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Towards Visual Insect Camera Traps

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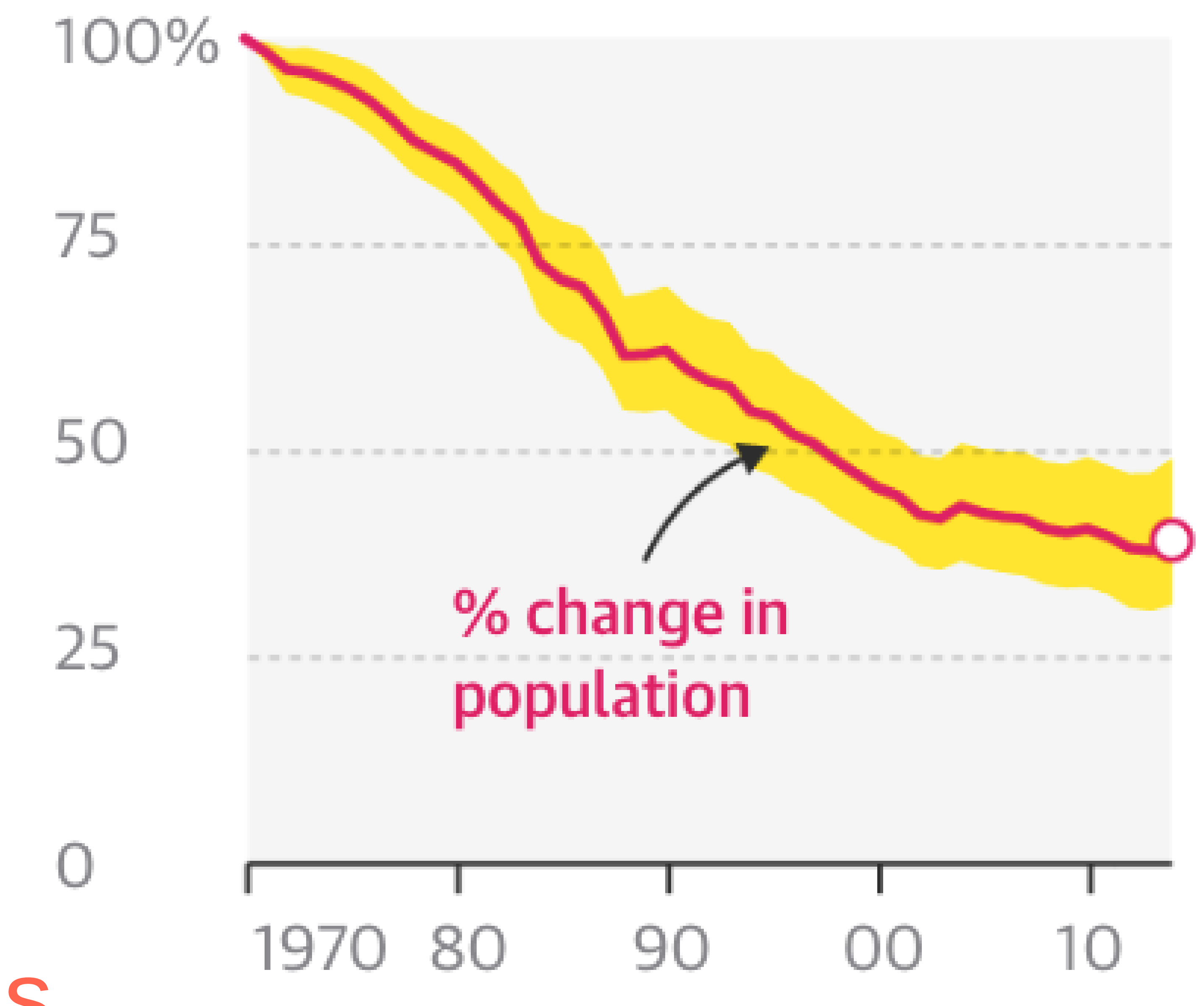
COMPUTER VISION & MACHINE LEARNING SYSTEMS

Decline in animal populations

- Quantitative data indicates extinction of vertebrates (caused by humans)
- 60% of the vertebrate animals have been lost since 1970
- However: more than 90% of all animal species are invertebrates
- Insects are crucial for the ecosystem
  - 90% of the flowering plants benefit from pollination [1]
  - Insect pollinators promote the production of 75% of major global agricultural crops [2]
  - Insects contribute by ~150 billion € to the global economy [3]
- Monitoring and quantifying invertebrates is more difficult



Living Planet index, WWF/ZSL, 2018

[1] Ollerton, J., Winfree, R. & Tarrant, S. How many flowering plants are pollinated by animals? Oikos 120, 321–326 (2011).
[2] Gallai, N., et al. Economic valuation of the vulnerability of world agriculture confronted with pollinator decline. Ecol. Econ. 68, 810–821 (2009).
[3] Eilers, E. J., et al. Contribution of Pollinator-Mediated Crops to Nutrients in the Human Food Supply. PLoS One 6, e21363 (2011).

Decline in insect populations

Plummeting insect numbers 'threaten collapse of nature'

- In the news: “Insects could vanish within a century”
- 41% of global insect species have declined over the past century [1], e.g. bees with 46% or caddisflies with 68%
- Terrestrial and non-terrestrial insect species are affected [2]
- How to quantify the decline of insect populations?

[1] Sánchez-Bayo, F. & Wyckhuys, K. A. G. Biological Conservation 232, 8–27 (2019).

[2] Dirzo, Rodolfo, et al. "Defaunation in the Anthropocene." Science 345.6195 (2014): 401-406.

Insect Camera Trap

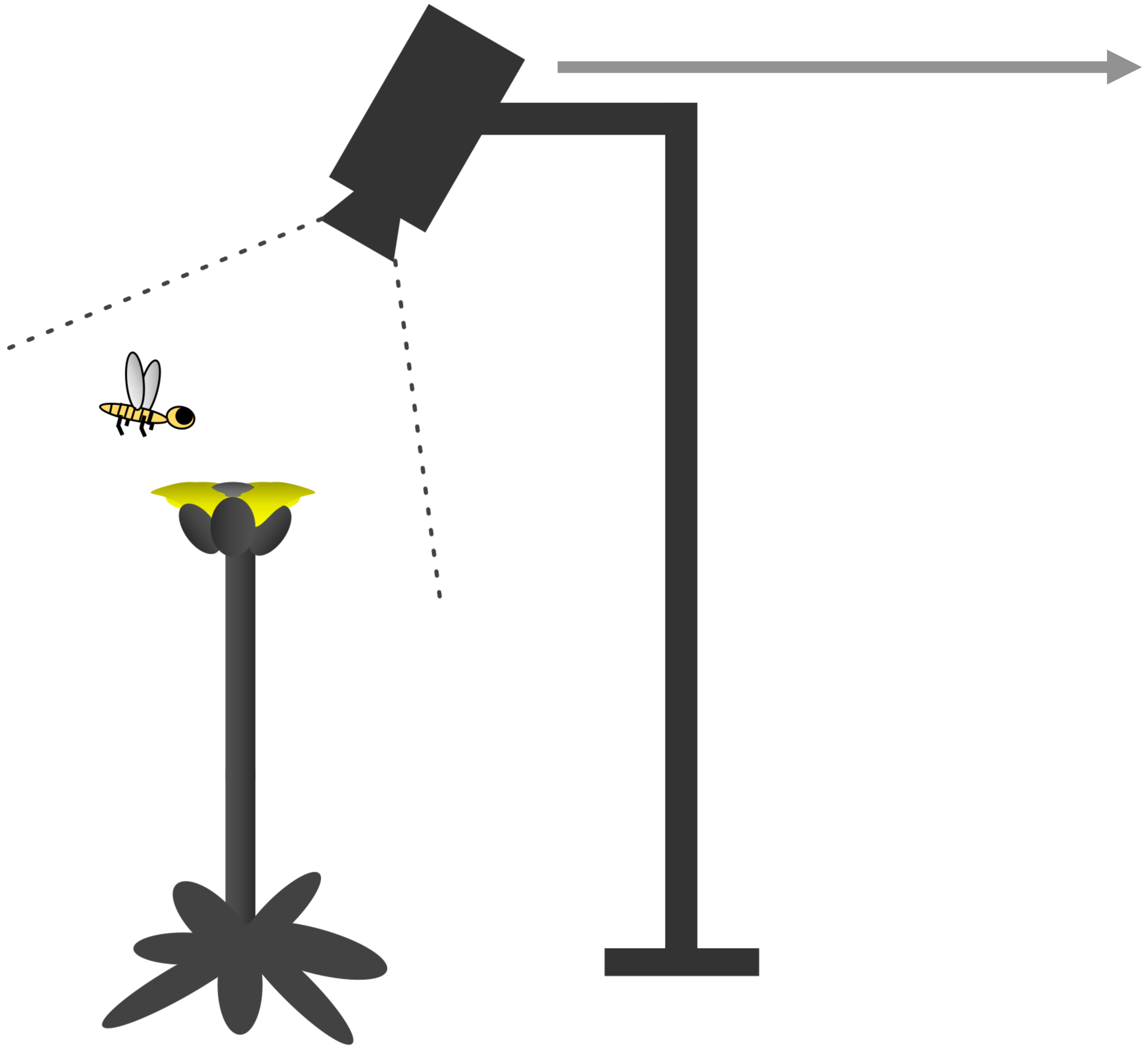
Motivation for a visual insect trap

Malaise Trap

Camera Trap

Insect Camera Trap

Motivation for a visual insect trap



? Save ?

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Dataset

- Common datasets are not well suited as training baselines/benchmarks for our proposed tasks (either insects too big or only image stills).
- We created a new dataset of experimental field plots of $\sim 2 \times 4.5\ m^2$ were recorded using a waterproof outdoor camera (Ricoh WG-50) under suitable weather conditions.
- Overall 16 cameras were installed to monitor different crop combinations in monocultures and mixtures.

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Dataset

- 35,129 frames were extracted, of which 22,008 images included at least one insect.
- For 50% of the frames location information was added by a domain expert using a custom annotation tool, amounting to 14,847 bounding boxes in total.
- With respect to the entire image, the average bounding box had a height of 7.5%, a width of 4.4% and covered an area of 0.4% pixel.

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Spatial vs. temporal cues

Visual Insect Trap Challenges:

small objects

fast motion

cluttered scene

dynamic background

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Insect presence detection (binary)

input

single
frame

no temporal cues…

neural network

output

insect present (save images)

no insect (do not save images)

two
classes

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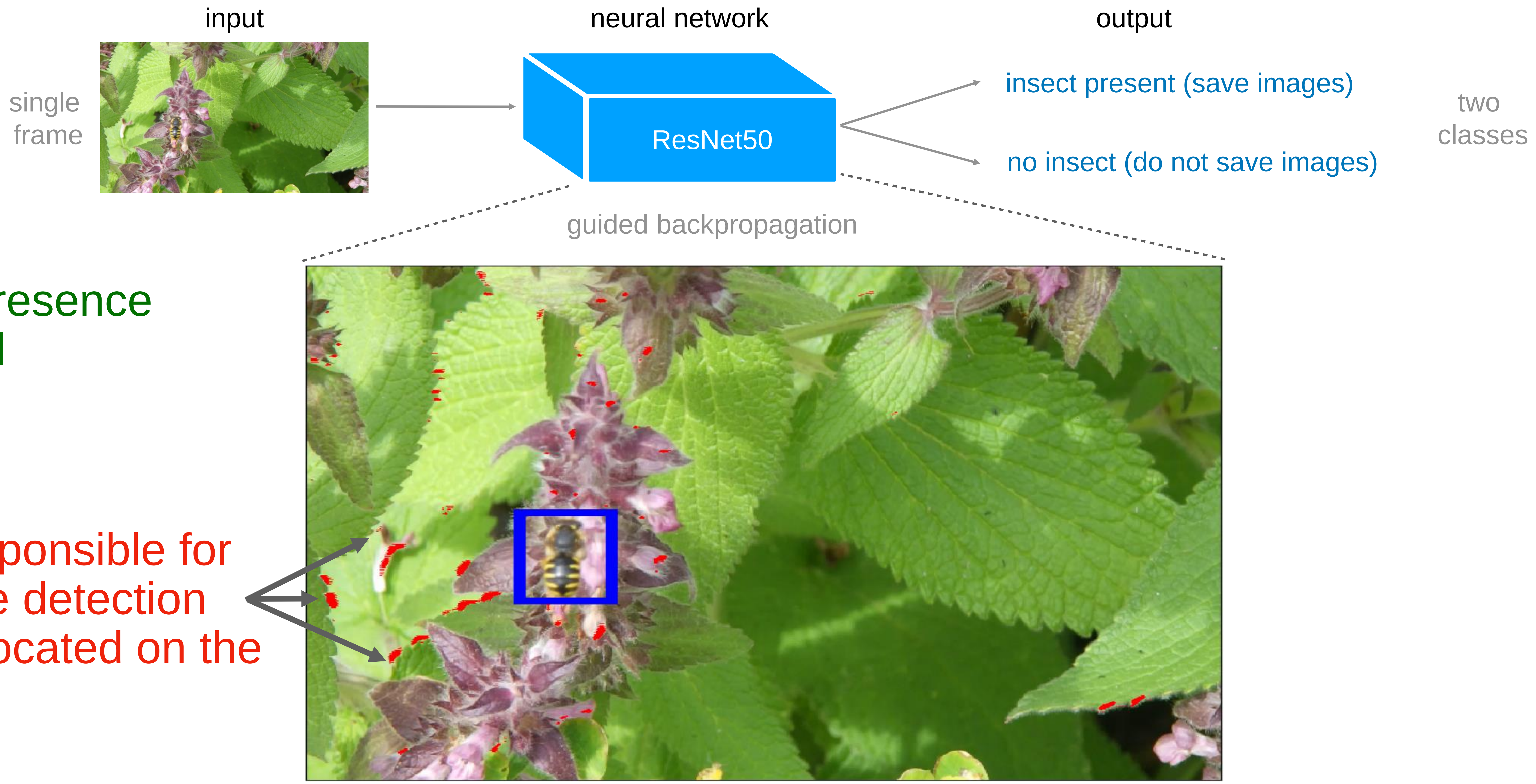
Insect presence detection (binary)



✓ Insect presence detected

- Pixel responsible for presence detection are not located on the insect!

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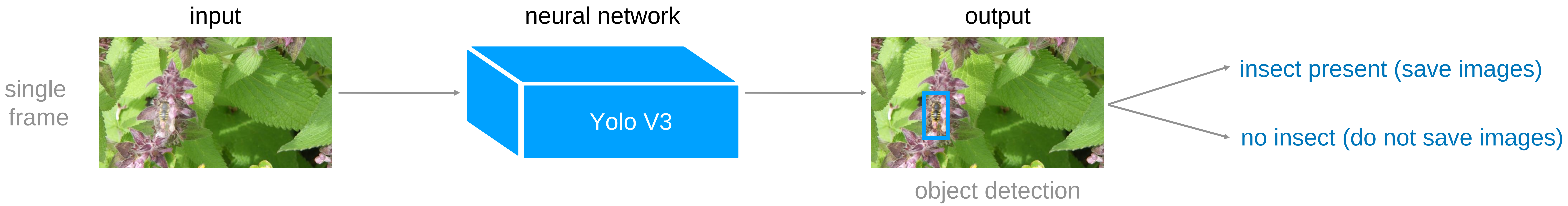
Insect presence detection (bounding box)



- The network is forced to detect the insects themselves, since it will otherwise not fullfill the training target.
- However, additional information through temporal cues in the input is still not utilised.

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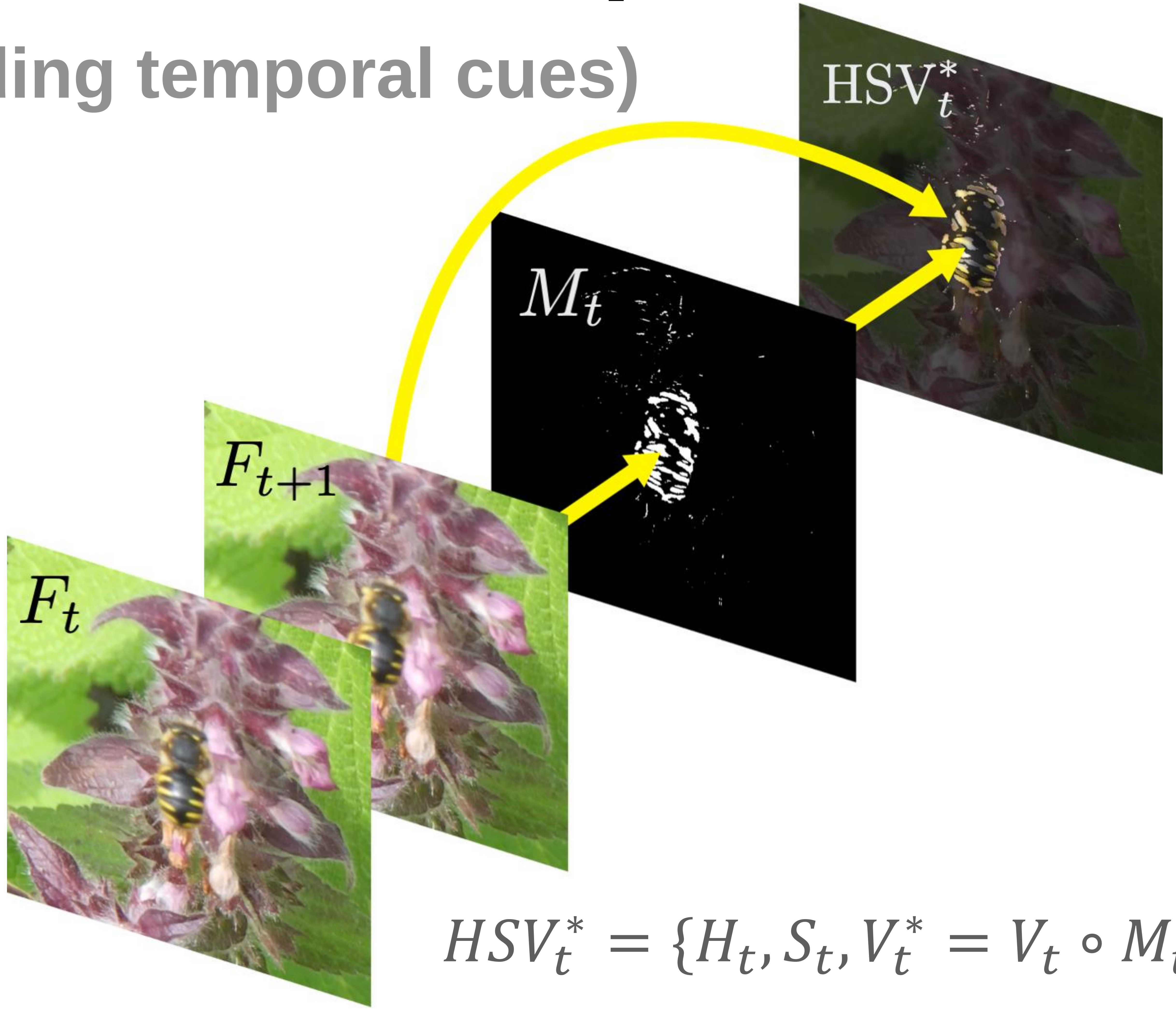
Insect presence detection (including temporal cues)



$$HSV_t^* = \{H_t, S_t, V_t^* = V_t \circ M_t\}$$

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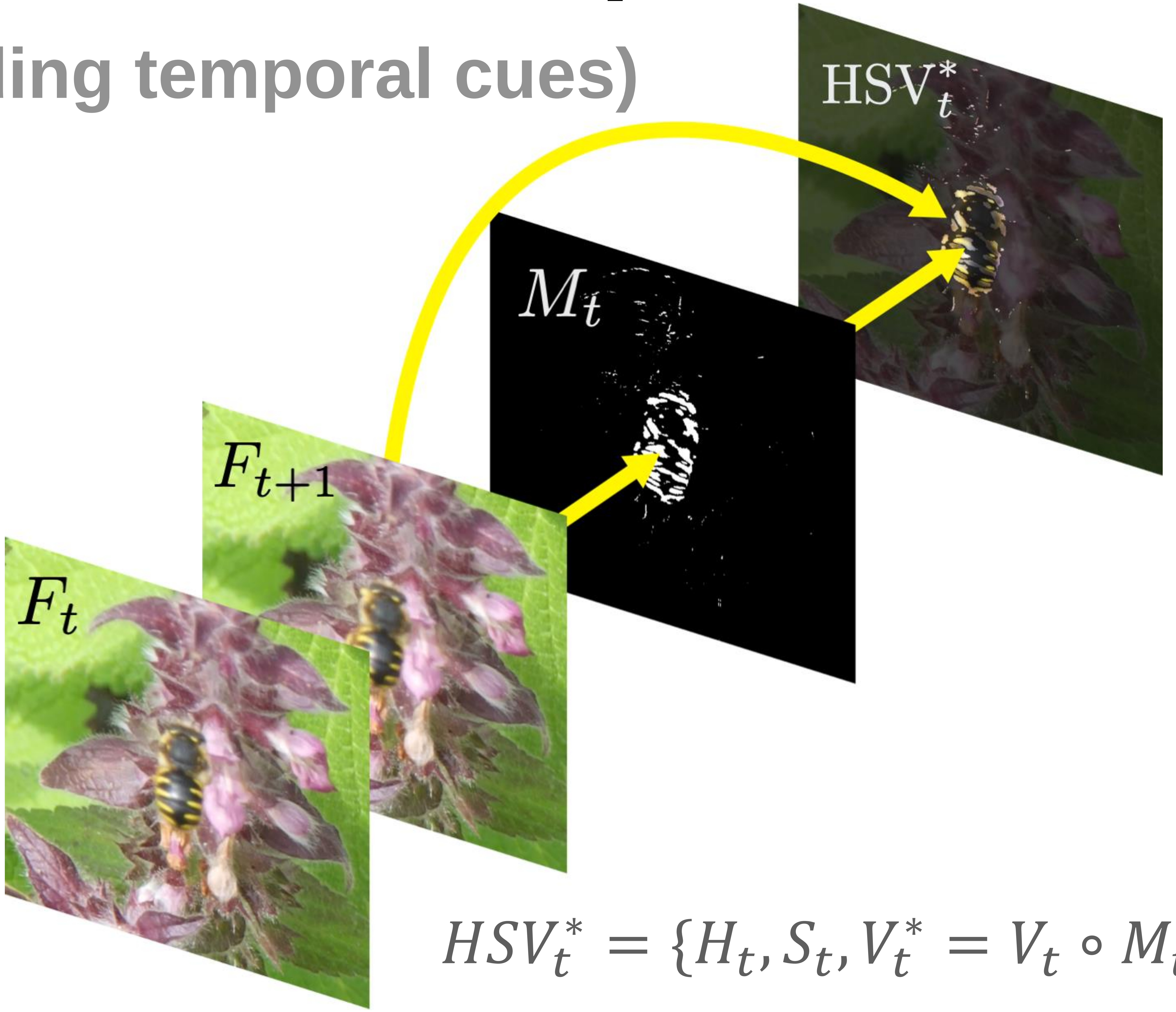
Insect presence detection (including temporal cues)



$$HSV_t^* = \{H_t, S_t, V_t^* = V_t \circ M_t\}$$

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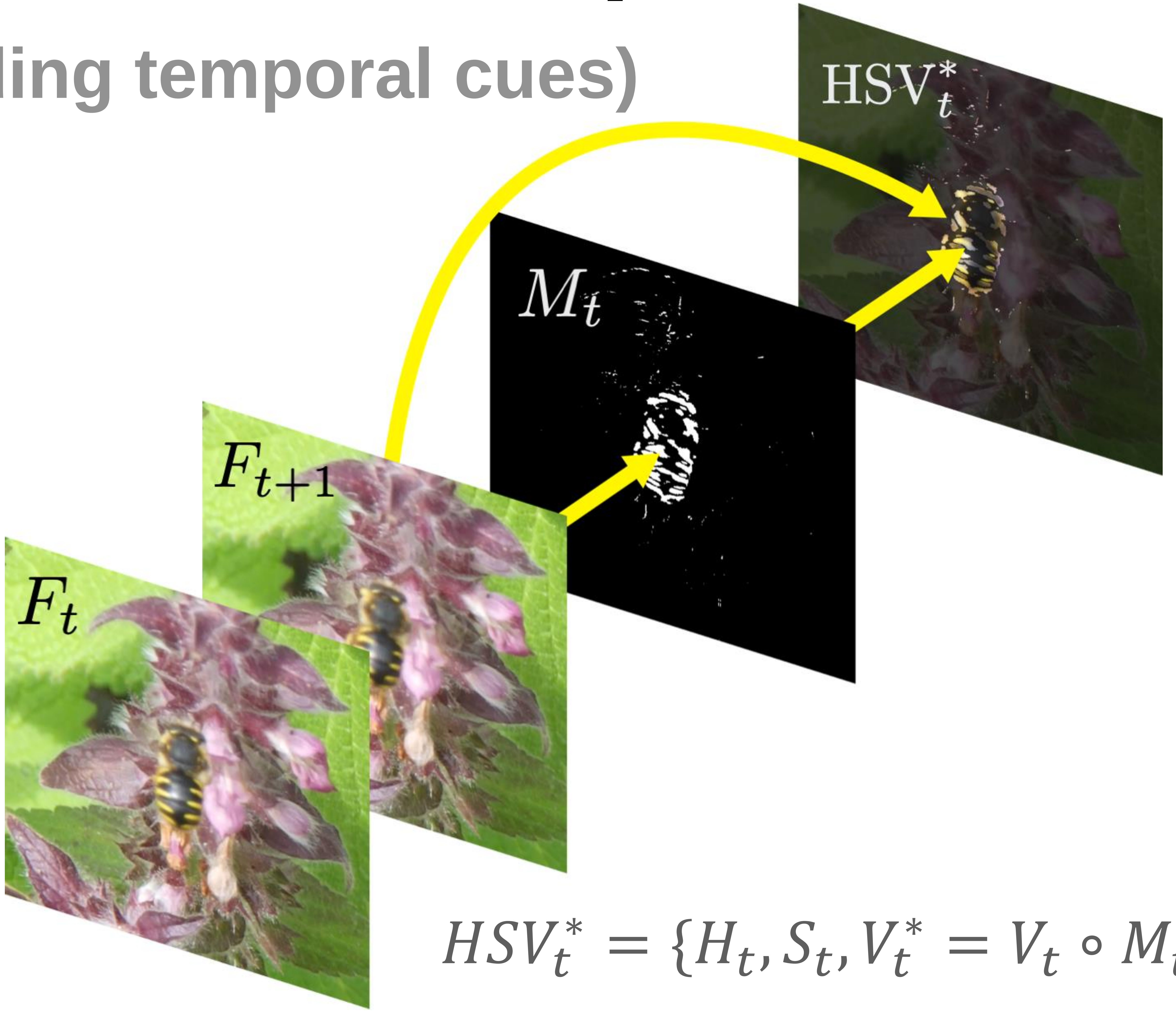
Insect presence detection (including temporal cues)



$$HSV_t^* = \{H_t, S_t, V_t^* = V_t \circ M_t\}$$

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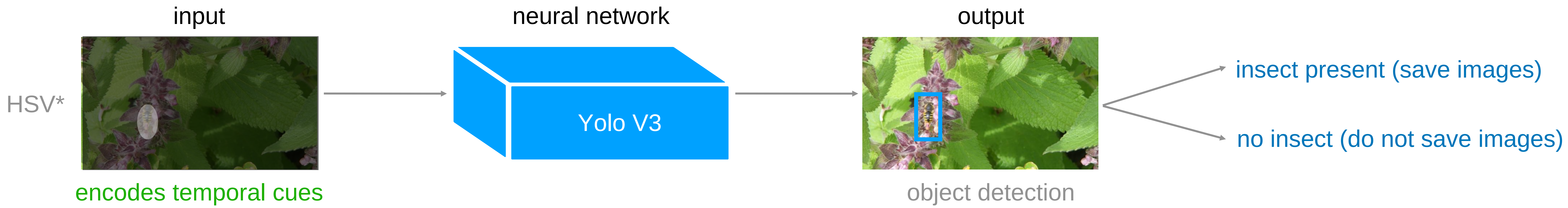
Insect detection accuracy using different models on HSV*



	Architecture	AP	Precision	Recall	F1	Time
RGB	YoloV3	74.15%	96%	70%	81%	2.5 fps
	Faster RCNN	71.95%	91%	80%	85%	0.3 fps
	MobileNet	69.82%	90%	70%	79%	0.45 fps
HSV*	YoloV3	78.07%	92%	72%	81%	2.5 fps
	Faster RCNN	74.39%	86%	82%	84%	0.3 fps
	MobileNet	72.41%	92%	71%	80%	0.45 fps

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Conclusion and Future Work

- Spatial information during training and temporal cues in the input are very helpful to the detection mechanism.
- Test additional state-of-the-art architectures made for sequential data
- Expand dataset (more adverse weather conditions, etc.)
- Improve the hardware (field of view, field of depth, etc.)