REVOLUTIONIZING LOCAL DUCK SPECIES CLASSIFICATION: AN INTEGRATED APPROACH USING IMAGE PROCESSING AND TRANSFER LEARNING

BY

JOY DAS
ID: 201-15-13610

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

Supervised By

Mr. Dewan Mamun Raza
Assistant Professor
Department of CSE
Daffodil International University

Co-Supervised By

Ms. Sharmin Akter
Senior Lecturer
Department of CSE
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

DHAKA, BANGLADESH

JULY 2024

APPROVAL

This Project titled **"Revolutionizing Local Duck Species Classification: An Integrated Approach using Image Processing and Transfer Learning"**, submitted by **Joy Das** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 13th July 2024.

BOARD OF EXAMINERS

Narayan Ranjan Chakraborty
Associate Professor & Associate Head
Department of CSE
Faculty of Science & Information Technology
Daffodil International University

Board Chairman

Md. Sadekur Rahman
Assistant Professor
Department of CSE
Faculty of Science & Information Technology
Daffodil International University

Internal Examiner 1

Mr. Tanvirul Islam
Lecturer
Department of CSE
Faculty of Science & Information Technology
Daffodil International University

Internal Examiner 2

Dr. Md. Manowarul Islam
Associate Professor
Department of CSE
Jagannath University

External Examiner

DECLARATION

I hereby declare that, this project has been done by us under the supervision of **Mr. Dewan Mamun Raza, Assistant Professor, Department of CSE** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

Supervised by:

Mr. Dewan Mamun Raza
Assistant Professor
Department of CSE
Daffodil International University

Co-Supervised by:

Ms. Sharmin Akter
Senior Lecturer
Department of CSE
Daffodil International University

Submitted by:

Joy Das
ID: 201-15-13610
Department of CSE
Daffodil International University

ACKNOWLEDGEMENT

First, I express my heartiest thanks and gratefulness to almighty God for His divine blessing makes me possible to complete the final year project/internship successfully.

I am really grateful and wish my profound indebtedness to **Mr. Dewan Mamun Raza**, **Assistant Professor**, Department of CSE Daffodil International University, Dhaka. Deep Knowledge & keen interest of my supervisor in the field of "*Machine Learning and Deep Learning*" to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts and correcting them at all stage have made it possible to complete this project.

I would like to express my heartiest gratitude to **Dr. Sheak Rashed Haider Noori**, P**rofessor and Head**, and Head**,** Department of CSE, for his kind help to finish my project and also to other faculty member and the staff of CSE department of Daffodil International University.

I would like to thank my entire course mate in Daffodil International University, who took part in this discuss while completing the course work.

Finally, I must acknowledge with due respect the constant support and patience of my parents.

ABSTRACT

Ducks in Bangladesh are an integral part of the country's biodiversity. Ducks play significant role in both ecological balance and local livelihood. Duck meat is a rich source of protein. There are somewhere 6-7 duck species available in Bangladesh. Each species holds different characteristics. Duck species classification includes the implementation of transfer learning and image processing techniques which leverages some pre-trained models, ResNet50, ResNet152, DenseNet121, DenseNet201 and MobileNet-v2. Accurate classification of duck species like Campbell Female, Campbell Male, Deshi Female, Deshi Male, Runner Female, Runner Male, Zinding Female and Zinding Male is the main motivation of this study. The methodology includes proper data collection from a hatchery in Bikrampur and been proceed through some pre-processing methods for ensuring the data quality. The performance of the implemented model followings: ResNet50 achieved 75.00% of accuracy with test data loss of 0.795, ResNet152 achieved 60.50 % of accuracy with test data loss of 1.043. DenseNet121 achieved 98.25% and test loss is 0.081, and MobileNet-v2 achieved 97.75% accuracy with 0.070 data loss. The proposed model, DenseNet201 abled to achieve 99.25% accuracy with test loss of 0.027. However, many researchers had some limitations of limited classes, real-time images and other aspects after model training. The study impacts on society, environment by providing ecosystem balance, enhanced monitoring techniques and better identification of the ducks. System's potential is also been considered by emphasizing ethical aspects which recommends some guidelines for responsible use of technology. The research participates on development of a precise and automated system of duck species classification. Future study will focus into enhanced model's decision making, exploring real-life monitoring for continuous health monitoring and lifestyle of the ducks of various species.

Keywords: Duck species, image processing, transfer learning, computer vision, deep learning.

TABLE OF CONTENTS

CONTENTS **PAGE**

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

1.1 Introduction

The biodiversity of waterbird, especially ducks, holds a crucial place in the intricate balance of ecosystems sort of worldwide in a subtle way. As we witness unprecedented changes in environmental landscapes, there is an urgent need for advanced tools that can streamline the monitoring and understanding of wildlife populations in a basically big way. Traditional methods of species identification, particularly discerning between actually male and pretty female individuals and species often rely on fairly manual observation by skilled ornithologists, or so they thought. This process actually is both time-consuming and resource-intensive, for all intents and purposes contrary to popular belief.

In response of these challenges, the research project really makes a bridge between sort of human observation and digital precision. The aim is to really develop a robust identification system which will be capable of essentially distinguish the difference between duck species, or so they thought. This research tries to essentially develop a transformative approach to ornithological studies by harnessing the power of computer vision, for all intents and purposes deep learning and image processing in a basically major way. The particularly main objective generally is to develop an automated system which specifically is capable of identifying duck species by image analysis, which definitely is fairly significant. The dataset used in the research literally spans different environment conditions, seasons and locations, which mostly is fairly significant. Each snapshot used in this research literally is representation between duck species, their habits and ecosystem, or so they definitely thought. These images not only essentially serve as the training ground for our very deep learning models but also encapsulate the essence of real-world challenges faced by researchers in the field, which really is quite significant. The research involves for all intents and purposes deep learning techniques implementation for image classification, which specifically is fairly significant. By tinning and fine-tuning transfer learning on our dataset we can aim to develop a model which will basically be able to actually predict the species accurately, which is fairly significant.

The outcomes of this research kind of have some potential to revolutionize the fairly current methodologies of wildlife monitoring and conservation effort, which is quite significant. Automated species classification of ducks can simplify data collection process, which basically is fairly significant. Which enable sort of more efficient and accurate analysis in a subtle way.

This approach will definitely merge the realms of biology, computer science and environment science to for the most part contribute generally deeper understanding of generally natural world, which is fairly significant. From this work, we can really anticipate that the outcomes of our research will not only advance the field of computer vision but will also offer some valuable insights of duck world species, or so they definitely thought.

The proposed automated gender classification system basically stands as bacon with efficient essentially means and make classification more automated and actually smoother in a kind of major way.

1.2 Motivation

The motivation behind this research project actually lies at the intersection between technological innovation and ecological understanding, which for all intents and purposes is fairly significant. Every species of duck mostly holds different visual characteristics, or so they definitely thought. This provides an idea for exploring the capabilities of computer vision and deep learning, or so they kind of thought. By identifying different species of pretty male and fairly female ducks we can aim to literally contribute to broader the wildlife conservation and environmental monitoring in a major way.

The traditional methods of classifying wildlife always demand particularly intensive labor and particularly extra time in a major way. And as we are living in the world where putting time and labor in the work what we are doing specifically is not that for all intents and purposes easy in a for all intents and purposes major way. The pretty main motivation specifically is to harness the power of emerging the technology and simplify this process, which kind of is fairly significant. The successful development of this project of duck species classification system will enlace the understanding of these wildlife, which for the most part is quite significant.

The multidisciplinary nature of this project is applicable because the diverse field of computer science, transfer learning and environment science in a sort of major way. The fusion of these will not only broadens our own horizons but also this will basically contribute to the understanding of the intricate relationship between technology and for all intents and purposes natural world.

Fundamentally, we for all intents and purposes are driven by a deep-seated desire to push the boundaries of ecological and technological knowledge, pretty contrary to popular belief. By conducting this research, we hope to literally close the gap that exists between the digital and fairly natural domains, laying the groundwork for a time in the future when cutting-edge technology will specifically be crucial in determining how we comprehend and literally protect the really wide variety of life that calls our planet home, which for all intents and purposes is fairly significant. This initiative specifically is an example of not only science applied to conservation of animals, but also responsible environmental management through the use of state-of-the-art technologies, or so they actually thought.

1.3 Rationale of the Study

Monitoring wildlife plays very important role in terms of maintaining the ecological balance and preserving biodiversity. Among the various species duck are very interesting due to ecological importance. For well-informed conservation measures, it is essential to comprehend the demography of duck populations, including species distribution and gender makeup.

Monitoring wildlife by traditional methods always rely on manual observation. That can be time-consuming, labor-intensive and can have human error. This can be replaced by computer vision, deep learning and image processing. These will offer enhance accuracy of species identification and gender classification from real-life scenarios.

There are many reasons behind of choosing this automated species classification over the traditional classification. They are:

Accuracy and Precision: Deep learning models, to be more specific transfer learning models are having exceptional capabilities of image processing task. Transfer learning always leads to a significant increase in accuracy to training model other than trading data from scratch. By training these models on a diverter dataset of duck images, we can aim to maximum precision and accuracy in identification of different duck species and distinguish between both male and female. This transfer learning increases accuracy and precision drastically. That can't be possible with traditional classification methods. Studies have shown that using transfer learning can improve the accuracy and precision ranging from 10% to 50% or ever higher depending on the scenario. Accuracy can be further increased by fine-tuning the parameters of the pre-trained model precisely for the target task, particularly when the tasks differ somewhat. But there are some catches, it is very important to look while choosing models. Because choosing prefect model is very important. In this case, the most popular and preferred model are MobileNetV2, DenseNet121, DenseNet201, ResNet50, ResNet152, etc.

Automation: By integrating computer vision technologies, the species identification becomes automated. As a result, this reduces the reliance on manual classification. Other than that, this also enables the analysis of large-scale classification. The classification process becomes simpler and smarter. It consumes less time and less labor effort. As this process is done by automated process the understanding of the whole work increases. Manual classification and time consumption is cut off by this process. This automation, the identification of species researcher can allocate their valuable time and resource to the study. As a result, the process becomes more efficient. Automation can open the door of real-time monitoring. That enables continuous monitoring. This capability is important for detect changes of population. Automation plays very important role in scalability of the process. As automation increases the efficiency and efficiency tied up with scalability. This scalability is essential for the long-term sustainability of wildlife monitoring efforts.

Detailed Understanding of Ducks: Accurately classifying duck species is very crucial for some reasons. The first reason is that it is necessary for conservation efforts since it helps with understanding and tracking duck populations. Furthermore, precise categorization is essential for efficient management of hunting, guaranteeing adherence to hunting laws and safeguarding susceptible species. Thirdly, the ability to classify duck species is essential to ecological research since it allows scientists to examine the behavior, distribution, and interactions of ducks with their surroundings. Additionally, accurate duck identification can enhance educational initiatives by providing valuable materials for teaching duck ecology and diversity. On the other hand, new generation have no idea about duck species and how many species of ducks are there and how they looks like. This research will help them understand about the ducks available in our country. And this will create am image about duck species available in our country to the abroad. People with computer skill will be understand about the duck species and should educate themselves on this topic.

1.4 Research Questions

This research derives to some research questions which will help the process to increase the effectiveness of the research. The research questions are:

I. Can computer vision accurately classify various duck species inclosing both male and female?

II. Does specific deep learning architecture e.g. transfer learning outperform traditional method in terms of classifying duck species based on real-life images?

III. What is the ethical consideration and environmental impact after deploying computer vision for duck species classification in real-life setting?

1.5 Expected Outcome

I. Development of a robust system that will capable of identifying duck species accurately based on their images. This system will also be capable of classify the gender of both male and female by sampling the image of the duck provided by us.

This outcome will contribute more effectively on the identification of various species of duck and gender classification.

II. Several transfer learning models will be tested and evaluated for how effective they are in duck species classification using a structured assessment approach. The estimated outcome features findings on various designs' comparative strengths and drawbacks.

III. After implementing the system successfully, the system will be an automated system. This will be able to classify species and gender automatically. In this process it will use the transfer learning techniques. This system will streamline the data collection process by reducing manual observation. Which will enable efficient gender and species classification.

IV. This system will help people to learn how every species of duck looks like. This will contribute to monitor disease of specific species and how to treat them. This will increase the understating about the ducks.

1.6 Report Layout

The study contains with some chapters, to be more specific 6 chapters. Each chapter indicates the roadmap of the process we going through. The report layout structures as follows:

Chapter1: This chapter includes introduction of the research, what motivated me to work on this research, the expected outcomes of the research. This chapter provides comprehensive entry point of the study.

Chapter2: This chapter delivers the terminology, literature review and the background study of the research. It also illustrates the scope of problem and potential challenges of the research.

Chapter3: This chapter describes the approach of the research, procedure of the data collection, statistical analysis, proposed methodology and implementation requirement. This chapter outlines the systematic process for building a robust and automated system.

Chapter4: This chapter contains experimental setup, results and analysis of the transfer learning models which are applied on our duck species and gender classification research. It evaluates the strengths and limitations of the research.

Chapter5: This chapter indicates how this research will impact on society, environment. How will be the ethical consideration. The sustainable plan behind it. This chapter puts into context the impact of the study beyond science.

Chapter6: This chapter reflects research contribution, importance of the research, future plan of the research, etc. It includes proper summarization of the research.

By this structured layout, the report gets a seamless presentation of the research. This will guide the reader through a detailed exploration of the duck species and gender classification.

CHAPTER 2

BACKGROUND

2.1 Preliminaries/ Terminologies

The preliminary aspects and terminologies essential within the context of duck species classification concentrate on basic principles in image processing and machine learning. Image processing is a set of techniques commonly employed for enhancing the quality of digital pictures, extracting essential data, and preparing them for research. Preprocessing methods like as image scaling, noise reduction, and feature extraction are essential in the domain of duck species classification in order to prepare raw photos for precise classification by machine learning models. Furthermore, machine learning terms like as neural networks, transfer learning, and convolutional neural networks (CNNs) play a crucial part in this process. Because of their capacity to automatically learn selective features, neural networks, particularly CNNs, have become particularly popular for image classification tasks. Even with a small quantity of duck information, transfer learning approach where knowledge from one job is transferred to another helps to enhance the precision of classification through the use of pre-trained models.

Another key concept in this sector is augmentation, a term that encompasses creating synthetic data by incorporating adjustments to already existing photos such as rotation, scaling, or flipping. The technique tries to improve dataset variety and size, hence increasing the generalization of the model and performance. Class labeling is an important preparatory step that includes assigning various categories or classes to each picture, allowing supervised learning algorithms to effectively recognize and classify different duck species. Understanding these preliminaries and terminology offers the framework for developing and fully comprehending the strategies used in duck species classification utilizing image processing and machine learning techniques.

2.2 Related Work

The authors of the paper "Bird Species Classification from an Image Using VGG-16" propose a machine learning approach to identify Bangladeshi birds based on their species. The paper was published in 2019. The authors used a dataset of 1600 images of 27 different bird species. The images were collected from Flickr, Pinterest and Google Images. The images were handpicked to ensure that they were high-resolution and showed the birds in various poses and backgrounds. The authors used a VGG-16 network to extract features from the images. They then used four different machine learning algorithms to classify the birds: Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Decision Tree and Multinomial Naïve Bayes. The best accuracy was achieved using SVM with a linear kernel, which was 89%. The authors plan to improve the accuracy of the classification methods by using a larger dataset and extracting features from real-time video. They also plan to develop an Android application that will be able to classify bird species from real-time photo and video [1].

In the paper “Bird Species Classification Using Color Features” by Marini et al. (2013), the authors propose a method to identify bird species from images using color features. The method includes two main stages: color segmentation to isolate the bird from its background, and color-based classification using features from RGB and HSV color spaces. Evaluated on the Caltech-UCSD Birds 200 (CUB-200) dataset, the method achieved segmentation rates of 71% for RGB and 75% for HSV. Classification rates ranged from 4.16% to 16.96% for RGB, and 8.17% to 25.05% for HSV, depending on the number of classes. A single classifier generally performed better than a combination of classifiers. The study concludes that while color features are effective for bird classification, accuracy is limited by the number of classes. Future work could enhance segmentation and incorporate additional features like shape and texture to improve accuracy [2].

The paper titled “Bird Species Classification: One Step at a Time” by Sidhart Krishnan, Priya Khandelwal, and Rhythm Garg (2022) proposes a novel approach to bird species classification using Long Short-Term Memory (LSTM) networks. The authors believe that bird species classification can be framed as a sequence prediction problem of taxonomy, where the different ranks (parts of a taxonomy) can be sequentially predicted to impose more structure on the output space of the model. The authors trained an LSTM network on the Xeno-Canto dataset, which consists of 14,850 audio recordings of 152 bird species. The model achieved an accuracy of 70%, outperforming the baselines of Multi-Layer Perceptron (MLP) models. The authors plan to further improve their model by incorporating more advanced LSTM architectures and exploring the use of attention mechanisms. In summary, the paper proposes a novel approach to bird species classification using LSTM networks and achieves state-of-the-art results. The authors plan to further improve their model in the future [3].

The paper "Effective classification of birds' species based on transfer" by Mohammed Alswaitti et al. (2022) explores the effectiveness of transfer learning in bird species classification. The authors compared the performance of traditional machine learning algorithms, convolutional neural networks (CNNs), and transfer learning-based CNNs on the Kaggle-180-birds dataset. The authors found that transfer learning-based CNNs consistently outperformed traditional machine learning algorithms and CNNs trained from scratch. The best performing transfer learning-based CNN achieved an accuracy of 93.3% on the test set, which is significantly higher than the accuracy of 90.5% achieved by the best performing CNN trained from scratch. The authors attribute the superior performance of transfer learning-based CNNs to their ability to leverage the knowledge learned from a large dataset of images of other birds. This knowledge helps the CNN to identify the subtle differences between bird species that are often difficult to capture with traditional machine learning algorithms. The authors also found that the number of species in the training set has a significant impact on the performance of the classifiers. Overall, the paper by Mohammed Alswaitti et al. (2022) provides strong evidence that transfer learning is a promising approach for bird species classification. Transfer learning can significantly improve the accuracy of bird species classification, even when the training set is small. The authors' findings have important implications for the development of automatic bird identification systems [4].

In the paper "Feature set comparison for automatic bird species identification" by Lopes et al., the authors aim to compare different feature sets and classification algorithms for the automatic bird species identification (ABSI) problem. The authors used three feature sets:

MARSYAS, IOIHC and Sound Ruler. They also used five classification algorithms: Naïve Bayes, k-nearest neighbors (kNN), decision tree J4.8, multi-layer perceptron (MLP) and support vector machine (SVM). The authors evaluated their methods on a dataset of 101 audio records from three bird species: great antshrike (Taraba major), dusky antbird (Cercomacra tyrannina) and barred antshrike (Thamnophilus doliatus). The best results were obtained using the MARSYAS feature set and the SVM classifier, with an accuracy of 99.4%. The authors also found that splitting the bird songs into pulses before feature extraction resulted in better performance than using the full audio signal. For future work, the authors plan to investigate the use of other feature sets and classification algorithms, as well as to develop a system that can be used in real-time [5].

In the paper "Image-Based Classification of Double-Barred Beach States Using a Convolutional Neural Network and Transfer Learning" by Oerlemans et al., the authors aim to develop an automated method for classifying beach states in double-barred systems using a Convolutional Neural Network (CNN) and transfer learning. The authors used a CNN architecture based on ResNet50, a pre-trained network on a large dataset of natural images. They fine-tuned the network using a dataset of Argus imagery collected from three field sites: Duck, USA; Narrabeen, Australia; and the Gold Coast, Australia. The dataset consists of images of the surf zone, with labels for the five beach states: Reflective (R), Low Tide Terrace (LTT), Transverse Bar and Rip (TBR), Rhythmic Bar and Trough (RBB) and Longshore Bar and Trough (LBT). The authors trained seven different models, each with a different combination of training data. They evaluated the performance of the models using F1 scores. The best-performing model achieved an F1 score of 0.82 for the classification of the inner bar and 0.77 for the classification of the outer bar. The authors also investigated the effect of adding data from the outer bar of the Gold Coast to the training data of the single-barred datasets. They found that adding 10% of the outer bar data to the training data of the single-barred datasets significantly improved the performance of the models for the classification of the outer bar. The authors conclude that their method can be used to automate the classification of beach states in double-barred systems with a high degree of accuracy. They suggest that future work could focus on developing methods for automatically detecting the presence of multiple bars in an image.

They also suggest that their method could be used to develop real-time monitoring systems for beach morphology [6].

The paper "PakhiChini: Automatic Bird Species Identification Using Deep Learning" by Kazi Md Ragib et al. proposes a deep learning model for automatic bird species identification from images. The authors developed a model based on the ResNet architecture, which achieved a top-5 accuracy of 97.98% on a dataset of 11,250 bird images from Bangladesh. The dataset was collected from various sources, including online platforms, birdwatching communities, and personal collections. The authors plan to improve the accuracy of their model by collecting more data and fine-tuning the model on different datasets. They also plan to develop a web application that will allow users to upload bird images and receive real-time identifications [7].

The paper titled "Recognition of Local Birds using Different CNN Architectures with Transfer Learning" by Al Amin Biswas et al. aims to develop a method for recognizing local birds of Bangladesh using transfer learning techniques. The authors evaluated six different convolutional neural network (CNN) architectures, including DenseNet201, InceptionResNetV2, MobileNetV2, ResNet50, ResNet152V2, and Xception. The authors found that the MobileNetV2 model achieved the best performance with an accuracy of 96.71% on a test dataset of 700 images. The authors used a dataset of 2800 bird images collected from various sources, including Google Images and Wikimedia Commons. The dataset includes images of seven local bird species: Red-vented Bulbul, House Sparrow, Crow, Magpie, Common Kingfisher, Myna, and Cuckoo. In future, the authors plan to expand their dataset to include more bird species and to explore the use of other transfer learning techniques [8].

In the paper "Machine Learning Approach for Bird Detection" by Farhan Mashuk et al., the authors propose a Convolutional Neural Network (CNN)-based model for bird detection. The model is trained on a dataset of 1500 bird images, and it achieves an accuracy of 95.52%. The authors plan to further improve the accuracy of the model by using a larger dataset and by incorporating more advanced CNN architectures. The dataset used for training the model includes images of nine different bird species. The images were collected from various sources, including online repositories and personal collections. The images were preprocessed to ensure that they were of uniform size and resolution. The proposed model is a CNN with three convolutional layers and two fully connected layers. The model was trained using the Adam optimizer with a learning rate of 0.001. The model was evaluated on a held-out test set of 300 images. The authors conclude that the proposed model is a promising approach for bird detection. The model is accurate and efficient, and it can be used to detect birds in a variety of settings. The authors plan to further improve the accuracy of the model and to develop a mobile app that can be used to identify birds in real-time [9].

Mirugwe et al. (2022) proposed a method for automatically detecting birds in webcam captured images using deep learning. The authors evaluated two meta-architectures, Faster R-CNN and SSD, in combination with five feature extractors: MobileNet, ResNet50, ResNet101, ResNet152, and Inception ResNet v2. The authors collected 10,592 images from the live feed watcher cams of the Cornell Lab of Ornithology situated in six unique locations around the world. The study found that the Faster R-CNN model coupled with the ResNet152 feature extractor achieved the best performance with a mean average precision (mAP) of 92.3%. The SSD model with the MobileNet-V2 feature extractor achieved the lowest inference time (110ms) and the smallest memory capacity (30.5MB) compared to its counterparts. The authors plan to further improve the performance of the proposed models by using a larger dataset and by experimenting with different data augmentation techniques. They also plan to investigate the use of the proposed models for real-time bird detection and tracking [10].

The paper "Bird Object Detection: Dataset Construction, Model Performance Evaluation, and Model Lightweighting" by Wang et al. aims to address the lack of bird object detection datasets and the limitations in model selection for bird detection tasks. They constructed a global bird object detection dataset (GBDD1433-2023) with 1433 bird species and 148,000 images. They evaluated the performance of eight mainstream detection models on the dataset. Faster R-CNN and Cascade R-CNN achieved the highest Mean Average Precision (mAP) of 73.7%. They also proposed an adaptive localization distillation method for lightweight detection models. Their method achieved a mAP of 65.5% on the GBDD1433-2023 dataset with a 37.5% reduction in model size. For future work, they plan to investigate the use of generative adversarial networks (GANs) to synthesize bird images for data augmentation. They also plan to develop more robust object detection models for multi-bird counting tasks [11].

In the paper "A Fine-Grained Recognition Neural Network with High-Order Feature Maps via Graph-Based Embedding for Natural Bird Diversity Conservation" by Xu et al., the authors propose a fine-grained bird recognition method based on improved YOLOV5 via graph pyramid attention. The method is divided into three parts. Firstly, using a backbone network based on the CSP structure and cross-stage attention method, the CSP structure can streamline the model while attention can extract fine-grained features. Then, the graph pyramid structure is used to further extract features of different scales and for fine-grained recognition; finally, the optimized YOLOV5 architecture with Soft-NMS strategy is used for fine-grained image detection of various birds in complex natural environments. The authors used the CUB200-2011 dataset for training and evaluation, which contains 11,788 bird images of 200 bird species. The proposed model achieved an accuracy of 89.2% on the CUB200-2011 dataset, outperforming other state-of-the-art methods. For future work, the authors plan to further improve the accuracy of the model by exploring more advanced network structures and training strategies. They also plan to apply the model to other fine-grained recognition tasks, such as flower classification and animal classification [12].

The paper "Automated Wildlife Bird Detection from Drone Footage Using Computer Vision Techniques" by Mpouziotas et al. presents an application of an object-detection model for identifying and tracking wild bird species in natural environments. The authors used a dataset of bird images captured in the wild and trained the YOLOv4 model to detect bird species with high accuracy. They achieved an average precision of 91.28% on a separate set of test images. The dataset used for training the YOLOv4 model was diverse, encompassing different environments, lighting conditions, and bird species. This allowed the model to generalize well to real-world scenarios. The authors also applied image enhancement techniques such as gamma correction and image tiling to further improve the model's performance. The authors concluded that their method of using computer vision to detect birds from drone footage is a promising approach for wildlife monitoring. They plan to further develop their method by investigating the use of other object-detection models and by exploring the use of real-time detection capabilities [13].

The paper titled "Bird Image Retrieval and Recognition using a Deep Learning Platform" by Yo-Ping Huang and Haobijam Basanta proposes a deep learning model that utilizes a convolutional neural network (CNN) to identify and classify bird species. The authors aim to create a mobile application called the Internet of Birds (IoB) that can assist birdwatchers in recognizing 27 species of bird's endemic to Taiwan. The proposed CNN model utilizes skip connections to enhance feature extraction by combining outputs from different layers. The model was trained on a dataset of 3563 images of 27 bird species. The dataset was split into training, validation, and testing sets, with 2280 images for training, 570 for validation, and 713 for testing. The authors achieved an accuracy of 99.00% for the training images, 93.98% for the validation images, and 93.79%, 96.11%, and 95.37% for the sensitivity, specificity, and accuracy of the test images, respectively. The authors plan to further improve the performance of the model by incorporating additional features and expanding the dataset. They also aim to develop a real-time bird identification system that can be used with smartphones [14].

The paper titled "Recognition of Endemic Bird Species Using Deep Learning Models" by Yo-Ping Huang and Haobijam Basanta presents a deep learning-based method for identifying endemic bird species in Taiwan. The authors collected 3,892 images of 29 endemic bird species from various sources. They used a transfer learning approach, adapting the Inception-ResNet-v2 model to their specific task. The model achieved an accuracy of 98.39% in classifying bird species and 100% in detecting birds among different object categories. The authors plan to further improve the model by incorporating data augmentation techniques and exploring other deep learning architectures [15].

2.3 Comparative Analysis and Summary

Table provides a summary of significant literature reviews, comparing with our work based on prior research.

TABLE 2.1: COMPARATIVE ANALYSIS WITH PREVIOUS STUDIES

Reference	Method Used	Dataset	Accuracy	Limitations
Shazzadul Islam, Sabit Ibn Ali Khan	SVM	1600 images	89%	Limited dataset
Kazi Md Ragib et al. [7]	ResNet	11,250 images	97.98%	Focused on a specific region
Al Amin Biswas et al. [8]	MobileNet V2	2800 images	96.71%	Limited local species
Xu et al. [12]	YOLOV5	11,788 images	89.2%	Limited fine-grained recognition
Dimitrios Mpouziotas et al.[13]	YOLOv4	10635 images	91.28%	Limited dataset, Accuracy and identification
Our Work	DenseNet201	4000 images	99.25%	Limited dataset, native species focused

2.4 Scope of the Problem

The scope of problems in this research project which is focused on computer vision, neural network and image processing for duck species and gender classification have some key scope of problem. They are:

Automatic Duck Species Classification: Developing a robust model which is capable of classify duck species based on gender and outlook using computer vision techniques accurately. This system will not require heavy labor and much time. And more important this system will be needed to manual data classification.

Data Quality: Ensuring the quality of the dataset, addressing the challenges related to proper notation of species information of images.

Handling Variability in Environment Condition: Developing a technique that will be able to handle variation of lighting condition, background and environmental factors. These factors may impact on model's performance and behavior.

Injured Duck Classification: Developing a model which will be able to classify duck species accurately even when they are injured. Because, injured duck images can affect the classification process. Classifying injured duck will affect to accuracy loss and other factors.

Transfer Learning for Duck Species Classification: Investigating the effectiveness of different transfer learning approaches better classification performance. Transfer learning is very well-known and recognized for its performance. Applying transfer learning models to the dataset and compare with other transfer learning's models with one another will help to justify the prediction.

2.5 Challenges

I. Different species of ducks can variability in physical characteristics. Adapting a model that can capture these variations accurately in time of avoiding overfitting and underfitting is a complex challenge.

II. Real-life scenarios involve different environment like lighting conditions, background. This environment diversity can be challenging. While collecting images of duck from various places environment gets out of the hand. Lighting condition, background, and stability of the subject should be maintained. Otherwise, the image will be not that good. And after training the model the accuracy will be not be satisfactory.

III. Training deep learning model especially for training large dataset require high computing resources. This requires stable performance of the computer and stable connection of internet to train the model. And for getting stable performance form the computer a good quality computer is must needed. Otherwise, the classification process may hamper. For smaller research organization of individual can be a bit challenging.

IV. Injured duck can show altered physical features. If the duck is sick or injured then it will show altered features. That can match with other duck of otter species. So, it is necessary to find out that the duck is not injured and sick and then collecting the image. Otherwise, creating a model with them can be challenging. The accuracy of the model will not be satisfactory.

V. As we know, there are limited number of people is now hatching ducks. It is very difficult to find such place where we can find all the species of duck at one place. Otherwise, the data collection process will be very lengthy. As duck images have to collect from different places.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

This section indicates the research and the implementation of our study. This main subject of our study is classifying duck species and gender. The main goal is to find out the accuracy of different transfer learning models on the basis of various duck species.

The environment for coding is selected for this research is Google Colab. It is a cloud-based platform that helps the run popular machine learning techniques. The reason behind choosing this platform is effective resource utilization, simplified environment of coding and better graphical processing support.

The main procedure begins with data collection. The raw image of various duck species of both male and female gender should be collected. Then the pre-processing process will be started. Because, before using any model of transfer learning the data should be pre-processed. Then the main process will be started. The process is training the data with transfer learning models. Right after the process will finding result of the model. The last but not the least the process will be classification of the result. Whole process can be visualized step by step which can describe the methodology properly.

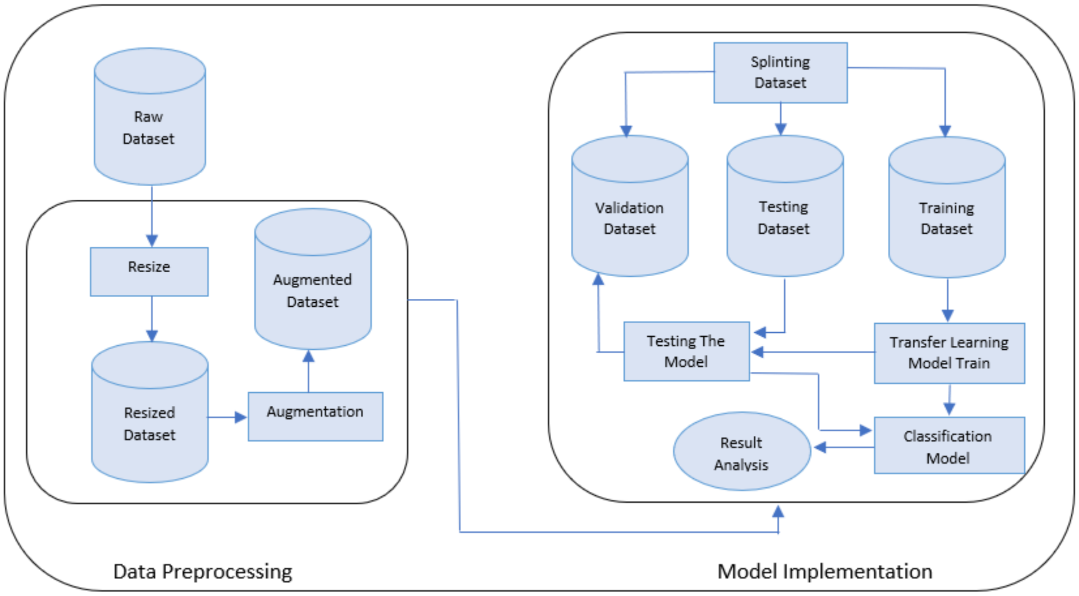

Figure 3.1: Methodology Workflow

The methodology workflow for Duck Species Classification involves two main stages: Data Preprocessing and Model Implementation.

In the Data Preprocessing stage, the process begins with collecting the dataset consisting of images of various duck species. These raw images are then resized to a uniform dimension to ensure the consistency across the dataset. This resizing is crucial as neural networks require input images to be of the same size. The resized images form the resized dataset. After that, an augmentation step is performed where various transformations, such as rotation, flipping, scaling, and adjusting brightness are applied to the resized images. This step is essential for increasing the diversity of the dataset, thus enhancing the robustness of the model. The output of this process is the augmented dataset, which includes both the original and augmented images, making it ready for the next stages of the workflow.

Right after the model implementation stage begins. the augmented dataset is first divided into three subsets training, validation, and testing datasets. The training dataset is used to train the model, the validation dataset helps in tuning hyperparameters and preventing overfitting during the training process, and the testing dataset is used to evaluate the final performance of the trained model. The training process involves transfer learning, where a pre-trained model is fine-tuned for the specific task of duck species classification. This results in a classification model that is capable of distinguishing between different duck species.

After training the classification model is tested using testing dataset. Here, model's performance is evaluated based on metrics called accuracy, precision, recall and F1 score. Finally, the result from the testing phase is analyzed in result analysis step. This analysis helps in understanding the model's performance, identifying any misclassified images, and determining the model's strengths and weaknesses.

3.2 Data Collection Procedure

The data collection process for the study starts by exploring a hatchery located in Bikrampur, right next to Dhaka city. Finding hatchery was bit complicated because the number of duck breeders are no that huge. There we found four species of ducks both male and female. There we abled to find duck species: Deshi, Indian Runner, Campbell and Zinding. Engaging with the hatchery owner by telling the main goal of our study, how we are going to do the work done. Then we managed to get the desired images of every duck species of both male and female.

From there, we were able to get total approximate 1851 images of all species ducks. To be more specific Campbell Female 224 images, Campbell Male 304 images, Deshi Female 147 images, Deshi Male 212 images, Runner Female 316 images, Runner Male 332 images, Zinding Female 175 images and Zinding Male 141 images.

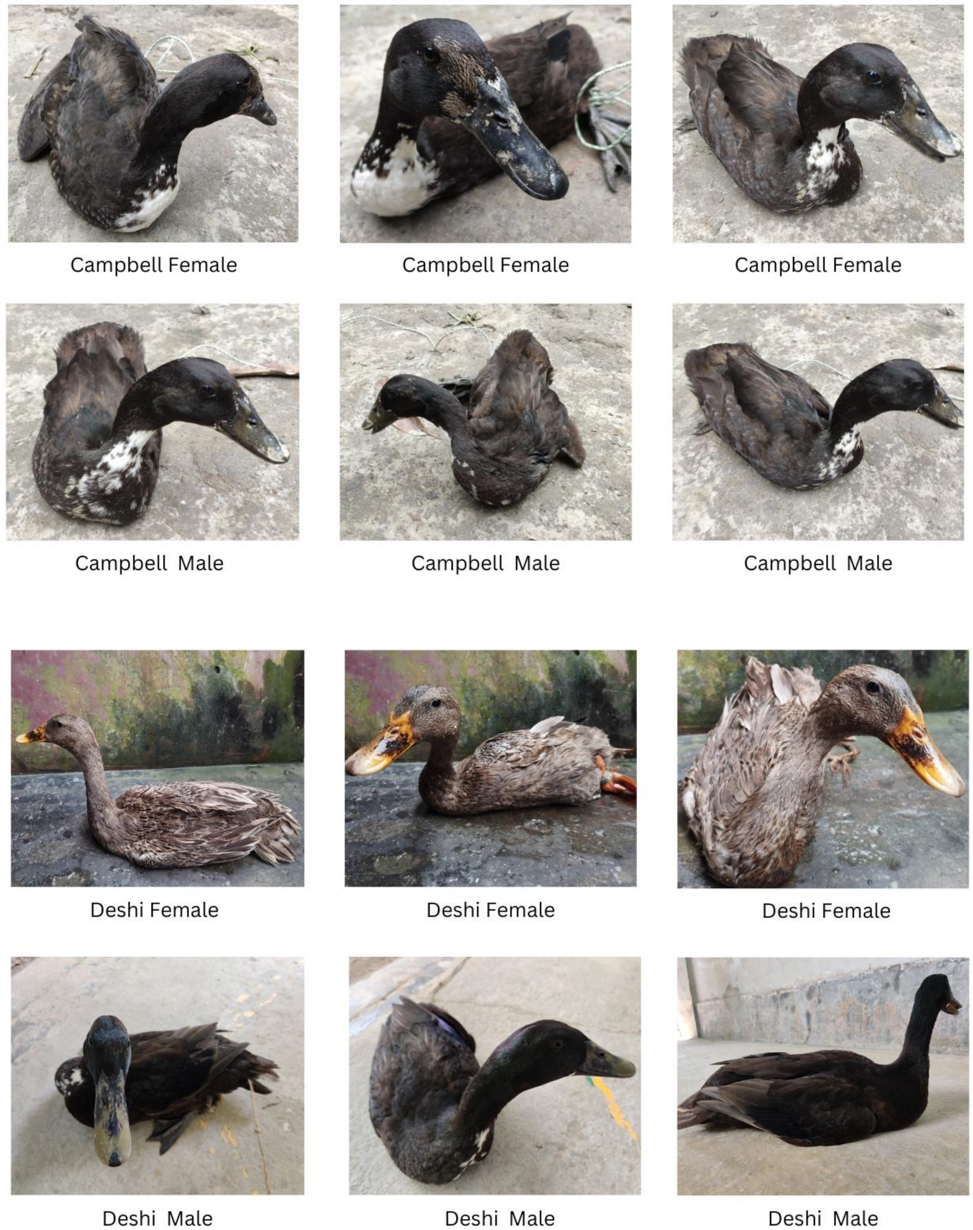

Figure 3.2: Dataset Sample

Figure 3.2 is showing the collected dataset of two species ducks. They are Campbell and Deshi. Here, both male and female of both species are displayed.

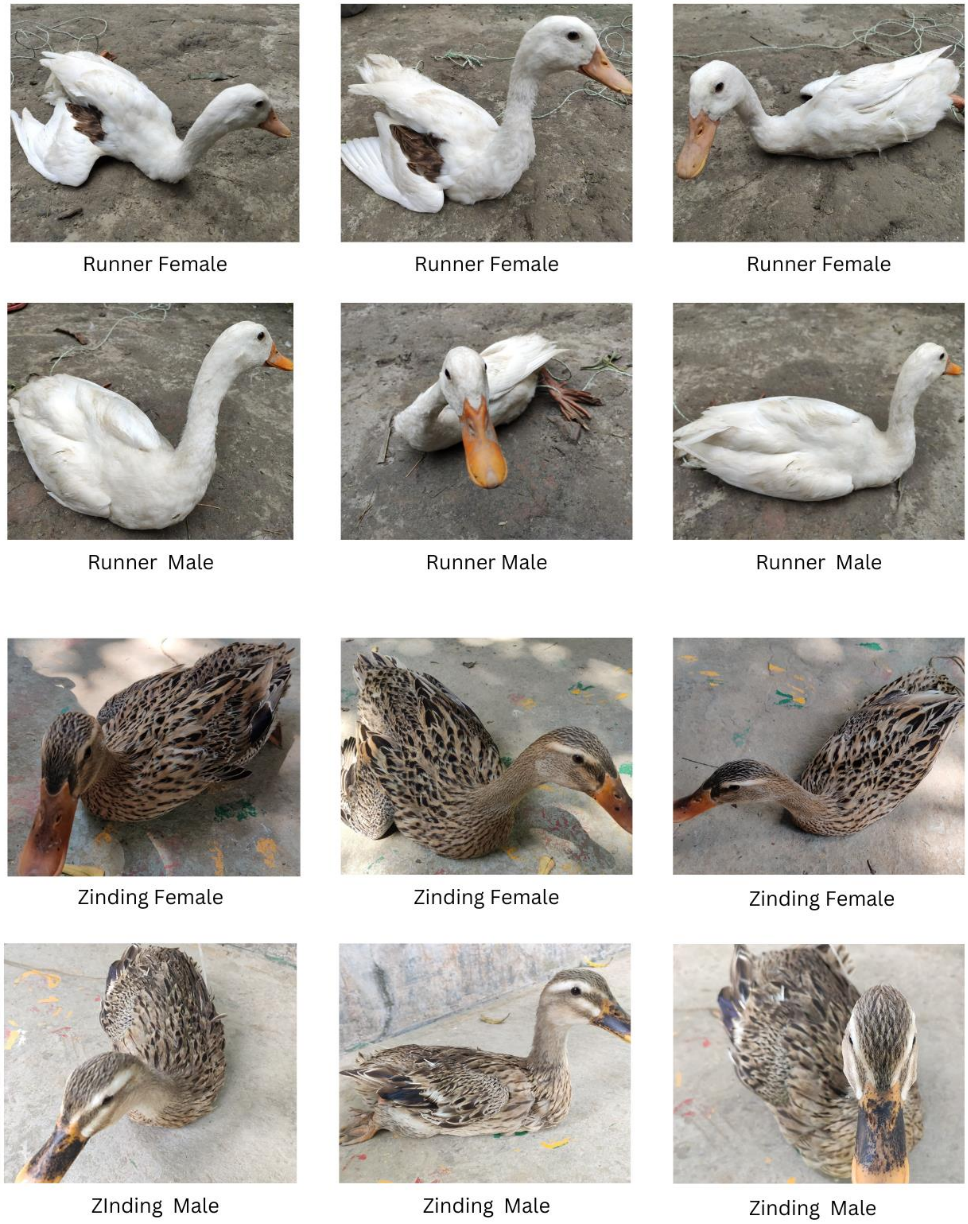

Figure 3.3: Dataset Sample

Figure 3.3 is displaying two duck species of Runner and Zinding. This figure is also showing the both male and female of these species.

3.3 Data Pre-Processing

The realm of developing automatic duck species and gender classification system using computer vision and deep learning data pre-processing plays very important role in terms of effective model training. This multifaceted process encompasses several critical tasks to enhance the quality and suitability of the input data

Firstly, image resizing is used to standardize the dimension of the images. This process is to ensure the consistent size of the images for model inputs. Subsequently, normalization is applied to scale pixel values within a common range. This is for preventing any single feature from dominating the learning process and assisting faster model convergence. Here, each figure size is 15X15 to be more specific. All images of each species are obtained with the help of smartphone at 3000 X 4000 pixels. And later have been scaled down to 300 X 300 pixels.

Data augmentation technique have been implemented to increase the size and variety of the dataset to overcome the data limitation restriction. Rotation within a -15 to +15-degree range, shearing within a 0.2 range, zooming in and out within a 0.2 range, horizontal and vertical flipping, random brightness modifications, plus guaranteeing no degraded regions in the output pictures were used as augmentation techniques. These changes expanded the dataset into 4,000 photos, and 500 images for each duck breed.

After that feature extraction methods should be taken in consideration. For this transfer learning techniques should be adopted because it will allow to utilize pre-trained models to extract features from our collected dataset of duck images. For this, some pre-trained architectures should be used. ResNet50, ResNet152, DenseNet121, DesnseNet201 and MobileNet-v2.

Figure 3.4: Augmented Dataset Sample

Figure 3.5 is showing the augmented batch of collected dataset. Every duck species of both male and female is augmented with some properties they are rotation, shear range, zoom range, horizontal and vertical flip and brightness. After augmented process the dataset batch of all species is displayed here.

Here is a table showing the details of dataset collected image counts and augmented dataset counts.

TABLE 3.1: DATASET DETAILS SHOWING COLLECTED IMAGE NUMBER AND AUGMENTED DATASET COUNTS

Class	Raw Dataset	Augmented Dataset
Campbell Female	224	500
Campbell Male	304	500
Deshi female	147	500
Deshi Male	212	500
Runner Female	316	500
Runner Male	332	500
Zinding Female	175	500
Zinding Male	141	500
Total	**1851**	**4000**

Table 3.1 is showing the comparison of raw dataset and augmented dataset count. Here, we can see, every single species of both male and female is augmented for increasing the number of dataset. Before augmentation the number of raw dataset were 1851 on the other hand after augmentation the number of dataset is increased to 4000.

3.4 Dataset Splitting

The stage Dataset Splitting plays very important role in terms of developing automated species and gender classification of ducks using computer vision and deep learning. This step involves dividing the dataset into distinct subsets, typically training, validation, and test sets, each serving specific purposes in the model development and evaluation process.

Data adaptation of data splitting ratio for training should be 80-10-10. Here total 80% of the data is for training for the model to learn complex patterns and features. The 10% is assigned for validation process. This will assist the fine-tuning the model. This is for preventing overfitting of the model. The other 10% is reserved for testing. This will help us to evaluate model's unseen performance.

TABLE 3:2: DATASET DETAILS SHOWING COLLECTED IMAGE NUMBER AND SPLIT IMAGE COUNTS

Class	**Original Dataset**	**Training Dataset (80%)**	**Validation Dataset (10%)**	**Testing Dataset (10%)**
Campbell Female	500	400	50	50
Campbell Male	500	400	50	50
Deshi female	500	400	50	50
Deshi Male	500	400	50	50
Runner Female	500	400	50	50
Runner Male	500	400	50	50
Zinding Female	500	400	50	50
Zinding Male	500	400	50	50
Total	**4000**	**3200**	**400**	**400**

Table 3.2 is displaying the dataset details of collected images number and splitting image counts. Each of the species' dataset is divided into three subsets. There 80% of original dataset is reserved for training dataset and 10% of original dataset is reserved for both validation dataset and testing dataset. As a result, from 4000 images of original dataset 80% which is 3200 images is reserved for training dataset and 10% which is 400 images for both of validation dataset and testing dataset.

3.5 Transfer Learning Model

Transfer learning approaches are carefully incorporated into our duck species classification research because we fully understand their critical importance, inherent value, and enormous potential for optimizing our customized dataset. Within the field of machine learning, transfer learning is an advanced technique in which models that were previously trained on large datasets are repurposed to extract relevant characteristics for new tasks. With limited datasets, transfer learning becomes important in the field of duck species classification. The basic idea is based on the pre-trained models' ability to extract high-level characteristics from various datasets. This ability significantly enhances the model's ability to identify complex patterns and traits linked to different breeds of ducks.

This study includes five architectures ResNet50, ResNet152, DenseNet121, DenseNet201 and MobileNet-v2. By traversing extensive datasets during their original training, offer a profound understanding of visual features that seamlessly adapts to the unique characteristics of our specialized dataset. By harnessing the potential of transfer learning, our models acquire an unparalleled capacity to discern nuanced patterns and features indicative of diverse duck species.

3.6 Proposed Methodology

DenseNet201

DenseNet201 is a convolutional neural network architecture that stands out for its unique dense connectivity pattern. It addresses challenges like vanishing gradients and feature reuse, often encountered in deep neural networks. The network consists of connected blocks. Each blocks contain multiple convolution layer. DenseNet201 has total of 201 layers. This includes input and output layers. It is incorporated with large image datasets. DenseNet201 provides improved parameter efficiency, enhance feature propagation, alleviation of vanishing gradients, feature reuse, etc. Figure 3:6 showing the general architecture of DenseNet201.

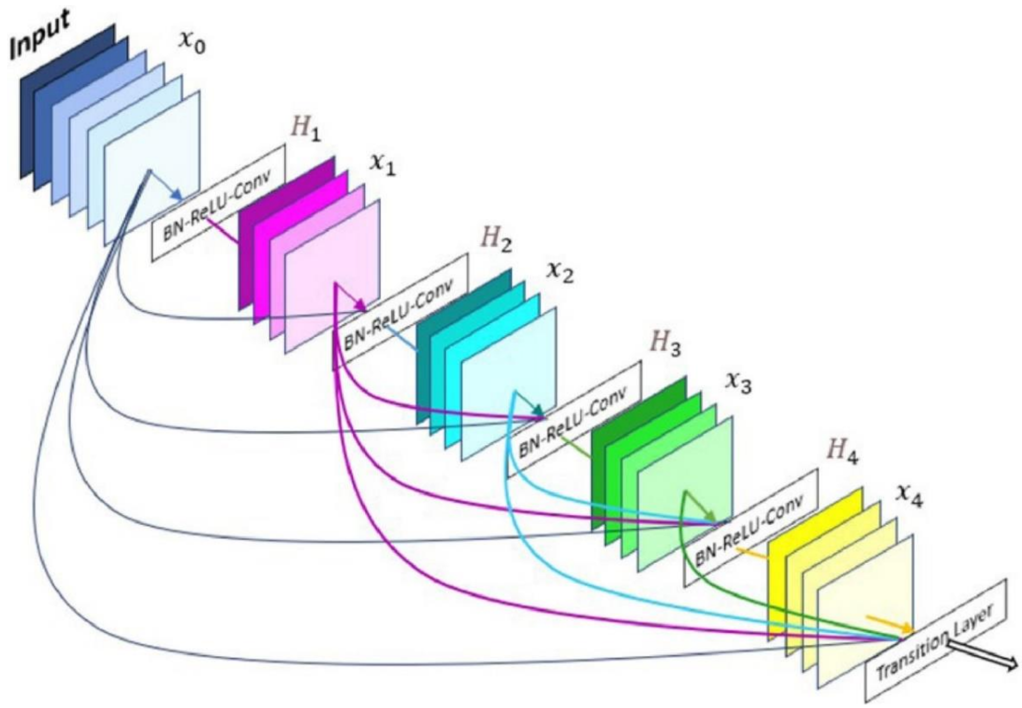

Figure 3.5: DenseNet201 General Architecture

3.7 Implementation of Requirements

The implementation of automated duck species classification successfully there are some demands of requirements that should be implemented. This implementation will help a lot in order to run the system seamlessly. The implementation of tools required for the system are:

Hardware Requirements: Model training requires intense graphical processing power. Utilizing those GPUs for faster model training is go to option. Ensuring the hardware has enough RAM to handle the dataset and model complexity and inference.

Software Requirements: The main environment for coding is Google Colab. Google Colab offers some advantages by which the process becomes way smoother and easier. Google Colab has built-in deep learning libraries. Such as: Pytorch, TensorFlow, etc. This both are very essential for classification of transfer learning models.

Model Architecture: Choosing suitable deep learning architectures for image classification. We considered leveraging pre-trained models of transfer learning. Implementation of model optimization techniques to efficiency of the model.

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Setup

Experimental setup includes five deep learning pre-trained models for our duck species classification study. The models are ResNet50, ResNet152, DenseNet121, DenseNet201, MobileNet-v2.

Pre-Trained Models Selection: For our automated duck species classification we chose five pre-trained architectures. From the ResNet family we chose ResNet50 and ResNet152. The reason behind choosing these architectures is to skip connection and alleviate the vanishing gradient problem. Other than the we chose two architectures from DenseNet Family. They are DenseNet121 and DenseNet201. The reason behind this is fostering the feature reuse across the layers. And lastly, we chose MobileNet-v2 from MobileNet family for the optimization of mobile and embedded devices.

Training Process: Every pre-trained model we chose should go through the process of fine-tuning. This process will help to get rid of issues that dataset have. The dataset training consists of labeled data of duck of all species e.g. Campbell Female, Campbell Male, Deshi Female, Deshi Male, Runner Female, Runner Male, Zinding Female and Zinding Male. In the time of training process adjusting the parameters is appreciated for minimizing the classification error.

Performance Evaluation: After training the dataset using the suitable pre-trained models the next process is performance evaluation. This process is described by the model's performance standard evaluation technique which are accuracy, recall, precision, F1 score. These metrics provides a clear knowledge of how the models are performing for the specific dataset and if there is any need of changing the model or not.

4.2 Experimental Results and Analysis

The experimental result and analysis process represents the testing accuracy of the pre-trained model on the dataset. This will draw the crucial insight into the employed duck species classification study. Table 2 showing the test accuracy and test loss of all the models.

TABLE 4.1: MODEL PERFORMACE SUMMARY

Models	Test Accuracy	Test Loss
ResNet50	75.00%	0.795
ResNet152	60.50%	1.043
DenseNet121	98.25%	0.081
DenseNet201	99.25%	0.027
MobileNet-v2	97.75%	0.070

The experiments show that while testing ResNet50 the test accuracy is 75.00% and test loss is 0.795. This test shows that, accuracy has some room of improvement. The result after testing ResNet152 shows that the test accuracy is 60.50% and test loss is 1.043. Here the accuracy reduction and increase in test loss. DenseNet121 show that the accuracy is 98.25% and test loss is 0.081. After performing DenseNet201 the test accuracy is 99.25% and test loss is 0.027. In this case, this model is performing best for this dataset. Last but not the least, MobileNet-v2 showing the test accuracy of 98.75% and test loss of 0.

4.3 Classification Report

After the classification process, the result shows some terms of accuracy, precision, recall, F1 score. Precision is the correctness of the positive predictions, recall is the model's ability to identify all true positives, and the F1 score combines precision and recall into a single metric. Support represents each class in the numerical foundation. All these metrics precision, recall, F1 score, and support are mentioned for the proposed model DenseNet201. The evaluation shows how well the model performs in identifying true positives and minimizing false positives, providing a comprehensive understanding of the DenseNet201 model's effectiveness in the classification task.

TABLE 4.2: CLASSIFICATION REPORT OF DANSENET201

Class	Precision	Recall	F1 Score	Support
Campbell Female	1.00	0.98	0.99	41
Campbell Male	1.00	0.98	0.99	50
Deshi Female	1.00	1.00	1.00	55
Deshi Male	0.95	1.00	0.97	39
Runner Female	1.00	0.98	0.99	45
Runner Male	0.98	1.00	0.99	53
Zinding Female	1.00	1.00	1.00	57
Zinding Male	1.00	1.00	1.00	60
Average	**0.99**	**0.99**	**0.99**	**400**

4.4 Training and Validation Curve

Figure 4:7 and Figure 4:8 visualizing the validation accuracy and loss curve respectively.

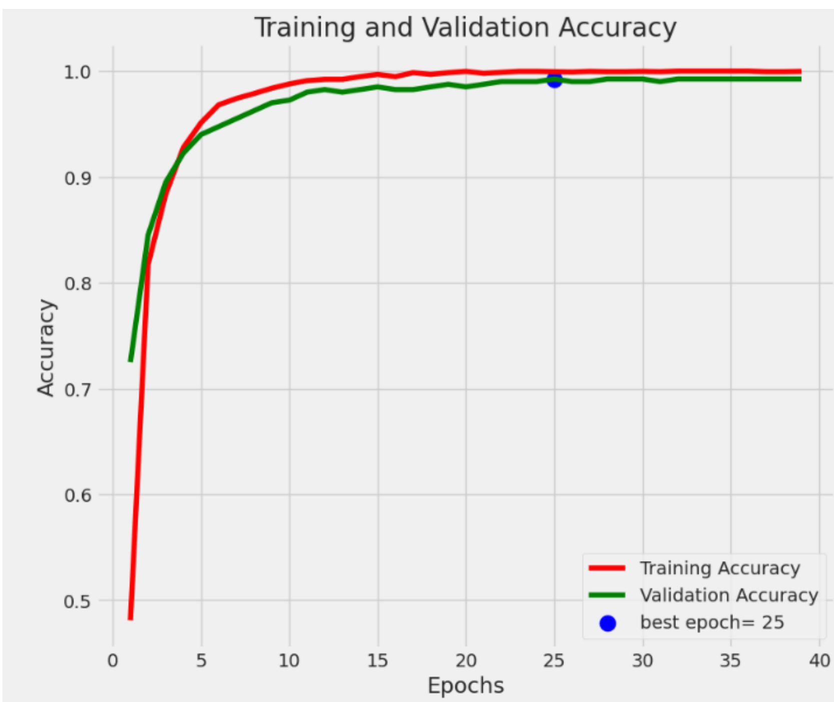

Figure 4.1: Training and Validation Accuracy Curve

This is the training and validation loss curve over a number of epochs. This graph is commonly used to monitor the process of a training model.

The red line indicated the training accuracy of the model and the green line indicates the validation accuracy of the model. Training accuracy reflects how well the model performs on the data it is trained on and the validation accuracy reflects how well the model performs on a separate set of data. From the graph we can see that the training accuracy increases steadily throughout the epochs. This means the model is effectively learning from the training data. On the other hand, the validation is also increasing until 25 epoch. Here best epoch is 25. That means the model achieved its best validation accuracy at epoch 25.

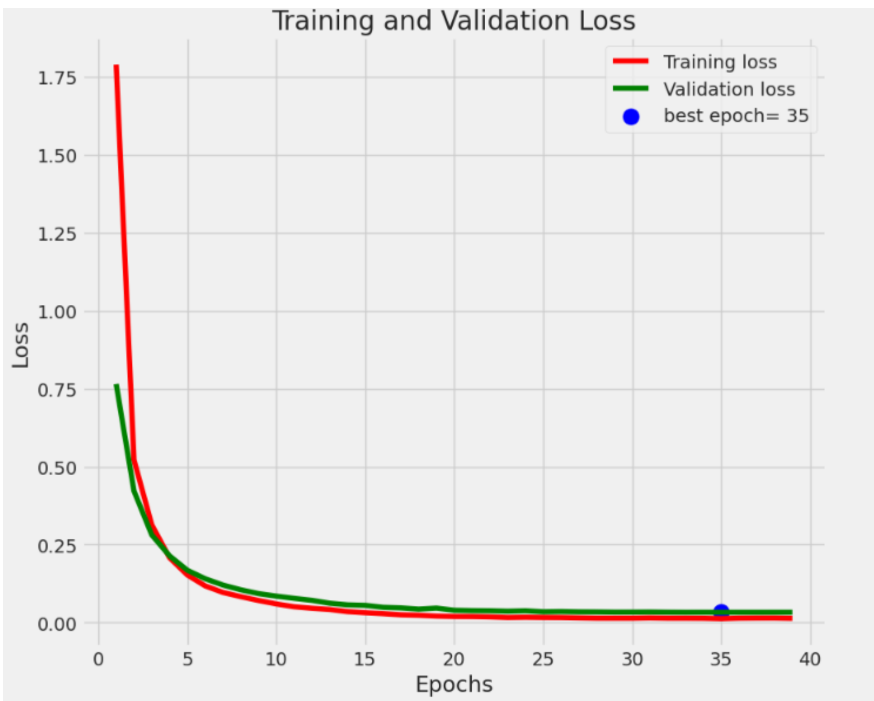

Figure 4.2: Training and Validation Loss Curve

This is the training and validation loss curve over a number of epochs. This graph is commonly used to monitor the process of a training model.

The red line indicates the training loss of the model and the green line indicated the validation loss of the model. The training loss reflects how well the model performs on the training data on the other hand, the validation loss reflects how well the model performs on a separate data set. The training loss decreases steadily over the course of training. This means the model is learning from the training data. On the other hand, the validation loss also decreases at the point of 35 epochs. That means the model is performing very well on the training data. In this graph, we can see that the best epoch is 35. That means that model achieved its best validation loss at epoch 35.

4.5 Confusion Matrix

The confusion matrix plays important role is assessing the performance of the duck species classification models. The table represent the model's prediction, highlights of correct and incorrect instances.

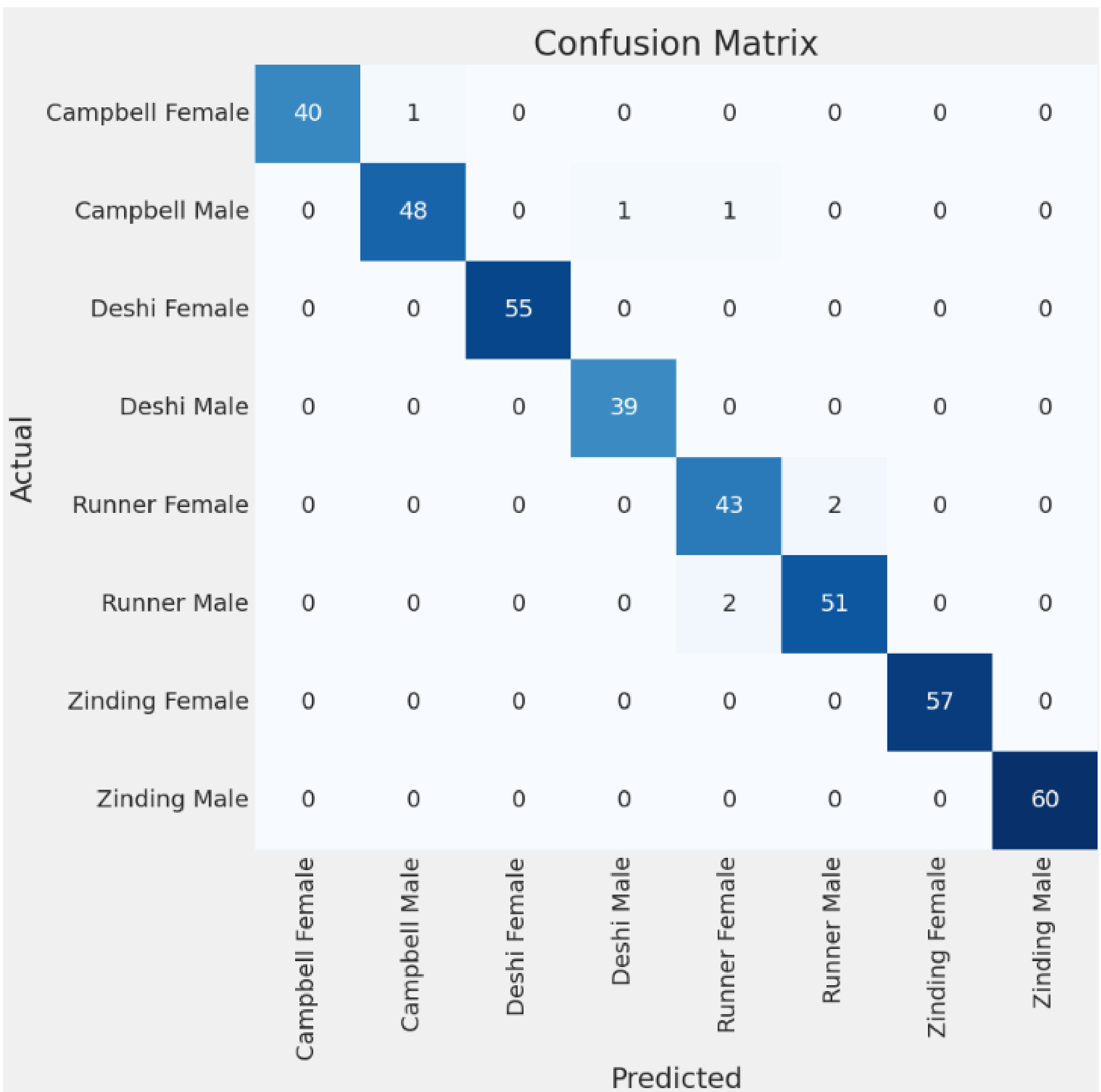

Figure 4.3: Confusion Matrix of the DenseNet201

The confusion matrix showing that all the duck species are predicted accurately. But still there are some errors while predicting the duck species. Here, 40 Campbell Females are predicted accurately but 1 Campbell Male was predicted in this process. In Campbell Male 48 was predicted accurately but 1 Deshi Male and 1 Runner Male was predicted in this case. And in time of Runner Male and Runner Female 2 Runner Female and Runner Male was predicted in this case. So, in this case we can see that, our proposed transfer learning model is predicting very well for out dataset.

4.6 Discussion

This study reveals the performance of the models in our duck species classification. Here, we have used five models such as: ResNet50, ResNet152 from ResNet family, DenseNet121 and DenseNet201 from DenseNet family, and MobileNet-v2 from MobileNet family. Every model performs at their own capability based on the dataset. In that scenario, we clearly can understand that ResNet model's accuracy was not that great. There were some rooms of accuracy that is 70.00% and 60.50%. Other than the test loss was also higher that is 0.795 and 1.043.

As we move forward from ResNet to DenseNet, there is a noticeable performance increase. DenseNet201 shows most optimal performance on this process that is 99.25% accuracy and 0.027 data loss. That is the most acceptable result among the models. Other than that, DenseNet 121 performed decent for out dataset. It managed to get 98.25% accuracy and 0.081 test loss. And last but not the least, MobileNet-v2 performed 97.75% accuracy and 0.070 data loss.

Higher accuracy value indicates the model adapt the classification more accurately. And lower test data loss indicates the model coverages more effectively. So, there is no brainer that, our proposed model DenseNet201 performing better other that the models and fulfilling our expectations.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

This project can contribute the educational awareness by providing information of various duck species to the people. This knowledge will disseminate through educational programs, online platforms, or interactive interfaces by raising awareness about wildlife conservation. This project will also contribute to effective wildlife management and conservation initiatives. Which will ensuring the protection of vulnerable species and their habitats. The research findings can be utilized in educational outreach programs and environmental workshops. This can inspire the next generation of scientists, conservationists, and environmentally conscious citizens. The project can generate scientific materials and educational resources for researchers. These materials can be used to enhance the understanding of duck ecology, behavior, and diversity. The availability of accurate data of duck species can enhance natural tourism. By providing accurate data of duck species by this research project we can contribute on natural tourism.

5.2 Impact on Environment

Ducks play an important role in ecosystem as both predator and prey. This project will contribute to understand and monitor the duck population and maintaining the ecosystem. Accurate classification of duck species aids in the management of hunting activities, ensuring sustainability and adherence to ethical practices. This contributes to the conservation of duck population. The ability to accurately classify duck species facilitates ecological research by providing researchers with reliable data on species behavior, distribution, and interactions with their surroundings. Accurate classification of duck species can contribute to biodiversity. The presence and behavior of various duck species should be understood. By developing advanced deep learning, image processing techniques can extend the duck classification ever more. It can enhance the capability of monitoring techniques which can allow the efficiency assessment of different wildlife populations and their activities.

5.3 Ethical Aspects

The dataset involves animal images. In this case, duck images. So, it is very important to consider the ethical treatment of duck during data collection. Respectful collection of duck images is ensured during the data collection. Providing clean information about the project, how the data will be used, how to process will work is strictly maintained. It is ensured that the dataset and the model is ensured fair representation of different duck species. Unbiased data collection and develop models is strictly followed during training.

5.4 Sustainable Plan

The efficacy and robustness of our duck species categorization system are underpinned by a long-term sustainability plan. Continuous assessment and development, inspired by ideas from bird professionals and conservationists, ensures its responsiveness to changing duck species identification needs. Collaboration with conservation groups and educational programs aims to convey knowledge about duck variety and habitat preservation, supporting sustainability in both urban and rural settings. Furthermore, ongoing research programs might investigate broader aspects of sustainability, such as connecting the system with environmental surveillance tools and its potential role in fostering urban biodiversity and eco-friendly urban development.

CHAPTER 6

SUMMARY, CONCLUSION, RECOMMENDATION AND IMPLICATION FOR FUTURE RESEARCH

6.1 Summary of the Study

The research is dedicated to development and evaluation of a duck species classification system that leverages transfer learning models. The dataset contains 8 classes – Campbell Female, Campbell Male, Deshi Female, Deshi Male, Runner Female, Runner Male, Zinding Female, Zinding Male. By implementing preprocessing deployment different transfer learning models, the study focuses to accurate and automated species classification system. From our study, we can create an idea about species of ducks available in our country and how different species looks like and basic difference of identification. By combining this with technology we will able to monitor continuously on the lifestyle of specific duck species.

6.2 Implications of Future Study

Our study lays a solid foundation for duck species classification but still it has some rooms for further exploration. Future study would focus into enhanced model's decision making, exploring real-life monitoring for continuous monitoring of health and lifestyle of the ducks of various species. Additionally, establishing a transparent ethical guideline for responsible use of technology in ducks to guarantee the treatment and facilities. And future sturdy would also include more species of duck available to get even broader understanding about ducks.

6.3 Conclusion

The study of duck species classification using transfer learning models provide acceptable accuracy. Here, we chose DenseNet201 as the optimal model. Reason behind this the impressive accuracy of the model is 99.25% and the minimal loss of 0.027. That make the model our main consideration for this study. The detailed analysis of confusion matrix delivers a clear understanding of the model's strength and area of improvement. Ethical considerations are crucial for deploying the technological solutions. Transparent communication with the duck breeders is crucial to ensure the decision making. This study contributes on impact on society, environment and other aspects by providing clear insights of duck species, health and lifestyle of ducks of different species. The impact of our research extends beyond conservation, potentially contributing to the preservation of urban biodiversity, the promotion of sustainable ecological practices, and the advancement of avian species management. These societal benefits underscore the significance of furthering research in the field of duck species classification and highlight the transformative potential of technological advancements in conservation efforts. The journey will further explore and collaborate to the new realm of duck species classification and contribute a sustainable future of ducks.

REFERENCES

[1] Islam, Shazzadul, Sabit Ibn Ali Khan, Md Minhazul Abedin, Khan Mohammad Habibullah, and Amit Kumar Das. "Bird species classification from an image using VGG-16 network." In Proceedings of the 7th International Conference on Computer and Communications Management, pp. 38-42. 2019.

[2] Marini, Andréia, Jacques Facon, and Alessandro L. Koerich. "Bird species classification based on color features." In 2013 IEEE international conference on systems, man, and cybernetics, pp. 4336-4341. IEEE, 2013.

[3] Krishnan, Sidhart, Priya Khandelwal, and Rhythm Garg. "Bird Species Classification: One Step at a Time." CLEF Working Notes (2022).

[4] Alswaitti, Mohammed, Liao Zihao, Waleed Alomoush, Ayat Alrosan, and Khalid Alissa. "Effective classification of birds' species based on transfer learning." International Journal of Electrical and Computer Engineering (IJECE) 12, no. 4 (2022): 4172-4184.

[5] Lopes, Marcelo Teider, Alessandro Lameiras Koerich, Carlos Nascimento Silla, and Celso Antonio Alves Kaestner. "Feature set comparison for automatic bird species identification." In 2011 IEEE International Conference on Systems, Man, and Cybernetics, pp. 965-970. IEEE, 2011.

[6] Oerlemans, Stan CM, Wiebe Nijland, Ashley N. Ellenson, and Timothy D. Price. "Image-based classification of double-barred beach states using a Convolutional neural network and transfer learning." Remote Sensing 14, no. 19 (2022): 4686.

[7] Ragib, Kazi Md, Raisa Taraman Shithi, Shihab Ali Haq, Md Hasan, Kazi Mohammed Sakib, and Tanjila Farah. "Pakhichini: Automatic bird species identification using deep learning." In 2020 Fourth world conference on smart trends in systems, security and sustainability (WorldS4), pp. 1-6. IEEE, 2020.

[8] Biswas, Al Amin, Md Mahbubur Rahman, Aditya Rajbongshi, and Anup Majumder. "Recognition of local birds using different cnn architectures with transfer learning." In 2021 International Conference on Computer Communication and Informatics (ICCCI), pp. 1-6. IEEE, 2021.

[9] Mashuk, Farhan, Abdus Sattar, and Nahida Sultana. "Machine learning approach for bird detection." In 2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV), pp. 818-822. IEEE, 2021.

[10] Mirugwe, Alex, Juwa Nyirenda, and Emmanuel Dufourq. "Automating Bird Detection Based on Webcam Captured Images using Deep Learning." In Proceedings of 43rd Conference of the South African Insti, vol. 85, pp. 62-76. 2022.

[11] Wang, Yang, Jiaogen Zhou, Caiyun Zhang, Zhaopeng Luo, Xuexue Han, Yanzhu Ji, and Jihong Guan. "Bird Object Detection: Dataset Construction, Model Performance Evaluation, and Model Lightweighting." Animals 13, no. 18 (2023): 2924.

[12] Xu, Xin, Cheng-Cai Yang, Yang Xiao, and Jian-Lei Kong. "A fine-grained recognition neural network with high-order feature maps via graph-based embedding for natural bird diversity conservation." International Journal of Environmental Research and Public Health 20, no. 6 (2023): 4924.

[13] Mpouziotas, Dimitrios, Petros Karvelis, Ioannis Tsoulos, and Chrysostomos Stylios. "Automated Wildlife Bird Detection from Drone Footage Using Computer Vision Techniques." Applied Sciences 13, no. 13 (2023): 7787.

[14] Huang, Yo-Ping, and Haobijam Basanta. "Bird image retrieval and recognition using a deep learning platform." IEEE access 7 (2019): 66980-66989.

[15] Huang, Yo-Ping, and Haobijam Basanta. "Recognition of endemic bird species using deep learning models." Ieee Access 9 (2021): 102975-102984.

[16] https://pytorch.org/hub/pytorch_vision_densenet/

REVOLUTIONIZING LOCAL DUCK SPECIES CLASSIFICATION AN INTEGRATED APPROACH USING IMAGE PROCESSING AND TRANSFER LEARNING

ORIGINALITY REPORT

19%	15%	11%	6%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	dspace.daffodilvarsity.edu.bd:8080 Internet Source	4%
2	www.mdpi.com Internet Source	3%
3	Submitted to Daffodil International University Student Paper	2%
4	Shazzadul Islam, Sabit Ibn Ali Khan, Md. Minhazul Abedin, Khan Mohammad Habibullah, Amit Kumar Das. "Bird Species Classification from an Image Using VGG-16 Network", Proceedings of the 2019 7th International Conference on Computer and Communications Management - ICCCM 2019, 2019 Publication	1%
5	ceur-ws.org Internet Source	1%