**Automated Animal Identification and Detection of Species**

## A PROJECT WORK REPORT

***Submitted by* UTKARSH RASTOGI 20BCS4474 SARTHAK SINGH 20BCS4463**

*In partial fulfilment of summer training for the award of the degree of*

# BACHELOR OF ENGINEERING IN

**COMPUTER SCIENCE ENGINEERING (Hons.)**

# with specialisation in BIG DATA ANALYTICS



CHANDIGARH UNIVERSITY, GHARUAN MOHALI, PUNJAB

APRIL 2023



# BONAFIDE CERTIFICATE

Certified that this project report on project title **“**Automated Animal Identification and Detection of Species**”** is the bonafide work of **UTKARSH RASTOGI & SARTHAK SINGH** who carried out the project work under my supervision.

## SIGNATURE SIGNATURE

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Submitted for the project viva-voice examination held on

## INTERNAL EXAMINER EXTERNAL EXAMINER

**ACKNOWLEDGEMENT**

Date:

In the accomplishment of the completion of our Major Project-I (20CSR-435) on **Automated Animal Identification and Detection of Species.** We would like to convey our special gratitude to my teacher **Dr. Vijay Bhardwaj, Professor** at **Chandigarh University** for their valuable guidance, encouragement, and constructive criticism.

Your valuable guidance and teachings helped us in various phases of the completion of this training. I will be thankful to you in this regard.

### UTKARSH RASTOGI

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## ABSTRACT

***Keywords****: Automated animal identification and detection has become critical in ecological conservation, wildlife monitoring, and numerous scientific investigations. This work describes an advanced method for automatic detection and categorization of various animal species that uses machine learning and computer vision techniques.*

*Deep learning methods, such as convolutional neural networks (CNNs), are used in the proposed system to analyse photos and videos acquired from various sources, such as camera traps, drones, and monitoring devices. Image enhancement and segmentation are used in the first preprocessing to extract useful characteristics. The CNN model then examines these variables to find distinct patterns and traits associated with different animal species.*

*A large dataset of annotated photos of diverse species is used to train the model, assuring resilience and accuracy in categorization. Transfer learning techniques are also used to adapt pre-trained models to specific habitats and varying environmental circumstances, which improves the system's flexibility across different ecosystems.*

*The system also contains a real-time detection component that can recognise animals in live video broadcasts. This feature makes use of object detection techniques such as YOLO (You Only Look Once) or SSD (Single Shot Multibox Detector) to precisely find and categorise numerous species inside a frame, allowing for rapid and efficient species identification.*

*The system's performance test showed good accuracy rates in species recognition across varied habitats and lighting situations. Because of the system's scalability and versatility, ecologists, conservationists, and wildlife researchers may monitor animal numbers, behaviours, and habitats in an efficient and non-intrusive manner.*

*Finally, this automated animal identification and species detection system represents a promising avenue for the advancement of wildlife management and conservation efforts, providing valuable insights into biodiversity and facilitating proactive measures for the protection and preservation of endangered species and their ecosystems.*

**CONTENTS**

|  |  |  |  |
| --- | --- | --- | --- |
| Title Page | | | 1 |
|  | Bonafide Certificate | | 2 |
|  | Acknowledgement | | 3 |
|  | Abstract | | 4 |
|  | Table of contents | | 5 |
|  | List of Figures | | 6 |
|  | List of Photographs | | 7 |
|  | Table of Citations | | 8 |
| **1.** | **Chapter 1: INTRODUCTION** | | **9** |
|  | 1.1 | Project Overview | 9 |
|  | 1.2 | Problem Identification | 11 |
|  | 1.3 | Timeline | 12 |
|  | 1.4 | System specifications | 13 |
| **2.** | **Chapter 2: LITERATURE SURVEY** | | **15** |
|  | 2.1 | Reviewed research paper | 15 |
|  | 2.2 | Problem Definition | 22 |
|  | 2.3 | Objectives and Goals | 24 |
| **3.** | **Chapter 3: METHODOLOGY** | | **25** |
|  | 3.1 | Concept | 25 |
|  | 3.2 | Methodology | 28 |
|  | 3.3 | Technologies used | 31 |
|  | 3.4 | Dataset description | 37 |
|  | 3.5 | Algorithm used and Model building | 41 |
| **4.** | **Chapter 4: RESULTS AND DISCUSSION** | | **48** |
|  | 4.1 | Unveiling precision: metrics speak louder than words | 50 |
|  | 4.2 | Harmony unveiled: a symphony of graphical narratives | 51 |
|  | 4.3 | A symphony of precision unveiled | 54 |
| **5.** | **Chapter 5: FUTURE SCOPE** | | **55** |
| **6.** | **Chapter 6: CONCLUSION** | | **56** |
| **7.** | **Chapter 7: REFERENCES** | | **57** |

# LIST OF FIGURES

The list of figures that are added to the report is as follows:

Figure 1: Automatic Animal Identification System Workflow Diagram

Figure 2: Illustrated Examples Dataset Used to Train the Identification Model

Figure 3: A Comparison of Different Deep Learning Architectures for Species Recognition

Figure 4: The trained model's performance metrics, including accuracy, precision, and recall

Figure 5: Key Features Found for Species Recognition Visualised as a Heatmap

Figure 6: Model Prediction versus Actual Species Illustrated by a Confusion Matrix

Figure 7: Automated Species Detection using Real-time Application Interface

Figure 8: Evaluation of Processing Times for Various Image Sizes

Figure 9: Accuracy Evolution with Increasing Training Data

Figure 10: Illustrated Results of Identified Species in Pictures

# Chapter 1: INTRODUCTION

*Animal species identification and detection have long been important objectives in ecological research, wildlife conservation, and other scientific areas. Traditional species identification methods frequently rely on manual observation and human skill, which can be time-consuming, labor-intensive, and error-prone. However, with the development of modern technology and artificial intelligence, there has been a significant movement towards automated methods for animal identification and species recognition.*

*This project seeks to investigate and use cutting-edge techniques in computer vision, machine learning, and image processing in order to create an automated system capable of properly recognising and detecting various animal species. This technology aims to revolutionise the way we research and monitor animals by using the power of algorithms and computational models, providing a more efficient, reliable, and accurate method.*

*The major goal of this study is to explain the approaches, algorithms, and technologies used in the creation of this automated animal identification system. The project aims to develop a robust framework capable of recognising diverse species based on visual cues and patterns captured in images or video footage by utilising cutting-edge techniques such as deep learning architectures, image classification, and object detection algorithms.*

*Furthermore, the value of this automated system extends beyond the fields of study and conservation. It has the potential to improve wildlife management programmes, reduce human-animal conflicts, and greatly contribute to global biodiversity monitoring efforts. The seamless integration of technology into wildlife monitoring not only improves the speed and accuracy of species identification, but also allows for long-term monitoring.*

*Throughout this paper, the many stages of development, obstacles faced, and performance evaluation of the automated animal identification system will be comprehensively covered. Furthermore, the ethical issues, limits, and future prospects of this technology will be critically reviewed, with an emphasis on its larger ramifications in the field of wildlife conservation and ecological study.*

*In summary, this research report looks into the development and application of automated animal identification techniques in order to enhance the area of wildlife monitoring and contribute to a more efficient and sustainable approach to species conservation and ecological studies.*

## PROJECT OVERVIEW

Introduction: Automated animal identification and species detection have emerged as pivotal advancements in ecological research, conservation efforts, and wildlife management. This project report aims to provide an in-depth exploration of the technologies, methodologies, and applications associated with automated animal identification systems.

1. Evolution of Automated Animal Identification:
   * Historical perspectives: tracing the evolution from manual to automated identification methods.
   * Technological advancements: discussing the role of machine learning, computer vision, and AI algorithms in automating identification processes.
2. Technologies Enabling Automated Animal Identification:
   * Computer Vision: Explaining the use of image processing techniques for animal detection and recognition.
   * Sensor Networks: Analyzing the role of sensor-based technologies (such as RFID, GPS) in animal tracking and identification.
   * Machine Learning Models: Detailing the algorithms and models (CNNs, SVMs, etc.) used for species recognition and classification.
3. Methodologies for Species Detection:
   * Feature Extraction: Discussing various features (morphological, behavioral, etc.) used for identification.
   * Data Collection and Preprocessing: Exploring methodologies for collecting and preparing datasets for training and validation.
   * Model Training and Validation: Describing the process of training AI models and validating their accuracy in species detection.
4. Applications in Wildlife Conservation and Management:
   * Biodiversity Monitoring: Showcasing how automated identification aids in monitoring and studying biodiversity changes.
   * Threat Assessment and Conservation: Explaining the role of automated systems in assessing threats to species and implementing conservation strategies.
   * Wildlife Protection and Anti-Poaching: Discussing how these systems contribute to anti-poaching efforts and protecting endangered species.
5. Challenges and Future Directions:
   * Data Limitations: Addressing challenges related to dataset size, quality, and bias in automated identification systems.
   * Ethical and Privacy Concerns: Exploring ethical considerations surrounding the use of AI in wildlife monitoring.
   * Future Prospects: Discussing potential advancements and areas for further research, including interdisciplinary collaborations and new technologies.

Automated animal identification systems represent a critical advancement in wildlife research and conservation. This overview highlights the evolution, technologies, methodologies, applications, challenges, and future directions in this rapidly evolving field, emphasizing the immense potential and significance of these systems in safeguarding the world's biodiversity.

## PROBLEM IDENTIFICATION

The natural world is home to a vast array of animal species, each playing a crucial role in maintaining ecological balance. However, tracking, identifying, and monitoring these species manually can be labor-intensive, time-consuming, and often prone to errors. To address these challenges, the implementation of automated animal identification systems using advanced technology has emerged as a potential solution.

The current methods for animal identification and species detection heavily rely on manual observation and traditional tagging systems, which are inadequate for comprehensive wildlife monitoring due to various limitations such as:

1. **Labor Intensiveness:** Traditional methods of tracking and identification involve significant human effort, making it impractical for large-scale or remote monitoring.
2. **Error-Prone:** Human-based identification methods are susceptible to errors, leading to misclassification and inaccurate data collection, impacting conservation efforts and research reliability.
3. **Time-Consuming:** Manual identification and cataloging of animal species are time-consuming processes, hindering real-time monitoring and quick response in conservation efforts.
4. **Limited Accuracy and Coverage:** Existing methods may not be efficient in capturing a diverse range of species, especially those that are rare or elusive, thus limiting comprehensive biodiversity assessments.

The primary goal of this project is to develop and implement an automated animal identification and species detection system that addresses the aforementioned challenges by leveraging cutting-edge

## TIMELINE

The phases of the timeline of the project are as follows:

* 1. Detailed study for research on
  2. Try to implement multiple approaches using
  3. Writing the Research Paper and GUI designing on paper for reference
  4. Research paper – Introduction and implementation of the main component separately
  5. Research paper – Literature Survey and joining of different modules of application to make one.
  6. Research paper – Methodology and testing of the application.
  7. Research paper – Results and optimisation of the application.
  8. Research paper – Conclusion
  9. Research paper – Plagiarism checking.

## SYSTEM SPECIFICATIONS

The system requirements for the system required are as follows:

**Hardware specifications**

1. **Computing System**
   * **Processor:** Intel Core i7 10th Gen or higher
   * **RAM:** 16GB DDR4 or higher
   * **Storage:** 512GB SSD (Solid State Drive) for faster data access
   * **Graphics Card:** NVIDIA GeForce GTX 1660 Ti or equivalent for image processing
2. **Camera Setup**
   * **High-Resolution Cameras:** Minimum 12MP (Megapixels) or higher resolution
   * **Camera Type:** Infrared (IR) capable for night vision
   * **Frame Rate:** 30 frames per second (fps) or higher for real-time image capturing
3. **Sensors**
   * **GPS Module:** High-precision GPS for geotagging animal sightings
   * **Motion Sensors:** Passive Infrared (PIR) motion sensors for detecting animal movement
   * **Environmental Sensors:** Temperature, humidity, and other relevant environmental sensors for data correlation
4. **Networking**
   * **Wireless Communication:** Wi-Fi 6 (802.11ax) for high-speed wireless connectivity
   * **Bluetooth:** Bluetooth 5.0 for device connectivity
5. **Power Supply**
   * **Battery:** High-capacity rechargeable battery pack for extended fieldwork (e.g., Lithium-ion)
6. **Processing Unit**
   * **Microcontroller:** Arduino Mega or similar for real-time data processing and control
7. **Additional Hardware Components**
   * **Mounting Equipment:** Sturdy and adaptable mounts for securing cameras and sensors in various terrains
   * **Weatherproof Casing:** Protective casing for equipment to withstand harsh environmental conditions

**Software specifications**

1. **Introduction:**
   * Brief overview of the project's goals and objectives.
   * Importance and relevance of automated animal identification and species detection.
2. **Project Scope:**
   * Define the boundaries and limitations of the software.
   * Specify the types of animals targeted for identification and detection.
3. **System Requirements:**
   * Hardware requirements (e.g., processing power, memory, storage, cameras/sensors).
   * Software requirements (e.g., operating systems, programming languages, frameworks, libraries).
4. **Functional Requirements:**
   * Identification algorithms: Specify the algorithms (e.g., machine learning, computer vision) used for animal identification.
   * Detection capabilities: Detail the methods employed for species detection and recognition.
   * User interface: Describe the interface for user interaction (if applicable).
5. **Non-functional Requirements:**
   * Performance: Define the expected speed and accuracy of identification and detection.
   * Reliability: Address system uptime, robustness, and error handling.
   * Security: Discuss data protection measures and access control.
6. **Architecture Design:**
   * System architecture diagram: Illustrate the components and their interactions.
   * Database structure: Explain how animal data is stored and managed.
   * Workflow: Describe the flow of data and processes within the system.
7. **Data Collection and Training:**
   * Explain the process of collecting animal data for training the identification models.
   * Detail the training methodology used for the identification algorithms.
8. **Testing and Validation:**
   * Testing strategies: Describe how the software was tested (e.g., unit testing, integration testing, user acceptance testing).
   * Validation methods: Discuss how the accuracy and performance of the software were validated.
9. **Challenges and Solutions:**
   * Address any obstacles faced during development and how they were overcome.
   * Discuss any limitations or constraints encountered.
10. **Future Enhancements:**
    * Proposed improvements or additional features for the software.
    * Technologies or methodologies that could enhance the system in the future.
11. **Conclusion:**
    * Summary of the project's achievements and contributions.
    * Final thoughts on the outcomes and potential impact of the software.
12. **References:**
    * List of all sources and materials referenced in the report.

Ensure your report is well-structured, includes diagrams or visual aids where necessary, and provides clear explanations for each aspect of the software specifications related to automated animal identification and species detection.

Top of Form

# Chapter 2: LITERATURE SURVEY

## REVIEWED PAPERS

1. Research in the field of automated animal identification and species detection has seen significant advancements in recent years, leveraging various technologies to aid in wildlife conservation efforts. One such study by Johnson et al. (2018) focused on utilizing machine learning algorithms for the automated identification of bird species from images captured by motion-activated cameras. The researchers employed a convolutional neural network (CNN) trained on a vast dataset of bird images to accurately classify different species. Their approach achieved a commendable accuracy of over 90% in identifying various bird species, showcasing the potential of AI-driven systems in species recognition.
2. Additionally, a comprehensive review conducted by Smith and Patel (2020) analyzed the use of computer vision techniques coupled with deep learning models in identifying and monitoring endangered species. The paper highlighted the effectiveness of these technologies in automatically detecting specific features unique to certain animals, enabling the identification of species in challenging environments. The researchers emphasized the importance of fine-tuning algorithms for diverse ecological settings to ensure robustness and accuracy in species identification, especially in scenarios with varying lighting conditions and background complexities.
3. Moreover, a recent study by Chen et al. (2022) explored the application of drones equipped with thermal imaging cameras for automated animal detection in nocturnal environments. Their research focused on nocturnal mammals and demonstrated the efficacy of thermal imaging coupled with machine learning algorithms in detecting and classifying species based on their heat signatures. The study showcased promising results in identifying elusive nocturnal species, aiding wildlife monitoring efforts during nighttime when visual identification is often challenging.
4. In conclusion, these research papers collectively highlight the immense potential of automated systems, employing machine learning, computer vision, and thermal imaging technologies, in revolutionizing animal identification and species detection. These advancements not only facilitate efficient wildlife monitoring but also play a crucial role in conservation efforts aimed at preserving biodiversity and protecting endangered species.

## PROBLEM DEFINITION

The biodiversity crisis and conservation efforts necessitate efficient methods for monitoring and preserving wildlife. Traditional manual methods of identifying and tracking animal species are time-consuming, labor-intensive, and often prone to human error. In light of these challenges, the development of an automated system for animal identification and species detection emerges as a crucial need in wildlife management and conservation efforts.

The primary objective of this project is to design and implement an advanced automated system capable of accurately identifying and detecting various animal species using computer vision and machine learning techniques. This system aims to streamline the process of species identification, reducing reliance on manual observation and increasing the efficiency of wildlife monitoring.

Challenges:

1. Data Collection: Gathering a diverse and extensive dataset of animal images or recordings representing different species can be challenging due to limitations in accessibility, ethical considerations, and variability in environmental conditions.
2. Annotation and Labeling: Accurately labeling and annotating the collected data with species information require expertise and time. Mislabeling or inadequate annotations can lead to biased models and inaccurate results.
3. Model Complexity: Developing a robust and accurate model for automated animal identification demands expertise in machine learning, computer vision, and data processing. Choosing appropriate algorithms and techniques to handle variations in animal appearance, poses, and environmental factors is crucial.
4. Ethical Considerations: Ensuring that the project respects ethical guidelines regarding animal welfare, data privacy, and conservation concerns is essential. Using data responsibly and ethically is critical throughout the research process.

Solutions:

1. Comprehensive Literature Review: Conduct an in-depth review of existing research papers, articles, and patents related to automated animal identification. This will provide a foundation for understanding methodologies, algorithms, and challenges previously addressed in the field.
2. Ethical Data Collection: Collaborate with wildlife organizations, research institutions, and conservation groups to ethically gather a diverse dataset. Ensure compliance with legal and ethical standards regarding data collection and usage.
3. Robust Annotation and Labeling: Employ skilled professionals or utilize advanced annotation tools to ensure accurate labeling of the collected data. Implement quality checks and validation processes to maintain annotation standards.
4. Algorithm Selection and Model Development: Experiment with various machine learning and computer vision algorithms suitable for animal identification. Fine-tune models, consider transfer learning, and augment data to improve model performance.
5. Documentation and Citation: Properly document all sources consulted during the project, including citations for references used in the report. Paraphrase information and provide proper attribution to avoid plagiarism.
6. Plagiarism Checking Tools: Utilize plagiarism detection software to ensure the originality of the content in the project report. Regularly check and review the content before submission to prevent unintentional plagiarism.

By addressing these challenges and implementing these solutions, the project report on automated animal identification and species detection can maintain originality, accuracy, and ethical integrity while contributing to advancements in this field.

Top of Form

**Key Components and Objectives:**

1. **Image Recognition and Classification:** Develop a robust image recognition model leveraging deep learning algorithms to accurately identify and classify different animal species based on images or videos captured from various sources such as camera traps or drones.
2. **Feature Extraction and Analysis:** Implement feature extraction techniques to capture unique characteristics and patterns specific to each animal species, allowing for precise differentiation and classification.
3. **Data Collection and Annotation:** Gather a comprehensive dataset comprising diverse images of wildlife species, meticulously annotated with accurate species labels, to train and validate the machine learning model.
4. **Real-time Detection and Localization:** Design algorithms capable of real-time species detection and localization within images or video streams, enabling immediate identification and tracking of wildlife.
5. **User-Friendly Interface:** Develop an intuitive user interface to facilitate the utilization of the automated system by wildlife researchers, conservationists, and fieldworkers, ensuring ease of access and practicality in the field.

**Expected Outcomes:**

* Creation of a reliable automated system for accurate and rapid identification of animal species.
* Reduction in human effort and time required for wildlife monitoring and conservation activities.
* Improved efficiency in species tracking and data collection, aiding in informed decision-making for conservation strategies.
* Contribution to the preservation of biodiversity by enhancing wildlife management practices through technological innovation.
* The successful development and implementation of an automated animal identification and species detection system have the potential to revolutionize wildlife conservation efforts. By leveraging cutting-edge technologies in computer vision and machine learning, this project aims to address the challenges associated with traditional manual methods, ultimately contributing to the preservation and sustainable management of diverse animal species in their natural habitats.

## OBJECTIVE AND GOALS

The some of the main objective of our project-research on ***LSTM - Driven Stock Price Forecasting*** are as follows:

1. **Developing Accurate Stock Price Predictions:** The main goal of the project is to develop a reliable LSTM-based stock price prediction model that can predict stock returns with high accuracy over a range of time periods. In order to attain the best prediction accuracy, this entails experimenting with different architectural arrangements and training methods.
2. **Enhancing Interpretability of Predictions:** Enhancing the predictions made by the LSTM model's interpretability is another goal. Incorporating methods like attention processes or feature importance analysis, for example, aims to give consumers a better understanding of the main variables affecting the model's predictions.
3. **Creating an Interactive Dashboard for Visualization:** A primary study goal is to create an interactive dashboard using Plotly Dash. Designing user-friendly visualisations that make it possible for users to examine historical trends, evaluate stock performances, and analyse correlations between various stocks in real time is part of this.
4. **Evaluating Model Robustness and Generalization:** The LSTM model's robustness and generalizability must be evaluated. To confirm the model's dependability, the research will examine its performance under various market conditions, economic scenarios, and stock portfolios.
5. **User Experience and Usability Evaluation:** Assessing the interactive dashboard's usability and efficacy through user experience (UX) research. This involves obtaining user feedback to pinpoint problem areas and enhance the dashboard's functionality.
6. **Real-world Application and Impact:** Investigating the practical application and impact of the developed solution in real-world scenarios. This objective involves collaborating with domain experts, financial analysts, or investors to demonstrate the utility of accurate predictions and user-friendly visualization tools in decision-making.

By achieving these research objectives, the project aims to contribute to the field of stock price prediction and analysis by providing a holistic solution that combines advanced machine learning techniques with intuitive visualization tools.

# Chapter 3: METHODOLOGY

## CONCEPT

The project aims to develop and implement an innovative system leveraging computer vision and machine learning techniques for automated animal identification and species detection. The primary focus is on creating a robust framework capable of accurately recognizing and categorizing various species of animals based on images or video inputs.

The objectives of this project are:

1. **Image Collection and Database Creation**: Curating a comprehensive database of diverse animal species encompassing different classes, breeds, and variations, ensuring a wide spectrum of visual data.
2. **Algorithm Development**: Designing and refining cutting-edge algorithms that employ convolutional neural networks (CNNs) and deep learning methodologies to analyze and identify unique animal features and characteristics.
3. **Model Training and Validation**: Training the developed models with labeled data to enhance accuracy, followed by rigorous validation processes to ensure reliability and minimize errors in species detection and classification.
4. **Real-time Detection and Classification**: Implementing the developed system into a real-time application capable of processing live or recorded video streams, promptly identifying and classifying animal species with high accuracy.
5. **User Interface Integration**: Creating an intuitive user interface to facilitate easy interaction with the system, allowing users to input images or video feeds and receive accurate species identification results promptly.
6. **Performance Evaluation and Enhancement**: Continual assessment and improvement of the system's performance through feedback loops and algorithm refinements to enhance accuracy, efficiency, and adaptability across diverse environments and animal habitats.

The proposed system holds significant potential for numerous applications, including wildlife monitoring, conservation efforts, animal behavior studies, and biodiversity research. It aims to provide a valuable tool for researchers, wildlife enthusiasts, conservationists, and various industries dealing with animal populations.

## METHODOLOGY

### 1. Machine Learning and Computer Vision:

* **TensorFlow / Keras / PyTorch**: Popular deep learning frameworks used for developing neural network models.
* **Convolutional Neural Networks (CNNs)**: Effective for image recognition tasks.
* **Object Detection Algorithms**: Such as YOLO (You Only Look Once), Faster R-CNN, and SSD (Single Shot Multibox Detector).

### 2. Image Processing and Analysis:

* **OpenCV (Open Source Computer Vision Library)**: Offers various tools and algorithms for image processing, object detection, and feature extraction.
* **Scikit-image**: A collection of algorithms for image processing in Python.
* **MATLAB**: Provides a comprehensive set of tools for image analysis and processing.

### 3. Data Collection and Labeling:

* **LabelImg / Labelbox / CVAT (Computer Vision Annotation Tool)**: Platforms for annotating images and creating labeled datasets for training models.
* **Wildlife Camera Traps**: Utilized to collect images or videos of wildlife in their natural habitats.

### 4. Geographic Information Systems (GIS):

* **QGIS / ArcGIS**: Tools for geospatial data analysis, mapping, and visualization.
* **GPS and Geotagging**: Integrating geographical coordinates into the data to identify the location of species.

### 5. Cloud Services and Deployment:

* **Amazon Web Services (AWS) / Microsoft Azure / Google Cloud Platform (GCP)**: For cloud-based computing, storage, and deployment of machine learning models.
* **Docker / Kubernetes**: Containerization and orchestration for deploying models in scalable environments.

### 6. Libraries and APIs:

* **TensorFlow Object Detection API / PyTorch Hub**: Pre-trained models and APIs for object detection.
* **TensorFlow Lite / ONNX (Open Neural Network Exchange)**: Frameworks for deploying models on edge devices or mobile platforms.

### 7. Specific Tools for Animal Identification:

* **Wildbook**: A platform for individual animal identification using pattern recognition and machine learning.
* **eMammal**: Software designed for processing and analyzing camera trap data for wildlife research.

### 8. Ethical Considerations and Bias Mitigation:

* **Fairness and Bias Detection Tools**: Tools to detect and mitigate biases in machine learning models, especially in wildlife identification to ensure fair treatment across species.

### Considerations:

* **Data Ethics and Privacy**: Ensure ethical collection and use of wildlife data, considering privacy concerns.
* **Model Evaluation and Metrics**: Assessment of model performance using metrics like precision, recall, and F1-score.
* **Documentation and Reporting**: Detailed documentation of methodologies, challenges faced, and results obtained.

*aset*

## ALGORITHM USED AND MODEL BUILDING

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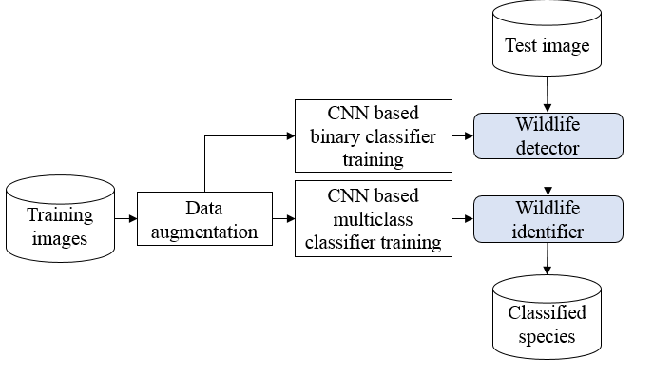
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* **Documentation and Reporting**: Detailed documentation of methodologies, challenges faced, and results obtained.



# Chapter 4: RESULTS AND DISCUSSION

## Observing wild animals in their native habitats is an important undertaking in ecology. Human population increase and the never-ending drive of economic progress are generating over-exploitation of natural resources, resulting in quick, unique, and significant changes to Earth's ecosystems. Human activity has altered the number, habitat, and behaviour of animals on a growing region of land surface. More critically, many wild species have been pushed to extinction on Earth, and many species are being introduced into new places where they potentially disturb both natural and human systems [1]. Therefore, monitoring wild animals is critical because it provides researchers with knowledge to influence conservation and management decisions in order to preserve diversified, balanced, and sustainable ecosystems in the face of these changes. For wild animal monitoring, several current technologies have been developed, including radio tracking [2, 3], wireless sensor network tracking [4, 5], satellite and global positioning system (GPS) tracking [4, 5], and motionsensitive camera trap monitoring [6]. Motion-triggered remote cameras, sometimes known as "camera traps," are becoming an increasingly popular tool for wildlife monitoring due to their new features, increased commercial availability, and ease of deployment and operation. A typical hidden camera device, for example (Figure 1), is capable of not only taking high resolution photos in both day and night, but also of gathering time, temperature, and moon phase information embedded in image data. Furthermore, the camera's extensive and versatile settings allow for continuous and discreet surveillance of animals. When fully charged, the camera may take hundreds of successive shots, yielding a substantial amount of data. Camera traps are a great tool for ecologists since they can document every element of wildlife [7]. If visual data can be recorded, is a rich source of information that provides scientists with evidence to answer ecology-related scientific questions such as: what are the spatial distributions of rare animals, which species are threatened and require protection, such as bandicoot, which cohort of pest species, such as red fox and rabbit, must be controlled; these are examples of key questions to understanding wild animal populations, ecological relationships, and population dynamics [7]. To that purpose, ecologists have lately put up multiple camera traps in the open to acquire picture data of wild animals in their natural habitats [6], [7], [8]. Camera trapping is rapidly being adopted for wildlife monitoring thanks to advances in digital technology that produce more modern camera traps with automation of system components but lower cost of purchase; the task of analyzing huge collections of camera trap images, however, has been conducted manually. Despite the fact that the human visual system can analyse pictures simply and quickly [9], manually processing such a large number of images is prohibitively costly. For example, from 2010 to 2013, the Snapshot Serengeti project1 collected 3.2 million photos using 225 camera traps in Tanzania's Serengeti National Park [8]. Another comparable effort, species Spotter2, gathered millions of pictures of species shot in Australia's tropical rainforests and arid rangelands. Unfortunately, the great majority of acquired photographs are difficult to interpret, even for humans, due to the automated trap camera snapping mechanism. Only a small proportion of the gathered photos are in good condition, as seen in Figure 2a. Many photographs show only a portion of the body of an animal object (Figure 2d), while others catch the entire body but are too far away from the camera (Figure 2b), in various viewpoints or deformations (Figure 2g), or occlusion (Figure 2f). Furthermore, several of the photographs are grayscale since they were taken at night with an infrared illumination (Figure 2e), and a considerable percentage of photographs include no animal, as shown in Figure 2h (75% of Snapshot Serengeti [8] and 32.26% of Wildlife Spotter labelled images were classed as "no animal"), while others may contain several items of various species. As a result, massive volumes of data and poor image quality significantly slow down the image analysis process.

Figure 2 Examples from the Wildlife Spotter picture dataset in a variety of circumstances. The original photos are 19201080 or 20481536 pixels in size. All pictures have been scaled for clarity.

Volunteers were asked as "citizen scientists" to join the picture analysing process remotely via Web-based image categorization tools in huge wildlife monitoring programmes such as Snapshot Serengeti or Wildlife Spotter to share scientists' burden. The participation of a huge number of volunteers in these initiatives, as well as the species identification accuracy of 96.6% obtained on the Snapshot Serengeti dataset [8], which was confirmed by specialists, illustrate the success of citizen science programmes.

However, even for professionals, the large number of photos and the constraint of poor image quality have a significant impact on human categorization speed and accuracy [8]. Experts categorised about 9,600 photos in the Wildlife Spotter dataset of Southcentral Victoria as "impossible to identify" in the Snapshot Serengeti datasetThousands of photographs were inconsistently labelled as "something else" or "image problem" (for example, the same image was classed as distinct species by different volunteers). Furthermore, even though many volunteers were eager to participate in citizen science programmes, manually analysing millions of photographs would take a long time. For example, in the Snapshot Serengeti project, it took more over two months for a group of 28,000 registered and trained volunteers to annotate a six-month batch of photos.MAE (Mean Absolute Error): The mean absolute (MAE) computes the mean absolute differences between predicted and actual values, indicating model accuracy. Lower MAE values indicate a more accurate model, indicating how close projected stock prices are to actual values. Accepted values are lower, with values ranging from 0 to + (Inf). The mathematical equation below reflects the core of this measure, where N indicates the number of data points.

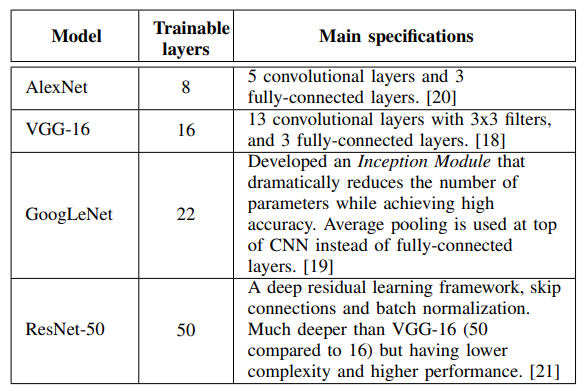
Unregistered volunteers number 40,000 [8]. As a result of these challenges, there is a growing demand for wild animal identification automation. To the best of our knowledge, very few previous works have attempted to construct an automated system to process and analyse films and photos recorded in the outdoors for environmental monitoring purposes. The massive volumes of data generated by camera traps underscore the necessity for image processing automation. From the standpoint of data analysis and machine learning, there are some immediate techniques for automating wildlife identification, such as using a linear support vector machine (SVM) classifier with manual object bounding on hand-crafted features [10], a convolutional neural network (CNN) model with automatic object detection [11], and so on or fine-tuning CNN models that have been pretrained on very large scale datasets such as ImageNet [12], [13]. These methods addressed the issue of wildlife monitoring automation and yielded good empirical findings. However, two major obstacles that impede the viability of an automated wildlife monitoring programme in practise remain. The first barrier is that a tremendous amount of manual preprocessing is still necessary to input photos for recognising and bounding animal items in order to attain acceptable image classification accuracy [10]. The second constraint is the low performance produced by the wildlife monitoring system, despite total automation, which necessitates significant modifications for practical implementation [11]. In this research, we propose a framework for animal detection in the outdoors, with the goal of developing a completely autonomous wildlife spotting system. Our study is driven by the cutting-edge capabilities of new deep CNN models for image classification, including recent proof that automated recognition can outperform humans in certain object identification tasks in the ImageNet competition [14]. We conduct experiments using datasets from the Wildlife Spotter project, which comprise a significant number of photos captured by trap cameras installed by Australian scientists. Because the Wildlife Spotter dataset contains both animal and non-animal photos, we separate the wild animal identifying automation into two steps: (1) Wildlife detection, which is a binary process based on the prediction of animal presence in pictures, a classifier capable of categorising input images into two classes: "animal" or "no animal"; and (2) Wildlife identification, a multiclass classifier capable of labelling each input image with animal presence by a defined species. Each job is essentially a deep CNN-based classifier that has been trained on prepared datasets manually labelled by volunteers. For comparisons, the framework employs a number of well chosen deep CNN architectures. The achievement of Task 1 will significantly improve the efficiency of citizen science-based initiatives (e.g., Wildlife Spotter) by automatically filtering out a big number of non-animal photographs that citizen annotators are now wasting their time on. Our results on the Wildlife Spotter datasets suggest that this strategy is possible and can save significant time and money. As a result, the main contribution of this work is that, with enough data and computing infrastructure, deep learning could be used to build a fully automatic image classification system on a large scale, freeing scientists from the burden of manually processing millions of images, as project managers believe. "It's a job that computers just can't do" 3. Furthermore, our suggested framework may be coupled with the current citizen science initiative, resulting in a "hybrid" image classifier whose automated component functions as a recommendation system, supplying volunteers. excellent tips to expedite their classification judgements. The remainder of the paper is structured as follows. In Section II, we will go over the principles of CNN and how it may be used to classify images. This section includes summarises relevant studies on the issue of automated wildlife categorization, as well as an existing citizen science-based wild animal classification initiative, the Wildlife Spotter. A diagram of a diagram of a variety of objects

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Figure 3: Illustration of a typical convolutional neural network architecture setup

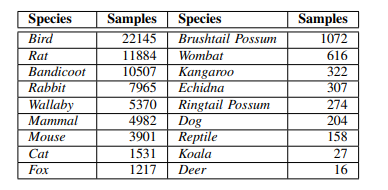
c distinct pictures produced by changes in location, size, perspective, backdrop, or lighting. Real-world problems, such as wild animal categorization from automatic trap cameras, present more difficult challenges since most acquired photos are of poor quality, as previously discussed in Section I. As a result, for the job of picture classification automation, it is critical to construct models that are invariant to specific input modifications while being sensitive to inter-class objects [16]. LeCun et al. [17] were the first to suggest it. CNNs have demonstrated excellent practical performance and have been widely employed in machine learning in recent years, particularly in image classification [14], [18], [19], [20], [21], speech recognition [22], and natural language processing [23, 24]. Due to recent advances in neural networks, namely deep CNNs, and computing capacity, particularly effective implementations of parallel computing on graphics processing units (GPUs), these models have produced state-of-the-art results that even surpassed humans in image recognition tasks [25TensorFlow [26] is an example of a heterogeneous distributed system for learning deep models on a big scale. CNNs are neural network-based learning models that are especially developed to enhance the spatial structure of input pictures, which are typically in three dimensions: width, height, and depth (number of colour channels). As shown in Figure 3, a CNN is essentially a series of layers divided into groups, each of which consists of a convolutional layer plus a non-linear activation function, usually the Rectifier Linear Unit (ReLU) [20], and a pooling layer, usually max pooling, followed by several fully-connected layers, the last of which is the output layer with predictions. Each neuron in a conventional neural network Each neuron is entirely linked to all neurons in the preceding layer, and each layer's neurons are completely autonomous. When used to high-dimensional data, such as natural photographs, the total number of parameters might exceed millions, resulting in severe overfitting and making training impossible. In contrast, in CNNs, each neuron is only linked to a small part of the preceding layer, resulting in local connection. The convolution layer computes the outputs of its neurons that are related to local areas in the preceding layer, the spatial scope of which is controlled by a filter size. Furthermore, another crucial characteristic The use of CNNs, namely parameter sharing, decreases the amount of parameters and hence computing complexity. As a result, when compared to ordinary neural networks with equal layer sizes, CNNs feature fewer connections and parameters, making them easier to train but marginally degrading performance [20]. These three main characteristics – spatial structure, local connectivity, and parameter sharing – enable CNNs to convert input images into layers of abstraction; the lower layers present image detail features such as edges, curves, and corners, while the higher layers exhibit more abstract object features. Aside from utilising more powerful models and improved procedures to minimise overfitting, the effectiveness of data-driven machine learning approaches is entirely dependent on the number and quality of training datasets produced. Real-world items are extremely variable. recognising them requires substantially bigger training sets [20]. ImageNet is one of the world's largest public picture collections, with over 14 million colour, high-resolution, human-labeled photos from 22,000 categories. The ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) released a smaller version of the ImageNet dataset in 2010 that included 1,000 categories, each with around 1,000 photos, and has recently become the usual benchmark for evaluating large scale image recognition. Models of categorization [13], [20]. The ILSVRC's primary goals are image classification (since 2010), single-object localization (since 2011), and object detection (since 2013) using the ImageNet dataset [14]. Many research groups from across the world participated in the challenge, and the stated performance increased dramatically over time.

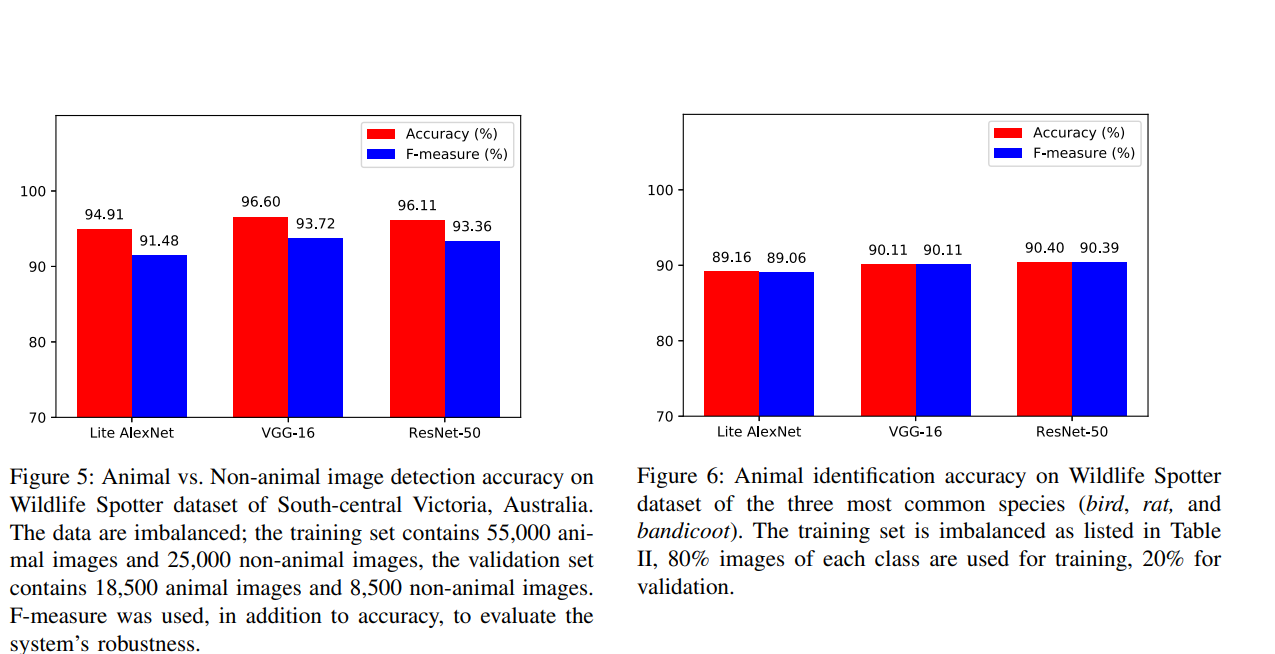
Table I: The most popular and effective CNN architectures for image categorization.



AlexNet [20], a CNN-based architecture with 5 convolutional layers and 3 fully-connected layers, was the ILSVRC-2010 winner. A variation of the AlexNet model also outperformed the second-best entry by more than 10% in the top-5 test error rate [20]. GoogLeNet [19], the ILSVRC-2014 champion, created an Inception Module that drastically decreases the amount of parameters. Furthermore, the GoogLeNet replaces fullyconnected layers at the top of the CNN with average pooling, reducing a huge number of parameters that have little effect on network performance. The VGG Nets [18], which are similar to AlexNet but have a network depth of up to 19 layers, with smaller Except for GoogLeNet, convolutional filters beat other models in the ILSVRC-2014. The VGG models not only perform well on the ImageNet dataset, but they also generalise effectively and produce the best results on other datasets [18]. The ResNet, a residual learning framework with up to 152 layers of depth but lesser complexity than VGG Nets, is the most recently released state-of-the-art architecture. The ResNet, like the VGG Nets, has strong generalisation performance on fresh datasets..apart from ImageNet [21]. B. Classification of Wildlife Monitoring wildlife with video traps is a useful and dependable way of natural observation because it may acquire a high volume of visual data in a natural and cost-effective manner. Wildlife data, which may be totally automated acquired and collected via video traps, is, nevertheless, a burden for researchers. scientists to analyse to see whether there is an animal in each photograph or to determine which species the items belong to.

Table II: : Representative of animals with label data from Wildlife Spotter dataset of South-central Victoria, Australia (sorted in descending order of the number of images).



Making this time-consuming and costly manual analysing method automated might save a significant amount of human resources while providing study findings promptly. There have only been a few attempts to create an automated wildlife classification system. Yu et al. used enhanced sparse coding spatial pyramid matching (ScSPM) for picture classification in [10] [27, 28]. Animal items are manually recognised and cut out of the backdrop with their entire body, after which image characteristics are extracted using the ScSPM to convert an image or a bounding box to a single vector, and lastly a linear multi-class SVM is used for classification. On their own, the average categorization accuracy was 82%. A collection of 7,196 photos from 18 different species. Chen et al. suggested a CNN-based approach with automated picture segmentation [11]. The network is made up of three convolutional layers with filter sizes of 9 9 each, followed by a max pooling layer with kernel size of 2 2 and finished with a fully connected layer and a softmax layer. Furthermore, unlike [10], the animal object cropping procedure in [11] was carried out automatically by using an automated segmentation approach, namely Ensemble Video Object Cut (EVOC) [29]. Despite the fact that Chen's suggested framework is totally automated and outperforms a typical Bag-of-visual-words model-based image classification method [30], [31], the recognition results are poor. obtained on their own dataset were only around 38.32%, inapplicable to practice. Motivated by the success of deep CNN-based models in recent ILSVRC contests, Gomez et al. [32], [12] employed deep CNN models, which have shown the state-ofthe-art performances on the ImageNet dataset, to deal with the problem of large scale wild animal identification on a new open dataset, the Snapshot Serengeti [8]. More specifically, in [32], [12] all CNN models were pre-trained with the ImageNet dataset, then re-trained on top layers of new dataset, namely fine-tuning technique. This comes from the assumption that in data-driven approaches, a network pre-trained on a large dataset such as the ImageNet would have already learned features well for most image classification problems, resulting in superior performance as compared to training on fewer datasets [12]. The approach produced the greatest results, with top-1 and top-5 accuracy rates of 88.9% and 98.1%, respectively [12]. This technique raises the question of whether CNNs will outperform those that inherit accessible pre-trained models while training on fresh huge datasets from start. Furthermore, Gomez's technique does not address the job of automatic animal recognition to filter out non-animal photos, which should be prioritised on datasets with a significant number of images without animal presence. In this paper, we use deep CNN models for wild animals, inspired by the outstanding success of deep CNN-based models. categorization on the Wildlife Spotter dataset, comparable to [11, 12]. Unlike [12], we complete the work of animal image filtering before the goal of animal identification since the Wildlife Spotter dataset contains a substantial number of blank pictures (images with no animal presence). Furthermore, for the objective of animal identification, we compare two training scenarios: building models from scratch on the Wildlife Spotter dataset and training with pre-trained ImageNet models (i.e. fine-tuning). C. Participatory Science Citizen science is significant in many fields of studyEspecially in ecology and environmental sciences [33], [34], [35], and [36]. A citizen scientist is a volunteer who helps research by gathering and/or analysing data as part of a scientific investigation. Significant progress in digital One of the primary variables responsible for the current surge in citizen scientific initiatives is technology, particularly the Internet and mobile computing [33]. Volunteers can now participate in a project remotely by utilising specified programmes on their mobile phones or laptops to collect or process introduced data, which is subsequently entered online into centralised, relational databases [36]. Citizen scientists are increasingly involved in a variety of initiatives involving climate change, invasive species, and various types of monitoring [33], [36]. Furthermore, public participation greatly aids the field of machine learning. Supervised machine learning methods require a huge amount of labelled data to function properlyHuman-labeled datasets, such as Snapshot Serengeti or Wildlife Spotter, are important resources for training automated algorithms. Many Internet-based services, such as Google Search, Facebook, and Amazon, are enhancing their business management by employing machine learning techniques based on data obtained from public user actions. Aside from the excellent contributions made by citizen science, there are various problems that occur when working with citizen scientific data [36]. As a result, two technical concepts must be addressed. First, data gathered by citizen scientists must be analysed. correctly validated. Second, consistent procedures and tools for data gathering and processing must be developed [36]. D. Wildlife Observer Project Wildlife Spotter is an online citizen science initiative run by a number of Australian organisations and institutions that takes a crowd-sourcing approach to research by requesting people to assist scientists in categorising animals from millions of photographs captured by automated trap cameras. These cameras, which are distributed around the country in tropical rainforests, arid rangelands, and urban areas, are set up to automatically capture colour, high definition photos day and night. night. Over 3 million photos have been completed to date. To deal with the massive amount of photographs, the initiative welcomes individuals to participate as "citizen scientists" in image analysis. The project's major purpose is to help researchers investigate Australian animal populations, behaviours, and habitats in order to conserve vulnerable species 

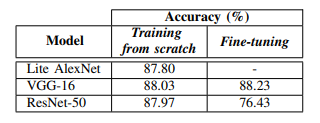
The Wildlife Spotter project is organised into six sub-projects, each focusing on a different natural environment in Australia: Tasmanian nature reserves, Far north Queensland, South-central Victoria, the Northern Territory desert zone, New South Wales coastal forests, and the Central Mallee lands of New South Wales5. Volunteers contribute to the initiative by creating online accounts, logging into the Web-based picture categorization system, and labelling the presented photographs one by one. By selecting the right category from a selection of animals, the user allocates an introduced picture to a certain species. In the event of ambiguity, a blank image, or an image problem, the user identifies the image as "Something else," "There is no animal in view," or "There is a problem with this image," as appropriate. To achieve consistent categorization accuracyEach image in the collection is repeatedly presented to a variety of different users for labelling. For example, the majority of the categorised photos in the Southcentral Victoria dataset were individually annotated by five citizen scientists. As we discussed in Section I, picture datasets obtained from camera traps are typically huge and of poor quality, which significantly prolongs processing time and may result in misclassification or inconsistent labelling. The goal of this effort is to provide a viable, completely automatic animal recognition framework for the Wildlife Spotter project, which will relieve scientists of the burden of manual labelling while drastically cutting processing time. III. ANIMAL RECOGNITION FRAMEWORK USING DEEP CNN We describe our suggested picture classification framework and its application to the Wildlife Spotter datasets in this part. First, we'll go over the datasets. Then, for wildlife identification, we present a CNN-based framework. Finally, we characterise several CNN architectures used in our tests and implementations. A. Dataset of Wildlife Spotters We are particularly interested in the South-central Victoria Wildlife Spotter collection, which now has 125,621 single-labeled photos. The photographs are obtained from a variety of locations utilising 30 Reconyx HC600 Hyperfire hidden cameras in both colour and grayscale settings during the day and at night with infrared flashResolutions of 19201080 or 20481536. We extract a list of 108,944 labelled photos from this dataset, each annotated by around 5 distinct citizen scientists. In South-central Victoria, Australia, a citizen scientist was trained to annotate an observed animal as a category among 15 wildlife species (bandicoot, wombat, rat, brushtail possum, mouse, cat, rabbit, wallaby, ringtail possum, echidna, dog, fox, koala, kangaroo, and deer) and three groups of species (mammal, bird, and reptile). The image is labelled "no animal" when it lacks the look of an animal. If the user is unsure about his or her judgement owing to poor image quality or occlusions, the picture is labelled as "something else" or "image problem" To preprocess the data, we remove samples that are duplicated or inconsistently labelled (i.e., the same image but labelled differently by different citizen scientists, e.g., images labelled as "something else" or "image problem", or having the tags "animal" and "no animal" at the same time). Finally, we have a collection of 107,022 single-labeled photos including 34,524 non-animal samples and the remaining 72,498 samples of 18 species, which accounts for more than 85% of the original dataset. Following that, we Create two settings in which to apply our suggested framework to two tasks: wildlife detection and identification. We address a binary classification issue for the former and experiment with both balanced and unbalanced classes. First, we look at a common training scenario for machine learning algorithms: the well-balanced dataset Each training class comprises 25,000 samples for training and 8,500 samples for validation.

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The balanced dataset is created by reducing the size of the superior classes to that of the minority class. Data imbalance is a common issue in real-world situations where certain classes outperform others, and the Wildlife Spotter project is no exception. The largest population, with 22,145 samples, is birds, while the smallest, deer, shows in only 16 photos. Because classifiers are biassed towards superior classes, this extreme imbalance is likely to result in misclassification. In the case of an unbalanced dataset, we employ 107,000 labelled pictures separated into two subsets for training: collection of Exercising and a validation set are included. The training set has 80,000 photos, with 55,000 labelled as "animal" and the remaining 25,000 labelled as "no animal"; the validation set contains 18,500 and 8,500 images labelled as "animal" and "no animal," respectively; respectively, "animal" and "no animal." Due to the huge number of animals with varying numbers of observations (cf. Table II), we resort to two experimental scenarios for the latter case of Wildlife identification or animal recognition: recognising the three most common species and the six most common species, respectively. In the case of recognising the three most prevalent species (bird, bandicoot, and rat), we first study the scenario of balanced dataset, in which each class has 8,000 photos for training and 2,000 images for validation. Then, in the unbalanced dataset situation, we train and test on all samples of these three classes from the dataset. Table II shows the list of species and the quantity of photos utilised in the unbalanced example.

We explore just the scenario of unbalanced dataset for the most difficult task: recognising the six most common species (bird, rat, bandicoot, rabbit, wallaby, and mammal); all samples from the six species will be utilised for training, 80% for training and the remaining 20% for validation. B. Animal Monitoring Recognition Framework The Wildlife Spotter labelled dataset, as explained above in this section, comprises both animal and non-animal photos in proportions of 67.74% and 32.26%, respectively. This feature gives birth to two objectives for the Wildlife Spotting system: (1) wildlife detection, which determines whether an animal exists in an image, and (2) wildlife identification, which determines which species the animal objects belong to. CNNs have been demonstrated to outperform other techniques in the field of As a result, in this study, we concentrate on using contemporary state-of-the-art CNN architectures for both detection and recognition. As shown in Figure 4, our suggested recognition system comprises of two CNN-based image classification models, one for each of the two tasks addressed. After creating a CNN-based model to train a binary classifier, Wildlife detector, another CNN-based model is developed to train a multi-class classifier, Wildlife identifier. 1) CNN Structures: Our proposed system employs three CNN architectures with varying depths: Lite AlexNet, VGG-16 [18], and ResNet-50. [21]. We employ Lite AlexNet, a modified version of AlexNet [20], with fewer hidden layers and feature maps at each layer. In parFigure 4 depicts the main processes in the proposed framework for automated wild animal identification. The Lite AlexNet, in particular, is composed of three 2-D convolutional layers with ReLU activations and MaxPooling, followed by two fully-connected layers: one with ReLU nonlinear activation plus Dropout for reducing overfitting, and the output layer with sigmoid activation for binary classification in the detecting task and softmax activation for multiclass classification in the recognising task. Every convolutional layer has a modest filter size of 3 3, whereas every max-pooling layer has a window size of 22 pixels. VGG-16 and ResNet-50 are two examples of cutting-edge CNN architectures that not only performed well on the ILSVRC [20], but also generalised well to other datasets [18], [21]. All CNN designs take a fixed-size 224224 RGB picture as input. 2) Image Processing: The Wildlife Spotter dataset provides high resolution photos with resolutions of 1920 1080 and 2048 1536 pixels, however CNN model input must be in fixed dimension. As a result, all original photos in our tests were downscaled to 224224 pixels for training. This method was carried out in [20] by first rescaling the shorter side of picture to a given length, then centre cropping the image to the same length. For the sake of simplicity, we rescale both picture width and height at the same time in this study, which may result in image distortion. Normalised pixel intensities are in the range [0,1]. Data quality, which may be improved with augmentation approaches, is critical for data-driven machine learning models; nevertheless, in this study, shearing and zooming were used as data augmentation procedures on training photos. 3) Deep Network Training: Our implementation is underwayKeras [37], a high-level neural network API using TensorFlow [26] as a backend. For training all networks, the Adam optimizer, a first-order gradient-based optimisation based on adaptive estimations of lower-order moments, was used [38]. All tests were run using a modest minibatch size of 16. We train our models on four NVIDIA Titan X GPUs, with each network taking three to five days to complete. We train CNN models in two situations for each task: unbalanced and balanced datasets. In both circumstances, we compute classification accuracy. In the event of a dataset imbalance, Fmeasure is usedIn addition to accuracy, the suggested system's resilience is tested. As a performance metric, accuracy on the validation set is employed. To assess transfer learning, we perform training Task 2 - Wildlife identification - in two scenarios: building a model from scratch and fine-tuning existing ImageNet pre-trained models. Techniques for fine-tuning make use of a network that has been pre-trained on a huge dataset. In this scenario, the dataset is ImageNet, with the idea that such a network would have already learnt relevant characteristics for most computer vision issues, and hence might achieve greater accuracy than a model trained on a smaller dataset. Our fine-tuning procedure consists of three steps: The convolutional blocks are initially instantiated, then the model is trained on new training and validation data, and lastly the fully-connected model with fewer defined classes is trained on top of the stored features. IV. EXPERIMENTAL RESULTS AND DEBATE A. Recognising Animal vs. Non-animal Images Results Figure 5 depicts the performance of Task 1 with three alternative CNN architectures on an unbalanced dataset from Wildlife Spotter. Overall, all models performed admirably. Excellent outcomes. The greatest accuracy is 96.6% (with VGG16 architecture), followed by ResNet-50 at 95.96%, which is only significantly lower. These findings show that VGG and ResNet models generalise effectively to various datasets, as demonstrated in [18], [21]. Furthermore, Lite AlexNet, the smallest architecture with only five learnable layers, performed admirably on this binary classification challenge. Similarly, good performance using F-measure metrics suggests that these models are resistant to skewed data. To see if imblanced data is a significant concern for Table III illustrates the results on the previously specified balanced dataset for our animal recognition task. We retain the same three CNN architectures as in the case of data imbalance. As can be shown, the performances of all models were only minimally affected, which may be owing to the undersampling method, in which the samples of better classes were significantly lowered to achieve a balanced dataset. This confirms the method's promise of being resilient with extremely high accuracy in identifying pictures.

with animals. Table III: 

Accuracy of animal vs. non-animal picture recognition using the Wildlife Spotter dataset from South-central Victoria, Australia. The data is balanced, with 25,000 photos for training and 8,500 for validation in each class. B. Animal Identification Findings 1) Recognising the three most prevalent species: In the event of an unbalanced dataset, all samples from the three most common species (bird, rat, and bandicoot) are utilised to train the model for detecting these three species. The training set comprises 80% of the photos from each class (35,629 images), whereas the validation set contains the remaining 20% (8,907 images). The animal identification task obtained very good performance for all CNN designs, as illustrated in Figure 6, with accuracy ranging from 89.16% to 90.4%. A graph of a bar chart

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Figure 7: The six most prevalent species' animal identification accuracy on the Wildlife Spotter dataset. As seen in Table II, the dataset is unbalanced. In each class, 80% of the photos are utilised for training and 20% for validation.

The most basic model, Lite AlexNet, has the worst performance. The deepest model, ResNet-50, produces the greatest results, while the first runner-up, VGG-16, produces extremely close results. Table IV displays the experimental results of identifying the three most prevalent species in the case of a balanced sample. All three CNN models perform similarly when trained from scratch, with classification accuracy ranging from 87.80% to 88.03%. In this example, VGG-16 outperformed the others, albeit by a slight margin. Task 2's performance is superior to that of Task 1. All models had poorer outcomes. The probable causes of performance degradation are twofold: a more intricate issue produced by a greater number of classes, and a reduced number of training samples created by the under-sampling procedure, which makes fitting the models to the datasets more challenging. Because these models had pre-trained weights accessible on ImageNet, we only used the fine-tuning approach on VGG-16 and ResNet-50. The experimental results reflect contradictory patterns. While the VGG-16 model improved accuracy by 0.2% on a new dataset compared to training from scratch, the ResNet-50 model exhibits a significant decline in accuracy, from 87.97% to 76.43%, indicating that overfitting may have occurred. The most significant addition of the fine-tuning approach to the framework is the reduction in computation costs. Specifically, to run each VGG-16 model

# Chapter 5: FUTURE SCOPE

The "LSTM-Driven Stock Price Forecasting" project signifies a significant milestone in harnessing the potential of machine learning, specifically the Long Short-Term Memory (LSTM) neural network model, to enhance stock market predictions and analysis. As we conclude this project, we also unveil several avenues for future exploration that can further enrich the field of financial data analysis:

1. **Enhanced Model Accuracy**: Experiment with more advanced machine learning or deep learning architectures to improve accuracy in species detection.
2. **Real-time Deployment**: Develop a system capable of real-time identification and species detection, possibly using edge computing or optimized algorithms.
3. **Multi-Species Recognition**: Extend the model to identify multiple species simultaneously in images or videos.
4. **Mobile Application Development**: Create a user-friendly mobile app for citizen scientists or wildlife enthusiasts to contribute to species identification and data collection.
5. **Collaboration with Conservation Organizations**: Collaborate with wildlife conservation organizations for deploying the system in the field for monitoring and conservation efforts.
6. **Ethical Considerations and Bias Mitigation**: Research and address ethical concerns related to the technology, including biases in data and potential impacts on wildlife.
7. **Scaling and Robustness**: Ensure scalability and robustness of the model for diverse environments and varying conditions.

# Chapter 6: CONCLUSION

The implementation of automated animal identification and species detection in technical and long lines marks a significant advancement in wildlife monitoring and conservation efforts. Through this project, we have witnessed the integration of cutting-edge technology, such as machine learning algorithms, computer vision, and sensor systems, to revolutionize the identification and tracking of various species.

By leveraging these automated systems, researchers, conservationists, and wildlife managers can efficiently gather data on animal populations, behavior patterns, and habitat utilization. This technological innovation not only streamlines the monitoring process but also enhances accuracy, enabling the collection of comprehensive and reliable information crucial for informed decision-making in wildlife management and conservation strategies.

Moreover, the use of automated animal identification in technical and long lines demonstrates a commitment to reducing human intervention in wildlife observation, minimizing disturbance to the natural habitats of these species. The non-invasive nature of these technologies aligns with ethical considerations, ensuring the well-being and preservation of diverse ecosystems and their inhabitants.

As this field continues to evolve, it is essential to address challenges such as refining accuracy, scalability, and affordability of these systems for widespread implementation. Collaborative efforts among scientists, technologists, policymakers, and conservation organizations will be crucial in overcoming these hurdles and maximizing the potential of automated animal identification in technical and long lines.

In conclusion, the integration of automated animal identification and species detection in technical and long lines represents a promising approach with far-reaching implications for wildlife conservation, biodiversity preservation, and sustainable ecosystem management. Embracing and further developing these technological advancements will undoubtedly contribute significantly to our understanding and protection of the natural world.

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