In [ ]:
```python
import keras
import tensorflow as tf
import numpy as np
import os
from sklearn.metrics import classification_report,confusion_matrix
import seaborn as sb
import cv2
os.system("rm /content/archive-4/train/.DS_Store")
os.system("rm /content/archive-4/test/.DS_Store")
os.system("rm /content/archive-4/valid/.DS_Store")
```

Out[ ]: 256

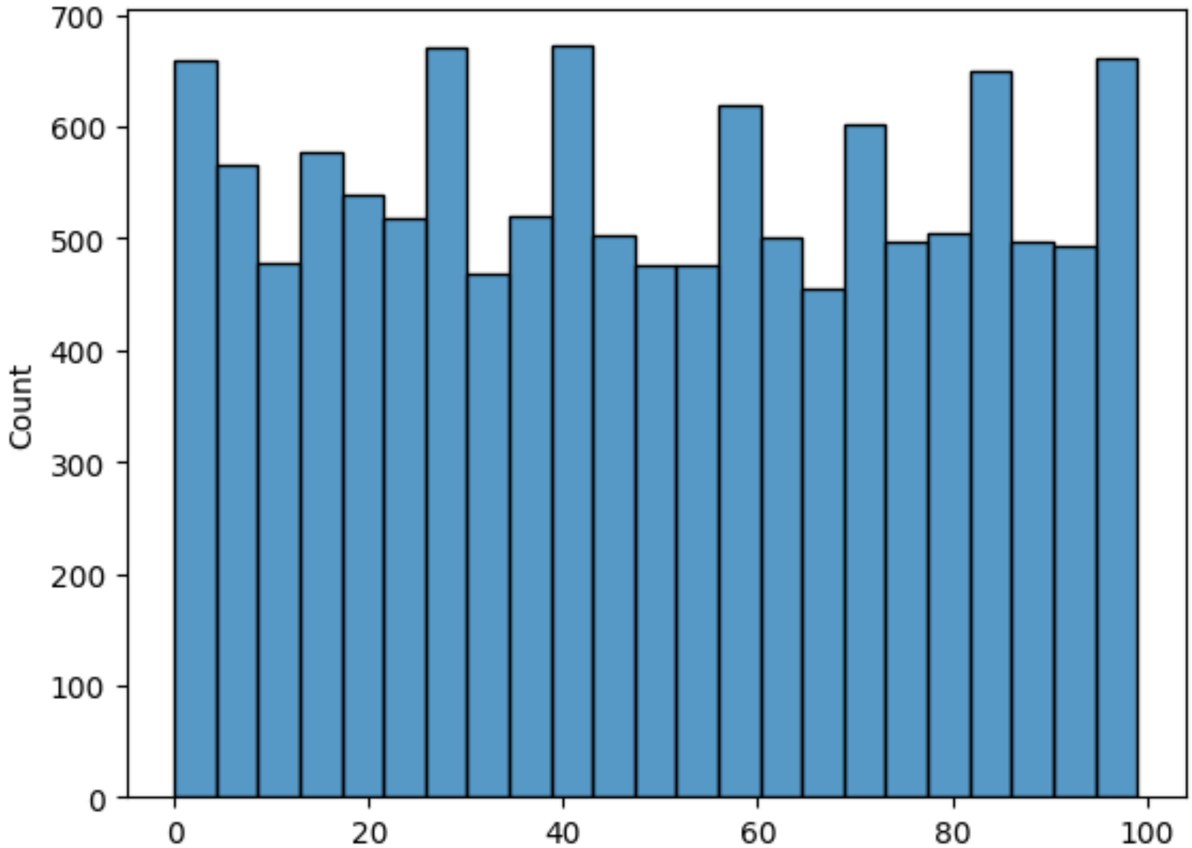
I will now import and standardize the data.

In [ ]:
```python
global labels
labels=os.listdir("/content/archive-4/train")

def getdataset(datapath):
    global labels
    imlen = 224
    data = []
    for label in labels:
        npath=os.path.join(datapath,label)
        nnum=labels.index(label)
        for image in os.listdir(npath):
            imageArray = cv2.imread(os.path.join(npath,image))[::-1]
            resized_arr = cv2.resize(imageArray, (imlen, imlen))
            if (len(resized_arr) == 224 and len(resized_arr[0]) == 224) and
                data.append([resized_arr,nnum])
            else:
                raise ValueError
    return data

train = getdataset("/content/archive-4/train")
validation = getdataset("/content/archive-4/valid")
test = getdataset("/content/archive-4/test")
```

Below is a graph counting the occurrences of each species given their number of appearance in the data.

In [ ]:
```python
l=list([x[1] for x in train])
sb.histplot(l)
```

Out[ ]: <Axes: ylabel='Count'>



As shown by the graph above, this dataset contains around 120 images for each of the 100 species of butterfly or moth in the dataset within the training data. Given the data, this model should be able to identify the species of a butterfly or a moth given its picture in the given format, as long as it is within the 100 species that are in the training dataset.

In [ ]:

```
x_train = []
y_train = []
x_val = []
y_val = []
x_test=[]
y_test=[]

for f1 in train:
    feature=f1[0]
    label=f1[1]
    x_train.append(feature)
    y_train.append(label)

for f2 in validation:
    feature=f2[0]
    label=f2[1]
    x_val.append(feature)
    y_val.append(label)

for f3 in test:
    feature=f3[0]
    label=f3[1]
    x_test.append(feature)
    y_test.append(label)

x_train=np.array(x_train)
y_train=keras.utils.to_categorical(np.array(y_train))
x_val=np.array(x_val)
y_val=keras.utils.to_categorical(np.array(y_val))
x_test=np.array(x_test)
y_test=keras.utils.to_categorical(np.array(y_test))
```

Below we begin working with two model architectures to identify the moths or butterflies.

In [ ]:

```python
model = tf.keras.Sequential()
model.add(tf.keras.layers.Conv2D(32,3,padding="same", activation="relu", inp
model.add(tf.keras.layers.MaxPool2D())
model.add(tf.keras.layers.Conv2D(32,3,padding="same", activation="relu", inp
model.add(tf.keras.layers.MaxPool2D())
model.add(tf.keras.layers.Conv2D(32,3,padding="same", activation="relu", inp
model.add(tf.keras.layers.MaxPool2D())
model.add(tf.keras.layers.Conv2D(32,3,padding="same", activation="relu", inp
model.add(tf.keras.layers.MaxPool2D())
model.add(tf.keras.layers.Flatten())
model.add(tf.keras.layers.Dense(128,activation="relu"))
model.add(tf.keras.layers.Dense(128,activation="relu"))
model.add(tf.keras.layers.Dense(128,activation="relu"))
model.add(tf.keras.layers.Dense(128,activation="relu"))
model.add(tf.keras.layers.Dense(128,activation="relu"))
model.add(tf.keras.layers.Dense(128,activation="relu"))
model.add(tf.keras.layers.Dense(len(labels), activation="softmax"))
model.summary()
#print(x_val.shape,y_val.shape)
opt = keras.optimizers.Adam(learning_rate=0.001)
model.compile(optimizer = opt ,
              loss='categorical_crossentropy',
              metrics = ['accuracy'])
history = model.fit(x_train,y_train,epochs = 50 , validation_data = (x_val,
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 224, 224, 32)      896

 max_pooling2d (MaxPooling2D  (None, 112, 112, 32)     0
 )

 conv2d_1 (Conv2D)           (None, 112, 112, 32)      9248

 max_pooling2d_1 (MaxPooling  (None, 56, 56, 32)       0
 2D)

 conv2d_2 (Conv2D)           (None, 56, 56, 32)        9248

 max_pooling2d_2 (MaxPooling  (None, 28, 28, 32)       0
 2D)

 conv2d_3 (Conv2D)           (None, 28, 28, 32)        9248

 max_pooling2d_3 (MaxPooling  (None, 14, 14, 32)       0
 2D)

 flatten (Flatten)           (None, 6272)              0

 dense (Dense)               (None, 128)               802944
```

```
 dense_1 (Dense)             (None, 128)               16512

 dense_2 (Dense)             (None, 128)               16512

 dense_3 (Dense)             (None, 128)               16512

 dense_4 (Dense)             (None, 128)               16512

 dense_5 (Dense)             (None, 128)               16512

 dense_6 (Dense)             (None, 100)               12900

=================================================================
Total params: 927,044
Trainable params: 927,044
Non-trainable params: 0
_________________________________________________________________
Epoch 1/50
394/394 [==============================] - 24s 34ms/step - loss: 4.4618 - a
ccuracy: 0.0250 - val_loss: 3.9146 - val_accuracy: 0.0620
Epoch 2/50
394/394 [==============================] - 12s 30ms/step - loss: 3.6523 - a
ccuracy: 0.0985 - val_loss: 3.2565 - val_accuracy: 0.1480
Epoch 3/50
394/394 [==============================] - 12s 31ms/step - loss: 2.9644 - a
ccuracy: 0.2244 - val_loss: 2.5998 - val_accuracy: 0.2940
Epoch 4/50
394/394 [==============================] - 13s 32ms/step - loss: 2.3904 - a
ccuracy: 0.3518 - val_loss: 2.2010 - val_accuracy: 0.3960
Epoch 5/50
394/394 [==============================] - 12s 31ms/step - loss: 1.9830 - a
ccuracy: 0.4370 - val_loss: 1.9783 - val_accuracy: 0.4420
Epoch 6/50
394/394 [==============================] - 12s 31ms/step - loss: 1.6262 - a
ccuracy: 0.5312 - val_loss: 1.9083 - val_accuracy: 0.4700
Epoch 7/50
394/394 [==============================] - 12s 30ms/step - loss: 1.3427 - a
ccuracy: 0.6053 - val_loss: 1.7770 - val_accuracy: 0.5540
Epoch 8/50
394/394 [==============================] - 12s 30ms/step - loss: 1.1393 - a
ccuracy: 0.6582 - val_loss: 1.8638 - val_accuracy: 0.5500
Epoch 9/50
394/394 [==============================] - 12s 30ms/step - loss: 0.9620 - a
ccuracy: 0.7111 - val_loss: 2.1989 - val_accuracy: 0.5340
Epoch 10/50
394/394 [==============================] - 12s 30ms/step - loss: 0.8272 - a
ccuracy: 0.7497 - val_loss: 2.0640 - val_accuracy: 0.5300
Epoch 11/50
394/394 [==============================] - 12s 29ms/step - loss: 0.7141 - a
ccuracy: 0.7822 - val_loss: 2.1819 - val_accuracy: 0.5360
Epoch 12/50
394/394 [==============================] - 12s 30ms/step - loss: 0.6528 - a
ccuracy: 0.8023 - val_loss: 2.2029 - val_accuracy: 0.5380
```

```
Epoch 13/50
394/394 [==============================] - 12s 29ms/step - loss: 0.5446 - a
ccuracy: 0.8349 - val_loss: 2.1010 - val_accuracy: 0.5860
Epoch 14/50
394/394 [==============================] - 12s 30ms/step - loss: 0.5313 - a
ccuracy: 0.8383 - val_loss: 2.4437 - val_accuracy: 0.5620
Epoch 15/50
394/394 [==============================] - 12s 30ms/step - loss: 0.4859 - a
ccuracy: 0.8573 - val_loss: 2.3873 - val_accuracy: 0.5740
Epoch 16/50
394/394 [==============================] - 12s 29ms/step - loss: 0.4238 - a
ccuracy: 0.8722 - val_loss: 2.5858 - val_accuracy: 0.5520
Epoch 17/50
394/394 [==============================] - 12s 29ms/step - loss: 0.3720 - a
ccuracy: 0.8896 - val_loss: 2.6152 - val_accuracy: 0.5760
Epoch 18/50
394/394 [==============================] - 12s 29ms/step - loss: 0.3956 - a
ccuracy: 0.8843 - val_loss: 2.5055 - val_accuracy: 0.5560
Epoch 19/50
394/394 [==============================] - 12s 29ms/step - loss: 0.3597 - a
ccuracy: 0.8964 - val_loss: 2.6001 - val_accuracy: 0.5820
Epoch 20/50
394/394 [==============================] - 12s 29ms/step - loss: 0.3238 - a
ccuracy: 0.9053 - val_loss: 2.4857 - val_accuracy: 0.5660
Epoch 21/50
394/394 [==============================] - 12s 30ms/step - loss: 0.3433 - a
ccuracy: 0.9030 - val_loss: 2.5267 - val_accuracy: 0.5300
Epoch 22/50
394/394 [==============================] - 12s 30ms/step - loss: 0.3005 - a
ccuracy: 0.9144 - val_loss: 3.0214 - val_accuracy: 0.5680
Epoch 23/50
394/394 [==============================] - 12s 29ms/step - loss: 0.3182 - a
ccuracy: 0.9082 - val_loss: 2.8637 - val_accuracy: 0.5120
Epoch 24/50
394/394 [==============================] - 12s 29ms/step - loss: 0.3019 - a
ccuracy: 0.9211 - val_loss: 2.7859 - val_accuracy: 0.5520
Epoch 25/50
394/394 [==============================] - 12s 30ms/step - loss: 0.2544 - a
ccuracy: 0.9286 - val_loss: 3.1251 - val_accuracy: 0.5440
Epoch 26/50
394/394 [==============================] - 11s 29ms/step - loss: 0.2763 - a
ccuracy: 0.9232 - val_loss: 3.0861 - val_accuracy: 0.5540
Epoch 27/50
394/394 [==============================] - 12s 29ms/step - loss: 0.2855 - a
ccuracy: 0.9246 - val_loss: 3.1869 - val_accuracy: 0.5480
Epoch 28/50
394/394 [==============================] - 12s 29ms/step - loss: 0.2181 - a
ccuracy: 0.9374 - val_loss: 2.8449 - val_accuracy: 0.5060
Epoch 29/50
394/394 [==============================] - 12s 29ms/step - loss: 0.2575 - a
ccuracy: 0.9288 - val_loss: 2.6481 - val_accuracy: 0.5440
Epoch 30/50
394/394 [==============================] - 12s 29ms/step - loss: 0.2449 - a
```

```
ccuracy: 0.9339 - val_loss: 2.8472 - val_accuracy: 0.5300
Epoch 31/50
394/394 [==============================] - 12s 29ms/step - loss: 0.2157 - a
ccuracy: 0.9417 - val_loss: 3.1575 - val_accuracy: 0.5400
Epoch 32/50
394/394 [==============================] - 12s 29ms/step - loss: 0.2465 - a
ccuracy: 0.9356 - val_loss: 2.9494 - val_accuracy: 0.5340
Epoch 33/50
394/394 [==============================] - 12s 29ms/step - loss: 0.2353 - a
ccuracy: 0.9387 - val_loss: 2.6987 - val_accuracy: 0.5920
Epoch 34/50
394/394 [==============================] - 12s 29ms/step - loss: 0.2258 - a
ccuracy: 0.9397 - val_loss: 3.1982 - val_accuracy: 0.5540
Epoch 35/50
394/394 [==============================] - 12s 29ms/step - loss: 0.2080 - a
ccuracy: 0.9457 - val_loss: 3.1328 - val_accuracy: 0.5280
Epoch 36/50
394/394 [==============================] - 12s 29ms/step - loss: 0.1913 - a
ccuracy: 0.9499 - val_loss: 3.0884 - val_accuracy: 0.5560
Epoch 37/50
394/394 [==============================] - 12s 29ms/step - loss: 0.1811 - a
ccuracy: 0.9543 - val_loss: 3.4198 - val_accuracy: 0.5340
Epoch 38/50
394/394 [==============================] - 12s 30ms/step - loss: 0.1578 - a
ccuracy: 0.9583 - val_loss: 3.1341 - val_accuracy: 0.5220
Epoch 39/50
394/394 [==============================] - 12s 29ms/step - loss: 0.2466 - a
ccuracy: 0.9358 - val_loss: 3.2955 - val_accuracy: 0.5660
Epoch 40/50
394/394 [==============================] - 12s 30ms/step - loss: 0.2419 - a
ccuracy: 0.9420 - val_loss: 3.4802 - val_accuracy: 0.5440
Epoch 41/50
394/394 [==============================] - 12s 29ms/step - loss: 0.1863 - a
ccuracy: 0.9505 - val_loss: 3.3242 - val_accuracy: 0.5300
Epoch 42/50
394/394 [==============================] - 12s 30ms/step - loss: 0.2155 - a
ccuracy: 0.9434 - val_loss: 3.1052 - val_accuracy: 0.5580
Epoch 43/50
394/394 [==============================] - 11s 29ms/step - loss: 0.1789 - a
ccuracy: 0.9532 - val_loss: 3.2570 - val_accuracy: 0.5340
Epoch 44/50
394/394 [==============================] - 12s 29ms/step - loss: 0.1858 - a
ccuracy: 0.9515 - val_loss: 3.3015 - val_accuracy: 0.5320
Epoch 45/50
394/394 [==============================] - 12s 29ms/step - loss: 0.1757 - a
ccuracy: 0.9559 - val_loss: 3.4653 - val_accuracy: 0.5600
Epoch 46/50
394/394 [==============================] - 12s 29ms/step - loss: 0.1891 - a
ccuracy: 0.9557 - val_loss: 3.4814 - val_accuracy: 0.5360
Epoch 47/50
394/394 [==============================] - 12s 29ms/step - loss: 0.1840 - a
ccuracy: 0.9555 - val_loss: 3.2866 - val_accuracy: 0.5540
Epoch 48/50
```

```
394/394 [==============================] - 12s 29ms/step - loss: 0.1591 - a
ccuracy: 0.9613 - val_loss: 3.7170 - val_accuracy: 0.5380
Epoch 49/50
394/394 [==============================] - 11s 29ms/step - loss: 0.1996 - a
ccuracy: 0.9497 - val_loss: 3.2041 - val_accuracy: 0.5520
Epoch 50/50
394/394 [==============================] - 12s 29ms/step - loss: 0.1878 - a
ccuracy: 0.9550 - val_loss: 3.4011 - val_accuracy: 0.5300
```

In [ ]:

```
model2 = tf.keras.Sequential()
model2.add(tf.keras.layers.Conv2D(32,3,padding="same", activation="relu", ir
model2.add(tf.keras.layers.MaxPool2D())
model2.add(tf.keras.layers.Conv2D(32,3,padding="same", activation="relu", ir
model2.add(tf.keras.layers.MaxPool2D())

model2.add(tf.keras.layers.Flatten())
model2.add(tf.keras.layers.Dropout(0.4))
model2.add(tf.keras.layers.Dense(128,activation="relu"))
model2.add(tf.keras.layers.Dense(128,activation="relu"))

model2.add(tf.keras.layers.Dense(len(labels), activation="softmax"))
model2.summary()
#print(x_val.shape,y_val.shape)
opt = keras.optimizers.Adam(learning_rate=0.001)
model2.compile(optimizer = opt ,
              loss='categorical_crossentropy',
              metrics = ['accuracy'])
history = model2.fit(x_train,y_train,epochs = 50 , validation_data = (x_val,
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_4 (Conv2D)           (None, 224, 224, 32)      896

 max_pooling2d_4 (MaxPooling  (None, 112, 112, 32)     0
 2D)

 conv2d_5 (Conv2D)           (None, 112, 112, 32)      9248

 max_pooling2d_5 (MaxPooling  (None, 56, 56, 32)       0
 2D)

 flatten_1 (Flatten)         (None, 100352)            0

 dropout (Dropout)           (None, 100352)            0

 dense_7 (Dense)             (None, 128)               12845184

 dense_8 (Dense)             (None, 128)               16512

 dense_9 (Dense)             (None, 100)               12900

=================================================================
```

```
Total params: 12,884,740
Trainable params: 12,884,740
Non-trainable params: 0
_________________________________________________________________
Epoch 1/50
394/394 [==============================] - 13s 32ms/step - loss: 15.9606 -
accuracy: 0.0270 - val_loss: 4.2316 - val_accuracy: 0.0840
Epoch 2/50
394/394 [==============================] - 12s 30ms/step - loss: 3.9294 - a
ccuracy: 0.1121 - val_loss: 3.8522 - val_accuracy: 0.1200
Epoch 3/50
394/394 [==============================] - 12s 30ms/step - loss: 3.1782 - a
ccuracy: 0.2473 - val_loss: 4.0430 - val_accuracy: 0.1460
Epoch 4/50
394/394 [==============================] - 12s 30ms/step - loss: 2.4018 - a
ccuracy: 0.4151 - val_loss: 3.8451 - val_accuracy: 0.1740
Epoch 5/50
394/394 [==============================] - 12s 30ms/step - loss: 1.7612 - a
ccuracy: 0.5613 - val_loss: 4.4897 - val_accuracy: 0.2080
Epoch 6/50
394/394 [==============================] - 12s 30ms/step - loss: 1.3370 - a
ccuracy: 0.6659 - val_loss: 4.7890 - val_accuracy: 0.1940
Epoch 7/50
394/394 [==============================] - 12s 30ms/step - loss: 1.0810 - a
ccuracy: 0.7249 - val_loss: 5.0338 - val_accuracy: 0.2060
Epoch 8/50
394/394 [==============================] - 12s 30ms/step - loss: 0.8954 - a
ccuracy: 0.7783 - val_loss: 6.0762 - val_accuracy: 0.1960
Epoch 9/50
394/394 [==============================] - 12s 30ms/step - loss: 0.7256 - a
ccuracy: 0.8186 - val_loss: 6.6165 - val_accuracy: 0.2180
Epoch 10/50
394/394 [==============================] - 12s 30ms/step - loss: 0.6357 - a
ccuracy: 0.8448 - val_loss: 6.2802 - val_accuracy: 0.2040
Epoch 11/50
394/394 [==============================] - 12s 30ms/step - loss: 0.5965 - a
ccuracy: 0.8572 - val_loss: 7.0893 - val_accuracy: 0.1660
Epoch 12/50
394/394 [==============================] - 12s 30ms/step - loss: 0.5497 - a
ccuracy: 0.8745 - val_loss: 7.5881 - val_accuracy: 0.2180
Epoch 13/50
394/394 [==============================] - 12s 30ms/step - loss: 0.4812 - a
ccuracy: 0.8822 - val_loss: 7.2021 - val_accuracy: 0.1880
Epoch 14/50
394/394 [==============================] - 12s 30ms/step - loss: 0.4651 - a
ccuracy: 0.8926 - val_loss: 7.1815 - val_accuracy: 0.2140
Epoch 15/50
394/394 [==============================] - 12s 30ms/step - loss: 0.5061 - a
ccuracy: 0.8896 - val_loss: 7.9525 - val_accuracy: 0.1820
Epoch 16/50
394/394 [==============================] - 12s 30ms/step - loss: 0.4348 - a
ccuracy: 0.9049 - val_loss: 8.5394 - val_accuracy: 0.2260
Epoch 17/50
```

```
394/394 [==============================] - 12s 30ms/step - loss: 0.3790 - a
ccuracy: 0.9108 - val_loss: 8.0896 - val_accuracy: 0.2060
Epoch 18/50
394/394 [==============================] - 12s 30ms/step - loss: 0.3562 - a
ccuracy: 0.9223 - val_loss: 8.9364 - val_accuracy: 0.2100
Epoch 19/50
394/394 [==============================] - 12s 30ms/step - loss: 0.3151 - a
ccuracy: 0.9255 - val_loss: 9.1967 - val_accuracy: 0.2220
Epoch 20/50
394/394 [==============================] - 12s 30ms/step - loss: 0.3927 - a
ccuracy: 0.9202 - val_loss: 8.5863 - val_accuracy: 0.2200
Epoch 21/50
394/394 [==============================] - 12s 30ms/step - loss: 0.3416 - a
ccuracy: 0.9250 - val_loss: 9.4951 - val_accuracy: 0.2240
Epoch 22/50
394/394 [==============================] - 13s 34ms/step - loss: 0.3621 - a
ccuracy: 0.9215 - val_loss: 9.3373 - val_accuracy: 0.2360
Epoch 23/50
394/394 [==============================] - 13s 34ms/step - loss: 0.3358 - a
ccuracy: 0.9279 - val_loss: 9.6100 - val_accuracy: 0.2320
Epoch 24/50
394/394 [==============================] - 12s 30ms/step - loss: 0.3788 - a
ccuracy: 0.9262 - val_loss: 10.0738 - val_accuracy: 0.2300
Epoch 25/50
394/394 [==============================] - 12s 29ms/step - loss: 0.3283 - a
ccuracy: 0.9302 - val_loss: 8.6381 - val_accuracy: 0.2560
Epoch 26/50
394/394 [==============================] - 12s 29ms/step - loss: 0.2987 - a
ccuracy: 0.9339 - val_loss: 9.8998 - val_accuracy: 0.2060
Epoch 27/50
394/394 [==============================] - 12s 30ms/step - loss: 0.2381 - a
ccuracy: 0.9497 - val_loss: 9.9193 - val_accuracy: 0.2280
Epoch 28/50
394/394 [==============================] - 12s 30ms/step - loss: 0.2901 - a
ccuracy: 0.9384 - val_loss: 9.3363 - val_accuracy: 0.2320
Epoch 29/50
394/394 [==============================] - 12s 30ms/step - loss: 0.2486 - a
ccuracy: 0.9512 - val_loss: 10.1749 - val_accuracy: 0.2360
Epoch 30/50
394/394 [==============================] - 12s 30ms/step - loss: 0.2582 - a
ccuracy: 0.9466 - val_loss: 9.2558 - val_accuracy: 0.2220
Epoch 31/50
394/394 [==============================] - 12s 30ms/step - loss: 0.2795 - a
ccuracy: 0.9452 - val_loss: 10.4508 - val_accuracy: 0.2340
Epoch 32/50
394/394 [==============================] - 12s 30ms/step - loss: 0.2173 - a
ccuracy: 0.9544 - val_loss: 10.8989 - val_accuracy: 0.2420
Epoch 33/50
394/394 [==============================] - 12s 29ms/step - loss: 0.2296 - a
ccuracy: 0.9506 - val_loss: 12.2893 - val_accuracy: 0.2280
Epoch 34/50
394/394 [==============================] - 12s 30ms/step - loss: 0.2450 - a
ccuracy: 0.9486 - val_loss: 10.6904 - val_accuracy: 0.2260
```

```
Epoch 35/50
394/394 [==============================] - 12s 30ms/step - loss: 0.2670 - a
ccuracy: 0.9491 - val_loss: 10.5507 - val_accuracy: 0.2880
Epoch 36/50
394/394 [==============================] - 12s 30ms/step - loss: 0.1864 - a
ccuracy: 0.9623 - val_loss: 10.9337 - val_accuracy: 0.2360
Epoch 37/50
394/394 [==============================] - 12s 30ms/step - loss: 0.2248 - a
ccuracy: 0.9557 - val_loss: 12.6483 - val_accuracy: 0.2520
Epoch 38/50
394/394 [==============================] - 12s 29ms/step - loss: 0.2487 - a
ccuracy: 0.9523 - val_loss: 11.0653 - val_accuracy: 0.2740
Epoch 39/50
394/394 [==============================] - 12s 29ms/step - loss: 0.2243 - a
ccuracy: 0.9565 - val_loss: 13.4816 - val_accuracy: 0.2140
Epoch 40/50
394/394 [==============================] - 12s 30ms/step - loss: 0.2433 - a
ccuracy: 0.9537 - val_loss: 11.2654 - val_accuracy: 0.2680
Epoch 41/50
394/394 [==============================] - 12s 29ms/step - loss: 0.2256 - a
ccuracy: 0.9572 - val_loss: 11.6863 - val_accuracy: 0.2520
Epoch 42/50
394/394 [==============================] - 12s 29ms/step - loss: 0.2345 - a
ccuracy: 0.9539 - val_loss: 13.0187 - val_accuracy: 0.2380
Epoch 43/50
394/394 [==============================] - 12s 29ms/step - loss: 0.2458 - a
ccuracy: 0.9595 - val_loss: 13.0893 - val_accuracy: 0.2080
Epoch 44/50
394/394 [==============================] - 12s 30ms/step - loss: 0.2835 - a
ccuracy: 0.9529 - val_loss: 12.1039 - val_accuracy: 0.2480
Epoch 45/50
394/394 [==============================] - 12s 29ms/step - loss: 0.1630 - a
ccuracy: 0.9684 - val_loss: 13.9239 - val_accuracy: 0.2560
Epoch 46/50
394/394 [==============================] - 12s 29ms/step - loss: 0.2106 - a
ccuracy: 0.9613 - val_loss: 12.4544 - val_accuracy: 0.2620
Epoch 47/50
394/394 [==============================] - 12s 30ms/step - loss: 0.1561 - a
ccuracy: 0.9682 - val_loss: 14.5487 - val_accuracy: 0.2720
Epoch 48/50
394/394 [==============================] - 12s 29ms/step - loss: 0.2140 - a
ccuracy: 0.9655 - val_loss: 13.0447 - val_accuracy: 0.2380
Epoch 49/50
394/394 [==============================] - 12s 29ms/step - loss: 0.1955 - a
ccuracy: 0.9661 - val_loss: 13.1110 - val_accuracy: 0.2660
Epoch 50/50
394/394 [==============================] - 12s 29ms/step - loss: 0.2061 - a
ccuracy: 0.9643 - val_loss: 14.8803 - val_accuracy: 0.2560
```

```python
predict_x=model.predict(x_val)
predictions=np.argmax(predict_x,axis=1)
lll=y_val.tolist()
llll=[]
for x in range(len(predictions)):
  vv=lll[x].index(1)
  llll.append(vv)
print(classification_report(llll, predictions,target_names=labels))
```

```
16/16 [==============================] - 0s 10ms/step
                              precision    recall  f1-score   support

                  ORANGE TIP       0.60      0.60      0.60         5
                LARGE MARBLE       0.00      0.00      0.00         5
           COMMON WOOD-NYMPH       0.20      0.20      0.20         5
             CHALK HILL BLUE       1.00      0.60      0.75         5
                  PAPER KITE       0.75      0.60      0.67         5
                       ATALA       0.80      0.80      0.80         5
            GREEN HAIRSTREAK       0.60      0.60      0.60         5
           BLUE SPOTTED CROW       0.00      0.00      0.00         5
          RED SPOTTED PURPLE       0.50      0.60      0.55         5
                 GOLD BANDED       0.45      1.00      0.62         5
           GARDEN TIGER MOTH       0.43      0.60      0.50         5
                 RED ADMIRAL       0.75      0.60      0.67         5
            MANGROVE SKIPPER       0.67      0.80      0.73         5
               INDRA SWALLOW       0.67      0.40      0.50         5
                     PEACOCK       0.67      0.80      0.73         5
             CAIRNS BIRDWING       1.00      0.60      0.75         5
                  COMET MOTH       1.00      0.40      0.57         5
                     IO MOTH       1.00      0.80      0.89         5
                 BROWN ARGUS       0.27      0.60      0.37         5
                     APPOLLO       0.50      0.40      0.44         5
      GREEN CELLED CATTLEHEART     0.57      0.80      0.67         5
                     VICEROY       0.71      1.00      0.83         5
             EMPEROR GUM MOTH      0.50      0.60      0.55         5
       MADAGASCAN SUNSET MOTH      0.75      0.60      0.67         5
               DANAID EGGFLY       0.14      0.20      0.17         5
           COMMON BANDED AWL       0.17      0.20      0.18         5
             ZEBRA LONG WING       0.83      1.00      0.91         5
    BANDED ORANGE HELICONIAN       0.33      0.40      0.36         5
                   GREAT JAY       0.67      0.80      0.73         5
              AMERICAN SNOOT       0.00      0.00      0.00         5
               MOURNING CLOAK      1.00      0.80      0.89         5
           EASTERN PINE ELFIN      0.38      0.60      0.46         5
              CLEARWING MOTH       0.67      0.80      0.73         5
                  WOOD SATYR       1.00      0.20      0.33         5
           TWO BARRED FLASHER      0.50      0.40      0.44         5
      WHITE LINED SPHINX MOTH      0.38      0.60      0.46         5
                   LUNA MOTH       0.80      0.80      0.80         5
                  PINE WHITE       1.00      0.60      0.75         5
          CHECQUERED SKIPPER       0.40      0.80      0.53         5
      MILBERTS TORTOISESHELL       0.67      0.80      0.73         5
            BROOKES BIRDWING       1.00      0.80      0.89         5
```

GREAT EGGFLY	0.29	0.40	0.33	5
CHESTNUT	0.83	1.00	0.91	5
HUMMING BIRD HAWK MOTH	0.22	0.40	0.29	5
PAINTED LADY	1.00	0.40	0.57	5
EASTERN DAPPLE WHITE	0.25	0.40	0.31	5
PIPEVINE SWALLOW	0.75	0.60	0.67	5
ARCIGERA FLOWER MOTH	0.57	0.80	0.67	5
MALACHITE	0.50	0.40	0.44	5
GREY HAIRSTREAK	0.25	0.20	0.22	5
OLEANDER HAWK MOTH	0.00	0.00	0.00	5
ELBOWED PIERROT	0.50	0.60	0.55	5
SIXSPOT BURNET MOTH	0.60	0.60	0.60	5
GIANT LEOPARD MOTH	0.29	0.40	0.33	5
BLUE MORPHO	0.33	0.20	0.25	5
BROWN SIPROETA	0.80	0.80	0.80	5
STRAITED QUEEN	0.80	0.80	0.80	5
AFRICAN GIANT SWALLOWTAIL	1.00	1.00	1.00	5
EASTERN COMA	0.36	0.80	0.50	5
BANDED TIGER MOTH	0.40	0.80	0.53	5
AN 88	1.00	1.00	1.00	5
QUESTION MARK	0.25	0.20	0.22	5
RED CRACKER	0.36	0.80	0.50	5
RED POSTMAN	0.50	0.40	0.44	5
ADONIS	0.60	0.60	0.60	5
YELLOW SWALLOW TAIL	0.60	0.60	0.60	5
CRIMSON PATCH	1.00	0.40	0.57	5
SOOTYWING	1.00	0.20	0.33	5
BECKERS WHITE	0.50	0.20	0.29	5
GLITTERING SAPPHIRE	0.56	1.00	0.71	5
BIRD CHERRY ERMINE MOTH	1.00	0.60	0.75	5
TROPICAL LEAFWING	0.00	0.00	0.00	5
METALMARK	0.60	0.60	0.60	5
PURPLE HAIRSTREAK	1.00	0.40	0.57	5
ORCHARD SWALLOW	0.50	0.40	0.44	5
ATLAS MOTH	1.00	0.80	0.89	5
HERCULES MOTH	0.57	0.80	0.67	5
CLODIUS PARNASSIAN	0.25	0.20	0.22	5
BLACK HAIRSTREAK	1.00	0.40	0.57	5
POLYPHEMUS MOTH	1.00	0.20	0.33	5
MONARCH	1.00	0.40	0.57	5
CLEOPATRA	0.75	0.60	0.67	5
MESTRA	0.00	0.00	0.00	5
CABBAGE WHITE	0.50	0.20	0.29	5
PURPLISH COPPER	0.18	0.40	0.25	5
SLEEPY ORANGE	0.38	0.60	0.46	5
SILVER SPOT SKIPPER	0.50	0.80	0.62	5
SOUTHERN DOGFACE	0.50	0.20	0.29	5
ROSY MAPLE MOTH	0.43	0.60	0.50	5
ORANGE OAKLEAF	0.50	0.40	0.44	5
JULIA	0.50	0.20	0.29	5
ULYSES	0.67	0.40	0.50	5
Iphiclus sister	0.29	0.40	0.33	5
CLOUDED SULPHUR	0.00	0.00	0.00	5

```
                  BANDED PEACOCK       1.00      0.80      0.89         5
                  SCARCE SWALLOW       0.60      0.60      0.60         5
                        POPINJAY       1.00      0.40      0.57         5
                     COPPER TAIL       0.20      0.20      0.20         5
                   CINNABAR MOTH       1.00      0.80      0.89         5
                         CRECENT       0.67      0.80      0.73         5

                        accuracy                           0.53       500
                       macro avg       0.58      0.53      0.52       500
                    weighted avg       0.58      0.53      0.52       500
```

```
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1
344: UndefinedMetricWarning: Precision and F-score are ill-defined and bein
g set to 0.0 in labels with no predicted samples. Use `zero_division` param
eter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1
344: UndefinedMetricWarning: Precision and F-score are ill-defined and bein
g set to 0.0 in labels with no predicted samples. Use `zero_division` param
eter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1
344: UndefinedMetricWarning: Precision and F-score are ill-defined and bein
g set to 0.0 in labels with no predicted samples. Use `zero_division` param
eter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

In [ ]:

```
predict_x2=model2.predict(x_val)
predictions2=np.argmax(predict_x2,axis=1)
lll2=y_val.tolist()
llll2=[]
for x in range(len(predictions2)):
  vv2=lll2[x].index(1)
  llll2.append(vv2)
print(classification_report(llll2, predictions2,target_names=labels))
```

```
16/16 [==============================] - 0s 10ms/step
                           precision    recall  f1-score   support

                      ORANGE TIP       0.25      0.20      0.22         5
                    LARGE MARBLE       0.00      0.00      0.00         5
               COMMON WOOD-NYMPH       0.20      0.20      0.20         5
                 CHALK HILL BLUE       0.20      0.20      0.20         5
                      PAPER KITE       0.17      0.20      0.18         5
                           ATALA       1.00      0.40      0.57         5
                GREEN HAIRSTREAK       0.00      0.00      0.00         5
               BLUE SPOTTED CROW       0.00      0.00      0.00         5
               RED SPOTTED PURPLE      0.00      0.00      0.00         5
                     GOLD BANDED       0.40      0.40      0.40         5
               GARDEN TIGER MOTH       1.00      0.20      0.33         5
                    RED ADMIRAL        0.50      0.60      0.55         5
                 MANGROVE SKIPPER      0.57      0.80      0.67         5
                   INDRA SWALLOW       0.00      0.00      0.00         5
                         PEACOCK       0.50      0.20      0.29         5
```

CAIRNS BIRDWING	0.18	0.40	0.25	5
COMET MOTH	0.11	0.20	0.14	5
IO MOTH	0.75	0.60	0.67	5
BROWN ARGUS	0.25	0.20	0.22	5
APPOLLO	0.33	0.20	0.25	5
GREEN CELLED CATTLEHEART	0.33	0.80	0.47	5
VICEROY	0.15	0.40	0.22	5
EMPEROR GUM MOTH	0.00	0.00	0.00	5
MADAGASCAN SUNSET MOTH	0.36	0.80	0.50	5
DANAID EGGFLY	0.08	0.20	0.12	5
COMMON BANDED AWL	0.00	0.00	0.00	5
ZEBRA LONG WING	0.25	0.60	0.35	5
BANDED ORANGE HELICONIAN	0.60	0.60	0.60	5
GREAT JAY	0.25	0.20	0.22	5
AMERICAN SNOOT	0.00	0.00	0.00	5
MOURNING CLOAK	0.75	0.60	0.67	5
EASTERN PINE ELFIN	0.00	0.00	0.00	5
CLEARWING MOTH	0.14	0.20	0.17	5
WOOD SATYR	0.00	0.00	0.00	5
TWO BARRED FLASHER	0.00	0.00	0.00	5
WHITE LINED SPHINX MOTH	0.12	0.20	0.15	5
LUNA MOTH	0.17	0.20	0.18	5
PINE WHITE	0.20	0.20	0.20	5
CHECQUERED SKIPPER	0.00	0.00	0.00	5
MILBERTS TORTOISESHELL	0.20	0.40	0.27	5
BROOKES BIRDWING	0.43	0.60	0.50	5
GREAT EGGFLY	0.29	0.40	0.33	5
CHESTNUT	0.33	0.20	0.25	5
HUMMING BIRD HAWK MOTH	0.00	0.00	0.00	5
PAINTED LADY	0.00	0.00	0.00	5
EASTERN DAPPLE WHITE	0.00	0.00	0.00	5
PIPEVINE SWALLOW	0.50	0.20	0.29	5
ARCIGERA FLOWER MOTH	0.40	0.40	0.40	5
MALACHITE	0.00	0.00	0.00	5
GREY HAIRSTREAK	0.11	0.20	0.14	5
OLEANDER HAWK MOTH	0.50	0.20	0.29	5
ELBOWED PIERROT	0.40	0.40	0.40	5
SIXSPOT BURNET MOTH	0.40	0.40	0.40	5
GIANT LEOPARD MOTH	1.00	0.20	0.33	5
BLUE MORPHO	0.00	0.00	0.00	5
BROWN SIPROETA	0.50	0.20	0.29	5
STRAITED QUEEN	0.33	0.80	0.47	5
AFRICAN GIANT SWALLOWTAIL	1.00	0.40	0.57	5
EASTERN COMA	0.00	0.00	0.00	5
BANDED TIGER MOTH	0.11	0.40	0.17	5
AN 88	0.71	1.00	0.83	5
QUESTION MARK	0.33	0.20	0.25	5
RED CRACKER	0.75	0.60	0.67	5
RED POSTMAN	0.60	0.60	0.60	5
ADONIS	0.33	0.20	0.25	5
YELLOW SWALLOW TAIL	0.38	0.60	0.46	5
CRIMSON PATCH	0.17	0.60	0.26	5
SOOTYWING	0.00	0.00	0.00	5

```
        BECKERS WHITE       0.00      0.00      0.00         5
  GLITTERING SAPPHIRE       0.14      0.20      0.17         5
BIRD CHERRY ERMINE MOTH     0.00      0.00      0.00         5
     TROPICAL LEAFWING      0.00      0.00      0.00         5
            METALMARK       0.67      0.40      0.50         5
    PURPLE HAIRSTREAK       0.20      0.20      0.20         5
       ORCHARD SWALLOW      0.50      0.40      0.44         5
           ATLAS MOTH       0.00      0.00      0.00         5
        HERCULES MOTH       0.00      0.00      0.00         5
    CLODIUS PARNASSIAN      1.00      0.20      0.33         5
     BLACK HAIRSTREAK       0.00      0.00      0.00         5
       POLYPHEMUS MOTH      0.00      0.00      0.00         5
              MONARCH       0.43      0.60      0.50         5
            CLEOPATRA       0.14      0.20      0.17         5
               MESTRA       0.00      0.00      0.00         5
        CABBAGE WHITE       0.50      0.20      0.29         5
      PURPLISH COPPER       0.00      0.00      0.00         5
        SLEEPY ORANGE       0.00      0.00      0.00         5
  SILVER SPOT SKIPPER       0.00      0.00      0.00         5
     SOUTHERN DOGFACE       0.00      0.00      0.00         5
       ROSY MAPLE MOTH      0.40      0.40      0.40         5
       ORANGE OAKLEAF       1.00      0.20      0.33         5
                JULIA       0.25      0.20      0.22         5
               ULYSES       0.50      0.40      0.44         5
      Iphiclus sister       0.44      0.80      0.57         5
      CLOUDED SULPHUR       0.17      0.20      0.18         5
       BANDED PEACOCK       0.25      0.20      0.22         5
       SCARCE SWALLOW       1.00      0.20      0.33         5
             POPINJAY       0.29      0.80      0.42         5
          COPPER TAIL       0.00      0.00      0.00         5
        CINNABAR MOTH       0.25      0.40      0.31         5
              CRECENT       0.11      0.20      0.14         5

             accuracy                           0.26       500
            macro avg       0.28      0.26      0.24       500
         weighted avg       0.28      0.26      0.24       500
```

```
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1
344: UndefinedMetricWarning: Precision and F-score are ill-defined and bein
g set to 0.0 in labels with no predicted samples. Use `zero_division` param
eter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1
344: UndefinedMetricWarning: Precision and F-score are ill-defined and bein
g set to 0.0 in labels with no predicted samples. Use `zero_division` param
eter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1
344: UndefinedMetricWarning: Precision and F-score are ill-defined and bein
g set to 0.0 in labels with no predicted samples. Use `zero_division` param
eter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

As the model reports above show, adding the dropout layer seems to have decreased the accuracy and not eliminated the overfitting problem. The most accurate outcome, at roughly 55%, was my first model, but the first and second models both suffered from overfitting. Below is my transfer learning model. This model performed much better than either of mine, but is considerably more robust and longer to train.

In [ ]:
```
model3= keras.models.load_model('/content/archive-4/TransferModel.h5', custo
opt3 = keras.optimizers.Adam(learning_rate=0.001)
model3.compile(optimizer = opt3 ,
              loss='categorical_crossentropy',
              metrics = ['accuracy'])
history = model3.fit(x_train,y_train,epochs = 10 , validation_data = (x_val,
```

```
Epoch 1/10
394/394 [==============================] - 83s 176ms/step - loss: 2.1032 -
accuracy: 0.7054 - val_loss: 1.4522 - val_accuracy: 0.8940
Epoch 2/10
394/394 [==============================] - 63s 161ms/step - loss: 1.3849 -
accuracy: 0.8753 - val_loss: 1.3350 - val_accuracy: 0.9020
Epoch 3/10
394/394 [==============================] - 64s 162ms/step - loss: 1.1407 -
accuracy: 0.9127 - val_loss: 1.0475 - val_accuracy: 0.9280
Epoch 4/10
394/394 [==============================] - 64s 163ms/step - loss: 1.0454 -
accuracy: 0.9250 - val_loss: 1.0181 - val_accuracy: 0.9420
Epoch 5/10
394/394 [==============================] - 64s 163ms/step - loss: 1.1246 -
accuracy: 0.9165 - val_loss: 1.0667 - val_accuracy: 0.9420
Epoch 6/10
394/394 [==============================] - 63s 161ms/step - loss: 0.9866 -
accuracy: 0.9338 - val_loss: 1.1080 - val_accuracy: 0.9140
Epoch 7/10
394/394 [==============================] - 63s 161ms/step - loss: 0.9599 -
accuracy: 0.9391 - val_loss: 1.1635 - val_accuracy: 0.9240
Epoch 8/10
394/394 [==============================] - 64s 162ms/step - loss: 1.0513 -
accuracy: 0.9290 - val_loss: 0.9737 - val_accuracy: 0.9460
Epoch 9/10
394/394 [==============================] - 63s 161ms/step - loss: 0.8876 -
accuracy: 0.9460 - val_loss: 1.0880 - val_accuracy: 0.9080
Epoch 10/10
394/394 [==============================] - 64s 162ms/step - loss: 0.9778 -
accuracy: 0.9389 - val_loss: 1.1002 - val_accuracy: 0.9200
```

In [ ]:
```
predict_x3=model3.predict(x_val)
predictions3=np.argmax(predict_x3,axis=1)
lll3=y_val.tolist()
llll3=[]
for x in range(len(predictions3)):
  vv3=lll3[x].index(1)
  llll3.append(vv3)
print(classification_report(llll3, predictions3,target_names=labels))
```

```
16/16 [==============================] - 2s 45ms/step
                           precision    recall  f1-score   support

               ORANGE TIP       1.00      0.80      0.89         5
             LARGE MARBLE       1.00      0.80      0.89         5
        COMMON WOOD-NYMPH       1.00      1.00      1.00         5
          CHALK HILL BLUE       0.75      0.60      0.67         5
               PAPER KITE       1.00      0.80      0.89         5
                    ATALA       1.00      1.00      1.00         5
         GREEN HAIRSTREAK       1.00      1.00      1.00         5
        BLUE SPOTTED CROW       1.00      0.80      0.89         5
       RED SPOTTED PURPLE       1.00      1.00      1.00         5
              GOLD BANDED       1.00      1.00      1.00         5
        GARDEN TIGER MOTH       0.71      1.00      0.83         5
             RED ADMIRAL        0.83      1.00      0.91         5
         MANGROVE SKIPPER       1.00      1.00      1.00         5
            INDRA SWALLOW       1.00      0.60      0.75         5
                  PEACOCK       1.00      1.00      1.00         5
          CAIRNS BIRDWING       1.00      1.00      1.00         5
               COMET MOTH       0.83      1.00      0.91         5
                  IO MOTH       1.00      1.00      1.00         5
              BROWN ARGUS       1.00      0.80      0.89         5
                  APPOLLO       1.00      1.00      1.00         5
   GREEN CELLED CATTLEHEART     1.00      1.00      1.00         5
                  VICEROY       1.00      1.00      1.00         5
         EMPEROR GUM MOTH       0.62      1.00      0.77         5
     MADAGASCAN SUNSET MOTH     1.00      1.00      1.00         5
            DANAID EGGFLY       0.80      0.80      0.80         5
        COMMON BANDED AWL       1.00      1.00      1.00         5
          ZEBRA LONG WING       1.00      1.00      1.00         5
   BANDED ORANGE HELICONIAN     1.00      1.00      1.00         5
                GREAT JAY       1.00      1.00      1.00         5
           AMERICAN SNOOT       1.00      1.00      1.00         5
           MOURNING CLOAK       1.00      1.00      1.00         5
       EASTERN PINE ELFIN       0.80      0.80      0.80         5
           CLEARWING MOTH       1.00      1.00      1.00         5
               WOOD SATYR       0.83      1.00      0.91         5
       TWO BARRED FLASHER       1.00      0.80      0.89         5
    WHITE LINED SPHINX MOTH     0.83      1.00      0.91         5
                LUNA MOTH       1.00      0.80      0.89         5
               PINE WHITE       1.00      1.00      1.00         5
       CHECQUERED SKIPPER       1.00      1.00      1.00         5
    MILBERTS TORTOISESHELL      1.00      0.80      0.89         5
          BROOKES BIRDWING      1.00      1.00      1.00         5
```

GREAT EGGFLY	1.00	1.00	1.00	5
CHESTNUT	0.83	1.00	0.91	5
HUMMING BIRD HAWK MOTH	0.83	1.00	0.91	5
PAINTED LADY	1.00	1.00	1.00	5
EASTERN DAPPLE WHITE	1.00	0.80	0.89	5
PIPEVINE SWALLOW	1.00	1.00	1.00	5
ARCIGERA FLOWER MOTH	1.00	1.00	1.00	5
MALACHITE	1.00	1.00	1.00	5
GREY HAIRSTREAK	0.83	1.00	0.91	5
OLEANDER HAWK MOTH	1.00	1.00	1.00	5
ELBOWED PIERROT	1.00	1.00	1.00	5
SIXSPOT BURNET MOTH	1.00	1.00	1.00	5
GIANT LEOPARD MOTH	0.83	1.00	0.91	5
BLUE MORPHO	1.00	0.80	0.89	5
BROWN SIPROETA	1.00	1.00	1.00	5
STRAITED QUEEN	1.00	1.00	1.00	5
AFRICAN GIANT SWALLOWTAIL	1.00	1.00	1.00	5
EASTERN COMA	0.57	0.80	0.67	5
BANDED TIGER MOTH	1.00	0.40	0.57	5
AN 88	1.00	1.00	1.00	5
QUESTION MARK	1.00	0.60	0.75	5
RED CRACKER	1.00	1.00	1.00	5
RED POSTMAN	1.00	1.00	1.00	5
ADONIS	0.67	0.40	0.50	5
YELLOW SWALLOW TAIL	0.60	0.60	0.60	5
CRIMSON PATCH	1.00	1.00	1.00	5
SOOTYWING	1.00	1.00	1.00	5
BECKERS WHITE	0.83	1.00	0.91	5
GLITTERING SAPPHIRE	1.00	1.00	1.00	5
BIRD CHERRY ERMINE MOTH	1.00	0.80	0.89	5
TROPICAL LEAFWING	0.80	0.80	0.80	5
METALMARK	1.00	1.00	1.00	5
PURPLE HAIRSTREAK	0.33	1.00	0.50	5
ORCHARD SWALLOW	1.00	1.00	1.00	5
ATLAS MOTH	1.00	1.00	1.00	5
HERCULES MOTH	1.00	1.00	1.00	5
CLODIUS PARNASSIAN	1.00	0.60	0.75	5
BLACK HAIRSTREAK	1.00	0.80	0.89	5
POLYPHEMUS MOTH	1.00	0.80	0.89	5
MONARCH	1.00	1.00	1.00	5
CLEOPATRA	1.00	1.00	1.00	5
MESTRA	0.80	0.80	0.80	5
CABBAGE WHITE	1.00	1.00	1.00	5
PURPLISH COPPER	1.00	0.20	0.33	5
SLEEPY ORANGE	1.00	0.80	0.89	5
SILVER SPOT SKIPPER	1.00	1.00	1.00	5
SOUTHERN DOGFACE	0.80	0.80	0.80	5
ROSY MAPLE MOTH	0.83	1.00	0.91	5
ORANGE OAKLEAF	1.00	1.00	1.00	5
JULIA	1.00	1.00	1.00	5
ULYSES	1.00	1.00	1.00	5
Iphiclus sister	1.00	1.00	1.00	5
CLOUDED SULPHUR	1.00	1.00	1.00	5

BANDED PEACOCK	1.00	1.00	1.00	5
SCARCE SWALLOW	1.00	1.00	1.00	5
POPINJAY	1.00	1.00	1.00	5
COPPER TAIL	0.62	1.00	0.77	5
CINNABAR MOTH	1.00	1.00	1.00	5
CRECENT	1.00	1.00	1.00	5
accuracy			0.92	500
macro avg	0.94	0.92	0.92	500
weighted avg	0.94	0.92	0.92	500

This model had a greater accuracy than both my other models combined at 94%. However, it takes about five times as long to train. Often, this is the tradeoff, and this knowledge can greatly affect which models I choose to train and what I choose to use for the application at hand.

Overall, I found this project to be very rewarding to complete. Regardless of the fact that my models were greatly outperformed by the prepared model that came with the dataset, I still obtained an accuracy that I am quite happy with, and I look forward to using this knowledge in the future.