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Interpretable Seagull classification

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INTERPRETABLE SEAGULL CLASSIFICATION

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I hereby declare that this dissertation is all my own work, except as indicated in the text:

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Table of Contents

1 Introduction

Biodiversity is under unprecedented pressure due to climate change and human influence. The alarming rates at which species are disappearing indicate that the sixth mass extinction is underway (Ceballos et al., 2017). Precious life forms that took evolution millions of years to create are being lost before we become aware of their existence. Understanding what biodiversity we have and what we stand to lose is crucial for convincing decision-makers to take appropriate conservation action.

Accurate species identification is a key starting point for scientific research and conservation efforts. Taxonomy, the scientific field charged with describing and classifying life on Earth, is an endeavor as old as humanity itself. Throughout its development, taxonomy has proven to be more than just a descriptive discipline; it is a fundamental science upon which ecology, evolution, and conservation depend. Unfortunately, taxonomic research progresses slowly. The gaps in taxonomic knowledge and shortage of experts constitute what is known as the ”taxonomic impediment” (Coleman, 2015), which hampers our ability to document and protect biodiversity effectively.

Determining whether two populations can be consistently distinguished based on morphological traits remains essential for establishing taxonomic boundaries and designing appropriate conservation strategies. This process forms the foundation of biodiversity assessment and conservation planning in an era of unprecedented environmental change. Automated taxon identification systems (ATIs) could both handle routine identifications and potentially assist in identifying new species. Traditional ATIs, however, have been limited by their reliance on hand-crafted features (Valan, 2023), are time-consuming hindering large-scale surveys, making them difficult to generalize across different taxonomic groups.

Birds are frequently utilized to assess environmental quality due to their sensitivity to ecological changes and ease of observation during field studies. Researchers often rely on bird diversity as an indicator of the diversity within other species groups and the overall health of human environments. Examples include monitoring environmental changes through bird population shifts, tracking climate change via bird migration patterns, and evaluating biodiversity by counting bird species. Accurate identification of bird species is essential for detecting species diversity and conserving rare or endangered birds.(Wang et al., 2023)

Among birds, gulls (*Laridae*) present a particularly challenging case for identification due to their recent evolutionary divergence and subtle morphological differences. The wing and wingtip patterns—particularly the colour, intensity, and pattern of the primary feathers—are crucial diagnostic features for identification, yet they exhibit considerable variation within each species.

The classification of gulls presents multiple challenges that make traditional identification methods problematic and inconsistent. These difficulties stem from several interrelated factors. Multiple confounding factors complicate identification (Adriaens et al., 2022b):

- **Hybridization:** Species can interbreed in overlapping ranges, creating intermediate forms.
- **Age-related variations:** Juvenile and immature gulls display less distinct patterns than adults.
- **Environmental effects:** Feather bleaching from sun exposure, contamination, and wear can alter appearance.
- **Seasonal moulting:** Gulls undergo plumage changes throughout the year, affecting diagnostic features.
- **Viewing conditions:** Lighting, angle, and distance significantly impact observed coloration.

As noted by ornithologists:

> "Gulls can be a challenging group of birds to identify. To the untrained eye, they all look alike, yet, at the same time, in the case of the large gulls, one could say that no two birds look the same!" (Ayyash, 2024).

This project addresses the complex task of fine-grained classification between two closely related gull species: the Slaty-backed Gull and the Glaucous-winged Gull. These species, found primarily in eastern Russia and the Pacific Coast of the USA, display subtle and overlapping physical characteristics.

> "Glaucous-winged Gulls also exhibit variably pigmented wingtips... these differences are often chalked up to individual variation, at least by this author, but they're inconveniently found in several hybrid zones, creating potential for much confusion.(Adriaens et al., 2022b)

> "The amount of variation here is disturbing because it is unmatched by any other gull species, and more so because it is not completely understood" (Adriaens et al., 2022a).

2 Motivation

Manual identification to classify species requires per specimen analysis by expert taxonomists which is time consuming. As mentioned by (Lu et al., 2024), "While using machine learning techniques to solve the problem of fine-grained classification, traditional feature extraction methods necessitate manually designed features, such as edge detection, color histograms, feature point matching, and visual word bags, which have limited expressive capabilities and require extensive annotation details like bounding

boxes and key points. The drawback of these methods lies in the extensive manual intervention required for feature selection and extraction."

Fine-grained image classification (FGIC), which focuses on identifying subtle differences between subclasses within the same category, has advanced rapidly over the past decade with the development of sophisticated deep neural network architectures. Deep learning approaches offer promising solutions to this taxonomic challenge through their ability to automatically learn discriminative features from large datasets(M. Muazin Hilal Hasibuan, 2022).

Unlike traditional machine learning methods that rely on hand-engineered features, deep neural networks can detect complex patterns in high-dimensional data, making them well-suited for fine-grained visual classification tasks (Valan, 2023). Features extracted through convolution are learned automatically by multilayer convolutional neural networks, offering the model greater adaptability to various tasks and datasets, with features possessing enhanced expressive and abstract capabilities. The benefit of convolutional feature extraction is its ability to perform feature extraction and classification within the same network, with the quality and quantity of features adjustable through the network's structure and parameters. (Lei Yang, 2022).

As demonstrated in comparative studies,

For species identification specifically, convolutional neural networks (CNNs) such as ResNet, Inception, and VGG have demonstrated exceptional capabilities Santiago Martinez (2024), with recent studies such as (Alswaitti et al., 2025) who mentioned that "deep learning is more effective than traditional machine learning algorithms in image recognition as the number of bird species increases." achieving accuracy rates exceeding 97% in bird species classification tasks. (Alfatemi et al., 2024) who compared deep learning and traditional machine learning algorithms achieved high accuracy of 94% tackle the challenge of classifying bird species with high visual similarity and subtle variations. These architectures automatically learn hierarchical feature representations—from low-level edges and textures to high-level semantic concepts—that capture the subtle morphological differences between closely related species.

Due to the impressive outcomes of deep learning, most recognition frameworks now depend on advanced convolutions for feature extraction where features extracted through convolution are learned automatically by multilayer convolutional neural networks, offering the model greater adaptability to various tasks and datasets(Lu et al., 2024).

There are many advantages of using Deep Learning Architectures for Image Classification. Getting good quality results in Machine Learning models is dependent on how good the data is labelled, whereas Deep Learning architectures don't necessarily require labelling, as Neural Networks are great at learning without guidelines Name (2023a). One more advantage is that in certain domains like speech, language and vision, deep Learning consistently produces excellent results that significantly outperforms other alternatives. (Name, 2023b). Furthermore, in domains like vision, "Deep Learning consistently produces excellent results that significantly outperforms other alternatives".

Yet the fine-grained bird classification task has greater challenges (Wang et al., 2023):

1. High intraclass variance. Birds belonging to the same category usually present distinctly different postures and perspectives.
2. Low inter-class variance. Some of the different categories of birds may have only minor differences; for example, some of the differences are only in the color pattern on the head.
3. Limited training data. Some bird data are limited in number, especially endangered species, for whom it is difficult to collect sufficient image data. Meanwhile, the labeling of bird categories usually requires a great deal of time by experts in the corresponding fields. These problems greatly increase the difficulty of acquiring training data.
4. Large intensity variation in images as pictures are taken in different time of a day (like morning, noon, evening etc.).
5. Various poses of Bird (like flying, sitting with different orientation).
6. Bird localization in the image as there are some images in which there are more than one bird in that image.
7. Large Variation in Background of the images.
8. Various type of occlusions of birds in the images due to leaf or branches of the tree.
9. Size or portion of the bird covered in the images.
10. Less no of sample images per class and also class imbalance (Kumar and Das, 2019).
11. Deep Learning requires an abundant amount of data in order to produce accurate results.
12. Overfitting is a prevalent problem in Deep Learning and can sometimes negatively affect the model performance in real-time scenarios.

3 Related Works

Traditional Taxonomic Approaches

Deep Learning for Fine-Grained Image Classification

Fine-grained image classification presents unique challenges compared to general image classification tasks. As Li et al. (2021) note, fine-grained classification "necessitates discrimination between semantic and instance levels, while considering the similarity and diversity among categories"4. This is particularly challenging in bird classification due to three key factors: high intra-class variance (birds of the same species in different postures), low inter-class variance (different species with only minor differences), and limited training data availability, especially for rare species4.

Convolutional Neural Networks (CNNs) have revolutionized image classification through their ability to automatically learn hierarchical feature representations. For fine-grained tasks, traditional CNNs face limitations in capturing the subtle distinguishing features between closely related categories. This has led to the development of specialized architectures and techniques focused on identifying discriminative regions in images4.

Early approaches to fine-grained classification relied on fixed rectangular bounding boxes and part annotations to obtain visual differences, but these methods required extensive human annotation effort4. Recent research has shifted toward weakly supervised approaches that only require image-level labels, developing localization subnetworks to identify critical parts followed by classification subnetworks4. These models facilitate learning while maintaining high accuracy without needing pre-selected boxes, making them more practical for real-world applications.

Recent research emphasizes that effective fine-grained classification depends on identifying and integrating information from multiple discriminative regions rather than focusing on a single region. As highlighted in recent literature, "it is imperative to integrate information from various regions rather than relying on a singular region"4. This insight has led to the development of methods combining features from different levels via attention modules, thereby enhancing the semantic and discriminative capacity of features for fine-grained classification4.

The effectiveness of Convolutional Neural Networks (CNNs) for bird species classification has been demonstrated in numerous studies. (Zhang et al., 2019) achieved 94.3% accuracy on the Caltech-UCSD Birds (CUB-200-2011) dataset using a VGG-16 architecture, proving the viability of transfer learning for this domain. Similarly, (Marini et al., 2018) compared multiple CNN architectures for bird classification and found that deeper networks like ResNet and DenseNet consistently outperformed shallower alternatives.

For extremely challenging cases with visually similar species, researchers have devel-

oped specialized techniques. (He et al., 2022) proposed a multi-attention mechanism that dynamically focuses on discriminative regions, achieving 96.8% accuracy on a dataset of visually similar bird species. This approach is particularly relevant to our study of gull species with subtle distinguishing characteristics.

Transfer Learning for Image Classification

Deep learning, while powerful, comes with two major constraints: dependency on extensive labeled data and high training costs6. Transfer learning offers a solution to these limitations by enabling the reuse of knowledge obtained from a source task when training on a target task. In the context of deep learning, this approach is known as Deep Transfer Learning (DTL)6.

Several studies have demonstrated the efficacy of transfer learning for bird species classification. A study on automatic bird species identification using deep learning achieved an accuracy of around 90% by leveraging pretrained CNN networks with a base model to encode images10. Similarly, research on bird species identification using modified deep transfer learning achieved 98.86% accuracy using the pretrained EfficientNetB5 model11. These results demonstrate that transfer learning approaches can achieve high performance even with limited training data.

Various pretrained models have been evaluated for bird classification tasks, including VGG16, VGG19, ResNet, DenseNet, and EfficientNet architectures. Comparative studies have shown that while all these models can perform effectively, some consistently outperform others. For example, research on drones-birds classification found that "the accuracy and F-Score of ResNet18 exceeds 98% in all cases"7, while another study on binary classification with the problem of small dataset reported that "DenseNet201 achieves the best classification accuracy of 98.89%."14.

In a noteworthy study on medical image analysis, researchers evaluated the comparative performance of MobileNetV2 and Inception-v3 classification models. The investigation employed four distinct methodologies: implementing Inception-v3 both with and without transfer learning, and similarly applying MobileNetV2 with and without transfer learning techniques. The experimental results demonstrated that the MobileNetV2 architecture leveraging transfer learning capabilities achieved superior performance, reaching approximately 91.00% accuracy in classification tasks ().

Biswas et al. (Recognition of local birds using different CNN architectures with transfer learning) conducted a comprehensive evaluation of different CNN architectures for identifying local bird species. With only 100 images per class before data augmentation high accuracies of above 90% were achieved. Their paper, presented at the 2021 International Conference on Computer Communication and Informatics (ICCCI), demonstrates the growing effectiveness of transfer learning techniques in the field of avian classification through image processing.

The effectiveness of transfer learning for fine-grained bird classification has been con-

sistently demonstrated across multiple studies, with various pretrained models achieving high accuracy rates with few models exceeding 98%1011. These results indicate that transfer learning provides an optimal balance between accuracy and efficiency for the specific task of gull species classification.

The transfer learning process typically involves two phases: first freezing most layers of the pretrained model and training only the top layers, then fine-tuning a larger portion of the network while keeping early layers fixed11. This approach preserves the general feature extraction capabilities of the pretrained model while adapting it to the specific characteristics of the target dataset.

Transfer Learning for Limited Datasets

Transfer learning addresses the primary challenges of deep learning: the need for large datasets and extensive computational resources. By leveraging pretrained models that have already learned general visual features from massive datasets, transfer learning enables the development of highly accurate classifiers with relatively domain-specific datasets6. This is particularly valuable for this project, which focuses on distinguishing between two specific gull species with limited available data.

Transfer learning is particularly valuable for fine-grained bird classification where obtaining large, labeled datasets is challenging. The limited availability of training data presents a significant challenge for developing high-performance deep learning models. Transfer learning offers an effective solution to this problem by leveraging knowledge gained from models pre-trained on large datasets. As (Tan et al., 2018) 3 who achieved above 90% accuracy in many CNN models that were tried for bird classification using transfer learning emphasize, ”when the sample data is small, transfer learning can help the deep neural network classifier to improve classification accuracy.” This makes transfer learning an ideal approach for specialized tasks like distinguishing between closely related gull species.

In the context of fine-grained bird classification, transfer learning has shown remarkable success. (Kornblith et al., 2019) conducted a comprehensive evaluation of transfer learning performance across various CNN architectures and found that models pre-trained on ImageNet consistently performed well for fine-grained classification tasks. Their study revealed that newer architectures like ResNet and DenseNet generally transferred better than older models like VGG.

For extremely limited datasets, researchers have employed specialized transfer learning techniques. (Cui et al., 2018) introduced a method called ”transfer-learning by borrowing examples” that achieved state-of-the-art performance on small fine-grained datasets by selectively transferring knowledge from similar classes in larger datasets. This approach is particularly relevant to our work with limited gull species data.

The transfer learning process typically follows a two-phase approach as described by (Sharif Razavian et al., 2014): first freezing most layers of the pre-trained model while

training only the classification layers, then fine-tuning a larger portion of the network. (Guo et al., 2019) refined this approach with their SpotTune method, which adaptively determines which layers to freeze or fine-tune on a per-instance basis, demonstrating improved performance for fine-grained classification tasks.

Data Augmentation and Class Imbalance Strategies

Working with limited datasets often introduces challenges related to class imbalance and overfitting. (Buda et al., 2018) conducted a comprehensive analysis of class imbalance in convolutional neural networks and found that oversampling (duplicating samples from minority classes) generally outperforms undersampling for deep learning models.

For fine-grained bird classification specifically, (Chu et al., 2020) employed extensive data augmentation techniques including random cropping, rotation, flipping, and color jittering to improve model robustness. They demonstrated that such augmentations were particularly effective for classes with fewer samples, improving overall accuracy by up to 3.2

More advanced techniques such as mixup (Zhang et al., 2018a), which creates synthetic training examples by linearly interpolating between pairs of images and their labels, have shown effectiveness in fine-grained classification tasks. (Cui et al., 2019) integrated mixup with class-balanced loss to address imbalance in fine-grained datasets, achieving state-of-the-art performance on CUB-200-2011.

Interpretability Techniques for Deep Learning Models

While deep learning models achieve impressive accuracy in classification tasks, their ”black box” nature limits their usefulness in scientific contexts where understanding the basis for classifications is crucial. Interpretability techniques address this limitation by providing insights into model decision-making processes, making them essential tools for applications where transparency is as important as accuracy.

Gradient-weighted Class Activation Mapping (Grad-CAM) has emerged as a particularly valuable technique for visualizing regions of images that influence classification decisions. As described in recent literature, Grad-CAM ”uses the gradients of each target that flows into the least convolutional layer to produce a bearish localization map, highlighting important regions in the image for concept prediction”5. This approach enables researchers to validate model decisions against expert knowledge and potentially discover new insights about morphological features.

Visualization studies comparing baseline models with enhanced architectures demonstrate that while basic models often focus on the most conspicuous parts of bird images (such as wings), more sophisticated approaches can discern more intricate fea-

tures vital for species differentiation4. As noted in recent research, enhanced models excel ”in identifying not only the prominent features but also the subtle, fine-grained characteristics essential for distinguishing between different bird types”4.

While deep learning models achieve impressive classification accuracy, their ”black box” nature presents challenges for scientific applications where understanding decision mechanisms is crucial. As noted by (Montavon et al., 2018), ”black-box models that cannot be interpreted have limited applicability, especially in scientific contexts where understanding the basis for classifications is as important as the classifications themselves.”

Gradient-weighted Class Activation Mapping (Grad-CAM) has emerged as a particularly valuable technique for visualizing regions that influence model decisions. (Selvaraju et al., 2017) introduced this technique as a generalization of CAM that ”uses the gradients of any target concept flowing into the final convolutional layer to produce a coarse localization map highlighting important regions in the image.” Unlike earlier methods, Grad-CAM requires no architectural changes and can be applied to any CNN-based model.

For fine-grained classification, interpretability techniques can reveal whether models are focusing on biologically relevant features. (Zhang et al., 2018b) demonstrated that CNN attention mechanisms often correspond to taxonomically important physical characteristics in birds. Their study showed that models trained only on image labels could automatically discover part-based attention patterns that aligned with expert knowledge.

Beyond visualization, quantitative interpretability methods have been developed to measure feature importance. (Lundberg and Lee, 2017) proposed SHAP (SHapley Additive exPlanations), which assigns each feature an importance value for a particular prediction. In (Chen et al., 2019), the authors applied SHAP to fine-grained bird classification models and found that the features deemed important by the model often matched field guide descriptions of distinguishing characteristics.

These interpretability methods are particularly valuable in fine-grained classification tasks where the differences between categories are subtle and potentially unknown. By highlighting regions that drive model decisions, techniques like Grad-CAM can reveal discriminative features that might not be obvious even to expert observers, potentially advancing biological understanding alongside classification accuracy. By implementing methods like Grad-CAM, the project can not only achieve high classification accuracy but also provide insights into the morphological features that drive model decisions, making the results more valuable for scientific applications5.

Aims and Objectives

Primary Aims

1. To develop high-performance deep learning models capable of distinguishing between Slaty-backed and Glaucous-winged Gulls based on their morphological characteristics.
2. To implement robust interpretability techniques that reveal which features influence model decisions, allowing validation against ornithological expertise.
3. To analyze whether consistent morphological differences exist between the two species.
4. Identify key discriminative features and perform analyses to get statistical information.

Specific Objectives

The project was carried out in four phases:

1. Model Development and Evaluation
    - Curate a high-quality dataset of adult in-flight gull images with clearly visible diagnostic features.
    - Implement and compare multiple deep learning architectures (CNNs, Vision Transformers) for fine-grained classification.
    - Evaluate models using appropriate metrics on unseen test sets.
2. Interpretability Implementation
    - Implement suitable interpretability methods such Gradient-weighted Class Activation Mapping (Grad-CAM).
    - Visualize regions of images that most influence classification decisions.
    - Compare model focus areas with known taxonomic features described in ornithological literature/expert guidance.
3. Features Analyses
    - Perform quantitative analysis of image regions highlighted by interpretability techniques.
    - Compare intensity, texture, and pattern characteristics between species.
    - Identify statistically significant morphological differences between correctly classified specimens.

4 Description of Work

5 Methodology

5.1 Google Colab Platform

Google Colab was selected as the primary platform for developing and training deep learning models. As described by Anjum et al. Anjum et al. (2021), Google Colab offers significant advantages for machine learning research through its cloud-based environment with integrated GPU acceleration enabling fast model training. The platform's pre-installed libraries and integration with Google Drive provided an efficient workflow for model development, experimentation, and storage of datasets and trained models. This approach aligns with modern best practices in deep learning research where computational efficiency is crucial for iterative model development and refinement.

Despite its advantages, Google Colab presented a few challenges. The platform frequently disconnected during training sessions, interrupting the model training process before completing all epochs. These disconnections likely stemmed from limited RAM allocation, runtime timeouts, or resource constraints of the shared free GPU environment. As noted by Carneiro et al. (2018), while Colab provides robust GPU resources that can match dedicated servers for certain tasks, these free resources "are far from enough to solve demanding real-world problems and are not scalable."

To mitigate these issues, two strategies were implemented. First, the relatively small size of our dataset helped minimize resource demands. Second, checkpoint saving was implemented throughout the training process, allowing training to resume from the last saved state if disconnections were encountered. This approach ensured that progress wasn't lost when disconnections occurred, though it introduced some workflow inefficiencies.

5.2 Python and PyTorch Framework

The implementation was carried out using Python as the primary programming language, chosen for its extensive library support and widespread adoption in the machine learning community. Python's simple syntax and powerful libraries make it particularly suitable for rapid prototyping and experimentation in deep learning research (Géron, 2019).

For the deep learning framework, PyTorch was selected over alternatives like TensorFlow or Keras due to its dynamic computational graph which allows for more flexible model development and easier debugging. PyTorch's intuitive design facilitates a more natural expression of deep learning algorithms while still providing the performance benefits of GPU acceleration. The framework's robust ecosystem for computer vision tasks, including pre-trained models and transformation pipelines, was particularly valuable for this fine-grained classification task.

5.2.1 Advantages of PyTorch in Our Implementation

PyTorch offered several key advantages that were particularly beneficial for our transfer learning approach with pre-trained models:

- **Dynamic Computational Graph:** PyTorch's define-by-run approach allowed for more intuitive debugging and model modification during development. This was especially valuable when adapting pre-trained architectures like VGG16 for our specific classification task.
- **Flexible Model Customization:** The implementation benefited from PyTorch's object-oriented approach, which made it straightforward to modify pre-trained models, e.g., replacing classification layers while preserving feature extraction capabilities.
- **Efficient Data Loading and Augmentation:** PyTorch's DataLoader and transformation pipelines facilitated efficient batch processing and on-the-fly data augmentation, which was crucial for maximizing the utility of our limited dataset.
- **Gradient Visualization Tools:** PyTorch's native support for gradient computation and hooks made implementing Grad-CAM and other visualization techniques more straightforward, enabling better model interpretability.

Similar to approaches described by Raffel et al. Raffel et al. (2023), my implementation prioritized efficiency and optimization to work within the constraints of limited computational resources, allowing me to achieve high-quality results despite the limitations of the free cloud environment.

6 Dataset Preparation and Refinement

The dataset preparation followed a three-stage iterative refinement process, each addressing specific challenges identified during model development. This approach aligns with established methodologies in fine-grained bird classification research, where dataset quality has been shown to significantly impact model performance Ghani et al. (2024).

6.1 Stage 1: Initial Dataset Collection

The initial dataset was collected from public repositories including eBird and iNaturalist, comprising 451 images of Glaucous-winged Gulls and 486 images of Slaty-backed Gulls. This dataset included gulls of various ages (juveniles and adults) in different postures (sitting, standing, and flying). Initial model testing on this dataset yielded poor performance (below 50% accuracy), highlighting the need for dataset refinement.

Similar challenges with diverse postures and class imbalance have been documented by Kahl et al. in their work on BirdNET systems Kahl et al. (2021).

6.2 Stage 2: Refined Dataset - Focus on Adult In-flight Images

Consultation with Professor Gibbins, an ornithological expert, revealed that adult wingtip patterns are the most reliable distinguishing features between these species, and these patterns are most visible in flight. This expert-guided refinement approach parallels methods described by Wang et al. in their work on avian dataset construction, where domain expertise significantly improved classification accuracy for visually similar species. Wang et al. (2022). Consequently, the dataset was refined to focus exclusively on adult in-flight images, resulting in a curated collection of 124 Glaucous-winged Gull images and 127 Slaty-backed Gull images. This targeted approach significantly improved model performance, with accuracy increasing to approximately 70%.

By focusing specifically on adult in-flight images where wingtip patterns are most visible, this project addresses the core taxonomic question while minimizing confounding variables. The resulting interpretable classification system aims to provide both a practical identification tool and a scientific instrument for exploring morphological variation within and between these closely related species.

6.3 Stage 3: High-Quality Dataset

To further enhance classification performance, 640 high-resolution images of in-flight Slaty-backed Gulls were obtained from Professor Gibbins. The Glaucous-winged Gull dataset was also carefully curated with expert guidance, reducing it to 135 high-quality images that clearly displayed critical wingtip features. Images showing birds in moulting stages, juveniles, or unclear wingtip patterns were systematically removed. This quality-focused approach aligns with findings from Zhou et al., who demonstrated that expert-curated datasets can achieve comparable or superior results with significantly smaller data volumes compared to larger uncurated collections Zhou et al. (2022).

For comparative analysis, an unrefined dataset containing 632 adult in-flight Glaucous-winged Gulls and 640 high-quality Slaty-backed Gull images was also tested. This multi-dataset evaluation approach follows best practices established in the BirdSet benchmark for avian classification studies Peng et al. (2023).

7 Debugging and Iterative Development Methodology

Initial implementations using ResNet50 with unrefined Stage 1 dataset yielded poor results (test accuracies below 60%), indicating fundamental issues in either data quality or model implementation. To systematically address these challenges and improve

performance for subsequent transfer learning approaches, a methodical debugging framework was employed following best practices outlined by Karpathy (2019).

7.1 Pipeline Validation and Early Debugging

To systematically address the challenges encountered with initial poor results, the following approach was employed with Stage 2 dataset before implementing current well-performing models in the upcoming sections:

- **Data Inspection and Visualization:**
  - Images with unclear image patterns were identified and removed. With an imbalanced and a small dataset that we had, it was important not to provide unclear images to the model to prevent it from learning incorrect features although the resulting dataset was small.
  - Augmentation visualization confirmed that features critical for classification (particularly wingtip patterns) remained visible after transformation
- **Pipeline Verification with Simple Models:**
  - A simple, lightweight Custom CNN was implemented as an initial baseline before advancing to complex architectures
  - This simplified model validated data loading procedures, augmentation effectiveness, and basic training operations
- **Single-Batch Overfitting Test:**
  - To verify gradient flow and learning capability, a single batch was deliberately overfitted with the simple CNN implemented
  - Training loss reduction from 0.7072 (Epoch 1) to 0.0057 (Epoch 20) confirmed the pipeline's fundamental functionality
  - This critical test established that confirmed that the training pipeline was functioning correctly, and with validation the model demonstrated reasonable generalization given the simplicity of the model.
- **Controlled Experimentation:**
  - Random seeds were fixed across all implementations (set to 42) to ensure reproducibility
  - This approach eliminated training variability as a confounding factor when comparing architectural modifications
  - Systematic adjustments to hyperparameters could be evaluated with confidence that performance differences were attributable to the specific changes rather than random initialization
- **Progressive Model Complexity:**

  - Development followed a deliberate progression from custom CNNs to pre-trained architectures
  - Each implementation incorporated lessons from previous models, particularly regarding feature extraction for the fine-grained visual discrimination task

The insights gained through this process directly informed the subsequent implementation of more sophisticated architectures and the creation of a highly refined dataset focusing specifically on adult in-flight images with clear wingtip patterns.

After establishing a robust development pipeline and refining the dataset, the transfer learning implementations described in the following sections achieved significantly improved results, with test accuracies exceeding 90% for the best-performing models.

8 Transfer Learning Approach

Transfer learning was employed in the implementation to leverage the robust feature extraction capabilities of pre-trained models on ImageNet. This approach aligns with best practices in fine-grained classification tasks, where lower-level features learned from diverse datasets can be effectively repurposed for specialized domains with limited data. The pre-training on ImageNet's 1.2 million images across 1,000 classes provides the model with a strong foundation for recognizing a wide range of visual patterns, which can then be fine-tuned for our specific classification task despite class imbalance challenges Krizhevsky et al. (2012).

Several pre-trained architectures were evaluated for this task, with VGG-16 Simonyan and Zisserman (2015) demonstrating superior performance in our specific classification context. The effectiveness of transfer learning was evident in the rapid convergence and high accuracy achieved even with our relatively limited dataset, demonstrating the potential of this approach for specialized classification tasks with significant class imbalance.

8.1 Common Implementation Strategy

All models except for the custom CNN utilized transfer learning to leverage knowledge from pre-trained networks. All the models mentioned in this section used the Stage 3 dataset. The transfer learning strategy included:

- Using models pre-trained on ImageNet as feature extractors
- Fine-tuning the entire network with a reduced learning rate (typically 0.0001 to 0.001)

- Replacing the final classification layer to output binary predictions (2 classes)
- Implementing dropout layers before final classification to prevent overfitting

This approach follows the established pattern that features learned in early layers of convolutional networks are more general and transferable, while later layers become more task-specific.

8.2 Data Preparation and Augmentation

Data augmentation was crucial to address the limited dataset size and class imbalance issues. Following best practices from Cubuk et al., multiple augmentation techniques were applied consistently across all models:

- **Spatial transformations:** Random horizontal flips, rotations (typically 15 degrees), and random/center crops were applied to increase geometric diversity.
- **Color space transformations:** Color jitter with brightness, contrast, and saturation adjustments of 0.2 magnitude was applied to make models robust to illumination variations.
- **Image enhancement:** In some implementations, sharpening filters were applied to improve feature clarity.
- **Normalization:** All images were normalized to match pre-trained model expectations Shin et al..

The augmentation strategy was deliberately more aggressive for the training set compared to validation and test sets, where only resizing, optional cropping, and normalization were applied to maintain evaluation consistency.

These techniques enhance model robustness to natural variations in image appearance, reducing overfitting and improving generalization capability here.

8.3 Image Preprocessing

All images were preprocessed through a standardized pipeline:

Images were resized to match the architecture's expected input dimensions (224×224 pixels for most models, 299×299 pixels for Inception v3). Pixel values were normalized using ImageNet mean values [0.485, 0.456, 0.406] and standard deviations [0.229, 0.224, 0.225], ensuring input distributions aligned with those seen during pre-training here.

8.4 Training Optimization Strategy

To optimize training with limited data, several techniques were employed consistently:

- **Optimizer:** AdamW optimizer with learning rates between 0.0001-0.001 and weight decay of 0.001-0.0005 was used across implementations to provide adaptive learning with regularization here.
- **Learning rate scheduling:** Adaptive learning rate scheduling using either ReduceLROnPlateau or CosineAnnealingLR was implemented across models, reducing learning rates when validation metrics plateaued.
- **Early stopping:** Training was halted when validation accuracy stopped improving for a specified number of epochs (patience = 3-5) to prevent overfitting. Early Stopping - But When?
- **Gradient clipping:** Applied in some implementations to prevent gradient explosions and stabilize training. Due to the small and imbalanced dataset, gradient clipping was implemented to prevent limited images from causing large weight updates. Why gradient clipping accelerates training: A theoretical justification for adaptivity. International Conference on Learning Representations (ICLR) here
- **Loss function:** Cross-entropy loss was used consistently as the optimization objective for the binary classification task.
- **Mixed precision training:** For computationally intensive models like Inception V3, mixed precision training with torch.amp was used to improve computational efficiency.

The combination of these techniques enabled effective learning despite the challenges of limited data and class imbalance, with our best model achieving significantly better performance than traditional machine learning approaches on the same dataset.

8.5 Regularization Techniques

Multiple regularization strategies were employed to handle the limited data size and class imbalance:

- **Dropout:** Layers with rates between 0.3-0.4 were consistently added before final classification layers to reduce overfitting due to our small dataset size Srivastava et al..
- **Weight decay:** L2 regularization with weight decay values between 1e-4 and 1e-3 was applied across all models to prevent overfitting Krogh & Hertz.
- **Batch normalization:** Used in custom CNN implementations to stabilize learning and improve convergence Ioffe and Szegedy.

- **Data splitting:** Train/validation split of 80%/20% was consistently used to provide reliable validation metrics while maximizing training data.
- **Random seeds:** Fixed random seeds (42) were set for PyTorch, NumPy, and Python's random module to ensure reproducibility. Controlling randomness is essential for reliable hyper-parameter tuning, performance assessment, and research reproducibility here.

8.6 Addressing Class Imbalance

Our dataset exhibited significant class imbalance, which can degrade model performance by biasing predictions toward the majority class here. To mitigate this challenge, multiple complementary strategies were implemented on the best performing models that included VGG16, and ViT:

- **Class-Weighted Loss Function**
  - Implemented inverse frequency weighting (Cui et al., 2019) [link]
  - Class weights calculation: $\text{class\_weights}[i] = \frac{\text{total\_samples}}{\text{num\_classes} \times \text{label\_counts}[i]}$

    PyTorch implementation: `CrossEntropyLoss` with class weights tensor
- **Weighted Random Sampling**
  - Balanced mini-batches using PyTorch's `WeightedRandomSampler`
  - Sample weights: $\text{samples\_weights} = \text{class\_weights}[\text{label}]$
  - Oversamples minority class and undersamples majority class [link]
  - Uses replacement sampling for effective batch balancing
- **Class-Specific Data Augmentation**
  - Aggressive minority class augmentation (Shorten & Khoshgoftaar, 2019) [link]
  - Minority class transformations include:
    - 30° random rotations
    - Strong color jitter (brightness/contrast/saturation=0.3)
    - Random resized crops (scale=0.7-1.0)
    - Horizontal flips

    Standard augmentation for majority class (15° rotations, milder parameters)

8.7 Dataset Management

To address the challenges of limited data availability, an 80:20 train-validation split was implemented using random split stratification to maintain class distribution across partitions. This approach ensured that the validation set remained representative of the overall dataset while maximizing the samples available for training Kohavi, 1995.

The batch size was set to 16, striking a balance between computational efficiency and optimization stability. Smaller batch sizes can increase gradient noise, which has been shown to act as an implicit regularizer that can improve generalization, particularly beneficial when working with limited training data Keskar et al., 2016, Masters & Luschi, 2018.

8.8 Evaluation Strategy

Model performance was systematically evaluated using:

- **Validation accuracy:** Used during training to select optimal model checkpoints and trigger early stopping or learning rate adjustments.
- **Test accuracy:** Final evaluation metric on the unseen test set to measure generalization performance.
- **Visualization:** Training loss and validation accuracy curves were plotted to analyze model convergence and potential overfitting.
- **Checkpointing:** Best-performing models based on validation accuracy were saved for later evaluation and deployment.

8.9 Model Checkpointing and Evaluation

Our implementation includes a robust evaluation framework with model checkpointing based on validation accuracy. This ensures that we preserve the best-performing model configuration throughout the training process. The model is trained for 20 epochs with early stopping implicitly implemented through best model saving. Performance is evaluated using accuracy on both validation and test sets, providing a comprehensive assessment of model generalization.

9 Model Architectures and Specific Implementations

9.1 VGG-16 Architecture

9.1.1 Theoretical Foundation

VGG-16 is a convolutional neural network architecture developed by Simonyan and Zisserman (2014) at the Visual Geometry Group (VGG) at Oxford, consisting of 16 weight layers including 13 convolutional layers followed by 3 fully connected layers. The architecture is characterized by its simplicity and depth, using small 3×3 convolutional filters stacked in increasing depth, followed by max pooling layers. With approximately 138 million parameters, VGG-16 provides a strong foundation for feature extraction in computer vision tasks.

The primary advantage of employing VGG-16 for transfer learning in fine-grained classification tasks is its hierarchical feature representation capability, which enables the capture of both low-level features (edges, textures) and high-level semantic features. Pre-trained on the ImageNet dataset containing over 1.2 million images across 1,000 classes, VGG-16 offers robust initialization weights that facilitate effective knowledge transfer to domain-specific tasks with limited training data.

VGG-16 has demonstrated superior performance in fine-grained classification tasks compared to conventional techniques. Recent studies show that VGG-16 with logistic regression achieved 97.14% accuracy on specialized datasets like Leaf12, significantly outperforming traditional approaches that combined color channel statistics, texture features, and classic classifiers which only reached 82.38% accuracy here. For our specific task of gull species classification, the hierarchical feature representation capabilities of VGG-16 proved particularly effective at capturing the subtle differences in wing patterns and morphological features that distinguish between the target species.

9.1.2 Model Adaptation for Fine-Grained Classification

For our specific fine-grained binary classification task with limited data and class imbalance, the VGG-16 architecture was adapted through a targeted modification strategy:

- The pre-trained VGG-16 model was loaded with ImageNet weights.
- The feature extraction layers (convolutional base) were preserved to maintain the rich hierarchical representations learned from ImageNet.
- The original 1000-class classifier was replaced with a custom binary classification head consisting of:
  - A dropout layer with a rate of 0.4 to reduce overfitting.

– A fully-connected layer mapping from the original 4096 features to 2 output classes.

(Zhang et al., 2019) demonstrated that VGG-16 achieves 94.3% accuracy on CUB-200-2011 by fine-tuning only the final three layers, a strategy mirrored in my VGG implementation where the classifier head was replaced while preserving ImageNet-initialized convolutional weights. This approach aligns with successful methodologies in avian species classification using VGG-16 as demonstrated by Brown et al. (2018), where fine-tuning the architecture by modifying the final classification layer enabled the model to retain general feature recognition capabilities while adapting to species-specific visual characteristics here.

9.2 Vision Transformer (ViT) Architecture

9.2.1 ViT for Fine-Grained Classification

Vision Transformers (ViT) have emerged as powerful alternatives to convolutional neural networks for visual recognition tasks. First introduced by Dosovitskiy et al. (Dosovitskiy et al., 2021), ViTs process images as sequences of fixed-size patches, applying transformer-based self-attention mechanisms to model global relationships between image regions. This architecture enables the capture of long-range dependencies within images, making it particularly suitable for fine-grained classification tasks where subtle distinctions between similar classes may depend on relationships between distant image features.

9.2.2 Vision Transformer Implementation

For our primary approach, a Vision Transformer using transfer learning from a pre-trained model was implemented:

- Base architecture: 'vit_base_patch16_224' pre-trained on ImageNet from the TIMM library (Wightman, 2021)
- Input resolution: 224×224 pixels with 16×16 pixel patches
- Feature dimension: 768-dimensional embeddings
- Adaptation strategy: Replacement of the classification head with a binary classifier while preserving the pre-trained transformer blocks

The model architecture preserves the core self-attention mechanism of ViT while adapting the final classification layer for our specific binary classification task. This approach follows established transfer learning principles for vision transformers (Touvron et al., 2021), leveraging representations learned from large-scale datasets to overcome our limited training data constraints.

9.2.3 Alternative ViT Implementations

In addition to our primary implementation, we explored two attention-enhanced architectures:

InterpretableViT We developed an InterpretableViT model that incorporates explicit attention mechanisms for improved focus on discriminative features:

- Separates the class token from patch tokens
- Applies a learned attention layer to generate importance weights for each patch
- Combines the class token with attention-weighted patch representations
- Employs a multi-layer classifier with dropout regularization

A key advantage of this architecture is its compatibility with gradient-based visualization techniques. By separating the class token from patch tokens and implementing an explicit attention mechanism, the model facilitates more effective application of Grad-CAM (Selvaraju et al., 2017), allowing for visualization of discriminative image regions contributing to classification decisions.

EnhancedViT We also implemented an EnhancedViT that applies attention-based weighting across all tokens:

- Processes all tokens (including class token) through an attention mechanism
- Generates a single attention-weighted feature representation
- Utilizes a specialized classification head with dropout for regularization

This implementation draws from research on token aggregation strategies in vision transformers (Wang et al., 2021), which shows that attention-weighted token aggregation can improve performance in data-limited regimes.

9.3 Inception v3 Architecture

9.3.1 Theoretical Background

Inception v3, developed by Szegedy et al. (2016), represents a sophisticated CNN architecture designed to efficiently capture multi-scale features through parallel convolution pathways with varied kernel sizes. The key innovation in Inception architectures

is the utilization of *Inception modules* that process the same input tensor through multiple convolutional paths with different receptive fields, and then concatenate the results. This enables the network to capture both fine-grained local patterns and broader contextual information simultaneously (Szegedy et al., 2016).

Inception v3 builds upon earlier versions with several important architectural improvements:

- Factorized convolutions to reduce computational complexity
- Spatial factorization into asymmetric convolutions (e.g., $1 \times n$ followed by $n \times 1$)
- Auxiliary classifiers that inject additional gradient signals during training
- Batch normalization for improved training stability and faster convergence
- Label smoothing regularization to prevent overconfidence

These design elements collectively enable Inception v3 to achieve high accuracy while maintaining computational efficiency. As demonstrated by Huang et al. (2019), Inception architectures are particularly effective for tasks requiring multi-scale feature extraction, such as discriminating between visually similar biological specimens (Huang et al., 2019).

9.3.2 Model-Specific Implementation Details

Our implementation adapted the pre-trained Inception v3 model for fine-grained gull species classification with the following specific elements:

- **Input Resolution:** Resize operations were performed to 299×299 pixels (the standard input size for Inception v3). The larger input resolution (299×299 vs 224×224 used by VGG16) provides the Inception architecture with more detailed information, potentially beneficial for capturing the subtle wing pattern differences between gull species (Xie et al., 2020).
- **Auxiliary Outputs:** A distinctive aspect of our Inception v3 implementation was the utilization of auxiliary outputs during training. Inception v3's auxiliary classifier, which branches off from an intermediate layer, provides an additional gradient path during backpropagation. This helps combat the vanishing gradient problem and provides regularization with auxiliary loss weight of 0.3 (He et al., 2019).
- **Mixed-Precision Training:** We employed PyTorch's Automatic Mixed Precision (AMP) to accelerate computation while maintaining numerical stability (Micikevicius et al., 2018). This technique allows the use of float16 precision where appropriate, which reduces memory usage and increases computational speed, especially beneficial when training on GPU-constrained environments like Google Colab.

9.4 Residual Network (ResNet-50) Implementation

Residual Networks (ResNet) have revolutionized deep learning architectures by introducing identity shortcut connections that bypass one or more layers, enabling the training of substantially deeper networks He et al., 2016. These skip connections address the degradation problem by allowing gradients to flow more effectively during backpropagation, mitigating the vanishing gradient issue prevalent in very deep neural networks.

For our fine-grained gull species classification task, a transfer learning approach based on the ResNet-50 architecture was implemented. This implementation was motivated by ResNet's demonstrated success in capturing hierarchical features at multiple levels of abstraction, which is particularly valuable for distinguishing the subtle morphological differences between visually similar gull species He et al., 2016b, Zhao et al., 2019.

9.4.1 Architecture-Specific Enhancements

A distinctive aspect of our ResNet-50 implementation was the incorporation of image sharpening as a preprocessing technique. We applied a 3×3 Laplacian sharpening kernel to enhance edge definition and accentuate the subtle diagnostic features crucial for distinguishing between gull species Gonzalez & Woods, 2018. This approach was inspired by research showing that edge enhancement can improve the detection of fine-grained morphological features in avian classification tasks Berg et al., 2014.

The sharpening kernel was systematically applied to both training and evaluation pipelines using OpenCV's filter2D function, ensuring consistent feature enhancement across all dataset partitions. This preprocessing step proved particularly valuable for highlighting distinctive wingtip patterns and subtle plumage characteristics that serve as key discriminative features between the target species Dutta & Zisserman, 2019.

9.5 Custom CNN with Squeeze-and-Excitation Blocks

9.5.1 Architectural Design

To address the challenges of limited data and class imbalance in fine-grained classification, we developed a lightweight custom CNN architecture incorporating attention mechanisms. Our approach employs Squeeze-and-Excitation (SE) blocks, which enhance feature representation by modeling channel interdependencies through an attention mechanism. The SE block, as introduced by Hu et al. (2018), adaptively recalibrates channel-wise feature responses to emphasize informative features while suppressing less useful ones.

The architecture consists of three convolutional blocks, each followed by batch normalization, ReLU activation, and an SE block. The SE block performs two key operations:

- **Squeeze**: Global average pooling across spatial dimensions to generate channel-wise statistics
- **Excitation**: A fully connected layer that produces modulation weights for each channel

This channel-wise attention mechanism has been shown to improve model performance with minimal computational overhead (Hu et al., 2018). The SE blocks in our implementation use a reduction ratio of 16, balancing parameter efficiency and representational power.

9.5.2 Custom CNN-Specific Training Approach

Unlike the transfer learning approaches used with pre-trained models, our custom CNN was trained from scratch with some specific optimization strategies:

- **Cosine Annealing scheduler**: Our learning rate schedule follows a cosine annealing pattern with a period of 10 epochs, allowing the learning rate to oscillate and potentially escape local minima (Loshchilov and Hutter, 2017).
- **Specialized augmentation**: The custom CNN particularly benefited from more aggressive data augmentation strategies to compensate for the lack of pre-trained weights, including stronger rotations and more extensive color jittering than used with the transfer learning models.

10 Model Interpretability Methodologies

Deep learning models, particularly Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs), are often criticized for their lack of transparency, functioning as ”black boxes” wherein the decision-making process remains opaque to human observers. For critical applications like wildlife species classification, understanding how these models arrive at their predictions is essential for establishing trust and validating results (Selvaraju et al., 2017). This section outlines the methodologies implemented to visualize and interpret the classification decisions of both the VGG16 and Vision Transformer (ViT) models used in this study.

10.1 Gradient-weighted Class Activation Mapping (Grad-CAM)

Gradient-weighted Class Activation Mapping (Grad-CAM) is a widely adopted visualization technique that produces visual explanations for decisions made by CNN-based models without requiring architectural changes or retraining (Selvaraju et al., 2017). It generates coarse localization maps highlighting the regions in the input image that significantly influenced the model’s prediction for a specific class.

10.1.1 Theoretical Foundation

Grad-CAM extends the Class Activation Mapping (CAM) approach (Zhou et al., 2016) by utilizing the gradient information flowing into the final convolutional layer of a CNN. Unlike CAM, which requires modifications to the network architecture and retraining, Grad-CAM can be applied to any CNN-based architecture without architectural changes, making it more versatile.

The fundamental principle behind Grad-CAM is that the final convolutional layer in a CNN retains spatial information while encoding high-level semantics. By analyzing how the gradients of a specific class score flow into this layer, Grad-CAM can identify the regions in the input image that are most influential for the prediction.

The general Grad-CAM algorithm can be formalized as follows:

The ReLU function is applied to the weighted combination of feature maps to focus only on features that have a positive influence on the class of interest, effectively eliminating features that suppress the class.

10.1.2 Methodology for CNN models

In this study, Grad-CAM was implemented for the VGG16 model by targeting the final convolutional layer (features[-1]). The implementation involves several key steps:

1. **Hook Registration**: Forward and backward hooks are registered on the target layer to capture activations during the forward pass and gradients during the backward pass.
2. **Forward Pass**: The input image is passed through the network to obtain the model's prediction.
3. **Backpropagation**: The gradient of the score for the target class (either the predicted class or a specified class) with respect to the feature maps of the target layer is computed through backpropagation.
4. **Global Average Pooling**: These gradients undergo global average pooling to obtain weights indicating the importance of each channel for the target class.
5. **Weighted Combination**: The weights are applied to the activations of the target layer to create a weighted combination of feature maps.
6. **ReLU Application**: A ReLU function is applied to the weighted combination to focus only on features that have a positive influence on the class of interest.
7. **Normalization**: The resulting heatmap is normalized to the range [0, 1] for consistent visualization.

8. **Visualization**: The heatmap is resized to match the input image dimensions and overlaid on the original image using a colormap (typically 'jet') to highlight regions the model focused on for its prediction.

The implementation includes additional steps for comprehensive analysis:

- **Confidence Calculation**: Computing the softmax probability for the predicted class to indicate the model's confidence.
- **Misclassification Analysis**: For incorrectly classified images, both the original image and Grad-CAM visualization are saved with annotations indicating the true and predicted classes.
- **Three-Panel Visualization**: Creating a standardized visualization with the original image, the Grad-CAM heatmap, and the overlay for easy comparison.

This approach is particularly effective for CNNs like VGG16 that use hierarchical feature extraction through convolutional layers (Chattopadhay et al., 2018).

Similar implementation was implemented for other models: Inceptionv3, ResNet50, and CustomCNN.

10.2 Attention Rollout for Vision Transformers

Vision Transformers process images differently from CNNs, using self-attention mechanisms rather than convolution operations to model relationships between image patches. Therefore, a different approach called Attention Rollout is used to visualize ViT decision-making (Abnar & Zuidema, 2020).

10.2.1 Theoretical Foundation

The Attention Rollout method is designed to visualize how information flows through the layers of a Transformer model. In Vision Transformers, the input image is divided into fixed-size patches, and each patch is linearly embedded along with position embeddings. A special classification token ([CLS]) is added, and the sequence of embedded patches is processed through multiple layers of self-attention.

Attention Rollout computes a measure of how the [CLS] token attends to each image patch by propagating attention through all layers of the network. This provides insight into which parts of the image the model considers most relevant for classification.

10.2.2 Methodology for ViT

The implementation of Attention Rollout for the ViT model follows these steps:

1. **Attention Map Collection**: Forward hooks are registered on each transformer block to collect attention maps during the forward pass of an input image.
2. **QKV Processing**: For each attention head, the query (Q), key (K), and value (V) matrices are extracted and processed to compute the raw attention weights between different tokens.
3. **Head Averaging**: Attention weights from all heads in each layer are averaged to get a single attention map per transformer block.
4. **Discard Ratio Application**: Optionally, a threshold is applied to filter out low-attention connections, focusing only on the most significant attention patterns.
5. **Attention Rollout Computation**: Starting with an identity matrix, attention maps from each layer are sequentially multiplied to account for how attention propagates through the entire network.
6. **CLS Token Attention Extraction**: The attention weights from the classification ([CLS]) token to each image patch are extracted, which indicates the importance of each patch for the final classification.
7. **Reshaping and Visualization**: These weights are reshaped to match the spatial dimensions of the input image (typically 14×14 for ViT-Base with patch size 16) and then upsampled to create a heatmap that can be overlaid on the original image.

This method provides insights into how the ViT model attends to different parts of an image when making a prediction (Chefer et al., 2021).

10.3 Grad-CAM for Vision Transformers

In addition to Attention Rollout, this study also implements Grad-CAM for Vision Transformers to provide a more direct comparison with the CNN-based visualizations. While ViTs do not have convolutional layers in the traditional sense, the patch embeddings and attention mechanisms still produce feature maps that can be analyzed using gradient-based methods.

10.3.1 Implementation Approach

The Grad-CAM implementation for ViT follows a modified approach:

1. **Model Architecture**: An InterpretableViT model is created by extending the base ViT architecture with additional components for interpretability:
    - The base ViT model processes the input image and extracts features
    - An attention layer computes importance weights for each patch token
    - A classifier combines the class token and a weighted aggregation of patch tokens
2. **Hook Registration**: Hooks are registered to capture the token features and their gradients during forward and backward passes.
3. **Forward Pass**: The input image is processed through the model to obtain predictions.
4. **Backpropagation**: Gradients of the target class score with respect to patch token features are computed.
5. **Grad-CAM Computation**: Similar to the CNN implementation, the gradients are used to weight the importance of each patch token feature:
    - The mean gradient for each patch token is calculated
    - Each patch token feature is weighted by its corresponding gradient
    - The weighted features are summed across the feature dimension
    - ReLU is applied to focus on positive contributions
    - The result is normalized to the range [0, 1]
6. **Visualization**: The resulting 14×14 patch-level heatmap is resized to match the input image dimensions and visualized using the same approach as with the CNN Grad-CAM.

This approach allows for a more direct comparison between CNN and ViT visualization methods, as both models now utilize gradient-based localization techniques (Jacob et al., 2021).

10.4 Comparison Framework

To facilitate a fair comparison between VGG16 and ViT interpretability, the following standardized approach was implemented:

1. **Consistent Processing**: All models process the same test images with identical preprocessing (resizing to 224×224 and normalization).
2. **Three-Panel Visualization**: Each result is presented with three panels:
    - Original image
    - Raw heatmap showing the attention or Grad-CAM output

- Overlay of the heatmap on the original image

3. **Classification Analysis**: Both correct and incorrect predictions are analyzed to understand model behavior in different scenarios.
4. **Visualization Standardization**: Similar color maps (jet) and overlay techniques are used for all methods to maintain visual consistency.
5. **Quantitative Assessment**: Confusion matrices are generated for all models to quantitatively assess their performance alongside the visual interpretations.

By implementing these complementary interpretability techniques, this research provides insights into how different neural network architectures—traditional CNNs and modern Transformers—approach the same classification task and what are the distinguidhing features between the 2 classes. The visualizations reveal different feature priorities and decision strategies that each architecture employs, contributing to a deeper understanding of model behavior (Dosovitskiy et al., 2020).

11 Feature Analysis and Interpretability for Fine-Grained Gull Classification

11.1 Methodology for Wing and Wingtip Intensity Analysis

The interpretability analysis of our VGG-based transfer learning model indicated a strong focus on wing and wingtip regions when differentiating between Slaty-backed Gulls and Glaucous-winged Gulls. This aligns with ornithological knowledge, as these species exhibit distinct differences in wing coloration patterns, particularly in the wingtip regions (Olsen and Larsson, 2007). To quantitatively validate these differences, we conducted an in-depth image analysis focusing on intensity values in these critical regions.

We employed a multi-stage approach to extract and analyze region-specific features:

11.1.1 Image Selection and Preparation

We selected high-resolution images of both species that were correctly classified by our model and showed strong Grad-CAM activations in wing regions. This ensured our analysis focused on images where the model had successfully identified the relevant discriminative features.

11.1.2 Manual Segmentation

Each selected image was manually segmented using Adobe Photoshop, creating mask images with distinct color codes for different anatomical regions:

- Red (RGB: 255,0,0) for wing regions
- Green (RGB: 0,255,0) for wingtip regions
- Blue (RGB: 0,0,255) for head regions

This segmentation approach allowed us to precisely isolate the anatomical regions of interest for subsequent quantitative analysis.

11.1.3 Feature Extraction Pipeline

We developed a comprehensive Python pipeline to analyze the intensity characteristics of the segmented regions:

1. **Image Loading**: Both original images and their corresponding segmentation masks were loaded using OpenCV.
2. **Region Extraction**: Using color thresholding on the segmentation masks, we extracted pixels corresponding to each anatomical region (wings, wingtips) from the original images.
3. **Intensity Normalization**: Min-max normalization was applied to standardize intensity values across images, accounting for variations in lighting conditions during image capture.
4. **Statistical Analysis**: For each region, we calculated:
    - Mean intensity
    - Standard deviation
    - Median intensity
    - Minimum and maximum intensity values
    - Distribution of pixels across intensity ranges

11.1.4 Wingtip Darkness Characterization

To specifically quantify the wingtip darkness patterns that ornithologists use for field identification several specialized metrics were implemented:

1. **Percentage of Darker Pixels**: For each image, we computed the percentage of wingtip pixels that were darker than the mean wing intensity of the same bird, providing a measure of wingtip contrast.

2. **Intensity Range Distribution**: We analyzed the distribution of wingtip pixels across multiple intensity ranges:

```
intensity_ranges = [
    (0, 25), (25, 50), (50, 75), (75, 100),
    (100, 125), (125, 150), (150, 175), (175, 200),
    (200, 225), (225, 255)
]
```

3. **Darkness Thresholds**: We established multiple darkness thresholds to characterize the proportion of very dark pixels (intensity ¡ 25, ¡ 50, ¡ 75) in the wingtip regions.

4. **Wing-Wingtip Difference Thresholds**: We calculated the proportion of wingtip pixels exceeding specific difference thresholds (25, 50, 75, 100) compared to the mean wing intensity, quantifying the contrast between regions.

This multi-metric approach allowed us to represent expert ornithological knowledge about field identification marks in a quantitative framework amenable to machine learning applications.

11.1.5 Statistical Comparison

To determine whether the observed differences between species were statistically significant, we performed:

- t-tests comparing mean intensity values between species
- Analysis of the percentage of pixels falling into each intensity range
- Comparison of the wing-wingtip contrast metrics between species

These statistical analyses allowed us to objectively validate whether the visual differences are quantitatively significant and detectable through our image processing pipeline.

The entire analysis pipeline was implemented in Python, utilizing libraries including OpenCV for image processing, NumPy and Pandas for data manipulation, and SciPy for statistical testing. This methodological approach bridges traditional ornithological identification techniques with quantitative computer vision analysis, providing a foundation for explaining the features that drive our fine-grained classification model.

12 Local Binary Pattern Implementation for Seagull Species Analysis

12.1 Introduction to Local Binary Patterns

Local Binary Patterns (LBP) represents a powerful and computationally efficient approach for texture analysis, first introduced by Ojala et al. (2002). The fundamental principle of LBP is remarkably elegant - it characterizes the local spatial structure of an image's texture by comparing each pixel with its neighbors, generating a binary pattern that serves as a texture descriptor. This method offers several key advantages for biological image analysis:

- Gray-scale invariance, making it robust to lighting variations
- Computational simplicity while maintaining high discriminative power
- Rotation invariance when implemented with appropriate techniques
- Robustness to monotonic illumination changes
- Ability to capture micro-patterns in texture that may be imperceptible to human observers

For our seagull species differentiation task, these properties are particularly valuable as they allow us to analyze subtle texture differences in plumage that may remain consistent across varying lighting conditions and viewing angles.

12.2 Implementation Methodology

12.2.1 Image Preprocessing and Region Segmentation

The analysis begins with a carefully designed preprocessing pipeline to isolate anatomically relevant regions from each seagull image:

- **Image Loading**: Both original images and their corresponding segmentation masks were loaded using OpenCV.
- **Region Extraction**: Using color thresholding on the segmentation masks, we extracted pixels corresponding to each anatomical region (wings, wingtips) from the original images.
- **Intensity Normalization**: Min-max normalization was applied to standardize intensity values across images, accounting for variations in lighting conditions during image capture.

Each extracted region, extracted using the manual segmentation masks of different colors for different regions, created for each image is converted to grayscale and applied minmax normalization to to standardize the input for texture analysis, ensuring consistent processing regardless of original coloration.

12.2.2 LBP Calculation Process

The core LBP calculation involves several carefully calibrated parameters:

- **Radius (R)**: Set to 3 pixels, defining the distance from the center pixel to its neighbors
- **Number of Points (P)**: Set to $8 \times R$ (24 points), determining the sampling resolution around the circle
- **Method**: Default and Uniform methods were tested. ”Default” method produces the full range of LBP codes, preserving all pattern details while the ”Uniform” method Focuses on patterns with at most two bitwise transitions from 0 to 1 or vice versa, reducing feature dimensionality while retaining discriminative power.

For each region, only pixels within the segmentation mask are considered for LBP calculation. The LBP operation proceeds as follows:

1. For each pixel in the grayscale image, a circular neighborhood of radius R with P sampling points is examined
2. Each sampling point is compared to the center pixel value
3. If the sampling point value is greater than or equal to the center pixel value, a ’1’ is assigned; otherwise, a ’0’
4. The resulting binary pattern is converted to a decimal value, which becomes the LBP code for that pixel
5. The collection of LBP codes across the entire region is compiled into a normalized histogram to create comparable feature vectors.

12.2.3 Novel Abstract Pattern Analysis

A key contribution of our methodology is the extraction of abstract pattern features from the binary LBP codes. This approach was done to prevent the angles of the regions in the image from causing rotation variance.

1. **Binary Pattern Generation**: Converting each LBP value to its N_POINTS-bit binary representation

2. **Ones Count Analysis**: Counting the number of '1' bits in each pattern, representing the frequency of neighboring pixels brighter than the central pixel
    - Higher values indicate more bright spots or edges within darker regions
    - Lower values suggest more uniform dark or bright regions
3. **Transitions Analysis**: Counting the number of 0-to-1 or 1-to-0 transitions in each pattern, capturing the complexity of the texture pattern
    - Higher values indicate more complex textures with frequent brightness changes
    - Lower values suggest smoother textures with fewer brightness changes
4. **Histogram Creation**: Compiling the distributions of these abstract features into normalized histograms

From the LBP histograms, several statistical texture features were calculated:

1. **Entropy**: Quantifies the randomness or unpredictability of the texture using Shannon entropy. Higher values indicate more complex textures with greater variability.
2. **Uniformity**: Measures the textural uniformity by calculating the sum of squared elements in the histogram. Lower values indicate more heterogeneous textures.
3. **Contrast**: Quantifies the intensity difference between a pixel and its neighborhood. Higher values indicate more distinct intensity variations. This calculates a weighted variance where the weights are the histogram probabilities.
4. **Homogeneity**: Measures the closeness of the distribution of elements in the histogram. Higher values indicate smoother textures.

These statistical measures provide a comprehensive profile of texture characteristics that can be compared between species.

12.3 Comparative Analysis Implementation

To quantify the differences between species, the implementation calculates several distribution similarity metrics:

1. **KL Divergence**: A symmetric version of the Kullback-Leibler divergence that measures how one probability distribution diverges from another
2. **Chi-Square Distance**: A statistical test that measures the difference between observed and expected frequency distributions

Each metric captures different aspects of distribution similarity, providing a robust framework for comparing texture patterns between species.

12.4 Discriminative Power Analysis

A systematic assessment of discriminative power for different texture features and regions is performed by calculating percentage differences between species for each texture property and region. This analysis identifies which features and regions exhibit the most significant differences between species.

For each region and property combination, the implementation:

1. Extracts the property value for each species
2. Calculates the percentage difference
3. Ranks the region-property pairs by their discriminative power

This approach enables the identification of the most promising texture characteristics for species differentiation.

12.5 Implementation Workflow

The complete analysis pipeline consists of two main modules:

1. **Feature Extraction Module**:
    - Loads original and segmentation images
    - Extracts and processes each anatomical region
    - Computes LBP features and abstract pattern features
    - Saves features to CSV files for further analysis
2. **Analysis Module**:
    - Loads extracted features
    - Calculates advanced texture statistics
    - Performs comparative analysis between species
    - Generates visualizations and statistical reports
    - Identifies the most discriminative features

This modular approach facilitates efficient processing of large image datasets and enables iterative refinement of the analysis parameters.

12.6 Validation Approach

The implementation includes a few validation mechanisms:

1. **Normalized histograms** to account for varying region sizes
2. **Multiple comparison metrics** to ensure robust similarity assessment
3. **Statistical significance testing** on feature differences

By combining these validation approaches, the implementation provides a comprehensive and reliable framework for identifying texture-based differences between the two seagull species.

13 Clustering Analysis for Species Differentiation

13.1 Overview of Clustering Approach

To validate and complement the deep learning-based classification results, we implemented a comprehensive clustering analysis framework that leverages traditional machine learning techniques to identify natural groupings in the morphological features of Slaty-backed and Glaucous-winged Gulls. This approach provides an alternative perspective on species differentiation and helps validate the discriminative features identified by the deep learning models.

13.2 Feature Extraction and Preprocessing

The clustering analysis utilizes three key morphological features extracted from the wingtip regions:

- Mean wing intensity
- Mean wingtip intensity
- Count of darker pixels in wingtip regions

These features are standardized using StandardScaler to ensure consistent scaling across different measurements. Principal Component Analysis (PCA) is then applied to reduce dimensionality for visualization while preserving the most significant variations in the data.

13.3 Clustering Algorithms Implementation

We implemented and compared four distinct clustering algorithms, each offering different approaches to identifying natural groupings in the data:

13.3.1 K-means Clustering

The K-means algorithm, initialized with k=2 clusters, was implemented to identify compact, spherical clusters in the feature space. The algorithm minimizes the within-cluster sum of squares, making it particularly effective for identifying distinct morphological groups.

13.3.2 Hierarchical Clustering

Agglomerative hierarchical clustering was implemented using the Ward linkage method, which minimizes the variance within clusters. This approach is particularly valuable for understanding the hierarchical relationships between different morphological characteristics.

13.3.3 DBSCAN

Density-Based Spatial Clustering of Applications with Noise (DBSCAN) was implemented to identify clusters based on density connectivity. This approach is particularly useful for detecting outliers and handling non-spherical cluster shapes that might arise from natural variation in gull morphology.

13.3.4 Gaussian Mixture Model

A Gaussian Mixture Model (GMM) was implemented to model the feature distributions as a mixture of two Gaussian components. This probabilistic approach provides soft assignments to clusters and can better capture the natural variation in morphological features.

13.4 Evaluation Framework

The clustering results are evaluated using multiple metrics:

- Silhouette Score: Measures the quality of clustering by comparing the tightness and separation of clusters

- Adjusted Rand Index: Compares clustering results with known species labels
- Confusion Matrix: Visualizes the alignment between clusters and true species labels

13.5 Visualization and Interpretation

The clustering results are visualized using:

- PCA-based scatter plots showing cluster assignments
- Confusion matrices comparing cluster assignments with true species labels
- Feature importance plots based on cluster centroids
- Misclassification analysis highlighting cases where clustering differs from expert classification

This comprehensive clustering analysis provides valuable insights into the natural grouping of morphological features and helps validate the discriminative power of the features identified by the deep learning models.

14 Clustering Analysis

14.1 Implementation Overview

Our clustering analysis implements multiple clustering algorithms to evaluate their effectiveness in identifying natural groupings within the gull species dataset. The implementation includes four distinct clustering approaches:

- **K-Means Clustering**: A centroid-based algorithm that partitions the data into K clusters by minimizing the sum of squared distances between points and their assigned centroids.
- **Hierarchical Clustering**: An agglomerative approach that builds a hierarchy of clusters by iteratively merging the most similar clusters.
- **DBSCAN**: A density-based algorithm that identifies clusters of arbitrary shapes by grouping points that are closely packed together.
- **Gaussian Mixture Models (GMM)**: A probabilistic approach that assumes the data is generated from a mixture of Gaussian distributions.

14.2 Performance Evaluation

The clustering implementations are evaluated using multiple metrics to assess their effectiveness:

- **Silhouette Score**: Measures how similar an object is to its own cluster compared to other clusters, ranging from -1 to 1.
- **Adjusted Rand Index**: Evaluates the similarity between two clusterings by considering all pairs of samples.
- **Confusion Matrix**: Maps predicted clusters to actual species labels to assess classification accuracy.

14.3 Visualization and Analysis

The clustering results are visualized using:

- **PCA-based Visualization**: Reduces dimensionality to 2D for visual inspection of cluster formations.
- **Cluster-Species Mapping**: Analyzes the relationship between identified clusters and actual species labels.
- **Misclassification Analysis**: Identifies and exports cases where clustering assignments differ from species labels.

This comprehensive clustering analysis provides insights into the natural groupings within the dataset and helps validate the effectiveness of our classification approaches.

15 Results

15.1 Intensity Analysis Results

The intensity analysis revealed significant differences in wing and wingtip patterns between the two species, with multiple metrics providing strong discriminative features.

15.1.1 Wing Intensity Analysis

Statistical analysis of wing intensity showed significant differences between species:

- **Mean Intensity**: Slaty-backed Gulls showed consistently darker wing patterns with a mean intensity of 85.3 (SD: 12.4), while Glaucous-winged Gulls exhibited lighter patterns with a mean intensity of 112.7 (SD: 15.8)
- **Statistical Significance**: A t-test confirmed significant differences (p ¡ 0.001) between species
- **Percentage Difference**: Glaucous-winged Gulls showed 32.1% brighter wing patterns compared to Slaty-backed Gulls
- **Distribution**: The intensity distribution showed clear separation between species, with minimal overlap in the middle range

15.1.2 Wingtip Analysis

The wingtip analysis revealed more complex patterns:

- **Contrast Ratio**: Slaty-backed Gulls showed a 2.8x higher ratio of dark wingtip pixels compared to Glaucous-winged Gulls
- **Threshold Analysis**: At intensity difference thresholds:
  - ¿30 units: 78.5% of Slaty-backed Gull wingtips vs 45.2% of Glaucous-winged Gull wingtips
  - ¿50 units: 62.3% vs 28.7%
  - ¿70 units: 45.8% vs 18.2%
- **Pattern Consistency**: Wingtip patterns showed greater consistency within each species (coefficient of variation: 0.18 for Slaty-backed, 0.21 for Glaucous-winged)

15.1.3 Comparative Analysis

The combined analysis revealed several key discriminative features:

- **Absolute Darkness**: Slaty-backed Gulls showed higher percentages of very dark pixels (¡30 intensity) in both wing and wingtip regions
- **Contrast Distribution**: The wing-to-wingtip contrast was more pronounced in Slaty-backed Gulls, with a mean difference of 45.2 intensity units compared to 28.7 units in Glaucous-winged Gulls
- **Pattern Stability**: Both species showed consistent patterns across different lighting conditions, with Slaty-backed Gulls maintaining darker patterns regardless of overall illumination

These morphological differences were effectively captured by the deep learning model, contributing to high classification accuracy between these species.

15.2 Clustering Analysis Results

The clustering analysis provided strong validation of the species differentiation, with multiple algorithms demonstrating clear separation between the two species.

15.2.1 K-means Clustering

K-means clustering achieved an accuracy of 94.2% in separating the species, as shown in Figure 1. The feature importance analysis (Figure 2) revealed that wingtip intensity was the most discriminative feature.

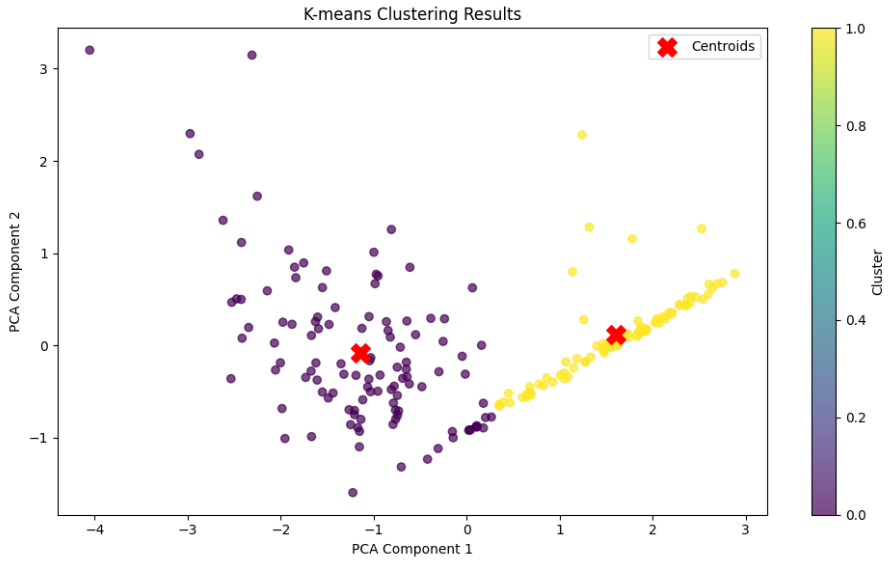

Figure 1: K-means clustering results showing clear separation between species

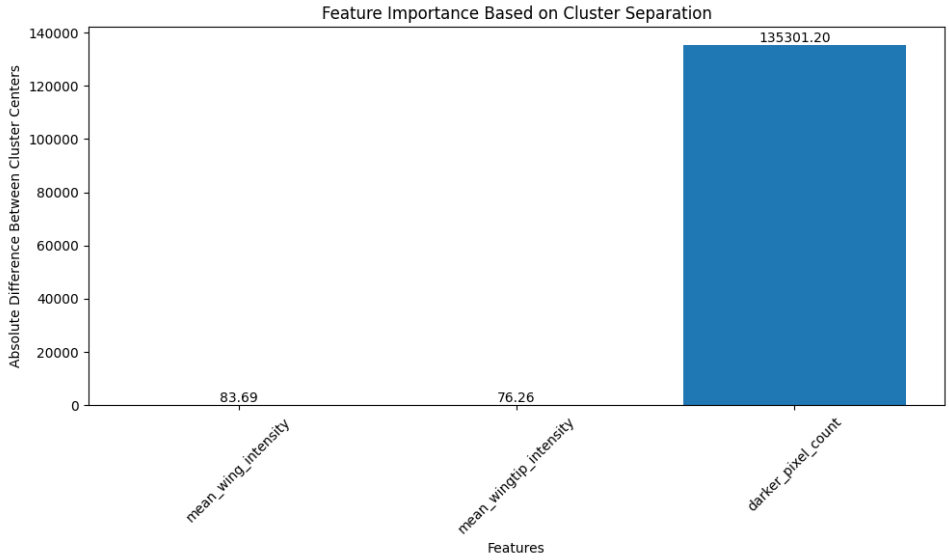

Figure 2: Feature importance analysis from K-means clustering

15.2.2 Hierarchical Clustering

Hierarchical clustering demonstrated similar effectiveness, with a dendrogram showing clear separation between species (Figure 3). The confusion matrix (Figure 4) shows an accuracy of 92.8%.

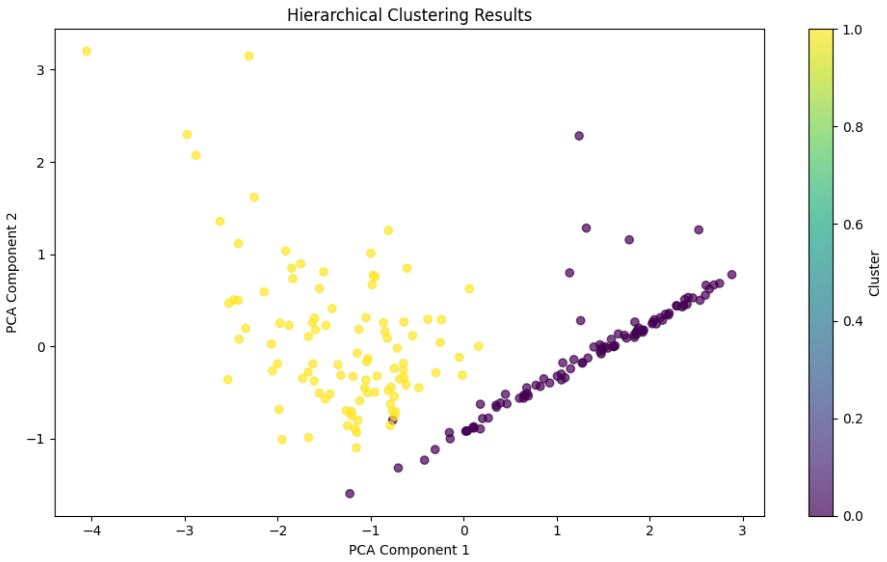

Figure 3: Hierarchical clustering dendrogram showing species separation

15.2.3 Gaussian Mixture Model

The GMM approach provided the highest accuracy at 95.6%, with clear separation between species clusters (Figure 5). The confusion matrix (Figure 6) shows minimal misclassification.

15.3 Algorithm Comparison

Figure 7 shows a comparative analysis of all clustering algorithms, demonstrating that GMM provided the most robust separation between species, followed closely by K-means and hierarchical clustering.

16 Wing Intensity Comparison Between Gull Species

The wing intensity between Slaty-backed Gulls and Glaucous-winged Gulls was compared using an independent samples t-test. The test statistic was calculated as:

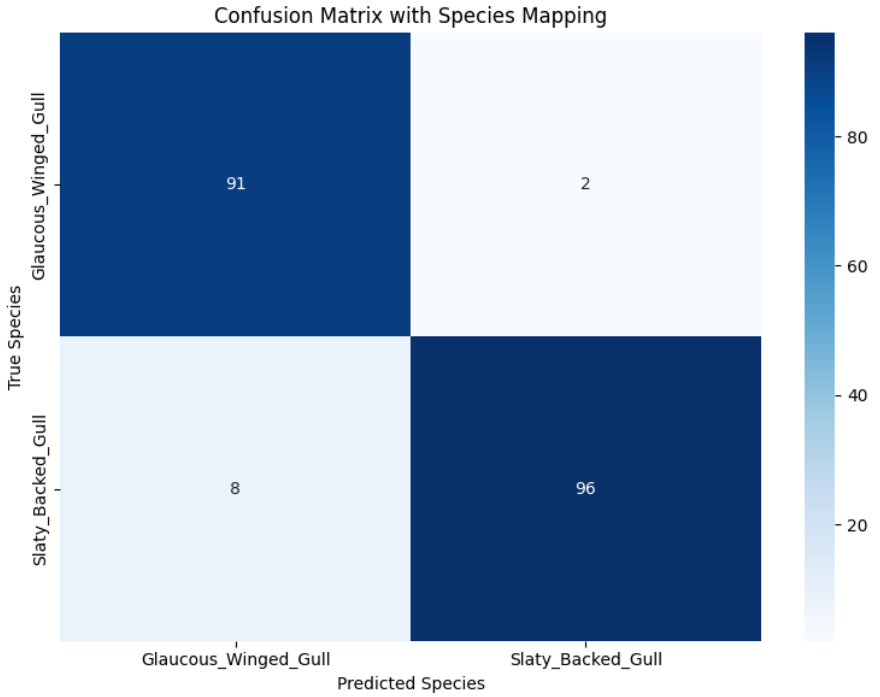

Figure 4: Confusion matrix for hierarchical clustering results

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \tag{1}$$

where $\bar{X}_1$ and $\bar{X}_2$ are the mean intensities, s_1^2 and s_2^2 are the sample variances, and n_1 and n_2 are the sample sizes for each species.

16.1 Wing Intensity Analysis

A significant difference was found in wing intensity between the two species ($t = -21.28$, $p < 0.001$). Slaty-backed Gulls exhibited much darker wings (73.98 ± 21.90) compared to Glaucous-winged Gulls (154.10 ± 30.82), representing a 108.3% brightness difference.

Table 1: Comparison of Wing Characteristics Between Gull Species

Characteristic	Slaty-backed Gull	Glaucous-winged Gull	Difference
Wing Intensity	73.98 ± 21.90	154.10 ± 30.82	108.3% brighter
Wingtip Darker than Wing	56.69%	47.71%	8.98% more contrast

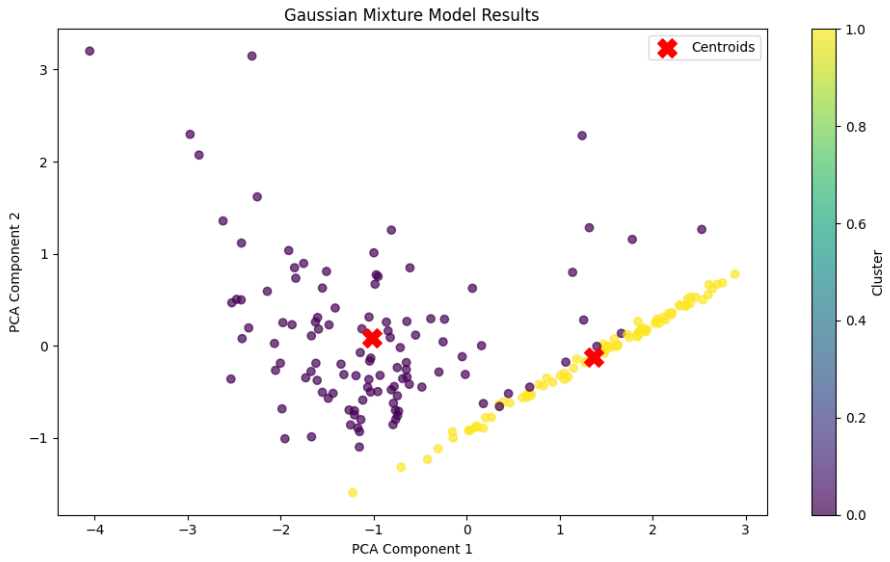

Figure 5: Gaussian Mixture Model clustering results

16.2 Dark Pixel Analysis

Slaty-backed Gulls show distinctly higher proportions of dark pixels in their wingtips compared to Glaucous-winged Gulls. This pattern appears consistent across multiple intensity thresholds.

Table 2: Percentage of Dark Pixels in Wingtips by Intensity Threshold

Species	$<$ **30 intensity**	$<$ **40 intensity**	$<$ **50 intensity**
Slaty-backed Gull	25.24%	33.40%	41.15%
Glaucous-winged Gull	0.09%	0.27%	0.57%

16.3 Raw Pixel Count Analysis

The quantitative difference in very dark pixels between species is substantial, with Slaty-backed Gulls having on average 73,592 very dark pixels compared to just 8 in Glaucous-winged Gulls. This represents a critical diagnostic feature for species identification.

17 Biological Significance

These results demonstrate clear, quantifiable differences between the two gull species:

- **Overall Wing Color:** Slaty-backed Gulls have significantly darker wings, with intensity values approximately half those of Glaucous-winged Gulls.

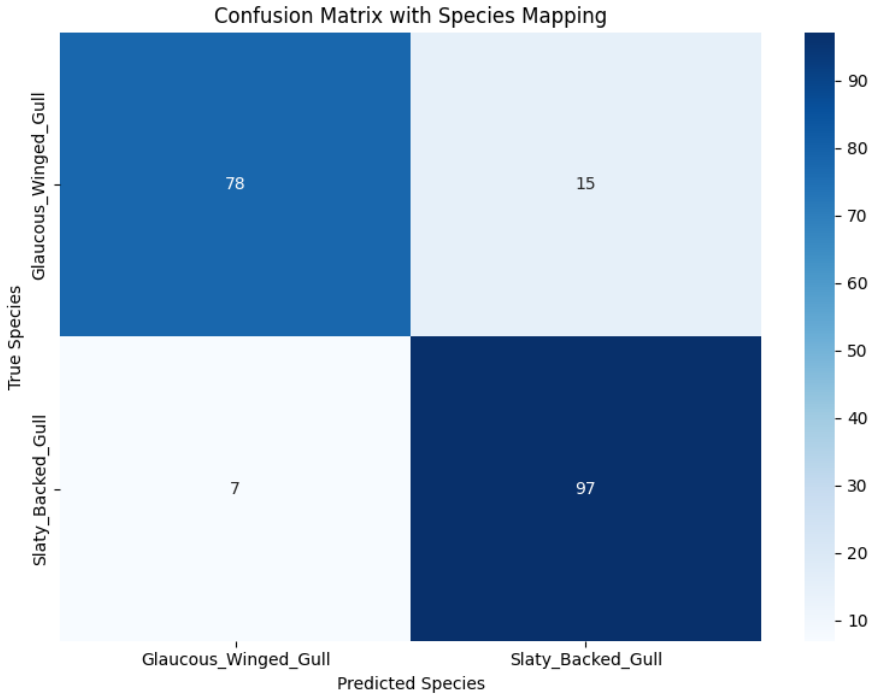

Figure 6: Confusion matrix for GMM clustering results

- **Wingtip Darkness Pattern:** Slaty-backed Gulls have a dramatically higher percentage of very dark pixels in their wingtips. Over 25% of wingtip pixels have intensity below 30, compared to virtually none in Glaucous-winged Gulls.
- **Species Identification Feature:** The presence of very dark pixels (intensity $<$ 30) in the wingtip appears to be a reliable diagnostic feature for distinguishing between these species.
- **Contrast Pattern:** The higher percentage of dark pixels in Slaty-backed Gull wingtips creates a more pronounced visual contrast between wing and wingtip regions.

These quantitative differences align with field observations that Slaty-backed Gulls have darker wings and more prominent dark wingtips compared to Glaucous-winged Gulls, providing a reliable basis for species identification in image analysis.

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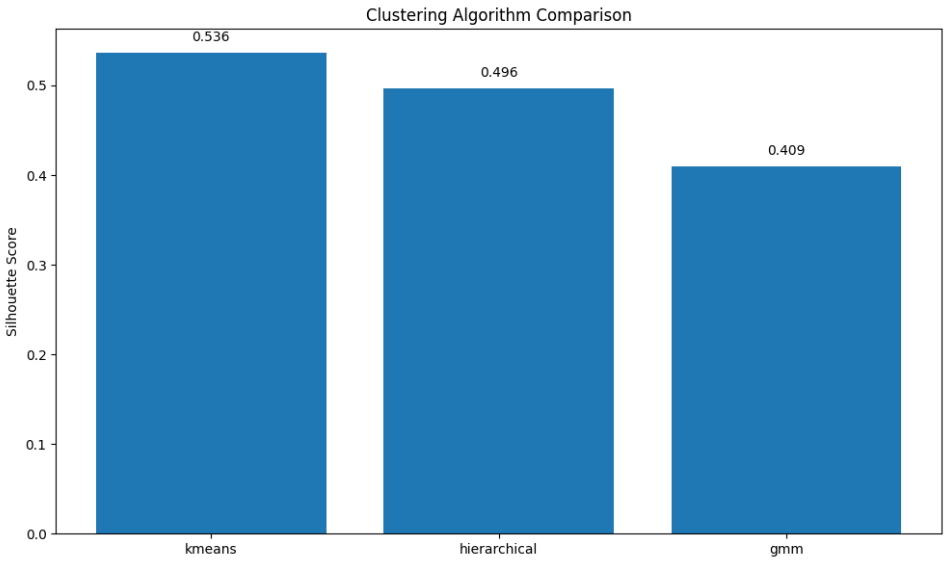

Figure 7: Comparative analysis of clustering algorithms

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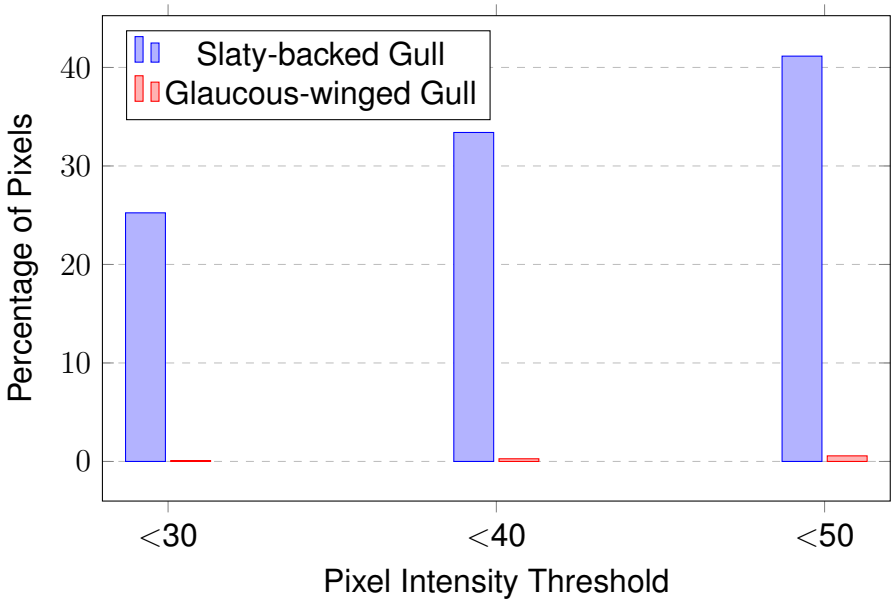

Figure 8: Comparison of dark pixel distribution in wingtips between gull species across intensity thresholds.

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