Monkey Species Identification Using CNN Model

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FINAL YEAR DESIGN PROJECT REPORT

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

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APPROVAL

This Project titled "Monkey Species Identification Using CNN Model," submitted by **Arif Hasan** 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 15-12-2024.

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I hereby declare that this project has been done by us under the supervision of **Dr. Arif Mahmud, Associate Professor,** Department of Computer Science and Engineering, Daffodil International University. I 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

The identification of monkey species using automated systems plays a crucial role in biodiversity research, wildlife conservation, and ecological studies. This study explores the application of Convolutional Neural Networks (CNNs) for classifying images of 10 monkey species collected from diverse sources, including the internet, zoos, and animal houses. A mixed dataset was developed, and six state-of-the-art CNN architectures—EfficientNet B7, DenseNet 201, VGG19, InceptionV3, MobileNet, and Xception—were evaluated for their performance. Among these, DenseNet 201 achieved the highest accuracy of 90.13% with a loss of 1.093, outperforming MobileNet, which attained 84.94% accuracy with 1.430 loss. EfficientNet B7 exhibited the lowest performance, with an accuracy of 64.28% and a loss of 3.76. To demonstrate the practical utility of the best-performing model, a web interface was developed using Python Flask API, enabling seamless image classification. This research provides valuable insights into the comparative performance of CNN architectures for species identification and highlights the potential of machine learning in advancing wildlife monitoring technologies.Using the Python Flask API, a web interface was created to show the best-performing model's usefulness in real-world scenarios by facilitating smooth picture categorization. This study demonstrates the potential of machine learning to advance wildlife monitoring technology and offers insightful information on the relative efficacy of CNN architectures for species identification.

Keywords- CNN architecture, Wildlife, Flask, API, EfficientNetB7, DenseNet201, VGG19, MobilNETV2, Xception, Accuracy

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Chapter 1

Introduction

Animal species classification is an important undertaking having applications in ecological study, agricultural management, and wildlife protection. Identifying species accurately may help in managing invasive species, identifying endangered animals, and monitoring biodiversity. Manual identification techniques, however, are frequently laborious, prone to mistakes, and need specialized knowledge. The development of machine learning and artificial intelligence has made automated solutions an attractive alternative.

1.1 Introduction

Animal species classification is an important undertaking having applications in ecological study, agricultural management, and wildlife protection. Identifying species accurately may help in managing invasive species, identifying endangered animals, and monitoring biodiversity. Manual identification techniques, however, are frequently laborious, prone to mistakes, and need specialized knowledge. The development of machine learning and artificial intelligence has made automated solutions an attractive alternative.

The most well-known of them is Convolutional Neural Networks (CNNs), which are perfect for image-based classification jobs because of their capacity to evaluate visual data and extract pertinent information. The goal of this study is to employ CNNs to create an automated system for categorizing ten different species of monkeys. Since monkeys are important to ecosystems and are frequently threatened by habitat loss, poaching, and climate change, accurate identification methods are crucial to conservation efforts.

The absence of a reliable, scalable, and effective method for recognizing monkey species under various circumstances is the issue that this study attempts to solve. Current solutions could be constrained by their incapacity to generalize across datasets or their heavy reliance on manual intervention. This research aims to assess and choose the best model for this job by utilizing many CNN architectures, such as DenseNet 201, VGG19, and MobileNet. Moreover, incorporating the top-performing model into an online interface guarantees usability and accessibility, enabling the tool to be used in real-world situations. This study assists ecological and conservation efforts in addition to advancing picture categorization technology.

1.2 Motivation

The need for accurate and efficient species identification is critical for biodiversity conservation, particularly for monkeys, which play vital ecological roles. Traditional methods are time-consuming, error-prone, and limited in scalability. The rapid advancements in artificial intelligence, especially Convolutional Neural Networks (CNNs), offer a transformative approach to addressing these challenges. This research aims to leverage CNNs for classifying 10 monkey species, providing an automated, accurate, and scalable solution. By integrating the best-performing model into a web application, the study seeks to make this technology accessible, contributing to wildlife conservation and advancing AI applications in ecology.

1.3 Objectives

The key objective of this study is to use convolutional neural networks (CNNs) to create an automated system that can correctly categorize ten different species of monkeys. In order to do this, a large collection of monkey photos is compiled from zoos, animal shelters, and internet sites, guaranteeing a range of settings and viewpoints. To find the best model for this classification challenge, six CNN architectures are trained and assessed: EfficientNet B7, DenseNet 201, VGG19, InceptionV3, MobileNet, and Xception. Hyperparameter tweaking, augmentation methods, and data pretreatment are used to improve generalizability and model performance. Using the Python Flask API, the top-performing model is included into a web application, allowing for real-time species identification in an intuitive user interface. The goal of this project is to provide a workable and scalable technology that may be used for ecological monitoring, conservation initiatives, and wildlife management.

1.4 Methodology

The methods used for this study include compiling a broad array of photos for ten monkey species from internet sources, zoos, and animal shelters. Images are carefully scaled to 500x500 pixels and added to increase dataset variety. The data is divided into two categories: 80% for training and 20% for testing. Six CNN architectures—EfficientNet B7, DenseNet 201, VGG19, InceptionV3, MobileNet, and Xception—are trained and tested on Google Colab and Kaggle using Python tools like TensorFlow and Keras. Each model is evaluated using measures like as accuracy and loss, and DenseNet 201 emerges as the top performer. The chosen model is used to classify monkey species in real time using a Python Flask API-based web application, guaranteeing practical use in conservation and ecological applications.

1.5 Project Outcome

The expected output of this research includes a comparative evaluation of six CNN models—EfficientNet B7, DenseNet 201, VGG19, InceptionV3, MobileNet, and Xception—for categorizing photos of ten monkey species, with DenseNet 201 likely to achieve the highest accuracy and lowest loss. In addition, the best-performing model will be used to create a web-based application that allows for real-time monkey species identification. This tool will be accessible to academics and conservationists, and the project will provide insights into how dataset quality affects CNN performance in animal categorization.

1.6 Organization of the Report

Chapter 1: Introduction

This chapter contains the following: the introduction of monkey identification, the motivation for this research work, the research question, the expected outcomes, and the project management and financial analysis from the study.

Chapter 2: Background Study

Here discuss the basic concept, a brief overview of the extent of the issue, and the scope of the problems and challenges within the research process.

Chapter 3: Research Methodology

This part presents research instruments,dataset, method, and requirements for executing the research.

Chapter 4: Experimental Result and Discussion

This chapter explains experimental results and analyzes this.

Chapter 5: Impact on Society, Environment and Sustainability

Here research's effects on the environment and society, as well as the study's ethical considerations and long-term plan.

Chapter 6: Summary, Conclusion, Recommendation and Implication for Future Research

This chapter offers a summary of all the findings, a conclusion, and suggestions for more study.Here put a chapter-wise structure of the report in narrative form.

Chapter 2

Background

This chapter presents the backdrop for the research by outlining the importance of automated animal species categorization and the relevance of deep learning techniques, namely Convolutional Neural Networks (CNNs), in solving this difficulty. It examines the study's importance to conservation efforts and emphasizes the technology breakthroughs that enable such systems.

2.1 Introduction

This part presents the necessary background information for understanding the future sections of this study. It describes the fundamental concepts, tools, and techniques that underpin the research, such as the role of Convolutional Neural Networks (CNNs) in image classification, the difficulties of identifying monkey species, and the significance of technological advancements in conservation efforts. In addition, the section covers why various CNN architectures were chosen, the function of preprocessing and data augmentation, and the study's practical implications. By providing this context, the section ensures that the procedures and objectives mentioned in the report are well understood.

2.2 Literature Review

Some Literature Review Are Given Below:

Table 2.1: Summary of Literature Reviewed.

Research	Model Architecture	Dataset	Accuracy	Novelty/Contribution
Kamepalli et al. (2021)	Deep CNN	Kaggle 10 Monkey Species	0.8050 (train), 0.7353 (validation)	Applies deep learning to primate breed classification
Wiranda et al. (2022)	CNN	Android App, Photos, Videos	93.6% (photos), 79% (videos)	Develops an app for primate identification in Indonesia
Xu et al. (2020)	Multi-view CNN	Wireless Acoustic Sensor Networks	High accuracy	Proposes a deep learning framework for acoustic animal classification
Kumar et al. (2021)	VGG19, YOLO	Google Open Images V4	97.19% TPR, 95.32% TNR	Develops deep learning models for real-time monkey detection
Pillai et al. (2023)	CNN	1370 images	81%	Applies deep learning to animal species identification and categorization
Taheri et al. (2018)	CNN + Appearance-based features	Animal Faces	95.31%	Proposes a novel method for animal face classification using feature fusion

2.2.1 Similar Applications

Some of related works are given below with their citation:

Zeng et al. (2021, December) research uses a 2D CNN to classify animal images, achieving 96.67% accuracy rates for training and nearly identical results for testing. This demonstrates the potential of CNNs in identifying subtle species differences, aiding in the conservation of rare species.[1]

In this study by Kamepalli et al. (2021) A deep Convolutional Neural Network was trained to classify and predict primate breeds using a 10 monkey species dataset from the Kaggle data science community. The model achieved an accuracy of 0.8050 on the training set and 0.7353 on the validation set, helping to identify and protect primate breeds from extinction. Future research could extend this process to automate the process using IoT.[2]

This study by Wiranda et al.(2022) discusses that Indonesia is home to six of the 25 most endangered primates, including Orangutan, Lutung, Bekantan, Tarsius tumpara, Kukang, and Simakobu. To preserve these primates, an android app was developed using the CNN method to identify them in Kalimantan wetlands. The app was tested using photos and video recordings, with an average accuracy of 93.6% for photos and 79% for videos.[3]

This paper by Xu et al. (2020) proposes a deep learning-based acoustic classification framework for Wireless Acoustic Sensor Networks (WASN) to improve automatic identification of animal species. The framework uses cloud architecture and a multi-view Convolutional Neural Network to extract short-, middle-, and long-term dependencies. The architecture achieves high accuracy and outperforms traditional classification systems in low SNR environments. The system's performance is evaluated in real-world environments.[4]

The study by Kumar et al. (2021). presents deep learning architectures for real-life and real-time detection of native Indian monkeys, aiming to assist farmers in protecting their crops from wild animal attacks. The researchers engineered a pre-trained VGG19 convolution neural network (CNN) and custom trained YOLO, a faster CNN architecture, using the Google Open Images V4 dataset. The custom trained architecture achieved a high true positive rate of 97.19% and true negative rate of 95.32%.[5]

This paper Sowmya et al. (2022). presents a classification system for animal images, including dogs, cats, elephants, pandas, and monkeys. The system uses MobileNet Architecture and an SVM classifier to categorize distinct animals. Experiments on an Animal Image Dataset of 800 images showed a 99% performance, benefiting forest services, research, and preventing domestic animal disturbance.[6]

This paper by Pillai et al. (2023, July) discusses A CNN model that was proposed to identify and categorize these species using 1370 and 272 images. The model achieved an 81% accuracy rate, demonstrating the value of deep learning methods for animal classification. This model can assist in monitoring animal populations, distributions, and behaviors, identifying threats and focusing conservation efforts more effectively.[7]

In this study by Taheri et al (2018). discuss a novel method for animal face classification is presented using a score-level fusion of convolutional neural network (CNN) features and appearance-based descriptor features. This method is better than other simple feature extraction techniques and can achieve even higher accuracy than CNN alone. The score-level fusion of CNN extracted features and appearance-based KFA method has a positive effect on classification accuracy, achieving a 95.31% classification rate on animal faces.[8]

2.2.2 Related Research

The reviewed research articles illustrate the tremendous potential of deep learning approaches, particularly CNNs, for accurately and efficiently classifying animal species. These approaches have the potential to transform wildlife conservation, ecological monitoring, and agriculture operations. However, issues like as data scarcity, processing costs, and model interpretability persist. Future research should concentrate on solving these problems and developing novel techniques to progress the discipline.

2.3 Gap Analysis

The gap analysis identifies various limitations in current animal species classification studies, specifically the use of Convolutional Neural Networks (CNNs) to identify monkey species. Many researches depend on tiny or non-diverse datasets, which limits the models' generalizability. Furthermore, while CNNs have demonstrated great accuracy in controlled environments, their real-world implementation remains difficult due to concerns such as computational resource constraints, latency, and adaptation to changing situations. Furthermore, few systems provide easily accessible tools, such as web interfaces, for non-expert users. This study fills these gaps by utilizing a broad dataset of ten monkey species, comparing several CNN architectures, and implementing the best model in a user-friendly online application, so contributing to both scientific advances and practical conservation applications.

2.4 Summary

This work makes use of important ideas and resources from computer vision and machine learning. Ten monkey species' photos are classified using a Convolutional Neural Network (CNN), and the model's efficacy is assessed using performance measures such as accuracy and loss. Images from zoos, animal houses, and internet sources make up the dataset, which is used to train and evaluate the algorithms. Using the top-performing CNN model, a web-based interface for real-time species identification is developed using Flask API. Transfer learning is one technique used to optimize performance with little data by fine-tuning pre-trained models. The models' classification capabilities are further evaluated using evaluation measures including accuracy, recall, and F1 score, and overfitting is closely watched to guarantee generalization to unobserved data. Together, these concepts and tools are central to the research, providing the necessary foundation for building and deploying an automated monkey species identification system.

Chapter 3

Research Methodology

This section outlines the methodology adopted for this research and details the requirements and design specifications for the system.

3.1 Methodology/Requirement Analysis & Design Specification

The methodology takes an organized approach, beginning with dataset collection and preprocessing and progressing through model selection, training, assessment, and deployment. Images of ten monkey species were acquired from various sources, scaled to 500x500 pixels, and divided into two groups: 80% for training and 20% for testing. Data augmentation techniques like flipping and rotation were used to increase dataset variety.

Six CNN architectures—EfficientNet B7, DenseNet 201, VGG19, InceptionV3, MobileNet, and Xception—were chosen for examination because to their shown performance in image categorization tests. Each model was trained and evaluated with Python libraries such as TensorFlow and Keras, which were run on sites such as Google Colab and Kaggle. The best model was selected based on performance criteria such as accuracy and loss. DenseNet 201, with an accuracy of 89.98%, emerged as the best model.

The system design includes a web-based interface built with Python Flask API, which allows users to upload photos for real-time categorization. The design combines a user-friendly interface with fast backend processing to achieve accurate forecasts. This part also takes into account computing resource needs, scalability, and the system's responsiveness for actual applications. By combining strong methodology with well-defined design criteria, the study guarantees that an efficient and deployable solution is developed.

3.1.1 Overview

This section describes the systematic strategy taken for this study, which included dataset preparation, model selection, and system design. Images of ten monkey species were gathered, reduced to 500x500 pixels, and divided between 80% training and 20% testing sets, with data augmentation used to increase variety. Six CNN models were tested, with DenseNet 201 attaining the greatest accuracy (89.98%). A web-based interface built using the Python Flask API was created for real-time species categorization, assuring scalability, efficiency, and user accessibility for practical applications.

3.1.2 Dataset Description

The dataset represents 10 different classes of monkey species. These are the classes:

"Bald Uakari, Emperor Tamarin, Golden Monkey, Gray Langur, Hamadryas Baboon, Mandril, Proboscis Monkey, Red Howler, Vervet Monkey, White Faced Saki". **Figure 3.1 shows the dataset Distriburtion**

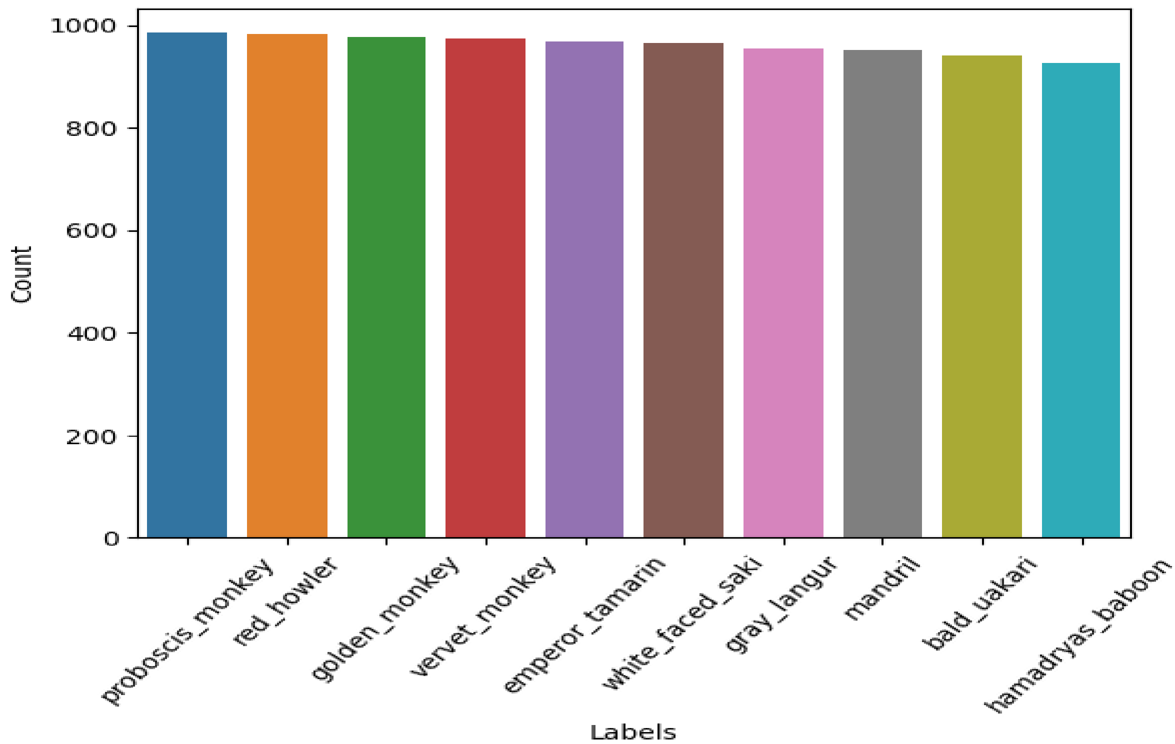
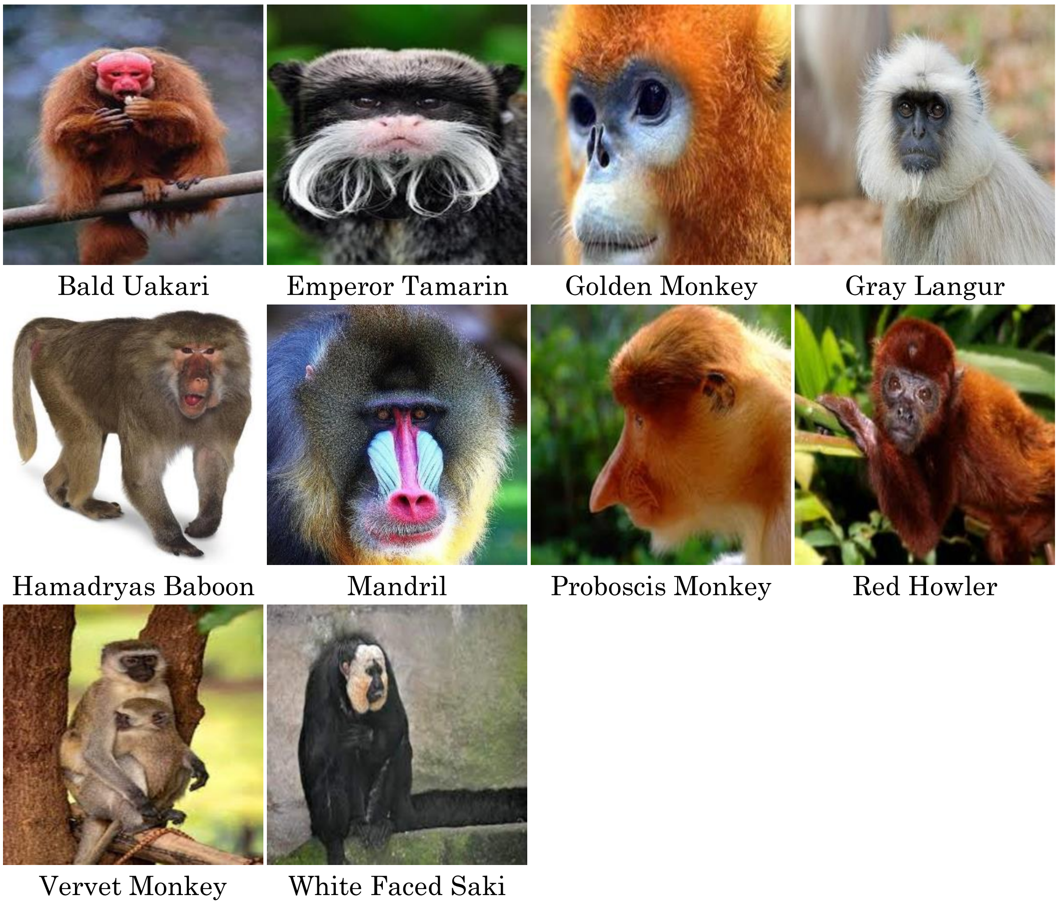


Figure 3.1: Distribution of monkey images in 10 classes shown by a bar chart.

Figure 3.2 shows the dataset image's ten classes, along with their respective names.



3.1.3 Statistical Analysis

Statistical Analysis of the Monkey Classification Dataset

Here, my dataset has total classes of 10 and total images of 9626 with an image resolution of 512x512 pixels.

Table 3.1: Statistical Analysis of Monkey Image Dataset

Class Name	Number of Image
Bald Uakari	942
Emperor Tamarin	968
Golden Monkey	978
Gray Langur	956
Hamadryas Baboon	926
Mandril	951
Proboscis Monkey	984
Red Howler	983
Vervet Monkey	973
White Faced Saki	965
Total	9626

3.1.4 Proposed Methodology/ System Design

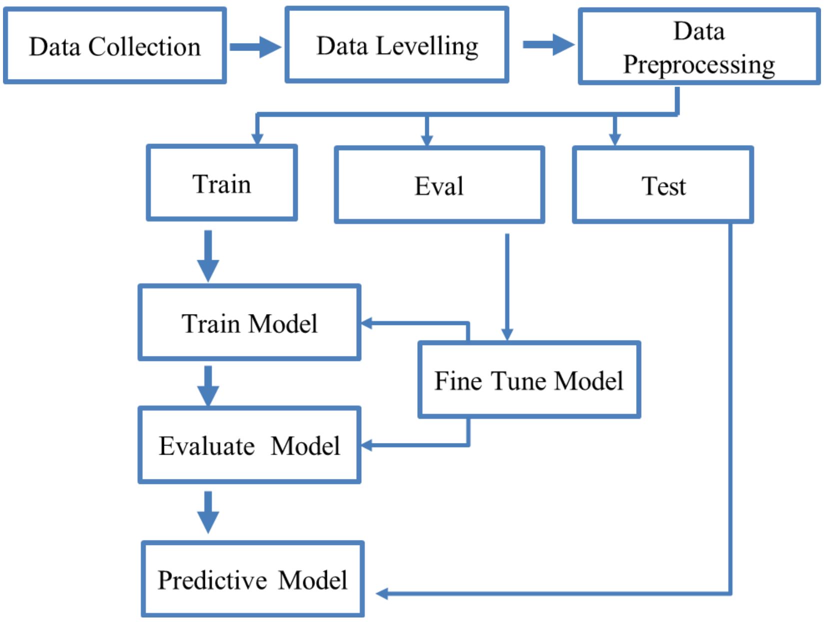


Figure 3.3: Methodology diagram

3.1.5 Functional and Nonfunctional Requirements

Functional Requirements

- Preprocess images by resizing to 500x500 pixels and applying data augmentation.
- Classify images into 10 monkey species accurately.
- Integrate the best-performing CNN model for deployment.
- Provide a real-time web interface for image uploads and classification.
- Display classification results, including accuracy and confidence scores.

Nonfunctional Requirements

- Ensure scalability to handle multiple inputs and future expansions.
- Maintain efficient processing with minimal latency.
- Deliver reliable performance across diverse input conditions.
- Design an intuitive and user-friendly interface.
- Ensure compatibility with cloud platforms like Google Colab.
- Provide secure data uploads and ensure user privacy.

3.1.6 UI Design

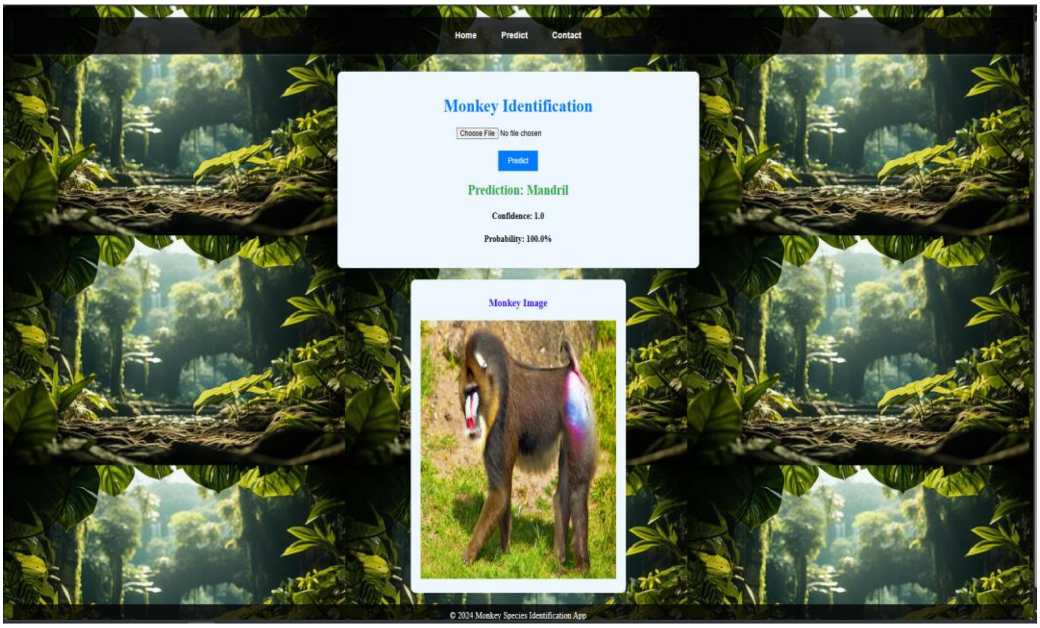


Figure 3.4: UI design

3.2 Detailed Methodology and Design

This section clarifies on the technique and design process used to create the monkey species categorization system. It describes the data collecting, preprocessing, model selection, training, assessment, and deployment processes, as well as the web-based application's design standards.

Data collection and preprocessing

A dataset of 10 monkey species was compiled from multiple sources, reduced to 500x500 pixels, and enhanced with techniques such as flipping, rotation, and brightness modifications. To properly evaluate model performance, the dataset was separated into two parts: 80% for training and 20% for testing.

Model Selection and Training

Six CNN architectures were chosen on the basis of how well they classified images. Python packages like as TensorFlow and Keras were used for training and testing on Google Colab and Kaggle. With an accuracy of 90.13%, DenseNet 201 fared better than the others.

System Design and Implementation:

A Python Flask API web interface was created for real-time categorization, which allows users to upload photos and view results. The DenseNet 201 model was incorporated for high accuracy and low latency, ensuring future scalability.

Performance Evaluation:

The model was verified on the testing dataset using measures such as accuracy, precision, recall, F1 score, and confusion matrix to ensure system reliability and robustness.

This organized methodology and well created architecture guarantee that the system is excellent at detecting monkey species while remaining simple to use and scalable.

3.3 Project Plan

The project is divided into five sections that span 12 weeks. The first step (2 weeks) entails gathering and preprocessing photos of 10 different monkey species, resizing them, performing data augmentation, and dividing the dataset into training (80%) and testing (20%) sets. The second step, which lasts three weeks, involves assessing and training six CNN models before picking the top performance, DenseNet 201. In the third phase (3 weeks), a user-friendly web interface is created using the Python Flask API, which incorporates the DenseNet 201 model for real-time classification. The fourth step (two weeks) consists of model evaluation utilizing precision, recall, F1 score, and confusion matrix, followed by revisions. Finally, in the fifth phase (two weeks), the final report is generated and the system is made available to the public.

3.4 Summary

This chapter provided an overview of the monkey species categorization system's project design, methodology, and work allocation. It covered the major processes, such as data collection and preprocessing, model selection and training, web interface creation, assessment and validation, and final deployment. Tasks were assigned to team members based on their areas of expertise, ensuring that each step was carried out efficiently. The chapter also outlined the project's timeframe, ensuring that the categorization system is developed and deployed successfully and on time.

Chapter 4

Implementation and Results

In this Chapter I discuss About the CNN Model Accuracy, Loss, Classification Report & Confusion Matrix. Here I Compare the 6 CNN model And Show the Comparison.

4.1 Environment Setup

This study uses a multi-stage experimental approach to use Convolutional Neural Networks (CNNs) to categorize photos of ten different monkey species. To begin, the photos are manually scaled to 500x500 pixels, then data augmentation techniques are used to enrich the dataset. To achieve robust model assessment, the data is divided into two sections: 80% for training and 20% for testing. Six CNN models—EfficientNet B7, DenseNet 201, VGG19, InceptionV3, MobileNet, and Xception—are trained using cloud-based platforms such as Google Colab and Kaggle using Python libraries like as TensorFlow and Keras, with GPUs being used for efficient training. The models are then scored using measures such as accuracy, loss, precision, recall, and F1 score. The best-performing model is chosen and incorporated into a web-based interface designed using Python Flask API for real-time monkey species identification, providing a user-friendly platform for classification tasks.

4.2 Testing and Evaluation/Performance/ Comparative Analysis

This work uses the Pretrain CNN model to categorize Monkey species. Data is preprocessed, which includes scaling, normalization, level generation, and data management. The data is separated into 80% training and 20% testing, with data generated using an image generator. Parameters and functions are used to customize the model layer, batch, epoch, and callback. Early stopping is employed depending on validation accuracy, with 100 epochs conducted and 30 epochs finished if the accuracy remains constant. The results are given in a sequential order.

Table 4.1: Comparison Analysis Based on Accuracy & Loss

CNN Model	Model Accuracy	Model Loss
DenseNet201	90.13%	1.09%
MobileNetV2	84.94%	1.43%
Xception	82.04%	1.76%
VGG19	72.07%	2.51%
InceptionV3	75.55%	2.56%
EfficientNetB7	64.28%	3.76%

Evaluation Criteria:

The efficacy of the CNN base algorithms is evaluated using metrics from machine learning classification models, including F1-score, accuracy, precision, recall, and confusion matrix. Additionally, these measures take into account characteristics related to false positives, false negatives, true negatives, and true positives. Using certain parameters, the performance of the comparison is estimated.

4.3 Results and Discussion

The corresponding Figure 4.1 represents the DenseNet201 models accuracy curves

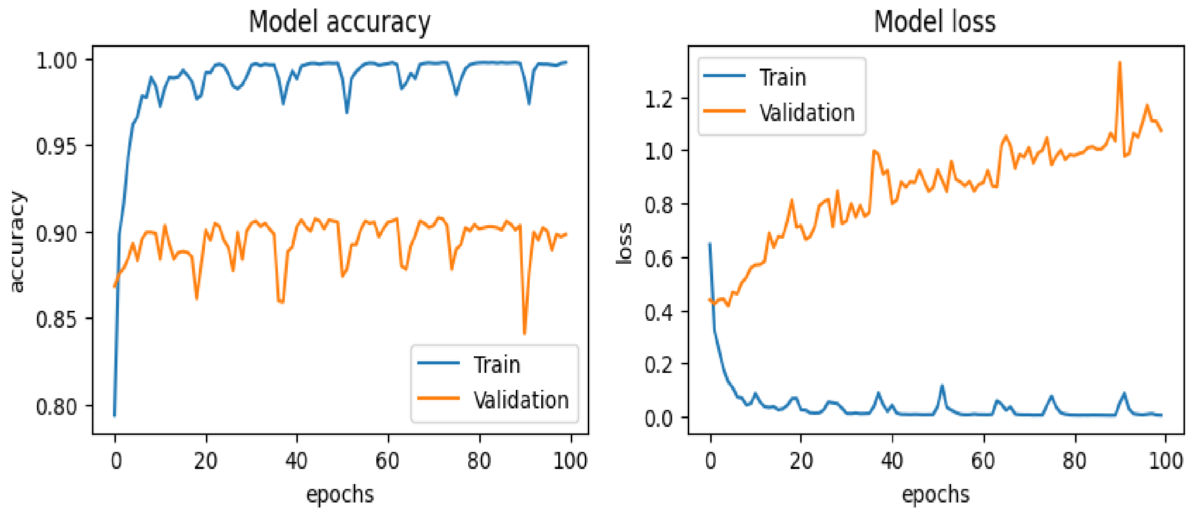


Figure 4.1: Accuracy Curve of DenseNet201

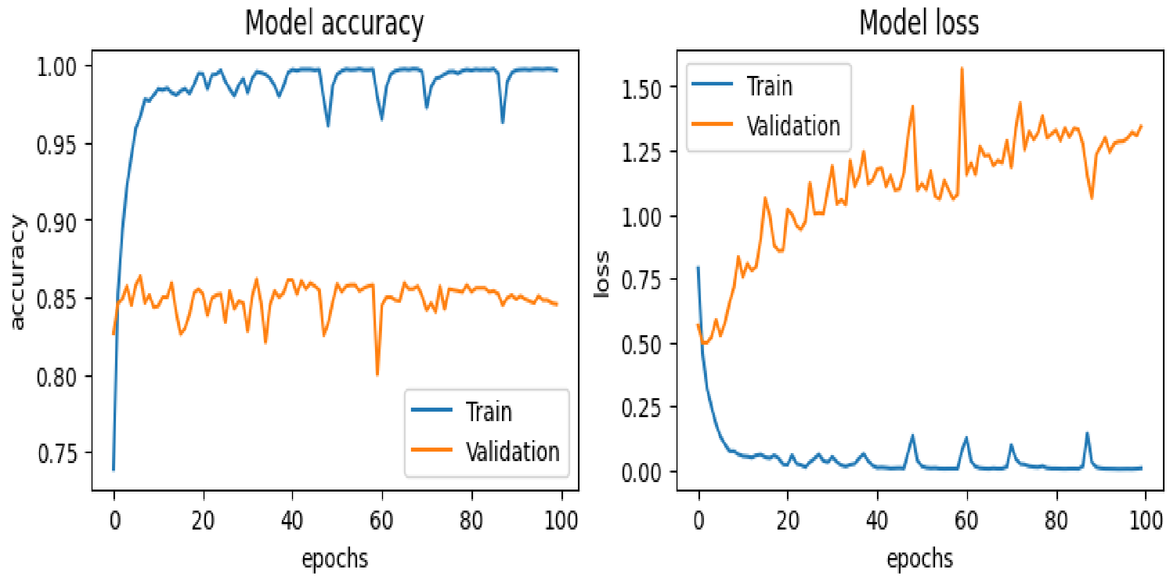


Figure 4.2: Accuracy Curve of MobileNetV2

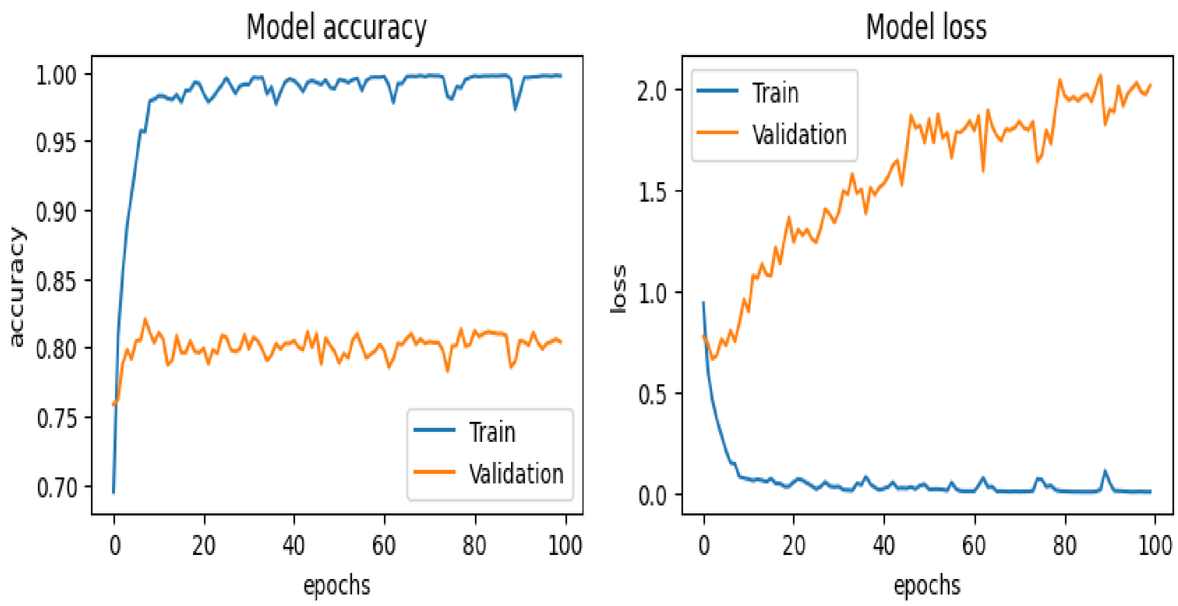


Figure 4.3: Accuracy Curve of Xception

The corresponding Figure 4.4 represents the VGG19 models accuracy curves

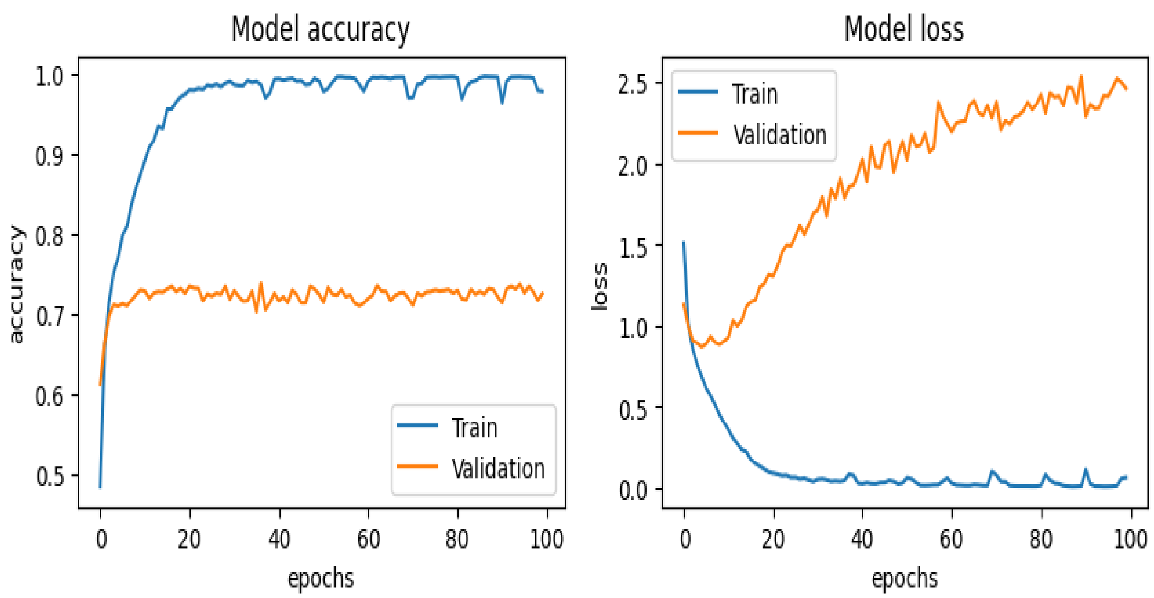


Figure 4.4: Accuracy Curve of VGG19

The corresponding Figure 4.5 represents the InceptionV3 models accuracy curves

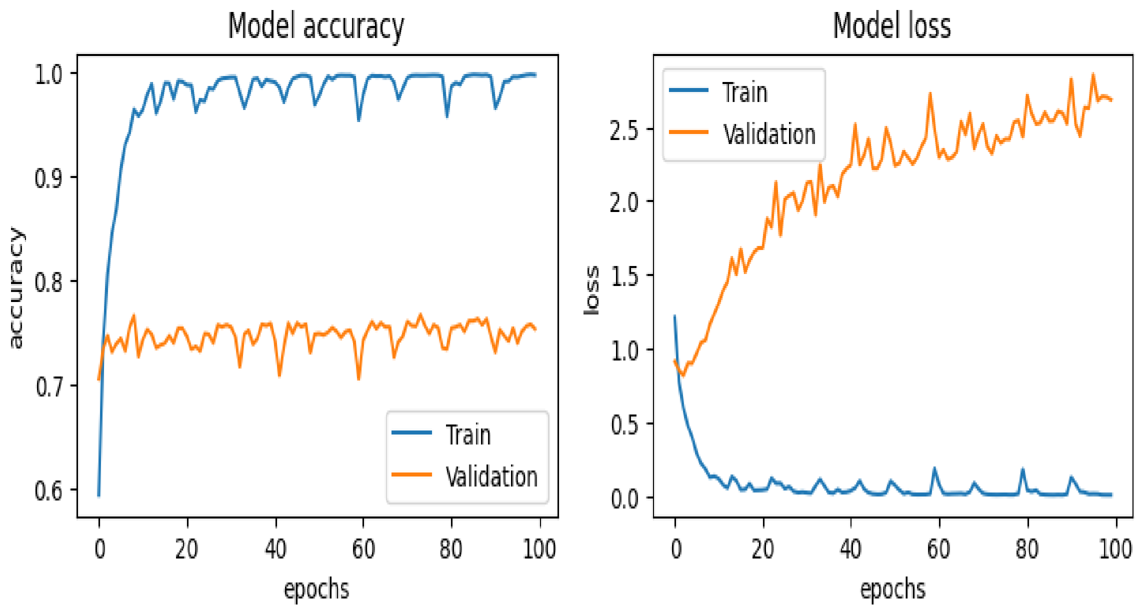


Figure 4.5: Accuracy Curve of InceptionV3

The corresponding Figure 4.6 represents the EfficientNetB7 models accuracy curves

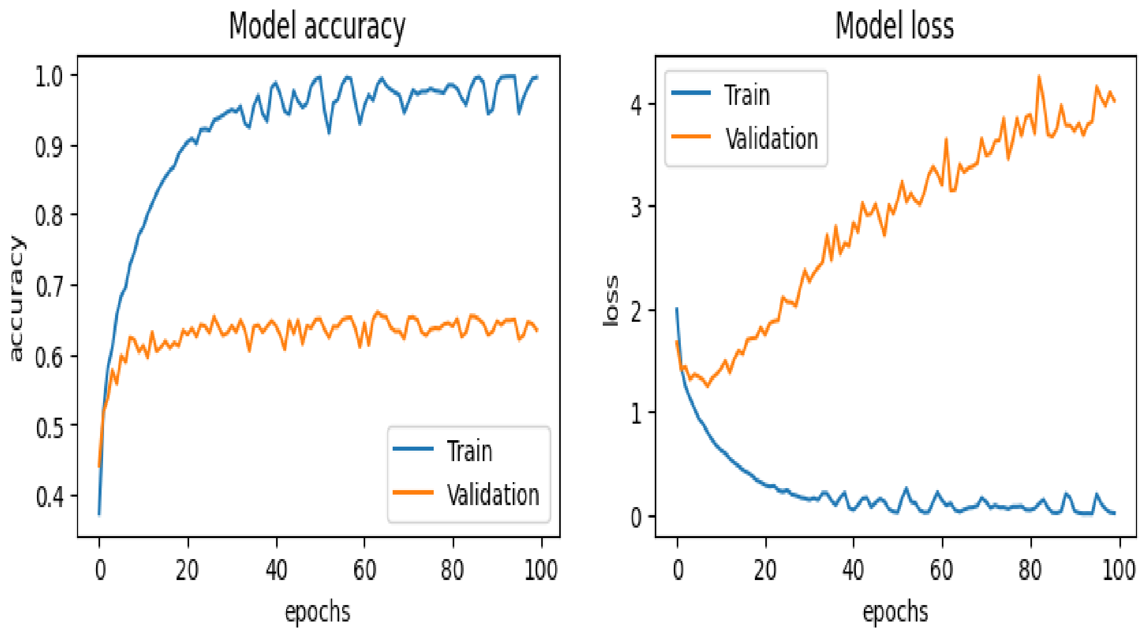


Figure 4.6: Accuracy Curve of EfficientNetB7

Now Confusion Matrix of those Comparative Model Are Given Below:

The corresponding Figure 4.7 represents the confusion matrix of DenseNet201

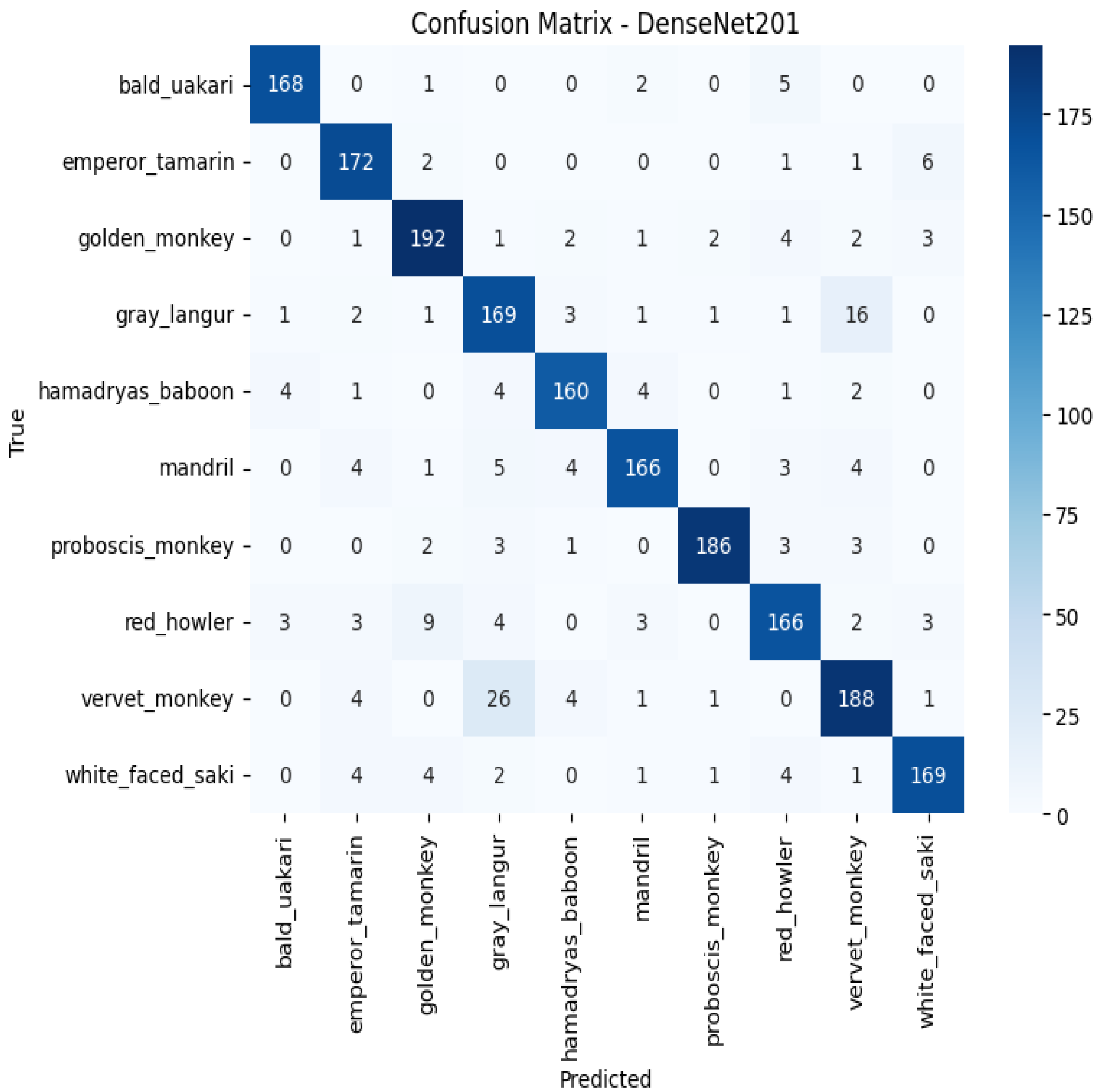


Figure 4.7: Confusion matrix of DenseNet201

Figure 4.7 demonstrate the confusion matrix of EfficientNetB7

The corresponding Figure 4.8 represents the confusion matrix of MobileNetV2

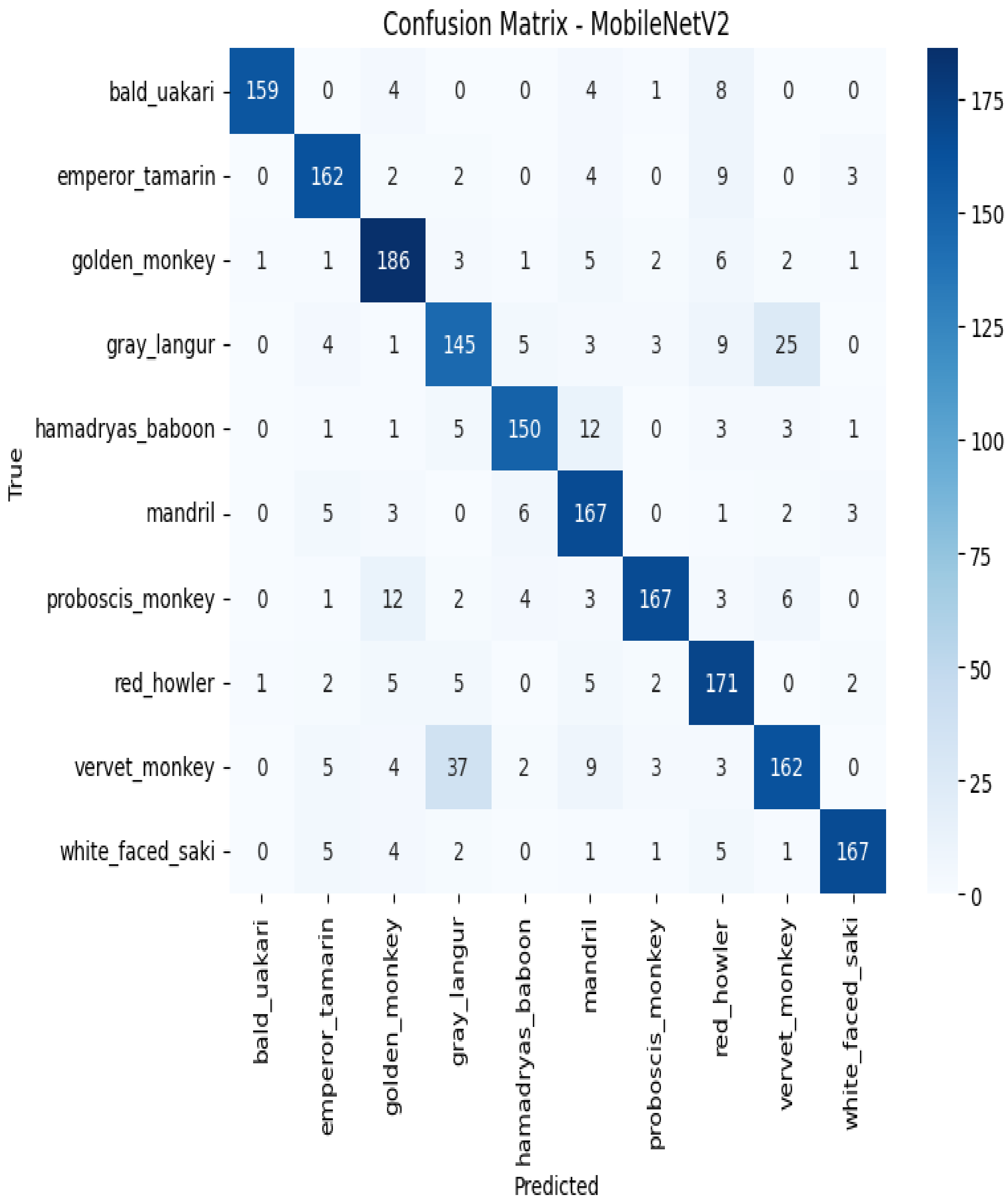


Figure 4.8: Confusion matrix of MobileNetV2

The Corresponding Figure 4.9 represents the confusion matrix of Xception

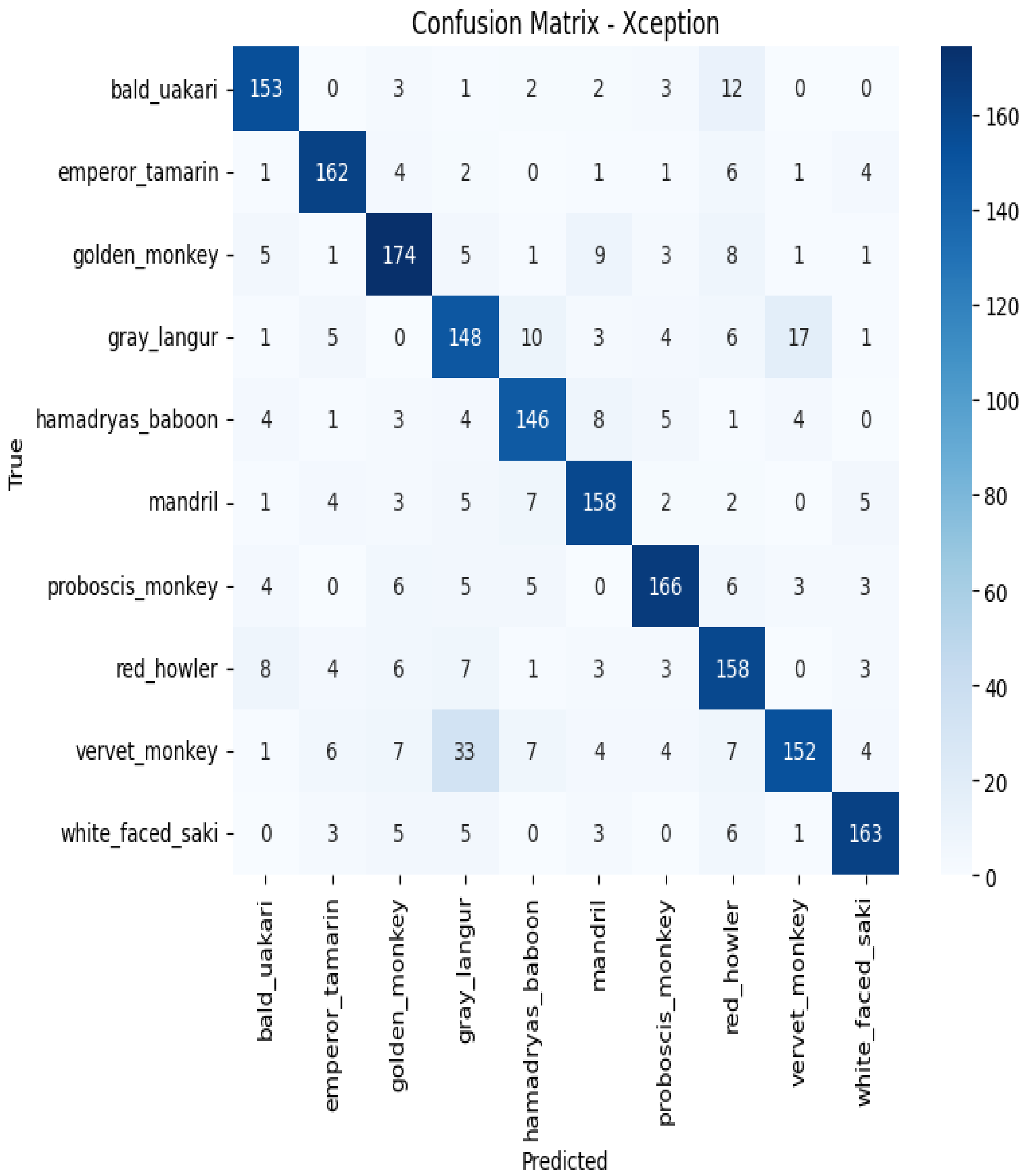


Figure 4.9: Confusion matrix of Xception

The Corresponding Figure 4.10 represents the confusion matrix of VGG19

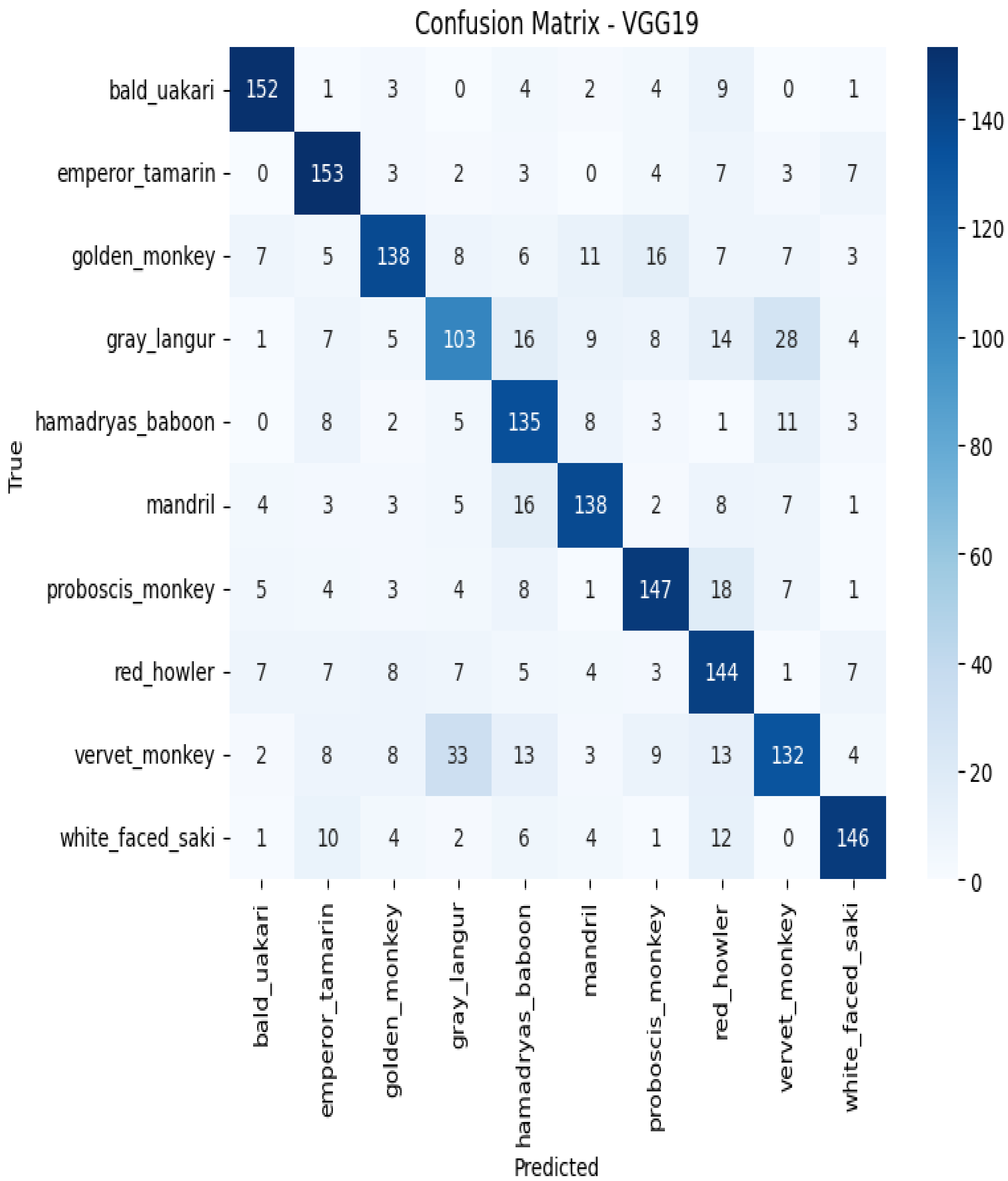


Figure 4.10: Confusion matrix of VGG19

The Corresponding Figure 4.11 represents the confusion matrix of InceptionV3

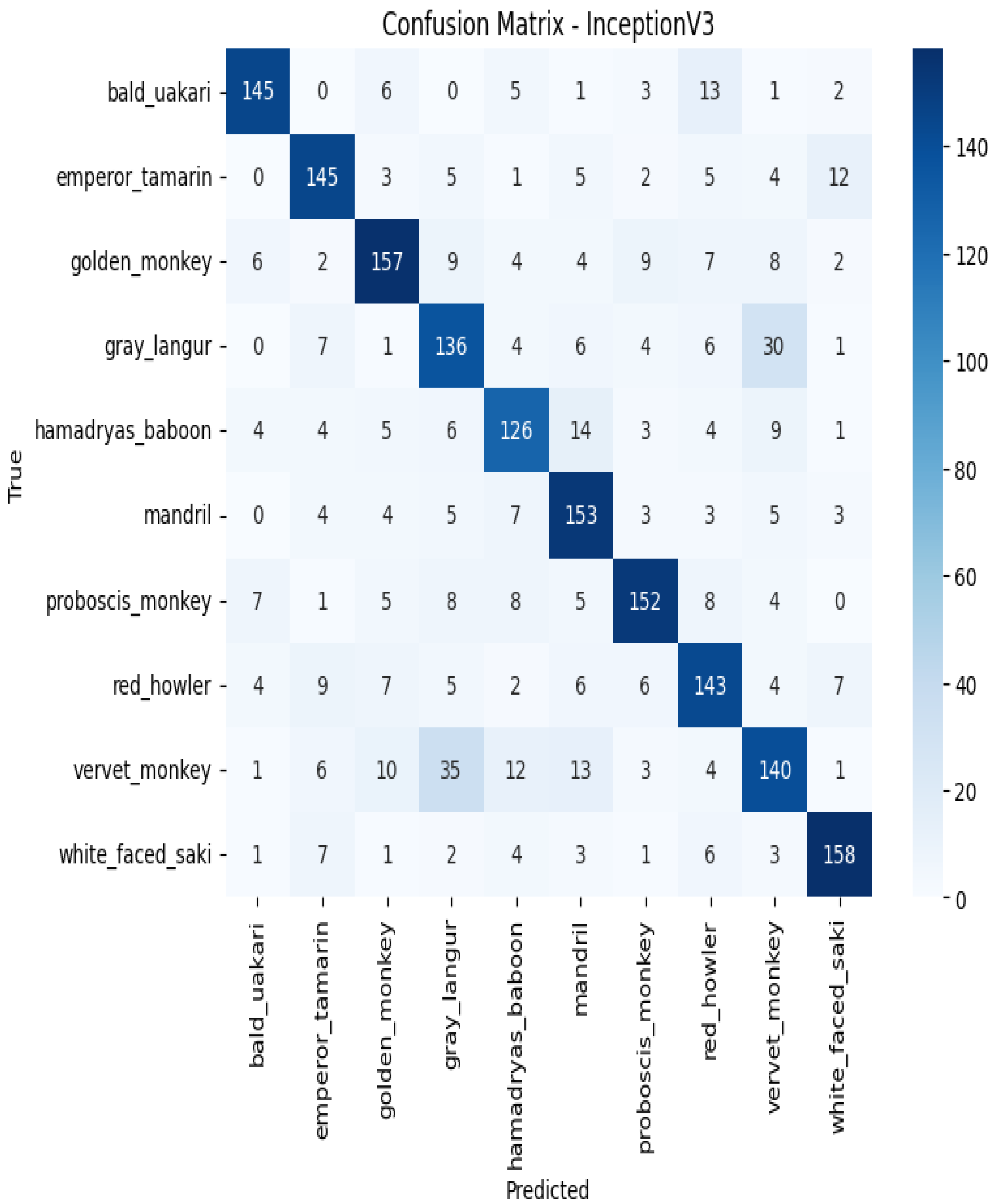


Figure 4.11: Confusion matrix of InceptionV3

The Corresponding Figure 4.12 represents the confusion matrix of InceptionV3

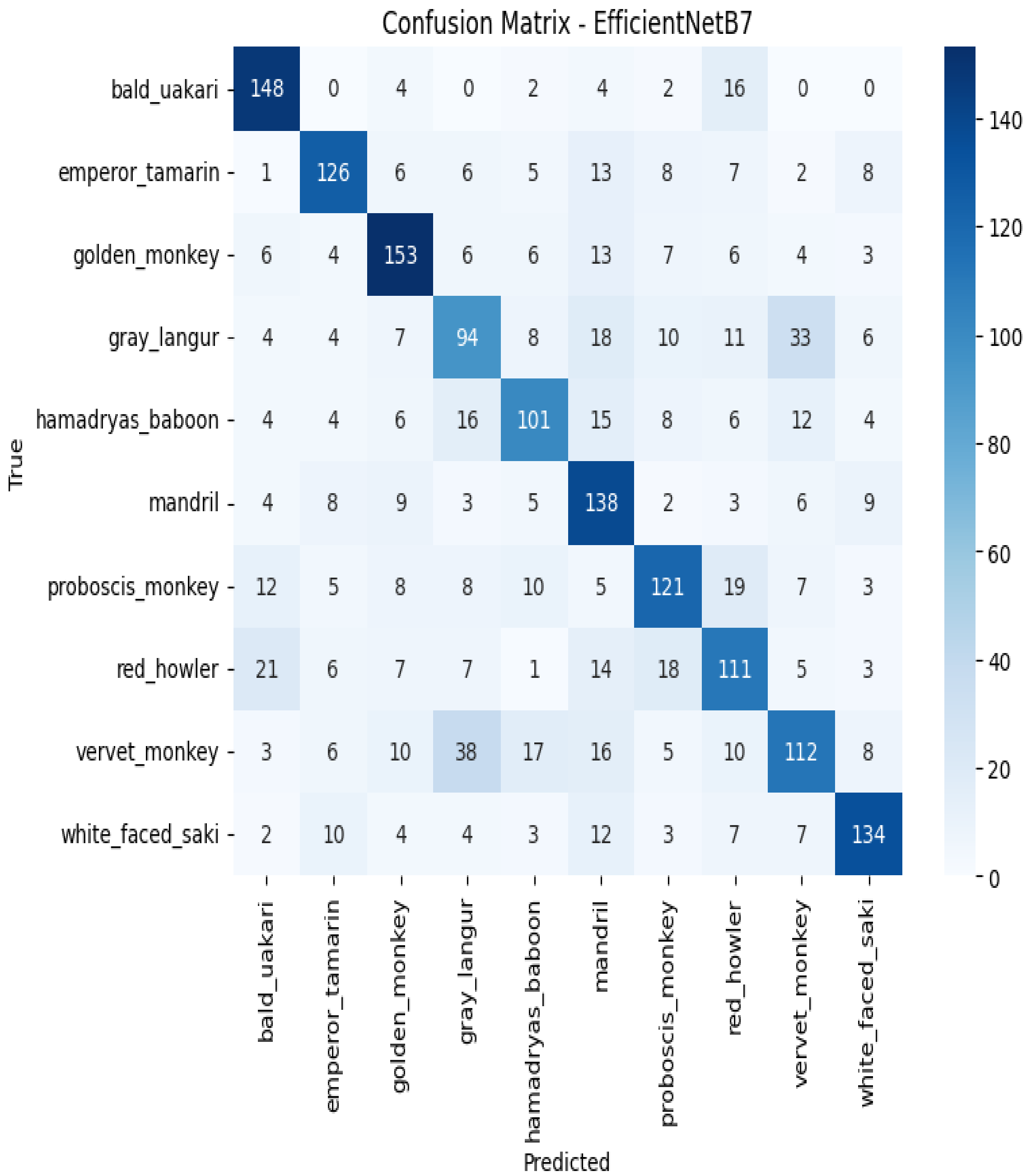


Figure 4.12: Confusion matrix of InceptionV3

The study analyzes Six CNN models, EfficientNetB7, DenseNet201, VGG19, Xception, InceptionV3 and MobileNetV3, to discover which one is better for Monkey species categorization. DenseNet201 surpasses the others in identifying different Monkey species. The model's implementation in a Flask API with a user-friendly interface displays its practical application, emphasizing the significance of technology and efficacy in monkey identification.

4.4 Summary

The study assessed several Convolutional Neural Network (CNN) models for identifying species of monkeys. Top performance Densenet201 achieved low loss and 90.13% accuracy. Following closely behind with 84.94% accuracy was MobileNetV2. Xception performed well as well, with 82.04% accuracy. For real-time applications, DenseNet201 was an attractive option because to its 90.13% accuracy and 1.09 loss. Interpretability studies to maximize performance in diverse monkey datasets may be the main focus of future study.

Chapter 5

Engineering Standards and Design Challenges

5.1 Compliance with the Standards

The project follows software, hardware, and communication standards for efficiency and scalability. PEP 8 ensures clean code, cloud platforms enable fast model training, and tools like Slack and GitHub facilitate team collaboration. The system uses a user-friendly interface for smooth communication. These standards ensure reliable development and deployment.

5.1.1 Software Standards

The monkey species classifying system is built with Python, TensorFlow, Keras, and Flask. Version control is handled by Git, and PEP 8 formatting is used. Error management, unit testing, and debugging ensure reliability. Security safeguards are in place to secure user data, and the system is built for speed and efficiency.

5.1.2 Hardware Standards

The project is developed on cloud-based platforms such as Google Colab and Kaggle, and it makes use of GPU/TPU resources to train models effectively. The web interface for seamless real-time categorization is hosted on a scalable server, while cloud services handle memory and storage. When training, computation is optimized using high-performance GPUs and TPUs.

5.2 Impact on Society, Environment and Sustainability

5.2.1 Impact on Society

This study has important social effects, especially for education and animal protection. Conservationists are able to monitor biodiversity and safeguard endangered species by using it to accurately identify monkey species. Researchers, educators, and the general public may now access this technology through the use of a web-based categorization tool, raising awareness and encouraging a more thorough comprehension of ecological variety. Furthermore, the research develops the use of AI and computer vision in biodiversity studies, showing how state-of-the-art technology can solve practical environmental problems and promote public participation in wildlife conservation initiatives.

5.2.2 Impact on Environment

This research has an important effect on the environment since it promotes biodiversity conservation and the protection of monkey species, many of which are fragile or endangered. Accurate species identification helps conservationists track population dynamics, detect habitat changes, and respond effectively to environmental hazards. The research contributes to the prevention of illicit wildlife trafficking and poaching, both of which pose serious hazards to many species, by offering a tool that aids in identification. Furthermore, the application of AI and computer vision reduces the necessity for intrusive identification procedures, lowering human intervention in natural ecosystems. These developments help to create more sustainable conservation techniques, ensuring that species are preserved while their habitats are not disrupted, eventually assisting worldwide efforts to restore ecological balance and prevent biodiversity loss.

5.2.3 Ethical Aspects

This research has an important effect on the environment since it promotes biodiversity conservation and the protection of monkey species, many of which are fragile or endangered. Accurate species identification helps conservationists track population dynamics, detect habitat changes, and respond effectively to environmental hazards. The research contributes to the prevention of illicit wildlife trade and poaching, both of which pose serious hazards to many species, by offering a tool that aids in identification. Furthermore, the application of AI and computer vision reduces the necessity for intrusive identification procedures, lowering human intervention in natural ecosystems. These developments help to create more sustainable conservation techniques, ensuring that species are preserved while their habitats are not disrupted, eventually assisting worldwide efforts to restore ecological balance and prevent biodiversity loss.

5.2.4 Sustainability Plan

- Design the web-based classification tool to be lightweight, modular, and easy to update.
- Enable the addition of more species or datasets as biodiversity monitoring expands.
- Release the tool as open-source to encourage community contributions and improvements.
- Collaborate with researchers, conservationists, and educators to enhance functionality and usability.
- Focus on image-based identification to minimize disturbance to wildlife and their habitats.
- Partner with conservation organizations to integrate the tool into biodiversity monitoring programs.
- Use the tool in educational initiatives to raise public awareness about species conservation.
- Promote long-term contributions to wildlife preservation, ecological balance, and responsible AI use.

5.3 Project Management and Financial Analysis

The research project is planned to last five months, with phases that include data collection (1 month), model construction and training (2 months), web application development (1 month), and analysis/reporting (1 month). Financially, the project will require funds for dataset collecting, cloud computing resources for model training, software tools for implementation, and web hosting for final app release. The budget will cover these necessary expenditures to guarantee that the project runs smoothly and successfully, with an emphasis on resource efficiency throughout each step.

5.4 Complex Engineering Problem

The classification of monkey species using CNN models represents a complex engineering problem due to its multifaceted challenges. It involves handling a mixed dataset collected from diverse sources like zoos, animal houses, and the internet, requiring extensive preprocessing to standardize image quality. Selecting and evaluating six advanced CNN architectures—EfficientNet B7, DenseNet 201, VGG19, InceptionV3, MobileNet, and Xception—demands expertise in deep learning and computational resources for training and testing. The integration of the best-performing model, DenseNet 201, into a user-friendly Python Flask-based web interface adds complexity in terms of real-time inference, system optimization, and deployment. This research requires multidisciplinary skills in data science, machine learning, and software development to address scalability, accuracy, and usability challenges effectively.

Conclusion

To Concluded, this study effectively exhibits the potential of Convolutional Neural Networks (CNNs) for accurate monkey species categorization. After examining many CNN designs, DenseNet 201 was found to be the most effective model, reaching high accuracy. The integration of the best-performing model into a web-based interface enables real-time species identification, contributing to both scientific improvements and practical conservation initiatives. Future enhancements, such as dataset enlargement and real-world testing, will increase the system's efficacy and use in animal monitoring and conservation.

6.1 Summary

The written works covered in this research are largely concerned with the use of deep learning techniques, particularly Convolutional Neural Networks (CNNs), for the categorization of animals. These studies illustrate CNNs' usefulness in extracting significant characteristics from photos, as well as their capacity to handle big, complicated datasets. To solve issues in species identification across domains, many CNN designs have been used, including 2D CNNs, deep CNNs, and multi-view CNNs. The study shows that big and diverse datasets are critical for obtaining high accuracy, with various studies highlighting the necessity for data augmentation, hyperparameter tweaking, and sophisticated model architectures to increase performance. Furthermore, real-world deployment of these models has been investigated, with research concentrating on their integration into mobile applications and edge devices for practical purposes. Despite improvements, difficulties like as processing resources, power consumption, and latency persist, and further work is required to improve the scalability and usability of these models in real-world applications.

6.2 Limitation

There are limits to this study because of the dataset, model performance, and practical implementation. Species and picture counts restrict the varied dataset, which might impact the generalizability of the approach. Inconsistencies may be introduced by poor image quality, particularly for species that are not frequently shot. Every CNN design has advantages and disadvantages, and implementing the top-performing model in a web-based interface comes with difficulties like as managing different input circumstances, resolving latency, and improving computing efficiency.

6.3 Future work

Future work could focus on expanding the dataset to include more species and images under varied conditions to improve model generalization. Exploring advanced techniques like transfer learning and ensemble models could enhance accuracy and robustness. Additionally, optimizing the web interface for faster processing and integrating the model into mobile or edge devices would improve real-time usability. Incorporating other data types, such as acoustic signals, and testing the model in real-world settings would further refine its applicability in conservation and wildlife monitoring.

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