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Efficient Computer Vision
Models for Silkworm Feeding Prediction
and Habitat Analysis

Università degli Studi di Roma **La Sapienza**
Computer Vision 2024-2025

Outline

Introduction
Related Works
Proposed Method
Dataset and Metrics
Implementation details
Experimental results
Conclusions and Future Works

Problem statement

Context: Silkworm rearing is traditionally labor-intensive and prone to human error

Objective: Automate the monitoring process of silkworms' rearing

Tasks:

- Supervised Binary Classification → Feeding or not feeding ?
- Unsupervised Semantic Segmentation → where is the worms, the leaves and the background?

Constraints: Design lightweight neural networks for limited hardwares

Deep Learning for Vision

CNN:

- Efficient extraction of local features, they use data's prior biases
- Necessity of depth to have a wide receptive field

ViT:

- Efficient extraction of global features by using self attention
- No prior biases, they need many parameters

Hybrid Architectures:

Local context + Global context

Hybrid architecture

Hybrid Architectures merge the advantages of CNNs and Transformers

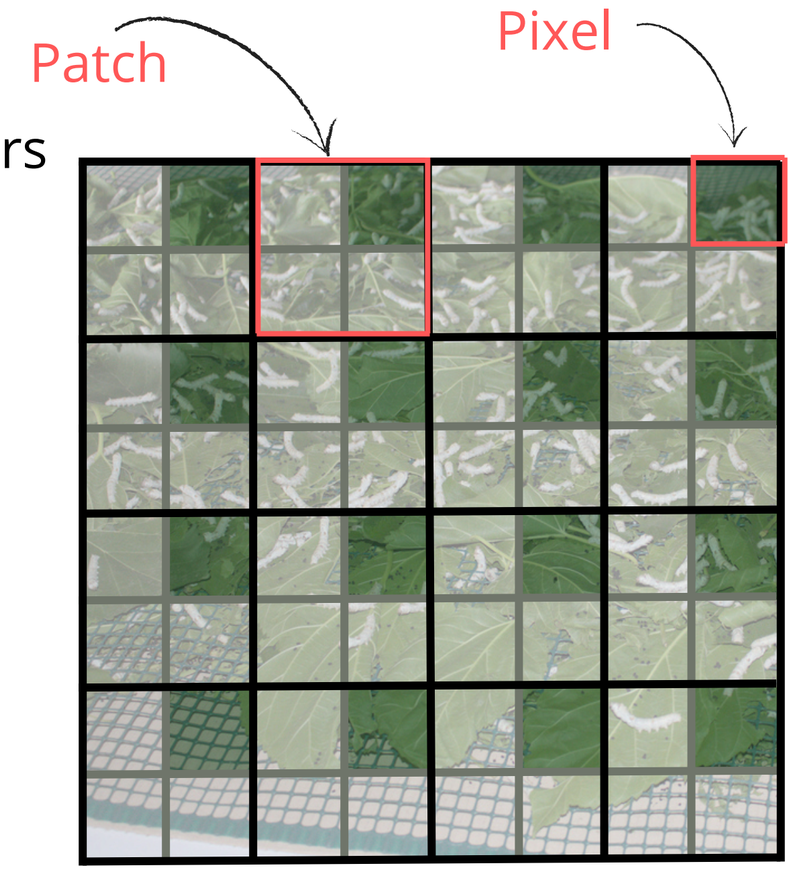
2DConv 3x3: every pixel sees his 8 nearest neighbours

+

Self Attention: every patch sees the others

=

Result: each pixel sees both the local and the global context



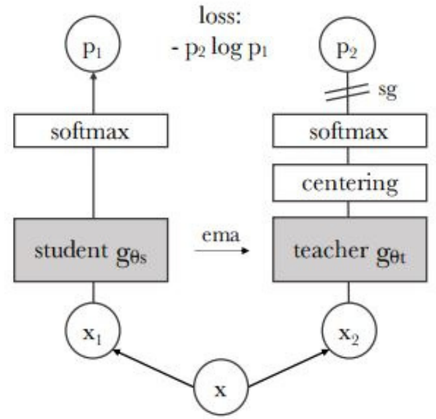
Unsupervised Semantic Segmentation

CNNs/Transformers used as feature **extractors**, followed by **clustering** on similar pixels.

It’s not clear how **supervised** models learn features

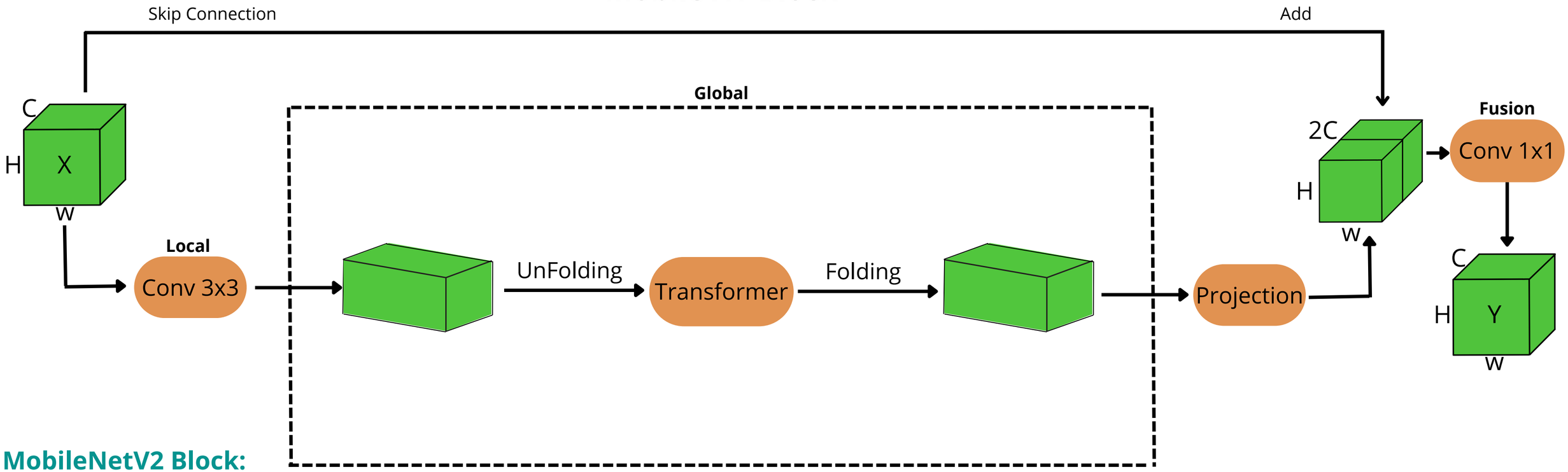
Self Supervised models highlight **semantic structures** such as edges and objects.

Dino is trained with self distillation approch



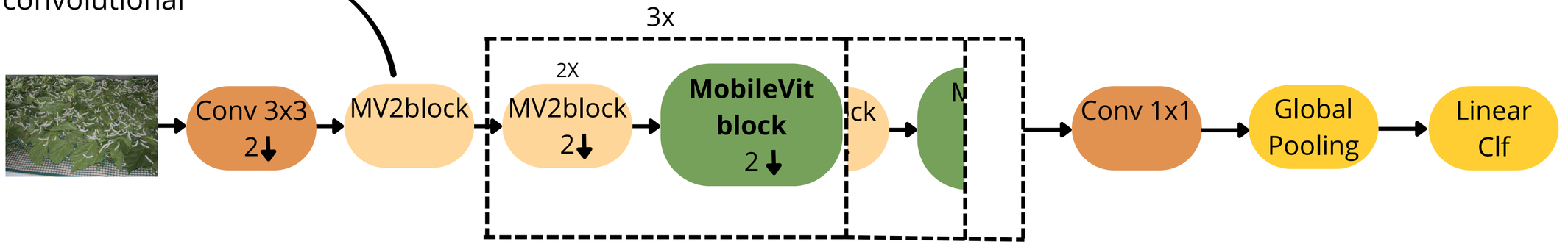
Proposed Method

MobileViT Block



MobileNetV2 Block:
use depthwise convolutional

MobileViT Network



Another Network

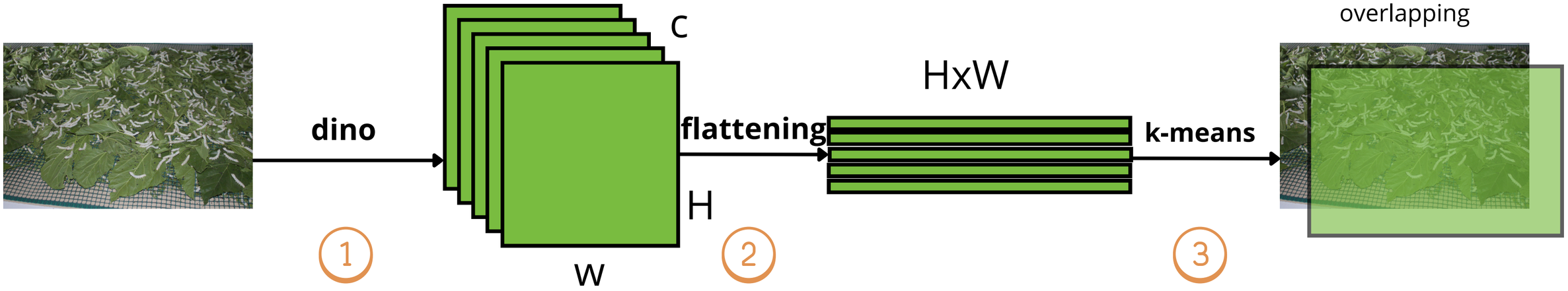
Let’s also consider a network that doesn’t use the Transformer Architecture

MiniCNN

Number of parameters for various configuration of models used in the project

Model	N_parameters
MiniCNN	948.130
MobileViT-xxs	1.040.898
MobileViT-xs	2.068.858
MobileViT-s	5.327.074

DINO as feature extractor



1. **Extracting** the feature from an intermedate layer of pretrained DINO

2. **Flattening** the spatial feature, prepare of k-means

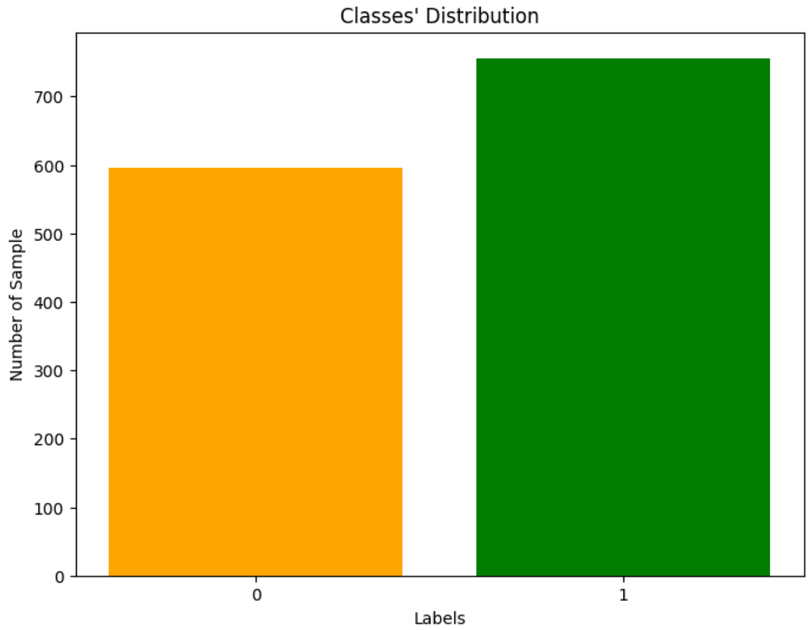
3.
   - **Clustering** the similar feature with k-means n_classses=3
   - **Upsampling** the clusters on the image
   - **Overlapping** with original image

Dataset

Let’s have a look at the dataset to understand which strategies to execute

1351 Labeled Image

- Size: (1559,1038)
- 2 classes: feed/no-feed
- no-feeding:600 / feeding:751



no-feeding

feeding

Metrics

Classification

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{F1} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

Avarage infer time per image [ms]

Semantic Segmentation

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i),\ b(i)\}}$$

$$\text{silhouette-score} = \frac{1}{N} \sum_{i=1}^{N} s(i)$$

Sperimental setup

Classification problem

Augmentation strategies:

Standard:
- RandomHorizontalFlip (50%)
- RandomRotation (10°)
- ColorJitter
- Normalize

Crop:
- RandomResizedCrop (60%-100%)
- + standard

Global Pooling strategies:

Attn pooling: Weighted sum of the spatial features
Avg pooling: AdaptiveAvaragePooling

Lightweight_models

Hyperparameters	N_epochs	Batch_size	Learning rate
Value	10	32	0.0001

Semantic segmentation Problem:

Dino+ k_means

BackBone	Layer	Input Size
Res-Net50	Third	(1559,1038)

Average Performance of Lightweight Models Across Augmentation and Pooling Strategiess

Augmentation	Pooling	F1_mean	F1_std	InferTime [ms]
standard_512	AdaAvgPooling	0,9534	0,0021	117,34
crop_512	Attn Pooling	0,9506	0,0104	119,97
crop_512	AdaAvgPooling	0,9489	0,0069	118,62
standard_512	Attn Pooling	0,9433	0,0109	118,97
standard_256	AdaAvgPooling	0,9431	0,012	26,05
crop_256	Attn Pooling	0,942	0,0134	26,61
standard_256	Attn Pooling	0,9383	0,0172	26,29
crop_128	Attn Pooling	0,9376	0,0129	4,84
standard_128	AdaAvgPooling	0,9368	0,007	5,365
crop_256	AdaAvgPooling	0,9335	0,0071	26,26
standard_128	Attn Pooling	0,9322	0,0112	4,745
crop_128	AdaAvgPooling	0,9258	0,0135	4,75

📌 Observations:

- Larger input sizes consistently lead to higher performances
- Attn pooling shows higher variance compared to average pooling → less stable
- Crop augmentation combined with attention pooling yields a synergistic effect

The best performance for input size: 128

Model	Augmentation	Pooling	F1_score	infer_time[ms]
MobileViT-S	standard_128	AdaAvgPooling	0,9397	8,58
MobileViT-S	crop_128	AdaAvgPooling	0,9238	7,3
MobileViT-S	standard_128	Attn Pooling	0,9386	7,43
MobileViT-S	crop_128	Attn Pooling	0,9447	7,54
MobileViT-XS	standard_128	AdaAvgPooling	0,9292	6,65
MobileViT-XS	crop_128	AdaAvgPooling	0,914	5,17
MobileViT-XS	standard_128	Attn Pooling	0,9156	5,11
MobileViT-XS	crop_128	Attn Pooling	0,9204	5,43
MobileViT-XXS	standard_128	AdaAvgPooling	0,9333	1,92
MobileViT-XXS	crop_128	AdaAvgPooling	0,9205	1,8
MobileViT-XXS	standard_128	Attn Pooling	0,9362	1,7
MobileViT-XXS	crop_128	Attn Pooling	0,9362	1,69
MINI_CNN	standard_128	AdaAvgPooling	0,9451	4,31
MINI_CNN	crop_128	AdaAvgPooling	0,9451	4,76
MINI_CNN	standard_128	Attn Pooling	0,9386	4,74
MINI_CNN	**crop_128**	**Attn Pooling**	**0,9492**	**4,7**

The best performance for input size: 256

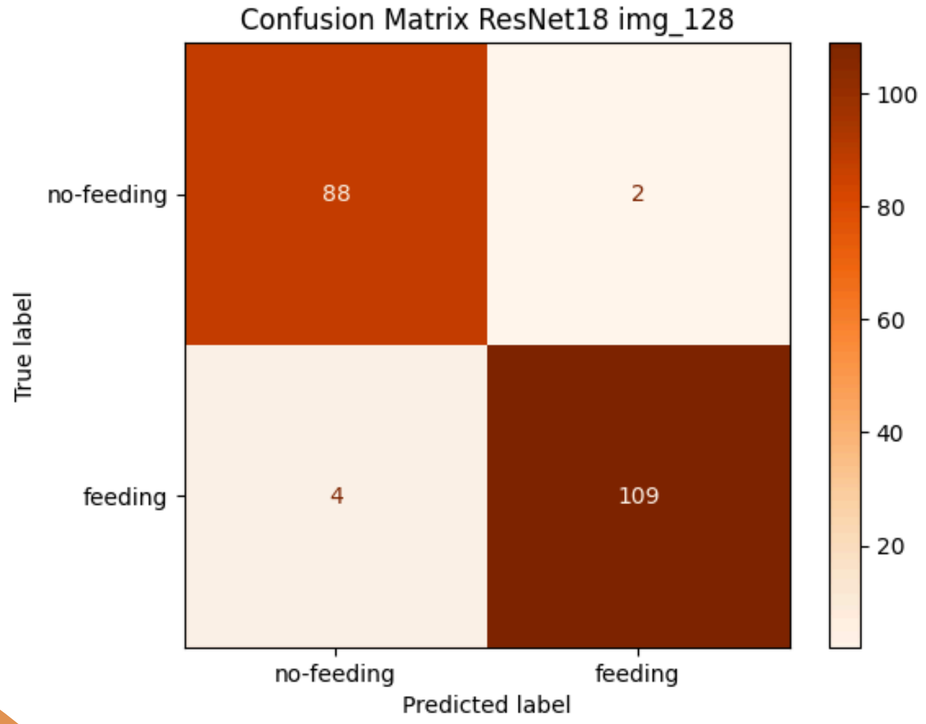
Model	Augmentation	Pooling	F1_score	infer_time[ms]
MobileViT-S	standard_256	AdaAvgPooling	0,9573	36,51
MobileViT-S	crop_256	AdaAvgPooling	0,9304	37,08
MobileViT-S	standard_256	Attn Pooling	0,9286	37,79
MobileViT-S	crop_256	Attn Pooling	0,9381	38,25
MobileViT-XS	standard_256	AdaAvgPooling	0,9386	28,61
MobileViT-XS	crop_256	AdaAvgPooling	0,9298	29,47
MobileViT-XS	standard_256	Attn Pooling	0,9565	28,63
MobileViT-XS	crop_256	Attn Pooling	0,9369	30,13
MobileViT-XXS	standard_256	AdaAvgPooling	0,9292	11,23
MobileViT-XXS	crop_256	AdaAvgPooling	0,9442	11,02
MobileViT-XXS	standard_256	Attn Pooling	0,9196	11,49
MobileViT-XXS	crop_256	Attn Pooling	0,9316	11,15
MINI_CNN	standard_256	AdaAvgPooling	0,9474	27,88
MINI_CNN	crop_256	AdaAvgPooling	0,9298	27,5
MINI_CNN	standard_256	Attn Pooling	0,9487	27,26
MINI_CNN	**crop_256**	**Attn Pooling**	**0,9617**	**26,94**

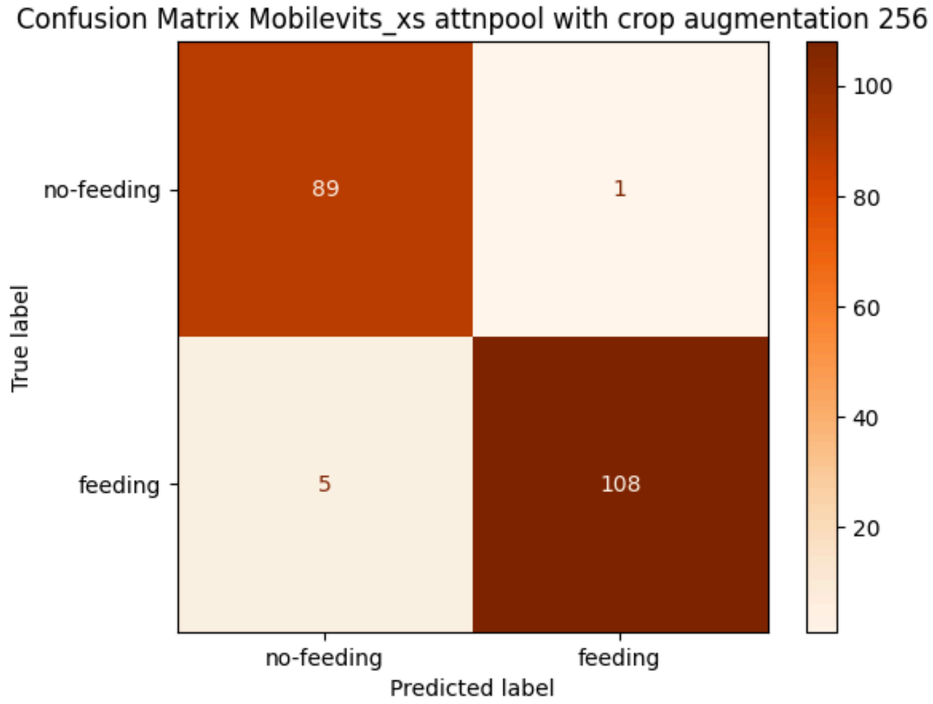
The best performance for input size: 512

Model	Augmentation	Pooling	F1_score	infer_time[ms]
MobileViT-S	standard_512	AdaAvgPooling	0,9565	164,01
MobileViT-S	crop_512	AdaAvgPooling	0,9397	166,38
MobileViT-S	standard_512	Attn Pooling	0,9524	165,28
MobileViT-S	**crop_512**	**Attn Pooling**	**0,9652**	**172,57**
MobileViT-XS	standard_512	AdaAvgPooling	0,9524	131,8
MobileViT-XS	crop_512	AdaAvgPooling	0,952	134,01
MobileViT-XS	standard_512	Attn Pooling	0,9279	136,07
MobileViT-XS	crop_512	Attn Pooling	0,9407	137,4
MobileViT-XXS	standard_512	AdaAvgPooling	0,9524	60,28
MobileViT-XXS	crop_512	AdaAvgPooling	0,9558	58,66
MobileViT-XXS	standard_512	Attn Pooling	0,9437	59,47
MobileViT-XXS	crop_512	Attn Pooling	0,9487	56,93
MINI_CNN	standard_512	AdaAvgPooling	0,9524	113,27
MINI_CNN	crop_512	AdaAvgPooling	0,9483	115,44
MINI_CNN	standard_512	Attn Pooling	0,9492	115,06
MINI_CNN	crop_512	Attn Pooling	0,9478	112,98

Lightweight Models vs Heavy Models

Model	Pooling	Augmentation	N_Parameters	Accuracy	F1-score	avg_infer_time[ms]
ResNet_18	AdaAvgPooling	standard_128	11.169.858	**0,9704**	0,9732	**84,72**
MobileViT-xxs	Attn Pooling	crop_256	1.040.898	0,9655	0,9692	11,03
MobileViT-xs	Attn Pooling	crop_256	2.068.858	**0,9704**	0,973	**29,19**
MobileViT-S	Attn Pooling	crop_256	5.327.074	0,9652	9.683	32,87





Future works

We want to minimize the false negatives for **welfare of silkworms**

Predict label ⟶ no-feeding

True label ⟶ feeding

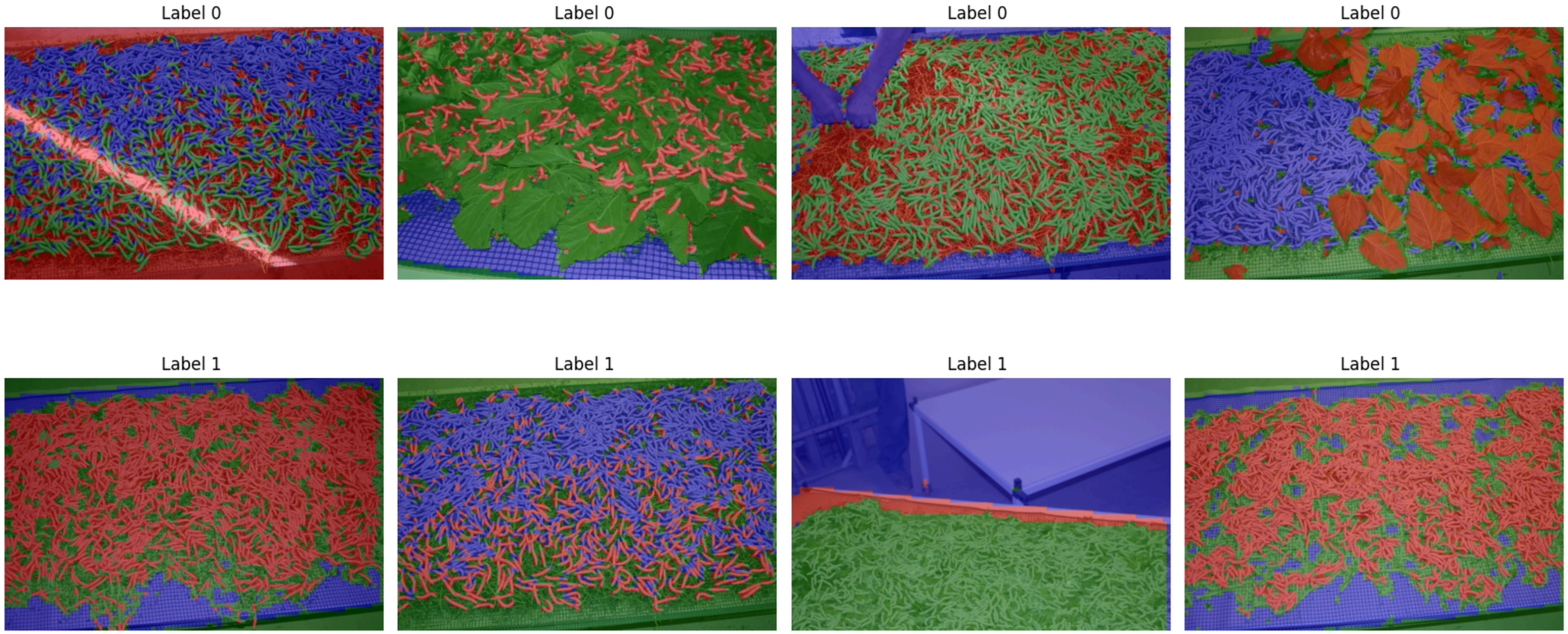
How to do this ?

Hyperparameter tuning to maximize the **recall**

$$\text{Recall} = \frac{TP}{TP + FN}$$

Results of semantic segmentation

Model output of some **representative examples:**



- Noisy backgrounds introduce segmentation confusion
- When a semantic class is missing from the image, the model overestimate the number of clusters

Future works

📌 Automitize the choice of n_clusters that **maximize** the **silhoutte score**

👁 **missing the leaves case**

n_clusters=2 ❓

DINO(ResNet50)_layer3 2clusters Sil_Score: 0.1667

Sil_score=0.17 👍

n_clusters=3 ❓

DINO(ResNet50)_layer3 3clusters Sil_Score: 0.0838

Sil_score=0.08 👎

📌 Let’s test the method to ensure that it doesn’t underestimate clusters when classes are well separated

👁 **All the classes are present case**

n_clusters=2 ❓

DINO(ResNet50)_layer3 2clusters Sil_Score: 0.0425

Sil_score=0.04 👎

n_clusters=3 ❓

DINO(ResNet50)_layer3 3clusters Sil_Score: 0.0753

Sil_score=0.07 👍

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Thanks for your attention

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