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Automated Bird Species Identification Using Neural Networks

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Abstract
Birds are the warm-blooded vertebrates constituting of class Aves, there are nearly 10 thousand living species of birds in the world with multifarious characteristics and appearances. Bird watching is often considered to be an interesting hobby by human beings in the natural environment. The human knowledge over the species isn't enough to identify a species of bird accurately, as it requires lot of expertise in the field of Ornithology. This paper presents an automated model based on the deep neural networks which automatically identifies the species of a bird given as the test data set. The model was trained and tested for 253 species of birds with the total images 7637 and 1853 images for train and test respectively and the model has shown a promising accuracy of 98% when tested with the test datasets.

Keywords: Neural Network, Image Classification, DNN, Machine Learning

1. Introduction

Birds help us to identify different creatures in the climate (for example creepy crawlies they food occurring) effectively via they react rapidly toward the ecological changes [2]. Yet, meeting and gathering data about birds requires enormous human exertion just as turns into a costlier strategy. In such case, a solid framework that will give huge scope handling of data about birds and will fill in as an important instrument for specialists, legislative offices, and so forth is required. Thus, bird species recognizable proof assumes a significant part in distinguishing that a specific picture of bird has a place with which species. Bird species distinguishing proof methods foreseeing the bird species has a place with which class by utilizing a picture. The recognizable proof should be possible through picture, sound or video. A sound handling procedure makes it conceivable to distinguish by catching the sound sign of birds. Yet, because of the blended sounds in climate like bugs, objects from genuine world, and so forth handling of such data turns out to be more convoluted. Normally, people discover pictures more successful than sounds or recordings. The IEEE International Machine Learning Workshop for Signal Processing (MLSP) declared a bird identification challenge in 2013 [14]. In this way, a way to deal with group bird utilizing a picture over sound [8] before general media is liked. To classify birds, it is therefore preferable to utilise a photograph rather than voice or video [15]. Fowl class distinguishing proof remaining parts a provoking errand to people just as to computational calculations that does such an assignment in a programmed design. Since numerous many years, ornithologists are dealing with issues in bird species recognizable proof. An ornithologist performs bird identification using Linnaeus classification system, which includes state, clan, rank, order, family, and species [10]. Ornithologists require concentrating every one of the subtleties of birds like their reality in climate, their science, their circulation, their environmental effect, and so on Bird ID is typically done by ornithology specialists dependent on arrangement future through Linnaeus: Empire, Phylum, Period, Instruction, Domestic, at that point Class [1]. Via picture based characterization frameworks are improving the undertaking of ordering, objects is moving into datasets with undeniably more classifications like Caltech-UCSD. Late work has seen a lot of accomplishment around there. Cal tech UC SD Birds 200(CUB-200-2011) is a notable dataset for bird pictures with photographs of 200 classes [4]. The dataset contains birds that are generally found in Northern America. Caltech-UCSD Birds 200 comprises of 11,788 pictures and comments like 15 Part Locations, 312 Binary Attributes, 1 Bounding Box. In this paper, rather than perceiving an enormous number of different classifications, the issue of perceiving countless classes inside one class is examined – that of birds. Characterizing birds represent an additional test over classifications, on account of the huge comparability between classes. Likewise, birds are non-inflexible items that can twist from numerous points of view, and thusly there is additionally an enormous variety inside classes. Past work on bird grouping has manage few classes, or finished speech.

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Figure 1: Caltech UCSD Birds 200 Dataset.

The image is receiving upload primary formerly after that copy the numerous arrangements determination remain careful such by way of skull, form, colour, bill then whole copy. Additional, apiece arrangement is assumed finished bottomless convocational system toward excerpt topographies available after manifold coatings of system [3]. Afterward that picture of the copy determination become reflect. Formerly on the foundation of it the categorizing consequence determination become made (i.e. topographies remain combined to transmission it to classifier) and the bird species will become originate.

2. Related Work

Bird songs were previously used to classify bird species. Visual features from bird images, such as SIFT (Scale invariant feature transform), and acoustic features were both used in traditional Machine learning algorithms to train a standard support vector machine (SVM) for classification. The earlier approaches for the species identification involved the bird songs where audio feature extraction was based on MARSYAS framework [1] and the classical Machine learning algorithms for classification, the visual features i.e. SIFT (Scale invariant feature transform) [2] from bird images and acoustic features both were used to train a standard SVM for classification. The fine-grained visual categorization [3] have shown great results of classification. Some studies have focused on discriminative features based on bird species local traits. Pose-normalization and model ensembles are often used to speed up the process of fine-grained detection by generating millions of key point sets using completely convolutional search.

Sound-based classification has gained prominence in recent years. Various works have been produced based on the sounds of various bird species. They suggested a method for identifying bird species based on audio classification. The method of speech recognition and new developments in the field of deep learning are demonstrated using nearest neighbour matching or decision trees using extracted guidance. For the classification and prediction processes, audio images such as spectrograms, ScatNet scattering representations, harmonic and percussion images are derived from the bird's audio signal. In both of these situations, there is a chance that background noise, such as ambient noise or insect noises, will be heard when recording the bird's song. This enhanced network includes the convolution layer, Batch Normalization layer, ReLU activation feature, Global Average Pooling, and Softmax. However, they did not use any animal or object datasets for the procedures, instead focusing on general biological images.

There are several methods for identifying birds, but they are both expensive and time consuming. To efficiently localise score detections, simultaneous detection and segmentation are used .The trajectory features, turn based features and shape movement features and wing beat frequencies [4] were considered from the video captures of bird moments and a combined naive Bayes classifier and SVM was used. The MFCC (Mel frequency cepstral centroids) [5] formed a feature matrix for class model and SVM was used to test the samples. The unkind normal non conformity then skewness of the RGB airplanes [6] of bird images have helped in classifying the species. The relation of coldness of judgement to the origin of mouth then the coldness of breadth of the mouth were also primarily considered for classification. An HSV model [7] (which is a combination of RGB and CMY) features were considered for color-based species identification. There are several methods for classifying biological images into various groups, but only a few of them are specifically based on species identification. This proposed study used a convolutional neural network architecture to tackle species recognition. A transmission learning-built technique through multistage learning [8] was used to mine together micro and macro equal features after the bird images aimed at organization in the recent years.

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Dataset
It is important to have a solid dataset on which the identification system can be trained and tested for bird image recognition. As a result, we used the Caltech UCSD Birds (200–2011) dataset, which is a fine-grained biological image classification dataset. This dataset was created by combining data from Caltech and UCSD, and it is an expanded version of the CUB-200 dataset. The Caltech-UCSD Birds 200 dataset is shown in Fig 1. There are 11,788 photos in the dataset representing 253 different bird species. The dataset was divided into two parts: a training set and a testing set. The classification model can then be trained using the data. The training set received more than 60% of the data, while the testing set received the remaining data.

3. Implementation

Image Acquisition
Images of 253 Species of different birds were collected from the online internet sources, and were rummage-sale aimed at exercise then challenging of the Deep neural network perfect.

Pre Paring the Data
The collected images were divided into train and test datasets i.e. 80 percent of the total images of the species were rummage-sale by way of exercise information then the residual 20 percent aimed at the purpose of testing the trained perfect.

Dataset Pre Processing
Before the image datasets can be used to train the algorithm, they must be pre processed. All the images are first scaled to same image size ratio and by making use of the CV2 libraries the image datasets are converted to the image pixel arrays. In order to reduce the harshness, Noise and disturbances in the images the pixel values are normalized and then can be used for training the model.

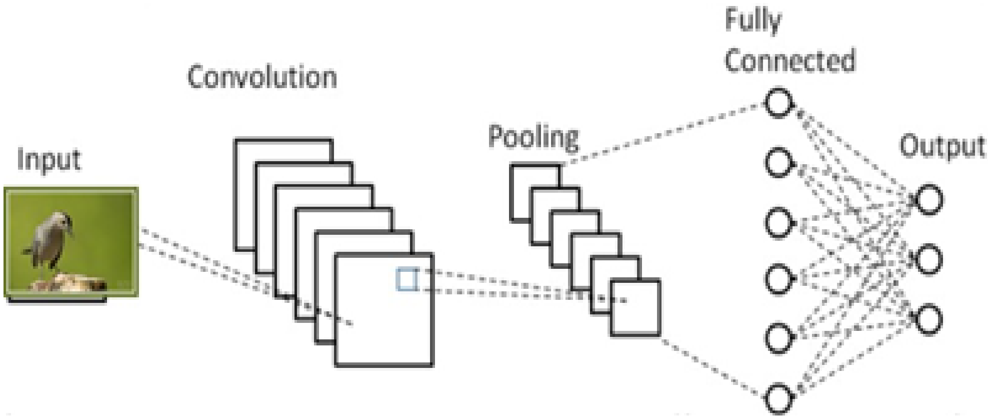

Figure 2: CNN Model.

A proposed neural network is a Deep learning algorithm which takes input images assign importance to various contents of the images and is self-capable of differentiating one from another. The input image is nothing but the pixel values in the computer vision, The RGB image consists of three planes RED, GREEN, BLUE. The main role of convolution neural network is to decrease the image into the procedure which is easy to process and to effectively mine all the features that could help in best classification.

Input Layer
The main purpose of the proposed input layer is to excerpt in height equal topographies after the copy. There is no limit for the number of these layers in the network, by including more layers we are capable of extraction every minute and major feature from the images such as edges, color gradients, Orientations etc. This layer makes use of kernel for generating the Convolved feature output, the kernel strides all through the image pixel values to generate a convolved feature matrix for the particular image.

Pooling Layer
Similar to convolution coating, the combining coating is capable of plummeting the three-dimensional scope of the extracted feature matrix by performing the pooling functions over it. This layer is responsible for extracting the dominant features from the images. We have used the Max pooling function which revenues the all-out value after the helping of the copy covered through kernel.

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Fully-Connected coating is a method of knowledge nonlinear blends of the great level highlights as addressed by the yield of the convolutional layer. After we have changed over our information picture into a reasonable structure for our Multi-Level Perceptron, it is essential that we will straighten the picture into a section vector. The straightened yield is taken care of to a feed-forward neural organization and backpropagation applied to each emphasis of preparing. Over a progression of ages, the model can recognize overwhelming and certain low-level highlights in pictures and group them utilizing the SoftMax Organization strategy.

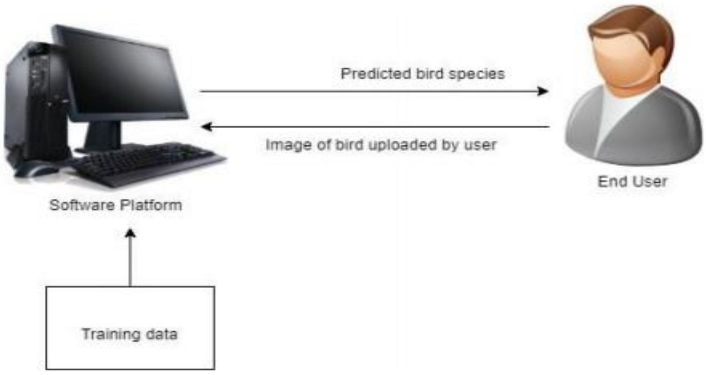

Figure 3: Client Server Architecture.

4. Result

Whenever we send a bird image for the testing process to identify the particular bird then the deep neural network algorithm will perform and it will give us the correct bird species name. Using the test image datasets, the build model was successfully tested, and the overall accuracy of the model developed was found to be 98 percent.

Figure 4: Different Bird Species.

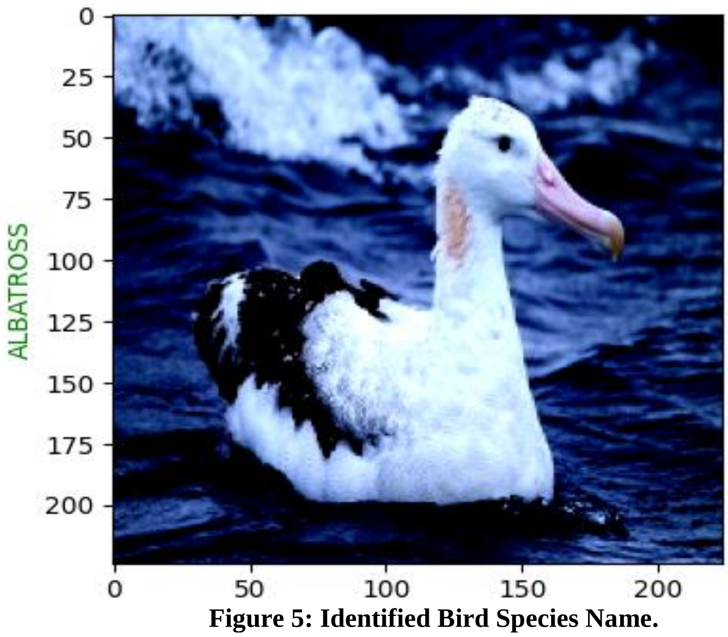

Figure 5: Identified Bird Species Name.

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5. Conclusions

This model helps building applications that helps tourist who go onto bird sanctuaries identify the bird species by just capturing a picture of a bird and uploading it as input to the model. As many species of birds have become endangered and are near to extinction many people have no knowledge about the species which are few in number, Thus application built using this model may be helpful in identifying the endangered species and help society in spreading awareness about the need of all the species for balance in the nature. As the model implies the knowledge of Deep proposed neural networks, we can infer that the DNN is the best algorithm for analyzing the visual imagery and image Classification.

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