FACULTY OF COMPUTER AND MATHEMATICAL SCIENCES

BACHELOR OF COMPUTER SCIENCE (HONORS)
CS230

SPECIAL TOPICS IN COMPUTER SCIENCE
(649)

GROUP PROJECT REPORT
TITLE:
BIRDS CLASSIFICATION SYSTEM IN MALAYSIA USING CNN

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Abstract - Due to the resemblances of the birds' features and environment images and the insufficient knowledge of the spectators, identifying birds can be a challenging task. So, in order to aid birdwatchers in identifying birds, computer-based photos are required. With convolutional neural networks (CNN) used to extract data from images, this study looks into the potential of deep learning for bird identification. A dataset of 450 species of birds from kaggle.com was used for the inquiry.

Keywords: birds classification, deep learning , convolutional neural networks (CNN).

1.0 Introduction

Nowadays people tend to spend their precious free time doing something that is “back to nature", for example camping, collecting flowers or doing bird watching. It is a good activity to be involved with to appreciate nature and provide relaxation to calm the mind and body. It can also offer health benefits and happiness from enjoying the time with nature.

To enjoy birdwatching, people usually go visiting local zoo to glance at various beautiful bird species or either to gain knowledge about the local bird or with a good chance birdwatcher also found a new gain discovery of the species that offer in the zoo that not only local bird but also the birds that are outside of Malaysia that can be display in the zoo. Understanding such differences between species can enhance our knowledge of exotic birds as well as their ecosystems and biodiversity. However, because of observer constraints such as location, distance, and equipment, identifying birds with the naked eye is based on basic characteristic features, and appropriate classification based on distinct features is often seen as tedious.

Normally, detection of object parts of the birds is challenging because of their complex variations or similar subordinate categories and fringes of objects. Intraclass and interclass variation in the silhouettes and appearances of birds is difficult to identify correctly because certain features are shared among species. To classify the aesthetics of birds in their natural habitats, in this study, our group developed a method using a convolutional neural network (CNN) that extracts information from bird images captured previously or in real time by identifying local features. First, raw input data of myriad semantic parts of a bird were gathered and localized. Second, the feature vectors of each generic part were detected and filtered based on shape, size, and color. Third, a CNN model was trained with the bird pictures by using Anaconda’s Python for feature vector extraction with consideration of the aforementioned characteristics, and subsequently the classified, trained data were stored on a local server to identify a target object. Information is obtained by gathering the dataset from online that contains 450 bird species images.

A computer programme or system called a "bird recognition system" is made to recognise birds from pictures. It can be applied to a range of projects, including scientific investigation, environmental protection, and instruction. Birds' visual characteristics, such as the size, color, and shape of their beaks, wings, and tails, are often taken into account by bird recognition systems. The most likely match is then determined by comparing these characteristics to a database of recognised bird species.The variety in appearance of various bird species, the low quality of some photos , and the lack of data are some of the difficulties in creating a trustworthy bird recognition system. Despite these difficulties, researchers have significantly advanced bird recognition systems. In this programme, our group want to achieve these objective:

1. 1 Objectives

1. To identify the different kinds of birds that inhabit in Malaysia.
2. To use Convolutional Neural Networks (CNN) to solve actual problems.

1.2 Project scope

Type of problem (forecasting/prediction/classification/detection etc.)

As there is hardly any software available for bird species recognition, we decided to develop a bird species identifier which identifies the species of the bird from an uploaded image. This system helps in removing the knowledge barrier and smooths the process on bird species identification. As there are many software that provide the information of birds but none of them provide the information which we will provide.

Data source and the target output

Our data source is from kaggle.com and the target output is the species type of the birds.

Amount the data used (show the sample of dataset)

A total of 70,626 training photos, 22500 test images (five images per species), and 2250 validation images (five images per species) were used.

Data description (list of parameters involved)

The parameters involved in this process include filters (or kernels) which have a small receptive field, data organization for classifying each image, the size of the images in dataset, number of classes or labels that the CNN need to be able to recognize the image, number of images, image preprocessing(cropping,resizing,normalization and data augmentation).

2.0 Related Works

Machine learning (ML) represents a set of techniques that allow systems to discover the required representations to feature detection or classification from the raw data. The performance of works in the classification system depends on the quality of the features. As such of this study can be categorized under the field of ML; this is to make a search in this area for the studies that belong to birds' identification.

In the literature review, there are number of studies conducted in the field of identifying birds. But they were conducted with different algorithms and different methods. In this field of research, our group uses image methods to recognize bird types.Our research used to recognise bird type using images of 275 types of species with at least 5 images per species. It is using the concept of transfer learning and pre-trained algorithm made feature extraction possible from an image. The results obtained were of high efficiency as the software could easily identify a bird species from an image whose dataset was present in the database. In this project there are four models used, (1) EfficientNet, (2) InseptionNet, (3) ResNet and (4) MobileNet. For this project, our group uses two of four architectures which are (1) and (4). The result was achieved on high accuracy. For EfficientNet the accuracy achieved is 95.56%. For MobileNet, the result shows 95.13%. The flow of this project with the (A) use of the pre-trained model using Anaconda. Next is (2) applying transfer learning for feature extraction. The pre-trained network is used as a starting point to learn a new task. The learned features are transferred using few training images. (3) Classification of the image with support vector machine classifier to supervised machine learning algorithm is used for classification. In this step the Fit Image Classifier and Classify Test Image are used to extract from the pre-trained images are used as predictor variables and are used to fit a multiclass, and need to classify the test images. This is done by the trained model on the basis of features extracted from the test images. Lastly (4) checking the accuracy test fraction of labels predicted by the model correctly.

Literature Review

No.	Title	Algorithm	Objectives	Problem Statement	Result	References
1.	Bird Sound Recognition Using a Convolutional Neural Network	CNN	to develop a CNN system that can classify bird sounds using transfer learning and spectrograms generated from the downloaded data as input to the neural network	The specific challenges include recognizing single audible species as well as separating multiple overlaid sounds in field recordings.	The accuracy of the model was assessed to be 70.9% based on training on the ILSVRC-2012-CLS image classification dataset.	(Incze et al., 2018)

2.	Automated System for Bird Species Identification Using CNN	CNN	1. To develop an automated system for the identification of bird species using convolutional neural networks (CNNs). 2. To address the challenges of bird identification, such as unclear labeling, variations in lighting and backdrop, and the difficulty of identifying birds from photographs. 3. To provide a quick and accurate method for identifying bird species, benefiting bird watchers and researchers. 4. To utilize deep learning and powerful texture descriptors in the computer vision field for automating the identification of birds. 5. To raise public awareness of bird watching, bird identification, and the identification of birds' native to India 6. To enhance observation by meeting new	The problem addressed in the study is the difficulty and challenges associated with bird identification. Bird identification is a challenging task due to unclear labeling, variations in lighting and backdrop, and the difficulty of identifying birds from photographs. Additionally, the proximity of bird features and the background of photos, as well as the typical inexperience of observers, make it challenging for bird watchers to identify birds accurately.	The specific results of the algorithm and its performance metrics are not explicitly mentioned in the provided excerpts. However, the study mentions that the approach using Convolutional Neural Networks (CNNs) showed 80% accuracy in predicting the discovery of new bird species.	(Siri et al., 2023)

			identification process optimization requirements. 7. To achieve a high level of numerical accuracy in bird species identification using CNNs. 8. To predict the discovery of new bird species with 80% accuracy using the automated bird species identification system.			

3.	Bird Species Identification Using CNN	CNN	The main goal of the study is to investigate the utility of deep learning, specifically CNNs, for bird identification. The authors aim to develop a system that can accurately classify various bird species from a photograph submitted by the user. Additionally, the study aims to streamline the process of bird identification, which can enhance bird viewing and aid in the preservation of biodiversity.	The problem statement is that identifying bird species from photographs is a challenging task that often leads to unclear labelling. Even professional bird watchers may disagree on the species of a bird in a photograph due to the unique characteristics of birds, such as their colour, size, and viewing angle. This problem puts a load on both the visual capacities of humans and computers. Therefore, the authors propose using CNNs to extract information from photos and develop a system that can accurately classify various bird species.	The study achieved an accuracy of 80% in predicting the discovery of bird species using the proposed method based on the generated findings.	(Dharaniya et al., 2022)

4.	Bird Species Identification Using Convolutional Neural Network	CNN	1. Presenting the implementation details of bird species identification using a Convolutional Neural Network (CNN). 2. Highlighting the importance of bird species classification in biodiversity preservation, ecosystem maintenance, and its applications in various activities like agriculture, landscape formation, and coral reef formation. 3. Discussing the challenges in bird species identification due to various appearances of birds, backgrounds, and environmental changes, and how recent developments in deep learning have made the classification of bird species more flexible. 4. Demonstrating the process of	Ornithologists and researchers face difficulties in accurately identifying bird species due to the diverse appearances of birds, varying backgrounds, and environmental changes. This uncertainty can hinder ecological studies and conservation efforts	The Convolutional Neural Network (CNN) achieved an accuracy ranging from 87% to 92% in identifying bird species from input images. This demonstrates the effectiveness of the CNN in accurately classifying bird species.	(Siri & Rangaraju, 2023)

			feature extraction and classification using CNN for bird species identification. 5. Providing insights into the accuracy and performance of the model, and discussing future work, including the development of a mobile application for real-time monitoring of bird species in sanctuaries			

5.	Bird Species Identifier using Convolutional Neural Network	CNN	1. Developing an automated system for identifying bird species from images captured in their natural habitat, with a focus on size, shape, and colour parameters. 2. Utilizing Convolutional Neural Networks (CNN) for feature extraction and image recognition, aiming to achieve an accuracy of 85%-90%. 3. Investigating the recognition of many bird species, addressing the challenges posed by the similarity between classes and the non-rigid nature of birds. 4. Simplifying the bird identification process and making bird-watching easier, with potential applications in wildlife research, monitoring, and camera trap technology.	1. The tedious and unreliable nature of manual bird species identification, which is often limited by human knowledge and local bird species familiarity. 2. The time-consuming and error-prone process of using bird audio for species identification, which requires extensive analysis and classification, making large-scale bird identification nearly impossible. 3. The difficulty in recognizing rare bird species, which presents a significant challenge for accurate prediction and classification. 4. The need for an automated system that can effectively and efficiently identify bird species from images, overcoming the limitations of manual and audio-based identification methods.	Successful implementation of a deep learning platform using Convolutional Neural Networks (CNN) for identifying bird species based on image inputs, achieving an accuracy of 85%-90%	(Jange et al., 2022)

			5. Exploring future enhancements such as developing a mobile app for user convenience and implementing the system using cloud technology for large-scale data storage and high computing power.			

6.	Bird Image Classification using Convolutional Neural Network Transfer Learning Architectures	CNN	1. To develop and evaluate deep learning models for accurately classifying bird species based on images. 2. To assess the effectiveness of transfer learning architectures, such as ResNet152 and VGG16, in classifying bird images. 3. To demonstrate the potential of convolutional neural networks in contributing to wildlife monitoring and conservation efforts. 4. To explore the application of advanced computer science techniques in addressing ecological and biodiversity challenges, particularly related to bird populations. 5. To identify the potential for real-world applications of the research findings in wildlife conservation, ecological	The problem statement for this paper is the need for accurate and efficient methods for identifying bird species from images. With the increasing threat of extinction and habitat loss, it is crucial to monitor and conserve bird populations. However, traditional methods of identifying bird species based on visual observations can be time-consuming and prone to errors. Therefore, the study aims to develop and evaluate deep learning models that can accurately classify bird species based on images, which can contribute to wildlife monitoring and conservation efforts. The research also aims to address the gap in existing approaches to bird image classification and identify the most effective transfer learning architectures for this task.	The ResNet152V2 model provided the highest accuracy of 95.45%, followed by DenseNet201 with an accuracy of 94.55%. InceptionV3 and MobileNetV2 achieved accuracies of 93.64% and 92.73%, respectively.	(Manna et al., 2023)

			research, and biodiversity monitoring.			
7.	Animal image identification and classification using deep neural networks techniques	k-means clustering, deep neural networks, annotation localization and classification, and exemplar-based geometric models	1. Developing a reliable learning strategy for animal categorization in naturally inhabited areas with noisy labels. 2. Testing the proposed method using publicly accessible camera-trap picture datasets. 3. Achieving high accuracy in classifying animal species from camera-trap photos despite high levels of label noise.	The problem addressed in the paper is the challenge of categorizing animals from camera-trap photos captured in naturally inhabited areas with high densities of people and noise. Specifically, the authors aim to tackle the issue of noisy labels in the training data, which can significantly impact the accuracy of animal species classification.	The paper reports the accuracy of the proposed method for classifying animal species from camera-trap photos. Specifically, the accuracy results are presented for different noise levels and sample fractions of the datasets. For example, the method achieves an accuracy of 73.09% for a noise level of 30% on the Snapshot Serengeti dataset. Additionally, the accuracy results for noise levels of 50% and 70% are also provided, demonstrating the performance of the method under varying levels of label noise.	(Battu & Reddy Lakshmi, 2023)

8.	Acoustic Classification of Bird Species Using an Early Fusion of Deep Features	CNN	1. to investigate the use of transfer learning and training from scratch for bird sound classification using deep learning models. 2. to compare the performance of different pre-trained models, including VGG16, ResNet50, EfficientB0, MobileNetV2, and Xception, for bird sound classification using transfer learning.	1. Insufficient annotated training data: The basic problem of insufficient annotated training data for bird sound classification is a significant challenge. Transfer learning is used to address this issue by leveraging pre-trained models and adapting them to the task of bird species classification. 2. Feature extraction from spectrograms: The study aims to effectively extract deep cascade features from spectrograms using pre-trained models such as VGG16 and MobileNetV2 to improve the classification performance of bird sounds. 3. Classification performance improvement: The study seeks to improve the classification performance of bird sounds by fusing deep cascade features extracted from different pre-trained models and applying	1. The highest balanced accuracy achieved for classifying 43 bird species using linear SVM was 94.89% ± 1.35%. 2. VGG16 demonstrated the best performance in terms of balanced accuracy among the pre-trained models used. 3. The study also mentioned balanced accuracies of 90.94% ± 1.53% and 90.92% for deep cascade features with different numbers of frozen layers	(Xie & Zhu, 2023)

				data augmentation techniques such as pitch shifting.		
9.	Bird Species Classification Based on Color Features	Support Vector Machines (SVM)	to evaluate simple feature descriptors in bird images and assess the expected classification performance when dealing with many bird species.	the classification of bird species based on colour features extracted from unconstrained images. The challenge of this problem is due to the variation in the background and illumination, as well as the pose, size, and angle of view of the birds in the images. Additionally, there is a high visual similarity between some bird species, making it difficult to distinguish between them.	The proposed colour segmentation approach achieved segmentation rates of 71.0% for RGB colour space and 75.0% for HSV colour space, demonstrating favourable results compared to previous work.	(Marini et al., 2013)

10.	Wild Animal Classification Using CNN	CNN	to develop a robust and reliable automated system for detecting and classifying wild animals in real-world environments.	The expansion of urban areas has resulted in the displacement of habitats in forested areas, forcing wild animals to venture into human settlements. This poses a tangible danger to humans and endangers the lives of endangered animals. The usage of technology and robust cameras is not a new concept in most major biosphere reserves and national parks around the world. However, software-based tools have not been explored to a satisfactory extent in these use cases.	The model achieved a training accuracy of 95% and a testing accuracy of 91% after 40 epochs.	(Sahil Faizal & Sanjay Sundaresan, 2022)

3.0 Method and implication

Chapter 3: Methodology

3.1 Introduction

This chapter lays the foundation for the development of the Convolutional Neural Networks (CNN) Bird Identification System, emphasizing transparency and reproducibility. The process begins with a detailed discussion of data collection, encompassing diverse dataset acquisition, and preprocessing techniques like image normalization and augmentation. The architecture of the CNN is then introduced, providing insights into layer selection and parameter tuning, followed by a comprehensive description of validation and testing procedures. Ethical considerations and potential biases are also addressed, providing an overview of the methodical approach taken in preparation for more in-depth exploration in subsequent chapters.

In the era of Industry 4.0, where technology has significantly evolved, making daily activities more convenient, leveraging advanced artificial intelligence becomes imperative. Deep learning, a subset of machine learning, emerges as a key player in this project. Deep learning involves multi-layered neural networks learning from vast datasets, drawing inspiration from the structure of the human brain. Among various neural network types, Convolutional Neural Networks (CNNs) stand out for image classification tasks. Specifically suited for bird identification, CNNs excel at detecting and identifying patterns in images. Their capability to break down an image into distinct components facilitates recognizing subtle differences between bird species, such as coloration and patterning. Furthermore, CNNs excel in capturing the context of an image, providing valuable assistance in the intricate process of bird identification.

3.2 Data Collection

A dataset of 450 bird species has been collected. The images total up to 70,626 training photos and 22500 test images. The quality of the dataset is extremely high where the details of the bird can be seen clearly, enhancing feature extraction for the algorithm chosen. In each of the images, the birds occupy more than 50% of the pixels. This allows for a higher accuracy of an object classification prediction,

Table 3.2.1: Classes of birds to be detected

ABBOTTS BABBLER	ABBOTTS BOOBY	ABYSSINIAN GROUND HORNBILL	AFRICAN CROWNED CRANE	AFRICAN EMERALD CUCKOO	AFRICAN FIREFINCH

AFRICAN OYSTER CATCHER	AFRICAN PIED HORNBILL	AFRICAN PYGMY GOOSE	ALBATROSS	ALBERTS TOWHEE	BAIKAL TEAL
BALD EAGLE	BALD IBIS	BALI STARLING	BALTIMORE ORIOLE	BANANAQUIT	BAND TAILED GUAN
BANDED BROADBILL	CAATINGA CACHOLOTE	CABOTS TRAGOPAN	CABOTS TRAGOPAN		

Table 3.2.1 describes a subset of classes of birds that is used to train the Convolutional Neural Network model. Each of the classes above have 5 images each for testing and training. The table describes 22 species out of 525 species the model is trained on.
The example of the image are as below.

Figure 1

Figure 2

3.3 Algorithm ; Convolutional Neural Network

This chapter focuses on the algorithmic foundation of the Bird Identification System, employing Convolutional Neural Networks (CNNs) as the core framework. CNNs have proven to be exceptionally effective in image recognition tasks, making them an ideal choice for the intricate task of bird species identification. The section begins with an in-depth exploration of the CNN architecture, elucidating the choice of layers, activation functions, and the rationale behind the model's design. The convolutional and pooling layers, integral to feature extraction, are explained in detail. Subsequently, the chapter addresses the training process, emphasizing the selection of hyperparameters, such as learning rates and batch sizes, to optimize model performance. Special attention is given to the transfer learning approach, if utilized, and its implications for the bird identification system. Through a systematic breakdown of the CNN algorithm, this chapter provides a clear understanding of the computational framework that underpins the subsequent evaluation and results presented in the following chapters.

Convolutional layers are fundamental building blocks of CNNs that are used to extract features from an image, such as edges, textures, and shapes. Each filter in a CNN slides or convolves across the input image, performing element-wise multiplications and summations to produce feature maps, the depth of which reflects the number of filters applied, capturing various aspects of the input. Convolutional layers are essential to the network's ability to automatically learn and recognize hierarchical representations of visual patterns, which prove particularly effective in image classification tasks like bird identification.

3.4 Process Flow

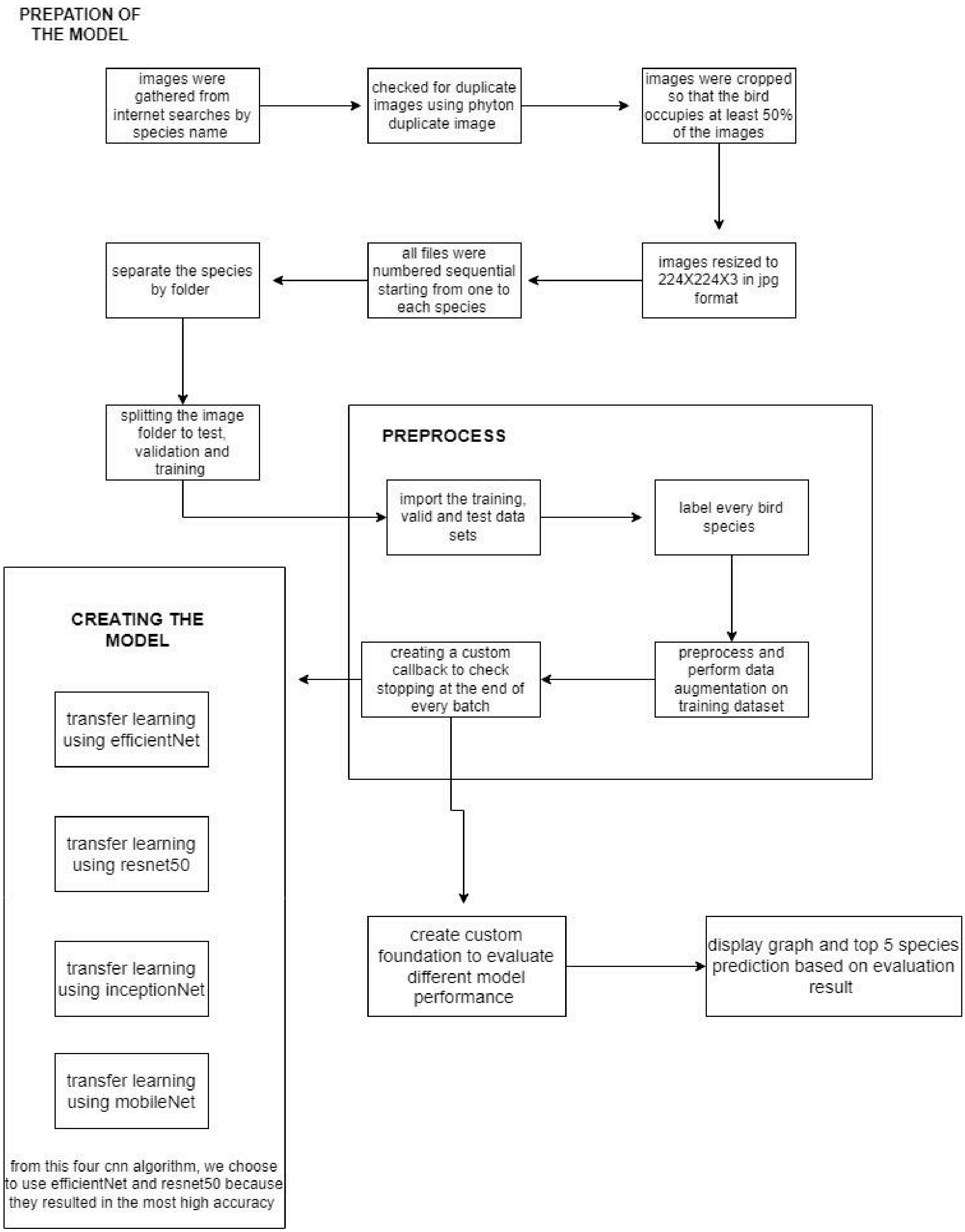

Figure 3 Flowchart of the process flow.

4.0 Project result and Discussion

During prototype development we use a pre-trained model that comes with Keras and then retrained on the Bird Species Dataset.

With a pre-trained model we try to transfer learning and use different kinds of CNN architecture and choose which with the highest accuracy. From all the results we get that EfficientNet and Resnet50 architecture get the most birds that can be identified.

4.1 Experiment result

Transfer learning pre-trained Image Classification Models using :

EfficientNet Architecture

EfficientNet is a convolutional neural network (CNN) architecture that was developed to provide a more efficient and accurate model for image classification. It achieves this by using a series of feature-wise and channel-wise scaling techniques that increase the model's width and depth. These techniques allow EfficientNet to achieve better accuracy and performance than other existing architectures. It is also a good choice for bird identification due to its high accuracy and efficient use of resources.

Feature-wise Efficiency:

Depthwise Convolution: Depthwise convolution is a type of convolution where the input channels are convolved independently. This type of convolution is more efficient than traditional convolution as it reduces the number of parameters in the network and allows for more efficient training.

Group Convolution: Group convolution is similar to depthwise convolution but instead of convolving each channel independently, it involves several channels at once. This allows for more efficient use of the network’s parameters and can also help reduce overfitting.

Pointwise Convolution: Pointwise convolution is a type of convolution where each input channel is convolved with its own set of weights. This type of convolution is more efficient than traditional convolution as it reduces the number of parameters in the network and allows for more efficient training.

Compound Scaling: Compound scaling is a novel method used by EfficientNet architectures to scale up the size of the model. This method combines depthwise convolution, group convolution, and pointwise convolution in order to scale up the model while keeping the number of parameters in the network to a minimum.

Channel-wise Efficiency:

Global Average Pooling: Global average pooling is a type of pooling layer commonly used in convolutional neural networks. This layer takes the average of all the inputs in the input layer, thus reducing the dimensionality of the output.

Squeeze-and-Excitation Networks: Squeeze-and-Excitation Networks (SE-Net) are a type of neural network architecture that incorporates a special type of layer known as a squeeze-and-excitation block. This layer helps to improve the network's overall accuracy by allowing the network to focus on important features in the input.

Grouped Convolutions: Grouped convolutions are a type of convolution where the convolutional filters are grouped together rather than being applied independently. This allows for better parameter sharing, which leads to more efficient use of the network's parameters and can also help reduce overfitting.

Depthwise Separable Convolutions: Depthwise separable convolutions are a type of convolution where the input channels are convolved independently and then combined. This helps to reduce the number of parameters in the network and allows for more efficient training.

```
90/90 [==============================] - 10s 89ms/step - loss: 0.2277 - accuracy: 0.9369
90/90 [==============================] - 8s 89ms/step - loss: 0.1434 - accuracy: 0.9587

Validation loss : 0.2277
Accuarcy on validation set is : 93.69 %


Test loss : 0.1434
Accuarcy on test set is : 95.87 %
```

After we trained and evaluated using EfficientNet architecture with a pre-trained model we got an accuracy of 93.69% on the validation set and an accuracy of 95.87% on the test set.

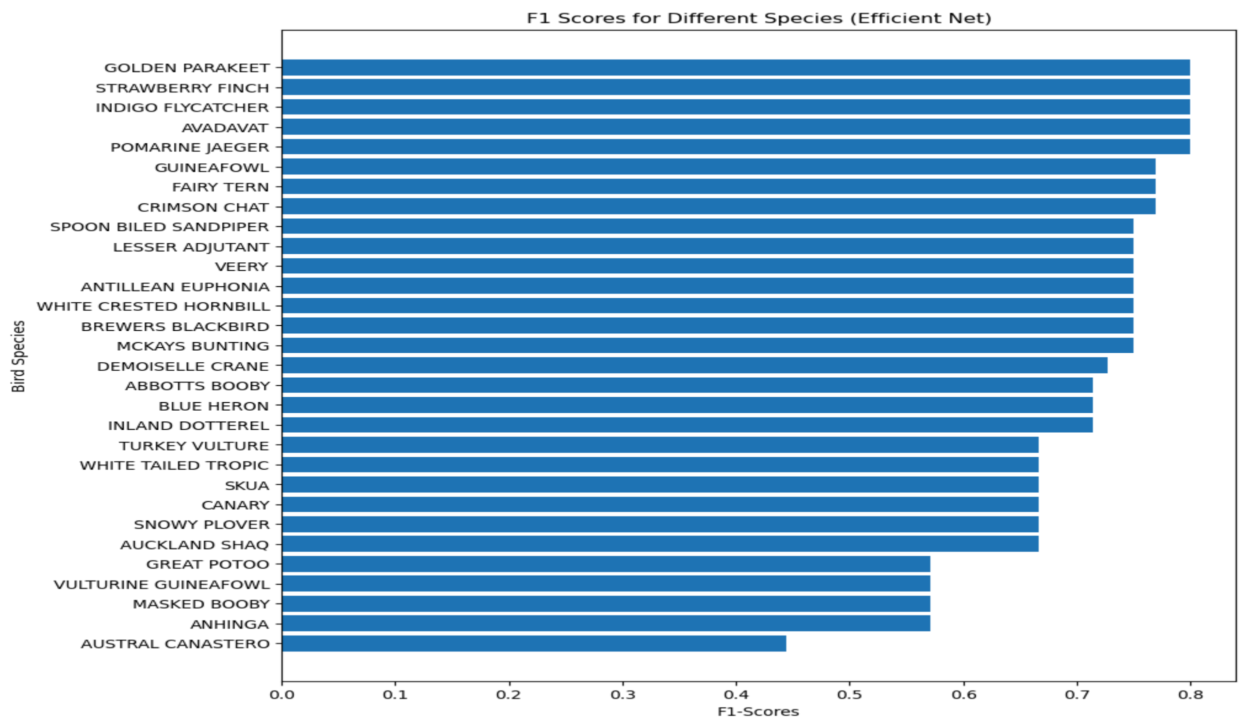

Figure 4

Efficient Net model has low prediction accuracy on:

- GILDED FLICKER
- TAKAHE
- NORTHERN CARDINAL
- CINNAMON TEAL

Above graph shown the f1 scores follow by bird species and we can make summary that some bird are easy to identified and some are hard.

After that,we try some example picture and create a graph that show 5 top highest f1 score.higher F1 score indicates that the model is correctly identifying more of the relevant data points and correctly rejecting more of the irrelevant ones. F1 score is used to evaluate the performance of a model for a binary classification problem.

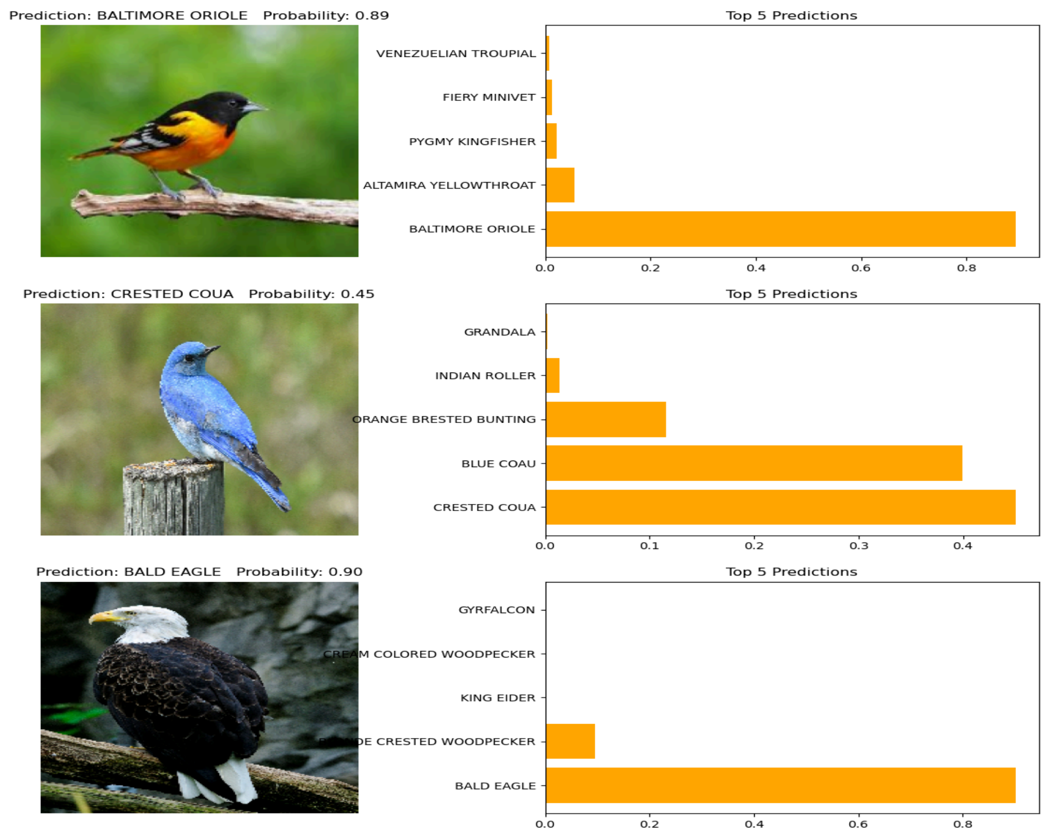

Figure 5

Resnet50 Architecture

ResNet50 is a deep convolutional neural network architecture developed by Microsoft that is widely used in computer vision tasks. It is a 50-layer convolutional neural network architecture based on the ResNet architecture. The network is characterized by its skip connections that allow information to pass between layers, which helps to reduce the amount of computation required to train the model. ResNet50 has been used to achieve state-of-the-art performance on several image classification tasks.

```
90/90 [==============================] - 11s 107ms/step - loss: 0.3155 - accuracy: 0.9098
90/90 [==============================] - 10s 108ms/step - loss: 0.2303 - accuracy: 0.9293

Validation loss : 0.3155
Accuarcy on validation set is : 90.98 %


Test loss : 0.2303
Accuarcy on test set is : 92.93 %
```

After we trained and evaluate using ResNet50 architecture with pre-trained model we get accuracy of

90.98% on validation set and accuracy of 92.93% on test set.

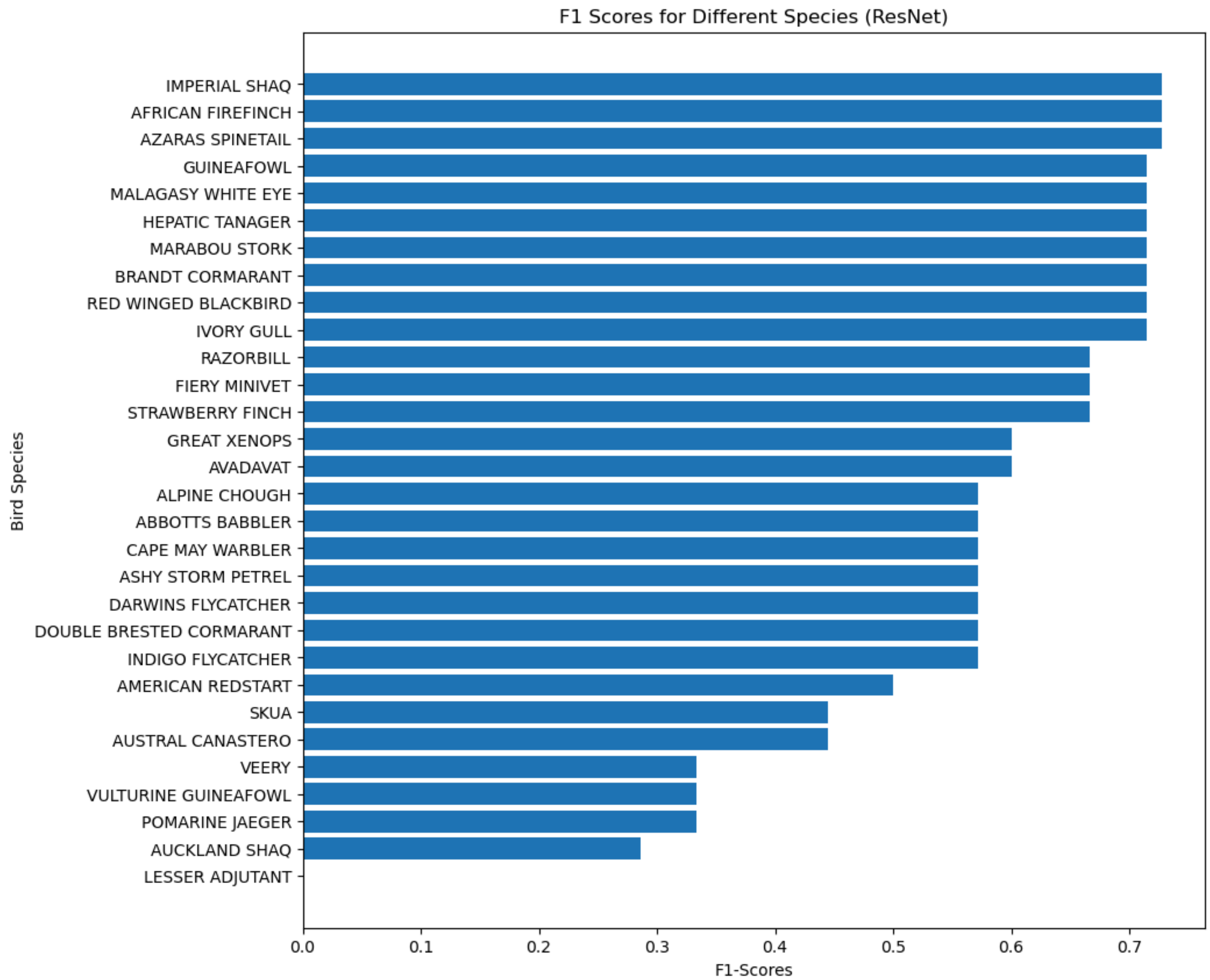

Figure 6

ResNet50 model has low prediction accuracy on:

- COMMON HOUSE MARTIN
- ANNAS HUMMINGBIRD

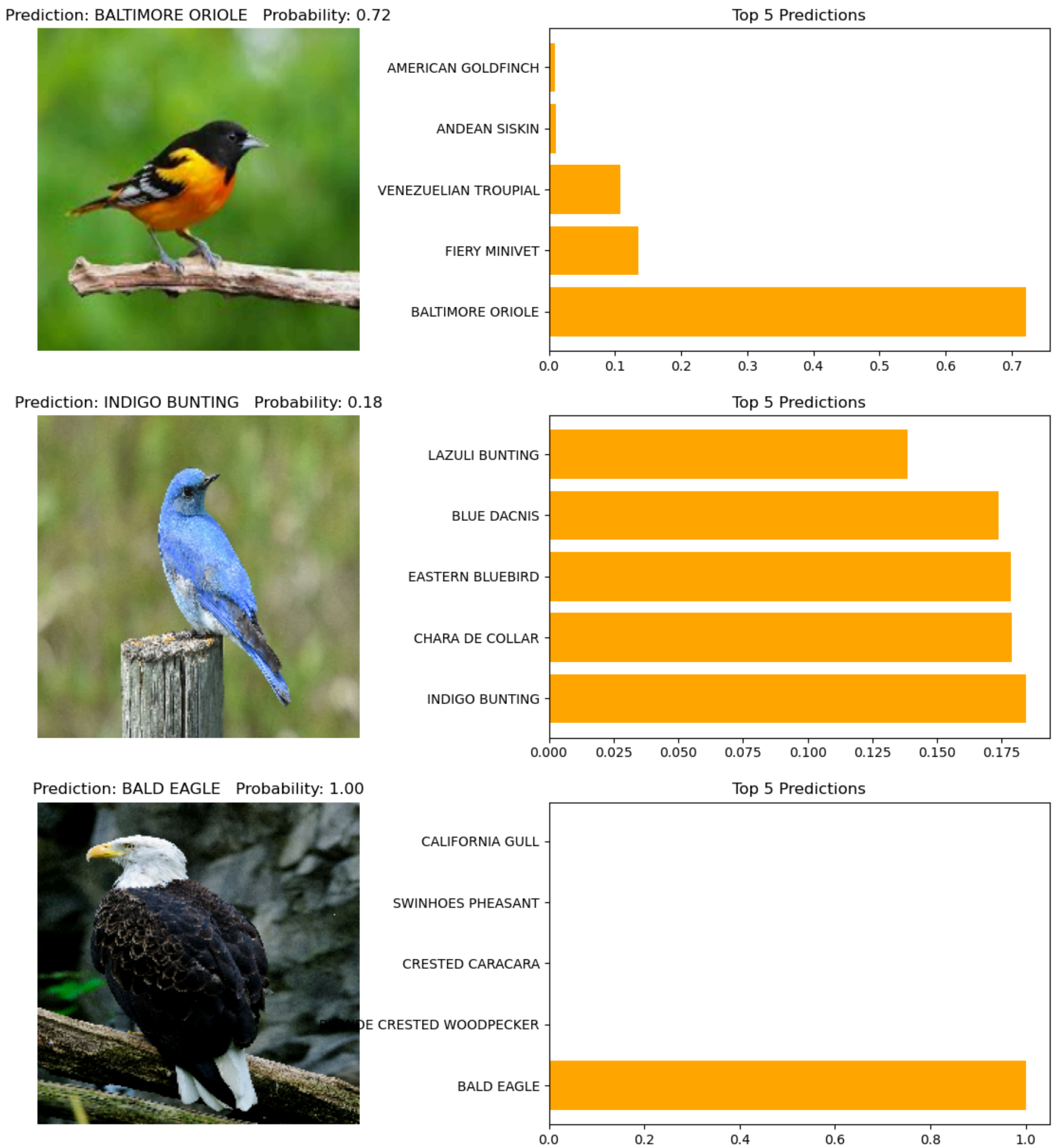
Prediction: BALTIMORE ORIOLE Probability: 0.72
Top 5 Predictions
AMERICAN GOLDFINCH
ANDEAN SISKIN
VENEZUELIAN TROUPIAL
FIERY MINIVET
BALTIMORE ORIOLE
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7
Prediction: INDIGO BUNTING Probability: 0.18
Top 5 Predictions
LAZULI BUNTING
BLUE DACNIS
EASTERN BLUEBIRD
CHARA DE COLLAR
INDIGO BUNTING
0.000 0.025 0.050 0.075 0.100 0.125 0.150 0.175
Prediction: BALD EAGLE Probability: 1.00
Top 5 Predictions
CALIFORNIA GULL
SWINHOES PHEASANT
CRESTED CARACARA
DE CRESTED WOODPECKER
BALD EAGLE
0.0 0.2 0.4 0.6 0.8 1.0

Figure 7

4.2 GUI for system application

GUI - Streamlit is a web framework for creation of data science applications. It provides a simple, intuitive interface for creating and sharing interactive data science tools and visualizations. Streamlit simplifies the process of creating data science apps by providing a set of pre-built components that can be quickly customized and shared. Streamlit also enables developers to create their own custom components, making it possible to quickly build complex, interactive applications.

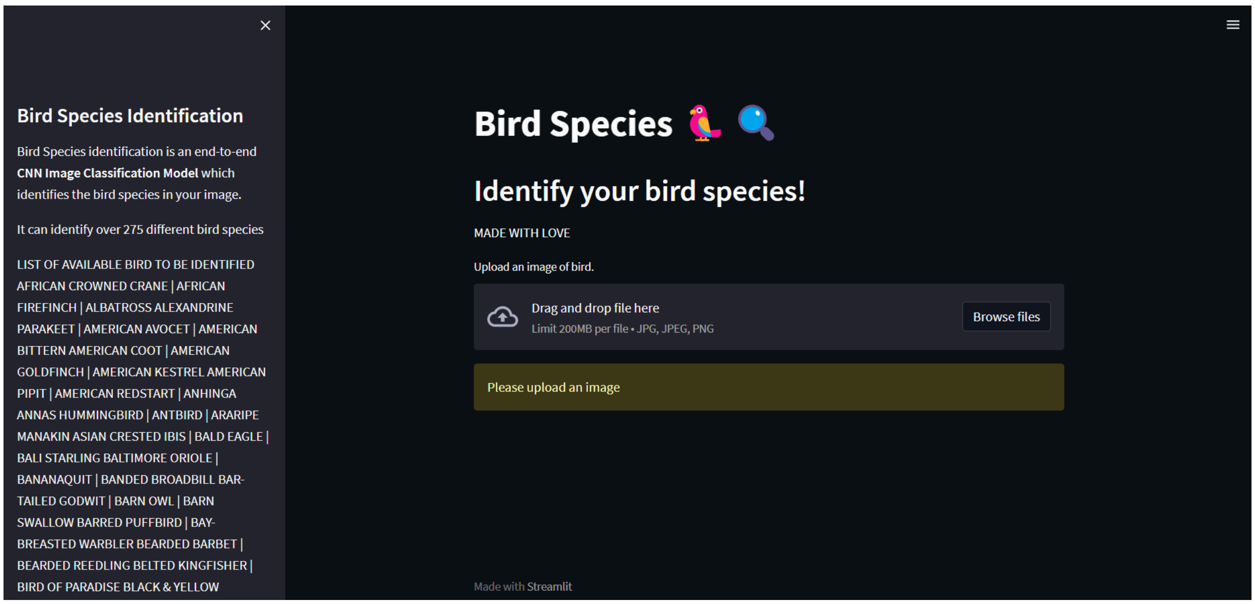

Figure 8

Tutorial on how to run our application

The application only can run one CNN model one at a time.
So the default model is efficientNet.

STEP 1- insert sample bird image

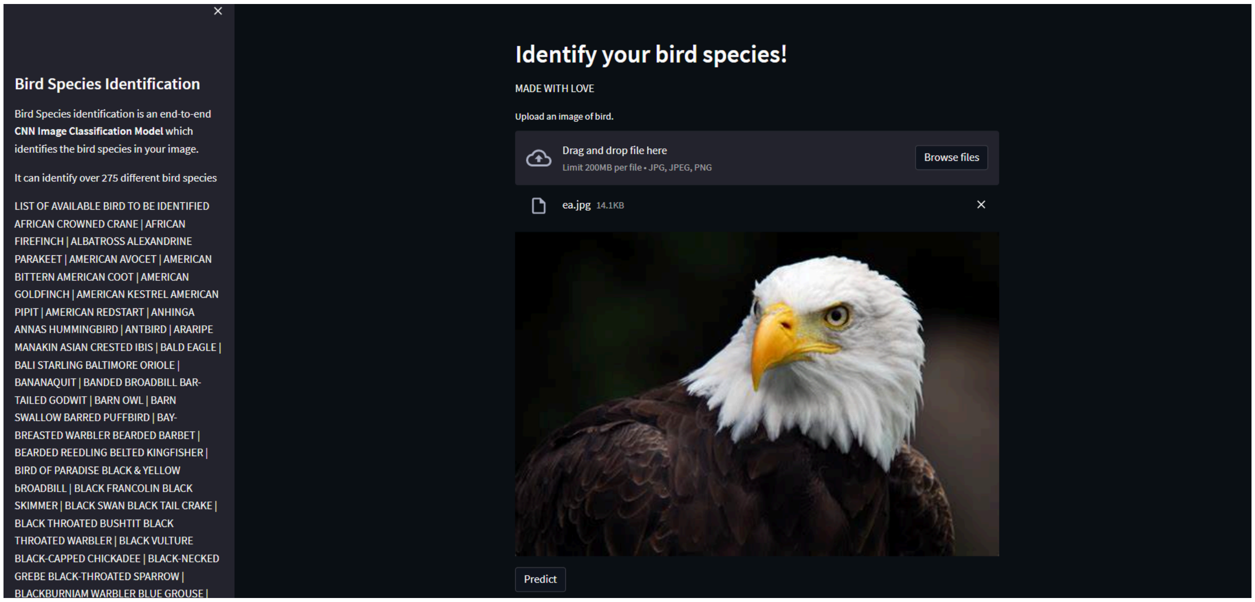

Figure 9

After inserting image, image will appear on button of prompt.

STEP 2 - click predict and get result

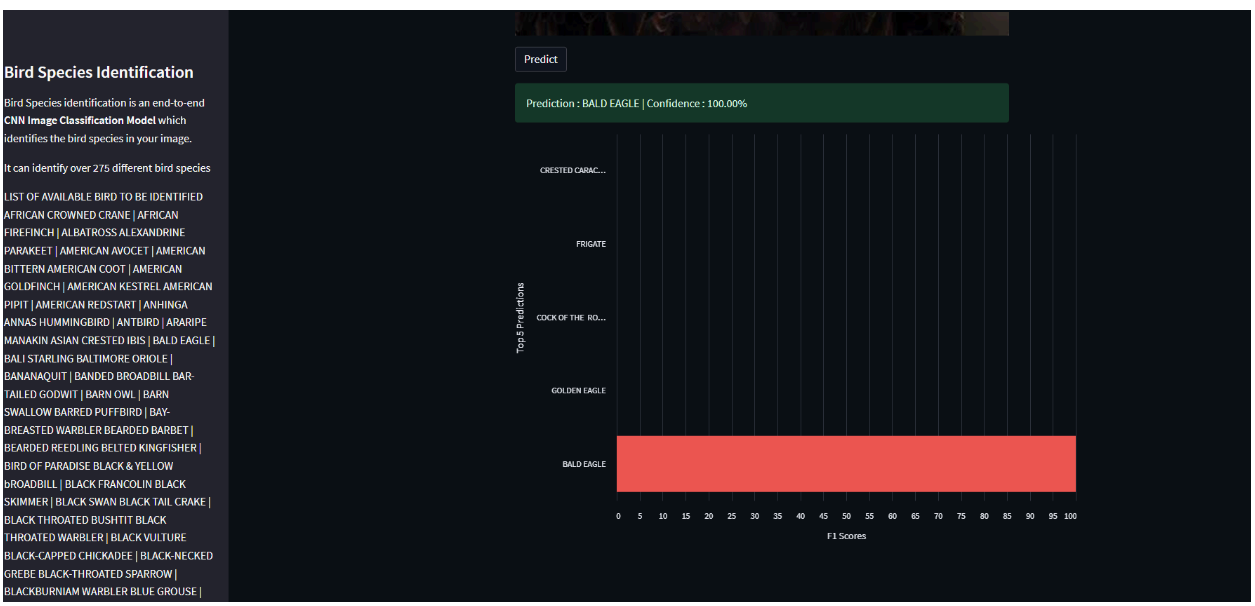

Figure 10

The application will predict using our trained model and will display the graph of the top 5 most accurate prediction.The result may vary from other trained model.High resolution and clear bird image also give a huge impact on accuracy.

Result Discussion

The results of the experiment to identify bird species offer important new information about how well Convolutional Neural Networks (CNNs) perform the task at hand. Promising outcomes were obtained from the use of two well-known CNN architectures, EfficientNet and ResNet50, demonstrating the potential of deep learning in precisely recognising bird species from photos. Designed for efficient image classification, EfficientNet is a CNN architecture that performed very well, with an excellent accuracy of 95.87% on the test set and 93.69% on the validation set. This high accuracy indicates that the model can generalize effectively to new data, which is important in real-world scenarios when the system comes across unfamiliar bird species.

However, ResNet50, a deeper CNN design with skip connections that help mitigate vanishing gradient problems, performed 92.93% on the test set and 90.98% on the validation set. ResNet50 demonstrated strong performance, while lagging slightly behind EfficientNet, highlighting the adaptability of CNNs in managing challenging image recognition tasks such as identifying different kinds of birds. A thorough analysis of the F1 scores showed subtle differences in the models' performance among different bird species. Higher F1 ratings for some species meant that the models were more accurate in their identification. Alternatively, other species were more difficult to distinguish, maybe because of differences in size, color, or complex patterns. The graphs showing the top 5 greatest F1 scores provide a thorough insight of the model's ability to identify particular species of birds.

These outcomes validate the effectiveness of the transfer learning strategy, which involved fine-tuning pre-trained models on a dataset containing 450 different bird species. The robustness of the selected CNN architectures is demonstrated by the models' ability to correctly identify birds in the face of obstacles such appearance fluctuations. More than just birdwatching lovers will find value in these discoveries since precise species identification has consequences for scientific research, environmental preservation, and educational initiatives.

Conclusion and future suggestions

1 Fine-Tuning

First and foremost, it is imperative to refine the models on a larger and more varied dataset. Adding more photos of different bird species especially ones with varying colors, patterns, and sizes would increase the flexibility and resilience of the system. This would entail working together with communities of birdwatchers and ornithologists to compile a more extensive collection of photos that illustrate a wider range of avian variety.

2 Interactive GUI Enhancements

Second, in order to provide a more engaging and user-friendly experience, the graphical user interface (GUI) may be significantly improved. Including functions like batch processing, picture uploads, and thorough result visualizations will empower users and improve the system's usability and accessibility. Users may additionally receive enhanced information about recognised bird species through a smooth application interaction with external databases or internet platforms.

3 Real-Time Recognition

Another exciting avenue for research is real-time recognition capabilities. It would be easier to identify bird species in outdoor environments on the move if the system could be modified to incorporate live video feeds or cameras on mobile devices. With the ability to quickly identify and record bird species, this would be very helpful for field researchers and birdwatchers.

4 Continuous Model Training

Sustaining the accuracy and relevance of the system over time requires ongoing model training. The system would remain up to date with new bird species traits and variations if fresh photos were added to the models on a regular basis and deep learning techniques were utilized.

5 Collaboration with Ornithologists

Working together with ornithologists and other subject matter experts might yield priceless insights into the unique difficulties associated with bird identification. In addition to improving the models' accuracy, this cooperative approach would guarantee that the system complies with the requirements and guidelines of the ornithological community.

5.0 Conclusion

In conclusion, the Convolutional Neural Networks (CNN) Bird Identification System represents a significant advancement in the realm of bird species recognition, addressing critical challenges through the application of cutting-edge technology. The project's methodology, outlined in Chapter 3, underscored a meticulous approach to data collection, encompassing a diverse dataset of 450 bird species with high-quality images totaling 70,626 training photos and 22,500 test images. Leveraging the power of CNNs, specifically EfficientNet and ResNet50 architectures, the system achieved impressive accuracy levels, with EfficientNet reaching 95.87% on the test set and 93.69% on the validation set, and ResNet50 demonstrating strong performance at 92.93% on the test set and 90.98% on the validation set.

The robustness of the CNN models was further highlighted through the utilization of transfer learning, fine-tuning pre-trained models on the comprehensive dataset. This approach ensured adaptability in overcoming challenges related to appearance fluctuations, contributing to the system's reliability in real-world scenarios and unfamiliar bird species. The graphical user interface (GUI) using Streamlit enhanced user interaction, allowing seamless image uploads and providing visualizations of the top five accurate classifications. The comparison with other studies emphasized the versatility of CNNs in addressing diverse bird identification challenges, showcasing their applicability in scientific research, environmental preservation, and educational initiatives. Future recommendations include expanding the dataset for fine-tuning, enhancing the GUI for user-friendliness, exploring real-time recognition capabilities for outdoor environments, and continuous model training to keep the system updated with new bird species traits. Collaborative efforts with birdwatching communities and ornithologists promise invaluable insights for refining the system and aligning it with the ornithological community's needs. Ultimately, the Bird Identification System emerges as a technological cornerstone, seamlessly merging advancements in deep learning with the intricacies of ornithology, fostering a profound understanding and appreciation for the diverse world of avian species.

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