

```
In [1]: import matplotlib.pyplot as plt
import numpy as np
import PIL
import tensorflow as tf
from os import listdir
import os
os.environ['KMP_DUPLICATE_LIB_OK']=True
from PIL import Image as PImage

import pathlib

from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.models import Sequential

# For Local testing, copy and paste the directory where your data is.
train_path = "/home/jgoh4/card_clf/train/"
data_dir_train = pathlib.Path(train_path).with_suffix('')
val_path = "/home/jgoh4/card_clf/valid/"
data_dir_val = pathlib.Path(val_path).with_suffix('')
test_path = "/home/jgoh4/card_clf/test/"
data_dir_test = pathlib.Path(test_path).with_suffix('')

print(data_dir_train)
```

```
2023-12-07 18:13:54.832410: I tensorflow/core/platform/cpu_feature_guard.cc:193] This TensorFlow binary is optimized
with oneAPI Deep Neural Network Library (oneDNN) to use the following CPU instructions in performance-critical operations: SSE4.1 SSE4.2 AVX AVX2 FMA
To enable them in other operations, rebuild TensorFlow with the appropriate compiler flags.
/home/jgoh4/card_clf/train
```

```
In [2]: image_count = len(list(data_dir_train.glob('*/*.jpg')))
print("Image Count: ", image_count)
```

```
Image Count: 7624
```

```
In [3]: # Here we read the .png images into a dataset (non-tabular, presumably) formatted as tensors
train_ds = tf.keras.utils.image_dataset_from_directory(
    data_dir_train,
    image_size = (224,224),
    batch_size = 32)
```

```

# Here we read the .png images into a dataset (non-tabular, presumably) formatted as tensors
val_ds = tf.keras.utils.image_dataset_from_directory(
    data_dir_val,
    image_size = (224,224),
    batch_size = 32
)

# read test images
test_ds = tf.keras.utils.image_dataset_from_directory(
    data_dir_test,
    image_size = (224,224),
    batch_size = 32
)

class_names = train_ds.class_names
print(class_names) # same as labels
num_classes = len(class_names)

```

Found 7624 files belonging to 53 classes.

2023-12-07 18:14:01.194871: I tensorflow/core/platform/cpu_feature_guard.cc:193] This TensorFlow binary is optimized with oneAPI Deep Neural Network Library (oneDNN) to use the following CPU instructions in performance-critical operations: SSE4.1 SSE4.2 AVX AVX2 FMA

To enable them in other operations, rebuild TensorFlow with the appropriate compiler flags.

2023-12-07 18:14:01.819172: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1616] Created device /job:localhost/relica:0/task:0/device:GPU:0 with 78962 MB memory: -> device: 0, name: NVIDIA A100-SXM4-80GB, pci bus id: 0000:01:00.0, compute capability: 8.0

Found 265 files belonging to 53 classes.

Found 7624 files belonging to 53 classes.

['ace of clubs', 'ace of diamonds', 'ace of hearts', 'ace of spades', 'eight of clubs', 'eight of diamonds', 'eight of hearts', 'eight of spades', 'five of clubs', 'five of diamonds', 'five of hearts', 'five of spades', 'four of clubs', 'four of diamonds', 'four of hearts', 'four of spades', 'jack of clubs', 'jack of diamonds', 'jack of hearts', 'jack of spades', 'joker', 'king of clubs', 'king of diamonds', 'king of hearts', 'king of spades', 'nine of clubs', 'nine of diamonds', 'nine of hearts', 'nine of spades', 'queen of clubs', 'queen of diamonds', 'queen of hearts', 'queen of spades', 'seven of clubs', 'seven of diamonds', 'seven of hearts', 'seven of spades', 'six of clubs', 'six of diamonds', 'six of hearts', 'six of spades', 'ten of clubs', 'ten of diamonds', 'ten of hearts', 'ten of spades', 'three of clubs', 'three of diamonds', 'three of hearts', 'three of spades', 'two of clubs', 'two of diamonds', 'two of hearts', 'two of spades']

In [4]: # Some kind of optimization - reduces training time
AUTOTUNE = tf.data.AUTOTUNE

```
train_ds = train_ds.cache().shuffle(1000).prefetch(buffer_size=AUTOTUNE)
val_ds = val_ds.cache().prefetch(buffer_size=AUTOTUNE)
```

```
In [5]: from tensorflow.keras.applications.resnet50 import ResNet50
from tensorflow.keras.preprocessing import image
from tensorflow.keras.applications.resnet50 import preprocess_input, decode_predictions
from tensorflow.keras.layers import BatchNormalization
```

Transfer Learning with ResNet50

```
In [6]: base_model = keras.applications.ResNet50(
    weights="imagenet", # Load weights pre-trained on ImageNet.
    input_shape=(224, 224, 3),
    include_top=False,
    pooling = max
) # Do not include the ImageNet classifier at the top.

# Freeze the base_model
base_model.trainable = False

# Data augmentation - necessary for addressing overfitting
data_augmentation = tf.keras.Sequential([
    tf.keras.layers.RandomFlip('horizontal'),
    tf.keras.layers.RandomRotation(0.2),
])

# Create new model on top
# inputs = keras.Input(shape=(224, 224, 3))

"""
# Re-scale
scale_layer = keras.layers.Rescaling(scale=1./255, offset=-1)
x = scale_layer(inputs)

x = base_model(x, training = False)
x = keras.layers.GlobalAveragePooling2D()(x)
x = keras.layers.Dropout(0.2)(x) # Regularize with dropout
outputs = keras.layers.Dense(num_classes)(x)
model = keras.Model(inputs, outputs)
"""
```

```
model = Sequential([
    layers.Rescaling(1./255, input_shape=(224, 224, 3)),
    base_model,
    BatchNormalization(),
    keras.layers.GlobalAveragePooling2D(),
    keras.layers.Dropout(0.2),
    keras.layers.Flatten(),
    keras.layers.Dense(num_classes, activation = 'softmax') # this Line MUST correspond to the number of classes/labels
])
```

```
In [7]: model.compile(optimizer=keras.optimizers.Adam(learning_rate=0.001),
                     loss='sparse_categorical_crossentropy', #SparseCategoricalCrossentropy exclusively for integer-labeled
                     metrics=['accuracy'])
```

```
In [8]: model.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
rescaling (Rescaling)	(None, 224, 224, 3)	0
resnet50 (Functional)	(None, 7, 7, 2048)	23587712
batch_normalization (BatchN ormalization)	(None, 7, 7, 2048)	8192
global_average_pooling2d (G lobalAveragePooling2D)	(None, 2048)	0
dropout (Dropout)	(None, 2048)	0
flatten (Flatten)	(None, 2048)	0
dense (Dense)	(None, 53)	108597

Total params: 23,704,501
Trainable params: 112,693
Non-trainable params: 23,591,808

```
In [9]: epochs = 20
res_hist = model.fit(train_ds, epochs=epochs, validation_data=val_ds)

Epoch 1/20
2023-12-05 01:47:16.343300: I tensorflow/stream_executor/cuda/cuda_dnn.cc:384] Loaded cuDNN version 8401
2023-12-05 01:47:17.092985: I tensorflow/core/platform/default/subprocess.cc:304] Start cannot spawn child process: No such file or directory
2023-12-05 01:47:17.150115: I tensorflow/stream_executor/cuda/cuda_blas.cc:1614] TensorFloat-32 will be used for the matrix multiplication. This will only be logged once.
```

239/239 [=====] - 12s 20ms/step - loss: 3.3001 - accuracy: 0.1891 - val_loss: 3.0539 - val_accuracy: 0.2868
Epoch 2/20
239/239 [=====] - 4s 15ms/step - loss: 2.6761 - accuracy: 0.3446 - val_loss: 2.4418 - val_accuracy: 0.3887
Epoch 3/20
239/239 [=====] - 4s 15ms/step - loss: 2.3671 - accuracy: 0.4234 - val_loss: 2.1332 - val_accuracy: 0.4792
Epoch 4/20
239/239 [=====] - 4s 15ms/step - loss: 2.1500 - accuracy: 0.4757 - val_loss: 2.0235 - val_accuracy: 0.5132
Epoch 5/20
239/239 [=====] - 4s 15ms/step - loss: 1.9905 - accuracy: 0.5153 - val_loss: 1.9308 - val_accuracy: 0.5321
Epoch 6/20
239/239 [=====] - 4s 15ms/step - loss: 1.8640 - accuracy: 0.5460 - val_loss: 1.8586 - val_accuracy: 0.5321
Epoch 7/20
239/239 [=====] - 4s 15ms/step - loss: 1.7535 - accuracy: 0.5727 - val_loss: 1.8592 - val_accuracy: 0.5283
Epoch 8/20
239/239 [=====] - 4s 15ms/step - loss: 1.6679 - accuracy: 0.5934 - val_loss: 1.8003 - val_accuracy: 0.5547
Epoch 9/20
239/239 [=====] - 4s 15ms/step - loss: 1.5863 - accuracy: 0.6132 - val_loss: 1.7673 - val_accuracy: 0.5623
Epoch 10/20
239/239 [=====] - 4s 17ms/step - loss: 1.5185 - accuracy: 0.6295 - val_loss: 1.7566 - val_accuracy: 0.5585
Epoch 11/20
239/239 [=====] - 4s 18ms/step - loss: 1.4538 - accuracy: 0.6445 - val_loss: 1.7385 - val_accuracy: 0.5698
Epoch 12/20
239/239 [=====] - 5s 19ms/step - loss: 1.4021 - accuracy: 0.6550 - val_loss: 1.7762 - val_accuracy: 0.5736
Epoch 13/20
239/239 [=====] - 4s 18ms/step - loss: 1.3417 - accuracy: 0.6735 - val_loss: 1.7169 - val_accuracy: 0.5660
Epoch 14/20
239/239 [=====] - 4s 17ms/step - loss: 1.2961 - accuracy: 0.6777 - val_loss: 1.7638 - val_accuracy: 0.5811
Epoch 15/20

```
239/239 [=====] - 4s 18ms/step - loss: 1.2544 - accuracy: 0.6929 - val_loss: 1.7911 - val_accuracy: 0.5925
Epoch 16/20
239/239 [=====] - 4s 18ms/step - loss: 1.2123 - accuracy: 0.7015 - val_loss: 1.7894 - val_accuracy: 0.5660
Epoch 17/20
239/239 [=====] - 4s 19ms/step - loss: 1.1746 - accuracy: 0.7108 - val_loss: 1.7578 - val_accuracy: 0.5698
Epoch 18/20
239/239 [=====] - 4s 18ms/step - loss: 1.1473 - accuracy: 0.7162 - val_loss: 1.7692 - val_accuracy: 0.6000
Epoch 19/20
239/239 [=====] - 4s 18ms/step - loss: 1.1151 - accuracy: 0.7231 - val_loss: 1.8363 - val_accuracy: 0.5698
Epoch 20/20
239/239 [=====] - 4s 18ms/step - loss: 1.0815 - accuracy: 0.7280 - val_loss: 1.7745 - val_accuracy: 0.5962
```

```
In [10]: # Without finetuning, overfitting with increasing epochs. Peak at 60%
# Fine-tune model. Unfreeze base model, train end-to-end with low Learning rate
base_model.trainable = True
model.summary()

model.compile(
    optimizer=keras.optimizers.Adam(1e-5), # Low Learning rate
    loss='sparse_categorical_crossentropy', #SparseCategoricalCrossentropy exclusively for integer-labeled
    metrics=['accuracy'])

epochs = 20
res_hist = model.fit(train_ds, epochs=epochs, validation_data=val_ds)
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
=====		
rescaling (Rescaling)	(None, 224, 224, 3)	0
resnet50 (Functional)	(None, 7, 7, 2048)	23587712
batch_normalization (BatchN ormalization)	(None, 7, 7, 2048)	8192
global_average_pooling2d (G lobalAveragePooling2D)	(None, 2048)	0
dropout (Dropout)	(None, 2048)	0
flatten (Flatten)	(None, 2048)	0
dense (Dense)	(None, 53)	108597
=====		

Total params: 23,704,501

Trainable params: 23,647,285

Non-trainable params: 57,216

Epoch 1/20

239/239 [=====] - 19s 61ms/step - loss: 8.9092 - accuracy: 0.1170 - val_loss: 15.4119 - val_accuracy: 0.0340

Epoch 2/20

239/239 [=====] - 14s 57ms/step - loss: 3.7628 - accuracy: 0.3808 - val_loss: 12.1304 - val_accuracy: 0.0755

Epoch 3/20

239/239 [=====] - 14s 57ms/step - loss: 1.9948 - accuracy: 0.5876 - val_loss: 6.5839 - val_accuracy: 0.2189

Epoch 4/20

239/239 [=====] - 14s 59ms/step - loss: 1.0996 - accuracy: 0.7263 - val_loss: 3.2015 - val_accuracy: 0.4453

Epoch 5/20

239/239 [=====] - 13s 56ms/step - loss: 0.5893 - accuracy: 0.8374 - val_loss: 2.3061 - val_accuracy: 0.5811

Epoch 6/20

239/239 [=====] - 13s 56ms/step - loss: 0.3291 - accuracy: 0.9035 - val_loss: 2.2252 - val_accuracy:

accuracy: 0.5849
Epoch 7/20
239/239 [=====] - 14s 57ms/step - loss: 0.1778 - accuracy: 0.9446 - val_loss: 2.1867 - val_accuracy: 0.6226
Epoch 8/20
239/239 [=====] - 14s 57ms/step - loss: 0.1183 - accuracy: 0.9634 - val_loss: 2.0859 - val_accuracy: 0.6189
Epoch 9/20
239/239 [=====] - 13s 56ms/step - loss: 0.0816 - accuracy: 0.9755 - val_loss: 2.0337 - val_accuracy: 0.6377
Epoch 10/20
239/239 [=====] - 14s 59ms/step - loss: 0.0551 - accuracy: 0.9860 - val_loss: 2.0388 - val_accuracy: 0.6189
Epoch 11/20
239/239 [=====] - 14s 57ms/step - loss: 0.0435 - accuracy: 0.9881 - val_loss: 2.0104 - val_accuracy: 0.6302
Epoch 12/20
239/239 [=====] - 14s 57ms/step - loss: 0.0329 - accuracy: 0.9924 - val_loss: 2.0378 - val_accuracy: 0.6264
Epoch 13/20
239/239 [=====] - 14s 57ms/step - loss: 0.0271 - accuracy: 0.9937 - val_loss: 2.0181 - val_accuracy: 0.6453
Epoch 14/20
239/239 [=====] - 14s 57ms/step - loss: 0.0230 - accuracy: 0.9938 - val_loss: 1.9652 - val_accuracy: 0.6377
Epoch 15/20
239/239 [=====] - 14s 57ms/step - loss: 0.0183 - accuracy: 0.9967 - val_loss: 1.9041 - val_accuracy: 0.6491
Epoch 16/20
239/239 [=====] - 14s 59ms/step - loss: 0.0174 - accuracy: 0.9966 - val_loss: 1.9843 - val_accuracy: 0.6717
Epoch 17/20
239/239 [=====] - 14s 59ms/step - loss: 0.0152 - accuracy: 0.9969 - val_loss: 1.9441 - val_accuracy: 0.6604
Epoch 18/20
239/239 [=====] - 14s 59ms/step - loss: 0.0143 - accuracy: 0.9972 - val_loss: 1.9522 - val_accuracy: 0.6642
Epoch 19/20
239/239 [=====] - 14s 57ms/step - loss: 0.0115 - accuracy: 0.9978 - val_loss: 2.0128 - val_accuracy: 0.6491
Epoch 20/20

```
239/239 [=====] - 14s 57ms/step - loss: 0.0094 - accuracy: 0.9984 - val_loss: 1.9493 - val_accuracy: 0.6830
```

```
In [11]: # save 'model history' as a dictionary
import pickle
with open('/trainHistoryDict', 'wb') as file_pi:
    pickle.dump(res_hist.history, file_pi)
```

```
-----
PermissionError                                                 Traceback (most recent call last)
Cell In [11], line 3
      1 # save 'model history' as a dictionary
      2 import pickle
----> 3 with open('/trainHistoryDict', 'wb') as file_pi:
      4     pickle.dump(res_hist.history, file_pi)

File /packages/envs/tensorflow-gpu-2.10.0/lib/python3.8/site-packages/IPython/core/interactiveshell.py:282, in _modified_open(file, *args, **kwargs)
    275 if file in {0, 1, 2}:
    276     raise ValueError(
    277         f"IPython won't let you open fd={file} by default "
    278         "as it is likely to crash IPython. If you know what you are doing, "
    279         "you can use builtins' open."
    280     )
--> 282 return io_open(file, *args, **kwargs)

PermissionError: [Errno 13] Permission denied: '/trainHistoryDict'
```

```
In [ ]: # Load history. for plotting Loss/accuracy
with open('/trainHistoryDict', "rb") as file_pi:
    res_history_load = pickle.load(file_pi)
```

```
In [12]: acc = res_hist.history['accuracy']
val_acc = res_hist.history['val_accuracy']
print(len(acc))
loss = res_hist.history['loss']
val_loss = res_hist.history['val_loss']

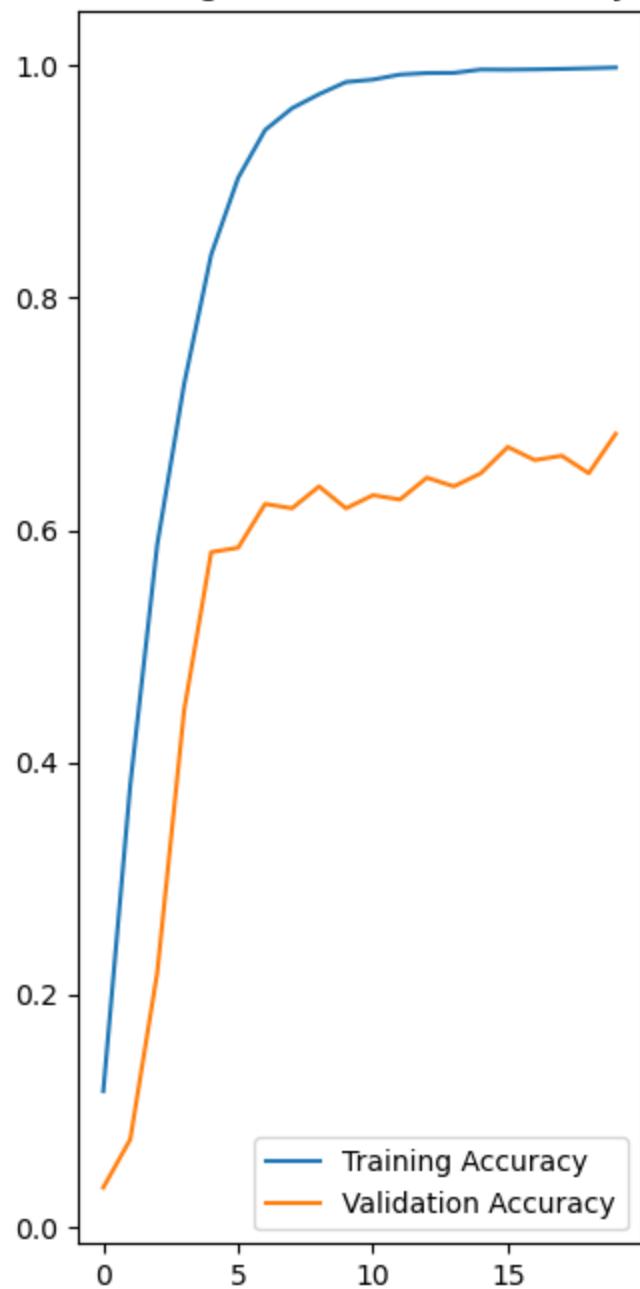
epochs_range = range(epochs)

plt.figure(figsize=(8, 8))
plt.subplot(1, 2, 1)
```

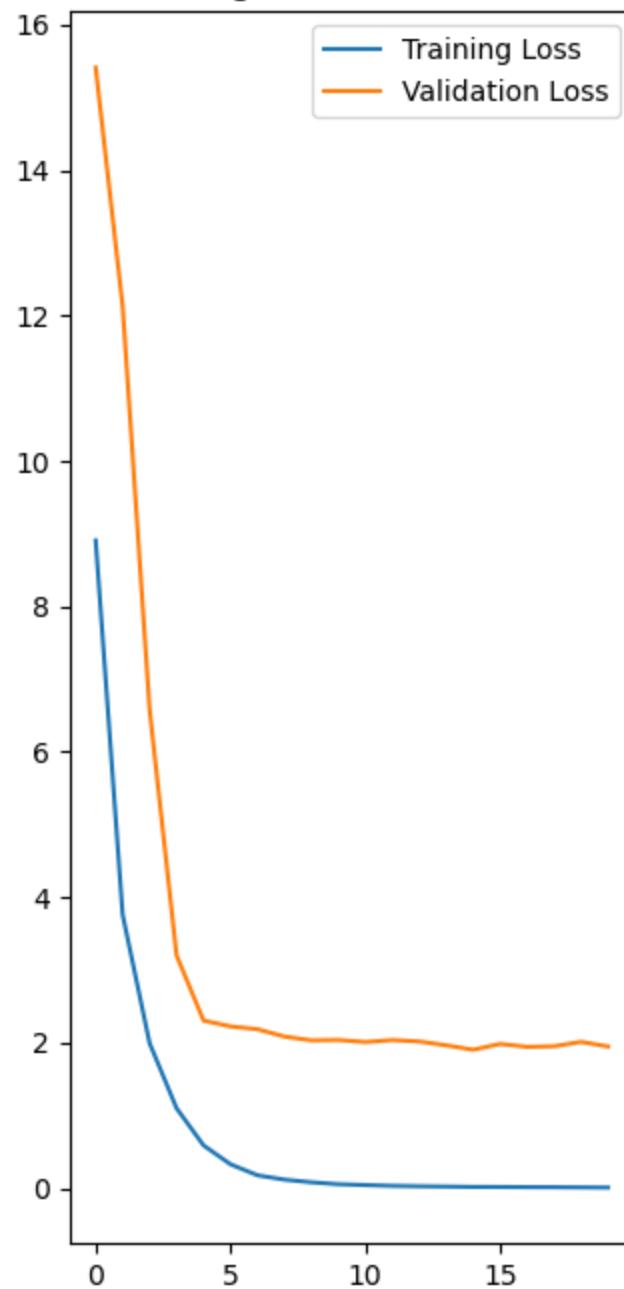
```
plt.plot(epochs_range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
# With fine-tuning, our validation accuracy plateaus
```

Training and Validation Accuracy



Training and Validation Loss



```
In [ ]: # with fine-tuning, we see diminishing returns in validation loss. Other methods must be utilized to address this overfitting
# Consider hypermodel for ResNet
```

HyperModel, based on GridSearch

```
In [6]: import keras_tuner as kt
from keras_tuner.applications import HyperResNet
```

```
In [7]: tuner_gs = kt.GridSearch(HyperResNet(include_top = False, input_shape=(224, 224, 3), classes=num_classes),
                             objective='val_accuracy',
                             max_trials=20, max_consecutive_failed_trials = 5)
```

Reloading Tuner from ./untitled_project/tuner0.json

```
In [8]: # Create a callback to stop training early after reaching a certain value for the validation Loss. If no improvement
stop_early = tf.keras.callbacks.EarlyStopping(monitor='val_loss', patience=5)
```

```
In [19]: # Run hyperparameter search!
# Same arguments as in model.fit
tuner_gs.search(train_ds, epochs=50, validation_data = val_ds, callbacks=[stop_early])
# Get the optimal hyperparameters
best_hps_hyp_gs=tuner_gs.get_best_hyperparameters(num_trials=1)[0]

print(f"""
The hyperparameter search (using HyperResNet) is complete. {best_hps_hyp_gs.values}
""")
```

The hyperparameter search (using HyperResNet) is complete. {'version': 'v2', 'conv3_depth': 4, 'conv4_depth': 6, 'pooling': 'avg', 'optimizer': 'adam', 'learning_rate': 0.001}

```
In [20]: # Build the model with the optimal hyperparameters and train it on the data for 50 epochs
model = tuner_gs.hypermodel.build(best_hps_hyp_gs)
model.compile(optimizer=keras.optimizers.Adam(learning_rate=best_hps_hyp_gs.get('learning_rate')),
              loss=keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])
history_hp_hyp_gs = model.fit(train_ds, epochs=50, validation_data=val_ds)

val_acc_per_epoch = history_hp_hyp_gs.history['val_accuracy']
```

```
best_epoch = val_acc_per_epoch.index(max(val_acc_per_epoch)) + 1
print('Best epoch: %d' % (best_epoch,))
```

Epoch 1/50

```
2023-12-07 18:24:41.556982: I tensorflow/stream_executor/cuda/cuda_dnn.cc:384] Loaded cuDNN version 8401
2023-12-07 18:24:47.514312: I tensorflow/core/platform/default/subprocess.cc:304] Start cannot spawn child process: No such file or directory
2023-12-07 18:24:48.093958: I tensorflow/stream_executor/cuda/cuda_blas.cc:1614] TensorFloat-32 will be used for the matrix multiplication. This will only be logged once.
```

239/239 [=====] - 27s 48ms/step - loss: 6.2392 - accuracy: 0.1272 - val_loss: 5.8682 - val_accuracy: 0.0981
Epoch 2/50
239/239 [=====] - 10s 42ms/step - loss: 5.0818 - accuracy: 0.2315 - val_loss: 5.7359 - val_accuracy: 0.0830
Epoch 3/50
239/239 [=====] - 10s 41ms/step - loss: 4.3152 - accuracy: 0.2933 - val_loss: 5.2067 - val_accuracy: 0.1660
Epoch 4/50
239/239 [=====] - 10s 42ms/step - loss: 3.7167 - accuracy: 0.3615 - val_loss: 3.2226 - val_accuracy: 0.2604
Epoch 5/50
239/239 [=====] - 10s 41ms/step - loss: 3.1697 - accuracy: 0.4334 - val_loss: 3.1604 - val_accuracy: 0.4000
Epoch 6/50
239/239 [=====] - 10s 42ms/step - loss: 2.7476 - accuracy: 0.4807 - val_loss: 2.5376 - val_accuracy: 0.4679
Epoch 7/50
239/239 [=====] - 10s 42ms/step - loss: 2.3854 - accuracy: 0.5414 - val_loss: 2.4351 - val_accuracy: 0.4830
Epoch 8/50
239/239 [=====] - 10s 42ms/step - loss: 1.9948 - accuracy: 0.6325 - val_loss: 1.2404 - val_accuracy: 0.7585
Epoch 9/50
239/239 [=====] - 10s 42ms/step - loss: 1.6609 - accuracy: 0.6910 - val_loss: 1.0199 - val_accuracy: 0.8038
Epoch 10/50
239/239 [=====] - 10s 42ms/step - loss: 1.3734 - accuracy: 0.7395 - val_loss: 1.5226 - val_accuracy: 0.7057
Epoch 11/50
239/239 [=====] - 10s 42ms/step - loss: 1.1161 - accuracy: 0.7911 - val_loss: 0.7631 - val_accuracy: 0.8717
Epoch 12/50
239/239 [=====] - 10s 42ms/step - loss: 0.8846 - accuracy: 0.8332 - val_loss: 0.6696 - val_accuracy: 0.8415
Epoch 13/50
239/239 [=====] - 10s 42ms/step - loss: 0.6902 - accuracy: 0.8762 - val_loss: 0.7393 - val_accuracy: 0.8453
Epoch 14/50
239/239 [=====] - 10s 42ms/step - loss: 0.5585 - accuracy: 0.9006 - val_loss: 0.8756 - val_accuracy: 0.8226
Epoch 15/50

239/239 [=====] - 10s 42ms/step - loss: 0.4790 - accuracy: 0.9154 - val_loss: 0.5746 - val_accuracy: 0.8906
Epoch 16/50
239/239 [=====] - 10s 42ms/step - loss: 0.3864 - accuracy: 0.9315 - val_loss: 0.8987 - val_accuracy: 0.8226
Epoch 17/50
239/239 [=====] - 10s 42ms/step - loss: 0.3086 - accuracy: 0.9523 - val_loss: 0.5815 - val_accuracy: 0.8830
Epoch 18/50
239/239 [=====] - 10s 42ms/step - loss: 0.2418 - accuracy: 0.9669 - val_loss: 0.5906 - val_accuracy: 0.8868
Epoch 19/50
239/239 [=====] - 10s 41ms/step - loss: 0.2100 - accuracy: 0.9708 - val_loss: 0.5732 - val_accuracy: 0.8792
Epoch 20/50
239/239 [=====] - 10s 42ms/step - loss: 0.1874 - accuracy: 0.9784 - val_loss: 0.4453 - val_accuracy: 0.8943
Epoch 21/50
239/239 [=====] - 10s 42ms/step - loss: 0.1854 - accuracy: 0.9738 - val_loss: 0.5979 - val_accuracy: 0.8906
Epoch 22/50
239/239 [=====] - 10s 42ms/step - loss: 0.1936 - accuracy: 0.9704 - val_loss: 0.6546 - val_accuracy: 0.8906
Epoch 23/50
239/239 [=====] - 10s 42ms/step - loss: 0.1599 - accuracy: 0.9774 - val_loss: 0.4620 - val_accuracy: 0.9094
Epoch 24/50
239/239 [=====] - 10s 42ms/step - loss: 0.1098 - accuracy: 0.9891 - val_loss: 0.5732 - val_accuracy: 0.8792
Epoch 25/50
239/239 [=====] - 10s 42ms/step - loss: 0.1165 - accuracy: 0.9865 - val_loss: 0.7066 - val_accuracy: 0.8792
Epoch 26/50
239/239 [=====] - 10s 42ms/step - loss: 0.1533 - accuracy: 0.9756 - val_loss: 0.7112 - val_accuracy: 0.8491
Epoch 27/50
239/239 [=====] - 10s 42ms/step - loss: 0.1594 - accuracy: 0.9727 - val_loss: 0.6624 - val_accuracy: 0.8755
Epoch 28/50
239/239 [=====] - 10s 41ms/step - loss: 0.1377 - accuracy: 0.9768 - val_loss: 0.4440 - val_accuracy: 0.9245
Epoch 29/50

239/239 [=====] - 10s 42ms/step - loss: 0.0707 - accuracy: 0.9941 - val_loss: 0.3475 - val_accuracy: 0.9321
Epoch 30/50
239/239 [=====] - 10s 42ms/step - loss: 0.0502 - accuracy: 0.9967 - val_loss: 0.3153 - val_accuracy: 0.9321
Epoch 31/50
239/239 [=====] - 10s 41ms/step - loss: 0.0364 - accuracy: 0.9987 - val_loss: 0.3194 - val_accuracy: 0.9321
Epoch 32/50
239/239 [=====] - 10s 42ms/step - loss: 0.0293 - accuracy: 0.9990 - val_loss: 0.2879 - val_accuracy: 0.9472
Epoch 33/50
239/239 [=====] - 10s 42ms/step - loss: 0.0222 - accuracy: 1.0000 - val_loss: 0.2986 - val_accuracy: 0.9434
Epoch 34/50
239/239 [=====] - 10s 42ms/step - loss: 0.0190 - accuracy: 1.0000 - val_loss: 0.3312 - val_accuracy: 0.9472
Epoch 35/50
239/239 [=====] - 10s 41ms/step - loss: 0.0169 - accuracy: 0.9999 - val_loss: 0.2954 - val_accuracy: 0.9358
Epoch 36/50
239/239 [=====] - 10s 41ms/step - loss: 0.0146 - accuracy: 1.0000 - val_loss: 0.3126 - val_accuracy: 0.9358
Epoch 37/50
239/239 [=====] - 10s 41ms/step - loss: 0.0132 - accuracy: 1.0000 - val_loss: 0.2989 - val_accuracy: 0.9396
Epoch 38/50
239/239 [=====] - 10s 42ms/step - loss: 0.0121 - accuracy: 1.0000 - val_loss: 0.3160 - val_accuracy: 0.9358
Epoch 39/50
239/239 [=====] - 10s 42ms/step - loss: 0.0114 - accuracy: 1.0000 - val_loss: 0.3139 - val_accuracy: 0.9472
Epoch 40/50
239/239 [=====] - 10s 42ms/step - loss: 0.0107 - accuracy: 1.0000 - val_loss: 0.3236 - val_accuracy: 0.9434
Epoch 41/50
239/239 [=====] - 10s 42ms/step - loss: 0.5108 - accuracy: 0.8810 - val_loss: 1.6088 - val_accuracy: 0.6566
Epoch 42/50
239/239 [=====] - 10s 42ms/step - loss: 0.3695 - accuracy: 0.9033 - val_loss: 0.5469 - val_accuracy: 0.8981
Epoch 43/50

```
239/239 [=====] - 10s 42ms/step - loss: 0.1007 - accuracy: 0.9814 - val_loss: 0.4272 - val_accuracy: 0.8981
Epoch 44/50
239/239 [=====] - 10s 42ms/step - loss: 0.0440 - accuracy: 0.9948 - val_loss: 0.3856 - val_accuracy: 0.9094
Epoch 45/50
239/239 [=====] - 10s 42ms/step - loss: 0.0272 - accuracy: 0.9978 - val_loss: 0.2816 - val_accuracy: 0.9396
Epoch 46/50
239/239 [=====] - 10s 41ms/step - loss: 0.0201 - accuracy: 0.9988 - val_loss: 0.3038 - val_accuracy: 0.9434
Epoch 47/50
239/239 [=====] - 10s 42ms/step - loss: 0.0128 - accuracy: 0.9999 - val_loss: 0.3224 - val_accuracy: 0.9434
Epoch 48/50
239/239 [=====] - 10s 42ms/step - loss: 0.0100 - accuracy: 0.9999 - val_loss: 0.2939 - val_accuracy: 0.9396
Epoch 49/50
239/239 [=====] - 10s 42ms/step - loss: 0.0080 - accuracy: 1.0000 - val_loss: 0.3119 - val_accuracy: 0.9396
Epoch 50/50
239/239 [=====] - 10s 42ms/step - loss: 0.0071 - accuracy: 1.0000 - val_loss: 0.3115 - val_accuracy: 0.9396
Best epoch: 32
```

In [23]: *# Re-instantiate the hypermodel and train it with the optimal number of epochs from above.*

```
hypermodel = tuner_gs.hypermodel.build(best_hps_hyp_gs)
hypermodel.compile(optimizer=keras.optimizers.Adam(learning_rate=best_hps_hyp_gs.get('learning_rate')),
                    loss=keras.losses.SparseCategoricalCrossentropy(from_logits=True),
                    metrics=['accuracy'])
# Retrain the model
final_hist_hyp_gs = hypermodel.fit(train_ds, epochs=best_epoch, validation_data = val_ds)
```

Epoch 1/32
239/239 [=====] - 13s 43ms/step - loss: 6.2046 - accuracy: 0.1403 - val_loss: 13.2003 - val_accuracy: 0.0302
Epoch 2/32
239/239 [=====] - 10s 41ms/step - loss: 5.0901 - accuracy: 0.2281 - val_loss: 6.7965 - val_accuracy: 0.0491
Epoch 3/32
239/239 [=====] - 10s 41ms/step - loss: 4.2955 - accuracy: 0.2926 - val_loss: 3.2618 - val_accuracy: 0.3585
Epoch 4/32
239/239 [=====] - 10s 41ms/step - loss: 3.7139 - accuracy: 0.3498 - val_loss: 3.5947 - val_accuracy: 0.2717
Epoch 5/32
239/239 [=====] - 10s 41ms/step - loss: 3.1901 - accuracy: 0.4218 - val_loss: 4.2741 - val_accuracy: 0.2113
Epoch 6/32
239/239 [=====] - 10s 41ms/step - loss: 2.7229 - accuracy: 0.4887 - val_loss: 1.8999 - val_accuracy: 0.5660
Epoch 7/32
239/239 [=====] - 10s 41ms/step - loss: 2.3089 - accuracy: 0.5771 - val_loss: 2.0587 - val_accuracy: 0.5925
Epoch 8/32
239/239 [=====] - 10s 41ms/step - loss: 1.9034 - accuracy: 0.6612 - val_loss: 1.2756 - val_accuracy: 0.6943
Epoch 9/32
239/239 [=====] - 10s 41ms/step - loss: 1.5828 - accuracy: 0.7065 - val_loss: 1.9173 - val_accuracy: 0.5887
Epoch 10/32
239/239 [=====] - 10s 41ms/step - loss: 1.3335 - accuracy: 0.7425 - val_loss: 1.4460 - val_accuracy: 0.7094
Epoch 11/32
239/239 [=====] - 10s 41ms/step - loss: 1.0974 - accuracy: 0.7871 - val_loss: 0.8477 - val_accuracy: 0.8113
Epoch 12/32
239/239 [=====] - 10s 41ms/step - loss: 0.8849 - accuracy: 0.8279 - val_loss: 0.7728 - val_accuracy: 0.8528
Epoch 13/32
239/239 [=====] - 10s 41ms/step - loss: 0.6963 - accuracy: 0.8699 - val_loss: 0.9548 - val_accuracy: 0.8189
Epoch 14/32
239/239 [=====] - 10s 41ms/step - loss: 0.5648 - accuracy: 0.8980 - val_loss: 0.9282 - val_accuracy: 0.8189

Epoch 15/32
239/239 [=====] - 10s 41ms/step - loss: 0.4433 - accuracy: 0.9264 - val_loss: 0.4958 - val_accuracy: 0.9132
Epoch 16/32
239/239 [=====] - 10s 41ms/step - loss: 0.3573 - accuracy: 0.9446 - val_loss: 0.6141 - val_accuracy: 0.8528
Epoch 17/32
239/239 [=====] - 10s 41ms/step - loss: 0.2988 - accuracy: 0.9566 - val_loss: 0.5357 - val_accuracy: 0.8906
Epoch 18/32
239/239 [=====] - 10s 41ms/step - loss: 0.2585 - accuracy: 0.9645 - val_loss: 0.6992 - val_accuracy: 0.8642
Epoch 19/32
239/239 [=====] - 10s 41ms/step - loss: 0.2265 - accuracy: 0.9668 - val_loss: 0.6887 - val_accuracy: 0.8604
Epoch 20/32
239/239 [=====] - 10s 41ms/step - loss: 0.1928 - accuracy: 0.9765 - val_loss: 0.5875 - val_accuracy: 0.8792
Epoch 21/32
239/239 [=====] - 10s 41ms/step - loss: 0.1974 - accuracy: 0.9718 - val_loss: 0.4862 - val_accuracy: 0.9019
Epoch 22/32
239/239 [=====] - 10s 41ms/step - loss: 0.1581 - accuracy: 0.9816 - val_loss: 0.4531 - val_accuracy: 0.8981
Epoch 23/32
239/239 [=====] - 10s 41ms/step - loss: 0.1588 - accuracy: 0.9772 - val_loss: 0.8614 - val_accuracy: 0.8189
Epoch 24/32
239/239 [=====] - 10s 41ms/step - loss: 0.1443 - accuracy: 0.9814 - val_loss: 0.5677 - val_accuracy: 0.8755
Epoch 25/32
239/239 [=====] - 10s 41ms/step - loss: 0.1525 - accuracy: 0.9755 - val_loss: 0.4463 - val_accuracy: 0.9094
Epoch 26/32
239/239 [=====] - 10s 41ms/step - loss: 0.1299 - accuracy: 0.9833 - val_loss: 0.4520 - val_accuracy: 0.8943
Epoch 27/32
239/239 [=====] - 10s 41ms/step - loss: 0.0893 - accuracy: 0.9904 - val_loss: 0.4161 - val_accuracy: 0.9132
Epoch 28/32
239/239 [=====] - 10s 41ms/step - loss: 0.0894 - accuracy: 0.9891 - val_loss: 0.3617 - val_accuracy: 0.9358

```
Epoch 29/32
239/239 [=====] - 10s 41ms/step - loss: 0.0660 - accuracy: 0.9945 - val_loss: 0.4139 - val_accuracy: 0.9283
Epoch 30/32
239/239 [=====] - 10s 41ms/step - loss: 0.2044 - accuracy: 0.9574 - val_loss: 0.8025 - val_accuracy: 0.8491
Epoch 31/32
239/239 [=====] - 10s 41ms/step - loss: 0.1121 - accuracy: 0.9822 - val_loss: 0.5978 - val_accuracy: 0.8906
Epoch 32/32
239/239 [=====] - 10s 41ms/step - loss: 0.0564 - accuracy: 0.9955 - val_loss: 0.3384 - val_accuracy: 0.9283
32
```

```
NameError Traceback (most recent call last)
Cell In [23], line 15
      12 loss = final_hist_hyp_gs.history['loss']
      13 val_loss = final_hist_hyp_gs.history['val_loss']
--> 15 epochs_range = range(epochs)
      17 plt.figure(figsize=(8, 8))
      18 plt.subplot(1, 2, 1)

NameError: name 'epochs' is not defined
```

```
In [24]: acc = final_hist_hyp_gs.history['accuracy']
val_acc = final_hist_hyp_gs.history['val_accuracy']
print(len(acc))
loss = final_hist_hyp_gs.history['loss']
val_loss = final_hist_hyp_gs.history['val_loss']

epochs_range = range(best_epoch)

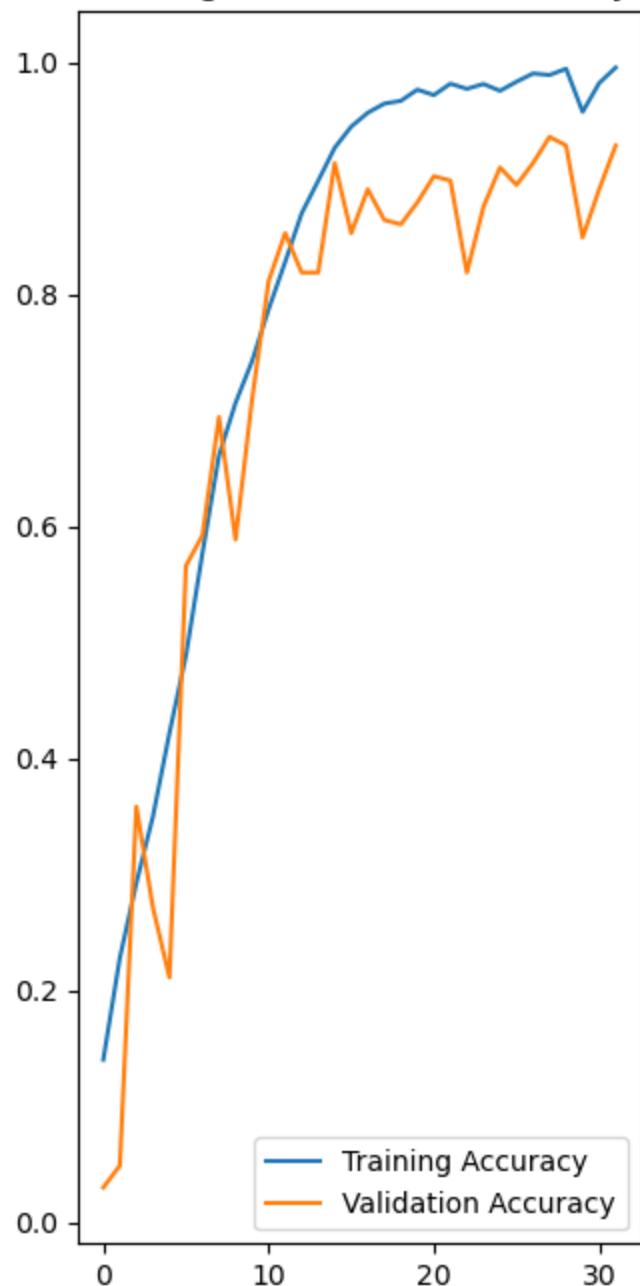
plt.figure(figsize=(8, 8))
plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
```

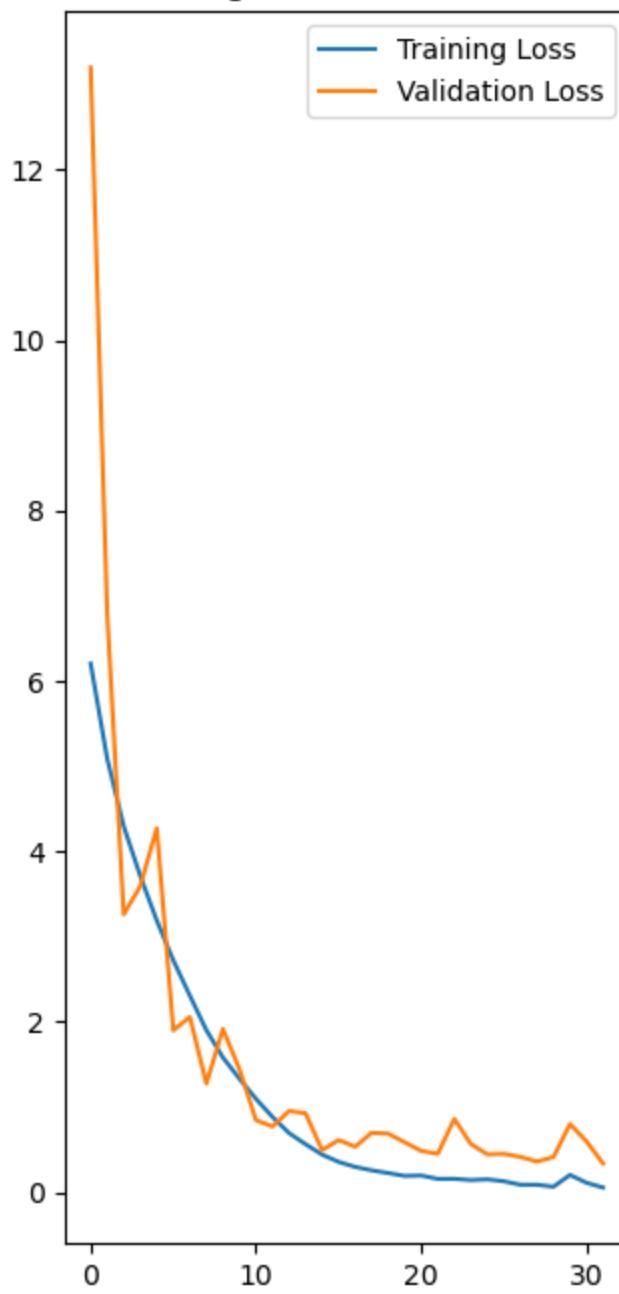
```
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```

32

Training and Validation Accuracy



Training and Validation Loss



```
In [25]: eval_result = hypermodel.evaluate(test_ds)
print("[test loss, test accuracy]:", eval_result)

239/239 [=====] - 4s 17ms/step - loss: 0.0527 - accuracy: 0.9871
[test loss, test accuracy]: [0.05265914276242256, 0.9871458411216736]
```

HyperModel, based on RandomSearch

```
In [50]: tuner_rs = kt.RandomSearch(HyperResNet(include_top = False, input_shape=(224, 224, 3), classes=num_classes),
                                 objective='val_accuracy',
                                 max_trials=20, max_consecutive_failed_trials = 200, max_retries_per_trial = 10) #force trials to

Reloading Tuner from ./untitled_project/tuner0.json
```

```
In [51]: # Create a callback to stop training early after reaching a certain value for the validation Loss. If no improvement
stop_early = tf.keras.callbacks.EarlyStopping(monitor='val_loss', patience=5)
```

```
In [52]: # Run hyperparameter search!
# Same arguments as in model.fit

tuner_rs.search(train_ds, epochs=50, validation_data = val_ds, callbacks=[stop_early])
# Get the optimal hyperparameters
best_hps_hyp_rs=tuner_rs.get_best_hyperparameters(num_trials=1)[0]

print(f"""
The hyperparameter search (using HyperResNet) is complete. {best_hps_hyp_rs.values}
""")
```

Trial 20 Complete [00h 00m 01s]

Best val_accuracy So Far: None
Total elapsed time: 04h 53m 42s

The hyperparameter search (using HyperResNet) is complete. {'version': 'v1', 'conv3_depth': 4, 'conv4_depth': 36, 'pooling': 'avg', 'optimizer': 'sgd', 'learning_rate': 0.1}

```
In [53]: # Build the model with the optimal hyperparameters and train it on the data for 50 epochs
# We search for the best epoch, with the best measures.
model = tuner_rs.hypermodel.build(best_hps_hyp_rs)
model.compile(optimizer=keras.optimizers.Adam(learning_rate=best_hps_hyp_rs.get('learning_rate')),
```

```
        loss=keras.losses.SparseCategoricalCrossentropy(from_logits=True),
        metrics=['accuracy'])
history_hp_hyp_rs = model.fit(train_ds, epochs=50, validation_data=val_ds)

val_acc_per_epoch = history_hp_hyp_rs.history['val_accuracy']
best_val_acc = max(val_acc_per_epoch)
best_epoch = val_acc_per_epoch.index(max(val_acc_per_epoch)) + 1
print('Best epoch: %d' % (best_epoch,))
```

Epoch 1/50
239/239 [=====] - 34s 105ms/step - loss: 4.6444 - accuracy: 0.0501 - val_loss: 80.3757 - val_accuracy: 0.0000e+00
Epoch 2/50
239/239 [=====] - 23s 96ms/step - loss: 3.3555 - accuracy: 0.1762 - val_loss: 6.8624 - val_accuracy: 0.1057
Epoch 3/50
239/239 [=====] - 24s 99ms/step - loss: 2.7122 - accuracy: 0.2836 - val_loss: 4.9408 - val_accuracy: 0.1358
Epoch 4/50
239/239 [=====] - 24s 101ms/step - loss: 2.4266 - accuracy: 0.3717 - val_loss: 12.7961 - val_accuracy: 0.1170
Epoch 5/50
239/239 [=====] - 24s 101ms/step - loss: 2.1455 - accuracy: 0.4620 - val_loss: 7.3751 - val_accuracy: 0.1019
Epoch 6/50
239/239 [=====] - 24s 100ms/step - loss: 1.8681 - accuracy: 0.5518 - val_loss: 6.1565 - val_accuracy: 0.3094
Epoch 7/50
239/239 [=====] - 24s 100ms/step - loss: 1.6756 - accuracy: 0.5989 - val_loss: 2.1631 - val_accuracy: 0.5472
Epoch 8/50
239/239 [=====] - 24s 101ms/step - loss: 1.4951 - accuracy: 0.6351 - val_loss: 5.0273 - val_accuracy: 0.2830
Epoch 9/50
239/239 [=====] - 24s 101ms/step - loss: 1.3649 - accuracy: 0.6742 - val_loss: 2.0160 - val_accuracy: 0.5811
Epoch 10/50
239/239 [=====] - 24s 99ms/step - loss: 1.2349 - accuracy: 0.7041 - val_loss: 2.4573 - val_accuracy: 0.5849
Epoch 11/50
239/239 [=====] - 23s 96ms/step - loss: 1.1257 - accuracy: 0.7299 - val_loss: 1.9958 - val_accuracy: 0.6566
Epoch 12/50
239/239 [=====] - 23s 96ms/step - loss: 1.0185 - accuracy: 0.7606 - val_loss: 1.1720 - val_accuracy: 0.7170
Epoch 13/50
239/239 [=====] - 23s 96ms/step - loss: 0.9518 - accuracy: 0.7715 - val_loss: 2.7374 - val_accuracy: 0.5547
Epoch 14/50
239/239 [=====] - 23s 97ms/step - loss: 0.8516 - accuracy: 0.7968 - val_loss: 3.9188 - val_accuracy: 0.4113

Epoch 15/50
239/239 [=====] - 23s 96ms/step - loss: 0.6993 - accuracy: 0.8207 - val_loss: 1.6296 - val_accuracy: 0.6528
Epoch 16/50
239/239 [=====] - 23s 96ms/step - loss: 0.5515 - accuracy: 0.8497 - val_loss: 0.8380 - val_accuracy: 0.7623
Epoch 17/50
239/239 [=====] - 23s 97ms/step - loss: 0.4425 - accuracy: 0.8696 - val_loss: 2.6282 - val_accuracy: 0.5585
Epoch 18/50
239/239 [=====] - 23s 97ms/step - loss: 0.3600 - accuracy: 0.8935 - val_loss: 1.4561 - val_accuracy: 0.6830
Epoch 19/50
239/239 [=====] - 23s 97ms/step - loss: 0.3292 - accuracy: 0.8970 - val_loss: 1.0045 - val_accuracy: 0.7849
Epoch 20/50
239/239 [=====] - 23s 97ms/step - loss: 0.2865 - accuracy: 0.9141 - val_loss: 2.1419 - val_accuracy: 0.6264
Epoch 21/50
239/239 [=====] - 23s 96ms/step - loss: 0.2408 - accuracy: 0.9250 - val_loss: 0.8964 - val_accuracy: 0.8151
Epoch 22/50
239/239 [=====] - 23s 97ms/step - loss: 0.1865 - accuracy: 0.9465 - val_loss: 1.8391 - val_accuracy: 0.6830
Epoch 23/50
239/239 [=====] - 23s 96ms/step - loss: 0.2286 - accuracy: 0.9277 - val_loss: 2.1349 - val_accuracy: 0.6302
Epoch 24/50
239/239 [=====] - 23s 97ms/step - loss: 0.2029 - accuracy: 0.9410 - val_loss: 0.9733 - val_accuracy: 0.7660
Epoch 25/50
239/239 [=====] - 23s 97ms/step - loss: 0.1660 - accuracy: 0.9482 - val_loss: 1.2359 - val_accuracy: 0.6906
Epoch 26/50
239/239 [=====] - 23s 97ms/step - loss: 0.1746 - accuracy: 0.9465 - val_loss: 1.4508 - val_accuracy: 0.7208
Epoch 27/50
239/239 [=====] - 23s 97ms/step - loss: 0.1603 - accuracy: 0.9499 - val_loss: 1.0852 - val_accuracy: 0.7849
Epoch 28/50
239/239 [=====] - 23s 97ms/step - loss: 0.0849 - accuracy: 0.9742 - val_loss: 0.3803 - val_accuracy: 0.9057

Epoch 29/50
239/239 [=====] - 24s 100ms/step - loss: 0.1674 - accuracy: 0.9461 - val_loss: 2.1947 - val_accuracy: 0.6604
Epoch 30/50
239/239 [=====] - 24s 101ms/step - loss: 0.1867 - accuracy: 0.9381 - val_loss: 1.2219 - val_accuracy: 0.7698
Epoch 31/50
239/239 [=====] - 24s 101ms/step - loss: 0.1238 - accuracy: 0.9621 - val_loss: 1.4223 - val_accuracy: 0.7358
Epoch 32/50
239/239 [=====] - 24s 101ms/step - loss: 0.0526 - accuracy: 0.9852 - val_loss: 0.4056 - val_accuracy: 0.8943
Epoch 33/50
239/239 [=====] - 24s 101ms/step - loss: 0.0724 - accuracy: 0.9797 - val_loss: 1.6772 - val_accuracy: 0.6981
Epoch 34/50
239/239 [=====] - 24s 101ms/step - loss: 0.2260 - accuracy: 0.9280 - val_loss: 1.5161 - val_accuracy: 0.7283
Epoch 35/50
239/239 [=====] - 24s 100ms/step - loss: 0.1051 - accuracy: 0.9658 - val_loss: 0.6309 - val_accuracy: 0.8604
Epoch 36/50
239/239 [=====] - 23s 97ms/step - loss: 0.1023 - accuracy: 0.9679 - val_loss: 0.9043 - val_accuracy: 0.7962
Epoch 37/50
239/239 [=====] - 23s 97ms/step - loss: 0.0802 - accuracy: 0.9761 - val_loss: 0.7293 - val_accuracy: 0.8302
Epoch 38/50
239/239 [=====] - 23s 97ms/step - loss: 0.0431 - accuracy: 0.9868 - val_loss: 0.5284 - val_accuracy: 0.8679
Epoch 39/50
239/239 [=====] - 23s 97ms/step - loss: 0.0973 - accuracy: 0.9715 - val_loss: 1.5026 - val_accuracy: 0.7472
Epoch 40/50
239/239 [=====] - 23s 97ms/step - loss: 0.1516 - accuracy: 0.9517 - val_loss: 0.9917 - val_accuracy: 0.7849
Epoch 41/50
239/239 [=====] - 23s 97ms/step - loss: 0.1497 - accuracy: 0.9511 - val_loss: 1.0229 - val_accuracy: 0.8226
Epoch 42/50
239/239 [=====] - 23s 97ms/step - loss: 0.0913 - accuracy: 0.9719 - val_loss: 0.5957 - val_accuracy: 0.8830

```
Epoch 43/50
239/239 [=====] - 23s 97ms/step - loss: 0.0611 - accuracy: 0.9816 - val_loss: 0.6509 - val_accuracy: 0.8755
Epoch 44/50
239/239 [=====] - 23s 97ms/step - loss: 0.0448 - accuracy: 0.9865 - val_loss: 0.5479 - val_accuracy: 0.8906
Epoch 45/50
239/239 [=====] - 23s 97ms/step - loss: 0.0280 - accuracy: 0.9917 - val_loss: 0.1835 - val_accuracy: 0.9585
Epoch 46/50
239/239 [=====] - 23s 97ms/step - loss: 0.0165 - accuracy: 0.9972 - val_loss: 0.3218 - val_accuracy: 0.9321
Epoch 47/50
239/239 [=====] - 23s 97ms/step - loss: 0.0527 - accuracy: 0.9849 - val_loss: 1.0849 - val_accuracy: 0.7887
Epoch 48/50
239/239 [=====] - 23s 97ms/step - loss: 0.3158 - accuracy: 0.9045 - val_loss: 2.1013 - val_accuracy: 0.6868
Epoch 49/50
239/239 [=====] - 23s 97ms/step - loss: 0.1153 - accuracy: 0.9641 - val_loss: 0.5746 - val_accuracy: 0.9057
Epoch 50/50
239/239 [=====] - 23s 97ms/step - loss: 0.0207 - accuracy: 0.9940 - val_loss: 0.2597 - val_accuracy: 0.9396
Best epoch: 45
```

```
In [54]: # Re-instantiate the hypermodel and train it with the optimal number of epochs from above.
hypermodel_rs = tuner_rs.hypermodel.build(best_hps_hyp_rs)
hypermodel_rs.compile(optimizer=keras.optimizers.Adam(learning_rate=best_hps_hyp_rs.get('learning_rate')),
                      loss=keras.losses.SparseCategoricalCrossentropy(from_logits=True),
                      metrics=['accuracy'])
# Retrain the model
final_hist_hyp_rs = hypermodel_rs.fit(train_ds, epochs=best_epoch, validation_data = val_ds)
```

Epoch 1/45
239/239 [=====] - 35s 107ms/step - loss: 4.6554 - accuracy: 0.0470 - val_loss: 19238.4219 - val_accuracy: 0.0000e+00
Epoch 2/45
239/239 [=====] - 24s 100ms/step - loss: 3.6611 - accuracy: 0.1327 - val_loss: 49.3472 - val_accuracy: 0.0340
Epoch 3/45
239/239 [=====] - 24s 100ms/step - loss: 3.1834 - accuracy: 0.2219 - val_loss: 9.7791 - val_accuracy: 0.0566
Epoch 4/45
239/239 [=====] - 24s 101ms/step - loss: 2.8172 - accuracy: 0.2971 - val_loss: 3.5670 - val_accuracy: 0.2453
Epoch 5/45
239/239 [=====] - 23s 98ms/step - loss: 2.5289 - accuracy: 0.3986 - val_loss: 4.1538 - val_accuracy: 0.2453
Epoch 6/45
239/239 [=====] - 23s 96ms/step - loss: 2.2205 - accuracy: 0.4873 - val_loss: 6.3383 - val_accuracy: 0.1811
Epoch 7/45
239/239 [=====] - 23s 96ms/step - loss: 1.9008 - accuracy: 0.5584 - val_loss: 4.0487 - val_accuracy: 0.3057
Epoch 8/45
239/239 [=====] - 23s 96ms/step - loss: 1.6842 - accuracy: 0.6013 - val_loss: 6.7021 - val_accuracy: 0.2226
Epoch 9/45
239/239 [=====] - 23s 96ms/step - loss: 1.4968 - accuracy: 0.6443 - val_loss: 2.8965 - val_accuracy: 0.4717
Epoch 10/45
239/239 [=====] - 23s 96ms/step - loss: 1.3519 - accuracy: 0.6772 - val_loss: 2.3589 - val_accuracy: 0.4830
Epoch 11/45
239/239 [=====] - 23s 96ms/step - loss: 1.2334 - accuracy: 0.7100 - val_loss: 1.9570 - val_accuracy: 0.5811
Epoch 12/45
239/239 [=====] - 23s 96ms/step - loss: 1.1228 - accuracy: 0.7394 - val_loss: 3.1450 - val_accuracy: 0.4717
Epoch 13/45
239/239 [=====] - 23s 96ms/step - loss: 1.0419 - accuracy: 0.7593 - val_loss: 2.4890 - val_accuracy: 0.5811
Epoch 14/45
239/239 [=====] - 23s 96ms/step - loss: 0.9294 - accuracy: 0.7913 - val_loss: 1.3747 - val_accuracy: 0.7245

Epoch 15/45
239/239 [=====] - 23s 96ms/step - loss: 0.8603 - accuracy: 0.8063 - val_loss: 1.3720 - val_accuracy: 0.7396
Epoch 16/45
239/239 [=====] - 23s 96ms/step - loss: 0.7998 - accuracy: 0.8237 - val_loss: 1.2791 - val_accuracy: 0.7472
Epoch 17/45
239/239 [=====] - 23s 96ms/step - loss: 0.7248 - accuracy: 0.8463 - val_loss: 1.6655 - val_accuracy: 0.6377
Epoch 18/45
239/239 [=====] - 23s 96ms/step - loss: 0.6630 - accuracy: 0.8642 - val_loss: 1.5576 - val_accuracy: 0.6830
Epoch 19/45
239/239 [=====] - 23s 96ms/step - loss: 0.6036 - accuracy: 0.8792 - val_loss: 2.7601 - val_accuracy: 0.5736
Epoch 20/45
239/239 [=====] - 23s 96ms/step - loss: 0.5937 - accuracy: 0.8821 - val_loss: 0.9456 - val_accuracy: 0.8113
Epoch 21/45
239/239 [=====] - 23s 96ms/step - loss: 0.3305 - accuracy: 0.9208 - val_loss: 2.5177 - val_accuracy: 0.6038
Epoch 22/45
239/239 [=====] - 23s 96ms/step - loss: 0.2997 - accuracy: 0.9083 - val_loss: 1.3854 - val_accuracy: 0.7019
Epoch 23/45
239/239 [=====] - 23s 96ms/step - loss: 0.2415 - accuracy: 0.9272 - val_loss: 2.1839 - val_accuracy: 0.6604
Epoch 24/45
239/239 [=====] - 24s 101ms/step - loss: 0.1916 - accuracy: 0.9410 - val_loss: 0.9870 - val_accuracy: 0.7547
Epoch 25/45
239/239 [=====] - 24s 101ms/step - loss: 0.1212 - accuracy: 0.9633 - val_loss: 1.7176 - val_accuracy: 0.6792
Epoch 26/45
239/239 [=====] - 24s 101ms/step - loss: 0.1016 - accuracy: 0.9714 - val_loss: 2.2547 - val_accuracy: 0.7170
Epoch 27/45
239/239 [=====] - 24s 101ms/step - loss: 0.2617 - accuracy: 0.9162 - val_loss: 1.4640 - val_accuracy: 0.7208
Epoch 28/45
239/239 [=====] - 24s 100ms/step - loss: 0.1906 - accuracy: 0.9384 - val_loss: 0.9704 - val_accuracy: 0.8038

Epoch 29/45
239/239 [=====] - 24s 101ms/step - loss: 0.1269 - accuracy: 0.9618 - val_loss: 1.0205 - val_accuracy: 0.8038
Epoch 30/45
239/239 [=====] - 24s 99ms/step - loss: 0.0788 - accuracy: 0.9781 - val_loss: 0.6584 - val_accuracy: 0.8377
Epoch 31/45
239/239 [=====] - 23s 96ms/step - loss: 0.0539 - accuracy: 0.9854 - val_loss: 0.5579 - val_accuracy: 0.8377
Epoch 32/45
239/239 [=====] - 23s 96ms/step - loss: 0.2256 - accuracy: 0.9283 - val_loss: 2.8216 - val_accuracy: 0.6340
Epoch 33/45
239/239 [=====] - 23s 96ms/step - loss: 0.1888 - accuracy: 0.9420 - val_loss: 0.7023 - val_accuracy: 0.8491
Epoch 34/45
239/239 [=====] - 23s 96ms/step - loss: 0.1187 - accuracy: 0.9612 - val_loss: 1.6246 - val_accuracy: 0.7434
Epoch 35/45
239/239 [=====] - 23s 96ms/step - loss: 0.0753 - accuracy: 0.9777 - val_loss: 0.3893 - val_accuracy: 0.9245
Epoch 36/45
239/239 [=====] - 23s 96ms/step - loss: 0.0289 - accuracy: 0.9936 - val_loss: 0.3197 - val_accuracy: 0.9132
Epoch 37/45
239/239 [=====] - 23s 97ms/step - loss: 0.0151 - accuracy: 0.9966 - val_loss: 0.3831 - val_accuracy: 0.9245
Epoch 38/45
239/239 [=====] - 23s 96ms/step - loss: 0.0058 - accuracy: 0.9988 - val_loss: 0.2582 - val_accuracy: 0.9434
Epoch 39/45
239/239 [=====] - 23s 96ms/step - loss: 0.0065 - accuracy: 0.9996 - val_loss: 0.3088 - val_accuracy: 0.9358
Epoch 40/45
239/239 [=====] - 23s 96ms/step - loss: 0.0120 - accuracy: 0.9974 - val_loss: 0.7758 - val_accuracy: 0.8755
Epoch 41/45
239/239 [=====] - 23s 96ms/step - loss: 0.6114 - accuracy: 0.8256 - val_loss: 2.0020 - val_accuracy: 0.6906
Epoch 42/45
239/239 [=====] - 23s 96ms/step - loss: 0.2271 - accuracy: 0.9281 - val_loss: 0.8667 - val_accuracy: 0.8151

```
Epoch 43/45
239/239 [=====] - 23s 96ms/step - loss: 0.0794 - accuracy: 0.9770 - val_loss: 0.4176 - val_accuracy: 0.9283
Epoch 44/45
239/239 [=====] - 23s 96ms/step - loss: 0.0445 - accuracy: 0.9878 - val_loss: 0.4196 - val_accuracy: 0.9094
Epoch 45/45
239/239 [=====] - 23s 96ms/step - loss: 0.0204 - accuracy: 0.9957 - val_loss: 0.2326 - val_accuracy: 0.9434
```

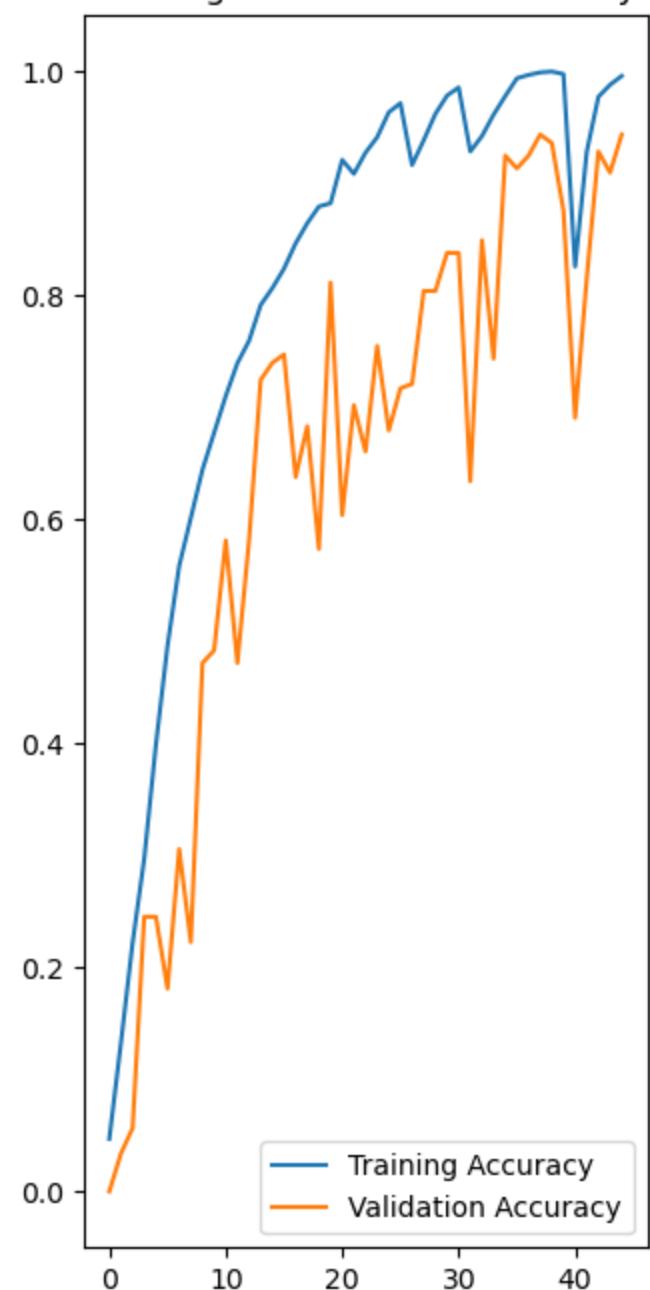
```
In [59]: acc = final_hist_hyp_rs.history['accuracy']
val_acc = final_hist_hyp_rs.history['val_accuracy']
print(len(acc))
loss = final_hist_hyp_rs.history['loss']
val_loss = final_hist_hyp_rs.history['val_loss']

epochs_range = range(best_epoch)

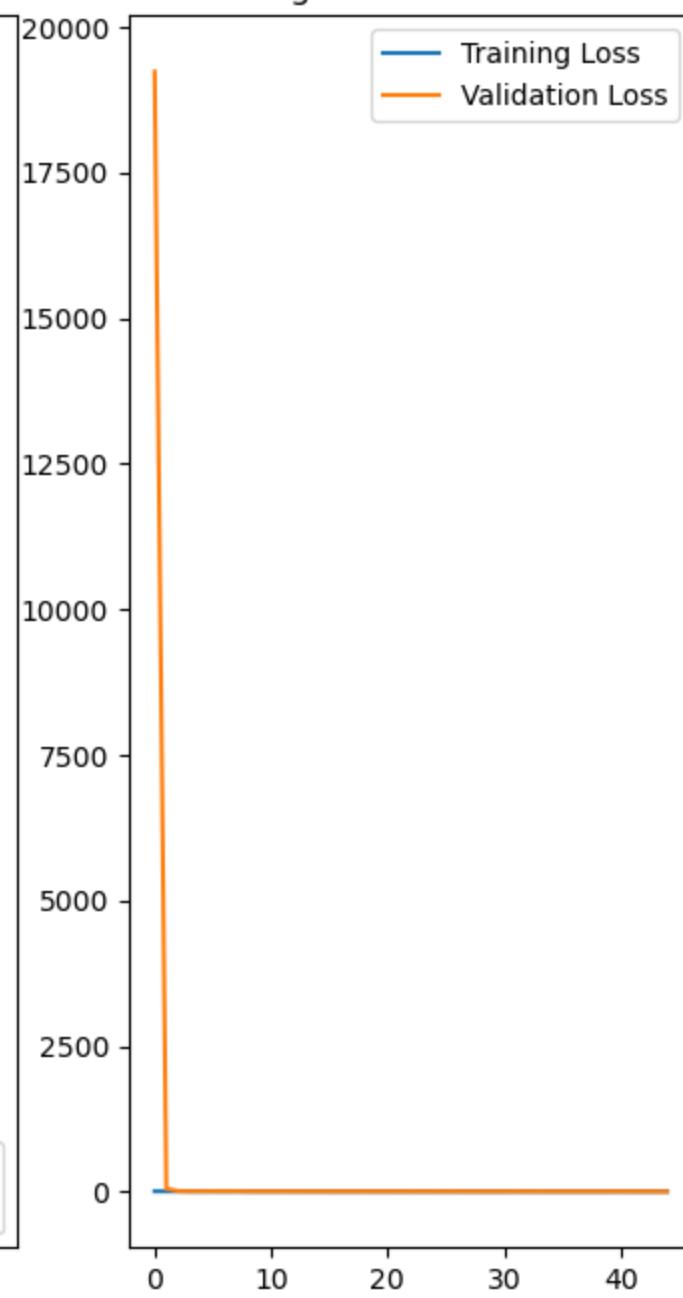
plt.figure(figsize=(8, 8))
plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```

Training and Validation Accuracy



Training and Validation Loss



```
In [57]: best_val_acc = max(val_acc_per_epoch)
print(best_val_acc)
```

```
0.9584905505180359
```

```
In [61]: print(val_loss)
```

```
[19238.421875, 49.34721374511719, 9.779139518737793, 3.5670363903045654, 4.153811454772949, 6.338341236114502, 4.048731327056885, 6.7021331787109375, 2.8964850902557373, 2.3589112758636475, 1.956958293914795, 3.1449942588806152, 2.4889564514160156, 1.3746660947799683, 1.3719632625579834, 1.2791045904159546, 1.6654750108718872, 1.5575944185256958, 2.7601399421691895, 0.945551335811615, 2.5176939964294434, 1.3853909969329834, 2.1838972568511963, 0.9869624376296997, 1.717570424079895, 2.254672050476074, 1.4640387296676636, 0.9703810214996338, 1.0205063819885254, 0.6584292650222778, 0.5578811764717102, 2.8216428756713867, 0.7023236155509949, 1.6246311664581299, 0.3892669975757599, 0.31965959072113037, 0.38308537006378174, 0.25823670625686646, 0.30876436829566956, 0.7758459448814392, 2.0019819736480713, 0.8666766285896301, 0.4176035523414612, 0.4196210205554962, 0.23262417316436768]
```

```
In [62]: eval_result = hypermodel_rs.evaluate(test_ds)
print("[test loss, test accuracy]:", eval_result)
```

```
239/239 [=====] - 13s 50ms/step - loss: 0.0275 - accuracy: 0.9919
[test loss, test accuracy]: [0.027490193024277687, 0.9918677806854248]
```