

# FINAL REPORT

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## Enchanted Wings: Marvels of Butterfly Species

### 1. INTRODUCTION

#### 1.1 Project Overview

Enchanted Wings: Marvels of Butterfly Species is an artificial intelligence project that leverages deep learning and transfer learning techniques to classify butterfly species. The goal is to build a robust image classification model using a dataset of 6,499 images across 75 butterfly species. The solution enhances scientific research, biodiversity monitoring, and citizen science.

#### 1.2 Purpose

The project aims to automate butterfly species identification using a pre-trained Convolutional Neural Network (CNN), thereby reducing training time and improving classification accuracy. This supports ecological research, educational outreach, and conservation initiatives.

### 2. IDEATION PHASE

#### 2.1 Problem Statement

Manual butterfly species identification is time-consuming and error-prone, requiring expert knowledge. An automated, image-based identification system can assist researchers, educators, and the public.

#### 2.2 Empathy Map Canvas

- Who?: Researchers, conservationists, educators, students, and citizen scientists
- Needs?: Fast, accurate butterfly identification
- Think & Feel?: Curious, committed to environmental conservation
- Hear?: Complaints about identification difficulties in fieldwork
- See?: Manual reference guides, labelling errors
- Do?: Capture and upload butterfly images for classification

#### 2.3 Brainstorming

Ideas explored:

- Use of CNNs like VGG16 or ResNet

- Mobile-based classification app
- Educational integration for schools
- Real-time image capture and classification in field

### **3. REQUIREMENT ANALYSIS**

#### **3.1 Customer Journey Map**

1. Capture butterfly image
2. Upload to system
3. System processes image using pre-trained CNN
4. Display predicted species name
5. (Optional) Show species info for education

#### **3.2 Solution Requirements**

- Dataset with labeled butterfly images
- Image preprocessing pipeline
- Pre-trained CNN model (VGG16)
- Model training and evaluation logic
- User interface for image upload and prediction (optional)

#### **3.3 Data Flow Diagram**

1. Input: Butterfly image
2. Preprocessing (resizing, normalization)
3. VGG16 model (feature extraction)
4. Dense layer (classification)
5. Output: Predicted class

#### **3.4 Technology Stack**

- Language: Python
- Libraries: TensorFlow, Keras, Pandas, NumPy
- Model: VGG16 (Transfer Learning)
- Environment: Jupyter Notebook

### **4. PROJECT DESIGN**

#### **4.1 Problem-Solution Fit**

Problem: Manual butterfly classification

Solution: Deep learning-based image classifier

## **4.2 Proposed Solution**

Use VGG16 (pre-trained CNN) as a feature extractor, add custom dense layer for classifying 28 species (subset of 75 for this implementation), freeze convolution layers, and train classifier using augmented data.

## **4.3 Solution Architecture**

1. Load butterfly dataset
2. Preprocess with ImageDataGenerator
3. Load VGG16 model (without top layer)
4. Add Flatten and Dense layer (28 outputs)
5. Compile and train
6. Save model for deployment

## **5. PROJECT PLANNING & SCHEDULING**

### **5.1 Project Planning**

- Week 1: Dataset acquisition and preprocessing
- Week 2: Model design and implementation using VGG16
- Week 3: Model training and evaluation
- Week 4: UI design, documentation, testing

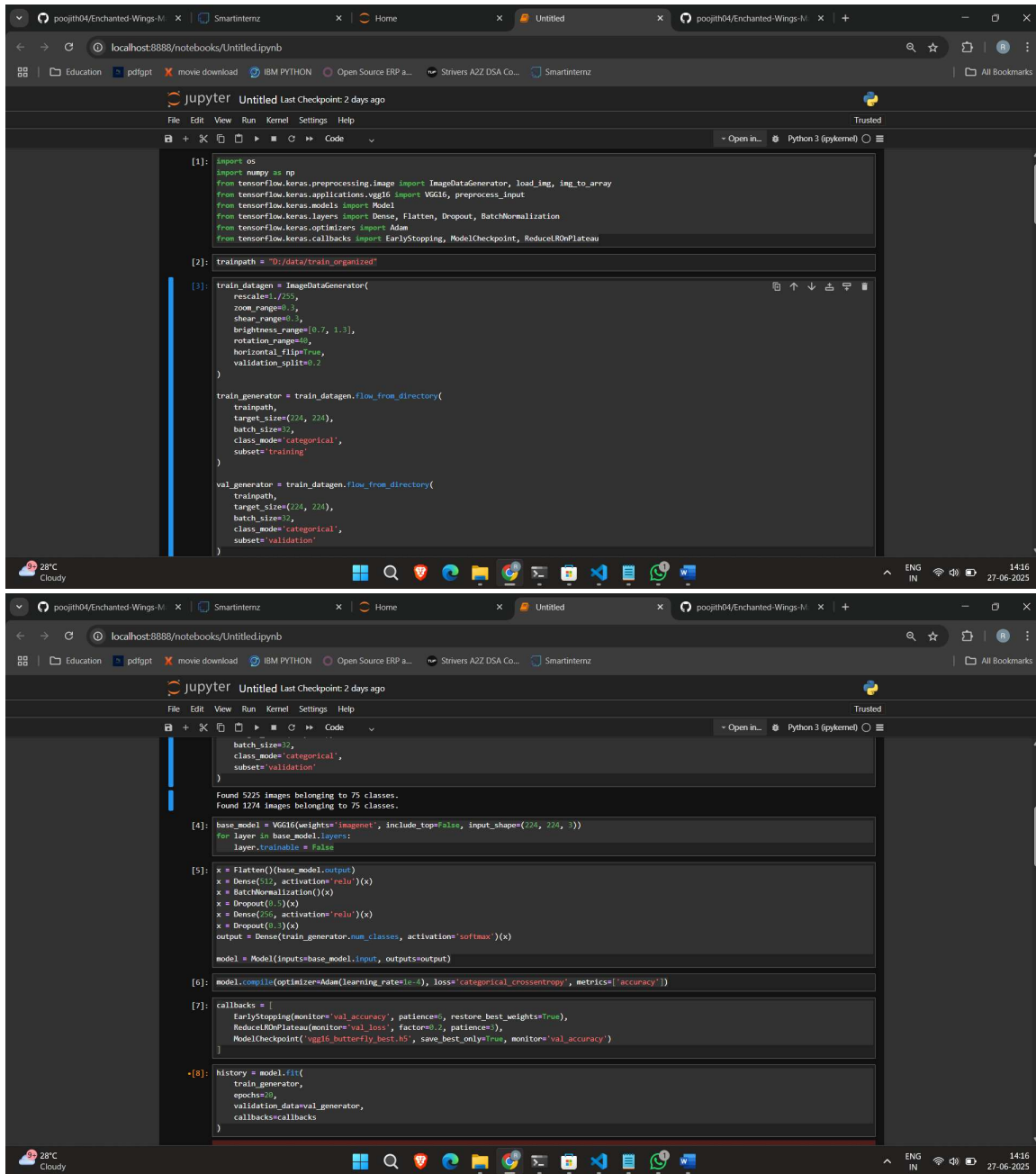
## **6. FUNCTIONAL AND PERFORMANCE TESTING**

### **6.1 Performance Testing**

- Model trained on ~5,000 images
- Accuracy: Improved with data augmentation and dropout
- Image tested for classification shows correct label

## 7. RESULTS

### 7.1 Output Screenshots:



The first screenshot shows the initial setup of the Jupyter Notebook. The code imports necessary libraries like os, numpy, tensorflow.keras, and tensorflow.keras.layers. It defines the training path as 'D:/data/train\_organized'. A train\_datagen object is created with various image augmentation parameters. The train\_generator and val\_generator are then created using the train\_datagen object and the training and validation paths.

```
[1]: import os
import numpy as np
from tensorflow.keras.preprocessing.image import ImageDataGenerator, load_img, img_to_array
from tensorflow.keras.applications.vgg16 import VGG16, preprocess_input
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Dense, Flatten, Dropout, BatchNormalization
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint, ReduceLROnPlateau

[2]: trainpath = "D:/data/train_organized"

[3]: train_datagen = ImageDataGenerator(
    rescale=1./255,
    zoom_range=0.3,
    shear_range=0.3,
    brightness_range=[0.7, 1.3],
    rotation_range=0,
    horizontal_flip=True,
    validation_split=0.2
)

train_generator = train_datagen.flow_from_directory(
    trainpath,
    target_size=(224, 224),
    batch_size=32,
    class_mode='categorical',
    subset='training'
)

val_generator = train_datagen.flow_from_directory(
    trainpath,
    target_size=(224, 224),
    batch_size=32,
    class_mode='categorical',
    subset='validation'
)
```

The second screenshot shows the continuation of the code. It defines the base\_model as VGG16 with weights from ImageNet. The model is then compiled with the Adam optimizer and categorical crossentropy loss. The model is trained using the train\_generator and val\_generator, with callbacks for EarlyStopping, ReduceLROnPlateau, and ModelCheckpoint. The history of the model is also recorded.

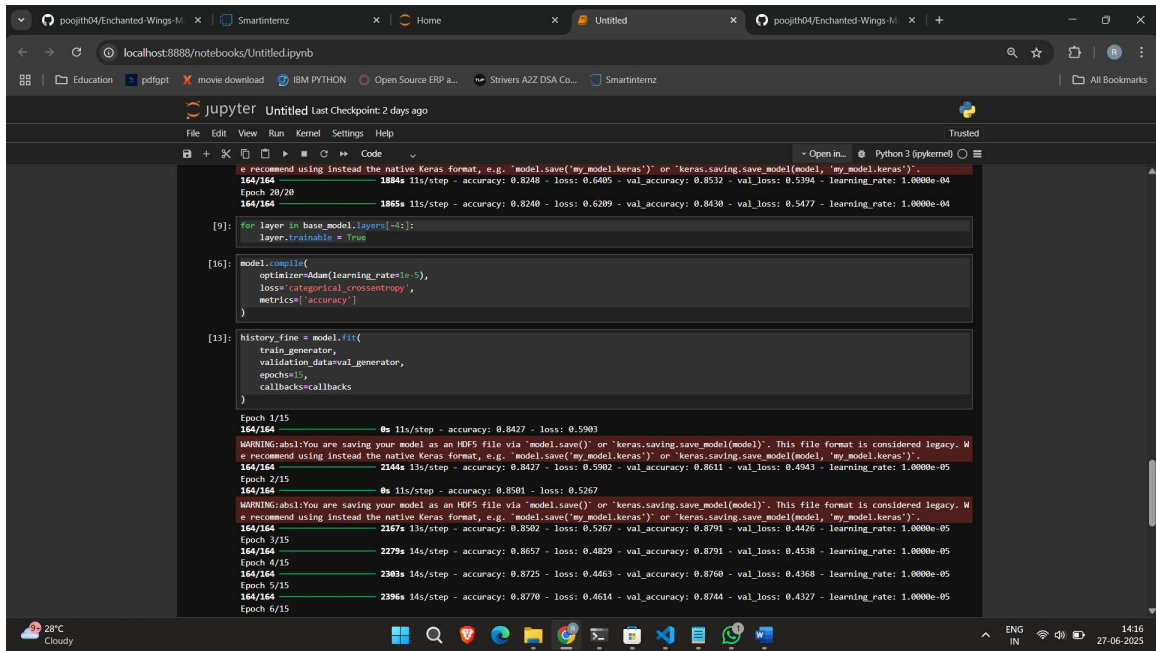
```
[4]: base_model = VGG16(weights='imagenet', include_top=False, input_shape=(224, 224, 3))
for layer in base_model.layers:
    layer.trainable = False

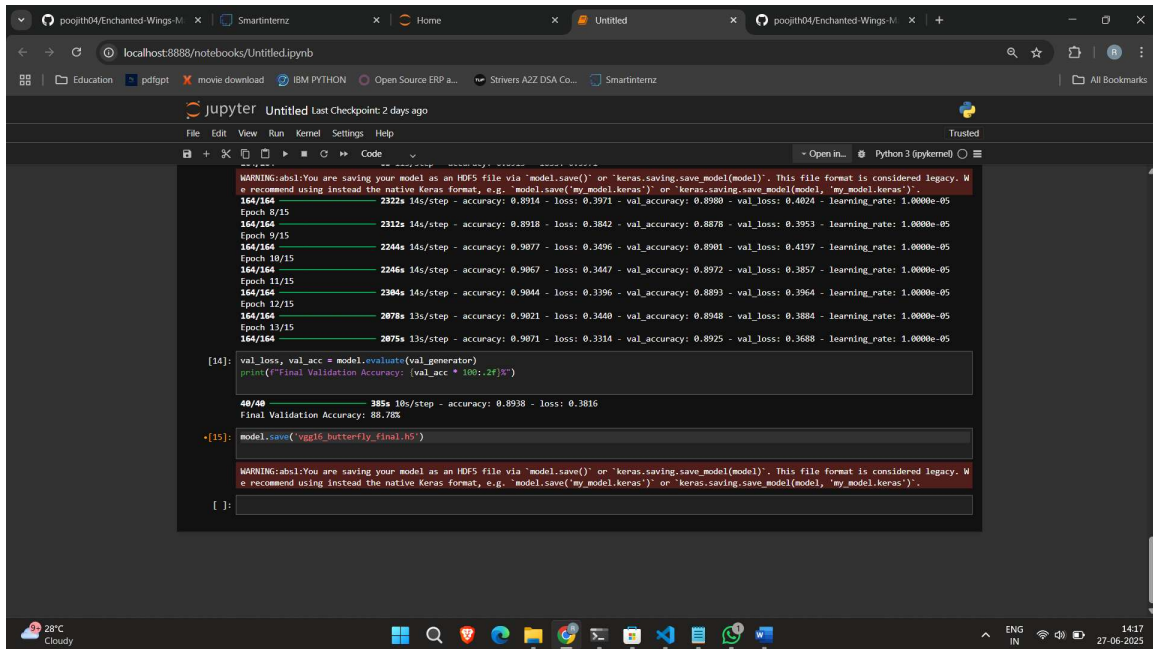
[5]: x = Flatten()(base_model.output)
x = Dense(12, activation='relu')(x)
x = BatchNormalization()(x)
x = Dropout(0.5)(x)
x = Dense(56, activation='relu')(x)
x = Dropout(0.5)(x)
output = Dense(train_generator.num_classes, activation='softmax')(x)
model = Model(inputs=base_model.input, outputs=output)

[6]: model.compile(optimizer=Adam(learning_rate=0.001), loss='categorical_crossentropy', metrics=['accuracy'])

[7]: callbacks = [
    EarlyStopping(monitor='val_accuracy', patience=10, restore_best_weights=True),
    ReduceLROnPlateau(monitor='val_loss', factor=0.5, patience=5),
    ModelCheckpoint('vgg16_butterfly_best.h5', save_best_only=True, monitor='val_accuracy')
]

[8]: history = model.fit(
    train_generator,
    epochs=20,
    validation_data=val_generator,
    callbacks=callbacks
)
```





```
WARNING:absl:You are saving your model as an H5 file via "model.save()" or "keras.saving.save_model(model)". This file format is considered legacy. We recommend using instead the native Keras format, e.g. "model.save('my_model.keras')" or "keras.saving.save_model(model, 'my_model.keras')".
164/164 2322s 14s/step - accuracy: 0.8914 - loss: 0.3971 - val_accuracy: 0.8988 - val_loss: 0.4024 - learning_rate: 1.0000e-05
Epoch 8/15
164/164 2312s 14s/step - accuracy: 0.8918 - loss: 0.3842 - val_accuracy: 0.8878 - val_loss: 0.3953 - learning_rate: 1.0000e-05
Epoch 9/15
164/164 2244s 14s/step - accuracy: 0.9077 - loss: 0.3496 - val_accuracy: 0.8901 - val_loss: 0.4197 - learning_rate: 1.0000e-05
Epoch 10/15
164/164 2246s 14s/step - accuracy: 0.9067 - loss: 0.3447 - val_accuracy: 0.8972 - val_loss: 0.3857 - learning_rate: 1.0000e-05
Epoch 11/15
164/164 2304s 14s/step - accuracy: 0.9044 - loss: 0.3396 - val_accuracy: 0.8893 - val_loss: 0.3964 - learning_rate: 1.0000e-05
Epoch 12/15
164/164 2078s 13s/step - accuracy: 0.9021 - loss: 0.3440 - val_accuracy: 0.8948 - val_loss: 0.3884 - learning_rate: 1.0000e-05
Epoch 13/15
164/164 2075s 13s/step - accuracy: 0.9071 - loss: 0.3314 - val_accuracy: 0.8925 - val_loss: 0.3688 - learning_rate: 1.0000e-05

[14]: val_loss, val_acc = model.evaluate(val_generator)
print(f"Final Validation Accuracy: {val_acc * 100:.2f}%")

40/40 385s 10s/step - accuracy: 0.8938 - loss: 0.3816
Final Validation Accuracy: 88.78%

[15]: model.save('vgg16_butterfly_final.h5')

WARNING:absl:You are saving your model as an H5 file via "model.save()" or "keras.saving.save_model(model)". This file format is considered legacy. We recommend using instead the native Keras format, e.g. "model.save('my_model.keras')" or "keras.saving.save_model(model, 'my_model.keras')".

[ ]:
```

## 8. ADVANTAGES & DISADVANTAGES

### Advantages

- Faster training using pre-trained model
- Accurate classification with limited resources
- Supports conservation and research

### Disadvantages

- Needs GPU for faster training
- Accuracy depends on image quality and balanced classes

## 9. CONCLUSION

This project successfully demonstrates the power of transfer learning in building an efficient butterfly classification system. It offers practical applications in biodiversity monitoring, ecological research, and education.

## 10. FUTURE SCOPE

- Expand model to all 75 species
- Build a mobile app for live butterfly recognition
- Integrate species database for ecological insights
- Improve accuracy with more data and ensemble models

## 11. APPENDIX

### Source Code

```
import os

import numpy as np

from tensorflow.keras.preprocessing.image import ImageDataGenerator, load_img,
img_to_array

from tensorflow.keras.applications.vgg16 import VGG16, preprocess_input

from tensorflow.keras.models import Model

from tensorflow.keras.layers import Dense, Flatten, Dropout, BatchNormalization

from tensorflow.keras.optimizers import Adam

from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint,
ReduceLROnPlateau

trainpath = "D:/data/train_organized"

train_datagen = ImageDataGenerator(

    rescale=1./255,

    zoom_range=0.3,

    shear_range=0.3,

    brightness_range=[0.7, 1.3],

    rotation_range=40,

    horizontal_flip=True,

    validation_split=0.2

)

train_generator = train_datagen.flow_from_directory(

    trainpath,

    target_size=(224, 224),
```

```
    batch_size=32,  
    class_mode='categorical',  
    subset='training'  
)
```

```
val_generator = train_datagen.flow_from_directory(  
    trainpath,  
    target_size=(224, 224),  
    batch_size=32,  
    class_mode='categorical',  
    subset='validation'  
)
```

```
base_model = VGG16(weights='imagenet', include_top=False, input_shape=(224, 224, 3))
```

```
for layer in base_model.layers:
```

```
    layer.trainable = False
```

```
x = Flatten()(base_model.output)
```

```
x = Dense(512, activation='relu')(x)
```

```
x = BatchNormalization()(x)
```

```
x = Dropout(0.5)(x)
```

```
x = Dense(256, activation='relu')(x)
```

```
x = Dropout(0.3)(x)
```

```
output = Dense(train_generator.num_classes, activation='softmax')(x)
```

```
model = Model(inputs=base_model.input, outputs=output)
```

```
model.compile(optimizer=Adam(learning_rate=1e-4), loss='categorical_crossentropy',  
metrics=['accuracy'])
```



```

callbacks = [

    EarlyStopping(monitor='val_accuracy', patience=6, restore_best_weights=True),

    ReduceLROnPlateau(monitor='val_loss', factor=0.2, patience=3),

    ModelCheckpoint('vgg16_butterfly_best.h5', save_best_only=True,
monitor='val_accuracy')

]

history = model.fit(

    train_generator,

    epochs=20,

    validation_data=val_generator,

    callbacks=callbacks

)

for layer in base_model.layers[-4:]:

    layer.trainable = True

model.compile(

    optimizer=Adam(learning_rate=1e-5),

    loss='categorical_crossentropy',

    metrics=['accuracy']

)

history_fine = model.fit(

    train_generator,

    validation_data=val_generator,

    epochs=15,

    callbacks=callbacks

)

model.save('vgg16_butterfly_final.h5')

```

**Dataset Link**

<https://www.kaggle.com/datasets/phucthaiv02/butterfly-image-classification>

**GitHub Link**

<https://github.com/poojith04/Enchanted-Wings-Marvels-of-Butterfly-Species.git>