Bird Species Classification using Machine Learning

Project Proposal

1. Problem Statement and Application

Birds are a crucial component of global biodiversity, and many species are threatened or endangered. These species are indigenous to a certain area of the nation, hence it is important to track and estimate their populations as precisely as possible [7]. A significant number of rare bird species have unintentionally been killed by wind turbines in various nations. Bird species recognition is a difficult task because of the varied illumination and multiple camera view positions [2]. Birds differ visually significantly across and among species. Hence, it is difficult to create models that can precisely recognize and distinguish various species as they have a variety of sizes, forms, colors, and other physical characteristics.

Our main objective is to study Machine Learning (ML) using both Decision Trees and Deep Neural Networks to address a machine learning problem from a real-world problem of identifying bird species, particularly to identify an endangering species of bird to promote broader participation in understanding and protecting the avian biodiversity, applying supervised and semi-supervised learning Classification, and comparing the performance of the different models

2. Dataset Selection

On several websites, like Kaggle, Google Datasets, and UCI, there are many distinct datasets available. From Kaggle, we have chosen the dataset of Indian bird species [1]. The chosen dataset in this case is balanced. Each photo was hand-picked and taken from the eBird Platform. A total of 22.6k photos, representing all 25 distinct bird species, have been painstakingly labeled by the author. Here is the dataset's detailed specification.

The given data set consists of around 925 images of 25 different kinds of species of birds. Images are taken from the bird conservation community Platform and consist of 1200*800 resolution. The cleaning process of the data set is to be done with a Python script to generate the proper balanced dataset for training, validation, and testing.

Label	No. of Observations
Asian Green Bee-Eater	924
Brown-Headed Barbet	924
Cattle Egret	918
Common Kingfisher	924
Common Myna	926
Common Rosefinch	919
Common Tailorbird	918
Coppersmith Barbet	778
Forest Wagtail	924
Gray Wagtail	926
Hoopoe	924
House Crow	924
Indian Grey Hornbill	922
Indian Peacock	919
Indian Pitta	629
Indian Roller	926
Jungle Babbler	930
Northern Lapwing	930
Red-Wattled Lapwing	930
Ruddy Shelduck	925
Rufous Treepie	860
Sarus Crane	930
White Wagtail	930
White-Breasted Kingfisher	930
White-Breasted Waterhen	930

Table 1. Labeled Data Observations

3. Possible Methodology

3.1. Handling/Processing the Data

Image Datasets often come in a variety of sizes and aspect ratios. The photos must be resized while retaining the aspect ratio to a standard size. This procedure lessens computing complexity during training and aids in ensuring homogeneity across the dataset. Techniques for data augmentation and image normalization should be taken into account to enhance convergence and performance, decrease overfitting, and increase the generalizability of the model. We must divide the dataset into subsets for training, validation, and testing in order to train, adjust hyper-parameters, track

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performance, and assess the performance of the final model.

3.2. Architectures Selection and Training

The labeled dataset has to be divided into training and evaluation parts in order to do classification using supervised Decision Tree Algorithms. Scale-Invariant Feature Transform (SIFT) [5] or Histogram of Oriented Gradients (HOG) [4] are needed to extract the necessary features from the bird photos for training. These features might be color histograms, texture descriptors, or shape-based features. We will employ data augmentation and pseudo-labeling to train the classifier using iterative training for the semi-supervised learning utilizing the decision tree.
Convolutional neural networks (CNNs) are frequently chosen for classifying birds with deep neural networks (DNNs) [3]. CNNs can automatically learn hierarchical characteristics from the input images, making them ideal for image-based applications. Stochastic Gradient Descent (SGD) or Adam, among other gradient-based optimization methods, can be used. The InceptionV3 [6] or ResNet [8] can also be used to train the model. Tuning the hyperparameters will improve performance.

3.3. Evaluation metrics

Model evaluation can be done using Confusion matrix : To help determine which species are frequently misclassified, it shows the number of true positive, true negative, false positive, and false negative forecasts for each species. F1 score: The F1 score can be useful for assessing the model's overall performance, taking into account both accurate species identification and reducing misclassification. Precision: It can be helpful in determining the percentage of correctly categorized species within a given class. We are going to use TSNE to visualize the performance because it can reveal patterns, resemblance or probable groupings among species, giving us a visual insight of how the model performs and how various species are related to one another.

3.4. Applications of Derived results

The overall results of our work can aid scientists in creating more accurate model designs, Bird populations can be monitored and tracked throughout different regions with the help of real-time species recognition. This data can be used by ecologists and conservationists to analyze migration patterns, spot potential threats, and monitor habitat changes in real time. Additionally, our trained model can be applied in other real-world scenarios, including: Real-time bird species identification in agriculture can assist farmers in evaluating possible pest control by particular bird species, resulting in more environmentally friendly and sustainable farming practises. A wide range of applications in wildlife conservation, ecological research, environmental monitoring, wildlife management, disease surveillance, and citizen science initiatives are made possible by real-time bird species classification using machine learning models.

References

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