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Bird Species Identification from Image Processing

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Abstract - Although viewing birds is a popular pastime, bird books are necessary to identify the species. We created a deep learning platform to help users identify 27 species of Taiwanese endemic birds using a smartphone app called the Internet of Birds (IoB), giving birdwatchers a convenient way to appreciate the beauty of birds. A convolutional neural network (CNN) was trained to identify key elements in bird photos. To balance the distribution of bird species, we first created and refined a circumscribed region of interest to fine-tune the object granularities' colors and shapes. To enhance feature extraction, the outputs of the prior and current layers were then linearly combined using a skip connection technique.

Lastly, a probability distribution of bird traits was obtained by applying the softmax function. Images submitted by mobile users were identified using the learned criteria of bird traits. For the training images, the suggested CNN model with skip connections had a higher accuracy of 99.00% than the CNN's 93.98% and the SVM's 89.00%. The average sensitivity, specificity, and accuracy for the test dataset were 93.79%, 96.11%, and 95.37%, in that order.

***Key Words*:** Bird image recognition, convolutional neural network, deep learning, mobile app.

INTRODUCTION:

Typically, daily life is busy, fast-paced, and packed with extracurricular activities. Bird watching is one activity that might help people relax and develop resilience in the face of daily hardship.

It can also provide satisfaction from taking in nature and health benefits.

Many people go to bird sanctuaries to look at the many species of birds or to compliment them on their exquisite plumage, hardly understanding the distinctions between the species and their characteristics. We can learn more about exotic birds, their ecosystems, and biodiversity by comprehending these species-to-species differences. However, because of observer limitations like location, distance, and equipment, bird identification with the naked eye depends on basic characteristic features, and accurate categorization based on differentiating features is occasionally thought to be time-consuming.

In the past, a lot of research has been done on computer vision and its subcategory of recognition, which uses methods like machine learning, to identify the unique characteristics of objects, such as fruits and vegetables, landmarks, clothes, cars, plants, and birds, within a given scene cluster. Nonetheless, there is still much space for improvement in terms of the precision and viability of methods for extracting bird features. Detecting object parts is challenging due to complex changes, similar subordinate categories, and object fringes.

Because some characteristics are shared between species, it can be challenging to accurately detect variations in bird silhouettes and appearances within and between classes.

LITERATURE SURVEY:

One important use case in computer vision and biodiversity monitoring is the identification of bird species from photos. Low inter-class variance (e.g., similar-looking species) and substantial intra-class variation (e.g., varied stances, lighting) make the task difficult. To address these issues, researchers turn to deep learning, particularly convolutional neural networks (CNNs).

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

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

[2] Zhang et al. (2014) – Part-based R-CNN for FineGrained Category Detection Approach: Used part-based models to identify bird parts (beak, wing, etc.) and improve classification accuracy.
Technique: Combined CNN features with bounding box and part annotations.

[3] Lin et al. (2015) – Bilinear CNNs for Fine-Grained Visual Recognition Approach: Proposed bilinear CNNs that capture local pairwise feature interactions.
Result: Outperformed standard CNNs on fine-grained classification, including birds.

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

[5] He et al. (2020) – Attention-based Approaches Method: Employed attention mechanisms to automatically focus on discriminative regions in bird images.
Improvement: Reduced reliance on part annotations, allowing end-to-end training.

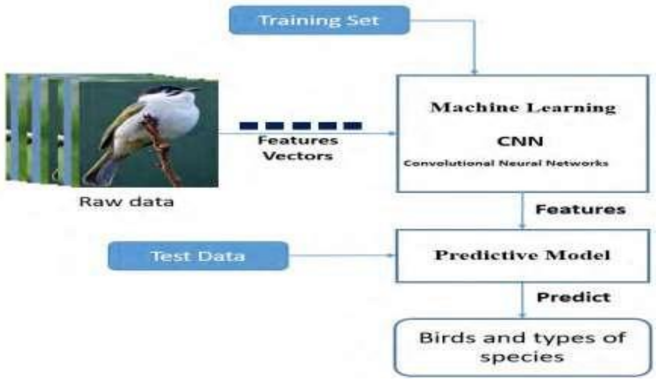
[6] Kumar et al. (2017) – Visual Species Identification using Citizen Science Images Context: Tackled variability in amateur photos using deep learning.
Finding: CNNs can generalize across low-quality, real world images with enough training data.

DESCRIPTION:

Based on the findings generated, the system has offered an 80% accuracy rate in predicting the species of bird. These features are then combined and sent to the classifier for categorization purposes.

PROPOSED SYSTEM:

Computer vision and image recognition have become extremely complicated cognitive problems as a result of the development of deep learning algorithms. Deep learning models have recently surpassed conventional picture classification algorithms to become the most widely used tool for artificial intelligence and big data analysis. They are now being down-scaled for practical mobile implementation. Here is a description of the CNN Framework-based deep learning model that has been suggested for classifying bird images.



CNN ARCHITECTURE:

A stack of convolutional layers, including one input layer, two FC layers, and one final output softmax layer, was used in the CNN configuration model for bird recognition. Convolution, BN, ReLU activation, and pooling layers make up each convolutional layer. The number of convolutional layers, the size of the kernels for each relative convolutional layer, the necessity of tuning the parameters and hyperparameters prior to training, and the probability of keeping the anode during dropout regularization for the dataset are all covered in this section.

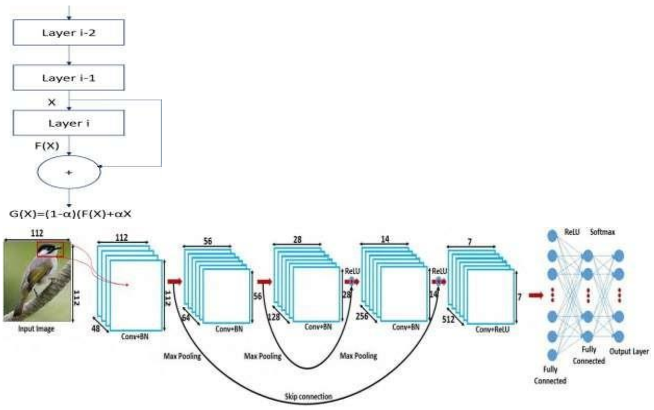


Fig: CNN Architecture for detecting birds images.

FEATURE EXTRACTION:

The main objective when gathering descriptive and pertinent information for fine-grained object recognition is to extract features from raw input photos. However, feature extraction is still difficult due to intra-class and semantic volatility. We discovered

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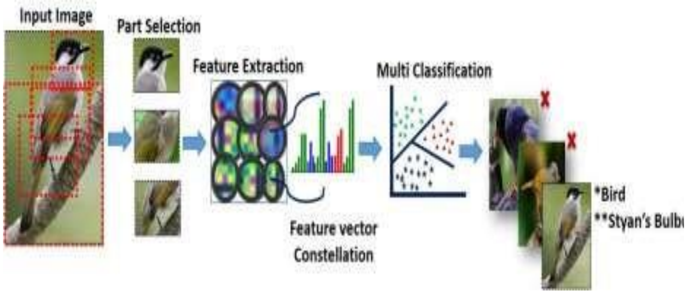
which parts of the model features were directly mapped to the corresponding parts after extracting the features in the appropriate locations for each component of an image independently. ReLU 5 and ReLU 6 were used to calculate the features. Object pieces defined by bounding box coordinates and their dimensions (width and height) in the image were located using localization.

Our model was set to have an intersection over union score >0.5 for the localization challenge. Bounding boxBx's location was predicted using an FC layer with a Rely. Subsequent step the learning algorithm were for learning the map of the feature vectors of the input image, deciding whether the region fit an object class of interest, and then assigning the appropriate labels to the image in order to classify the desired output.



SYSTEM IMPLEMENTATION:

In this article, we describe how to use a high-resolution smartphone camera to recognize and categorize bird data using deep learning. We developed a client-server architecture to bridge the communication gap between a mobile device and the cloud via a network in order to finish the semantic bird search mission. The following is how the full setup was carried out:

- CNN learnt parameters on the GPU platform by distilling raw bird photos to remove unnecessary sections. The workstation then created a TF inference model that was implemented on the smartphone.
- The output was identified via the web or an Android app platform.

Fig: Client-Server architecture for bird detection.

EXPERIMENTAL RESULTS AND ANALYSIS

Fig: Dataset of Bird Species.

Prediction results of images uploaded from smart phones.

Subjects	Predicted Bird	Predicted Non-bird
Bird	100%	0%
Non-bird	0%	0%

Fig: Hardware/software specifications used to execute the object detection model.

Hardware/Software	*Specification*
GPU	12 Intel Xeon CPUs, 32 GB memory, NVIDIA GeForce 2, 11GB GTX 1080Ti graphic cards.
Android Phone	5.0 or higher devices.
Android SDK, NDK	SDK is Android interface for main activity, and NDK helps to bridge the SDK and TF platform.
TensorFlow	Execute numerical computation using data flow graphs.
PyCharm	Python IDE programmers coding interface.

CONCLUSION:

This work created a mobile application platform that recognizes bird species from digital photos that users upload on their smartphones using cloud-based deep learning for image processing. The primary focus of this investigation was the identification of 27 indigenous bird species. With a 98.70% overall accuracy rate for the training dataset, the suggested system was able to identify and distinguish uploaded photos as birds. The final goal of this research was to create an autonomous system that could distinguish fine-grained items from bird photos that had similar basic traits but slight visual differences. We plan to add more bird species to our database and create a technique for forecasting distinct generations of certain bird species within intra-class and interclass variations.

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