BISS Biodiversity Information Science and Standards

Biodiversity Information Science and Standards 10: e182719
doi: 10.3897/biss.10.182719

OPEN ACCESS

Conference Abstract

AI for Wildlife Trafficking: Automated Species Identification of Snake Goods

Avellina M.Y. Leong‡, Arianna Salili-James‡, Sanson T.S. Poon‡, Louise Gibson§

‡ Natural History Museum, London, United Kingdom
§ The Zoological Society of London, London, United Kingdom

Corresponding author: Avellina M.Y. Leong (avellina.leong@nhm.ac.uk)

Received: 17 Dec 2025 | Published: 14 Jan 2026

Citation: Leong AMY, Salili-James A, Poon STS, Gibson L (2026) AI for Wildlife Trafficking: Automated Species Identification of Snake Goods. Biodiversity Information Science and Standards 10: e182719. https://doi.org/10.3897/biss.10.182719

Abstract

Introduction

The wildlife trade significantly contributes to the ongoing biodiversity crisis. While charismatic taxa receive more attention (Colléony et al. 2017), reptiles, which are the most traded fauna, are often overlooked, despite the fact that approximately 90% of traded reptile species are captured from the wild (Marshall et al. 2020). Curtailing this trade begins with species identification, yet enforcement officers at border control facilities often lack the access to herpetological expertise, hindering law enforcement efforts. However, with recent advances in artificial intelligence (AI), particularly in computer vision, various automated species identification applications have emerged (Zhang et al. 2024). Thus far, computer vision models have successfully classified different reptile species. For example, Patel et al. (2020) used Fast R-CNN (Region-based Convolutional Neural Networks) and ResNet models to classify nine endemic snake species of the Galapagos Islands from live snake images to achieve an accuracy of 75%. However, existing research focuses on classifying images of live reptiles and has not ventured into classifying processed reptillian goods, where common distinguishing features such as colour, body shape and positioning are not present, posing significant challenges. Unlike previous studies, our aim is to classify species solely through the dorsal textural pattern of their skin, allowing classification without taxonomically diagnostic features.

© Leong A et al. This is an open access article distributed under the terms of the Creative Commons Attribution License (CC BY 4.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

In this study, we focus on snakes and introduce a multi-model pipeline to identify illegal snake goods to the species level. Our approach involves training segmentation (identification of snake bodies within images) and classification (identification of distinct snake species) models to classify species based on skin texture patterns captured from live snake imagery. With this pattern-based classification approach, our trained model is generalised to recognise these same patterns in processed goods. This ensures that snake goods that have been processed artificially can still be classified despite losing features used to identify live reptile specimens.

Methods

To reliably build a model to classify snake goods, a large dataset of snake skins is required. However, we utilise live snake images, rather than illegal snake goods, as they are more easily accessible. Our pipeline includes four key stages to ensure the model learns skin textural patterns rather than factors like body shape or colour:

1. isolating snakes and snake goods from their background through two segmentation models;
2. production of the box image dataset (splitting segmented images into boxes) to ensure only skin pattern is used for model training (Fig. 1);
3. training an EfficientnetB0 model (Tan and Le 2019) to classify snakes from the skin pattern of live snake data and
4. application of the EfficientnetB0 model on snake goods.

The pipeline evaluates the model's performance across eight snake classes in two stages, when:

1. fed live snake image data, and
2. fed illegal snake goods image data

Evaluation across these two points in the pipeline allows us to understand whether the model maintains its classification abilities from live snake images to illegal snake goods.

Results and Discussion

When testing the model’s classification ability when fed live snake image data, an overall accuracy of 0.77 and AUC-ROC (Area Under the Curve-Receiver Operating statistic) scores ranging from 0.86 to 0.95 were obtained. These scores indicate that although final class predictions suffered some misclassification, the underlying probability estimates demonstrated strong discriminative ability across classes. When testing the model’s classification ability on illegal snake goods data, the overall accuracy is maintained at 0.77, demonstrating successful generalisation to snake goods and that classification via skin textual patterns is a viable method.

In future, we plan to expand the training dataset with underrepresented species, and include more species from other CITES (Convention on International Trade in Endangered Species of Wild Fauna and Flora) taxa. Once trained optimally, pipeline

deployment as a mobile app could assist law enforcement, and border and custom agencies on the ground. This would deliver a cost-effective method to combat wildlife trafficking at UK and international borders, increasing the likelihood of successful reptile trade prosecutions. Overall, we highlight the potential of interdisciplinary AI applications to wildlife trade challenges, offering promising scalability and adaptability for a time and cost-efficient tool.

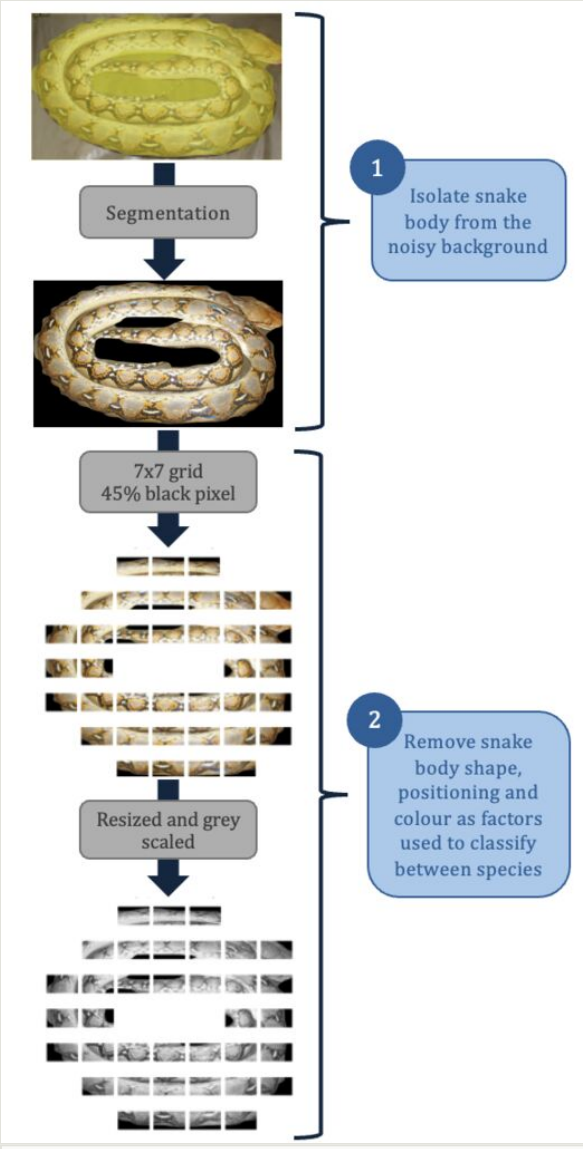

Figure 1.

A diagram of preprocessing steps. This includes segmentation, image splitting, resizing and applying grayscale (steps 1 to 2). © 2025 Avellina M.Y. Leong. Licensed under CC BY-4.0.

Keywords

machine learning, wildlife trade, snake identification

Presenting author

Avellina M.Y. Leong

Presented at

Living Data 2025

Funding program

DCMS AI Pilot Programme

Conflicts of interest

The authors have declared that no competing interests exist.

References

- Colléony A, Clayton S, Couvet D, Saint Jalme M, Prévot A (2017) Human preferences for species conservation: Animal charisma trumps endangered status. Biological Conservation 206: 263-269. https://doi.org/10.1016/j.biocon.2016.11.035
- Marshall B, Strine C, Hughes A (2020) Thousands of reptile species threatened by under-regulated global trade. Nature Communications 11 (1). https://doi.org/10.1038/s41467-020-18523-4
- Patel A, Cheung L, Khatod N, Matijosaitiene I, Arteaga A, Gilkey J (2020) Revealing the Unknown: Real-Time Recognition of Galápagos Snake Species Using Deep Learning. Animals 10 (5). https://doi.org/10.3390/ani10050806
- Tan MX, Le VQ (2019) EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks. In: Chaudhuri K, Salakhutdinov R (Eds) Proceedings of the 36th International Conference on Machine Learning. 97. PMLR, Long Beach, California, USA, 6105--6114 pp. URL: https://proceedings.mlr.press/v97/tan19a.html
- Zhang Q, Ahmed K, Sharda N, Wang H (2024) A Comprehensive Survey of Animal Identification: Exploring Data Sources, AI Advances, Classification Obstacles and the Role of Taxonomy. International Journal of Intelligent Systems 2024 (1). https://doi.org/10.1155/2024/7033535