Enhancing Wildlife Protection: Poacher Detection Using Machine Learning Models

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***Abstract*—Wildlife conservation is a pressing global concern, with illegal poaching posing a severe threat to many endangered species. In recent years, advanced technologies like machine learning and digital signal processing have shown significant potential in supporting conservation efforts by detecting and preventing illegal poaching. This work explores the integration of these technologies into wildlife conservation strategies, focusing on their role in identifying and combating poachers. Two datasets are utilized: "Poacher Detection 3 Classes" and "Illegal Poacher Detection". Several machine learning models including Support Vector Machines (SVM), Random Forest (RF), Decision Trees (DT), and Convolutional Neural Networks (CNN) are applied to detect illegal activities in these datasets. For the first dataset, the SVM model achieved the best accuracy of 93%, while the CNN model performed best on the second dataset, achieving accuracy of 75%. In the final phase, both datasets were combined, and augmented images were introduced to increase data diversity. On the combined dataset, the Random Forest model achieved the highest accuracy of 83%. These results demonstrate the effectiveness of machine learning in improving wildlife conservation efforts.**

***Index Terms*—Wildlife Conservation, Poacher detection, machine learning, Decision tree, Random Forest, CNN, Support vector machine.**

I. Introduction

The illegal poaching of wildlife remains a persistent challenge, driven by factors such as the high demand for exotic animal products, traditional medicine, and the destruction of natural habitats [1]. Despite numerous conservation efforts, the scale and sophistication of poaching operations continue to rise, threatening the survival of some of the world's most iconic species [2]. The escalating threat of poaching poses a significant risk to individual species, such as tigers, rhinos, bears, and elephants, and also to entire ecosystems [3]. The potential loss of these species could trigger cascading ecological impacts, ultimately reshaping biodiversity and disrupting the balance of natural habitats [4].

Conventional conservation approaches, such as ranger patrolling and static monitoring, are often insufficient in addressing poaching on a large scale [5]. Rangers are frequently limited by the vastness of the wilderness and challenging terrain, arriving at poaching sites too late to prevent harm [6]. The slow response time and lack of predictive capabilities leave wildlife vulnerable to poachers who adapt their tactics to evade detection. As poaching activities become more sophisticated, there is an urgent need to incorporate advanced technologies to improve the effectiveness of conservation efforts [7].

The integration of machine learning (ML) and digital signal processing (DSP) technologies presents a promising solution for wildlife conservation [8]. These technologies enable the analysis of vast datasets collected from a variety of sources, including satellite imagery [9], camera traps [10], acoustic recordings [11], and motion sensors [12], to identify patterns associated with poaching activities [13]. Machine learning models can predict potential poaching hotspots, while DSP techniques can analyze audio-visual data to detect sounds or movements indicative of illegal activities [14]. By leveraging these technologies, conservationists can receive real-time insights, allowing for more proactive interventions and faster responses to threats [8].

This paper explores the technical aspects of implementing a framework to detect poachers and evaluates its potential to enhance wildlife conservation. The primary objective of this study is to demonstrate how ML and DSP contribute to the early detection of poaching activities, enabling timely alerts and interventions. Various machine learning models, including Decision Trees (DT), Support Vector Machines (SVM), Random Forest (RF), and Convolutional Neural Networks (CNN), are utilized in this work. These models are trained on two distinct datasets that contain images of wildlife with and without the presence of poachers.

This study contributes to wildlife conservation by leveraging advanced machine learning models to detect illegal poaching activities in real-time. By applying various models, including SVM, RF, DT, and CNN, on multiple datasets, we demonstrate

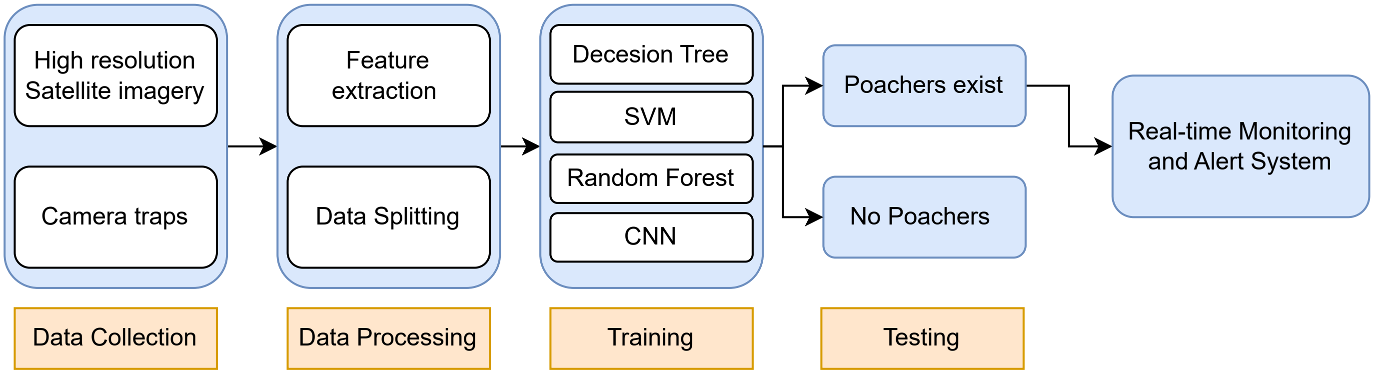


Fig. 1: The Proposed Framework for Poacher Detection

the potential of these techniques to enhance the accuracy and timeliness of poacher detection. This work also emphasizes the integration of data augmentation and real-time alert systems to improve conservation efforts on a larger scale.

The rest of this paper is organized as follows: Section II provides a review of recent techniques applied in poacher detection. Section III outlines the methodology, including dataset collection, preprocessing steps, and a technical overview of the models trained. Section IV presents the results of the experiments, while Section V concludes the paper with a discussion of the findings and future work.

II. Related Work

Numerous studies have demonstrated the potential of machine learning in wildlife conservation, showcasing its ability to automate the identification of threats, especially in detecting poachers.

Brown et al. [15] proposed a robust system for automatic, real-time poacher detection and wildlife counting by integrating thermal and UAV technologies with computer vision techniques. The primary objective of the system is to effectively detect malevolent humans for poacher detection, while the secondary objective is to count animals and classify them into their types. A two-layer CNN was employed for object detection in thermal images. The study's results showed perfect human identification in all test frames, although cats were occasionally misidentified as horses. Importantly, no animals were misidentified as humans, ensuring reliable poacher detection. The system demonstrated high accuracy in tracking both humans and animals.

De Knegt et al. [16] utilized sentinel animal movement data to develop an approach for timely poacher detection and localization. By leveraging the movement patterns of sentinel animals, they were able to build a system that is capable of effectively detecting and localizing potential poaching activities in wildlife reserves using logistic regression (LR). LR model achieved an accuracy of 86.1% in distinguishing intrusions from controls, with a precision of 82.6% and recall of 89.2%. The addition of additional features in the detection classifier led the predictive accuracy to increase to 91%. However, it was noted that adding more features could potentially lower the generalizability of the model to other areas due to overfitting.

Hambrecht et al. [17] conducted a pioneering study on detecting poachers with drones in miombo woodlands, Tanzania. They employed a generic linear model technique for the RGB image data and a multilevel model for the thermal infrared (TIR) image data analysis. By utilizing a drone fitted with RGB and TIR imaging sensors, they investigated the probability of detecting human presence in a miombo woodland in Tanzania. In addition, they also examined how variables such as camera type, canopy cover, subject contrast against the background, subject distance from the image centerline, and drone altitude influenced detection probability. Their results indicated that the TIR camera showed a greater detection probability (41%) compared to the RGB camera (24%) for detecting poachers. Factors that significantly influenced the detection probability in TIR images were the subject distance from the image centerline, canopy density, and the image analyst.

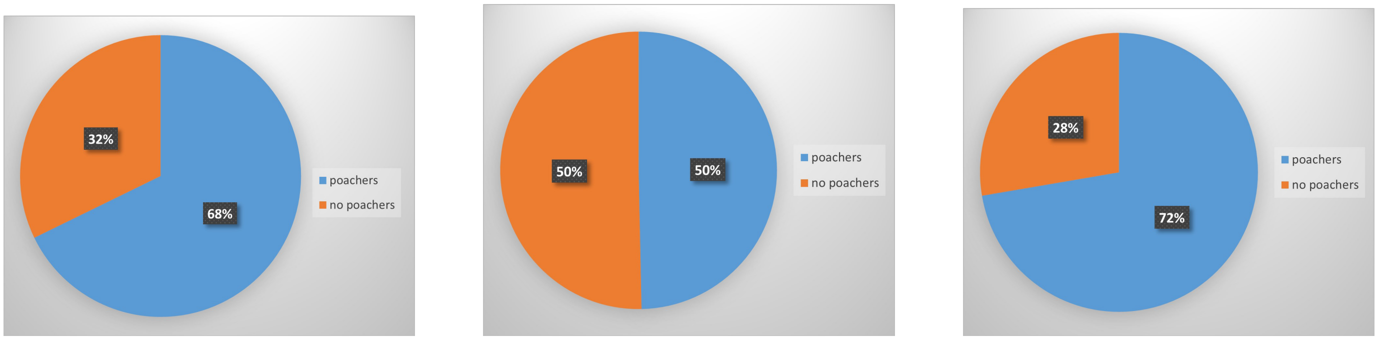
Dertien et al. [18] proposed a real-time camera-based alert system, known as TrailGuard AI, to detect poachers and monitor endangered tigers in India. The ability of the system to detect and transmit images rapidly aids in monitoring endangered tigers, detecting poaching activities, and offering early warnings for human-wildlife conflict. Forest staff and researchers received more than 70 distinct tiger notifications sent and received within about 30 seconds of the camera being triggered.

III. Framework design

In this section, the proposed framework, which integrates machine learning and image processing to aid in wildlife conservation, is presented. Figure 1 illustrates the framework and outlines the main stages of the process, including data collection, data processing, model training, testing, and alerting conservation authorities. The following subsections provide a detailed explanation of each of these key steps.

A. Data Collection

Two different datasets from Kaggle are used in the data collection stage to investigate and detect wildlife poachers.



(a) 'Poacher detection 3 classes' dataset (b) 'Illegal poacher detection' dataset (c) Combined dataset

Fig. 2: Class distribution of the datasets

The first dataset, titled "Poacher Detection 3 classes," contains 270 images of wildlife both with and without poachers [19]. To increase the dataset size and improve model robustness, data augmentation techniques such as rotations, translations, scaling, cropping, and adjustments to brightness and contrast are applied, resulting in an expanded dataset of 4,721 images. The second dataset, "Illegal Poacher Detection," consists of 749 images [20]. Figure 2 presents the class distribution of both datasets, as well as the combined dataset.

These images can be obtained using high-resolution satellite imagery, which monitors vast wilderness areas and detect potential illegal poaching activities by analyzing changes in vegetation, water sources, or signs of human presence. Another method involves deploying motion-sensor-equipped camera traps that capture images of wildlife and potential poachers, enriching the dataset with valuable visual information. Camera traps are cost-effective, easy to install, and capable of capturing high-quality image sequences when triggered by animals. These images are detailed enough to identify species, age, sex, behavior, health, and predator-prey interactions [21].

B. Data Processing and Splitting

Before utilizing the data, image processing techniques are applied to extract key features from the visual data, such as identifying human figures, vehicles, or other objects related to poaching activities from the camera trap images and satellite imagery. It is standard practice to divide the dataset into separate subsets before applying ML classification models. In this study, an 80-20 splitting method is employed for both datasets, where 80% of the data is used for training the models, and the remaining 20% is reserved for evaluating their performance.

C. Classifications models

Four machine learning models—SVM, DT, RF, and CNN—are used in this study to identify illegal wildlife poachers. In order to extract spatial characteristics from the images, the CNN model is built with two Conv1D layers, each of which is followed by MaxPooling layers. It is compiled using binary cross-entropy loss and the Adam optimizer, which guarantees efficient learning and model convergence. The specific parameters for each model are listed in Table I. Figure 3 shows the structure of the implemented CNN model.

TABLE I: Parameters of the Machine Learning Models

Model	Parameters
SVM	kernel: 'linear', probability: True , C: 1.0 , degree: 3, gamma: 'scale', shrinking: True, max_iter: -1, random_state: None.
DT	criterion: 'gini', splitter: 'best', min_samples_split: 2, min_samples_leaf: 1, min_weight_fraction_leaf: 0.0, random_state: None.
RF	n_estimators: 100, criterion: 'gini', max_depth: None, min_samples_split: 2, min_samples_leaf: 1, max_features: 'sqrt', bootstrap: True, n_jobs: None.
CNN	Conv1D Layer 1= Filters: 32, Kernel Size: 3, Activation: ReLU. MaxPooling1D Layer 1= Pool Size: 2. Conv1D Layer 2= Filters: 64, Kernel Size: 3, Activation: ReLU. MaxPooling1D Layer 2: Pool Size: 2 Flatten Layer. Dense Layer 1= Units: 64, Activation: ReLU. Dense Output Layer= Units: 1, Activation: Sigmoid·Compilation Parameters= Optimizer: Adam, Loss Function: Binary Crossentropy, Metrics: Accuracy

D. Real-time Monitoring and Alert Systems

Establishing a real-time monitoring system that integrates with conservation patrols allows for immediate responses to detected poaching activities. This can be achieved by developing algorithms that generate automated alerts when potential poaching incidents are identified, providing location information and relevant details to enable swift intervention by conservation authorities or law enforcement agencies [22].

IV. Results and Discussions

This section presents the results of the experiments, which are divided into three main parts. In the first and second parts, preprocessing steps are applied to the "Poachers Detection 3 classes" and "Illegal Poachers Detection" datasets for binary classification, followed by the construction of four models without feature selection. In the third part, the two datasets are properly combined, and to increase the number of images,

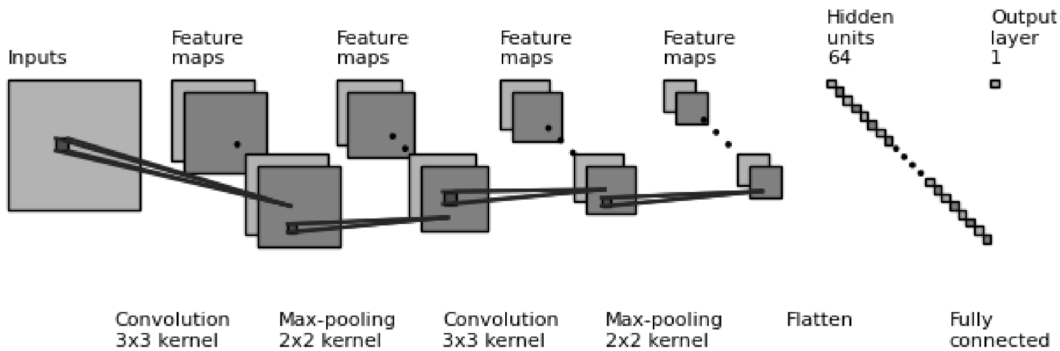
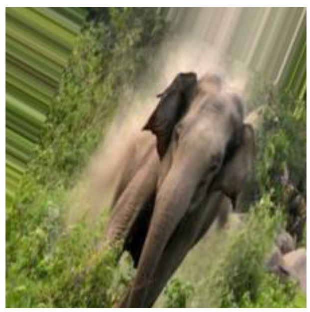


Fig. 3: CNN model Structure

augmented data is incorporated. Figure 4 provides an example of an augmented image. Additionally, several evaluation metrics are employed to assess the performance of the models.

(a) The original image



(b) The augmented image

Fig. 4: Example of Image Augmentation

A. The First Dataset

The first part of the experiments focuses on preprocessing the first dataset and applying ML models to determine whether poachers are present in the images by identifying humans, vehicles, or weapons. Approximately 3,780 features were extracted from the images. Table II displays the performance of the models on this dataset. As indicated in Table II, the SVM model achieved the highest performance, with an accuracy of 93.0% and 92.0% across all other evaluation metrics. In contrast, the DT model demonstrated the lowest performance among all models.

TABLE II: Results of binary-classification on 'Poacher Detection 3 Classes' dataset

	SVM	**DT**	**RF**	**CNN**
Accuracy	0.93	0.78	0.85	0.89
Precision	0.92	0.76	0.86	0.90
Recall	0.92	0.78	0.81	0.85
F1 Score	0.92	0.77	0.83	0.87

B. The Second Dataset

Continuing from the first part, the same experiment is conducted on the second dataset, which contains a larger number of images than the first dataset. Table III displays the performance of the models on the second dataset. As shown in Table III, the CNN model outperformed the others, achieving 75.0% across all metrics. By comparing the performance of all models across both datasets, it is evident that they attained better metrics on the first dataset.

TABLE III: Results of binary-classification on 'Illegal Poacher Detection' dataset

	SVM	**DT**	**RF**	**CNN**
Accuracy	0.66	0.63	0.73	0.75
Precision	0.67	0.64	0.73	0.75
Recall	0.67	0.64	0.73	0.75
F1 Score	0.67	0.63	0.73	0.75

C. Combined Datasets

In this part, both datasets are properly combined, and several augmented images from the first dataset are added. The models are then applied to detect illegal poachers. Table IV presents the performance of the models on the combined datasets. As shown in Table IV, the RF model achieved the highest accuracy and precision among all models. However, the CNN model obtained a higher recall, F1 score, and an accuracy of 81% with precision, recall, F1 score of 81%, 71%, and 74% respectively.

V. Conclusion

The integration of machine learning and digital signal processing presents a significant opportunity to enhance the efficiency and effectiveness of wildlife conservation efforts, particularly in the detection of illegal poaching activities. This study proposed a framework combining machine learning and digital signal processing to detect poachers from imagery data. Several machine learning models, including SVM, DT, RF, and CNN, were employed, and two different datasets were

TABLE IV: Results of binary-classification on the combined datasets

	SVM	DT	RF	CNN
Accuracy	0.80	0.72	0.83	0.81
Precision	0.74	0.65	0.81	0.76
Recall	0.75	0.66	0.71	0.77
F1 Score	0.75	0.65	0.74	0.76

analyzed. The machine learning models demonstrated promising results in detecting illegal poaching activities, with SVM achieving 93% accuracy on the first dataset, CNN reaching 75% accuracy on the second dataset, and Random Forest obtaining 83% accuracy when both datasets were combined. These results highlight the potential of machine learning in enhancing wildlife conservation efforts.

A prospective avenue for further research could involve expanding the use of digital signal processing algorithms to analyze audio recordings and capture attributes like frequency, amplitude, and duration of sounds linked to poaching activities, such as gunshots, vehicle noises, and animal distress calls. This would broaden the scope of detection methods, potentially improving response times and aiding conservation authorities in their efforts to protect endangered species.

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