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Evaluating the Effectiveness of Artificial Intelligence in the Conservation of Pangolins: Methods

Pangolins are the most trafficked mammals in the world (Wang et al., 2022) and the IUCN Red List (2019) lists all eight pangolin species as threatened. There is still a lot that is not known about this elusive animal (Khwaja et al., 2019) and thus they need to be monitored to aid in their conservation. Artificial intelligence (AI) technologies such as, machine learning, computer vision and deep learning, are becoming increasingly effective in monitoring wildlife (Tuia et al., 2022). Pangolin recognition models can be designed by utilising AI to recognise and track pangolins in images and videos (Zhong et al., 2025). Despite its potential, AI-driven pangolin monitoring faces challenges including small datasets, expensive labelling samples, trouble identifying the different species because of their similar appearances and rarity, and ethical issues that may arise (Fergus et al., 2024; Zhong et al., 2025). This research aims to evaluate the effectiveness of AI in supporting pangolin conservation efforts.

**Research Question**

The main research question of this study is:

How effective is artificial intelligence in supporting pangolin conservation efforts?

Sub research questions include:

* What is the detection accuracy of AI-powered drones and camera traps compared to traditional monitoring methods?
* What is the average processing speed of AI models analysing data from camera traps and drones?
* What is the cost comparison between AI-powered monitoring methods and traditional field surveys?
* How does AI performance vary under different environmental conditions?

**Hypothesis:**

AI-powered monitoring methods, such as drones and camera traps, significantly improve the accuracy and efficiency of pangolin detection compared to traditional methods.

The hypothesis is consistent with a post-positivism worldview since it can be measured objectively through empirical observation and statistical analysis. The study adopts a quantitative approach that focuses on numerical data and statistical comparisons to evaluate the effectiveness of AI in pangolin monitoring and conservation. Data from AI-powered monitoring devices will be collected and compared to traditional pangolin observation techniques.

The independent variables are the AI-powered monitoring methods and the dependent variable is the effectiveness of pangolin monitoring which is measured by accuracy, performance and cost-effectiveness. The control variables include the dataset size, AI model type, camera resolution and monitoring duration. The expected relationship is that AI-powered methods will indicate a significant improvement in detection accuracy and efficiency compared to traditional methods.

Various types of quantitative data will be collected to test the hypothesis. The collected data will undergo statistical analysis to determine the effectiveness of AI-powered pangolin monitoring methods.

To test the accuracy of AI monitoring models the data will include true positives (TP), false positives (FP), and false negatives (FN), which enables the calculation of accuracy rates, precision, and recall. These metrics will be compared between AI-powered methods and traditional monitoring techniques. The accuracy rates will be analysed using descriptive statistics, with the use of a confusion matrix to measure true positives, false positives, and false negatives. A t-test will be conducted to compare the detection accuracy of AI versus traditional methods and assess the statistical significance.

Efficiency will be tested by using data that focuses on the time taken per detection, the number of pangolins detected per hour, the area monitored and the operational time of AI-powered devices. Efficiency will be analysed using time-series analysis to compare the average time taken per detection for AI-powered and traditional field surveys. Independent t-tests will be used to compare the mean detection time and regression analysis will examine the relationship between AI efficiency and environmental variables.

Cost-effectiveness will be tested by gathering data that includes the cost of equipment, maintenance, and the overall return on investment (ROI) when using AI technology. It will be assessed through cost-benefit analysis and ROI calculations, which will compare the cost of AI-powered monitoring to traditional methods over time. Sensitivity analysis will be applied to evaluate how variations in cost and detection accuracy impact the overall cost-effectiveness of AI-powered methods.

Environmental factors, such as weather conditions and habitat complexity, will also be assessed to determine their impact on AI accuracy and efficiency. Correlation analysis will be used to determine the influence of environmental factors such as lighting, weather, and terrain on AI performance.

**Potential Difficulties**

There are many technical, environmental and ethical difficulties that may arise during this research. Technical issues may include dataset limitations and drone battery and range constraints. AI also requires significant computing resources for real-time processing, and the large volume of video and image data may need extensive storage. Environmental difficulties such as weather conditions and the detection of other animals may lead to inaccurate results. Ethical problems include the impact drones may have on pangolins and their safety, and flash-based or motion sensitive cameras may cause unintentional disruptions to wildlife.

# References

Fergus, P., Chalmers, C., Longmore, S., & Wich, S. (2024). Harnessing Artificial Intelligence for Wildlife Conservation. *Conservation*, *4*(4), 685–702. https://doi.org/10.3390/conservation4040041

IUCN. (2019). *IUCN Red List*. https://www.iucnredlist.org/search/list?query=pangolin&searchType=species

Khwaja, H., Buchan, C., Wearn, O. R., Bahaa-el-din, L., Bantlin, D., Bernard, H., Bitariho, R., Bohm, T., Borah, J., Brodie, J., Chutipong, W., Preez, B. du, Ebang-Mbele, A., Edwards, S., Fairet, E., Frechette, J. L., Garside, A., Gibson, L., Giordano, A., … Challender, D. W. S. (2019). Pangolins in global camera trap data: Implications for ecological monitoring. *Global Ecology and Conservation*, *20*. https://doi.org/10.1016/j.gecco.2019.e00769

Tuia, D., Kellenberger, B., Beery, S., Costelloe, B. R., Zuffi, S., Risse, B., Mathis, A., Mathis, M. W., van Langevelde, F., Burghardt, T., Kays, R., Klinck, H., Wikelski, M., Couzin, I. D., van Horn, G., Crofoot, M. C., Stewart, C. V., & Berger-Wolf, T. (2022). Perspectives in machine learning for wildlife conservation. In *Nature Communications* (Vol. 13, Issue 1). Nature Research. https://doi.org/10.1038/s41467-022-27980-y

Wang, X. M., Janssens, G. P. J., Xie, C. G., Xie, B. W., Xie, Z. G., He, H. J., Wang, Y. N., & Xu, J. (2022). To Save Pangolins: A Nutritional Perspective. In *Animals* (Vol. 12, Issue 22). MDPI. https://doi.org/10.3390/ani12223137

Zhong, J., Wei, S., Chen, Q., & Niu, B. (2025). Unlocking the power of artificial intelligence for pangolin protection: Revolutionizing wildlife conservation with enhanced deep learning models. *Expert Systems with Applications*, *267*. https://doi.org/10.1016/j.eswa.2024.126206