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Detection and Tracing of Wild Animals using Machine Learning

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Abstract: *Monitoring wild animals is essential. It is key to discovering Their population and Studying behavior as well as habits. At the inception of wild animal monitoring reliance on human effort was high. It was the main method. Despite being time-consuming It Was also dangerous. Safety risks made this method less than optimal. Development Of pattern recognition technology has been continuous. These techniques are crucial. They have enabled automated wildlife detection. This method uses algorithms driven by image Content analysis. Such algorithms have progressed. They have been Advanced due to these developments. However implementation Of current methods often falls short Recognition accuracy remains a challenge Robustness too often fails to meet practical application requirements Based on these considerations we advocate using RCNN. The method is field animal detection It has been spotlighted in our study We aim to localize and recognize wild animals. We analyzed the effects of different scenes on recognition accuracy This was especially true for Scenes containing multiple targets. We also focused on scenes with small or occluded targets. Our experiments Were vast. We used a Plethora of them. They were used to confirm the feasibility of this method. This method is entirely reliable. Its ability to deliver accurate results have Been proven*

Keywords: animal detection, deep learning, RCNN

I. INTRODUCTION

Conservation areas like zoos, national parks, and wildlife sanctuaries have been established to offer protection and a safe environment for threatened species. However, monitoring and locating animals within these large and often remote areas remains a challenge. Deep learning particularly object detection techniques, offers a promising solution to this issue Project implements a Region Based Convolutional Neural Network (RCNN) model for detecting and classifying animals through camera feeds. When an animal is detected, its species name and GPS coordinates are captured and relayed to a website, allowing users to locate the animal on a map. This system can enhance tourist experiences by providing real time information on animal whereabouts and can serve as a tool for conservationists to track and monitor wildlife health.

1.1 NETWORK STRUCTURE

Network structure by RCNN involves Following three main parts Backbone Neck and Head. First part replaces SPP using CSP-Darknet53 [3] to enhance performance. For Neck PANet is employed to enhance Network capability [5 ,9]. In Head RCNN adopts Same three detection layers as utilized in prior version. Below is detailed description of Backbones of RCNNs. It can be found in Table 1 'From' signifies to layer That parameters will be gathered from. Value of '-1' in there means The previous layer .'Number' signifies number of modules set to be used. If number is not 1 its size is subject to depth_multiple. Parameters 'depth_multiple' And 'width_multiple' will be brought up again later on. 'Module' is what we call type of module in existence in particular layer. Details are laid out in commonpy file. Out of them 'Conv' is CBS. It has a set up of A Conv2d a BatchNorm2d and SiLU. C3 is another module called CSP. It holds three CBS and a Bottleneck. C3 is different when in neck as well. In addition RCNN takes on SPPF. It replaces the previous SPP And significantly sped up calculation process. The term 'Args' refers to the module's output parameters. Hence it also has an impact on number of Inputs in following layers. Its size will be affected By width_multiple.

from	number	module	args
-1	1	Conv	[64, 6, 2]
-1	1	Conv	[128, 3, 2]
-1	2	C3	[128]
-1	1	Conv	[256, 3, 2]
-1	6	C3	[256]
-1	1	Conv	[512, 3, 2]
-1	9	C3	[512]
-1	1	Conv	[1024, 3, 2]
-1	3	C3	[1024]
-1	1	SPPF	[1024, 5]

Fig.1 Network Structure

As Fig 1 shows this first image illustrates the Neck portion of RCNN while the Head block is last. The "Conv" Functionality remains consistent in this model.

II. LITERATURE SURVEY

[1] Redmon, Joseph, et al. "You only look once: Unified, real-time object detection." Proceedings of the IEEE conference on computer vision and pattern recognition. 2016. Redmon et al.'s 2023 paper "You Only Look Once" (RCNN) revolutionized object detection by introducing a unified, single-stage framework. Unlike traditional methods with separate proposal and classification stages, RCNN directly predicts bounding boxes and class probabilities in one pass through the image, enabling real-time object detection. This efficiency makes RCNN ideal for applications requiring fast processing speeds, and the paper likely explores the network architecture, training process, and performance compared to existing methods, highlighting its potential for various object detection tasks. This shift towards a single-stage approach paved the way for significant advancements in the field.

[2] Redmon, Joseph, and Ali Farhadi. "RCNNv3: An incremental improvement." arXiv preprint arXiv:1804.02767 (2022). Redmon and Farhadi's 2022 paper, "RCNNv3: An Incremental Improvement," likely explores advancements to this real-time approach. RCNN revolutionized the field by directly predicting bounding boxes and object class probabilities in a single image pass, achieving significant speed gains. RCNNv3 focuses on further refining this foundation. The paper might delve into specific areas of improvement, such as modifications to the convolutional neural network architecture used in RCNN. These enhancements could aim to boost accuracy, speed, or memory efficiency. Additionally, the paper might discuss optimizations to the training process, including utilizing different data augmentation techniques or hyperparameter tuning to enhance network performance. Finally, the authors might compare RCNNv3's performance on benchmark datasets against the original RCNN and other leading object detection algorithms, highlighting the achieved improvements. Through these incremental advancements, RCNNv3 likely strives to solidify its position as a powerful and efficient framework for real-time object detection tasks across various applications.

[3] Tao, Jing, et al. "An object detection system based on RCNN in traffic scene." 2022 6th International Conference Computer Science and Network Technology (ICCSNT). IEEE, 2022 This study by Tao et al. delves into object detection within traffic scenes, aiming to enhance traffic flow, optimize operations, and prevent accidents. Their research likely proposes a method for identifying and tracking objects (vehicles, pedestrians, etc.) within traffic environments using computer vision or related techniques. This technology could be implemented in various ways to improve traffic safety. For instance, real-time object detection can be used to warn drivers of potential hazards, such as pedestrians crossing the road unexpectedly. Additionally, the data collected through object detection can be employed to optimize traffic light timings and identify bottlenecks within traffic networks, ultimately promoting smoother traffic

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flow and reducing congestion. Overall, Tao et al.'s research on object detection in traffic scenes holds promise for advancements in traffic safety and management.

[4] Zhao Lulu, Wang Xueying, Zhang Yi, Zhang Meiyue, "Research on Vehicle target Detection Technology based on RCNNs fusion SENet", Journal of Graphics, vol. 43, no. 05, pp. 776-782, 2022 Zhao et al. tackle the challenge of inaccurate vehicle detection in traffic monitoring videos during congested periods. This is where vehicles are frequently obscured by one another. The authors propose an enhanced RCNNs network to address this issue. SE modules, known for emphasizing important details, are incorporated into key parts of the RCNNs network – the Backbone, Neck, and Head. These SE modules effectively guide the model to focus on critical vehicle characteristics, filtering out irrelevant background information. By incorporating these modules, Zhao et al. aim to significantly improve the accuracy of vehicle detection in traffic monitoring scenarios. This is achieved by enabling the model to prioritize crucial vehicle features and minimize the influence of distracting background elements, leading to a reduction in both false and missed detections.

[5] "Animal Detection using Inception-v3 and you only look once version2 (RCNN V2) " by Abdulaziz Alwadani and Abdulrahman Al-Salman (2020) This paper by Alwadani and Al-Salman (2020) tackles animal detection in images or videos using a twopronged deep learning approach. The first line of defense is Inception-v3, a powerful image classification model. Inception-v3 scans the image, meticulously dissecting various sections to identify the presence of animals. Essentially, it acts as a sieve, separating animal-containing regions from the background clutter.Once Inception-v3 pinpoints these potential animal areas, RCNNv2 (You Only Look Once version 2) comes into play. RCNNv2 excels at object detection – not just classifying objects but also predicting their exact location and size within the image using bounding boxes. In this case, RCNNv2 takes over for the animal-containing sections flagged by Inception-v3. It meticulously analyzes these sections and precisely pinpoints the animals' locations by drawing bounding boxes around them.By combining the strengths of Inception-v3's classification and RCNNv2's object localization, this approach strives to achieve high accuracy in animal detection. In essence, it leverages the best of both worlds: Inception-v3's ability to identify animals and RCNNv2's talent for pinpointing their exact location.

[6] Kamali, M., & Tahir, M. (2020). You only look once version3 (RCNN V3): A Comprehensive Guide to Object Detection with Deep Learning. arXiv preprint arXiv:2005.10857. serves as a learning resource, not a research paper. It likely dissects the RCNNv3 architecture, explaining its deep learning core and concepts like bounding boxes and class probabilities. The guide aims to empower users by providing practical instructions for utilizing RCNNv3 in real-world applications, including setting up the environment, training the model, and making object detections on new images.

[7] "Real-Time Wild Animal Detection and Alert System using Deep Convolutional Neural Networks and Raspberry Pi" by Ankit Pandey and Ramendra Singh (2019) In their 2019 paper, "Real-Time Wild Animal Detection and Alert System using Deep Convolutional Neural Networks and Raspberry Pi," Pandey and Singh propose a system for real-time wild animal detection and alerting. This system leverages deep convolutional neural networks (CNNs), known for their image recognition capabilities. By training a CNN on a dataset of wild animal images, the system can identify animals in real-time using a Raspberry Pi, a low-cost and compact computer. This allows for deployment in remote areas where traditional monitoring methods might be impractical. The paper likely details the chosen CNN architecture, the training process, and the integration with the Raspberry Pi. Additionally, it might discuss the system's performance and its potential applications in wildlife conservation or mitigating humanwildlife conflicts.

[8] You Only Look Once: Unified, Real-Time Object Detection, by Joseph Redmon. Their prior work is on detecting objects using a regression algorithm. To get high accuracy and good predictions they have proposed RCNN algorithm in this paper [1]. Understanding of Object Detection Based on CNN Family and RCNN, by Juan Du. In this paper, they generally explained about the object detection families like CNN, R-CNN and compared their efficiency and introduced RCNN algorithm to increase the efficiency

[9]. Learning to Localize Objects with Structured Output Regression, by Matthew B. Blaschko. This paper is about Object Localization. In this, they used the Bounding box method for localization of the objects to overcome the

drawbacks of the sliding window method. System proposes a new approach to barcode decoding that bypasses binarization. This technique relies on deformable templates and exploits all of the gray-level information of each pixel. Due to this parameterization of these templates, system can efficiently perform maximum likelihood estimation independently on each digit and enforce spatial coherence in a subsequent step. System show by way of experiments on challenging UPC-A barcode images from five different databases that this approach outperforms competing algorithms. Implemented on a Nokia N95 phone, this algorithm can localize and decode a barcode on a VGA image (640 480, JPEG compressed) in an average time of 400-500 ms.

III. ARCHITECTURE DESIGN

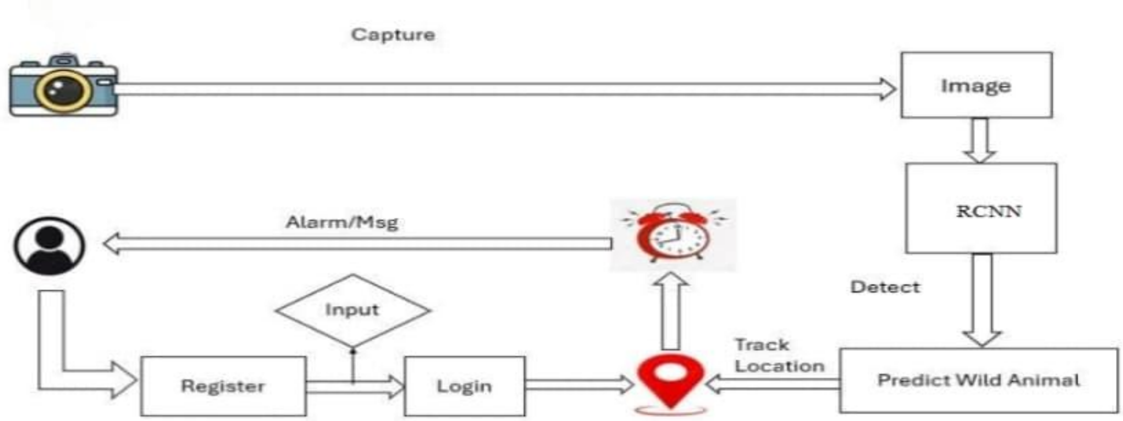


Figure 2.1. System Architecture

IV. RCNN Algorithm

4.1. Input Image Preprocessing

- **Resize**: The input image is often resized to a standard size to reduce computational complexity.
- **Normalization**: The pixel values of the image may be normalized (e.g., scaling the pixel values to a range of 0 to 1).

4.2. Selective Search for Region Proposal

- **Selective Search** is used to generate region proposals. This is an unsupervised algorithm that identifies potential object locations in an image.
- It works by segmenting the image and merging segments that are similar, generating bounding boxes that likely contain objects.
- In the context of animal detection, these region proposals are expected to contain potential areas where animals might be located.

4.3. Feature Extraction Using CNN

- Each region proposal generated from Selective Search is passed through a Convolutional Neural Network (CNN) to extract features.

- The CNN can be pre-trained on a large dataset like ImageNet and then fine-tuned for the specific task (e.g., animal detection).
- Typically, a CNN like AlexNet, VGG, or ResNet is used to generate a feature map for each region proposal.

4.4. Classification Using SVM (Support Vector Machine)

- The extracted features are then passed through a classifier. In RCNN, the classifier used is typically a Support Vector Machine (SVM).
- The SVM classifies each region as either belonging to an animal (positive class) or not (negative class).
- The classifier can be trained with a labeled dataset of animal and non-animal images.

4.5. Bounding Box Regression

- After classification, bounding box regression is used to refine the coordinates of the region proposals.
- This step improves the localization of the object within the bounding box. The goal is to make the bounding box as tight as possible around the animal.
- Bounding box regression uses a regression model to predict adjustments to the original bounding box.

V. TECHNOLOGY STACK

Java:
We have used java to create registration and login page to authorize the user. JDBC connection is used to validate user credential and to store user info.

Python:
Using Python to interact with block-chain for storing fingerprint data involves several key steps. Here's an overview of how Python can be used to store fingerprint hashes on the block-chain and verify them. Since directly storing fingerprint images on a block-chain isn't practical (due to size and cost), a more efficient approach is to store the hash of the fingerprint and optionally store the link to the fingerprint image on a decentralized storage network like IPFS

Backend Integration:

1. Email Sending using python
Sending an email using Python can be done using the Python Mail API. This API provides a platform-independent and protocol-independent framework for sending and receiving emails.
To send an email alert using Python when it's time to take medicine, we can create a program that sends an email to the user at a specified time or when triggered by a specific event.
Python Mail API: This is needed to send emails via Java. Scheduler/Timer: To trigger the alert at a specific time or interval.
SMTP Server: For sending emails (e.g., Gmail, Outlook, etc.).

Scalability and Performance :
When developing a **Animal Tracker**, scalability and performance become critical to ensure that the system is able handle a large number of users, data, and requests efficiently. Our system operates efficiently and delivers quick response times even under load. Since animal recognition and animal tracking involve critical real-time operations, performance optimizations are done.

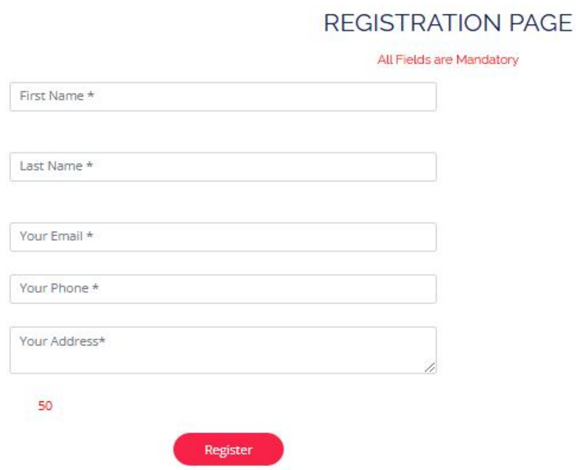
Performance Metrics :
1. Animal Recognition Latency:
Metric: 12 sec is time taken to match a animal to a dataset record.

2. API Response Time:
Metric: 5sec is the time it takes for the system to respond to
API calls such as retrieving animal data from dataset.

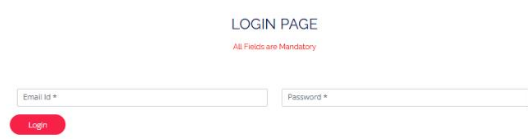
3. Database Query Latency:
Metric: 5 sec is the time it takes to query the database for information (e.g., login info).

VI. RESULTS AND ANALYSIS

Module 1: Registration Page:



Module 2: Login Page



Module 3: Animal Detection

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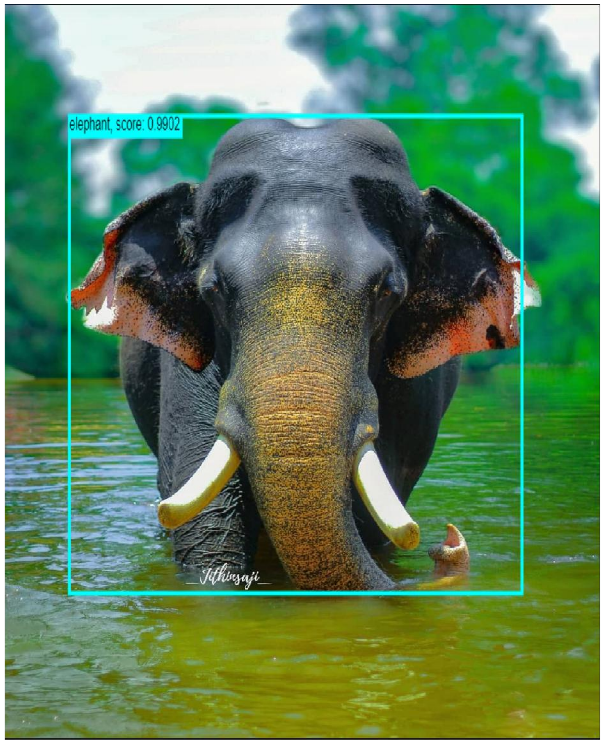
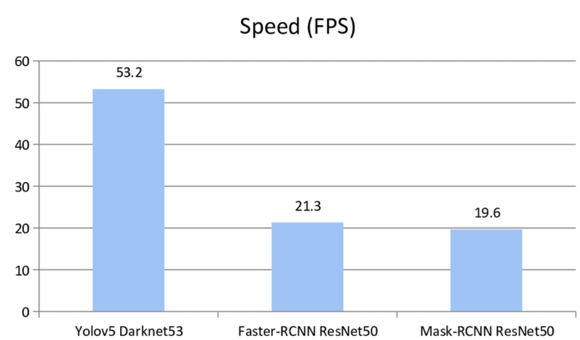


Feature	RCNN	RCNN
Processing Time (per image)	2-3 seconds	0.016 - 0.033 seconds
FPS (Frames per Second)	< 1 FPS	30-60 FPS
Real-time Capable	No	Yes
Suitable for Videos	No	Yes



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VII. ADVANTAGES

Real-Time Detection:

- **Aim:** Implement RCNN to accurately and swiftly detect animals in live video streams captured by mobile devices.
- **Outcome:** Achieve high accuracy in identifying various animal species in different environments and conditions.

Effective Tracking:

- **Aim:** Integrate tracking algorithms with RCNN detections to maintain continuous tracking of identified animals across frames.
- **Outcome:** Enable consistent and reliable tracking of animal movement, providing dynamic data on behavior and location.

User-Friendly Interface:

- **Aim:** Develop an intuitive Android application that presents detection and tracking information clearly to users.
- **Outcome:** Ensure ease of use for researchers, conservationists, and pet owners by providing real-time visualization of tracked animals and actionable insights.

Adaptability and Scalability:

- **Aim:** Train the RCNN model to recognize a diverse range of animal species and adapt the system to various environmental conditions.
- **Outcome:** Create a versatile tool that can be customized for different wildlife monitoring needs or pet tracking applications.

VIII. CHALLENGES FACED

- **Lack of Annotated Data:** Large-scale, labeled datasets for animals in the wild are limited.
- **Class Imbalance:** Endangered species are underrepresented in datasets, leading to poor model performance.
- **Data Variability:** Animals may vary in appearance due to age, sex, seasonal changes, or environmental conditions.

Research Gap

- **Accuracy in Complex Environments:** RCNN may struggle with animals camouflaged in dense forests or under poor lighting.
- **Small Object Detection:** Tracking small animals from long distances is difficult.
- **Real-Time Processing Limitations:** On resource-constrained devices like drones, real-time performance may degrade.

IX. CONCLUSION

Identifying and classifying species is an essential first step in determining the long-term viability of animals and how our actions may affect them. It aids people in recognizing predators and non-predatory animals, both of which might pose a significant threat to local species and humans. This can potentially reduce the number of traffic accidents in various regions since some animals are regularly spotted on roadways, resulting in several collisions with automobiles

X. FUTURE SCOPE

1. Real-time Animal Monitoring: Track endangered species to monitor their population and prevent poaching.
2. Behavior Analysis: Study animal movement patterns, feeding behavior, and migration.
3. Illegal Activity Detection: Detect poachers and monitor protected areas using drones equipped with RCNN-based systems.

REFERENCES

[1] Redmon, Joseph, et al. "You only look once: Unified, real-time object detection." Proceedings of the IEEE conference on computer vision and pattern recognition. 2024.

[2] Redmon, Joseph, and Ali Farhadi. "RCNNv3: An incremental improvement." arXiv preprint arXiv:1804.02767 (2023).

[3] Tao, Jing, et al. "An object detection system based on RCNN in traffic scene." 2023 6th International Conference Computer Science and Network Technology (ICCSNT). IEEE, 2023

[4] Zhao Lulu, Wang Xueying, Zhang Yi, Zhang Meiyue, "Research on Vehicle target Detection Technology based on RCNNs fusion SENet", Journal of Graphics, vol. 43, no. 05, pp. 776-782, 2022

[5] "Animal Detection using Inception-v3 and you only look once version2 (RCNN V2) " by Abdulaziz Alwadani and Abdulrahman Al-Salman (2020)

[6] Kamali, M., & Tahir, M. (2020). You only look once version3 (RCNN V3): A Comprehensive Guide to Object Detection with Deep Learning. arXiv preprint arXiv:2005.10857.

[7] "Real-Time Wild Animal Detection and Alert System using Deep Convolutional Neural Networks and Raspberry Pi" by Ankit Pandey and Ramendra Singh (2019)

[8]S. K. L., A. Edison, Wild Animal Detection using Deep Learning, in 2022 IEEE 19th India Council International Conference (INDICON), Kochi, India, pp. 1-5 (2019).

[9]P. Manikandan, G. Ramesh, P. Lokesh, P. N. Raju, M. D. Prasad, P. Madhu, IOT Based Farm Protection System from Animals and Humans Theft using ESP32 with Camera Module, in 2019 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), Greater Noida, India, pp. 1861-1864 (2019).

[10]D. Ma., J. Yang, RCNN-Animal: An efficient wildlife detection network based on improved RCNN, in 2018 International Conference on Image Processing, Computer Vision and Machine Learning (ICICML), Xi'an, China, pp. 464-468 (2018).

[11] N. Mamat, M. F. Othman, F. Yakub, Animal Intrusion Detection in Farming Area using RCNN Approach, in 2022 22nd International Conference on Control, Automation, and Systems (ICCAS), Jeju, Korea, Republic of, pp. 1-5, (2018).

[12].Sahu, S., & Mohanta, H. C. (2021). A Pine Shaped Dual-Band Frequency Reconfigurable Antenna. Journal of Engineering Research and Reports, 20(12), 42-52.

[13].Sahoo M., and Mohanta, Harish Chandra., 2020. Design of a compact dual-band fork-shaped monopole antenna, Shodh Sanchar Bulletin, vol. 10 (40), pp. 1-6.

[14].Mohanta, G., and Mohanta, Harish Chandra., 2019. Image compression using different vector quantization algorithms and its comparison, IJITEE journal, vol. 8, issue 9.

[15].Prasad, L. B., Mohanta, H. C., & Vinay, K. P. (2022, January). Wide Band Conformal Coplanar Benz Shaped Circular Ring Antenna for C and X Band Applications. In 2022 International Conference on Computing, Communication and Power Technology (IC3P) (pp. 44-47). IEEE.