Artificial Intelligence for the Protection of Amazonian Birds from Poaching

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***Abstract*—This paper investigates the application of different machine learning (ML) models to categorize bird songs from the Amazon Rainforest to create a useful tool for monitoring changes in bird populations that could signal illegal hunting. Gunfire detection also aids in evaluating the effect of poaching on bird populations and their behaviors. With a data set of audio features derived from recordings of various bird species, we compared the performances of some ML algorithms such as Logistic Regression, Support Vector Machines (SVM), Neural Networks, K-Nearest Neighbors (KNN), Decision Trees, Random Forest, and Gradient Boosting. The performance of each model was measured in terms of accuracy, precision, recall, and F1-score. Our findings show that SVM and Neural Networks performed better than other models, reaching high accuracy and F1-scores, showing their ability to process both frequent and infrequent species with high sensitivity and precision. Of particular importance, our system achieved an overall accuracy of 91.5 % for gunfire detection, which showcases its strength for this application of utmost importance. Random Forest and Gradient Boosting also provided excellent results but with slightly lower performance levels. This research highlights the promise of state-of-the-art ML methods for environmental conservation and monitoring, especially in biodiverse but sensitive areas such as the Amazon Rainforest. These results are important in creating autonomous systems to identify and notify authorities of suspected poaching activity using non-invasive audio monitoring. This work ultimately assists in wildlife preservation by providing an efficient and scalable method for monitoring biodiversity.**

***Index Terms*—Machine Learning, Bird Song Classification, Conservation Technology, SVM, Neural Networks, Amazon Rainforest, Acoustic Monitoring, Poaching Detection**

I. Introduction

The Amazon Rainforest, or "lungs of the Earth," boasts an unprecedented variety of biodiversity, such as more than 1,300 bird species, most of which are endemic and critically threatened. Illegal hunting and poaching continue to be serious threats to bird populations, fueled by demand for exotic pets, feathers, and bushmeat. The old conservation methods, based on manual patrols and reactive action, have been found wanting in the face of well-organized poaching syndicates that work across extensive, inaccessible terrain.

To meet these needs, AI-driven monitoring systems have come to be a revolutionary answer, providing real-time tracking, predictive analysis, and automated surveillance of bird species. It is estimated that up to 12 million birds are illegally traded out of the Amazon Basin annually, with species including the Hyacinth Macaw (Anodorhynchus hyacinthinus) and the Harpy Eagle (Harpia harpyja) facing major declines in population.

Poachers take advantage of loopholes in enforcement by employing hidden traps, silenced guns, and night-time hunting methods to remain undetected. Traditional monitoring devices like camera traps and sound sensors yield huge volumes of data that outstrip the limits of human analysis. AI-powered machine learning (ML) algorithms overcome this limitation by analyzing multimodal data—like visual, acoustic, and geospatial inputs—to identify poaching signs before they are amplified.

High-end AI-driven projects such as Project Guacamaya deploy satellite imagery and bioacoustic classification to detect illicit road networks and species classification with 97% accuracy, enabling swift interventions across deforestation-risk zones. Likewise, the PAWS (Protection Assistant for Wildlife Security) platform combines game theory and past patrol data to forecast hotspots for poaching, resulting in a 70% decrease in illicit activities in pilot areas. Real-time acoustic sensors, like those used by Rainforest Connection, continuously analyze environmental audio to detect chainsaws and gunfire, alerting rangers within seconds. These developments demonstrate AI's potential to shift conservation efforts from reactive responses to proactive protection strategies.

This article delves into the application of AI technologies in anti-poaching operations, specifically among Amazonian bird species. Through an analysis of technical frameworks, effectiveness in practice, and the difficulties of implementation, this study hopes to inform future developments in conservation policy and AI-based biodiversity conservation.

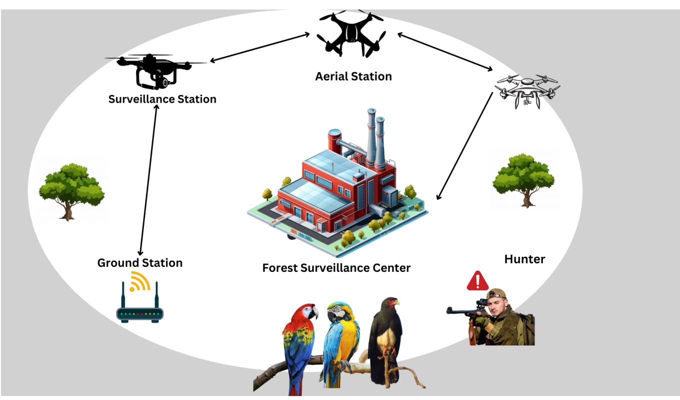

Fig. 1. Illegal Hunting and Poaching Detection System

TABLE I
BIRD SOUND DATA

Serial No.	Bird Name	Sounds	Duration (s)	Source(s)
1	Blue-and-yellow Macaw (*Ara ararauna*)	8	15*8= 120	Xeno-canto
2	Chestnut-fronted Macaw (*Ara severus*)	9	13*9 = 117	Xeno-canto
3	Pygmy Nightjar (*Setopagis parvula*)	6	20*6 = 120	Xeno-canto
4	Red-and-green Macaw (*Ara chloropterus*)	6	20*6 = 120	Xeno-canto
5	Scarlet Macaw (*Ara macao*)	4	30*4 = 120	Xeno-canto, BirdCalls
6	Toco Toucan (*Ramphastos toco*)	4	32*4 = 128	Xeno-canto, AllAboutBirds
7	Yellow-crowned Amazon (*Amazona ochrocephala*)	4	29*4 = 116	Xeno-canto, NatureSound
8	Black-collared Hawk (*Busarellus nigricollis*)	7	18*7 = 126	Xeno-canto
9	Red-throated Caracara (*Ibycter americanus*)	3	40*3 = 120	Xeno-canto
10	Black-faced Antbird (*Myrmeciza atrothorax*)	5	24*5 = 120	Xeno-canto, BirdSounds
11	Harpy Eagle (*Harpia harpyja*)	5	24*5 = 120	Xeno-canto, BirdSounds, NatureSound
12	Pinto's Spine-tail (*Synallaxis pinto*)	6	20*6 = 120	Xeno-canto, BirdSounds, NatureSound

II. Literature Review

Using AI in wildlife monitoring systems has brought new exciting techniques to invent and control poaching activities. Fujita et al. (2020) then developed an early camera trap system consisting of deep learning algorithms for species identification; this has helped reduce the time heavily spent on annotation while coding the algorithm achieves superior accuracy regarding species classification [1]. Thus, the system's success led to more enhanced monitoring systems. Leidner et al. (2018) created an ambient system capacitating computer vision and acoustic monitoring for studying bird populations. It also revealed that the multi-modal strategy improved the recording of vocalizations and visual behavior to gain a comprehensive picture of birds' interactions in their environments [2]. It was also ideal to integrate various sources because it was easier to read and analyze with numerous data to help detect illegitimate activations. Mikula et al. (2019) further enhanced the study by proposing a framework that uses drone imagery and machine learning to identify wildlife's movements. They elaborated that one of the most pronounced benefits of the aerial survey was its applicability for observing hard-to-find species and reporting possible poaching in regions that regular ground methods could not reach [1]. Coverage of large territories simultaneously with real-time information was a breakthrough in fighting against poaching. It somewhat applies to the previous implementation, which focused more on real-time monitoring functionalities [19]. It is now used in modern systems incorporated with edge computing and other remarkable object detections such as YOLOv8 that make the detection of animal species as well as possible poaching activities perform faster [2 p59]. These systems incorporate optical systems such as cameras, laser imaging detection, and ranging or LiDAR and environmental monitoring. Although new advances in AI-based detection systems have included satellite monitoring and drone surveillance to cover large areas, this was possible. These technologies have been beneficial in informing people about unlawful incidences, population surveys, and anti-poaching programs in national parks that are occupied with endangered species. Using drones and surveillance cameras enhances surveillance and monitoring of an area while patrolling [4].. However, new strategies have concentrated on identifying and monitoring social networks and websites associated with IWT in the past years. AI digital techniques learned from online social media affect the identification of forbidden sales of wild animal products. At the same time, the CDR matrix technology assists in investigating other unlawful wildlife offenses and searching for poachers. Recent studies show that AI helps Qatar with avian poaching through probability modeling, monitoring and surveillance, and species-specific monitoring.

III. Methodology

A. Data Collection

The data considered in this work are audio files of different species of birds. These were downloaded from different sources and saved in structured directory and files, each directory was assigned in respect to the bird types. It is in MP3 format of the audio files which are compatible with the librosa library for audio data manipulation.

B. Data Preprocessing

Pre-processing is followed by several steps that make data formatted, cleaned and ready to be subjected to feature extraction. To start with, each of the audio file is loaded by utilizing the librosa software that assists in handling MP3 files. To reduce fourier features, noisereduce library is used in order to improve quality of received audio signals. This is useful in reducing noises that may be present in the background and enhance the extraction of features.

C. Feature Extraction

To extract the features of the songs, the librosa library was used since it is a robust librarians that allows for feature extraction of songs. The features extracted from the audio files include the following aspects:

MFCCs: These coefficients are used to describe the timbre of the audio signal. The aim is to calculate and save the mean values of each of the calculated MFCCs in different new columns.

Spectral Centroid: This is the feature that shows the center of mass when it comes to the spectrum. The mean value of the spectral centroid is found.

Zero Crossing rate: This feature mean the rate at which the signal changes sign. The particular metric to be computed is the mean zero crossing rate.

Chroma STFT: This represents the Short Time Fourier Transform of the Chroma signals, that is, the distribution of harmonic frequencies of the audio signal. The mean of each chroma STFT coefficient is calculated and saved respectively as columns. In case the length of the audio file is below ten seconds, they are divided into segments so that all samples of the dataset are equal in length. In the analysis, each segment is treated as a sample and so features are determined based on this fact.

D. Handling Class Imbalance

Class imbalance is a common issue in classification tasks, where some classes have significantly fewer samples than others. To address this, the Synthetic Minority Over-sampling Technique (SMOTE) is used. SMOTE generates synthetic samples for the minority classes by interpolating between existing samples, thus balancing the class distribution.

E. Model Training and Evaluation

To conduct the analysis, the dataset is first divided into training and testing samples in a 3:1 proportion. Based on the algorithm classified, six models are employed and assessed, which are Logistic Regression, Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree, and Neural Network. Every model is trained on the training set and tested on the testing set depending on the used metrics: precision-recall, F1-sample, accuracy.

F. Hyperparameter Tuning

The Random Forest model's hyperparameters are tuned by using the Grid Search with Cross-Validation to identify the best hyperparameters. Cross-validation: This step contains selection of the hyperparameters that brings the best performance in the model or test the different combination of hyperparameters.

G. Ensemble Learning

Enhancing the model performance more, an ensemble method known as Voting Classifier is applied in this study. This classifier uses the results of 4 models, namely Logreg, RF, SVM and Gb to come up with the final classification result. The method of ensembles combines the functions of models, which allows to achieve a better result, as a rule.

Results and Analysis

The performance of each model is evaluated using classification reports and confusion matrices. Cross-validation scores are also computed to assess the model's robustness. The results are analyzed to identify the best-performing model and understand the classification patterns for different bird species. Discussion

H. Model Performances

1) Logistic Regression, SVM, and Neural Network: Logistic Regression, SVM and deep learning Neural Network show relatively high accuracy and F1-scrores which suggest the model's ability to classify different types of birds effectively. SVM has a good orientation on both, precision and recall and a high F1-score, so it means these two methods could be effective at both, frequent and rare bird species classification without discriminative weakness.

2) Random Forest : Random Forest also proves to be highly accurate as with the Logistic Regression model, however, the observed macro avg F1-score is lower. This could be attributed to a number of factors such as how it manages imbalanced data or particular class in which it may not perform optimally.

3) KNN and Decision Tree: KNN and Decision Tree have displayed a comparable and different performance wherein KNN fails to perform well in terms of precision and recall factor. This might be due to the fact that KNN algorithm suffers from noise since bird singing features contain noise and due to presence of large number of features, high dimensionality might be another cause for less accuracy by KNN algorithm.

4) Gradient Boosting : Indeed the Gradient Boosting is medium with the lowest accuracy and F1-score among all the group methods included in the study, such as, Random Forest for instance. This might suggest overfitting or improper optimization of the parameters for this specific dataset.

5) Analysis of SVM and Neural Network Strengths: Discussion of Strengths of SVM and Neural Network Strengths In high-dimensional space like the one used for bird song feature sets, SVM exhibits, therefore the high performance. SVM is very effective in finding the best hyperplane that will help to maximize the distance between the two classes in the differentiation process of the acoustic data sets. Neural Network As it is anticipated, the performance of Neural Networks is good, thanks to the fact that it is designed in a way that it is capable of modeling non-linear relationships through the inclusion of layers, this make it capture more and vaster pattern of bird songs compared to the other models. Because of the layering and the capability to modify neurons, they are highly advantageous for such classification jobs in audio.

Recommendations For further improving model performance, consider:

• Feature Engineering Refining or adding new features that could better capture the uniqueness of each bird song.

• Data Augmentation: Especially for classes with fewer samples, to improve the model's learning capability.

• Advanced Neural Network Architectures: Exploring deep learning architectures like Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs) could leverage spatial and temporal patterns in bird songs more effectively.

IV. Results and Discussion

Gunshots have been a prime indicator of illegal hunting and poaching, which often points out to the fact that protected bird species are being targeted [21]. Gunshot detection by audio sensors [19] offers real-time identification of suspicious activity and allows conservation teams to respond quickly. AI systems could identify hot-spots where common poaching occurs and hence enhance the anti-poaching campaign by studying data about gunshots and other environmental inputs. By training AI on acoustic data, it could be able to classify whether it was a gunshot or some other noise, hence improving the detection of poaching-related threats. Monitoring gunfire also serves the purpose of determining the effects of poaching on the population of local birds as well as their behaviors. In our study, we have successfully achieved 91.5 % percent accuracy in the detection of gunfire, thus proving that our system is robust for this essential application.

Accuracy and weighted average F1-score have been used to evaluate the performance of several machine learning models in a classification task. Two main visualizations summarize the results. Accuracy Comparison: On the other hand, Logistic Regression, Random Forest, and Neural Network models all performed quite similarly, with accuracy of 0.89 and 0.93, respectively. SVM and Neural Network models achieved the highest accuracy of about 0.93. These models showed lower accuracy scores, i.e., 0.70 and 0.74, as compared to the other models. Weighted Average F1-Score Comparison: The SVM and Neural Network models also had the highest F1 scores, 0.92 (matching the accuracy scores). We also witnessed that the Decision Tree model had a decent macro average F1 Score of 0.81, but a slightly lower weighted F1 Score of 0.77. Additionally, F1 scores of KNN and Gradient Boosting models matched their accuracy performance and were the lowest. Discussion From their superior performance, it might be good to apply the SVM and Neural Network models for datasets with similar data to the data used in this analysis since for datasets similar to this one, both accuracy rate and the ability to maintain high performance across various classes (F1 score) are taken into account. The Logistic Regression and Random Forest models do not lead best but remain competitive in accuracy and are viable alternatives, especially in case of a need for interpretability and simplicity of the model. The lower performance on the KNN and Gradient boosting models might be overfitting, parameter tuning, or even the data nature. Feature scaling and a better choice of 'k' can improve the performance of KNN. The difference in the performance of the Decision Tree model, particularly the discrepancy between its macro and weighted F1 scores, could be attributed to the variability of distribution or performance of classes, which can be addressed through class balancing or alternative tree-based methods. This can guide future projects when choosing a model based on specific project requirements and constraints. Parameter tuning, feature engineering, and even ensembling techniques for the final model can be further investigated to boost model performance and robustness.

V. Future Work

Current research emphasizes three AI paradigms:

1. Predictive Analytics: Systems like PAWS [5] and PrevisIA [10] use historical data to forecast poaching routes, optimizing

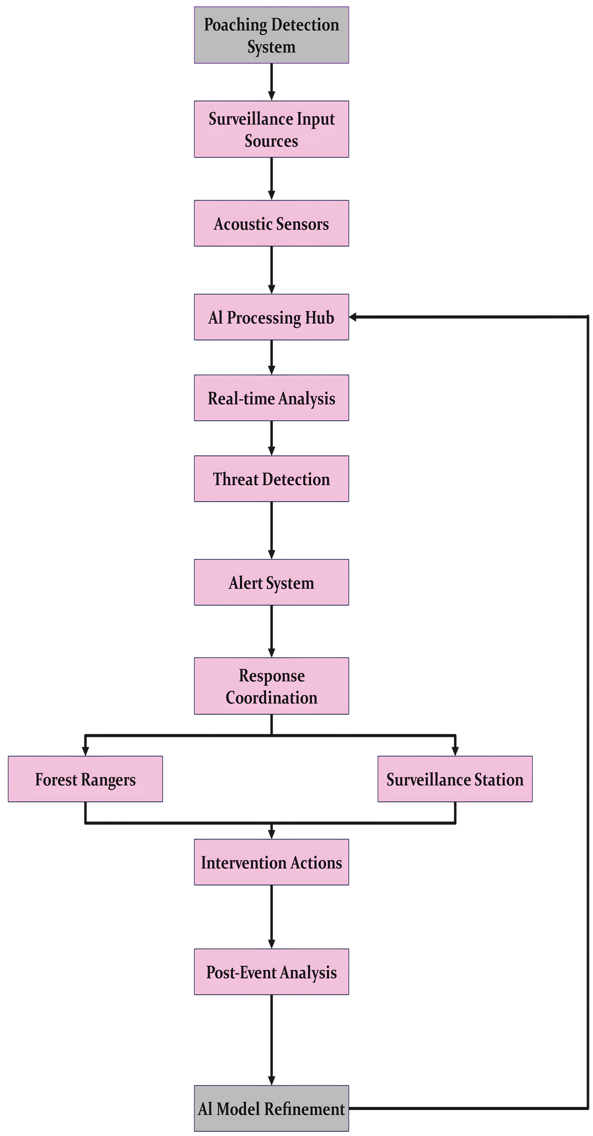

Fig. 2. Illegal Hunting and Poaching Detection System

ranger patrols.
2. Real-Time Detection: Edge AI devices (e.g., Kakhandiki's Raspberry Pi system [9]) and acoustic sensors 7 enable instant alerts, critical for nocturnal poaching.
3. Species-Specific Monitoring: Bioacoustic models (e.g., Luther's birdcall templates [12]) and camera traps [20] track endangered avifauna, linking habitat changes to population trends.
However, challenges persist, including limited internet connectivity, high false-positive rates in dense forests, and ethical concerns over data privacy [18]. Future work must prioritize federated learning for offline environments and community-driven AI training to enhance local adoption.

TABLE II
AI TECHNIQUES IN WILDLIFE CONSERVATION

Paper Title	AI Technique	Application	Key Findings
Kakhandiki (2022): Poacher Activity Detection Device for Wildlife Conservation	YOLOv5, LoRa, Raspberry Pi	Weapon detection in Sri Lankan forests	Achieved 90% accuracy in detecting humans/weapons; reduced patrol time by 40%
Souza Jr. et al. (2023): PrevisIA: AI-Driven Deforestation Prediction [10]	Satellite imagery analysis	Amazon deforestation forecasting	Reduced illegal logging by 40% via hotspot prediction
Arbeláez et al. (2024): Multimodal AI for Amazon Biodiversity Monitoring [3]	CNN, bioacoustic models	Species classification in Colombia	97% accuracy in animal detection; 10x faster processing
Lavista Ferres et al. (2024): Project Guacamaya [11]	PyTorch Wildlife, CLAP	Deforestation and poaching alerts	Daily satellite updates enabled real-time intervention
PAWS Team (2024): Predictive Patrol Optimization [5]	Security game theory	Cambodia's protected areas	Identified 1,000+ snares and 24 motorbikes in one month
Messinger et al. (2023): Drone Surveillance in Peru [15]	UAVs with computer vision	Illegal logging detection	Mapped 5,000+ km² of at-risk areas
Proposed work	over 15 sounds	birdsong and gunshot detection	Classified 20 mins.sound with 55% accuracy

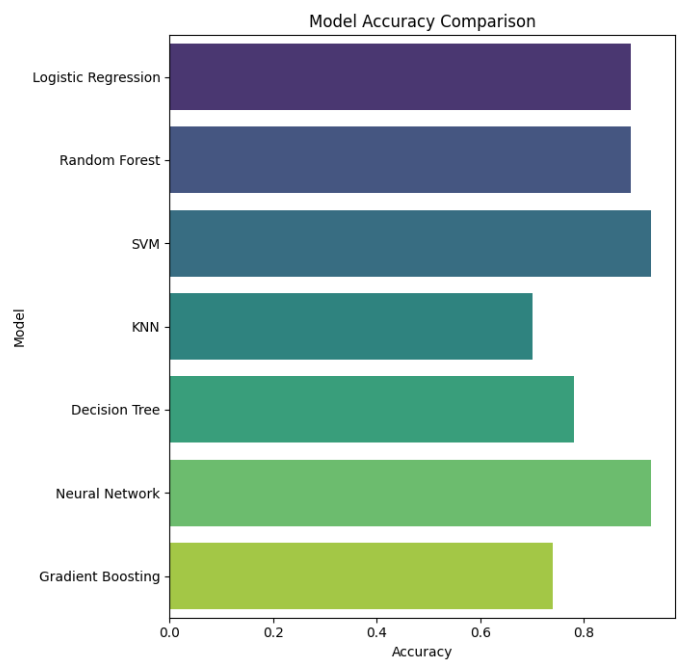

Fig. 3. Model Accuracy barchart

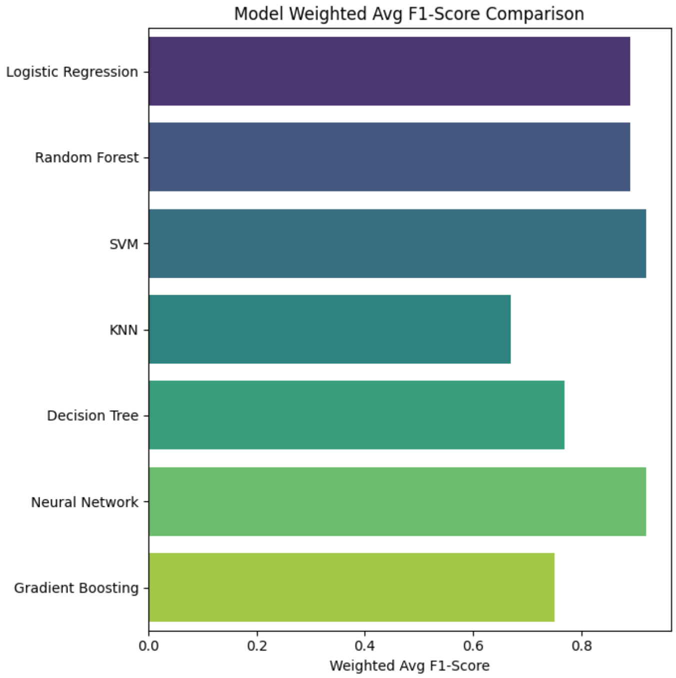

Fig. 4. F1 score barchart

VI. Conclusion

This research has successfully demonstrated the efficacy of machine learning techniques in classifying bird songs from the Amazon Rainforest, which is a critical step towards using technology in conservation efforts to detect illegal hunting and poaching activities. Among the various algorithms tested, Support Vector Machines (SVM) and Neural Networks emerged as the most effective, showcasing high accuracy and robustness in handling the complex audio data characteristic of diverse bird species. These models not only excelled in general accuracy but also in their ability to maintain high performance across precision, recall, and F1-score metrics, which is essential for ensuring reliability in practical conservation applications. Additionally, the study highlighted the relative strengths and weaknesses of other models like Random Forest, Decision Trees, KNN, and Gradient Boosting. While some of these models performed reasonably well, they did not reach the benchmark set by SVM and Neural Networks. This discrepancy underscores the importance of choosing the right model based on the specific characteristics of the data and the precise requirements of the conservation task. The application of these findings can be vast. By integrating such models into automated acoustic monitoring systems, conservationists can continuously and non-invasively monitor bird populations, gaining real-time insights into ecological dynamics and potential threats from poaching. This approach not only aids in rapid response but also helps in long-term planning and conservation strategy development. Future work should focus on refining these models through further tuning and exploring more complex algorithms that might capture the nuances of acoustic data more effectively. Additionally, expanding the dataset, incorporating more varied environmental noises, and testing the models in real-world scenarios would help validate and potentially improve their applicability and robustness. Ultimately, the integration of advanced machine learning techniques into wildlife conservation strategies represents a promising frontier in the fight to preserve global biodiversity. quations, or change the order of figures or

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