Objective

The cassave plant is the third largets source of carbohydrates in the world. Unfortunately due to diseases, there has not been a harvest yield increase globaly in 25 years.

Using machine learning I will build an image classifier to detect whether a cassava plant has a disease and which of the top 4 most common diseases it is.

While the main priority is to identify whether or not a plant has a disease, it is also very important to identify which disease it is so that the farmers know how to properly handle the situation. For some diseases, the plant can be recovered by simply removing any infected parts before it spreads. With others, the plant needs to be fully removed, dried and burned.

The Data

The data used for this is about 21,000 images gathered by Uganda's National Crops Resources Research Institute. This data is near for my objective as it is vast, as well as being sourced directly from farmers who took pictures of their crops. The Institute then went through and labeled each image.

The one downside of this dataset was the massive imbalance in its data. Among the 5 classes there was a ratio of 1:2:2:2:13

In another notebook I sorted and prepared the data for the models.

Imports

In [1]:

```
import tensorflow as tf

import numpy as np

from tensorflow.keras.utils import image_dataset_from_directory,\
to_categorical, array_to_img, img_to_array, load_img

from keras.utils.vis_utils import plot_model

from tensorflow.keras import datasets

from tensorflow.keras.models import Sequential

from tensorflow.keras import layers
from tensorflow.keras.layers import Dense, Flatten, Conv2D,\
MaxPooling2D, Dropout, BatchNormalization, Activation

from tensorflow.keras.regularizers import l2

from tensorflow.keras.metrics import Recall, Precision,\
CategoricalAccuracy

from tensorflow.keras.applications.resnet50 import ResNet50

from tensorflow.keras.callbacks import EarlyStopping

from PIL import Image

import os

from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
```

```
import os

import matplotlib.pyplot as plt

import seaborn as sns

from tensorflow.math import confusion_matrix

from keras.preprocessing.image import ImageDataGenerator

from tensorflow import concat
```

In [2]:

```
from google.colab import drive
drive.mount('/content/drive', force_remount=True)
```

```
Mounted at /content/drive
```

In [3]:

```
os.getcwd()
```

Out[3]:

```
'/content'
```

In [ ]:

```
#Offline
#os.chdir('C:\\Users\\musaa\\Documents\\Cassava\\Cassava-Disease-Classification')
#os.getcwd()
```

Load Data

Data is stored in TTVS (train, test, and validation split) directory. 21,000 images split amount 5 classes. After a 60, 20, 20 split, the training data was massivley imbalanced with the following quantities

CBB 652; CBSD 1313; CGM 1431; CMD 7894; Healthy 1546

Useing random selection the CMD class was reduced to 5000 images and using data augmentation methods the other classes were increased to 5000 images.

This was done to deal with the datasets inherent class imbalance, which would skew the training and lead to overfitting of the class with a greater quantity of data.

While other meds do exist to deal with the class imbalance, this method was chosen due to it affecting the dataset and not the model, thus making the various models run faster.

In [4]:

```
# Google Colab was used for its GPU, thus two file paths exist
# depending on offline or online notebook usage
train_path_colab = "drive/MyDrive/Capstone/TTVS/train"
val_path_colab = "drive/MyDrive/Capstone/TTVS/val"
test_path_colab = "drive/MyDrive/Capstone/TTVS/test"
train_path_offline = "Data/TTVS/train"
val_path_offline = "Data/TTVS/val"
test_path_offline = "Data/TTVS/test"

train_ds = image_dataset_from_directory(
    train_path_colab,
    labels="inferred",
    label_mode="categorical",
    class_names=None,
    color_mode="rgb",
    batch_size=128,
```

```
    image_size=(600, 600),
    shuffle=True,
    seed=1,
    validation_split=None,
    subset=None,
    interpolation="bicubic",
    follow_links=False,
    crop_to_aspect_ratio=False,
)

validation_ds = image_dataset_from_directory(
    val_path_colab,
    labels="inferred",
    label_mode="categorical",
    class_names=None,
    color_mode="rgb",
    batch_size=128,
    image_size=(600, 600),
    shuffle=True,
    seed=1,
    validation_split=None,
    subset=None,
    interpolation="bicubic",
    follow_links=False,
    crop_to_aspect_ratio=False,
)

test_ds = image_dataset_from_directory(
    test_path_colab,
    labels="inferred",
    label_mode="categorical",
    class_names=None,
    color_mode="rgb",
    batch_size=128,
    image_size=(600, 600),
    shuffle=True,
    seed=1,
    validation_split=None,
    subset=None,
    interpolation="bicubic",
    follow_links=False,
    crop_to_aspect_ratio=False,
)
```

```
Found 25020 files belonging to 5 classes.
Found 4277 files belonging to 5 classes.
Found 4284 files belonging to 5 classes.
```

Convolutional Neural Network (CNN) model

Base Model

In [5]:

```
# to fit the data into the model, all values in the data arrays need to
# be rescaled to be between 0 and 1
rescaling_layer = layers.experimental.preprocessing.Rescaling(
    scale=1. / 255,
    input_shape=(600, 600, 3)
)
```

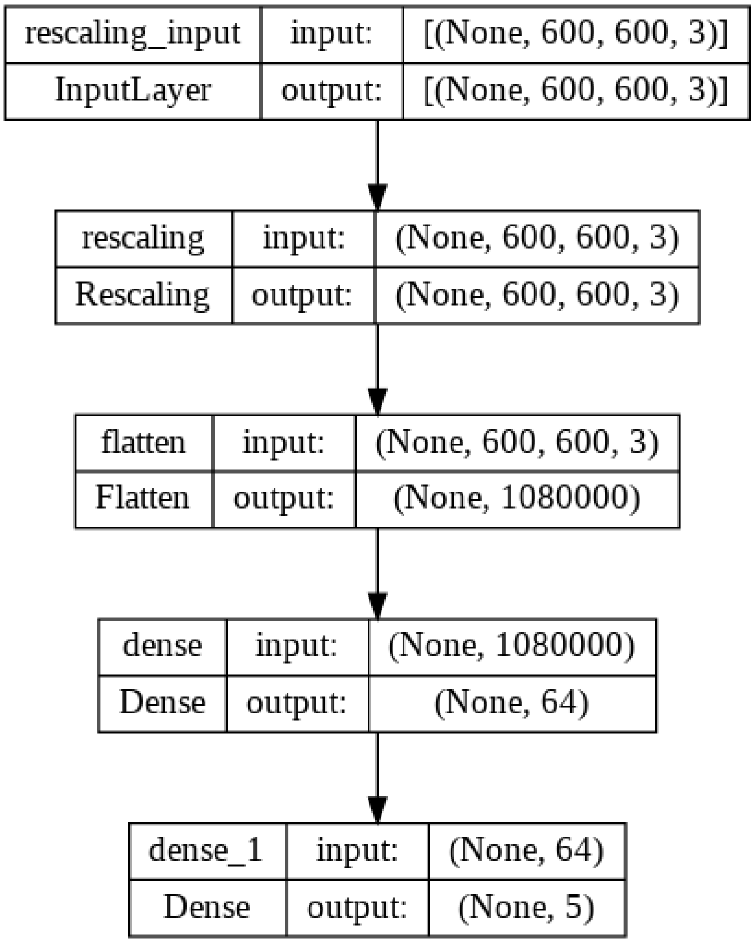
In [6]:

```
model = Sequential()

model.add(rescaling_layer)

model.add(Flatten())
```

```
model.add(Dense(64, activation="relu"))
model.add(Dense(5, activation="softmax"))

model.summary()
plot_model(model, show_shapes=True, show_layer_names=True)
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 rescaling (Rescaling)       (None, 600, 600, 3)       0

 flatten (Flatten)           (None, 1080000)           0

 dense (Dense)               (None, 64)                69120064

 dense_1 (Dense)             (None, 5)                 325

=================================================================
Total params: 69,120,389
Trainable params: 69,120,389
Non-trainable params: 0
_________________________________________________________________
```

Out[6]:



The base was model was created simply with the rescaling layer, a layer to flatten the data so that it then fits into the dense layer, a dense layer, and on more dense to get one of 5 classes.

In [7]:

```
model.compile(optimizer='adam', loss='categorical_crossentropy',  metrics=['CategoricalA
ccuracy'])
```

My metric for success chosen was Categorical Accuracy as it gives the most straighforward answer for how often the model predicts the correct class.

In [9]:

```
history = model.fit(train_ds, validation_data=validation_ds, epochs= 20)
```

```
Epoch 1/20
196/196 [==============================] - 750s 4s/step - loss: 29.4968 - categorical_acc
uracy: 0.2104 - val_loss: 1.6118 - val_categorical_accuracy: 0.1209
Epoch 2/20
196/196 [==============================] - 55s 274ms/step - loss: 1.6103 - categorical_ac
curacy: 0.1979 - val_loss: 1.6108 - val_categorical_accuracy: 0.1206
Epoch 3/20
196/196 [==============================] - 55s 273ms/step - loss: 1.6102 - categorical_ac
curacy: 0.1950 - val_loss: 1.6101 - val_categorical_accuracy: 0.1204
Epoch 4/20
196/196 [==============================] - 56s 276ms/step - loss: 1.6097 - categorical_ac
curacy: 0.1956 - val_loss: 1.6091 - val_categorical_accuracy: 0.1204
Epoch 5/20
196/196 [==============================] - 56s 276ms/step - loss: 1.6095 - categorical_ac
curacy: 0.1976 - val_loss: 1.6090 - val_categorical_accuracy: 0.1204
Epoch 6/20
196/196 [==============================] - 55s 273ms/step - loss: 1.6095 - categorical_ac
curacy: 0.1934 - val_loss: 1.6091 - val_categorical_accuracy: 0.1204
Epoch 7/20
196/196 [==============================] - 55s 273ms/step - loss: 1.6095 - categorical_ac
curacy: 0.1942 - val_loss: 1.6089 - val_categorical_accuracy: 0.1022
Epoch 8/20
196/196 [==============================] - 56s 275ms/step - loss: 1.6095 - categorical_ac
curacy: 0.1967 - val_loss: 1.6081 - val_categorical_accuracy: 0.1204
Epoch 9/20
196/196 [==============================] - 53s 264ms/step - loss: 1.6095 - categorical_ac
curacy: 0.1970 - val_loss: 1.6087 - val_categorical_accuracy: 0.1204
Epoch 10/20
196/196 [==============================] - 55s 274ms/step - loss: 1.6095 - categorical_ac
curacy: 0.1959 - val_loss: 1.6086 - val_categorical_accuracy: 0.1204
Epoch 11/20
196/196 [==============================] - 56s 278ms/step - loss: 1.6095 - categorical_ac
curacy: 0.1966 - val_loss: 1.6077 - val_categorical_accuracy: 0.6152
Epoch 12/20
196/196 [==============================] - 55s 270ms/step - loss: 1.6095 - categorical_ac
curacy: 0.1961 - val_loss: 1.6086 - val_categorical_accuracy: 0.1204
Epoch 13/20
196/196 [==============================] - 54s 268ms/step - loss: 1.6095 - categorical_ac
curacy: 0.1967 - val_loss: 1.6087 - val_categorical_accuracy: 0.1204
Epoch 14/20
196/196 [==============================] - 55s 272ms/step - loss: 1.6095 - categorical_ac
curacy: 0.1959 - val_loss: 1.6079 - val_categorical_accuracy: 0.1204
Epoch 15/20
196/196 [==============================] - 54s 270ms/step - loss: 1.6095 - categorical_ac
curacy: 0.1962 - val_loss: 1.6085 - val_categorical_accuracy: 0.1022
Epoch 16/20
196/196 [==============================] - 54s 267ms/step - loss: 1.6095 - categorical_ac
curacy: 0.1972 - val_loss: 1.6088 - val_categorical_accuracy: 0.1204
Epoch 17/20
196/196 [==============================] - 55s 272ms/step - loss: 1.6095 - categorical_ac
curacy: 0.1975 - val_loss: 1.6078 - val_categorical_accuracy: 0.1204
Epoch 18/20
196/196 [==============================] - 54s 269ms/step - loss: 1.6095 - categorical_ac
curacy: 0.1964 - val_loss: 1.6075 - val_categorical_accuracy: 0.1204
Epoch 19/20
196/196 [==============================] - 55s 274ms/step - loss: 1.6095 - categorical_ac
curacy: 0.1944 - val_loss: 1.6085 - val_categorical_accuracy: 0.1022
Epoch 20/20
196/196 [==============================] - 54s 266ms/step - loss: 1.6095 - categorical_ac
curacy: 0.1964 - val_loss: 1.6084 - val_categorical_accuracy: 0.1204
```

In [13]:

```
history.params["epochs"]
```

Out[13]:

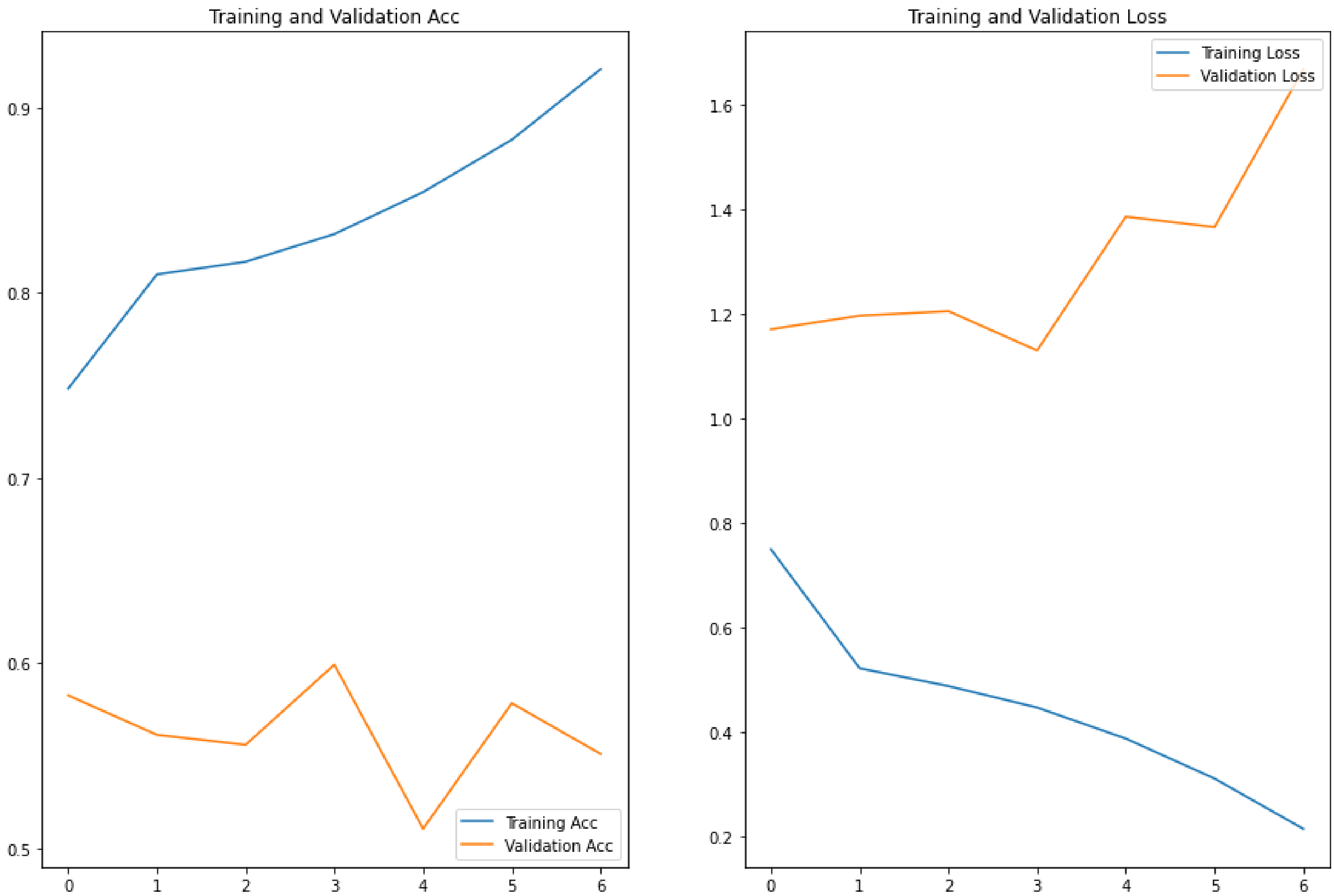
```
20
```

In [44]:

```
def plot_history(history_v):

  acc = history_v.history['categorical_accuracy']
  val_acc = history_v.history['val_categorical_accuracy']

  loss = history_v.history['loss']
  val_loss = history_v.history['val_loss']

  epochs_range = range(len(history_v.history["loss"]))

  plt.figure(figsize=(15, 10))
  plt.subplot(1, 2, 1)
  plt.plot(epochs_range, acc, label='Training Acc')
  plt.plot(epochs_range, val_acc, label='Validation Acc')
  plt.legend(loc='lower right')
  plt.title('Training and Validation Acc')

  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()
```

In [37]:

```
plot_history(history)
```



Model 1

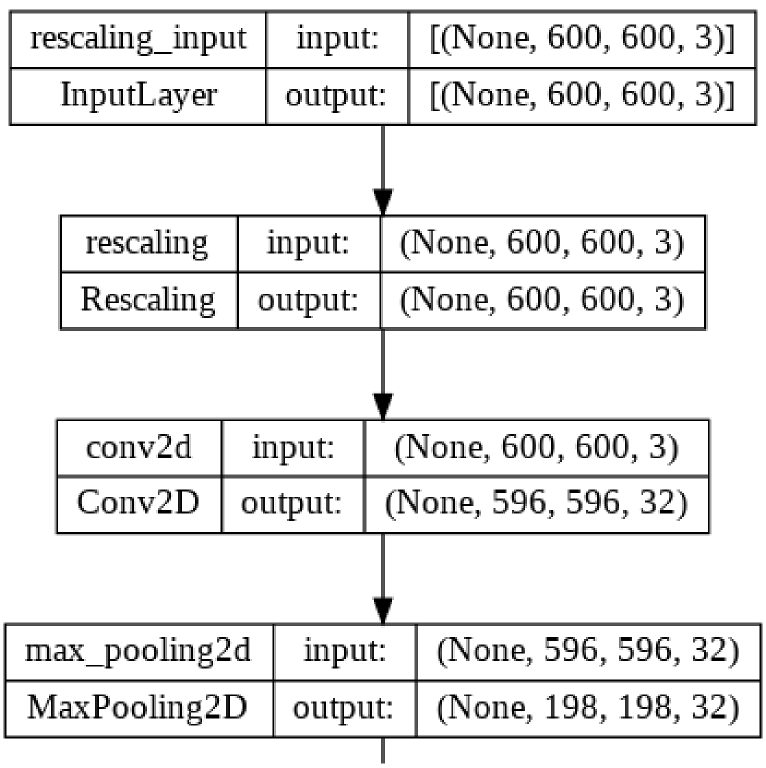
In [22]:

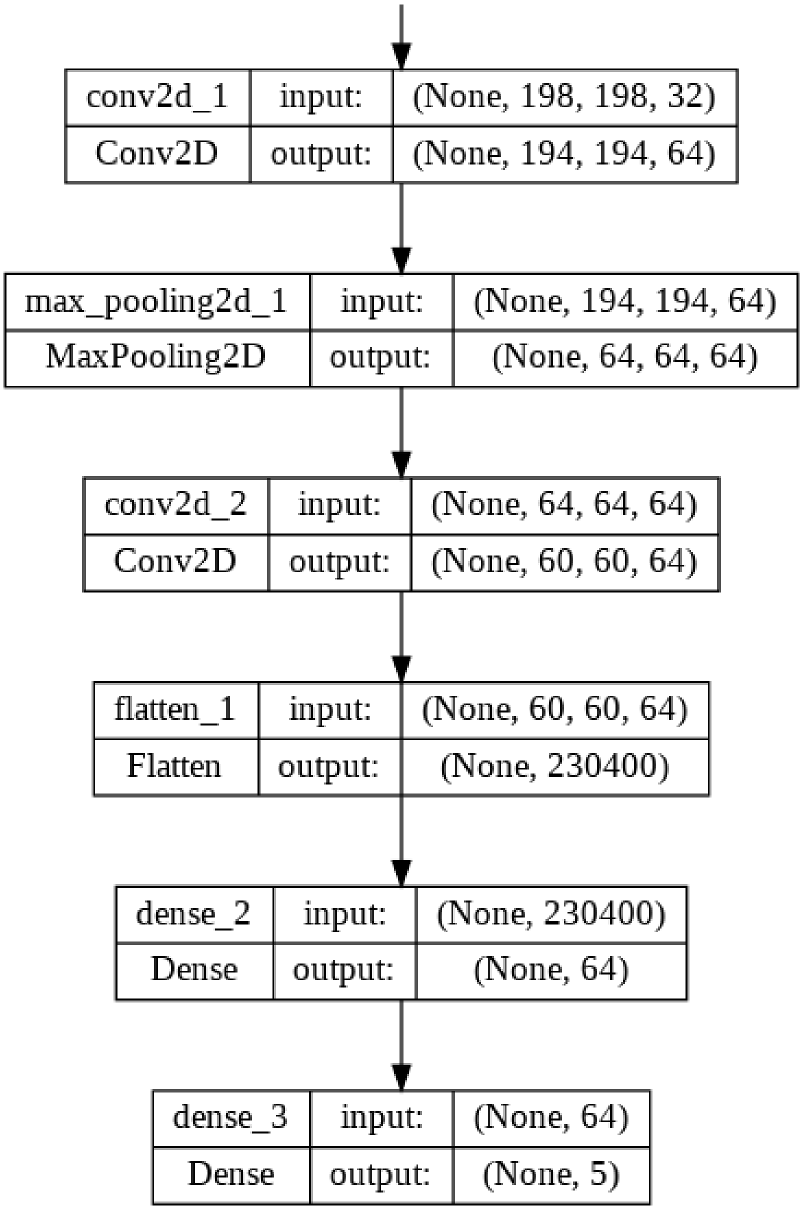
```
model1 = Sequential()

model1.add(rescaling_layer)

model1.add(Conv2D(
```

```
filters= 32, kernel_size = (5, 5), activation = "relu",
input_shape = (600, 600, 3)))

model1.add(MaxPooling2D(pool_size = (3, 3)))

model1.add(Conv2D(64, (5, 5), activation = "relu"))
model1.add(MaxPooling2D(pool_size = (3, 3)))
model1.add(Conv2D(64, (5, 5), activation = "relu"))

model1.add(Flatten())
model1.add(Dense(64, activation="relu"))
model1.add(Dense(5, activation="softmax"))

model1.summary()
plot_model(model1, show_shapes=True, show_layer_names=True)
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 rescaling (Rescaling)       (None, 600, 600, 3)       0

 conv2d (Conv2D)             (None, 596, 596, 32)      2432

 max_pooling2d (MaxPooling2D  (None, 198, 198, 32)     0
 )

 conv2d_1 (Conv2D)           (None, 194, 194, 64)      51264

 max_pooling2d_1 (MaxPooling  (None, 64, 64, 64)       0
 2D)

 conv2d_2 (Conv2D)           (None, 60, 60, 64)        102464

 flatten_1 (Flatten)         (None, 230400)            0

 dense_2 (Dense)             (None, 64)                14745664

 dense_3 (Dense)             (None, 5)                 325

=================================================================
Total params: 14,902,149
Trainable params: 14,902,149
Non-trainable params: 0
_________________________________________________________________
```

Out[22]:





For the next model, additional layers are added for increased depth and complexity. The biggest change is that the model has been changed from a simple dense neural network it is now a convolutional neural net. This has been done by adding Conv2D layers. Additionaly Maxpooling layers were added to reduce overfitting.

In [23]:

```
model1.compile(optimizer='adam', loss='categorical_crossentropy',  metrics=CategoricalAc
curacy())
```

In [25]:

```
es_callback = EarlyStopping(monitor='val_loss', patience=3)
```

In [27]:

```
history = model1.fit(train_ds, validation_data= validation_ds, epochs= 30, callbacks= es
_callback)
```

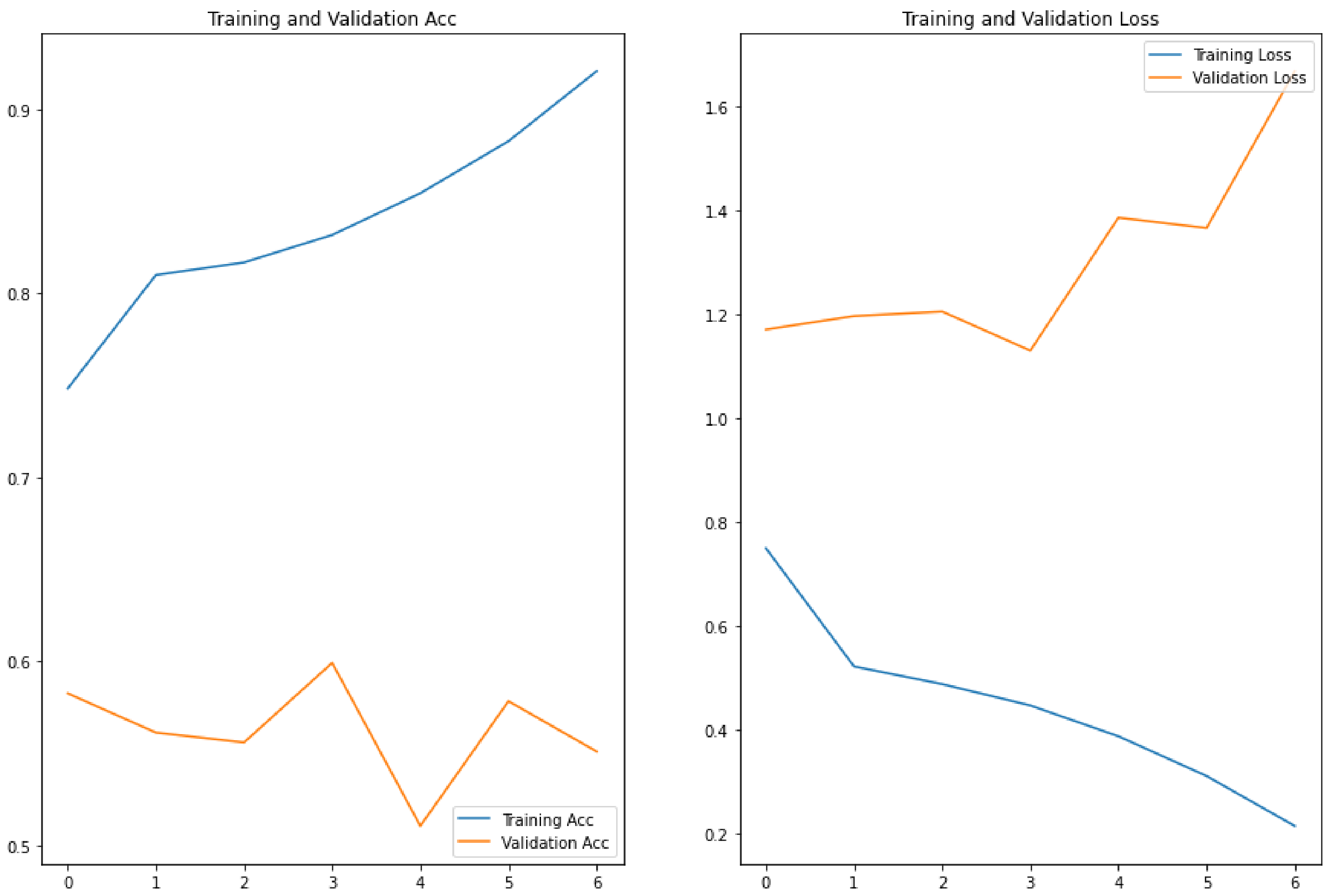
```
Epoch 1/30
196/196 [==============================] - 80s 398ms/step - loss: 0.7496 - categorical_ac
curacy: 0.7480 - val_loss: 1.1702 - val_categorical_accuracy: 0.5824
Epoch 2/30
196/196 [==============================] - 78s 390ms/step - loss: 0.5222 - categorical_ac
curacy: 0.8097 - val_loss: 1.1961 - val_categorical_accuracy: 0.5611
Epoch 3/30
196/196 [==============================] - 78s 390ms/step - loss: 0.4881 - categorical_ac
curacy: 0.8165 - val_loss: 1.2048 - val_categorical_accuracy: 0.5558
Epoch 4/30
196/196 [==============================] - 78s 390ms/step - loss: 0.4471 - categorical_ac
curacy: 0.8315 - val_loss: 1.1297 - val_categorical_accuracy: 0.5990
```

```
Epoch 5/30
196/196 [==============================] - 78s 391ms/step - loss: 0.3878 - categorical_accuracy: 0.8541 - val_loss: 1.3855 - val_categorical_accuracy: 0.5104
Epoch 6/30
196/196 [==============================] - 78s 389ms/step - loss: 0.3113 - categorical_accuracy: 0.8824 - val_loss: 1.3654 - val_categorical_accuracy: 0.5782
Epoch 7/30
196/196 [==============================] - 78s 390ms/step - loss: 0.2153 - categorical_accuracy: 0.9204 - val_loss: 1.6671 - val_categorical_accuracy: 0.5509
```

An early stop was added to stop the training of the model should the validation accuracy consistently drop after 3 epochs

In [38]:

```
plot_history(history)
```



Model 2

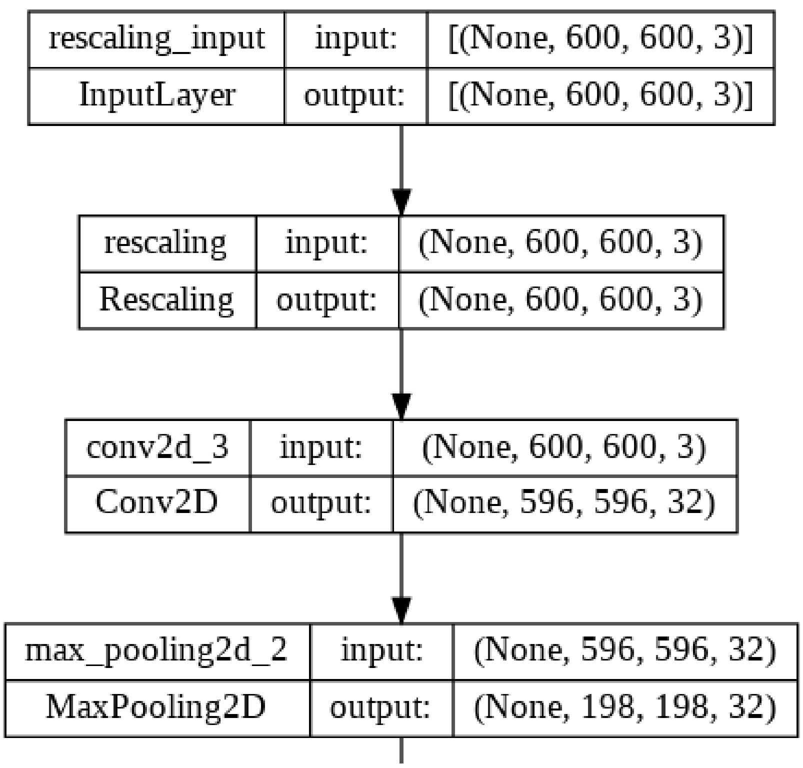
In [39]:

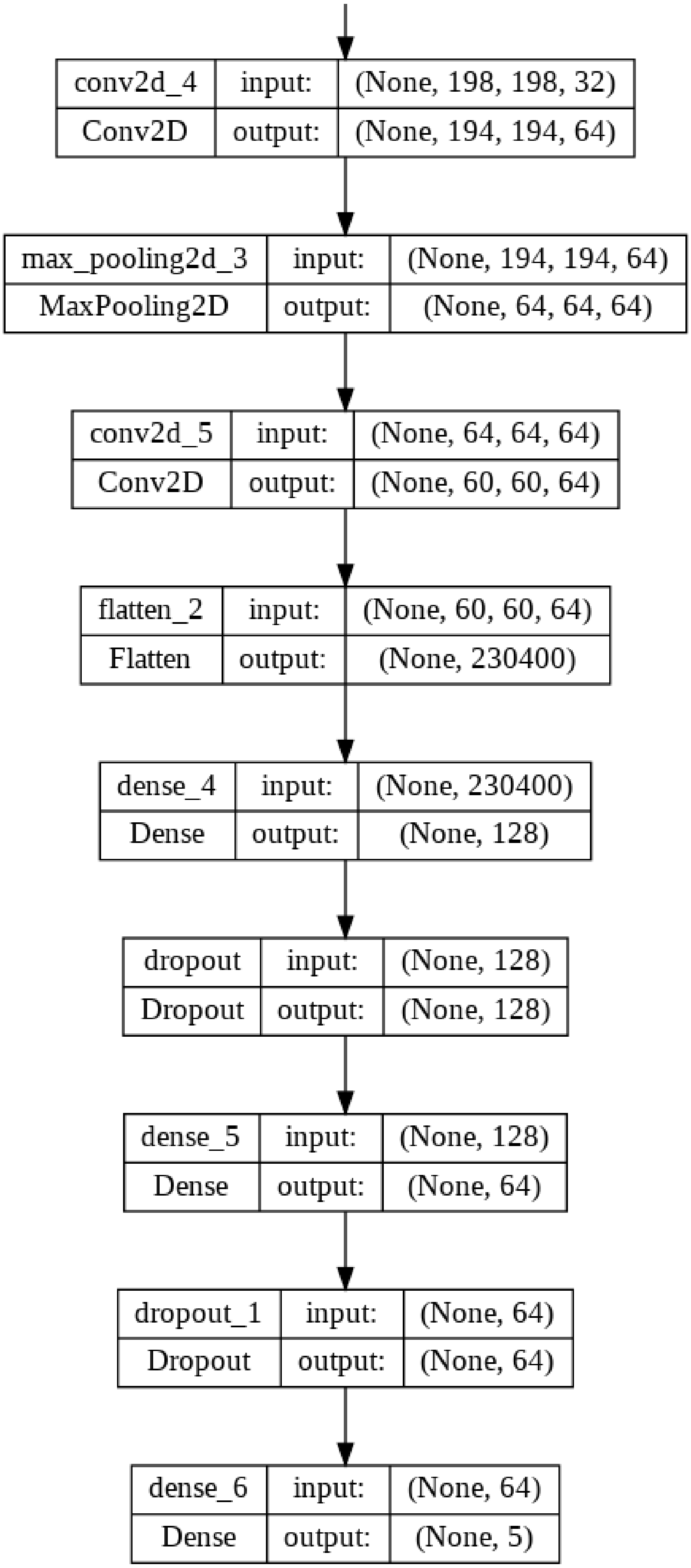
```
model2 = Sequential()

model2.add(rescaling_layer)

model2.add(Conv2D(
filters= 32, kernel_size = (5, 5), activation = "relu",
input_shape = (600, 600, 3), kernel_regularizer = l2(5e-4) ))

model2.add(MaxPooling2D(pool_size = (3, 3)))

model2.add(Conv2D(64, (5, 5), activation = "relu", kernel_regularizer = l2(5e-4)))
model2.add(MaxPooling2D(pool_size = (3, 3)))
model2.add(Conv2D(64, (5, 5), activation = "relu", kernel_regularizer = l2(5e-4)))

model2.add(Flatten())
model2.add(Dense(128, activation="relu"))
```

```
model2.add(Dropout(0.2))

model2.add(Dense(64, activation="relu"))
model2.add(Dropout(0.2))

model2.add(Dense(5, activation="softmax"))

model2.summary()
plot_model(model2, show_shapes=True, show_layer_names=True)
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 rescaling (Rescaling)       (None, 600, 600, 3)       0

 conv2d_3 (Conv2D)           (None, 596, 596, 32)      2432

 max_pooling2d_2 (MaxPooling  (None, 198, 198, 32)     0
 2D)

 conv2d_4 (Conv2D)           (None, 194, 194, 64)      51264

 max_pooling2d_3 (MaxPooling  (None, 64, 64, 64)       0
 2D)

 conv2d_5 (Conv2D)           (None, 60, 60, 64)        102464

 flatten_2 (Flatten)         (None, 230400)            0

 dense_4 (Dense)             (None, 128)               29491328

 dropout (Dropout)           (None, 128)               0

 dense_5 (Dense)             (None, 64)                8256

 dropout_1 (Dropout)         (None, 64)                0

 dense_6 (Dense)             (None, 5)                 325

=================================================================
Total params: 29,656,069
Trainable params: 29,656,069
Non-trainable params: 0
_________________________________________________________________
```

Out[39]:





For this next model, an additional layer types was added to further reduce overfitting, and thus increase accuracy. The layer added was dropout. Additionaly, L2 regularization was added to the conv2D, for the same reason.

In [40]:

```
model2.compile(optimizer='adam', loss='categorical_crossentropy',  metrics=CategoricalAc
curacy())
```

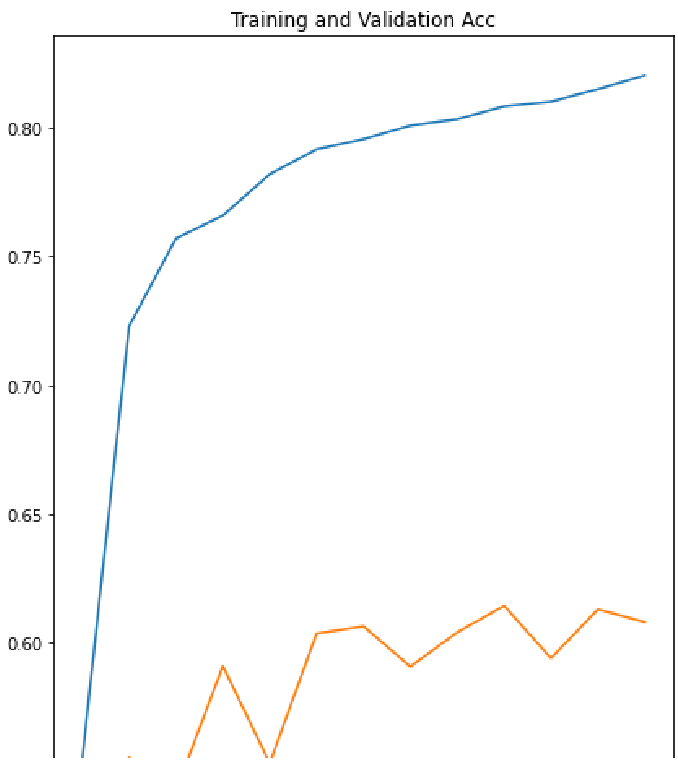
In [41]:

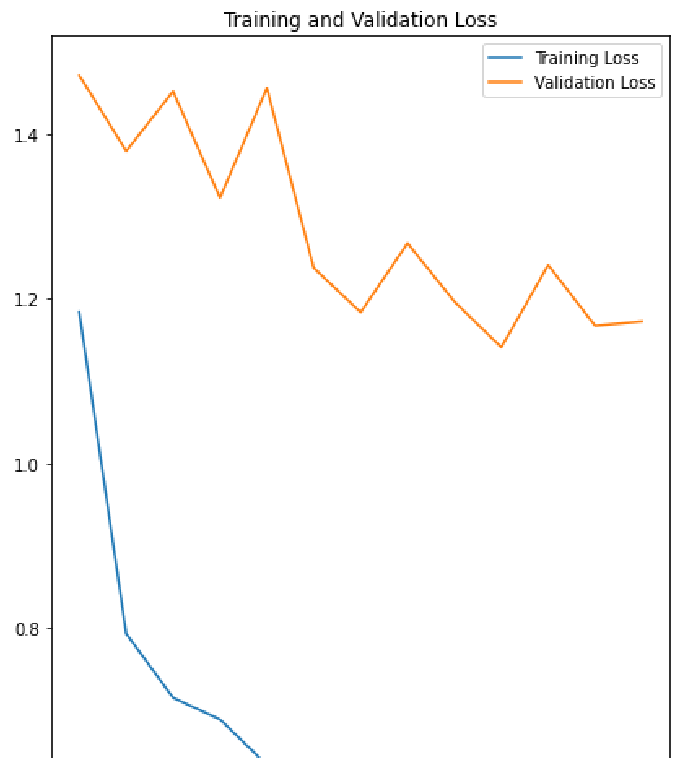
```
history2 = model2.fit(train_ds, validation_data= validation_ds, epochs= 40, callbacks = [es_callback])
```

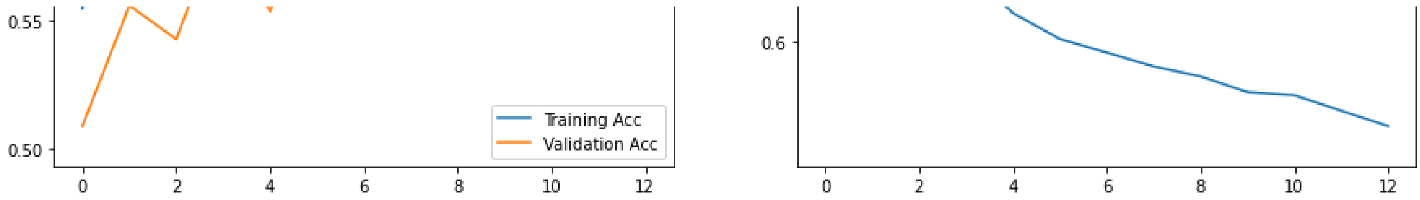
```
Epoch 1/40
196/196 [==============================] - 80s 394ms/step - loss: 1.1839 - categorical_ac
curacy: 0.5546 - val_loss: 1.4712 - val_categorical_accuracy: 0.5090
Epoch 2/40
196/196 [==============================] - 78s 391ms/step - loss: 0.7934 - categorical_ac
curacy: 0.7228 - val_loss: 1.3794 - val_categorical_accuracy: 0.5558
Epoch 3/40
196/196 [==============================] - 78s 390ms/step - loss: 0.7156 - categorical_ac
curacy: 0.7568 - val_loss: 1.4520 - val_categorical_accuracy: 0.5427
Epoch 4/40
196/196 [==============================] - 78s 390ms/step - loss: 0.6894 - categorical_ac
curacy: 0.7657 - val_loss: 1.3225 - val_categorical_accuracy: 0.5911
Epoch 5/40
196/196 [==============================] - 78s 392ms/step - loss: 0.6342 - categorical_ac
curacy: 0.7817 - val_loss: 1.4559 - val_categorical_accuracy: 0.5534
Epoch 6/40
196/196 [==============================] - 78s 390ms/step - loss: 0.6029 - categorical_ac
curacy: 0.7914 - val_loss: 1.2374 - val_categorical_accuracy: 0.6037
Epoch 7/40
196/196 [==============================] - 78s 391ms/step - loss: 0.5861 - categorical_ac
curacy: 0.7953 - val_loss: 1.1836 - val_categorical_accuracy: 0.6065
Epoch 8/40
196/196 [==============================] - 78s 391ms/step - loss: 0.5694 - categorical_ac
curacy: 0.8006 - val_loss: 1.2675 - val_categorical_accuracy: 0.5908
Epoch 9/40
196/196 [==============================] - 78s 392ms/step - loss: 0.5572 - categorical_ac
curacy: 0.8030 - val_loss: 1.1966 - val_categorical_accuracy: 0.6042
Epoch 10/40
196/196 [==============================] - 78s 391ms/step - loss: 0.5382 - categorical_ac
curacy: 0.8080 - val_loss: 1.1410 - val_categorical_accuracy: 0.6144
Epoch 11/40
196/196 [==============================] - 78s 390ms/step - loss: 0.5345 - categorical_ac
curacy: 0.8098 - val_loss: 1.2410 - val_categorical_accuracy: 0.5941
Epoch 12/40
196/196 [==============================] - 78s 391ms/step - loss: 0.5156 - categorical_ac
curacy: 0.8147 - val_loss: 1.1673 - val_categorical_accuracy: 0.6130
Epoch 13/40
196/196 [==============================] - 78s 389ms/step - loss: 0.4970 - categorical_ac
curacy: 0.8200 - val_loss: 1.1725 - val_categorical_accuracy: 0.6081
```

In [45]:

```
plot_history(history2)
```







Model 3

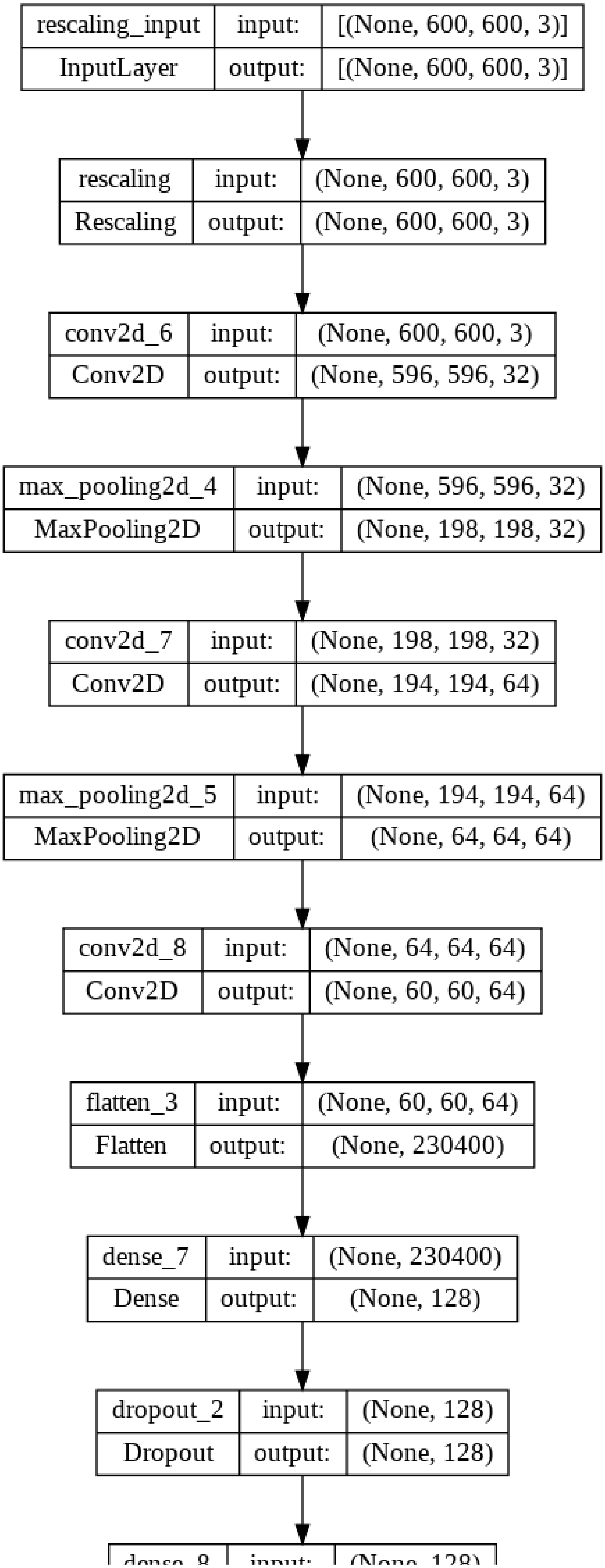
In [46]:

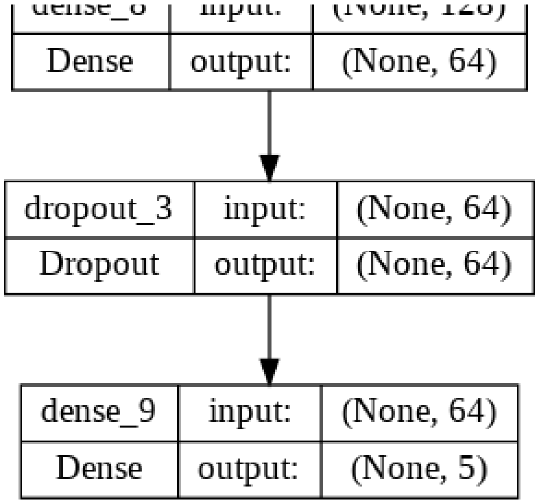
```
model3 = Sequential()

model3.add(rescaling_layer)

model3.add(Conv2D(
filters= 32, kernel_size = (5, 5), activation = "relu",
input_shape = (600, 600, 3), kernel_regularizer = l2(.01) ))

model3.add(MaxPooling2D(pool_size = (3, 3)))

model3.add(Conv2D(64, (5, 5), activation = "relu", kernel_regularizer = l2(.01)))
model3.add(MaxPooling2D(pool_size = (3, 3)))
model3.add(Conv2D(64, (5, 5), activation = "relu", kernel_regularizer = l2(.01)))

model3.add(Flatten())
model3.add(Dense(128, activation="relu"))
model3.add(Dropout(0.2))

model3.add(Dense(64, activation="relu"))
model3.add(Dropout(0.2))

model3.add(Dense(5, activation="softmax"))

model3.summary()
plot_model(model3, show_shapes=True, show_layer_names=True)
```

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 rescaling (Rescaling)       (None, 600, 600, 3)       0

 conv2d_6 (Conv2D)           (None, 596, 596, 32)      2432

 max_pooling2d_4 (MaxPooling  (None, 198, 198, 32)     0
 2D)

 conv2d_7 (Conv2D)           (None, 194, 194, 64)      51264

 max_pooling2d_5 (MaxPooling  (None, 64, 64, 64)       0
 2D)

 conv2d_8 (Conv2D)           (None, 60, 60, 64)        102464

 flatten_3 (Flatten)         (None, 230400)            0

 dense_7 (Dense)             (None, 128)               29491328

 dropout_2 (Dropout)         (None, 128)               0

 dense_8 (Dense)             (None, 64)                8256

 dropout_3 (Dropout)         (None, 64)                0

 dense_9 (Dense)             (None, 5)                 325

=================================================================
Total params: 29,656,069
Trainable params: 29,656,069
```

```
Non-trainable params: 0
_________________________________________________________________
```

Out[46]:





In [47]:

```
model3.compile(optimizer='adam', loss='categorical_crossentropy',  metrics=CategoricalAc
curacy())
```

The changes for the third model were simply making the model more layers. This was done in hopes of gaining even more accurate results.

In [48]:

```
es_callback = EarlyStopping(monitor='val_loss', patience=3)
```

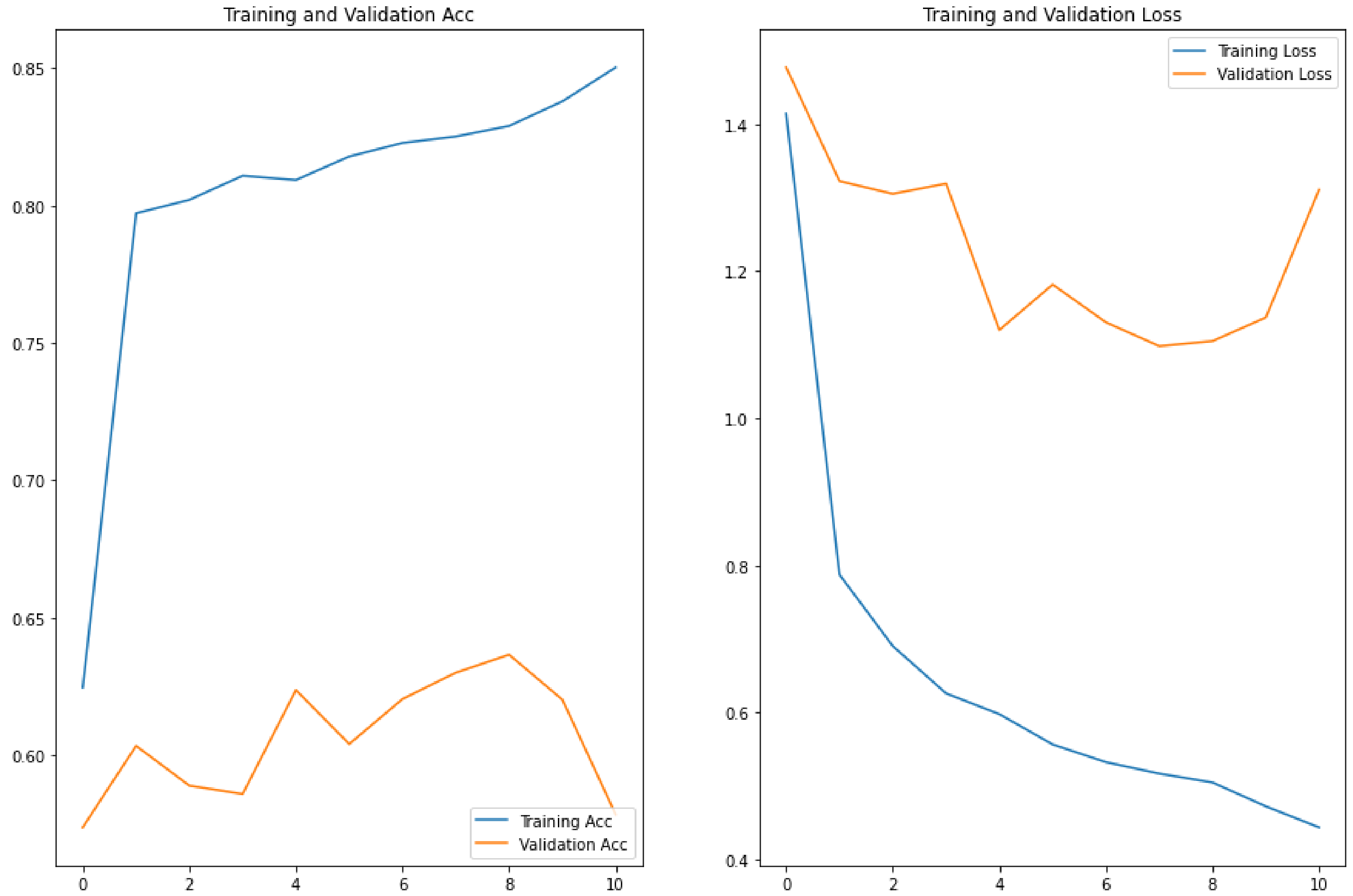
In [49]:

```
history3 = model3.fit(train_ds, validation_data= validation_ds, epochs= 100, callbacks =
[es_callback])
```

```
Epoch 1/100
196/196 [==============================] - 80s 394ms/step - loss: 1.4140 - categorical_ac
curacy: 0.6245 - val_loss: 1.4768 - val_categorical_accuracy: 0.5735
Epoch 2/100
196/196 [==============================] - 78s 391ms/step - loss: 0.7872 - categorical_ac
curacy: 0.7972 - val_loss: 1.3222 - val_categorical_accuracy: 0.6032
Epoch 3/100
196/196 [==============================] - 78s 391ms/step - loss: 0.6900 - categorical_ac
curacy: 0.8020 - val_loss: 1.3049 - val_categorical_accuracy: 0.5887
Epoch 4/100
196/196 [==============================] - 78s 391ms/step - loss: 0.6256 - categorical_ac
curacy: 0.8108 - val_loss: 1.3188 - val_categorical_accuracy: 0.5857
Epoch 5/100
196/196 [==============================] - 79s 392ms/step - loss: 0.5974 - categorical_ac
curacy: 0.8093 - val_loss: 1.1197 - val_categorical_accuracy: 0.6236
Epoch 6/100
196/196 [==============================] - 79s 392ms/step - loss: 0.5562 - categorical_ac
curacy: 0.8178 - val_loss: 1.1817 - val_categorical_accuracy: 0.6039
Epoch 7/100
196/196 [==============================] - 78s 391ms/step - loss: 0.5321 - categorical_ac
curacy: 0.8228 - val_loss: 1.1302 - val_categorical_accuracy: 0.6203
Epoch 8/100
196/196 [==============================] - 78s 391ms/step - loss: 0.5165 - categorical_ac
curacy: 0.8251 - val_loss: 1.0978 - val_categorical_accuracy: 0.6299
Epoch 9/100
196/196 [==============================] - 78s 390ms/step - loss: 0.5044 - categorical_ac
curacy: 0.8290 - val_loss: 1.1046 - val_categorical_accuracy: 0.6364
Epoch 10/100
196/196 [==============================] - 78s 390ms/step - loss: 0.4720 - categorical_ac
curacy: 0.8379 - val_loss: 1.1367 - val_categorical_accuracy: 0.6201
Epoch 11/100
196/196 [==============================] - 78s 390ms/step - loss: 0.4433 - categorical_ac
curacy: 0.8503 - val_loss: 1.3106 - val_categorical_accuracy: 0.5782
```

In [50]:

```
plot_history(history3)
```



In [51]:

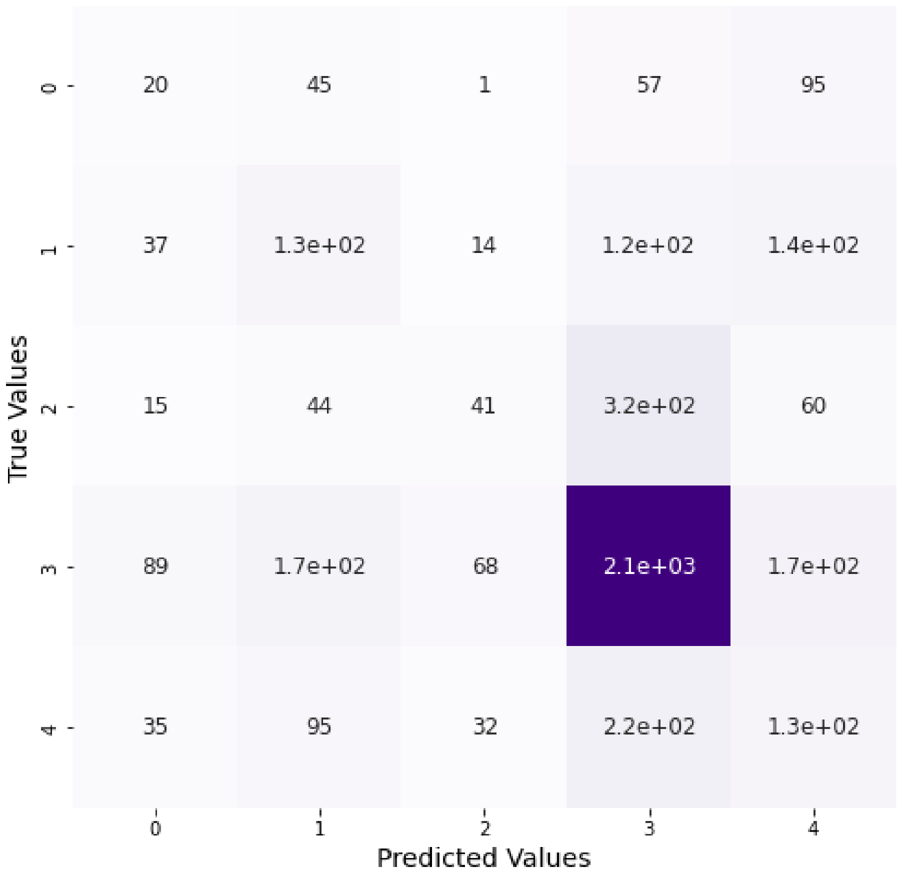
```
predictions = np.array([])
labels =  np.array([])
for x, y in test_ds:
  predictions = np.concatenate([predictions, np.argmax(model3.predict(x), axis = -1)])
  labels = np.concatenate([labels, np.argmax(y.numpy(), axis=-1)])
```

```
4/4 [==============================] - 1s 41ms/step
4/4 [==============================] - 0s 46ms/step
4/4 [==============================] - 0s 46ms/step
4/4 [==============================] - 0s 47ms/step
4/4 [==============================] - 0s 47ms/step
4/4 [==============================] - 0s 46ms/step
4/4 [==============================] - 0s 47ms/step
4/4 [==============================] - 0s 46ms/step
4/4 [==============================] - 0s 47ms/step
4/4 [==============================] - 0s 46ms/step
4/4 [==============================] - 0s 46ms/step
4/4 [==============================] - 0s 46ms/step
4/4 [==============================] - 0s 46ms/step
4/4 [==============================] - 0s 46ms/step
4/4 [==============================] - 0s 46ms/step
4/4 [==============================] - 0s 46ms/step
4/4 [==============================] - 0s 47ms/step
4/4 [==============================] - 0s 46ms/step
4/4 [==============================] - 0s 47ms/step
4/4 [==============================] - 0s 46ms/step
4/4 [==============================] - 0s 46ms/step
4/4 [==============================] - 0s 46ms/step
4/4 [==============================] - 0s 46ms/step
4/4 [==============================] - 0s 47ms/step
4/4 [==============================] - 0s 46ms/step
4/4 [==============================] - 0s 44ms/step
4/4 [==============================] - 0s 45ms/step
4/4 [==============================] - 0s 44ms/step
4/4 [==============================] - 0s 45ms/step
4/4 [==============================] - 0s 45ms/step
```

```
4/4 [==============================] - 0s 45ms/step
4/4 [==============================] - 0s 45ms/step
4/4 [==============================] - 0s 44ms/step
2/2 [==============================] - 0s 291ms/step
```

In [52]:

```
cm = confusion_matrix(labels, predictions)
fig = plt.figure(figsize = (8,8))
ax1 = fig.add_subplot(1,1,1)
sns.set(font_scale=1.4) #for label size
sns.heatmap(cm, annot=True, annot_kws={"size": 12},
     cbar = False, cmap='Purples');
ax1.set_ylabel('True Values',fontsize=14)
ax1.set_xlabel('Predicted Values',fontsize=14)
plt.show()
```



In [ ]:

```
test_ds
```

Model 4

In [53]:

```
rescaling_layer = layers.experimental.preprocessing.Rescaling(
    scale=1. / 255, input_shape=(600, 600, 3))
```

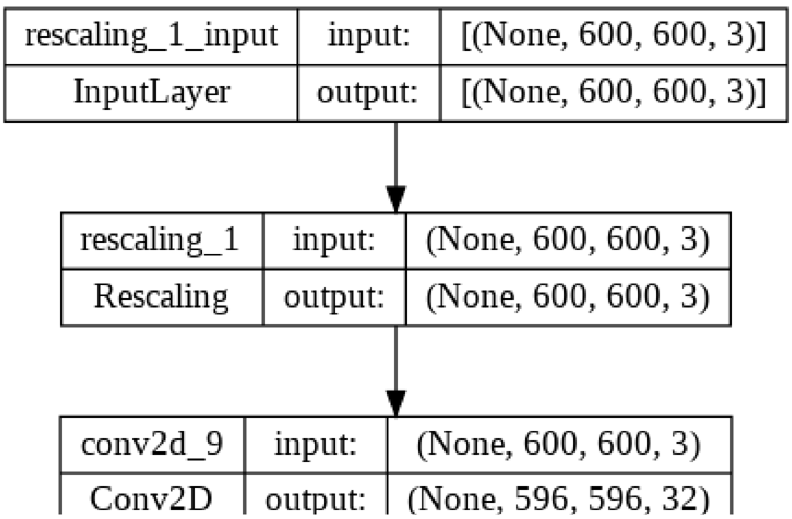
In [54]:

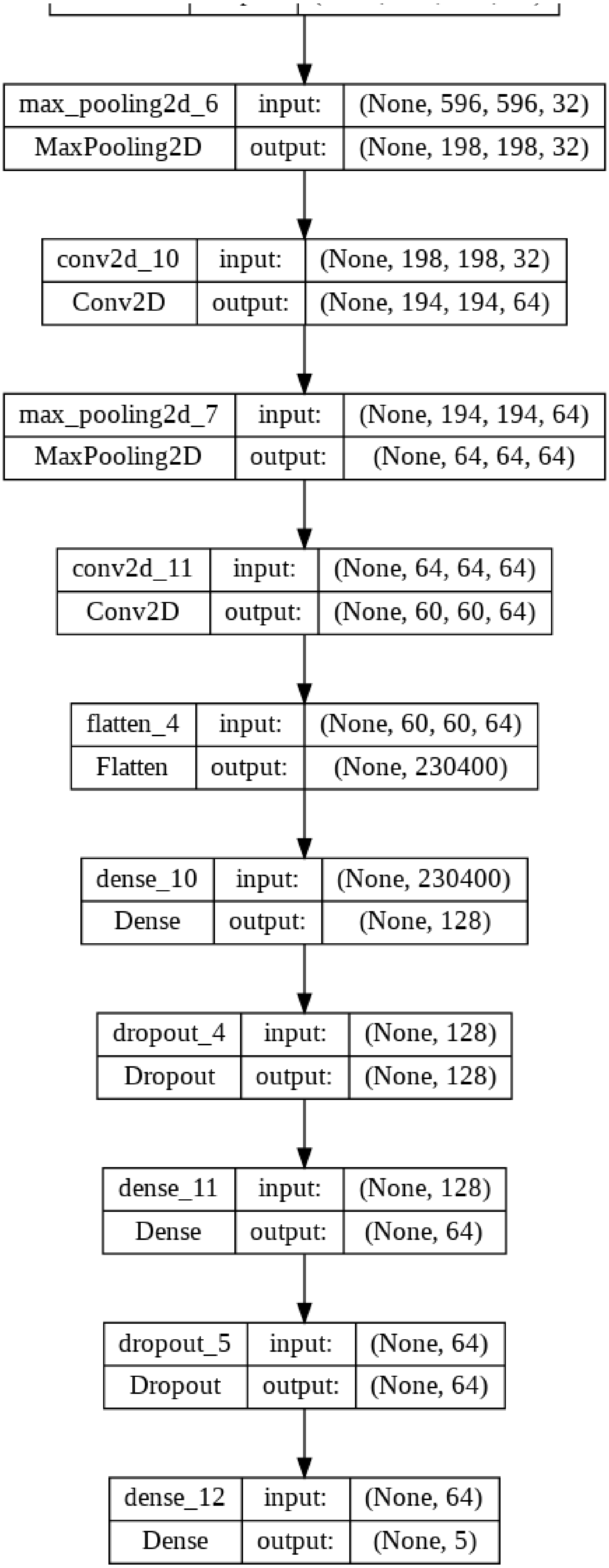
```
model4 = Sequential()

model4.add(rescaling_layer)

model4.add(Conv2D(
filters= 32, kernel_size = (5, 5), activation = "relu",kernel_regularizer = l2(.01), inp
ut_shape = (600, 600, 3) ))
```

```
model4.add(MaxPooling2D(pool_size = (3, 3)))

model4.add(Conv2D(64, (5, 5), activation = "relu", kernel_regularizer = l2(.01)))
model4.add(MaxPooling2D(pool_size = (3, 3)))
model4.add(Conv2D(64, (5, 5), activation = "relu", kernel_regularizer = l2(.01)))

model4.add(Flatten())
model4.add(Dense(128, activation="relu"))
model4.add(Dropout(0.2))

model4.add(Dense(64, activation="relu"))
model4.add(Dropout(0.2))

model4.add(Dense(5, activation="softmax"))

model4.summary()
plot_model(model4, show_shapes=True, show_layer_names=True)
```

```
Model: "sequential_4"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 rescaling_1 (Rescaling)     (None, 600, 600, 3)       0         
                                                                 
 conv2d_9 (Conv2D)           (None, 596, 596, 32)      2432      
                                                                 
 max_pooling2d_6 (MaxPooling  (None, 198, 198, 32)     0         
 2D)                                                             
                                                                 
 conv2d_10 (Conv2D)          (None, 194, 194, 64)      51264     
                                                                 
 max_pooling2d_7 (MaxPooling  (None, 64, 64, 64)       0         
 2D)                                                             
                                                                 
 conv2d_11 (Conv2D)          (None, 60, 60, 64)        102464    
                                                                 
 flatten_4 (Flatten)         (None, 230400)            0         
                                                                 
 dense_10 (Dense)            (None, 128)               29491328  
                                                                 
 dropout_4 (Dropout)         (None, 128)               0         
                                                                 
 dense_11 (Dense)            (None, 64)                8256      
                                                                 
 dropout_5 (Dropout)         (None, 64)                0         
                                                                 
 dense_12 (Dense)            (None, 5)                 325       
                                                                 
=================================================================
Total params: 29,656,069
Trainable params: 29,656,069
Non-trainable params: 0
_________________________________________________________________
```

Out[54]:





In [55]:

```
model4.compile(optimizer='adam', loss='categorical_crossentropy',  metrics=[CategoricalA
```

```
ccuracy(), Recall()])
```

In [61]:

```
es_callback = EarlyStopping(monitor='val_loss', patience=10)
```

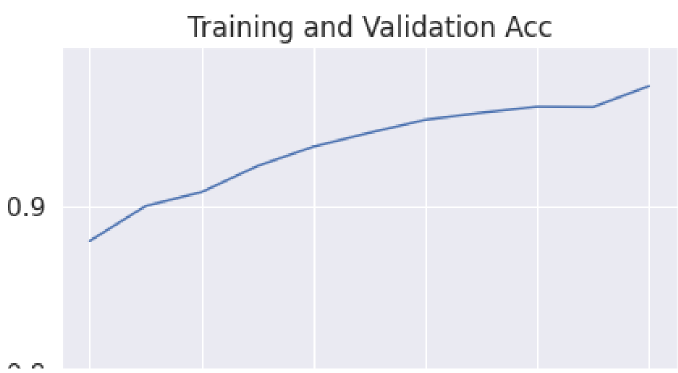
In [62]:

```
history4 = model4.fit(train_ds, validation_data= validation_ds, epochs= 100, callbacks =
[es_callback])
```

```
Epoch 1/100
196/196 [==============================] - 78s 390ms/step - loss: 0.3678 - categorical_ac
curacy: 0.8789 - recall: 0.8361 - val_loss: 1.4673 - val_categorical_accuracy: 0.5796 - v
al_recall: 0.5125
Epoch 2/100
196/196 [==============================] - 78s 391ms/step - loss: 0.3147 - categorical_ac
curacy: 0.8998 - recall: 0.8657 - val_loss: 1.7888 - val_categorical_accuracy: 0.5001 - v
al_recall: 0.4307
Epoch 3/100
196/196 [==============================] - 78s 391ms/step - loss: 0.2971 - categorical_ac
curacy: 0.9082 - recall: 0.8790 - val_loss: 1.7580 - val_categorical_accuracy: 0.5305 - v
al_recall: 0.4753
Epoch 4/100
196/196 [==============================] - 78s 391ms/step - loss: 0.2597 - categorical_ac
curacy: 0.9238 - recall: 0.8999 - val_loss: 2.0739 - val_categorical_accuracy: 0.5668 - v
al_recall: 0.5406
Epoch 5/100
196/196 [==============================] - 78s 390ms/step - loss: 0.2300 - categorical_ac
curacy: 0.9354 - recall: 0.9174 - val_loss: 1.9544 - val_categorical_accuracy: 0.4933 - v
al_recall: 0.4400
Epoch 6/100
196/196 [==============================] - 78s 391ms/step - loss: 0.2021 - categorical_ac
curacy: 0.9437 - recall: 0.9301 - val_loss: 2.0116 - val_categorical_accuracy: 0.4971 - v
al_recall: 0.4473
Epoch 7/100
196/196 [==============================] - 78s 391ms/step - loss: 0.1862 - categorical_ac
curacy: 0.9515 - recall: 0.9402 - val_loss: 2.1538 - val_categorical_accuracy: 0.5083 - v
al_recall: 0.4744
Epoch 8/100
196/196 [==============================] - 78s 391ms/step - loss: 0.1734 - categorical_ac
curacy: 0.9557 - recall: 0.9464 - val_loss: 2.5587 - val_categorical_accuracy: 0.5151 - v
al_recall: 0.4887
Epoch 9/100
196/196 [==============================] - 78s 391ms/step - loss: 0.1651 - categorical_ac
curacy: 0.9594 - recall: 0.9506 - val_loss: 2.5000 - val_categorical_accuracy: 0.5326 - v
al_recall: 0.5134
Epoch 10/100
196/196 [==============================] - 78s 390ms/step - loss: 0.1678 - categorical_ac
curacy: 0.9592 - recall: 0.9522 - val_loss: 2.3956 - val_categorical_accuracy: 0.4992 - v
al_recall: 0.4739
Epoch 11/100
196/196 [==============================] - 78s 389ms/step - loss: 0.1308 - categorical_ac
curacy: 0.9717 - recall: 0.9665 - val_loss: 2.5195 - val_categorical_accuracy: 0.5298 - v
al_recall: 0.5113
```

In [63]:

```
plot_history(history4)
```



In [64]:

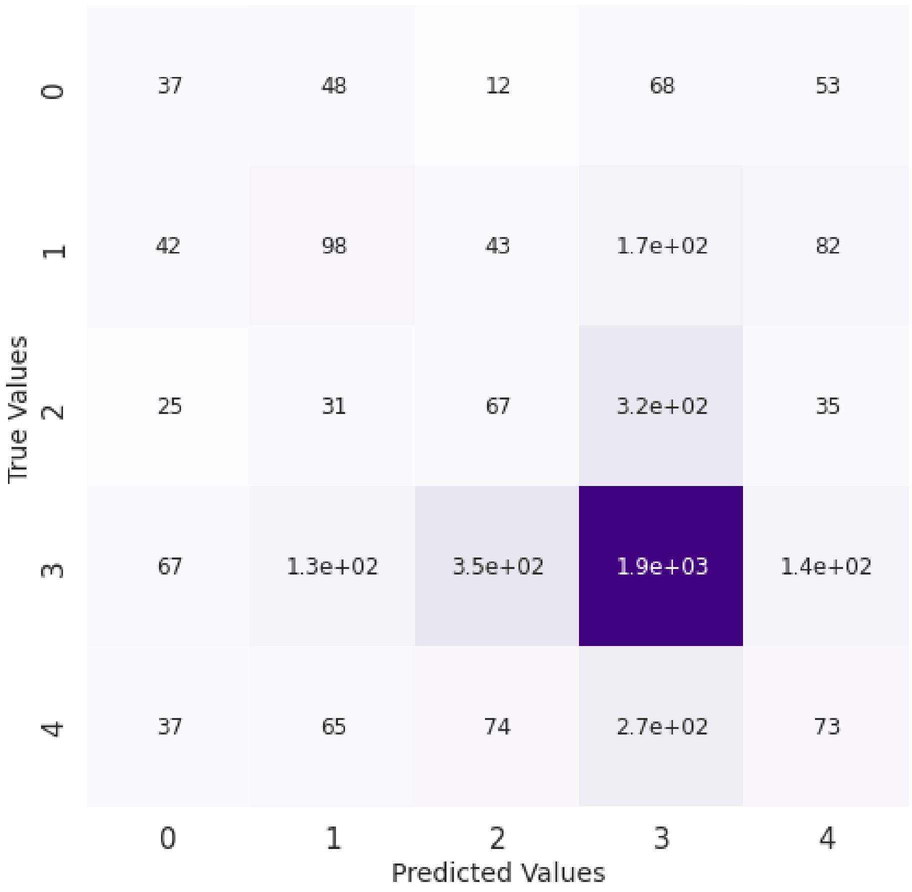
```
predictions = np.array([])
labels =  np.array([])
for x, y in test_ds:
    predictions = np.concatenate([predictions, np.argmax(model4.predict(x), axis = -1)])
    labels = np.concatenate([labels, np.argmax(y.numpy(), axis=-1)])
```

```
4/4 [==============================] - 0s 46ms/step
4/4 [==============================] - 0s 46ms/step
4/4 [==============================] - 0s 45ms/step
4/4 [==============================] - 0s 45ms/step
4/4 [==============================] - 0s 47ms/step
4/4 [==============================] - 0s 45ms/step
4/4 [==============================] - 0s 47ms/step
4/4 [==============================] - 0s 47ms/step
4/4 [==============================] - 0s 46ms/step
4/4 [==============================] - 0s 47ms/step
4/4 [==============================] - 0s 47ms/step
4/4 [==============================] - 0s 47ms/step
4/4 [==============================] - 0s 48ms/step
4/4 [==============================] - 0s 46ms/step
4/4 [==============================] - 0s 47ms/step
4/4 [==============================] - 0s 47ms/step
4/4 [==============================] - 0s 46ms/step
4/4 [==============================] - 0s 46ms/step
4/4 [==============================] - 0s 48ms/step
4/4 [==============================] - 0s 46ms/step
4/4 [==============================] - 0s 46ms/step
4/4 [==============================] - 0s 46ms/step
4/4 [==============================] - 0s 46ms/step
4/4 [==============================] - 0s 46ms/step
4/4 [==============================] - 0s 45ms/step
4/4 [==============================] - 0s 45ms/step
4/4 [==============================] - 0s 45ms/step
4/4 [==============================] - 0s 45ms/step
4/4 [==============================] - 0s 45ms/step
4/4 [==============================] - 0s 45ms/step
4/4 [==============================] - 0s 45ms/step
4/4 [==============================] - 0s 45ms/step
4/4 [==============================] - 0s 45ms/step
2/2 [==============================] - 0s 41ms/step
```

In [65]:

```
cm = confusion_matrix(labels, predictions)
fig = plt.figure(figsize = (8,8))
ax1 = fig.add_subplot(1,1,1)
sns.set(font_scale=1.4) #for label size
sns.heatmap(cm, annot=True, annot_kws={"size": 12},
     cbar = False, cmap='Purples');
```

```
ax1.set_ylabel('True Values',fontsize=14)
ax1.set_xlabel('Predicted Values',fontsize=14)
plt.show()
```



Resnet50

In [66]:

```
resmodel = ResNet50(
    include_top=False,
    weights="imagenet",
    input_tensor=None,
    input_shape=(600, 600, 3),
    pooling=None,
    classes=None)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/resnet
/resnet50_weights_tf_dim_ordering_tf_kernels_notop.h5
94765736/94765736 [==============================] - 1s 0us/step
```

In [67]:

```
resmodel.trainable = False
```

In [84]:

```
inputs = tf.keras.Input(shape=(600, 600, 3))

x = resmodel(inputs, training=False)

x = Conv2D(64, (5, 5), activation = "relu", kernel_regularizer = l2(.01))(x)

x = tf.keras.layers.GlobalAveragePooling2D()(x)

x = tf.keras.layers.Dense(128)(x)

x = tf.keras.layers.Dense(64)(x)

x = tf.keras.layers.Dropout(.02)(x)
```

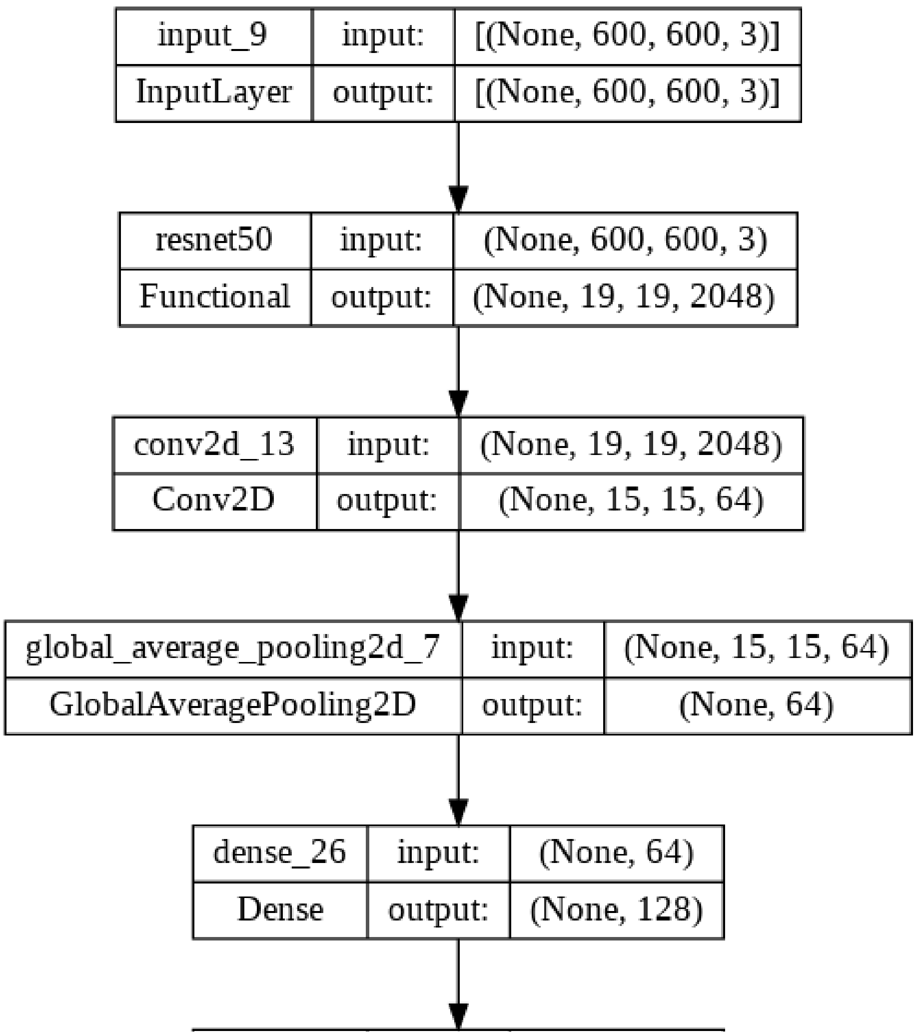
```
outputs = tf.keras.layers.Dense(5)(x)

model = tf.keras.Model(inputs, outputs)
```

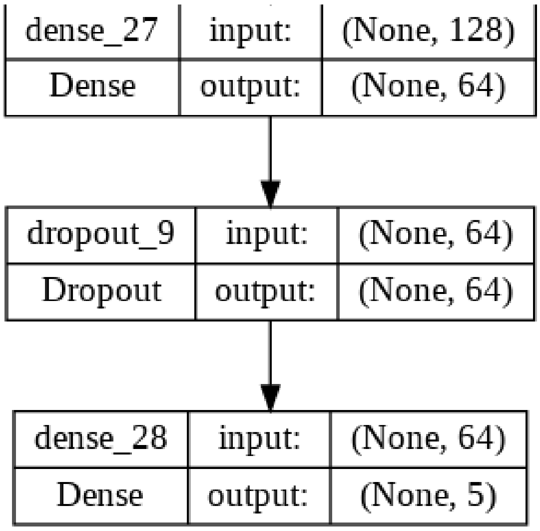
In [85]:

```
model.summary()
plot_model(model, show_shapes=True, show_layer_names=True)
```

```
Model: "model_5"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_9 (InputLayer)        [(None, 600, 600, 3)]     0

 resnet50 (Functional)       (None, 19, 19, 2048)      23587712

 conv2d_13 (Conv2D)          (None, 15, 15, 64)        3276864

 global_average_pooling2d_7   (None, 64)               0
 (GlobalAveragePooling2D)

 dense_26 (Dense)            (None, 128)               8320

 dense_27 (Dense)            (None, 64)                8256

 dropout_9 (Dropout)         (None, 64)                0

 dense_28 (Dense)            (None, 5)                 325

=================================================================
Total params: 26,881,477
Trainable params: 3,293,765
Non-trainable params: 23,587,712
_________________________________________________________________
```

Out[85]:





In [86]:

```
es_callback = EarlyStopping(monitor='val_loss', patience=3)
```

In [87]:

```
model.compile(optimizer="adam", loss="categorical_crossentropy",
              metrics=['CategoricalAccuracy'])


model.fit(train_ds, epochs=100, callbacks=es_callback, validation_data=validation_ds)
```

```
Epoch 1/100
196/196 [==============================] - 131s 644ms/step - loss: 8.0586 - categorical_a
ccuracy: 0.1968 - val_loss: 10.9524 - val_categorical_accuracy: 0.1115
Epoch 2/100
196/196 [==============================] - 127s 638ms/step - loss: 6.6040 - categorical_a
ccuracy: 0.1998 - val_loss: 10.7863 - val_categorical_accuracy: 0.1115
Epoch 3/100
196/196 [==============================] - 127s 638ms/step - loss: 6.4944 - categorical_a
ccuracy: 0.1983 - val_loss: 10.3192 - val_categorical_accuracy: 0.1115
Epoch 4/100
196/196 [==============================] - 126s 637ms/step - loss: 6.5284 - categorical_a
ccuracy: 0.1890 - val_loss: 8.5690 - val_categorical_accuracy: 0.1115
Epoch 5/100
196/196 [==============================] - 127s 638ms/step - loss: 6.4252 - categorical_a
ccuracy: 0.1667 - val_loss: 5.9369 - val_categorical_accuracy: 0.1120
Epoch 6/100
196/196 [==============================] - 127s 639ms/step - loss: 6.2778 - categorical_a
ccuracy: 0.1045 - val_loss: 4.9998 - val_categorical_accuracy: 0.1022
Epoch 7/100
196/196 [==============================] - 127s 638ms/step - loss: 7.3660 - categorical_a
ccuracy: 0.0916 - val_loss: 5.1682 - val_categorical_accuracy: 0.0816
Epoch 8/100
196/196 [==============================] - 127s 639ms/step - loss: 8.4699 - categorical_a
ccuracy: 0.1604 - val_loss: 5.3823 - val_categorical_accuracy: 0.1012
Epoch 9/100
196/196 [==============================] - 126s 637ms/step - loss: 8.9584 - categorical_a
ccuracy: 0.1915 - val_loss: 13.5164 - val_categorical_accuracy: 0.0507
```

Out[87]:

```
<keras.callbacks.History at 0x7f5456a43b50>
```

In [ ]:

```

```

Ignore

In [ ]:

```
rescaling_layer = layers.experimental.preprocessing.Rescaling(
    scale=1./255, input_shape=(600, 600, 3))

layer1 = Conv2D(filters=32, kernel_size=(3,3), input_shape=(600, 600, 3),
                activation="relu", kernel_regularizer=l2(.001))

layerpool = MaxPooling2D(pool_size=(3, 3))

layerconv = Conv2D(64, (5, 5), activation="relu", kernel_regularizer=l2(.01))

layerflat = Flatten()

layerdense1 = Dense(128, activation="relu")

layerdense2 = Dense(64, activation="relu")

layerdropout = Dropout(0.2)

finallayer = Dense(5, activation="softmax")
```

In [ ]:

```
model5 = Sequential([rescaling_layer, layer1, layerpool, layerconv,
                    layerpool, layerflat, layerdense1, layerdense2,
                    layerdropout, finallayer])
```