Butterfly and Moth Species Detection and Classification Using Deep Learning

MSc Research Project
Data Analytics

Deepak Yadav
Student ID: x21219991

School of Computing
National College of Ireland

Supervisor: Mr. Hicham Rifai

National College of Ireland
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Butterfly and Moth Species Detection and Classification Using Deep Learning

Deepak Yadav
x21219991

Abstract

Butterflies bring to mind images of meadows, colorful flower filled landscapes and lively summer gardens. Aside from their appeal, areas rich in butterflies and moths indicate an ecosystem that supports a wide variety of invertebrate populations. This research delves into the classification of images specifically focusing on identifying 100 species of butterflies and moths. The dataset used consists of 12,594 training images 500 validation images and 500 test images all sized at 224 x 224 pixels. By employing four models including pretrained models such as EfficientNetB0, ResNet50, VGG19 Models and a custom CNN model named ButterflyNet. ResNet50 stands out with a test accuracy of 95% closely followed by EfficientNetB0 at 93.60% VGG19 Model at 92.80% and ButterflyNet at 85.40%. Moreover incorporating an interactive Streamlit UI enhances accessibility by allowing users to conduct real time tests. In conclusion ResNet50 emerges as the model while ButterflyNet shows promising potential. Future efforts should explore tuning techniques, ensemble methods and continuous model optimization to contribute to the evolving field of image classification and its crucial role, in biodiversity conservation through technological advancements.

Keywords : ButterflyNet Model, CNN, deep learning, image processing

1 Introduction

The importance of butterflies and moths goes beyond pollination and contributes to the diversity and well-being of ecosystems to being a factor in the economic growth of past civilizations. The Silk Road, originating during China's Han Dynasty, played a role in the flourishing of the dynasty and connected the civilizations of the East and West. It fostered the exchange of goods, ideas and cultures shaping interconnected civilizations and leaving a lasting impact on history (Rudge, 2022). The global prevalence of butterflies is truly remarkable since they can be found in ecosystems and regions around the world (Pinkert et al., 2022). It is fascinating to see how butterflies inhabit every corner of diverse ecosystems across the globe (Parikh et al., 2021). These insects play a crucial role in pollinating plants, and their visual appeal is recognized by various creatures (The Editors of Encyclopaedia, 2023). Understanding and conserving their diversity is imperative due to its implications for overall biodiversity and ecosystem balance.

Butterflies are part of the Papilionoidea family, they are found everywhere around the globe expect Antarctica. Within this lineage there are suborders that house their distinct species. From moths to a vibrant array of butterflies there is a wide variety among them. These fluttering wonders can be found in habitats such as fields, forests and even extreme locations like mountain peaks and deserts (Filali et al., 2023). Similarly, the European continent boasts about 482 known species contributing to a diverse and vibrant landscape (Warren et al., 2021). Among the 27 member countries of the European Union an impressive 451 species have found their home showcasing diversity within the region (Franke et al., 2022). What makes this European collection more intriguing is that approximately 30% of its butterfly population is exclusive to European territories, known as endemic species (Van Swaay et al., 2020). It is worth mentioning that among butterfly families, the Nymphalidae family stands out due to the highest rate of endemism. In contrast, the Papilionidae family, which is primarily found in regions has a comparatively lower percentage of European endemics (Van Swaay et al., 2010). Therefore, conserving these creatures and accurately identifying butterfly species hold utmost importance.

Indisputably, butterflies held the fascination of nature enthusiasts and researchers for an exceptionally long time, allured by their pivotal ecological significance and mesmerizing beauty. As pivotal pollinators and indicators of environmental health, the conservation and precise identification of butterfly species hold paramount importance. In recent years, considerable progress in automated butterfly identification was achieved through the incorporation of deep learning techniques like Convolutional Neural Networks (CNNs) (Ruoyan Zhao, 2019), Artificial Neural Networks (ANN) (Kaya et al., 2015), Grey -Level Co-occurrence Matrix (GLCM) (Yasmin et al., 2023) and Local Binary Patterns (LBP) (Kaya et al., 2015). These advancements produced promising results in the precise and efficient categorization of butterfly species.

Identifying butterflies poses challenges due to their intricate wing coloration, morphological evolution and color patterns. Manual identification procedures are time consuming, prone to error and require specialized knowledge. These challenges limit the scope of research and conservation efforts emphasizing the need for methodologies to explore the diversity of butterfly species.

This research aims to explore the identification and classification of 100 species of butterflies and moths—an unprecedented scope compared to earlier studies (Yasmin et al., 2023). This research introduces a model that is worth mentioning. To evaluate its performance, this research compares it to known pretrained models like EfficientNetB0, ResNet50 and VGG19 Custom Models. In the Results section, this paper delves into discussions about the accuracy of the models shedding light on how effective and promising the innovative approach is, for future advancements.

Research Question:

In addressing the limitations posed by manual identification techniques and recognizing the potential advancements offered by deep learning, the research questions guiding this study arise:

1. How can a CNN architecture be accustomed to classify 100 butterfly species?
2. To what extent does the custom CNN model (ButterflyNet) outperform or align with pre-trained models in accuracy and loss?

The organization of this paper unfolds in the subsequent manner: In Section 2, there is a detailed exploration of the current state of research concerning butterfly detection and recognition. Moving on to Section 3, this paper dives into the specifics of research methods and specifications, encompassing aspects such as scope of work, data collection methodology and the deep learning framework employed. The conclusive findings are encapsulated in Section 6.

2 Literature Review

This research delves into the effects of learning and computer vision with a specific emphasis on Convolutional Neural Network's (CNNs) aid in identifying butterfly species. Focused on identifying 100 butterfly and moth species the research explores image processing and CNNs improved and automated identification methods showcasing the possibilities for revolutionizing species identification.

2.1 Butterfly Species Identification

The task of identifying butterfly species in the wild is challenging due to their patterns and distinctions (Xie et al., 2021). Traditional methods of identification such as using taxonomy keys rely heavily on individuals for classification. However, this manual process is known to be inefficient and time consuming given the distribution and wide variety of butterfly species (Wang et al., 2012). Advancements in computer vision have opened promising possibilities, for automating this specialized task. Butterflies exhibit a range of wing shapes, patterns, colors and textures that play a role in their identification. These visible characteristics can now be analysed automatically through techniques. Figure 1 provides a representation of the anatomy of a butterfly including its head, mouthparts, antennae, wing veins, wing cells abdomen hindwing forewing thorax (Perveen, 2017). The combination of tools and computer vision has the potential to make the process of identifying butterfly species efficient thereby addressing the difficulties caused by their intricate variations.

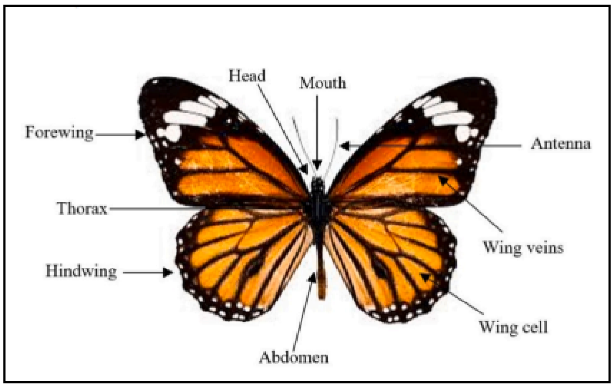

Figure 1: Anatomy of a butterfly (Perveen, 2017)

While certain traits can serve as criteria, within a species, a crucial factor in distinguishing between species lies in carefully examining their external structural attributes, particularly the male genitalia. However, these procedures are complex time consuming and prone to errors. Molecular investigations have emerged as a method for identifying features (Hebert and Gregory, 2005). Although they do not consistently provide results recent research suggests that morphological characteristics are still considered the method for butterfly identification even though they may not be completely conclusive.

2.2 Traditional method for classifying Butterfly and moth species

In an overview of techniques for detecting and classifying butterflies, (Yasmin et al., 2023) offered valuable insights into this challenging task. Traditional machine learning algorithms tackle butterfly identification by extracting features and categorizing objects accordingly. Commonly used techniques for feature extraction include Grey level co matrix (GLCM) local binary pattern (LBP) and Histograms of multi scale curvature (HoMSC). At the time established algorithms, like KNN and SVM have been employed with kNN demonstrating superior performance compared to SVM.

In the phase it is important to note that deep learning models have shown accuracy reaching 100% in identifying butterflies. However, this success heavily relies on having an amount of data, for training the models. In their research Yasmin et al. (2023) proposed an automated approach that combines learning, cloud computing and entomology to streamline the time-consuming process of categorizing butterfly species. By capturing butterfly images using cameras or smartphones and uploading them to a computing platform researchers can utilize deep learning-based methods to identify the species in these photos. This automated process removes the need for involvement. Leads to faster and more precise identification procedures.

In a context traditional method of recognizing butterfly species have relied on human observation skills and the expertise of entomologists or taxonomists. However, these approaches have limitations that affect their accuracy and efficiency. To overcome these constraints computer vision techniques are increasingly being employed. Prior studies have demonstrated results with image-based classification methods, particularly those utilizing innovative attributes, like Convolutional Neural Networks (CNN) in accurately identifying butterfly species in their natural habitats. These methods utilize the groundbreaking abilities of tools and computer vision to address the challenges posed by the patterns and variations found in different butterfly species.

2.3 Deep Learning Approaches in Butterfly Species Detection

According toYasmin, Das, Rozario and Islam (2023), researchers have utilized learning techniques to address various challenges in autonomous butterfly identification. In this section this research will review research on the recognition and classification of butterfly species using learning methods. (Kaya et al., 2015) employed Artificial Neural Networks (ANNs) which proved effective in identifying butterfly species. They used Local Binary Pattern (LGB) for feature extraction. Fed its output into ANNs for model training. The resulting model achieved a 98% accuracy during evaluation.

Convolutional Neural Networks (CNNs) are widely recognized as the extensively used deep learning techniques for butterfly detection and classification as highlighted by (Yasmin et al., 2023). Rajeena P. P. et al. (2022) leveraged pre trained CNN models such, as VGG16, VGG19, MobileNet, Xception, ResNet50 and InceptionV3 and fine-tuned them specifically for butterfly species recognition tasks. According to the research findings the CNN model, with architecture achieved an accuracy rate of 94.66%. However, it is important to note that this study has a limitation as it solely relies on image data.

(Fan et al., 2022) employed ResNet as another algorithm in the butterfly recognition field. They used the dataset of 12,956 images of papilionidae for species identification. After optimizing the model with different optimization algorithms such as SGD

(Stochastic Gradient Descent), RMSprop, Adam and Adamax, the authors proposed the outcome with the best recognition accuracy of ResNet-50 was 87.47% which had been optimized by Adamax. Additionally, the authors also suggested that Adamax algorithm offers the advantages of being simple to develop, highly efficient, requiring minimal memory, and automatically adjusting the learning rate.

Peer Learning Network with Distribution-Aware Penalty Mechanism or PLN-DPM proposed by (Xu et al., 2022) for automatic species recognition. This study suggested a peer learning network with a distribution-aware penalty mechanism. On a sizable dataset of butterflies (Butterfly-914),the obtained model achieves a highest accuracy rate of 86.2% which was even better the ResNet-50 model.It demonstrated its potential for agricultural species identification. However, there are not many studies that use this approach for species recognition tasks, so it is necessary to assess the effectiveness of this algorithm for various datasets with such a similar duty. Generally, deep learning techniques, especially Convolutional Neural Networks (CNNs), have significantly improved autonomous butterfly species identification. Among the CNN models, InceptionV3 and ResNet-50 achieved great accuracy rates of 94.66% and 87.47%, respectively. Meanwhile, the efficiency of ANNs model development with a larger number of classes has not yet been stated. Furthermore, innovative approaches like PLN-DPM also demonstrated potential, with an accuracy of 86.2%.

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2.4 Research Niche

The review studies use different machine learning method to identify species among a species among 100 butterflies and moths. It combines image processing and deep learning specifically Convolutional Neural Networks (CNNs). The interdisciplinary nature of this research brings together entomology focusing on butterfly and moth taxonomy with computer vision techniques that involve image processing and deep learning. This unique study aims to efficiently identify 100 species of butterflies and moths while utilizing technologies, for automated identification. To strengthen the credibility of this approach researcher have developed custom CNN models for each of the 100 classes. Study then compared their accuracy against pretrained models. Through this evaluation process it display the performance of the custom CNN model but also position it in comparison to established benchmarks. By conducting this analysis research contributes to the advancement of identification techniques but also validates the effectiveness of the models, within the specific context of butterfly and moth species.

3 Research Methodology

In the domain of identifying species of butterflies and moths this research follows a known research methodology called CRoss Industry Standard Process, for Data Mining (CRISP DM) model. This approach enables the utilization of deep learning algorithms, training models evaluating their performance and ultimately creating a user interface (UI) using

Streamlit. The methodology comprises steps that contribute to the analysis and practical application of these models.

Drawing upon the work of Yasmin et al. (2023) this research utilizes Convolutional Neural Networks (CNNs) to detect and classify butterflies. Adjusted pre trained models, like VGG19, ResNet50 and EfficientB0 are employed for the purpose of recognizing butterfly species. Figure 2 displays the CRISP DM model that was used in this research. Each step will be explained in detail in the subsection.

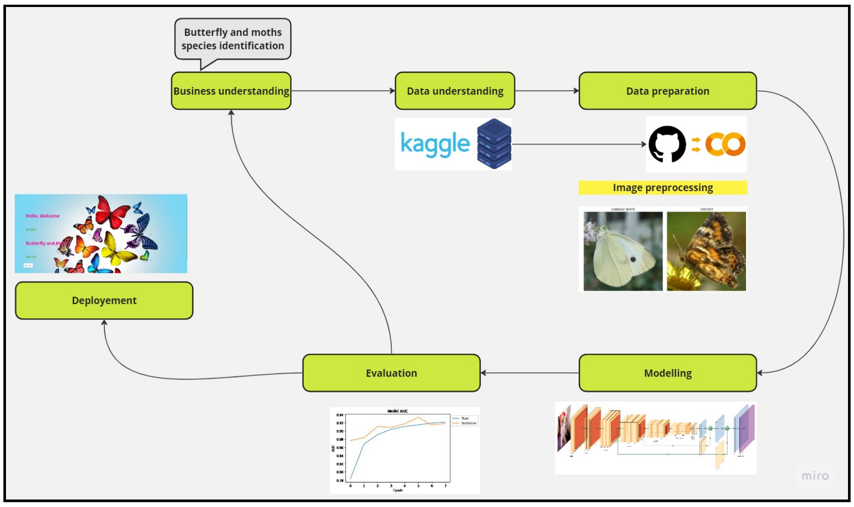

Figure 2: CRISP DM Model

3.1 Business understanding

The effort to tackle the task of identifying butterfly and moth species through image classification goes beyond technological advancements and delves into the crucial realm of environmental conservation. It is vital to identify these species as they serve as indicators for the health and diversity of ecosystems. Using image recognition models this research generates data that helps us understand species distribution, behavior and how ecosystems function. This knowledge guides targeted interventions to protect these species and contributes to conservation efforts in the face of challenges like climate change and habitat loss.

To make this research more accessible and practical an interactive Webpage UI has been developed using the Streamlit library. This user-friendly platform allows individuals to upload images enabling real time testing of models. The seamless and intuitive interface not simplifies the research process but also engages a wider audience in the pursuit of environmental preservation.

3.2 Data understanding

The data used for this study was obtained from Kaggle [1]. The dataset consists of images depicting 100 species, employing 12,000 images for training and allocating an extra 500 for validation. This study utilizes a diverse set of images, each sized at 224 x 224 pixels and saved in the JPG format.

[1]Kaggle Dataset: `https://www.kaggle.com/datasets/gpiosenka/butterfly-images40-species`

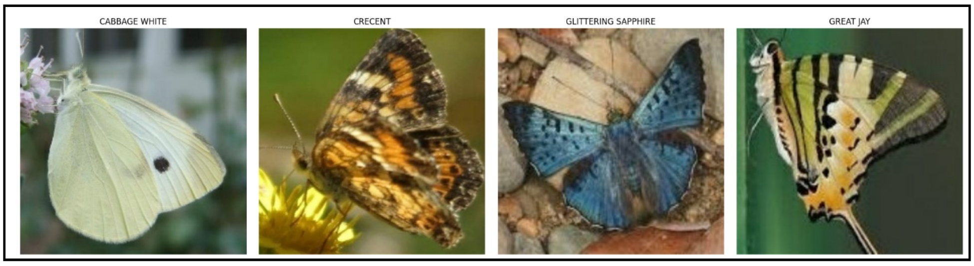

Figure 3: Sample Images from Dataset

3.2.1 Exploratory data Analysis

During the phase of exploratory data analysis (EDA) this research thoroughly examined the distribution of images across categories to gain valuable insights. This examination allowed us to understand the structure of the dataset and identify any differences in the number of images, per species. Figure 4 provides a representation that helps to spot any potential imbalances or patterns that could impact the training and performance of models.

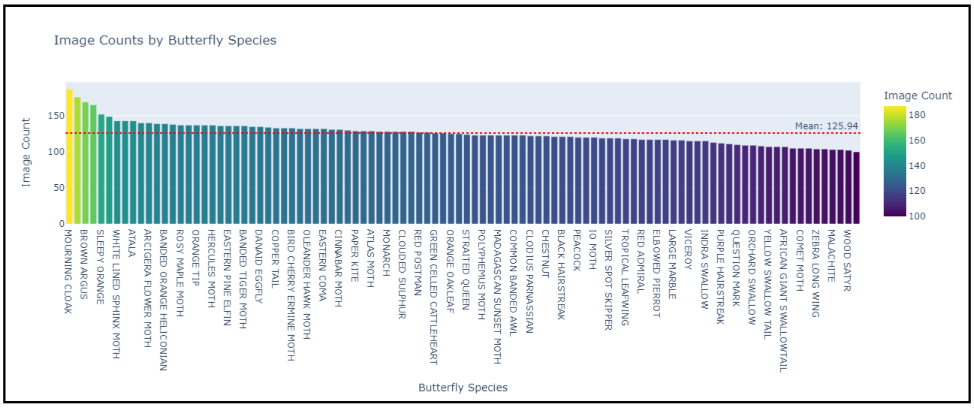

Figure 4: Class distribution Plot

In the following sections This study will delve into each modeling approach providing an understanding of its architectural intricacies and methodologies used.

3.3 Data preparation

Given the size of the dataset it was decided to store it on GitHub, a platform known for its version control capabilities. This choice ensures access and reduces dependency on the Kaggle website server thus enhancing the efficiency of the data preparation process. To enhance the quality of the dataset various cleaning methods were implemented. Images that are not in JPEG, JPG or PNG formats are excluded to maintain consistency, in data format.

3.4 Modelling

In this section, the researcher explores various models considered for the research, encompassing EfficientNetB0, VGG19, ResNet50, and the custom-designed Convolutional Neural Network (CNN) known as ButterflyNet. Each model undergoes a detailed training process, offering valuable insights into the identification of diverse butterfly and moth species.

3.4.1 ButterflyNet Model

In the architecture of the ButterflyNet Model, each layer serves a distinct purpose, collectively contributing to the model's ability to discern intricate patterns in image data. Commencing with the Conv2D input layer, the model processes images of dimensions (224, 224, 3), where 224 signifies height and width, and 3 denotes RGB color channels. Following this, Batch Normalization stabilizes training, optimizing the learning process. Subsequent MaxPooling2D layers down sample the data, preserving essential information. To prevent overfitting, Dropout layers randomly deactivate neurons during training.Figure 5 represents the CNN architecture used.

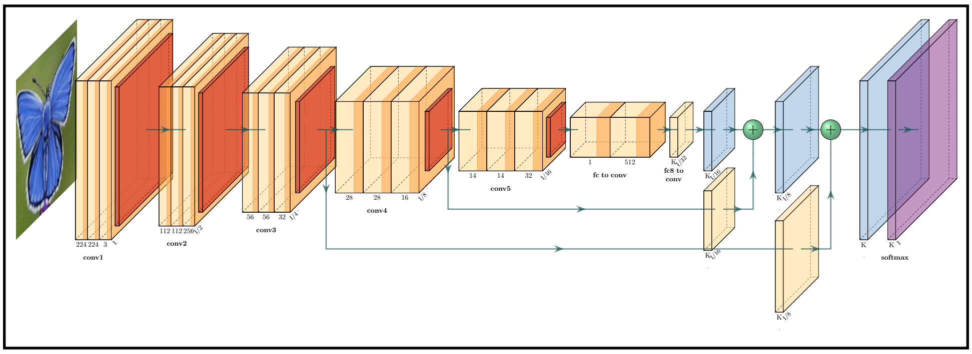

Figure 5: ButterflyNet Model

This process is iteratively refined through additional Convolutional Blocks, each comprising Conv2D, Batch Normalization, MaxPooling2D, and Dropout layers. The Flatten layer acts as a transition, converting 3D feature maps into a 1D vector for dense layers. The sequential stack of dense layers, accompanied by Batch Normalization and Dropout, fine-tunes the learned representations. The output layer, with softmax activation, categorizes images into 100 distinct classes.

3.4.2 EfficientNetB0 Model

The architecture of the EfficientNetB0 is displayed in figure 6. Apart, from the representation EfficientNetB0 utilizes a larger mobile inverted bottleneck convolution, which demonstrates its effectiveness in tasks related to image classification.This deep learning architecture has proven to be particularly adept at handling complex visual recognition challenges. In the research approach, the trained EfficientNetB0 model, equipped with weights from ImageNet, undergoes refinement by excluding the top classification layer.

To focus specifically on identifying types of butterflies and moths this research have incorporated additional layers into the base model. A flattening layer is used to transform the 3D feature maps into a 1D vector making it easier to connect with layers.this study use

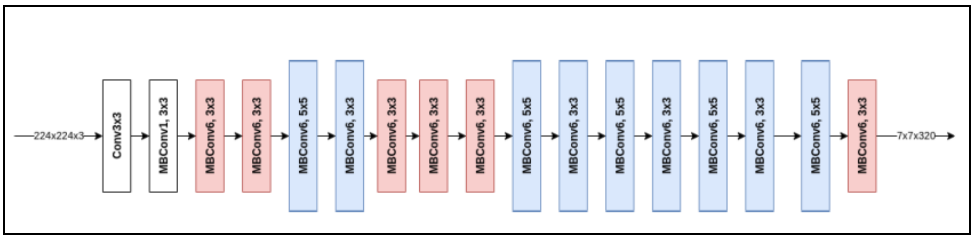

Figure 6: The architecture of EfficientNetB0 CNN (Amin et al., 2022)

a layer with 256 neurons that are activated by Rectified Linear Unit (ReLU) to enhance feature learning and representation. The stability of the model is improved through batch normalization and overfitting is prevented by incorporating a dropout layer with a rate of 0.5. This ensures that model can adapt effectively. The final dense layer consists of 100 neurons. Utilizes the softmax activation function to accurately predict the probability distribution, across various species of butterflies and moths.

3.4.3 VGG19 model

By making adjustments to the VGG19 model this research aims to align it with the goals of the project without requiring retraining of all its layers. This modification maintains the effectiveness of the layers, which are skilled, at detecting features while customizing other layers to focus on the intricate aspects related to butterfly and moth identification.

The model is built using the Sequential API starting with the trained VGG19 model as shown in figure 7 of the architecture. This research use a flattening layer to convert the feature maps into a 1D vector and then utilize layers with ReLU activation to enhance understanding of complex features. it also include batch normalization, for stability.

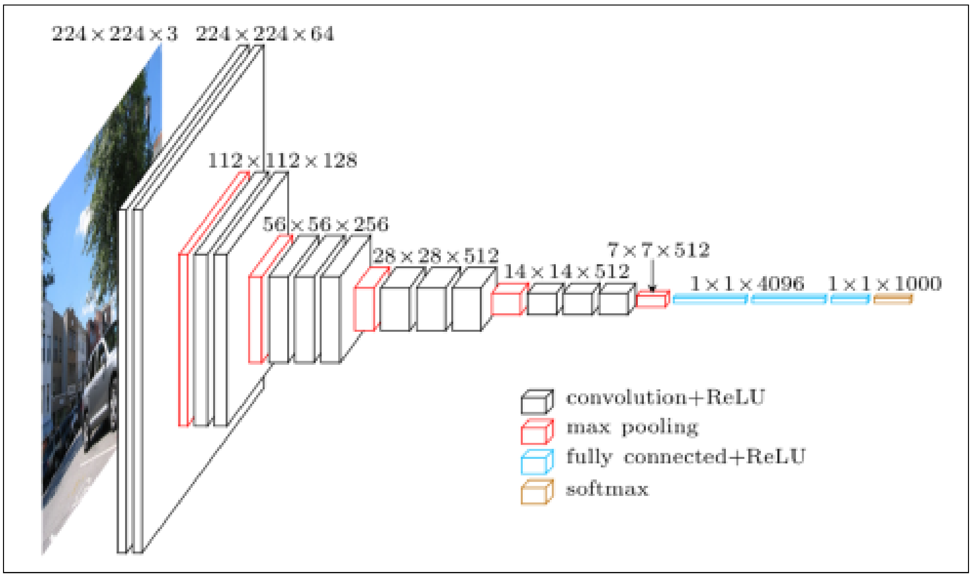

Figure 7: VGG19 Model (Simonyan and Zisserman, 2014)

The final layer, which uses softmax activation is intended to handle the classification task involving classes. It helps generate a probability distribution for butterfly and moth species. The entire model is built using the Adam optimizer. Utilizes cross entropy as the loss function with accuracy serving as the evaluation metric.

This modified VGG19 architecture combines the benefits of fine tuning techniques. It is specifically designed to excel in identifying butterfly and moth species. The comprehensive summary provides insights into aspects of the model including its architecture, parameters and configuration. This further enhances its suitability, for meeting research objectives.

3.4.4 ResNet50 model

This research have utilized the ResNet50 model (depicted in figure 8) which is widely used in machine learning. Aim was to repurpose it for the identification of butterfly and moth species. Initially the ResNet50 model was trained on the ImageNet dataset making it a reliable tool, for extracting features and recognizing patterns.

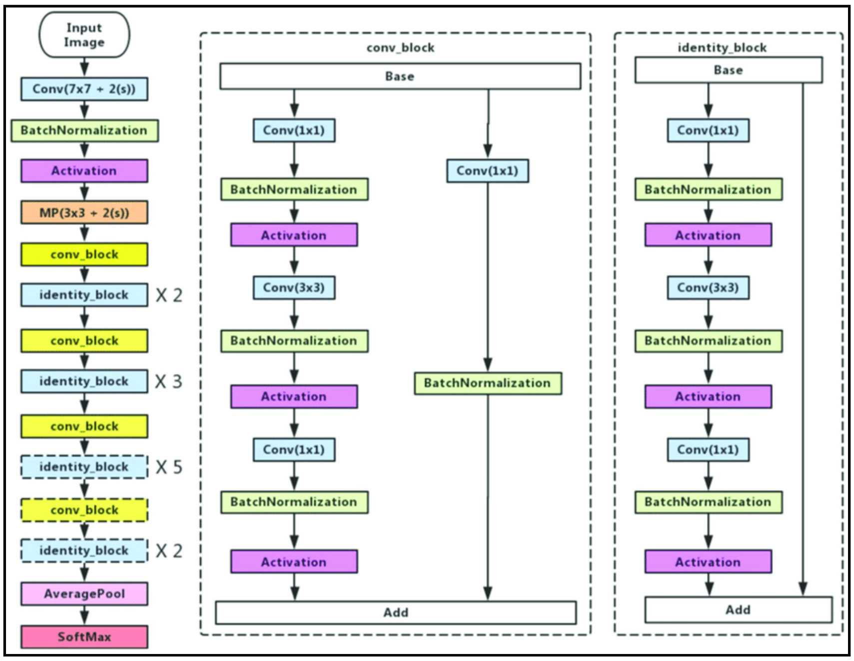

Figure 8: ResNet50 Model Architecture by Ji, Huang, He and Sun (2019)

To adapt ResNet50 for this task all its trained layers were frozen. This approach ensures that the initial layers maintain their proficiency in recognizing features while this research introduce custom layers to tackle the complexities associated with identifying butterfly and moth species.

To enable feature learning it includes a flattening layer that converts the 3D feature maps into a 1D vector and connected layers are utilized. In order to ensure stability batch normalization is implemented. Dropout is implemented to reduce the risks of overfitting.

The final dense layer utilizes softmax activation, which generates a probability distribution. The architecture of this ResNet50 model combines trained features with tuning techniques to accurately identify various species. The optimization algorithm used is Adam, with cross entropy as the loss function and accuracy as the metric for evaluation. This offers an overview of the structure, parameters, and settings of the customized ResNet50 architecture designed for the identification of butterflies and moths.

3.5 Evaluation

In this section, analysis of the deployed models is implemented, considering performance measures such as validation loss and accuracy. Post-training, an evaluation on the test dataset includes a examination of precision, recall, F1 score, and overall accuracy.

3.5.1 Precision, Recall, and Accuracy Calculation:

The evaluation process initiates with the computation of precision, recall, and accuracy metrics.

$$\textbf{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \tag{1}$$

$$\textbf{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$\textbf{Recall} = \frac{TP}{TP + FN} \tag{3}$$

The visualization of the model's performance is facilitated by a heatmap known as the confusion matrix. This matrix offers a visual representation of the true and predicted labels across various classes, providing comprehensive insights into the model's strengths and weaknesses.

Additionally, the test loss and accuracy for each model applied to the test dataset are computed and presented. The loss metric quantifies the model's predictive error, while accuracy measures the overall correctness of the predictions.

3.6 Deployment

In this part of the research methodology, a method aligning with the CRoss Industry Standard Process for Data Mining (CRISP DM) model was chosen. Streamlit was utilized to create a web application that is user-friendly and visually engaging. The purpose of this deployment is to provide an experience for users interested in identifying different species of butterflies and moths.

4 Design and Implementation

The dataset used for this project consisted of 12,594 training images, 500 test images and 500 validation images. All the images had dimensions of 224 x 224. The entire modeling process was carried out using Google Colab's Jupyter notebook, with Python and TensorFlows Keras being the tools utilized. OpenCV and TensorFlow were employed for image processing while Keras played a role in constructing Convolutional Neural Networks (CNNs). Visualizations were enhanced using Plotly and important metrics like precision and recall were obtained through scikit learn. To improve the resilience of the model, class weight computation and stopping callbacks were implemented. Additionally pre trained models such, as EfficientNetB0, VGG19 and ResNet50 were employed to enhance the efficiency of image classification.

4.1 Models

Below are the Implementation of the Models as described in research methodology sections.

4.1.1 ButterflyNet Model

The ButterflyNet model is created in a way that follows a step by step approach. It includes layers that use convolution and batch normalization, along with dropout to extract features and avoid overfitting. Batch normalization helps in keeping the training stable while max pooling downsamples the data while retaining information. Dropout layers, at each stage also contribute to preventing overfitting.

Additional convolutional layers with 256 and 512 filters enhance the network's depth for more intricate feature extraction. A flatten layer is introduced to convert 3D feature maps into a 1D vector. The dense layers, with 512 and 256 neurons, facilitate advanced feature learning. Dropout and batch normalization are applied to these dense layers for regularization.

The last layer of the model, which has 100 neurons using softmax activation is designed to classify 100 species of butterflies and moths. To train the model this research use the Adam optimizer along with a crossentropy loss function. A learning rate scheduler is implemented to help improve the models convergence. In summary the ButterflyNet model demonstrates a designed structure that effectively combines convolutional and dense layers along, with regularization techniques to achieve accurate identification of butterfly and moth species.

4.1.2 EfficientNetB0 Model

The custom model was constructed based on the pre-trained EfficientNetB0. It followed a structured approach, utilizing the pre-trained EfficientNetB0 model with specific fixed layers. The initial step involved leveraging the layers of EfficientNetB0, trained on ImageNet, for feature extraction. Subsequently, additional layers were incorporated, including flattening, a dense layer with 256 neurons and ReLU activation, followed by batch normalization and dropout for regularization. The final layer featured softmax activation, tailored for the classification task of identifying 100 different species of butterflies and moths.

The model is built using the Adam optimizer and a loss function called crossentropy. To ensure convergence during training a learning rate scheduler is used with a learning rate of 0.001. This architecture combines a trained model, with extra layers, for specialized learning creating a well balanced structure that accurately identifies different species of butterflies and moths.

4.1.3 VGG19 Model

The model used is VGG19, which is initialized with trained weights, from ImageNet. It doesn't include the connected layers. The input shape is specified as (224, 224 3). To keep the trained features intact all layers of the VGG19 model are frozen. Then a custom model is created where the VGG19 model is added as the layer to take advantage of its feature extraction capabilities.

After the layers a Flatten layer is used to convert the 3D feature maps into a 1D vector. This is followed by a layer with 256 units and ReLU activation function to introduce non linearity. To enhance stability Batch Normalization is used. Dropout with a rate of 0.5 helps prevent overfitting.The last Dense layer provides probability outputs for 100 classes to align with classification task. Tensorflow compile the model using Adam optimizer, categorical cross entropy loss function and accuracy as evaluation metric. This architecture effectively combines the trained VGG19 with additional layers, for accurate classification.

4.1.4 ResNet50 Model

This study utilized the ResNet50 model as a tool for feature extraction. To initialize the model it used trained weights from ImageNet. The input shape is set as (224, 224 3).To preserve the acquired features all layers of the ResNet50 model were kept frozen. Then carefully constructed a custom model where ResNet50 served as the initial layer. This played a role in extracting robust features.

Following the layers a Flatten layer was introduced to transform the 3D feature maps into a 1D vector. To introduce non linearity a layer with 256 units and ReLU activation is added. Batch Normalization was used to ensure stability in model. Additionally Dropout at a rate of 0.5 was applied to prevent overfitting.

The final Dense layer generated probabilities for classifying into 100 categories relevant to task of interest. For model compilation the Adam optimizer with cross entropy as loss function and accuracy, as evaluation metric is used. This architectural design seamlessly integrated trained ResNet50 with additional layers to achieve effective classification performance in this research.

4.2 Streamlit

Once the models have been trained and saved a Streamlit application is developed that allows for easy interaction. The application consists of two pages. On the page 2 users can effortlessly upload an image, which is then resized to 224x224 pixels and sent to the models for prediction.

The deployment process unfolds across two pages, each serving a specific purpose and contributing to the overall user experience.

4.2.1 Page 1: Introduction and Welcome

The initial page sets the atmosphere, for the Butterfly and Moth World enticing visitors with captivating pictures and engaging text that makes use of Streamlits capabilities. By using Streamlits page configuration you can customize the title, icon and layout to create an branded experience that aligns with the overall theme of the research. This ensures a cohesive and branded experience, aligning with the theme of the research.

4.2.2 Page 2: Butterfly/Moth Species Prediction

Page 2 transforms the deployment into a practical tool for users keen on identifying butterfly and moth species. Figure 9 displays the Webpage snapshot. Components on Page 2 include a file uploader for butterfly or moth images and a dropdown menu for selecting pre-trained models like ButterflyNet,

EfficientNetB0, ResNet50, and VGG19 Custom Models. The chosen model predicts the species and provides information on the predicted class and confidence level.

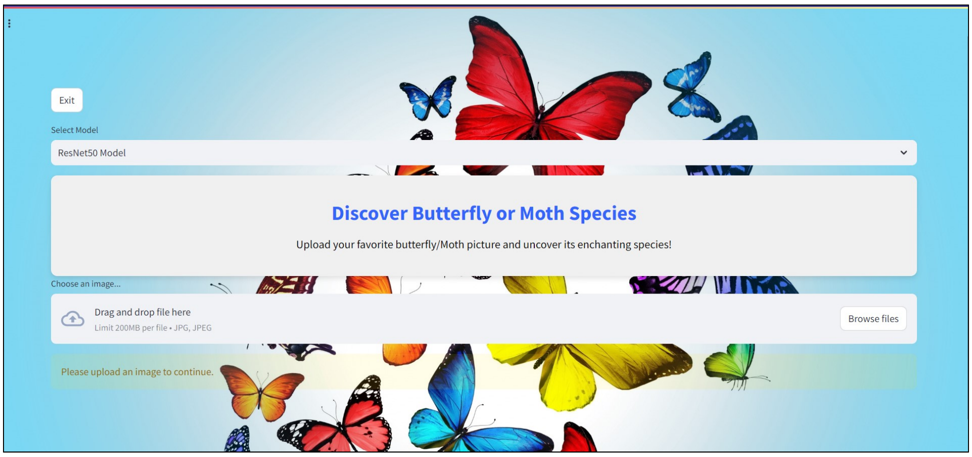

Figure 9: Streamlit Webpage page 2

An "Exit" button is incorporated on the second page, providing users with the option to return to the introduction/welcome page at any point, enhancing the overall user experience and flexibility.

5 Evaluation

In this section, analysis of the deployed models is implemented, considering performance measures such as precision, recall, F1 score, and overall accuracy. To provide insights into the performance of the models, visual representations in the form of accuracy and loss plots are presented. Additionally, the confusion matrix is explained to offer understanding.

5.1 ButterflyNet Model

During the 14 epochs of training, the ButterflyNet model progressed from an initial accuracy of 10.12% and a loss of 4.1275 in the first epoch to a notable improvement, achieving an accuracy of 85.40% and a reduced loss of 0.5081 by the tenth epoch. Similarly, the validation accuracy showed a positive trend, starting at 20.80% and reaching 82.40% in the fourteen epoch (refer Table 1).

The duration of each epoch, ranging from 56 to 73 seconds, reflects the computational load and complexity of the training process. Refer to Figure 10 for insights into the loss plot and Figure 11 for a graphical representation of accuracy during training.

Table 1: Summary of Evaluation Metrics for ButterflyNet Model

Metric	**Value**
Accuracy	85.40%
Precision	87.37%
Recall	85.40%
Macro Avg	0.854
Weighted Avg	0.854
Test Loss	0.5081

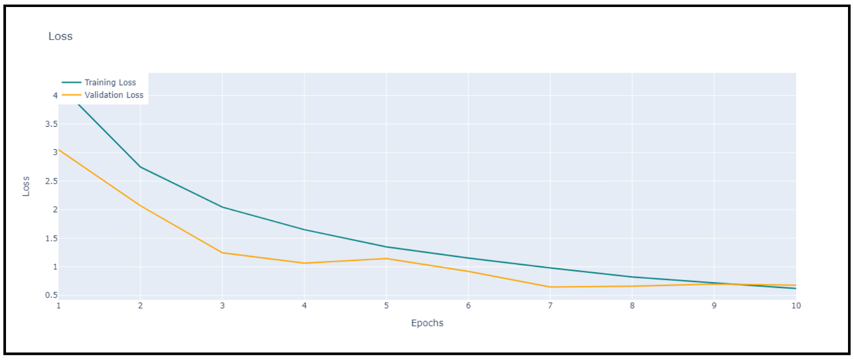

Figure 10: ButterflyNet Loss Plot

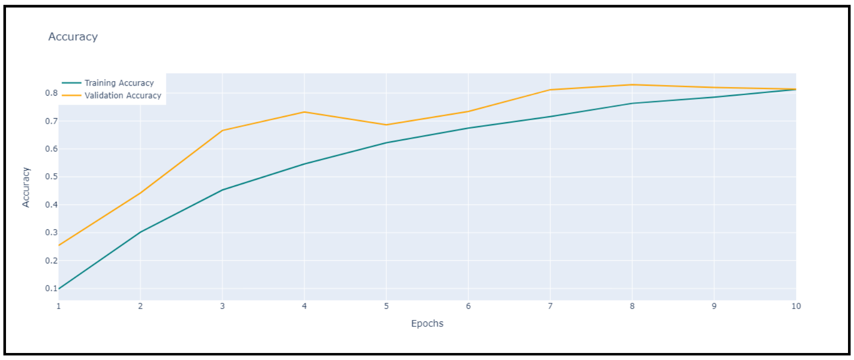

Figure 11: ButterflyNet Accuracy Plot

The classification report offers a comprehensive assessment of ButterflyNet's performance on the test dataset. Strong performance is observed in classes like 'AMERICAN SNOOT,' 'BANDED PEACOCK,' and 'COMMON WOOD-NYMPH,' with high precision, recall, and F1-scores.

Macro and weighted averages showcase an overall model accuracy of 85.40%, with balanced performance across different classes. Further evaluation metrics include a test loss of 0.5081 and a test accuracy of 85.40%. These metrics affirm the model's effectiveness in accurate predictions on unseen data, providing a reliable foundation for real-world applications across diverse classes.

5.2 EfficientNetB0 Model

The EfficientNetB0 model underwent a eight-epoch training regimen with an early stopping mechanism, each epoch lasting approximately 30 seconds. The model's proficiency steadily improved, starting with a training loss of 1.5105 and 65.56% accuracy in the first epoch. Validation metrics showed a loss of 0.3920 and an accuracy of 90.20%. Subsequent epochs demonstrated significant progression, reaching a training accuracy of 98.43% in the eighth epoch. The early stopping mechanism triggered after the eighth epoch, indicating satisfactory performance and preventing overfitting.

Refer to Table 2 for Evaluation metrics, Figure 12 for insights into the loss plot and Figure 13 for a graphical representation of the accuracy during training.

The classification report provides detailed breakdowns for each class, showcasing pre-

Table 2: Summary of Evaluation Metrics for EfficientNetB0 model

Metric	**Value**
Accuracy	93.60%
Precision	94.86%
Recall	93.60%
Macro Avg	0.950
Weighted Avg	0.950
Test Loss	0.2349

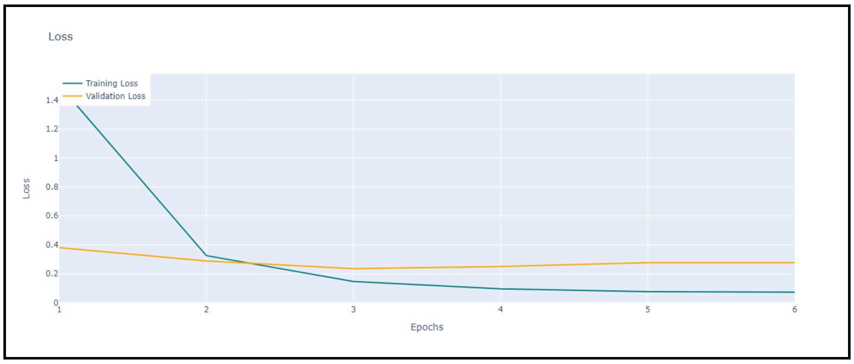

Figure 12: EfficientNetB0 Loss Plot

cision, recall, and F1-score. Notable performance is observed in classes like 'AFRICAN GIANT SWALLOWTAIL,' 'AMERICAN SNOOT,' 'APPOLLO,' and 'ATLAS MOTH,' achieving high precision, recall, and F1-scores. It aslo reveals impressive overall accuracy of 93.60%. Precision scores ranged from 0.50 to 1.00, reflecting accurate identification of positive instances. Recall scores varied from 0.20 to 1.00, indicating the model's sensitivity. The F1-score, harmonizing precision and recall, demonstrated balanced performance across classes. The test loss was 0.2349, confirming the model's efficiency in minimizing classification errors. This evaluation underscores the EfficientNetB0 model's robustness and reliability in accurately categorizing butterfly and moth species.

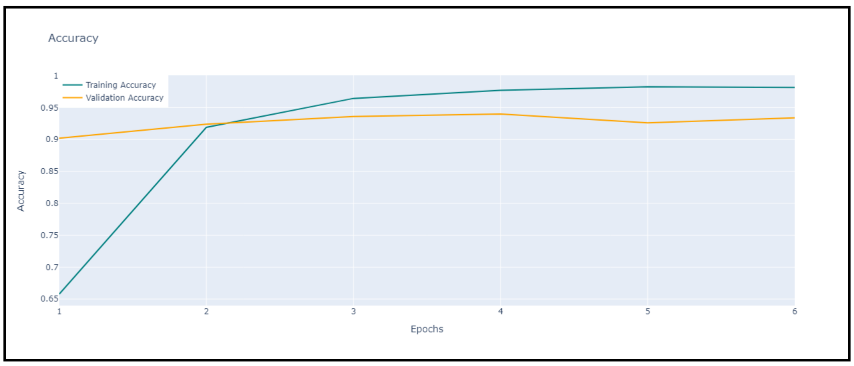

Figure 13: EfficientNetB0 Accuracy Plot

5.3 VGG19 Model

The training process of the Vgg19 model was executed with a predefined early stopping mechanism, ensuring optimal performance while preventing overfitting. The model underwent 6 epochs, each providing insights into its evolving accuracy and loss. In the first epoch, the model achieved a training accuracy of 62.86% with a corresponding loss of 1.6642. The validation set, concurrently, exhibited a promising accuracy of 89.20% and a reduced loss of 0.4914.

Refer to Table 3 for Evaluation metrics, Figure 14 for insights into the loss plot and Figure 15 for a graphical representation of the accuracy during training.

Table 3: Summary of Evaluation Metrics for VGG19 Model

Metric	**Value**
Accuracy	92.80%
Precision	93.73%
Recall	92.80%
Macro Avg	0.94
Weighted Avg	0.94
Test Loss	0.277

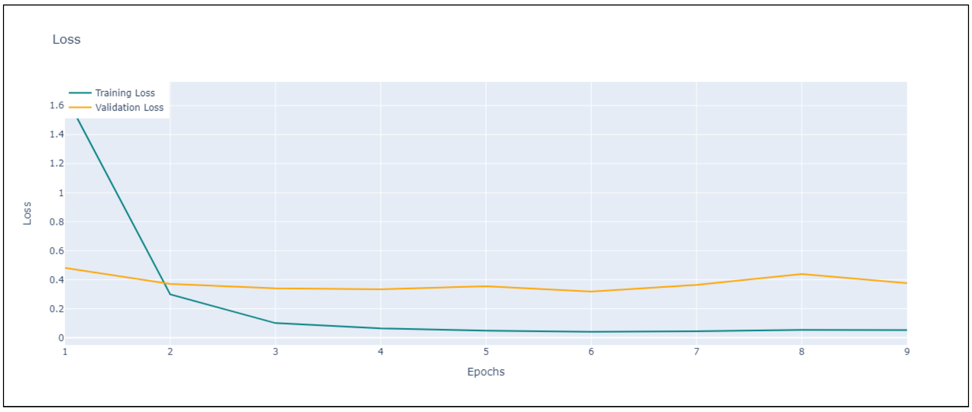

Figure 14: VGG19 Loss Plot

As training progressed, the VGG19 model demonstrated its capability to learn intricate patterns, with accuracy steadily increasing. By the end of the training phase, the model reached an impressive training accuracy of 99.19%. However, it's noteworthy that the validation accuracy plateaued around 90%, indicating a potential need for further optimization or model complexity adjustment.

The classification report reveals that the VGG19 model achieved an overall accuracy of 92.80% on the test set. Precision measures the accuracy of positive predictions, recall assesses the coverage of positive instances, and F1-score combines both metrics, providing a balanced evaluation.Some categories, such as "AFRICAN GIANT SWALLOWTAIL" and "ATLAS MOTH," received high precision, recall, and F1-score, indicating excellent performance. However, certain categories like "APPOLLO" and "CABBAGE WHITE" showed variations in precision and recall, suggesting potential areas for improvement.The test loss for the VGG19 model on the test set was 0.2771, and the test accuracy reached 92.80%, providing a comprehensive summary of the model's effectiveness in classification.

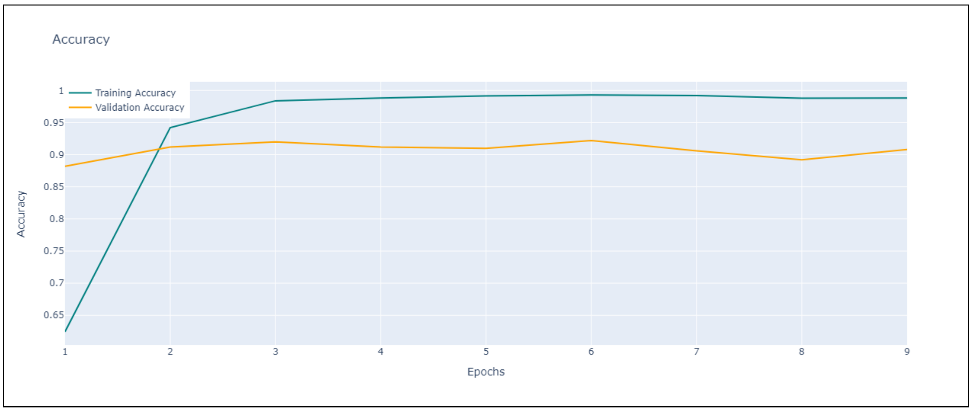

Figure 15: VGG19 Accuracy Plot

5.4 ResNet50 Model

The ResNet50 model, trained over 6 epochs with an early stopping callback to prevent overfitting, exhibited noteworthy performance. In the initial epoch, it achieved a training accuracy of 67.32% and a training loss of 1.4695. Simultaneously, the validation accuracy reached 89.80%, accompanied by a validation loss of 0.4035. Substantial progress emerged, with the model attaining outstanding training accuracy of 99.83% by the sixth epoch, maintaining a validation accuracy of 92.20% and a validation loss of 0.3193.

Refer to Table 4 for Evaluation metrics, Figure 16 for the loss plot and Figure 17 for a graphical representation of accuracy during training.

Table 4: Summary of Evaluation Metrics for ResNet50 Model

Metric	**Value (%)**
Accuracy	95.00%
Precision	95.66%
Recall	95.00%
Macro Avg	0.96
Weighted Avg	0.96
Test Loss	0.228

The classification report on the test dataset highlighted the model's robust performance in categorizing butterfly species, achieving an overall accuracy of 950%. Precision, recall, and F1-scores consistently excelled across various butterfly types, showcasing the model's accurate identification and classification abilities.

Noteworthy results include perfect precision, recall, and F1-score for classes like "AFRICAN GIANT SWALLOWTAIL," "AN 88," "ARCIGERA FLOWER MOTH," and "BANDED PEACOCK." Even classes with slightly lower scores, such as "APPOLLO," "BROWN ARGUS," and "CLEOPATRA," demonstrated commendable performance.

In summary, the ResNet50 model's classification report underscores its strong and precise performance in accurately categorizing butterfly species, providing valuable insights into its effectiveness across different classes in the test dataset.

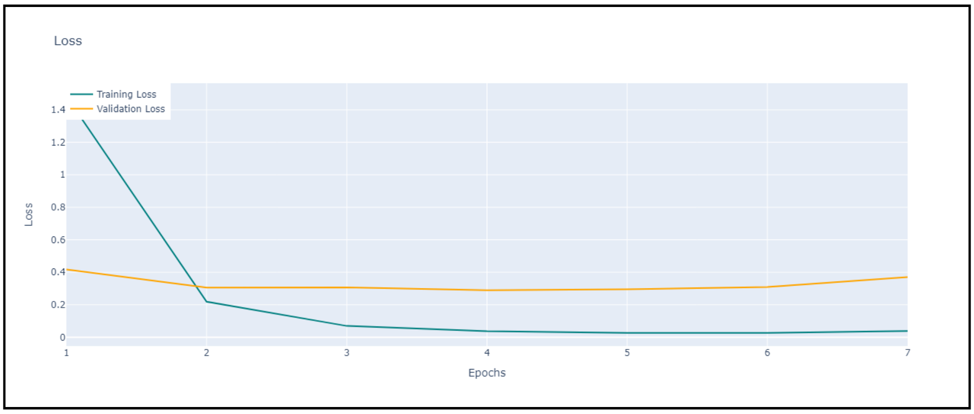

Figure 16: RestNet50 Loss Plot

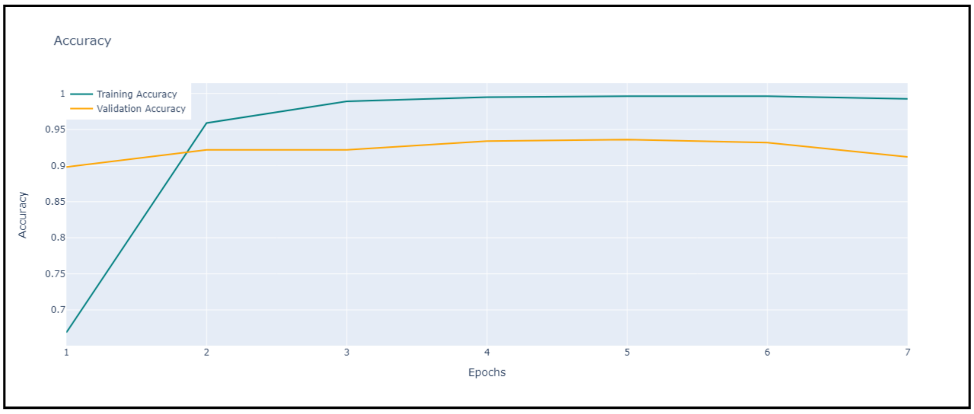

Figure 17: RestNet50 Accuracy Plot

5.5 Discussion & Limitations

The ResNet50 model emerged as the top-performing model among the four implemented models, as depicted by Table 5, showcasing exceptional efficiency and accuracy in the classification task. It achieved the lowest test loss of 0.2285, demonstrating its ability to generalize well to new images. The corresponding test accuracy was an impressive 95%, highlighting its robust classification capabilities. Notable misclassifications were observed in classes such as "Brown Argus" and "Cabbage White," potentially attributed to the intricate patterns and subtle color variations in these species. As depicted in Figure 18, "Cabbage White" has a light color with no distinct pattern, while "Brown Argus" has multiple intrinsic patterns on wings.

The EfficientNetB0 Model demonstrated strong performance with a test loss of 0.2349

Table 5: Test Results Summary for All Models

Model	Epochs	Test Loss	Test Accuracy
ResNet50 Model	6	0.2285	95.00%
EfficientNetB0 Model	8	0.2349	93.60%
VGG19 Model	6	0.2771	92.80%
ButterflyNet Model	14	0.5081	85.40%

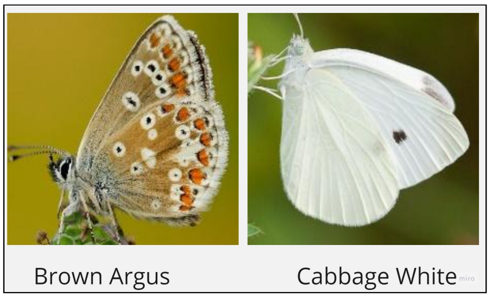

Figure 18: Sample of Misclassified Images by ResNet50 Model

and a test accuracy of 93.60%, as depicted by Table 5, showcasing exceptional efficiency and accuracy in the classification task. While EfficientNetB0 exhibited exceptional performance across most classes, challenges were encountered in classes (Figure 19), such as "Clouded Sulphur," "Comet Moth," and "Great Eggfly," possibly due to dark patterns in wing patterns and similar visual characteristics between "Clouded Sulphur" and "Comet Moth."

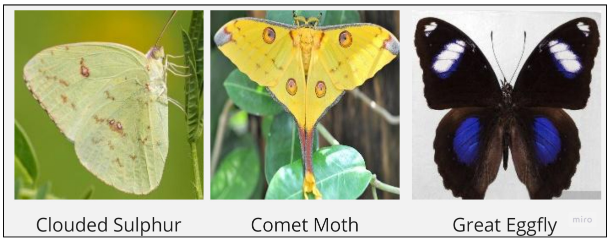

Figure 19: Sample of Misclassified Images by EfficientNetB0 Model

The VGG19 Custom Model delivered commendable results with a test loss of 0.2771 and a test accuracy of 92.80%, showcasing reliable performance in the classification task. Challenges were faced with classes like "Eastern Pine Elfin" and "Monarch," where complex wing structures and subtle markings may have posed difficulties depicted in figure 20.

Figure 20: Sample of Misclassified Images by VGG19 Model

Turning attention to the ButterflyNet Model, despite a higher test loss of 0.5081 and a test accuracy of 85.40%, it exhibited reasonable competence in classification. Exceptional performance in certain classes suggested its potential for specialized applications, but challenges arose in predicting classes like "Crimson Patch" and "Two Barred Flasher," possibly due to intricate details and overlapping features, as shown in Figure 21.

Figure 21: Sample of Misclassified Images by ButterflyNet Model

In summary, while ResNet50 stands out as the overall preferred choice for its exceptional performance across various metrics, each model has its unique merits. EfficientNetB0 and VGG Custom Model offer reliable alternatives, while ButterflyNet, with its specific strengths and challenges, presents a promising avenue for further exploration and refinement. The choice of the ideal model depends on the specific requirements and nuances of the butterfly and moth classification task at hand.

6 Conclusion and Future Work

The purpose of this research was to overcome the drawbacks of identification methods and examine how deep learning can improve the classification and differentiation of 100 different species of butterflies and moths. The results offer valuable insights into the effectiveness of the deep learning models developed. Among the models that were implemented the *ResNet50* model stood out as the performer. It showed efficiency and accuracy with a test loss of only 0.2285 and an impressive test accuracy of 95%. Although it performed well for most classes there were some difficulties encountered in specific categories.

ButterflyNet showed competency in classification despite having a higher test loss of 0.5081 and a test accuracy of 85.40%. Its performance, in classes was particularly noteworthy indicating potential for applications. Comparing it with trained models like *EfficientNetB0* and *VGG19* model highlighted the distinct strengths and challenges of ButterflyNet offering an encouraging path, for further exploration and improvement.

Future work in this research involves refining and enhancing the performance of the developed models. Fine-tuning the *ButterflyNet* model by optimizing hyperparameters and exploring alternative architectures could lead to improved accuracy. Introducing more diverse images, applying advanced data augmentation techniques, and investigating ensemble models are avenues to enhance generalization and overall classification accuracy. It can be used to identify "*ULYSES*" species effectively. Additionally, exploring methods for explaining model decisions, especially in misclassification scenarios, and assessing the feasibility of real-world deployment in applications like mobile devices or field equipment are crucial steps towards practical implementation. Continuous research and refinement are essential to unlock the full potential of deep learning models in accurately classifying diverse butterfly and moth species.

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