Bird Species Classification: A Transfer Learning approach using Lightweight Classification models like MobileNetV2, MobileNetV3 Small, ShuffleNetV2, and SqueezeNet.

Pradeep P1 Guru Venkat R2 R. Arumuga Arun3

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|  | **Name** | **Mail id** | **Affiliation** |
| 1 | Pradeep P (CB.EN.U4CSE20646) | cb.en.u4cse20646@cb.students.amrita.edu | Students of the Department of Computer Science and Engineering, Amrita School of Computing, Coimbatore, Amrita Vishwa Vidyapeetham, India |
| 2 | Guru Venkat R (CB.EN.U4CSE20619) | cb.en.u4cse20619@cb.students.amrita.edu |
| 5 | R. Arumuga Arun | [r\_arumugaarun@cb.amrita.edu](mailto:r_arumugaarun@cb.amrita.edu) | Department of Computer Science and Engineering, Amrita School of Computing, Coimbatore, Amrita Vishwa Vidyapeetham, India |

**ABSTRACT:**

Bird species classification plays a crucial role in various fields, including ornithology, conservation, and wildlife management. To facilitate research in this area, we present a comprehensive dataset comprising 10 classes, each representing a distinct species of bird. With approximately 550 high-resolution images per class, our dataset offers a diverse collection of bird images, showcasing various poses and environments. Each image is meticulously annotated with accurate labels indicating the corresponding bird species. This dataset serves as a valuable resource for training and evaluating machine learning models tailored for bird species classification tasks. The images are of exceptional quality, capturing intricate details of the birds' physical features and plumage. Researchers can utilize this dataset to advance the state-of-the-art in bird species classification algorithms, explore the interplay between morphology and classification accuracy, and gain insights into the ecology and behavior of different bird species. Additionally, this dataset has the potential to contribute to the development of practical applications such as automated bird identification systems and biodiversity monitoring tools.​

**INTRODUCTION:**

Bird species classification is an important research area that has gained much attention from both academia and industry in recent years. With the increasing availability of image data and advances in deep learning techniques, it is now possible to build models that can accurately classify bird species based on their visual features. The main goal of this research is to investigate the performance of lightweight classification models in bird species classification and to evaluate their suitability for real-time classification on embedded devices.

Bird species play a crucial role in maintaining ecological balance and biodiversity. However, many bird species are facing threats such as habitat loss, climate change, and human activities, which are causing their populations to decline. Therefore, it is essential to monitor bird populations and migration patterns to identify and address these threats in a timely manner.

Traditional methods of bird monitoring involve manual counting and observation, which can be time-consuming, labor-intensive, and subject to human error. Moreover, these methods may not provide accurate data on the population of rare or endangered bird species. By using image-based classification methods, we can automate the process of bird monitoring and obtain more accurate and reliable data. This can help us identify the population of different bird species and their distribution in a particular region.

The primary objective of this research is to evaluate the performance of lightweight classification models in bird species classification. We will use four lightweight models – MobileNetV2, MobileNetV3 Small, and VGG16 – and train them on a dataset of bird images. We will evaluate the performance of these models based on their accuracy, speed, and memory usage.

The second objective of this research is to investigate the trade-offs between model complexity and performance. Deep learning models with high complexity tend to have better performance, but they require more computational resources and may not be feasible for real-time classification on embedded devices. By evaluating the performance of lightweight models, we can identify the best-performing model that can be used for real-time classification on embedded devices.

The third objective of this research is to demonstrate the practical application of lightweight classification models in bird monitoring and conservation efforts. By identifying the best-performing model for real-time classification on embedded devices, we can develop a system that can monitor bird populations and migration patterns in a more efficient and accurate manner. This can help us identify the population of different bird species and their distribution in a particular region, which can be used to develop conservation strategies for the protection of these species.

In summary, this research aims to evaluate the performance of lightweight classification models in bird species classification, investigate the trade-offs between model complexity and performance, and demonstrate the practical application of these models in bird monitoring and conservation efforts.

**LITERATURE SURVEY:**

The literature survey serves as the foundation for any conference paper, providing a comprehensive overview of existing research and scholarly works related to the topic at hand. In this section, we aim to synthesize and analyze the existing body of literature to identify knowledge gaps and establish the context for our research.

The paper by Zonguan Gu and Alex Bewley presents a novel system called MixDCNN for fine-grained image classification. It partitions images into subsets and learns an expert deep convolutional neural network (DCNN) for each subset. The outputs from the expert DCNNs are combined to form a single classification decision. The system allows for joint end-to-end training of the expert DCNNs, outperforming previous techniques and achieving state-of-the-art results. The proposed approach eliminates the need for a separate gating network and improves the classification accuracy by effectively capturing the subtle differences between similar samples. But the model is too complex to be used on the mobile devices for real-time classification of bird species.

This research paper focuses on bird species identification using image processing and convolutional neural networks (CNN). The authors, Shruthishree S H and Zabeeulla, propose a system that can aid birdwatchers in identifying bird species by analyzing photographs. They explore the feasibility of using deep learning and CNN for feature extraction from bird images. The system converts color images to black-and-white and calculates scores for each node using autographs, predicting the bird species based on the score analysis. The Caltech-UCSD Birds 200 dataset is used for training and evaluation. The effectiveness of the system is demonstrated, allowing anyone to quickly identify bird species of interest. The proposed system combines DNN, CNN, computer vision, and bird species classification. The proposed system is not suitable for mobile and edge devices which is our main research interest.

This paper by Pureti Anusha, Kundurthi ManiSai presents a novel deep learning-based approach for bird species classification using the Caltech-UCSD Birds 200 dataset. The proposed methodology incorporates unsupervised learning algorithms and deep convolutional neural network (DCNN) layers, contributing to accurate classification with an 89% accuracy rate. One of the key strengths is the use of grayscale bird images, which reduces complexity and computational requirements. However, a drawback of the study is the lack of comparison with existing state-of-the-art methods, making it difficult to assess the true performance improvement. Nonetheless, this research highlights the potential of image-based classification for bird species identification.

The paper "MobileNetV2 Model for Image Classification" by Ke Dong, Chengjie Zhou, Yihan Ruan, Yuzhi Li presents a deep learning model based on MobileNetV2 architecture for image classification tasks. The authors leverage the efficient design of MobileNetV2, which utilizes depth-wise separable convolutions and inverted residual blocks, to achieve high accuracy while minimizing computational complexity and model size. The proposed model demonstrates superior performance on various image classification benchmarks, showcasing its effectiveness in resource-constrained scenarios such as mobile devices. The research contributes to the field of efficient deep learning models for image classification and offers practical implications for real-world applications. Our inspiration for using the MobileNetV2 model came from this paper.

In conclusion, this literature survey highlights the need for evaluating and comparing the lightweight classification models to find out which one would be much suitable for real-time classification of bird species. MobileNetV2, MobileNetV3 Small and VGG16 are the models we chose to use for this purpose because of the smaller number of parameters they contain. By training these models using transfer learning with pre-trained weights from ImageNet Dataset we can even reduce the time for training and evaluating the models in the context of real-time bird species classification on embedded devices. By directly comparing these models in terms of accuracy, inference speed, memory usage, and potentially other metrics, this research aims to identify the most suitable lightweight model for efficient and accurate real-time classification.

**PROPOSED WORK:**

Our goal is to find out which lightweight classification model would be efficient, accurate and suitable for transfer learning for the real-time classification of species in embedded devices. For this purpose we use check the performance and efficiency of three models namely MobileNetV2, MobileNetV3Small, VGG16. We first start with the data collection, for this we have collected the images of 10 different bird species which are found in Indian lands.

For the data pre-processing part all the images in the dataset are resized to 128x128, some images were converted to grayscale, the pixel values were normalized. The training and validation split is 80:20 4299 images for training, 1071 images for validation.

The pre-trained models MobileNetV2, MobileNetV3Small, VGG16 were imported from Keras with the weights from imagenet dataset. Two dense layers with 256, 128 neurons were added respectively with ‘relu’ activation function, followed by a dropout layer of 0.5 is added, last output layer of 10 neurons, 1 for each class is added with ‘softmax’ activation function. The model was compiled with ‘adam’ optimizer and loss function as ‘sparse\_categorical\_crossentropy’. The training of the models were carried out with early stopping callback to stop the training if the validation loss increases.

**EXPERIMENTAL ENVIRONMENT AND EVALUATION METRICS:**

Software frameworks used were TensorFlow, CUDA Toolkit, cuDNN.

Accuracy: Calculate the accuracy of the classification models by comparing the predicted bird species labels with the ground truth labels in the dataset.

Inference Time: Measure the time taken by the models to perform inference. This metric is crucial for assessing real-time performance.​

Memory Usage: Assess the memory utilization of the models during inference, as limited memory is a common constraint in embedded devices.​

Classification report: Precision, Recall, F1-score.

**RESULTS:**​

The models MobileNetV2, MobileNetV3Small, VGG16 obtained an accuracy of 97.49%, 11.37%, 88.63%. The total training time of MobileNetV2, MobileNetV3Small, VGG16 are 19.55 minutes, 5.7 minutes, 9.12 minutes. The inference time for each model were in ms. The average memory used while training are 1.57GB, 0.69 GB, 0.99GB for MobileNetV2, MobileNetV3Small, VGG16 respectively.

In conclusion the VGG16 performs the best out of the three when feeded with an unseen data, it is able to classify the bird to the correct species. The saved model can be used for the real-time classification of bird species.

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