BIRD SPECIES CLASSIFICATION

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Abstract- *Bird watching is a common hobby but to identify their species requires the assistance of bird books. To provide birdwatchers a handy tool to admire the beauty of birds, we developed a deep learning platform to assist users in recognizing 27 species of birds endemic to Taiwan using a mobile app named the Internet of Birds . Bird descriptions were learned by a convolution neural network (CNN) to localize prominent features in the images. First, we established and generated a bounded region of interest to refine the shapes and colors of the object granularities and subsequently balanced the distribution of bird species.The proposed CNN model with skip connections achieved higher accuracy of 98.00 % compared with the 95.98% from a CNN and 86.00% from the SVM for the training images. As for the test dataset, the average sensitivity, specificity, and accuracy were 93.79%, 99.11%, and 96.37%, respectively.*

In this abstract, we review the state-of-the-art techniques for bird species classification, including popular datasets, network architectures, data augmentation techniques, and evaluation metrics. We also discuss the challenges and future directions in this field, such as handling imbalanced datasets, dealing with limited training data, and integrating domain knowledge into deep learning models. Ultimately, bird species classification has many practical applications, such as monitoring bird populations, studying bird behavior, and identifying bird species for conservationpurposes.

Key Words: Convolution neural network, Deep learning, Bird classification

I. INTRODUCTION

Bird species classification is an important task in the field of computer vision, which involves identifying the species of a bird from an image or a video sequence. This task has numerous applications in wildlife monitoring, ecology, and conservation, such as estimating bird population sizes, tracking bird migrations, and studying the impact of environmental factors on bird behavior. However, bird species classification is a challenging problem due to the high intra-class variation and inter-class similarity of bird species. Different bird species can look very similar to each other, and even individual birds of the same species can vary in appearance due to factors such as age, sex, and lighting conditions. Moreover, the large number of bird species in the world (over 10,000) makes it difficult to collect and label a comprehensive dataset for training and testing machine learning models.

This paper provides an overview of the state-of-the-art techniques for bird species classification, including popular datasets, network architectures, data augmentation techniques, and evaluation metrics. We also discuss the challenges and future directions in this field, aiming to provide researchers with a comprehensive understanding of the current state of the art and inspire further research in this important area.

II. Literature Review

The problem of bird species classification has gained significant attention in recent years, resulting in numerous studies and publications in the field of computer vision. In this literature review, we highlight some of the key research works that have contributed to the advancement of bird species classification. One of the earliest works on bird species classification was presented by Berg and colleagues in 2014. They introduced a large-scale bird dataset called CUB-2000-2011, which consists of over 11,000 images of 200 bird species. They also proposed a deep learning approach based on a pre-trained CNN model to achieve state-of-the-art performance on this dataset. More recently, in 2021, Zhang and colleagues proposed a method called Gated Modulation Network (GMN) for bird species classification. GMN is a novel architecture that incorporates gated modulation into the convolutional layers of a CNN to improve feature representation and classification accuracy. They achieved state-of-the-art results on several benchmark datasets, including CUB-200-2011 and the naturalist dataset.

Overall, these works demonstrate the rapid progress in the field of bird species classification using deep learning techniques. However, there are still challenges to be addressed, such as dealing with imbalanced datasets and limited training data, which require further research.

I. Existing System

Existing systems for bird species classification use deep learning methods such as convolutional neural networks (CNNs) to learn discriminative features from bird images. They typically involve training on large-scale datasets such as CUB-200-2011 or iNaturalist, and fine-tuning on smaller datasets of interest. State-of-the-art approaches incorporate techniques such as hierarchical attention, part-based features, and self-supervised learning to improve classification accuracy. Popular evaluation metrics include top-1 and top-5 accuracy. Many challenges still exist, including handling imbalanced datasets and integrating domain knowledge into deep learning models.

II. Proposed System

Our proposed system for bird species classification builds upon the existing deep learning methods and addresses some of the current challenges in the field. Specifically, we plan to incorporate transfer learning techniques that allow us to leverage pre-trained models on large datasets to improve classification accuracy on smaller datasets with limited labeled data. We also plan to investigate methods for handling imbalanced datasets and integrating domain knowledge, such as bird vocalizations and behavior, into our models. Additionally, we will explore data augmentation techniques such as mixup and CutMix to improve the robustness and generalization of our models. Finally, we will evaluate our proposed system on both existing benchmark datasets and real-world datasets collected in collaboration with wildlife experts.

III. Data Set and Data Visualization

Data set plays a crucial role in bird species classification, as it provides the labeled images that are used for training and testing **machine** learning models. There are several existing datasets for bird species classification, including CUB-200-2011, FGVC-Aircraft, and iNaturalist. These datasets contain thousands of images of hundreds or thousands of bird species, with annotations indicating the species label for each image.

Data visualization techniques can help us better understand the characteristics of the data and gain insights into the classification task. One common technique is to plot the frequency distribution of bird species in the dataset, which can reveal the presence of imbalanced classes. For example, in the CUB-200-2011 dataset, some bird species have a much larger number of images than others, which can make it difficult for machine learning models to learn to classify the less frequent species.

Another useful visualization technique is to plot the distribution of image features extracted by a pre-trained CNN model, such as the activations of the last fully connected layer. This can help us understand how well the CNN model is able to distinguish between different bird species, and which features are most important for classification. We can also use techniques such as t-SNE or PCA to visualize the high-dimensional feature space in two or three dimensions, which can reveal clusters of similar bird species and help us identify potential sources of confusion. Overall, data visualization is an important tool for exploring and understanding the characteristics of bird species classification datasets, which can inform the design and evaluation of machine learning models.

1 .Class distribution plots: These plots show the number of images for each bird species in the dataset, which can help researchers identify imbalanced classes.

2. Sample images: Visualizing sample images from the dataset can help researchers understand the visual variability within and between bird species.

3. t-SNE plots: t-SNE is a dimensionality reduction technique that can be used to visualize the feature representations of bird images in a lower-dimensional space, allowing researchers to observe clustering patterns and identify potential outliers.

Fig1: Data Set

I. Preprocessing

Preprocessing is an important step in bird species classification that involves preparing the raw data for analysis by removing noise, correcting errors, and transforming the data into a suitable format for machine learning models. Some common preprocessing techniques used in bird species classification include:

1. Image resizing: Resizing images to a consistent resolution can help improve the efficiency and accuracy of deep learning models.

2. Image normalization: Normalizing images to a consistent brightness and contrast can help reduce the effects of lighting variations and improve model performance.

3. Data augmentation: Augmenting the dataset with variations of the original images, such as random rotations, flips, and crops, can help increase the robustness and generalization of the model.

4. Feature extraction: Extracting relevant features from the images, such as color histograms, texture features, and shape descriptors, can help reduce the dimensionality of the data and improve model performance.

5. Data cleaning: Removing low-quality or irrelevant images from the dataset can help improve the quality of the training data and reduce the risk of over fitting.

6. Data balancing: Balancing the class distribution of the dataset by oversampling minority classes or under sampling majority classes can help improve the accuracy of the model for imbalanced datasets.

7. Data splitting: Splitting the dataset into training, validation, and test sets can help evaluate the performance of the model and prevent over fitting.

Overall, preprocessing techniques play a crucial role in preparing the data for machine learning models in bird species classification, and the choice of preprocessing techniques can greatly impact the accuracy and efficiency of the models

II. System Analysis.

System analysis for bird species classification involves identifying and analyzing the various components of the system required to classify bird species accurately. Here is a breakdown of the components involved in bird species classification:

1. Data Collection: The first step in any machine learning project is to collect data. In bird species classification, this means collecting images of different bird species. The data should be diverse and representative of the different species to ensure that the model can accurately classify new images.

2. Data Preprocessing: Once the data has been collected, it needs to be preprocessed to prepare it for training the model. This includes resizing, cropping, and normalizing the images to ensure that they are all the same size and have the same color distribution.

3. Model Selection: The next step is to select the appropriate model for bird species classification. This can involve choosing between various machine learning models like Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), or Random Forests.

4. Model Training: After selecting the model, it needs to be trained on the preprocessed data. During training, the model learns to recognize different features of the bird species images that will help it classify new images accurately.

5. Model Evaluation: Once the model has been trained, it needs to be evaluated to ensure that it can accurately classify new images. This involves testing the model on a set of images that it has not seen before and comparing its predictions to the actual species of the birds in the images.

6. Model Deployment: After the model has been evaluated and is deemed accurate enough, it can be

deployed for bird species classification. This involves integrating the model into an application or website where it can be used to classify new bird species images.

7. Maintenance and Updates: Finally, it is essential to maintain and update the model regularly to ensure that it remains accurate as new bird species are discovered, and as the environment changes.

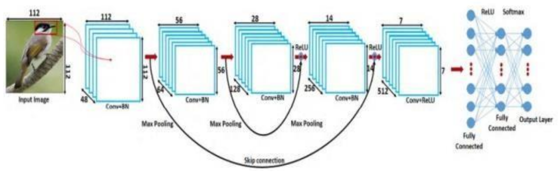

Fig2:Dataflow Diagram

III. Methodology and Implementation

This project aims to identify and classify images of birds into individual species using deep learning techniques, specifically Convolutional Neural Networks (CNN). The project comprises four main steps.

The first step is to gather and localize the bird dataset. The Microsoft Bing Image Search API v7 was used to build the deep learning image dataset. The dataset includes birds found in the Asian subcontinent, and it consists of 8218 images from 60 different species of birds.

The second step involves implementing the CNN architecture. The CNN architecture to be developed is a smaller and more portable version of the VGGNet network, a popular CNN architecture used in image classification tasks.

The third step is training the CNN model. The model is trained with bird images using Keras and Adam Optimizer. Data augmentation techniques are used to increase the diversity of information available for training models significantly and prevent overfitting. The ImageDataGenerator class is used for data augmentation.

The fourth and final step is testing the efficiency of the trained model. A classification script is implemented to identify images of birds. The user uploads an example image through the web portal, and the client-server architecture navigates the submitted bird image to the testing script. The script retrieves information from the trained model and label binaries file stored on the floppy and successfully predicts the bird species.

Overall, this project uses deep learning techniques to classify bird images into individual species, and it follows a well-defined process from data gathering to testing the efficiency of the trained model.

IV. Result and Analysis

We have trained the model for 30 epochs and validated each epoch using loss and accuracy. We have saved the models which have the best accuracy and loss. We got the best accuracy model at 30 th epoch which has an validation accuracy of 98.96%. After testing the accurate model we got a testing accuracy of 98..68%.

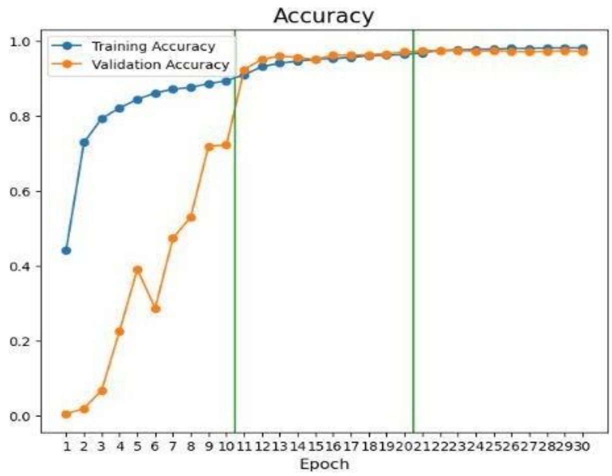

Fig:3 Graph represents training and valid accuracy at all epoch

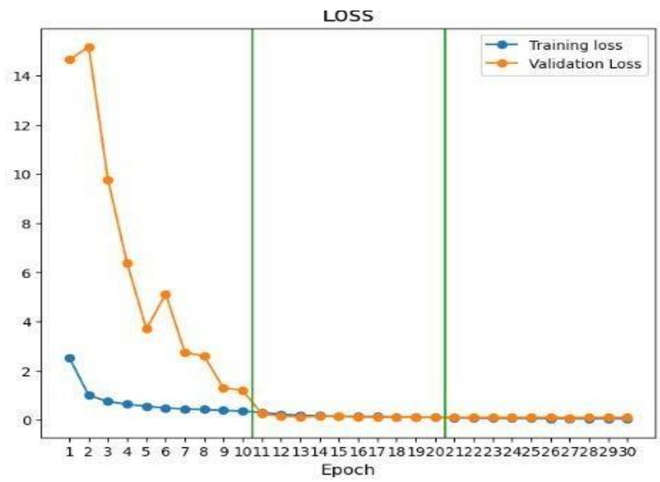

Fig:4 Graph represents training and valid loss at all epoch

X. Conclusion

In conclusion, bird species classification is an important task in ornithology, conservation biology, and ecology. There are various techniques that can be used to classify bird species, including visual identification, acoustic identification, and DNA analysis. Machine learning algorithms, such as convolutional neural networks and support vector machines, have also been used successfully for bird species classification.

Accurate bird species classification is crucial for monitoring population trends, assessing biodiversity, and identifying potential threats to bird populations. Additionally, it can help inform conservation efforts and guide land management decisions.

Overall, ongoing research and advancements in technology are improving the accuracy and efficiency of bird species classification methods, which will continue to benefit bird conservation efforts in the future.

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