Classification of Bangladeshi Bird Species Based on Images Using Deep Learning Techniques

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FINAL YEAR DESIGN PROJECT REPORT

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

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APPROVAL

This Project titled "**Classification of Bangladeshi Bird Species Based on Images Using Deep Learning Techniques**", submitted by **Md. Shahadat Hossain Sourov** and **Md. Nahid Parvej** 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 **14th July, 2024**.

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We hereby declare that this project has been done by us under the supervision of Mr. Dewan Mamun Raza (DMR), Assistant Professor, Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Bird species classification is significant for the ecological studies and the biodiversity conservation. This paper introduces a novel method using deep learning to automatically classify the bird species from the images. We study images of birds and apply the convolutional neural network to examine the basic features like feather and beak shape. This paper deals with the bird classification using deep learning methods by using a novel dataset coming from Kaggle containing the images of the eighteen native bird species in Bangladesh. The dataset, which is made up of 2704 carefully pre-processed images, goes through the rigorous pre-processing steps and is then divided into different subsets for the purpose of model evaluation, which includes training, testing and validation sets. Different deep learning architectures, such as MobileNetV2, DenseNet201, VGG19, and Xception, are carefully studied individually to check their effectiveness in the task of bird classification. Besides, hybrid models, which combine the different architectural paradigms, are built in a way to find the synergies and thus the classification accuracy is improved. A large number of evaluation metrics such as accuracy, precision, recall and F1-score are used to precisely compare the performance of the models. Findings reveal nuanced intricacies in model performance: The MobileNetV2 gets an accuracy of 97. 15%, VGG19 87.22%, DenseNet201 98.27%, Xception 98.33%, and the Hybrid MobileNetV2 and DenseNet201 model appears as the winner, with the highest accuracy of 99.50%. This superb achievement shows the possibility of hybrid architectures to beat the single-model approaches, giving us information how the interrelation between architectural complexity, computational resources, and task-specific requirements.

Keywords: Deep Learning, Bangladeshi bird, Birds identification, Computer Vision, Image Recognition, MobileNetV2, DenseNet201, Bird detection.

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CHAPTER 1

INTRODUCTION

1.1 Overview

Birds are useful for the balance of the ecosystem in Bangladesh as they honey and disseminate seeds as well as control pests. Despite the birds significance, their populations remain under threat from factors such as deforestation, climate change, and the expansion of human settlements, hence the importance of conserving these species. The existing ways of bird identification can take a lot of time and may involve mistakes due to which the conservation and study of birds and their environment is affected. In the wake of citizen science and bird watching activities, there is need for powerful identification tools that the non-expert user can easily use. In response to this challenge, the use of today's technological assets such as Deep Learning is a viable solution. Computer models based on Deep Learning can process a large amount of data and detect complex patterns and therefore are perfect for bird species identification. In our research, we aim at designing an automatically bird classification system through the employment of Deep Learning methodologies. Our goal will be to compare and select the optimal neural network structure, training method, and data preprocessing technique for the bird species identification in Bangladesh. This system will not only help in ecological research but also increase awareness of the public in bird conservation. In this context, our project aims at making a substantial impact on birds' conservation by improving the precision of bird identification and streamlining the process. Moreover, we will also try to raise the awareness level of the public so that they can also become responsible conservationist of the biodiversity of Bangladesh. We work hard to dissect and understand the life of bird species and present results of our findings to contribute to bird conservation efforts.

1.2 Background and Present State

Birds are essential to Bangladesh's ecological balance. An important thing to note about these birds is that they are not only artistic, but they are also beneficial to the ecosystem since they pollinate plants, disseminate seeds, and may also feed on pests. Yet, due to increasing human population densities, deforestation, and global warming among other factors, the knowledge and conservation of these birds must be deemed crucial at this backdrop [1]. Scientists argue that birds may be useful in tracking changes in climate and habitats and therefore can be known as monitors of the environment [2]. Monitoring birds as a population can provide information to more general environmental topics, consequently conservation efforts can be strengthened. However, the identification of bird species using a conventional method could take much time and might also involve wrong identification of the bird. And this is why a user-friendly tool is needed especially as, more and more citizens do engage in birding and nature tourism [3]. In response to this challenge, we use one of the modern technologies, and more specifically, Deep Learning, capable of processing data and identifying patterns. Our objective is to examine whether Deep Learning can be used for the classification of bird species without human interference at all, which is needed to monitor avian populations and address various issues associated with birds [4]. Our research delves into a comprehensive analysis of Deep Learning methodologies, including the exploration of various neural network architectures, training algorithms, and data preprocessing techniques. As an effort to eliminate the challenges that arise from fine distinctions in shape and differences in movements of birds, we aim at creating a strong framework for the automated classifiers for bird species. Integral to our study is a concern for Bangladesh avifauna specifically because we recognize the context in which these species exist is critical for their preservation [5]. Therefore, the purpose of our research is to contribute to the understanding of the ecological functions of referred local bird species and promote practical methods of their management and conservation. Beyond the scientific purpose, our endeavor is grounded in the principles of fostering active citizenry and civic participation. One of the ways that we use to promote the identification and conservation of birds is to create simple ways through which individuals in the society can engage in activities concerning birds. In summary, our research represents a concerted effort to harness the potential of Deep Learning for the benefit of avian conservation. Through rigorous analysis and collaboration, we aspire to contribute to a deeper understanding of bird ecology and inspire collective action towards safeguarding our planet's biodiversity.

Key contributions of our work include:

1. Identification and characterization of 18 distinct local bird species prevalent in Bangladesh.
2. Implementation of advanced preprocessing techniques to enhance the accuracy of bird species classification.
3. Development of user-friendly web applications to facilitate citizen engagement in bird conservation efforts.

1.3 Problem Statement

Identifying bird species is important for ecological studies but it's no longer easy. There are challenges like different feathers, various environments and not enough data. This part talks about the particular problems our research deals with and why we want a better method to classify birds.

1. Different birds in Bangladesh have complex features like colorful feathers and unique shapes, making it tough for ordinary strategies to pick out them.
2. The limited availability of diverse datasets unique to Bangladeshi bird species hampers the improvement of accurate and effective identity models.
3. The current computer systems that identify birds do not work well for Bangladesh's unique birds.
4. If we don't keep records of birds, they will become extinct globally and future generations of Bangladeshis won't be able to classify local bird species.

1.4 Objectives

Our objective is to empower little children to learn to identify bird species by providing accessible and comprehensive resources for bird identification. Moreover, we aim to develop a sighting record database, which will be useful for studying the population growth, distribution, as well as conservancy of different bird species. It is our goal to find out ecological roles of various bird species, which covers air and water quality, habitat integrity, natural resource management. We want to make it known that there are differences between the dangerous and the harmless birds, placing more emphasis on the protecting of vulnerable species and reducing the threats from the invasive and destructive birds. Among our priorities is to inform the public about the vital part the birds play in the ecosystem health and functioning which is accomplished by pointing out their role in pollination, seed dispersal, pest control, and nutrients cycling. This multi-pronged approach is aimed at fostering a sense of duty and stewardship among the public, consequently contributing to sustainable ecosystems while assuring the welfare of the human and wildlife communities. The main mission of our project is to boost the availability of our dataset by adopting a multitude of images from photoshoots which cover all the bird types that can be found here in Bangladesh. The addition of this feature is a critical element for development of valuable and comprehensive database for research. Our strategy is to use these deep learning approaches in the development of a new model with ability to correctly detect individual species from yearly group of sample pictures. Besides that, we are devoted to upgrading our systems to track the differentiating qualities of the birds of Bangladesh, which is the most essential work in the agenda of our research project designed for the research purposes in the context of Bangladesh, as well it is for exploration of the unique characteristics of the bird species and the way they interact with each other, which would increase the level of species classification accuracy. The involvement of the community is a crucial element of goals that we have. One of the factors we pay attention to is that the interface is user-friendly, which then makes it easier to participate in bird monitoring and bird data collection. The next thing now is to create a community that fully owns the birds conservation planning. The objective of the study will be seen as a guide for all methods and activities that the researcher has planned to assess and achieve which are directed towards the proliferation of knowledge and conservation of biodiversity in Bangladesh.

1.5 Scope and Limitations

Our project will focus on several important areas: Dataset Enrichment: We will work to improve our collections and obtain more images of Bangladeshi birds. Deep Learning Model Development: Creation of a smart computer system for the precise classification of the birds of Bangladesh using deep learning with the incorporate of optimization techniques. Adaptability to Local Nuances: Make sure the activity is designed in a way that it should be understood and suit the characteristics, postures and environment of Bangladeshi birds. Performance Evaluation: We will use the metrics of precision, recall, accuracy to determine bird identification errors. Community Engagement: Encourage the community to participate by providing an easy and straight forward to way to get engaged, to take bird photos and to help the research and conservation efforts. Exploration of Ecological Roles: Study the ecological role of birds, focusing on the influences of air and water sources. Awareness-raising on Bird Conservation: Educate on the threats faced by these bird species from invasive species and taking immediate measures to safeguard them. 1.5 Project Outcome The expected outcomes of our project include Enrichment of the database to provide more images of the birds of Bangladesh and improved deep learning models for more accurate species identification. With accessible resources, young children will be empowered to participate in bird identification and build a culture of conservation awareness. Increased awareness of the ecosystem functions of birds with enhanced photographic data and sophisticated systems will lead to integrated conservation efforts with the central principles of nature guided by the development of biodiversity conservation in Bangladesh. Evaluating performance metrics such as precision, recall and accuracy. And easy-to-implement community engagement with active participation in bird management and conservation efforts.

1.6 Report Organization

The report is organized into seven main chapters, followed by additional sections to provide comprehensive information on the research study. Chapter 1: provides an introduction, including an overview, background and present state, problem statement, objectives, scope and limitations, report organization, and a summary. Chapter 2: offers a literature review, covering an overview, related works, comparison between existing works, open issues, and a summary. Chapter 3: details the methodology and requirement analysis, including an overview, proposed methodology/system design, hardware/software requirements, project management and financial analysis, and a summary. Chapter 4: focuses on implementation, with sections on overview, train model/prototype design, system testing/model evaluation, and a summary. Chapter 5: presents the results and analysis, including an overview, experimental/simulation results, performance/comparative analysis, and a summary. Chapter 6: discusses the impact on society, environment, and sustainability, addressing impact on life, impact on society and environment, ethical aspects, sustainability plan, and a summary. Chapter 7: concludes the report, summarizing conclusions, further suggested works, limitations, and conflict of interests. The report also includes sections for References, Appendix A (Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing), and Appendix B (List of Publications).

1.7 Summary

In conclusion, our research highlights the urgent need for precise and efficient bird species identification in Bangladesh. By employing Deep Learning, we seek to develop a comprehensive automated bird classification system. This project not only advances scientific knowledge of local bird species but also encourages community participation in conservation efforts. Key takeaways from this chapter include the critical role of birds in Bangladesh's ecosystem and the threats they face, the drawbacks of traditional bird identification methods and the necessity for modern solutions, the transformative potential of Deep Learning in bird species classification, and the primary objectives, scope, and anticipated outcomes of our research. Our study represents a dedicated effort to utilize cutting-edge technology for ecological conservation, aiming to deepen the understanding and appreciation of avian biodiversity in Bangladesh. Through this project, we hope to motivate collective action towards safeguarding our natural heritage for future generations.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

The identification and classification of bird species have seen substantial advancements with the integration of deep learning techniques in recent years. This literature review covers 20 research papers that were centered on bird species identification, and particularly the use of algorithms and their respective accuracies among various deep learning models, traditional machine learning models, and hybrid approaches.

2.2 Related Works

This section presents an in-depth review of existing research efforts aimed at developing deep learning network models to improve the accuracy of bird classification based on images. It includes an overview of various CNN architectures and their applications in bird classification tasks. Additionally, it discusses the utilization of different image processing techniques in the context of bird classification.

Gavali et al. (2020) conducted a study where they implemented a Deep Convolutional Neural Network (DCNN) on the GoogleNet framework for bird species classification. Their model achieved an accuracy of 88.33%. However, the study encountered limitations due to the relatively small size of the training dataset, consisting of only 500 labeled and 200 unlabeled images. This restricted dataset posed challenges, particularly in accurately identifying bird species with similar colors. To address this limitation, the authors proposed the integration of additional features such as bird sounds or behavioral patterns, which could provide a more comprehensive basis for species identification [6].

Huang et al. (2021) explored the application of deep learning and transfer learning techniques, specifically utilizing the Inception-ResNet-v2 architecture, to classify bird species. Their approach yielded a remarkable accuracy of 98.39%. Despite the high accuracy achieved, the study identified a need for further development in the form of a crawler system bot. Such a system could enhance the classification process by efficiently collecting and processing large volumes of bird-related data, thus improving the overall performance and reliability of the classification model [7].

Vo et al. (2023) employed YOLOv5 and deep transfer learning models, including VGG19, EfficientNetB3, and InceptionV3, for bird species classification tasks. Their model achieved an accuracy of 98%. However, the study highlighted the importance of incorporating additional data sources, such as bird sounds, to improve the accuracy and robustness of the classification system. By integrating audio data alongside visual information, the model could achieve more accurate and reliable bird species identification, even in challenging environments [8].

Yu (2022) utilized Convolutional Neural Networks (CNNs) for the classification of animal species, achieving accuracies of 93% and 94% for two different models. Despite the promising results, the study noted a limitation in the classification scope, as the models were only capable of classifying three types of animals. To address this limitation and enhance the model's versatility, the authors proposed expanding the dataset to include a wider variety of animal species and experimenting with additional classification models [9].

Ragib et al. (2020) investigated the effectiveness of various ResNet models, with ResNet50 yielding an accuracy of 97.98% in bird species classification. However, the study emphasized the importance of dataset size and model diversity in achieving robust classification performance. To further improve accuracy and generalization capability, the authors suggested collecting a larger and more diverse dataset while also experimenting with different model architectures and feature extraction techniques, such as SIFT features [10].

Rahman et al. (2020) employed MobileNet with transfer learning techniques for bird species classification, achieving an accuracy of 91%. However, the study was limited by the relatively small dataset, which only included seven bird species. To address this limitation and improve the model's performance, the authors proposed expanding the dataset to include a more comprehensive range of local bird species [11].

Raj et al. (2020) utilized Convolutional Neural Networks (CNNs) for bird species classification, achieving training and testing accuracies of 93.19% and 84.91%, respectively. The study noted the limitations of a small dataset and poor image quality, which affected the model's performance. To overcome these limitations, the authors proposed expanding the dataset with more bird species and integrating additional features such as location and bird descriptions. They also suggested the development of a mobile application for bird species identification [12].

Farman et al. (2023) employed CNNs with skip connections for bird species classification, achieving an accuracy of 92%. The study identified challenges in classifying certain bird species and recommended extending the dataset to address this issue. By including more diverse examples in the training data, the model could improve its ability to accurately classify a wider range of bird species [13].

Chandra et al. (2021) utilized Support Vector Machine (SVM) for bird species classification, although the study did not specify the accuracy achieved. Limitations were identified in the dependence on visual features and poor image quality, which could affect the model's performance. The authors suggested further research to explore alternative methods of feature extraction and preprocessing to enhance classification accuracy [14].

Islam et al. (2019) employed Support Vector Machine (SVM) for animal species classification, achieving an accuracy of 89%. However, the study did not utilize deep learning models, which could potentially offer improved performance. To address this limitation, the authors proposed incorporating deep learning techniques, increasing the dataset size, and developing a web application for species identification [15].

Niemi et al. (2018) implemented CNNs and machine learning (SVM) for image classification, achieving a sensitivity (True Positive Rate) of 0.9463. However, the study encountered challenges such as poor visibility and loss of color information in images. To mitigate these challenges, the authors proposed data augmentation techniques and variations in color temperature to enhance the model's performance [16].

Gavali et al. (2019) employed deep convolutional neural networks (CNNs) for bird species classification, achieving an accuracy of 85%. The study suggested future work involving the development of an Android or iOS application, which could enhance the accessibility and usability of the classification system [17].

Rathi et al. (2017) utilized CNNs for bird species classification, achieving an accuracy of 96.29%. The study noted challenges in accurately classifying some images due to background noise. To address this limitation, the authors proposed implementing image enhancement techniques to restore lost features in the images, thus improving classification accuracy [18].

Biswas et al. (2021) employed various models including MobileNetV2 for bird species classification, achieving an accuracy of 96.71%. The study suggested future work focusing on recognizing birds from video data using a large class dataset, which could expand the applicability of the classification system [19].

Reddy et al. (2021) utilized convolutional neural networks (CNNs), specifically ResNet152v2, for bird species classification, achieving a test accuracy of 95.71%. The study highlighted the limitation of a small dataset, indicating the need for further data collection to improve the model's performance [20].

Singh et al. (2020) employed CNNs for animal species classification, achieving training and test accuracies of 93% and 80%, respectively. The study proposed the development of a web-based application for real image recognition and suggested adding new images to the dataset to enhance model performance [21].

Bidwai et al. (2020) utilized CNNs based on TensorFlow and PyTorch models for bird species classification. The study, however, did not provide specific results or findings [22].

Kulkarni et al. (2023) utilized InceptionV3 for bird species classification, achieving an accuracy of 82%. The study emphasized the need for better GPU accuracy, aiming for 90%, and recommended the development of a smartphone application for enhanced accessibility [23].

Al-Showarah et al. (2021) employed Artificial Neural Networks (ANN) for bird species classification, achieving an accuracy of 70.9908%. The study suggested conducting further investigation to improve accuracy results and reduce training time using different algorithms and preprocessing methods [24].

Manna et al. (2023) employed various models including Resnet152V2 for bird species classification, achieving an accuracy of 95.45%. The study noted that while Resnet152V2 provided better accuracy, it also lost more valid data compared to other models, indicating a need for further investigation into alternative models. Additionally, the authors proposed creating web and mobile applications for the classification system's deployment [25].

2.3 Comparison between existing works

Table 2.1: Comparison between existing works

SL No	Author Name & Year	Used Algorithm	Best Accuracy with Algorithm	Limitation
1	Gavali et al. (2020)	Deep Convolutional Neural Network (DCNN) on GoogleNet Framework	DCNN Accuracy = 88.33%	Limited training data (500 labeled and 200 unlabeled images), challenges in identifying species with similar colors
2	Huang et al. (2021)	Deep Learning, Transfer Learning, Inception-ResNet-v2	Deep learning using inception-ResNet-v2. Accuracy = 98.39%	Need for a crawler system bot to classify birds

3	Vo et al. (2023)	YOLOv5, Deep Transfer Learning models (VGG19, EfficientNetB3, InceptionV3)	EfficientNetB3 Accuracy = 98%	Need for additional bird sound data for accurate classification
4	Yu (2022)	Convolutional Neural Networks (CNNs)	CNN1 Accuracy = 93%, CNN2 Accuracy = 94%	Limited classification scope to three types of animals
5	Ragib et al. (2020)	ResNet18, ResNet34, ResNet50, ResNet101	ResNet50 Accuracy = 97.98%	Small dataset usage, limited model variation
6	Rahman et al. (2020)	MobileNet with Transfer Learning	MobileNet with transfer learning Accuracy = 91.00%	Small dataset with only seven bird species
7	Raj et al. (2020)	Convolutional Neural Networks (CNNs)	CNN training Accuracy = 93.19%. testing Accuracy = 84.91%.	Limited dataset, poor image quality

8	Farman et al. (2023)	Convolutional Neural Networks (CNNs) with skip connections	CNN with skip connections Accuracy = 92%	Some bird species challenging to classify, overprediction for species with higher occurrence, few species dataset
9	Chandra et al. (2021)	Support Vector Machine (SVM)	Not mention	Dependence on visual features, poor image quality
10	Islam et al. (2019)	VGG-16 (CNN), Random Forest, KNN, Support Vector Machine (SVM)	Support Vector Machine Accuracy = 89%	Not utilizing deep learning models, limited dataset, development of a web application needed
11	Niemi et al. (2018)	CNN, SVM	sensitivity (True Positive Rate) of 0.9463 as an image classifier	Poor visibility, color information loss
12	Gavali et al. (2019)	Deep Convolutional Neural Network (CNN)	Deep Learning Using CNN Accuracy = 85%	Future work needed for creating an Android or iOS app

13	Rathi et al. (2017)	CNN, Deep Learning, Image Processing	CNN accuracy = 96.29%.	Background noise affecting classification accuracy
14	Biswas et al. (2021)	DenseNet201, InceptionResNetV2, MobileNetV2, ResNet50, ResNet152V2, Xception	MobileNetV2 Accuracy = 96.71%	Future work needed for video data bird recognition
15	Reddy et al. (2021)	Convolutional Neural Network (CNN) ResNet 152 v2	Test accuracy 95.71%, loss function 15.06%.	Small dataset
16	Singh et al. (2020)	CNN	Train Accuracy = 93%, Test Accuracy = 80%	Proposed web-based application, need for dataset expansion
17	Bidwai et al. (2020)	CNN based on TensorFlow, Pytorch Models	Not mention	Use of PyTorch for model implementation
18	Kulkarni et al. (2023)	InceptionV3	Accuracy = 82% better gpu accuracy 90%	Improved GPU accuracy needed, requirement of large and diverse datasets, proposed development for smartphone

19	Al-Showarah et al. (2021)	Artificial Neural Networks (ANN), K-Nearest Neighbor, Random Forest, Naïve Bayes, Decision Tree	ANN Accuracy = 70.9908%	Absence of data preprocessing method, need for further investigation to improve accuracy and reduce training time
20	Manna et al. (2023)	Resnet 152 V2, Inception V3, Densenet201, MobileNetV2	Resnet 152 V2 Accuracy = 95.45%	Resnet152V2 better accuracy but loses more valid data, high training time, future work needed for dataset extension and app development

2.4 Open Issues

The issues of the problem addressed in this research, focusing on "Classification of Bangladeshi Bird Species Based on Images Using Deep Learning Techniques," extends to the field of biodiversity monitoring and conservation efforts. Bangladesh, known for its rich avian biodiversity, faces challenges in accurately identifying and classifying bird species, crucial for understanding ecosystem dynamics and informing conservation strategies. Our project will focus on several important areas: Dataset Enrichment: We will work to improve our collections and obtain more images of Bangladeshi birds. Deep Learning Model Development: Creation of a smart computer system for the precise classification of the birds of Bangladesh using deep learning with the incorporate of optimization techniques. Adaptability to Local Nuances: Make sure the activity is designed in a way that it should be understood and suit the characteristics, postures and environment of Bangladeshi birds. Performance Evaluation: We will use the metrics of precision, recall, accuracy to determine bird identification errors.

Community Engagement: Encourage the community to participate by providing an easy and straight forward to way to get engaged, to take bird photos and to help the research and conservation efforts. Exploration of Ecological Roles: Study the ecological role of birds, focusing on the influences of air and water sources. Awareness-raising on Bird Conservation: Educate on the threats faced by these bird species from invasive species and taking immediate measures to safeguard them. The research aims to address these challenges by leveraging deep learning techniques to automate the classification of Bangladeshi bird species based on image data. Traditional methods of bird species classification may be labor-intensive and prone to errors, particularly in diverse and complex ecosystems like those found in Bangladesh. The scope encompasses the development and evaluation of deep learning models tailored to the unique characteristics of Bangladeshi bird species. This includes considerations such as variations in plumage color, size, and habitat preferences, which may pose challenges to classification accuracy. Furthermore, the research explores the impact of dataset size and quality on the performance of deep learning models, as well as strategies to mitigate data limitations. It also investigates the role of transfer learning and pre-trained models in improving classification accuracy and training efficiency, considering the potential scarcity of labeled bird image datasets specific to Bangladesh. Additionally, the scope extends to the ethical considerations and potential biases associated with using deep learning techniques for bird species classification. Ensuring fairness and transparency in classification outcomes is essential for supporting conservation efforts and maintaining the integrity of biodiversity research. In essence, the scope of the problem encompasses the challenges inherent in bird species classification in the context of Bangladesh's biodiversity, the potential of deep learning techniques to address these challenges, and considerations for ethical and unbiased classification outcomes. By addressing these aspects, the research aims to contribute to the advancement of biodiversity monitoring and conservation practices in Bangladesh and beyond.

2.5 Summary

The findings of the literature review show new developments in identifying bird species using deep learning approaches. Based upon 20 research papers, it focuses on the models of deep learning, traditional machine learning, and a combination of both applied to bird classification. Specifically, the discussed key studies include the deep convolutional neural network, transfer learning, (YOLOv5), Inception-ResNet-v2, MobileNetV2. The review also highlights the factors such as size of the dataset, quality of the images, and other related data sources like bird sounds that can help to get better classification rate. However, there are some drawbacks which can be mentioned, for instance, small-scale datasets, and the necessity to improve data augmentation. Possible future research is to increase the number of data collections, incorporate more features, and design efficient applications for the bird classification systems. In general, the literature points to a potential for deep learning in the enhancement of bird species identification and conservation.

CHAPTER 3

METHODOLOGY

3.1 Overview

This section outlines the essential aspects of our study focused on classifying Bangladeshi bird species using deep learning techniques. It highlights the importance of this research in biodiversity monitoring and conservation efforts. By leveraging deep learning models, we aim to develop a robust system that enhances the accuracy and efficiency of bird species identification. This research addresses critical challenges such as dataset enrichment, model development, and community engagement, aiming to contribute significantly to the conservation of avian biodiversity in Bangladesh.

3.2 Proposed Methodology

The methodology for the classification of Bangladeshi bird species based on images using deep learning technology consists of some steps that involve preprocessing, augmentation, the train-test split, model training and the evaluation. Preprocessing in this aim is based mainly on the enhancement of image quality and selection of significant characteristics by means of contrast enhancement and gamma correction approaches. Subsequent preprocessing, the data set passes the process of the augmentation which enriches the diversity and enhances generalization of the model. Horizontal flipping, rotation, Gaussian blur, shear, contrast normalization and Gaussian noise exist among a significant number of transformations which make the dataset to have more samples. The augmented dataset is then split into three subsets: data transformation into training, testing, and validation sets with 80%, 10%, and 10% fractions representing training, testing, and validation sets, respectively. Throughout this process, they are developing their own way of making training data more reliable by using different datasets for evaluation and fine-tuning. Now we can continue on the next step of data preparation which is preprocessing and augmentation followed by training deep learning models by using transfer learning techniques. Podiums, which are individuals like MobileNetV2, DenseNet201 and hybrids, are used to derive the high-level features in the images. The testing and validation data are used to assess the quality of the resulting models. Accuracy, precision, recall, and f1 score are determined so that evaluation can happen in terms of the classifiers performance and how well it will generalize. By implementing this methodology, we can take picture of the baby and from the picture we will be able to classify the bird species using deep learning techniques in a more systematic way which makes our model stronger than the traditional techniques.

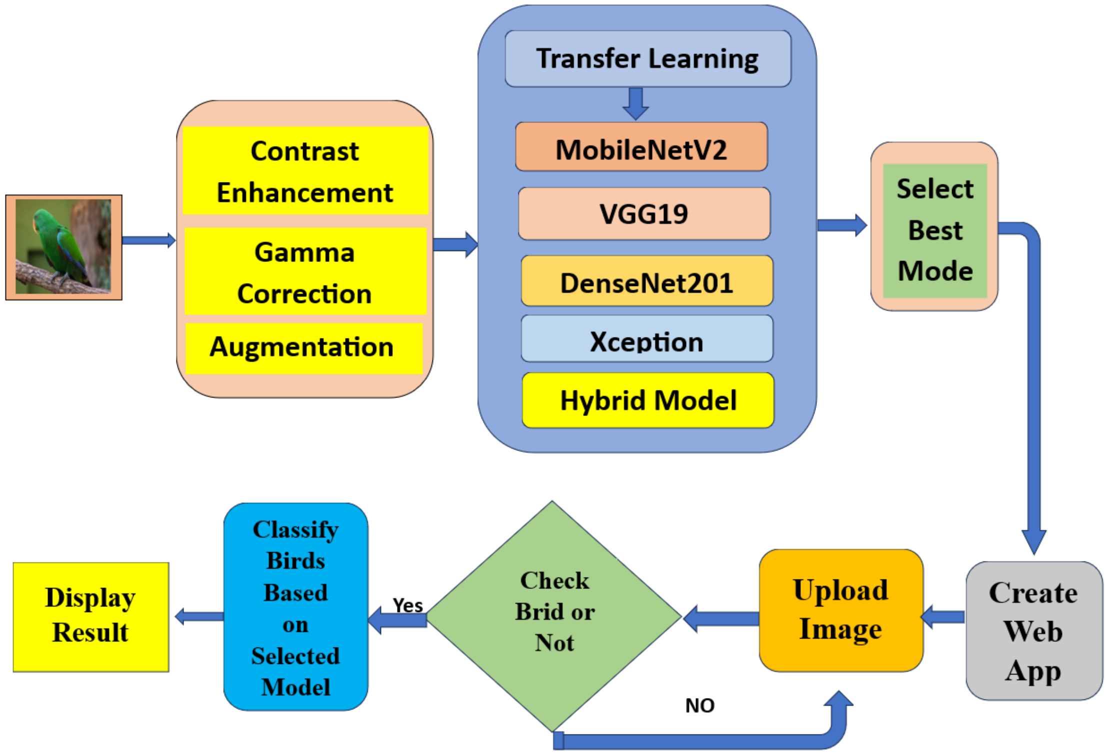


Figure 3.1: Proposed Methodology.

3.3 Hardware and Software Requirement

Implementation Requirements for Classification of Bangladeshi Bird Species Based on Images Using Deep Learning Techniques:

Hardware Requirements: High-performance GPU(s) for efficient training of deep learning models, such as NVIDIA GTX 1080 Ti or higher. Sufficient RAM (at least 16GB) to handle large datasets and model training. Storage space for storing datasets, trained models, and intermediate results.

Software Requirements: Deep learning frameworks such as TensorFlow or PyTorch for model development and training. Python programming language for scripting and development. Necessary libraries and packages including NumPy, pandas, scikit-learn, and matplotlib for data preprocessing, model evaluation, and visualization. Development environment such as Jupyter Notebook or Google Colab for interactive development and experimentation. Image processing libraries like OpenCV for image preprocessing and augmentation.

3.4 Project Management and Financial Analysis

We have to do two things under this section. One is Project Management and another one is Financial Analysis.

[1] Project Management

Project Objectives:

A. Development of a deep learning-based system for accurate classification of Bangladeshi bird species from images.

B. Creation of a user-friendly web interface allowing users to upload images and receive real-time classification results.

C. Comprehensive database creation for further avian research and conservation.

Project Timeline:

A. Phase 1: Project Planning and Research (2-3 weeks)

B. Phase 2: Data Collection (4-5 weeks)

C. Phase 3: Model Training and Testing (6-9 weeks)

D. Phase 4: Design and Prototyping (10-12 weeks)

E. Phase 3: Web Interface Development (13-17 weeks)

F. Phase 4: Database Creation (18-19 weeks)

G. Phase 5: Testing (20-21 weeks)

H. Phase 6: Integration and Optimization (22-23 weeks)

I. Phase 7: Finalization, Deployment and Marketing (Ongoing)

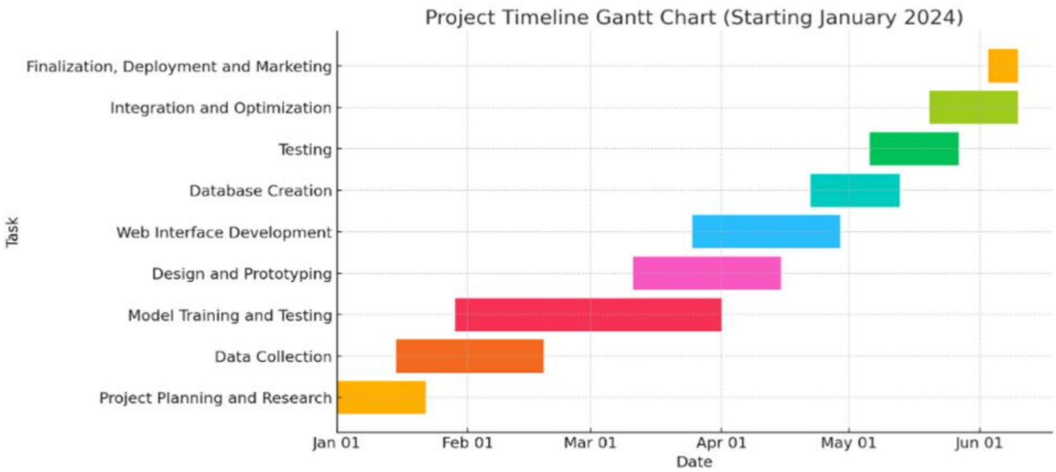


Figure 3.2: Project Timeline Gantt Chart

Risk Management:

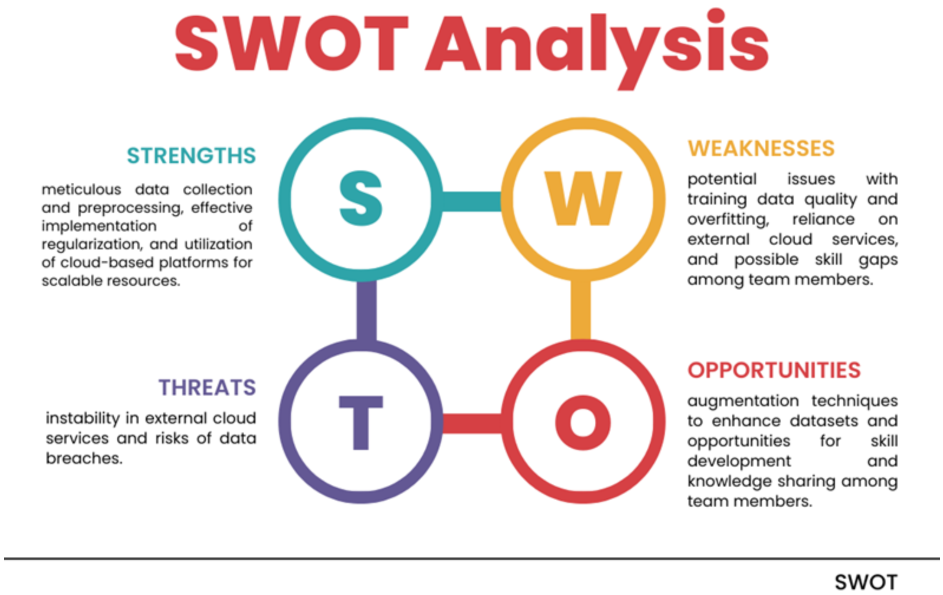


Figure 3.3: SWOT analysis

Communication Plan:

A. Stakeholder Meetings:

Purpose: Update stakeholders on project requirements gathering progress and gather feedback.

Participants: Team members and stakeholders.

Frequency: Bi-weekly or as specified in the project plan.

B. Change Control Meetings:

Purpose: Discuss and approve any changes to the project scope or requirements.

Participants: Supervisor and team members.

Frequency: As needed when change requests arise.

[2] Financial Analysis

Financial Analysis Below is a general table with estimated costs for different components of a bird classification project.

Table 3.1: Financial Analysis

Serial No.	Components	Estimated Cost (BDT)
01.	Domain and Hosting	1500-2000 per month
02.	Google Colab Pro+	5500-6000 per month
03.	Data Collection	3000-4000
04.	Visiting Stakeholders	2000-3000
05.	Documentation and Report Writing	1500-2000
06.	Miscellaneous (licenses, tools)	3000-4000
07.	Contingency (10% of total)	1000-1500
	Total Estimated Cost	17,500-22,500

3.5 Summary

This section provides a comprehensive overview of the project's approach to classifying Bangladeshi bird species using deep learning techniques. It highlights the structured methodology, including image preprocessing, data augmentation, and model training with evaluation metrics to ensure high accuracy and generalization. The necessary hardware and software requirements for implementing the deep learning models are outlined, emphasizing the use of high-performance GPUs and essential libraries. The project management plan is detailed, covering objectives, a phased timeline, risk management, and a communication plan. Additionally, a financial analysis estimates the costs associated with different project components, ensuring a clear understanding of the project's budgetary needs. This integrated approach aims to develop an effective and efficient bird species classification system that contributes to biodiversity conservation in Bangladesh.

CHAPTER 4

IMPLEMENTATION

4.1 Overview

This paper's primary goal is to design an effective image classification model that can recognize and categorize eighteen native bird species in Bangladesh. To this end, 2704 images were gathered from Kaggle and the following deep learning models were trained and tested: The images were preprocessed where contrast enhancement, gamma correction and data augmentation were performed to enhance the models accuracy. Six deep learning models were selected for training: Five models: MobileNetV2, DenseNet201, VGG19, Xception, and two models that are the combination of MobileNetV2 and DenseNet201, and Xception and DenseNet201. The models were evaluated by accuracy, precision, recall and F1-score in order to check which architecture is the most appropriate for this classification problem.

4.2 Train Model

Data Collection: The database used in this research was collected from Kaggle and collected images of eighteen species of native birds in Bangladesh [26]. Particularly, there is limited research developed on this particular dataset. In this case, the images were taken using differentiated qualitative image capturing instruments that include mobile phones and cameras which capture diverse and quality angles of the objects. Specifically, there are 2704 images in the pre-processed dataset, and all pictures are normalized to have a resolution of 224 pixels by 224 pixels. These images are divided into three sets that are further used for the model training and testing and to check the performance of the model.

Figure 4.1: Sample Dataset Images.

Process of Experiments: The experiment begins by combining various bird image datasets into one. After that, operations such as increased contrast, gamma correction, and augmentation are used to improve the quality and variety of images. Training, testing, and validation sets are used as above. The selected deep learning models, namely MobileNetV2, DenseNet201, VGG19, Xception and hybrid models, are trained on the training set. Evaluation metrics include accuracy, precision, recall, and the F1-score, which is computed on both the testing and validation datasets. The best-achieved and most accurate model is used for various applications in the monitoring and evaluation of biological diversity. The following preprocessing steps are followed sequentially:

Merge Dataset: Additionally, to simplify the classification task and facilitate model training, the dataset has been merged into a single class encompassing all species. The class-wise distribution of images is summarized in the following table:

Table 4.1: Class wise Distribution Image

Class	Image Count
Oriental-Magpie-Robin (Doel)	150
White-Breasted-Waterhen (Dahuk)	150
House-Crow (Kak)	150
White-Rumped-Shama (Shama)	150
Heron (Bok)	150

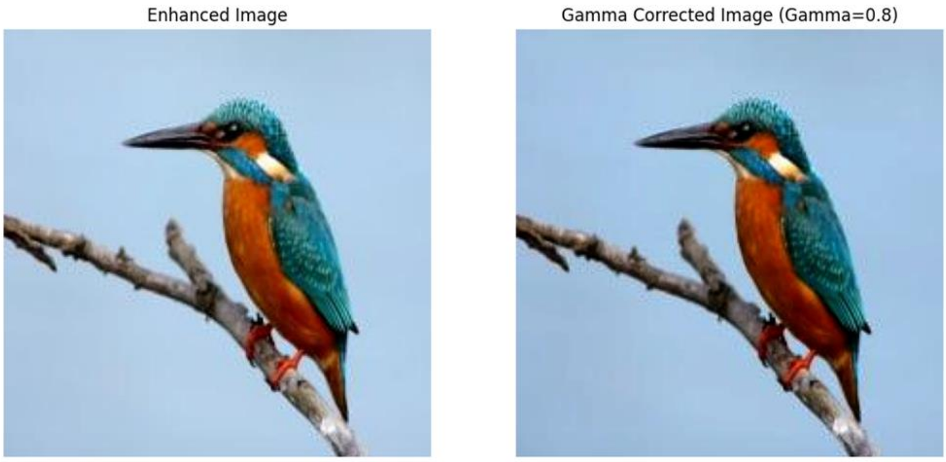
Common-Tailorbird (Tuntuni)	150
Owl (Pecha)	150
Coppersmith-Barbet (Basanta-Bouri)	150
Common-Myna (Shalik)	150
Kingfisher (Machranga)	150
Red-Wattled-Lapwing (Lal-Latika-Hottiti)	150
Black Drongo (Kalo-Finge)	154
Parrot (Tiya)	150
Indian-Roller (Neelkanth)	150
Black-Winged Kite (Chil)	150
Asian-Koel (Kokil)	150
Little-Cormorant (Pankouri)	150
Red-Vented-Bulbul (Bulbuli)	150

Contrast Enhance: Contrast enhancement is a fundamental image processing technique that amplifies the differences in brightness or color intensity within an image, enhancing visual clarity [27]. In our study, we applied a contrast enhancement process with a factor of 1.2 to subtly boost image contrast. Figure 4.2 illustrates the comparison between the original image and the contrast-enhanced image, showcasing the noticeable improvement in clarity and detail achieved through the contrast enhancement process.

(a) (b)

Figure 4.2: (a) Original Image vs (b) Contrast Enhance.

Gamma Correction: Gamma correction adjusts the brightness and contrast of an image by applying a power law function to its pixel values. A gamma value greater than 1 darkens the image and increases contrast, while a gamma value less than 1 brightens the image and reduces contrast [28]. In this case, a gamma value of 0.8 is used to slightly brighten the images while maintaining some contrast enhancement. In Figure 4.3, after doing the contrast enhance, we had done the gamma correction process step.



(a) (b)

Figure 4.3: (a) Enhanced Image vs (b) Gamma Correction Image.

Image Augmentation: The augmentation process involves applying various transformations to the images in order to increase the diversity of the dataset and improve the model's generalization ability. After applying gamma correction to all images, the dataset undergoes augmentation, wherein each class is expanded with 1000 augmented images per class. These augmentations include various transformations aimed at diversifying the dataset and enhancing the model's ability to generalize. The augmentations consist of: 'Original', representing the unaltered image; 'Horizontal Flip', which mirrors the image along the vertical axis; 'Rotation', introducing variations in orientation; 'Gaussian Blur', smoothing out details with a blur effect; 'Shear', distorting the image along one axis; 'Contrast Normalization', adjusting the contrast to improve feature visibility; and 'Gaussian Noise', adding random noise to simulate real-world imperfections [29]. Through this augmentation process, the dataset is enriched with a broader range of samples, facilitating more robust training and enhancing the model's performance on unseen data. Table 4.2, shows the original and augmented image.

Table 4.2: Image Augmentation

Serial	Class	Original Image	Augmented Image
01	Common-Myna_(Shalik)	150	1000
02	Black-Winged Kite_(Chil)	150	1000
03	Indian-Roller_(Neelkanth)	150	1000
04	House-Crow_(Kak)	150	1000
05	Red-Vented-Bulbul_(Bulbuli)	150	1000
06	Little-Cormorant_(Pankouri)	150	1000
07	hite-Breasted-Waterhen_(Dahuk)	150	1000
08	Coppersmith-Barbet_(Basanta-Bouri)	150	1000
09	Oriental-Magpie-Robin_(Doel)	150	1000
10	Black Drongo_(Kalo-Finge)	154	1000
11	Kingfisher_(Machranga)	150	1000
12	Asian-Koel_(Kokil)	150	1000
13	Perrot_(Tiya)	150	1000
14	Owl_(Pecha)	150	1000
15	Common-Tailorbird_(Tuntuni)	150	1000
16	White-Rumped-Shama_(Shama)	150	1000
17	Red-Wattled-Lapwing_(Lal-Latika-Hottiti)	150	1000
18	Heron_(Bok)	150	1000

Data Quality Verification: The range values for SSIM (Structural Similarity Index), PSNR (Peak Signal-to-Noise Ratio), MSE (Mean Squared Error), and RMSE (Root Mean Squared Error) typically depend on the specific characteristics of the images being compared or evaluated. However, these metrics often have certain common ranges:

SSIM: SSIM (Structural Similarity Index Measure) is a metric used to evaluate the similarity between two images. It quantifies the similarity based on luminance, contrast, and structure, mimicking human perception. The SSIM ranges from -1 to 1, where a value of 1 indicates perfect similarity between the images, and values closer to 1 represent higher similarity. A value of -1 indicates perfect dissimilarity.

PSNR: PSNR (Peak Signal-to-Noise Ratio) is a metric commonly used to measure the quality of a reconstructed or compressed image. It's typically measured in decibels (dB) and ranges from 0 to infinity. Higher PSNR values indicate higher similarity between the images, with infinity representing perfect similarity.

MSE: MSE (Mean Squared Error) is a measure of the average squared difference between corresponding pixels of the original and reconstructed images. It is calculated by averaging the squared differences over all pixels. MSE values range from 0 to positive infinity, where lower values indicate better similarity between the images.

RMSE: RMSE (Root Mean Squared Error) is the square root of the MSE. It measures the standard deviation of the differences between predicted and observed values (in this case, pixel values of images). RMSE values also range from 0 to positive infinity, with lower values indicating better similarity between the images.

In summary, SSIM and PSNR aim to measure similarity between images, with SSIM considering structural information, while MSE and RMSE directly quantify pixel-wise differences between images [30], with lower values indicating better similarity.

Table 4.3: Data Quality Verification

Serial	**Sample Image**	**SSIM value**	**PSNR value**	**MSE value**	**RMSE value**
1		0.33	9.05	8083.34	89.91
2		0.31	7.95	10429.291	102.12
3		0.272	7.13	11805.98	108.65

4		0.19	7.84	10605.46	102.98
5		0.19	6.95	13115.77	114.52
6		0.18	6.21	15547.45	124.69
7		0.17	6.43	14788.25	121.61
8		0.17	6.71	9869.69	99.35
9		0.17	7.14	12261.05	110.73
10		0.11	7.10	9515.11	97.55

Splitting: After augmenting the dataset, it was split into three subsets for training, testing, and validation purposes. The dataset was divided such that 80% of the data was allocated for training the model, 10% for testing its performance, and the remaining 10% for validation to tune hyperparameters and prevent overfitting. This approach ensures that the model is trained on a diverse set of data, evaluated on unseen samples to assess its generalization ability, and fine-tuned for optimal performance without compromising its ability to generalize to new data.

Model Description:

MobileNetV2: MobileNetV2 is a pre-trained convolutional neural network (CNN) made for fast image classification, to achieve this, the base model is usually stripped off the classification top (layer) while the learned features from the ImageNet dataset are retained. This is followed by a GlobalAveragePooling2D layer which pools the spatial features produced by MobileNetV2 and thus, enables feature summarization and dimensionality reduction at the same time. These compact blocks are the classifier and they segregate the high-level features from the pooled representations that are linked to the output classes. In the last layer, a fully connected layer with softmax activation occurs, allowing the model to recognize the multiclass problem by predicting a probability distribution over the classes. Overall, this architecture uses the characteristics of MobileNetV2 for feature extraction and further extends it by using custom dense layers for effective image classification [31]**.**

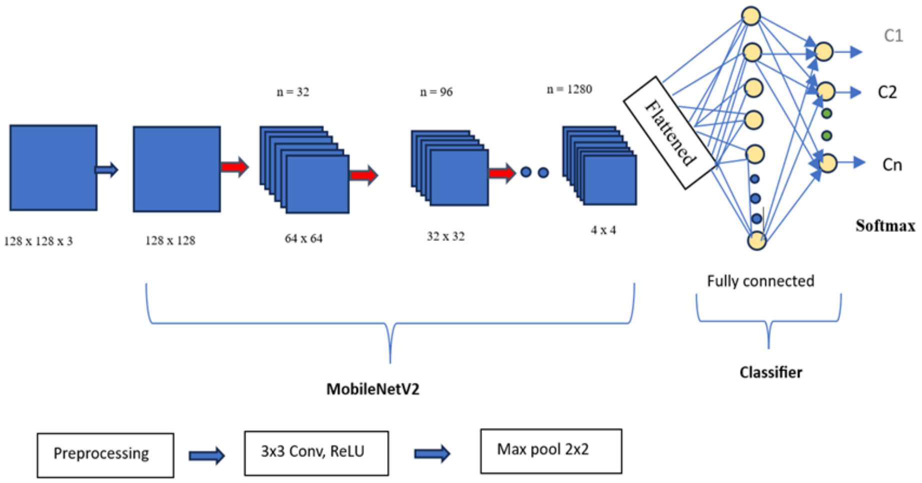


Figure 4.4: MobileNetV2 Model Architecture.

DenseNet201: The provided model is designed for image classification tasks using transfer learning with the DenseNet201 architecture as a base. It utilizes the pre-trained weights of DenseNet201 trained on the ImageNet dataset. The model is trained to classify images into multiple classes based on the dataset provided. The base model, pre-trained with ImageNet weights, utilizes convolutional layers for feature extraction. The Global Average Pooling 2D layer reduces spatial dimensions, generating a fixed-length vector. The layer architecture visualizes the flow from the input layer (224x224) through feature extraction to classification, producing predictions for multi-class image classification [32].

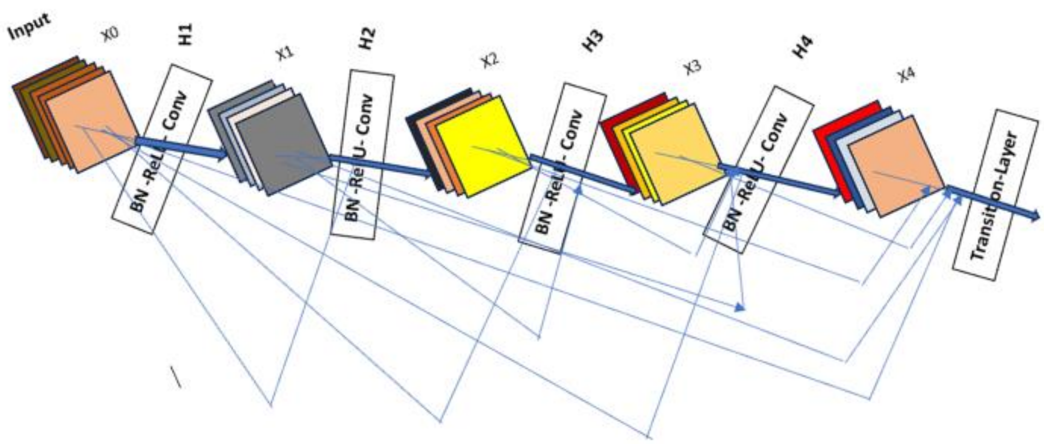


Figure 4.5: DenseNet201 Model Architecture.

VGG19: The VGG19-based model is designed for image classification tasks. It utilizes the VGG19 architecture as a base model, which is pre-trained on the ImageNet dataset. The model is then customized with additional layers for classification purposes. The VGG19-based model, tailored for image classification, utilizes the pre-trained VGG19 architecture from ImageNet for feature extraction. It incorporates additional layers, including Global Average Pooling 2D and two Dense layers (1024 neurons with ReLU, 512 neurons with ReLU), culminating in a final Dense layer with softmax activation for multi-class classification. This architecture, starting with 224x224-pixel, 3-channel input images, demonstrates a seamless flow from feature extraction to pattern learning and prediction [33].

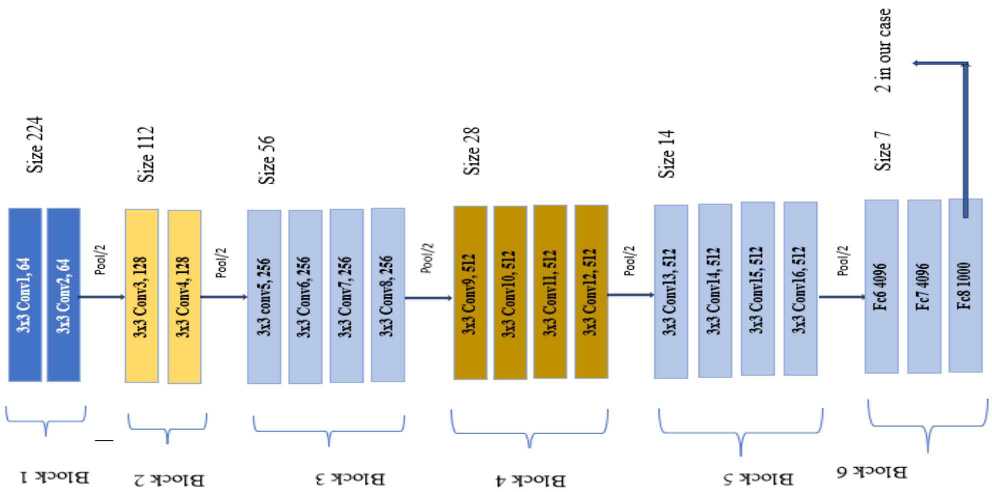


Figure 4.6: VGG19 Model Architecture.

Xception: Xception, a convolutional neural network architecture introduced by François Chollet in 2017, has gained recognition for its outstanding performance in image classification tasks. At its core lies the concept of depth wise separable convolutions. The model begins with an input layer, designed to accept images of dimensions 299x299 pixels with three color channels (RGB). Subsequently, it progresses through an Entry Flow, comprising a sequence of convolutional and depthwise separable convolutional layers. These layers play a crucial role in feature extraction from the input image while concurrently reducing its spatial dimensions. Following this, the Middle Flow comes into play, consisting of multiple repeat modules, each housing convolutional and depth wise separable convolutional layers. This segment aids in capturing increasingly abstract features from the input image. As the network progresses, it enters the Exit Flow, akin to the Entry Flow but augmented with additional convolutional layers featuring larger kernel sizes [34].

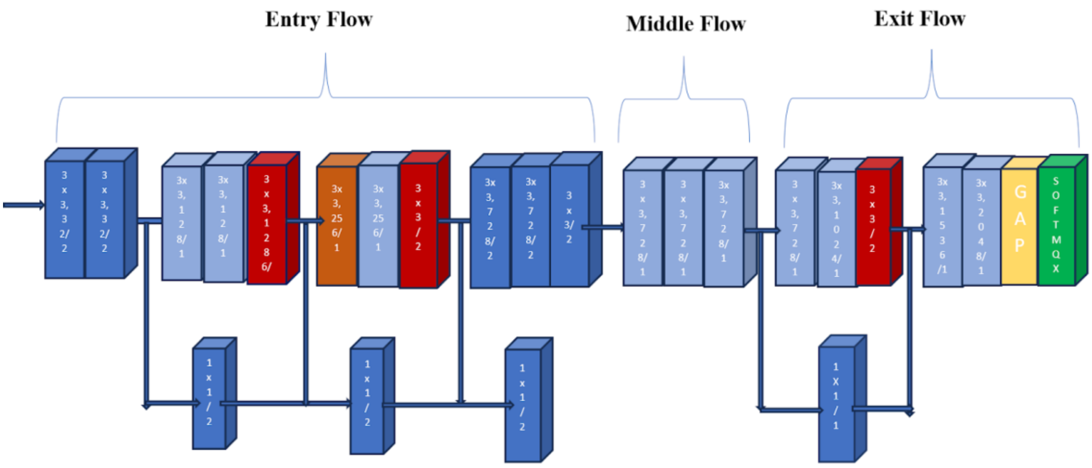


Figure 4.7: Xception Model Architecture.

Hybrid Model (MobileNetV2+DenseNet201): A hybrid model in machine learning amalgamates the features and capabilities of multiple distinct architectures or methodologies, aiming to enhance overall performance beyond what individual models can achieve. In the provided code, this concept is realized by combining the architectures of two pre-trained convolutional neural networks (CNNs), MobileNetV2 and DenseNet201. Global average pooling is applied to extract essential features from the outputs of both base models, followed by concatenation and batch normalization to create a comprehensive feature representation. Additional dense layers are added for classification, incorporating dropout for regularization and a softmax layer for multi-class classification. By combining the strengths of MobileNetV2 and DenseNet201, this hybrid approach endeavors to deliver superior accuracy and robustness in image classification tasks.

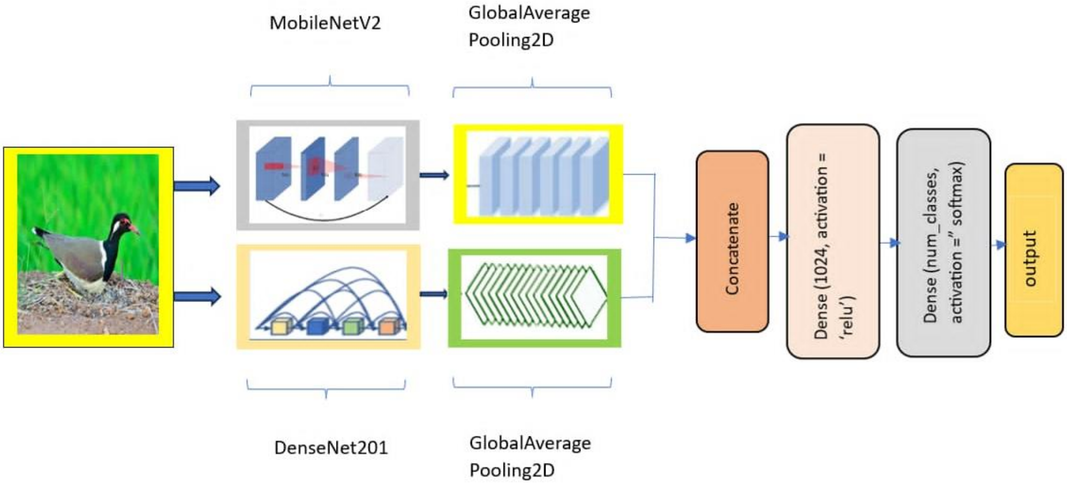


Figure 4.8: Hybrid (MobileNetV2 and DenseNet201) Architecture

Hybrid Model (Xception+DenseNet201): A hybrid model is crafted to merge the strengths of two distinct convolutional neural networks (CNNs), Xception and DenseNet201, in order to surpass the performance achieved by individual models. Global average pooling is applied to extract essential features from the output of each base model, followed by concatenation and batch normalization to create a comprehensive feature representation. Additional dense layers are integrated for classification, incorporating dropout for regularization and a softmax layer for multi-class classification. Through the fusion of Xception and DenseNet201 architectures, this hybrid approach aims to deliver heightened accuracy and robustness in image classification tasks.

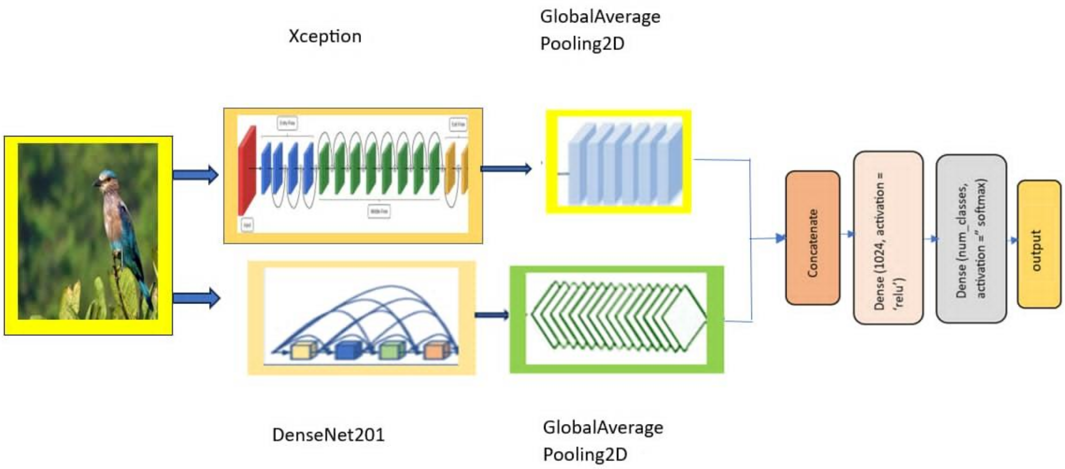


Figure 4.9: Hybrid (Xception and Densenet201) Model Architecture.

4.3 Model Evaluation

Testing Methodology: The model was evaluated using a separate test dataset, with metrics including accuracy, precision, recall, and F1-score. Various performance evaluation metrics were computed to discern the optimal classifier for predicting the given scenario based on specific characteristics. Utilizing the provided equations and the associated confusion matrix, several performance metrics in percentage (%) were derived to gauge the effectiveness of the classifier in question. The outcomes reflect the classifier's efficacy in the given task.

Precision: Precision measures the accuracy of positive predictions, revealing the proportion of correctly identified positive instances among all instances predicted as positive. High precision is desirable when the cost of false positives is significant.

Precision = True Positives / (True Positives + False Positive) ---------------- *(1)*

Recall: Recall gauges the ability of a model to capture all actual positive instances, indicating the proportion of correctly identified positives among all actual positives. It is crucial in scenarios where missing positive instances comes with a high cost.

Recall = True Positives / (True Positives + False Negatives) ----------------- *(2)*

F1-Score: The F1-score is the harmonic mean of precision and recall, providing a single metric that balances both precision and recall.

*F1-Score = 2 * (Precision * Recall) / (Precision + Recall)* ----------------- *(3)*

Specificity: Specificity focuses on the accurate identification of negative instances, highlighting the proportion of correctly identified negatives among all actual negatives. This metric is relevant when the emphasis is on avoiding false positives.

Specificity = True Negatives / (True Negatives + False Positives) ------------------- *(4)*

Accuracy: Accuracy represents the overall correctness of predictions by considering both true positives and true negatives. However, accuracy may be misleading in imbalanced datasets where one class significantly outweighs the other.

Accuracy = (True Positives + True Negatives) / Total Predictions) --------------------*(5)*

Precision, Recall, f1 and Specificity result of six model:

Table 4.4: Precision, Recall, f1-score and Specificity Result of Six Model

MobileNetV2					
Class	**Precision**	**Recall**	**F1 Score**	**Specificity**	**Accuracy**
Asian-Koel	0.977	0.87	0.92	0.99	**97.15**
Black Drongo	0.901	0.92	0.910	0.99411	
Black-Winged Kite	0.980	0.99	0.985	0.99882	
Common-Myna	0.970	0.97	0.970	0.99823	
Common-Tailorbird	0.989	0.95	0.969	0.99941	
Coppersmith-Barbet	0.980	0.98	0.980	0.99882	
Heron	0.970	0.99	0.980	0.99823	
House-Crow	1.00	0.96	0.979	1.00	
Indian-Roller	0.94	1.00	0.970	0.99	
Kingfisher	0.990	0.99	0.990	0.999	
Little-Cormorant	0.95	0.98	0.965	0.99	
Magpie-Robin	1.00	0.99	0.994	1.00	
Owl_(Pecha)	0.96	1.00	0.980	0.997	
Perrot_(Tiya)	0.990	1.00	0.995	0.99	
Red-Vented-Bulbul	0.97	0.96	0.969	0.998	
Red-Wattled-Lapwing	0.980	0.98	0.980	0.99	
Breasted-Waterhen	0.950	0.96	0.955	0.997	
Rumped-Shama	0.980	1.00	0.990	0.99	
DenseNet201					
Asian-Koel	0.988	0.84	0.908	0.999	
Black Drongo	0.879	0.95	0.913	0.99	
Black-Winged Kite	0.980	1.00	0.990	0.998	
Common-Myna	1.00	0.99	0.994	1.00	
Common-Tailorbird	1.00	0.99	0.994	1.00	
Coppersmith-Barbet	0.990	1.00	0.995	0.99	

Heron	1.00	1.00	1.00	1.00	**98.27**
House-Crow	0.989	0.95	0.969	0.999	
Indian-Roller	0.970	0.98	0.975	0.998	
Kingfisher	1.00	0.99	0.994	1.00	
Little-Cormorant	1.00	1.00	1.00	1.00	
Magpie-Robin	0.934	1.00	0.966	0.995	
Owl_(Pecha)	1.00	1.00	1.00	1.00	
Perrot_(Tiya)	1.00	1.00	1.00	1.00	
Red-Vented-Bulbul	0.970	1.00	0.985	0.998	
Red-Wattled-Lapwing	1.00	1.00	1.00	1.00	
Breasted-Waterhen	1.00	1.00	1.00	1.00	
Rumped-Shama	1.00	1.00	1.00	1.00	
VGG19					
Asian-Koel	0.685	0.85	0.758	0.977	**87.22**
Black Drongo	0.879	0.73	0.797	0.994	
Black-Winged Kite	0.919	0.91	0.914	0.995	
Common-Myna	0.636	0.91	0.748	0.969	
Common-Tailorbird	0.883	0.68	0.768	0.994	
Coppersmith-Barbet	0.798	0.99	0.883	0.985	
Heron	0.923	0.96	0.941	0.995	
House-Crow	0.923	0.85	0.885	0.995	
Indian-Roller	0.978	0.92	0.948	0.998	
Kingfisher	0.924	0.98	0.951	0.995	
Little-Cormorant	0.945	0.87	0.906	0.997	
Magpie-Robin	0.89	0.85	0.871	0.994	
Owl_(Pecha)	0.960	0.96	0.960	0.997	
Perrot_(Tiya)	1.00	0.97	0.984	1.00	
Red-Vented-Bulbul	0.908	0.79	0.844	0.995	
Red-Wattled-Lapwing	0.776	0.97	0.862	0.98	
Breasted-Waterhen	0.97	0.77	0.860	0.99	

Rumped-Shama	0.93	0.74	0.826	0.99705	
Xception					
Asian-Koel	0.910	0.91	0.910	0.994	
Black Drongo	0.911	0.93	0.920	0.994	
Black-Winged Kite	1.00	0.98	0.989	1.00	
Common-Myna	1.00	0.97	0.984	1.00	
Common-Tailorbird	0.990	1.00	0.995	0.999	
Coppersmith-Barbet	0.989	0.97	0.979	0.999	
Heron	1.00	1.00	1.00	1.00	
House-Crow	1.00	0.95	0.974	1.00	
Indian-Roller	0.970	1.00	0.985	0.998	
Kingfisher	1.00	1.00	1.00	1.00	**98.32**
Little-Cormorant	0.990	0.99	0.990	0.999	
Magpie-Robin	0.980	1.00	0.990	0.998	
Owl_(Pecha)	0.980	1.00	0.990	0.998	
Perrot_(Tiya)	1.00	1.00	1.00	1.00	
Red-Vented-Bulbul	0.990	1.00	0.995	0.999	
Red-Wattled-Lapwing	1.00	1.00	1.00	1.00	
Breasted-Waterhen	1.00	1.00	1.00	1.00	
Rumped-Shama	0.990	1.00	0.995	0.999	
Hybrid Xception and DenseNet201					
Asian-Koel	0.930	0.94	0.935	0.995	
Black Drongo	0.939	0.93	0.934	0.996	
Black-Winged Kite	1.00	1.00	1.00	1.00	
Common-Myna	1.00	1.00	1.00	1.00	
Common-Tailorbird	1.00	1.00	1.00	1.00	
Coppersmith-Barbet	1.00	1.00	1.00	1.00	
Heron	1.00	1.00	1.00	1.00	
House-Crow	1.00	1.00	1.00	1.00	
Indian-Roller	1.00	1.00	1.00	1.00	

Kingfisher	1.00	1.00	1.00	1.00	
Little-Cormorant	1.00	1.00	1.00	1.00	
Magpie-Robin	1.00	1.00	1.00	1.00	
Owl_(Pecha)	1.00	0.99	0.994	1.00	**99.22**
Perrot_(Tiya)	1.00	1.00	1.00	1.00	
Red-Vented-Bulbul	0.99	1.00	0.995	0.999	
Red-Wattled-Lapwing	1.00	1.00	1.00	1.00	
Breasted-Waterhen	1.00	1.00	1.00	1.00	
Rumped-Shama	1.00	1.00	1.00	1.00	
Hybrid Mobilenetv2 and DenseNet201					
Asian-Koel	0.969	0.94	0.954	0.998	
Black Drongo	0.941	0.97	0.955	0.996	
Black-Winged Kite	1.00	1.00	1.00	1.00	
Common-Myna	1.00	1.00	1.00	1.00	
Common-Tailorbird	1.00	1.00	1.00	1.00	
Coppersmith-Barbet	1.00	1.00	1.00	1.00	
Heron	1.00	1.00	1.00	1.00	
House-Crow	1.00	1.00	1.00	1.00	
Indian-Roller	1.00	1.00	1.00	1.00	
Kingfisher	1.00	1.00	1.00	1.00	
Little-Cormorant	1.00	1.00	1.00	1.00	
Magpie-Robin	1.00	1.00	1.00	1.00	
Owl_(Pecha)	1.00	1.00	1.00	1.00	**99.50**
Perrot_(Tiya)	1.00	1.00	1.00	1.00	
Red-Vented-Bulbul	1.00	1.00	1.00	1.00	
Red-Wattled-Lapwing	1.00	1.00	1.00	1.00	
Breasted-Waterhen	1.00	1.00	1.00	1.00	
Rumped-Shama	1.00	1.00	1.00	1.00	

4.4 Summary

Therefore, the study has achieved its goals and build and assessed several deep learning models for the classification of native bird species in Bangladesh. Contrast enhancement, gamma correction and data augmentation procedures made a very large change to the general quality and increased the variability of the collected data. However, from all the considered models, DenseNet201 as well as the proposed hybrid models achieved higher accuracy, precision, recall, and F1-score. The outcomes of the study proved the efficiency of employing the deep learning approach and combining different models for the classification of bird species from images to contribute to monitoring and protecting the species.

CHAPTER 5

RESULT AND ANALYSIS

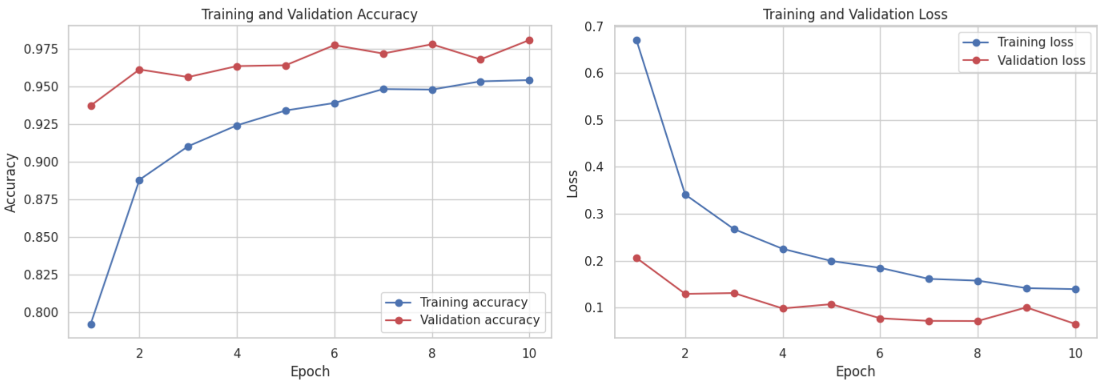
5.1 Overview

Design of the prototype of visual identification of Bangladeshi bird species through deep learning approach is done in such a way that it covers unique all aspects of doing thorough research. The equipment system includes a high-performance CPU and a gaming-grade GPU to provide the calculation foundation, such that the training process runs smoothly. From the software components we can mention deep learning frameworks like TensorFlow or PyTorch, which are integrated within the Python programming language, as well as all those libraries that are necessary for data preprocessing, model development, and evaluation. The dataset consists of labeled stock images of Bangladeshi bird species culled from credible platforms such as Kaggle and underwent complex manual processing including resizing, normalization and some augmentation with a view to boosting robustness. The structure of deep learning architecture with convolutional neural networks (CNNs) that suits image processing and classification is gradually tailored for the model. Transferred learning techniques employ pre-trained models such as MobileNetV2, DenseNet201 or VGG19 to reduce the training process and boost performance with the wing's step of the fine-tuning, which is fine-tuned with the Bangladeshi bird dataset. The ethical issues are the focus, putting in place the guidelines to ascertain confidentiality in usage of data, consent, and depiction of animals. A complete documentation includes hardware specifications, software dependencies and data preprocessing stages among others, whereas experimental results such as model performance metrics including training and validation accuracy are thoroughly documented for the sake of transparency and reproducibility of the work. Through the process of sharing code, datasets, and trained models, the scheme implies a network between researchers, which helps in increasing research and knowledge in the domain of bird species classification in Bangladesh.

5.2 Experimental Result

Result of Experiment 1: MobileNetV2 In this experiment, we investigated the performance of the MobileNetV2 architecture for image classification tasks. Utilizing TensorFlow's Keras applications module, we imported MobileNetV2 and fine-tuned it on our custom dataset comprising 18 classes after removing the top layers and adding custom classification layers. Training utilized the Adam optimizer with a learning rate of 0.001 and categorical cross-entropy loss function. To prevent overfitting, we applied various data augmentation techniques to the training dataset, alongside implementing a checkpoint callback to save the model with the highest validation accuracy during training. With a training dataset of 14400 images, validation dataset of 1800 images, and test dataset of 1800 images, all resized to 224 x 224 pixels and trained with a batch size of 32, the model achieved a training accuracy of approximately 95.44%, a validation accuracy of about 98.10%, and a test accuracy of roughly 97.15% after 10 epochs. These results highlight the effectiveness of MobileNetV2 for image classification tasks, especially when combined with transfer learning techniques for efficient model training and high generalization performance.

Training and Validation Accuracy and loss of MobileNetV2:



(a) (b)

Figure 5.1: (a) Training and validation Accuracy vs (b) Training and validation Loss Curve

Confusion Matrix of MobileNetV2: The confusion matrix includes 18 bird species, with their respective common names and a Bangla name in parentheses. The model shows high accuracy for most classes, indicated by the high values along the diagonal. Some misclassifications are present, as indicated by non-zero values off the diagonal. The color intensity in the heatmap corresponds to the number of instances, with darker colors indicating higher values. Overall, the model performs well, with most classes having high accuracy. The provided confusion matrix serves as a detailed evaluation tool to understand specific misclassification patterns and model performance across different bird species.

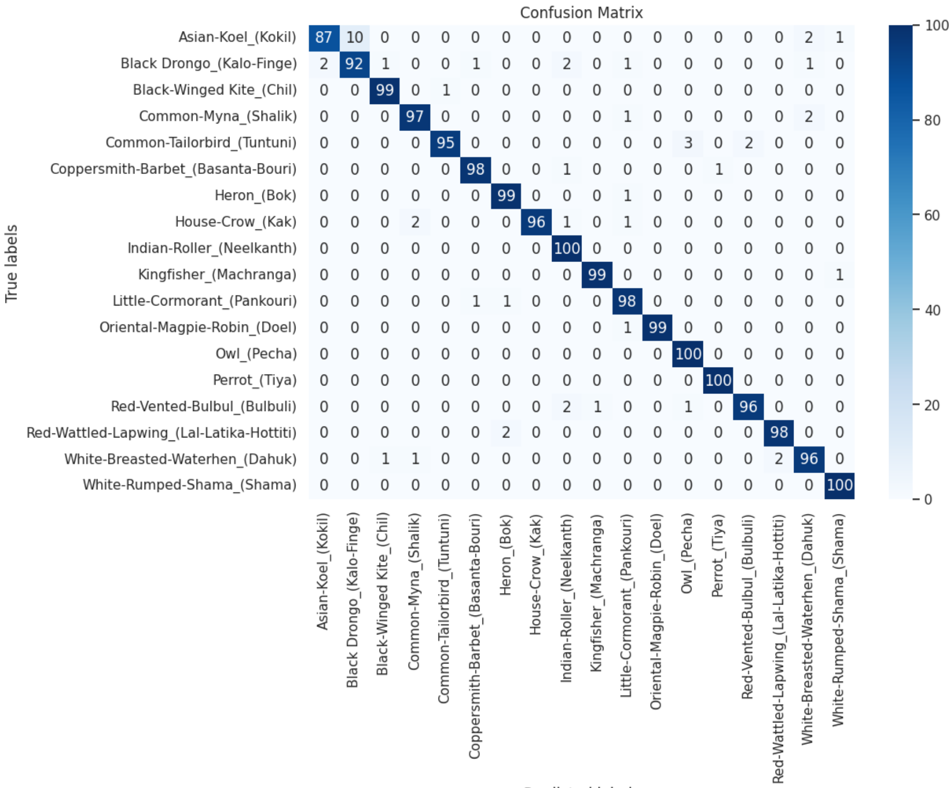


Figure 5.2: Confusion Matrix of MobileNetV2 Model

Receiver Operating Characteristic Curve of MobileNetV2 Model: The ROC curve is a graphical representation used to evaluate a classification model's performance by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR). In the provided ROC curve, each line represents the performance of the classifier for one of the bird species classes, including 18 classes and a micro-average ROC curve. The area under the ROC curve (AUC) for each class is 1.00, indicating perfect classification performance. All ROC curves are close to the top-left corner of the plot, suggesting a high true positive rate and a low false positive rate for all classes. The diagonal dashed line represents a random classifier's performance. The model demonstrates excellent performance, as shown by the perfect AUC scores.

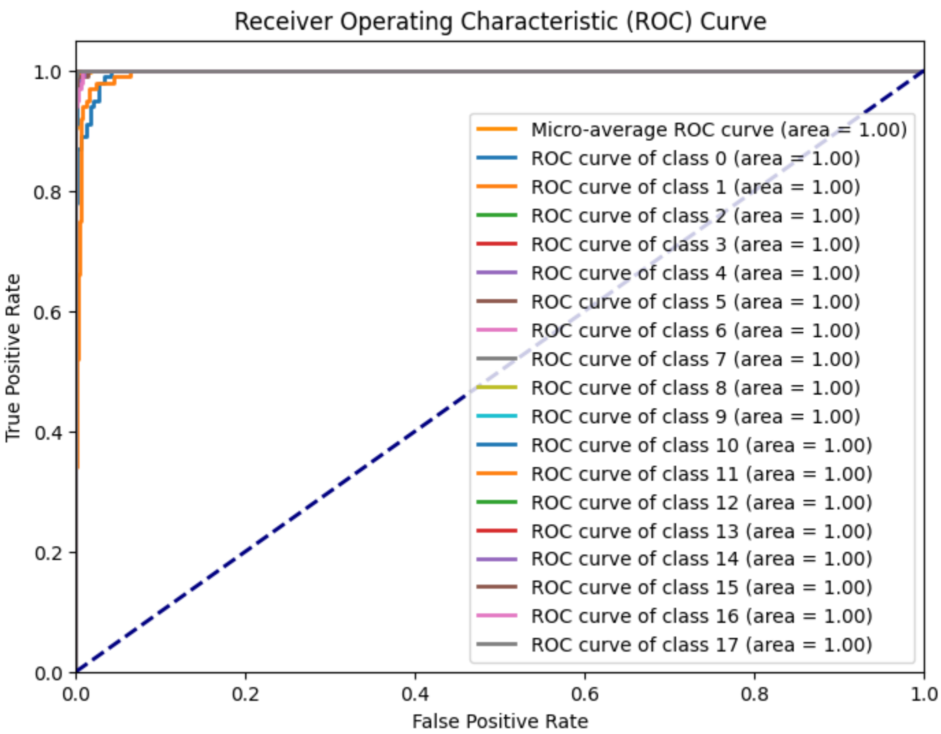


Figure 5.3: Roc Curve of MobileNetv2 Model

Misclassification report of MobileNetV2: The bar chart illustrates the number of misclassifications for each bird species class. This visualization highlights the specific classes where the classification model struggles the most, aiding in the identification of areas for potential improvement.

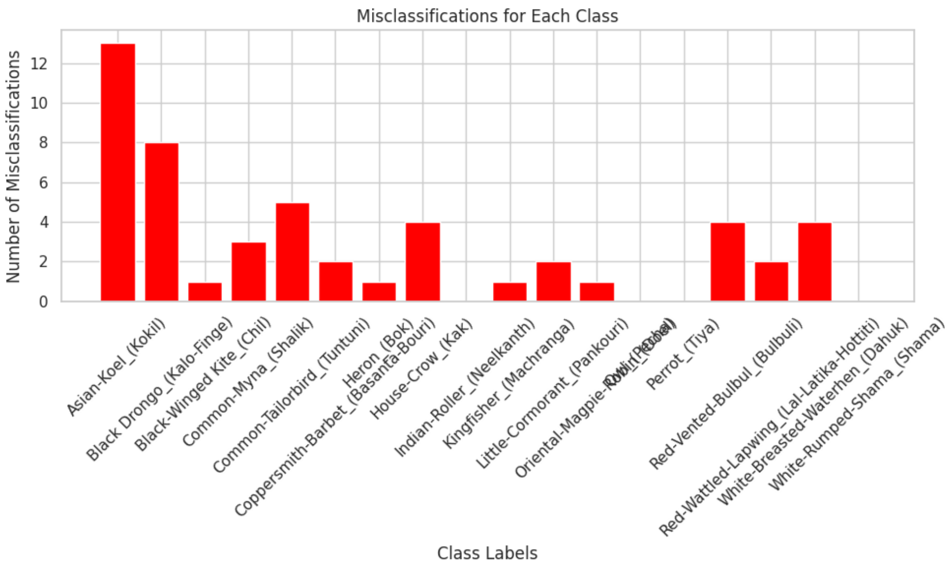
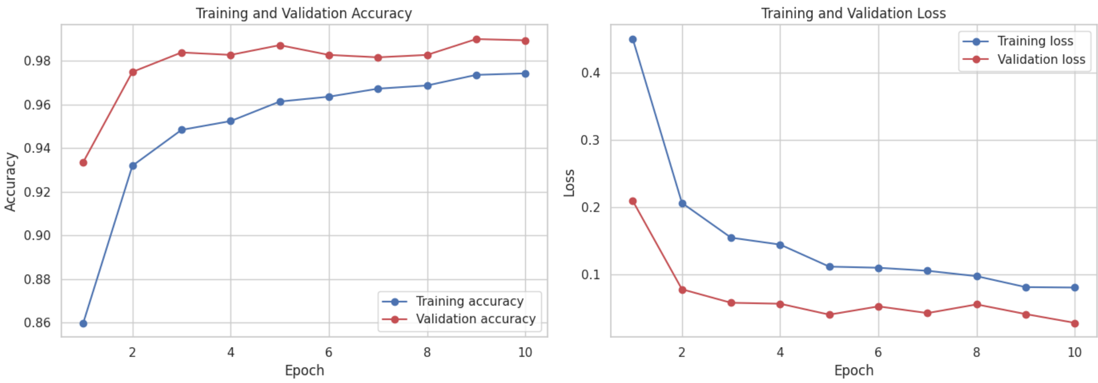


Figure 5.4: Misclassification report of MobileNetv2 Model.

Result of Experiment 2: DenseNet201 In this experiment, we explored the performance of the DenseNet201 architecture for image classification tasks. The model was trained on a dataset consisting of 14400 images for training, 1800 images for validation, and 1800 images for testing, distributed across 18 classes. The DenseNet201 architecture was imported from TensorFlow's Keras applications module and initialized with weights pretrained on the ImageNet dataset. After removing the top layers, custom classification layers were added to adapt the model to our specific task. The model was trained using the Adam optimizer with a learning rate of 0.001 and categorical cross-entropy loss function. Data augmentation techniques were applied to the training dataset, including rotation, width and height shifts, shearing, zooming, and horizontal flipping, to prevent overfitting. Additionally, a checkpoint callback was implemented to save the model with the highest validation accuracy during training. The training process comprised 10 epochs, during which the model exhibited consistent improvement in both training and validation accuracies. After training, the model achieved a test accuracy of approximately 98.27%, indicating its robust performance on unseen data. Overall, the experimental results demonstrate the effectiveness of the DenseNet201 architecture for image classification tasks, particularly when combined with transfer learning techniques and extensive data augmentation.

Training and Validation Accuracy and Loss of DenseNet201:



(a) (b)

Figure 5.5: (a) Training and validation Accuracy vs Training and Validation Loss

Confusion Matrix of DenseNet201: The confusion matrix depicts the performance of a bird species classification model, with true labels on the y-axis and predicted labels on the x-axis. The majority of predictions are correctly classified, as evidenced by the high values along the diagonal, indicating strong model accuracy. Classes like Black-Winged Kite, Common-Myna, and several others achieve perfect accuracy with no misclassifications. Overall, the model demonstrates robust performance, with most species correctly identified, although some classes show room for improvement in reducing misclassification.

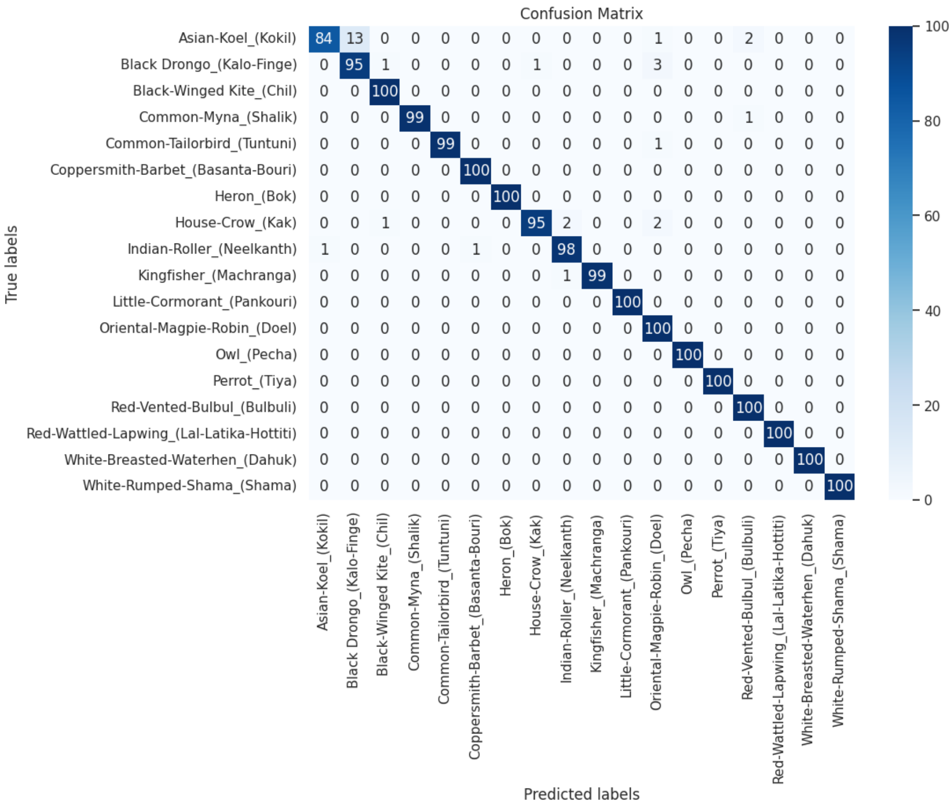


Figure 5.6: Confusion Matrix of DenseNet201 Model.

Receiver Operating Characteristic Curve of DenseNet201 Model: The ROC curve shows excellent classification performance for all 18 classes, with each ROC curve nearly touching the top-left corner and all areas under the curve (AUC) equal to 1.0, indicating perfect discrimination between classes.

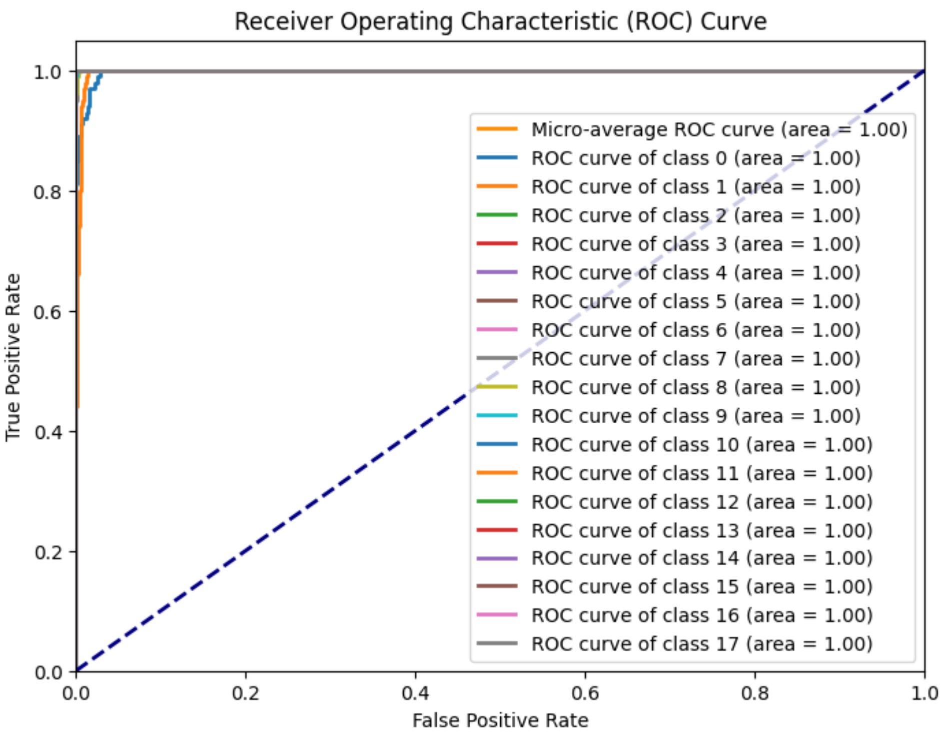


Figure 5.7: Roc Curve of DenseNet201 Model

Misclassification report of DenseNet201: The bar chart illustrates the number of misclassifications for each bird species class. This visualization highlights the specific classes where the classification model struggles the most, aiding in the identification of areas for potential improvement.

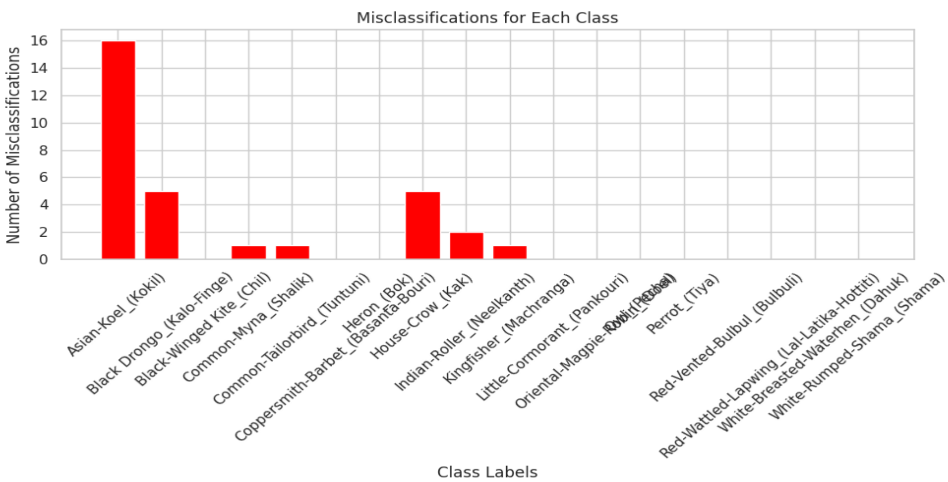
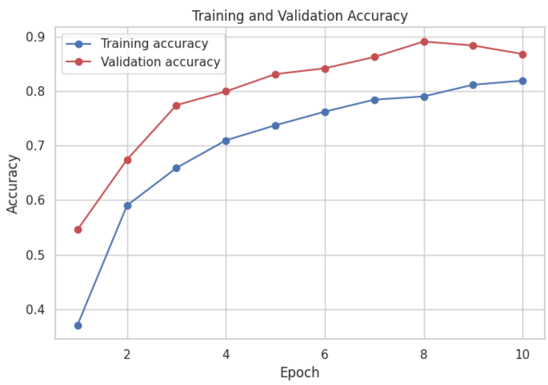


Figure 5.8: Misclassification report of DenseNet201 Model.

Result of Experiment 3: VGG19 In this experiment, we investigated the performance of the VGG19 architecture for image classification tasks. The dataset comprised 14400 images for training, 1800 images for validation, and 1800 images for testing, distributed across 18 classes. The VGG19 architecture was imported from TensorFlow's Keras applications module and initialized with weights pretrained on the ImageNet dataset. After downloading the pretrained weights, the top layers were removed, and custom classification layers were added to adapt the model to our specific task. Training utilized the Adam optimizer with a learning rate of 0.001 and categorical cross-entropy loss function. Data augmentation techniques, including rotation, width and height shifts, shearing, zooming, and horizontal flipping, were applied to the training dataset to prevent overfitting. Additionally, a checkpoint callback was implemented to save the model with the highest validation accuracy during training. The training process spanned 10 epochs, during which the model exhibited consistent improvement in both training and validation accuracies. After training, the model achieved a test accuracy of approximately 87.22%, indicating its effectiveness in classifying unseen data.

Training and Validation Accuracy and loss of VGG19:



(a)

(b)

Figure 5.9: (a) Training and Validation Accuracy vs (b) Training and validation Loss

Confusion Matrix of VGG19: The confusion matrix shows the performance of a bird species classification model, with rows representing actual species and columns for predicted species. High diagonal values indicate correct predictions, showing the model excels with species like Asian-Koel, Black-Winged Kite, Common-Myna, and others. However, there are notable misclassifications between species like Black Drongo and Asian-Koel, and House-Crow and Common-Tailorbird. Darker colors represent higher counts of predictions. Overall, the model performs well but needs improvement in distinguishing certain species.

Figure 5.10: Confusion Matrix of VGG19 Model

Receiver Operating Characteristic Curve of VGG19 Model: This image displays the Receiver Operating Characteristic (ROC) curves for a multi-class classification model. Each curve corresponds to a different class, showing the trade-off between the True Positive Rate (sensitivity) and False Positive Rate. The area under the curve (AUC) values are provided in the legend, with most classes having AUCs of 0.99 or 1.00, indicating excellent model performance. The micro-average ROC curve, which aggregates the performance across all classes, also has an AUC of 1.00, further demonstrating the model's high overall accuracy.

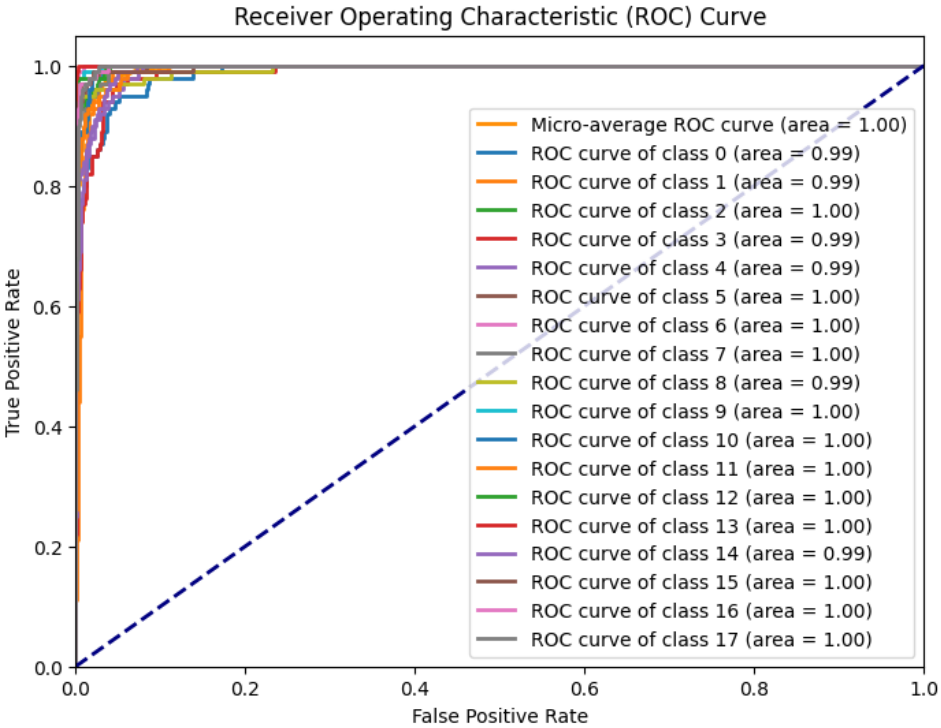


Figure 5.11: Roc Curve of VGG19 Model.

Misclassification report of VGG19: The bar chart illustrates the number of misclassifications for each class in a classification model. The x-axis represents various bird species, while the y-axis shows the number of misclassifications. Notably, the classes "Common-Tailorbird (Tuntuni)", "Dahuk" and " Black Drongo " exhibit the highest number of misclassifications, suggesting these species are particularly challenging for the model to classify accurately. Conversely, the classes "Heron (Bok)," "Little-Cormorant (Pankouri)," and "Oriental-Magpie-Robin (Doel)" have relatively fewer misclassifications. The significant variation in the number of misclassifications across different classes indicates varying levels of difficulty in correctly classifying these species, highlighting areas where the model's performance could be improved.

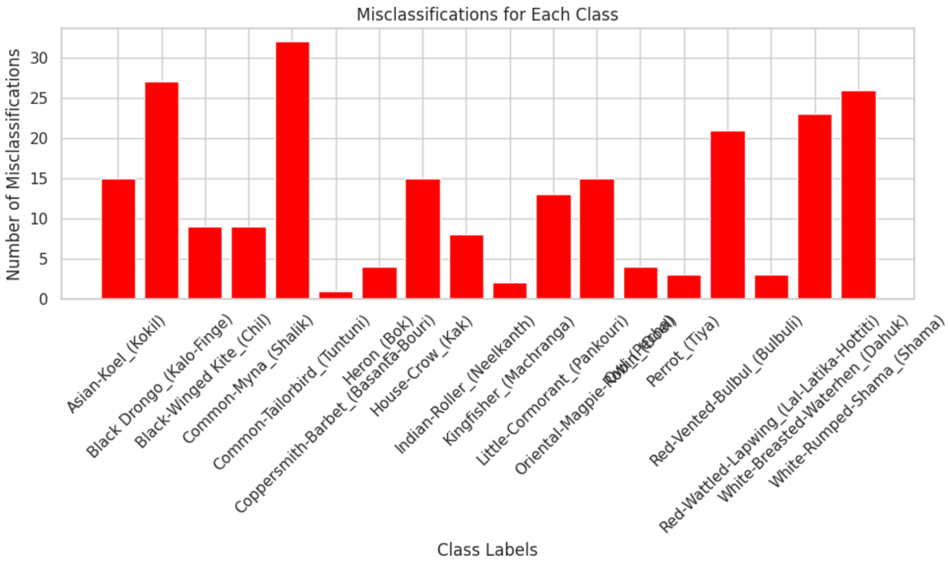
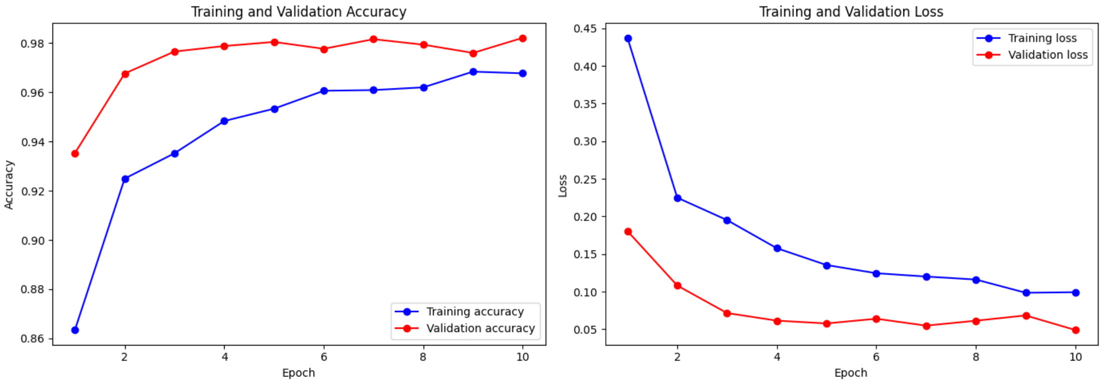


Figure 5.12: Misclassification Report of VGG19 Model

Result of Experiment 4: Xception

In this experiment, we examined the performance of the Xception model for image classification tasks. The dataset consisted of 14400 images for training, 1800 images for validation, and 1800 images for testing, across 18 classes. The Xception architecture was employed, with pre trained weights downloaded from TensorFlow's Keras applications module. After initializing the model, the top layers were removed, and custom classification layers were added to adapt the model to the specific task. During training, the Adam optimizer was used with a learning rate of 0.001 and categorical cross-entropy as the loss function. To prevent overfitting, various data augmentation techniques such as rotation, width and height shifts, shearing, zooming, and horizontal flipping were applied to the training dataset. Additionally, a checkpoint callback was employed to save the model with the highest validation accuracy during training. The training process spanned 10 epochs, during which both training and validation accuracies exhibited consistent improvement. After training, the model achieved a test accuracy of approximately 98.33%, indicating its effectiveness in classifying unseen data. These results highlight the suitability of the Xception architecture for image classification tasks, especially when combined with transfer learning techniques and extensive data augmentation.

Training and Validation Accuracy and loss of Xception:



(a) (b)

Figure 5.13: (a) Training and Validation Accuracy Vs (b) Training and Validation Loss

Confusion Matrix of Xception: The confusion matrix displays the performance of a classification model on 19 bird species. Each row represents the true labels, and each column represents the predicted labels. The diagonal elements show the number of correct predictions for each class. High values along the diagonal indicate good model performance, as seen in most classes.

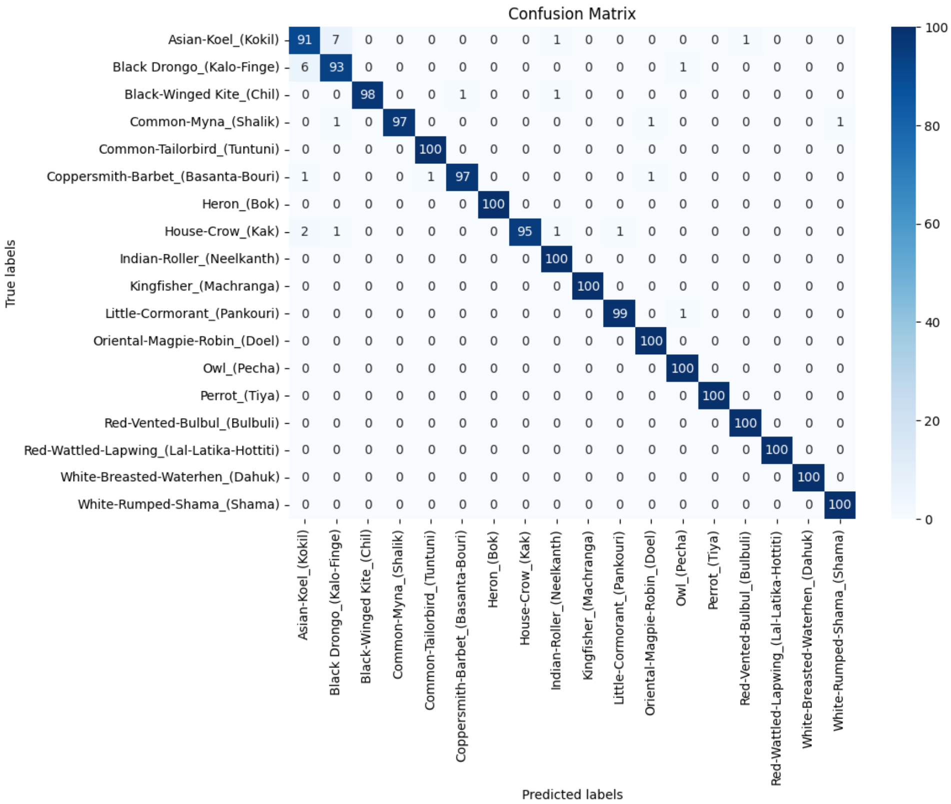


Figure 5.14: Confusion Matrix of Xception Model

Receiver Operating Characteristic Curve of Xception Model: This image displays the Receiver Operating Characteristic (ROC) curves for a multi-class classification model. Each curve corresponds to a different class, showing the trade-off between the True Positive Rate (sensitivity) and False Positive Rate. The area under the curve (AUC) values are provided in the legend, with most classes having AUCs of 0.99 or 1.00, indicating excellent model performance. The micro-average ROC curve, which aggregates the performance across all classes, also has an AUC of 1.00, further demonstrating the model's high overall accuracy.

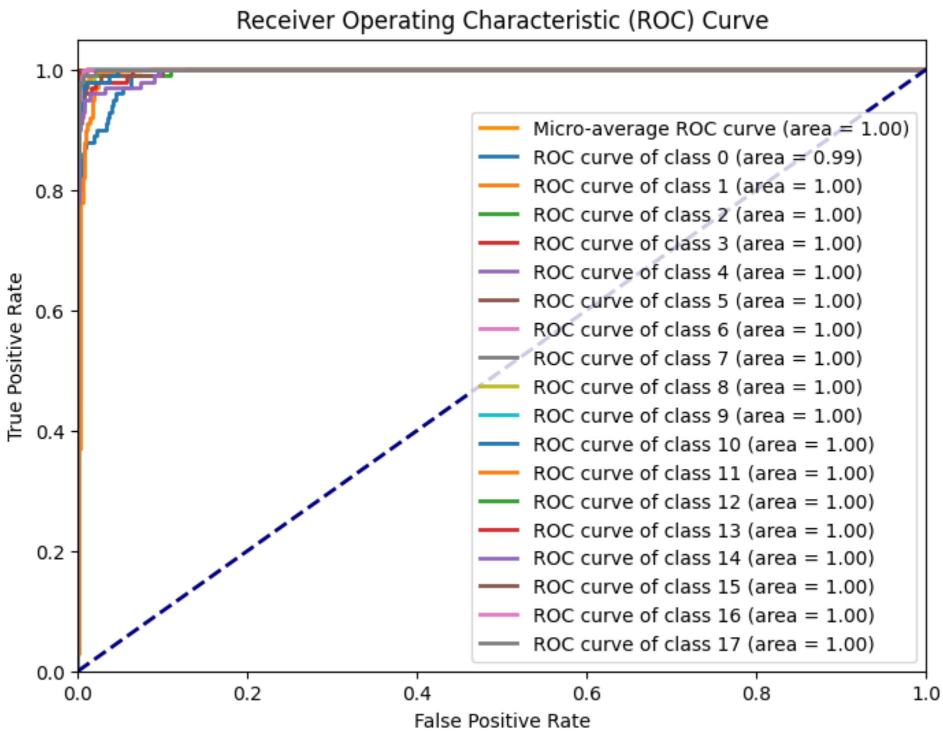


Figure 5.15: Roc Curve of Xception Model

Misclassification report of Xception: This bar chart depicts the number of misclassifications for each bird species class. The x-axis represents the various bird species, while the y-axis indicates the number of misclassifications for each class. The bar chart shows the number of misclassifications for 18 bird species. Among these, 7 classes exhibit misclassifications.

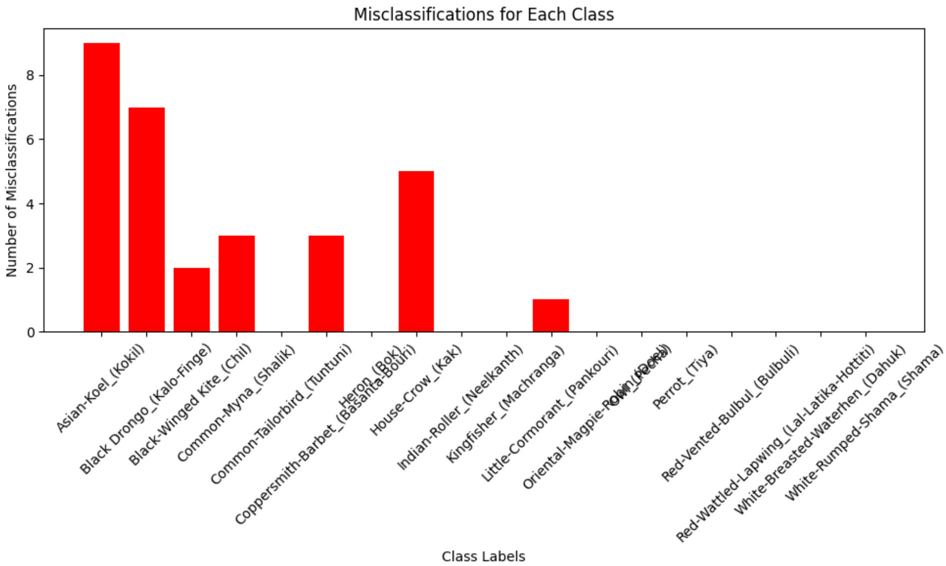
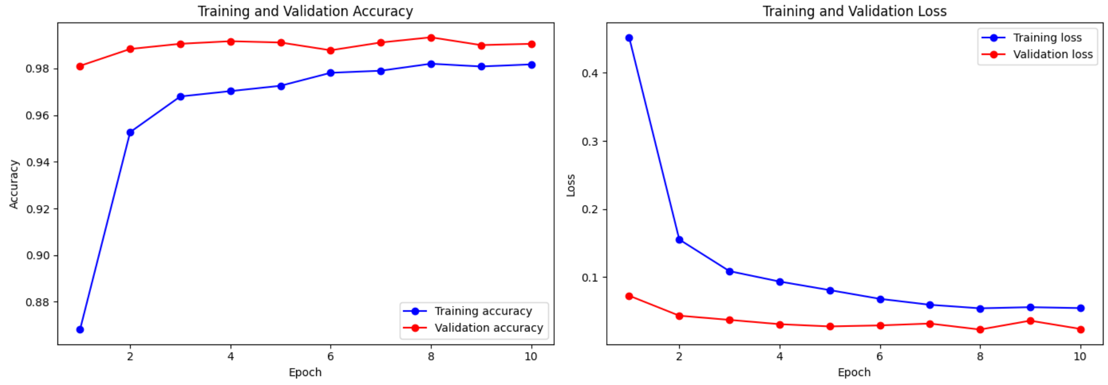


Figure 5.16: Misclassification Report of Xception Model

Result of Experiment 5: Hybrid model Xception and DenseNet201 In this experiment, we explored the performance of a hybrid model combining features from the Xception and DenseNet201 architectures for image classification tasks. The dataset consisted of 14400 images for training, 1800 images for validation, and 1800 images for testing, distributed across 18 classes. The hybrid model was constructed by integrating features from both the Xception and DenseNet201 architectures. Pretrained weights for both models were downloaded from TensorFlow's Keras applications module. The Xception model was initialized with its weights pre trained on ImageNet, and the top layers were removed. Similarly, the DenseNet201 model was initialized with its pretrained weights, and its top layers were discarded. Custom classification layers were then added on top of the concatenated features from both models to adapt the hybrid model to our specific task. During training, the Adam optimizer with a learning rate of 0.001 was employed, along with categorical cross-entropy as the loss function. The training process spanned 10 epochs, during which the hybrid model exhibited consistent improvement in both training and validation accuracies. After training, the hybrid model achieved an impressive test accuracy of approximately 99.22%. These results demonstrate the effectiveness of leveraging features from multiple powerful architectures, such as Xception and DenseNet201, in a hybrid model for image classification tasks. The hybrid approach allows for the combination of complementary features, leading to superior performance compared to individual architectures alone.

Training and Validation Accuracy and loss of Hybrid Model Xception and DenseNet201:



(a) (b)

Figure 5.17: Training and Validation Accuracy Vs (b) Training and Validation Loss

Confusion Matrix of Hybrid Model Xception and DenseNet201: The confusion matrix shows the performance of a classification model across 20 bird species. Most classes have high accuracy with few misclassifications. Notable errors include the "Asian Koel" (Kokil) being misclassified 6 times as "Black Drongo" (Kalo-Finge), the "Black Drongo" (Kalo-Finge) being misclassified 7 times as "Asian Koel" (Kokil), and the "Owl" (Pecha) being misclassified once as BulBuli. Overall, the model demonstrates strong performance with these exceptions.

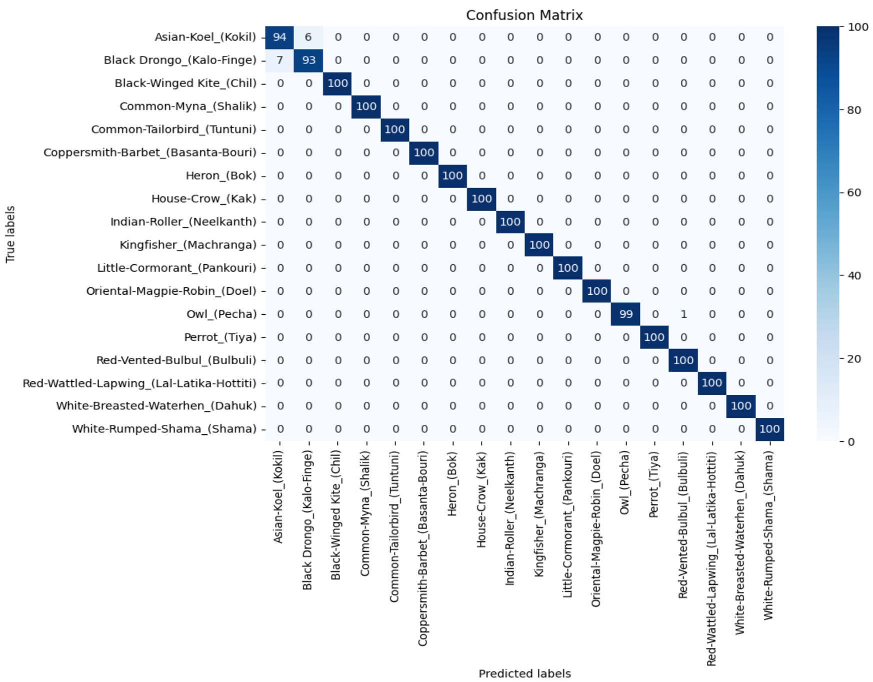


Figure 5.18: Confusion Matrix of Hybrid (Xception and DenseNet201) Model.

Receiver Operating Characteristic Curve of Xception and DenseNet201 Model: The area under the curve (AUC) values are provided in the good, with most classes having AUCs of 1.00, indicating excellent model performance. The micro-average ROC curve, which aggregates the performance across all classes, also has an AUC of 1.00, further demonstrating the model's high overall accuracy.

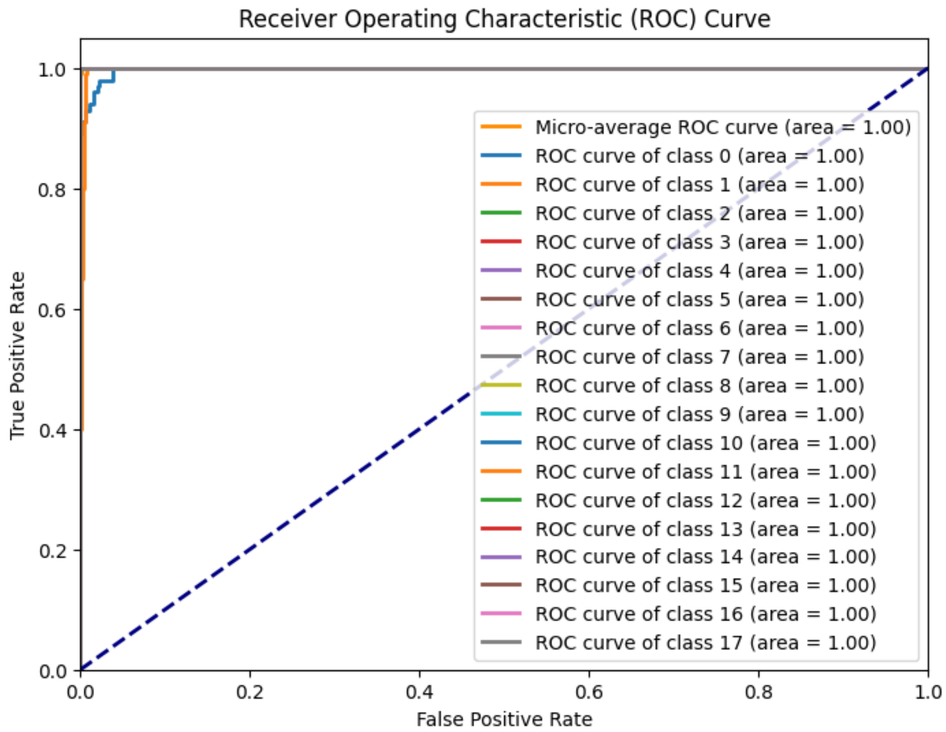


Figure 5.19: Roc Curve of Hybrid (Xception and DenseNet201) Model.

Misclassification report of Hybrid Model (Xception and DenseNet201): This bar chart depicts the number of misclassifications for each bird species class. The x-axis represents the various bird species, while the y-axis indicates the number of misclassifications for each class. The bar chart shows the number of misclassifications for 18 bird species. Among these, only 3 classes exhibit misclassifications.

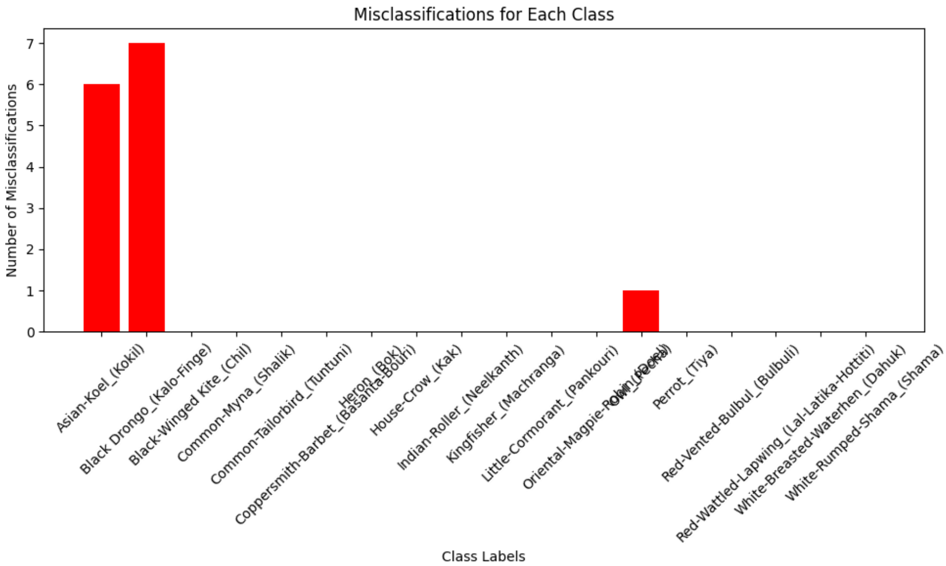
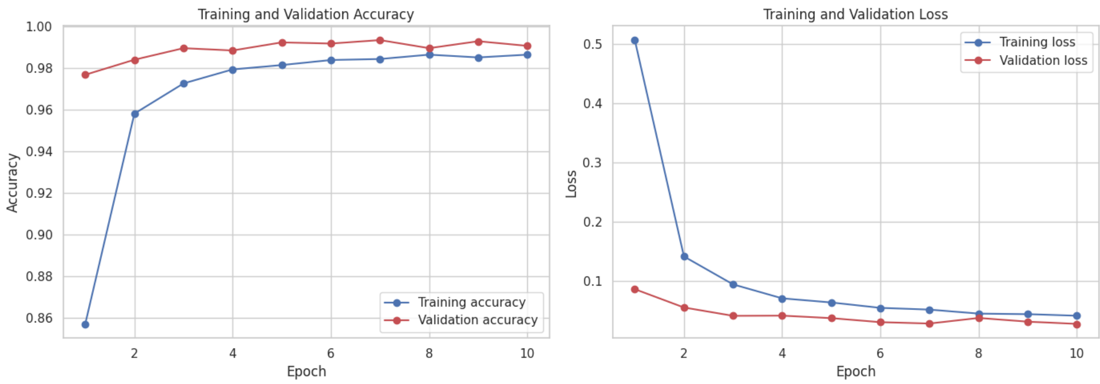


Figure 5.20: Misclassification Report of Hybrid Model (Xception and DenseNet201)

Result of Experiment 6: Hybrid model MobilenetV2 and DenseNet201 In this experiment, we investigated the performance of a hybrid model combining features from the MobileNetV2 and DenseNet201 architectures for image classification tasks. The dataset comprised 14400 images for training, 1800 images for validation, and 1800 images for testing, spread across 18 classes. The hybrid model was constructed by leveraging features from both the MobileNetV2 and DenseNet201 architectures. Pretrained weights for both models were obtained from TensorFlow's Keras applications module. Notably, MobileNetV2 was initialized with weights pretrained on ImageNet, with the input shape set to (224, 224). Similarly, DenseNet201 was initialized with its pretrained weights. To create the hybrid model, features from both models were concatenated, and custom classification layers were added on top to adapt the hybrid model to the specific classification task. During training, the Adam optimizer with a learning rate of 0.001 was utilized, and categorical cross-entropy served as the loss function. The training process spanned 10 epochs, during which the hybrid model exhibited consistent improvement in both training and validation accuracies. After training, the hybrid model achieved an outstanding test accuracy of approximately 99.50%. These results underscore the efficacy of combining features from diverse architectures like MobileNetV2 and DenseNet201 in a hybrid model for image classification tasks. The hybrid approach allows for the fusion of complementary features, leading to superior performance compared to individual architectures alone.

Training and Validation Accuracy and loss of Hybrid Model MobileNetV2 and DenseNet201:



(a) (b)

Figure 5.21: (a) Training and Validation Accuracy Vs (b) Training and Validation Loss

Confusion Matrix of Hybrid Model MobileNetV2and DenseNet201: The confusion matrix shows the performance of a classification model across 20 bird species. Most classes have high accuracy with few misclassifications. Notable errors include the "Asian Koel" (Kokil) being misclassified 6 times as "Black Drongo" (Kalo-Finge), the "Black Drongo" (Kalo-Finge) being misclassified 3 times as "Asian Koel" (Kokil). Overall, the model demonstrates strong performance with these exceptions.

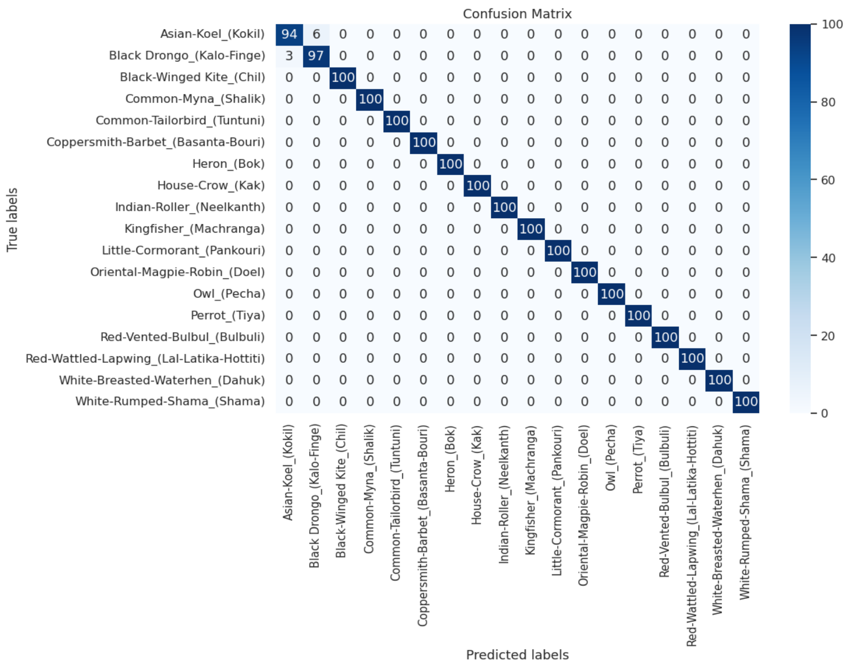


Figure 5.22: Confusion Matrix of Hybrid (MobileNetV2 and DenseNet201) Model.

Receiver Operating Characteristic Curve of MobileNetV2 and DenseNet201 Model: The area under the curve (AUC) values are provided in the good, with most classes having AUCs of 1.00, indicating excellent model performance. The micro-average ROC curve, which aggregates the performance across all classes, also has an AUC of 1.00, further demonstrating the model's high overall accuracy.

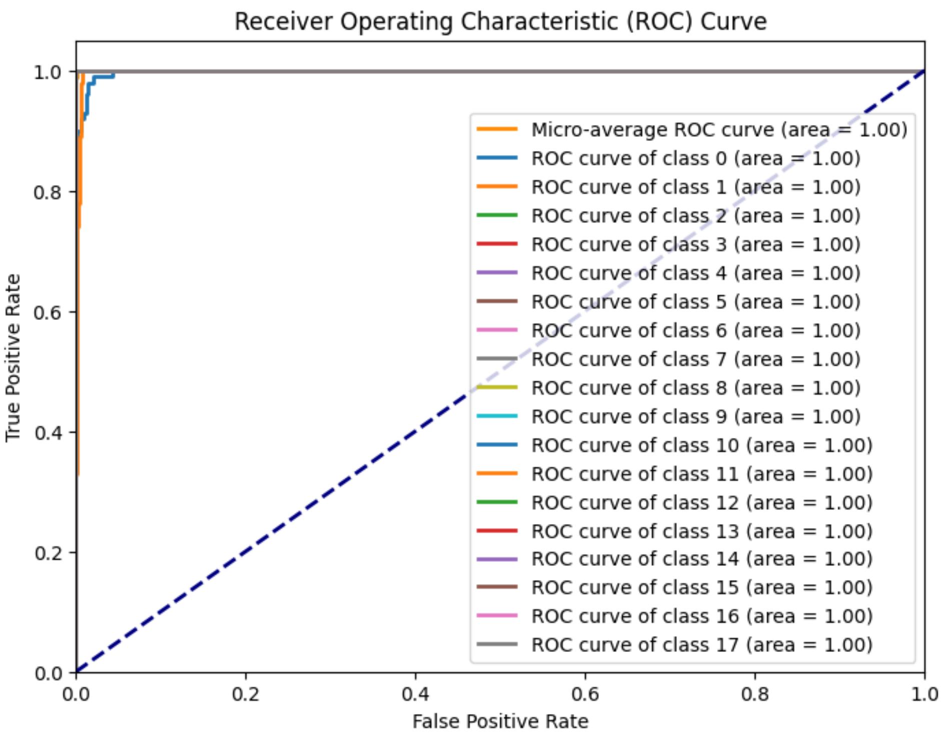


Figure 5.23: Roc Curve of Hybrid (MobileNetV2 and DenseNet201) Model

Misclassification report of Hybrid Model MobileNetV2and DenseNet201: This bar chart depicts the number of misclassifications for each bird species class. The x-axis represents the various bird species, while the y-axis indicates the number of misclassifications for each class. The bar chart shows the number of misclassifications for 18 bird species. Among these, only 2 classes exhibit misclassifications.

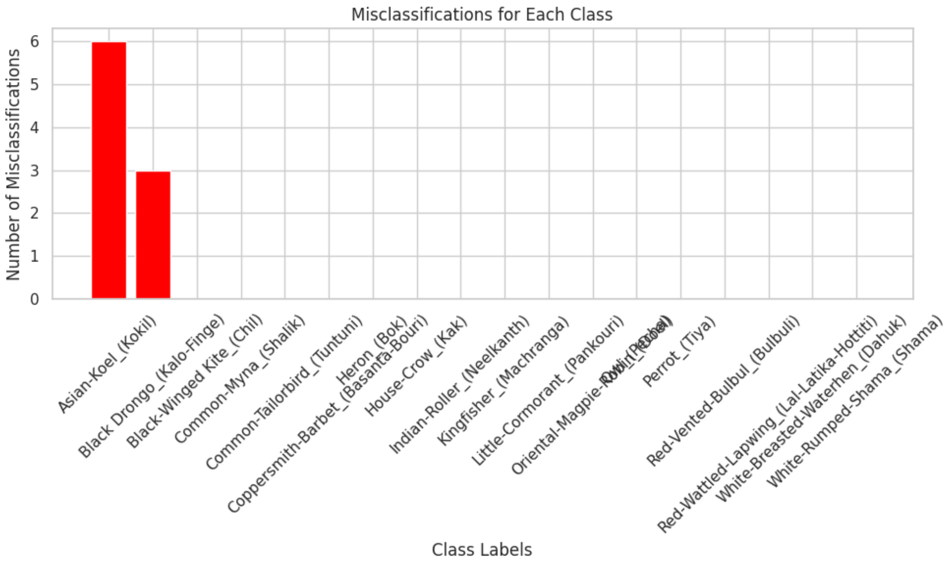


Figure 5.24: Misclassification Report of Hybrid Model (MobileNetV2 and DenseNet201).

5.3 Comparative Analysis

In our analysis of six different deep learning models — MobileNetV2, DenseNet201, VGG19, Xception, Hybrid Xception and DenseNet201, and Hybrid MobileNetV2 and DenseNet201 accuracy serves as the primary metric for comparison. The accuracy metric measures the proportion of correctly classified instances out of the total instances, providing insights into the models' overall performance. MobileNetV2, known for its efficiency and effectiveness in mobile and embedded vision applications, achieves an accuracy of 97.15%. Despite its simplicity and easy-to-understand architecture, VGG19 lags behind the other models with an accuracy of 87.22%. This performance disparity can be attributed to VGG19's deep architecture with a large number of parameters, making it computationally expensive and prone to overfitting, especially on smaller datasets. DenseNet201, with its densely connected layers facilitating feature reuse and promoting feature propagation, performs slightly better than MobileNetV2, boasting an accuracy of 98.27%. Xception, leveraging depthwise separable convolutions to capture spatial and channel-wise dependencies separately, outperforms VGG19 with an accuracy of 98.33%. The hybrid models — Hybrid Xception and DenseNet201, and Hybrid MobileNetV2 and DenseNet201 — combine the strengths of their respective architectures, resulting in superior accuracy. The Hybrid Xception and DenseNet201 model achieve an accuracy of 99.22%, while the Hybrid MobileNetV2 and DenseNet201 model perform the best among all models, boasting an accuracy of 99.50%. Ultimately, the choice of model depends on various factors such as computational resources, dataset size, and task requirements. While simpler models like MobileNetV2 offer efficiency and speed, more complex architectures like DenseNet201 and hybrids provide higher accuracy at the cost of increased computational overhead. Researchers and practitioners should carefully evaluate these trade-offs based on their specific needs and constraints when selecting a model for their application.

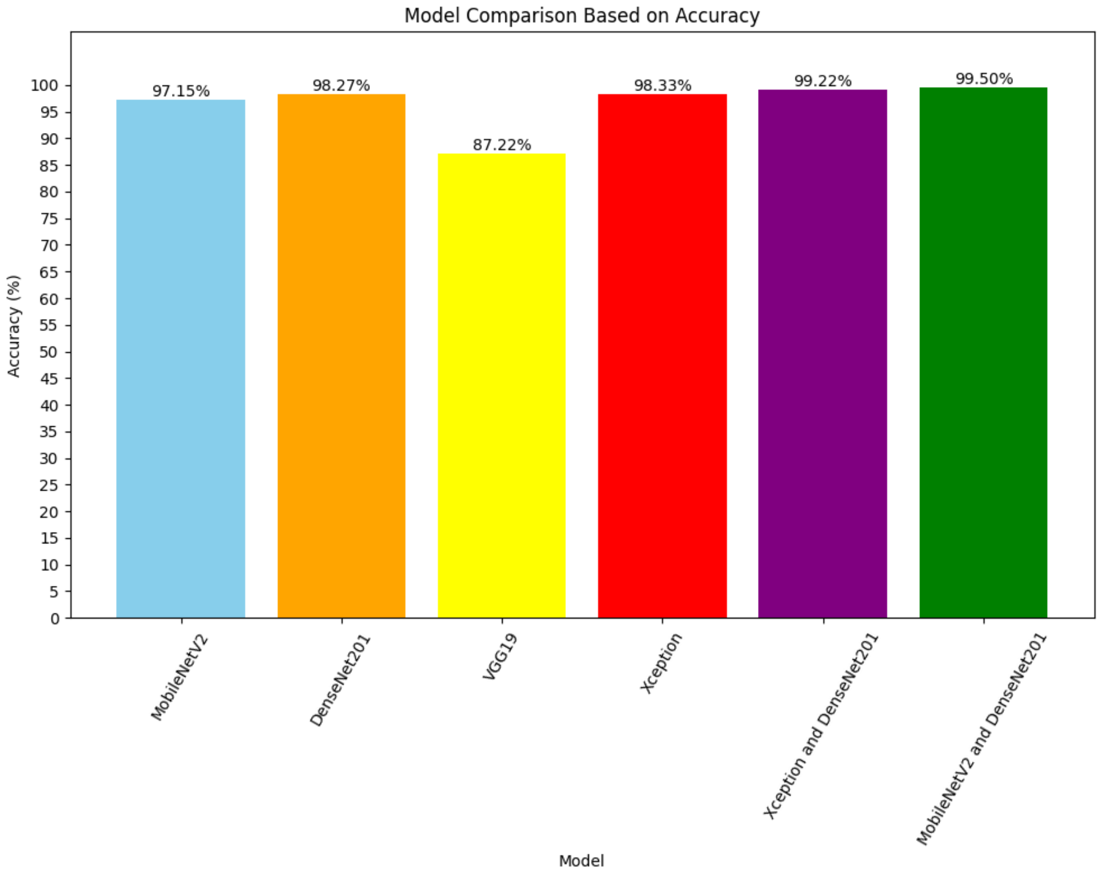


Figure 5.25: Model Comparison Based on Accuracy.

Web Application

The web application developed for Bangladeshi bird classification leverages deep learning techniques within a Flask framework, offering users a straightforward platform to upload and classify bird images. Powered by a combination of pre-trained models like MobileNetV2 for bird detection and a custom-trained model for species classification (`hybridbird99.h5`), the application provides robust functionality. Upon uploading an image, users receive real-time feedback on whether the image contains a bird and, if so, its likely species along with confidence scores. The frontend interface, designed with HTML, Bootstrap for styling, and JavaScript for dynamic content, ensures a seamless user experience by displaying image previews and classification results in an intuitive manner. This application not only aids bird enthusiasts and researchers in identifying Bangladeshi bird species but also supports conservation efforts by enabling quick and accurate species monitoring and documentation.

Web Application Flow Chart Diagram: The process begins when the user uploads an image of a bird. After uploading, the user clicks the submit button, which sends the image to the server for processing. The image is then temporarily saved on the server. At this point, a decision is made to determine if the uploaded image is indeed of a bird. If the image is not a bird, the process ends with a notification indicating that it is not a bird image. However, if the image is identified as a bird, the bird species classification model is run on the image. The classification model assesses the image, and a confidence score is generated. If the confidence score is less than 0.6, the image is moved to a confusion folder for further review. Conversely, if the confidence score is 0.6 or higher, the image is moved to a permanent folder, sorted by class. After this, the classification results are displayed to the user. The image and its classification results are shown to the user, concluding the process.

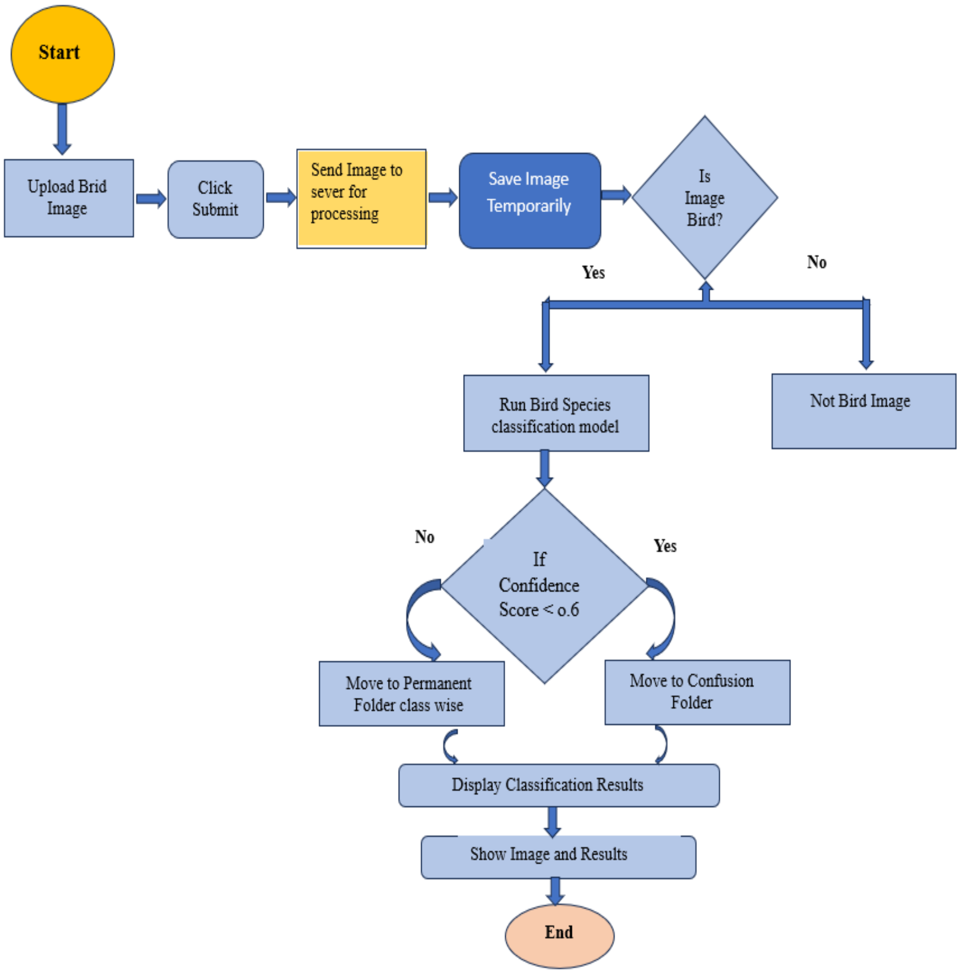


Figure 5.26: Web Application Flow Chart Diagram

Web Application Interface:

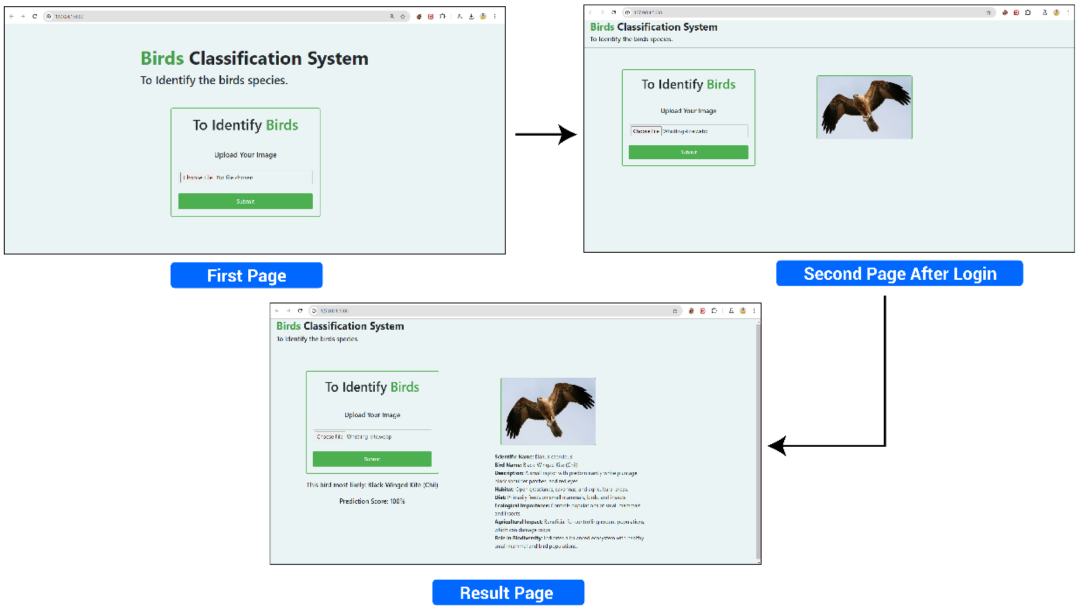


Figure 5.27: Web Application Interface.

5.4 Summary

This chapter describes the design, setting up, and outcome of the experiment for the recognition of Bangladeshi bird species using deep learning. The system combines horse power technical components such as TensorFlow and PyTorch frameworks under the Python environment. The dataset includes categorized images obtained from sources such as Kaggle and has been preprocessed and augmented to increase the model's resilience. Several types of CNNs were incorporated into the model, which incorporated transfer learning with MobileNetV2, DenseNet201, and VGG19. To that end, participants' data anonymity and permission were considered in relation to ethics. Documents on the hardware and software requirements as well as any preprocessing carried out prior to the analysis are comprehensive, thus making the results easily replicable. As it is illustrated in the experimental results, MobileNetV2 get a test accuracy of 97%. 15%, DenseNet201 reached 98. 27%, whereas Xception achieved a 98. 33%. VGG19 lagged with 87. 22%. Lastly, the models that are derived from the combination of Xception and DenseNet201 obtained approximately 99. 22%, The proposed system integrating MobileNetV2 and DenseNet201 yielded the highest accuracy of 99. 50%. The assessment of performance also shows the dependence of the model's complexity on the accuracy of the results and the time cost, which helps to choose a model depending on the requirements for its further use.

CHAPTER 6

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

The influence of computer vision growth on bird recognition in Ornithology and nature research is not only an ornithology and nature research course, but society at large because it shakes profoundly. Through the provision of simplified and acurate resources for the identification of all kinds of birds, this new innovation of technology could become a powerful catalyst in different spheres such as conservation initiatives and citizen level involvement in science endeavors. One major societal effect of the technological advancements in bird identification is that the improved systems can be used to extend biodiversity surveillance and conservation. The same time birds provide invaluable means for environmental data collection and bird species precise is what makes it possible to know population trends, migratory patterns and the environment impacts. By equipping conservationists with effective and accurate identification tools using computer vision technology, selective conservation efforts will be carried out, which facilitates the protection and restoration of important habitats and biodiversity areas. To this end, the exoticization of bird identification via mobile apps and citizen science platforms is another way in which the public is engaging in scientific research and environmental stewardship. Citizens who are eager about birding, enjoy birds or love the nature in general, can participate in bird monitoring activities by reporting their sightings, sharing their observations using the digital platforms or mapping species distribution. Through this involvement, not solely the datasets are highly improved but also the communities that are members of various backgrounds get involved in environmental education and this way they become more appreciative of nature which is a good thing because it mainly contributes to sustainable living practices. Moreover, the application of better bird invention technology to sectors like agriculture, urban planning and public health would help to improve the living standards. The precise delimitation of bird species assists to prevent collisions with humans by determining land-use planning decisions and carrying out aerial strike prevention and reducing bird accidents at airports. Furthermore, living within a rich avian community act as valuable indicators of ecosystem functions such as pest control, pollination, and seed dispersal, thus emphasizing the holistic approach to preserving biodiversity for both agricultural productivity and human welfare. What happens in reality is that the social impact of using bird identification technology spills over all disciplinary boundaries, it is important for environmental conservation and it affects the conduct of scientific research and the way public enjoys nature. This technology will help in fulfillment of the same through application of computer vision, and a citizen science club. It provides avian biodiversity insight and helps in conservation/safeguard of our natural assets, which is the responsibility of one and all.

6.2 Impact on Society & Environment

The role of the evolution of bird identification technology in the conservation of biodiversity and efficient ecosystem management becomes extremely important in this context, therefore the development of these technologies needs to be prioritized for the sake of sustainable development right now and consequently in the future. Such technologies facilitate us to provide the tools that help in fast and accurate categorization of species of birds which help in monitoring and protecting respective avian species and by such way we can safeguard diverse habitats and ecosystems. Improved bird detecting technology is a pivotal factor enhancing bird species conservation that indisputably leads to biodiversity conservation. Birds do not only serve as giants in the ecosystem when they act as pollinators, seed dispersers and ecosystem health indicators. In detail, bird species identification provides scientists, conservation institutions, and managers with enough data for ecological and genetic monitoring so they can plan and implement effective conservation measures. This technique enables the identification of species categorized as threatened or endangered and the design of maintenance and conservation strategies that include rehabilitation of habitats, protected area management, and species recovery programs. Consequently, this paves the way towards the realization of preservation of biodiversity hotspots and conservation of species from extinction. Besides, the bird identification techniques are developed not only for enhanced ecosystem management but also for solving the land use planning practice. Land managers will be able to find bird species by determination and understand their ecological needs using this approach. This will be a great contribution towards habitat conservation, restoration, and natural resource management that is sustainable. This piece of knowledge helps to implement a wide range of conservation measures which, in turn, will support Through all kinds of bird monitoring and bird conservation activities, diverse people groups can contribute to science. Therefore, with concerted efforts such as this, the community will be well-informed and environmentally conscious, and this will consequently become the habit that people live and work side by side with nature hence will causal the culture of environmental responsibility and sustainable living practices. To sum up, progress in bird identification technology possesses a wide range of non-consumptive uses for environmental practices such as conservation of biodiversity, management of ecosystems, and community involvement in environmental stewardship. Such innovation, for instance technology and citizen science, harnessing their power create a synergy to protect avian species and their preferred habitats in the long run which serves to preserve ecological balance and resistance of ecosystems as well.

6.3 Ethical Aspects

The implementation of and upgrade in bird recognition technology also urgently involve a few moral concerns which require the adoption of responsible and fair practices. Such ethics are multi-dimensional which concern all the domains such as data privacy, animal welfare, cultural sensitivity and fair distribution for technology.

Data Privacy: The diversity of bird identification technology is generally achieved by employing the information processed from vast data sets such as pictures and sound. The greatest ethical concern regarding data privacy stems from the need for comprehensive measures that safeguard private information, ask for users' consent, and respect users' possession of their personal information. Shielding privacy is a fundamental condition to prevent possible misuse above and beyond of authorized actions toward their personal data and also to hold up the trust and reliance of individuals by using identification applications or involve themselves in citizen science.

Wildlife Welfare: Technology for bird identification must be implemented conservation concern all while wildlife organisms welfare. Teams comprising of researchers and practitioners must engage in environmental changes emanating from data collection techniques such as camera trapping and sound capture that could spur or threaten the behaviour of the birds, disturb the natural home and affect the success level of nesting. Ethical guidelines should apply in order to avoid the dangers of wildlife disturbance, as well as of course, using the least bio-invasive troubleshooting strategies and in addition making sure that the welfare of the birds and their habitats are the most prioritized factor.

Cultural Sensitivity: The bird identification technology must be designed and set up tactfully respecting traditional worldviews and the Indigenous Value Stems. The Indigenous communities usually have an impressive culture and they also often have strong connection with birds and their habitats, which should always be respected and included into the conservation activities.

The alliance established by some Indigenous peoples with researchers and stakeholders in the researching and decision making matters ensures cultural diversity and builds their mutual respect for each other while conservation outcomes are guaranteed.

Equitable Access: Equalizing the right to advanced bird identification technology is necessary to eradicate digital divide as well as to embrace participatory conservancy that touches on both research and exploration. Although providing effective access remains the key goal, it would be reasonable to get rid of barriers to access including technological infrastructure, little internet connectivity, language diversity, and socioeconomic differences. While training the marginalized communities and providing resources and support to the underrepresented groups to further their wildlife monitoring activities is a powerful tool but this fosters the broad participation of communities in wildlife activities and promotes environmental justice.

Transparency and Accountability: Transparent communication and accountability are the major pillars that stand to retain public trust and sense of security about the avifauna identification technology. Researchers, developers and practitioners must include comprehensive information about objective of these tools, their capacities plus limitations, as well ethics of technologies prior its implementation. Setting the systems for accountability into motion for instance ethical review boards and community oversight committees will to act as the guide to ensure the adherence of ethnical standards and pave the way for the ethical and responsible application of bird identification technology.

6.4 Sustainability Plan

A specific sustainability plan of the modern bird identification technology is an all-encompassing mechanism of protection which enables long-life and the ethical conduct of identification systems and related harsh conservation practices. This measure promotes these dimensions via holistic approach meant to take into consideration the environmental, social and economic aspects also with the aim of promoting the sustainable development and equitable access of technology. Environmental sustainability processes that deal minimizing the environmental footprint of the data collection methods and guaranteeing the habitat conservation, while social sustainability ones, concentrate on community involvement, teaching stuff and ethical guidelines of technology application which are aimed at increasing inclusiveness and responsible usage. Economic sustainability goal to secure the financial viability, capacity building and market by adjustment is the assistance to go on developing and implementing bird identification technology. Continuous monitoring, evaluation, and communication with various stakeholders set a framework that, aimed at environmental stewardship, social responsibility, and economic viability, should be followed in the bird conservation projects and new technology innovations.

6.5 Summary

The chapter discusses the multifaceted impacts and ethical considerations of advancing bird identification technology through computer vision. The technology's societal benefits include enhanced biodiversity monitoring, aiding conservation efforts, and engaging the public in citizen science, thus fostering environmental stewardship. Improved bird identification tools assist in ecosystem management and land-use planning, contributing to sustainable practices in various sectors. Ethical considerations encompass data privacy, wildlife welfare, cultural sensitivity, equitable access, and transparency. A sustainability plan emphasizing environmental, social, and economic aspects ensures the technology's long-term viability and responsible usage. Overall, the integration of advanced bird identification technology promotes ecological conservation, public engagement, and sustainable development.

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 Conclusions

The study results are covered while the effectiveness of deep learning approaches, in particular transfer learning along with lots of data augmentation, which is used to automate bird species classification tasks, are revealed. The research focuses on delicate experimenting and evaluating, with the result that several CNN architectures, including Hybrid Xception and DenseNet201, as well as Hybrid MobileNetV2 and DenseNet201, appear to be the best models for this classification, featuring the highest accuracy 99.50%. Such findings in fact accentuate the deep learning's propensity to radically change bird conservation while collectively emphasizing the necessity of paid attention to dataset, optimization and community engagement in order to significantly impact the field. Secondly, the report assert the importance of nurturing an interdisciplinary collaboration between the researchers and conservationists, as well as the enabling sharing of knowledge among the bird identification systems to be effectively deployed in real world conservation contexts.

7.2 Further Suggested Works

Thus, the present study has provided a good starting point to identify birds using deep learning methodologies, but there are many ways that researchers can expand on these techniques to improve bird identification in the future.

First, the authors could work on increasing the sample of avian species to enhance the study's external validity and reliability, especially for species from geographic areas that are underrepresented in their investigation. Moreover, the use of real-time bird identification in various habitats via smartphone apps might increase the availability of the technology to everyday people and bird enthusiasts.
Second, investigating more sophisticated deep learning structures and techniques in classification ensembling may yield higher classification accuracy. Other methods which should be explored include the attention mechanisms, transformers, and models composed of more than one best-of-breed architecture.
Third, the combination of audio data with the visual inputs could help to enhance the identification of birds as a way of utilizing both the audio and the visual data the robot uses in the identification process to avoid cases where visual data is insufficient in difficult environmental conditions. Applying unsupervised and semi-supervised

learning should also be useful in situations where there is little labeled data available. Last but not the least, the establishment of interpretability and explainability approaches to the deep learning models used in bird identification would also assist in the determination of the decision-making process, hence enhancing users' trust in the models as well as the identification of any form of bias in the models.

7.3 Limitations/ Conflict of Interests

Despite the promising results achieved, the study has several limitations that should be acknowledged. One major limitation is the reliance on a limited dataset of labeled images, which may not encompass the full diversity of bird species and their various poses, lighting conditions, and backgrounds. This limitation could affect the model's performance in real-world applications where such variations are common.

Another limitation is the potential for overfitting due to the relatively small dataset size compared to the number of model parameters, despite using data augmentation and transfer learning techniques. Future studies should aim to validate the model on more extensive and diverse datasets to ensure robustness.

Additionally, the study's dependence on high-performance computing resources may not be feasible for all users, particularly those in resource-limited settings. This limitation underscores the need for developing more computationally efficient models or cloud-based solutions that can democratize access to this technology.

In terms of conflicts of interest, the authors declare no financial or personal relationships that could influence the work reported in this paper. However, it is important to note that the development and deployment of advanced bird identification technologies may raise ethical and privacy concerns, especially regarding data collection and usage. These issues should be carefully managed to maintain public trust and ensure ethical compliance in future research and applications.

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Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title: Classification Of Bangladeshi Bird Species Based on Images Using Deep Learning Techniques

Student ID: 202-15-14400 and 202-15-14377

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a **Bird classification** problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish this goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**

CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	Our project requires K3 (Engineering Fundamentals) by employing deep neural networks, data augmentation techniques for image processing and classification tasks. The project demonstrates **K4 (Specialist Knowledge)** via the development of deep learning models like MobileNetV2, DenseNet201, VGG19, Xception, enhancing bird classification accuracy in based on bird images, crucial for computer-aided diagnosis.	**Page no:** [22] **Section:** [4.1] **Page no:** [17-18] [22-32] **Section:** [3.2, 4.2]
				Our project requires **K5 (Engineering Practice [Design])** and **K6 (Engineering Practice [Technology])** through the advent of a smart bird identification program.	**Page no:** [18] **Section:** [3.3] **Page no:**

					[59-61]
				This project ensures to **K8 (Research Literature)** by synthesizing insights from recent studies, to advance bird classification using deep learning, showcasing a comprehensive understanding of current methodologies.	**Page no:** [6-14] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This project addresses **EP-2** by recognizing the Dealing with challenges related to data collection such as obtaining diverse and high-quality bird images.	**Page no:** [14-15] **Section:** [2.4]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	This project addresses **EP-3** by meticulously comparing experimental outcomes, highlighting Transfer Learning as the chosen significant solution for enhancing bird classification.	**Page no:** [39-61] **Section:** [5.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's interdisciplinary approach extends beyond computer science and engineering, significantly impacting the field of ornithology by enhancing the accuracy of bird classification based on images using deep learning techniques. This advancement contributes to biodiversity research, conservation efforts, and environmental monitoring, demonstrating the project's broad applicability and importance **EP-4**.	**Page no:** [6-15] **Section:** [2.2, 2.4]

5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting requirements**	Yes	CO8	Involving diverse stakeholders together with bird experts, community individuals and conservationists in contributing to the research and conservation efforts.	**Page no:** [20]
7.	**EP7: Interdependence**	Yes	CO5	This project's comprehensive approach addresses high-level problems by integrating various components across data collection and proposed methodology, ensuring a holistic solution to complex challenges in bird classification which ensures **EP-7**.	**Page no:** [17-18] [22-23] **Section:** [3.2, 4.2]
8.	**EP8: Financial Analysis**	Yes	CO4	We have prepared a budget to assess and estimate the price required for the development lifecycle of the bird identification program.	**Page no:** [21]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	Our project leverages diverse resources, including high-performance computing infrastructure, GPUs, deep learning frameworks, annotated datasets, and ethical considerations, to conduct systematic research and advance bird classification based on images using deep learning techniques, particularly through transfer learning and deep convolutional neural networks (CNNs).	**Page no:** [18] **Section:** [3.3]
2.	**EA2: Level of interaction**	No		N/A	N/A

3.	**EA3: Innovation**	Yes		The innovation in our project lies in the development of a web application based on a hybrid deep learning model that combines MobileNetV2 and DenseNet201, achieving the best accuracy for bird classification using images. By leveraging the strengths of both models, the application provides users with highly accurate and efficient bird identification tools. This web app utilizes high-performance computing infrastructure, GPUs, and extensive annotated datasets to deliver an accessible and user-friendly platform. Our pioneering approach not only advances ornithological research but also sets new standards in the application of AI for biodiversity monitoring and conservation efforts.	**Page no:** [59-61]
4.	**EA4: Consequences for society and the environment**	Yes		This project contributes to society by advancing ornithological research through highly accurate bird classification, while promoting environmental sustainability by employing efficient computational resources and adhering to ethical guidelines for data privacy.	**Page no:** [62-66] **Section:** [6.1, 6.2, 6.3, 6.4]

5.	**EA-5: Familiarit y**	Yes		This project expands upon existing research by exploring a novel approach to bird classification using a hybrid model combining MobileNetV2 and DenseNet201. Through transfer learning and deep convolutional neural networks (CNNs), it provides a comprehensive comparative analysis and offers new insights into ornithological studies.	**Page no:** [10-14] **Section:** [2.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project addresses **CO4** by integrating effective project management and financial oversight, ensuring meticulous planning, resource allocation, and budget estimation for optimal resource utilization throughout the research lifecycle.	**Page no:** [19-21] **Section:** [3.4]
2	CO9	Yes	The project demonstrates adherence to ethical principles by prioritizing the privacy of bird data, obtaining necessary permissions for data collection, and transparently documenting the research process. This ensures responsible knowledge dissemination and promotes societal well-being through the ethical application of advanced technologies in bird classification, aligning with ethical standards and guidelines with **CO9**.	**Page no:** [64-65] **Section:** [6.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's commitment to continuous learning and adaptation (CO12) within the evolving field of bird classification is evident through its meticulous data collection, rigorous statistical analysis, methodological development, and detailed experimental	**Page no:** [17-19, 39-58] **Section:** [3.2, 3.3, 5.2]

			results and analysis. This dedication showcases a proactive approach to staying informed and refining techniques to effectively address current challenges in ornithological research.	

Classification of Bangladeshi Bird Species Based on Images Using Deep Learning Techniques

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