Bringing Computer Vision and AI to the Orchard:

Four Case Studies in Fruit Cultivation

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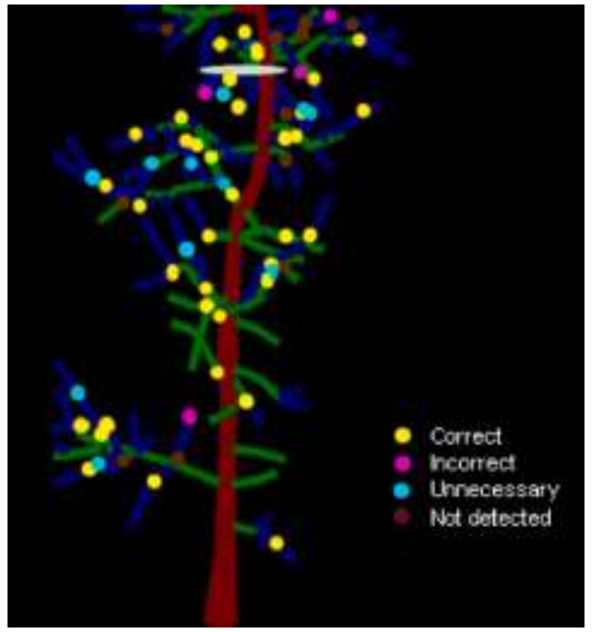
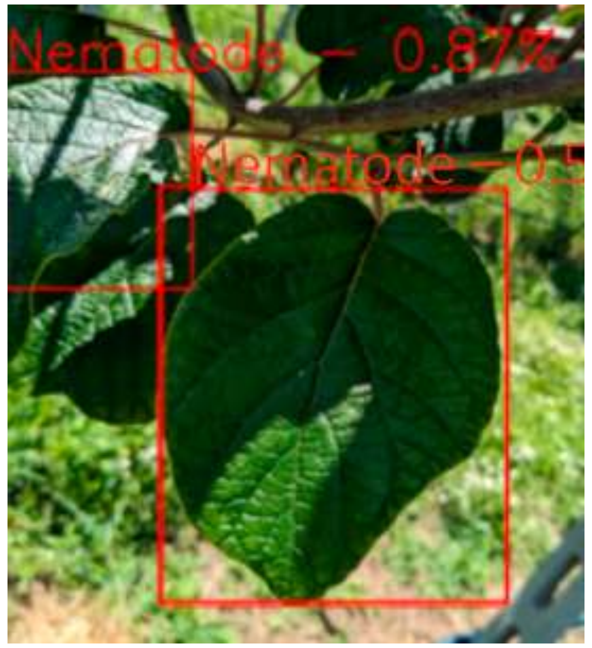
1st Workshop on Computer Vision and Artificial Intelligence in Fruit Cultivation
SoftCOM2025, 18-20 September, 2025, Split, Croatia

Outline





Meet MLV

Our mission is to develop and promote machine learning and computer vision cutting-edge technologies in any discipline.

Grapes

General guidelines for the application of computer vision in precision viticulture tasks.

Pomegranate

Comparative performance evaluation of deep learning models for pomegranate quality assessment.

Cherries

A vision-based pruning algorithm for cherry tree structure elements segmentation and exact pruning points determination

Kiwifruits

A vision-based pruning algorithm for cherry tree structure elements segmentation and exact pruning points determination

Machine Learning & Vision Research Group

MACHINE LEARNING & VISION RESEARCH GROUP

DEMOCRITUS UNIVERSITY OF THRACE

1. HISTORY

Founded in 2021 by Prof. George A. Papakostas in the Department of Informatics. Since March 13, 2024, it is part of the Democritus Univeristy of Thrace, Kavala, Greece.

Est. 2021

2. MEMBERS

41 Members, including:
3 Professors, 1 Teaching Staff, 5 PostDocs, 11 PhDs, 11 Master Students, 10 BSc students.

41 members

3. COLLABORATIONS

6 Collaborations including:
1 Enterprise, 1 Greek University, 4 Universities abroad.

6 collaborations

4. RESOURCES

16 Public repositories including open image datasets and open codes.
2 National patents.

16 open resources
2 patents

5. AWARDS

6 Awards including:
3 Best paper awards, 2 Publications selected as issue covers, 1 Proposal distinction in the 1st Innovation Competition of the Ministry of National Defense

6 awards

6. RESEARCH

6 Competitive research programs within the last 5 years, total budget of 4.956.841,1 €.

6 projects

7. PUBLICATIONS

112 Pulished works, including:
57 Journals, 42 Conf. Proceedings, 8 Book Chapters, 5 Books.
6 Special issues organized.

112 publications
6 special issues

8. DISTINCTIONS

The Head of MLV included in the 2% of top researchers worldwide for 2022 and 2023 in the field "Artificial Intelligence & Image Processing" based on the database of Stanford University.

2% top researcher

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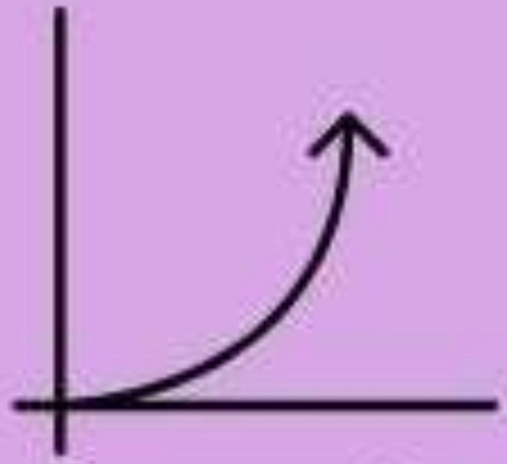

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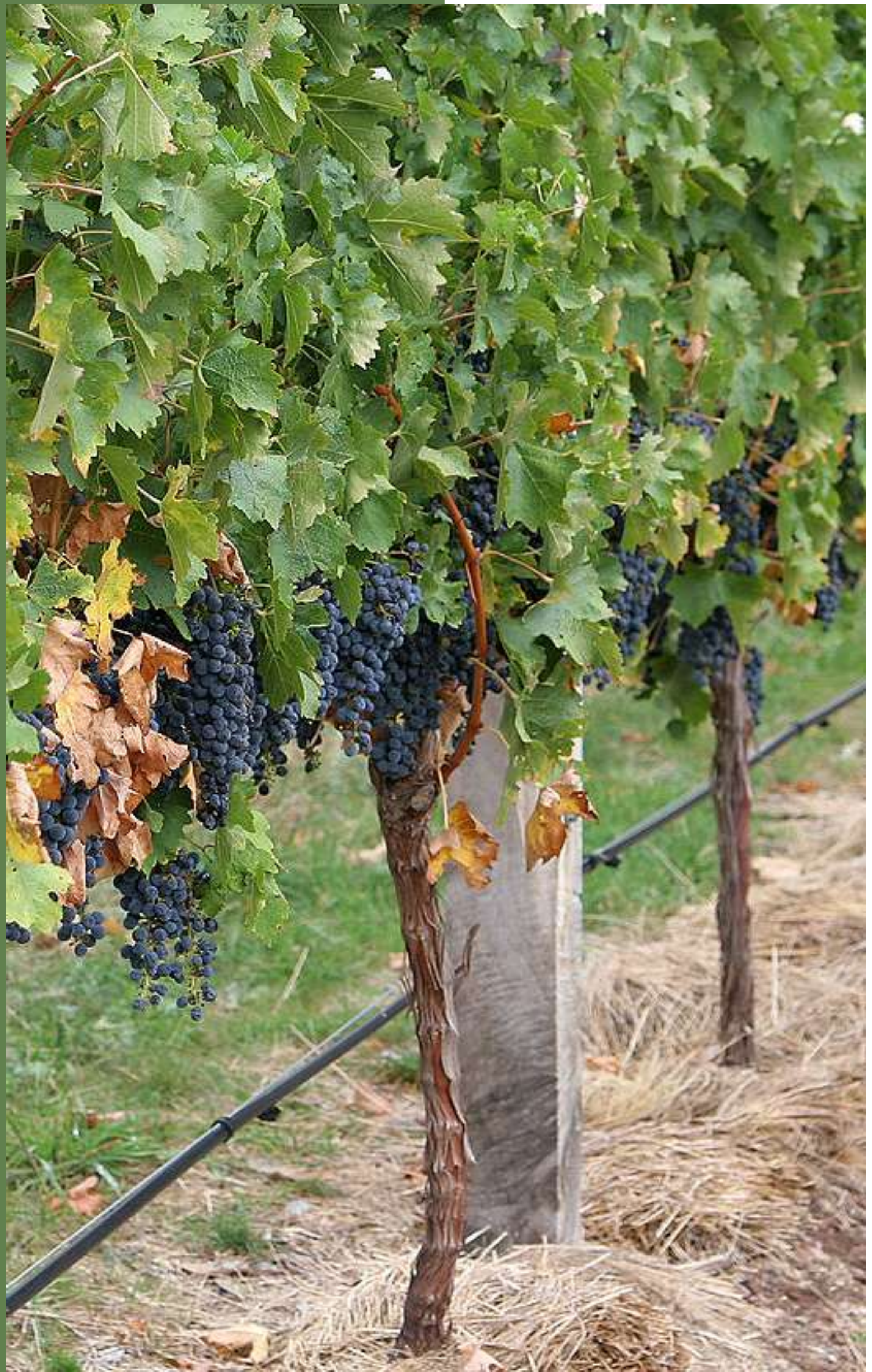
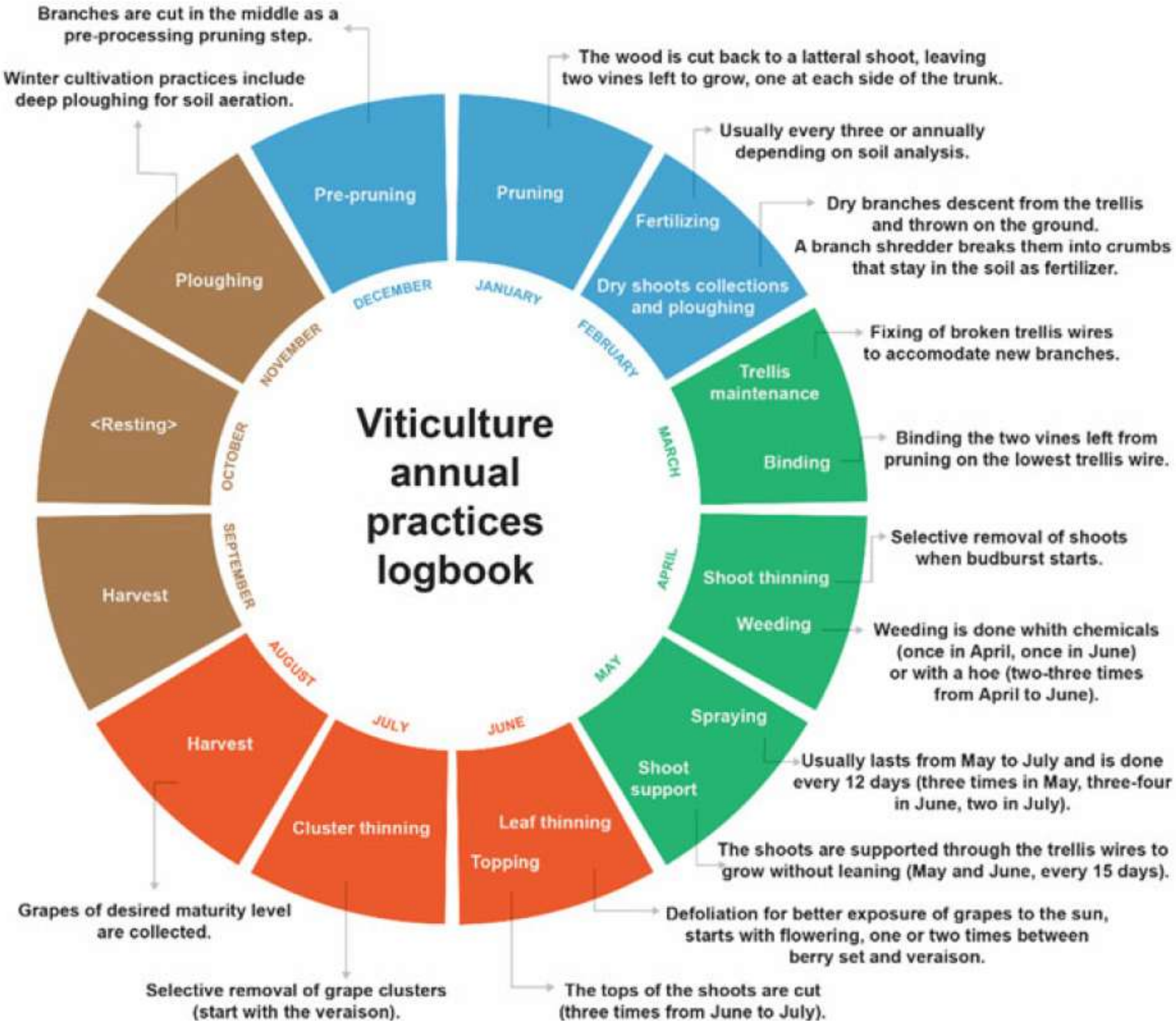


Grapes

Grapes

Identification of viticulture practices over the year

Even if there are deviations in time, the phases remain the same, making it possible to provide the basic frameworks for work activities in the vineyard.



Grapes

Towards Computer Vision-Based Automated Logbook

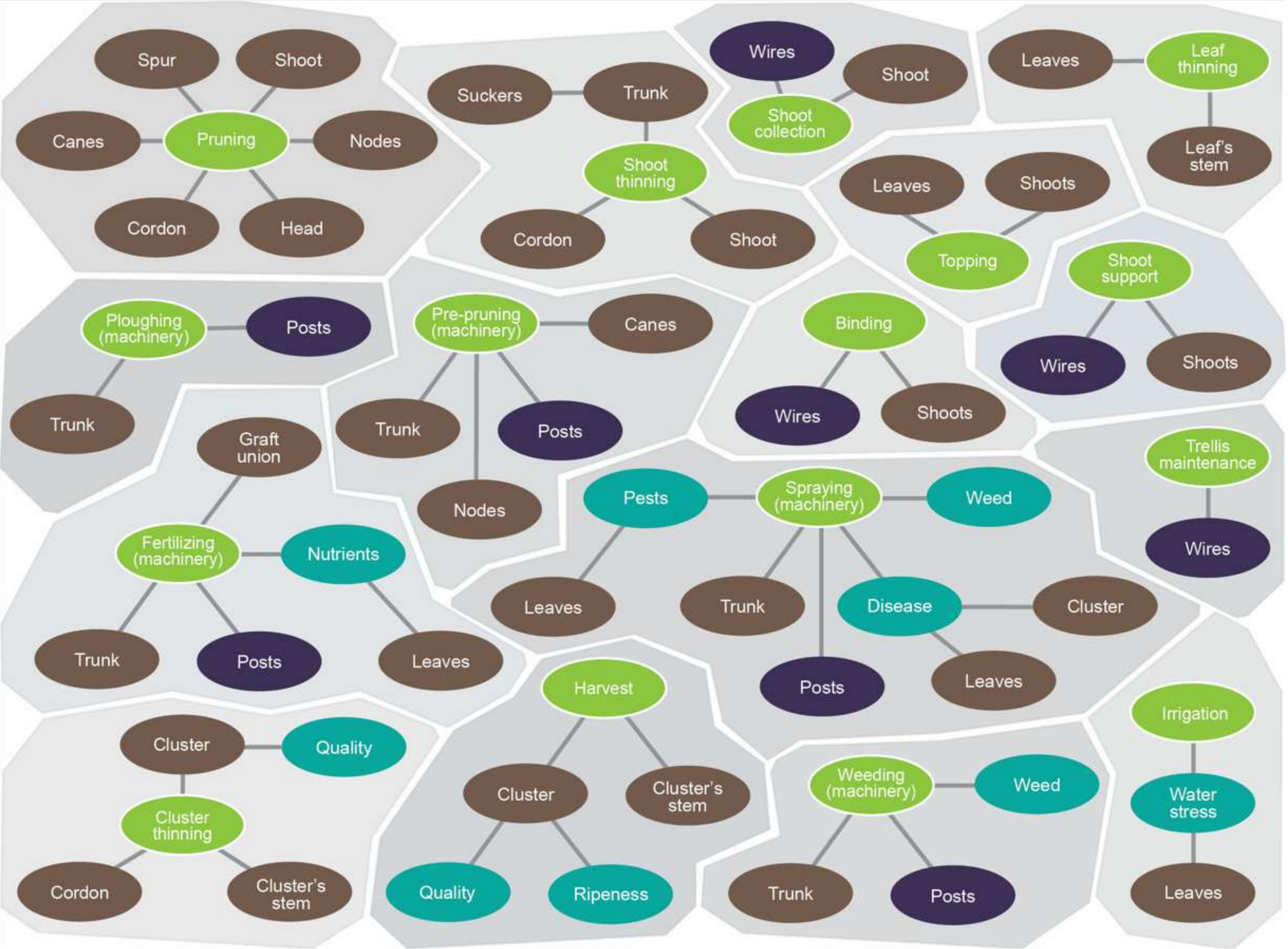
Current status of computer vision in overall implementation of precision viticulture practices (2013–2023).

Computer vision for vine/grape/vineyard	Number of papers
Pre-pruning	0
Pruning	3
Fertilizing	0
Dry shoots collection	0
Ploughing	0
Trellis maintenance	0
Binding	0
Shoot thinning	3
Weeding	1
Spraying	0
Shoot support	0
Leaf thinning	1
Topping	0
Cluster thinning	1
Harvest	1
Irrigation	0

Grapes

Relation of computer vision subtasks towards automation of all annual viticulture practices

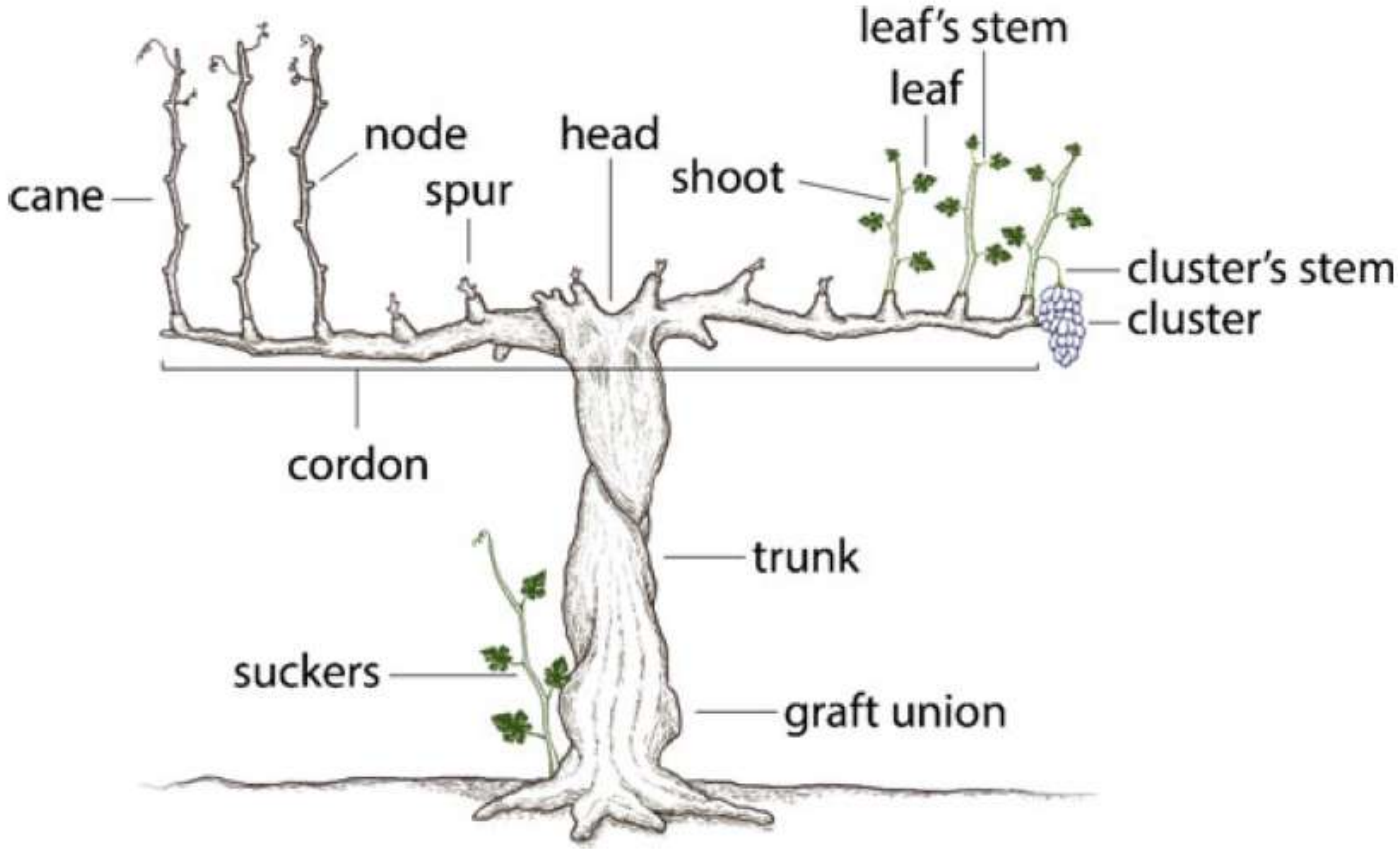
Viticulture practices are in green, detection subtasks related to plants phenology are in brown, detection subtasks related to vineyard structural elements are in dark blue, and supplementary detection subtasks are in veraman.



Grapes

Identified research gap in computer vision-based viticultural tasks

Detection of the basic parts of the vine tree, of the structural elements of a vineyard and supplementary detection subtasks, could form a set of preliminary computer vision subtasks that need to be implemented towards the automation of the basic viticultural practices.



Viticultural task	Identified research gap
Pre-pruning	• Indication of exact cutting point by detecting and counting the nodes on each cane • Indication of specified cutting height from the top of the vine
Pruning	• Efficient cordon/crown and canes detection methodologies • Determination of canes thickness to guide cutting actions (tool selection and force)
Fertilizing	• Graft union detection for targeted application • Nutrients detection in soil • Efficient nutrients detection in foliage
Dry shoots collection	• Detection of attachment points of cut shoots to each other • Detection of attachment points of cut shoots to the wires
Ploughing	–
Trellis maintenance	• Detection of cut trellis wires • Detection of loose wires
Binding	• Detection and orientation of shoots • Parallelization of shoots to the wire
Shoot thinning	• Detecting and counting shoots in both directions of the cordon • Detection of suckers on the trunk
Weeding	• Intra-row weeding control
Spraying	• Detection of grape clusters zone • Detection of defected leaf/cluster areas
Shoot support	• Detection of shoots and vertically orient them between horizontal wires
Leaf thinning	• Detection of grape clusters zone • Detection of leaves stems
Topping	• Detection and counting of leaves at each shoot
Cluster thinning	• Detection and counting of all clusters in the cordon in both directions
Harvest	• Efficient ripeness estimation methodologies • Efficient quality assessment methodologies
Irrigation	• Efficient water stress detection in leaves

Grapes

Detection of Vine Parts

Vine Trunk Detection
Spur Detection
Shoot Detection
Nodes (or Buds) Detection
Canes Detection
Cordon Detection
Head Region Detection
Leaves Detection
Leaves Stem Detection
Grape Cluster Detection
Grape Stem Detection
Graft Union Detection
Suckers Detection

Structural Elements Detection

Trellis wires Detection
Posts (or poles) Detection

Supplementary Detection Subtasks

Nutrients Detection
Ripeness Estimation
Quality Assessment
Water Stress Detection
Disease Detection
Pest Detection
Weed Detection

For more insights…

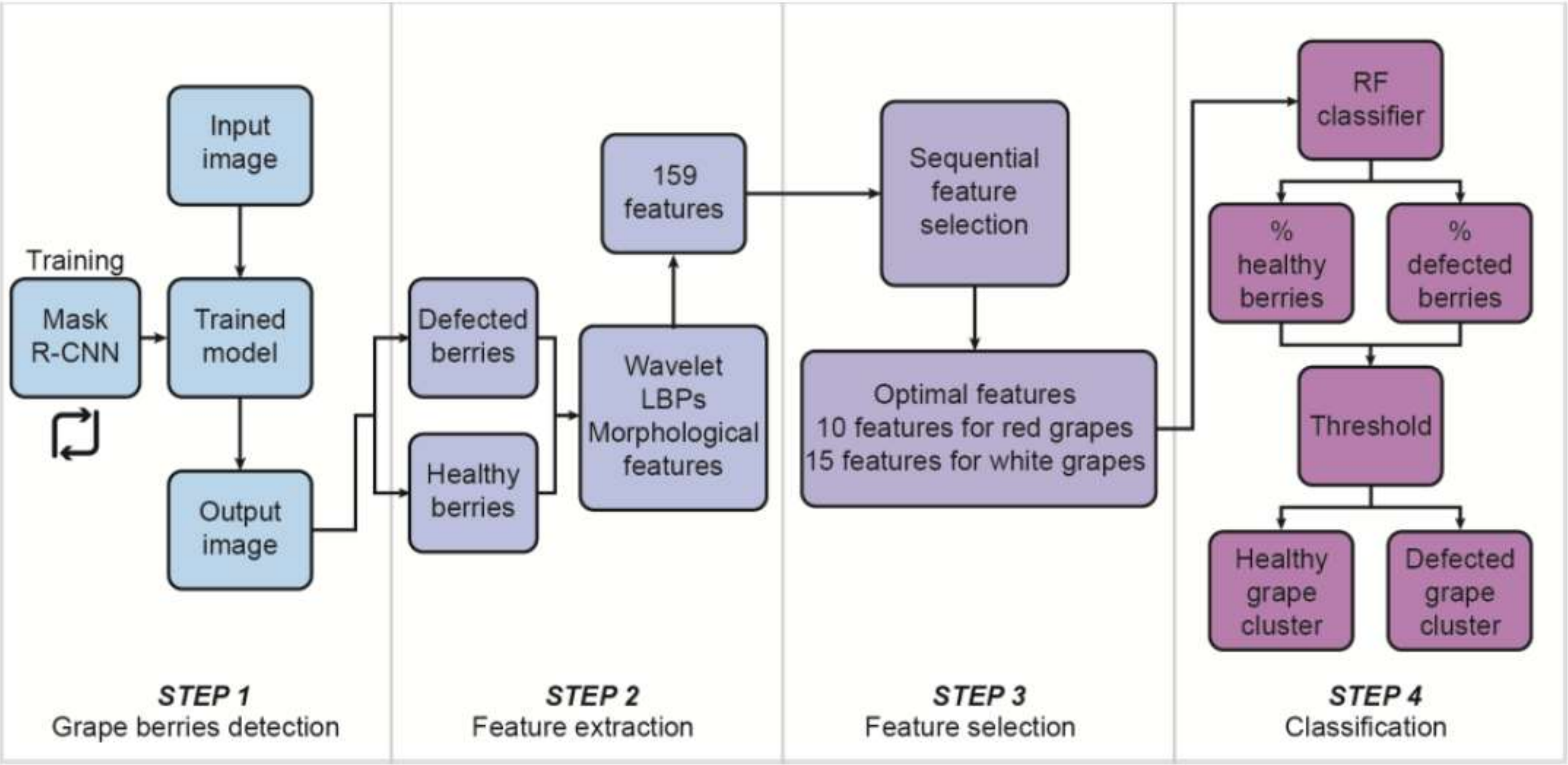
Vrochidou, E., Papakostas, G.A. (2023). Leveraging Computer Vision for Precision Viticulture. In: Bansal, J.C., Uddin, M.S. (eds) Computer Vision and Machine Learning in Agriculture, Volume 3. Algorithms for Intelligent Systems. Springer, Singapore. https://doi.org/10.1007/978-981-99-3754-7_13

Grapes

Case study: Grape quality assessment

The proposed method consists of four main steps:
(1) grape berries detection,
(2) feature extraction,
(3) Feature selection and
(4) classification.

The objective is to detect all berries in a grape cluster and classify them as healthy or defected based on descriptive features. Classification results on each cluster derive a healthy-defected berries ratio, upon which the user, by introducing a threshold, can decide on the overall quality of the cluster.

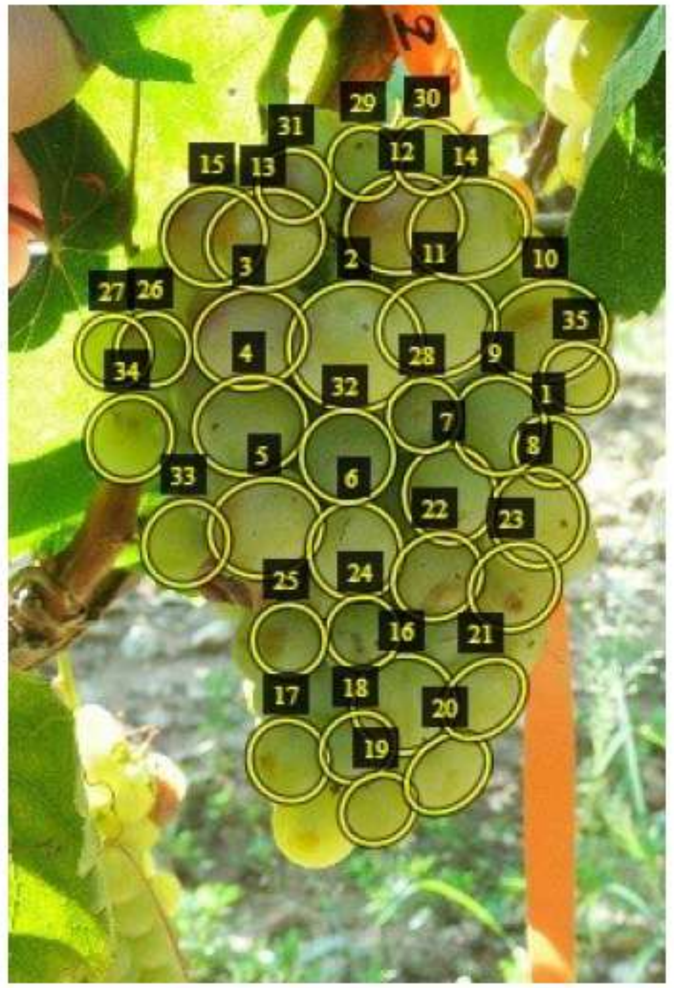


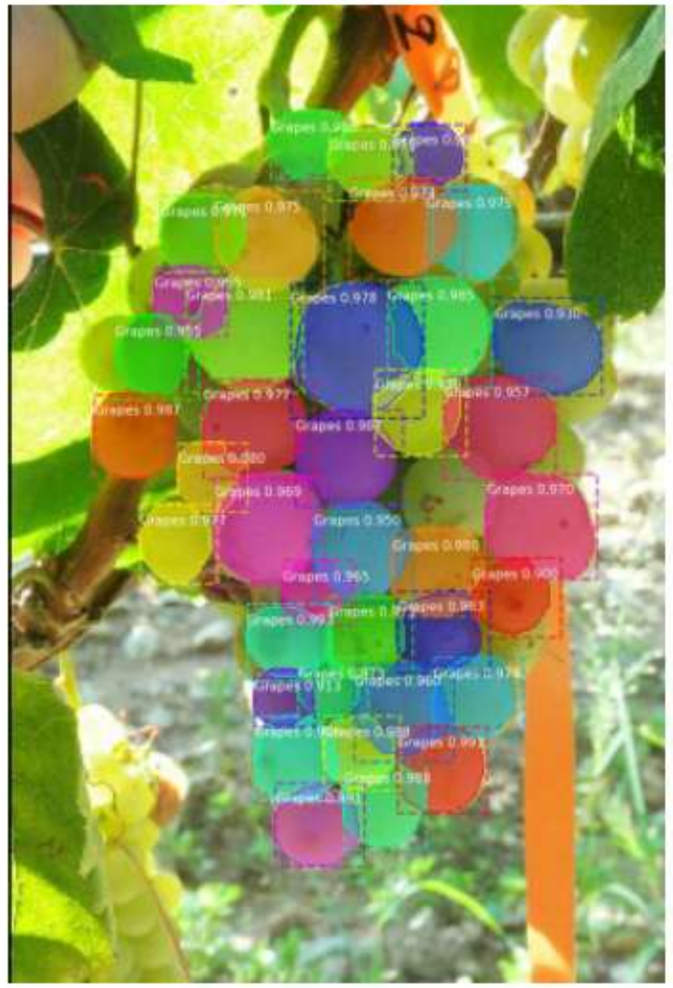
Grapes

Novelties

(1) the introduction of a methodology for the automation of cluster thinning for the first time and
(2) the visual quality assessment of grape clusters by working on a berry scale.

The proposed method constitutes a small step being taken towards the pre-harvest quality improvement practice of automated cluster thinning in vineyards.





For more insights…

T. Kalampokas, **E. Vrochidou** and G. A. Papakostas, "Machine Vision for Grape Cluster Quality Assessment," 2022 International Conference on Applied Artificial Intelligence and Computing (ICAAIC), **2022**, pp. 916-921, https://doi.org/10.1109/ICAAIC53929.2022.9792817

Pomegranate

Pomegranate

Scope:

Instead of training a network from the beginning, in this work, pre-trained open-source learning models were used and fine-tuned.

Here, 14 Convolutional Neural Networks (CNNs) models are considered and tested on the acquired dataset for pomegranate quality assessment:
MobileNet, ResNet50, InceptionV3, Xception, DenseNet121, DenseNet169, DenseNet201, NASNet Mobile, VGG16, VGG19, ResNet101, ResNet152, MobileNetV2 and ResNet50V2

Indicative images from the dataset: Three classes corresponding to three quality grades: Class 1 - Quality A, Class 2 - Quality B and Class 3 - Quality C.

Contributions:

(1) the introduction of a novel image dataset of pomegranate fruits of three different quality grades related to their intended use, and
(2) a comparative performance evaluation of 14 well-known deep learning models for pomegranate quality assessment, in the introduced dataset. Grad-CAM algorithm was used for interpretability.

Pomegranate

Results

The most defected area of the fruit is taken under consideration.

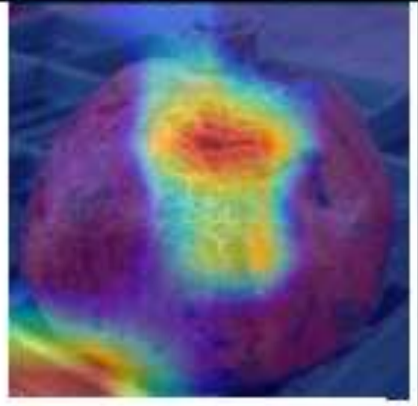
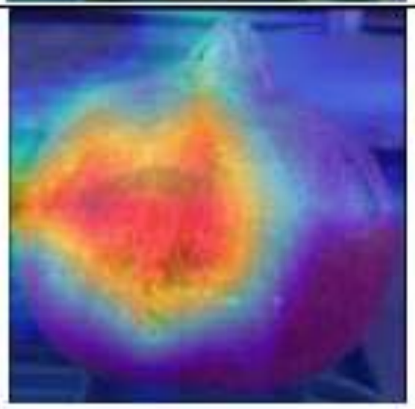
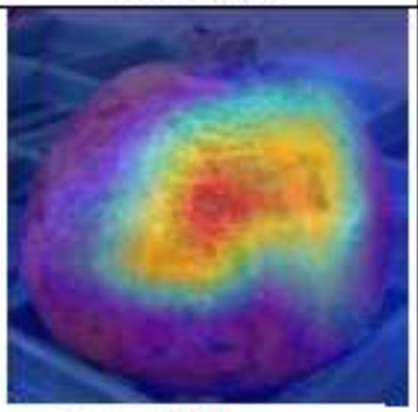
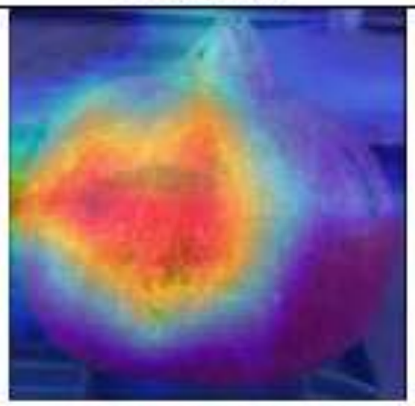
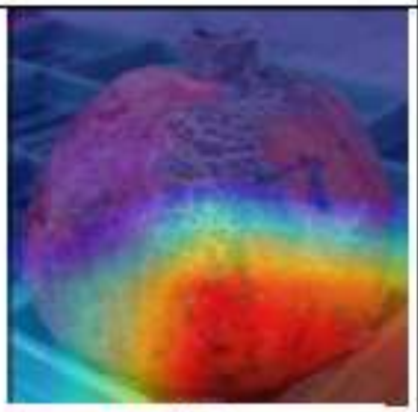
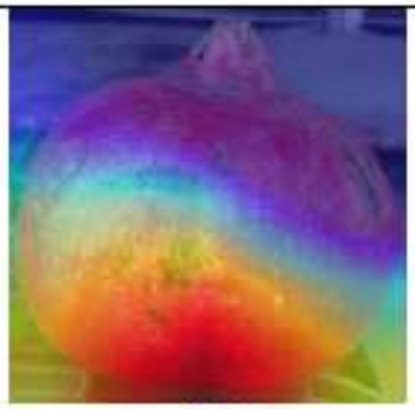
Classification performances of up to 94.12% for the MobileNet model.

Transfer learning could provide accurate results in fruit sorting problems with limited data.

For more insights…

A. Koufatzis, **E. Vrochidou** and G. A. Papakostas, "Visual Quality Inspection of Pomegranate Crop Using a Novel Dataset and Deep Learning," 2022 29th International Conference on Systems, Signals and Image Processing (IWSSIP), 2022, pp. 1-4, https://doi.org/10.1109/IWSSIP55020.2022.9854435

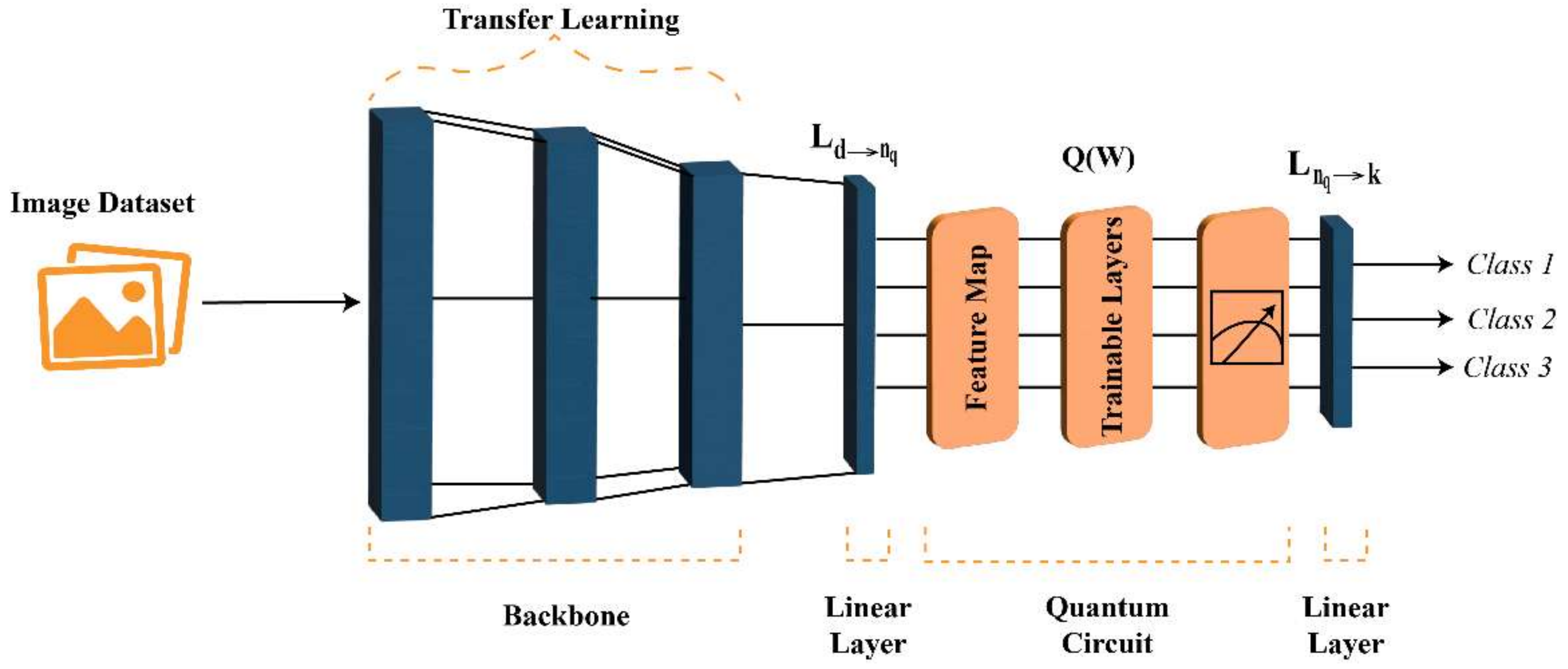
Model	**Accuracy**
MobileNet	**94.12%**
ResNet50	84.97%
InceptionV3	**91.50%**
Xception	90.85%
DenseNet121	86.93%
DenseNet169	89.54%
DenseNet201	87.58%
NASNet Mobile	80.39%
VGG16	88.24%
VGG19	85.62%
ResNet101	86.27%
ResNet152	90.20%
MobileNetV2	81.70%
ResNet50V2	**93.46%**

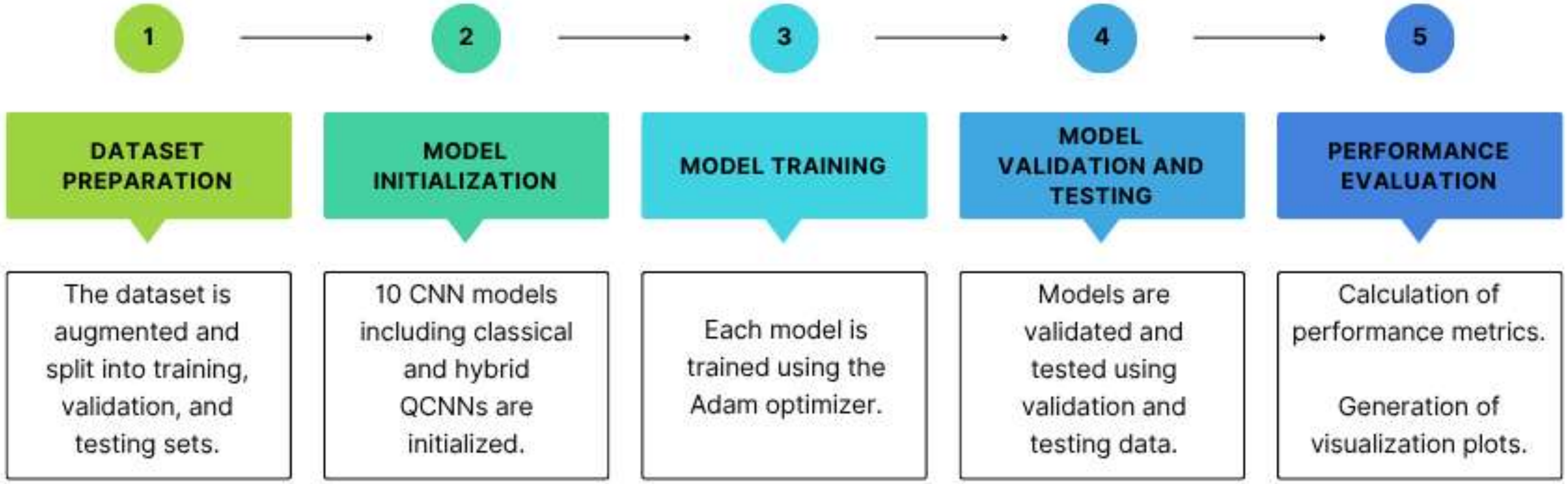
	Image 1	**Image 2**
Model		
MobileNet	 Confidence 99.90%	 Confidence 99.38%
ResNet50V2	 Confidence 100%	 Confidence 98.60%
InceptionV3	 Confidence 99.86%	 Confidence 99.90%

Pomegranate

Quantum-Assisted Visual Quality Assessment of Pomegranates Using Hybrid Transfer Learning

Hybrid transfer learning towards visual quality assessment of pomegranates.
Performance comparison of 10 QCNNs with the corresponding classic Convolutional Neural Networks (CNN).





The term $L_{d \to n_q}$ is the classical projection from CNN feature map to qubit inputs, $Q(W)$ is the parameterized variational quantum circuit and $L_{n_q \to k}$ is the classical linear layer that turns the variational circuit measurement into k classes estimation.

Pomegranate

Results

In the testing phase, quantum models outperformed classical CNNs in 7 out of 10 cases, indicating that the QCNNs are more capable of capturing essential generalization patterns.

Hybrid CQ transfer learning can achieve competitive results with the traditional CNN, despite minor differences in training or validation performance.

Overall, findings confirm that hybrid classical-quantum transfer learning is a viable and competitive approach for real-world agricultural tasks, especially when leveraging powerful, pretrained feature extractors.

Model	Validation		Training		Testing			
	Accuracy	Loss	Loss	Accuracy	Accuracy	Precision	Recall	F1-score
ResNet-152	0.923	0.238	**0.047**	**0.991**	0.924	0.893	0.901	0.896
ResNet-101	0.921	0.238	0.074	0.988	0.909	0.877	0.875	0.876
ResNet-50	0.932	0.215	0.095	0.981	0.907	0.884	0.877	0.879
ResNet-50-v2	0.932	0.188	0.086	0.981	0.922	0.897	0.895	0.895
VGG19	0.867	0.357	0.287	0.891	0.875	0.886	0.845	0.861
VGG16	0.847	0.465	0.279	0.891	0.877	0.881	0.846	0.859
DenseNet-201	**0.939**	**0.187**	0.115	0.958	**0.928**	**0.901**	**0.906**	**0.903**
DenseNet-169	0.932	0.208	0.147	0.955	0.913	0.881	0.899	0.883
DenseNet-121	0.908	0.273	0.227	0.927	0.921	0.908	0.897	0.902
MoblieNet-v2	0.908	0.277	0.233	0.913	0.905	0.907	0.864	0.882

QCNN Model	Validation		Training		Testing			
	Accuracy	Loss	Loss	Accuracy	Accuracy	Precision	Recall	F1-score
ResNet-152	0.915	0.268	0.069	0.981	0.924	0.892	0.893	0.892
ResNet-101	0.919	0.255	0.056	0.985	0.909	0.881	0.876	0.879
ResNet-50	0.936	0.218	**0.041**	**0.989**	0.915	0.891	0.882	0.885
ResNet-50-v2	**0.936**	**0.211**	0.048	0.986	0.913	0.891	0.891	0.888
VGG19	0.843	0.454	0.349	0.874	0.881	0.898	0.845	0.866
VGG16	0.861	0.468	0.378	0.873	0.877	0.885	0.842	0.861
DenseNet-201	0.928	0.214	0.135	0.958	0.911	0.874	0.881	0.877
DenseNet-169	0.934	0.243	0.155	0.961	**0.943**	**0.929**	**0.918**	**0.923**
DenseNet-121	0.915	0.281	0.173	0.941	0.935	0.931	0.904	0.916
MoblieNet-v2	0.915	0.284	0.191	0.932	0.911	0.901	0.885	0.891

Model	Validation		Training		Testing	
	QCNN	CNN	QCNN	CNN	QCNN	CNN
ResNet-152	0	1	0	1	0	1
ResNet-101	0	1	1	0	1	0
ResNet-50	1	0	1	0	1	0
ResNet-50-v2	0	1	1	0	0	1
VGG19	0	1	0	1	1	0
VGG16	1	0	0	1	1	0
DenseNet-201	0	1	0	1	0	1
DenseNet-169	0	1	0	1	1	0
DenseNet-121	1	0	1	0	1	0
MoblieNet-v2	0	1	1	0	1	0

Cherries

Cherries

A vision-based pruning algorithm for cherry tree structure elements segmentation and exact pruning points determination

Contributions

The first machine vision-based complete algorithm following strict and precise pruning rules defined by agronomists for dormant cherry trees of the Central Leader training system. First, multi-class segmentation is performed by testing U-Net with three different feature extraction backbones, so as to detect the best performing combination. Then, precise geometrical calculations take place to locate the exact cutting points on the detected trunks, branches and shoots

. The proposed methodology is the first in the bibliography to propose a vision-based pruning algorithm based on strict pruning rules, and the first methodology to provide performance metrics for both the segmentation of basic tree structural elements, as well as for the determination of exact pruning points.

Moreover, the proposed implementation refers to the Central Leader Training System for dormant cherry trees, which has not been previously reported in the literature.

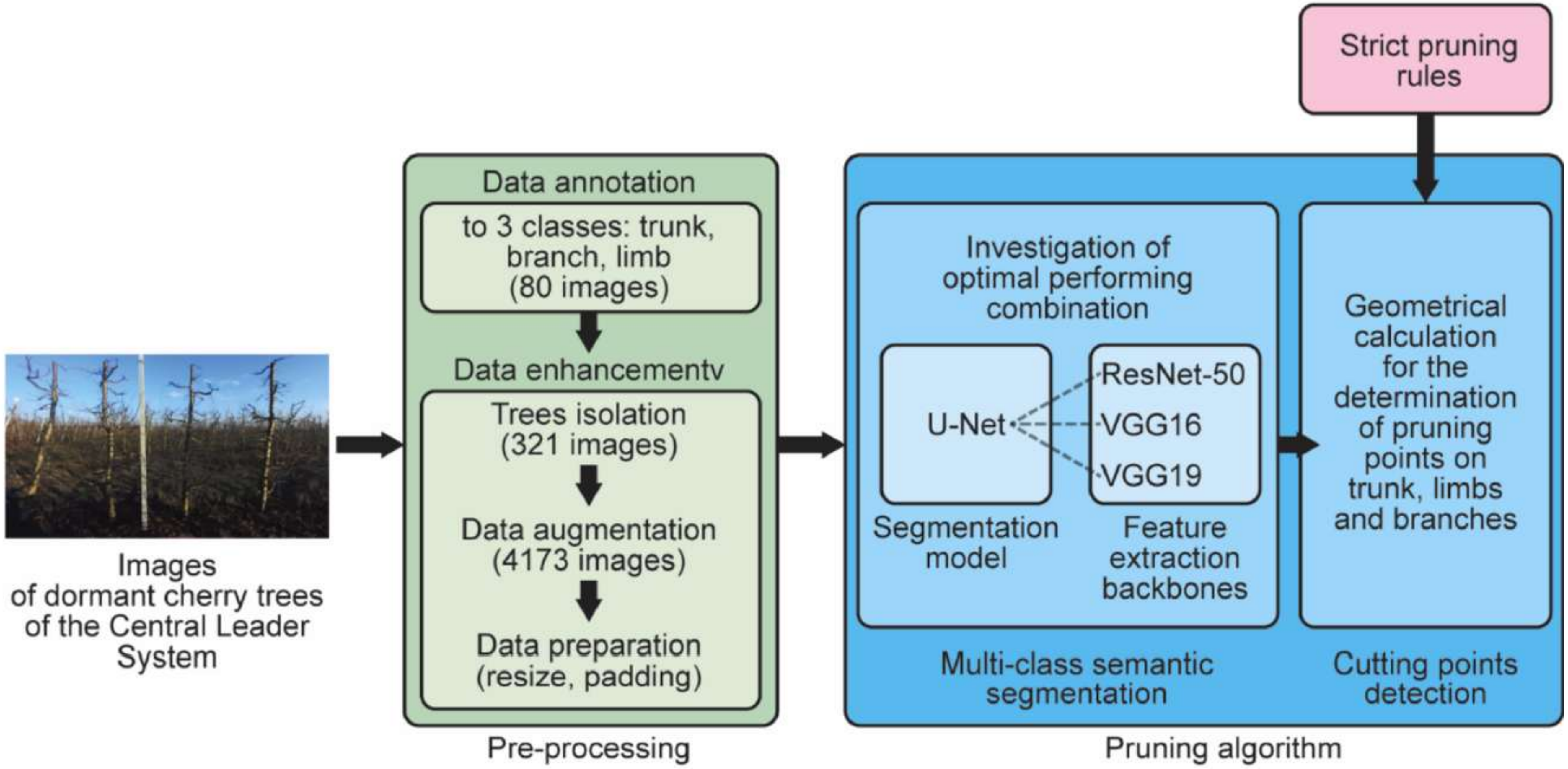
Note that Central Leader Training System is a recent training system for cherries, as well as other trees, that is widely applied in modern orchards today. Moreover, the adopted pruning strategy is for the annual formulation of the tree shape, aiming to cover all types of selective pruning tasks, as well as a highly adaptive methodology.

Cherries

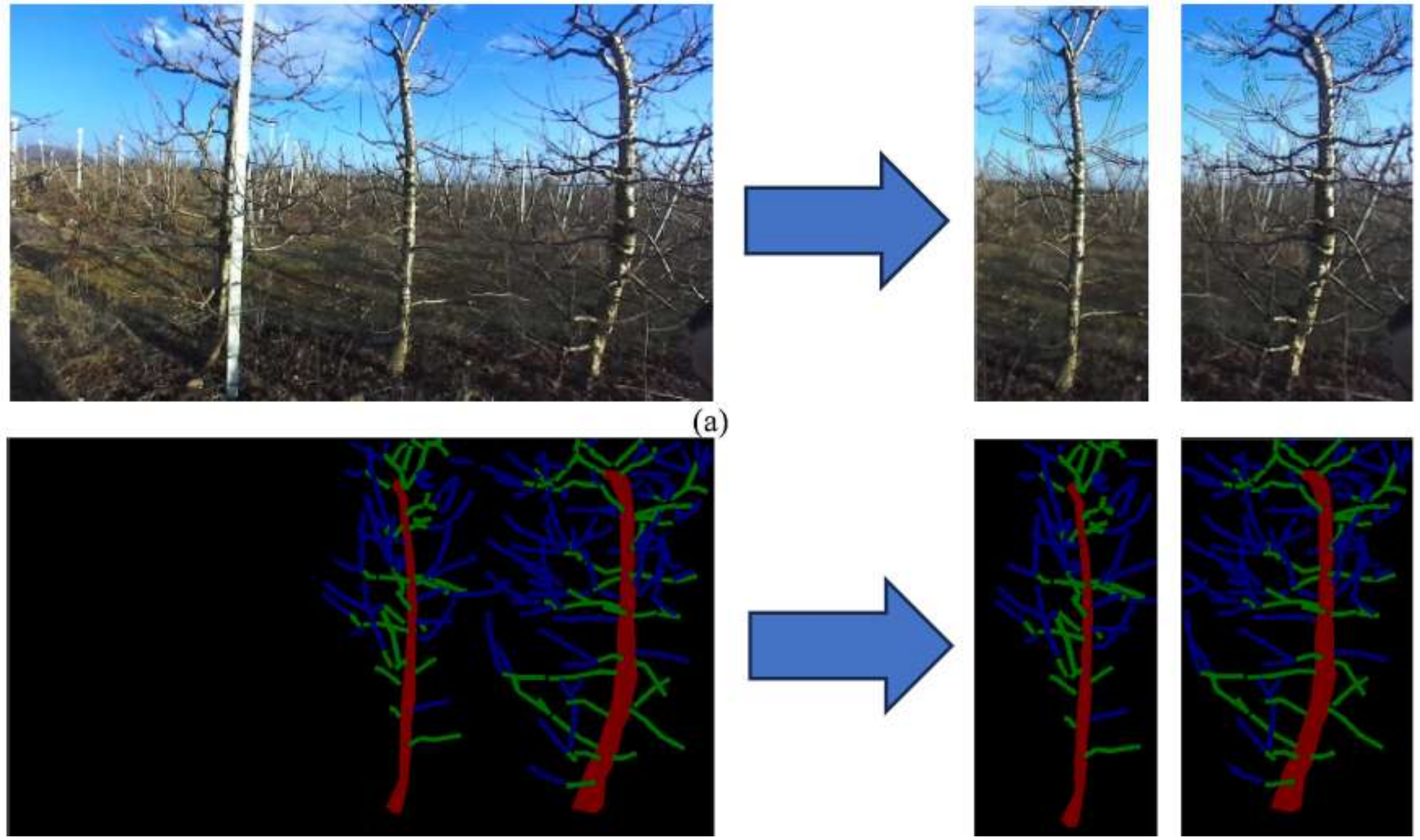
Methodology

The proposed pruning algorithm is based on a multi-class semantic segmentation model (three model combinations are investigated) able to segment the structure of cherry trees without leaves, to distinguish the trunk, thick branches and thin shoots and finally, based on pruning rules and geometric calculations, to accurately locate the exact cutting points for pruning.

Overall, the efficiency of the proposed methodology was tested by:
(1) evaluating the segmentation performance of the model combinations,
(2) evaluating the cutting points determinations on eight tree samples from two different perspectives: (i) expert knowledge, (ii) ground truths.



Cherries



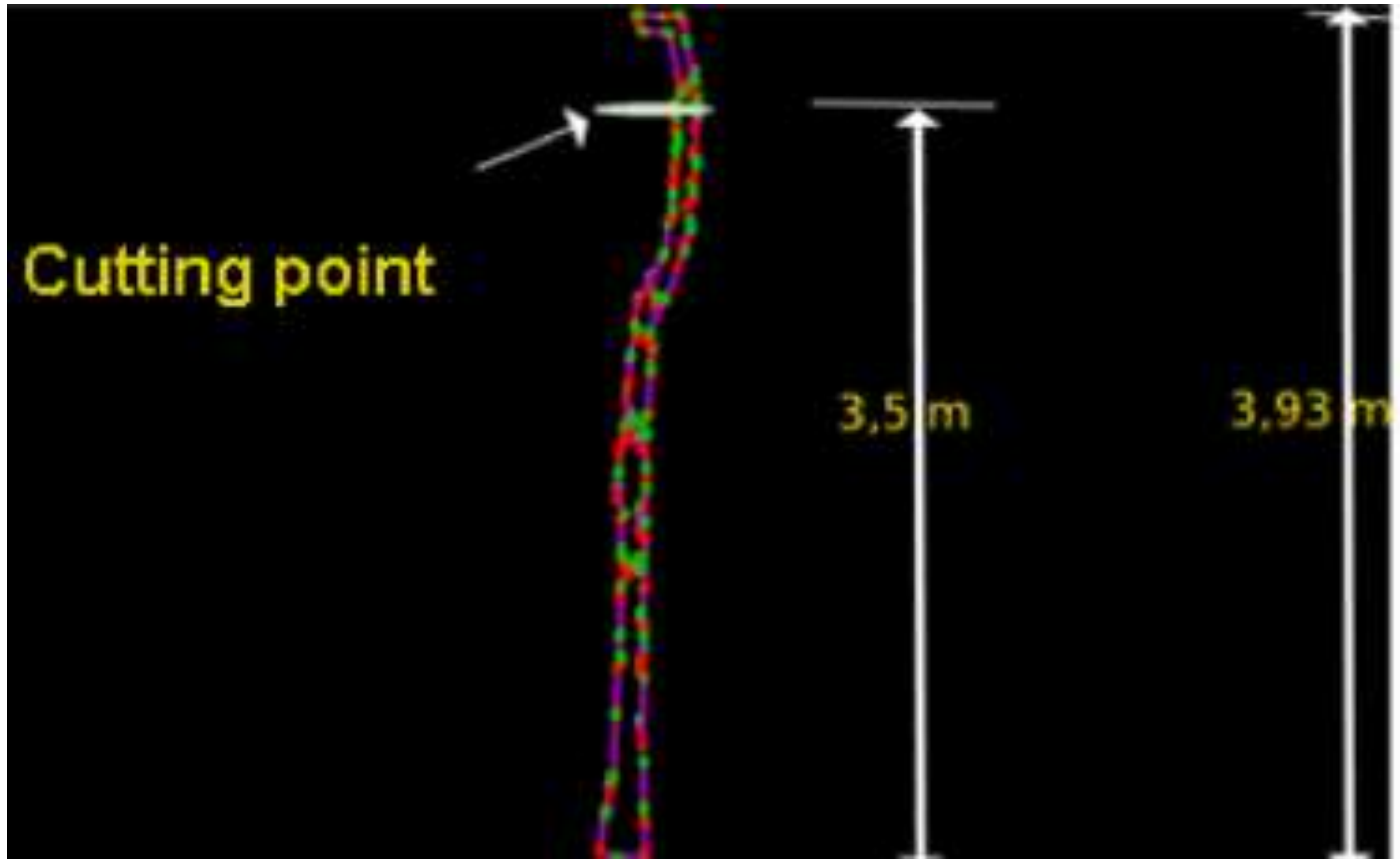
Annotation

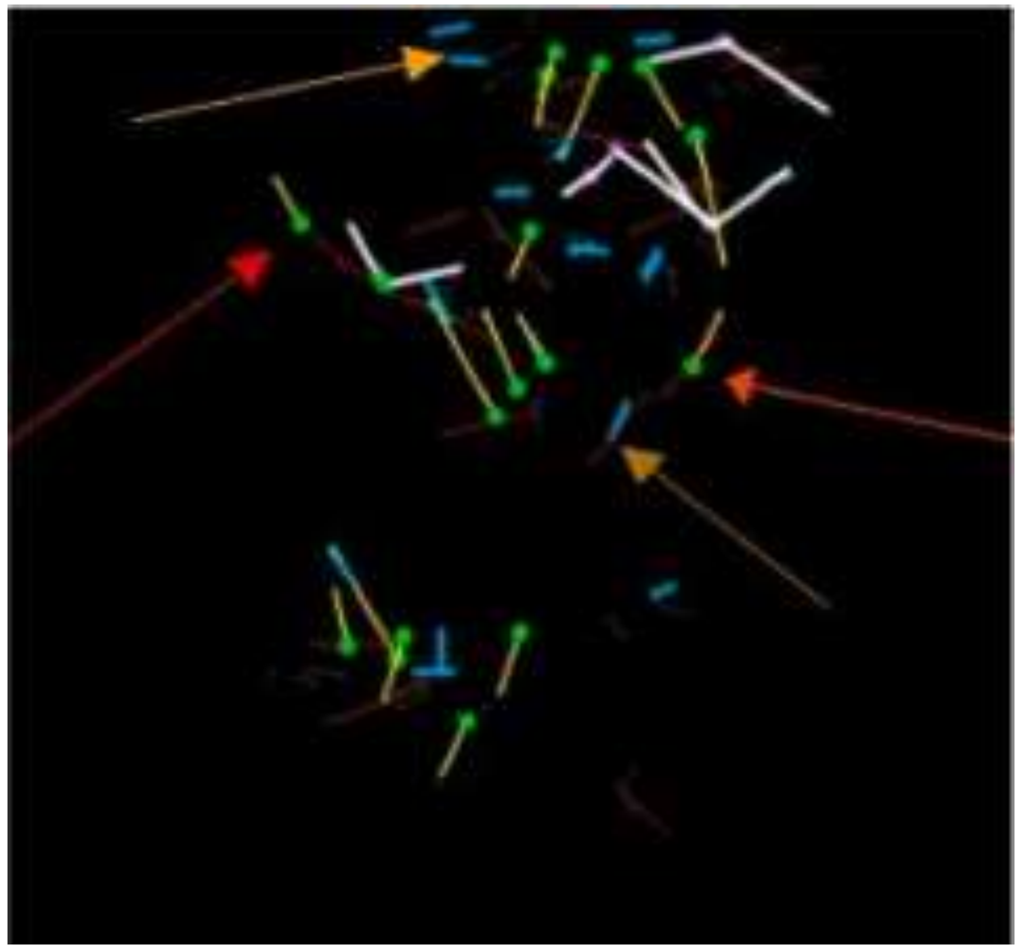
Original image and annotation mask depicting two trees, trunks with red, branches with green, and limbs with blue.

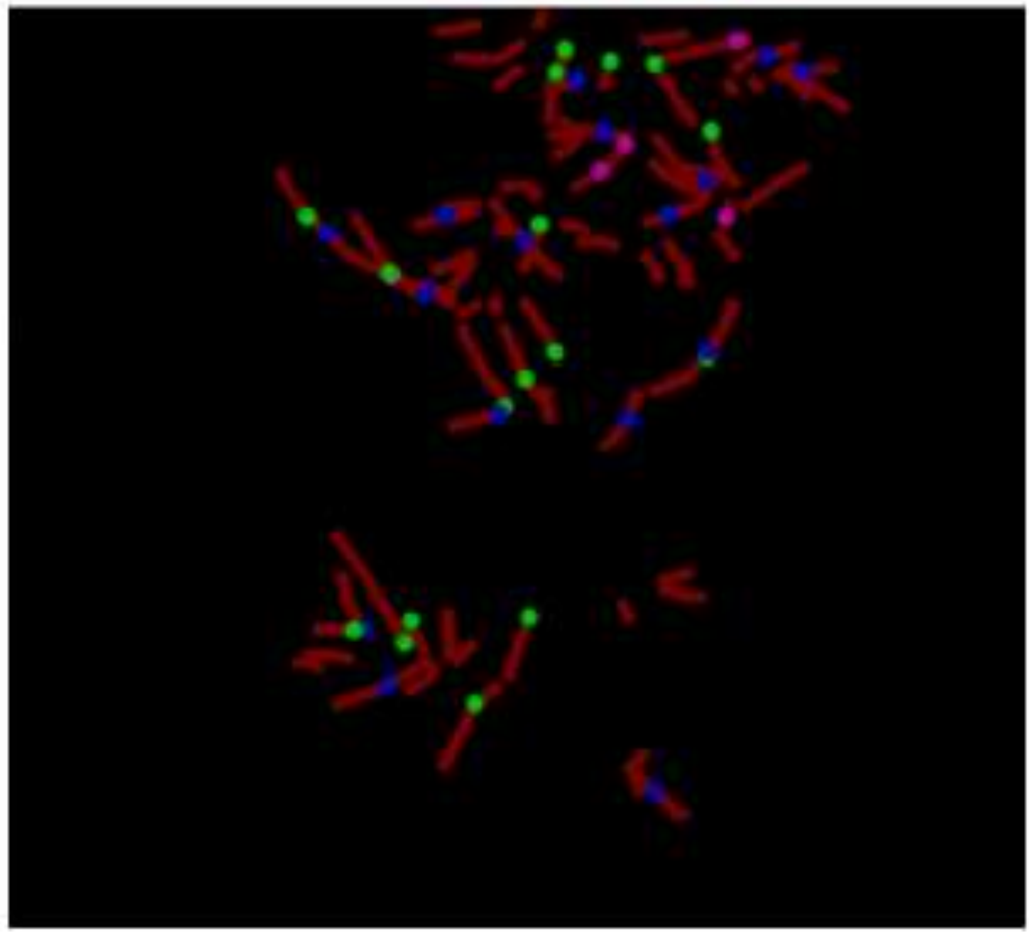
Trees isolation

For the enhancement of the dataset, towards creating images depicting single trees.

Cherries







Segmentation and cutting points determination

On the trunk, branches and limbs, based on strict pruning rules and geometrical calculations.

Cherries

Results

Segmentation results reported an IoU of 98.5 % for three classes (trunk, branches, shoots) by using U-Net with VGG16

Testing performance of segmentation model combinations.

Model combination	Dice loss	Precision	Recall	IoU	F1-score
U-Net_ResNet50	0.0101	0.989	0.989	0.98	0.989
U-Net_VGG16	0.0074	0.992	0.992	0.985	0.992
U-Net_VGG19	0.0079	0.992	0.992	0.984	0.992

Cumulative results for cutting point evaluation in eight tree samples using performance indices.

Part	Precision	Recall	F1-score
Branch	88.75 %	78.02 %	83.04 %
Limb	91.25 %	85.88 %	88.48 %
Trunk	100 %	100 %	100 %
Average performance:	93.33 %	87.97 %	90.51 %

Cumulative results for cutting point evaluation in eight tree samples from an expert agronomist.

Part	Tree sample	Correct cut	Not detected cut	Unnecessary cut	Incorrect cut
Limb	Tree 1	16 (84.21 %)	2	12	1
	Tree 2	35 (83.33 %)	4	21	3
	Tree 3	21 (65.63 %)	9	11	2
	Tree 4	21 (94.45 %)	1	4	0
	Tree 5	29 (72.50 %)	8	10	3
	Tree 6	28 (70.00 %)	9	5	3
	Tree 7	35 (83.33 %)	2	21	5
	Tree 8	34 (87.18 %)	1	25	4
	Total	219 (79.35 %)	36	109	21
Branch	Tree 1	6 (75.00 %)	2	2	0
	Tree 2	9 (69.23 %)	4	1	0
	Tree 3	8 (72.72 %)	2	0	1
	Tree 4	7 (70.00 %)	1	0	2
	Tree 5	7 (63.64 %)	3	1	1
	Tree 6	13 (72.22 %)	3	2	2
	Tree 7	9 (64.29 %)	3	2	2
	Tree 8	12 (80 %)	2	4	1
	Total	71 (71 %)	20	12	9
Trunk	Total	8 (100 %)	0	0	0
Overall results for all trees parts:		298 (77.6 %)	56	121	30

Cherries

Results

Numerical results indicate the efficiency of the proposed methodology, highlighting its potential to be integrated into an autonomous robotic cherry pruner for in-field experimentation in the future. It is worth noting that the proposed methodology is scalable and can also be adapted to other tree types by adjusting the pruning rules accordingly.

For more insights…

Axios Kefalas, Theofanis Kalampokas, Eleni Vrochidou, George A. Papakostas. A vision based pruning algorithm for cherry tree structure elements segmentation and exact pruning points determination, Computers and Electronics in Agriculture, Volume 237, Part C, 2025, 110735, ISSN 0168-1699,
https://doi.org/10.1016/j.compag.2025.110735

Kiwifruit

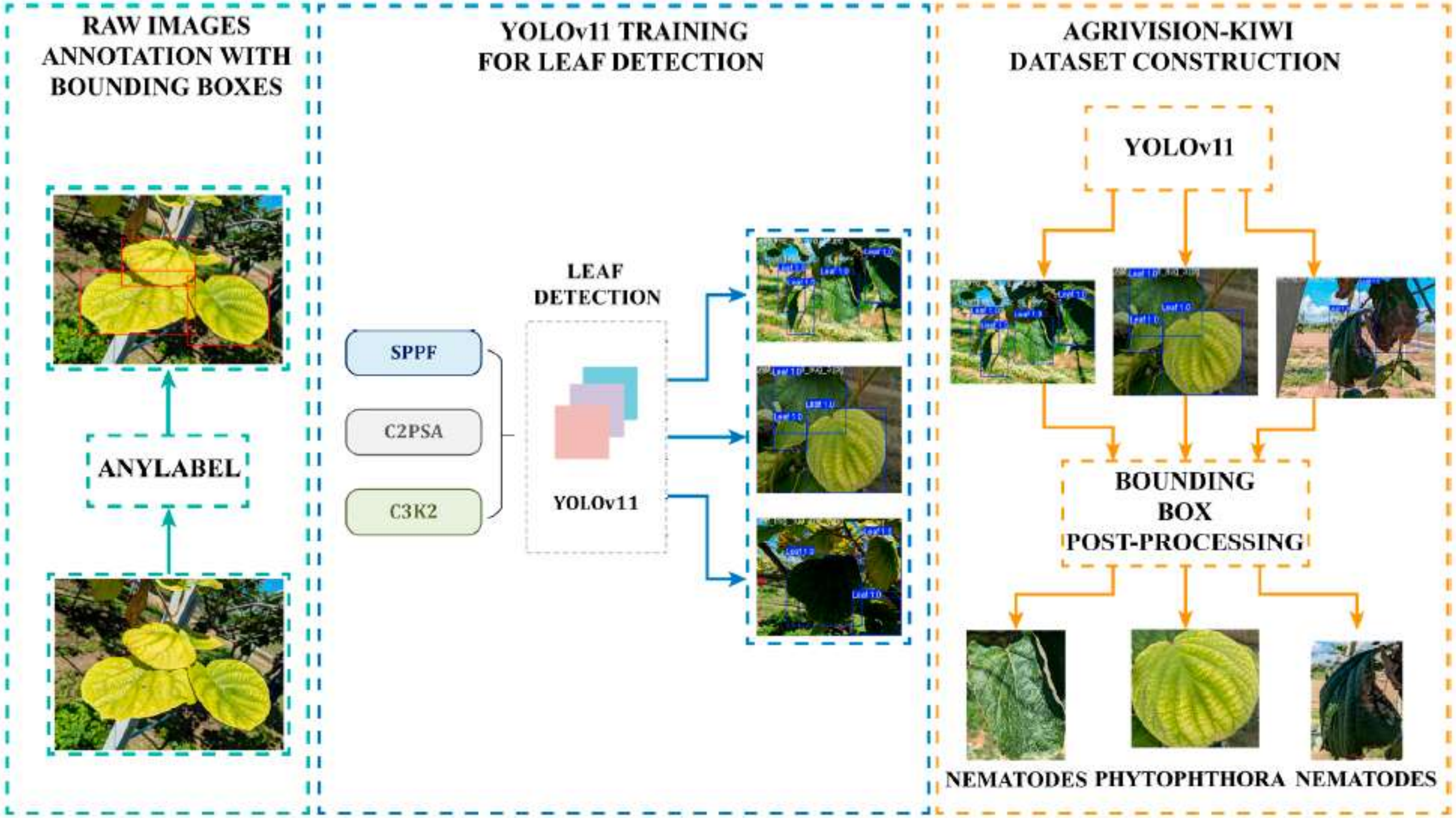
Kiwifruit

Empowering Kiwifruit Cultivation with AI: Leaf Disease Recognition Using AgriVision-Kiwi Open Dataset

Contributions

The first-reported open dataset for kiwifruit leaf disease recognition, including Alternaria, Nematodes and Phytophthora, while image datasets of Nematodes have not been previously reported.

The proposed dataset, named has been used first for leaf detection with You Only Look Once version 11 (YOLOv11), reporting a bounding box loss of 0.053, and then to train various deep learning models for kiwifruit diseases recognition, reporting accuracies of 98.80% ± 0.5, e.g., 98.30% to 99.30%, after 10-fold cross-validation.



- Data Acquisition
- Data Preprocessing
- Data Annotation (Leaf Detection)

- Train YoloV11
- Data Labeling (AgriVision-Kiwi Dataset)
- Dataset Construction (Disease Recognition)

- Six DL Models Selection
- 10 Fold Cross Validation
- Metrics Calculation

Kiwifruit

Results

Metric	YOLOv11
Train-box-loss	0.053
Train-cls-loss	0.060
Val-box-loss	0.043
Val-cls-loss	0.041
Precision(B)	0.99
Recall(B)	0.99
Precision(M)	0.99
Recall(M)	0.99
F1 score	0.99
Confidence score	0.99

YOLOv11 training and validation results.

Kiwifruit

Results

Disease recognition results and inference times.

Model	AlexNet	DenseNet-121	EfficientNet-B3	MobileNet-V3	ResNet-50	VGG-16
Fold 1	0.989	0.996	0.981	0.982	0.989	0.984
Fold 2	0.989	0.995	0.987	0.987	0.992	0.990
Fold 3	0.990	0.989	0.990	0.984	0.986	0.984
Fold 4	0.982	0.995	0.976	0.989	0.993	0.995
Fold 5	0.982	0.993	0.981	0.981	0.981	0.986
Fold 6	0.993	0.995	0.982	0.993	0.987	0.986
Fold 7	0.984	0.992	0.981	0.981	0.990	0.987
Fold 8	0.982	0.990	0.984	0.987	0.987	0.978
Fold 9	0.990	0.993	0.986	0.989	0.990	0.982
Fold 10	0.979	0.995	0.979	0.992	0.989	0.973
Mean	0.986	**0.993**	0.983	0.986	**0.989**	0.984

Model	AlexNet	DenseNet-121	EfficientNet-B3	MobileNet-V3	ResNet-50	VGG-16
Time	192 ms	676 ms	602 ms	496 ms	600 ms	579 ms

For more insights…

Kalampokas T, Vrochidou E, Mavridou E, Iliadis L, Voglitsis D, Michalopoulou M, Broufas G, Papakostas GA. Empowering Kiwifruit Cultivation with AI: Leaf Disease Recognition Using AgriVision-Kiwi Open Dataset. Electronics. 2025; 14(9):1705. https://doi.org/10.3390/electronics14091705

Kiwifruit

DIGI European digital innovation hub Hellas AGRIFOOD

Implementation of the algorithm in the context of DigiAgriFood project (https://digiagrifood.gr/en/) to deliver a mobile application for kiwifruit disease detection, that currently over 100 kiwifruit producers are using in the Region of Eastern Macedonia and Thrace (EMT).

Thank you

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