COMPUTER VISION-BASED TRANSFER LEARNING TECHNIQUES FOR CLASSIFICATION OF LOCAL PIGEON SPECIES IN BANGLADESH: A COMPARATIVE ANALYSIS

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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 "**Computer Vision-Based Transfer Learning Techniques for Classification of Local Pigeon Species in Bangladesh: A Comparative Analysis**", submitted by Md. Mehedi Hasan, Student ID: 201-15-14030 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 21st January 2024.

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DECLARATION

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

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ABSTRACT

In the realm of avian conservation, this thesis embarks on a pioneering journey to enhance the classification of pigeon species within Bangladesh. Leveraging the powerful Xception model, we present a breakthrough approach that attains an exceptional testing accuracy of 99.47% and minimal loss of 0.025. Our study encompasses a comprehensive dataset of 7500 images, spanning 15 pigeon species, and employs transfer learning for swift and reliable classification. While the results underscore the efficacy of our approach, the study acknowledges the challenge of subjective criteria in species classification and calls for future exploration into enhancing interpretability. Ethical considerations are central to our findings, advocating transparent communication with conservationists and the establishment of stringent ethical guidelines for responsible technology application in avian conservation. This research, a significant stride at the intersection of technology and ethics, not only contributes to avian conservation but also lays the groundwork for future investigations, paving the way for a sustainable future in avian species management and urban biodiversity preservation.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1
INTRODUCTION

1.1 Introduction

Pigeons, ubiquitous and widely distributed avian inhabitants, hold a prominent position in the avian fauna of the global landscape, including the region of Bangladesh. These birds are celebrated for their remarkable adaptability to diverse environmental niches and possess distinctive attributes, most notably their exceptional homing instincts. Such unique traits have elevated pigeons to a significant role in the annals of human culture and history. Within the confines of Bangladesh, pigeons not only serve as cherished pets but also find utility in pursuits such as racing and other multifaceted applications. However, it is imperative to underscore that the systematic classification of pigeon species within the geographical precincts of Bangladesh remains a formidable undertaking, replete with complexities. The confluence of challenges emanates from a dearth of a comprehensive pigeon species database, coupled with the intricacies involved in differentiating between various pigeon species. These intricacies are further exacerbated by the dearth of specialized databases dedicated to racing pigeon species, which, given their prized attributes of speed and endurance, occupy a pivotal role in the realms of breeding and training.

It is noteworthy that the classification of pigeon species holds profound ramifications, transcending the purview of mere taxonomical cataloging. Pigeons have ingrained themselves into the tapestry of human culture and history over millennia. They have been instrumental in communication, served as carriers in transportation networks, and even contributed as a sustenance source. The role of pigeons as racing specimens is of paramount significance, commensurate with their exceptional speed and enduring capabilities. Precisely classifying these racing pigeon species assumes pivotal importance for breeders and trainers, enabling them to discern the most suitable birds for purposes of selective breeding and training. Furthermore, it is essential to underscore the broader ecological ramifications attached to the classification of pigeon species. These avian creatures serve as invaluable indicators of environmental health and biodiversity. Accordingly, the accurate categorization of pigeon species within the Bangladeshi context assumes a dual facet one rooted in cultural preservation and the other in the sustenance of ecological equilibrium.

In light of these multifaceted challenges and considerations, the present study proposes a pioneering methodology for the classification of pigeon species within Bangladesh. This novel approach hinges upon the fusion of image-processing techniques with cutting-edge deep-learning models. A meticulously curated dataset comprising pigeon images, sourced manually, forms the cornerstone of our approach. These images, subsequently subjected to state-of-the-art deep learning models, are discerningly categorized into distinct species. This paper represents a significant stride toward enhancing the accuracy and consistency integral to pigeon species classification in Bangladesh. This holds particularly true for the classification of racing pigeon species, which has heretofore been marred by the subjectivity inherent in relying upon physical attributes. The absence of a comprehensive racing pigeon species database within Bangladesh only amplifies these challenges.

In summation, this research endeavor endeavors to impart pivotal advancements in the realm of pigeon species classification within the confines of Bangladesh. By leveraging the synergy of image processing and deep learning, our methodology strives to mitigate the intrinsic complexities associated with this task. We ardently anticipate that this undertaking will contribute tangibly toward the development of a comprehensive pigeon species database within Bangladesh, thereby actively nurturing the preservation of both cultural and ecological facets intertwined with these avian denizens.

1.2 Motivation

The motivation behind this research derived from the real-world need to simplify as well as improve pigeon species identification. Identifying local pigeon species is becoming more and more important as the demand for pigeon breeding and farming grows upward. This research intended to incorporate cutting-edge techniques like image classification and Deep Learning to come up with a simple and accurate to identify local pigeon species. For individuals handling a large number of pigeon breeds, especially on farms or lofts in scenarios like this, the practical use of automated pigeon classification provides significant promise. This research endeavors to streamline the classification process by developing a robust classification system, enabling pigeon enthusiasts, breeders, and farmers to maintain and record their pigeon populations effectively.

For anyone interested in certain breeding programs or conservation initiatives targeted at maintaining specific pigeon breeds, the simplicity provided by a computer vision-based identification system can be extremely beneficial. Following that, the ultimate objective of this research is to close the gap between traditional identification methods and modern technological advancements, thereby making pigeon species identification more convenient and accurate for a wide range of individuals and organizations in pigeon breeding and farming sectors.

1.3 Rationale of the Study

The rationale behind this study derives from the crucial necessity of transforming the identification method of pigeon breeds utilizing technological advances. In the present time, pigeon species identification is mostly based on human observation with years of experience and skill that can be unreliable, time-consuming, and error-prone. This research aims to solve the aforementioned problems by automating and enhancing the pigeon species classification process using transfer learning and image processing techniques.

The primary objective is to develop an effective classification system that will enhance pigeon species identification. This technological advancement is essential due to how it significantly improves both the precision and the effectiveness of pigeon species identification, particularly when dealing with instances like huge pigeon populations, such as on farms or in conservation environments. In addition, the research aims at encouraging pigeon breeding techniques and conservation measures. A greater degree of precision and a user-friendly system for recognizing pigeon breeds could contribute to helping breeders preserve breed purity and variation in genetics. It aims to provide pigeon enthusiasts, breeders, environmental activists, and farming societies with a trustworthy, effective, and cutting-edge technique.

1.4 Research Questions

This research is being driven by several specific research inquiries on how well the system works and the implications of using image processing and transfer learning in pigeon species classification. The key questions driving this research are as follows:

1. What improvements in accuracy as well as effectiveness do the proposed methodologies offer over traditional pigeon identification?
2. To what extent could possibly the transfer learning techniques aid in the accurate classification of diverse pigeon species concerning their unique visual characteristics and traits?
3. When evaluating different transfer learning approaches in terms of their application and performance in the area of pigeon species classification, what are the distinguishing strengths and constraints?

These queries are the basis of the study's guiding framework, conducting the exploration into the challenging field of pigeon species classification using image processing and transfer learning techniques.

1.5 Expected Outcome

This study anticipated many different kinds of noteworthy outcomes in the field of pigeon species classification which combines image processing with transfer learning, and aims to uncover unique insights with real-world implications. The expected outcome is as follows:

1. Development of an Advanced Classification System: One of the primary outcomes of this research is to develop a consistent and precise pigeon breed identification system. The system is expected to extract unique features of bird species and precisely identify each individual bird.
2. Transfer Learning Model Evaluation and Comparison: Several transfer learning models will be tested and evaluated for how effective they are in pigeon species classification using a structured assessment approach. The estimated outcome features findings on various designs' comparative strengths and drawbacks.

3. Methodological Advancements: The endeavor aims to deliver insights into enhancing image processing algorithms, particularly associated with classifying pigeon species. This entails extensively exploring ways to approach extracting characteristics, normalization as well as any other early evaluating processes.
4. Real-world Application for Firms and Lofts: The developed classification system has the potential to be transformed into concrete benefits for pigeon breeders. This could encompass early illness monitoring, more effective decision-making processes, and greater efficiency in general.

The anticipated objectives aim to make a contribution to the enhancement of pigeon species classification by developing innovative techniques for environmental preservation, management, and greater benefit to society.

1.6 Report Layout

The pivotal chapter named as report layout summarizes the distributed division of the report's chapters and its coherence ensuring clarity and easy navigation, creating a vivid roadmap for any chapter path.

Chapter 1: The introduction of the overall work describing the brief history, relevance and problem definition of the work.

Chapter 2: The literature review section delves into the background literature works finding out the most appropriate and relevant work in the similar work domain.

Chapter 3: Methodological exploration and instrumentation along with implementation details are step wise described.

Chapter 4: Implemented model's performance and evaluation metrics are discussed.

Chapter 5: The societal and environmental effects and impacts are taken under consideration of.

Chapter 6: Finally, conclusions are drawn and future research implications are described.

CHAPTER 2
BACKGROUND

2.1 Preliminaries/ Terminologies

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

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

2.2 Related Works

In a remarkable breakthrough for bird observation, the authors developed an unsupervised bird classification system that uses real-time cameras along with deep learning techniques. A Faster R-CNN architecture was implemented on the bird classification system, which achieved an accuracy rate of 96.71%. The dataset used for training and testing consisted of 32982 images of 10 different birds. To further enhance the performance of computer vision models for bird monitoring, authors suggested several future researches, emphasizing the necessity to investigate optimal camera arrangement and configuration [1]. Dimitrios Mpouziotas et al. (2023) proposed an automated bird identification and identification system by utilizing the YOLOv4 model. Because monitoring and manual identification of bird species is a time-consuming process, to overcome this situation and make wildlife monitoring more efficient they have come up with this brilliant concept. The YOLOv4 model attained a remarkable average accuracy of 91.28% utilizing a large dataset consisting of 10635 images preprocessed from three videos [2].

By enhancing the YOLOV5 architecture using a graph pyramid attention convolution operation, Xin Xu and his team proposed a fine-grained detection neural network for detecting birds. The proposed model was tested on three different datasets, which are CUB-200-2011 (11,788 images), Bird-400 (60,388 images), and AF-bird50 (more than 10,000 images). The proposed model outperformed the current advanced models in both bird classification and detection, with accuracies of 99.3% and 89.37%, respectively. In the future, the authors plan to explore more accurate and effective models for bird classification and detection [3]. Kang Wang et al. (2023) suggested a fine-grained bird classification method based on attention and decoupled knowledge distillation utilizing the DenseNet121 and ShuffleNetV2 models. They developed a unique and effective lightweight fine-grained bird classification model using an attention-gained data augmentation method and a decoupled knowledge distillation model compression method. CUB-200-2011 was used as a dataset and achieved an accuracy of 87.6% while using 67% fewer parameters and 1.2 G of computation. The authors plan to achieve an adaptive ground setting of the window throughout the process of crucial component region localization [4]. Yang et al. (2023) conducted an extensive study on bird object detection technology, addressing various challenges such as limited datasets and evaluation benchmarks. The researchers created the GBDD1433-2023 dataset, the world's largest bird object detection dataset with 148,000 annotated images. Eight commonly used models were analyzed and found that two-stage models (e.g., Faster R-CNN, Cascade R-CNN) delivered impressive results, achieving a Mean Average Precision (mAP) of 73.7%. Their future plan includes optimizing lightweight models using adaptive localization distillation and exploring integration with other compression techniques. To effectively contribute to the recognition of bird intelligence and conservation, they plan to expand the dataset and test new models [5].

The authors proposed an improved Faster R-CNN model for accurate bird species detection in natural scenes. The model leveraged multi-scale fusion and a depth residual network to extract features. The K-means clustering technique improves accuracy by enhancing anchoring. The Soft Non-Maximum Suppression approach reduced missed detections of overlapping birds. The proposed model was assessed using a dataset containing over 3,000 images of 10 different bird species, achieving a mean average precision (mAP) of 89.0%. However, it has low detection speed and FPS [6]. The study conducted by the researchers aimed to evaluate the effectiveness of deep learning architectures for detecting birds in webcam images. They evaluated two object detection meta-architectures: Single-shot Detector (SSD) and Faster R-CNN with different feature extractors, using a dataset of 10592 images of birds. The SSD with MobileNet showed the fastest inference time (110ms) and the smallest memory capacity (30.5 MB), while the Faster R-CNN model with ResNet152 achieved the highest mean average precision (92.3%). The findings of this research validated the effectiveness of deep learning algorithms in bird detection across diverse habitats, proposing potential uses for ecologists in species monitoring and identification [7].

In 2021, Huang et al. elaborated on their previous work Internet of Birds (IoB). They have used a transfer learning-based approach with Inception-ResNet-V2. With this model, they have achieved 98.39% accuracy in species classification and 100% accuracy in bird detection among distinct object categories. A total of 3,892 images featuring 29 distinct birds across Taiwan were utilized as their dataset. They swapped misclassified data and validated the transferred learning model using multistage model validation. They want to develop a web crawler system in the future that could identify distinctive bird species worldwide. This cutting-edge technology will estimate the diversity of endangered and uncommon species of birds [8]. A multi-object detection algorithm named YOLOBIRDS that improves the precision and predictability of bird detection models was developed by Yang and Song in 2021. By utilizing Focal loss and Depthwise separable convolution, YOLOBIRDS maximizes the effectiveness of detection and controls the sample imbalance. The algorithm outperformed YOLOv3 by 2.71% more accurate mean average precision with a lower parameter count of 79.88% and 19.98% higher frames per second (FPS) while tested on a bird dataset from Hengshui Lake. They are intended to further research and make improvements to the proposed algorithm to deal with difficulties like lighting, weather, and FPS [9].

The research conducted by Al Amin Biswas and his team focuses on implementing transfer learning techniques to recognize local birds. Six different CNN architectures were utilized in this research, including DenseNet201, InceptionResNetV2, MobileNetV2, ResNet50, ResNet152V2, and Xception. The models were trained and tested using 3500 images of birds. MobileNetV2 outperformed other models in terms of accuracy, precision, recall, and F1-score, with values of 96.71%, 96.93%, 96.71%, and 96.75%, respectively. In the future, the authors plan to extend the recognition to video data with a larger dataset [10]. The authors aim to employ the Convolutional Neural Network (CNN) method for image recognition, specifically bird identification. The validation accuracy of the research is 95.52% while employing CNN and the YOLOV3 framework for object detection. 1500 images were used to train and evaluate the model. Future plans include reducing computation time, expanding the detection process to video, learning additional object classes, developing an Android app system, and increasing the database's accuracy output [11].

Through the utilization of Artificial Intelligence, Akçay and his team aim to solve the challenging task of counting migrating bird populations. They implemented deep-learning algorithms on a dataset consisting of 647 images of 4885 distinct birds. The authors analyzed several state-of-the-art generic object detection models (Bow, SSD, and Faster R-CNN), achieving accuracies of 0.86, 0.88, and 0.94, respectively. They highlighted how neural networks can improve human-assisted bird surveillance and also achieve large-scale bird mapping by encouraging citizen participation [12]. Kazi Md Ragib et al. (2020) introduce a deep-learning model for identifying distinct birds in images. They leverage pre-trained Convolutional Neural Networks (CNN) and, in particular, the ResNet model as a pre-trained CNN model. The research was performed on a dataset of 14,000 images of 200 classes. In terms of classifications, the proposed model achieved a top-5 accuracy of 97.98% on the classifications. The authors intend to collect more data in the future to improve precision and explore more classification models, such as SIFT features [13].

Huang et al., 2019, developed a deep-learning platform called the Internet of Birds (IoB) that can identify 27 different types of native bird species in Taiwan. Convolutional Neural Networks(CNN) with skip connections were utilized to achieve high accuracy. For training, testing, and validation they used a total of 3563 images. The cloud-based mobile application Internet of Birds (IoB) identifies bird species from user-uploaded mages with an accuracy of 98.70%. Throughout the study, they have aimed for automated fine-grained native bird species classification [14]. Utilizing deep learning techniques, the authors developed object detection models to precisely detect birds in aerial images collected by a UAV. The study compared the performance of five different deep-learning-based detection methods, including Faster R-CNN, R-FCN, SSD, Retinanet, and YOLO, and compared their speed and accuracy. A dataset consisting of 28,007 bird images was used, extracted from aerial images captured by UAVs. According to the test results, YOLO was the fastest among the models, and Faster R-CNN was the most accurate with an accuracy of 95.44% (IOU thresholds: 0.3). The authors aim to improve deep-learning models for bird detection, including counting, tracking migrating birds, and identifying habitats [15].

With the utilization of cutting-edge methods, a model that was developed in 2018 shows outstanding performance in fine-grained bird recognition. Leveraging a triple network along with bilinear techniques, incorporating Xception, the model achieved an accuracy of 88.91% and 85.58% on the Birds-1096 and Caltech-UCSD datasets, respectively. The Caltech-UCSD dataset consisted of 11,788 photos of 200 bird subcategories, whereas the remarkable Birds-1096 dataset has 459,828 images including 1096 bird categories. The potential for merging losses across different branches will be analyzed in the future, along with the incorporation of an attention mechanism to handle more complicated fine-grained categories [16].

2.3 Comparative Analysis and Summary

Table 1 provides a summary of significant literature reviews, comparing them with our work based on prior research.

TABLE 1: COMPARATIVE ANALYSIS WITH PREVIOUS STUDIES

Reference	Method Used	Dataset	Accuracy	Limitations
Dimitrios Mpouziotas et al.[2]	YOLOv4	10635 images	91.28%	Limited dataset, Accuracy and identification
Xin Xu [3]	YOLOv5	11,788 images	99.3%	Limited dataset, environmental conditions
Kang Wang [4]	Decoupled knowledge distillation	11,788 images	87.6%	Dataset focus, computational cost
Akçay et al. [12]	Faster R-CNN	647 images	94%	Small dataset, model complexity
Huang et al. [14]	CNN with skip connections	3563 images	98.70%	Small Dataset, Interpretability and Bias
Our Work	Xception	7500 images	99.47%	Limited dataset, native species focused

2.4 Scope of The Problem

The scope of the problem in bird classification and identification is addressed by research undertaken between 2018 and 2023. These research projects, carried out by a variety of authors, have made major contributions to the advancement of methodology in bird species identification and surveillance. The underlying objective is to improve the accuracy, efficiency, and applicability of deep learning-based models for accurate bird identification and classification.

Dimitrios Mpouziotas et al. (2023), Xin Xu et al. (2023), Kang Wang et al. (2023), and Yang et al. (2023), as well as others, have made significant steps in improving model performance. Deep learning architectures are being improved, attention mechanisms are being integrated, transfer learning techniques are being developed, and innovative approaches such as graph pyramid attention convolution are under consideration. These experiments have resulted in outstanding accuracy rates with values ranging from 85.58% to 98.70% within a variety of datasets.

With the great advances in precision, maintaining a balance between accuracy and processing speed remains an immense challenge. Models with greater accuracy rates, such as YOLOv5 or Faster R-CNN with ResNet152, may have longer processing times. Models that prioritize acceleration, such as SSD with MobileNet, could negatively impact accuracy to some degree.

The scope of this research also includes the real-world use of these models in ecological studies, wildlife surveillance, and citizen-assisted bird monitoring. Further study goals, as highlighted by Yang et al. (2023) along with other researchers, include expanding datasets, improving models for real-time applications, and investigating novel ways to increase precision as well as effectiveness in bird species classification.

In a nutshell, the topic ranges from improving the accuracy of deep learning models to refining these models for real-world use in bird surveillance and ecological studies. The ultimate goal is to create an appropriate balance between efficiency and precision while developing approaches for exact bird species categorization and identification in real-world circumstances.

2.5 Challenges

The challenges that arise from the dataset that was utilized for pigeon species classification include a wide range of issues. There are inconsistencies with the dataset's quality and consistency, as seen by variances in focus, irregular lighting, and fuzzy pictures. Furthermore, there are undesired objects or impediments surrounding the pigeon cages, making it difficult to take pristine and unobstructed pictures. These challenges must be addressed carefully, nevertheless, they may have an impact on the dataset's overall dependability and usefulness. Furthermore, high-resolution images captured with smartphones may not be immediately appropriate with deep neural network (DNN) evaluation, necessitating scaling for optimal model performance. nonetheless, the downsizing procedure may jeopardize some of the image's finer details.

Furthermore, utilizing transfer learning models to classify pigeon breeds has unique challenges. Throughout the model training process, computational needs increase significantly, necessitating the use of significant computer resources. The entire procedure of fine-tuning pre-existing models to be compatible with the complexities of pigeon species classification gets complicated which requires hyperparameter optimization and model architecture adaption.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

In this section, our primary focus centers on the classification of various pigeon species, encompassing breeds such as Black Racer, Budapest, Chila, Dalmechan, Dobaz, Grizzle Racer, Kaldom Giribaj, Lal Khaki, Maxi Racer, Mili Racer, Red Checker, Shobi Racer, Sobuj Gola Giribaj, Shurma Khaki Giribaj, and White Racer. To support rigorous data analysis and model training, we employ a standard desktop computer with computational capabilities. We utilize Google Colab as our coding environment, a cloud-based platform that seamlessly integrates popular machine learning libraries and provides GPU support for efficient model training. This strategic amalgamation of focusing on pigeon species classification and employing a personal desktop computer with Google Colab as our coding environment forms the foundation of our research methodology. This setup ensures an optimal balance between computational efficiency and accessibility, strengthening the credibility and reliability of our research findings. Figure 1 visually outlines the procedural steps embedded within our methodology.

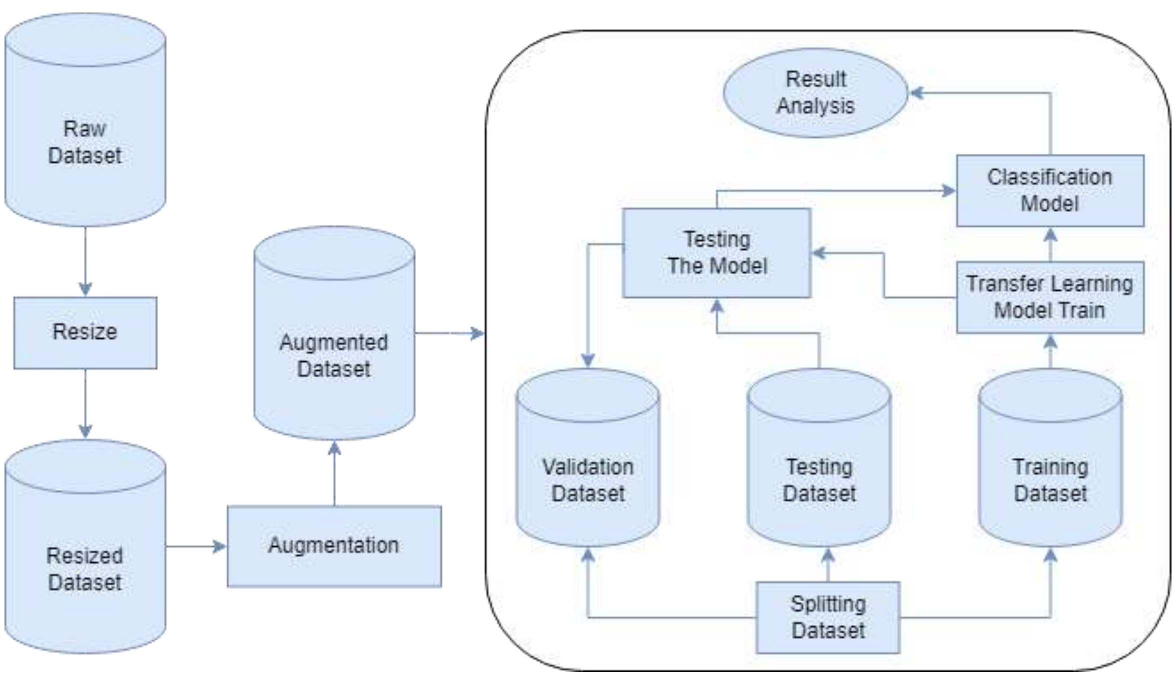

Figure 1: Methodology Workflow

3.2 Data Collection Procedure/Dataset Utilized

The data-collection process for pigeon species classification was meticulously planned in order to create a complete dataset that is necessary for training and evaluating the classification algorithms. The dataset, which was termed the "Local Pigeon Dataset," was collected from a pigeon farm in Dhaka, Bangladesh, which housed a wide variety of pigeon species. The objective of this endeavor was to collect precise images from multiple pigeon species, which would serve as an initial basis for proper classification.

The pigeon images were chosen and captured working together with the farm owner in order to find pigeons with good health and particular breed features. Each and every pigeon breed was meticulously picked, and 1-2 sample pigeons were chosen to begin the image-capturing procedure. In order to offer a suitable setting for image capturing, the pigeon cages were adequately sized, making it possible for the birds to have freedom of movement freely while reducing the disturbances throughout the shooting sessions.

In order to capture good pictures, the image-collecting phase required precise navigation, which necessitated the repositioning of any obstacles or unneeded objects surrounding the cages. Patience was essential since pigeons, affectionately known for their lively and inquisitive nature, required an adapting period to adjust to the image-capturing procedure, making it possible for the collection of clean and focused images exhibiting unique pigeon breeds characteristics.

Following image capture, data quality was ensured by comprehensive manual checking and labeling. The dataset was subjected to an extensive thorough picture refining procedure to resolve flaws such as focus inconsistencies, exposure discrepancies, and blurred appearance. This stage attempted to compile a high-quality dataset that represented a variety of pigeon species. The raw dataset consisted of approximately 2,070 images that had been meticulously sorted into 15 separate pigeon breed classifications, serving as the core resource for further rounds of dataset preparation and model training.

Figure 2: Dataset Sample

Figure 3: Dataset Sample

Figure 4: Dataset Sample

3.3 Data Pre-processing

The raw pigeon image dataset has been enhanced by utilizing data pre-processing to ensure its quality, consistency, and appropriateness to facilitate efficient training of models in the pigeon species classification tasks. The initial dataset was meticulously processed to remove inherent flaws and improve its applicability for the use of machine learning methods.

Considering thorough image capturing, the raw dataset has flaws such as focus discrepancies, exposure discrepancies, blurred images, and the inclusion of undesirable components. Each of the pigeon breed classes in the dataset was thoroughly examined in order to detect and eliminate photos that were impacted by the aforementioned imperfections. This process attempted to provide a more detailed and exact dataset that was devoid of any disruptions that could potentially hinder model performance.

Given the computational restrictions of evaluating high-resolution images with deep neural networks, a resolution compression was required to maximize model training performance. The initially high-resolution images, obtained with smartphones at 3000 x 4000 pixels, have been scaled down to 300 x 300 pixels. The resulting modification guaranteed interoperability with deep neural network architectures while simultaneously limiting the possibility of hardware resources being limited during the training of models.

Data augmentation techniques have been employed to increase the size and variety of the dataset, overcoming the restrictions associated with limited data quantity. Rotation within a -15 to +15-degree range, shearing within a 0.2 range, zooming in and out within a 0.2 range, horizontal and vertical flipping, random brightness modifications, plus guaranteeing no degraded regions in the output pictures were used as augmentation techniques. These changes substantially expanded the dataset, resulting in 7,500 photos, and 500 images for each pigeon breed class.

Figure 5: Augmented Dataset Sample

3.4 Dataset Splitting

During the dataset splitting step, the pigeon image dataset was properly separated into training, testing, and validation subsets. This deliberate allocation allowed for model learning, unbiased evaluation, and parameter tuning, which led to the construction of a trustworthy pigeon species classification model.

The dataset-splitting procedure entailed carefully dividing the pre-processed images into three basic subsets: training, testing, and validation. A significant percentage of the overall 7,500 photos encompassing 15 pigeon breed classes, 6,000 images, was assigned to the training subset. This bigger training sample served as the model's fundamental data, making it possible to understand subtle characteristics and properties unique to different pigeon breeds throughout iterative procedures.

Following the training subset, 750 images have been set aside, particularly for the purpose of testing. During the training phase, the model wasn't given access to these images, therefore they were merely utilized for testing the model's performance and accuracy. Evaluating the model on this specific fraction enabled an unbiased assessment of its classification competency on fresh, previously unidentified data, highlighting its capacity to make generalizations beyond the training images.

An additional 750 images had been placed aside to feed the validation subset. This subset was used to fine-tune model parameters, optimize hyperparameters, and develop the model's architecture without jeopardizing the testing subset's integrity. The validation set was crucial in improving the model's accuracy and adaptability, which helped improve the efficiency of the pigeon species classification model.

TABLE 2: DATASET DETAILS SHOWING COLLECTED IMAGE NUMBER AND AUGMENTED DATASET COUNTS

Class	Raw Dataset	Augmented Dataset
Black Racer	151	500
Budapest	130	500
Chila	141	500
Dalmechan	107	500
Dobaz	203	500
Grizzle Racer	125	500
Kaldom Giribaj	111	500
Lal Khaki	78	500
Maxi Racer	138	500
Mili Racer	190	500
Red Checker	130	500
Shobji Racer	69	500
Sobuj Gola Giribaj	128	500
Shurma Khaki Giribaj	121	500
White Racer	238	500
Total	2070	7500

3.5 Transfer Learning Model

The strategic integration of transfer learning methodologies into our pigeon species classification study stems from a profound comprehension of its imperative need, intrinsic significance, and its immense potential to optimize our tailored dataset. In the domain of machine learning, transfer learning embodies a sophisticated approach wherein models previously trained on extensive datasets are repurposed to extract pertinent features for distinct tasks. In the sphere of pigeon species classification, marked by limited datasets, transfer learning becomes a cornerstone. The fundamental rationale resides in the pre-trained models' adeptness at capturing high-level features from diverse datasets. This proficiency significantly augments the model's discernment of intricate patterns and characteristics associated with various pigeon breeds.

The relevance of integrating transfer learning into our study becomes evident when considering the intricate nuances and variations prevalent among pigeon species. Pretrained models, having assimilated knowledge from broader datasets, expedite the learning process in our specific domain. This method significantly mitigates the risk of overfitting, particularly in scenarios where dataset sizes are constrained. Transfer learning ensures that the models extract relevant features, thereby contributing significantly to the robustness and adaptability of the classification system.

This approach extends beyond technical considerations; it aligns with a strategic imperative. Transfer learning acts as a safeguard against potential challenges when training models from scratch in specialized domains like pigeon species classification, where limited labeled data presents challenges. This methodological choice underscores a meticulous understanding of the intricacies of pigeon species classification and a dedication to developing a classification system that surpasses conventional limitations.

The potential of transfer learning becomes especially pronounced when applied to a custom dataset meticulously crafted to encapsulate the diversity among pigeon breeds. In our dataset, images encapsulate the richness of pigeon breed variations, and transfer learning harnesses the wealth of knowledge embedded in pre-trained models. Architectures such as ResNet50, Inception-ResNet-v2, DenseNet-201, MobileNetV2, and Xception, having traversed extensive datasets during their original training, offer a profound understanding of visual features that seamlessly adapts to the idiosyncrasies of our specialized dataset. By harnessing the potential of transfer learning, our models acquire an unparalleled capacity to discern nuanced patterns and features indicative of diverse pigeon breeds.

3.6 Proposed Methodology

Xception

The Xception architecture, which stands for "extreme inception," is a powerful and complicated Convolutional Neural Network (CNN) design distinguished by its 71-layer depth. Unlike its predecessor, Inception, Xception's architecture consists of a linear stack of depthwise separable convolution layers linked by residual connections. This novel design enables Xception to expedite feature extraction procedures, improving computing efficiency while maintaining accuracy.

The alteration of the compression phases in Xception marks a significant divergence from the Inception architecture. To increase the model's capacity to extract subtle and nuanced characteristics from input photos, Xception reverses these processes. Its early pretraining phases made use of the large ImageNet dataset, a benchmark repository with over a million tagged pictures. This ImageNet fundamental training aided in the construction of generic feature representations inside Xception, acting as a framework for later fine-tuning or transfer learning in a variety of applications.

Xception is configured to process images with a default resolution of 299x299 pixels. Its architecture is structured to categorize images into a thousand distinct classes, encompassing a wide spectrum of living and non-living objects. One of Xception's standout features is its adeptness in integrating depthwise separable convolutions effectively. This integration optimizes parameter utilization, substantially reducing computational overhead while maintaining high accuracy, a critical aspect for various computer vision tasks.

The utilization of depthwise separable convolutions within Xception signifies its efficiency in capturing intricate image features. By separating the spatial and channel-wise operations, this architectural design significantly reduces computational complexity compared to traditional convolutions, ensuring better parameter efficiency.

This streamlined design, balancing accuracy, and computational efficacy, has made Xception a popular choice across diverse applications in computer vision. Its versatility and efficiency in handling complex image processing tasks have positioned Xception as a favored architecture, finding extensive usage in fields such as image classification, object detection, and segmentation tasks within the realm of artificial intelligence and machine learning.

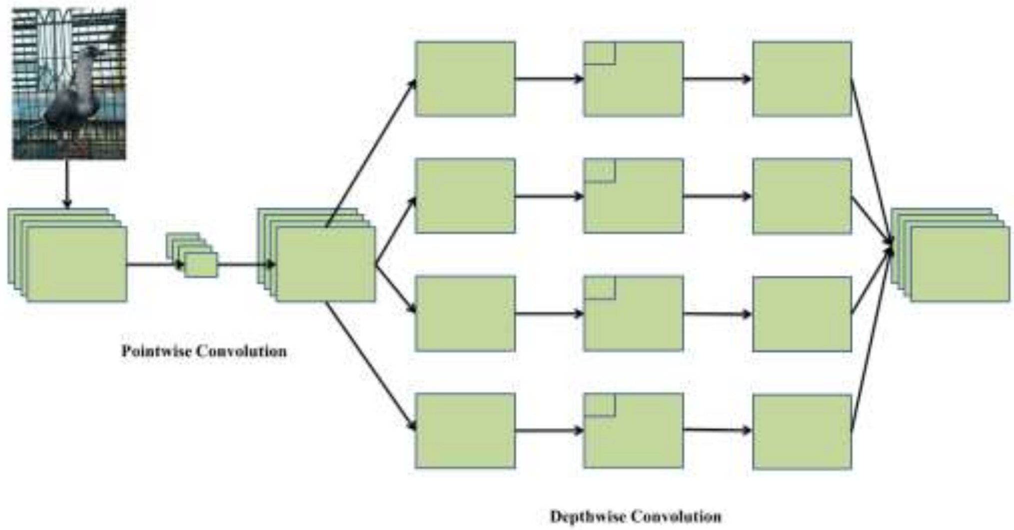

Figure 6: Basic Architecture of Xception

3.7 Implementation Requirements

The pigeon species classification system in Google Colab necessitates careful consideration of several criteria, which might include both software and hardware aspects. This section gives a quick description of the critical implementation conditions required for the smooth execution of the developed architecture in Google Colab.

Software Tools

A set of key software resources is required for the development of the pigeon species classification system in the Google Colab environment. Python is the most commonly used language for programming because of its flexibility in machine learning and large libraries such as TensorFlow and Keras. TensorFlow, a prominent open-source machine learning framework, has been utilized to design and train neural networks. Because of its interoperability with Colab, it enables seamless integration, consequently allowing for greater effectiveness in model creation and evaluation.

Moreover, Keras, a high-level neural networks API, supplements TensorFlow by offering a user-friendly interface for building neural network topologies. This adaptable tool streamlines the complex process of creating, training and deploying neural networks, which is required for the creation of our pigeon classification model. Additionally, the Matplotlib and Seaborn libraries help with data visualization, allowing for a clear comprehension of model performance metrics and dataset properties. These visualization tools are critical in evaluating and presenting findings, improving the understandability of the classification system's indicators of performance and outcomes. The combination of the aforementioned software applications in the Google Colab environment provides a solid platform for designing, training and assessing the pigeon species classification system.

Hardware Specifications

The effective execution of the pigeon species classification system in Google Colab demands careful consideration of hardware characteristics advantageous to fast model training and execution. Google Colab provides a cloud-based computing environment with accessibility to strong resources, most notably GPU (Graphics Processing Unit) capability. When compared to CPU-only environments, using GPU acceleration dramatically accelerates the training of the model by processing complicated computations in parallel.

Google Colab offers free computing resources like RAM (Random Access Memory) and disk space, which are essential for storing datasets and model barriers during training periods. Sufficient RAM is allocated to allow the effective handling of large-scale datasets, while plenty of disk space supports model content, datasets, and intermediate outputs. These hardware specs made available by Google Colab make it possible for researchers to take advantage of high-performance computing capabilities, allowing for faster model training and execution in the development of robust pigeon species classification systems.

Data Integration

The pigeon species classification method requires an exhaustive procedure of harmonizing and absorbing various information into a consistent format appropriate for model training as well as evaluation. Initially, raw pigeon image datasets gathered from various sources are subjected to preprocessing operations such as picture scaling, normalization, and quality inspections. Following that, the preprocessed photos are sorted into various groups to ensure uniformity and transparency in pigeon breed classification.

The combined dataset is separated into training, testing, and validation subsets after a thorough splitting step. This split guarantees that the model is trained on a varied set of data, tested on previously unseen instances, and verified for robustness. A fundamental part of data integration is the merging of various datasets into a common format, followed by painstaking subset generation. This organized technique assures the dataset's dependability, consistency, and adaptability for constructing a trustworthy pigeon species classification system.

Code Modularity and Documentation

Code modularity and good documentation are critical for our implementation's long-term sustainability and consistency. We achieve smooth debugging, maintenance, and future upgrades by structuring the code into modular frameworks and encapsulating separate operations. Furthermore, detailed documentation, such as inline comments within Google Colab, illustrates the reasoning behind each code segment, the functionality of employed methods, and the overall implementation flow.

CHAPTER 4
EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Setup

In our experimental setup for the pigeon species classification study, we meticulously evaluate the performance of five unique pre-trained deep-learning models. Specifically, these models—ResNet50, Inception-ResNet-v2, DenseNet-201, MobileNetV2, and Xception are meticulously trained, validated, and tested individually using our custom dataset. This rigorous assessment approach enables us to thoroughly analyze each model's performance and appropriateness for accurately classifying pigeon breeds.

Selection of Pre-trained Models

The selected pre-trained models encompass a diverse array of architectures recognized for their proficiency in computer vision tasks. ResNet50 and Xception are part of the ResNet and Xception families, respectively, renowned for their deep-layer structures and innovative design elements. ResNet50 employs skip connections, mitigating the vanishing gradient problem, while Xception integrates a series of depthwise separable convolutions, enhancing computational efficiency.

DenseNet201, known for its dense connectivity pattern, promotes robust feature reuse across layers, contributing to comprehensive feature learning. MobileNetV2, designed for mobile and edge devices, strategically utilizes depthwise separable convolutions, ensuring computational efficiency without compromising accuracy. These chosen models each offer unique architectural characteristics, representing a spectrum of innovative approaches tailored for different computational requirements and performance expectations in computer vision tasks.

Training Procedure

In the tailored training process for pigeon species classification, each chosen pre-trained model undergoes a fine-tuning phase to adapt to the nuances of our pigeon dataset. Initially initialized with pre-trained weights, these models serve as the starting point, allowing them to learn from and adjust to our specific dataset. The training occurs across a predetermined number of epochs, incorporating a meticulously chosen learning rate that ensures model convergence while averting overfitting concerns.

Our training dataset, comprising images annotated with distinct pigeon species, forms the foundational learning material for these models. Throughout the training phase, the models iteratively adjust their parameters to minimize classification errors, leveraging the dataset's diversity and complexity to extract relevant features indicative of various pigeon breeds. This process enables the models to discern and learn the distinguishing characteristics specific to each pigeon species.

Validation and Hyperparameter Tuning

For the validation and hyperparameter tuning phase in pigeon species classification, a distinct validation dataset is employed to assess the models' ability to generalize. Throughout the training process, this separate dataset plays a crucial role in evaluating the models' performance and preventing overfitting.

Hyperparameters such as learning rate, batch size, and choice of optimizer are meticulously adjusted and fine-tuned based on the model's performance on the validation dataset. The mentioned iterative tuning method is designed to achieve a careful balance across enabling the models to learn the detailed patterns from training data and guaranteeing that they're capable of generalizing well to previously unforeseen instances.

By leveraging a dedicated validation dataset and iteratively adjusting hyperparameters, we aim to optimize the models' performance, ensuring they achieve a robust capacity to classify pigeon species accurately and generalize well beyond the training dataset.

4.2 Evaluation Metrics

Evaluating the efficiency of pre-trained models involves a thorough set of metrics, each offering detailed perspectives on their classification performance.

Accuracy: Accuracy is defined as a proportion of accurately predicted values over all predicted values. The mathematical formulation of every parameter can be represented by the following equation:

$$\text{Accuracy} = \text{TP+FNTP+TN+FP+FN} \qquad (1)$$

Precision: The proportion of positive to negative predictions illustrates the precision of a model. The mathematical formulation of precision:

$$\text{Precision} = \text{TPTP+FP} \qquad (2)$$

Recall: The number of positive cases that were accurately predicted as positive is represented by the recall score. Recall's mathematical expression:

$$\text{Recall} = \text{TPTP+FN} \qquad (3)$$

F1-Score: The f1-score is calculated in order to evaluate the classification and accuracy of an architecture. The formula for calculating the f1-score is shown below:

$$\text{F1-Score} = 2*(\text{Precision}*\text{Recall})/(\text{Precision}+\text{Recall}) \qquad (4)$$

4.3 Experimental Results & Analysis

The culmination of the Experimental Results and Analysis phase marks a pivotal moment in our study, involving a comprehensive evaluation of deep learning models for pigeon species classification. This critical stage intricately dissects the testing accuracy and performance nuances exhibited by each model – ResNet50, Inception-ResNet-v2, DenseNet-201, MobileNetV2, and Xception. The derived insights not only reveal distinctive trends but also provide a nuanced understanding of the individual strengths and limitations inherent in these models, offering valuable perspectives for the broader implications of our research in avian conservation and technology integration.

TABLE 3: MODEL PERFORMANCE SUMMARY IN TESTING PERFORMANCES

Model	Test Accuracy	Test Loss
ResNet50	75.60%	0.85
DenseNet-201	83.43%	0.75
MobileNetV2	97.20 %	0.079
Inception-ResNet-v2	98.40 %	0.072
Xception	99.47%	0.025

In evaluating the testing performances of various models, our results showcase distinct accuracy levels and loss metrics. ResNet50 achieves a test accuracy of 75.60% with a loss of 0.85, while DenseNet-201 exhibits improved performance at 83.43% accuracy and 0.75 loss. MobileNetV2 demonstrates notable accuracy at 97.20%, accompanied by a minimal loss of 0.079. Inception-ResNet-v2 further enhances accuracy to 98.40% with a 0.072 loss. Xception emerges as the top performer, achieving an impressive 99.47% accuracy and the lowest loss among the models at 0.025.

4.4 Training and Validation Curves

The visual data in Figure 7 and Figure 8 provide a comparative view of the training versus validation accuracy and loss curves, respectively, showcasing the learning dynamics within our pigeon species classification models. These graphs are instrumental in gauging the performance and understanding the behavior of the models during the training phase.

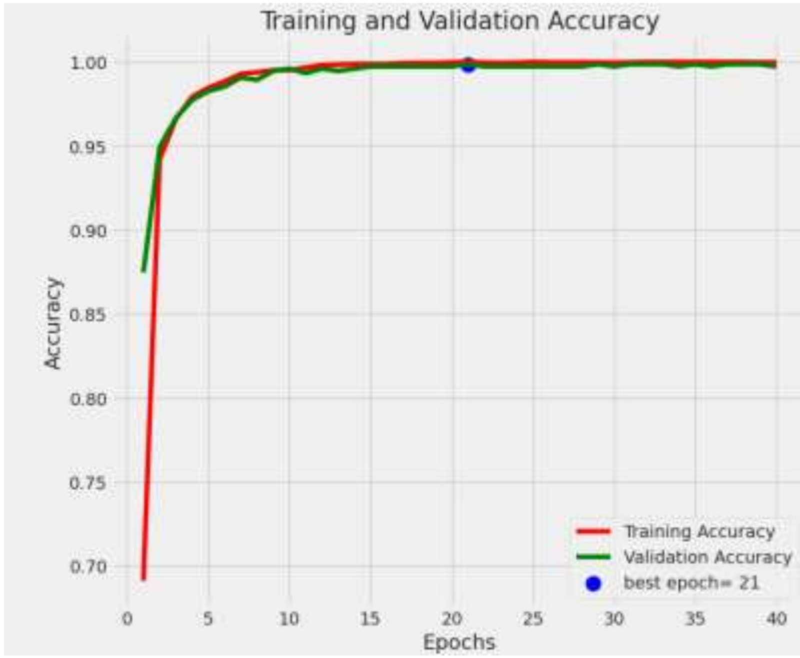

Figure 7: Training and Validation Accuracy Curves

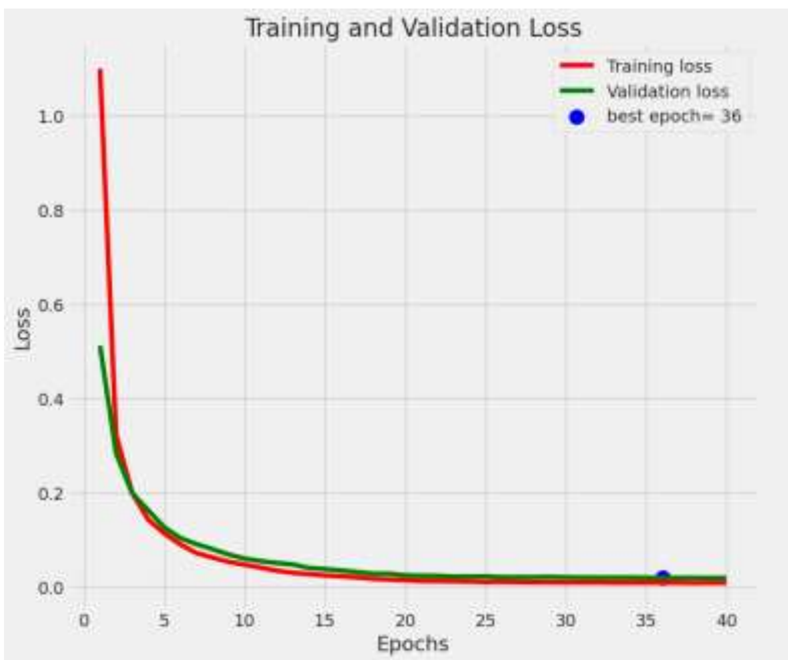

Figure 8: Training and Validation Loss Curves

The training loss curve depicts the model's proficiency in minimizing errors as it learns from the training data, while a descending trend indicates effective learning. Conversely, the validation loss curve acts as a measure of the model's ability to generalize beyond the training set. An increase in validation loss, especially when training loss continues to decrease, signals potential overfitting, highlighting the necessity for prudent model selection.

These curves serve as essential guides for decision-making in model development. They contribute to establishing early stopping criteria, preventing the model from overfitting by capturing pertinent patterns in the data without memorizing irrelevant noise. Furthermore, they aid in fine-tuning model hyperparameters and ensuring robustness, aligning the learning trajectory with the practical demands of pigeon species classification.

4.5 Classification Report of Xception

The classification report of the Xception model presents a comprehensive breakdown of Precision, Recall, F1-Score, and Support values for each class within the pigeon dataset. Precision refers to the accuracy of positive predictions, Recall denotes the model's ability to identify true positives, while the F1-Score harmonizes Precision and Recall, reflecting a balanced measure of accuracy and inclusivity. Support values provide the count of instances in each class, offering a numerical foundation for evaluation. This detailed analysis offers invaluable insights into the model's performance across various pigeon species, enabling a strategic understanding of its classification accuracy and its ability to discern distinct classes within the dataset.

TABLE 4: CLASSIFICATION REPORT OF XCEPTION MODEL (PROPOSED MODEL)

Class	Precision	Recall	F1-Score
Black Racer	1.00	1.00	1.00
Budapest	1.00	1.00	1.00
Chila	1.00	1.00	1.00
Dalmechan	1.00	1.00	1.00
Dobaz	0.98	1.00	0.99

Grizzle Racer	1.00	0.98	0.99
Kaldom Giribaj	1.00	0.98	0.99
Lal Khaki	1.00	0.98	0.99
Maxi Racer	1.00	1.00	1.00
Mili Racer	1.00	1.00	1.00
Red Checker	1.00	1.00	1.00
Shobi Racer	1.00	1.00	1.00
Sobuj Gola Giribaj	0.98	1.00	0.99
Shurma Khaki Giribaj	0.98	0.98	0.98
White Racer	0.98	1.00	0.99
Average	0.99	0.99	0.99

The Xception model's classification report offers detailed insights into its performance across various pigeon species classes, including Black Racer, Budapest, Chila, Dalmechan, and others. This report, outlining Precision, Recall, F1-Score metrics for each class, aids in evaluating the model's accuracy in categorizing diverse pigeon breeds within the dataset.

Handling Class Imbalance

In the case of pigeon species classification, the Xception model's classification report provides insights into how effectively it manages potential class imbalance among distinct pigeon breeds. Through the Precision, Recall, and F1-Score metrics for each class, the report demonstrates the model's capability to maintain accurate classification results, even when dealing with varying degrees of representation among different pigeon species within the dataset.

Generalization Across Classes

The Xception model's classification report highlights its proficiency in generalizing across various pigeon breeds. The consistently high values of precision, recall, and F1-score for each pigeon species underscore the model's robustness in effectively recognizing and categorizing diverse breeds. Such generalization capabilities are crucial for practical applications, ensuring the model's adaptability to distinct characteristics and features exhibited by different pigeon species in real-world scenarios.

4.6 Confusion Matrix

The confusion matrix stands as an indispensable evaluation tool for scrutinizing the performance of our pigeon species classification models. This matrix presents a comprehensive breakdown of model predictions, delineating instances of correct and erroneous classifications among different pigeon breeds (Black Racer, Budapest, Chila, Dalmechan, Dobaz, Grizzle Racer, Kaldom Giribaj, Lal Khaki, Maxi Racer, Mili Racer, Red Checker, Shobi Racer, Sobuj Gola Giribaj, Shurma Khaki Giribaj, White Racer). Its significance lies in providing a detailed glimpse into the model's predictive accuracy, unveiling its strengths and potential areas that require enhancement. Figure 9 illustrates the confusion matrix representing the model's performance in classifying various pigeon breeds.

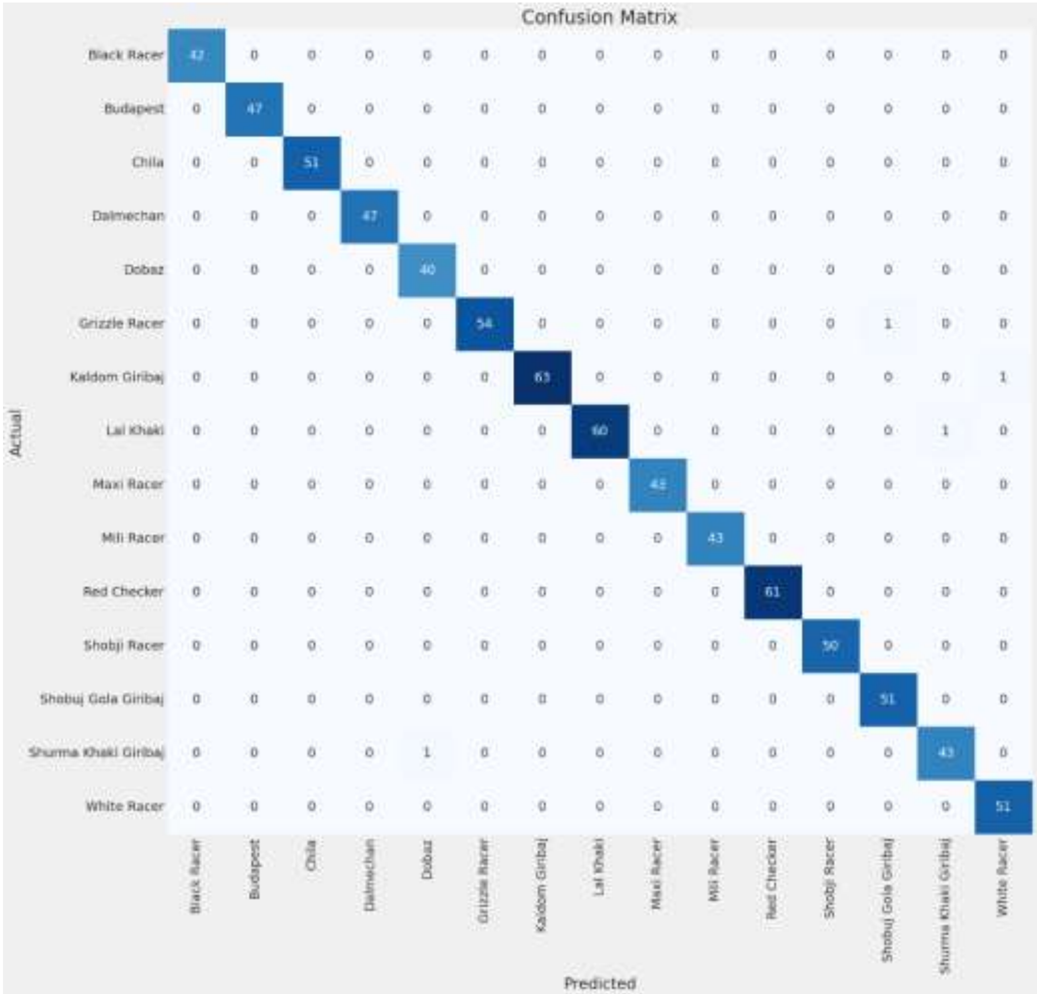

Figure 9: Confusion Matrix of the model Xception

4.7 Discussion

The analysis of various pre-trained models employed in our pigeon species classification task showcases diverse performance outcomes. Among the evaluated models (ResNet50, Inception-ResNet-v2, DenseNet-201, MobileNetV2, and Xception), Xception stands out as the most proficient, closely followed by DenseNet-201. The intricate architectural design of Xception, consisting of depthwise separable convolutions and residual connections, contributes to its exceptional performance. DenseNet-201, with its dense connectivity pattern fostering effective feature reuse, emerges as another robust performer. Notably, MobileNetV2 exhibits impressive accuracy, surpassing ResNet50 and Inception-ResNet-v2, showcasing its efficiency in capturing nuanced features among pigeon species.

The variance in accuracy and loss values underscores the importance of model selection tailored to the complexities within the pigeon dataset. Evaluating these metrics across models reveals significant disparities, indicating varying capacities to discern between pigeon breeds. As we transition from ResNet50 to Xception, there's a discernible upward trend in testing accuracy, signifying the models' increased ability to distinguish among pigeon breeds. This progressive increase in accuracy highlights the efficacy of architectural complexities and training strategies adopted in the models.

DenseNet-201 emerges as a competitive model, showcasing a balance between accuracy and computational efficiency. Its dense connectivity fosters robust feature extraction, contributing to its commendable performance. However, Xception claims the spotlight with the highest testing accuracy (99.47%) among the models. Its intricate architecture enables precise classification, suggesting its aptness for nuanced pigeon species identification. Hence, designating Xception as the primary model aligns with its superior performance, emphasizing its suitability for our pigeon species classification task and its potential for real-world applications.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

The implementation of our pigeon species classification system bears significant implications for society. Precision in identifying distinct pigeon breeds contributes to fostering a deeper understanding and preservation of avian diversity. Enthusiasts, researchers, and breeders in the pigeon community benefit from a reliable tool that swiftly and accurately distinguishes between various pigeon breeds. This technological advancement not only aids in preserving the unique traits and characteristics of each breed but also contributes to the promotion of avian diversity and heritage. Additionally, such a system can facilitate informed breeding practices, supporting efforts to conserve and propagate endangered or less common pigeon breeds. Ultimately, the availability of a robust classification system enhances the appreciation and conservation of pigeon species diversity, promoting a sustainable approach to avian husbandry and research.

5.2 Impact on Environment

In the context of pigeon species classification, our system bears a significant impact on environmental stewardship. By enabling precise identification and monitoring of pigeon breeds, it aids in conservation efforts by accurately cataloging various species and their distribution. This information is vital in understanding the ecological roles and population dynamics of different pigeon breeds, fostering conservation strategies aimed at preserving biodiversity.

The classification system can contribute to urban planning initiatives by providing insights into the distribution patterns of pigeon breeds in urban areas. Understanding these patterns aids in developing humane and eco-friendly strategies to manage pigeon populations, reducing potential conflicts and promoting coexistence between urban development and wildlife. The accurate identification and monitoring of pigeon species through our classification system promotes environmental awareness, supporting efforts to maintain ecological balance and biodiversity in both urban and natural habitats.

4.3 Ethical Aspects

Ethical considerations play a pivotal role in guiding our system's development and application. Our system contributes to ethical wildlife management by enabling non-invasive monitoring and classification of pigeon breeds. This aids in fostering a respectful and humane approach toward understanding and preserving avian diversity without disturbing their natural habitats.
Moreover, the system promotes ethical urban planning by providing insights into pigeon populations in urban areas. This information facilitates the development of humane strategies to manage pigeon-human interactions, respecting the needs of both urban residents and wildlife. By fostering coexistence and reducing potential conflicts, our classification system supports ethical practices in urban wildlife management. Our system's ethical implications revolve around promoting conservation efforts, respecting wildlife, and enabling informed decision-making for harmonious cohabitation between humans and pigeon species.

5.4 Sustainability Plan

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

CHAPTER 6

SUMMARY, CONCLUSION, RECOMMENDATION, AND IMPLICATION FOR FUTURE RESEARCH

6.1 Summary of the Study

This study pioneers avian conservation by enhancing the classification of pigeon species in Bangladesh using advanced deep learning models. With a meticulously curated dataset of 7,500 images spanning 15 pigeon species, the research leverages transfer learning, including models like ResNet50, Inception-ResNet-v2, DenseNet-201, MobileNetV2, and Xception. Notably, Xception achieves a remarkable testing accuracy of 99.47%. The study emphasizes the crucial role of tailored model selection and highlights an increasing accuracy trend with more complex architectures. Beyond technical achievements, the research aligns with the strategic imperative for avian conservation, offering insights for practical applications. This work not only contributes significantly to avian conservation efforts but also establishes a foundation for future endeavors at the intersection of technology and ethical avian biodiversity preservation.

6.2 Implication for Further Study

Our study has provided a strong foundation for classifying pigeon species, but there are many areas where we can explore and improve further. In the future, we can focus on making the model's decision-making process clearer and more interpretable. We can also develop real-time monitoring systems to keep track of pigeon species' health continuously. Expanding the classification framework to cover a wider range of avian health conditions would be beneficial. Additionally, it's important to evaluate how adaptable and applicable the system is across different geographic regions and farming contexts for broader adoption and practicality.

Considering ethics is crucial when implementing technological solutions for avian species management. Maintaining open communication with conservationists about the system's capabilities and limitations is vital for informed decision-making. Establishing explicit ethical guidelines for the responsible use of technology in avian conservation is essential to ensure the ethical treatment of avian species and promote environmentally sustainable conservation practices.

6.3 Conclusion

Our comprehensive exploration across diverse models for pigeon species classification concluded with the recognition of Xception as the most optimal model, exhibiting an outstanding testing accuracy of 99.47% and a negligible loss of 0.025. Through a meticulous analysis of the confusion matrix, we gained profound insights into the model's strengths and identified potential avenues for improvement. This robust performance highlights the pivotal role of the proposed pigeon species classification system as a critical tool in avian conservation, offering invaluable support in the timely identification and management of pigeon species.

In implementing technological solutions for conservation purposes, ethical considerations remain paramount. Transparent communication with conservationists regarding the system's capabilities and limitations is vital to ensure informed decision-making. Moreover, the establishment of stringent ethical guidelines for the responsible application of technology in avian conservation is crucial to upholding humane treatment and environmentally conscious practices. The impact of our research extends beyond conservation, potentially contributing to the preservation of urban biodiversity, the promotion of sustainable ecological practices, and the advancement of avian species management. These societal benefits underscore the significance of furthering research in the field of pigeon species classification and highlight the transformative potential of technological advancements in conservation efforts. Our study represents a significant stride in avian conservation, aligning advanced technology with ethical considerations and societal impact to pave the way for an evolved understanding of avian species and their habitats. The journey initiated by this research offers a platform for future investigations and collaboration, encouraging further exploration to unveil novel dimensions in avian species monitoring and bolster efforts toward a sustainable future for avian conservation and urban biodiversity.

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COMPUTER VISION-BASED TRANSFER LEARNING TECHNIQUES FOR CLASSIFICATION OF LOCAL PIGEON SPECIES IN BANGLADESH: A COMPARATIVE ANALYSIS

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