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Species Identification from An Image

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Abstract

This project focuses on the development of a system for animal and bird species identification using Convolutional Neural Networks (CNNs). Wildlife conservation and ecological research demand accurate species recognition, and the proposed system employs deep learning to fulfill this need. By training the CNN on a diverse dataset of animal and bird images, the system achieves high accuracy in species identification, contributing to conservation efforts. The project addresses the urgency of species preservation in the face of environmental threats. Traditional methods of species identification are often time-consuming and prone to human error. The CNN-based approach offers a more efficient and accurate solution. The foundation of the project lies in a comprehensive image dataset, encompassing a wide range of species, enabling the CNN to recognize subtle visual distinctions. This project not only involves training the CNN but also creating a user-friendly interface for easy image upload and rapid species identification. This accessibility ensures that a broad audience can benefit from this technology, supporting the cause of species preservation. By leveraging CNNs, this project represents a powerful tool for wildlife conservation, accelerating the process of species identification, facilitating effective conservation measures, and aiding in the monitoring of biodiversity. It highlights the importance of collaborative efforts to protect our planet's natural heritage.

Keywords: *Convolutional Neural Networks(CNN), Species Identification.*

1. Introduction

In an era marked by rapid technological advancements, artificial intelligence has penetrated various domains, and its applications in ecological research and wildlife conservation are no exception. The project at hand delves into the development of a cutting edge system aimed at the identification of animal and bird species from images using Convolutional Neural Networks (CNNs). This innovative approach harnesses the power of deep learning to address the pressing need for accurate and efficient species recognition, a cornerstone of wildlife conservation and ecological monitoring. The significance of such a system is underscored by the increasing threats to biodiversity and ecosystems worldwide. Conservationists and researchers face the daunting task of tracking and protecting numerous species in the face of habitat destruction, climate change, and illegal wildlife trade. Traditional methods of species identification, reliant on field observations and manual cataloging, are time-consuming and often prone to error. To overcome these challenges, this project leverages CNNs, a class of deep learning algorithms specifically designed for image analysis. By utilizing diverse dataset of animal and bird images, the system is trained to learn the visual features that distinguish various species. The deep neural network architecture of the CNN is capable of automatically detecting and classifying species with remarkable accuracy, making it an invaluable tool for wildlife conservation efforts. The foundation of this project lies in the extensive collection of images, encompassing a wide range of animal and bird species. These images are used for both training and testing the CNN, enabling it to recognize subtle distinctions in coloration, markings, and morphology that are often imperceptible to the human eye. The system's effectiveness is further enhanced by transfer learning, where pre-trained models are fine-tuned to optimize performance. The research and development effort behind this project not only entails the design and training of the CNN but also the creation of a user-friendly interface, allowing conservationists, researchers, and wildlife enthusiasts to easily upload images and receive rapid species identification results. This accessibility ensures that the benefits of this technology can be harnessed by a broad audience, further aiding the cause of species preservation. By harnessing the capabilities of CNNs, this project stands as a beacon of hope for 2 wildlife conservation. It offers a powerful and reliable tool that can accelerate the process of species identification, thus facilitating more effective conservation measures. The ability to promptly identify and track species in real-time is an invaluable asset in addressing urgent threats to biodiversity. This project's implications extend beyond species identification, potentially enabling the monitoring of population dynamics, tracking the spread of invasive species, and aiding in the preservation of fragile ecosystems.

2. Needs & Applications

2.1 Needs

The “Animals and Birds Species Identification from an Image” project addresses several important needs:
1. Biodiversity Conservation: It can aid in wildlife conservation efforts by accurately identifying and tracking animal and bird species, helping scientists monitor populations and habitats.
2. Education and Awareness: The project promotes awareness and education about various species, contributing to wildlife education and nature conservation.
3. Citizen Science: It empowers citizen scientists to contribute to biodiversity data collection, making valuable contributions to scientific research.
4. Pest and Disease Control: Identifying species in agricultural and forestry contexts can assist in pest and disease control.

2.2 Applications

The “Animal and Bird Species Identification from an Image” project has various practical applications:
1. Wildlife Research: Researchers can use it for wildlife population studies, behaviour observation, and habitat monitoring.
2. Field Biologists: Field biologists and naturalists can utilize it for on-the-spot species identification.
3. Agriculture: It can help in identifying pests, beneficial insects, and crop diseases.
4. Education: Educational institutions can employ it for teaching and learning about wildlife and ecosystems.
5. Nature Enthusiasts: Nature enthusiasts and hikers can use it for species identification during outdoor activities.

3. Literature Survey

The automatic identification of animal and bird species from images has emerged as a vital area of research, holding immense promise for wildlife conservation and ecological studies. Utilizing Convolutional Neural Networks (CNNs), deep learning techniques have revolutionized the field of species identification from visual data.
In this literature survey, our focus is directed towards an in-depth exploration of the existing body of research that specifically pertains to the identification of animal and bird species through image analysis using CNNs. By critically examining prior work in this domain, our objective is to gain insights into the current state of the art, uncover challenges, and establish a strong foundation for our project. This project seeks to build upon and further refine the accuracy and usability of systems dedicated to the recognition and conservation of animal and bird species.

3.1 Summary Of Literature Survey

- Li Jian, Zhang Lei et al (2014) [1], proposed an effective automatic bird species identification based on the analysis of image features. Used the database of standard images and the algorithm of similarity comparisons.
- Madhuri A. Tayal, Atharva Magrulkar et al (2018) [2], developed a software application that is used to simplify the bird identification process. This bird identification software takes an image as an input and gives the identity of the bird as an output. The technology used is transfer learning and MATLAB for the identification process.
- Andreia Marini, Jacques Facon et al (2013) [3], proposed a novel approach based on color features extracted from unconstrained images, applying a color segmentation algorithm in an attempt to eliminate background elements and to delimit candidate regions where the bird may be present within the image. Aggregation processing was employed to reduce the number of intervals of the histograms to a fixed number of bins. In this paper, the authors experimented with the CUB-200 dataset and results show that this technique is more accurate.
- Marcelo T. Lopes, Lucas L. Gioppo et al (2011) [4], focused on the automatic identification of bird species from their audio recorded song. Here the authors dealt with the bird species identification problem using signal processing and machine learning techniques with the MARSYAS feature set. Presented a series of experiments conducted in a database composed of bird songs from 75 species out of which problem obtained in performance with 12 species.
- Mario Lasseck et al (2013) [5], presented deep convolutional neural networks and data augmentation techniques for audio based bird species identification. In this paper, the author used the Xeno-Canto set of audio recordings of bird species.
- Fang, Y., Du, S., Abdoola, R., Djouani, K., & Richards, C. (2016) [6] discussed a technique to move animal detection by

taking benefit of global patterns of pixel motion. In the dataset, where animals make obvious movement against the background, motion vectors of every pixel were estimated by applying optical flow techniques. A coarse segmentation then eliminates most parts of the background via applying a pixel velocity threshold. Using the segmented regions, another threshold was used to filter out negative candidates, which could belong to the background.

- Jaskó, G., Giosan, I., & Nedevschi, S. (2017) [7] presented a system capable of detecting different huge sized wild animals from traffic scenes. Visual data was obtained from a camera with monocular color vision. The objective was to analyze the traffic scene image, to locate the regions of interest and to correctly classify them for discovering the animals that were on the road and might cause an accident. A saliency map was generated from the traffic scene image using intensity, color and orientation features. The salient regions of this map were assumed to be regions of interest. A database was compiled from a large number of images containing various four-legged wild animals. Relevant features were extracted from these and were utilized for training Support Vector Machine (SVM) classifiers.
- Nguyen, H., Maclagan, S. J., Nguyen, T. D., Nguyen, T., Flemons, P., Andrews, K., ... & Phung, D. (2017) [8] investigated a main obstacle to scientists and ecologists to monitor wildlife in an open environment. Leveraging on recent advances in deep learning approaches in computer vision, a framework was introduced to build automated animal recognition in the wild, aiming at an automated wildlife monitoring system.
- Matuska, S., Hudec, R., Kamencay, P., Benco, M., & Zachariasova, M. (2014) [9] discussed a new approach for object recognition by using hybrid local descriptors. This approach was utilized a combination of a few techniques (SIFT - Scale-invariant feature transform, SURF - Speeded Up Robust Features) and consists of second parts. The applicability of the presented hybrid techniques were demonstrated on a few images from dataset. Dataset classes represent big animals situated in Slovak country, namely wolf, fox, brown bear, deer and wild boar.
- Gupta, P., & Verma, G. K. (2018) [10] proposed a technique for detection of visual wild animals in images by dictionary learning. Discriminative Feature-oriented Dictionary Learning was utilized for learning discriminative features of positive images, that have animals present in positive class, in addition to of negative images that do not have animals present in that class. The system was created dictionaries that were class-specific and was capable of automatic feature extraction by example training image samples. The proposed approach was learned these dictionaries through positive (animal class and negative background class) sparse representation of image samples.

3.2 Limitations Of Existing System

1. Li Jian, Zhang Lei et al (2014):

- Limited discussion on the generalizability of the method to a diverse range of bird species.
- Relied on a database of standard images, which might not fully capture the variability of real-world bird images.

2. Madhuri A. Tayal, Atharva Magrulkar et al (2018):

- The software application may have limitations in identifying bird species in challenging environmental conditions or with poor image quality.
- Transfer learning and MATLAB based approaches might require a certain level of technical expertise, limiting accessibility.

3. Andreia Marini, Jacques Facon et al (2013):

- The method's effectiveness could vary in situations with complex backgrounds and challenging lighting conditions.
- Limited discussion on the method's adaptability to various image conditions and different bird species.

4. Marcelo T. Lopes, Lucas L. Gioppo et al (2011):

- The approach was focused on a subset of bird species, potentially limiting its application to a broader range of avian species.
- The system may not be suitable for situations where audio recordings are of poor quality or contain overlapping bird songs.

5. Mario Lasseck et al (2013):

- The deep convolutional neural network approach may require substantial computational resources for real-time processing.
- The model's performance may be limited in cases where audio recordings contain noise or interference.

6. Fang, Y., Du, S., Abdoola, R., Djouani, K., & Richards, C. (2016):

- The technique may not be suitable for scenarios with complex and dynamic backgrounds where animals blend with their surroundings.
- Performance limitations in scenarios with poor image quality or complex motion patterns.

7. Jaskó, G., Giosan, I., & Nedevschi, S. (2017):

- Limited discussion on the system's performance in challenging weather conditions and varying lighting situations.

- The effectiveness of the system in detecting animals that are partially obscured or in crowded traffic scenes might be a limitation.

8. Nguyen, H., Maclagan, S. J., Nguyen, T. D., Nguyen, T., Flemons, P., Andrews, K., ... & Phung, D. (2017):

- The method's performance may be influenced by the availability of diverse training data and the generalization to various wildlife species.
- Limited discussion on the challenges and limitations of deep learning techniques in the wild, including computational and data requirements.

9. Matuska, S., Hudec, R., Kamencay, P., Benco, M., & Zachariasova, M. (2014):

- The presented hybrid techniques may not be suitable for all object recognition tasks, and their limitations in different applications are not thoroughly discussed.
- The limited number of images used for demonstrating applicability might not fully represent the complexity of real world scenarios.

10. Gupta, P. & Verma, G. K. (2018):

- The technique's performance may depend on the availability of a substantial amount of labeled training data for both positive and negative classes.
- The creation of class-specific dictionaries and sparse representation of image samples could be resource intensive and may have limitations in real-time applications.

4. Problem Statements & Objectives

4.1 Problem Statements

The problem of animal and bird identification from images is essential for various applications, including wildlife conservation, ecological monitoring, and research. Traditional methods often rely on manual observation and identification, which is time consuming and may not be practical in remote or large-scale environments. The use of Convolutional Neural Networks (CNNs) can significantly enhance the efficiency and accuracy of species identification from images. However, building a robust CNN-based system for animal and bird identification faces several challenges:

- ❖ **Data Variability:** Wildlife images captured in the field can exhibit considerable variation in lighting, backgrounds, poses, and occlusions. Developing a system that can handle this variability is a significant challenge.
- ❖ **Large-Scale Datasets:** Collecting and annotating a diverse and comprehensive dataset of animal and bird species images is resource-intensive. It is essential to have a sufficiently large and representative dataset for training a CNN.
- ❖ **Real-Time processing:** In some applications, real-time processing is critical, such as in camera traps for wildlife monitoring. Achieving high identification accuracy in real time presents computational challenges.

4.2 Objectives

In this project, the primary goal is to develop a state-of-the-art Convolutional Neural Network (CNN)-based model for accurate and efficient animal and bird species identification from images. To achieve this, several key objectives have been outlined:

1. **Dataset Collection and Curation:**
   - ✓ Gather a large and diverse dataset of images containing various animal and bird species.
   - ✓ Annotate the dataset with species labels to create a comprehensive training set.
2. **Model Development:**
   - ✓ Design and implement a deep learning model based on Convolutional Neural Networks (CNNs) for image classification.
   - ✓ Fine-tune and optimize the model architecture to handle the variability in wildlife images.
3. **Real- Time Processing:**
   - ✓ Develop techniques to optimize the model for real-time processing, suitable for applications like camera traps or drones.
   - ✓ Investigate the trade-offs between accuracy and processing speed.
4. **Accuracy and Evaluation:**
   - ✓ Assess the model's accuracy and performance using appropriate evaluation metrics.
   - ✓ Ensure the system can handle challenging scenarios, including different lighting conditions, occlusions, and diverse backgrounds.
5. **User – Friendly Interface:**
   - ✓ Develop a user-friendly interface for wildlife researchers and conservationists to access the system.

- ✓ Ensure the system's results are interpretable and actionable for users.

6. **Scalability and Generalization:**
   - ✓ Investigate the scalability of the system to work with a wide range of animal and bird species.
   - ✓ Assess the generalization of the model to adapt to different environmental conditions.

5. Proposed System

5.1 Introduction

The proposed system is a web-based platform designed for animal and bird identification using Flask and Convolutional Neural Networks (CNNs). It offers users a streamlined process for uploading images, which are then analyzed by a pre-trained CNN model to identify animals and birds. The integration of an external Image Recognition API further enhances the accuracy of these predictions. Additionally, the system includes a database for data storage and retrieval, ensuring a personalized user experience. This comprehensive solution is tailored to meet the demands of image-based animal and bird identification, catering to enthusiasts and researchers alike.

5.2 Architecture

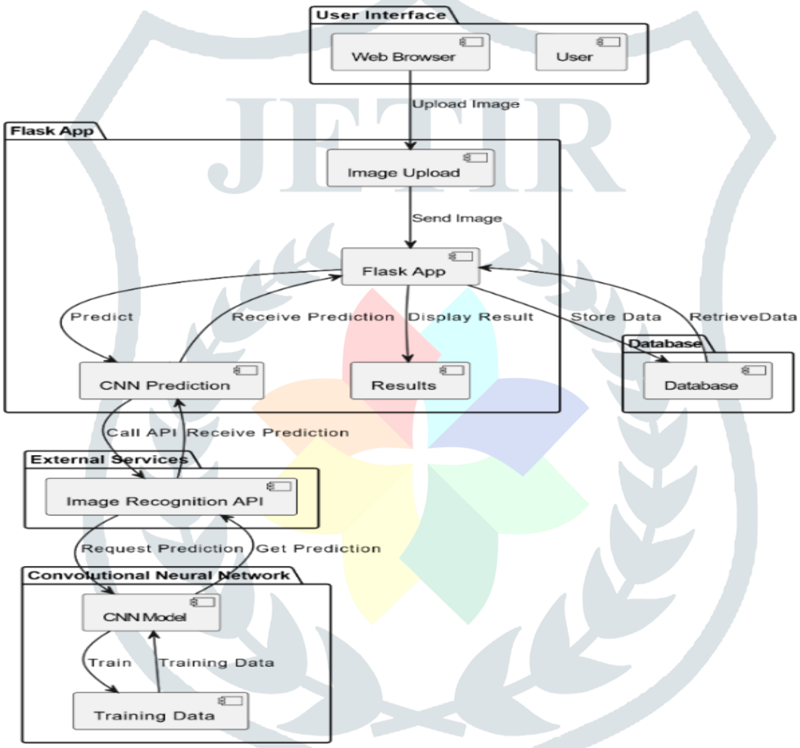

Fig. 5.2 Architecture For Animal and Birds Species Identification

Certainly, let's break down the components and their interactions in the diagram:

1. **User interface:**
   - **[USER]:** Represents the end user who interact with the system.
   - **[Web Browser]:** The user accesses the system via a web browser.
2. **Flask App:**
   - **[Flask App]:** The core of your web application built with Flask, which handles user requests.
   - **[Image Upload]:** This component receives image uploads from the user.
   - **[CNN Prediction]:** Responsible for making predictions using the Convolutional Neural Network (CNN).
   - **[Results]:** Displays the prediction results to the user.
3. **Convolutional Neural Network:**
   - **[CNN MODEL]:** Your trained Convolutional Neural Network model, which can identify animals and birds from images.
   - **[Training Data]:** The dataset that was used to train the CNN.
4. **External Services:**
   - **[Image Recognition API]:** An external service that the Flask App uses to perform image recognition. It sends

image data to this service for analysis.

5. **Database:**
   - **[Database]:** Represents a database where you might store and retrieve data, such as user preferences or historical data for future improvements.

Now, let's follow the flow:

1. The [User] interacts with the system through a [Web Browser] and uploads an image.
2. The uploaded image is received by [Image Upload] in the Flask App.
3. The Flask App forwards the image to [CNN Prediction] for processing.
4. [CNN Prediction] needs to perform image recognition, but it relies on an [Image Recognition API] to do this. It sends the image data to the external service.
5. The [Image Recognition API] utilizes the [CNN Model] to make predictions on the image. The [Training Data] was used to train this model in advance.
6. The prediction results are sent back from the [Image Recognition API] to [CNN Prediction].
7. Finally, the results are displayed to the user through [Results]. The Flask App may also store or retrieve data from the [Database] to enhance the user experience or keep track of previous results.

5.3 Algorithm & Process Design

5.3.1 Algorithm

Step 1: Start.
Step 2: Prompt the user to upload an image.
Step 3: Check if an image was uploaded.
Step 4: If no image was uploaded, return to step 2 to prompt the user to upload an image again.
Step 5: If an image was uploaded, proceed with the following steps:
Step 5.1: Preprocess the uploaded image (resize, normalize, etc.).
Step 5.2: Apply a trained Convolutional Neural Network (CNN) model to the pre-processed image for species identification.
Step 5.3: Check if the identification was successful.
Step 5.4: If a species is identified, retrieve species information.
Step 5.5: Display the species information to the user.
Step 5.6: If no species is identified, display "No Species Identified ".
Step 6: End.

5.3.2 Process Design

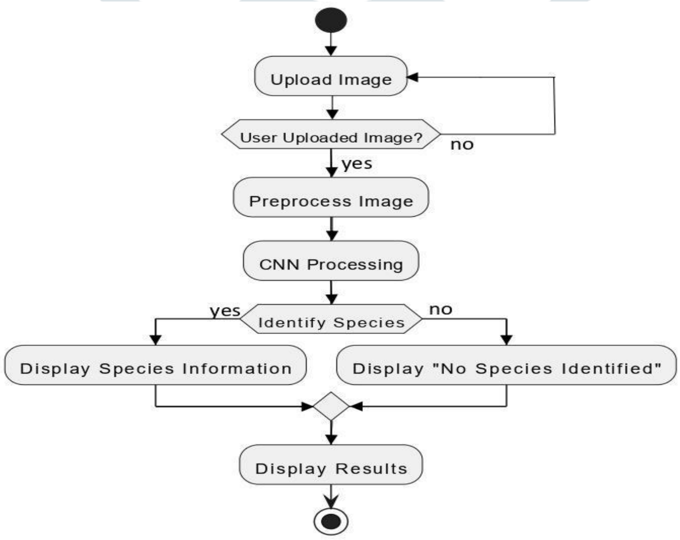

Fig. 5.3.2 Flowchart for Animal & Bird Species Identification

6. Experimental Set Up

6.1 Details Of Database Or Details About Input To Systems Or Selected Data

1. **Image Dataset:** To build and train our species identification system, we collected a diverse dataset of animal and bird

images, meticulously labelled with their corresponding species. This dataset is crucial for training and evaluating our machine learning model.

2. **Data Labelling:** We assigned accurate species labels to each image in our dataset. This required expert knowledge in the field, ensuring precise species identification.
3. **Data Split:** The dataset was divided into three parts: the training set to teach our model, the validation set to fine-tune its performance, and the testing set to evaluate its accuracy.
4. **Data Augmentation:** To enhance the model's robustness, we employed data augmentation techniques, creating variations of images through rotations, scaling, and other transformations.
5. **Database Management:** For efficient storage and retrieval of our extensive dataset, we used a database management system.
6. **Input to the System:** Our system allows users to upload images for species identification. These uploaded images undergo preprocessing and CNN processing.
7. **Species Information Database:** To provide users with informative species details, we maintain a separate database containing information about various animal and bird species, including common names, scientific names, habitats, and behaviours.
8. **APIs and Libraries:** We integrated external APIs and libraries for tasks like image processing, machine learning, and database management.
9. **User Feedback:** We actively collect and consider user feedback to continually improve our system's accuracy and performance.

6.2 Performance Evaluation Parameters For Validation

In the context of our project, "Performance Evaluation Parameters for Validation" are essential metrics used to assess the accuracy and effectiveness of our “Animal & Bird species identification from an image” system. These parameters are key to measuring the system's precision, recall, and user satisfaction, ensuring it meets its intended goals.

1. **Accuracy**: This measures how often our system correctly identifies the species from the images users upload. It gives us an idea of how reliable and precise our system is in identifying species.
2. **Precision**: Precision shows us the percentage of correct species identifications when our system makes a positive prediction. It helps assess the quality of our results, aiming for high precision to minimize errors.
3. **Recall (Sensitivity)**: Recall tells us how well our system captures all the instances of species in the images. It ensures we don't miss identifying species when they are present.
4. **User Feedback and Usability**: In addition to technical metrics, gathering user feedback is crucial. It helps us understand how user-friendly and satisfying our system is for real users. User feedback is invaluable for continuous improvement.

6.3 Accuracy & Loss Graph Of Our Project

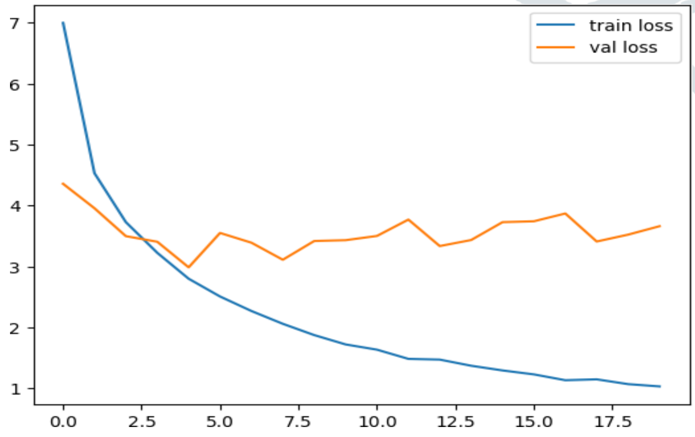

Fig. 6.3.1 Loss Graph

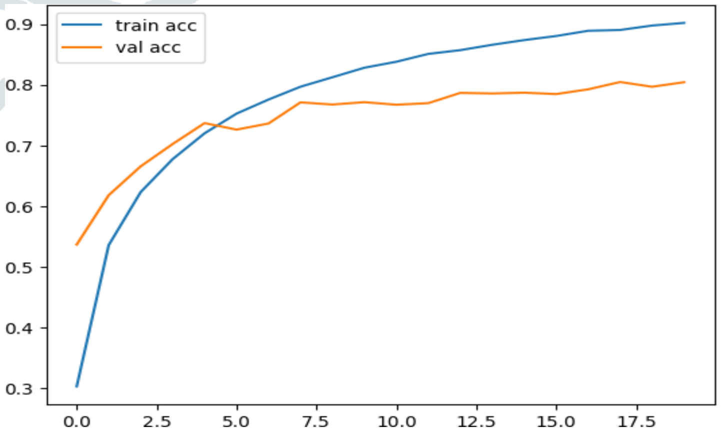

Fig. 6.3.2 Accuracy Graph

7. Conclusion

Our Animal and Bird Identification System, developed using Flask and Convolutional Neural Networks (CNNs), offers an efficient and user-friendly solution for the precise classification of animals and birds in images. By combining Flask and CNN technology, we have created a user-friendly web application that simplifies the identification process. The integration of an external Image Recognition API significantly enhances the system's prediction accuracy. Additionally, our database functionality enables users to store and retrieve data, providing a personalized and interactive user experience. This project addresses the increasing demand for effective image-based animal and bird identification, catering to a diverse audience, from wildlife enthusiasts to scientific researchers. The seamless blend of technology and user-centric design ensures that our system serves as a valuable resource for individuals interested in identifying and learning more about the animal and bird species in our environment. With its simplicity and robust features, this project makes a substantial contribution to the field of image recognition and species identification.

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