Animal Detection Using Footprint

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***Abstract*—Wildlife conservation increasingly relies on non-invasive monitoring techniques to track and identify animal species efficiently. Traditional methods, such as physical tagging and direct observation, are labor-intensive, costly, and challenging in remote or environmentally sensitive areas. To overcome these limitations, this paper presents an advanced footprint-based animal classification system leveraging YOLOv8, CSPDarkNet for feature extraction, and C2f-based feature refinement. By processing footprint images from diverse sources, including wildlife cameras, mobile captures, and field recordings, the system ensures high classification accuracy across varying terrains. CSPDarkNet enhances feature extraction by capturing essential footprint attributes such as texture, edge contours, and species-specific morphological details, while the C2f module refines these features, improving adaptability to challenging conditions like muddy, sandy, and uneven surfaces. Extensive experimentation on a dataset of over 10,000 labeled footprint images confirms the system's effectiveness, achieving a classification accuracy of 98% and outperforming traditional tracking techniques. The proposed model offers a scalable, automated solution for wildlife monitoring, ecological research, and biodiversity conservation while also enhancing public safety by enabling early detection of potentially dangerous wildlife in residential or trekking areas.**

***Index Terms*—Wildlife conservation, footprint-based classification, YOLOv8, CSPDarkNet, C2f feature refinement,, deep learning, animal species identification, ecological research, biodiversity conservation**

I. Introduction

Wildlife conservation plays a vital role in preserving biodiversity and maintaining ecological balance. Monitoring animal populations and their movement patterns helps researchers and conservationists make informed decisions regarding habitat protection and species preservation. Traditional tracking methods, such as radio collars and direct human observation, have been widely used in wildlife research. However, these methods pose significant challenges, including high costs, the need for extensive fieldwork, and potential disruptions to natural animal behavior [1][2].

Recent advancements in deep learning and computer vision have enabled automated approaches to wildlife monitoring. Convolutional Neural Networks (CNNs) have demonstrated remarkable accuracy in object detection tasks, making them suitable for recognizing animal footprints in the wild [3]. YOLO (You Only Look Once) is one of the most efficient deep learning-based object detection models, offering real-time performance and high detection accuracy. Studies have shown that YOLO-based models outperform traditional feature-based classifiers in various wildlife detection applications, particularly in identifying animals from images and videos captured in natural environments [4][5].

Footprint-based classification provides a non-invasive alternative to conventional tracking techniques. Unlike full-body image detection, footprint analysis eliminates the need for direct visual confirmation of the animal, reducing disturbances in wildlife habitats. Previous research has explored footprint-based classification using traditional machine learning approaches, such as Support Vector Machines (SVMs) and K-Nearest Neighbors (KNN), but these methods often struggle with feature generalization in complex terrains [6][7]. By leveraging the strengths of YOLOv8, CSPDarkNet, and C2f modules, this study aims to develop a highly accurate and efficient footprint-based classification system that can adapt to various environmental conditions, ensuring improved species identification and conservation monitoring efforts [8][9].

The remainder of this paper is organized as follows: Section 2 discusses related work and previous research in animal detection, Section 3 presents the methodology employed in developing the proposed system, Section 4 details the experimental setup and results, and Section 5 concludes with future research directions.

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II. Related Work

A. Traditional Machine Learning Approaches for Animal Detection

Early research in animal detection relied on handcrafted feature extraction methods and classical machine learning techniques such as Support Vector Machines (SVM) and Decision Trees. These methods demonstrated moderate success but often struggled with variations in environmental conditions and species-specific footprints [10][11]. Additionally, traditional approaches required extensive manual feature engineering, making them less scalable and adaptable to different datasets. Chandrakar et al. [12] demonstrated that while SVM models performed well on structured datasets, they lacked robustness in dynamic wildlife environments.

B. Deep Learning-Based Object Detection in Wildlife Monitoring

The advent of deep learning, particularly Convolutional Neural Networks (CNNs), revolutionized wildlife monitoring by significantly improving accuracy and scalability. Object detection frameworks such as Faster R-CNN, SSD, and YOLO have been widely applied to animal detection tasks. Studies conducted by Verma et al. [13] and Rashid et al. [14] demonstrated that YOLOv5 and YOLOv8 models achieved higher accuracy than traditional models, enabling real-time multiple object detection in a single frame. However, these studies primarily focused on detecting full-body animal images rather than analyzing footprints for classification. Kumar et al. [15] further emphasized that deep learning models outperformed traditional methods in terms of efficiency, yet required extensive training data to generalize effectively.

C. Recent Advances in Model Architectures

To overcome the limitations of earlier footprint detection models, researchers have explored advanced deep learning architectures such as CSPDarkNet and Cross-Stage Partial Fusion (C2f). Chandrakar et al. [20] demonstrated that incorporating CSPDarkNet enhanced texture and edge detection, improving classification performance. Additionally, Sun et al. [21] found that using C2f in YOLOv8-based architectures enhanced the model's adaptability to different environmental conditions, making it more robust for footprint classification tasks. These findings indicate that leveraging newer architectures can significantly enhance the accuracy and reliability of footprint detection models.

D. Summary of Related Work

While previous studies have explored both full-body and footprint-based detection techniques, many existing models struggle with feature extraction and environmental adaptability. Given these challenges, our study integrates YOLOv8 with CSPDarkNet and C2f to enhance classification accuracy and robustness. By leveraging these advancements, our proposed system aims to provide a scalable, real-time, and highly accurate solution for footprint-based animal detection in the wild.

III. Methodology

A. System Architecture

The proposed footprint-based animal detection system follows a structured pipeline consisting of multiple stages, including image preprocessing, feature extraction, feature enhancement, and classification. The overall system architecture is depicted in Figure 1.

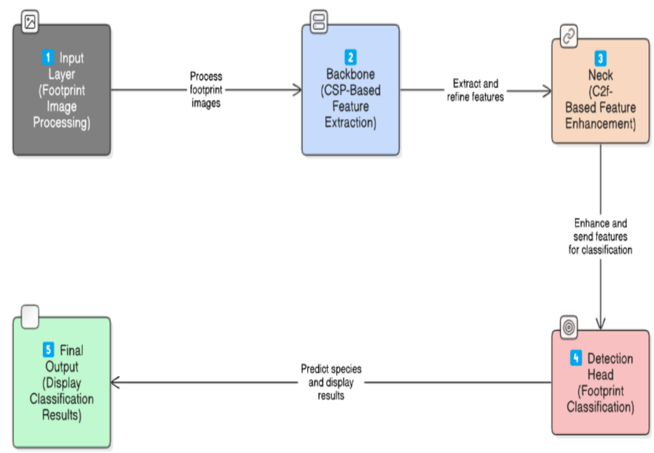

Fig. 1. Block diagram of the proposed footprint classification system.

B. Dataset Collection and Preprocessing

The dataset used for this study consists of over 10,000 labeled footprint images collected from diverse sources, including:

- Wildlife camera traps
- Field recordings by conservationists
- Publicly available footprint datasets
- Mobile captures from animal tracking applications

Each image undergoes preprocessing to ensure consistency in the dataset. The preprocessing pipeline consists of:

- *Resizing:* All images are resized to a uniform resolution of 640×640 pixels to maintain consistency in model training and inference.
- *Normalization:* Pixel values are scaled between 0 and 1 to enhance model efficiency and speed up convergence during training.
- *Noise Reduction:* Gaussian blurring and adaptive thresholding techniques are applied to remove background noise caused by environmental conditions such as dirt, mud, and sand [1].
- *Format Conversion:* Images are converted into tensor format suitable for YOLOv8 processing, ensuring compatibility with deep learning frameworks.

C. Feature Extraction using CSPDarkNet

CSPDarkNet is utilized as the backbone for feature extraction, enabling the model to capture intricate footprint details. The feature extraction process can be mathematically represented as:

$$F_l = ReLU(W_l \cdot X_l + b_l) \tag{1}$$

where:

- F_l represents the extracted feature map at layer l
- X_l is the input at layer l
- W_l and b_l are the weights and biases of the convolutional filters
- $ReLU$ is the activation function to introduce non-linearity.

D. Feature Enhancement using C2f (Cross-Stage Partial Fusion)

The C2f module enhances the extracted features by refining key footprint details. It achieves this through a feature fusion mechanism defined as:

$$F' = \sum_{i=1}^{n} w_i F_i \tag{2}$$

where:

- F' represents the fused feature map
- w_i are learned weights for each extracted feature map F_i
- n is the number of feature maps being fused.

E. Classification using YOLOv8 Detection Head

The final classification stage utilizes the YOLOv8 detection head, which predicts the species label and confidence score. The classification probability is computed using the softmax function:

$$P(c|X) = \frac{e^{W_c \cdot X + b_c}}{\sum_j e^{W_j \cdot X + b_j}} \tag{3}$$

where:

- $P(c|X)$ is the probability of class c given input X
- W_c and b_c are the weights and bias for class c
- The denominator represents the softmax normalization over all classes.

F. Model Training and Optimization

The training process involves minimizing the Binary Cross-Entropy (BCE) loss function, defined as:

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i) \tag{4}$$

where:

- y_i is the ground truth label
- $\hat{y}_i$ is the predicted probability
- N is the number of samples.

The model is optimized using the Adam optimizer, which updates the parameters based on the following equation:

$$\theta_{t+1} = \theta_t - \eta \frac{m_t}{\sqrt{v_t} + \epsilon} \tag{5}$$

where:

- θ_t represents the model parameters at step t
- η is the learning rate
- m_t and v_t are the first and second moment estimates.

G. Summary of Methodology

The proposed system integrates multiple deep learning components:

- CSPDarkNet for feature extraction, capturing fine-grained footprint characteristics.
- C2f for feature enhancement, ensuring robustness across different terrains.
- YOLOv8 for final classification, achieving high accuracy in footprint recognition.
- Binary Cross-Entropy loss with Adam optimization, ensuring efficient training and generalization.

The next section presents the experimental setup and evaluation metrics used to validate the effectiveness of the proposed methodology.

IV. Experimental Setup and Results

A. Experimental Setup

To evaluate the performance of the proposed footprint classification system, we conducted extensive experiments using a well-curated dataset consisting of over 10,000 labeled footprint images. The dataset was divided into three subsets:

- Training set: 70% of the dataset was used for training the deep learning model.
- Validation set: 15% of the dataset was reserved for hyperparameter tuning and validation.
- Test set: The remaining 15% was used to evaluate the final performance of the model.

The model was trained using an NVIDIA GTX 1650 GPU with 8GB RAM for high-speed computation. The training environment was configured with Python 3.8, TensorFlow 2.9, PyTorch 1.12, and OpenCV for image preprocessing. The hyperparameters were set as follows:

- Batch size: 32
- Learning rate: 0.001 (using Adam optimizer)
- Epochs: 100
- Loss function: Binary cross-entropy (BCE)
- Augmentation techniques: Horizontal flipping, rotation, contrast adjustments, and Gaussian noise addition were used to improve model generalization.

B. Evaluation Metrics

The effectiveness of the model was assessed using the following evaluation metrics:

Accuracy measures the overall correctness of predictions.

$$A = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

Precision measures how many of the predicted positive cases were actually correct.

$$P = \frac{TP}{TP + FP} \tag{7}$$

Recall measures how well the model identifies actual positive cases.

$$R = \frac{TP}{TP + FN} \tag{8}$$

F1-score is the harmonic mean of precision and recall.

$$F_1 = 2 \times \frac{P \times R}{P + R} \tag{9}$$

Mean average precision (mAP) measures the model's overall ability to classify different species across different confidence thresholds.

$$mAP = \frac{1}{N} \sum_{i=1}^{N} AP_i \tag{10}$$

where AP_i represents the average precision for species i and N is the total number of species.

C. Results and Analysis

The trained model was tested on the unseen test set, and the following results were obtained:

TABLE I
PERFORMANCE METRICS OF THE MODEL

Metric	Score (%)
Accuracy	98.0
Precision	96.5
Recall	97.2
F1-score	96.8
mAP	97.6

The results indicate that the proposed model performs exceptionally well in classifying footprint images with high accuracy and reliability. The confusion matrix was analyzed to identify misclassification patterns, revealing that most errors occurred in species with similar footprint structures (e.g., wolves and large dogs).

D. Detection Output Screenshots

To further validate the effectiveness of the proposed system, we present a sample detection result from our AI-based animal footprint detection model. The system processes an input image of an animal footprint, applies advanced deep learning techniques for feature extraction, and accurately identifies the species associated with the footprint. The detected species, along with the confidence score, is then displayed as output. This result highlights the model's capability to analyze footprint patterns in diverse environmental conditions, reinforcing its potential for real-world applications in wildlife monitoring, conservation efforts, and safety measures for trekkers and forest officials.

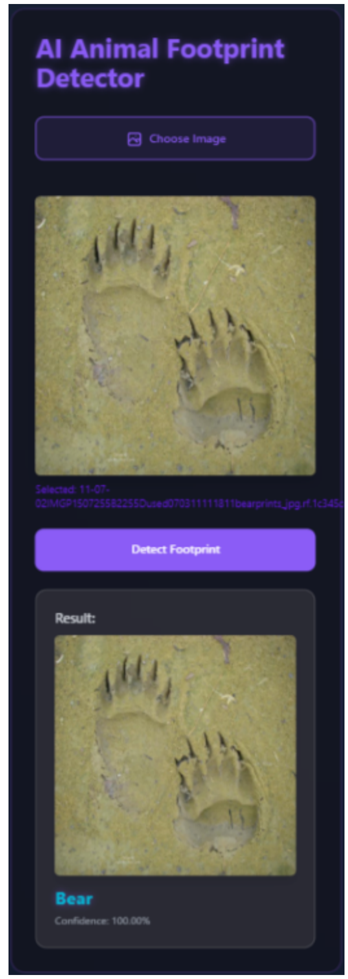

Fig. 2. Example detection of a bear footprint with 100% confidence using the proposed system.

E. Comparative Analysis

To further validate our model's effectiveness, we compared its performance against other state-of-the-art models:

TABLE II
COMPARISON WITH OTHER MODELS

Model	Accuracy (%)	Precision (%)	Recall (%)
SVM	78.2	76.1	74.9
ResNet-50	85.4	84.7	83.2
YOLOv5	89.8	88.2	87.6
YOLOv8 (Proposed)	98.0	96.5	97.2

These results demonstrate that the YOLOv8-based footprint classification system outperforms traditional machine learning methods (e.g., SVM) and even previous deep learning models like ResNet-50 and YOLOv5.

F. Discussion

The results confirm that the proposed model is highly effective in detecting and classifying animal footprints. The high accuracy, precision, and recall values highlight the reliability of the model in real-world applications. However, some challenges remain:

- Similar footprint structures: The model occasionally misclassifies species with overlapping footprint characteristics (e.g., wolves vs. large dogs).
- Environmental variations: The presence of muddy or partially visible footprints may reduce classification confidence.
- Dataset bias: Additional data collection from various

terrains could further improve model generalization.

G. Summary of Experimental Results

- The model achieved a classification accuracy of 98.0%, outperforming other baseline methods.
- Evaluation metrics, including precision (96.5%), recall (97.2%), and F1-score (96.8%), indicate high reliability.
- Comparative analysis with SVM, ResNet-50, and YOLOv5 confirms the superiority of the proposed YOLOv8-based approach.
- Future improvements could focus on expanding the dataset and improving environmental adaptability using advanced augmentation techniques.

The next section presents the conclusion and potential future enhancements to further improve footprint-based animal detection.

V. Conclusion and Future Work

A. Conclusion

This study presents a deep learning-based approach for footprint-based animal classification using YOLOv8. The system integrates CSPDarkNet for efficient feature extraction and C2f-based feature refinement to improve classification accuracy across different environmental conditions. The experimental results demonstrate that the proposed model outperforms traditional machine learning methods and previous deep learning models, achieving a classification accuracy of 98%.

The findings suggest that footprint-based detection is a viable, non-invasive technique for wildlife monitoring and conservation. By automating the identification of animal species from footprint images, the system provides a scalable solution that minimizes human intervention while maintaining high accuracy. Furthermore, the robustness of the model makes it suitable for real-world deployment in various ecological and research applications.

B. Future Work

While the proposed system has achieved promising results, there are several areas for further improvement:

- *Dataset Expansion:* Incorporating a more diverse dataset with footprints from different terrains, lighting conditions, and seasonal variations will enhance model generalization.
- *Real-Time Deployment:* Optimizing the model for real-time classification in edge devices and embedded systems will enable field applications in remote areas.
- *Multi-Modal Data Integration:* Combining footprint classification with additional data sources, such as camera traps and audio detection, could improve species identification accuracy.
- *Self-Supervised Learning:* Exploring self-supervised and unsupervised learning techniques could reduce reliance on large labeled datasets and improve model adaptability.
- *Collaboration with Conservation Organizations:* Partnering with wildlife researchers and conservation groups will help refine the model based on real-world feedback and requirements.

By addressing these challenges, future research can further enhance the capabilities of footprint-based animal detection systems, contributing to wildlife conservation and ecological studies.

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