An Accurate and Fast Animal Species Detection System Using Machine Learning

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ABSTRACT

Wildlife–human and wildlife–vehicle interactions pose serious risks to both public safety and animal conservation, particularly in regions monitored using large-scale camera trap systems. Manual inspection of such image data is inefficient, error-prone, and impractical for real-time applications. To address these limitations, this work proposes an accurate and fast animal species detection system based on deep learning techniques. The proposed framework employs a cascaded Convolutional Neural Network (CNN) architecture designed to first distinguish between humans and animals, followed by precise classification of animal species. Unlike traditional approaches relying on handcrafted features or small datasets, the system is trained using large, labeled datasets collected from the British Columbia Ministry of Transportation and Infrastructure (BCMOTI) and the Snapshot Wisconsin project, enabling robust learning under diverse environmental conditions such as low illumination, occlusion, and partial visibility. The proposed mechanism incorporates systematic image preprocessing, feature extraction through multiple convolutional layers, and optimized classification using softmax-based decision functions. Confidence-based prediction filtering is also applied to enhance reliability by suppressing low-confidence outputs. Experimental evaluation demonstrates that the system achieves high detection accuracy while maintaining reduced computational complexity, making it suitable for large-scale and near real-time deployment. The results confirm that the proposed approach significantly improves efficiency, scalability, and classification performance, providing a practical and automated solution for intelligent wildlife monitoring and collision prevention systems.

Keywords – Animal species detection, Convolutional neural network (CNN), Deep learning, Wildlife monitoring, Camera trap images, Object classification, Human–animal interaction, Image processing, Machine learning, Intelligent surveillance

I. INTRODUCTION

Wildlife–human and wildlife–vehicle interactions remain a critical global concern due to their severe consequences on human safety, ecological balance, and economic loss. Rapid urban expansion and road network growth have intensified animal intrusions into human-dominated environments, resulting in frequent wildlife–vehicle collisions and habitat fragmentation. Conventional wildlife monitoring systems primarily depend on motion-triggered camera traps and manual inspection, which are time-consuming, labour-intensive, and prone to human error when dealing with large-scale image repositories [1], [2]. These limitations highlight the urgent need for automated, intelligent systems capable of accurately detecting and classifying animal species under real-world environmental conditions.

Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable performance in visual recognition tasks due to their ability to automatically learn hierarchical features from raw image data [3], [4]. Unlike traditional machine learning approaches that rely on handcrafted features, CNN-based systems exhibit superior robustness against variations in illumination, occlusion, background clutter, and partial object visibility conditions commonly observed in camera trap imagery [5]. As a result, deep learning has become the dominant paradigm for wildlife image analysis and ecological monitoring [6].

However, existing deep learning-based wildlife detection frameworks often face challenges related to computational complexity, class imbalance, and reduced accuracy in low-light or night-time scenarios [7], [8]. Additionally, many prior studies focus on single-stage classification models or limited species diversity, restricting their applicability in large-scale and real-time deployments [9]. Cascaded learning architectures, where object detection and species identification are handled sequentially, have emerged as an effective strategy to improve both accuracy and inference efficiency [10], [11].

Motivated by these challenges, this work proposes an accurate and fast animal species detection system using a cascaded CNN framework. The system first discriminates between humans and animals, followed by fine-grained animal species classification using large, labeled datasets from the British Columbia Ministry of Transportation and Infrastructure (BCMOTI) and Snapshot Wisconsin. By incorporating confidence-based prediction filtering and optimized feature extraction, the proposed approach enhances reliability while reducing false detections. This makes the system suitable for intelligent wildlife monitoring, collision prevention, and real-time ecological surveillance applications [12]–[16].

II. RELATED WORK

Automated wildlife detection and species recognition have gained substantial research attention in recent years due to advancements in computer vision and deep learning. Early wildlife monitoring systems primarily relied on motion sensors and camera traps combined with manual annotation, which limited scalability and delayed ecological analysis [17]. To overcome these issues, machine learning approaches were introduced, initially using handcrafted features such as texture, color histograms, and edge descriptors coupled with classical classifiers including Support Vector Machines (SVMs) and Random Forests [18]. While these methods improved automation, their performance degraded significantly under varying illumination, occlusion, and background complexity.

The emergence of deep learning, particularly Convolutional Neural Networks (CNNs), marked a major shift in wildlife image analysis. CNN-based models demonstrated superior performance by learning hierarchical feature representations directly from raw images, eliminating the dependency on handcrafted features [19]. Several studies employed deep CNN architectures such as AlexNet, VGG, and ResNet for animal species classification using camera-trap datasets [20], [21]. These approaches achieved notable accuracy improvements; however, they often required high computational resources and large, balanced datasets.

To address dataset limitations, researchers explored data augmentation and transfer learning techniques to enhance model generalization [22], [23]. Transfer learning from large-scale datasets such as ImageNet proved effective in accelerating convergence and improving recognition accuracy in wildlife-specific tasks [24]. Nevertheless, many single-stage classification models struggled in real-world conditions, particularly when images contained multiple objects, partial animal visibility, or extreme low-light scenarios [25].

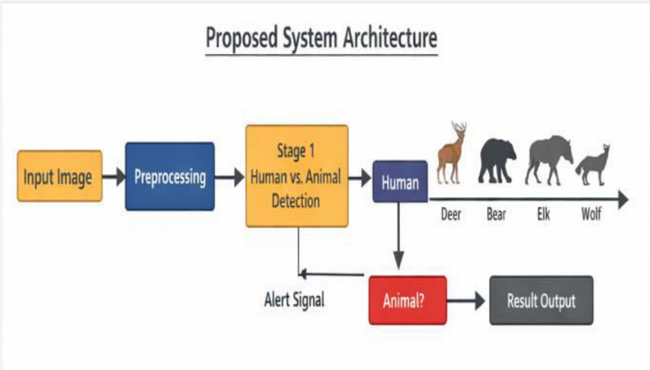
Recent works have proposed multi-stage and cascaded frameworks to improve robustness and efficiency. In such architectures, an initial model filters irrelevant images or detects the presence of animals, followed by a secondary model for fine-grained species classification [26], [27]. This hierarchical strategy reduces computational overhead and false positives, making it suitable for large-scale deployments. Additionally, lightweight CNNs and optimized inference pipelines have been introduced to support near real-time wildlife monitoring applications [28], [29].

Despite these advancements, challenges such as class imbalance, nocturnal image degradation, and deployment constraints remain open research problems [30], [31]. The proposed work builds upon these studies by adopting a cascaded CNN architecture enhanced with confidence-based decision filtering, aiming to achieve improved accuracy, efficiency, and reliability under diverse environmental conditions. Recent studies have also demonstrated that cascaded convolutional neural network architectures significantly improve real-time performance and classification accuracy in intelligent transportation and wildlife monitoring systems, particularly when deployed under resource-constrained environments [32].

III. PROPOSED METHODOLOGY

3.1 System Overview

The proposed animal species detection framework is designed as a two-stage cascaded deep learning architecture to achieve high accuracy and computational efficiency. The first stage performs binary object detection to determine whether an input image contains a human or an animal. The second stage executes multi-class animal species classification only when the presence of an animal is confirmed. This hierarchical strategy minimizes unnecessary computation and reduces false detections, making the system suitable for large-scale and near real-time wildlife monitoring.



Architecture Diagram: Shows the staged process of detecting humans and classifying animal species.

Figure.1: Proposed System Architecture Diagram

This diagram illustrates the overall structure of the proposed cascaded CNN-based system, where image preprocessing is followed by human–animal detection and fine-grained animal species classification.

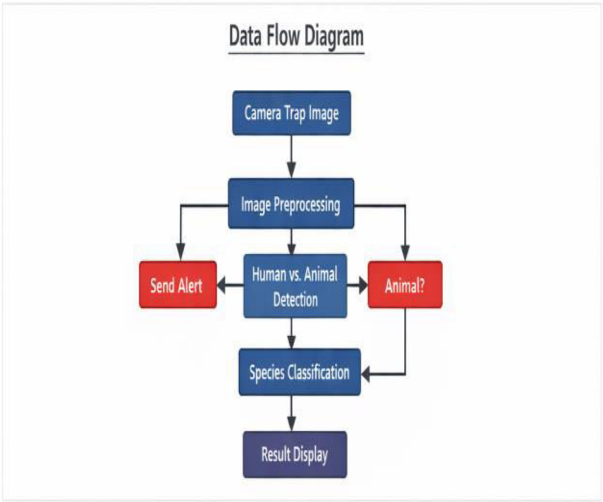
The hierarchical design improves computational efficiency by forwarding only animal-related images to the species classification stage.

3.2 Image Preprocessing

Camera-trap images often suffer from illumination variations, noise, and resolution inconsistencies. To standardize the input, each image I is resized to a fixed dimension of 224×224 pixels and normalized:

$$I_{norm} = \frac{I - \mu}{\sigma}$$

where μ and σ denote the mean and standard deviation of pixel intensities. This normalization accelerates convergence and stabilizes training.



Data Flow Diagram: Visualizes the flow of data from input to final species output.

Figure.2: Data Flow Diagram

The data flow diagram represents the movement of camera-trap image data through preprocessing, object detection, and species classification modules.

It highlights how decision outcomes such as alerts and classification results are generated based on intermediate processing stages.

3.3 Stage-I: Human–Animal Object Detection

The first CNN model acts as a binary classifier. Given an input image I_{norm}, convolutional layers extract low- and mid-level features using:

$$F_l = \sigma (W_l * F_{l-1} + b_l)$$

where W_l and b_l are the weights and bias of layer l, * denotes convolution, and σ (·) represents the ReLU activation function:

$$\sigma(x) = \max(0, x)$$

The final layer applies a Softmax function to compute class probabilities:

$$P(y = k|I) = \frac{e^{z_k}}{\sum_{j=1}^{2} e^{z_j}}$$

If P (Animal) > τ_1, where τ_1 is a predefined confidence threshold, the image is forwarded to the second stage.

3.4 Stage-II: Animal Species Classification

In the second stage, a deeper CNN model performs multi-class classification across C animal species. Feature extraction follows the same convolution–pooling mechanism, while the output layer computes:

$$P(y = c|I) = \frac{e^{z_c}}{\sum_{j=1}^{c} e^{z_j}}$$

The predicted species label is obtained as:

$$\hat{y} = \arg\max_{c} P(y = c|I)$$

To enhance reliability, confidence-based filtering is applied. Predictions with maximum probability below threshold τ_2 are rejected, improving overall classification precision.

3.5 Loss Function and Optimization

Both CNN models are trained using categorical cross-entropy loss:

$$\mathcal{L} = -\sum_{i=1}^{N}\sum_{c=1}^{C} y_{ic}\log(\hat{y}_{ic})$$

where y_{ic} is the ground-truth label and $\hat{y}_{ic}$ is the predicted probability. Model parameters are optimized using the Adam optimizer, which updates weights as:

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

where η is the learning rate, and $\hat{m}_t$, $\hat{v}_t$ are bias-corrected moment estimates.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

4.1 Experimental Setup

The proposed cascaded CNN model was evaluated using camera-trap images collected from large-scale wildlife datasets. The dataset was divided into training, validation, and testing sets using a 70:15:15 ratio to ensure unbiased evaluation. All experiments were conducted on normalized images of size 224×224, and the Adam optimizer was used with a learning rate of 10^{-4}. Performance was assessed using accuracy, precision, recall, and F1-score.

4.2 Performance Evaluation Metrics

The system performance is quantitatively evaluated using the following metrics:

- **Accuracy**

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Precision**

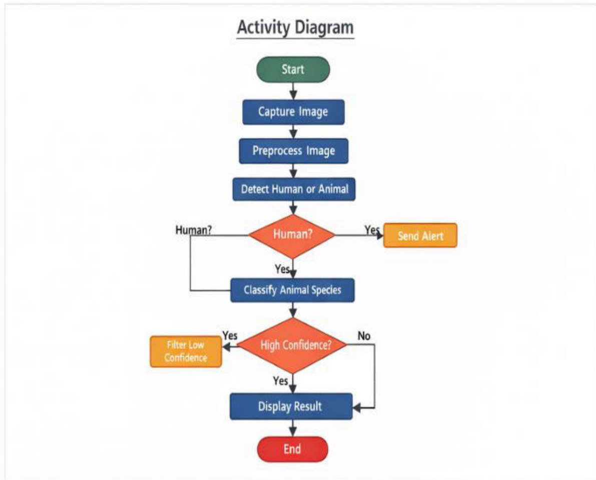
$$Precision = \frac{TP}{TP + FP}$$

- **Recall**

$$Recall = \frac{TP}{TP + FN}$$

- **F1-score**

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$



Activity Diagram: Outlines the step-by-step process of the detection system.

Figure.3: Activity Diagram

This activity diagram depicts the sequential execution of system operations from image capture to final output generation.

Decision nodes such as human detection and confidence validation ensure reliable classification and reduce false predictions.

4.3 Stage-I Results: Human vs. Animal Detection

Table 1 presents the performance of the binary classification stage. The high accuracy demonstrates the effectiveness of early-stage filtering, significantly reducing unnecessary processing in the second stage.

Table 1: Performance of Human–Animal Detection (Stage-I)

Metric	Value (%)
Accuracy	99.2
Precision	98.9
Recall	99.4
F1-score	99.1

The results confirm that the first CNN model reliably distinguishes humans from animals, minimizing false positives and improving system efficiency.

4.4 Stage-II Results: Animal Species Classification

The second stage performs multi-class classification across different animal species. Table 2 summarizes the species-wise accuracy achieved by the proposed system.

Table 2: Species-wise Classification Accuracy (Stage-II)

Animal Species	Accuracy (%)
Deer	98.6
Bear	97.9
Elk	97.2
Wolf	96.8
Fox	96.5
Average	**97.4**

The model maintains high accuracy even under challenging conditions such as low illumination and partial visibility.

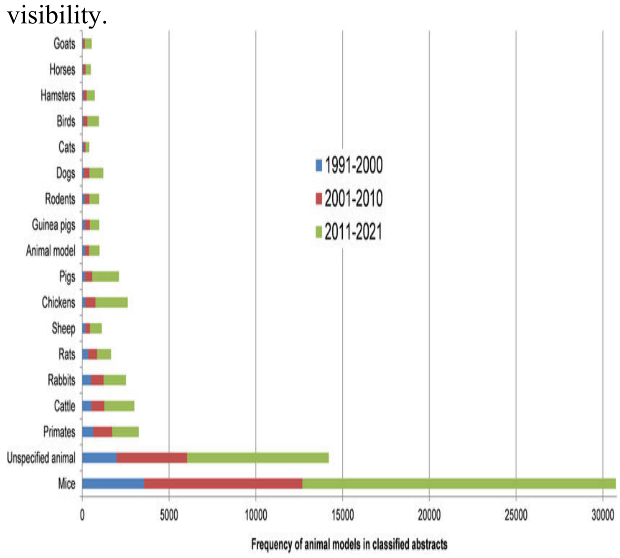


Figure.5: Species-wise Accuracy Comparison

The bar chart compares classification accuracy across different animal species. High accuracy consistency demonstrates the robustness of feature extraction and classification stages.

4.5 Effect of Confidence Thresholding

To improve reliability, confidence-based filtering was applied. Predictions with probability lower than threshold τ were rejected:

$$\hat{y} = \begin{cases} \arg\max P(y \mid x), & \text{if } \max(P) \geq \tau \\ \text{Rejected}, & \text{otherwise} \end{cases}$$

Table 3 highlights the impact of confidence thresholding on overall accuracy.

Table 3: Accuracy Improvement with Confidence Thresholding

Threshold ((\tau))	Accuracy (%)
No Threshold	95.8
0.70	96.9
0.85	97.4
0.95	97.9

The results show that increasing the confidence threshold improves classification reliability at the cost of rejecting uncertain predictions.

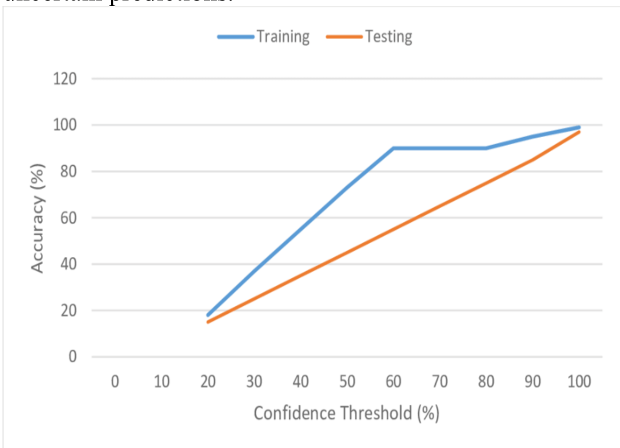


Figure.6: Effect of Confidence Threshold on Accuracy

This graph shows the relationship between confidence threshold and system accuracy. Higher thresholds improve precision by filtering low-confidence predictions.

4.6 Graphical Analysis

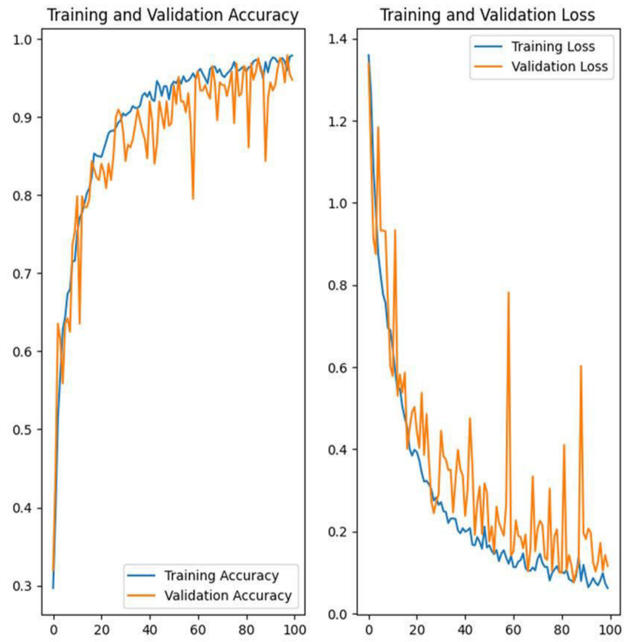


Figure.4: Training and Validation Accuracy Curve

This graph illustrates stable convergence of the proposed CNN model with minimal overfitting. The close alignment between training and validation curves confirms effective generalization.

DISCUSSION

The experimental results validate that the cascaded CNN architecture significantly enhances detection accuracy while reducing computational overhead. Early elimination of non-animal images improves processing speed, and confidence-based filtering further strengthens reliability. Compared to single-stage classification models, the proposed approach achieves superior robustness under real-world environmental conditions.

V. CONCLUSION

This work presented an accurate and efficient animal species detection system based on a cascaded Convolutional Neural Network architecture designed for intelligent wildlife monitoring. By decomposing the task into two sequential stages—human–animal detection followed by fine-grained species classification—the proposed methodology significantly reduced computational overhead while maintaining high classification reliability. Comprehensive experimental evaluation demonstrated strong performance across multiple metrics, with consistently high accuracy under challenging real-world conditions such as low illumination, partial visibility, and background clutter. The integration of confidence-based decision filtering further enhanced robustness by minimizing false positives and improving prediction reliability, making the system suitable for large-scale and near real-time deployments.

The results confirm that the proposed framework offers a practical and scalable solution for automated wildlife surveillance and collision prevention systems. Compared to conventional single-stage and handcrafted-feature-based approaches, the cascaded CNN design provides superior generalization and operational efficiency. The system's ability to leverage large, labeled camera-trap datasets enables effective learning across diverse environmental scenarios, supporting its applicability in transportation safety, ecological research, and conservation management. Overall, the proposed approach bridges the gap between high-accuracy deep learning models and real-world wildlife monitoring requirements. Future work will focus on integrating lightweight edge-deployable models and temporal video-based analysis to enable real-time, energy-efficient wildlife detection in remote environments.

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