p-ISSN : 2721-5393, e-ISSN : 2721-5385
www.jurnalp3k.com/index.php/J-P3K/index

Jurnal Penelitian Pendidikan, Psikologi Dan Kesehatan (J-P3K) 2026, Vol. 7 (No. 2) : 97-108

Memperkaya Klasifikasi Hewan Bersayap Melalui Analisis Gambar

Advancing Winged Animal Classification Through Image Analysis

Prasetya Triputra Nugraha[1*] & Imam Yuadi[2]

[1]Magister of Human Resources Development, Graduate School, Airlangga University, Indonesia

[2]Department of Information and Library Science, Faculty of Social and Political Sciences, Airlangga University, Indonesia

Disubmit: 20 April 2026; Direview: 29 April 2026; Diaccept: 04 Juni 2026; Dipublish: 08 Juni 2026

**Corresponding author*: prasetya.triputra.nugraha-2024@pasca.unair.ac.id

Abstrak

Penelitian ini bertujuan untuk mengevaluasi seberapa baik kinerja dua algoritma klasifikasi, yaitu Support Vector Machine (SVM) dan Regresi Logistik, ketika dipadukan dengan teknik ekstraksi fitur berbasis deep learning, termasuk Inception V3, VGG-16, dan VGG-19. Metodologi penelitian ini meliputi prapemrosesan kumpulan foto hewan terbang, menggunakan tiga desain jaringan saraf konvolusional (CNN) untuk mengekstraksi fitur, dan menerapkan kedua algoritma tersebut untuk melakukan klasifikasi. AUC, Akurasi Klasifikasi (CA), Skor F1, Presisi, Recall, dan MCC merupakan beberapa metrik penting yang digunakan untuk mengevaluasi model. Berdasarkan temuan, Inception V3 menunjukkan kinerja yang lebih baik daripada VGG-16 dan VGG-19 pada setiap parameter, dengan Regresi Logistik memperoleh skor yang hampir sempurna (AUC = 1.000, CA = 0.987, F1 = 0.987). Meskipun sedikit kurang efektif dibandingkan Regresi Logistik (AUC = 0,998, CA = 0,943, F1 = 0,946), SVM juga menunjukkan kinerja yang baik dengan Inception V3. Teknik ekstraksi fitur yang menunjukkan kinerja terburuk adalah VGG-16 dan SVM secara khusus (CA = 0,890, F1 = 0,891). Hasil ini menyoroti keefektifan Regresi Logistik untuk klasifikasi dalam konteks ini serta peningkatan kemampuan ekstraksi fitur multi-skala pada Inception V3. Penelitian ini menunjukkan bagaimana klasifikasi yang efektif dan arsitektur CNN mutakhir, seperti Inception V3, dapat digabungkan untuk mengklasifikasikan hewan bersayap secara otomatis.

Kata Kunci: Hewan; Klasifikasi; Jaringan Saraf Konvolusional; Regresi Logistik; Mesin Vektor Pendukung.

Abstract

This study is to assess how well two classification algorithms, Support Vector Machine (SVM) and Logistic Regression, work with deep learning-based feature extraction techniques, including Inception V3, VGG-16, and VGG-19. The methodology comprised preprocessing a collection of photos of flying animals, using the three convolutional neural network (CNN) designs to extract features, and applying the two algorithms to do classification. AUC, Classification Accuracy (CA), F1 Score, Precision, Recall, and MCC were among the important metrics used to assess the models. According to the findings, Inception V3 performed better than VGG-16 and VGG-19 on every parameter, with Logistic Regression obtaining nearly flawless scores (AUC = 1.000, CA = 0.987, F1 = 0.987). Although it was marginally less effective than Logistic Regression (AUC = 0.998, CA = 0.943, F1 = 0.946), SVM also did well with Inception V3. The feature extraction techniques that performed the worst were VGG-16 and SVM in particular (CA = 0.890, F1 = 0.891). These results highlight the effectiveness of Logistic Regression for classification in this setting and the improved multi-scale feature extraction capabilities of Inception V3. This study demonstrates how effective classifiers and cutting-edge CNN architectures, such as Inception V3, may be combined to automatically classify winged animals.

Keywords: *Animal; Classification; Convilutional Neural Network; Logistic Regression; Support Vector Machine.*

DOI: https://doi.org/10.51849/j-p3k.v7i2.994

Rekomendasi mensitasi :
Nugraha, P. T. & Yuadi, I. (2026), *Advancing Winged Animal Classification Through Image Analysis*. *Jurnal Penelitian Pendidikan, Psikologi dan Kesehatan (J-P3K)*, 7 (2): 97-108.

INTRODUCTION

The Birds, bats, and insects are vital to ecosystem health since they facilitate pollination, seed dispersal, and pest control. In current day, pollution, climate change, and habitat loss present significant obstacles to their populations; thus, conservation efforts rely on effective monitoring (Smith et al., 2020). Utilizing conventional methods for the identification and classification of these species necessitates manual observation, which is labor-intensive, susceptible to human error, and challenging for large-scale implementation.

Advancements in machine learning and image analysis facilitate automatic and accurate species identification, yielding promising solutions. Nonetheless, challenges such as variable image quality, species resemblance, and insufficient training datasets hinder widespread implementation (Jones & Patel, 2021). Enhancing conservation techniques and understanding biodiversity dynamics necessitate tackling these issues. This study examines how modern image processing techniques can enhance the classification of flying organisms to address deficiencies in current methodologies and advance ecological research.

The species like birds, bats, and insects has increase in photograph research of flying animals. Research on these creatures is crucial for conservation due to their importance in pollination, pest management, and biodiversity maintenance (Smith et al., 2020). Large collections of photographs of winged animals are now more accessible than ever before to researchers thanks to the development of high-resolution cameras and drones. As a result of the growth of image-based research, species identification and behavioral analysis can now be automated (Brown et al., 2019).

Despite technical advancements, challenges persist, such as managing species similarities, variable lighting, and image noise (Jones & Lee, 2021). Furthermore, the incorporation of deep learning has significantly enhanced classification accuracy; still, optimal outcomes necessitate a substantial volume of training data (Patel et al., 2020). Researchers are investigating hybrid models that combine contemporary computational methods with conventional approaches to overcome these limitations (Garcia & Wang, 2022). Using image analysis to avian species study anticipated to grow with technological progress, providing novel insights into their distribution and behavior.

Convolutional neural networks (CNNs) have been extensively employed in prior image analysis research for the classification of winged animals due to their ability to extract complex features from images. The straightforwardness and effectiveness of VGG-16 and VGG-19 in image classification tasks have resulted in their extensive use. Although these structures have a high processing demand, they have demonstrated remarkable accuracy in differentiating between bird species and other flying creatures. They are composed of sequential convolutional layers (Simonyan & Zisserman, 2015; Zhang et al., 2019).

Szegedy et al. (2016) assert that Inception V3 has gained prominence due to its ability to collect multi-scale features via its inception modules, rendering it particularly effective for classifying species with subtle visual differences. Studies by Ahmed and Khan (2021) and Li et al. (2020) demonstrated that these models perform effectively with controlled datasets but struggle with noisy or real-world data. Hybrid approaches that include transfer learning with fine-tuning, utilizing pretrained weights from extensive datasets like as ImageNet, have been explored as a remedy for these issues (Deng et al., 2009).

Additionally, to improve accuracy and reliability, ensemble methods combining predictions from VGG-16, VGG-19, and Inception V3 have been suggested (Wang et al., 2022). Notwithstanding these developments, extensive datasets and approaches are crucial for effectively tackling environmental unpredictability.

This research addresses the challenges of categorizing avian species using sophisticated image processing techniques. This article is organized as follows: it examines the methodologies and models often utilized in image-based categorization, focusing specifically on Inception V3, VGG-16, and VGG-19. The resources and processes, including dataset preparation, deep learning model development, and preprocessing techniques.

Recent years have seen a notable increase in the amount of research on image analysis-based winged animal categorization, driven by developments in deep learning and the growing accessibility of massive image datasets. Manual identification was the mainstay of traditional approaches, which took a lot of time and skill and frequently produced inaccurate results, especially for species with minute morphological distinctions (Smith et al., 2020).

Due to these constraints, the discipline began to move toward automated solutions, with convolutional neural networks (CNNs) leading the way. CNN's automation of feature extraction and classification has greatly increased accuracy while reducing human labor. Their deep, sequential structures, which successfully capture complex patterns in ecological datasets, have made VGG-16 and VGG-19 industry standards for picture analysis. These models' utility for tasks like classifying insects and birds has been demonstrated by their persistent high performance in controlled situations (Simonyan & Zisserman, 2015; Zhang et al., 2019).

Their relevance in ecological research has also been further cemented by their versatility through transfer learning, which allows for efficient application even in situations with little labeled data. The influence of CNNs like VGG-16 and VGG-19 highlights how cutting-edge computational methods can revolutionize biodiversity research.

Inception V3 has demonstrated better performance in classifying species with overlapping visual traits because to its inception modules that are meant to collect multi-scale aspects (Szegedy et al., 2016). Li et al. (2020), for instance, classified bird species using Inception V3 with an accuracy that was higher than that of conventional models. The efficacy of transfer learning with pretrained VGG models was also shown by Ahmed and Khan (2021), who used features from

ImageNet to achieve notable gains on small datasets (Deng et al., 2009).

In addition to solo models, ensemble techniques that combine several architectures have drawn interest for enhancing the robustness of categorization. The ensemble framework that Wang et al. (2022) created, which combined VGG-16, VGG-19, and Inception V3, performed better than individual models in difficult real-world situations. Furthermore, hybrid models have been investigated to improve performance in noisy and changeable lighting scenarios by combining deep learning with conventional image processing methods (Garcia & Wang, 2022).

Challenges including dataset constraints, environmental variability, and computational needs still exist in spite of these developments. More thorough datasets and domain adaption strategies are needed to enhance deep learning models' generalization in a variety of ecological contexts, according to recent research (Jones & Lee, 2021). Building on previous research, this study investigates how sophisticated CNN architectures and hybrid techniques might be used to tackle the challenges of classifying winged animals.

METHOD RESEARCH

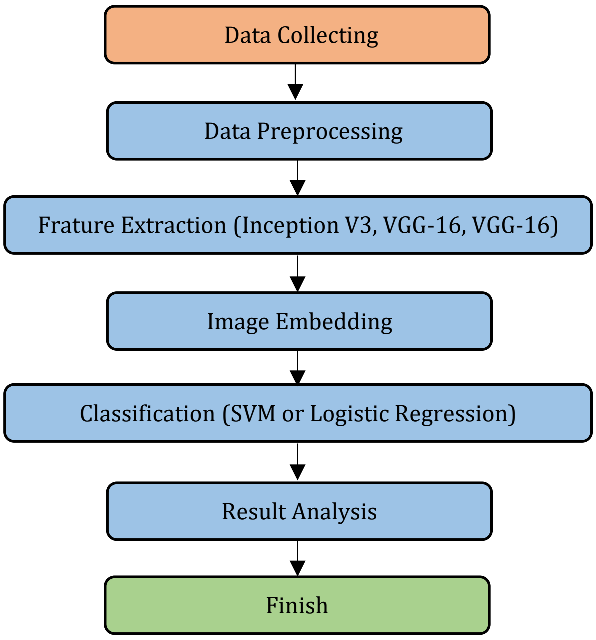

Chart 1. Flowchart Methodology

Datasets are collected from sources like local storage, datasets, and picture repositories. These sources include photos and the labels that go with them. The next step is data cleaning, which eliminates noise such as outliers and fuzzy images, handles missing data by filling in empty pixels, and makes sure the dataset is error-free overall. The dataset is then artificially expanded using data augmentation techniques, which include rotation, scaling, flipping, cropping, and the addition of Gaussian noise to enhance model generalization. The next step is data normalization or standardization, which scales pixel values to a common range (such as 0–1 or -1–1) to guarantee consistency in the way various models interpret pixel information.

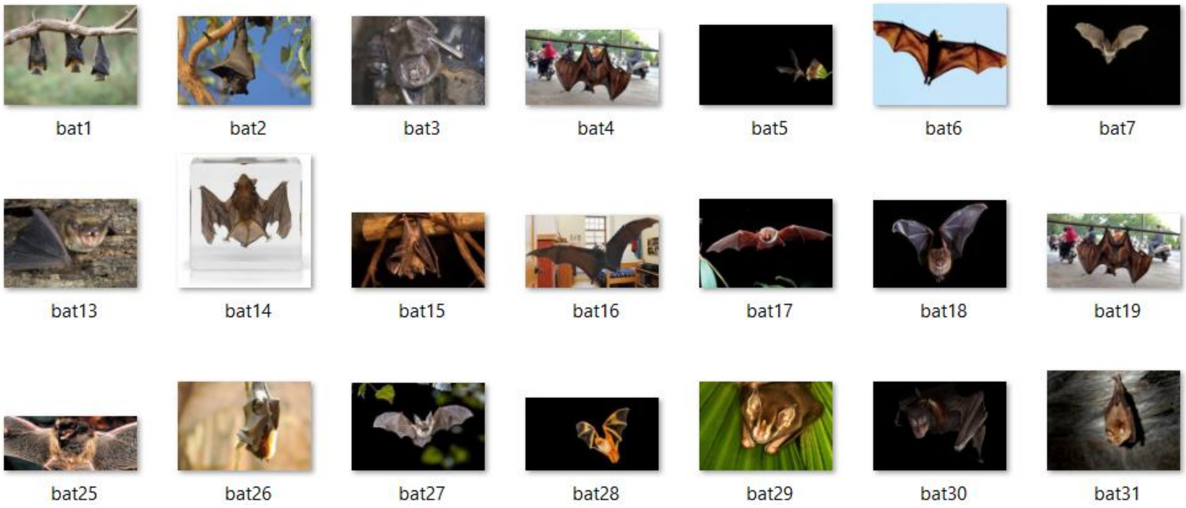

Figure 1. Data Sample 1: Bat

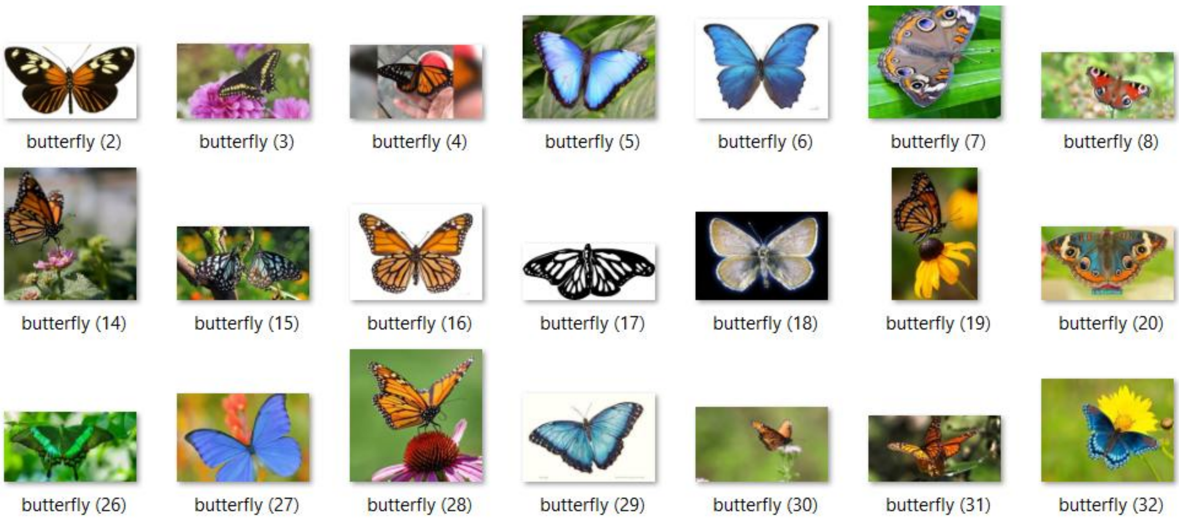

Figure 2. Data Sample 2: Butterfly

Figure 3. Data Sample 3: Dragonfly

p-ISSN : 2721-5393, e-ISSN : 2721-5385
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Figure 4. Data Sample 4: Eagle

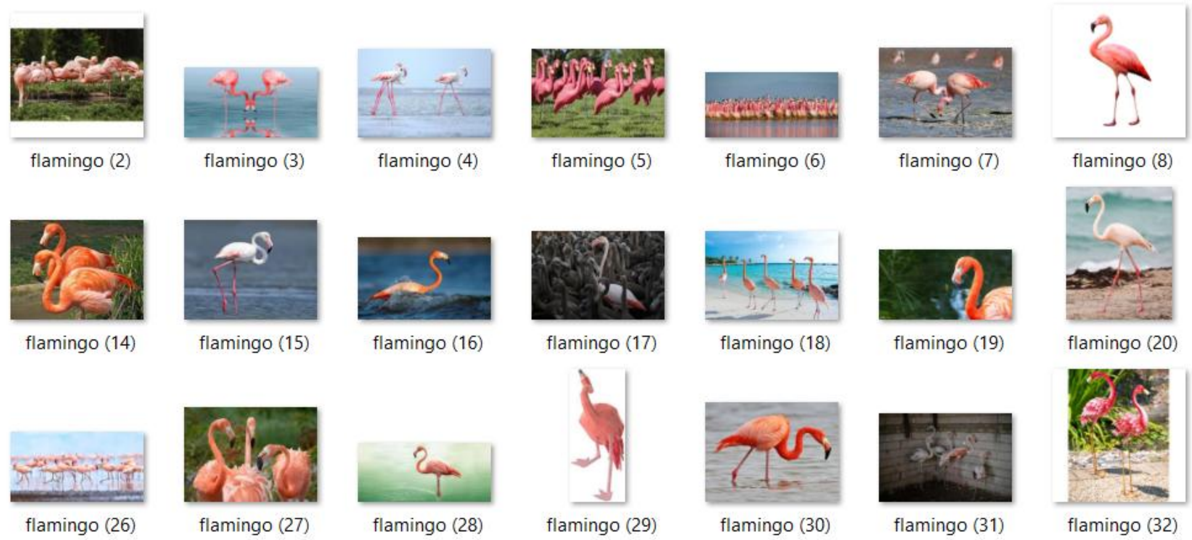


Figure 5. Data Sample 5: Flamingo

Figure 6. Data Sample 6: Woodpecker

Image Embedding. Data preprocessing is a critical phase in machine learning pipelines to ensure data quality and enhance model performance. It involves cleaning, transformation, and normalization (Han et al, 2011). Preprocessing the photos by scaling them to a common size, like 224x224, and normalizing pixel values to make sure they stay inside a predetermined range are two steps in the image embedding process. Pre-trained deep learning models, such as VGG-16, VGG-19, or Google Inception V3, which have already acquired rich feature representations from sizable datasets, are fed these preprocessed photos subsequently. The third phase involves the models' extraction of feature vectors from their output layers, which provides numerical representations for additional analysis and classification by capturing the most significant and pertinent information found in the images.

Classification. Machine learning models use the feature vectors that have been derived from the photos as input data. The main representation of the photos for further analysis is provided by these features. The second phase involves training a Support Vector Machine (SVM) to choose the best hyperplane for classifying the data. SVM is ideally suited for jobs involving picture data because of its efficiency in managing high-dimensional areas. SVM is a maximum margin classification algorithm that is very effective for high-dimensional data, such as image feature representations (Hsu et al, 2016). The third phase involves the application of a more straightforward model called logistic regression, which classifies data using a linear decision boundary. Small to medium-sized datasets benefit greatly from this method, which offers an effective and comprehensible means of making predictions.

Result Analysis. Key measures including as accuracy, precision, recall, and F1-score are measured in order to assess model performance. These metrics give a clear picture of each model's performance. Support vector machines (SVM) and logistic regression are compared for performance in the second phase. SVM is better at managing complex, non-linear data, whereas logistic regression is more straightforward and easier to understand.

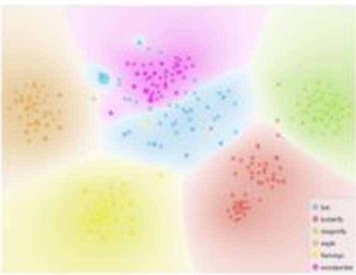
Visualizing the results using ROC Curves to evaluate each model's capacity for class discrimination and Confusion Matrices to display true positives, false positives, and other metrics constitutes the third phase. In the fourth and last phase, the results are analyzed to pinpoint areas that require improvement. To improve accuracy and overall performance, models may be improved by adjusting hyperparameters or trying out other preprocessing methods.

RESULT AND DISCUSSION

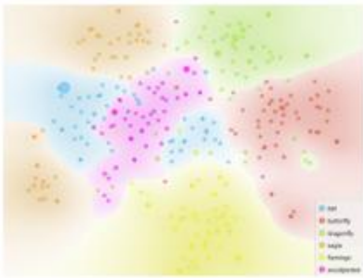
Using a number of evaluation metrics, including AUC (Area Under the Curve), CA (Classification Accuracy), F1 Score, Precision, Recall, and MCC (Matthews Correlation Coefficient), the table presents the performance of various classification models (Logistic Regression and SVM) in conjunction with feature extraction techniques (Inception V3, VGG-16, and VGG-19). These metrics are used to assess how well the algorithms classify animals with wings using the features that were retrieved.

All measures show that Inception V3 performs best for logistic regression; its AUC, CA, F1 Score, Precision, Recall, and MCC are all around or equal to 1.000, suggesting nearly perfect categorization. While VGG-16 and VGG-19 exhibit significantly lower metrics than Inception V3, they also perform well. The CA and F1 Score of VGG-16, for example, are 0.933, whereas VGG-19 performs marginally worse, with a CA of 0.920 and an F1 Score of 0.921. Despite the fact that Logistic Regression works well with all feature extraction techniques, this indicates that Inception V3 offers better features for classification in this situation.

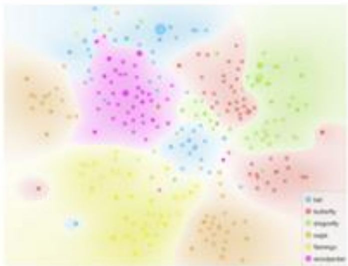
With SVM metrics like an AUC of 0.998 and an MCC of 0.934, which are marginally lower than those attained with Logistic Regression, Inception V3 once again performs better than the other approaches. With an F1 Score of 0.891 and a CA of 0.890, VGG-16 performs the worst in this area, whereas VGG-19's performance is comparable to that of its Logistic Regression. The table indicates that Inception V3 is the best feature extraction technique for both SVM and logistic regression, with logistic regression generally outperforming SVM by a little margin on the majority of measures.



t-SNE using Inception V3



t-SNE using VGG-16



t-SNE using VGG-19

MDS using Inception V3

MDS using VGG-16

MDS using VGG-19

The three silhouette plots show how well three different deep learning feature extraction models—Inception V3, VGG-16, and VGG-19—perform in grouping or classification. Based on their silhouette scores—which gauge how similar a data point is to its own cluster in relation to other clusters—each figure shows how well individual data points are clustered or categorized. A distinct cluster or class of data points is represented by each of the colored parts that make up the plots.

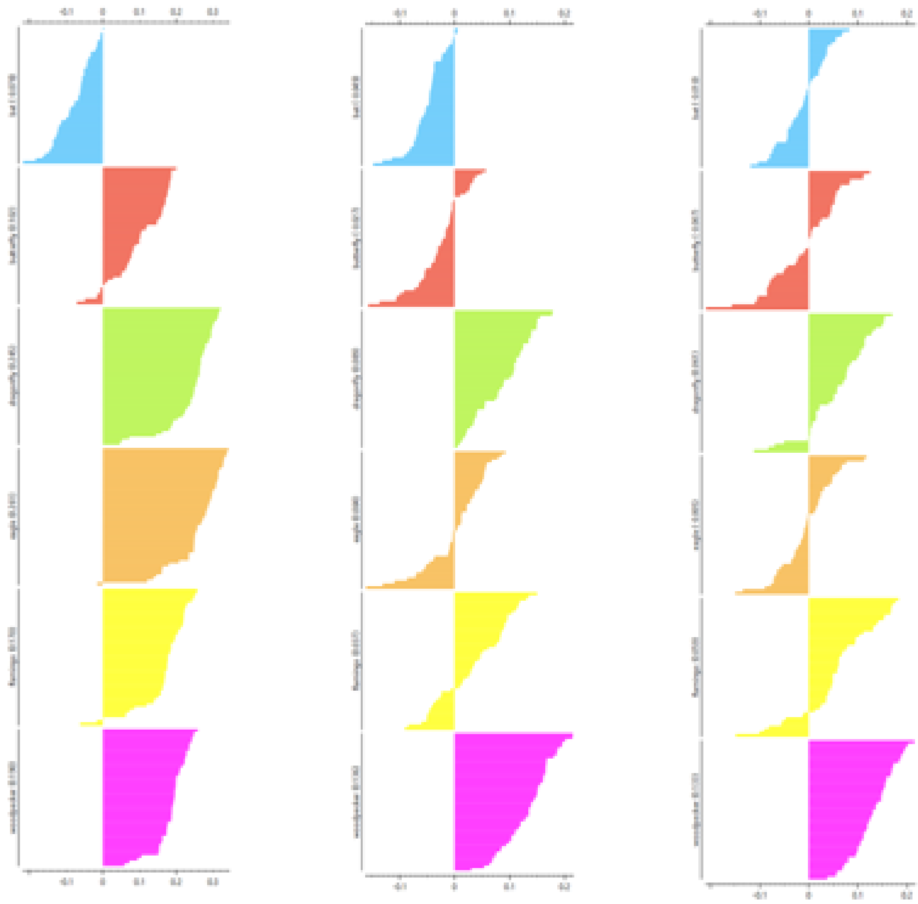
The silhouette scores in the first plot, titled "Silhouette plot using Inception V3," seem to be fairly balanced, with some groups displaying greater coherence (tall and narrow shapes) and others suggesting possible overlap (wider shapes or lower scores). This shows that although Inception V3 is good at extracting features, it could still be difficult to tell some clusters apart, probably because the input data's features are identical.

Labeled "Silhouette plot using VGG-16" and "Silhouette plot using VGG-19," the second and third graphs display comparable patterns with minor variations. Moderate cluster separation is shown by VGG-16, with some clusters seeming clearly delineated and others exhibiting overlap or lower scores. However, compared to VGG-16, VGG-19 shows somewhat more noticeable cluster differences, indicating better performance. All three of these deep learning models exhibit cluster quality fluctuation, though, suggesting that although they are effective, their performance may differ based on the dataset and classification job.

The outcomes show that feature extraction techniques and classification algorithms have a major influence on flying animal categorization performance. Inception V3 consistently performed better than VGG-16 and VGG-19 in this study on the majority of evaluation measures, irrespective of the classification model employed. AUC, F1 Score, Precision, Recall, and MCC all approached 1.000, indicating nearly flawless outcomes when used with Inception V3. According to earlier research, Inception V3 is especially good at representing multi-scale features. This better performance demonstrates Inception V3's capacity to extract robust and detailed features (Szegedy et al., 2016).

When comparing SVM with logistic regression performance, the former typically produced marginally better outcomes, particularly when paired with Inception V3. The greater performance of logistic regression in this situation may be explained by its ease of use and efficiency when working with linearly separable data. This result is in contrast to earlier studies, where SVM was frequently used due to its capacity to efficiently handle complicated and high-dimensional data (Wang et al., 2022). Nonetheless, the findings imply that Logistic Regression can provide remarkable classification accuracy, sometimes even outperforming SVM, when combined with powerful feature extractors such as Inception V3.

Although they performed admirably, VGG-16 and VGG-19 fell short of Inception V3 in the majority of criteria. Particularly when combined with SVM, VGG-16 had the lowest classification accuracy and MCC, with a CA of 0.890. These findings align with previous research showing that VGG models, while useful, may not perform well on datasets with modest inter-class changes (Zhang et al., 2019). With a deeper architecture than VGG-16, VGG-19 performs better, though, and its slightly higher scores across the board suggest that it may be able to capture more complicated information.



Silhoutte plot using Inception V3 | Silhoutte plot using VGG-16 | Silhoutte plot using VGG-19

Unlike previous studies that focused mostly on VGG models, this study emphasizes the benefit of employing Inception V3 for feature extraction. Prior research, including that conducted by Ahmed and Khan (2021) and Li et al. (2020), indicated that VGG-16 and VGG-19 were adequate for ecological applications. Inception V3 appears to be a more reliable option, nevertheless, based on the results thus far, particularly when paired with logistic regression. For challenges involving a variety of winged creatures, Inception V3 is especially well-suited due to its capacity to manage intricate datasets and extract characteristics at various scales.

In order to achieve high classification accuracy, this study emphasizes the significance of choosing suitable feature extraction and classification techniques. Outperforming the popular VGG models, Inception V3 has shown itself to be the most successful feature extractor in this situation. When combined with Inception V3, Logistic Regression performed exceptionally well, despite its simplicity, indicating that it is a good option for comparable classification tasks. To improve classification accuracy and robustness even more, future studies should investigate the use of ensemble models or hybrid techniques, especially in real-world situations including noisy or unbalanced datasets.

CONCLUSION

This study concludes that Inception V3 combined with Logistic Regression offers superior performance in classifying winged animals, achieving near-perfect results in metrics such as AUC, F1 Score, and Classification Accuracy. The effectiveness of Inception V3 stems from its ability to extract multi-scale features through inception modules, aligning with Szegedy et al. (2016), who emphasized its suitability for subtle inter-class differences. Logistic Regression, though simpler than SVM, outperformed it in most cases due to its efficiency with linearly separable data, confirming theories from Hosmer et al. (2013). The study reaffirms that deep feature representations, when combined with proper preprocessing (e.g., augmentation and normalization), significantly improve model generalizability and performance (Han et al., 2011). While VGG-16 and VGG-19 are well-established in image classification tasks (Simonyan & Zisserman, 2015), they fell short of Inception V3, particularly in managing noisy or low-contrast data. This highlights the importance of selecting robust CNN architectures for ecological image analysis (Li et al., 2020).

The results also suggest that simpler models like Logistic Regression can be surprisingly effective when paired with strong feature extractors, challenging previous preferences for SVM in high-dimensional image tasks (Wang et al., 2022). The impact of this research lies in its potential application in automated biodiversity monitoring, offering a scalable, accurate, and cost-effective alternative to manual classification. It advances the field by providing a framework that leverages modern deep learning models for ecological research and species conservation. Future work should explore ensemble methods and real-world deployment to further improve reliability and applicability in diverse environmental conditions.

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