Project Overview

Butterfly Recognition Using CNN and Transfer Learning

This project utilizes Convolutional Neural Networks (CNN) and Transfer Learning to classify images of butterflies into distinct species categories accurately. The goal is to aid entomological research and conservation efforts by automating butterfly identification, leveraging a dataset composed of images collected from various online sources.

Importance of Automated Butterfly Recognition

Automated recognition systems are essential in entomology for the efficient cataloging of species, monitoring lepidopteran biodiversity, and aiding in ecological conservation. These systems provide quick and accurate identification of various butterfly species, facilitating research on migration patterns, population dynamics, and climate change impacts on butterfly populations.

Project Execution Steps

1. Image Preprocessing:
   - Adjusting images to a consistent scale
   - Applying data augmentation techniques to improve model robustness
   - Handling varying lighting conditions and backgrounds
2. Normalization:
   - Standardizing pixel values across all images to facilitate model training
   - Implementing color space normalization to account for varying photograph conditions
3. Model Development:
   - Employing CNN for feature extraction
   - Utilizing Transfer Learning to leverage pre-trained networks
   - Enhancing the ability to distinguish subtle differences between similar butterfly species
4. Performance Evaluation:
   - Assessing accuracy and making iterative improvements
   - Validating model performance across different environmental conditions
   - Testing robustness against varying wing positions and angles

Applications and Impact

1. Conservation Efforts:
   - Monitoring butterfly population dynamics
   - Tracking species distribution changes
   - Supporting habitat conservation initiatives
2. Educational Tools:

    - Enhancing entomological education
    - Supporting citizen science initiatives
    - Facilitating public engagement in butterfly conservation
3. Research Applications:
    - Studying migration patterns
    - Analyzing species diversity
    - Investigating the effects of climate change on butterfly populations

About the Dataset

The Butterfly Classification Dataset consists of approximately 4000 images derived from online sources including nature photography databases, scientific collections, and citizen science contributions. The dataset is designed to enhance the development of lepidopteran recognition models using photographs taken in natural settings.

Dataset Characteristics:

- Source: Images collected from nature photography databases and scientific collections
- Classes: Multiple butterfly species including common families such as Nymphalidae, Pieridae, and Papilionidae
- Resolution: Variable, typically ranging from 320x240 to 640x480 pixels
- Total Images: ~4000
- Variability: Different angles, lighting conditions, and natural backgrounds

Conclusion

This project demonstrates the significant potential of CNN and Transfer Learning in butterfly species recognition, offering a valuable tool for entomological research, conservation efforts, and educational applications. It highlights the intersection of computer vision technology and lepidopterology, promoting both scientific research and public engagement in butterfly conservation.

```
import pandas as pd
import os
import logging
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix
import tensorflow as tf
from tensorflow.keras import layers, models
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.preprocessing.image import load_img,
img_to_array
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten,
Dense
```

```
from tensorflow.keras import regularizers
import warnings
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '3'
tf.compat.v1.logging.set_verbosity(tf.compat.v1.logging.ERROR)
logging.getLogger('tensorflow').setLevel(logging.ERROR)
warnings.filterwarnings("ignore", category=UserWarning, message=r"Your
`PyDataset` class should call `super().__init__\(\*\*kwargs\)`")
```

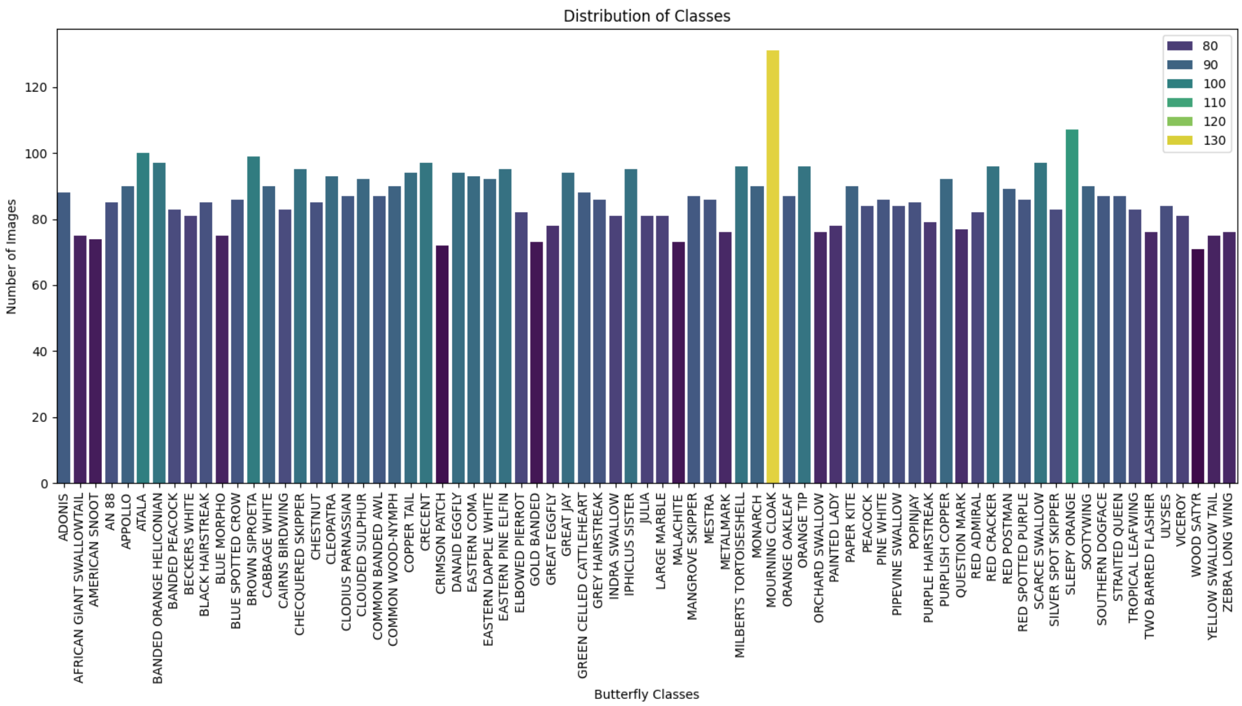
```
df = pd.read_csv('Butterfly_Dataset/Training_set.csv')
df.head(15)
```

	filename	label
0	Image_1.jpg	SOUTHERN DOGFACE
1	Image_2.jpg	ADONIS
2	Image_3.jpg	BROWN SIPROETA
3	Image_4.jpg	MONARCH
4	Image_5.jpg	GREEN CELLED CATTLEHEART
5	Image_6.jpg	CAIRNS BIRDWING
6	Image_7.jpg	GREEN CELLED CATTLEHEART
7	Image_8.jpg	EASTERN DAPPLE WHITE
8	Image_9.jpg	BROWN SIPROETA
9	Image_10.jpg	RED POSTMAN
10	Image_11.jpg	MANGROVE SKIPPER
11	Image_12.jpg	BLACK HAIRSTREAK
12	Image_13.jpg	CABBAGE WHITE
13	Image_14.jpg	RED ADMIRAL
14	Image_15.jpg	PAINTED LADY

```
len(df)
```

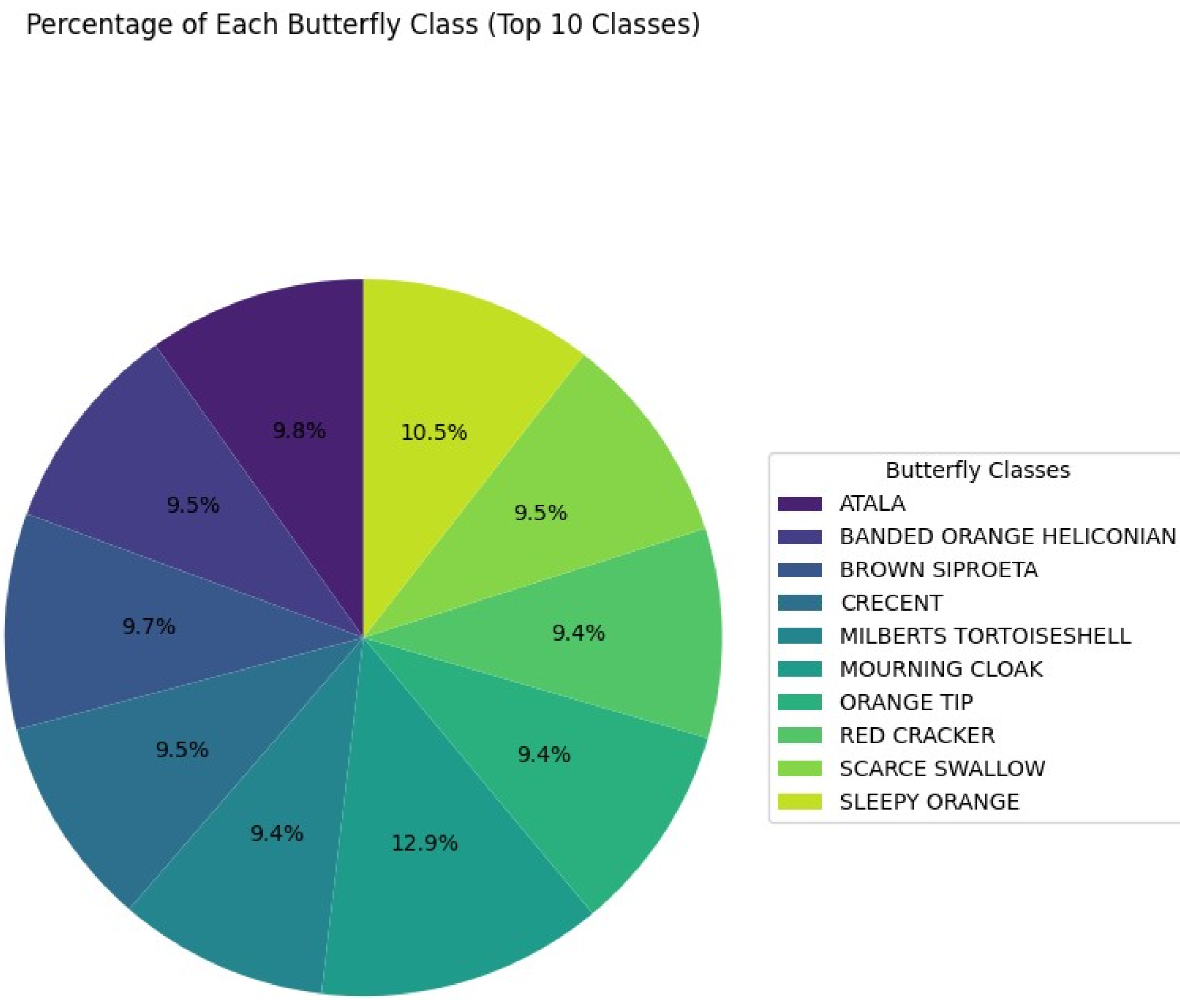
```
6499
```

```
classes = df['label'].value_counts().sort_index()
# classes.head(10)
plt.subplots(figsize=(14, 8))
sns.barplot(x=classes.index,
y=classes.values,hue=classes.values,palette="viridis")
plt.title("Distribution of Classes")
plt.xlabel("Butterfly Classes")
plt.ylabel("Number of Images")
plt.xticks(rotation=90)
plt.tight_layout()
plt.show()
```




```python
import matplotlib.pyplot as plt
import seaborn as sns

# Define color palette for top 10 classes
top_classes = df['label'].value_counts().nlargest(10).sort_index()
colors = sns.color_palette("viridis", len(top_classes))

# Plot
plt.figure(figsize=(8, 8))  # Adjust figure size for readability
plt.pie(
    top_classes.values,
    labels=None,
    autopct='%1.1f%%',
    startangle=90,
    colors=colors
)

# Add title and equal aspect ratio
plt.title('Percentage of Each Butterfly Class (Top 10 Classes)')
plt.axis('equal')  # Equal aspect ratio ensures the pie is a circle

# Add legend with class names
plt.legend(
    top_classes.index,
    title="Butterfly Classes",
    loc="center left",
    bbox_to_anchor=(1, 0.5)
)
```

```
plt.tight_layout()
plt.show()
```




```
image_dir = "Butterfly_Dataset/train"

sample_images = df.sample(9, random_state=50)


fig, axes = plt.subplots(3, 3, figsize=(15, 15))
```

```python
for i, (index, row) in enumerate(sample_images.iterrows()):
    img_path = os.path.join(image_dir, row['filename'])
    img = load_img(img_path, target_size=(150,150))
    img_array = img_to_array(img) / 255.0  # Normalize the image

    ax = axes[i // 3, i % 3]
    ax.imshow(img_array)
    ax.set_title(f"Class: {row['label']}")
    ax.axis('off')

plt.tight_layout()
plt.show()
```


```
image_shape = (150,150,3)
epochs = 50
target_size=(150, 150)
batch_size=32

train_df, val_df = train_test_split(df, test_size=0.2,
random_state=42)
test_df = pd.read_csv("Butterfly_Dataset/Testing_set.csv")
train_dir = "Butterfly_Dataset/train"
test_dir = "Butterfly_Dataset/test"

train_datagen = ImageDataGenerator(
```

```
    rescale=1./255,
    rotation_range=40,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    fill_mode='nearest'
)

val_datagen = ImageDataGenerator(rescale=1./255)

train_generator = train_datagen.flow_from_dataframe(
    dataframe=train_df,
    directory=train_dir,
    x_col='filename',
    y_col='label',
    target_size=target_size,
    batch_size=batch_size,
    class_mode='categorical'
)

val_generator = val_datagen.flow_from_dataframe(
    dataframe=val_df,
    directory=train_dir,
    x_col='filename',
    y_col='label',
    target_size=target_size,
    batch_size=batch_size,
    class_mode='categorical'
)

test_generator = val_datagen.flow_from_dataframe(
    dataframe=test_df,
    directory=test_dir,
    x_col='filename',
    y_col=None,
    target_size=target_size,
    batch_size=batch_size,
    class_mode=None
)
```

```
Found 5199 validated image filenames belonging to 75 classes.
Found 1300 validated image filenames belonging to 75 classes.
Found 2786 validated image filenames.
```

```
model_CNN = models.Sequential([
    # 1st Convolutional Block
    layers.Conv2D(32, (3, 3), activation='relu',
```

```
input_shape=image_shape),
    layers.BatchNormalization(),
    layers.MaxPooling2D((2, 2)),

    # 2nd Convolutional Block
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.BatchNormalization(),
    layers.MaxPooling2D((2, 2)),

    # 3rd Convolutional Block
    layers.Conv2D(128, (3, 3), activation='relu'),
    layers.BatchNormalization(),
    layers.MaxPooling2D((2, 2)),

    # 4th Convolutional Block (optional, for deeper representation)
    layers.Conv2D(256, (3, 3), activation='relu'),
    layers.BatchNormalization(),
    layers.MaxPooling2D((2, 2)),

    # Global Average Pooling instead of Flatten
    layers.GlobalAveragePooling2D(),

    # Fully Connected Layers
    layers.Dense(512, activation='relu',
kernel_regularizer=regularizers.l2(0.001)),
    layers.Dropout(0.5),  # 50% dropout for better generalization
    layers.Dense(75, activation='softmax')  # Output layer with
softmax for classification
])

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

model_CNN.summary()

Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 148, 148, 32)      896

 batch_normalization (BatchN  (None, 148, 148, 32)     128
 ormalization)

 max_pooling2d (MaxPooling2D  (None, 74, 74, 32)       0
 )

 conv2d_1 (Conv2D)           (None, 72, 72, 64)        18496
```

```
 batch_normalization_1 (Batc  (None, 72, 72, 64)       256
 hNormalization)

 max_pooling2d_1 (MaxPooling  (None, 36, 36, 64)       0
 2D)

 conv2d_2 (Conv2D)           (None, 34, 34, 128)       73856

 batch_normalization_2 (Batc  (None, 34, 34, 128)      512
 hNormalization)

 max_pooling2d_2 (MaxPooling  (None, 17, 17, 128)      0
 2D)

 conv2d_3 (Conv2D)           (None, 15, 15, 256)       295168

 batch_normalization_3 (Batc  (None, 15, 15, 256)      1024
 hNormalization)

 max_pooling2d_3 (MaxPooling  (None, 7, 7, 256)        0
 2D)

 global_average_pooling2d (G  (None, 256)              0
 lobalAveragePooling2D)

 dense (Dense)               (None, 512)               131584

 dropout (Dropout)           (None, 512)               0

 dense_1 (Dense)             (None, 75)                38475

=================================================================
Total params: 560,395
Trainable params: 559,435
Non-trainable params: 960
_________________________________________________________________
```

```
history = model_CNN.fit(
    train_generator,
    steps_per_epoch=train_generator.samples //
train_generator.batch_size,
    epochs=epochs,
    validation_data=val_generator,
    validation_steps=val_generator.samples // val_generator.batch_size
)
```

```
Epoch 1/50
162/162 [==============================] - 33s 136ms/step - loss:
3.8888 - accuracy: 0.1231 - val_loss: 6.9778 - val_accuracy: 0.0164
```

```
Epoch 2/50
162/162 [==============================] - 16s 101ms/step - loss:
3.0902 - accuracy: 0.2584 - val_loss: 6.3184 - val_accuracy: 0.0336
Epoch 3/50
162/162 [==============================] - 16s 101ms/step - loss:
2.7096 - accuracy: 0.3308 - val_loss: 4.4681 - val_accuracy: 0.0969
Epoch 4/50
162/162 [==============================] - 16s 100ms/step - loss:
2.4136 - accuracy: 0.4026 - val_loss: 2.4113 - val_accuracy: 0.4250
Epoch 5/50
162/162 [==============================] - 16s 100ms/step - loss:
2.1671 - accuracy: 0.4595 - val_loss: 2.6072 - val_accuracy: 0.3734
Epoch 6/50
162/162 [==============================] - 16s 101ms/step - loss:
1.9317 - accuracy: 0.5247 - val_loss: 2.2386 - val_accuracy: 0.4531
Epoch 7/50
162/162 [==============================] - 17s 102ms/step - loss:
1.7161 - accuracy: 0.5789 - val_loss: 2.4956 - val_accuracy: 0.3914
Epoch 8/50
162/162 [==============================] - 17s 103ms/step - loss:
1.5835 - accuracy: 0.6172 - val_loss: 1.8268 - val_accuracy: 0.5398
Epoch 9/50
162/162 [==============================] - 17s 102ms/step - loss:
1.4247 - accuracy: 0.6538 - val_loss: 1.3518 - val_accuracy: 0.6812
Epoch 10/50
162/162 [==============================] - 17s 102ms/step - loss:
1.3341 - accuracy: 0.6826 - val_loss: 1.7687 - val_accuracy: 0.5719
Epoch 11/50
162/162 [==============================] - 17s 104ms/step - loss:
1.2545 - accuracy: 0.7008 - val_loss: 1.3277 - val_accuracy: 0.6891
Epoch 12/50
162/162 [==============================] - 16s 101ms/step - loss:
1.1515 - accuracy: 0.7283 - val_loss: 1.3375 - val_accuracy: 0.6836
Epoch 13/50
162/162 [==============================] - 17s 103ms/step - loss:
1.1120 - accuracy: 0.7368 - val_loss: 1.5659 - val_accuracy: 0.6336
Epoch 14/50
162/162 [==============================] - 18s 109ms/step - loss:
1.0516 - accuracy: 0.7501 - val_loss: 1.2763 - val_accuracy: 0.7094
Epoch 15/50
162/162 [==============================] - 18s 111ms/step - loss:
1.0078 - accuracy: 0.7629 - val_loss: 1.2448 - val_accuracy: 0.7125
Epoch 16/50
162/162 [==============================] - 17s 104ms/step - loss:
0.9535 - accuracy: 0.7825 - val_loss: 1.1064 - val_accuracy: 0.7516
Epoch 17/50
162/162 [==============================] - 17s 104ms/step - loss:
0.9142 - accuracy: 0.7871 - val_loss: 1.0961 - val_accuracy: 0.7336
Epoch 18/50
```

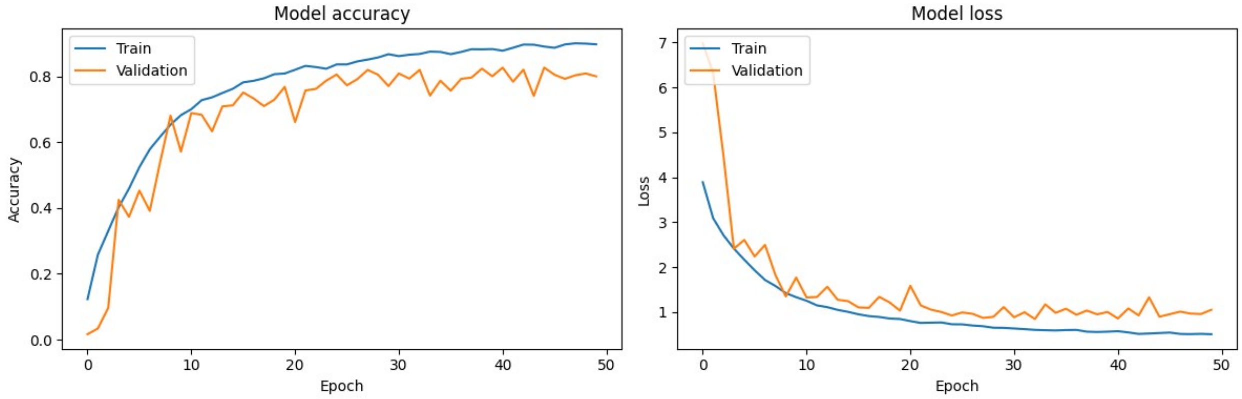
```
162/162 [==============================] - 17s 103ms/step - loss:
0.8942 - accuracy: 0.7947 - val_loss: 1.3407 - val_accuracy: 0.7102
Epoch 19/50
162/162 [==============================] - 17s 102ms/step - loss:
0.8600 - accuracy: 0.8072 - val_loss: 1.2172 - val_accuracy: 0.7297
Epoch 20/50
162/162 [==============================] - 17s 103ms/step - loss:
0.8489 - accuracy: 0.8094 - val_loss: 1.0350 - val_accuracy: 0.7688
Epoch 21/50
162/162 [==============================] - 17s 106ms/step - loss:
0.8019 - accuracy: 0.8208 - val_loss: 1.5867 - val_accuracy: 0.6617
Epoch 22/50
162/162 [==============================] - 17s 104ms/step - loss:
0.7612 - accuracy: 0.8326 - val_loss: 1.1508 - val_accuracy: 0.7578
Epoch 23/50
162/162 [==============================] - 17s 102ms/step - loss:
0.7673 - accuracy: 0.8289 - val_loss: 1.0562 - val_accuracy: 0.7625
Epoch 24/50
162/162 [==============================] - 17s 103ms/step - loss:
0.7716 - accuracy: 0.8239 - val_loss: 1.0042 - val_accuracy: 0.7875
Epoch 25/50
162/162 [==============================] - 17s 102ms/step - loss:
0.7314 - accuracy: 0.8370 - val_loss: 0.9267 - val_accuracy: 0.8062
Epoch 26/50
162/162 [==============================] - 16s 100ms/step - loss:
0.7294 - accuracy: 0.8370 - val_loss: 0.9948 - val_accuracy: 0.7734
Epoch 27/50
162/162 [==============================] - 17s 103ms/step - loss:
0.7034 - accuracy: 0.8461 - val_loss: 0.9639 - val_accuracy: 0.7922
Epoch 28/50
162/162 [==============================] - 16s 101ms/step - loss:
0.6879 - accuracy: 0.8518 - val_loss: 0.8737 - val_accuracy: 0.8203
Epoch 29/50
162/162 [==============================] - 16s 101ms/step - loss:
0.6547 - accuracy: 0.8581 - val_loss: 0.8975 - val_accuracy: 0.8055
Epoch 30/50
162/162 [==============================] - 16s 101ms/step - loss:
0.6517 - accuracy: 0.8680 - val_loss: 1.1133 - val_accuracy: 0.7711
Epoch 31/50
162/162 [==============================] - 17s 102ms/step - loss:
0.6379 - accuracy: 0.8622 - val_loss: 0.8880 - val_accuracy: 0.8094
Epoch 32/50
162/162 [==============================] - 17s 105ms/step - loss:
0.6242 - accuracy: 0.8665 - val_loss: 0.9996 - val_accuracy: 0.7937
Epoch 33/50
162/162 [==============================] - 17s 102ms/step - loss:
0.6077 - accuracy: 0.8688 - val_loss: 0.8479 - val_accuracy: 0.8203
Epoch 34/50
162/162 [==============================] - 17s 102ms/step - loss:
```

```
0.6005 - accuracy: 0.8759 - val_loss: 1.1742 - val_accuracy: 0.7422
Epoch 35/50
162/162 [==============================] - 17s 103ms/step - loss:
0.5947 - accuracy: 0.8750 - val_loss: 0.9855 - val_accuracy: 0.7875
Epoch 36/50
162/162 [==============================] - 17s 102ms/step - loss:
0.6035 - accuracy: 0.8682 - val_loss: 1.0778 - val_accuracy: 0.7570
Epoch 37/50
162/162 [==============================] - 16s 100ms/step - loss:
0.6070 - accuracy: 0.8750 - val_loss: 0.9422 - val_accuracy: 0.7930
Epoch 38/50
162/162 [==============================] - 16s 101ms/step - loss:
0.5674 - accuracy: 0.8833 - val_loss: 1.0368 - val_accuracy: 0.7969
Epoch 39/50
162/162 [==============================] - 16s 101ms/step - loss:
0.5604 - accuracy: 0.8829 - val_loss: 0.9533 - val_accuracy: 0.8242
Epoch 40/50
162/162 [==============================] - 16s 100ms/step - loss:
0.5673 - accuracy: 0.8837 - val_loss: 1.0048 - val_accuracy: 0.8008
Epoch 41/50
162/162 [==============================] - 16s 100ms/step - loss:
0.5783 - accuracy: 0.8787 - val_loss: 0.8603 - val_accuracy: 0.8273
Epoch 42/50
162/162 [==============================] - 16s 101ms/step - loss:
0.5508 - accuracy: 0.8877 - val_loss: 1.0832 - val_accuracy: 0.7844
Epoch 43/50
162/162 [==============================] - 16s 101ms/step - loss:
0.5178 - accuracy: 0.8974 - val_loss: 0.9285 - val_accuracy: 0.8211
Epoch 44/50
162/162 [==============================] - 16s 101ms/step - loss:
0.5267 - accuracy: 0.8970 - val_loss: 1.3314 - val_accuracy: 0.7414
Epoch 45/50
162/162 [==============================] - 16s 101ms/step - loss:
0.5372 - accuracy: 0.8914 - val_loss: 0.8994 - val_accuracy: 0.8273
Epoch 46/50
162/162 [==============================] - 16s 100ms/step - loss:
0.5475 - accuracy: 0.8876 - val_loss: 0.9565 - val_accuracy: 0.8055
Epoch 47/50
162/162 [==============================] - 16s 101ms/step - loss:
0.5178 - accuracy: 0.8978 - val_loss: 1.0129 - val_accuracy: 0.7930
Epoch 48/50
162/162 [==============================] - 17s 102ms/step - loss:
0.5126 - accuracy: 0.9013 - val_loss: 0.9696 - val_accuracy: 0.8039
Epoch 49/50
162/162 [==============================] - 16s 101ms/step - loss:
0.5193 - accuracy: 0.9003 - val_loss: 0.9593 - val_accuracy: 0.8094
Epoch 50/50
162/162 [==============================] - 16s 101ms/step - loss:
0.5113 - accuracy: 0.8982 - val_loss: 1.0538 - val_accuracy: 0.8008
```

```
model_CNN.save("Custom_CNN_Model.h5")

train_score = model_CNN.evaluate(train_generator, verbose=1)
valid_score = model_CNN.evaluate(val_generator, verbose=1)

print('-' * 20)
print("Train Loss: ", train_score[0])
print("Train Accuracy: ", train_score[1])
print('-' * 20)
print("Validation Loss: ", valid_score[0])
print("Validation Accuracy: ", valid_score[1])
print('-' * 20)
```

```
163/163 [==============================] - 16s 97ms/step - loss:
0.5304 - accuracy: 0.8956
41/41 [==============================] - 1s 25ms/step - loss: 1.0480 -
accuracy: 0.8008
--------------------
Train Loss:  0.5304201245307922
Train Accuracy:  0.8955568671226501
--------------------
Validation Loss:  1.047988772392273
Validation Accuracy:  0.8007692098617554
--------------------
```

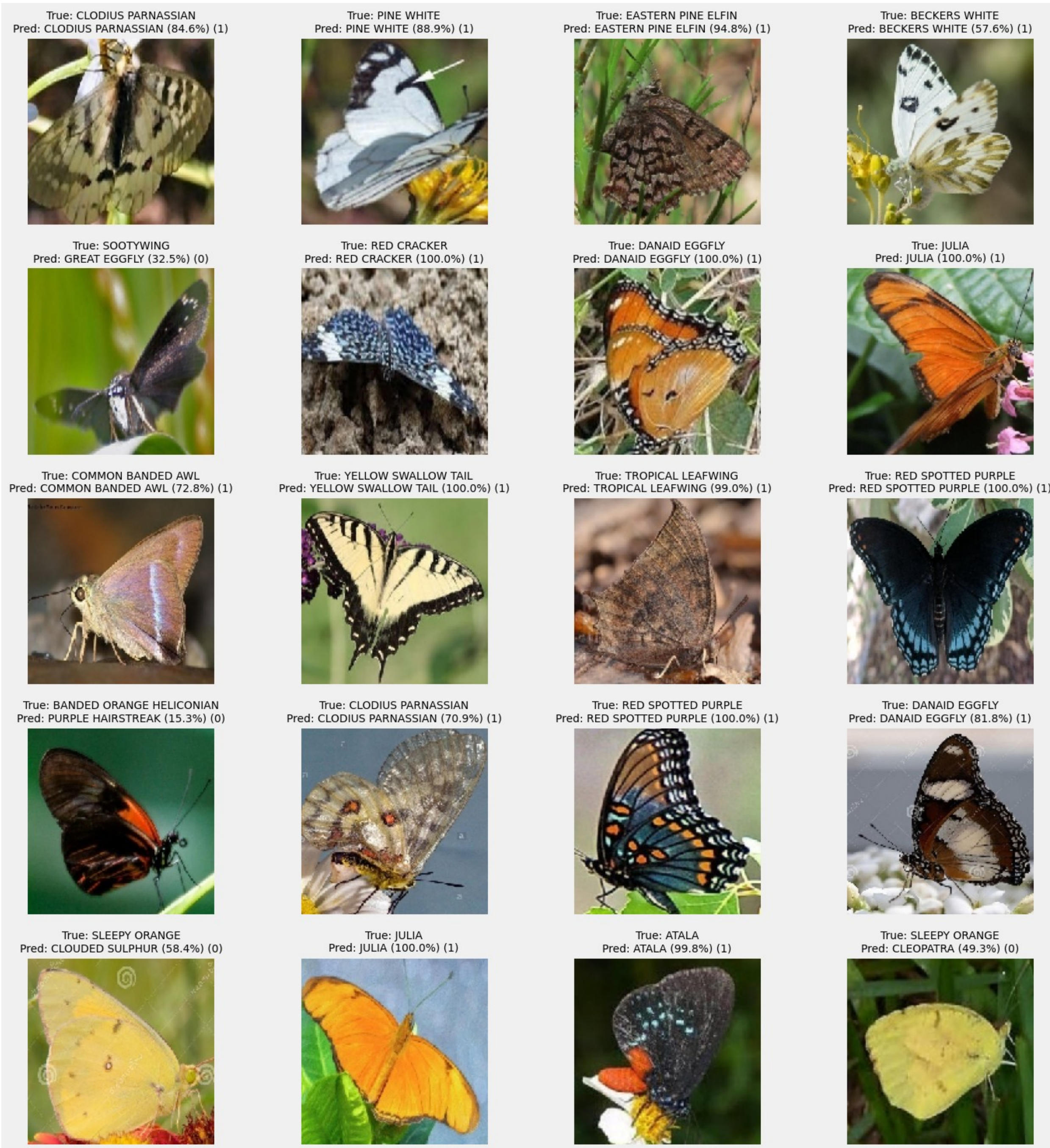
```
plt.figure(figsize=(12, 4))

plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper left')

plt.subplot(1, 2, 2)
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper left')

plt.tight_layout()
plt.show()
```




```
# Get a batch of validation images and labels
val_images, val_labels = next(val_generator)

# Make predictions
pred_probs = model_CNN.predict(val_images)  # Get prediction probabilities
pred_labels = np.argmax(pred_probs, axis=1)
true_labels = np.argmax(val_labels, axis=1)

# Get class names
class_indices = val_generator.class_indices
class_names = {v: k for k, v in class_indices.items()}

# Function to display images with true labels, predicted labels, and confidence
def display_images_with_confidence(images, true_labels, pred_labels, pred_probs, class_names, num_images):
    plt.figure(figsize=(15, 15))  # Adjust figure size for more images
    for i in range(num_images):
        plt.subplot(5, 4, i + 1)  # Create a grid of 5 rows and 4 columns
        plt.imshow(images[i])

        true_label = class_names[int(true_labels[i])]
        pred_label = class_names[int(pred_labels[i])]
        confidence = pred_probs[i][pred_labels[i]] * 100  # Get confidence as percentage
        Flag = 0
        if(true_label == pred_label):
            Flag = 1


        # Display true label, predicted label, and confidence with smaller font
        plt.title(f"True: {true_label}\nPred: {pred_label} ({confidence:.1f}%) ({Flag})", fontsize=10)
        plt.axis('off')
```

```python
    plt.tight_layout()
    plt.show()

# Display 20 images with true labels, predicted labels, and confidence
display_images_with_confidence(val_images, true_labels, pred_labels,
pred_probs, class_names, num_images=20)
```

```
1/1 [==============================] - 0s 20ms/step
```



```
STEP_SIZE_TEST=(test_generator.samples // test_generator.batch_size) +
int(test_generator.samples % test_generator.batch_size != 0)
test_generator.reset()
pred=model_CNN.predict(test_generator,
steps=STEP_SIZE_TEST,
verbose=1)
```

```
88/88 [==============================] - 5s 52ms/step
```

```
predicted_class_indices=np.argmax(pred,axis=1)

labels = (train_generator.class_indices)
labels = dict((v,k) for k,v in labels.items())
predictions = [labels[k] for k in predicted_class_indices]

filenames=test_generator.filenames
results=pd.DataFrame({"Filename":filenames,
                      "Predictions":predictions})
results.to_csv("results.csv",index=False)
```

VGG16 architecture

```
image_shape = (224,224,3)
epochs = 50
target_size=(224,224)
batch_size=32

train_df, val_df = train_test_split(df, test_size=0.2,
random_state=42)

train_dir = "Butterfly_Dataset/train"

train_aug_generator = ImageDataGenerator(
    rescale=1./255,
    rotation_range=40,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    fill_mode='nearest'
)

val_test_generator = ImageDataGenerator(rescale=1./255)

train_gen_vgg = train_aug_generator.flow_from_dataframe(
    dataframe=train_df,
    directory=train_dir,
    x_col='filename',
```

```
    y_col='label',
    target_size=target_size,
    batch_size=batch_size,
    class_mode='categorical'
)

val_gen_vgg = val_test_generator.flow_from_dataframe(
    dataframe=val_df,
    directory=train_dir,
    x_col='filename',
    y_col='label',
    target_size=target_size,
    batch_size=batch_size,
    class_mode='categorical'
)
```

```
Found 5199 validated image filenames belonging to 75 classes.
Found 1300 validated image filenames belonging to 75 classes.
```

```
from keras.applications.vgg16 import VGG16
conv_base = VGG16(
    weights='imagenet',
    include_top = False,
    input_shape=image_shape
)

conv_base.summary()
```

```
Model: "vgg16"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 input_4 (InputLayer)        [(None, 224, 224, 3)]     0         
                                                                 
 block1_conv1 (Conv2D)       (None, 224, 224, 64)      1792      
                                                                 
 block1_conv2 (Conv2D)       (None, 224, 224, 64)      36928     
                                                                 
 block1_pool (MaxPooling2D)  (None, 112, 112, 64)      0         
                                                                 
 block2_conv1 (Conv2D)       (None, 112, 112, 128)     73856     
                                                                 
 block2_conv2 (Conv2D)       (None, 112, 112, 128)     147584    
                                                                 
 block2_pool (MaxPooling2D)  (None, 56, 56, 128)       0         
                                                                 
 block3_conv1 (Conv2D)       (None, 56, 56, 256)       295168    
                                                                 
 block3_conv2 (Conv2D)       (None, 56, 56, 256)       590080    
```

```
 block3_conv3 (Conv2D)       (None, 56, 56, 256)       590080

 block3_pool (MaxPooling2D)  (None, 28, 28, 256)       0

 block4_conv1 (Conv2D)       (None, 28, 28, 512)       1180160

 block4_conv2 (Conv2D)       (None, 28, 28, 512)       2359808

 block4_conv3 (Conv2D)       (None, 28, 28, 512)       2359808

 block4_pool (MaxPooling2D)  (None, 14, 14, 512)       0

 block5_conv1 (Conv2D)       (None, 14, 14, 512)       2359808

 block5_conv2 (Conv2D)       (None, 14, 14, 512)       2359808

 block5_conv3 (Conv2D)       (None, 14, 14, 512)       2359808

 block5_pool (MaxPooling2D)  (None, 7, 7, 512)         0

=================================================================
Total params: 14,714,688
Trainable params: 14,714,688
Non-trainable params: 0
_________________________________________________________________
```

```
set_trainable = False

for layer in conv_base.layers:
  if layer.name == 'block5_conv1':
    set_trainable = True
  if set_trainable:
    layer.trainable = True
  else:
    layer.trainable = False

for layer in conv_base.layers:
  print(layer.name,layer.trainable)
```

```
input_4 False
block1_conv1 False
block1_conv2 False
block1_pool False
block2_conv1 False
block2_conv2 False
block2_pool False
block3_conv1 False
block3_conv2 False
block3_conv3 False
block3_pool False
```

```
block4_conv1 False
block4_conv2 False
block4_conv3 False
block4_pool False
block5_conv1 True
block5_conv2 True
block5_conv3 True
block5_pool True
```

```python
data_augmentation = tf.keras.Sequential([
    layers.RandomFlip("horizontal"),
    tf.keras.layers.RandomRotation(0.2),
    # tf.keras.layers.RandomZoom(0.2),
    # tf.keras.layers.RandomBrightness(0.2),
    # tf.keras.layers.RandomContrast(0.2),
])
```

```python
from keras import layers, applications, optimizers , callbacks,Input
model = Sequential([
    Input(shape=image_shape),
    data_augmentation,
    conv_base,
    Flatten(),
    Dense(512, activation='relu'),
    tf.keras.layers.Dropout(0.2),
    Dense(75, activation='softmax')
])

model.compile(
    optimizer=tf.keras.optimizers.RMSprop(learning_rate=1e-5),
    loss='categorical_crossentropy',
    metrics=['accuracy']
)

model.summary()
```

```
Model: "sequential_6"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 sequential_5 (Sequential)   (None, 224, 224, 3)       0         
                                                                 
 vgg16 (Functional)          (None, 7, 7, 512)         14714688  
                                                                 
 flatten_3 (Flatten)         (None, 25088)             0         
                                                                 
 dense_6 (Dense)             (None, 512)               12845568  
                                                                 
 dropout_3 (Dropout)         (None, 512)               0         
```

```
 dense_7 (Dense)             (None, 75)                38475

=================================================================
Total params: 27,598,731
Trainable params: 19,963,467
Non-trainable params: 7,635,264
_________________________________________________________________

early_stopping = callbacks.EarlyStopping(
    monitor='val_loss',
    patience=3,
    restore_best_weights=True
)


history = model.fit(
    train_gen_vgg,
    epochs=100,
    validation_data=val_gen_vgg,
    callbacks=[early_stopping]
)

Epoch 1/100
163/163 [==============================] - 37s 215ms/step - loss:
3.6611 - accuracy: 0.1604 - val_loss: 2.4179 - val_accuracy: 0.3962
Epoch 2/100
163/163 [==============================] - 35s 213ms/step - loss:
2.4068 - accuracy: 0.3835 - val_loss: 1.5700 - val_accuracy: 0.5823
Epoch 3/100
163/163 [==============================] - 35s 215ms/step - loss:
1.8668 - accuracy: 0.4993 - val_loss: 1.2025 - val_accuracy: 0.6792
Epoch 4/100
163/163 [==============================] - 35s 213ms/step - loss:
1.5349 - accuracy: 0.5807 - val_loss: 1.0077 - val_accuracy: 0.7300
Epoch 5/100
163/163 [==============================] - 35s 213ms/step - loss:
1.3456 - accuracy: 0.6399 - val_loss: 0.9102 - val_accuracy: 0.7662
Epoch 6/100
163/163 [==============================] - 35s 214ms/step - loss:
1.1719 - accuracy: 0.6736 - val_loss: 0.8283 - val_accuracy: 0.7792
Epoch 7/100
163/163 [==============================] - 35s 216ms/step - loss:
1.0543 - accuracy: 0.7048 - val_loss: 0.7616 - val_accuracy: 0.7869
Epoch 8/100
163/163 [==============================] - 35s 213ms/step - loss:
0.9510 - accuracy: 0.7346 - val_loss: 0.6619 - val_accuracy: 0.8215
Epoch 9/100
163/163 [==============================] - 35s 216ms/step - loss:
0.8754 - accuracy: 0.7515 - val_loss: 0.6444 - val_accuracy: 0.8277
Epoch 10/100
```

```
163/163 [==============================] - 35s 214ms/step - loss:
0.8483 - accuracy: 0.7611 - val_loss: 0.6053 - val_accuracy: 0.8346
Epoch 11/100
163/163 [==============================] - 35s 211ms/step - loss:
0.7954 - accuracy: 0.7753 - val_loss: 0.6249 - val_accuracy: 0.8269
Epoch 12/100
163/163 [==============================] - 35s 213ms/step - loss:
0.7464 - accuracy: 0.7827 - val_loss: 0.5940 - val_accuracy: 0.8462
Epoch 13/100
163/163 [==============================] - 35s 214ms/step - loss:
0.6897 - accuracy: 0.8050 - val_loss: 0.5567 - val_accuracy: 0.8462
Epoch 14/100
163/163 [==============================] - 35s 215ms/step - loss:
0.6648 - accuracy: 0.8046 - val_loss: 0.5513 - val_accuracy: 0.8500
Epoch 15/100
163/163 [==============================] - 35s 216ms/step - loss:
0.6118 - accuracy: 0.8234 - val_loss: 0.5101 - val_accuracy: 0.8638
Epoch 16/100
163/163 [==============================] - 35s 215ms/step - loss:
0.5921 - accuracy: 0.8311 - val_loss: 0.5221 - val_accuracy: 0.8577
Epoch 17/100
163/163 [==============================] - 35s 216ms/step - loss:
0.5646 - accuracy: 0.8302 - val_loss: 0.5041 - val_accuracy: 0.8685
Epoch 18/100
163/163 [==============================] - 35s 215ms/step - loss:
0.5288 - accuracy: 0.8525 - val_loss: 0.5178 - val_accuracy: 0.8623
Epoch 19/100
163/163 [==============================] - 35s 216ms/step - loss:
0.5077 - accuracy: 0.8498 - val_loss: 0.5164 - val_accuracy: 0.8677
Epoch 20/100
163/163 [==============================] - 36s 219ms/step - loss:
0.5152 - accuracy: 0.8482 - val_loss: 0.5006 - val_accuracy: 0.8623
Epoch 21/100
163/163 [==============================] - 36s 220ms/step - loss:
0.4672 - accuracy: 0.8600 - val_loss: 0.5195 - val_accuracy: 0.8623
Epoch 22/100
163/163 [==============================] - 35s 215ms/step - loss:
0.4613 - accuracy: 0.8619 - val_loss: 0.5195 - val_accuracy: 0.8677
Epoch 23/100
163/163 [==============================] - 35s 216ms/step - loss:
0.4330 - accuracy: 0.8727 - val_loss: 0.4946 - val_accuracy: 0.8654
Epoch 24/100
163/163 [==============================] - 36s 218ms/step - loss:
0.4204 - accuracy: 0.8752 - val_loss: 0.4950 - val_accuracy: 0.8715
Epoch 25/100
163/163 [==============================] - 35s 215ms/step - loss:
0.4226 - accuracy: 0.8784 - val_loss: 0.4789 - val_accuracy: 0.8769
Epoch 26/100
163/163 [==============================] - 35s 216ms/step - loss:
```

```
0.4047 - accuracy: 0.8809 - val_loss: 0.4730 - val_accuracy: 0.8777
Epoch 27/100
163/163 [==============================] - 36s 217ms/step - loss:
0.3732 - accuracy: 0.8838 - val_loss: 0.4775 - val_accuracy: 0.8800
Epoch 28/100
163/163 [==============================] - 35s 217ms/step - loss:
0.3696 - accuracy: 0.8948 - val_loss: 0.5100 - val_accuracy: 0.8662
Epoch 29/100
163/163 [==============================] - 35s 215ms/step - loss:
0.3722 - accuracy: 0.8888 - val_loss: 0.4992 - val_accuracy: 0.8723
```

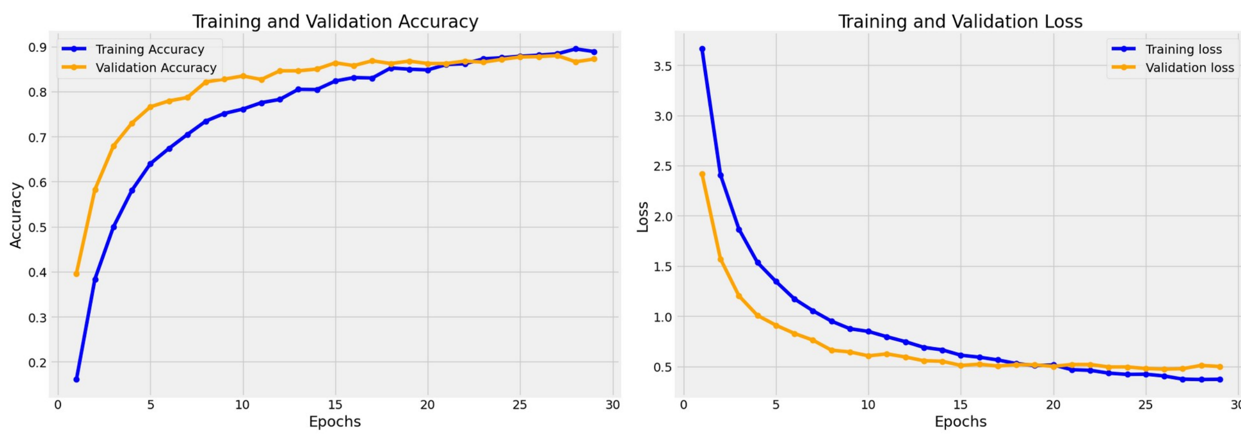
```
model.save("VGG16_model.h5")
```

```
train_score = model.evaluate(train_gen_vgg, verbose=1)
valid_score = model.evaluate(val_gen_vgg, verbose=1)

print('-' * 20)
print("Train Loss: ", train_score[0])
print("Train Accuracy: ", train_score[1])
print('-' * 20)
print("Validation Loss: ", valid_score[0])
print("Validation Accuracy: ", valid_score[1])
print('-' * 20)
```

```
163/163 [==============================] - 51s 308ms/step - loss:
0.2434 - accuracy: 0.9292
41/41 [==============================] - 6s 137ms/step - loss: 0.4730
- accuracy: 0.8777
--------------------
Train Loss:  0.24340416491031647
Train Accuracy:  0.9292171597480774
--------------------
Validation Loss:  0.4729710519313812
Validation Accuracy:  0.8776922821998596
--------------------
```

```
def model_performance(history):
    # Extract training and validation statistics
    tr_acc = history.history['accuracy']
    tr_loss = history.history['loss']
    val_acc = history.history['val_accuracy']
    val_loss = history.history['val_loss']

    # Generate a range for epochs
    epochs = range(1, len(tr_acc) + 1)

    # Setup the plotting environment
    plt.figure(figsize=(20, 7))
    plt.style.use('fivethirtyeight')

    # Plot training and validation accuracy
```

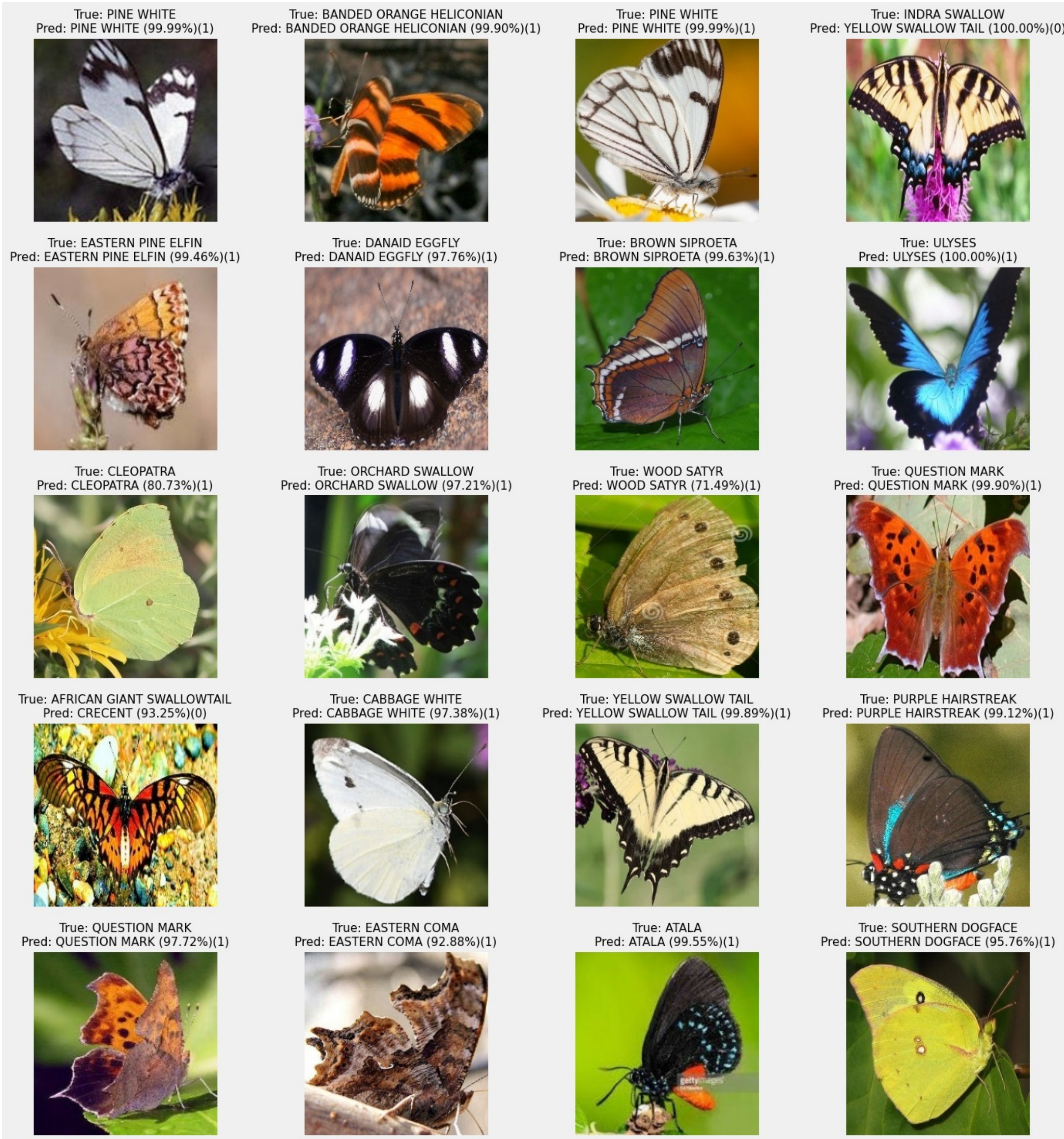
```
    plt.subplot(1, 2, 1)
    plt.plot(epochs, tr_acc, 'blue', marker='o',label='Training
Accuracy')
    plt.plot(epochs, val_acc, 'orange', marker='o',label='Validation
Accuracy')
    plt.title('Training and Validation Accuracy')
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
    plt.legend()

    # Plot training and validation loss
    plt.subplot(1, 2, 2)
    plt.plot(epochs, tr_loss, 'blue',marker='o', label='Training
loss')
    plt.plot(epochs, val_loss, 'orange', marker='o',label='Validation
loss')
    plt.title('Training and Validation Loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.legend()

    plt.tight_layout()
    plt.show()

 model_performance(history)
```




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

# Get a batch of validation images and labels
val_images, val_labels = next(val_gen_vgg)

# Make predictions
pred_probs = model.predict(val_images)  # Get prediction probabilities
pred_labels = np.argmax(pred_probs, axis=1)
true_labels = np.argmax(val_labels, axis=1)
```

```
# Get class names
class_indices = val_gen_vgg.class_indices
class_names = {v: k for k, v in class_indices.items()}

# Function to display images with true labels, predicted labels, and
confidence
def display_images_with_confidence(images, true_labels, pred_labels,
pred_probs, class_names, num_images):
    plt.figure(figsize=(15, 15))  # Adjust figure size for more images
    for i in range(num_images):
        plt.subplot(5, 4, i + 1)  # Create a grid of 5 rows and 4
columns
        plt.imshow(images[i])

        true_label = class_names[int(true_labels[i])]
        pred_label = class_names[int(pred_labels[i])]
        confidence = pred_probs[i][pred_labels[i]] * 100  # Get
confidence as percentage
        Flag = 0
        if(true_label == pred_label):
            Flag = 1
        # Display true label, predicted label, and confidence with
smaller font
        plt.title(f"True: {true_label}\nPred: {pred_label}
({confidence:.2f}%)({Flag})", fontsize=11)
        plt.axis('off')

    plt.tight_layout()
    plt.show()

# Display 20 images with true labels, predicted labels, and confidence
display_images_with_confidence(val_images, true_labels, pred_labels,
pred_probs, class_names, num_images=20)
```

```
1/1 [==============================] - 1s 567ms/step
```


True: PINE WHITE
Pred: PINE WHITE (99.99%)(1)
True: BANDED ORANGE HELICONIAN
Pred: BANDED ORANGE HELICONIAN (99.90%)(1)
True: PINE WHITE
Pred: PINE WHITE (99.99%)(1)
True: INDRA SWALLOW
Pred: YELLOW SWALLOW TAIL (100.00%)(0)
True: EASTERN PINE ELFIN
Pred: EASTERN PINE ELFIN (99.46%)(1)
True: DANAID EGGFLY
Pred: DANAID EGGFLY (97.76%)(1)
True: BROWN SIPROETA
Pred: BROWN SIPROETA (99.63%)(1)
True: ULYSES
Pred: ULYSES (100.00%)(1)
True: CLEOPATRA
Pred: CLEOPATRA (80.73%)(1)
True: ORCHARD SWALLOW
Pred: ORCHARD SWALLOW (97.21%)(1)
True: WOOD SATYR
Pred: WOOD SATYR (71.49%)(1)
True: QUESTION MARK
Pred: QUESTION MARK (99.90%)(1)
True: AFRICAN GIANT SWALLOWTAIL
Pred: CRECENT (93.25%)(0)
True: CABBAGE WHITE
Pred: CABBAGE WHITE (97.38%)(1)
True: YELLOW SWALLOW TAIL
Pred: YELLOW SWALLOW TAIL (99.89%)(1)
True: PURPLE HAIRSTREAK
Pred: PURPLE HAIRSTREAK (99.12%)(1)
True: QUESTION MARK
Pred: QUESTION MARK (97.72%)(1)
True: EASTERN COMA
Pred: EASTERN COMA (92.88%)(1)
True: ATALA
Pred: ATALA (99.55%)(1)
True: SOUTHERN DOGFACE
Pred: SOUTHERN DOGFACE (95.76%)(1)