International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 05 | May - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

Ornithological Imaging: Transforming Bird Species Identification with Technology

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In recent years, the field of ornithology has been revolutionized by advancements in image-based bird species identification. This study explores the application of machine learning and computer vision techniques to accurately classify bird species from photographic data. Leveraging convolutional neural networks (CNNs), we developed a robust model capable of distinguishing between diverse bird species with high accuracy. Our dataset, comprising thousands of labeled bird images, facilitated the training and validation of the model. The results demonstrate significant improvements in identification precision compared to traditional methods. This research not only enhances bird monitoring and conservation efforts but also opens new avenues for citizen science and automated wildlife observation.

I. INTRODUCTION

Bird species identification has long been a crucial aspect of ornithology, providing essential insights into biodiversity, ecology, and conservation. Traditional methods of bird identification, which rely heavily on human expertise and manual field observations, are often time-consuming and susceptible to errors due to variability in individual observer skills and environmental conditions. The advent of digital imaging and advancements in artificial intelligence (AI) offer promising alternatives to these conventional approaches.

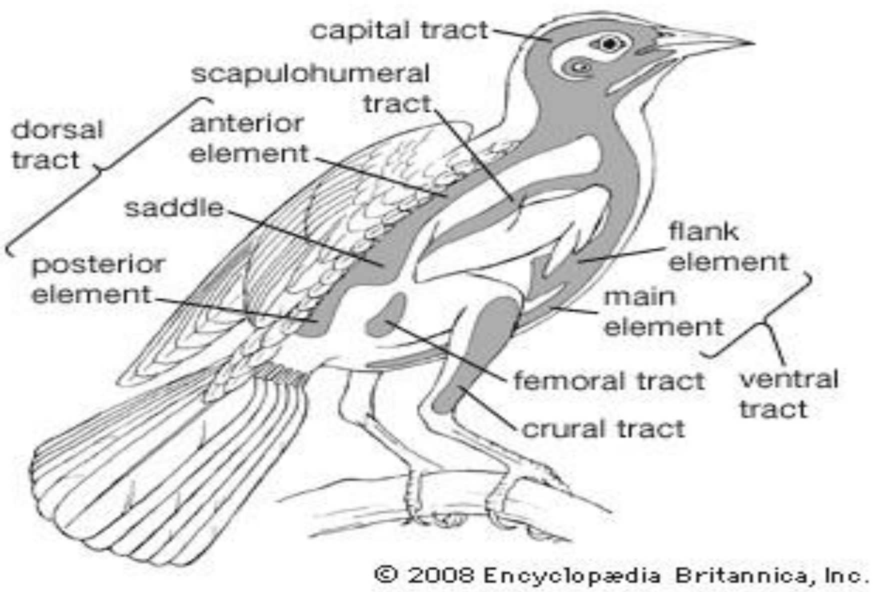

Figure 1:Traditional Bird Identification Methods [1]

In recent years, image-based identification systems have gained traction, leveraging the power of machine learning and computer vision to automate and enhance the accuracy of species recognition. Among the various machine learning techniques, convolutional neural networks (CNNs) have proven particularly effective in image classification tasks due to their ability to capture and learn from complex visual patterns.

This paper presents a comprehensive study on the application of CNNs for bird species identification. By training our model on an extensive dataset of bird images, we aim to develop a highly accurate and efficient system that can assist both researchers and amateur bird watchers in identifying bird species from photographs.

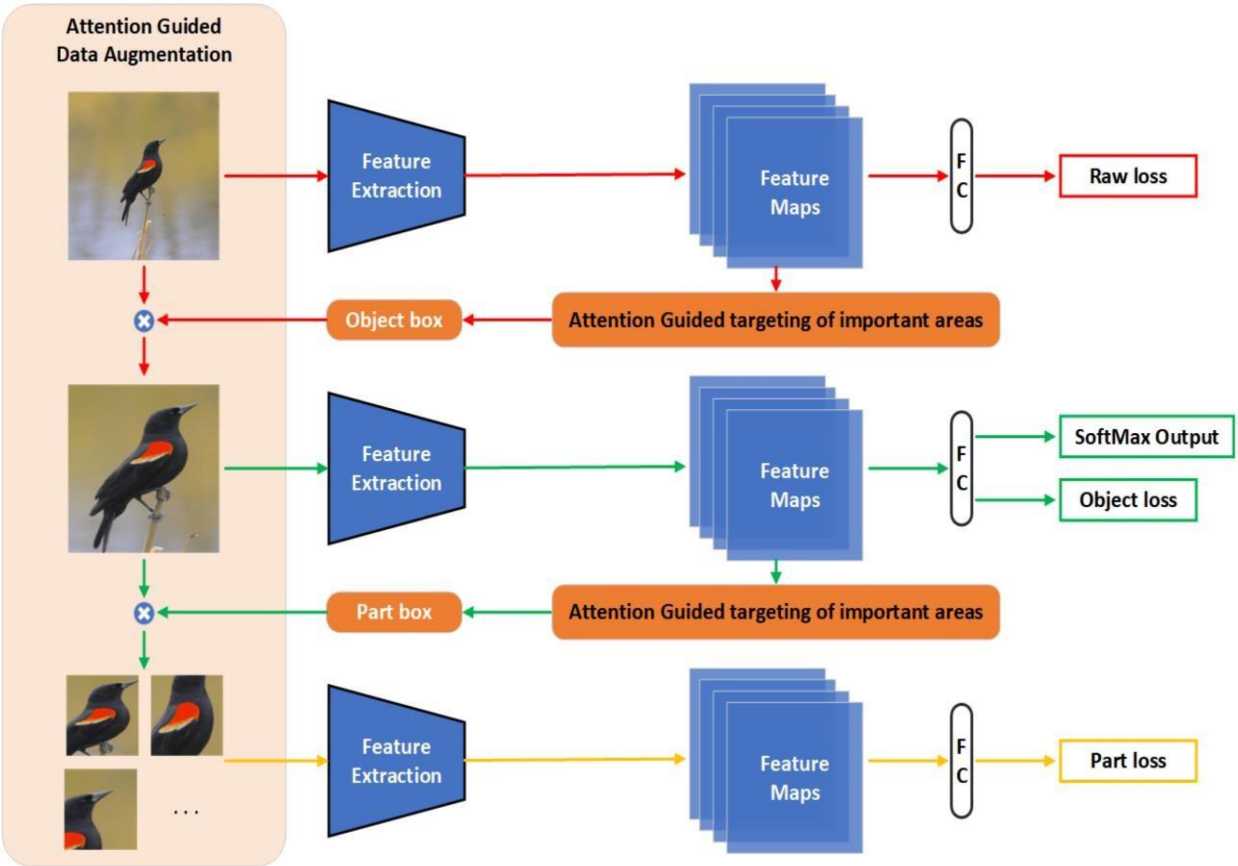

Figure 2: Overview of the Image-Based Bird Species Identification Process[2]

Illustrates the workflow of our proposed identification system. The process begins with image acquisition, where photographs of birds are collected from various sources, including online databases and citizen science contributions. These images are then preprocessed to standardize dimensions and enhance features. The preprocessed images are fed into a CNN model trained to recognize distinctive features of different bird species. The model outputs the predicted species, providing users with identification results along with confidence scores.

Our study demonstrates the potential of combining advanced AI techniques with ornithological research, highlighting significant improvements in identification accuracy and speed. Furthermore, the deployment of such automated systems can contribute to large-scale biodiversity monitoring and conservation efforts, providing valuable data that would be challenging to gather through traditional means.

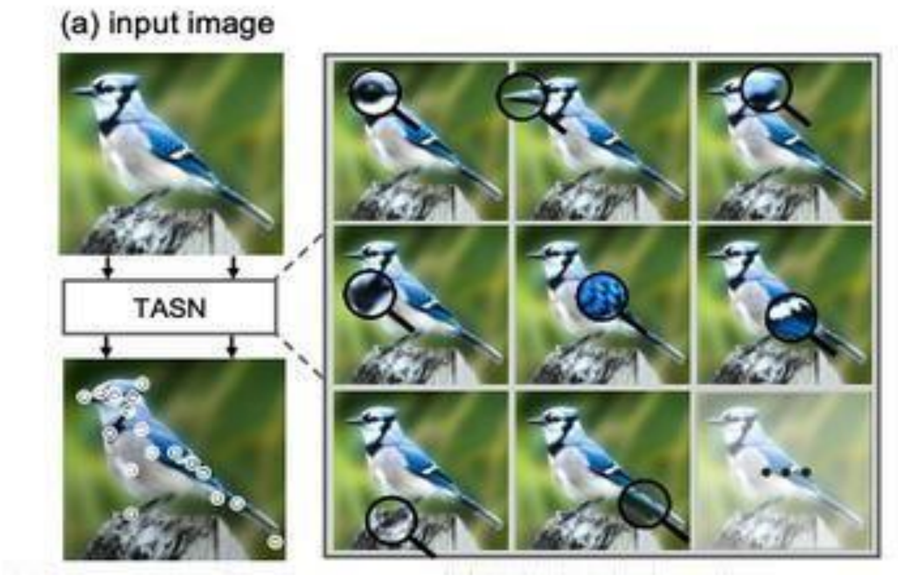

Figure 3: Sample Bird Images Used for Training[3]

showcases a variety of bird images from our dataset, illustrating the diversity of species and image conditions used to train our model. This diversity is crucial for developing a robust identification system capable of performing well across different environments and bird species.

In conclusion, this research underscores the transformative impact of integrating AI with ecological studies. By advancing the capabilities of image-based bird species identification, we pave the way for more efficient and accurate biodiversity assessments, ultimately supporting global conservation initiatives.

Figure 3: Schematic representation of the architecture of Convolutional Neural Network Related Work

- Nadimpalli et al. [4] created a novel model leveraging image processing techniques to recognize birds in aquaculture ponds, facilitating a more flexible distribution of predatory birds. Three image processing algorithms—image morphology, artificial neural networks (ANN), and template matching—were designed and tested. They enhanced the algorithm to enable real-time bird recognition and developed necessary algorithms using the image processing and neural network toolboxes of MATLAB 6.5. Training the ANN model took three minutes, but results were instantly obtained during testing.

- Christiansen et al. [5] employed digital image processing techniques to automatically detect and study animals in video recordings. The animals' thermal radiation, which exceeds that of the background, makes them appear brighter in the images. However, sunlight can reduce the thermal difference, causing some grass spots to radiate similarly to the animals. They used the Laplacian of Gaussian filter to enhance the animals' appearance, achieving detection rates close to 100%, although dense crops could impede detection.

- Nadimpalli et al. [6] focused on bird detection using various techniques: motion detection with image subtraction, bird detection with template matching, and bird detection with the Viola-Jones algorithm. The Viola-Jones algorithm, with an 87% accuracy and low false positive rate, proved the most effective. This method is suitable for integration with hardware to create a smart scarecrow system, as the object classifier training is slow, but detection is fast, enabling web browser and mobile implementations.

- Moreira et al. [7] reviewed the state-of-the-art video detection and tracking of marine vehicles. The dynamic maritime environment poses challenges, including noise, clutter, waves, sunlight reflection, and environmental conditions, affecting detection and tracking efficiency. The algorithm struggled in real-time situations, particularly with low-contrast vessels, due to these complexities.

- Shalika et al. [8] developed an algorithm for detecting and tracking animal faces in wildlife videos, based on human face detection using Haar-like features and AdaBoost classifiers. They combined the Kanade-Lucas-Tomasi tracker with a specific tracking model, achieving reliable and temporally coherent detection/tracking. This method supports automatic wild animal detection, focusing on classification and recognition.

- Nguyen et al. [9] utilized the Wildlife Spotter dataset to develop a deep learning-based automated wildlife monitoring system. Their approach, which includes balancing and improving the dataset, applying deeper CNN models, and utilizing camera-specific features, demonstrates strong and stable performance. They plan to enhance this system with transfer learning for imbalanced data and create a hybrid classification system for the Wildlife Spotter project.

- Niemi et al. [10] explored image classification using non-deep CNN models, showing acceptable performance for real-world applications, especially with limited training data. They demonstrated that data augmentation significantly improves classifier performance. The classifier's performance was achieved without radar parameters, which could further enhance accuracy by providing additional relevant information.

- Nyaga et al. [11] developed a mobile application for recognizing Kenyan bird species from images and creating a bird map of observations. By reviewing current bird identification methods and utilizing machine learning, specifically transfer learning and convolutional neural networks, they created an effective bird species identification system. The mobile app performed well in identifying bird species and allowed users to save and retrieve results.

- Huang et al. [12] designed an automatic model to classify 27 endemic Taiwanese birds using a skipped CNN model. The skip connection addressed the vanishing gradient problem, leading to superior performance compared to models without skip connections and SVMs. Despite achieving 100% accuracy in identifying birds, the model sometimes struggled with interspecific comparisons due to minute visual similarities. The test dataset showed 93.79% sensitivity and 96.11% specificity.

- Gavali et al. [13] addressed the challenge of identifying bird species within a single category due to high intra-class similarity and variability. Using a deep learning algorithm on a dataset with 200 bird categories and 11,788 photos, they developed a system connected to a user-friendly website. The model detects parts, extracts CNN features from multiple convolutional layers, and uses these features for classification, providing accurate identification of bird species from uploaded photos.

III. PROPOSED SOLUTION

The proposed solution for the model is described below, detailing the project's workflow and functionalities. The user will be able to capture and upload images to the system. If the uploaded image is not already present in the dataset, it will be stored in the database. The image will then be processed by the system using a Convolutional Neural Network (CNN). Key features of the image, such as the face, expression, angle, beak, etc., will be extracted. The classifier will analyze these features, compare them with the trained dataset, and make a prediction.

Diagrams:

Work Flow Diagram:

The workflow of the model is illustrated in Figure 4. Initially, the user uploads an image as input. If the image is not already in the database, it gets stored. The system then retrieves the image, applies the CNN, and compares it with the pre-trained model. Subsequently, the image's features are extracted. The classifier processes these features and provides the required result.

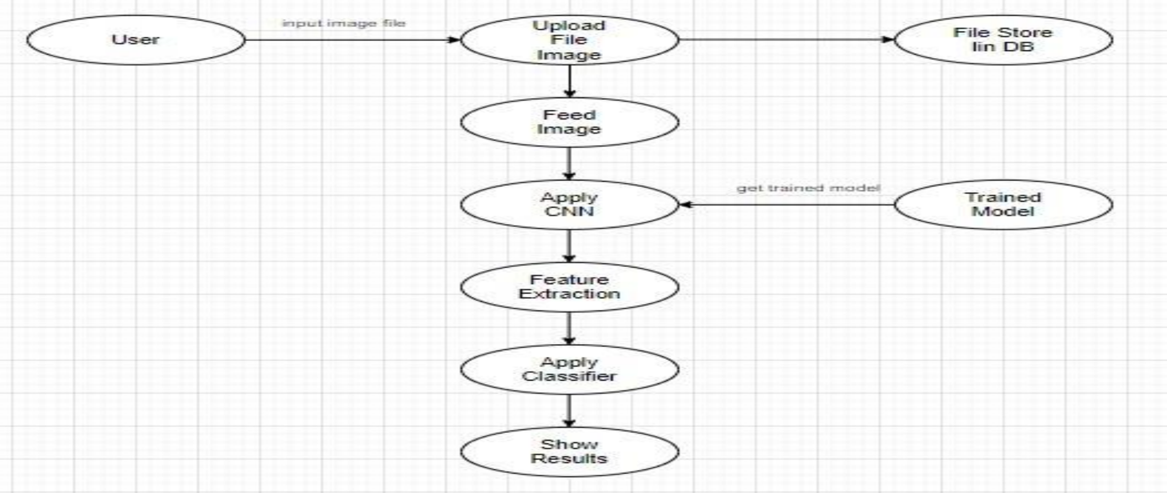

Figure 4: Work Flow Diagram

Use Case Diagram:

The use case diagram, shown in Figure 5, indicates that the model can be accessed by two types of participants: the administrator and the user.

System Administrator: The administrator is responsible for pre-processing the dataset and training the model. Once the model is trained, the administrator can generate it for future comparisons. The administrator can also upload images by either capturing them directly or selecting them from the gallery to update the dataset.

User: Users can register and log into the system. They can make inferences by uploading images, either by capturing them in real time or by selecting them from their gallery. Users then receive the desired results based on the model's predictions.

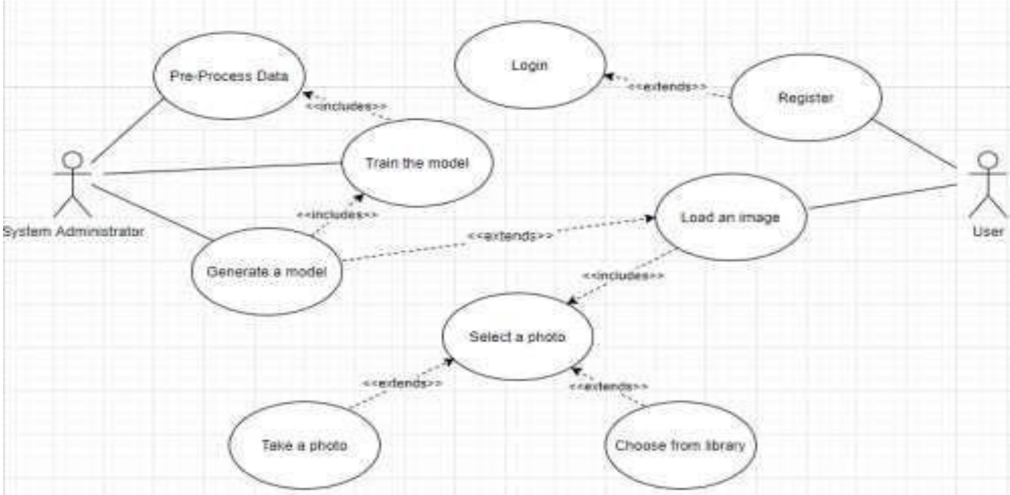

Figure 5: Use Case Diagram

IMPLEMENTATION

OpenCV is utilized in the model's implementation. An essential component of computer vision and image processing is object detection, which is made easier by OpenCV (Open Source Computer Vision Library). This technique recognizes semantic items in digital photos and videos of different classes, including people, cars, and buildings. OpenCV was first created by Intel and is now maintained by Itseez. Willow Garage provided initial support for the program. It may be used with programming languages like C, C++, and Python and is compatible with a variety of operating systems, including Mac, Windows, and Linux.

A selection of C and C++ algorithms and functions make up the OpenCV library. Because of its high computing efficiency and adaptability for real-time applications in a variety of sectors, including vision and manufacturing products, it is widely employed.

This is how the Image Processing in the model will be done-

Acquisition

This initial step involves capturing the image.

The primary tasks here include:

1. Scaling: Adjusting the image size.

• Color Conversion: Changing the image color space, such as converting from RGB to grayscale or vice versa.

2. Image Enhancement:

• This step focuses on improving the visual appearance of an image or extracting hidden details. It is often considered one of the simplest yet most appealing aspects of image processing.

3. Image Restoration:

• This involves improving the appearance of an image based on mathematical or probabilistic models of image degradation. The goal is to recover an image that has been corrupted.

4. Color Image Processing:

• This encompasses handling both pseudo-color and full-color images. Various color models are applied in digital image processing to enhance or modify images.

5. Wavelets and Multi-Resolution Processing:

• This method represents images at various degrees of resolution. It is foundational for efficiently encoding and analyzing image data.

6. Image Compression:

• This step aims to reduce the size or resolution of an image to save storage space or transmission time. It involves developing algorithms and functions for effective compression.

7. Morphological Processing:

• This process includes a set of operations that probe an image with a structuring element. It is useful for extracting components that are essential for the representation and description of shapes.

8. Segmentation Procedure:

• Segmentation involves partitioning an image into its constituent parts or objects. It is one of the most challenging tasks in image processing due to its complexity and the need for accurate object identification.

9. Representation and Description:

• Following segmentation, this stage involves choosing an appropriate representation for the segmented data. This transformation from raw data to processed data is crucial for further analysis.

10. Object Detection and Recognition:

• This final stage assigns labels to objects based on their descriptors. It is a process where the system identifies and categorizes objects within an image.

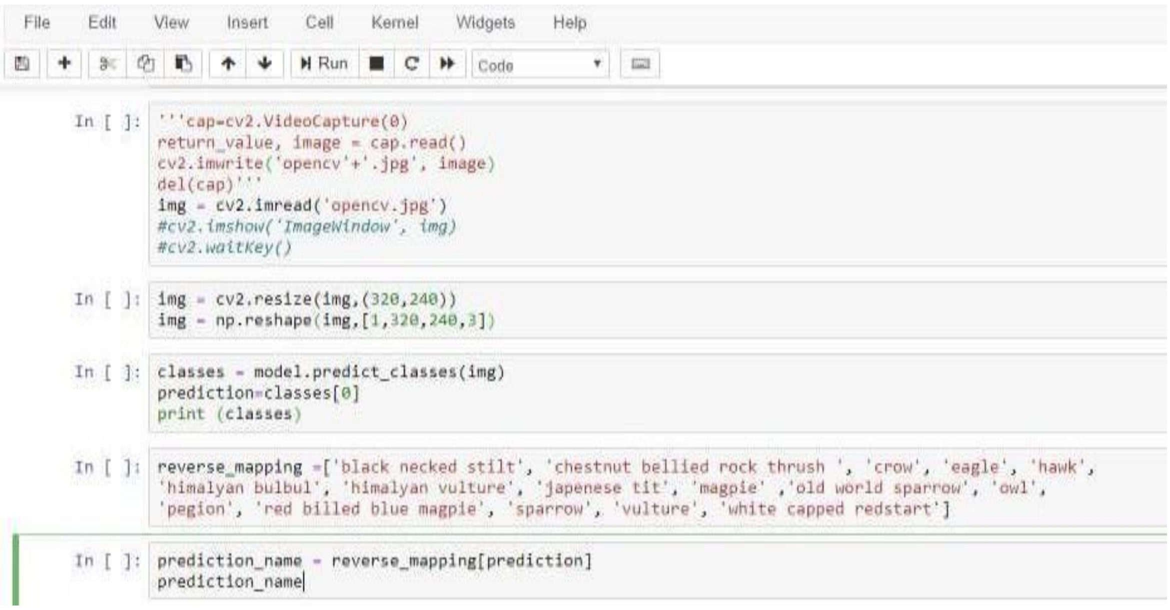

Figure 6: Image recognition

Algorithm:

1. Extract Strongest Scatters:

• From the test image, identify the N strongest scatterers by their location (A, B) and magnitude (R).

2. Sort Scatterers:

• Order the scatterer data points (A, B, R) in descending order based on their magnitude (R).

3. Iterate Over Scatterers:

• For each scatterer origin O (from 1 to N), perform the following steps

4. Pair Scatterers:

• For each scatterer point M (from O+1 to N), calculate the differences

5. Calculate Differences:

- Compute dA = Ap - Ao and dB = Bp - Bo.

6. Search Neighboring Differences:

- For each difference value DA from dA-1 to dA+1, do the following:

7. Further Neighboring Search:

- For each difference value DB from dB-1 to dB+1, execute the next steps:

8. Weighted Voting:

- Calculate the weighted vote as |DA| + |DB|.

9. Model Data Lookup:

- Retrieve the list of model data entries corresponding to DA and DB.

10. Evaluate Model Entries:

- For each entry C in the model list, check the following conditions:

11. Apply Translation and Magnitude Limits:

- If |ta = Ao - Ae| < translational_limit and |tb = Bo - Be| < translational_limit
- If |1 - Reo/Ro| < magnitude_limit and |1 – Rep/Rp| < magnitude_limit
- If all conditions are met, increment the accumulator array [Specie, Az, ta, tb] by the weighted vote.

12. Query Accumulator Array:

- For each Specie, Az, ta, and tb, sum the votes within a 3x3 neighborhood in the translation subspace around ta and tb. Record the maximum vote_sum and the corresponding Species.

13. Determine Result:

- If the maximum vote_sum exceeds the threshold, the result is the Species with the highest vote. Otherwise, the result is “Not found”.

Result

This study developed a software platform that leverages deep learning for real-time bird species identification from digital images uploaded or captured by users on smartphones. To create this system, a trained dataset is essential for image classification. The dataset consists of two parts: the training results and the testing results. The dataset must be retrained periodically to achieve higher identification accuracy. The initial trained dataset is developed using 50,000 training steps, with accuracy improving as the number of steps increases. The trained dataset achieves an accuracy of 93%, while the testing dataset, comprising nearly 1,000 images, has an accuracy of 80%.

When a user uploads an image, it is temporarily stored in a database. This input image is then processed by the system using a Convolutional Neural Network (CNN), which is integrated with the trained dataset. The system considers various features such as the bird's head, body, color, beak, shape, and the entire image to ensure maximum classification accuracy. Each feature is analyzed through the deep convolutional network to extract relevant characteristics, which are then forwarded to the classifier.

The classifier compares the input image with the pre-trained dataset images and generates a score sheet. This score sheet lists the top five matching results, with the highest matching score indicating the identified bird species.

Consider the figure below as an example input for the bird classification system. Let's examine the procedure:

1. Image Upload and Storage:

- The user uploads a bird image, which is stored in the database temporarily.

2. Feature Extraction:

- The image is passed through a CNN, which extracts features such as the bird's head, body, color, beak, and shape.

3. Classification:

- The extracted features are compared with the trained dataset using the classifier.

4. Score Sheet Generation:

- A score sheet is generated, listing the top five matching bird species based on similarity scores.

5. Result Identification:

- The species with the highest matching score is identified as the result.
- This process ensures that the platform can accurately and efficiently identify bird species from user-uploaded images in real time.

S.No.	Species	Score Obtained
1.	Elegant tern	0.00943
2.	Red Faced cormorant	0.00924
3.	Brant cormorant	0.0082
4.	Pelagic cormorant	0.0082
5.	White pelican	0.00808

Figure 7: Score Sheet Table

Figure 8: Image of Elegant tern

CONCLUSION

The study uses a neural network to classify bird species based on a dataset. While multiple-width frequency delta data augmentation does not outperform raw spectral data in raising classification accuracy, it achieves results close to the state-of-the-art and offers computational efficiency advantages. Incorporating additional metadata improves the ranking of species predictions but does not significantly enhance the top-1 accuracy, indicating that the model effectively narrows down the list of potential species without drastically improving the accuracy of the top prediction. An analysis of the dataset reveals an uneven distribution of training samples across bird species, leading to model bias favoring certain species, and highlights that some species are more challenging to classify than others.

This study has implications beyond ornithology, extending to fields such as image processing, fault detection in industrial settings, and medical image segmentation. A noted limitation is that the accuracy of these algorithms heavily depends on the quality of the camera and the angle of view between the camera and the target object. In some cases, the results were inaccurate when the camera angle exceeded a certain range.

Future Scope

The future of image processing is poised to be revolutionized by intelligent, digital automated robots developed by research scientists globally. This progress encompasses advancements in various image-processing applications. As these technologies evolve, millions of robots will emerge, transforming everyday life. Research in image processing and artificial intelligence will include capabilities such as responding to voice commands, anticipating information needs for governments, translating languages, recognizing and tracking individuals and objects, diagnosing medical conditions, performing surgeries, reprogramming defects in human DNA, and enabling autonomous driving across all forms of transportation.

In the realm of image-based species recognition, particularly for birds, the system can be significantly enhanced with cloud integration. This feature allows for the storage of large datasets for comprehensive comparisons and, when utilizing neural networks, offers high computing power for processing.

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