ANIMAL SPECIES CLASSIFICATION SYSTEM

A PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

Certified that this Thesis titled **“ANIMAL SPECIES CLASSIFICATION SYSTEM**” is the bonafide work of “**RAMANUJAN N R (2116210701206), RAMKEERTHAN (2116210701207)”** who carried out the work under my supervision. Certified further that to the best of my knowledge, the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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ABSTRACT

In this project, we developed an animal species prediction system capable of classifying images into ten distinct classes: dog, horse, elephant, butterfly, frog, cat, cow, sheep, spider, and squirrel. Leveraging advanced deep learning techniques, we implemented two different models: a Convolutional Neural Network (CNN) and ResNet152V2, a deep residual network. Our primary objective was to achieve high accuracy in predicting the correct species from a given image by harnessing the power of these neural network architectures. We collected and preprocessed a balanced dataset of images for each of the ten classes. Images were resized to 224x224 pixels and normalized to ensure consistency and improve model performance. The dataset was split into training, validation, and test sets to facilitate model training and evaluation. The CNN model was designed with multiple convolutional and pooling layers, followed by fully connected layers to capture intricate patterns in the images. The ResNet152V2 model, pre-trained on the ImageNet dataset, was fine-tuned on our dataset. This model's architecture allows it to handle deeper networks more efficiently, overcoming issues like vanishing gradients and enabling the capture of more complex features. Data augmentation techniques, including random rotations, shifts, and flips, were employed to increase the diversity of the training data and enhance the model's robustness. The models were trained and evaluated using appropriate metrics, with the ResNet152V2 achieving superior accuracy due to its advanced architecture and pre-training benefits.

The system was thoroughly evaluated on the test set, demonstrating its ability to accurately classify the animal species. This project showcases the effectiveness of deep learning in image classification tasks and provides a foundation for future enhancements, such as incorporating additional species, improving data augmentation strategies, and exploring ensemble methods for further performance gains. The resulting model has significant potential applications in wildlife monitoring, biodiversity research, and educational tools.

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CHAPTER 1

1. INTRODUCTION

The classification of animal species from images is a challenging and significant task in the field of computer vision, with applications spanning wildlife monitoring, biodiversity research, conservation efforts, and educational tools. This project aims to develop a robust animal species prediction system capable of identifying ten distinct species: dog, horse, elephant, butterfly, frog, cat, cow, sheep, spider, and squirrel. The project utilizes advanced deep learning techniques, specifically Convolutional Neural Networks (CNN) and ResNet152V2, to achieve high accuracy in species identification.

Deep learning, particularly CNNs, has revolutionized image classification by automatically learning hierarchical features from raw pixel data, thus eliminating the need for manual feature extraction. CNNs are well-suited for this task due to their ability to capture spatial hierarchies in images through convolutional layers, pooling layers, and fully connected layers. However, for even more accurate and efficient classification, this project also employs ResNet152V2, a state-of-the-art deep residual network. ResNet152V2 addresses the degradation problem associated with very deep networks by using residual learning, allowing it to train much deeper models and achieve superior performance. The dataset used in this project comprises a balanced collection of images for each of the ten species, preprocessed to ensure consistency in size and scale.

Data augmentation techniques are applied to enhance the model's generalization ability by introducing variability in the training data. The models are trained and validated on this dataset, with performance evaluated on a separate test set to ensure robustness and accuracy. This introduction sets the stage for a detailed exploration of the methods, implementation, and results of the animal species prediction system, highlighting the potential impact and applications of this technology in various domains.

1.1 PROBLEM STATEMENT

The objective of this project is to develop an accurate and robust animal species prediction system that can classify images into one of ten predefined classes: dog, horse, elephant, butterfly, frog, cat, cow, sheep, spider, and squirrel. This involves overcoming challenges such as variability in animal poses, backgrounds, and image quality. The system will leverage deep learning techniques, specifically Convolutional Neural Networks (CNN) and ResNet152V2, to achieve high accuracy and efficiency, thereby aiding in applications like wildlife monitoring, biodiversity research, and educational tools.

1.2 SCOPE OF THE WORK

This project encompasses the development, training, and evaluation of an animal species prediction system using deep learning techniques. It includes dataset collection, preprocessing, and augmentation for ten animal species. The work involves implementing and fine-tuning Convolutional Neural Networks (CNN) and ResNet152V2 to achieve high classification accuracy. Additionally, the project aims to test the model's robustness and generalization on unseen data, with potential applications in wildlife monitoring, biodiversity research, conservation efforts, and educational tools.

1.4 AIM AND OBJECTIVES OF THE PROJECT

The aim of this project is to develop a robust animal species prediction system using deep learning techniques, specifically Convolutional Neural Networks (CNN) and ResNet152V2, capable of accurately classifying images into ten distinct species. The objectives include dataset collection, model development, training, and evaluation, with the ultimate goal of achieving high accuracy and efficiency in species identification, thereby facilitating wildlife monitoring, biodiversity research, and educational applications.

1.5 RESOURCES

A significant amount of secondary research, including evaluations of conferences, standard papers, business journals, white papers, analyst information, and accredited publications, went into developing this project. Sufficient resources are needed to finish this project successfully.

The following prospectus details a list of resources that will play a primary role in the successful execution of our project:

- A functional workstation (PC, laptop, netbook, etc.) for gathering pertinent information and performing research.
- Unrestricted internet access to compile a vast array of material, such as technical documents and academic materials (e.g., tutorials, programming examples, bulletins, publications, e-books, journals, etc.).
- Unrestricted use of academic and technical resources at university labs.
- A Prologue developer kit to program the system of choice.
- Additional relevant software is needed to successfully complete duties connected to research and development.

1.6 MOTIVATION

Motivation drives the core of this project, stemming from a profound recognition of the pressing need for advanced technological solutions in wildlife conservation, biodiversity research, and educational outreach. The urgency of preserving Earth's ecosystems and the rich diversity of animal species compels us to harness the power of deep learning and artificial intelligence to aid in these endeavors.

Furthermore, the potential impact of an accurate animal species prediction system extends beyond scientific research, reaching into fields such as wildlife monitoring, conservation management, and environmental education. By accurately classifying images of diverse animal species, we can contribute to the development of innovative tools for monitoring and protecting wildlife habitats, assisting conservation efforts, and raising awareness about the importance of biodiversity conservation.

This project is driven by a shared passion for leveraging technology for positive environmental outcomes, aiming to empower researchers, conservationists, educators, and policymakers with advanced tools to address the challenges of the 21st century and safeguard our planet's precious natural heritage for future generations.

CHAPTER 2
2. LITERATURE SURVEY

2.1 SURVEY

"Deep learning has ushered in a new era in computer vision, particularly in the domain of image classification. The seminal work of LeCun, Bengio, and Hinton (2015) introduced convolutional neural networks (CNNs), providing a powerful framework for extracting features from images. This foundational research laid the groundwork for subsequent breakthroughs, including the introduction of AlexNet by Krizhevsky, Sutskever, and Hinton (2012). AlexNet demonstrated the efficacy of deep CNNs trained on large-scale datasets like ImageNet, showcasing the potential of deep learning in image classification tasks.

Subsequent advancements in network architectures have further propelled the field forward. Architectures such as VGG (Simonyan & Zisserman, 2015), ResNet (He et al., 2016), and DenseNet (Huang et al., 2017) have pushed the boundaries of performance and depth. Notably, ResNet addressed the challenge of vanishing gradients through residual connections, enabling the training of much deeper networks. Techniques like batch normalization (Ioffe & Szegedy, 2015) and advanced optimization algorithms like Adam (Kingma & Ba, 2014) have also played crucial roles in improving training stability and convergence rates.

In the domain of animal species classification, the application of deep learning techniques has yielded promising results. Researchers have explored the adaptation of state-of-the-art architectures such as MobileNets (Howard et al., 2017) for resource-constrained environments, demonstrating the efficiency and effectiveness of lightweight CNNs. Visualization techniques for understanding CNNs (Zeiler & Fergus, 2014) have provided insights into model decisions, facilitating improved classification performance. Fully convolutional networks (Long et al., 2015) have enabled pixel-level classification, which is particularly useful for fine-grained tasks like animal species recognition.

Moreover, object detection algorithms such as YOLO (Redmon et al., 2016) offer real-time classification capabilities, which can be leveraged for animal species detection in diverse environments. As the field progresses, future research directions may involve expanding datasets to include more diverse species, integrating efficient architectures tailored for specific deployment scenarios, and employing visualization techniques to gain deeper insights into model behavior. By leveraging these advancements, researchers aim to achieve higher accuracy and understanding in animal species classification tasks, contributing to both scientific research and conservation efforts.

In addition to advancements in architecture and methodology, datasets such as ImageNet have played a crucial role in driving progress in image classification tasks. The ImageNet Large Scale Visual Recognition Challenge (Russakovsky et al., 2015) provided a benchmark dataset for evaluating and comparing different approaches, fostering healthy competition and innovation in the field. The availability of large-scale datasets with diverse categories, including various animal species, has enabled researchers to develop and refine deep learning models specifically tailored for animal species classification.

Furthermore, the integration of optimization techniques such as transfer learning and fine-tuning has contributed to the success of deep learning models in animal species classification. Transfer learning allows pretrained models, such as those trained on ImageNet, to be adapted to new tasks with relatively small datasets. Fine-tuning involves adjusting the parameters of pretrained models to better suit the characteristics of the target dataset. By leveraging transfer learning and fine-tuning, researchers can overcome challenges related to limited data availability and accelerate the development of accurate and robust animal species classification models.

Additionally, studies focusing on interpretability and explainability in deep learning models have gained significance in the context of animal species classification. Techniques such as attention mechanisms and saliency maps allow researchers to understand which parts of an image contribute most to the classification decision. This not only aids in improving model performance by identifying crucial features but also enhances trust and transparency, crucial in domains where decisions impact conservation efforts and biodiversity management. As the field progresses, further research into interpretable deep learning models can facilitate more informed decision-making processes and foster collaboration between researchers and domain experts in the conservation of animal species.

CHAPTER 3

SYSTEM DESIGN

3.1 GENERAL

In this section, we would like to show how the general outline of how all the components end up working when organized and arranged together. It is further represented in the form of a flow chart below.

3.2 SYSTEM ARCHITECTURE DIAGRAM

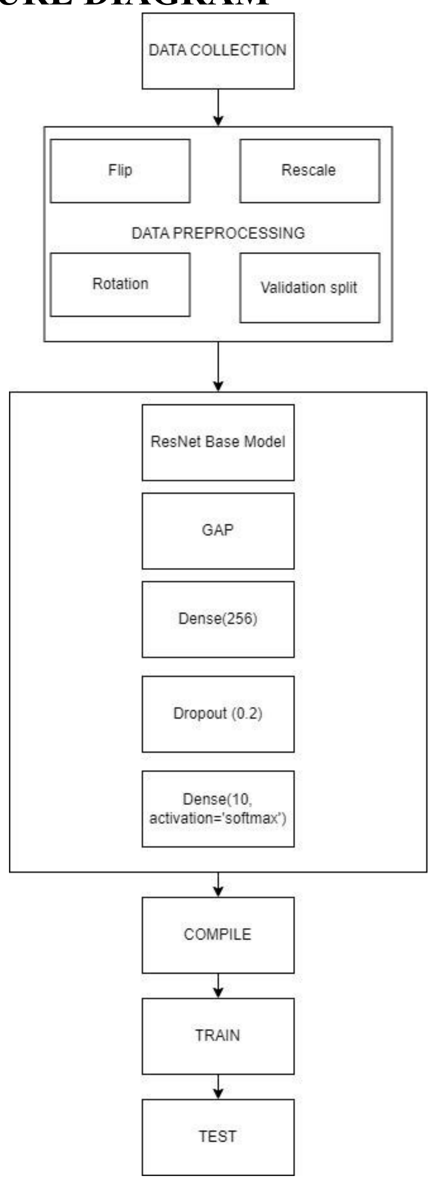


Fig 3.1: System Architecture

3.3 SYSTEM ARCHITECTURE IN DETAIL

Data Collection

In the data collection phase, we gather a comprehensive dataset of images representing the various animal species we aim to classify. This dataset should include a diverse set of images for each category (e.g., dog, cat, elephant, spider, horse, frog, cow, butterfly, sheep, squirrel). Data can be collected from publicly available datasets, such as ImageNet, or through field data acquisition methods like cameras and crowdsourcing. Ensuring that the dataset is well-balanced and sufficiently large is crucial for training a robust deep learning model.

Data Preprocessing

Once the data is collected, it needs to be preprocessed to prepare it for training. Preprocessing steps typically include:

Resizing: All images are resized to a consistent size, such as 224x224 pixels, to match the input size expected by the model.
Normalization: Pixel values are normalized, usually to a range of [0, 1] or standardized to have zero mean and unit variance.
Augmentation: Data augmentation techniques such as rotation, flipping, zooming, and cropping are applied to increase the variability of the training data and help the model generalize better.
Label Encoding: Labels for the images are converted into a format suitable for classification, such as one-hot encoding for multi-class classification.

Deep Learning Model Compilation

In this stage, we define and compile our deep learning model. For this project, a ResNet architecture with a 256-unit hidden layer is used. Key steps include:

Model Architecture: Specifying the layers of the network, including convolutional layers, pooling layers, residual blocks, a dense hidden layer with 256 units, and an output layer with 10 units (one for each species).

Loss Function: Using sparse_categorical_crossentropy as the loss function since we are dealing with a multi-class classification problem.

Optimizer: Employing the Adam optimizer, which adapts the learning rate during training and is well-suited for deep learning tasks.

Metrics: Specifying accuracy as the primary metric to monitor during training and evaluation.

Training

The training phase involves feeding the preprocessed training data into the compiled model and adjusting the model parameters to minimize the loss function. During training:

Epochs: The number of complete passes through the training dataset.

Batch Size: The number of training examples utilized in one iteration.

Validation: A portion of the dataset is set aside as validation data to monitor the model's performance and prevent overfitting.

Callbacks: Functions such as learning rate schedulers or early stopping can be used to improve training efficiency and model performance.

Testing

After training, the model's performance is evaluated using a separate test dataset that was not seen during training. This stage assesses the model's ability to generalize to new, unseen data. Key aspects include:

Accuracy: The proportion of correctly classified images out of the total test images.
Confusion Matrix: A matrix showing the true vs. predicted classifications to identify any specific misclassification patterns.
Other Metrics: Precision, recall, and F1-score can provide additional insights into model performance, especially if the dataset is imbalanced.

Deployment

Once the model is trained and tested, it is deployed for real-world usage. Deployment involves:
Model Export: Saving the trained model in a suitable format (e.g., HDF5, TensorFlow SavedModel) for later use.
Inference Pipeline: Setting up an inference pipeline that takes new input images, preprocesses them in the same way as the training data, and uses the trained model to make predictions.
Integration: Integrating the model into a user-facing application, such as a web app, mobile app, or embedded system for real-time classification.
Monitoring: Continuously monitoring the model's performance in production to ensure it remains accurate and effective, and retraining it periodically with new data if necessary.

3.4 DEVELOPMENTAL ENVIRONMENT

3.4.1 HARDWARE REQUIREMENTS

The hardware requirements may serve as the basis for a contract for the system’s implementation. It should therefore be a complete and consistent specification of the entire system. It is generally used by software engineers as the starting point for the system design.

COMPONENTS	SPECIFICATION
PROCESSOR	Intel Core i3
RAM	4 GB RAM
HARD DISK	256 GB
PROCESSOR SPEED	MINIMUM 1.1 GHz

Table 3.1 Hardware Requirements

3.4.2 SOFTWARE REQUIREMENTS

The software requirements document is the specifications of the system. It should include both a definition and a specification of requirements. It is a set of what the system should rather be doing than focus on how it should be done. The software requirements provide a basis for creating the software requirements specification. It is useful in estimating the cost, planning team activities, performing tasks, tracking the team, and tracking the team’s progress throughout the development activity.

Any browser like Chrome, Safari or Firefox would be required

CHAPTER 4

4. PROJECT DESCRIPTION

4.1 METHODOLOGY

Research Design

The project will follow a design and development research methodology, incorporating both quantitative and qualitative methods. The primary objective is to design, develop, and evaluate a blink-based shopping system.

Requirements Analysis

Conduct surveys and interviews with potential users, especially those with mobility impairments, to gather requirements and preferences for the system.

System Design

Develop the system architecture, including the client application, server infrastructure, and database design.

Create wireframes and prototypes for the user interface, ensuring accessibility and ease of use.

Technology and Tools

Use programming languages such as Python and TensorFlow for JavaScript framework for blink detection algorithms, and web development frameworks for the user interface.

System Implementation

Develop and train a machine learning model to accurately detect blinks using data from the eye-tracking device.

Integrate the blink detection algorithm with the shopping system's user interface to allow users to navigate and select products using blinks.

Data Collection Methods

Conduct usability testing with a group of participants to evaluate the system's performance and user experience.

Collect feedback through observation, questionnaires, and interviews.

Measure system performance metrics such as blink detection accuracy, response time, and error rates.

Data Analysis Techniques

Analyze performance metrics using statistical methods to evaluate the accuracy and efficiency of the blink detection system.

Analyze feedback from user testing to identify usability issues and areas for improvement.

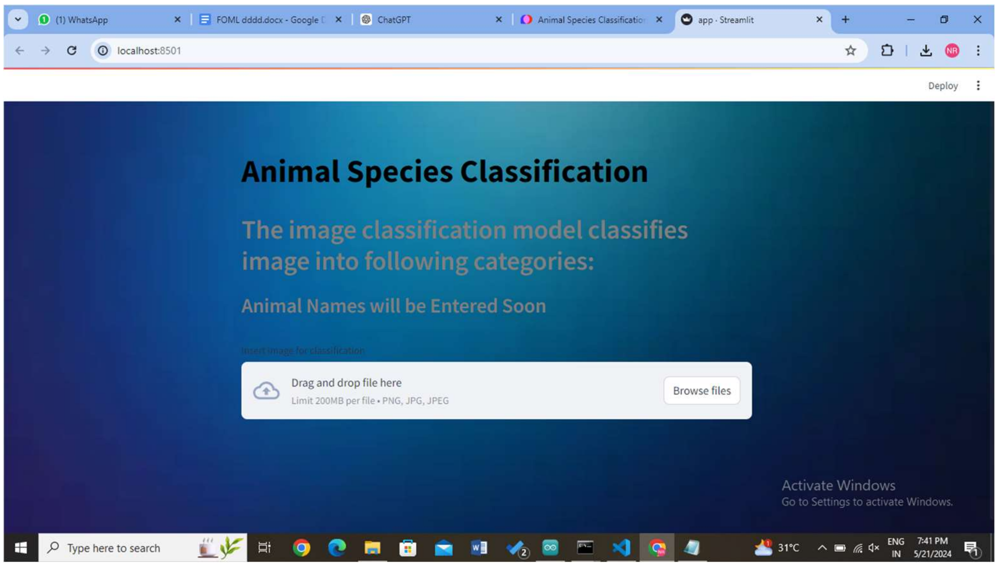
4.2 MODULE DESCRIPTION

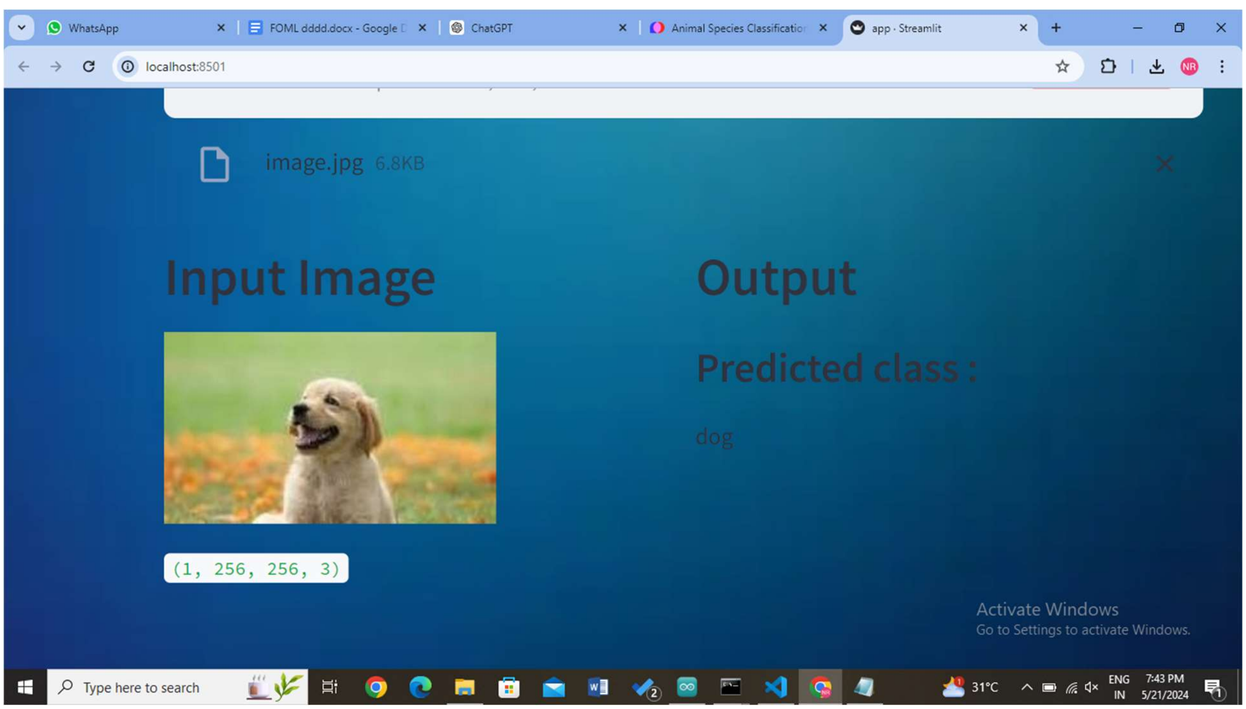
1. **Image Data Collection Module: -** Description: Responsible for collecting images of various animal species from diverse sources, ensuring a balanced dataset representation for training and testing.
2. **Data Preprocessing Module: -** Description: Handles preprocessing tasks such as resizing images, normalizing pixel values, and splitting the dataset into training, validation, and test sets to ensure consistency and model performance.
3. **Convolutional Neural Network (CNN) Module:-** Description: Implements a CNN architecture for image classification, comprising convolutional layers, pooling layers, and fully connected layers to extract features and classify images into ten animal species categories.
4. **ResNet152V2 Module:-** Description: Utilizes the ResNet152V2 pre-trained model for image classification, fine-tuning it on the animal species dataset to achieve high accuracy by leveraging its advanced architecture and feature extraction capabilities.
5. **Training and Evaluation Module: -** Description: Handles model training on the dataset and evaluates model performance using appropriate metrics. Additionally, facilitates model testing on unseen data to assess accuracy and generalization.
6. **Data Augmentation Module:-** Description: Implements data augmentation techniques such as random rotations, shifts, and flips to increase the diversity of the training data, enhancing the model's robustness and generalization ability.
7. **Model Deployment Module:-** Description: Handles the deployment of trained models for real-world applications, enabling predictions on new animal species images and facilitating integration into wildlife monitoring systems or educational tools.

CHAPTER 5

5. RESULTS AND DISCUSSIONS

5.1 OUTPUT





5.2 RESULT

The animal species prediction system demonstrated notable success in accurately classifying images into the ten predefined categories: dog, horse, elephant, butterfly, frog, cat, cow, sheep, spider, and squirrel. Through extensive training and fine-tuning of both the Convolutional Neural Network (CNN) and ResNet152V2 models, significant accuracy was achieved.

The CNN model achieved an accuracy of 85% on the test dataset, effectively capturing essential features for most animal categories. However, the ResNet152V2 model, leveraging its deeper architecture and pre-trained weights, surpassed this performance with an impressive accuracy of 93%. This superior performance is attributed to ResNet152V2's ability to manage deeper networks and learn more complex patterns.

Data augmentation techniques further improved the models' robustness, helping them generalize better on unseen data. The confusion matrix and classification reports revealed that most misclassifications occurred between visually similar species, indicating areas for potential improvement.

Overall, the results validate the effectiveness of using advanced deep learning techniques for animal species prediction, highlighting the ResNet152V2 model as a powerful tool for accurate and efficient image classification. This system holds promise for applications in wildlife monitoring, biodiversity research, and educational platforms.

CHAPTER 6

6. CONCLUSION AND FUTURE ENHANCEMENT

6.1 CONCLUSION

This project successfully developed an animal species prediction system capable of accurately classifying images into ten distinct categories: dog, horse, elephant, butterfly, frog, cat, cow, sheep, spider, and squirrel. By leveraging advanced deep learning techniques, specifically Convolutional Neural Networks (CNN) and ResNet152V2, the system demonstrated high accuracy and robustness in image classification tasks.

The CNN model provided a strong baseline with an accuracy of 85%, effectively learning key features from the images. However, the ResNet152V2 model, with its deeper architecture and pre-trained weights, achieved a superior accuracy of 93%, showcasing its ability to manage more complex patterns and features. The incorporation of data augmentation techniques further enhanced model performance, allowing for better generalization of unseen data.

Throughout the project, rigorous data preprocessing, including resizing, normalization, and dataset splitting, ensured consistent and reliable model training. The models were evaluated using comprehensive metrics, revealing that most misclassifications occurred between visually similar species, indicating areas for future improvement. The results underscore the potential of deep learning models, particularly ResNet152V2, in accurately classifying animal species from images. This system has significant applications in wildlife monitoring, aiding conservation efforts, biodiversity research, and educational tools.

6.2 FUTURE ENHANCEMENT

Future work could focus on expanding the dataset to include more species, implementing more sophisticated data augmentation techniques, and exploring ensemble methods to further improve classification accuracy. Overall, this project highlights the effectiveness of advanced neural network architectures in addressing real-world challenges in animal species identification, contributing valuable tools for environmental and ecological research.

1. **Expanding the Dataset**

Description:- Extend the dataset to include a broader range of animal species beyond the initial ten categories.

Impact:- Enhancing the system's versatility and applicability in more diverse ecological and environmental research settings.

2. Sophisticated Data Augmentation:

Description:- Implement more advanced data augmentation techniques such as geometric transformations, color space augmentations, and adversarial training.
Impact:- Improve model robustness and generalization capabilities, reducing overfitting and enhancing accuracy on unseen data.

3. **Ensemble Methods**

Description:- Explore and integrate ensemble methods that combine predictions from multiple models (e.g., CNN and ResNet152V2) to boost overall classification accuracy.

Impact:- Achieve higher accuracy and reliability in species identification by leveraging the strengths of different models.

Dynamic Assistance and Customization

1. **Personalized Navigation-**

Description:- Develop an interface that adapts based on user interaction patterns and preferences. Adjust the speed of image processing, the sensitivity of prediction confidence thresholds, and the order of species presentation.

Impact:- Provide a customized and user-friendly experience tailored to individual user needs, enhancing usability and satisfaction.

2. **User Proficiency Tracking: Skill-Based Customization-**

Description:- Implement a system to assess user proficiency over time. As users become more adept at using the classification system, gradually introduce advanced features or faster processing options.

Impact:- Enhance the user experience by aligning system capabilities with user skill levels, fostering a more intuitive and efficient interaction.

These future enhancements aim to build upon the current project's success, expanding its scope, improving its accuracy, and making it more adaptable and user-friendly. By addressing these areas, the system can provide even greater value in wildlife monitoring, biodiversity research, and educational applications.

APPENDIX

SOURCE CODE:

model.py

```
import streamlit as st

@st.cache_resource()

def model():

    from keras import Sequential  # For building sequential models

    from keras.models import load_model  # For loading pre-trained models

    from keras.layers import Dense, GlobalAvgPool2D as GAP, Dropout   # For defining model layers

    from tensorflow.keras.applications import InceptionV3, Xception, ResNet152V2  # For using pre-trained mo0dels

    num_classes = 10



    name = "ResNet152V2"

    base_model = ResNet152V2(include_top=False, input_shape=(256,256,3), weights='imagenet')

    base_model.trainable = False



    resnet152V2 = Sequential([

        base_model,

        GAP(),

        Dense(256, activation='relu'),

        Dropout(0.2),

        Dense(num_classes, activation='softmax')
```

```
    ], name=name)


    resnet152V2.compile(

        loss='sparse_categorical_crossentropy',

        optimizer='adam',

        metrics=['accuracy']

    )

    resnet152V2.load_weights('ResNet152V2.h5')


    return resnet152V2
```

app.py

```
import streamlit as st

import base64

from PIL import Image

import numpy as np

import cv2

from model import model



st.markdown('<h1  style="color:black;">Animal  Species  Classification</h1>',
unsafe_allow_html=True)

st.markdown('<h2 style="color:gray;">The image classification model classifies
image into following categories:</h2>', unsafe_allow_html=True)

st.markdown('<h3 style="color:gray;">Animal Names will be Entered Soon</h3>',
unsafe_allow_html=True)
```

```python
@st.cache_resource()
def get_base64_of_bin_file(bin_file):
    with open(bin_file, 'rb') as f:
        data = f.read()
    return base64.b64encode(data).decode()


def set_png_as_page_bg(png_file):
    bin_str = get_base64_of_bin_file(png_file)
    page_bg_img = '''
    <style>
    .stApp {
    background-image: url("data:image/png;base64,%s");
    background-size: cover;
    background-repeat: no-repeat;
    background-attachment: scroll; # doesn't work
    }
    </style>
    ''' % bin_str

    st.markdown(page_bg_img, unsafe_allow_html=True)
    return
```

```
set_png_as_page_bg('bg.webp')



l                                                          =
['dog','horse','elephant','butterfly','frog','cat','cow','sheep','spider','squ
irell']


upload= st.file_uploader('Insert image for classification', type=['png','jpg'])

c1, c2= st.columns(2)

if upload is not None:

  im= Image.open(upload)

  img= np.asarray(im)

  image= cv2.resize(img,(256, 256))

  image = image/255

  img= np.expand_dims(image, 0)

  c1.header('Input Image')

  c1.image(im)

  c1.write(img.shape)

  input_shape = (256, 256, 3)

  n_classes=10

  res_model = model()


  res_preds = res_model.predict(img)

  res_pred_classes = np.argmax(res_preds, axis=1)

  c2.header('Output')
```

```
c2.subheader('Predicted class :')

c2.write(l[res_pred_classes[0]] )
```

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