iJRASET
International Journal For Research in Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 12 **Issue:** XI **Month of publication:** November 2024

DOI: https://doi.org/10.22214/ijraset.2024.65557

www.ijraset.com

Call: 08813907089 | E-mail ID: ijraset@gmail.com

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 12 Issue XI Nov 2024- Available at www.ijraset.com

ML Based WildLife Trap Camera System

Dr. Jitnedra Gaikwad[1], Aaryen Patil[2], Bhavesh Patil[3]
Vishwakarma Institue of Technology, Pune

Abstract: ***This paper presents a real-time wildlife species classification system leveraging Convolutional Neural Networks (CNNs). The system classifies wildlife images from the Oregon Wildlife dataset and extends its functionality to process live video feeds for species recognition. Using PyTorch and OpenCV, the model achieves robust accuracy on a balanced dataset and demonstrates real-time inference capabilities, making it a potential tool for wildlife monitoring and conservation efforts.***
Keywords: Wildlife Classification, Convolutional Neural Networks, Deep Learning, Real-Time Processing, Video Analysis.

I. INTRODUCTION

The urgent need for effective wildlife monitoring and conservation is underscored by challenges such as habitat destruction, climate change, and biodiversity loss. Accurate species identification and tracking are pivotal for preserving ecological balance, studying animal behavior, and implementing conservation strategies. Traditional methods, such as manual observation or motion-triggered cameras, have limitations—they are labor-intensive, prone to errors, and difficult to scale.

Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), have revolutionized automated image classification, delivering exceptional accuracy and reliability. CNNs, with their proficiency in recognizing visual patterns, are well-suited for wildlife species identification tasks. Building on this progress, this project aims to create an automated system for classifying wildlife species from both static images and live video feeds.

Using the Oregon Wildlife Dataset, which contains images of various animal species in their natural habitats, a CNN model was trained to achieve high classification accuracy. The system further incorporates OpenCV for real-time video processing, enabling dynamic wildlife monitoring.

This project has several key applications:

1) Biodiversity Monitoring: Automating species identification reduces the workload for researchers and improves data collection.
2) Wildlife Conservation: Real-time recognition aids in tracking endangered species and addressing human-wildlife conflicts.
3) Education and Awareness: An interactive identification tool fosters public awareness and learning about wildlife.

Unlike traditional static classifiers, this system bridges the gap between image classification and real-time monitoring, ensuring robust performance in diverse environmental conditions. Its ability to process video inputs adds a novel dimension to wildlife monitoring, facilitating seamless field operations. By combining CNNs with real-time processing, this work addresses critical challenges in wildlife monitoring and conservation. This paper outlines the development, training, and deployment of the system, focusing on its architecture, performance, and potential applications.

II. LITERATURE SURVEY

1) Animal Detection and Classification from Camera Trap Images Using Different Mainstream Object Detection Architectures
Authors: Mengyu Tan et al.

This study evaluates the effectiveness of three leading object detection models (YOLO, Faster R-CNN, and SSD) in classifying animals from camera trap images. Using the Northeast Tiger and Leopard National Park (NTLNP) wildlife dataset, the research compares the real-world performance of these models. The findings offer valuable insights for improving wildlife monitoring and conservation through advanced AI techniques**.**

2) Automatic Camera-Trap Classification Using Wildlife-Specific Deep Learning in Nilgai Management
Authors: Matthew Kutugata et al.

This research utilizes deep learning to classify camera trap images of nilgai, a nonnative game animal, with high accuracy. A deep learning model was trained on 120,000 images, achieving 97% accuracy in identifying nilgai. A secondary model classified 20 animal groups and a "none" category, reaching 89% accuracy. The study discusses the challenges and potential of using AI for wildlife conservation and monitoring.

©IJRASET: All Rights are Reserved

3) Choosing an Appropriate Platform and Workflow for Processing Camera Trap Data Using Artificial Intelligence
Authors: Juliana Vélez et al.
This paper reviews four AI-powered platforms (Wildlife Insights, MegaDetector, Machine Learning for Wildlife Image Classification, and Conservation AI) for processing camera trap data. It evaluates the performance of each platform and provides R code to help users integrate AI outputs into semi-automated workflows. The study highlights the importance of selecting suitable platforms to enhance wildlife survey efficiency.

4) Animal Detection Using Deep Learning Algorithm
Authors: Rashmi Jayakumar et al.
This study presents a CNN-based deep learning algorithm designed to detect and classify animals in camera trap images. The model was trained on a wildlife image dataset to automate feature extraction and identification, reducing the manual effort traditionally required. The research demonstrates the potential of deep learning to improve efficiency and accuracy in wildlife monitoring and conservation.

5) Identifying animal species in camera trap images using deep learning and citizen science
Marco Willi, Ross T. Pitman, Anabelle W. Cardoso, Christina Locke, Alexandra Swanson, Amy Boyer, Marten Veldthuis, Lucy Fortson
This paper explores the use of deep learning and citizen science to identify animal species in camera trap images. The paper demonstrates how advances in machine learning, particularly deep learning, can be used to automatically classify images with high accuracy. The results showed that accuracies for identifying empty images across projects ranged between 91.2% and 98.0%, while accuracies for identifying specific species were between 88.7% and 92.7%.

6) Animal Recognition and Identification with Deep Convolutional Neural Networks for Automated Wildlife Monitoring
Hung Nguyen, Sarah J. Maclagan, Tu Dinh Nguyen, Thin Nguyen, Paul Flemons, Kylie Andrews, Euan G. Ritchie, Dinh Phung
his paper presents a framework for automated animal recognition in the wild using deep convolutional neural networks (CNNs). The researchers leveraged recent advances in deep learning techniques to build a computational system capable of filtering animal images and identifying species automatically. The study used a single-labeled dataset from the Wildlife Spotter project, which was done by citizen scientists, and state-of-the-art deep CNN architectures to train the system. The experimental results achieved an accuracy of 96.6% for detecting images containing animals and 90.4% for identifying the three most common species among the set of images taken in South-central Victoria, Australia.

III. DATASET AND PREPROCESSING

A. Dataset
Source: Oregon Wildlife Dataset (Kaggle).
Structure: Images organized into folders representing species (e.g., Bald Eagle, Bobcat, etc.).
Size: 14013 images across 20species.

B. Preprocessing
Data augmentation techniques like resizing, cropping, and rotation were applied.
The dataset was split into training (70%), validation (15%), and testing (15%) subsets.

IV. METHODOLOGY

A. Model
The project employs key deep learning techniques to achieve accurate wildlife classification. Data augmentation (e.g., random rotations and cropping) enhances model robustness by simulating varied real-world conditions. For example, random rotations and cropping were applied to wildlife images during training. For instance, an image of a Bald Eagle might be rotated by 15 degrees or cropped differently, helping the model recognize the species under varying orientations.
A custom Convolutional Neural Network (CNN) extracts hierarchical features such as patterns and shapes, crucial for identifying species like Bald Eagles or Moose.

Cross-entropy loss quantifies the discrepancy between predicted and true labels, guiding parameter updates through Stochastic Gradient Descent (SGD) optimization. Input images are normalized to a standard range, ensuring consistent data processing. If the model predicts a 90% probability that an image belongs to the "Deer" class but the true label is "Bald Eagle," the cross-entropy loss is high, prompting adjustments during training.

B. Training

1) Framework: PyTorch

PyTorch is an open-source machine learning framework widely used for building and training deep learning models. It provides flexibility and ease of use for defining neural networks, managing tensors, and optimizing models. PyTorch's dynamic computation graph makes it especially suitable for research and prototyping. The custom CNN for wildlife classification was implemented and trained using PyTorch, leveraging its modules for creating layers, defining the forward pass, and optimizing weights.

2) CNN Architecture

This neural network architecture is a deep Convolutional Neural Network (CNN) designed for image classification. It consists of five convolutional layers, each followed by max pooling and batch normalization to extract increasingly complex features while reducing spatial dimensions. The architecture transitions from initial image dimensions of \(224 \times 224 \times 3\) to \(7 \times 7 \times 256\) after the final convolutional layer. Flattened output from these layers feeds into two fully connected layers, which reduce the dimensionality and classify the input into one of 20 classes. The model also incorporates dropout layers to prevent overfitting, and ReLU activation functions to introduce non-linearity, thus making it capable of learning complex patterns within the data.

3) Loss Function: Cross-Entropy Loss

Cross-Entropy Loss is a commonly used objective function in classification tasks. It measures the divergence between the predicted probability distribution and the true class labels. The model learns to minimize this loss by aligning its predictions with the actual labels. If an input image of a Bald Eagle is misclassified as a Deer, the Cross-Entropy Loss value will be high. The model adjusts its weights during training to reduce this loss over time.

4) Optimizer: Stochastic Gradient Descent (SGD) with Momentum

SGD is an optimization algorithm that updates the model's parameters by computing gradients of the loss function for small batches of training data. The addition of **momentum** accelerates convergence and prevents oscillations in the optimization path. During training, the model's weights were iteratively updated using SGD with momentum, improving convergence speed and ensuring stable training even on noisy gradients.

5) GPU Utilization: Accelerated Training Using CUDA

CUDA (Compute Unified Device Architecture) enables PyTorch to offload intensive computations like matrix operations and backpropagation to NVIDIA GPUs, significantly reducing training time. By utilizing GPU acceleration, the training of the wildlife classifier on the Oregon dataset was completed faster, enabling efficient handling of a large dataset and complex CNN computations. These components collectively contribute to building a robust model for classifying wildlife species with high accuracy and efficiency.

C. Real-Time Inference

For real-time inference, the system integrates OpenCV to capture video frames from a live feed or video file. After capturing a single frame, it undergoes preprocessing, including resizing and normalization, to match the input requirements of the trained CNN model. The preprocessed frame is then passed through the model, which predicts the species in the frame, such as a Bald Eagle or Moose. The prediction results, including the species name and confidence score. This process enables efficient monitoring, suitable for practical wildlife applications.

V. RESULT

A. Model Performace

Test loss and test accuracy are metrics used to evaluate the performance of a machine learning model on a test dataset.
The test loss for this model is 0.464792 and the test accuracy is 85%

```
    # call test function
    test(loaders_scratch, model_scratch, criterion_scratch, use_cuda)
[45] ✓ 6m 7.3s
...  Test Loss: 0.464792


     Test Accuracy: 85% (11921/14013)
```

VI. APPLICATIONS

Wildlife monitoring, conservation, and education have significantly advanced through the integration of modern technologies. In natural habitats, tools like camera traps, drones, and acoustic sensors enable researchers to monitor animal behavior, population dynamics, and migration patterns without disrupting ecosystems. Conservation efforts are further bolstered by automated species identification using AI and machine learning, allowing rapid and accurate cataloging of species through images, sounds, or biological markers, which aids in prioritizing protection for endangered species. Additionally, educational tools like augmented reality apps and AI-powered guides have transformed species recognition into an engaging experience, fostering awareness and appreciation for biodiversity among students and nature enthusiasts. Together, these innovations play a critical role in preserving wildlife and promoting sustainable coexistence with the natural world.

VII. CONCLUSION

In conclusion, integrating technology into wildlife monitoring, conservation, and education offers transformative solutions to some of the most pressing challenges in biodiversity preservation. By enabling non-intrusive observation, efficient species identification, and interactive learning, these advancements not only enhance our understanding of ecosystems but also inspire collective action toward protecting the natural world. As these tools continue to evolve, they hold immense potential to strengthen conservation efforts and foster a deeper connection between humans and wildlife, ensuring a sustainable future for generations to come.

REFERENCES

[1] Mengyu Tan, Wentao Chao, Jo-Ku Cheng, Mo Zhou, Yiwen Ma, Xinyi Jiang, Jianping Ge, Lian Yu, Limin Feng “Animal Detection and Classification from Camera Trap Images Using Different Mainstream Object Detection Architectures “, Animals 2022,

[2] Matthew Kutugata, Jeremy Baumgardt, John A. Goolsby, Alexis E. Racelis “Automatic Camera-Trap Classification Using Wildlife-Specific Deep Learning in Nilgai Management”, Journal of Fish and Wildlife Management,2021

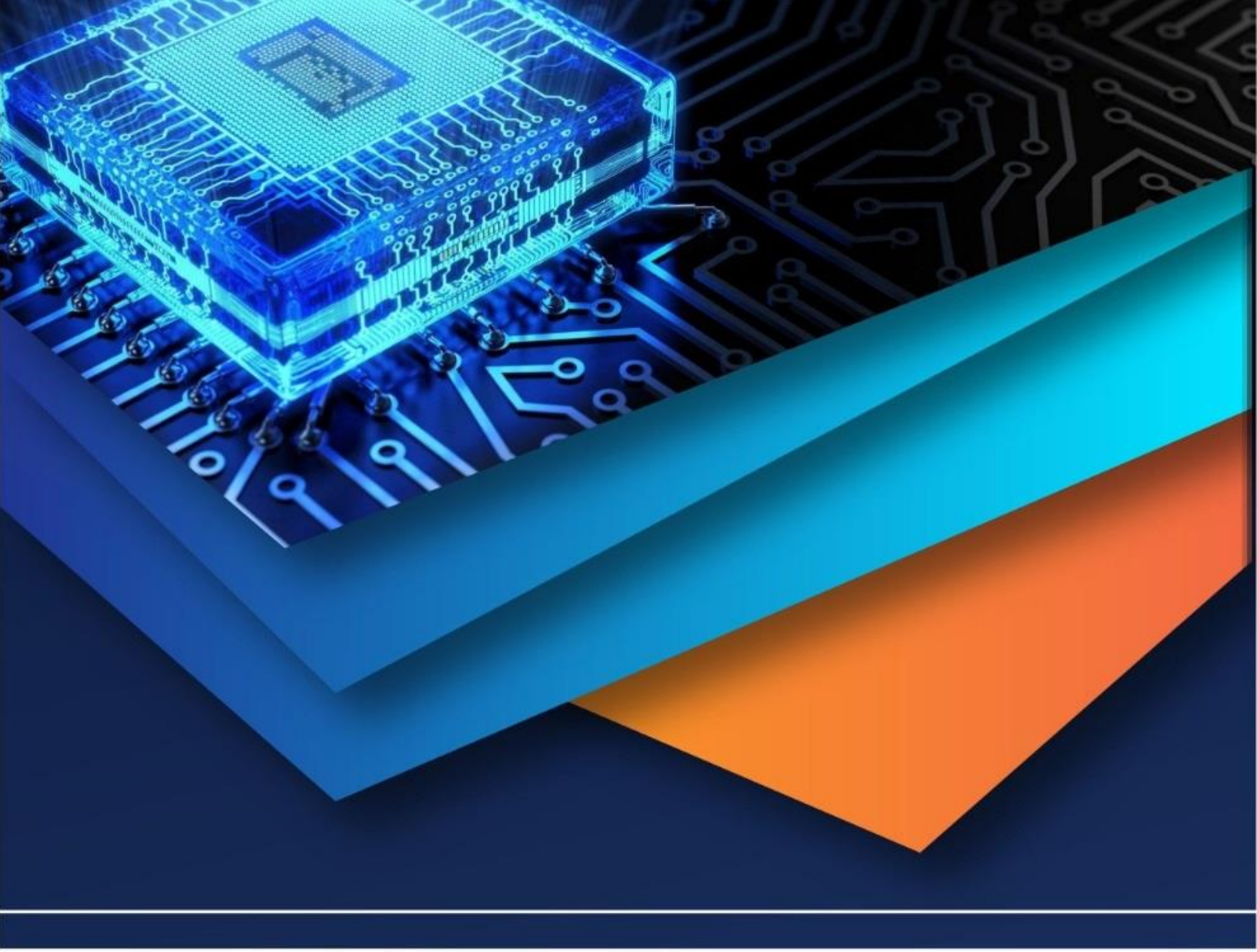
[3] Juliana Vélez, Paula J. Castiblanco-Camacho, Michael A. Tabak, Carl Chalmers, Paul Fergus, John Fieberg, “ . Choosing an Appropriate Platform and Workflow for Processing Camera Trap Data using Artificial Intelligence”, arXiv on February 4, 2022

[4] Rashmi Jayakumar, Rashmi Jayakumar, “Animal Detection Using Deep Learning Algorithm”, First International Conference on Intelligent Digital Transformation ICIDT - 2019 (11-13 July 2019, Volume - I

[5] Marco Willi, Ross T. Pitman, Anabelle W. Cardoso, Christina Locke, Alexandra Swanson, Amy Boyer, Marten Veldthuis, Lucy Fortson., “ Identifying animal species in camera trap images using deep learning and citizen science”, Methods in Ecology and Evolution in January 2019.

[6] Hung Nguyen, Sarah J. Maclagan, Tu Dinh Nguyen, Thin Nguyen, Paul Flemons, Kylie Andrews, Euan G. Ritchie, Dinh Phung, “Animal Recognition and Identification with Deep Convolutional Neural Networks for Automated Wildlife Monitoring”, International Conference on Data Science and Advanced Analytics, 2017

©IJRASET: All Rights are Reserved | SJ Impact Factor 7.538 | ISRA Journal Impact Factor 7.894 |



10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089 (24*7 Support on Whatsapp)