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Application of Machine Learning in Drone Technology for Tracking of Tigers

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ABSTRACT

Background: Tigers, as iconic apex predators and symbols of biodiversity conservation, face numerous threats to their existence. Effective tracking and monitoring are essential for understanding and preserving these majestic creatures and their habitats. The convergence of machine learning and drone technology has emerged as transformative tools in the field of tiger tracking. Drones, or Unmanned Aerial Vehicles (UAVs), have rapidly become invaluable assets in wildlife conservation. Machine learning algorithms, with their capacity to analyze complex datasets, make predictions and automate decision-making processes, offer a novel approach to processing the massive amounts of data generated by drones, including images, sounds and sensor readings.

Methods: This paper explores the historical significance of tiger tracking, the pivotal role of drones in conservation and the transformative capabilities of machine learning in wildlife monitoring. In this work, an accurate framework for tiger detection based on YOLOv8 is utilized.

Result: By examining the interplay between machine learning, drone technology and tiger conservation, this paper highlights the potential for innovation and the challenges that lie ahead, promising a brighter future for these iconic creatures and their ecosystems. The fine-tuned YOLOv8 model demonstrates exceptional object detection performance, boasting a mAP50 of 0.9820 and a mAP50-95 of 0.6856, coupled with precise classification (precision 0.9646) and robust instance capture (recall 0.9580).

Key words: Conservation, Drone, Ecosystem, Machine-learning, Tiger.

INTRODUCTION

The monitoring and preservation of tigers pose a crucial and long-lasting problem for both environmentalists and conservationists (Sarkar *et al*., 2021). Technological advancements have greatly impacted wildlife conservation efforts, with drones, also known as Unmanned Aerial Vehicles (UAVs), emerging as a particularly valuable tool for conservationists. (Ancin-Murguzur *et al*., 2020). Machine learning utilizes the capabilities of artificial intelligence (AI) to analyze complex patterns, generate forecasts and automate decision-making procedures (Aguilar-Lazcano *et al*., 2023).

This paper explores the convergence of machine learning and drone technology in tiger tracking. It discusses the significance of tiger tracking, the role of drones in conservation and the transformative capabilities of machine learning in wildlife monitoring. The paper highlights the relevance of AI-powered drone technology in ensuring the survival of tigers and their ecosystems. The experimental data is acquired using YOLOv8. The dataset is obtained from the Kaggle database. The number of individual animals that can be observed by humans is restricted due to their physical and cognitive limitations (Browning, 2022). A thorough approach to tiger monitoring in difficult environments is ensured by integrating data from various sources, such as ground sensors and local knowledge. This enables researchers to study tigers in their own environments while minimizing any disruption (Kamran *et al*., 2021). Furthermore, the unobtrusive characteristic of drones minimizes anxiety in tigers and guarantees the preservation of their innate habits without disturbance (Li *et al*., 2023). This tackles a prevalent issue linked to conventional land-based tracking techniques. Drones are widely recognized for their capacity to rapidly traverse extensive regions, rendering them very efficient and economical for gathering data (Hodge *et al*., 2021).

Literature review

Drones have become essential instruments in the field of tiger conservation, allowing conservationists to view and track the activities of these elusive top predators in ways that were previously difficult or invasive (Hossain, 2022; Choi *et al*., 2023; Min *et al*., 2024). Artificial intelligence (AI) has proven useful in a variety of fields besides the cultivation of legume crops, such as big data analysis and animal

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research. AI algorithms are being used more and more to handle enormous volumes of data effectively, providing insights and forecasts that help decision-makers across a range of industries. Furthermore, artificial intelligence (AI) methods are being used in animal research to investigate behavior patterns, genetic variables and health outcomes, among other topics, advancing our knowledge of and efforts to improve animal welfare (Na *et al*., 2024; Kim and Kim, 2023; Porwal *et al*. 2024; Wasik and Pattinson 2024). Quadcopters and hexacopters offer a unique combination of stability and agility that makes them ideal for shooting close-up photos and movies over water or in densely forested areas since they can take off and land vertically. These drones' observation time varies based on factors including battery capacity and flying mission conditions (Hildmann *et al*., 2019; Wilson *et al*., 2022). In a single flight, hexacopters and quadcopters may often record observation times of 20 to 30 minutes. Table 1 presents the advantages and disadvantages of quadcopters/hexacopters compared to traditional methods.

Machine learning and its applications

Machine learning is widely used in various fields, such as healthcare, finance and notably, animal tracking (Directions 2023). Some techniques that have been developed using machine and deep learning are mentioned in Table 2 for wild life conservation.

The integration of machine learning with drone technology

Machine learning algorithms analyze this data, enabling instantaneous decision-making and automation. Machine learning enabling the recognition of tigers in photographs taken by drones and offers understanding of their actions (Alrayes *et al*., 2022; Cho, 2024; Maltare, 2023). The methods employed for the collection of data are:

Cameras

They provide crucial visual data for the purpose of monitoring (Tuia *et al*., 2022). High-quality cameras provide intricate photos and films, facilitating the identification of individual tigers through distinctive characteristics (Shi *et al*., 2022). Also, thermal imaging cameras which are capable of detecting variations in temperature, rendering them highly effective for following nocturnal activities and detecting tigers in settings with little illumination (Butcher *et al*., 2021).

Sensors

Various types of sensors are employed to gather diverse sets of information, enhancing the understanding of tiger behavior, movements and ecological interactions (Ram *et al*., 2023). Similarly, LiDAR (Light Detection and Ranging) technology produces intricate 3D maps of the landscape, which can assist in evaluating habitats and delineating tiger territory (Shanley *et al*., 2021). The LiDAR-based habitat model had the lowest classification accuracy (OOB = 5.8%, k = 0.77). Multispectral and Hyperspectral Sensors have the ability to gather data that extends beyond the range of wavelengths visible to the human eye, thereby uncovering specific information about the well-being of vegetation and the surrounding environmental circumstances (Adão *et al*., 2017).

Satellite imagery

Satellite imagery offers a bird's-eye view of tiger habitats and can be used to assess changes in land cover and habitat fragmentation (Ahmad *et al*., 2023). The accuracy evaluation revealed a Kappa value of 0.87 and an overall classification accuracy of 88.5%.

Data Pre-processing and feature extraction

There are a number of machine learning techniques and algorithms that are frequently used in the field of wildlife monitoring, with a specific focus on tigers:

i). Supervised learning algorithms

Support Vector Machines (SVM)

SVM are commonly employed for the purpose of species classification. It operates by identifying the most advantageous hyper plane that effectively distinguishes several categories of data, such as tigers from other animals or background (Vidal *et al*., 2021).

Decision trees

Decision trees are highly efficient for the purpose of species identification. The classification of animals is accomplished by the utilization of a hierarchical decision tree graph, which takes into account characteristics such as size, stripes and color patterns (Song and Lu, 2015).

ii). Unsupervised learning techniques

Clustering Algorithm

Clustering techniques such as k-means are useful for categorizing tigers according on their activities. For instance, they can assist in identifying social hierarchies or detecting atypical behavioural patterns, which could potentially indicate the presence of sickness or stress (Tabianan *et al*., 2022).

iii). Deep learning

Convolutional neural networks (CNNs)

CNNs are highly proficient in image analysis and are commonly employed to detect and monitor tigers in photos and videos obtained from camera traps or drones (Kishore *et al*., 2021). By discerning distinctive characteristics, they can distinguish certain individuals, enabling the continuous tracking of individual tigers (Fergus *et al*., 2023). The experiment showed that, with an accuracy of 99.31%, it is feasible to obtain high animal detection accuracy across the 12 species.

Recurrent neural networks (RNNs)

RNNs are utilized in the study of time-series data, enabling the monitoring of actions and movements over a while. They can assist in comprehending tiger behaviors such as mating, hunting, or territorial patrolling (Zhang, 2012).

2.4 Tracking and localization algorithms

Tiger monitoring relies on tracking and localization algorithms, which offer up-to-date data on the exact whereabouts and motion of these creatures. Various algorithms are utilized for this objective such as.

Kalman filters

Kalman filters are iterative estimators that forecast the future whereabouts of a tiger by leveraging its past coordinates. These devices are extremely useful for accurately tracking and determining the location of objects or individuals in real-time, especially in scenarios where the data may be unreliable or ambiguous. In contrast to tigers (AUC= 0.83, TSS= 0.66), leopard distribution maps had a notably high degree of discrimination (AUC= 0.90, TSS= 0.80) (Rather *et al*., 2020).

Particle filters

Particle filters are capable of estimating the probability distribution of a tiger's location, which makes them well-suited for situations where there is uncertainty or variability in the tracking data. They are especially beneficial for monitoring numerous tigers concurrently (Kambhampati *et al*., 2004).

Hidden markov models (HMMs)

Hidden markov models (HMMs) are employed to represent the locomotion patterns of tigers. Through the analysis of seen data, it is possible to make predictions about concealed states, such as the whereabouts of a tiger, as well as the transitions that occur between these states (Joo *et al*., 2013).

Image and video analysis techniques

Convolutional Neural Networks (CNNs) play a crucial role in the detection of tigers and can accurately distinguish individual tigers by recognizing their unique stripe patterns and facial traits (Shi *et al*., 2020). In addition, tigers may be rapidly detected and localized in photos or movies using object detection techniques. YOLO (You Only Look Once) techniques provide swift detection and delineation of tigers, hence facilitating expedient analysis (Srivastava *et al*., 2021). On the basis of this data, predictive algorithms, which frequently employ recurrent neural networks (RNNs), can predict future tiger behavior. These predictions are useful for organizing conservation strategies and mitigating conflicts between humans and tigers (Chatterjee *et al*., 2022).. In Sumatra, Indonesia, machine learning and thermal imaging drones were utilized to monitor leopards at night. This innovative method revealed crucial behavioural insights, such as foraging patterns and territorial migrations (Rietz *et al*., 2023). Machine learning algorithms were employed at the Chitwan National Park in Nepal to analyze LiDAR data collected by drones. The provision of precise 3D maps of the park's landscape significantly improved habitat preservation efforts (Wu *et al*., 2023).

MATERIALS AND METHODS

Dataset description

The dataset is sourced from Kaggle. The dataset contains a total of 4413 images of tigers. It is divided into training, validation and test datasets in the ratio of 80:10:10.

YOLOv8 overview

In this work, the tiger detection method is implemented using YOLOv8 from Ultralytics.

The most recent version of the YOLO object detection model, known as YOLOv8, keeps the same architecture as its predecessors while bringing about several notable improvements. Feature pyramid network (FPN) and Path aggregation network (PAN) are two innovative neural network designs that are noteworthy advances. Furthermore, a new labeling tool with features like customizable hotkeys, labeling shortcuts and auto-labeling expedites the annotation process. Together, these tools make image annotation for model training simpler. The FPN creates feature maps that can detect objects at a variety of scales and resolutions by methodically decreasing spatial resolution while expanding feature channels. The PAN design, on the other hand, improves the network's capacity to capture features at various scales and resolutions by aggregating features from several network levels through skip connections. This capacity is essential for accurately identifying items that differ in size and shape.

The backbone, neck and head are the three primary parts of the YOLOv8 model's overall architecture. From the input image, the backbone network extracts relevant features. The neck functions as a bridge between the head and backbone networks, improving feature resolution and decreasing feature map dimensions at the same time. The head network is made up of three detection networks, one for each type of object such as small, medium and large

Table 1: Comparison of Quadcopters/hexacopters and traditional flying methods.

Methods	Advantage	Disadvantage	Flight tim
Quadcopters/Hexacopters	Vertical takeoff/landing, agility, stability	Limited flight time	20-30 minutes per flight
Fixed-wing drones	Longer flight times	Limited agility in confined spaces	1-2 hours per flight
Manned aircraft	Large coverage area, longer flight times	Expensive, less agility, environmental impact	Several hours
Ground-based methods	Cost-effective, stable platform	Limited mobility, restricted viewpoints	Continuous monitoring

that work together to provide an all-encompassing and adaptable object detection system.

Parameters and metrices

Learning rates (lr/pg0, lr/pg1, lr/pg2)

The amount that the model modifies its parameters while being trained is determined by learning rates. The model will effectively converge without fluctuating or becoming stuck if the learning rate is balanced. To get the best performance out of the tiger tracking model, these rates may have to be adjusted.

Metrics

mAP50-95(B) and mAP50(B)

One important metric for object detection is Mean Average Precision (mAP), It displays the model's object location accuracy. Higher mAP values, especially in the 50–95% confidence interval, signify improved tiger tracking precision.

Precision (B) and Recall (B)

Precision measures the accuracy of tiger predictions, while recall assesses the model's ability to detect all actual tigers. A balance is crucial; high precision ensures accurate predictions, while high recall prevents missing tigers.

Features of the model

Model/GFLOPs

The model's computational complexity is reflected in the quantity of floating-point operations performed per second. For real-time applications, like tracking tigers, a lower GFLOPs value ensures more efficient processing.

Model/parameters

The complexity of the model is indicated by the number of parameters. To capture the finer details of tigers without overfitting the training set, complexity must be balanced.

PyTorch model/speed_ms

The processing efficiency of the model is indicated by speed in milliseconds. For real-time tiger tracking, faster processing is preferred because it allows for quicker reactions to environmental changes.

Loss Values (val/box_loss, val/cls_loss, val/dfl_loss, train/box_loss, train/cls_loss, train/dfl_loss)

The model's learning efficiency from the tiger tracking dataset is indicated by loss values experienced during training and validation. Lower loss values signify successful training, ensuring that the model performs better when applied to new data.

RESULTS AND DISCUSSION

Graph 1 shows graphics of different metrics and values associated with the YOLOv8 model's training and evaluation for tracking tigers.

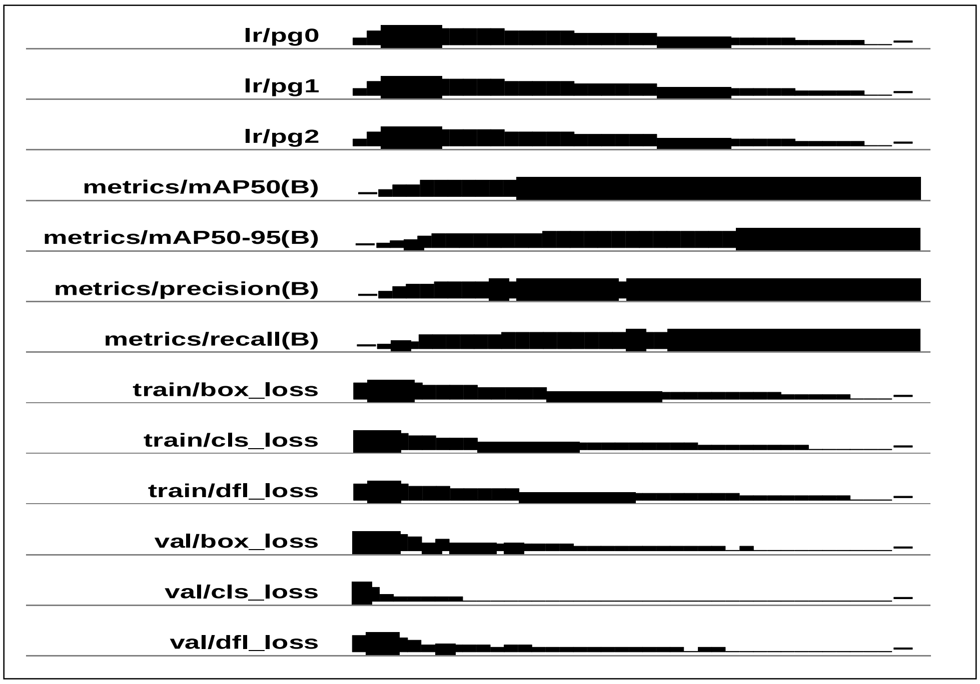
The outputs of tiger tracking using YOLOv8 are presented in Table 3. The learning rates (lr/pg0, lr/pg1, lr/pg2) are set to 0.0001. The model has outstanding object detection capabilities, with an accuracy of 0.9820 for mean average precision at 50% intersection over union (mAP50). A larger range of intersection over union criteria (50-95%) is taken into account and the mAP50-95 of 0.6856 indicates strong performance over a variety of detection accuracy levels. With high precision and recall metrics of 0.9646 and 0.9580, respectively, the model demonstrates its accuracy in identifying and capturing tigers.

The computational efficiency of the model is demonstrated by the number of parameters (26,854,899) and GFLOPs (79.10). In terms of performance, the model shows a relatively fast inference time, analyzing data in 6.60 milliseconds using PyTorch. In the training (train/box_loss, train/cls_loss, train/dfl_loss) and validation (val/box_loss, val/cls_loss, val/dfl_loss) phases, the model's performance

Table 2: Resources for machine and deep learning based wild life conservation.

Name	Description	References
AIDE	Tasks: Annotation; detection; classification; segmentation This is a web-based labeling platform that is free, open source and intended primarily for large-scale ecological picture studies.	(Kellenberger *et al*., 2020)
Wildbook	Tasks: Detection Utilized TensorFlow object detection API with bounding boxes on hundreds of thousands of camera trap photos from various ecosystems.	(Berger-wolf *et al*., 2017)
DeepLabCut	Tasks: Pose estimation and behavioral analysis This is a posture estimation toolbox that is both free and open-source. It utilizes deep learning techniques.	(Mathis *et al*., 2021)
Wildlife Insights	Tasks: Filtering Wildlife Insights employs a filtering system to remove empty photographs and offers species identification for images that receive high scores from the computer vision model.	(Ahumada *et al*., 2019)
DeepPoseKit	Tasks: Pose estimation and behavioral analysis	(Graving *et al*., 2019)

This is a posture estimation toolbox that is both free and open-source. It is built on deep learning techniques.



Graph 1: Graphics of different metrices.

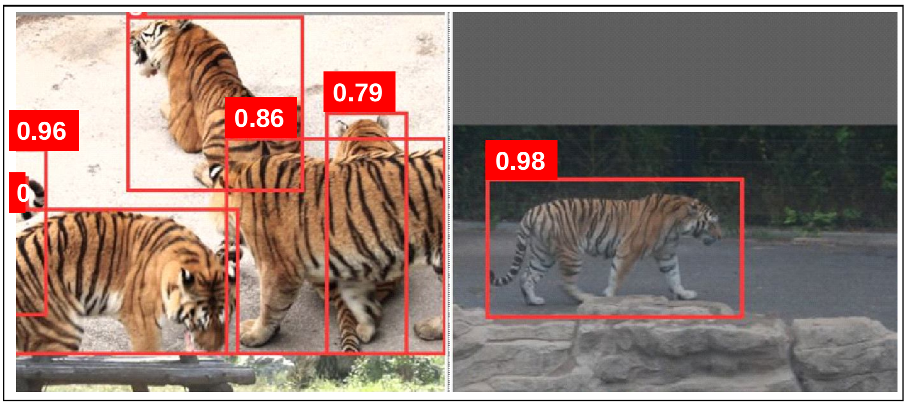


Fig 1: The sample picture of tracking of tigers using YOLOv8.

Table 3: Results of tiger tracking using YOLOv8.

Learning rates (lr/pg0, lr/pg1, lr/pg2)	0.0001
metrics/mAP50(B)	0.9820
metrics/mAP50-95(B)	0.6856
metrics/precision(B)	0.9646
metrics/recall(B)	0.9580
model/GFLOPs	79.10
model/parameters	26854899
model/speed_PyTorch(ms)	6.60
train/box_loss	0.8345
train/cls_loss	0.3717
train/dfl_loss	1.105
val/box_loss	1.1832
val/cls_loss	0.4189
val/dfl_loss	1.336

in bounding box prediction, class prediction and detection face localization is indicated by the specified losses. The results show that the model is well-trained and achieves a good balance between precision and recall.

Fig 1 shows the sample results for the YOLOv8 model. The YOLOv8 method has the highest degree of confidence in detecting every target.

CONCLUSION

The combination of drone technology and machine learning has fundamentally transformed the field of tiger tracking, providing novel and effective answers to the obstacles encountered in their conservation efforts. The welfare and protection of tigers are of utmost importance for conservationists and researchers. In order to ensure their ethical treatment, it is essential to minimize stress and disturbance, strictly adhere to appropriate protocols and collaborate with local communities and stakeholders, where necessary, to obtain their consent and involve them in conservation efforts (Rieder *et al*., 2021). Ethical tiger tracking should focus on conservation outcomes that safeguard tiger populations and their habitats, with transparent reporting through accurate documentation and conscientious utilization of tracking data for conservation purposes (Isabelle and Westerlund, 2022).

In this paper, tiger detection is done using YOLOv8. Exhibiting outstanding object detection capabilities, the fine-tuned YOLOv8 model achieves a remarkable mAP50 of 0.9820 and a mAP50-95 of 0.6856. It excels in precise classification (precision 0.9646) and adeptly captures instances with a strong recall of 0.9580.

Future directions

The integration of drone technology and machine learning offers a promising solution for solving the conservation difficulties faced by tigers, thereby shaping the future of tiger tracking. Moreover, there is an increasing emphasis on incorporating cutting-edge sensor technologies such as LiDAR, hyperspectral imaging and thermal imaging into drone systems. Furthermore, there is a requirement for improvements in the real-time data processing capabilities of drones to facilitate prompt analysis and decision-making in addressing emergent conservation concerns.

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Author contributions

All authors contributed toward data analysis, drafting and revising the paper and agreed to be responsible for all aspects of this work.

Data availability statement

Not applicable.

Declarations

Authors declare that all works are original and this manuscript has not been published in any other journal.

Conflict of interest

The authors declare that they have no conflict of interest.

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