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TOWARDS THE AUTOMATION OF LARGE MAMMAL AERIAL SURVEY IN AFRICA

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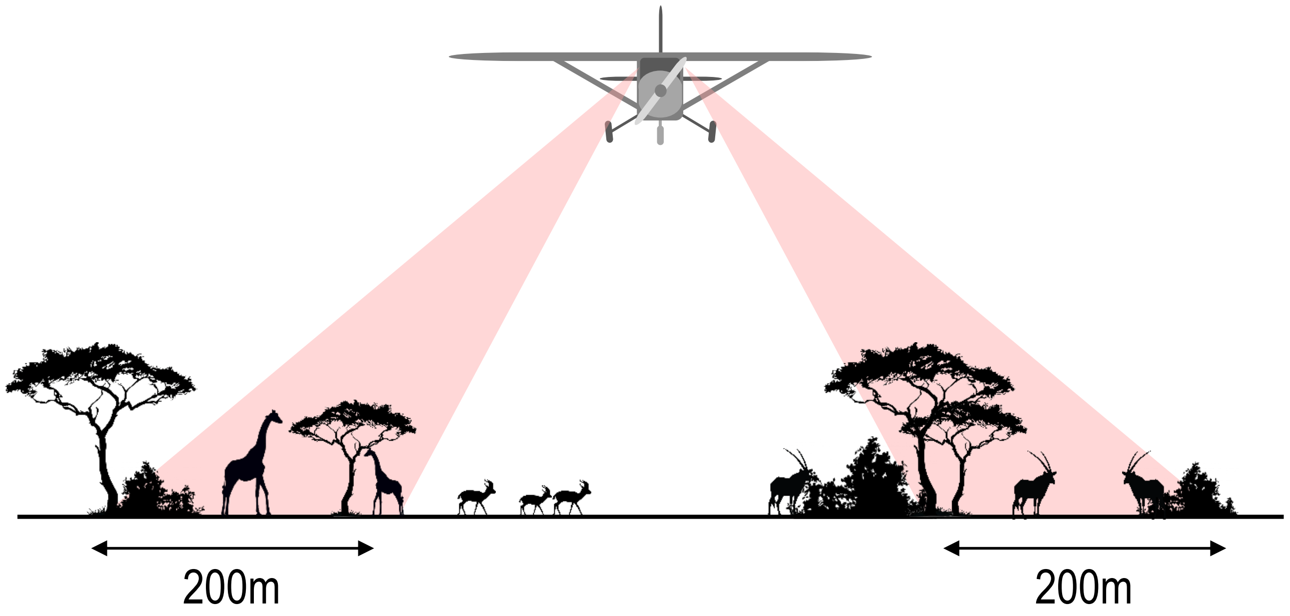
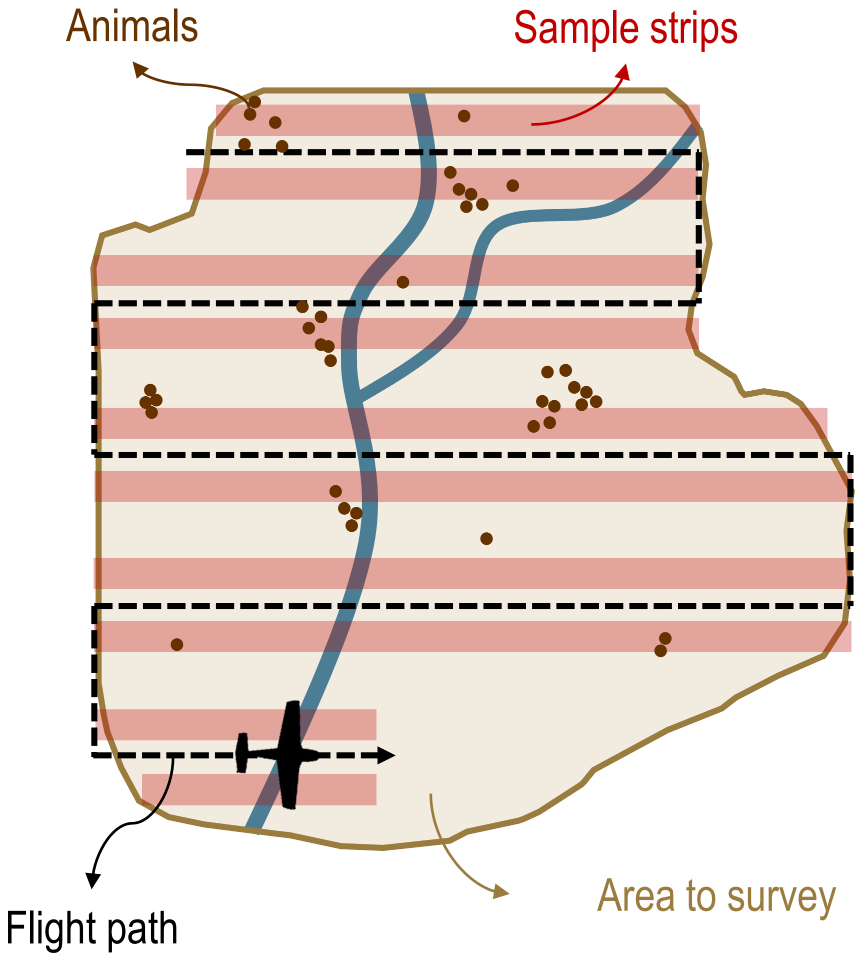
PRINCIPLES OF AERIAL SURVEYS

- **Standard survey method**

  Two (or more) observers in aircraft flying at low altitude (300 ft) and high speed (~180 km/h) following systematic sample strips

  → Real time on-sight count





THE USE OF ON-BOARD CAMERAS

- **Real time on-sight count:** not an easy task…
  → Population estimates **not precise** due mainly to short observation time (~5 s)

- **How to reduce such bias?**
  → Using **on-board cameras** that replace observers

  Large volume of **data** to process
  → Time-consuming manual processing (few seconds to several minutes)

Figure from Lamprey *et al*. (2020) [1]

Precise counts

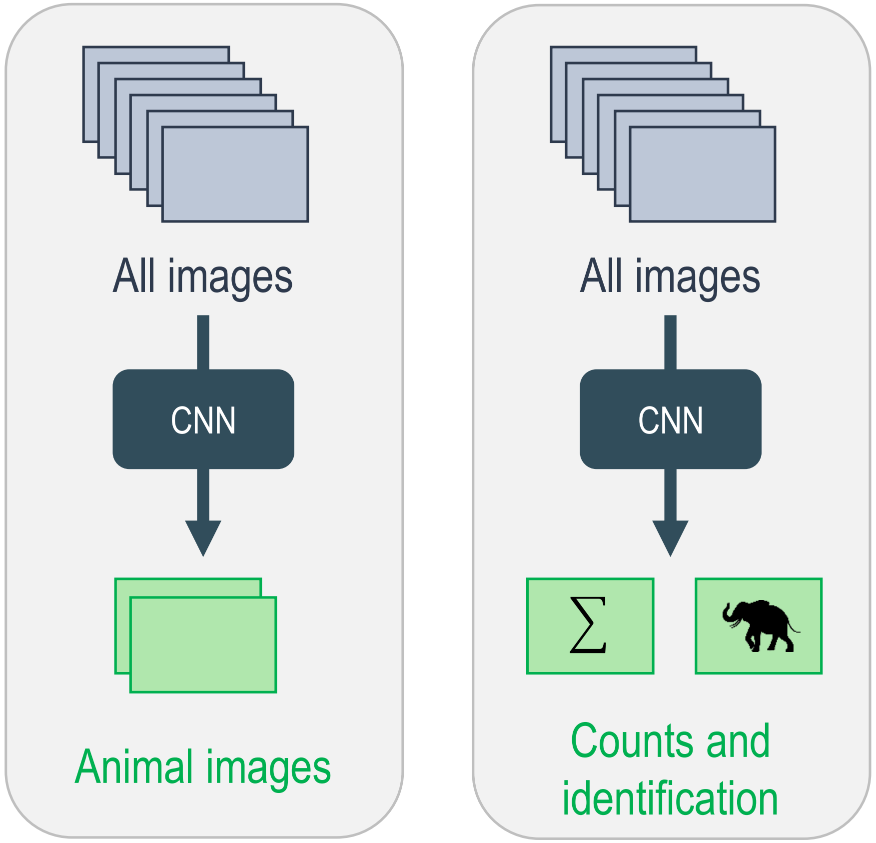
More coherent population estimates

DEEP LEARNING FOR DATA PROCESSING

- **How to automate image processing?**
  - → **Promising avenue**: Deep Learning using Convolutional Neural Networks (**CNN**)

- **Protected area managers' expectations?**
  - → **At least**: Model that filters out non-animal images (i.e. >90%)
  - → **At best**: Model that gives precise counts and identification

Are we there yet?



ACHIEVEMENTS

- **Semi-automated methods** [2,3,4]
  → Towards the "at least" expectation
- **Nearly-automated methods** [5]
  → Towards the "at best" expectation
- **Weakly-supervised methods** [6]
  → Towards freedom from costly annotations
- **Counting with density maps** [7,8]
  → Towards precise counts of close-by animals

How to reach a fully automatic system?

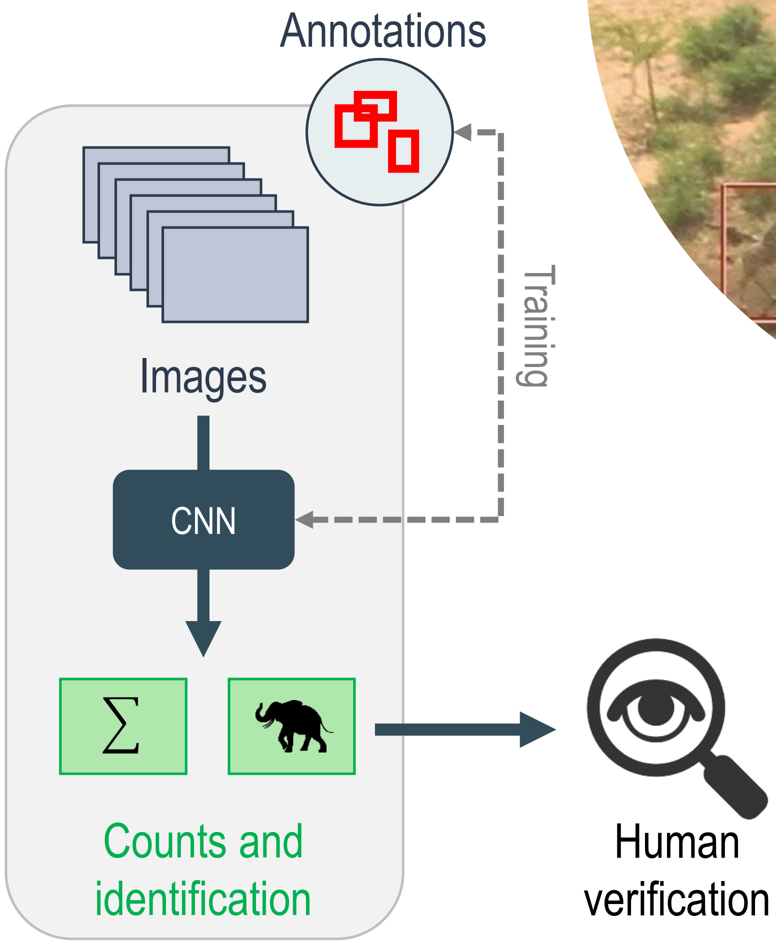
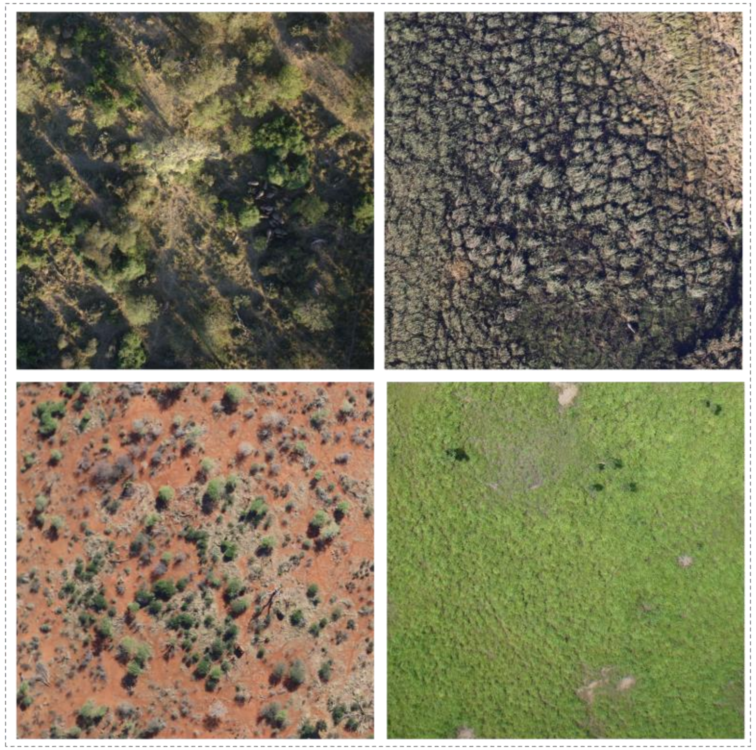


Figure from Eikelboom *et al.* (2019) [3]

REDUCING THE FALSE POSITIVES

- Mainly caused by the natural **heterogeneity** of African landscapes



- Accentuated for **dense herds** and **close-by** animals

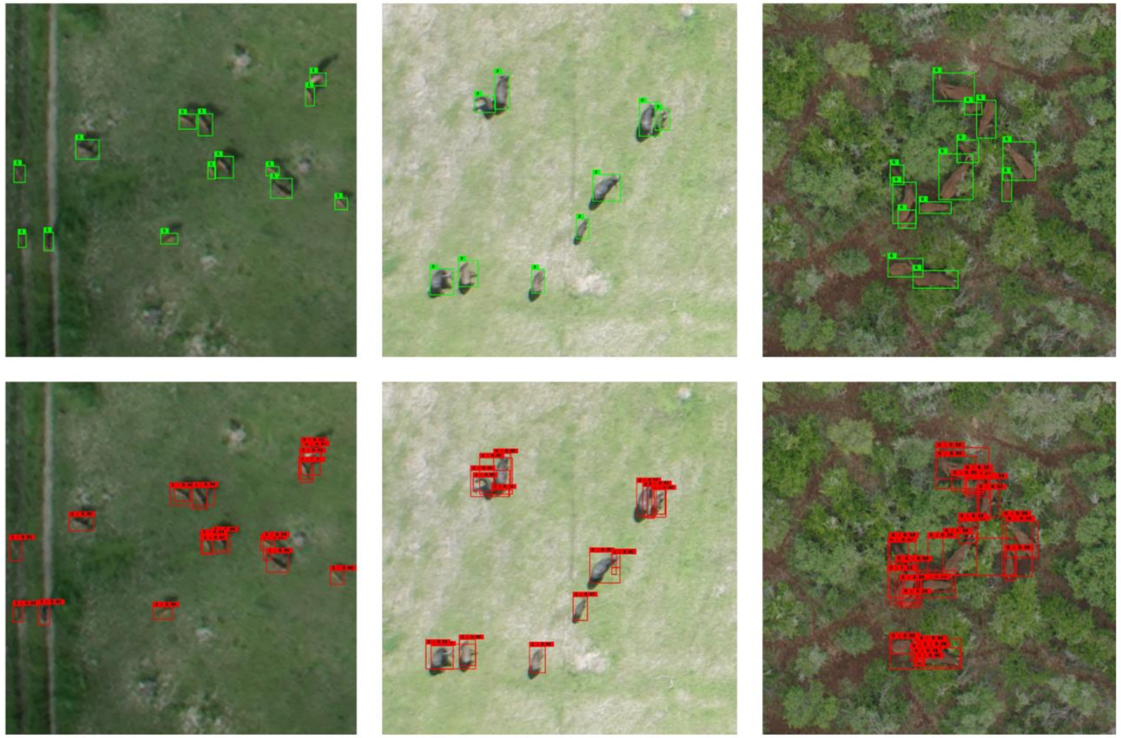
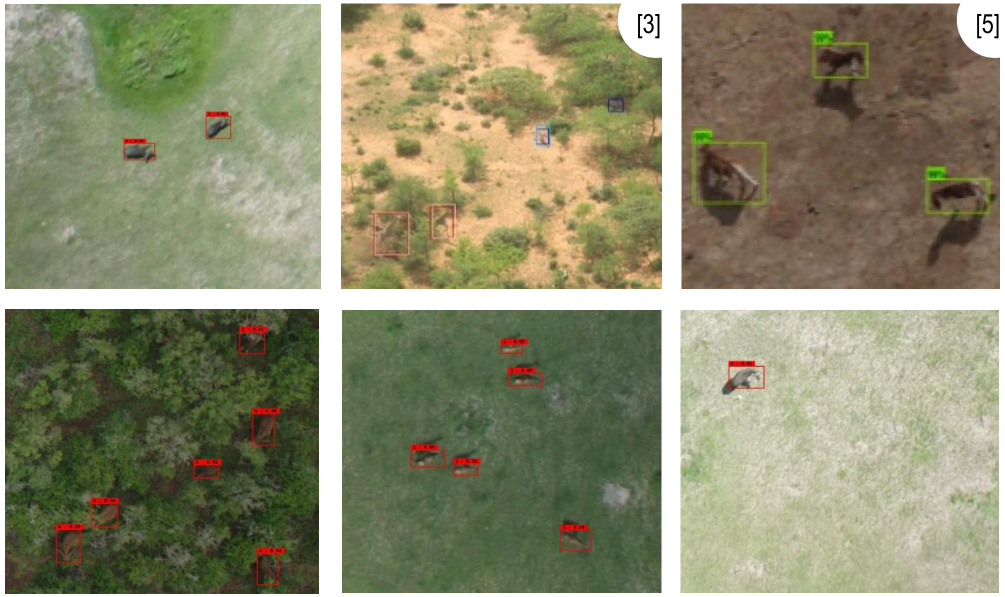


Figure from Delplanque *et al.* (2022) [4]

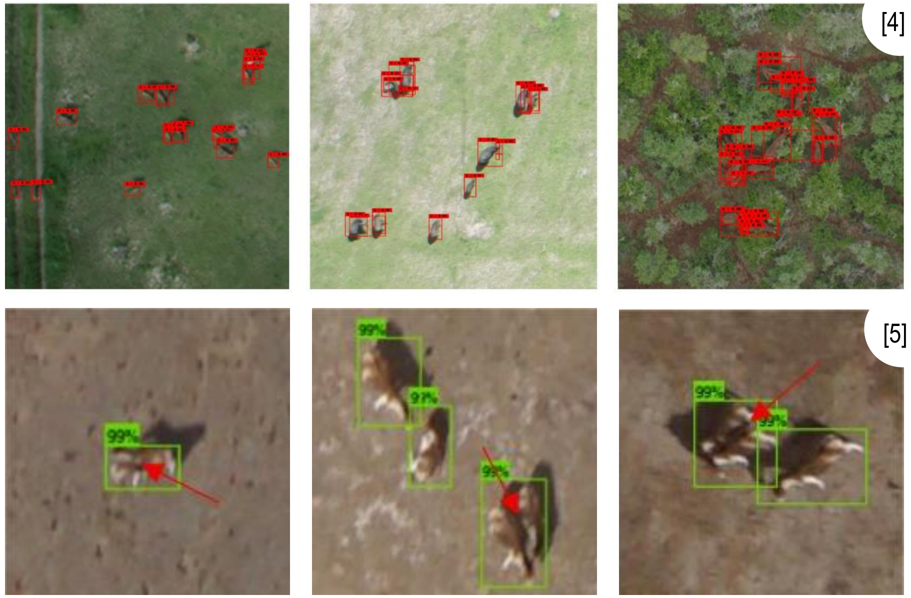
INCREASING THE PRECISION OF CLOSE-BY ANIMALS

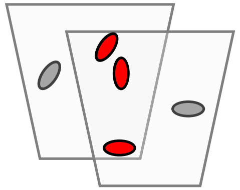
- **CNN Anchor-based object detectors** (e.g. Faster-RCNN, RetinaNet)

✓ Good performances for **isolated** mammals and **sparse** herds[3,4,5]



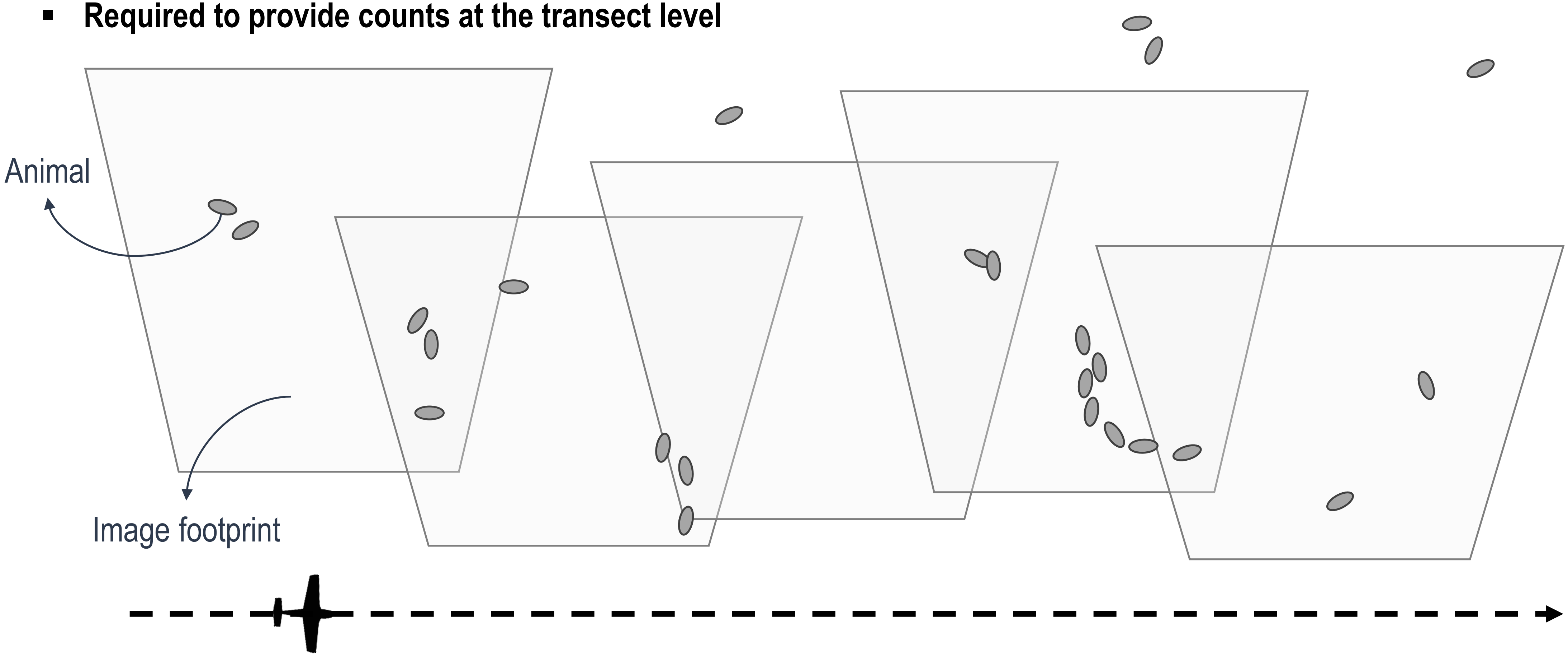
✗ Drop in performances for dense **herds** and **close-by** individuals[4,5]





MANAGING DOUBLE COUNTING

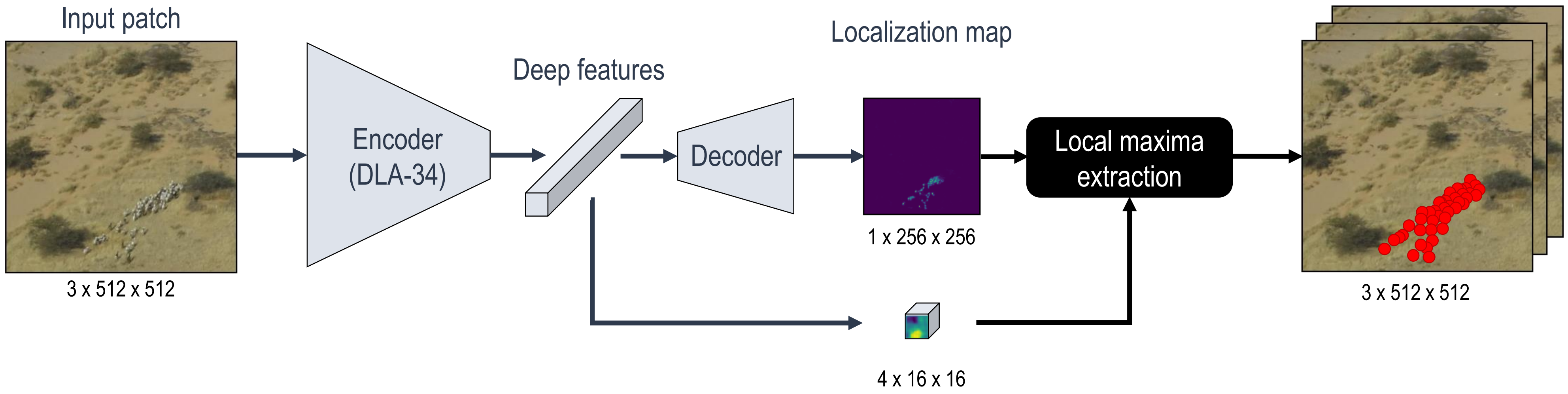
- **Required to provide counts at the transect level**



STUDY AREA AND DATASET

- **Ennedi Natural and Cultural Reserve (Chad)**
  - Sahelo-Saharan desertic landscape
  - Vital resource for local semi-nomadic livestock
- **Two Nikon D5000 SLR on a Cessna 182**
  - Oblique position
  - Image capture when group > 10 individuals
- **914 images of 24MP containing challenging livestock groups**
  - 3,741 camels
  - 1,227 donkeys
  - 17,839 sheep and goats (a.k.a. shoats)
- **Point annotations**
  - Split in train/validation/test set (70-10-20)

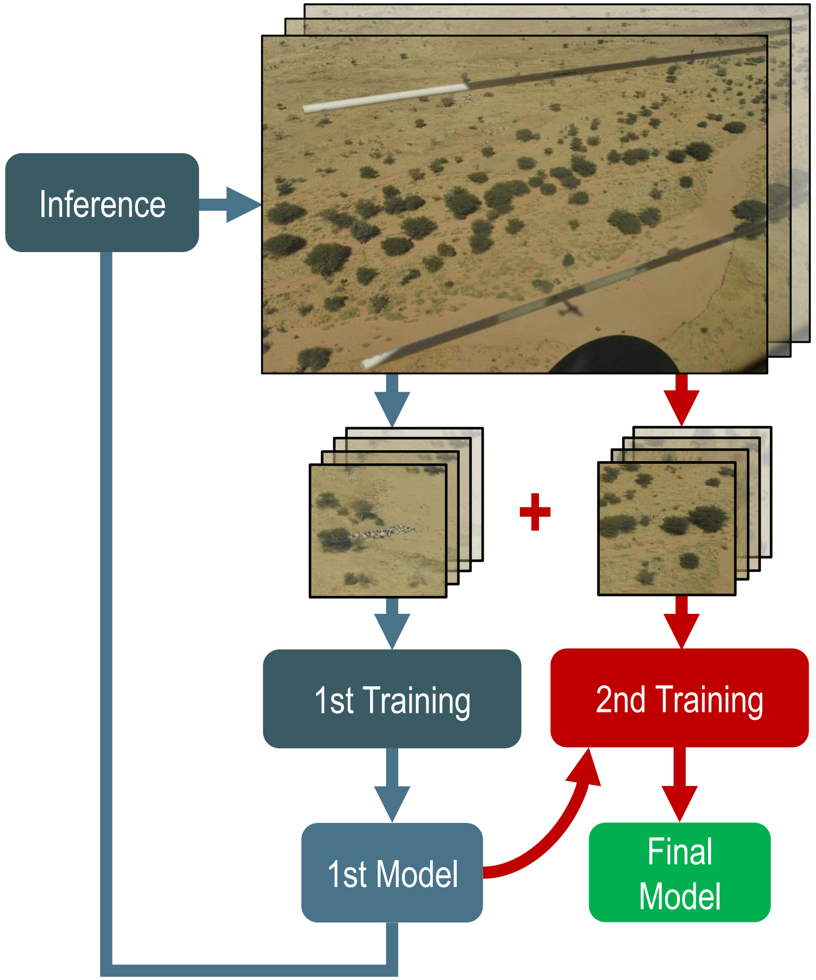
OUR POINT-BASED CNN : "HERDNET"



- Compared to 2 other approaches
  - ✓ Anchor-based CNN: **Faster-RCNN**[9] (baseline for localization)
  - ✓ Density-based CNN: adapted **DLA-34**[10] (baseline for counting)

Hard negative patch mining

- **Principle:** harvest hard negatives on full training images after a first training step and then use the patches that contain them for a second training step
  → **Hard negatives** = detections with high confidence score
  → **Objective**: reducing the number of false positives generated by background heterogeneity

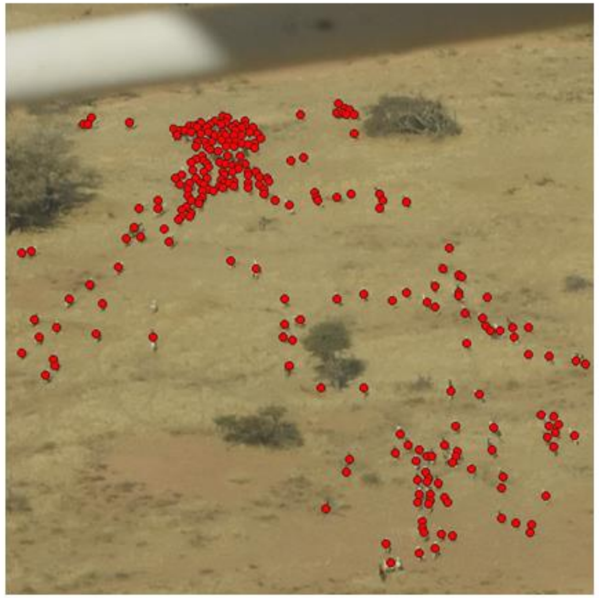


LOCALIZATION PERFORMANCE

LOCALIZATION

$$Recall = \frac{TP}{TP + FN} \qquad Precision = \frac{TP}{TP + FP} \qquad F1\ score = \frac{2 \times r \times p}{r + p}$$

Approach	Faster-RCNN	HerdNet	HerdNet + HNP
Recall	65.2%	**77.7%**	70.2%
Precision	28.9%	51.6%	**77.5%**
F1 score	40.0%	62.0%	**73.6%**
Processing time	5.0 sec.	**3.6 sec.**	**3.6 sec.**



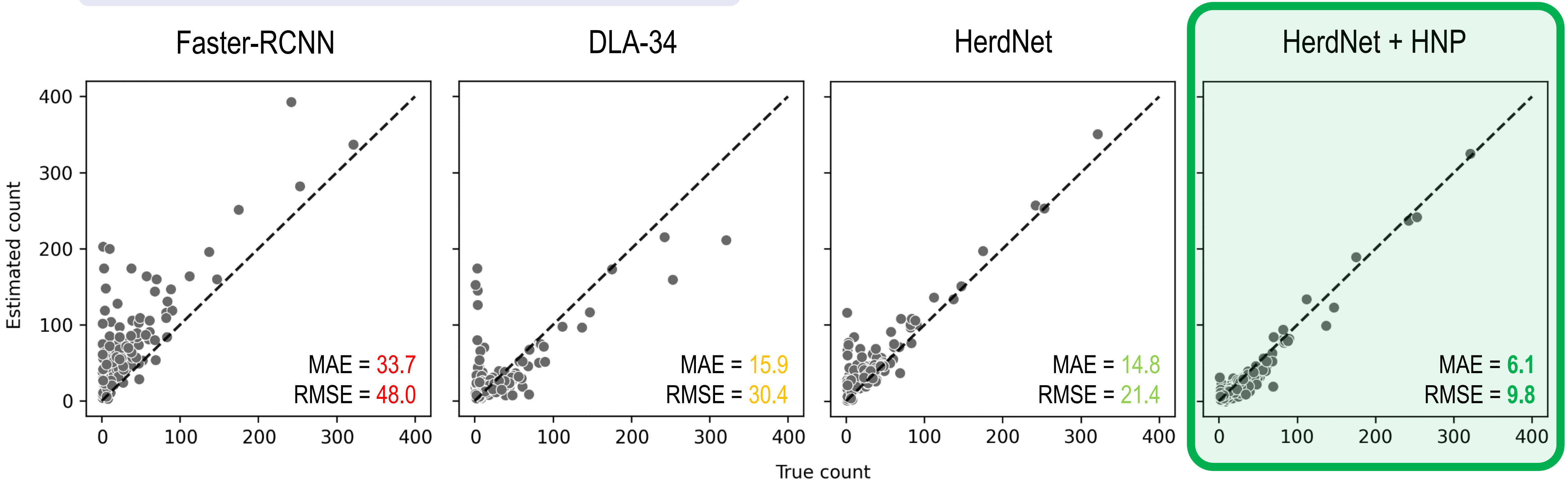
Counting performance

COUNTING

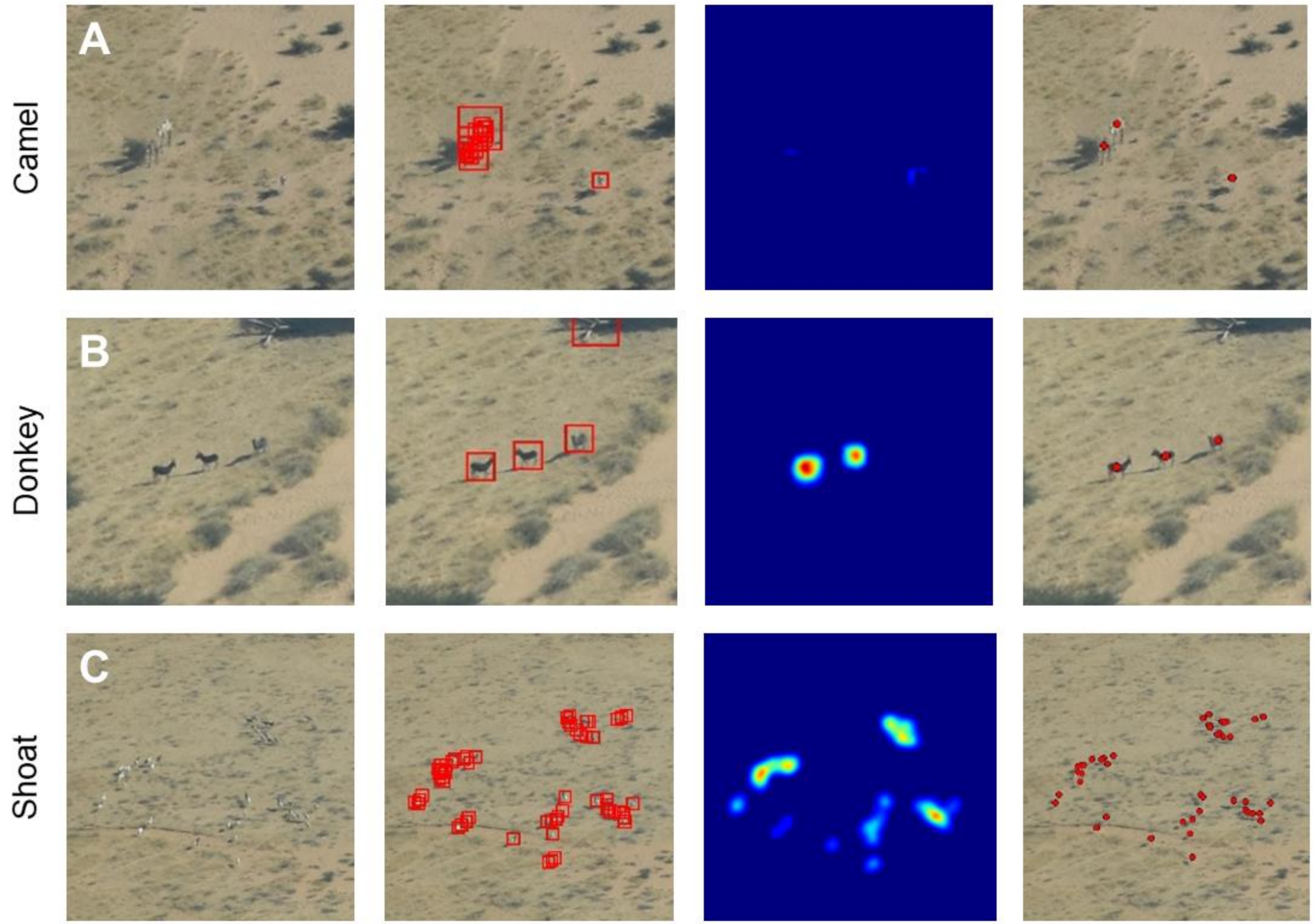
$$MAE^{a} = \frac{1}{N}\sum_{i=1}^{N}\left|\widehat{C}_i - C_i\right| \qquad RMSE^{b} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\widehat{C}_i - C_i\right)^2}$$

[a]Mean Absolute Error

[b]Root Mean Square Error

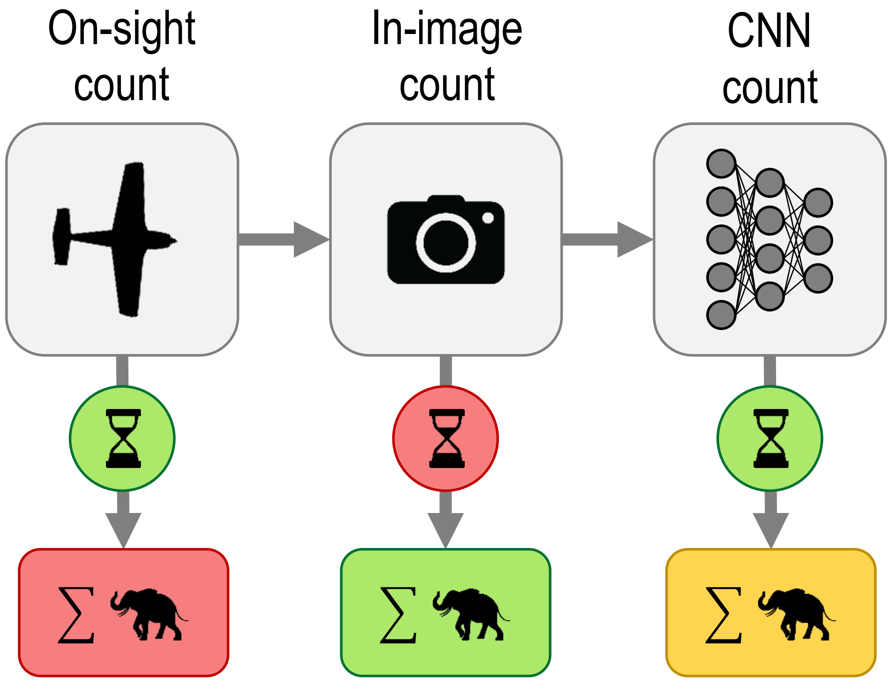


IDENTIFICATION PERFORMANCE



	Camel	Donkey	Shoat
N	753	239	3,579
Faster-RCNN			
MAE	7.0	6.5	22.5
RMSE	9.7	9.2	37.0
DLA-34			
MAE	3.6	**1.6**	15.2
RMSE	6.5	**3.3**	27.8
HerdNet + HNP			
MAE	**2.6**	2.5	**7.0**
RMSE	**4.8**	4.6	**10.7**

Conclusion & Future work

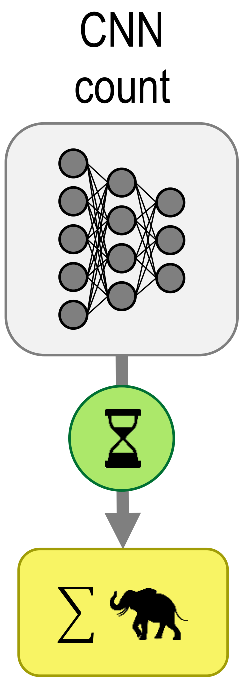


Towards fully automatic system

1. False positives → Hard Negative Patch Mining
2. Close-by animals → Point-based CNN: HerdNet
3. Double counts

Will be addressed in future work

+ Evaluation of model robustness



THANK YOU FOR YOUR ATTENTION, ANY QUESTIONS ?

August 18, 2022

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