Frontiers in Health Informatics
ISSN-Online: 2676-7104
www.healthinformaticsjournal.com
2024; Vol 13: Issue 8
Open Access

Deep Learning for Biodiversity: Multiclass Animal Image Recognition

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Cite this paper as: Arshad Rafiq Khan, Dr. Poonam Dev, Dr. S.Narsaiah, Dr. Yashwant Singh Sangwan,Dr. Deepak Chandra Uprety, Dr. Sharvan Kumar Garg (2024) Deep Learning for Biodiversity: Multiclass Animal Image Recognition *Frontiers in Health Informatics, 13* (8), 2483-2489

Abstract: Abstract- Human-Animal Conflict presents serious problems including threats to human life and resource loss, which calls for careful monitoring and preventive actions. This work aims to create an advanced animal detection and identification system leveraging motion-triggered cameras, sometimes referred to as camera traps, images obtained. Poor contrast between animals and cluttered backgrounds as well as high false-positive rates brought on by dynamic backgrounds cause existing techniques to suffer with low detection rates. We propose a two-stage approach to overcome these difficulties: first, using advanced image processing techniques to generate animal object region proposals; second, using artificial intelligence (AI) methods for detection and classification. The system validates region proposals and accurately identifies animals using eXtreme Gradient Boosting (XGBoost), Particle Swarm Optimisation (PSO), and CNN. The suggested system finds use in animal intrusion detection in industrial settings close to residential areas, agricultural fields, factories, and avoidance of animal-vehicle collisions. This method seeks to raise detection accuracy and dependability, so supporting more effective and safer methods of human-animal coexistence.
Key Words: Image processing, Artificial Intelligence, XGB, Particle Swarm Optimization (PSO), Convolutional Neural Network (CNN)

1. INTRODUCTION

Man-animal conflict shows itself in several forms and usually has major effects on people as well as animals. Deforestation, where wild animals stray from their natural habitats in search of food, crosses highways and runs the danger of fatal vehicle collisions [1], is a main reason of such conflicts. While their arrival into agricultural fields usually results in significant crop damage, animals invading residential areas can result in loss of human life and property. Automated animal detection systems are absolutely vital since human ability to monitor and identify animal movement around-clock is inadequate.

Thanks to their extensive practical uses, animal detection has become a major focus of study. New directions for animal detection innovation have been opened by computer science's developments. The adaptability of computer science instruments makes their use possible in many disciplines, from ocean engineering to meteorology. Particularly, thanks to major increases in computational capacity, artificial intelligence (AI) and machine learning methods have become rather well-known recently. Deep learning, a subfield of artificial intelligence, is especially useful in animal detection since it allows the reuse of algorithms across several datasets, so saving the need to create new algorithms for every particular dataset. Deep Learning is a necessary tool in animal detection systems since of its adaptability and efficiency.

Different animal detection and warning systems have been created to handle particular use cases, such spotting dangerous animal intrusions in residential areas, spotting animals close to roads to prevent vehicle collisions, and researching the locomotive behaviour of targeted animals [2]. In real-life situations when human-animal conflict presents serious hazards, these systems are absolutely vital. For example, hundreds of camel-vehicle accidents are recorded yearly in Saudi Arabia, resulting in many deaths and millions of Saudi Riyals in property damage. An intelligent Camel Vehicle Accident-Avoidance System (CVAAS) was developed with global positioning system (GPS) technology [2] to help to offset this.

Apart from road safety, animal detection systems find application in other vital fields. For instance, they help fishermen find fish schools in deep seas, so increasing their efficiency and means of livelihood. By spotting possibly dangerous animal intrusions into homes [2], these systems also help to provide human safety and security. Existing animal detection systems do, however, have low accuracy, high false positives, and poor environmental adaptation ability. The choice and optimisation of strong algorithms is therefore very important since the effectiveness of these systems mostly depends on the classification techniques applied.

High-accuracy animal detection systems must be developed if we are to solve these constraints. By precisely determining animal presence, such systems seek to reduce human-animal conflict by so averting accidents, property damage, and life-saving actions. These systems can provide scalable and effective answers to lessen the negative effects of human-animal conflict in different environments by using cutting-edge AI methods and computational tools. There is great possibility for encouraging coexistence between people and animals by including animal detecting systems into daily life. From safeguarding agricultural fields to preventing traffic accidents, their uses highlight their importance in meeting the difficulties presented by interactions between humans and animals. Future animal detection systems seem to be more dependable, effective, and powerful as artificial intelligence and computational technologies keep developing.

The work is organised to fully discuss the difficulties and developments in animal detection systems. It starts with a Introduction stressing the need of reducing conflicts between humans and animals as well as the part technology can play in solving problems. Analysing current approaches, their uses, and constraints including low accuracy and high false-positive rates [1][2] a literature review follows. The proposed system architecture describes how Deep Learning, XGBoost, and PSO might be combined to improve adaptation and detection accuracy. The section Implementation and Experiments covers the development of the system including methods of data preprocessing, training, and evaluation. The results and discussion show the performance of the suggested system against current techniques employing criteria including accuracy and efficiency. The conclusion summarises the research contributions and emphasises the need of sophisticated animal detection systems in lowering human-animal conflicts. The part on challenges and future directions addresses constraints like adjusting to dynamic surroundings and advises using new technologies to raise system performance.

2. LITERATURE SURVEY

Aiming at avoiding animal-vehicle collisions, Aditiba Rao and Viral Parekh [1] undertook an extensive study on several animal detection techniques. An overview of several animal detecting methods was given by Sharma, Sachin, and D. J. Shah [2]. Using Probabilistic Neural Networks (PNN) and K-Nearest Neighbours (KNN), Kumar, Y.H. Sharath et al. [3] developed a method for animal classification. Although the KNN classifier had better accuracy (66.98%) than PNN (56.66%), it suffered with long execution times and large memory needs. Using Convolutional Neural Networks (CNN), Favorskaya, Margarita et al. [4] classified animals, obtaining 80.6% Top-1 and 94.1% Top-5 accuracy on balanced datasets but reporting lowered accuracy (38.7% Top-1) on unbalanced datasets. With Gabor features, Radhakrishnan, Saieshwar et al. [5] developed a Support Vector Machine (SVM) model with low accuracy of 54.32% for animal intrusions in agricultural fields.

Using Deep Convolutional Neural Networks (DCNN) for wildlife monitoring, Chen, Guobin et al. [6] proposed the first completely automatic species recognition system with an accuracy of 38.315% but fell short of complete automation criteria. Using the You Only Live Once (YOLO) classifier, Parham, Jason et al. [7] obtained an accuracy of 72.75%; R. Pavithra et al. [8] used Cascaded Random Classifiers for an automatic object detection system, so reporting an 82.5% accuracy in lion detection. Using thermal cameras and KNN classifiers, Christiansen, Peter et al. [9] demonstrated partial invariance to translation and posture but found difficulty spotting animals at great distances.

Using CNNs for fast animal detection in UAV images, Kellenberger, Benjamin et al. [10] achieved lowered false positives but high false-negative rates with Precision=0.60, Recall=0.74, and F1=0.66. Developing a very deep convolutional neural network to classify Grant's Gazelle, Villa et al. [11] achieved 82.1% accuracy using Citizen Science data.

Using HOG and Cascade Classifier, Sharma, Sachin Umesh et al. [12] built an animal detection system with an 82.5% detection rate but restricted to single-animal detection. With SVM and AdaBoost, Boukerche, Azzedine et al. [13] achieved over 83% accuracy but limited to side-view detection for moose detection from roadside cameras. With an accuracy of 82.49% and an F-measure of 81.40%, Nguyen, Hung et al. [14] presented the "Lite AlexNet" DCNN model for automated wildlife monitoring, so proving robustness and stability for wild image recognition (Table 1).

Table 1: Literature Review Summary

Ref.	Description	Results	Limitations
[1]	Survey on animal detection methods to prevent vehicle collisions.	No specific results reported.	Overview lacks implementation details.
[2]	Overview of animal detection methods.	No specific results reported.	Lacks comparative analysis.
[3]	Classification using PNN and KNN.	KNN: 66.98%, PNN: 56.66%.	Long execution time, high memory usage.
[4]	Animal classification using CNN.	[illegible]0.6% Top-1, 94.1% Top-5 on balanced datasets; 38.7% Top-1 on unbalanced datasets.	Poor performance on unbalanced datasets.
[5]	SVM with Gabor Features for intrusion detection.	[illegible]4.32% accuracy.	Low accuracy.
[6]	Fully automatic species recognition with DCNN.	[illegible]8.315% accuracy.	Incomplete automation.
[7]	YOLO classifier for animal classification.	[illegible]2.75% accuracy.	Moderate accuracy.
[8]	Cascaded Random Classifier for object detection.	[illegible]2.5% lion detection accuracy.	Focused only on lion detection.
[9]	KNN classifier with thermal cameras.	Partly invariant to transformations.	Poor far-range recognition.
[10]	CNN for fast animal detection in UAV images.	Precision=0.60, Recall=0.74, F1=0.66.	High false-negative rate.
[11]	Deep CNN for Grant's Gazelle classification.	Citizen Science: 82.1%, ConvNet: 65.0%.	Focused on a single species.
[12]	HOG and Cascade Classifier for detection.	[illegible]2.5% accuracy for cows.	Limited to single-animal detection.
[13]	SVM and AdaBoost for moose detection.	Over 83% accuracy.	Limited to side-view detection.
[14]	Lite AlexNet for wildlife monitoring.	[illegible]2.49% accuracy, F-measure: [illegible]1.40%.	Results depend on dataset quality.

3. SYSTEM ARCHITECTURE OF THE PROPOSED ANIMAL DETECTION SYSTEM

Figure 1 illustrates the system architecture of the proposed animal detection system, which comprises several key modules:

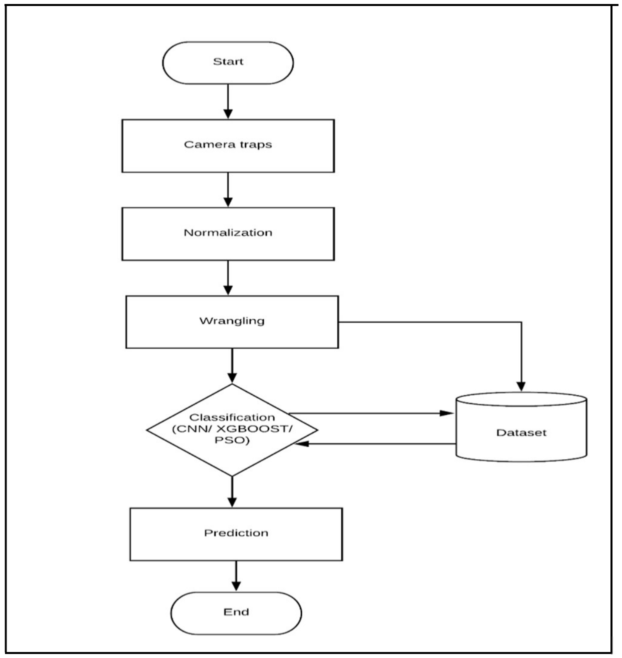

Figure 1. System Architecture of the Proposed Animal Detection System

Camera Traps

This stage involves collecting images using camera traps. Images can be obtained through various methods, and they serve as the primary input for subsequent steps. For this study, the "Missouri Camera Trap Images" and "Oregon Wildlife Dataset" datasets were utilized for training and testing the models.

Normalization

Normalization standardizes the pixel values of images, ensuring they fall within a specific range. This preprocessing step scales the images appropriately before feeding them into the model, enhancing the performance of the classification process.

Wrangling

Raw data from datasets often contain inaccuracies, making them unsuitable for direct model training. Wrangling involves cleaning and transforming these images into a usable format. In this paper, images with missing or incorrect data, such as those lacking animals or featuring multiple species in the same frame, were excluded from the dataset to improve the quality of training data.

Dataset

The dataset generated from the previous stages serves as the foundation for training and validating the models. A total of 4,330 images were divided into two subsets: 85% for training and 15% for validation.

Classification

Three independent classification models were employed:

- Convolutional Neural Network (CNN): A specialized artificial neural network for image classification, performing a mathematical operation called convolution.
- Extreme Gradient Boosting (XGBoost): A machine learning algorithm based on decision trees that uses gradient descent to minimize loss, applicable for both regression and classification tasks.
- Particle Swarm Optimization (PSO): A computational method that finds optimal solutions by iteratively improving candidate solutions known as particles.

These algorithms were trained on the dataset to classify input images effectively.

Prediction

In this stage, the trained models predict the class (species) of the animal in the input image. Additionally, localization is performed, where the model highlights the animal's face, specifies the species name, and provides the accuracy of the prediction. This modular approach ensures a systematic workflow from data collection to final prediction, enabling reliable animal detection and classification.

Table 2: Experimental results

LGORITHM	TRAIN CCURACY (%)	ALIDATION ACCURACY (%)	TEST CCURACY (%)
NN	98.17	92.72	91
GBOOST	99.9	89.97	90
SO	43.65	44.33	53

4. RESULTS AND DISCUSSION

The results showcase the performance of three algorithms—CNN, XGBoost, and PSO—across training, validation, and test datasets. Here's a detailed explanation:

4.1 Convolutional Neural Network (CNN):

- ***Training Accuracy (98.17%)***: The CNN demonstrated excellent performance on the training data, indicating its ability to learn patterns and features effectively.
- ***Validation Accuracy (92.72%)***: There was a slight drop compared to training accuracy, reflecting the model's generalization ability on unseen data. The reduction is acceptable and indicates minimal overfitting.
- ***Test Accuracy (91%)***: The test accuracy, slightly lower than validation accuracy, confirms that the model generalizes well to entirely unseen data, making CNN the most balanced performer among the three algorithms.

4.2 Extreme Gradient Boosting (XGBoost):

- ***Training Accuracy (99.9%)***: XGBoost achieved near-perfect accuracy on the training set, showcasing its strength in fitting the data. However, this high value raises concerns about potential overfitting.
- ***Validation Accuracy (89.97%)***: The significant drop from training accuracy suggests that XGBoost may have overfitted the training data, leading to reduced generalization ability.
- ***Test Accuracy (90%)***: While test accuracy is close to validation accuracy, the slight improvement indicates decent generalization but highlights the overfitting issue compared to CNN.

4.3 Particle Swarm Optimization (PSO):

- ***Training Accuracy (43.65%)***: PSO struggled significantly with the training data, indicating an inability to capture the underlying patterns effectively.
- ***Validation Accuracy (44.33%)***: The marginal increase from training accuracy shows that the model has limited learning capacity, performing almost at random.
- ***Test Accuracy (53%)***: Interestingly, the test accuracy is higher than both training and validation accuracies, possibly due to chance or the nature of the test dataset. However, this performance is insufficient for practical applications.

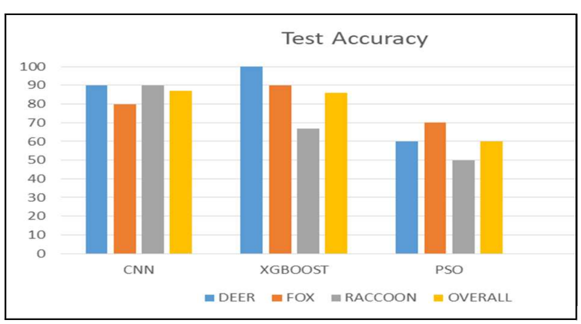

Figure 2. *Test Accuracy*

4.4 Comparison and Insights:

- CNN came out as the best performer since it clearly balanced training, validation, and test accuracy, which qualifies for practical animal detection projects.
- XGBoost struggled with overfitting, so compromising its performance on validation and test datasets even while it showed great accuracy during training.
- PSO indicated poor performance on all measures, suggesting it is not fit for the complexity of the classification problem in this work.

CNN is advised overall as the main algorithm for use because of its dependability and consistent performance. Table 2 lists these findings. The test accuracies of the models are shown in Figure 2 as a bar-graph.

5. CONCLUSION

For the task of animal detection and classification, this work assessed three algorithms: Particle Swarm Optimisation (PSO), Extreme Gradient Boosting (XGBoost), and CNN. With a training accuracy of 98.17%, a validation accuracy of 92.72%, and a test accuracy of 91%, CNN proved among the algorithms the most effective. Its most appropriate for real-world uses in animal detection systems since it can generalise effectively over datasets. Although XGBoost displayed the best training accuracy—99.9%—it showed indications of overfitting, which would have reduced validation (89.97%) and test (90%) accuracy over CNN. The overfitting problem reduces the dependability of the competitive performance for generalisation. Conversely, PSO proved unsuitable for this use since it failed to efficiently learn from the data and obtained low accuracies over all datasets. Finally, CNN is the most suitable option for creating a precise and effective animal detection system since of its better performance and generalisation capacity. Future research could investigate hybrid approaches or ensemble methods to mix the strengths of several algorithms, so enhancing system resilience and performance.

Though several issues and future directions must be addressed to improve its real-world applicability, the proposed animal detection system shows good results. Managing imbalanced datasets is a major difficulty since it usually results in biassed classification of under-represented species. The system might also suffer in cluttered or dynamic backgrounds, leading to either great false positives or negatives. Computational restrictions continue to be a challenge for real-time deployment on edge devices; another restriction is generalising the model over several datasets and areas. Often leading to false negatives, detecting animals partially hidden by vegetation or in difficult circumstances like low light, severe weather, or from UAV and thermal imaging also presents challenges. Ethical and privacy issues about UAV use or camera traps demand careful thought to guarantee non-intrusive deployment. Furthermore, improving performance and scalability are optimising models to manage different environmental conditions and including domain adaptation, advanced feature extraction, and multi-modal sensor inputs. Dealing with these restrictions will help the system to be more strong, accurate, and efficient in reducing human-animal conflicts.

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