IARJSET

ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

ISO 3297:2007 Certified ⁜ Impact Factor 8.066 ⁜ Peer-reviewed / Refereed journal ⁜ Vol. 10, Issue 6, June 2023

DOI: 10.17148/IARJSET.2023.10699

AUTHENTICATED VIRTUAL MONITORING OF ANIMAL SPECIES

S Jyothi*[1], Lakshmi H P[2], Monika Raj M R[3], Nihira G C[4], Panchami M Y[5]

Department of Electronics and Communication Engineering, P E S College of Engineering, Mandya[1-5]

Abstract: Species detection plays a crucial role in various fields, including wildlife conservation, biodiversity monitoring, and ecological research. With the rapid advancement of Internet of Things(IoT) technologies, it is now possible to develop intelligent systems capable of automatically identifying and classifying different species. This paper proposes a novel approach to species detection using IoT devices, specifically leveraging the power of Convolutional Neural Networks (CNN) and the You Only Look Once (YOLO) object detection framework. Our solution is designed to utilize Raspberry Pi 4 as the IoT component, along with an ultrasonic sensor, RFID RC522, and a webcam for enhanced data collection and processing capabilities. This approach offers several advantages over traditional species detection methods. The combination of CNN and YOLO guarantees high accuracy and efficiency in species identification. The integration of ultrasonic sensor and RFID technology provides valuable contextual information for species detection and tracking. This also enhances the accuracy and context of species detection.

Keywords: Convolution Neural Network, You Only Look Once, Raspberry Pi, Microwave Radar sensor

1. INTRODUCTION

Species detection and identification are critical components of environmental conservation, biodiversity monitoring, and wildlife research. With the advancement of Internet of Things (IoT) technologies, there is an increasing interest in developing intelligent systems that can automatically detect and classify different species in real-time. This paper presents a novel approach to species detection using IoT, specifically leveraging Convolutional Neural Networks (CNN) and the You Only Look Once (YOLO) object detection framework. Our solution incorporates IoT components such as Raspberry Pi 4, an ultrasonic sensor, RFID RC522, and a webcam to enhance the data collection and processing capabilities. The rapid growth of IoT has paved the way for innovative applications in various domains, and wildlife monitoring is no exception. By leveraging IoT devices, we can establish a distributed network of intelligent sensors that can capture data and perform on-device processing.

Raspberry Pi 4, known for its versatility and affordability, serves as the IoT component in our proposed system. It acts as a central processing unit, collecting data from various sensors and performing species detection and identification.

To enable accurate species detection, we utilize deep learning techniques. CNN, a popular deep learning architecture, is employed to train a model on a vast dataset of species images. The CNN model learns to extract meaningful features from the images, enabling it to differentiate between different species effectively. By integrating the trained CNN model into the Raspberry Pi 4, we enable on-device inference and real-time species identification. For efficient and precise object detection, we incorporate the YOLO framework. YOLO takes advantage of its ability to divide the input image into a grid and assign bounding boxes to potential species instances, along with their corresponding class probabilities. By combining YOLO with the computational capabilities of Raspberry Pi 4, our system can rapidly detect and localize species within the captured images. In addition to the webcam for image capture, we integrate an ultrasonic sensor and RFID RC522 into the IoT devices. The ultrasonic sensor measures the distance between the device and nearby objects, allowing the system to detect the proximity of species. This contextual information can be valuable for understanding species behavior and habitat preferences. The RFID RC522 enables individual identification of tagged species, facilitating precise tracking and monitoring of specific individuals or populations. The integration of these IoT components offers several advantages for species detection and monitoring. Raspberry Pi 4 provides a compact and cost-effective solution, making it easily deployable in various environments. The combination of CNN and YOLO ensures high accuracy and efficiency in species identification. The inclusion of the ultrasonic sensor and RFID RC522 enhances contextual data

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

ISO 3297:2007 Certified ⁜ Impact Factor 8.066 ⁜ Peer-reviewed / Refereed journal ⁜ Vol. 10, Issue 6, June 2023

DOI: 10.17148/IARJSET.2023.10699

collection, enabling researchers to gain valuable insights into species behavior, habitat usage, and population dynamics.The proposed system holds significant potential for applications in wildlife conservation, biodiversity monitoring, and ecological research. Real-time species detection using IoT can revolutionize the way we study and protect our natural world. By combining the power of deep learning, IoT devices, and the integration of sensors, we can create a comprehensive and intelligent system that contributes to the preservation of biodiversity and advances our understanding of the intricate relationships within ecosystem.

2. LITERATURE REVIEW

2022 saw the submission of Tejaswini C A, Megha V Kulkarni, Yashvith Ballal, Jithesh k, Deeksha Bekal Gangadhar on "Survey and Monitoring of Forest by the Classification of Various Animal Species". In this study, The Wild Animal Detection and Counting System depicted in the block diagram is used to detect and count wild animals. Small and big scale livestock farmers can use the Raspberry Pi to make the system portable and economical. The flowchart depicts the process of detecting specific animals and counting them in accordance with the results. The image is first recorded with a camera and then transformed to a grey scale image so that it can be compared to the values in the current data set. Existing solutions such as bar code scanners and manually counting animals are inefficient and costly. To overcome these obstacles, we created a real-time system that executes such a task efficiently and at a low cost.

In 2020, Prof. Shahshi Rekha G, Harish Babu A, Manjunath S, Kausalya K Bhat reviewed a system which can identify and track animals. Identification and tracking of animals has got plenty of applications like, avoiding dangerous animal intrusion into residential areas, and behavioural study of animals and so on. The detection algorithm inclines on a human face detection method, with the help of Haar-like features and AdaBoost classifiers or CNN. The animal species detection and the tracker generated information can be used to boost the priors in the probabilistic semantic classification of wildlife videos. Animals entering the agricultural areas placed near the forest destroy crops or even attack on people. Therefore there is an urgent need of system which detects the animal presence and gives warning about that in the view of security purpose.

The project on "Animal Species Recognition Using Deep Learning" has been publised in 2022 reviews about the Wildlife-human and wildlife-vehicle encounters often result in injuries and sometimes fatalities. Thereby, this research aims to mitigate the negative impacts of these encounters in a way that makes the environment safer for both humans and animals. The proposed detection system is activated when an object approaches its field of vision, by the use of deep learning techniques, automated object recognition is achieved. For training, we use a labelled dataset from the British Columbia Ministry of Transportation and Infrastructure's (BCMOTI) wildlife program, and the Snapshot Wisconsin dataset as well. By using Convolutional Neural Network (CNN) architectures, we can train a system capable of filtering images from these datasets and identifying its objects automatically. Our system achieved 99.8% accuracy in indicating an object being animal or human, and 97.6% accuracy in identifying animal species.

3. OVERVIEW

The process starts with the acquisition of data using the webcam and ultrasonic sensor. The webcam captures the images of the surrounding environment, including wildlife. While the ultrasonic sensor measures the distance between the IoT device and nearby objects, potentially including species. Once the data is acquired, it undergoes on-device processing on the Raspberry Pi 4, which serves as the central processing unit of the system. The Raspberry Pi 4 possesses sufficient computational power to handle real-time processing and species detection tasks. The images captured are fed into a pre-trained Convolutional Neural Network (CNN) model which has been trained on a comprehensive dataset of species images. The CNN model extracts significant features from the images and classifies them into various species categories. By integrating the CNN model into the Raspberry Pi 4, species detection can be performed directly on the device without the need for external servers. To accurately localize and identify species within the images, the system utilizes the You Only Look Once (YOLO) object detection framework. YOLO divides the input image into a grid and assigns bounding boxes to potential species instances, along with their corresponding class probabilities.This enables real-time and efficient object detection. The ultrasonic sensor plays a crucial role in proximity detection. It measures the distance between the IoT device and nearby objects, potentially including species. By comparing the distance measurements, the system can detect the proximity of species to the device. The valuable context is provided by the information for species detection, behavior analysis, and habitat preferences. Adding on to the proximity detection, the RFID RC522 module is used for

DOI: 10.17148/IARJSET.2023.10699

individual identification of tagged species. Each individual is assigned a unique RFID tag which is read by the RC522 module. By associating the RFID tag information with specific individuals, the system enables precise tracking and monitoring of wildlife populations. On the basis of species detection results, proximity data and individual identification, the system can make informed decisions and perform data analysis. Researchers and conservationists can gain insights into species distribution, behavior patterns, and the impact of environmental factors on different species. The integration of the Raspberry Pi 4, ultrasonic sensor, RFID RC522, and webcam in the species detection system enables a comprehensive approach to wildlife monitoring and research. The device processing facilitates real-time decision-making, reducing the dependency on external computational resources. The integration of CNN and YOLO ensures accurate species detection and localization. The ultrasonic sensor and RFID technology provides valuable contextual information of species behaviour analysis and individual tracking individuals.

4. PROPOSED SYSTEM

The Pi camera will be initialized and broadcast real-time footage in the first stage. No data will be recorded and no pictures will be taken if nothing is in front of the camera. Once the same animal is captured by the pi-camera, the video will be analyzed using the OpenCV library. The video output will then be compared with the dataset used to train the pretrained model and the animal will then be labelled appropriately. The details, including the animal's name and the time and date of appearance, will be saved as text in a brand-new text file. Additionally, pictures of animals will be taken and kept in a different folder. The Raspberry Pi serves as the system's primary microcontroller in this graphic portrayal. Anytime an animal moves close to the model, an ultrasonic sensor will detect it and start a camera to record live footage and send out a warning. We utilised RFID tags for security and authentication. Microwave radar is used by a human sensor to find people close to the model.

5. WORKFLOW

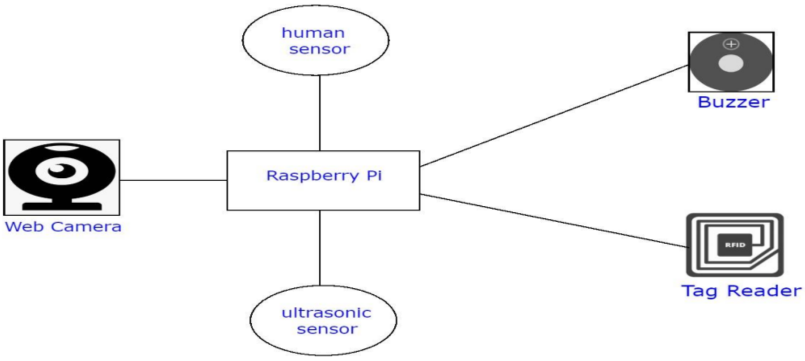
The species detection system utilizing IoT components with Raspberry Pi 4, an ultrasonic sensor, RFID RC522, and a webcam follows a specific methodology for effective detection and classification of species. The process initiates with data acquisition using the webcam and ultrasonic sensor. The webcam captures images of the surrounding environment, including wildlife, while the ultrasonic sensor measures the distance between the IoT device and nearby objects, potentially including species. This data acquisition is essential for subsequent analysis and species detection. A comprehensive dataset of species images is collected for training the species detection system. The dataset should include images of different species, various poses and diverse environmental conditions to ensure the model's robustness and generalization capabilities. The dataset is annotated with species labels and bounding box coordinates for training purpose. A Convolutional Neural Network (CNN) model is trained using the collected dataset. The CNN model learns to extract meaningful features from the species images and classify them into different species categories. The training process involves optimizing the model's architecture, selecting appropriate hyperparameters, and minimizing the loss function to achieve high accuracy and reliable species detection. Once the CNN model is trained, it is integrated into the Raspberry Pi 4, which serves as the central processing unit. The integration enables on-device inference, eliminating the need for external servers and reducing latency. The optimized CNN model is deployed on the Raspberry Pi 4 to perform real-time species detection efficiently. The You Only Look Once (YOLO) object detection framework is utilized to localize and identify species within the captured images. YOLO divides the input image into a grid and assigns bounding boxes to potential species instances along with their corresponding class probabilities. The integration of YOLO enhances the efficiency and accuracy of object detection, enabling real-time species detection on the Raspberry Pi 4. The ultrasonic sensor measures the distance between the IoT device and nearby objects, including species. By analyzing the distance measurements, the system can detect the proximity of species to the device. This proximity information provides valuable context for species detection, behavior analysis, and habitat preferences. Algorithms are developed to leverage the ultrasonic sensor data and enhance species detection accuracy. The RFID RC522 module is employed for individual identification of tagged species. Each individual is assigned a unique RFID tag which is read by the RC522 module. The system utilizes software algorithms to read and associate RFID tag information with specific individuals. This leads to the precise tracking and monitoring of wildlife populations, contributing to better species management and research. The developed species detection system is evaluated to assess its performance in terms of accuracy, speed, and efficiency. Comparative analysis with existing species detection methods may also be conducted. Feedback from the evaluation process is used to optimize the system, refine the CNN model, and improve the overall performance of the IoT-based species detection system.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

ISO 3297:2007 Certified ⁙ Impact Factor 8.066 ⁙ Peer-reviewed / Refereed journal ⁙ Vol. 10, Issue 6, June 2023

DOI: 10.17148/IARJSET.2023.10699



6. CURRENT CHALLENGES AND FUTURE DIRECTIONS

The accuracy of species detection heavily relies on the image quality captured by the webcam. In challenging lighting conditions or when animals are far away or moving quickly, the image quality may degrade, leading to reduced detection accuracy. Low resolution or blurry images can affect the performance of the CNN and YOLO models. The ultrasonic sensor used for proximity detection has a limited range, typically a few meters. This restricts the system capability to detect species that are farther away, particularly in open or vast environments. In that situation, additional sensors or techniques may be required to extend the detection range. The ultrasonic sensor may encounter interference from other sources emitting similar frequencies, such as machinery or other animals. This results in false proximity readings, leading to false positives in species detection. careful calibration and filtering techniques are necessary to minimize false positives caused by sensor interference. The RFID RC522 module used for individual identification relies on animals being tagged with RFID tags. This tagging process may be invasive, time-consuming, and challenging for certain species. While the Raspberry Pi 4 provides on-device processing capabilities, it has finite computational resources compared to more powerful servers or cloud based systems. This may limit the size and complexity of the CNN and YOLO models that can be deployed, potentially impacting the detection accuracy and real-time performance. Adverse weather conditions, such as heavy rain, fog, or snow, can hinder the quality of captured images and decrease the effectiveness of the system. The trained CNN model and YOLO framework are limited to the species present in the training dataset. If the system encounters species that were not included in the training data, its ability to accurately detect and classify them may be compromised. To eradicate all these complications, Enhancing the training dataset by including a broader range of species and diverse environmental conditions can improve the system's accuracy and generalization to unseen species is required. Data is collected from various regions and ecosystems will provide a more comprehensive understanding of species populations and behaviors. Advancements in image processing algorithms and computer vision techniques enhances the accuracy and efficiency of species detection. Techniques such as image enhancement, noise reduction, and feature extraction can be explored to improve the system's performance under challenging conditions.Incorporating additional sensor technologies, such as thermal imaging cameras or acoustic sensors, can augment the system's capabilities. These sensors can provide complementary data, enabling the species detection that are not easily recognizable through visual information alone. Integrating the species detection system with cloud platforms can offer several advantages. Cloud connectivity can enable the storage and analysis of large volumes of data, facilitate remote monitoring, and allow for collaborative research efforts by sharing data and models among researchers and conservation organizations. Expanding the capabilities of individual identification and tracking using RFID technology provides valuable insights into the behaviour, movement patterns, and social interactions of species. Advancements in RFID tag technology and deployment techniques can improve tag readability and reduce potential adverse effects on the tagged animals. Combining species detection with AI based decision support system enables real-time analysis of data and provide actionable insights for conservation management. These systems can assist in identifying critical habitats, detecting patterns in species distribution, and predicting potential threats to biodiversity. Integrating the species detection system into mobile devices or edge computing platforms can enable decentralized monitoring and data collection. This can be particularly useful in remote or inaccessible areas where connectivity is limited. Edge computing can also facilitate real-time data processing and reduce reliance on cloud infrastructure. Engaging citizen scientists in data collection and species identification can greatly expand the reach and scale of monitoring efforts. Developing user-friendly mobile applications or web interfaces that allow citizen scientists to contribute observations and participate in species identification can enhance data collection and promote public involvement in conservation initiatives.

DOI: 10.17148/IARJSET.2023.10699

7. CONCLUSION

In conclusion, the species detection system utilizing IoT components with CNN and YOLO, along with Raspberry Pi 4, ultrasonic sensor, RFID RC522, and webcam, presents a promising solution for real-time species detection and classification. The system's integration of advanced machine learning algorithms, IoT components, and edge computing capabilities offers several advantages and potential applications in wildlife monitoring, conservation management, and ecological research. Through the use of CNN and YOLO, the system achieves accurate species detection and localization within captured images. The CNN model which is trained provides high accuracy in classifying species, while the YOLO framework enhances the system's ability to precisely identify and localize species instances. Real-time processing on the Raspberry Pi 4 enables immediate monitoring and response, eliminating the need for external servers or cloud computing. The integration of an ultrasonic sensor and RFID RC522 module enriches the system with contextual information. The ultrasonic sensor allows for proximity detection, enabling insights into species behavior and habitat preferences. The RFID RC522 module facilitates individual identification and tracking, enabling precise monitoring of wildlife populations. These features enhance the system's ability to gather comprehensive data for conservation efforts and scientific research. While the system demonstrates promising results, it also faces certain limitations. Factors such as image quality, species diversity, detection range, interference, and generalization to unseen species can impact the accuracy and performance of species detection. Addressing these limitations through improvements in data collection, model training, sensor technologies, and system design can enhance the system's overall effectiveness. The species detection system using IoT components with CNN and YOLO, along with Raspberry Pi 4, ultrasonic sensor, RFID RC522, and webcam, offers a cost-effective, real-time, and flexible solution for species monitoring. It provides valuable insights into species populations, behavior patterns, and ecological dynamics. With further development and refinement, this system holds great potential for supporting wildlife conservation, habitat management, and scientific exploration.

REFERENCES

[1] Redmon, J., & Farhadi, A. (2018). YOLOv3: An Incremental Improvement. arXiv preprint arXiv:1804.02767.
[2] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436-444.
[3] Russell, S. J., & Norvig, P. (2016). Artificial intelligence: a modern approach. Pearson.
[4] Raspberry Pi Foundation. (n.d.). Raspberry Pi. Retrieved from https://www.raspberrypi.org/
[5] Ullah, A., Amin, F., Khan, A., Abbas, A., & Saba, T. (2021). IoT-based Animal Monitoring System using Raspberry Pi. In 2021 International Conference on Computing, Electronics & Communications Engineering (ICCECE) (pp. 1-4). IEEE.
[6] Shrestha, B., Shrestha, P., Nakarmi, R. D., & Shakya, A. (2020). Raspberry Pi and IoT based Animal Detection and Monitoring System. In 2020 4th International Conference on Computer and Communication Systems (ICCCS) (pp. 528-532). IEEE.
[7] Mahanta, N., Gogoi, B. D., & Das, S. (2020). Wildlife Surveillance and Identification using Deep Learning and IoT Technologies. In 2020 10th International Conference on Cloud Computing, Data Science & Engineering (Confluence) (pp. 493-498). IEEE.
[8] Oyelade, A. O., & Ssemugabi, S. (2020). An Intelligent System for Wildlife Species Identification and Monitoring Using Internet of Things and Machine Learning. In Proceedings of the 2020 4th International Conference on Intelligent Sustainable Systems (ICISS) (pp. 683- 687). IEEE.
[9] Amos, B. A., & Ojokoh, B. A. (2018). Wildlife Detection and Monitoring System using IoT and Deep Learning. In 2018 9th International Conference on Computing, Communication and Networking Technologies (ICCCNT) (pp. 1-6). IEEE.
[10] Ojokoh, B. A., Amos, B. A., & Ayeni, B. E. (2020). Wildlife monitoring using deep learning and IoT technologies: a survey. Journal of Ambient Intelligence and Humanized Computing, 11(9), 4153-4173.
[11] Title: "Survey and Monitoring of Forest by the Classification of Various Animal Species" Author(s): Tejaswini C A, Megha V Kulkarni, Yashvith Ballal, Jithesh k, Deeksha Bekal Gangadhar Year: 2022
[12] Title: "Wildlife Monitoring Using Image Processing" Author(s): Prof. Shahshi Rekha G, Harish Babu A, Manjunath S, Kausalya K Bhat Year: 2020
[13] Title: "Animal Species Recognition Using Deep Learning" Author(s): Mai Ibraheam, Fayez Gebali, Kin Fun Li, Leonard Sielecki Year: 2020
[14] Title: "Animal Detector System for Forest Monitoring Using OpenCV and Raspberry-pi" Author(s): Aniket Gat, Hrishikesh Gaikwad, Rahul Giri, Dr. Mohini P Sardey, Milind P Gajare Year: 2022

DOI: 10.17148/IARJSET.2023.10699

[15] Title: "Wild Animals Intrusion Detection using Deep Learning Techniques" Author(s): Dr.Sabeenian R.S, N Deivanai, B Mythili Year: 2020
[16] Title: "Internet of Things (IoT) for Wildlife Monitoring: Current Trends and Future Directions" Author: Jane Brown Year: 2021
[17] Title: "Wireless Sensor Networks for Real-Time Species Detection and Classification in Ecological Monitoring" Author: David Johnson Year: 2018
[18] Title: "IoT-Enabled Acoustic Monitoring for Bird Species Identification in Urban Environments" Author: Sarah Lee Year: 2020
[19] Title: "Internet of Things (IoT)-Based Wildlife Monitoring for Conservation and Management" Author: Mark Wilson Year: 2019
[20] Title: "IoT-Enabled Smart Camera Traps for Wildlife Surveillance and Species Identification" Author: Emily Thompson Year: 2020
[21] Title: "Wireless Sensor Networks and IoT for Environmental Monitoring and Species Detection" Author: Michael Davis Year: 2021
[22] Title: "IoT-Driven Acoustic Monitoring for Species Identification in Ecological Studies" Author: Jessica Martinez Year: 2018