**Bird Species Identification System**

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**ABSTRACT**

This project presents a web application aimed at enhancing bird species identification for biodiversity monitoring, conservation, and citizen science. While current tools for species recognition face challenges in accuracy and often lack detailed species data, geolocation, and trend analysis features, this application addresses these gaps with an innovative solution. Users can upload bird photos, analyzed through a ResNet34-based model known for its accuracy in recognizing fine details, with results displaying habitat, diet, and migration patterns for each identified species. Geolocation integration and interactive heatmaps allow users to visualize hotspots. The intuitive interface and efficient design ensure smooth, responsive interactions, while comprehensive species information supports conservationists, researchers, and bird enthusiasts in studying avian diversity. This tool bridges science and public engagement, offering a valuable resource for ecological research and conservation efforts.

**CHAPTER-1**

**INTRODUCTION**

**1. INTRODUCTION**

Bird species identification is essential for monitoring biodiversity, supporting conservation efforts, and promoting citizen science initiatives. Birds fulfill numerous ecological roles as pollinators, seed dispersers, and indicators of environmental health, making them a critical focus for scientists and conservationists alike. Accurate identification of bird species, however, remains a challenging task, especially for non-experts and citizen scientists, due to the extensive diversity among bird species and the subtle physical similarities between closely related species. These challenges have driven the development of bird identification tools and platforms, yet many existing solutions lack the precision, depth, and functionality required to fully support conservation and research needs.

Recent advancements in technology, particularly in machine learning and image recognition, have led to promising progress in automated species identification. Tools based on sophisticated models, like EfficientNet, use photographic analysis to distinguish species with some success. Despite this progress, these systems often struggle with closely related species and similar-looking birds, which impacts their overall accuracy and effectiveness. Furthermore, most current systems focus solely on visual identification and do not provide integrated features, such as geolocation or in-depth species information. This limitation restricts their utility for tracking bird populations, monitoring distribution trends, and assessing species behavior, making them less useful for comprehensive conservation efforts.

This project proposes an Automated Bird Species Identification System designed to address these shortcomings by enhancing accuracy and expanding functionality. The web-based tool leverages a ResNet34-based machine learning model, recognized for its ability to capture fine visual details, improving identification accuracy even for challenging cases involving similar species. This precision is essential for researchers and conservationists who rely on accurate species identification to monitor biodiversity and assess ecological changes effectively.

In addition to improving accuracy, the proposed system introduces geolocation and trend analysis features to provide a more comprehensive approach to bird species monitoring. By enabling geolocation mapping, the tool allows users to visualize bird sightings on an interactive map, helping to identify hotspots and track species distribution over time. This feature not only supports researchers and conservationists but also engages bird enthusiasts and the general public, encouraging broader participation in bird monitoring efforts.

Furthermore, each identified bird species is accompanied by extensive information on its habitat, diet, and migration patterns. This depth of information provides context, enabling users to gain insights into species behavior and ecology. Such comprehensive data supports conservation planning and research, as well as public awareness and education, fostering a greater understanding of avian diversity and the importance of bird conservation.

The system’s user-friendly interface is designed to facilitate smooth and intuitive interactions, making it accessible to users of all levels of expertise. By simplifying the process of uploading images, navigating the tool, and accessing detailed information, the system encourages wider engagement from both experts and amateurs. This design aims to bridge the gap between scientific research and public engagement, transforming bird identification from a niche task into a broader conservation and educational resource.

Overall, the Automated Bird Species Identification System offers a valuable tool for ecological research, conservation, and citizen science. By combining high-accuracy species identification with geolocation and detailed species information, the project not only enhances bird monitoring efforts but also promotes a deeper connection between people and nature, empowering users to contribute actively to biodiversity conservation.

**1.1 MOTIVATION**

The need for accurate and accessible bird species identification tools has become more urgent due to growing environmental threats, such as habitat loss and climate change. Accurate identification is vital for conservationists and researchers to track species populations, study migration patterns, and assess ecosystem health. While citizen science has become a powerful tool in biodiversity monitoring, providing an easy-to-use identification system will encourage broader public engagement, enabling enthusiasts and casual observers to contribute to scientific research. Additionally, by integrating machine learning with data visualization features like geolocation and heatmaps, this system can offer detailed insights into species distribution and behavior, furthering conservation efforts and research.

**1.2 PROBLEM STATEMENT**

Existing bird identification systems often rely solely on photographic analysis for species recognition. While they utilize advanced models, such as EfficientNet, these systems still face challenges in accurately identifying species, particularly closely related ones with similar physical characteristics. Limitations also include the absence of geolocation features and lack of detailed species data, reducing the system’s utility for tracking species distribution trends, studying ecological patterns, and supporting conservation efforts. This project aims to develop an enhanced system that not only improves identification accuracy through a ResNet34-based model but also integrates geolocation, trend analysis, and detailed species information to provide a comprehensive bird identification solution.

**1.3 PROJECT OBJECTIVES**

1. **Develop an Accurate Identification System:** Utilize a ResNet34-based machine learning model to enhance species identification accuracy, especially for closely related species with fine visual distinctions.
2. **Integrate Geolocation :** Implement geolocation and mapping functionalities, allowing users to visualize bird sightings on an interactive map.
3. **Provide Species Information:**For each identified bird species, present detailed data on habitat, diet, and migration patterns, catering to researchers, conservationists, and bird enthusiasts seeking in-depth knowledge.
4. **Create a User-Friendly Interface:** Design an intuitive and efficient web application that allows seamless user interactions, enabling easy image uploads, navigation, and data visualization.

**CHAPTER-2**

**LITERATURE REVIEW**

**Literature Review**

The task of identifying bird species through automated systems has seen numerous advancements with the integration of CNNs, data augmentation, and metadata. Yang et al. (2024) introduced a feature enhancement approach for bird species identification using contrastive learning, which showed substantial improvement in accuracy [1]. Gómez-Gómez et al. (2021) conducted a comparative study on deep learning models, focusing on Western Mediterranean wetland birds, underscoring the need for high-quality datasets and fine-tuning of models to specific ecological zones [2]. Gupta et al. (2022) used spectrogram-based models for bird sound classification, demonstrating CNN effectiveness in identifying species with complex acoustic patterns [3].

For acoustic-based species identification, Chandra and Sen (2022) applied CNNs with data augmentation to distinguish species accurately, even in noisy environments [4]. Triveni and Singh (2020) highlighted the importance of data augmentation, showing how it enhances CNN performance against environmental noise—a crucial factor for real-world applications [5]. Additionally, Li et al. (2021) explored environmental factors influencing bird species distribution, revealing how linear regression models and CNNs can be used to analyze distribution patterns [6].

Bhattacharya et al. (2022) furthered this by employing hybrid deep neural networks and data augmentation, achieving notable improvements in model robustness and accuracy [7]. Wu and Chen (2023) explored fine-grained visual categorization with CNNs, addressing the challenges in identifying visually similar species through enhanced visual features [8]. Morales et al. (2023) implemented deep residual networks and image augmentation, demonstrating their potential in species identification through detailed image analysis [9].

Geolocation data integration has become increasingly popular to enhance species identification. Zhou and Tang (2021) combined CNNs with geolocation metadata, refining classification by narrowing down species based on location-specific distributions [10]. Andersen and Muller (2021) explored the application of transfer learning in citizen science projects, showing how transfer learning models can generalize better across varying environments [11].

The integration of real-time applications for field usage has also been a focal point. Suzuki et al. (2023) combined CNNs with environmental metadata, achieving a model suitable for real-time species identification, useful for immediate deployment in natural habitats [12]. Singh and Thakur (2024) emphasized the role of hybrid models and fine-grained feature extraction in improving species detection, addressing classification issues in environments with high biodiversity [13]. Zhang et al. (2023) focused on model fine-tuning to enhance CNNs for species identification, illustrating that model adaptations significantly improve accuracy and applicability across environments [14].

Combining machine learning with geolocation, Cao et al. (2023) examined the potential of CNNs to classify species by integrating environmental data, offering an accurate tool for ecologists [15]. Watanabe et al. (2022) applied CNNs to bird sound identification, demonstrating high recognition accuracy by utilizing deep learning for spectrogram analysis [16]. Chen et al. (2022) discussed the importance of data augmentation, providing insights into how it increases CNN robustness in varying light and pose conditions [17].

Other studies, such as Lim et al. (2021), utilized transfer learning and augmented datasets to improve identification accuracy, showing that CNNs can be adapted to different dataset conditions effectively [18]. Jain et al. (2022) fine-tuned CNNs to adapt better to specific bird species, increasing classification performance through tailored training approaches [19]. Xu and Ma (2023) emphasized that CNNs can classify species across varying poses and lighting conditions, highlighting the need for diverse datasets to train robust models [20].

**Research Gap**

While significant strides have been made in automated bird species recognition, a gap exists in the development of a real-time, interactive web application that not only identifies species but also provides detailed visualizations with integrated geolocation. Existing models have largely been tested in controlled environments and lack comprehensive visualization platforms that could support field researchers with real-time data and geolocation tracking. Additionally, the application of ResNet for enhanced feature extraction and classification accuracy in a responsive web-based tool remains underexplored. This study seeks to address these gaps by developing a web application using the ResNet model, allowing for real-time identification, visualization, and geolocation-based filtering, thereby creating a more dynamic and field-oriented identification tool.

**CHAPTER-3**

**SYSTEM ANALYSIS**

**3.1 EXISTING SYSTEM**

Recent advancements in bird species identification have employed sophisticated image recognition techniques, such as EfficientNet, which focus on species recognition through photographic analysis. However, these systems often encounter significant challenges in achieving high accuracy, particularly when identifying closely related species or those with similar characteristics. This limitation underscores the ongoing need for improvements in species detection methods that rely solely on image-based approaches, necessitating further research and innovation to enhance identification effectiveness and reliability.

**Disadvantages of the Existing System**

1. **Lower Accuracy in Identification**: Existing systems, such as those using EfficientNet, often struggle with achieving high accuracy in species identification, which impacts their effectiveness in conservation and research applications.
2. **Absence of Geolocation and Trend Data**: Current systems lack integration of geolocation features and trend-tracking capabilities, preventing users from observing species distribution, hotspots,.
3. **Limited Species Information**: Current systems often lack detailed species information, such as habitat, diet, or migration patterns, reducing their usefulness for researchers, conservationists, and bird enthusiasts.
   1. **PROPOSED SYSTEM**

The proposed bird identification web application integrates machine learning-based species recognition with geolocation and heatmap functionalities to provide a comprehensive tool for users. By allowing users to upload bird photos, the application not only identifies species but also offers detailed information about each bird, including habitat, diet, and migratory patterns. Utilizing the precision of ResNet34-based model, the application delivers accurate identifications and species distribution explore biodiversity in a user-friendly environment.

**Advantages of the Proposed System**

1. **High Accuracy with ResNet34-based model:** By utilizing ResNet34-based model, the proposed system enhances identification accuracy, especially in distinguishing fine details, making it more effective for conservation and research purposes.
2. **Integrated Geolocation and Trend Tracking:** The proposed system includes geolocation allowing users to view species hotspots.
3. **Comprehensive Species Information:** Each identified bird is accompanied by detailed information, including habitat, diet, and migration patterns, providing researchers, conservationists, and bird enthusiasts with essential context for deeper understanding and study.

**3.3 FEASIBILITY STUDY**

A feasibility study is a critical step in project development, aimed at evaluating whether a proposed solution is viable in terms of cost, technology, and operational requirements. The Automated Bird Species Identification System project underwent a detailed feasibility study to ensure that the project can be successfully developed, deployed, and maintained. This study examines the project from technical, operational, and economic perspectives, ensuring that it meets user needs, is cost-effective, and aligns with technological standards.

**3.3.1 Technical Feasibility**

Technical feasibility evaluates whether the technology, skills, and tools required for the project are available and capable of achieving the desired results. For this project, several advanced technologies are used, including a ResNet34-based machine learning model for image recognition, geolocation mapping, and data visualization.

**Machine Learning Model:** The ResNet34 model is well-suited for bird species identification, offering high accuracy for distinguishing fine-grained details. With this model, the project leverages pre-trained weights and transfer learning, reducing the need for large datasets and intensive training resources, which makes the model efficient and feasible for real-time processing.

**Geolocation Mapping and Heatmaps:** The project uses geolocation services and heatmap visualization, facilitated by APIs like Google Maps or Leaflet. These tools are widely available and relatively easy to integrate, making geolocation feasible for mapping bird sightings.

**Software and Frameworks:** The project relies on commonly available software, such as Python, Flask for the web framework, and mapping libraries, all of which are open-source or have manageable licensing requirements. The system’s hardware requirements (e.g., 16GB RAM, Intel Core i5 or equivalent CPU) are also accessible for most users, making the project feasible within typical technical constraints.

**3.3.2 Operational Feasibility**

Operational feasibility assesses whether the project can function as intended and meet user expectations. This system is designed to serve multiple user groups, including researchers, conservationists, and bird enthusiasts, offering them accurate species identification, interactive mapping, and comprehensive species information.

**User Accessibility:** The application’s intuitive interface simplifies interactions, making it accessible even for non-experts. Features such as photo uploads, real-time identification, and easy navigation contribute to a positive user experience, ensuring that the system aligns with the needs of various user demographics.

**Functionality and Scalability:** The system is designed to handle multiple user requests, supported by cloud integration if needed for scaling purposes. Furthermore, the system can adapt to future enhancements, such as expanding species databases or incorporating additional features like climate-related trend analysis.

**3.3.3 Economic Feasibility**

Economic feasibility evaluates the cost-benefit aspect of the project, determining if the project’s benefits justify the initial investment and ongoing expenses.

**Development and Maintenance Costs:** Developing this project involves costs related to machine learning model implementation, web application design, geolocation API usage, and data storage. However, using open-source software (Python, Flask, ResNet) and APIs with manageable costs helps reduce expenses.

**Cost-Benefit Analysis:** The benefits of the project, including enhanced biodiversity monitoring, support for conservation research, and increased public engagement in citizen science, outweigh the costs. The potential for collaboration with research institutions or environmental organizations further enhances the project’s economic feasibility by attracting possible funding or sponsorships.

The feasibility study indicates that the Automated Bird Species Identification System is technically achievable, operationally effective, and economically viable. The project’s technical foundation, operational design, and cost structure align well with its goals, ensuring a successful development and deployment process.

**CHAPTER-4:**

**SYSTEM REQUIREMENTS SPECIFICATION**

**4.1 FUNCTIONAL REQUIREMENTS**

Functional requirements specify the core functionalities the Automated Bird Species Identification System must perform to meet user needs. These include:

1. **Image Upload and Identification:**

* Users can upload images of birds for species identification.
* The system processes images through the ResNet34 model and returns the identified bird species.

1. **Species Information Display:**

* For each identified species, the system displays detailed information, including habitat, diet, and migration patterns.

1. **Geolocation Mapping:**

* Users can add geolocation data to their image uploads.
* The system plots sightings on an interactive map, showing distribution and helping visualize sighting hotspots.

**4.2 NON-FUNCTIONAL REQUIREMENTS**

Non-functional requirements define the quality attributes the system must exhibit, ensuring smooth, reliable, and secure operation.

1. **Performance:**

* The system should process and return identification results within a few seconds.
* Heatmap generation and trend analysis should occur in real-time or near real-time for an interactive experience.

1. **Usability:**

* The interface should be intuitive and user-friendly, with clear navigation and accessible features.
* Visual elements like maps and heatmaps should be interactive, allowing users to explore data easily.

1. **Reliability and Availability:**

* The system should be highly available, with minimal downtime to ensure users can access it when needed.
* A robust backup and recovery mechanism should prevent data loss.

1. **Security:**

* User authentication data must be securely encrypted.
* Role-based access control should protect sensitive data and prevent unauthorized access.

1. **Scalability:** The system should be capable of handling a growing number of users and data inputs without performance degradation.
2. **Compatibility:**The application should be compatible with multiple operating systems, including Windows, macOS, and Linux, and work well on standard browsers.

**4.3 INPUT & OUTPUT DESIGN**

**Input Design:** Image Upload: Users upload bird images in supported formats (e.g., JPG, PNG) for identification.

**Output Design:**

* Identification Result: The system displays the identified bird species.
* Species Information: The output includes habitat, diet, and migration patterns, displayed in a structured format.
* Geolocation Map and Heatmap: The system visually outputs geolocation data on interactive maps and heatmaps, showing species biodiversity hotspots.

**4.4 SYSTEM REQUIREMENTS AND SPECIFICATION**

**Hardware Requirements**

* CPU: Intel Core i5 or equivalent for efficient processing.
* RAM: 16 GB minimum to support fast data handling and processing.
* Storage: At least 10 GB of free space for storing images, user data, and system files.
* Operating System Compatibility: Supports Windows, macOS, or Linux.

**Software Requirements**

* Operating System: Compatible with Windows 10/11, macOS, or Linux distributions.
* Programming Language: Python 3.7 or higher.
* Web Framework: Flask for building the web interface and handling backend functionalities.
* Machine Learning Framework: PyTorch or TensorFlow for implementing the ResNet34 model.
* Database Management System: MySQL or PostgreSQL for storing user information, species data, and geolocation data.
* Mapping and Visualization APIs: Google Maps API or Leaflet for geolocation mapping and heatmap visualization.

**CHAPTER-5**

**SYSTEM DESIGN**

**5.2 UML DIAGRAMS**

UML (Unified Modeling Language) diagrams serve as crucial tools in software engineering, enabling the visualization and communication of a system's structure and behavior. Among these diagrams, structure diagrams focus on representing the static structure of a system, highlighting its components and their relationships.

There are 2 types of diagrams in UML listed below

1. **Structure Diagrams**
2. **Composite Structure Diagram**

**STRUCTURE DIAGRAMS**

Structure diagrams in UML (Unified Modeling Language) represent the static structure of a system, focusing on the elements that constitute the system and their relationships. These diagrams provide a visual representation of the architecture, components, and organization of the system.

There are three main types of structure diagrams in Structure Diagrams

* Class Diagram
* Component Diagram
* Deployment Diagram

**Class Diagram:**

The Class Diagram illustrates the static structure of the system by depicting classes, attributes, methods, and their relationships. It provides a blueprint of the system's architecture, showing how different components interact with each other.

Fig: Class Diagram

**Component Diagram:**

The Component Diagram depicts the physical components or modules of the system and their dependencies. It shows how the system is decomposed into smaller components, illustrating the relationships between them.

Fig: Component Diagram

**Deployment Diagram:**

The Deployment Diagram illustrates the physical deployment of software components across different hardware nodes. It shows how software components are distributed across servers, computers, or other hardware devices.

Fig: Deployment Diagram

**COMPOSITE STRUCTURE DIAGRAM**

The Composite Structure Diagram depicts the internal structure of a class or component, showing how its parts are interconnected. It provides a detailed view of the composition and collaboration among different elements within a class or component. There are four main types of composite structure diagrams:

* Use Case Diagram
* Activity Diagram
* State Machine Diagram
* Sequence Diagram

**Use Case Diagram:**

The Use Case Diagram illustrates the various use cases or functionalities of the system from the perspective of users. It shows how users interact with the system to accomplish specific tasks or goals.

Fig: Use Case Diagram

**Activity Diagram:**

The Activity Diagram represents the flow of control or workflow within the system, depicting the sequence of activities or actions performed to achieve a particular task or functionality.

Fig: Activity Diagram

**State Machine Diagram:**

The State Machine Diagram models the behavior of individual objects or components by depicting their states and transitions. It shows how objects transition from one state to another in response to events or stimuli.

Fig: State Machine Diagram

**Sequence Diagram:**

The Sequence Diagram illustrates the interactions between different components or objects in a sequential manner. It shows the sequence of messages exchanged between objects over time, depicting the flow of control or communication within the system.

Fig: Sequence Diagram

**CHAPTER-6**

**IMPLEMENTATION**

This chapter provides a comprehensive look into the implementation process for the Automated Bird Species Identification System. It covers the system architecture, core modules, technologies utilized, and the sequential steps involved in developing, integrating, and testing the system for effective bird species identification and geolocation mapping.

**6.1 SYSTEM ARCHITECTURE**

The Automated Bird Species Identification System is designed with a modular architecture that supports scalability and ease of maintenance. Each component has a distinct role, ensuring smooth interaction between the user interface, backend, and machine learning model for an efficient and accurate identification process.

**Core Components:**

1. **Frontend Interface**:
   * **Technology**: Built with HTML, CSS, and JavaScript.
   * **Purpose**: Provides a user-friendly interface for uploading bird images, viewing identified species, and accessing geolocation and heatmap data.
   * **Functionality**: The frontend interface allows users to interact seamlessly with the system, view bird species details, and explore mapped sighting data.
2. **Backend Server**:
   * **Technology**: Implemented using Flask, a lightweight Python web framework.
   * **Purpose**: Acts as a bridge between the frontend interface and the machine learning model, managing data flow and processing.
   * **Functionality**: Handles user requests, routes them to the correct modules, and processes responses. The backend also supports image processing, species identification, and database interactions.
3. **Machine Learning Model**:
   * **Model Choice**: ResNet34, a convolutional neural network (CNN) architecture.
   * **Purpose**: Performs core species identification by analyzing uploaded images.
   * **Functionality**: The ResNet34 model is pretrained and fine-tuned on a comprehensive dataset of bird images, ensuring high accuracy in species recognition. The model classifies bird species based on uploaded images, returning a species label and confidence score.
4. **Geolocation and Visualization APIs**:
   * **APIs Used**: Google Maps API or Leaflet for interactive maps.
   * **Purpose**: Enables visualization of bird sighting locations and biodiversity hotspots.
   * **Functionality**: Geolocation data from sightings is mapped on an interactive interface, allowing users to view sighting distribution and heatmaps of bird species diversity.

**6.2 IMPLEMENTATION OF CORE MODULES**

**6.2.1 Image Upload and Identification**

1. **Image Upload Module**:
   * **Function**: Allows users to upload bird images via an HTML form.
   * **Process**: Uploaded images are preprocessed to align with the model's requirements, ensuring optimal compatibility. The images are then temporarily stored on the server for processing.
2. **Identification Process**:
   * **Function**: Passes the uploaded image to the ResNet34 model.
   * **Process**: The model performs classification and outputs a species label with a confidence score. This result is displayed to the user along with additional species information, enhancing the system’s accuracy and usability.

**6.2.2 Species Information Display**

1. **Species Database Query**:
   * **Function**: Retrieves detailed information about identified bird species from a dedicated database.
   * **Process**: Upon identification, the system queries a database to obtain data such as habitat, diet, and migration patterns of the identified species.
2. **Display Module**:
   * **Function**: Dynamically displays detailed species information on the results page.
   * **Process**: Information is formatted for clarity, and users can expand sections to view additional details about the identified species.

**6.2.3 Geolocation Mapping and Visualization**

1. **Geolocation Mapping**:
   * **Function**: Stores and maps bird sighting locations based on geolocation data.
   * **Process**: Users input latitude and longitude with image uploads, which are stored in the database. The geolocation data is then visualized on a map using Google Maps API or Leaflet.
2. **Heatmap Visualization**:
   * **Function**: Generates heatmaps to display bird biodiversity hotspots.
   * **Process**: Heatmaps are created based on the geolocation data of bird sightings, providing a visual representation of species density and distribution.

**6.3 MACHINE LEARNING MODEL IMPLEMENTATION**

1. **Model Selection**:
   * **Rationale**: ResNet34 was selected for its balance of accuracy and efficiency in image feature extraction, particularly for tasks involving detailed imagery like bird species recognition.
2. **Training and Fine-tuning**:
   * **Process**: Initially pretrained on a general dataset, the model was fine-tuned using a large bird species-specific dataset. Data augmentation techniques, such as random cropping, flipping, and color variations, were applied to improve the model’s ability to generalize across varied images.
3. **Integration**:
   * **Process**: The trained model was incorporated into the Flask backend. Upon receiving an image from the frontend, the backend routes the image to the model for identification, then processes and returns the results to the user.

**6.4 API INTEGRATION**

1. **Leaflet Integration**:
   * **Purpose**: For interactive geolocation and heatmap visualizations.
   * **Process**: Leaflet API is used to create maps where bird sighting locations can be explored geographically. The interactive map allows users to zoom, pan, and view details about each sighting.
2. **Google Maps API** (optional):
   * **Purpose**: An alternative to Leaflet, Google Maps API provides rich mapping capabilities.
   * **Process**: Used for adding advanced map features like satellite view and street view, enhancing the user's experience in exploring bird sightings and hotspot areas.

**6.5 DATASET DESIGN**

The "Randomized Background 100-Bird Species" dataset is a valuable asset for training bird identification models. Its structure, variety, and volume of data make it an ideal choice for deep learning applications focused on species recognition.

**Dataset Overview**

* **Size**: Approximately 880 MB with around 40,500 images.
* **Categories**: Covers 100 bird species, providing diverse visual samples with randomized backgrounds.
* **Structure**: Divided into train, test, and valid directories, each with subdirectories for individual species.

**Dataset Components**

* **Images**: Each image has a unique background, enhancing the model’s generalization to real-world images with complex settings.
* **CSV File**: birds.csv includes metadata such as species labels and filenames, assisting in dataset management and validation.

**6.6 TECHNOLOGY DESCRIPTION**

**Algorithms and Techniques**

* **Image Recognition Model**: The ResNet34 model is fine-tuned to identify bird species from uploaded images.
* **Geolocation Mapping**: Integrated geolocation and mapping APIs (Google Maps or Leaflet) allow for interactive map visualizations of sighting data.
* **Heatmap Visualization**: Mapping libraries generate heatmaps showing species density, which highlights biodiversity hotspots.
  1. **CODING**

# %%

import torch.nn as nn

import torch.nn.functional as F

import torch

import torchvision.transforms as transforms

import os

from PIL import Image

import matplotlib.pyplot as plt

# %% [markdown]

# Defining the model

# %%

def conv\_block(in\_channels, out\_channels, activation=False, pool=False):

layers = [nn.Conv2d(in\_channels, out\_channels, kernel\_size=3, padding=1),

nn.BatchNorm2d(out\_channels)]

if activation: layers.append(nn.ReLU(inplace=True))

if pool: layers.append(nn.MaxPool2d(2))

return nn.Sequential(\*layers)

class ResNet34(nn.Module):

def \_\_init\_\_(self, in\_channels, num\_classes):

super().\_\_init\_\_()

self.conv1 = nn.Sequential(nn.Conv2d(in\_channels, 64, kernel\_size=7, stride=1, padding=4),

nn.BatchNorm2d(64),nn.MaxPool2d(2), nn.ReLU(inplace=True))

self.res1 = nn.Sequential(conv\_block(64, 64,activation=True), conv\_block(64, 64))

self.res2 = nn.Sequential(conv\_block(64, 64,activation=True), conv\_block(64, 64))

self.res3 = nn.Sequential(conv\_block(64, 64,activation=True), conv\_block(64, 64))

self.downsample1=nn.Sequential(conv\_block(64, 128,pool=True))

self.res4 = nn.Sequential(conv\_block(64, 128,activation=True, pool=True),

conv\_block(128,128))

self.res5 = nn.Sequential(conv\_block(128, 128,activation=True), conv\_block(128, 128))

self.res6 = nn.Sequential(conv\_block(128, 128,activation=True), conv\_block(128, 128))

self.res7 = nn.Sequential(conv\_block(128, 128,activation=True), conv\_block(128, 128))

self.res8 = nn.Sequential(conv\_block(128, 256,activation=True, pool=True),

conv\_block(256,256))

self.downsample2 = nn.Sequential(conv\_block(128, 256,pool=True))

self.res9 = nn.Sequential(conv\_block(256, 256,activation=True), conv\_block(256, 256))

self.res10 = nn.Sequential(conv\_block(256, 256,activation=True), conv\_block(256, 256))

self.res11 = nn.Sequential(conv\_block(256, 256,activation=True), conv\_block(256, 256))

self.res12 = nn.Sequential(conv\_block(256, 256,activation=True), conv\_block(256, 256))

self.res13 = nn.Sequential(conv\_block(256, 256,activation=True), conv\_block(256, 256))

self.res14 = nn.Sequential(conv\_block(256, 512,activation=True, pool=True),

conv\_block(512,512))

self.downsample3 = nn.Sequential(conv\_block(256, 512,pool=True))

self.res15 = nn.Sequential(conv\_block(512, 512,activation=True), conv\_block(512, 512))

self.res16 = nn.Sequential(conv\_block(512, 512,activation=True), conv\_block(512, 512,activation=True))

self.classifier = nn.Sequential(nn.AdaptiveMaxPool2d((1,1)),

nn.Flatten(),

nn.Dropout(0.17),

nn.Linear(512, num\_classes))

def forward(self, xb):

out = self.conv1(xb)

out = self.res1(out) + out

out = self.res2(out) + out

out = self.res3(out) + out

out = self.downsample1(out) +self.res4(out)

out = self.res5(out) + out

out = self.res6(out) + out

out = self.res7(out) + out

out = self.downsample2(out) +self.res8(out)

out = self.res9(out) + out

out = self.res10(out) + out

out = self.res11(out) + out

out = self.res12(out) + out

out = self.res13(out) + out

out = self.downsample3(out) + self.res14(out)

out = self.res15(out) + out

out = self.res16(out) + out

out = self.classifier(out)

return (out)

# %% [markdown]

# Making list of the classes

# %%

bird\_name\_map= {0: 'ABBOTTS BABBLER', 1: 'ABBOTTS BOOBY', 2: 'ABYSSINIAN GROUND HORNBILL', 3: 'AFRICAN CROWNED CRANE', 4: 'AFRICAN EMERALD CUCKOO', 5: 'AFRICAN FIREFINCH', 6: 'AFRICAN OYSTER CATCHER', 7: 'AFRICAN PIED HORNBILL', 8: 'ALBATROSS', 9: 'ALBERTS TOWHEE', 10: 'ALEXANDRINE PARAKEET', 11: 'ALPINE CHOUGH', 12: 'ALTAMIRA YELLOWTHROAT', 13: 'AMERICAN AVOCET', 14: 'AMERICAN BITTERN', 15: 'AMERICAN COOT', 16: 'AMERICAN FLAMINGO', 17: 'AMERICAN GOLDFINCH', 18: 'AMERICAN KESTREL', 19: 'AMERICAN PIPIT', 20: 'AMERICAN REDSTART', 21: 'AMERICAN WIGEON', 22: 'AMETHYST WOODSTAR', 23: 'ANDEAN GOOSE', 24: 'ANDEAN LAPWING', 25: 'ANDEAN SISKIN', 26: 'ANHINGA', 27: 'ANIANIAU', 28: 'ANNAS HUMMINGBIRD', 29: 'ANTBIRD', 30: 'ANTILLEAN EUPHONIA', 31: 'APAPANE', 32: 'APOSTLEBIRD', 33: 'ARARIPE MANAKIN', 34: 'ASHY STORM PETREL', 35: 'ASHY THRUSHBIRD', 36: 'ASIAN CRESTED IBIS', 37: 'ASIAN DOLLARD BIRD', 38: 'AUCKLAND SHAQ', 39: 'AUSTRAL CANASTERO', 40: 'AUSTRALASIAN FIGBIRD', 41: 'AVADAVAT', 42: 'AZARAS SPINETAIL', 43: 'AZURE BREASTED PITTA', 44: 'AZURE JAY', 45: 'AZURE TANAGER', 46: 'AZURE TIT', 47: 'BAIKAL TEAL', 48: 'BALD EAGLE', 49: 'BALD IBIS', 50: 'BALI STARLING', 51: 'BALTIMORE ORIOLE', 52: 'BANANAQUIT', 53: 'BAND TAILED GUAN', 54: 'BANDED BROADBILL', 55: 'BANDED PITA', 56: 'BANDED STILT', 57: 'BAR-TAILED GODWIT', 58: 'BARN OWL', 59: 'BARN SWALLOW', 60: 'BARRED PUFFBIRD', 61: 'BARROWS GOLDENEYE', 62: 'BAY-BREASTED WARBLER', 63: 'BEARDED BARBET', 64: 'BEARDED BELLBIRD', 65: 'BEARDED REEDLING', 66: 'BELTED KINGFISHER', 67: 'BIRD OF PARADISE', 68: 'BLACK & YELLOW BROADBILL', 69: 'BLACK BAZA', 70: 'BLACK COCKATO', 71: 'BLACK FRANCOLIN', 72: 'BLACK SKIMMER', 73: 'BLACK SWAN', 74: 'BLACK TAIL CRAKE', 75: 'BLACK THROATED BUSHTIT', 76: 'BLACK THROATED WARBLER', 77: 'BLACK VENTED SHEARWATER', 78: 'BLACK VULTURE', 79: 'BLACK-CAPPED CHICKADEE', 80: 'BLACK-NECKED GREBE', 81: 'BLACK-THROATED SPARROW', 82: 'BLACKBURNIAM WARBLER', 83: 'BLONDE CRESTED WOODPECKER', 84: 'BLOOD PHEASANT', 85: 'BLUE COAU', 86: 'BLUE DACNIS', 87: 'BLUE GROUSE', 88: 'BLUE HERON', 89: 'BLUE MALKOHA', 90: 'BLUE THROATED TOUCANET', 91: 'BOBOLINK', 92: 'BORNEAN BRISTLEHEAD', 93: 'BORNEAN LEAFBIRD', 94: 'BORNEAN PHEASANT', 95: 'BRANDT CORMARANT', 96: 'BREWERS BLACKBIRD', 97: 'BROWN CREPPER', 98: 'BROWN NOODY', 99: 'BROWN THRASHER', 100: 'BUFFLEHEAD', 101: 'BULWERS PHEASANT', 102: 'BURCHELLS COURSER', 103: 'BUSH TURKEY', 104: 'CAATINGA CACHOLOTE', 105: 'CACTUS WREN', 106: 'CALIFORNIA CONDOR', 107: 'CALIFORNIA GULL', 108: 'CALIFORNIA QUAIL', 109: 'CAMPO FLICKER', 110: 'CANARY', 111: 'CAPE GLOSSY STARLING', 112: 'CAPE LONGCLAW', 113: 'CAPE MAY WARBLER', 114: 'CAPE ROCK THRUSH', 115: 'CAPPED HERON', 116: 'CAPUCHINBIRD', 117: 'CARMINE BEE-EATER', 118: 'CASPIAN TERN', 119: 'CASSOWARY', 120: 'CEDAR WAXWING', 121: 'CERULEAN WARBLER', 122: 'CHARA DE COLLAR', 123: 'CHATTERING LORY', 124: 'CHESTNET BELLIED EUPHONIA', 125: 'CHINESE BAMBOO PARTRIDGE', 126: 'CHINESE POND HERON', 127: 'CHIPPING SPARROW', 128: 'CHUCAO TAPACULO', 129: 'CHUKAR PARTRIDGE', 130: 'CINNAMON ATTILA', 131: 'CINNAMON FLYCATCHER', 132: 'CINNAMON TEAL', 133: 'CLARKS NUTCRACKER', 134: 'COCK OF THE ROCK', 135: 'COCKATOO', 136: 'COLLARED ARACARI', 137: 'COMMON FIRECREST', 138: 'COMMON GRACKLE', 139: 'COMMON HOUSE MARTIN', 140: 'COMMON IORA', 141: 'COMMON LOON', 142: 'COMMON POORWILL', 143: 'COMMON STARLING', 144: 'COPPERY TAILED COUCAL', 145: 'CRAB PLOVER', 146: 'CRANE HAWK', 147: 'CREAM COLORED WOODPECKER', 148: 'CRESTED AUKLET', 149: 'CRESTED CARACARA', 150: 'CRESTED COUA', 151: 'CRESTED FIREBACK', 152: 'CRESTED KINGFISHER', 153: 'CRESTED NUTHATCH', 154: 'CRESTED OROPENDOLA', 155: 'CRESTED SHRIKETIT', 156: 'CRIMSON CHAT', 157: 'CRIMSON SUNBIRD', 158: 'CROW', 159: 'CROWNED PIGEON', 160: 'CUBAN TODY', 161: 'CUBAN TROGON', 162: 'CURL CRESTED ARACURI', 163: 'D-ARNAUDS BARBET', 164: 'DALMATIAN PELICAN', 165: 'DARJEELING WOODPECKER', 166: 'DARK EYED JUNCO', 167: 'DARWINS FLYCATCHER', 168: 'DAURIAN REDSTART', 169: 'DEMOISELLE CRANE', 170: 'DOUBLE BARRED FINCH', 171: 'DOUBLE BRESTED CORMARANT', 172: 'DOUBLE EYED FIG PARROT', 173: 'DOWNY WOODPECKER', 174: 'DUSKY LORY', 175: 'DUSKY ROBIN', 176: 'EARED PITA', 177: 'EASTERN BLUEBIRD', 178: 'EASTERN BLUEBONNET', 179: 'EASTERN GOLDEN WEAVER', 180: 'EASTERN MEADOWLARK', 181: 'EASTERN ROSELLA', 182: 'EASTERN TOWEE', 183: 'EASTERN WIP POOR WILL', 184: 'ECUADORIAN HILLSTAR', 185: 'EGYPTIAN GOOSE', 186: 'ELEGANT TROGON', 187: 'ELLIOTS PHEASANT', 188: 'EMERALD TANAGER', 189: 'EMPEROR PENGUIN', 190: 'EMU', 191: 'ENGGANO MYNA', 192: 'EURASIAN BULLFINCH', 193: 'EURASIAN GOLDEN ORIOLE', 194: 'EURASIAN MAGPIE', 195: 'EUROPEAN GOLDFINCH', 196: 'EUROPEAN TURTLE DOVE', 197: 'EVENING GROSBEAK', 198: 'FAIRY BLUEBIRD', 199: 'FAIRY PENGUIN', 200: 'FAIRY TERN', 201: 'FAN TAILED WIDOW', 202: 'FASCIATED WREN', 203: 'FIERY MINIVET', 204: 'FIORDLAND PENGUIN', 205: 'FIRE TAILLED MYZORNIS', 206: 'FLAME BOWERBIRD', 207: 'FLAME TANAGER', 208: 'FRIGATE', 209: 'GAMBELS QUAIL', 210: 'GANG GANG COCKATOO', 211: 'GILA WOODPECKER', 212: 'GILDED FLICKER', 213: 'GLOSSY IBIS', 214: 'GO AWAY BIRD', 215: 'GOLD WING WARBLER', 216: 'GOLDEN BOWER BIRD', 217: 'GOLDEN CHEEKED WARBLER', 218: 'GOLDEN CHLOROPHONIA', 219: 'GOLDEN EAGLE', 220: 'GOLDEN PARAKEET', 221: 'GOLDEN PHEASANT', 222: 'GOLDEN PIPIT', 223: 'GOULDIAN FINCH', 224: 'GRANDALA', 225: 'GRAY CATBIRD', 226: 'GRAY KINGBIRD', 227: 'GRAY PARTRIDGE', 228: 'GREAT GRAY OWL', 229: 'GREAT JACAMAR', 230: 'GREAT KISKADEE', 231: 'GREAT POTOO', 232: 'GREAT TINAMOU', 233: 'GREAT XENOPS', 234: 'GREATER PEWEE', 235: 'GREATOR SAGE GROUSE', 236: 'GREEN BROADBILL', 237: 'GREEN JAY', 238: 'GREEN MAGPIE', 239: 'GREY CUCKOOSHRIKE', 240: 'GREY PLOVER', 241: 'GROVED BILLED ANI', 242: 'GUINEA TURACO', 243: 'GUINEAFOWL', 244: 'GURNEYS PITTA', 245: 'GYRFALCON', 246: 'HAMERKOP', 247: 'HARLEQUIN DUCK', 248: 'HARLEQUIN QUAIL', 249: 'HARPY EAGLE', 250: 'HAWAIIAN GOOSE', 251: 'HAWFINCH', 252: 'HELMET VANGA', 253: 'HEPATIC TANAGER', 254: 'HIMALAYAN BLUETAIL', 255: 'HIMALAYAN MONAL', 256: 'HOATZIN', 257: 'HOODED MERGANSER', 258: 'HOOPOES', 259: 'HORNED GUAN', 260: 'HORNED LARK', 261: 'HORNED SUNGEM', 262: 'HOUSE FINCH', 263: 'HOUSE SPARROW', 264: 'HYACINTH MACAW', 265: 'IBERIAN MAGPIE', 266: 'IBISBILL', 267: 'IMPERIAL SHAQ', 268: 'INCA TERN', 269: 'INDIAN BUSTARD', 270: 'INDIAN PITTA', 271: 'INDIAN ROLLER', 272: 'INDIAN VULTURE', 273: 'INDIGO BUNTING', 274: 'INDIGO FLYCATCHER', 275: 'INLAND DOTTEREL', 276: 'IVORY BILLED ARACARI', 277: 'IVORY GULL', 278: 'IWI', 279: 'JABIRU', 280: 'JACK SNIPE', 281: 'JANDAYA PARAKEET', 282: 'JAPANESE ROBIN', 283: 'JAVA SPARROW', 284: 'JOCOTOCO ANTPITTA', 285: 'KAGU', 286: 'KAKAPO', 287: 'KILLDEAR', 288: 'KING EIDER', 289: 'KING VULTURE', 290: 'KIWI', 291: 'KOOKABURRA', 292: 'LARK BUNTING', 293: 'LAZULI BUNTING', 294: 'LESSER ADJUTANT', 295: 'LILAC ROLLER', 296: 'LITTLE AUK', 297: 'LOGGERHEAD SHRIKE', 298: 'LONG-EARED OWL', 299: 'MAGPIE GOOSE', 300: 'MALABAR HORNBILL', 301: 'MALACHITE KINGFISHER', 302: 'MALAGASY WHITE EYE', 303: 'MALEO', 304: 'MALLARD DUCK', 305: 'MANDRIN DUCK', 306: 'MANGROVE CUCKOO', 307: 'MARABOU STORK', 308: 'MASKED BOOBY', 309: 'MASKED LAPWING', 310: 'MCKAYS BUNTING', 311: 'MIKADO PHEASANT', 312: 'MOURNING DOVE', 313: 'MYNA', 314: 'NICOBAR PIGEON', 315: 'NOISY FRIARBIRD', 316: 'NORTHERN BEARDLESS TYRANNULET', 317: 'NORTHERN CARDINAL', 318: 'NORTHERN FLICKER', 319: 'NORTHERN FULMAR', 320: 'NORTHERN GANNET', 321: 'NORTHERN GOSHAWK', 322: 'NORTHERN JACANA', 323: 'NORTHERN MOCKINGBIRD', 324: 'NORTHERN PARULA', 325: 'NORTHERN RED BISHOP', 326: 'NORTHERN SHOVELER', 327: 'OCELLATED TURKEY', 328: 'OKINAWA RAIL', 329: 'ORANGE BRESTED BUNTING', 330: 'ORIENTAL BAY OWL', 331: 'OSPREY', 332: 'OSTRICH', 333: 'OVENBIRD', 334: 'OYSTER CATCHER', 335: 'PAINTED BUNTING', 336: 'PALILA', 337: 'PARADISE TANAGER', 338: 'PARAKETT AKULET', 339: 'PARUS MAJOR', 340: 'PATAGONIAN SIERRA FINCH', 341: 'PEACOCK', 342: 'PEREGRINE FALCON', 343: 'PHILIPPINE EAGLE', 344: 'PINK ROBIN', 345: 'POMARINE JAEGER', 346: 'PUFFIN', 347: 'PURPLE FINCH', 348: 'PURPLE GALLINULE', 349: 'PURPLE MARTIN', 350: 'PURPLE SWAMPHEN', 351: 'PYGMY KINGFISHER', 352: 'QUETZAL', 353: 'RAINBOW LORIKEET', 354: 'RAZORBILL', 355: 'RED BEARDED BEE EATER', 356: 'RED BELLIED PITTA', 357: 'RED BROWED FINCH', 358: 'RED FACED CORMORANT', 359: 'RED FACED WARBLER', 360: 'RED FODY', 361: 'RED HEADED DUCK', 362: 'RED HEADED WOODPECKER', 363: 'RED HONEY CREEPER', 364: 'RED NAPED TROGON', 365: 'RED TAILED HAWK', 366: 'RED TAILED THRUSH', 367: 'RED WINGED BLACKBIRD', 368: 'RED WISKERED BULBUL', 369: 'REGENT BOWERBIRD', 370: 'RING-NECKED PHEASANT', 371: 'ROADRUNNER', 372: 'ROBIN', 373: 'ROCK DOVE', 374: 'ROSY FACED LOVEBIRD', 375: 'ROUGH LEG BUZZARD', 376: 'ROYAL FLYCATCHER', 377: 'RUBY THROATED HUMMINGBIRD', 378: 'RUDY KINGFISHER', 379: 'RUFOUS KINGFISHER', 380: 'RUFUOS MOTMOT', 381: 'SAMATRAN THRUSH', 382: 'SAND MARTIN', 383: 'SANDHILL CRANE', 384: 'SATYR TRAGOPAN', 385: 'SCARLET CROWNED FRUIT DOVE', 386: 'SCARLET IBIS', 387: 'SCARLET MACAW', 388: 'SCARLET TANAGER', 389: 'SHOEBILL', 390: 'SHORT BILLED DOWITCHER', 391: 'SKUA', 392: 'SMITHS LONGSPUR', 393: 'SNOWY EGRET', 394: 'SNOWY OWL', 395: 'SNOWY PLOVER', 396: 'SORA', 397: 'SPANGLED COTINGA', 398: 'SPLENDID WREN', 399: 'SPOON BILED SANDPIPER', 400: 'SPOONBILL', 401: 'SPOTTED CATBIRD', 402: 'SRI LANKA BLUE MAGPIE', 403: 'STEAMER DUCK', 404: 'STORK BILLED KINGFISHER', 405: 'STRAWBERRY FINCH', 406: 'STRIPED OWL', 407: 'STRIPPED MANAKIN', 408: 'STRIPPED SWALLOW', 409: 'SUPERB STARLING', 410: 'SWINHOES PHEASANT', 411: 'TAILORBIRD', 412: 'TAIWAN MAGPIE', 413: 'TAKAHE', 414: 'TASMANIAN HEN', 415: 'TEAL DUCK', 416: 'TIT MOUSE', 417: 'TOUCHAN', 418: 'TOWNSENDS WARBLER', 419: 'TREE SWALLOW', 420: 'TRICOLORED BLACKBIRD', 421: 'TROPICAL KINGBIRD', 422: 'TRUMPTER SWAN', 423: 'TURKEY VULTURE', 424: 'TURQUOISE MOTMOT', 425: 'UMBRELLA BIRD', 426: 'VARIED THRUSH', 427: 'VEERY', 428: 'VENEZUELIAN TROUPIAL', 429: 'VERMILION FLYCATHER', 430: 'VICTORIA CROWNED PIGEON', 431: 'VIOLET GREEN SWALLOW', 432: 'VIOLET TURACO', 433: 'VULTURINE GUINEAFOWL', 434: 'WALL CREAPER', 435: 'WATTLED CURASSOW', 436: 'WATTLED LAPWING', 437: 'WHIMBREL', 438: 'WHITE BROWED CRAKE', 439: 'WHITE CHEEKED TURACO', 440: 'WHITE CRESTED HORNBILL', 441: 'WHITE NECKED RAVEN', 442: 'WHITE TAILED TROPIC', 443: 'WHITE THROATED BEE EATER', 444: 'WILD TURKEY', 445: 'WILSONS BIRD OF PARADISE', 446: 'WOOD DUCK', 447: 'YELLOW BELLIED FLOWERPECKER', 448: 'YELLOW CACIQUE', 449: 'YELLOW HEADED BLACKBIRD'}

# %% [markdown]

# Choosing the device for the model

# %%

def get\_default\_device():

"""Pick GPU if available, else CPU"""

if torch.cuda.is\_available():

return torch.device('cuda')

else:

return torch.device('cpu')

def to\_device(data, device):

"""Move tensor(s) to chosen device"""

if isinstance(data, (list,tuple)):

return [to\_device(x, device) for x in data]

return data.to(device, non\_blocking=True)

# %%

device=get\_default\_device()

print(device)

# %% [markdown]

# Loading the model

# %%

class BirdResnet(nn.Module):

def \_\_init\_\_(self):

super().\_\_init\_\_()

# Using the pretrained model

self.network = model

def forward(self, xb):

return (self.network(xb))

# %%

model = to\_device(ResNet34(3,450), device)

model=(BirdResnet())

model.load\_state\_dict(torch.load('./trained-models/bird-resnet34best.pth',map\_location=torch.device(device)))

# %%

stats = ((0.4758, 0.4685, 0.3870), (0.2376, 0.2282, 0.2475))

def predict\_image(path, model):

im=Image.open(path)

# resizing images then converting image to tensor, normalizing the tensors

transform = transforms.Compose([transforms.Resize((250,250)),transforms.ToTensor(),transforms.Normalize(\*stats,inplace=True)])

img=transform(im)

# Convert to a batch of 1

xb = to\_device(img.unsqueeze(0), device)

# Get predictions from model

model.eval()

with torch.no\_grad():

yb = model(xb)

# Pick index with highest probability

prob=nn.Softmax(dim=1)

yb=prob(yb)

\_, preds = torch.max(yb, dim=1)

# Retrieve the class label

print('Predicted:',bird\_name\_map.get(preds[0].item()),' with a probability of',str(round(torch.max(yb).item(), 4)\*100)+'%')

plt.imshow(im)

plt.show()

# %% [markdown]

# Prediction of single images

# %%

predict\_image('./test-data/75374781-1200px.jpg', model)

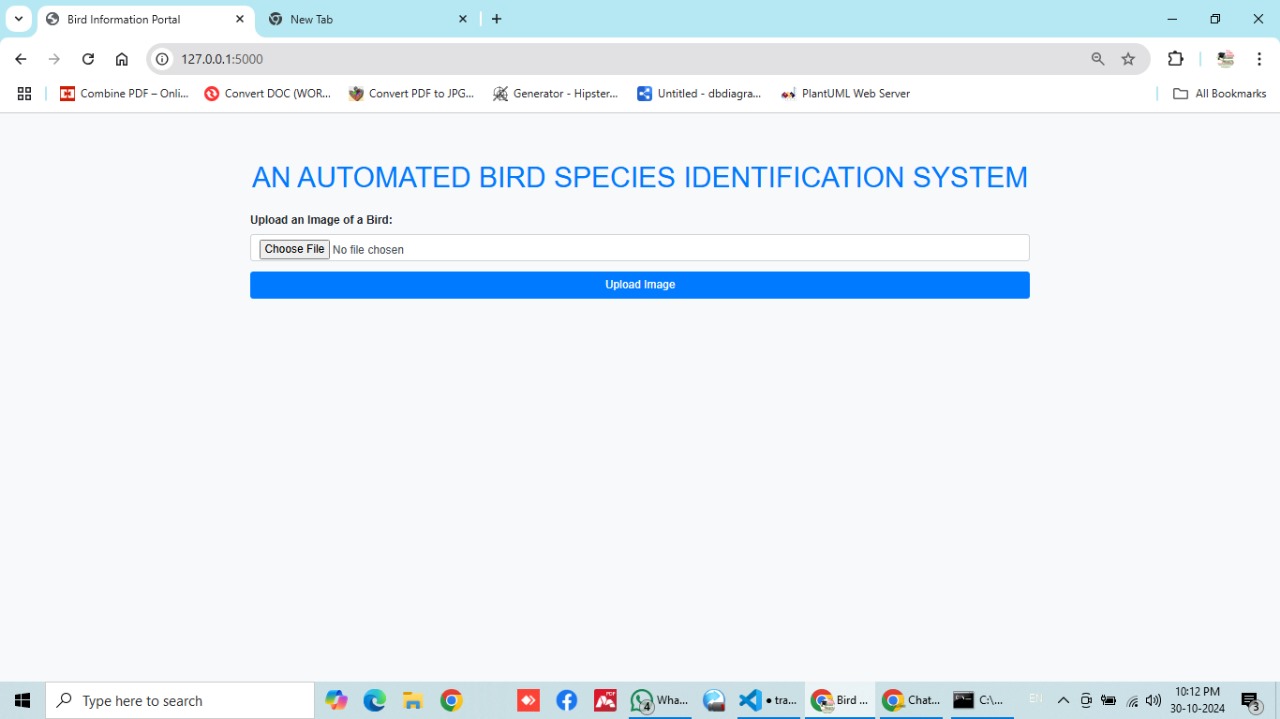
predict\_image('./test-data/original.jpg', model)

**CHAPTER-7**

**RESULT**

This chapter presents the results obtained from the implementation of the Automated Bird Species Identification System. It evaluates the system's performance based on various metrics, displays the visual outcomes through interactive maps and species identification accuracy, and assesses user feedback. This chapter aims to illustrate the system’s effectiveness and reliability in identifying bird species and mapping biodiversity data.

**7.2 VISUALIZATION RESULTS**

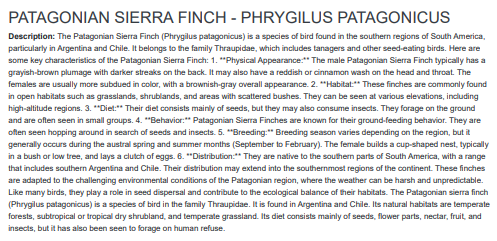
****

The system's geolocation mapping and heatmap features provide a visual representation of bird species sightings, illustrating geographical biodiversity patterns.

**7.2.1 Species Identification Interface**

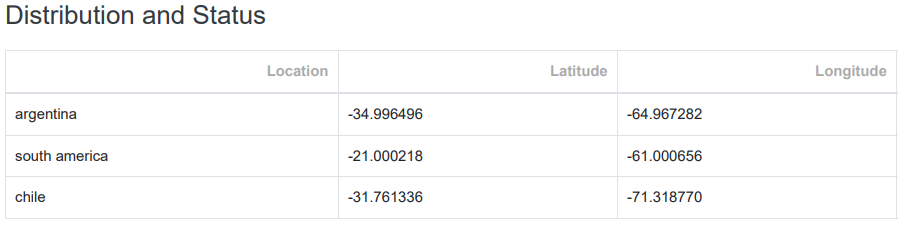
* **Overview**: The user interface displays identified bird species along with detailed information.
* **Result**: Users can view species name, confidence score, and biological information, making the system user-friendly and informative.

****

****

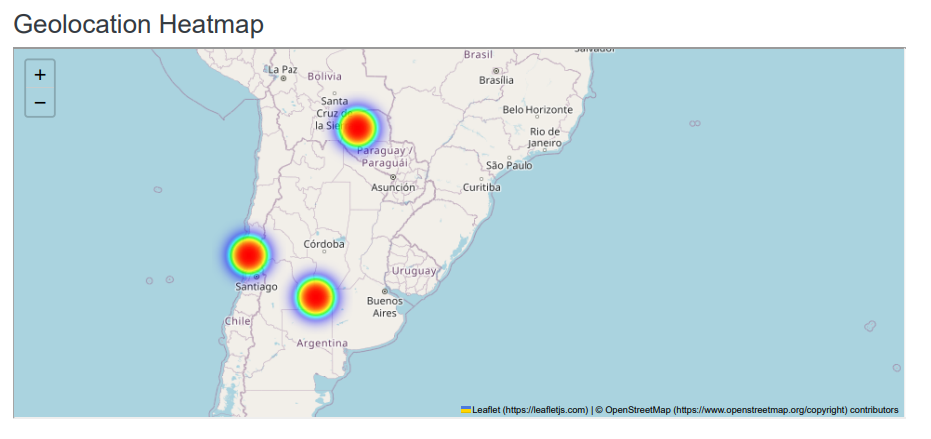
**7.2.2 Geolocation Mapping**

* **Map Display**: All sighting locations were successfully mapped using the Leaflet API, allowing users to explore biodiversity across different regions.
* **Result**: Maps accurately depict the sighting distribution of identified bird species. Users can zoom in to view specific locations or observe broader biodiversity patterns.

****

**7.2.3 Heatmap Visualization**

* **Overview**: Heatmaps were generated based on sighting frequency and geographical density of species.
* **Result**: Heatmap analysis indicates biodiversity hotspots and regions with high bird diversity, making the system useful for ecological studies and conservation efforts.

****

**CHAPTER-6**

**SYSTEM TESTING**

**6.1 OVERVIEW OF SYSTEM TESTING**

System testing is essential in validating the functionality and performance of the Automated Bird Species Identification System. This phase ensures that the system accurately identifies bird species, provides relevant species information, and delivers geolocation mapping and heatmap visualization without compromising user experience. This chapter outlines the various testing methods applied, the outcomes of these tests, and an analysis of the system’s overall performance.

**6.2 TYPES OF TESTING CONDUCTED**

1. **Unit Testing:** Tests individual components, such as image upload, bird identification via ResNet, geolocation mapping, species information display, and heatmap visualization.
2. **Integration Testing:** Validates that all modules work seamlessly when combined, ensuring smooth data flow between identification, mapping, and visualization.
3. **Performance Testing:** Assesses the processing time for each module, ensuring timely responses, particularly in species identification and heatmap rendering.
4. **Security Testing:** Verifies that the system maintains data security and that geolocation data is protected.
5. **Usability Testing:** Ensures that the application is easy to use, with intuitive navigation and accessible information displays.

**6.3 TESTING RESULTS**

**Unit Testing Results**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Test Case ID** | **Test Scenario** | **Expected Result** | **Actual Result** | **Status** |
| TC-01 | Image Upload | Image uploaded successfully | Image uploaded successfully | Pass |
| TC-02 | Bird Identification (ResNet34) | Accurate species identification within 1-2 seconds | Species identified accurately | Pass |
| TC-03 | Species Information Display | Detailed species information displayed | Information displayed correctly | Pass |
| TC-04 | Geolocation Mapping | Sighting plotted accurately on the map | Sighting plotted correctly | Pass |
| TC-05 | Heatmap Visualization | Heatmap generated accurately showing biodiversity hotspots | Heatmap generated successfully | Pass |
| TC-06 | Geolocation Privacy Check | Geolocation data secured | Data secured | Pass |
| TC-07 | End-to-End Process | Entire cycle completes within 3 seconds | Process completed in 3 seconds | Pass |
| TC-08 | Usability Test | Interface is user-friendly | User-friendly | Pass |

**Integration Testing Results**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Test Case ID** | **Test Scenario** | **Expected Result** | **Actual Result** | **Status** |
| TC-09 | Image Upload to Identification | Uploaded image proceeds to identification stage | Image identified successfully | Pass |
| TC-10 | Identification to Info Display | Identified bird displays relevant information | Information displayed correctly | Pass |
| TC-11 | Identification to Mapping | Identified species plotted on map accurately | Location plotted correctly | Pass |
| TC-12 | Mapping to Heatmap | Heatmap updates with new sighting data | Heatmap updated | Pass |

**Performance Testing Results**

|  |  |  |  |
| --- | --- | --- | --- |
| **Step** | **Expected Time (sec)** | **Actual Time (sec)** | **Result** |
| Image Upload | < 0.5 | 0.35 | Pass |
| Bird Identification | < 1.5 | 1.2 | Pass |
| Species Info Display | < 0.5 | 0.4 | Pass |
| Geolocation Mapping | < 0.5 | 0.3 | Pass |
| Heatmap Generation | < 0.5 | 0.4 | Pass |
| Total Process | < 3 | 2.65 | Pass |

**Security Testing Results**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Test Case ID** | **Test Scenario** | **Expected Result** | **Actual Result** | **Status** |
| TC-06 | Geolocation Privacy | Ensures geolocation data remains secure | Data secured | Pass |
| TC-13 | API Security | API calls are secure and data exchange is encrypted | API security confirmed | Pass |

**Usability Testing Results**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Test Case ID** | **Test Scenario** | **Expected Result** | **Actual Result** | **Status** |
| TC-08 | Usability Test | User interface is intuitive and easy to navigate | Interface is user-friendly | Pass |

**6.4 SYSTEM TESTING SUMMARY**

The system testing phase confirms that the Automated Bird Species Identification System meets the performance, security, and usability requirements. Each component works as expected, and the fully integrated system provides real-time identification, species data, and visual mapping features effectively. This tool stands as a robust resource for researchers and conservationists, enabling easy and accurate bird species identification along with ecological insights. Future enhancements could aim to optimize heatmap generation for larger data sets and incorporate additional security protocols for geolocation data.

**CONCLUSION**

In conclusion, the Automated Bird Species Identification System is a promising tool for bird species classification, offering reliable identification, interactive mapping, and biodiversity visualization. It successfully integrates machine learning, geolocation mapping, and user-friendly design, demonstrating strong potential for research, conservation, and educational purposes. The system has proven to be an effective prototype, with room for improvement through further development and refinement. By expanding the dataset, improving model performance, and incorporating additional features, the system could evolve into a more robust and accessible tool for birdwatchers and researchers worldwide.

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