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DEPARTMENT OF INFORMATION TECHNOLOGY

Fundamentals Of Digital Image Processing FA-2 Project Report

of

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On

Endangered Species Detection using Digital Image Processing and AI

By

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Problem Statement

The planet's endangered species count is rising at an alarming pace. Natural habitats are being destroyed by urbanization, deforestation, poaching, and climate change. Manual patrols, field surveys, and the analysis of thousands of camera-trap images are examples of traditional monitoring techniques that are labor-intensive, slow, and frequently result in late interventions.

The main issue is **how to swiftly and precisely identify, categorize, and track endangered species in large and intricate environments**. Many animals might become extinct before we even notice their declining numbers if there is no trustworthy solution.

Motivation

1. **Loss of biodiversity:** Ecosystems become unstable whenever a species disappears. For instance, forests are harmed by unregulated deer population growth in the absence of tigers.
2. **Drawbacks of traditional monitoring:** Human-led surveys can take months or years to complete, and by the time they are published, their results are frequently out of date.
3. **The technological potential:** AI and Digital Image Processing (DIP) have given us the ability to analyze images in a couple of seconds, identify patterns that are invisible to the human eye, and notify conservationists in real time.

Objectives

1. To analyze the use of digital image processing in the identification of endangered species.
2. To investigate various deep learning and AI methods applied to wildlife monitoring.
3. To evaluate current approaches and point out their advantages and disadvantages.
4. To pinpoint areas that are worthy of more research and offer ideas for future paths to improve conservation outcomes.

Introduction

The subject of wildlife conservation has entered a new era in which technology is essential to biodiversity management, monitoring, and protection. Conservationists now have access to vast amounts of image and video data thanks to the expanding use of **camera traps, drone photography, and satellite** monitoring. But without effective processing, this data is useless.

A solution is offered by digital image processing (DIP), which gives computers the ability to "see" understand and interpret images. Object detection in complex environments is made possible by DIP techniques like **feature extraction, segmentation, noise reduction, and image enhancement**. DIP can accurately identify animal species when paired with deep learning algorithms such as **Convolutional Neural Networks (CNNs).**

According to recent research, automated systems can achieve detection accuracies of 85–90%, which significantly decreases the need for manual labor [1], [3]. Furthermore, distinctive designs like stripes, shells, or tusks can be used to identify endangered species like tigers, snow leopards, elephants, and marine turtles in addition to their body shape. This ability makes it possible to **conduct habitat analysis, anti-poaching alerts, and non-invasive population monitoring [5].**

Therefore, using DIP to monitor endangered species is not only a technological advancement but also a lifeline for global conservation initiatives.

Related Work

The use of artificial intelligence (AI) and digital image processing (DIP) for the detection of endangered species has been the subject of numerous studies. These studies' main goal is to automate wildlife identification and monitoring, which will save human time and increase the efficiency and precision of conservation efforts [1][2]. These projects primarily use satellite imagery, drone footage, and camera-trap images to collect significant data sets for analysis.

To accurately classify species, even in difficult environments like dense forests or underwater habitats, many methods rely on deep learning models like YOLO, CNNs, and ResNet [3][4]. While some studies focus on handling overlapping animals or cluttered backgrounds, others emphasize enhancing detection in low light. In addition, real-time monitoring and alerts for anti-poaching measures are provided by hybrid systems that combine sensors and IoT devices [5].

When everything is considered, these studies have enhanced wildlife monitoring using automated, non-invasive techniques. Detecting rare species, managing low light levels, and scaling for wide regions continue to cause challenges. Their characteristics, approaches, and research gaps are compiled in the table below.

Sr. No.	Name of the Study	Features	Methodology	Research Gaps
1	Wang et al. (2018) – “Deep Learning for Wildlife Recognition”	Real-time animal recognition	Used YOLOv3 for camera-trap images, achieved ~80% accuracy	Weak in low light/night conditions [1]
2	Tabak et al. (2019) – “Machine Learning for Camera Trap Image Classification”	Classified multiple species	Trained CNN models on large datasets, ~88% accuracy	Rare species had too little data [2]
3	Norouzzadeh et al. (2018) – “Identifying, Counting, and Describing Wild Animals”	Automated detection and counting	Used ResNet-based deep CNN, reached ~90% accuracy	Overlapping animals created misclassifications [3]

4	Beery et al. (2021) – “Species Detection in Complex Environments”	Focused on tough natural backgrounds	Faster R-CNN with transfer learning	High false positives in dense forests [4]
5	Sharma et al. (2022) – “AI for Endangered Species Conservation”	Combined AI with GPS and sensor data	Hybrid DIP + sensor fusion	Still in testing stage, not widely deployed [5]

Methodology

DIP's endangered species detection methodology is a multi-step process that combines innovative AI-driven classification models with conventional image processing methods. There are six main stages to the approach:

1. Image Acquisition

- **Sources:** include satellite imagery, drones, underwater cameras, and camera traps.
- **Environment:** Information gathered from a variety of environments, including oceans, deserts, and dense forests.
- **Difficulty:** Pictures frequently have problems with motion blur, dim lighting, or partially visible animals.

2. Image Pre-processing : This stage prepares raw images for analysis

- **Noise Reduction:** Background noise is lessened by median and Gaussian filters.
- Contrast Enhancement: In dimly lit environments, visibility is improved by histogram equalization.
- **Normalization**: Assures uniform image scales and sizes for input into neural networks.
- **Background Subtraction:** Assists in separating moving creatures from still environments.

3. Segmentation : Segmentation divides the image into meaningful regions

- Animals are separated by thresholding according to pixel intensity.
- Animal outlines are shown by Edge Detection (Canny/Sobel).
- Continuous regions that represent animal bodies have been identified using region-based methods.

In order to separate the subject (an animal) from insignificant background elements like trees, rocks, or water, this step is necessary.

4. Feature Extraction : The system identifies unique animal characteristics

- Texture Features: Design elements like leopard spots or tiger stripes.
- Body outlines and tusks are examples of shape features.
- Turtle shell colors or unique fur are examples of color features.

These characteristics are converted into numerical descriptors so that AI models can examine them.

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5. **Classification Using AI Models :**Once features are extracted, AI models perform grouping
    - YOLO (You Only Look Once): This feature allows for quick real-time detection.
    - Convolutional neural networks, or CNNs, are capable of learning hierarchical features from unprocessed images.
    - Faster R-CNN: Focuses on detecting objects in cluttered or dense settings.

    Depending on the quality of the dataset and the surrounding circumstances, these models can achieve accuracies of 80% to 90% [1], [2], [4].

6. Output and Real-time Alerts

- Images that have been classified are kept in databases for analysis.
- Rangers get real-time alerts in the event that poachers or endangered species are spotted.
- The reports generated cover habitat analysis, migration trends, and population counts.

Conclusion

contrast to traditional techniques, this study investigated how **AI and Digital Image Processing (DIP)** can aid in the detection of endangered species by providing faster and more accurate monitoring. The topic was selected because the loss of biodiversity is a serious worldwide issue, and current manual methods are inadequate and slow to handle the problem's urgency. By automating the identification of animals in difficult natural settings, DIP offers a feasible and adaptable solution.

According to the reviewed research, species detection and classification accuracy levels of 85–90% are achieved when DIP techniques are paired with deep learning models like CNNs, YOLO, and Faster R-CNN. Although these techniques minimize human error and allow for non-invasive monitoring, problems still arise when scenarios involving dense forests, low light levels, or rare species with limited image data. For improved outcomes, these gaps point out the necessity of hybrid approaches that integrate DIP with sensor, GPS, and IoT data.

In conclusion, the use of DIP for endangered species detection is both a **technological innovation and a requirement for conservation**. It facilitates real-time decision-making, reduces human effort, and advances global biodiversity objectives. Even though these systems have limitations, they can be made even more effective through continuous development and integration with new technologies, ensuring that future generations will be able to see endangered species in their natural environments.

References

[1] J. Wang, A. Smith, and L. Brown, “Deep Learning for Wildlife Recognition,” *IEEE Transactions on Image Processing*, vol. 27, no. 11, pp. 5552–5565, 2018.

[2] M. A. Tabak, M. S. Norouzzadeh, D. W. Wolfson, et al., “Machine Learning to Classify Wildlife in Camera Trap Images,” *Ecology and Evolution*, vol. 9, no. 2, pp. 593–604, 2019.

[3] M. S. Norouzzadeh, A. Nguyen, M. Kosmala, A. Swanson, M. Palmer, C. Packer, and J. Clune, “Automatically Identifying, Counting, and Describing Wild Animals in Camera-Trap Images with Deep Learning,” *Proceedings of the National Academy of Sciences (PNAS)*, vol. 115, no. 25, pp. E5716–E5725, 2018.

[4] S. Beery, E. Cole, and P. Perona, “Species Detection in Complex Environments Using Deep Learning,” in *Proc. IEEE/CVF Conf. on Computer Vision and Pattern Recognition (CVPR)*, pp. 10321–10330, 2021.

[5] R. Sharma, V. Kumar, and S. Singh, “Artificial Intelligence for Endangered Species Conservation: A Hybrid Approach,” in *Lecture Notes in Computer Science*, Springer, pp. 245–258, 2022.