 - loss:
0.9272 - val_accuracy: 0.9280 - val_loss: 0.4167
Working on Fold 2 ...
24/24 ----- 110s 5s/step - accuracy: 0.7461 - loss:
0.8385 - val_accuracy: 0.9440 - val_loss: 0.3642
Working on Fold 3 ...
24/24 ----- 110s 5s/step - accuracy: 0.7664 - loss:
0.7577 - val_accuracy: 0.9480 - val_loss: 0.3310
Working on Fold 4 ...
24/24 ----- 110s 5s/step - accuracy: 0.7684 - loss:
0.7234 - val_accuracy: 0.9880 - val_loss: 0.2129
Training Time: 16.589684812227883 mins

from tensorflow.keras.models import load_model

# Save model
model.save('augment_transfer_model.keras')

```

Some preliminary metrics will be shown ...

```

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)}')

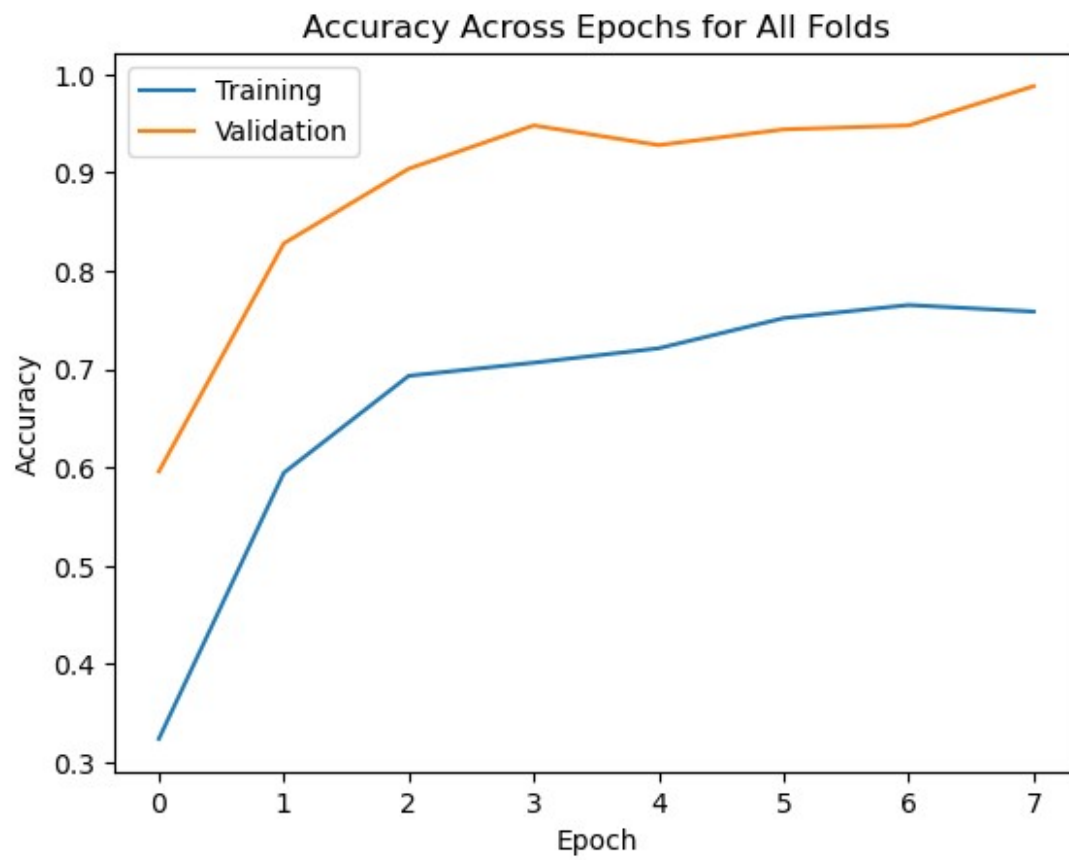
```

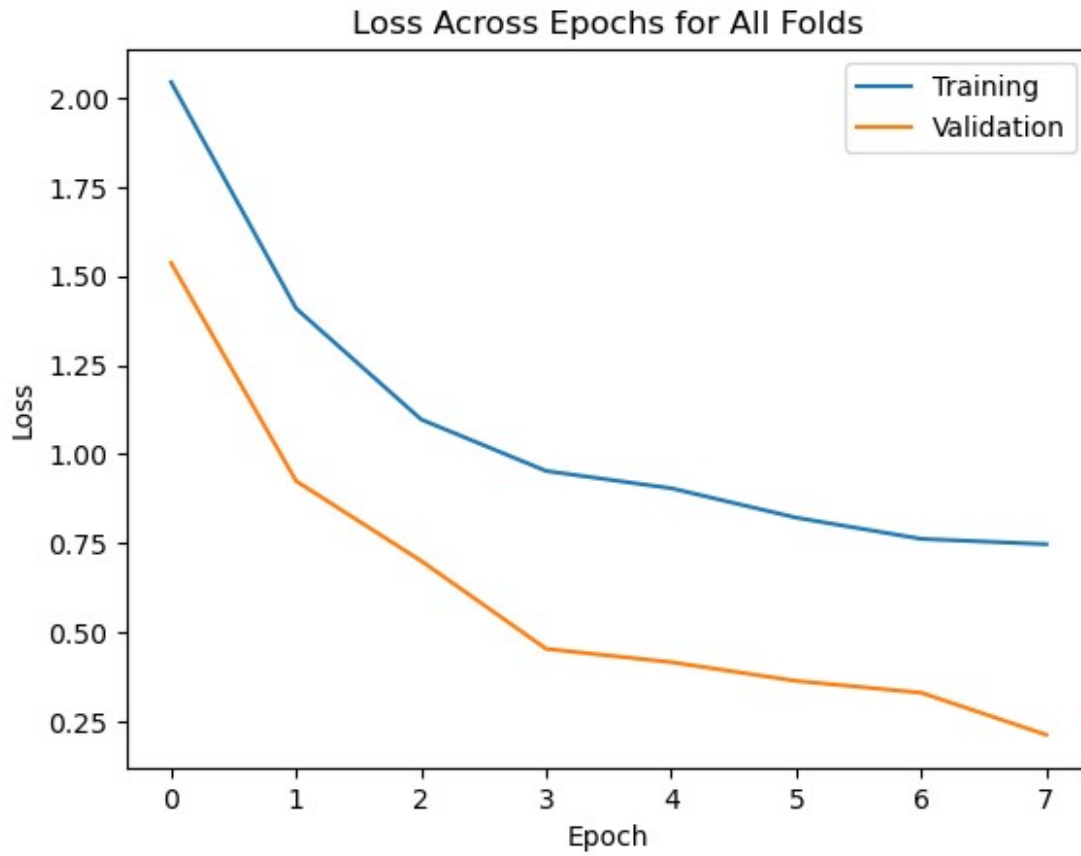
```
print(f'Last Training Accuracy: {train_accuracy[-1]}')
print(f'Last Validation Accuracy: {val_accuracy[-1]}')

# 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: 0.765333354473114
Best Validation Accuracy: 0.9879999756813049
Average Training Accuracy: 0.6644999980926514
Average Validation Accuracy: 0.8854999989271164
Last Training Accuracy: 0.7586666941642761
Last Validation Accuracy: 0.9879999756813049
```



Since images were augmented randomly, performance will be shown on the original images without transformations. This will give a more direct comparison to the baseline model.

```
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 == total_batches_to_train:
        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

```

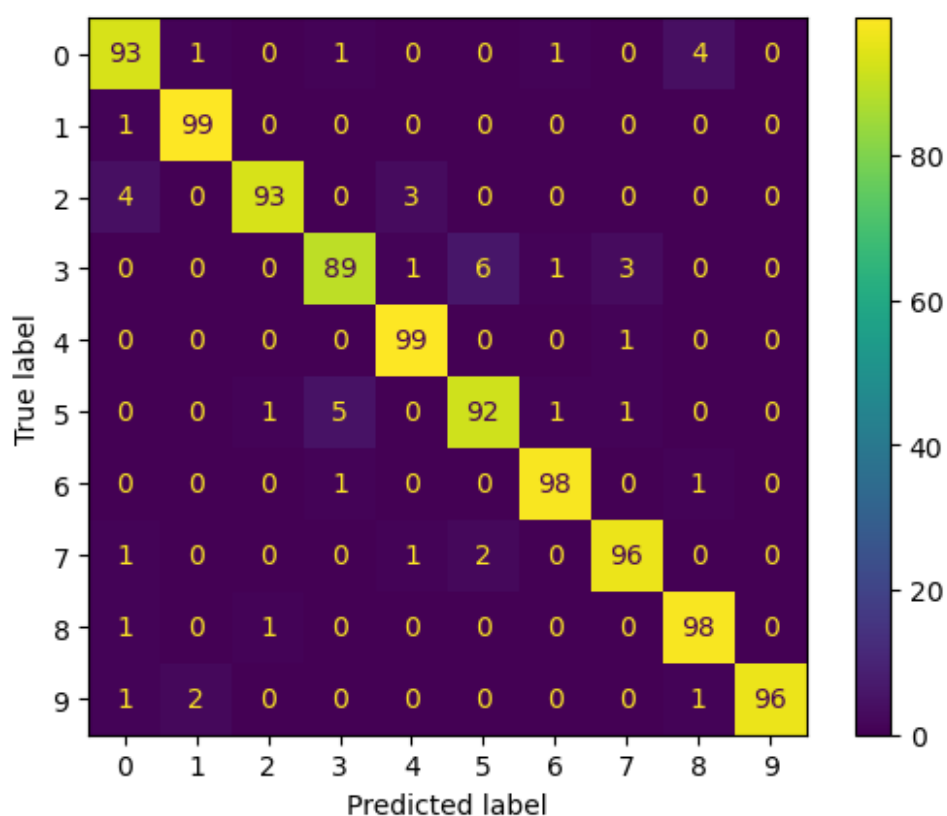
-----
32/32 ----- 112s 3s/step
Time to Predict: 111.83010053634644 secs

```

Classification Report

| | precision | recall | f1-score | support |
|---|-----------|--------|----------|---------|
| 0 | 0.92 | 0.93 | 0.93 | 100 |
| 1 | 0.97 | 0.99 | 0.98 | 100 |
| 2 | 0.98 | 0.93 | 0.95 | 100 |
| 3 | 0.93 | 0.89 | 0.91 | 100 |

| | | | | |
|------------------|------|------|------|------|
| 4 | 0.95 | 0.99 | 0.97 | 100 |
| 5 | 0.92 | 0.92 | 0.92 | 100 |
| 6 | 0.97 | 0.98 | 0.98 | 100 |
| 7 | 0.95 | 0.96 | 0.96 | 100 |
| 8 | 0.94 | 0.98 | 0.96 | 100 |
| 9 | 1.00 | 0.96 | 0.98 | 100 |
| | | | | |
| accuracy | | | 0.95 | 1000 |
| macro avg | 0.95 | 0.95 | 0.95 | 1000 |
| weighted avg | 0.95 | 0.95 | 0.95 | 1000 |
| | | | | |
| Confusion Matrix | | | | |



Training Performance for Batch 2

32/32

110s 3s/step

Time to Predict: 110.46808576583862 secs

Classification Report

| | precision | recall | f1-score | support |
|---|-----------|--------|----------|---------|
| 0 | 0.98 | 0.95 | 0.96 | 100 |

Regularization

Experimentation will be repetitive so the code I've been using has been put into a `general_training.py` file for reuse. We will try a regularization dense layer and dropout after.

```
from general_training import train_model
from tensorflow.keras.layers import Input, Dense, Layer, Permute,
RandomFlip, RandomRotation, RandomZoom, Dropout
from tensorflow.keras.models import Sequential
from transformers import TFSViTModel
from tensorflow.keras.regularizers import l2

trial_name = 'regularize'

# Train model
header_layers = Sequential([
    Input(shape=(3, 224, 224)),
])

footer_layers = Sequential([
    Dense(64, activation='relu', kernel_regularizer=l2(0.001),
kernel_initializer='he_normal'),
    Dropout(0.3)
])

train_model(trial_name, header_layers=header_layers,
footer_layers=footer_layers)
```

/apps/tensorflow/2.18/lib/python3.11/site-packages/tqdm/auto.py:21:
TqdmWarning: IPProgress 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 16:25:47.172563: E
external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:467] Unable to
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cuDNN when one has already been registered
E0000 00:00:1744835147.200148 679796 cuda_blas.cc:1407] Unable to
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cuBLAS when one has already been registered
W0000 00:00:1744835147.216412 679796 computation_placer.cc:177]
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W0000 00:00:1744835147.216425 679796 computation_placer.cc:177]

```
computation placer already registered. Please check linkage and avoid
linking the same target more than once.
W0000 00:00:1744835147.216428 679796 computation_placer.cc:177]
computation placer already registered. Please check linkage and avoid
linking the same target more than once.
W0000 00:00:1744835147.216429 679796 computation_placer.cc:177]
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tensorflow/core/platform/cpu_feature_guard.cc:210] This TensorFlow
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To enable the following instructions: AVX2 FMA, in other operations,
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failed call to cuInit: INTERNAL: CUDA error: Failed call to cuInit:
UNKNOWN ERROR (303)
```

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- 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.

Original Layers

<transformers.models.vit.modeling_tf_vit.TFViTMainLayer object at 0x151e2ef90610>

Using header and footer layers ...

Model: "sequential_2"

| Layer (type) | Output Shape | |
|--------------|--------------|--|
| Param # | | |
| | | |

| | | |
|-----------------------------|---|---|
| sequential (Sequential) | ? | 0 |
| (unbuilt) | | |
| base_transformer (ViTLayer) | ? | 0 |
| (unbuilt) | | |
| sequential_1 (Sequential) | ? | 0 |
| (unbuilt) | | |
| classifier (Dense) | ? | 0 |
| (unbuilt) | | |

Total params: 0 (0.00 B)

Trainable params: 0 (0.00 B)

Non-trainable params: 0 (0.00 B)

None

Working on Batch 1 ...

Working on Fold 1 ...

24/24 111s 4s/step - accuracy: 0.3747 - loss: 2.0109 - val_accuracy: 0.9120 - val_loss: 0.7763

Working on Fold 2 ...

24/24 95s 4s/step - accuracy: 0.8754 - loss: 0.6882 - val_accuracy: 0.9440 - val_loss: 0.3793

Working on Fold 3 ...

24/24 94s 4s/step - accuracy: 0.9284 - loss: 0.4216 - val_accuracy: 0.9600 - val_loss: 0.2798

Working on Fold 4 ...

24/24 95s 4s/step - accuracy: 0.9641 - loss: 0.3183 - val_accuracy: 0.9840 - val_loss: 0.2234

Working on Batch 2 ...

Working on Fold 1 ...

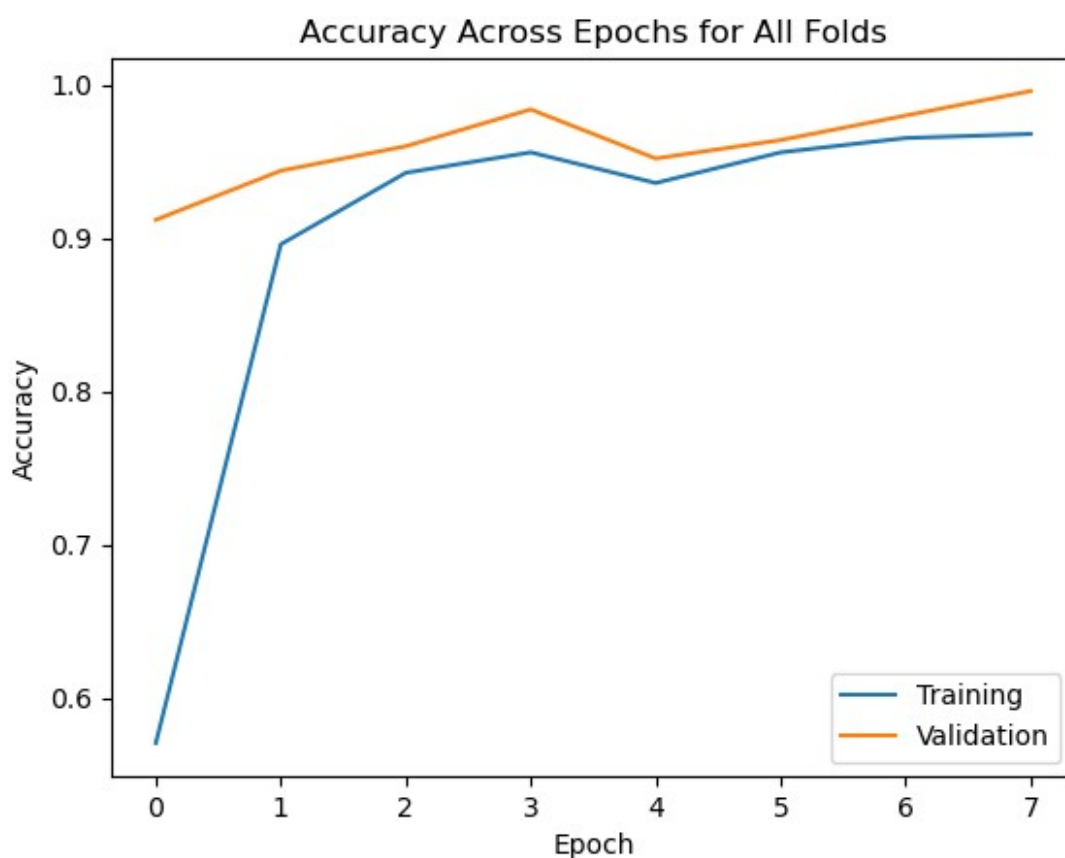
24/24 95s 4s/step - accuracy: 0.9378 - loss: 0.3617 - val_accuracy: 0.9520 - val_loss: 0.2895

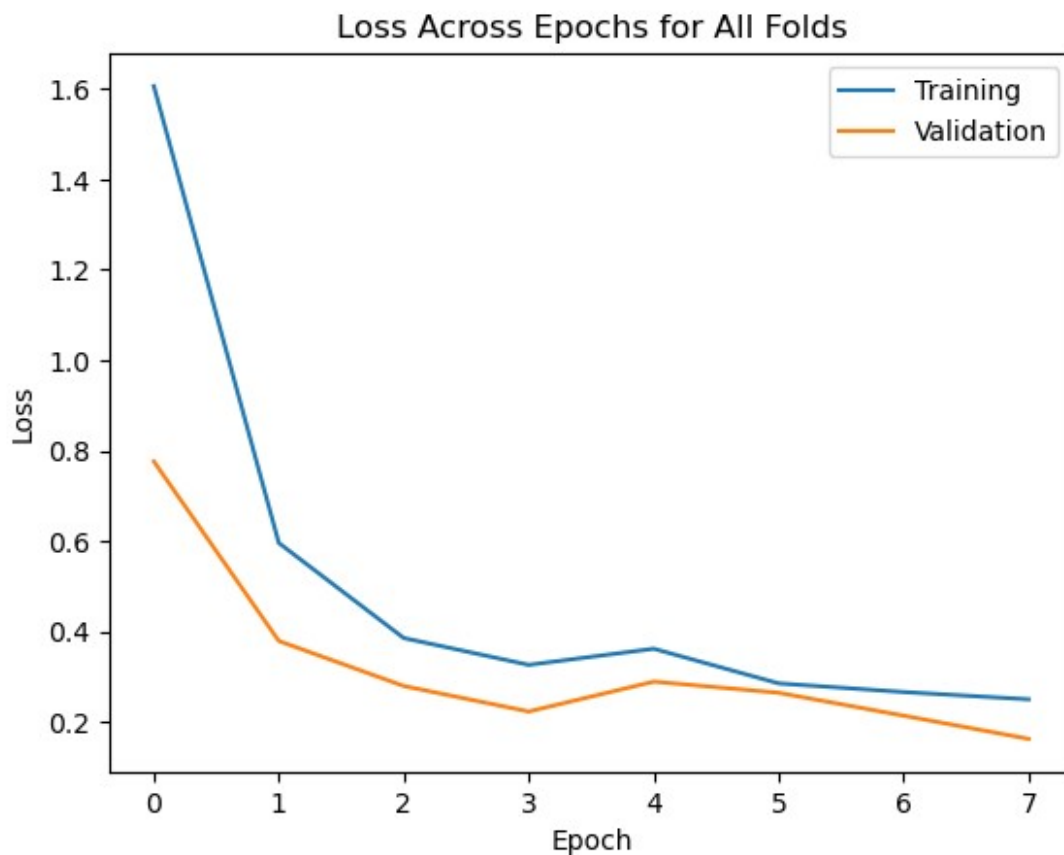
Working on Fold 2 ...

24/24 94s 4s/step - accuracy: 0.9544 - loss: 0.2984 - val_accuracy: 0.9640 - val_loss: 0.2649

Working on Fold 3 ...


```
24/24 ————— 95s 4s/step - accuracy: 0.9681 - loss:
0.2627 - val_accuracy: 0.9800 - val_loss: 0.2142
Working on Fold 4 ...
24/24 ————— 95s 4s/step - accuracy: 0.9587 - loss:
0.2613 - val_accuracy: 0.9960 - val_loss: 0.1630
Training Time: 15.0729074716568 mins
Best Training Accuracy: 0.9679999947547913
Best Validation Accuracy: 0.9959999918937683
Average Training Accuracy: 0.8988333269953728
Average Validation Accuracy: 0.9615000039339066
Last Training Accuracy: 0.9679999947547913
Last Validation Accuracy: 0.9959999918937683
```





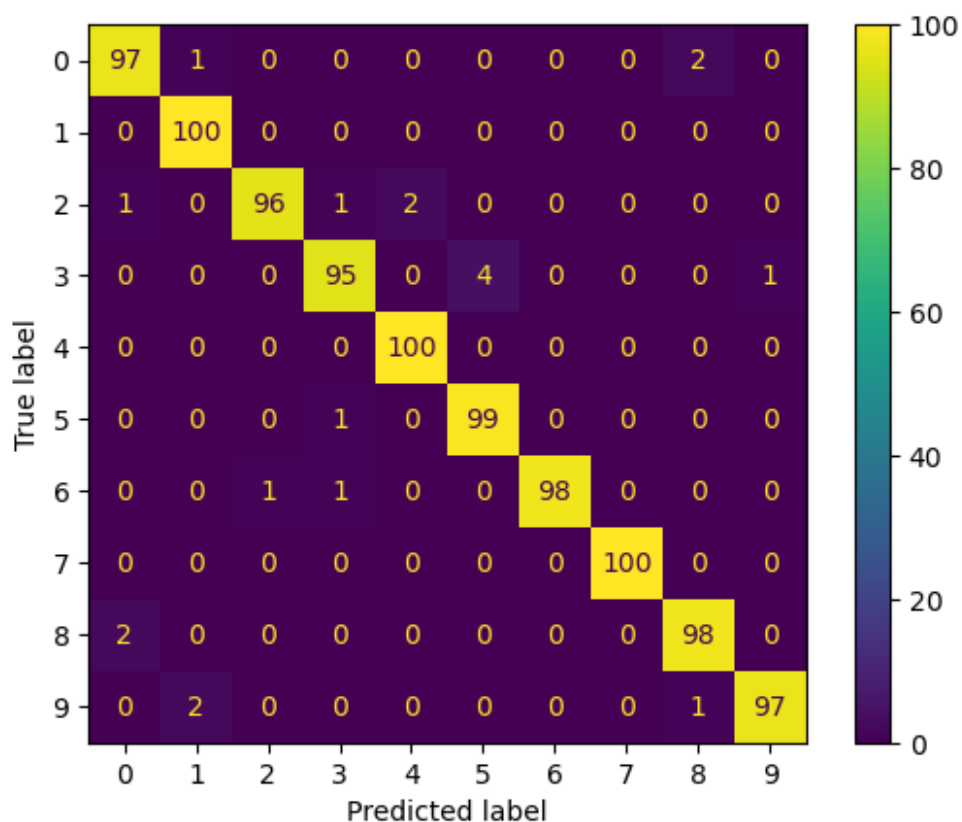
Training Performance for Batch 1

32/32 100s 3s/step
Time to Predict: 100.08172369003296 secs

Classification Report

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0 | 0.97 | 0.97 | 0.97 | 100 |
| 1 | 0.97 | 1.00 | 0.99 | 100 |
| 2 | 0.99 | 0.96 | 0.97 | 100 |
| 3 | 0.97 | 0.95 | 0.96 | 100 |
| 4 | 0.98 | 1.00 | 0.99 | 100 |
| 5 | 0.96 | 0.99 | 0.98 | 100 |
| 6 | 1.00 | 0.98 | 0.99 | 100 |
| 7 | 1.00 | 1.00 | 1.00 | 100 |
| 8 | 0.97 | 0.98 | 0.98 | 100 |
| 9 | 0.99 | 0.97 | 0.98 | 100 |
| accuracy | | | 0.98 | 1000 |
| macro avg | 0.98 | 0.98 | 0.98 | 1000 |
| weighted avg | 0.98 | 0.98 | 0.98 | 1000 |

Confusion Matrix



Training Performance for Batch 2

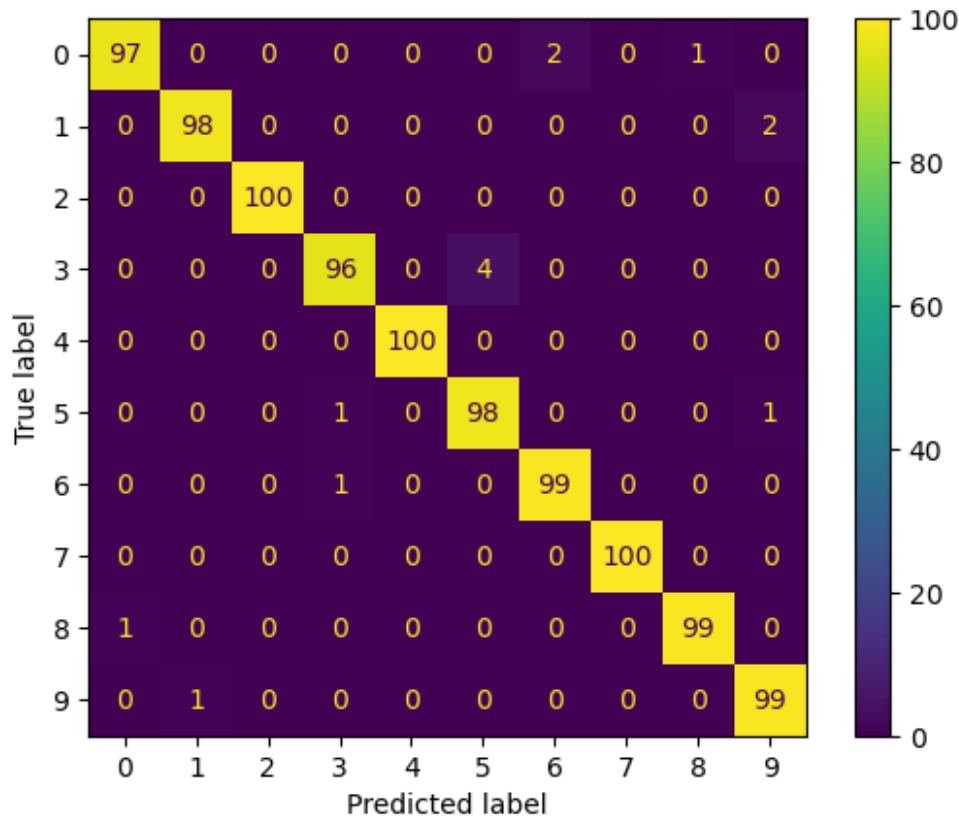
32/32 ----- 95s 3s/step
 Time to Predict: 94.57675385475159 secs

Classification Report

| | precision | recall | f1-score | support |
|----------|-----------|--------|----------|---------|
| 0 | 0.99 | 0.97 | 0.98 | 100 |
| 1 | 0.99 | 0.98 | 0.98 | 100 |
| 2 | 1.00 | 1.00 | 1.00 | 100 |
| 3 | 0.98 | 0.96 | 0.97 | 100 |
| 4 | 1.00 | 1.00 | 1.00 | 100 |
| 5 | 0.96 | 0.98 | 0.97 | 100 |
| 6 | 0.98 | 0.99 | 0.99 | 100 |
| 7 | 1.00 | 1.00 | 1.00 | 100 |
| 8 | 0.99 | 0.99 | 0.99 | 100 |
| 9 | 0.97 | 0.99 | 0.98 | 100 |
| accuracy | 0.99 | | | 1000 |

| | | | | |
|--------------|------|------|------|------|
| macro avg | 0.99 | 0.99 | 0.99 | 1000 |
| weighted avg | 0.99 | 0.99 | 0.99 | 1000 |

Confusion Matrix



Now we will try regularization with data augmentation.

```

from general_training import train_model
from tensorflow.keras.layers import Input, Dense, Layer, Permute,
RandomFlip, RandomRotation, RandomZoom, Dropout
from tensorflow.keras.models import Sequential
from transformers import TFSViTModel
from tensorflow.keras.regularizers import l2

trial_name = 'regularize_and_augment'

# Train model
header_layers = Sequential([
    Input(shape=(3, 224, 224)),
    Permute((2, 3, 1)),

```

```

        RandomFlip('horizontal'),
        RandomRotation(0.2),
        RandomZoom(0.1),
        Permute((3, 1, 2))
    ])

    footer_layers = Sequential([
        Dense(64, activation='relu', kernel_regularizer=l2(0.001),
        kernel_initializer='he_normal'),
        Dropout(0.3)
    ])

    train_model(trial_name, header_layers=header_layers,
    footer_layers=footer_layers)

```

Loading from Hugging Face ...

Some weights of the PyTorch model were not used when initializing the TF 2.0 model TFFViTModel: ['classifier.bias', 'classifier.weight']
 - This IS expected if you are initializing TFFViTModel 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 TFFViTModel 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 TFFViTModel 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.

Original Layers

<transformers.models.vit.modeling_tf_vit.TFFViTMainLayer object at 0x151d7492a810>

Using header and footer layers ...

Model: "sequential_5"

| Layer (type) Param # | Output Shape |
|---------------------------|---------------------|
| sequential_3 (Sequential) | (None, 3, 224, 224) |
| 0 | |

| | | | |
|--------|-----------------------------|-------------|--|
| 0 | base_transformer (ViTLayer) | (None, 768) | |
| | | | |
| 49,216 | sequential_4 (Sequential) | (None, 64) | |
| | | | |
| 650 | classifier (Dense) | (None, 10) | |
| | | | |

Total params: 49,866 (194.79 KB)

Trainable params: 49,866 (194.79 KB)

Non-trainable params: 0 (0.00 B)

None

Working on Batch 1 ...

Working on Fold 1 ...

24/24 112s 4s/step - accuracy: 0.2153 - loss: 2.3531 - val_accuracy: 0.7680 - val_loss: 1.4212

Working on Fold 2 ...

24/24 96s 4s/step - accuracy: 0.5747 - loss: 1.5326 - val_accuracy: 0.9160 - val_loss: 0.7408

Working on Fold 3 ...

24/24 95s 4s/step - accuracy: 0.6929 - loss: 1.0744 - val_accuracy: 0.9280 - val_loss: 0.5158

Working on Fold 4 ...

24/24 96s 4s/step - accuracy: 0.7094 - loss: 0.9907 - val_accuracy: 0.9400 - val_loss: 0.3738

Working on Batch 2 ...

Working on Fold 1 ...

24/24 96s 4s/step - accuracy: 0.6980 - loss: 0.9965 - val_accuracy: 0.9360 - val_loss: 0.4121

Working on Fold 2 ...

24/24 96s 4s/step - accuracy: 0.7612 - loss: 0.8921 - val_accuracy: 0.9400 - val_loss: 0.3815

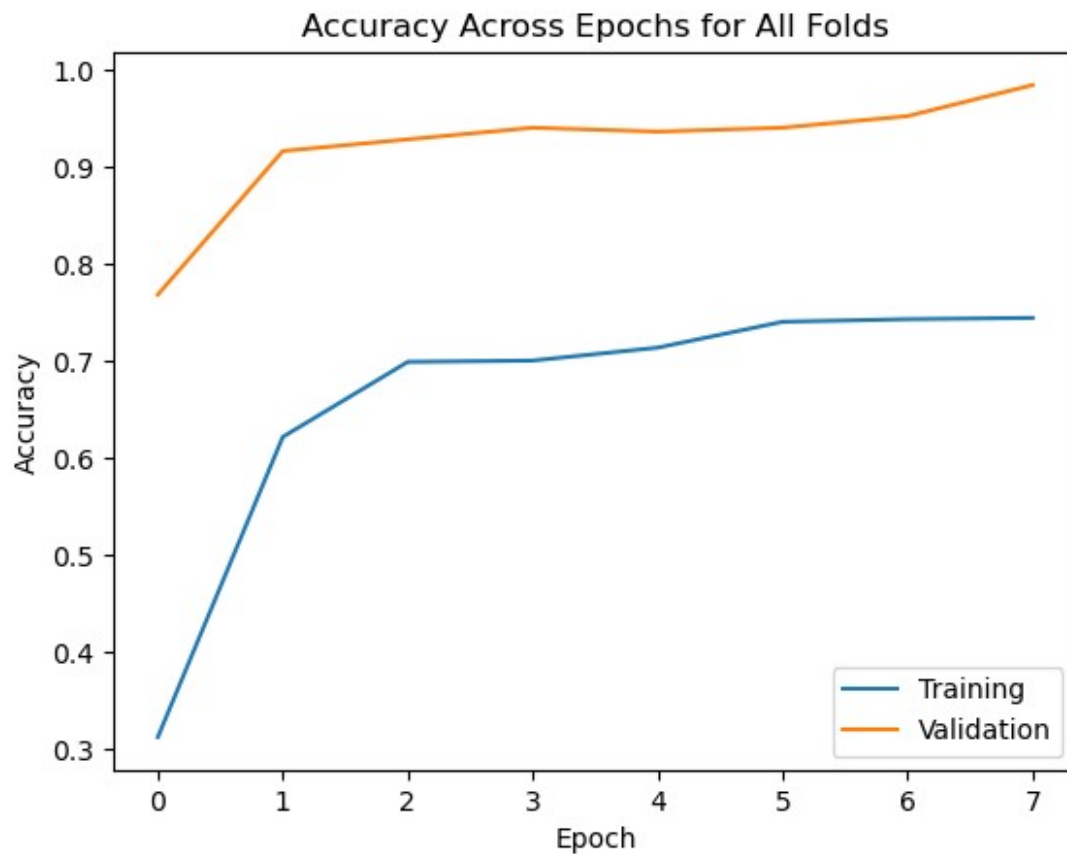
Working on Fold 3 ...

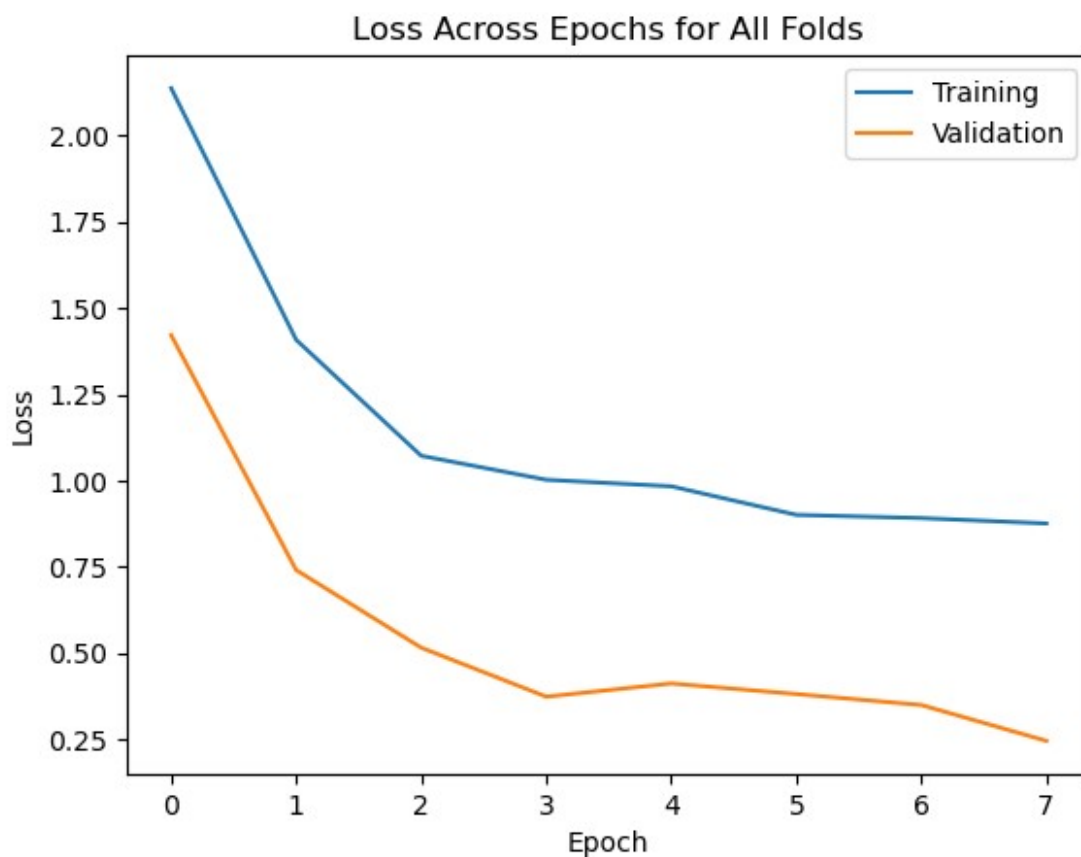
24/24 96s 4s/step - accuracy: 0.7505 - loss: 0.8786 - val_accuracy: 0.9520 - val_loss: 0.3497

Working on Fold 4 ...

24/24 95s 4s/step - accuracy: 0.7557 - loss: 0.8686 - val_accuracy: 0.9840 - val_loss: 0.2459

Training Time: 15.23844792842865 mins
Best Training Accuracy: 0.7440000176429749
Best Validation Accuracy: 0.984000027179718
Average Training Accuracy: 0.6590000055730343
Average Validation Accuracy: 0.9205000028014183
Last Training Accuracy: 0.7440000176429749
Last Validation Accuracy: 0.984000027179718





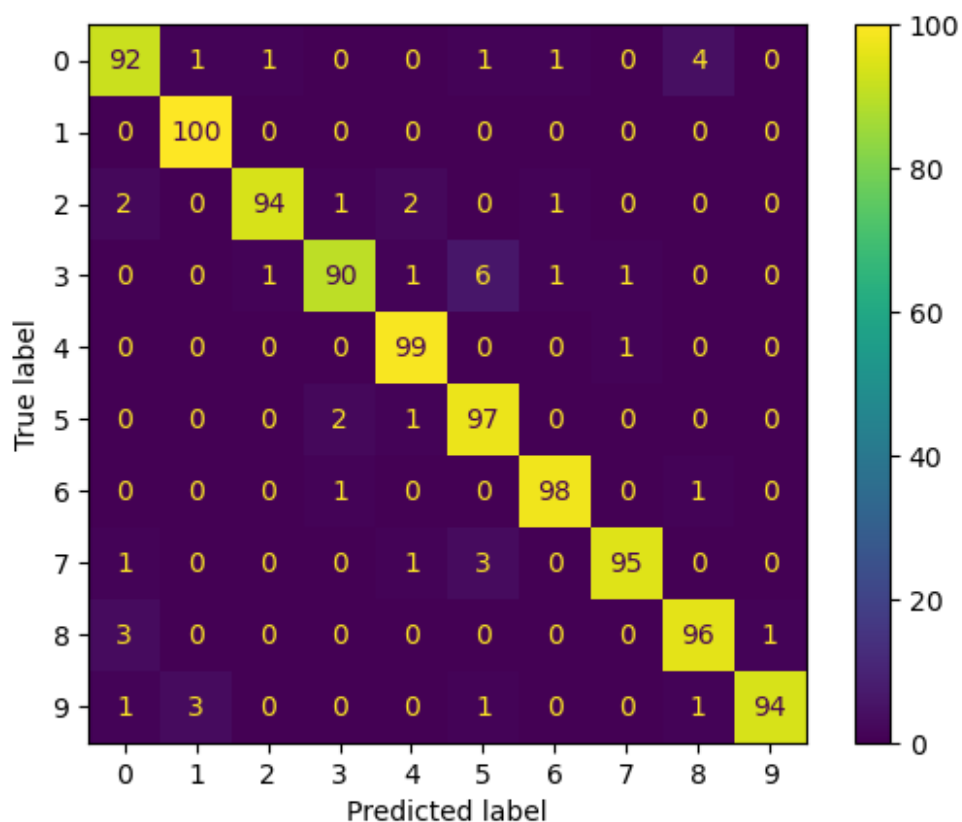
Training Performance for Batch 1

32/32 ————— 100s 3s/step
Time to Predict: 99.81954193115234 secs

Classification Report

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0 | 0.93 | 0.92 | 0.92 | 100 |
| 1 | 0.96 | 1.00 | 0.98 | 100 |
| 2 | 0.98 | 0.94 | 0.96 | 100 |
| 3 | 0.96 | 0.90 | 0.93 | 100 |
| 4 | 0.95 | 0.99 | 0.97 | 100 |
| 5 | 0.90 | 0.97 | 0.93 | 100 |
| 6 | 0.97 | 0.98 | 0.98 | 100 |
| 7 | 0.98 | 0.95 | 0.96 | 100 |
| 8 | 0.94 | 0.96 | 0.95 | 100 |
| 9 | 0.99 | 0.94 | 0.96 | 100 |
| accuracy | | | 0.95 | 1000 |
| macro avg | 0.96 | 0.95 | 0.95 | 1000 |
| weighted avg | 0.96 | 0.95 | 0.95 | 1000 |

Confusion Matrix



Training Performance for Batch 2

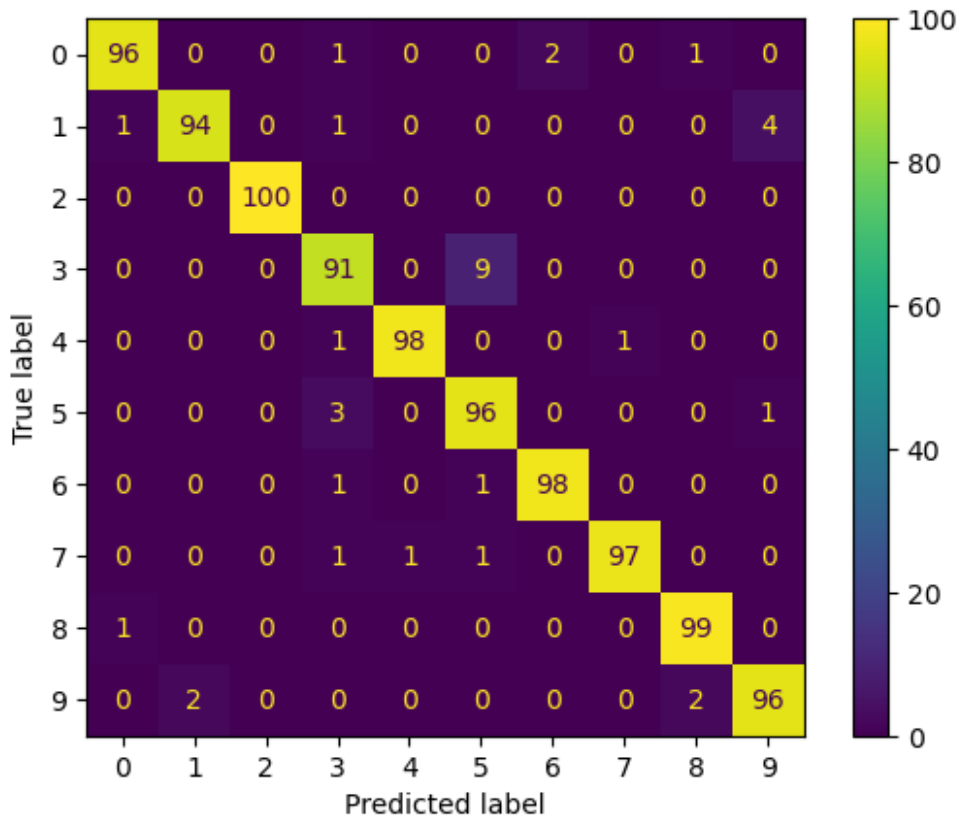
32/32 94s 3s/step
 Time to Predict: 94.25846982002258 secs

Classification Report

| | precision | recall | f1-score | support |
|----------|-----------|--------|----------|---------|
| 0 | 0.98 | 0.96 | 0.97 | 100 |
| 1 | 0.98 | 0.94 | 0.96 | 100 |
| 2 | 1.00 | 1.00 | 1.00 | 100 |
| 3 | 0.92 | 0.91 | 0.91 | 100 |
| 4 | 0.99 | 0.98 | 0.98 | 100 |
| 5 | 0.90 | 0.96 | 0.93 | 100 |
| 6 | 0.98 | 0.98 | 0.98 | 100 |
| 7 | 0.99 | 0.97 | 0.98 | 100 |
| 8 | 0.97 | 0.99 | 0.98 | 100 |
| 9 | 0.95 | 0.96 | 0.96 | 100 |
| accuracy | 0.96 | | | 1000 |

| | | | | |
|--------------|------|------|------|------|
| macro avg | 0.97 | 0.96 | 0.97 | 1000 |
| weighted avg | 0.97 | 0.96 | 0.97 | 1000 |

Confusion Matrix



A personal learning rate schedule was implemented in `general_training.py` similar to the logic of `ReduceLROnPlateau`, monitoring validation loss. A patience of 0 with exponentially reduced learning rates and a low initial learning rate is used to see if we can prevent overshooting the optimal loss and get a more fine-tuned model.

```
from general_training import train_model, train_model_lr,
keep_training_lr
from tensorflow.keras.layers import Input, Dense, Layer, Permute,
RandomFlip, RandomRotation, RandomZoom, Dropout, Conv2D,
BatchNormalization, MaxPooling2D, Reshape, Flatten
from tensorflow.keras.models import Sequential
from transformers import TFBViTModel
from tensorflow.keras.regularizers import l2

new_trial_name = 'baseline_lr'
```

```

old_trial_name = 'baseline'

# Continue training
model = keep_training_lr(new_trial_name=new_trial_name,
old_trial_name=old_trial_name, lr_patience=0,
total_batches_to_train=4, lr_initial=1e-4, lr_min=1e-7, lr_factor=0.5)

/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
2025-04-20 16:03:11.288820: 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 00:00:1745179391.309357 3821908 cuda_dnn.cc:8579] Unable to
register cuDNN factory: Attempting to register factory for plugin
cuDNN when one has already been registered
E0000 00:00:1745179391.315706 3821908 cuda_blas.cc:1407] Unable to
register cuBLAS factory: Attempting to register factory for plugin
cuBLAS when one has already been registered
W0000 00:00:1745179391.331258 3821908 computation_placer.cc:177]
computation placer already registered. Please check linkage and avoid
linking the same target more than once.
W0000 00:00:1745179391.331271 3821908 computation_placer.cc:177]
computation placer already registered. Please check linkage and avoid
linking the same target more than once.
W0000 00:00:1745179391.331273 3821908 computation_placer.cc:177]
computation placer already registered. Please check linkage and avoid
linking the same target more than once.
W0000 00:00:1745179391.331275 3821908 computation_placer.cc:177]
computation placer already registered. Please check linkage and avoid
linking the same target more than once.
2025-04-20 16:03:11.336166: 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.
2025-04-20 16:03:15.442211: 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)
All model checkpoint layers were used when initializing TFFiTModel.

All the layers of TFFiTModel were initialized from the model
checkpoint at baseline_vit_model.

```

If your task is similar to the task the model of the checkpoint was trained on, you can already use TFFiTModel for predictions without further training.

All model checkpoint layers were used when initializing TFFiTModel.

All the layers of TFFiTModel were initialized from the model checkpoint at baseline_vit_model.

If your task is similar to the task the model of the checkpoint was trained on, you can already use TFFiTModel for predictions without further training.

Model: "sequential"

| Layer (type) Param # | Output Shape |
|----------------------------|--------------|
| 0 vit_layer (ViTLayer) | (None, 768) |
| 7,690 classifier (Dense) | (None, 10) |

Total params: 23,072 (90.13 KB)

Trainable params: 7,690 (30.04 KB)

Non-trainable params: 0 (0.00 B)

Optimizer params: 15,382 (60.09 KB)

None

Working on Batch 1 ...

Working on Fold 1 ...

24/24 147s 6s/step - accuracy: 0.9645 - loss: 0.1074 - val_accuracy: 0.9640 - val_loss: 0.0856

LEARNING RATE PATIENCE EXCEEDED: adjusting rate to 5e-05

Working on Fold 2 ...

24/24 135s 6s/step - accuracy: 0.9660 - loss: 0.0954 - val_accuracy: 0.9680 - val_loss: 0.1123

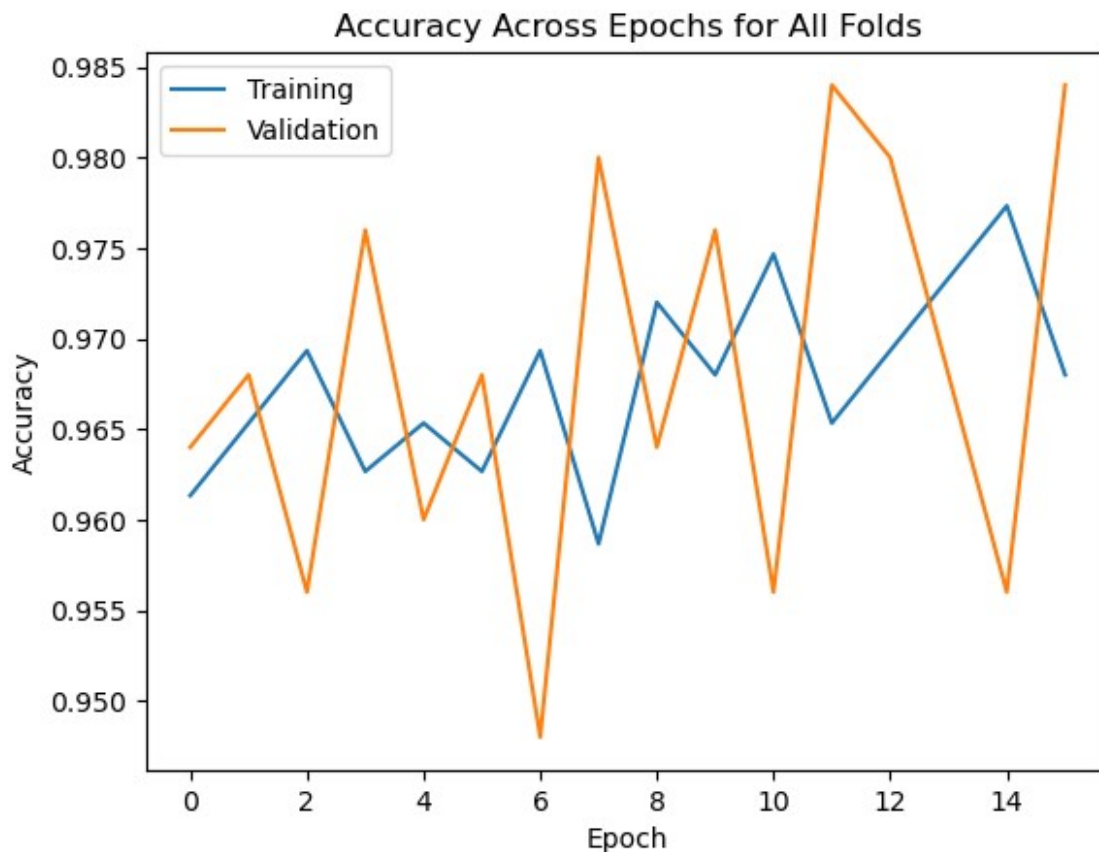
LEARNING RATE PATIENCE EXCEEDED: adjusting rate to 2.5e-05

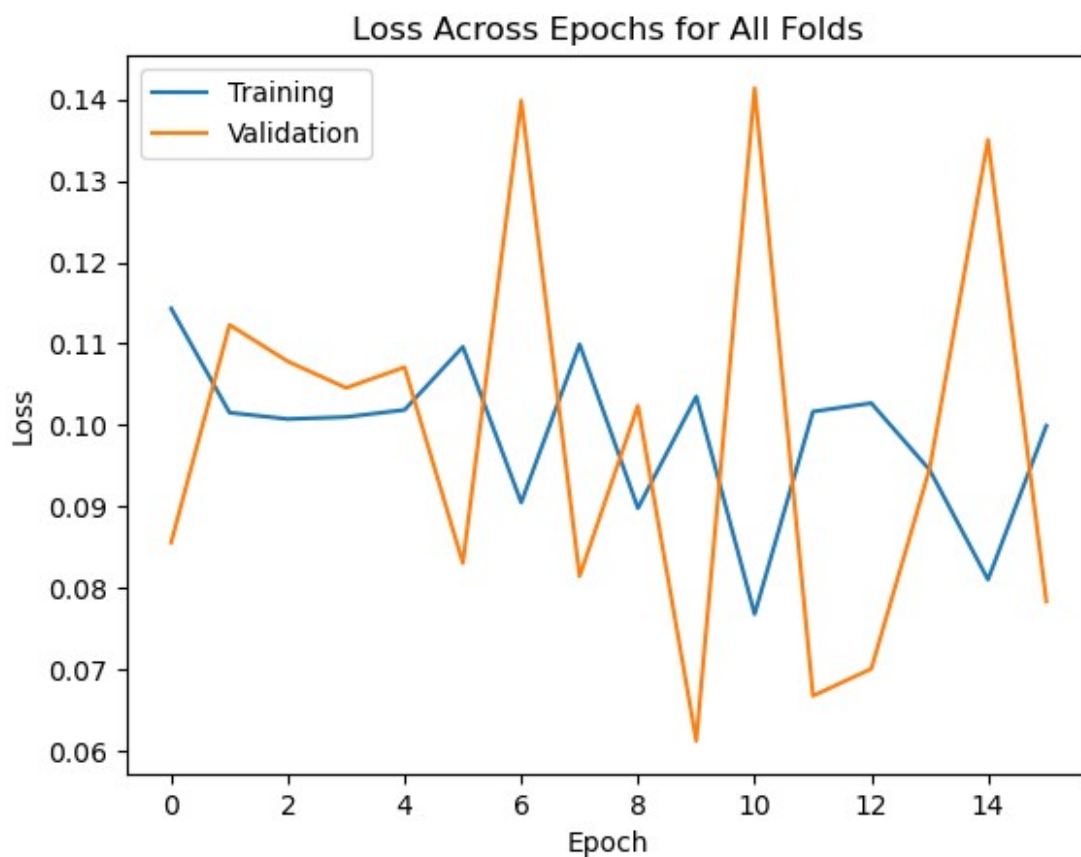
Working on Fold 3 ...

24/24 136s 6s/step - accuracy: 0.9662 - loss: 0.1086 - val_accuracy: 0.9560 - val_loss: 0.1078

```
LEARNING RATE PATIENCE EXCEEDED: adjusting rate to 1.25e-05
Working on Fold 4 ...
24/24 _____ 135s 6s/step - accuracy: 0.9548 - loss:
0.1179 - val_accuracy: 0.9760 - val_loss: 0.1046
LEARNING RATE PATIENCE EXCEEDED: adjusting rate to 6.25e-06
-----
Working on Batch 2 ...
-----
Working on Fold 1 ...
24/24 _____ 135s 6s/step - accuracy: 0.9583 - loss:
0.1276 - val_accuracy: 0.9600 - val_loss: 0.1071
LEARNING RATE PATIENCE EXCEEDED: adjusting rate to 3.125e-06
Working on Fold 2 ...
24/24 _____ 135s 6s/step - accuracy: 0.9557 - loss:
0.1271 - val_accuracy: 0.9680 - val_loss: 0.0831
LEARNING RATE PATIENCE EXCEEDED: adjusting rate to 1.5625e-06
Working on Fold 3 ...
24/24 _____ 135s 6s/step - accuracy: 0.9676 - loss:
0.1028 - val_accuracy: 0.9480 - val_loss: 0.1398
LEARNING RATE PATIENCE EXCEEDED: adjusting rate to 7.8125e-07
Working on Fold 4 ...
24/24 _____ 134s 6s/step - accuracy: 0.9638 - loss:
0.0942 - val_accuracy: 0.9800 - val_loss: 0.0814
LEARNING RATE PATIENCE EXCEEDED: adjusting rate to 3.90625e-07
-----
Working on Batch 3 ...
-----
Working on Fold 1 ...
24/24 _____ 135s 6s/step - accuracy: 0.9685 - loss:
0.0856 - val_accuracy: 0.9640 - val_loss: 0.1024
LEARNING RATE PATIENCE EXCEEDED: adjusting rate to 1.953125e-07
Working on Fold 2 ...
24/24 _____ 136s 6s/step - accuracy: 0.9765 - loss:
0.0778 - val_accuracy: 0.9760 - val_loss: 0.0612
LEARNING RATE PATIENCE EXCEEDED: adjusting rate to 1e-07
Working on Fold 3 ...
24/24 _____ 137s 6s/step - accuracy: 0.9736 - loss:
0.0841 - val_accuracy: 0.9560 - val_loss: 0.1414
LEARNING RATE PATIENCE EXCEEDED: adjusting rate to 1e-07
Working on Fold 4 ...
24/24 _____ 136s 6s/step - accuracy: 0.9697 - loss:
0.0843 - val_accuracy: 0.9840 - val_loss: 0.0668
LEARNING RATE PATIENCE EXCEEDED: adjusting rate to 1e-07
-----
Working on Batch 4 ...
-----
Working on Fold 1 ...
24/24 _____ 137s 6s/step - accuracy: 0.9731 - loss:
0.0818 - val_accuracy: 0.9800 - val_loss: 0.0701
```

```
LEARNING RATE PATIENCE EXCEEDED: adjusting rate to 1e-07
Working on Fold 2 ...
24/24 _____ 136s 6s/step - accuracy: 0.9658 - loss:
0.1026 - val_accuracy: 0.9680 - val_loss: 0.0947
LEARNING RATE PATIENCE EXCEEDED: adjusting rate to 1e-07
Working on Fold 3 ...
24/24 _____ 137s 6s/step - accuracy: 0.9838 - loss:
0.0675 - val_accuracy: 0.9560 - val_loss: 0.1350
LEARNING RATE PATIENCE EXCEEDED: adjusting rate to 1e-07
Working on Fold 4 ...
24/24 _____ 137s 6s/step - accuracy: 0.9762 - loss:
0.0848 - val_accuracy: 0.9840 - val_loss: 0.0784
LEARNING RATE PATIENCE EXCEEDED: adjusting rate to 1e-07
Training Time: 40.56421426137288 mins
Best Training Accuracy: 0.9773333072662354
Best Validation Accuracy: 0.984000027179718
Average Training Accuracy: 0.9676666744053364
Average Validation Accuracy: 0.9679999984800816
Last Training Accuracy: 0.9679999947547913
Last Validation Accuracy: 0.984000027179718
```





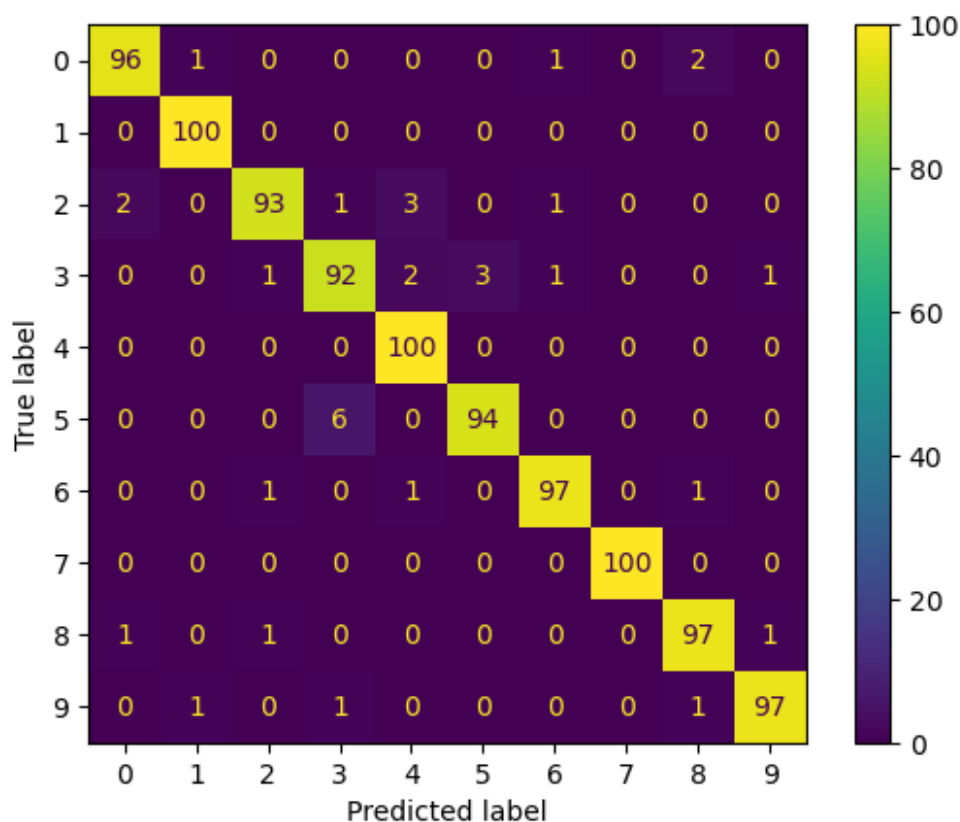
Training Performance for Batch 1

32/32 140s 4s/step
 Time to Predict: 140.27123594284058 secs

Classification Report

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0 | 0.97 | 0.96 | 0.96 | 100 |
| 1 | 0.98 | 1.00 | 0.99 | 100 |
| 2 | 0.97 | 0.93 | 0.95 | 100 |
| 3 | 0.92 | 0.92 | 0.92 | 100 |
| 4 | 0.94 | 1.00 | 0.97 | 100 |
| 5 | 0.97 | 0.94 | 0.95 | 100 |
| 6 | 0.97 | 0.97 | 0.97 | 100 |
| 7 | 1.00 | 1.00 | 1.00 | 100 |
| 8 | 0.96 | 0.97 | 0.97 | 100 |
| 9 | 0.98 | 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 4

32/32 ----- 136s 4s/step
 Time to Predict: 135.58464670181274 secs

Classification Report

| | precision | recall | f1-score | support |
|----------|-----------|--------|----------|---------|
| 0 | 0.98 | 0.94 | 0.96 | 100 |
| 1 | 0.97 | 0.97 | 0.97 | 100 |
| 2 | 0.99 | 0.96 | 0.97 | 100 |
| 3 | 0.90 | 0.96 | 0.93 | 100 |
| 4 | 0.93 | 0.97 | 0.95 | 100 |
| 5 | 0.96 | 0.95 | 0.95 | 100 |
| 6 | 0.97 | 0.95 | 0.96 | 100 |
| 7 | 1.00 | 0.97 | 0.98 | 100 |
| 8 | 0.95 | 0.98 | 0.97 | 100 |
| 9 | 0.98 | 0.97 | 0.97 | 100 |
| accuracy | 0.96 | | | 1000 |

| | | | | |
|--------------|------|------|------|------|
| macro avg | 0.96 | 0.96 | 0.96 | 1000 |
| weighted avg | 0.96 | 0.96 | 0.96 | 1000 |

Confusion Matrix

