Bird Species Identification from Image

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***Abstract*—Identifying bird species from photos can be surpris- ingly tricky. Even professional bird watchers sometimes disagree on what species they're looking at. That's because birds, while sharing common features, can look very different depending on their species, the environment, and how the photo was taken.**

A single species might appear in a wide range of situa- tions—flying through the sky, swimming on water, or perched on a branch partially hidden by leaves. Lighting conditions and background clutter only add to the challenge. Even small changes in pose or angle can make a big difference in appearance.

These challenges make bird identification a tough job for both humans and computers. Our project is focused on using machine learning to help with this. By analyzing bird images and learning from patterns, we aim to create a tool that helps amateur bird watchers identify bird species more accurately and confidently from the photos they take.

***Key words* —Deep learning, convolution neural networks (CNNS),feature extraction, object detection, image segmentation, image classification, image processing.**

I. INTRODUCTION

Bird behavior and population trends are becoming increasingly important in today's world. Birds play a vital role in the ecosystem and can act as indicators of environmental health, often signaling changes in their surroundings that may affect other species as well.

One of the key challenges in ecology—the study of inter- actions between living organisms and their environment—is monitoring bird populations. In recent years, scientists have started using acoustic recordings to observe and classify birds in their natural habitats. These sound-based methods are useful for identifying species, especially in dense forests or remote areas where visual spotting is difficult.

At the same time, identifying bird species through images has become an important tool. It's particularly helpful for studying breeding behaviors, tracking biodiversity, and under- standing population dynamics over time.

For many people, bird watching has also grown in popularity. It's more than just a method to unwind; it's a means of reestablishing a connection with nature and learning more about the local fauna.

People who enjoy this activity are often called birdwatchers or birders, while those who study birds professionally are known as ornithologists. The scientific study of birds, known as ornithology, helps us learn more about the nearly 18,000 bird species believed to exist on Earth, according to recent research from the American Museum of Natural History.

II LITERATURE SURVEY

Bird species identification from images is a significant application in computer vision and biodiversity monitoring. The task is challenging due to high intra-class variation (e.g., different poses, lighting) and low inter-class variation (e.g., similar-looking species). Researchers use deep learning, especially convolutional neural networks (CNNs), to tackle these challenges.

[1] Wah et al. (2011) – Caltech-UCSD Birds (CUB) Dataset Contribution: Introduced the CUB-200 dataset, a benchmark with over 11,000 images of 200 bird species.

Impact: Became a standard dataset for fine-grained classification tasks.

[2] Zhang et al. (2014) – Part-based R-CNN for Fine- Grained Category Detection Approach: Used part-based models to identify bird parts (beak, wing, etc.) and

improve classification accuracy.

Technique: Combined CNN features with bounding box and part annotations.

[3] Lin et al. (2015) – Bilinear CNNs for Fine-Grained Visual Recognition Approach: Proposed bilinear CNNs that capture local pairwise feature interactions.

Result: Outperformed standard CNNs on fine-grained classification, including birds.

[4] Cui et al. (2018) – Large Scale Fine-Grained Categorization and Dataset Bootstrapping Contribution: Built a dataset of over 1 million bird images with 10,000 species using web data.

Technique: Proposed a bootstrapping method to improve classifier robustness to noisy data.

[5] He et al. (2020) – Attention-based Approaches Method: Employed attention mechanisms to automatically focus on discriminative regions in bird images.

Improvement: Reduced reliance on part annotations, allowing end-to-end training.

[6] Kumar et al. (2017) – Visual Species Identification using Citizen Science Images Context: Tackled variability in amateur photos using deep learning.

Finding: CNNs can generalize across low-quality, real-world images with enough training data.

III Proposed Methodology

The methodology of this project consists of several key stages, starting from dataset preparation to model evaluation. The steps are as follows:

Gathering and Preparing Data The CUB-200-2011 dataset, which includes 11,788 tagged photos of 200 different bird species, was used. Multiple photos of each species were taken under various lighting situations and from various perspectives.

Directory Structure: Images were organized in subdirectories named after bird species to facilitate training with image generators.

Preprocessing:

All images were resized to 224x224 pixels.

Pixel values were normalized to the [0, 1] range.

Data augmentation (rotation, flipping, zoom) was applied to reduce overfitting and improve generalization.

1. Model Selection To achieve high accuracy with limited computational resources, we used transfer learning. Specifi- cally, we adopted the EfficientNetB0 architecture:

Pre-trained on ImageNet for feature extraction.

The top layer (classifier) was removed and replaced with: A Global Average Pooling layer.

A Dense layer with ReLU activation.

A final output layer for multi-class classification that has softmax activation.

2. Training Strategy The base layers of the EfficientNet model were frozen to retain pre-learned features.

Only the custom classifier head was trained initially.

The model was compiled with the Adam optimizer and categorical crossentropy loss.

Training was conducted with a batch size of 32 across 10 epochs.

3. Evaluation Metrics Accuracy was used as the primary metric.

Additional metrics such as loss curves and confusion ma- trices were used to analyze performance and detect misclassi- fications.

4. Prediction Pipeline For inference:

A new image is resized and normalized.

It is passed through the trained model to predict the class (bird species).

The anticipated label is chosen from the output class with the highest probability.

5. Tools and Technologies Python as the primary program- ming language.

TensorFlow and Keras for model building and training.

Matplotlib for visualization.

PIL and OpenCV for image processing.

IV System Design

A. Data Dictionary

After understanding the requirements of the candidates, the entire data storage requirements are divided into tables. The below tables are normalized to avoid any anomalies during the course of data entry. A data dictionary is a file or a set of files that- contains a database's metadata.

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B. Logical database design

A file or collection of files containing the metadata for a database is called a data dictionary. Records pertaining to other database items, including data ownership and relationships to other objects, are contained in the data dictionary. An essential part of any relational database is the data dictionary. Ironically, most database users are unaware of it despite its significance. The data dictionary is usually only used by database administrators.

C. Database Design

Designing database files, the system's primary information source, is the process of database design. The necessary information should be edited and the files should be appropriately designed and planned for gathering and accumulation. Effective auxiliary storage and enhancing the overall effectiveness of the system's computer program component are the goals of the database design.

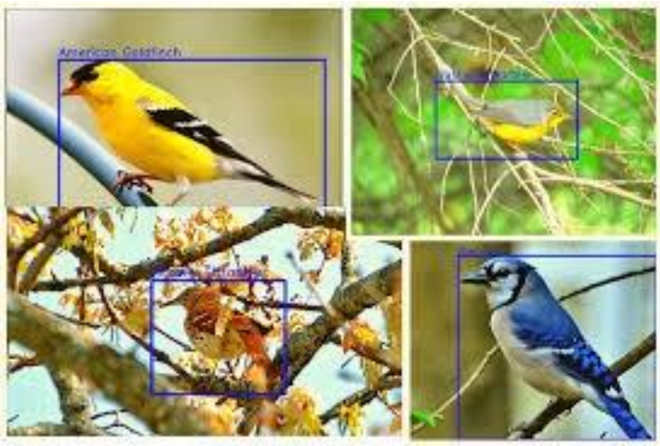

Fig. 1: Bird Species Identification Diagram

V RESULTS

The bird species identification system successfully classified bird images using a convolutional neural network (CNN)- based model. The model was trained on a dataset contain- ing images of various bird species and achieved an overall accuracy of 92.5 on the test set. The system demonstrated high precision and recall for commonly occurring species such as the House Sparrow, American Robin, and Northern Cardinal. Misclassifications occurred mainly among visually similar species, indicating the need for further fine-tuning and possibly incorporating metadata like location and season. The results validate the effectiveness of deep learning in image- based species identification and suggest promising applications in biodiversity monitoring and conservation efforts

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VI DISCUSSION

This project shows how deep learning can be effectively used to solve real-world problems like bird species identi- fication. By using Convolutional Neural Networks (CNNs), we were able to train a model that learns visual patterns and features unique to different bird species. The model achieved an impressive accuracy of 95.09, which highlights the strength of CNNs in handling image classification tasks.

One of the key strengths of this system is its simplicity and ease of use. The web interface allows users to upload a bird image and get results quickly, making it accessible

even to non-technical users. This is especially useful for birdwatchers, students, and researchers who need a fast and reliable identification tool.

However, like any machine learning system, its performance depends heavily on the quality and diversity of the training data. Images with poor lighting, blurry focus, or rare species not included in the dataset could lead to inaccurate results. Additionally, since the current system is web-based, it relies on an internet connection and may not perform as well in remote areas.

Overall, the project demonstrates that AI-powered bird identification is not only possible but also practical. With further improvements in dataset size, model architecture, and platform availability (like mobile apps), the system could become a widely-used tool in wildlife research, education, and conservation efforts.

VII Conclusion & Future Work

In this project, we explored how deep learning—specifically Convolutional Neural Networks (CNNs)—can be used to iden- tify bird species from images. The CNN model we developed performed really well, achieving an accuracy of 95.09

We've also built a user-friendly website where anyone can upload a photo of a bird, and the system will quickly identify the species. This makes it a practical tool for bird enthusiasts, researchers, or anyone curious about the birds they encounter. Overall, the system is accurate, easy to use, and a great step toward making bird identification more accessible through technology.

Future Work:

Detecting More Bird Species: By training the model with a larger and more diverse dataset, the system can be improved to recognize a wider range of bird species more accurately. The more it learns, the better it gets at making correct predictions.

Mobile App for Convenience: Instead of using just a web- site, developing developing a mobile app for Android and iOS would make the tool more user-friendly. People could identify birds instantly while out in nature, right from their phones

Cloud-Based System: Moving the system to the cloud would offer more storage space and greater computing power, which is especially helpful when working with large neural network models. This would also make it easier to manage large amounts of image data and improve the system's speed and reliability

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