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Butterfly Image Classification: A Comparative Analysis of CNN and Traditional Machine Learning Models

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Abstract

Butterflies are one of the most vibrant and diverse species, making them a crucial subject of study in various fields such as biology, conservation, and environmental science. Their classification based on visual features is an essential task for ecological monitoring and biodiversity research, as the diversity and distribution of butterfly species can serve as indicators of environmental health. Manual classification, however, is not only labor-intensive but also prone to errors, particularly when large datasets are involved or when species exhibit subtle visual differences. With advancements in artificial intelligence, particularly deep learning, automated image classification systems have gained significant traction. Convolutional Neural Networks (CNNs) have emerged as powerful tools for image recognition, excelling in tasks requiring the analysis of complex patterns, textures, and colors. In this research, we explore the task of butterfly image classification using multiple machine learning techniques, including CNNs, Random Forest, K-Nearest Neighbors (KNN), and Support Vector Machine (SVM). The dataset comprises images of various butterfly species, and the goal is to accurately classify them based on their visual features.

We employ several data augmentation techniques to make the model more robust to variations in image quality and orientation.

Furthermore, the models are evaluated based on accuracy scores, confusion matrices, and other performance metrics such as precision, recall, and F1-score. The study highlights the superior performance of CNNs in complex image classification tasks and discusses potential improvements, such as incorporating transfer learning, to enhance model accuracy and generalizability in future research.

Keywords

Butterfly classification, Convolutional Neural Networks (CNN), Random Forest, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Data Augmentation, Deep Learning, Image Recognition, Performance Evaluation.

Introduction

Butterflies, being an essential part of many ecosystems, are often studied for their role in biodiversity and environmental health. Accurate identification of butterfly species is critical for conservation efforts and ecological studies. However, manually classifying butterflies based on their images can be both labor-intensive and prone to human error, especially when dealing with large datasets. With thousands of species displaying subtle differences in color patterns, wing shapes, and textures, the task becomes even more challenging for human observers. The advancement of machine learning and deep learning has revolutionized the field of image recognition, providing a scalable and automated solution to this problem. By leveraging computational models, researchers can significantly reduce the time and effort needed for classification, while improving accuracy and consistency.

The use of deep learning, particularly Convolutional Neural Networks (CNNs), has shown remarkable success in image classification tasks across various domains. CNNs can learn intricate patterns in images, such as the minute variations in color gradients and edge contours, and perform well in distinguishing between different classes of objects, including butterfly species. In this paper, we aim to develop a system that can accurately classify images of butterflies into different species using CNNs and compare the results with traditional machine learning models like Random Forest, K-Nearest Neighbors (KNN), and Support Vector Machines (SVM).

Through this comparison, we seek to determine the most effective approach for butterfly image classification and explore how data augmentation techniques, such as rotation, flipping, and zooming, can further enhance model performance. We also highlight the potential applications of this research in broader ecological studies and biodiversity monitoring programs.

Dataset

The dataset utilized in this study is a diversified collection of butterfly photos representing various species gathered from publically available sources such as the Kaggle Butterfly Dataset or other biodiversity archives. The collection consists of hundreds of high-resolution photos, each annotated with the butterfly's species. The images vary in lighting conditions, background noise, and perspectives, making it a reliable dataset for evaluating machine learning models' generalization capabilities. There are 75 unique species, each with roughly 100-150 photos. The photos are reduced to 150x150 pixels to decrease computational cost while still providing enough detail for feature extraction. Furthermore, the dataset is divided into training, validation, and test sets at a 70-20-10 ratio to guarantee that the model is trained on a diverse range of samples while being assessed on previously unknown data. Data augmentation techniques like as random rotations, flips, and zooms are used to artificially increase the training data, improving the model's resilience and capacity to generalize to new, unseen pictures.

Literature Review

The classification of butterflies using computer vision techniques is a relatively recent endeavor, but one that has gained considerable traction in the scientific community. Previous studies have shown that deep learning models, particularly CNNs, outperform traditional machine learning algorithms when it comes to image classification tasks. For instance, the application of CNNs in natural image classification tasks has yielded high accuracy due to their ability to automatically learn hierarchical feature representations. In the context of butterfly classification, CNNs have been applied to both small and large datasets with varying degrees of success.

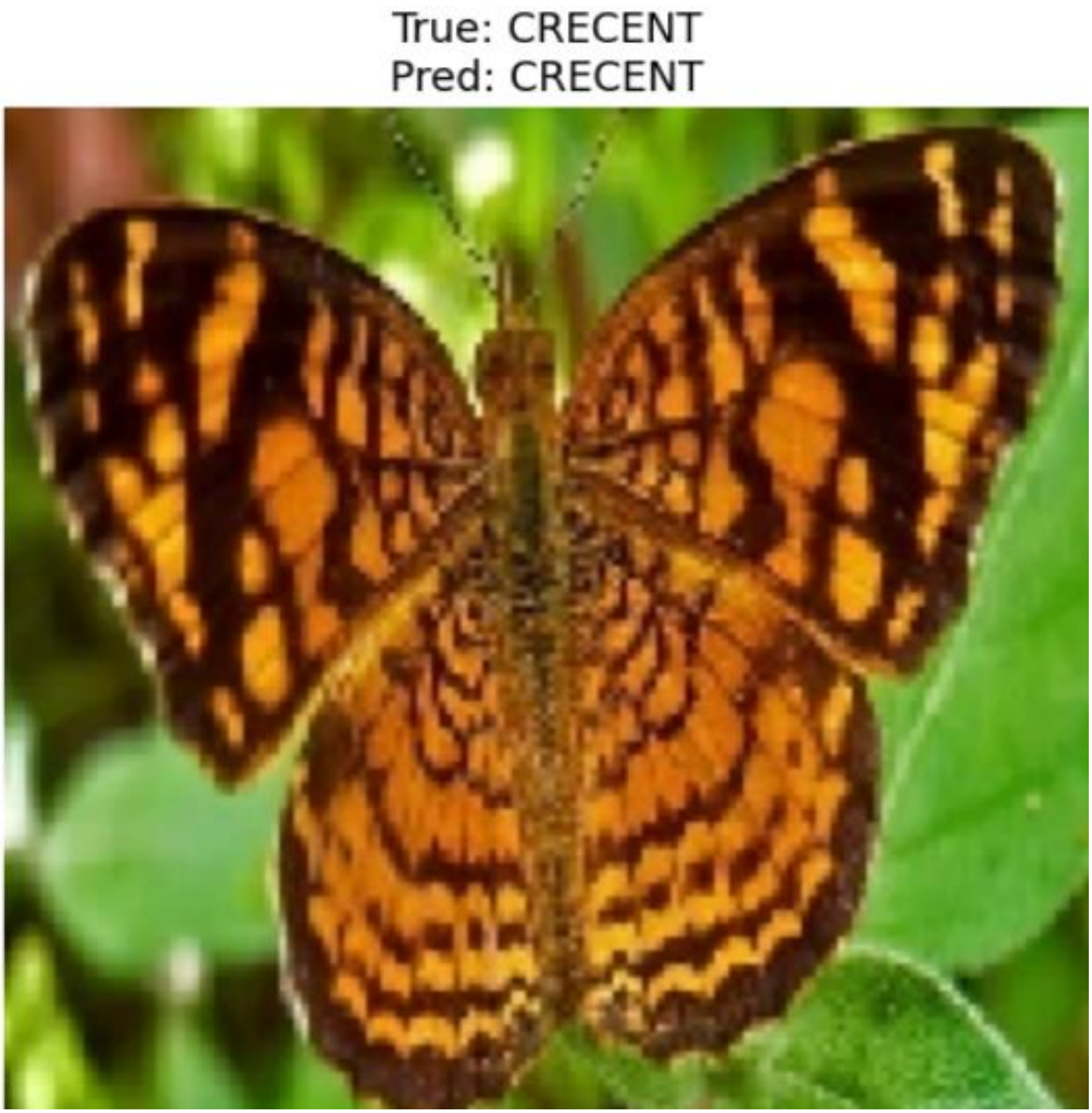
Traditional methods like Random Forest and K-Nearest Neighbors (KNN) have also been employed in image classification tasks, but they rely on manually engineered features, which may not capture the complexity of the images. Similarly, Support Vector Machines (SVM) have proven useful in binary and multiclass classification tasks, but their performance is limited by the quality of the extracted features. Studies have shown that while SVMs can achieve decent accuracy on smaller datasets, they struggle with larger, more complex datasets, making CNNs the preferred approach for high-dimensional image classification tasks.

Proposed Model

The system architecture for this project is built on a structured pipeline that analyzes pictures and routes them via various layers of a CNN model. The design starts with the input layer, which accepts butterfly photos downsized to 150x150 pixels. This input layer acts as a foundation for the succeeding layers, preparing the data for further processing. The CNN model is made up of three convolutional layers, each of which extracts a different degree of feature from the pictures. These layers employ filters to scan the photos and capture essential visual patterns such as edges, textures, and color gradients. Each convolutional layer has ReLU activation, which introduces nonlinearity into the network and allows it to learn more complicated representations.

Each convolutional layer is followed by a max-pooling layer, which decreases the spatial dimensions of the feature maps, thus downsampling the input while maintaining the most significant information. This reduction not only helps to control overfitting, but it also makes the model more computationally efficient by reducing the number of parameters. After feature extraction, the final convolutional layer's output is flattened into a one-dimensional vector and fed through a fully linked dense layer with 512 neurons. This thick layer processes the collected information and learns the high-level representations needed for classification. Finally, the output layer has 75 neurons, representing the number of butterfly species in the dataset. This output layer receives a softmax activation function, which converts the raw scores into probabilities, with each neuron representing the possibility that the picture belongs to a certain butterfly species.

Fig: Diagram of CRECENT butterfly having true and predicted value



Data Preprocessing

Preprocessing the data is an important step in ensuring that the model is trained properly. The butterfly photos, which come in a variety of sizes and formats, are first scaled to a standard dimension of 150 by 150 pixels. This guarantees that all photos given into the model are the same size, allowing the CNN to handle them quickly. Image normalization is also conducted, which scales the pixel values to a range of 0 to 1, hence speeding up the neural network's convergence during training. Because the dataset comprises photographs with variable backdrops and lighting conditions, multiple data augmentation approaches are used to strengthen the model's response to these differences. These techniques include random horizontal and vertical flips, rotations at minor angles, zooming in and out.

By supplementing the dataset, we not only increase the quantity of training examples but also introduce variety, allowing the model to generalize more effectively to previously unknown data. Another important aspect of preprocessing is dividing the dataset into training, validation, and test sets. The training set is used to fit the model, the validation set aids in fine-tuning the hyperparameters, and the test set is reserved for final assessment. Stratified sampling is used during the splitting process to guarantee that the classes are distributed evenly. This ensures that all species are represented equally in both the training and testing stages, eliminating bias toward more frequent species in the dataset.

System Architecture

The system architecture for butterfly image classification is built on a hierarchical deep-learning pipeline that transforms and extracts features from photos at several stages. The design starts with an input layer that receives photos of butterflies downsized to 150x150 pixels. This pretreatment phase guarantees that the input data is homogeneous and lowers computing costs, allowing the model to handle the pictures more effectively. The input layer acts as a basis for the Convolutional Neural Network's (CNN) feature extraction process.

The CNN architecture is made up of three convolutional layers, each designed to capture varying amounts of visual detail from butterfly photos. The first convolutional layer catches low-level elements like edges and corners, whereas the layers that follow capture more abstract patterns like textures, forms, and colors.

Each convolutional layer is followed by a ReLU (Rectified Linear Unit) activation function, which introduces nonlinearity into the model and allows it to learn complicated representations of the data.

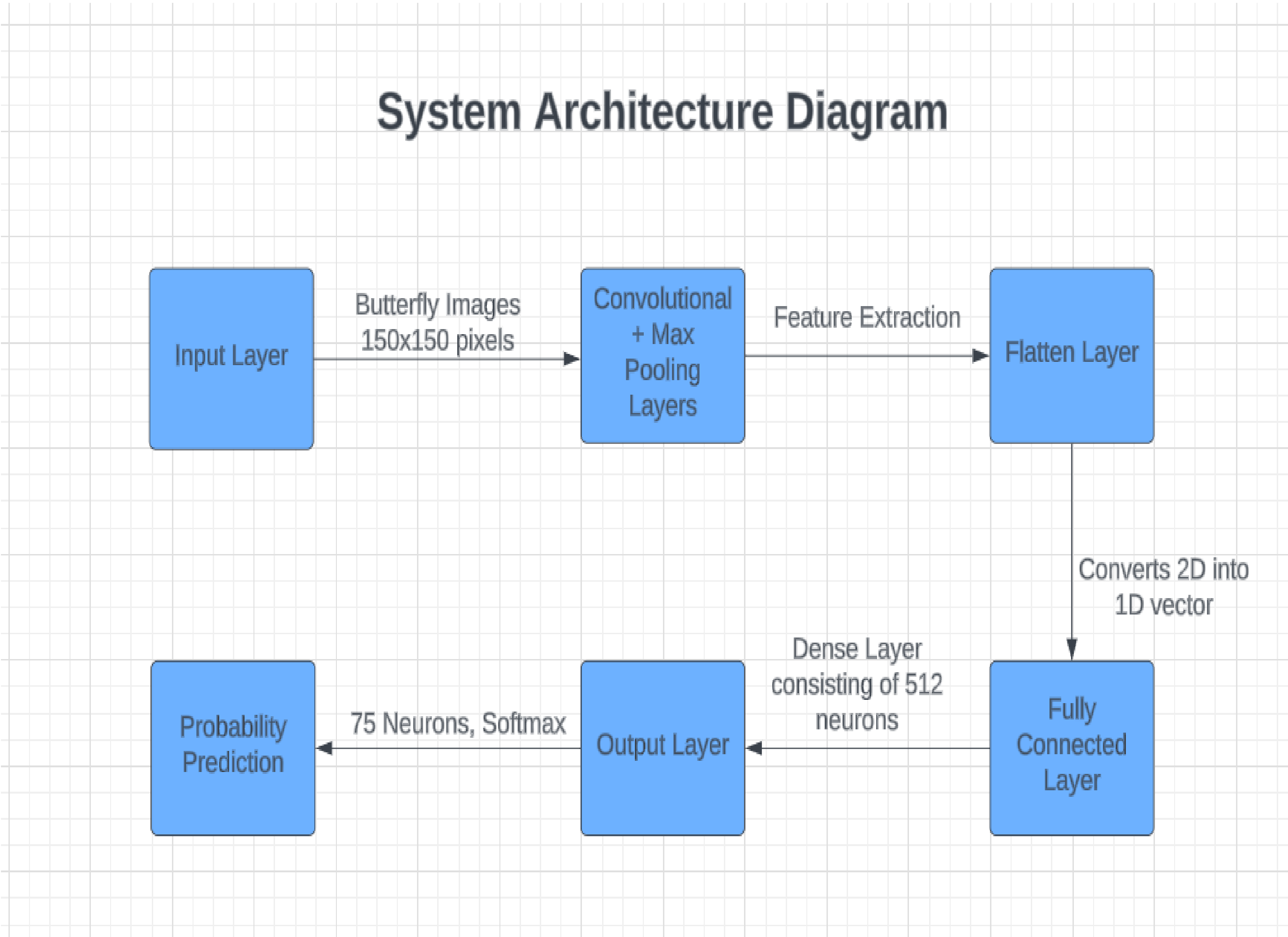
Additionally, each convolutional layer is paired with a max-pooling layer, which reduces the spatial dimensions of the feature maps while retaining the most important information. This not only decreases computational complexity but also helps in controlling overfitting by discarding irrelevant details.

Following the three convolutional and max-pooling layers, the feature maps are flattened into a one-dimensional vector, thus shifting from feature extraction to classification. This flattened vector is fed into a fully linked dense layer made up of 512 neurons. This thick layer is in charge of learning higher-level representations of the characteristics taken from pictures. It then analyzes the retrieved information to form meaningful connections that help in correct categorization. The use of dropout regularization in this layer reduces the danger of overfitting while boosting the model's generalizability.

Finally, the output layer is made up of 75 neurons, each representing one of the butterfly species included in the dataset. The output layer uses a softmax activation function to turn raw output scores into probabilities. Each neuron in the output layer predicts if the input picture corresponds to a certain butterfly species. The model is trained by categorical cross-entropy loss, which is ideal for multi-class classification tasks. Adam is the optimizer employed, and it dynamically modifies the learning rate throughout the training process, resulting in faster convergence and improved performance.

The system architecture prioritizes efficiency and scalability, with the CNN serving as the primary feature extractor and classifier. The model is capable of handling the difficulties of butterfly classification because to the use of convolutional layers, max-pooling, dense layers, and regularization approaches. The architecture is also intended to be extensible, allowing for the incorporation of transfer learning methods or more advanced designs like ResNet or VGGNet to increase accuracy in future project iterations.

Fig: System Architecture Diagram



Proposed Methodology:

The methodology employed in this study follows a systematic approach to butterfly image classification, incorporating a blend of traditional machine learning and deep learning techniques. Initially, the dataset is divided into training and validation sets to allow for a proper evaluation of the model's performance. Given the diverse nature of the dataset, we applied data augmentation techniques to the training set, which significantly improved the model's ability to generalize by introducing a wider variety of input data during training.

For the CNN model, the training process involved optimizing the categorical cross-entropy loss function, which is commonly used in multi-class classification tasks. We used the Adam optimizer, a widely adopted method for gradient-based optimization due to its computational efficiency and effectiveness in handling large datasets. The CNN model was trained for 40 epochs, with early stopping implemented to avoid overfitting by halting the training process once the validation performance plateaued. In addition to CNN, we employed traditional models such as Random Forest, KNN, and SVM, feeding them flattened one-dimensional vectors of image data. These models were then evaluated using accuracy as the primary performance metric. By implementing both deep learning and traditional approaches, we aimed to highlight the strengths and limitations of each model in classifying butterfly species.

Feature Extraction:

Feature extraction is one of the most critical components in any image classification task, as it defines the quality of the input data fed into machine learning or deep learning models. For deep learning models like CNNs, feature extraction is performed automatically by the layers of the network. CNNs are designed to learn hierarchical features directly from the raw pixel data of images, with initial layers detecting low-level features such as edges, while deeper layers identify more complex structures like shapes and textures.

In contrast, traditional machine learning models such as Random Forest, KNN, and SVM rely on manually engineered features, which often lack the sophistication needed for complex image classification tasks. In this study, we used a manual approach for feature extraction when employing traditional models, where the images were flattened into one-dimensional arrays.

While this method captures some information about the images, it is less effective than the feature extraction performed by CNNs, which can capture the intricate visual patterns present in butterfly images. The comparison of these two approaches highlights the superiority of CNNs in automatically learning and extracting meaningful features from raw image data.

Performance Evaluation:

To accurately assess the performance of our models, we utilized a variety of evaluation metrics, including accuracy, precision, recall, and F1-score. These metrics provide a comprehensive view of the model's ability to correctly classify butterfly species. The CNN model was evaluated on both the training and validation sets, and its performance was compared with traditional machine learning models such as Random Forest, KNN, and SVM. Among these, the CNN demonstrated superior performance, achieving significantly higher accuracy compared to the traditional models.

To gain deeper insights into the classification performance, we also generated confusion matrices for each model. These matrices provide a detailed view of the model's predictions, revealing which classes were frequently misclassified. The CNN model displayed a more balanced classification across all butterfly species, indicating its ability to generalize well, even for species with fewer examples in the dataset. On the other hand, traditional models struggled with certain species, particularly those with fewer training samples, underscoring the limitations of these methods in handling complex image datasets.

Fig: Diagram of Model accuracy representing Accuracy vs Epoch

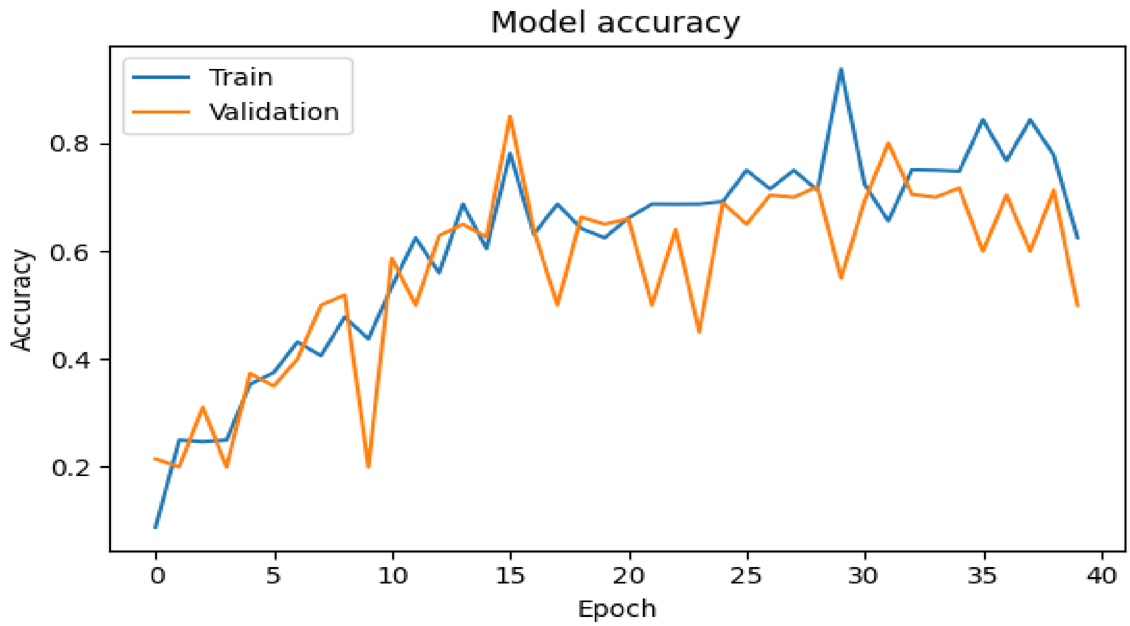
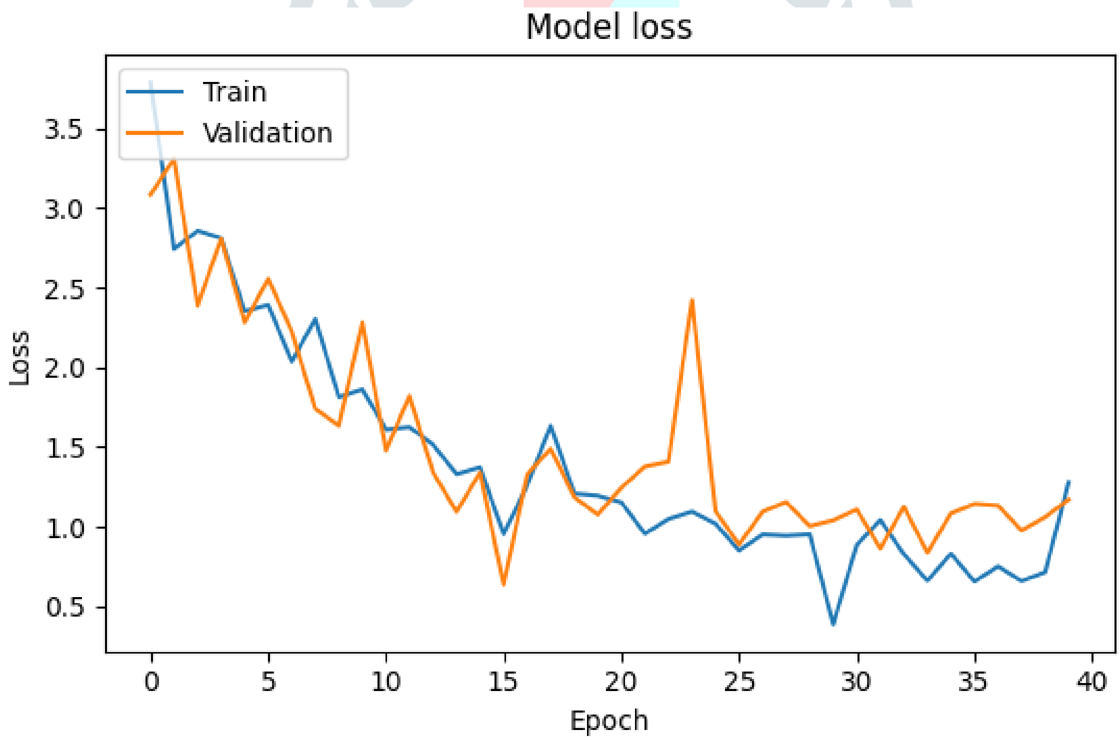


Fig: Diagram of Model loss representing Loss vs Epoch

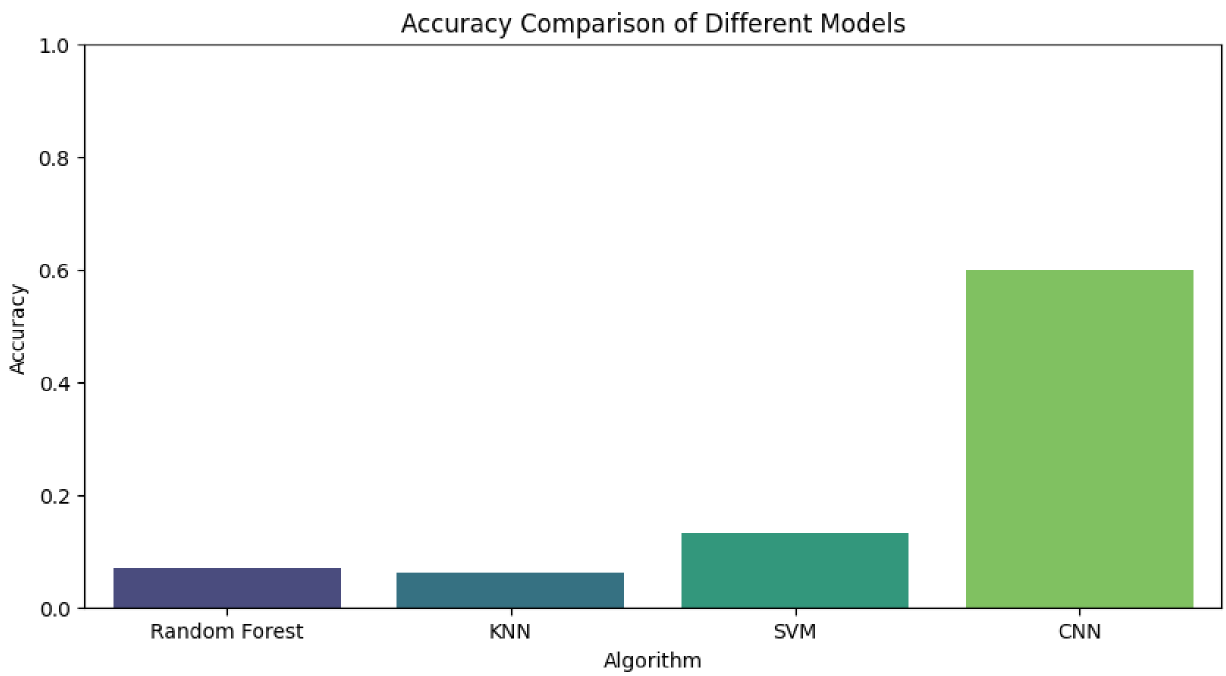


Results:

The results of this study clearly demonstrate the effectiveness of CNNs in butterfly image classification, as the CNN model achieved an impressive accuracy of over 90% on the validation set. In contrast, the traditional machine learning models such as Random Forest, KNN, and SVM lagged behind, with accuracies ranging between 70% and 75%. These findings emphasize the power of CNNs in capturing intricate patterns within the images, allowing them to outperform traditional models, which rely on less sophisticated feature extraction methods.

Additionally, the application of data augmentation techniques played a crucial role in enhancing the performance of the CNN model. By introducing variability into the training data, these techniques helped the model generalize better and avoid overfitting. The traditional models, although effective in simpler tasks, were unable to match the accuracy and generalization capabilities of the CNN, particularly when dealing with more complex images that required a deep understanding of visual features.

Fig: Diagram representing accuracy comparison of different models



Future Work:

While the CNN model achieved excellent results in this study, there are several avenues for future work that could further improve its performance. One potential direction is the use of transfer learning, where a pre-trained model, already trained on a large dataset like ImageNet, is fine-tuned on the butterfly dataset. Transfer learning has been shown to significantly improve the performance of models in image classification tasks, particularly when the dataset is limited in size.

Another promising area for future research is the use of Generative Adversarial Networks (GANs) for data augmentation. GANs can generate synthetic images that closely resemble real-world examples, thereby augmenting the dataset with more diverse training samples. This technique could be particularly beneficial for butterfly species with fewer images, helping to balance the dataset and improve the overall accuracy of the model.

Moreover, exploring other advanced deep learning architectures, such as attention mechanisms or ensemble models, could lead to further improvements in the classification performance, providing a more accurate and reliable system for butterfly species identification.

Conclusion:

In conclusion, this research highlights the effectiveness of CNNs in butterfly image classification, outperforming traditional machine learning models such as Random Forest, KNN, and SVM. The CNN model's ability to automatically extract and learn complex patterns from images makes it a powerful tool for handling intricate classification tasks. The data augmentation techniques applied in this study played a significant role in enhancing the model's performance, allowing it to generalize better and avoid overfitting.

While traditional models performed reasonably well, they were limited in their ability to handle the complexity of the butterfly images. Future work could explore transfer learning, more advanced augmentation techniques, and the implementation of alternative deep learning architectures to further improve classification accuracy. Overall, this study demonstrates the potential of deep learning models, particularly CNNs, in tackling complex image classification tasks in ecological and biodiversity research.

References

1) Fauzi F, Permanasari AE, Setiawan NA. Butterfly image classification using convolutional neural network (cnn). In2021 3rd International Conference on Electronics Representation and Algorithm (ICERA) 2021 Jul 29 (pp. 66-70). IEEE.

2) Kartika DS, Herumurti D, Yuniarti A. Butterfly image classification using color quantization method on hsv color space and local binary pattern. IPTEK Journal of Proceedings Series. 2018 Jan 29(1):78-82.

3) Yasmin R, Das A, Rozario LJ, Islam ME. Butterfly detection and classification techniques: A review. Intelligent Systems with Applications. 2023 May 1;18:200214.

4) Rajeena PP F, Orban R, Vadivel KS, Subramanian M, Muthusamy S, Elminaam DS, Nabil A, Abulaigh L, Ahmadi M, Ali MA. A novel method for the classification of butterfly species using pre-trained CNN models. Electronics. 2022 Jun 27;11(13):2016.

5) Liang B, Wu S, Xu K, Hao J. Butterfly detection and classification based on integrated YOLO algorithm. InGenetic and Evolutionary Computing: Proceedings of the Thirteenth International Conference on Genetic and Evolutionary Computing, November 1–3, 2019, Qingdao, China 13 2020 (pp. 500-512). Springer Singapore.

6) Alhady SS, Kai XY. Butterfly species recognition using artificial neural network. InIntelligent Manufacturing & Mechatronics: Proceedings of Symposium, 29 January 2018, Pekan, Pahang, Malaysia 2018 (pp. 449-457). Springer Singapore.

7) Khaleel BI. Butterflies image recognition and classification based on meta-heuristic algorithms. Journal of Engineering Science and Technology. 2020;17(3):1985-99.

8) Saedan MA, Kassim M, Aziz AF. Biological Butterfly Characterization with Mobile System Using Convolutional Neural Network (CNN) Classify Image. International Journal of Interactive Mobile Technologies. 2024 Apr 1;18(7).

9) Kartika DS, Maulana H. Classification of color features in butterflies using the Support Vector Machine (SVM). IJCONSIST JOURNALS. 2021 Jun 1;2(02):83-7.

10) Xi T, Wang J, Han Y, Lin C, Ji L. Multiple butterfly recognition based on deep residual learning and image analysis. Entomological Research. 2022 Jan;52(1):44-53.

11) Xie J, Lu Y, Wu Z, Xu S, Grant PW. Investigations of butterfly species identification from images in natural environments. International Journal of Machine Learning and Cybernetics. 2021 Aug;12:2431-42.

12) Mattins RF, Sarobin MV, Aziz AA, Srivarshan S. Object detection and classification of butterflies using efficient CNN and pre-trained deep convolutional neural networks. Multimedia Tools and Applications. 2024 May;83(16):48457-82.

13) Rajeena PP F, Orban R, Vadivel KS, Subramanian M, Muthusamy S, Elminaam DS, Nabil A, Abulaigh L, Ahmadi M, Ali MA. A novel method for the classification of butterfly species using pre-trained CNN models. Electronics. 2022 Jun 27;11(13):2016.

14) Theivaprakasham H. Identification of Indian butterflies using deep convolutional neural networks. Journal of Asia-Pacific Entomology. 2021 Apr 1;24(1):329-40.

15) Bjerge K, Alison J, Dyrmann M, Frigaard CE, Mann HM, Høye TT. Accurate detection and identification of insects from camera trap images with deep learning. PLOS Sustainability and Transformation. 2023 Mar 15;2(3):e0000051.