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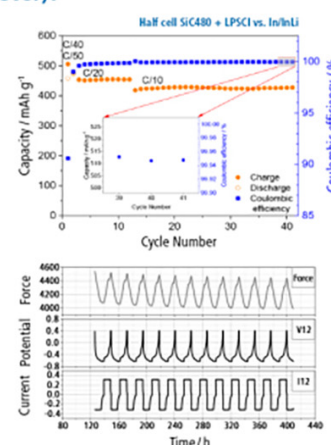
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Smart Agriculture Insurance Based on Artificial Intelligence – Object Detection

Marco Fiorentini¹, Stefano Zenobi¹, Federico Mammarella^{1,2,*}, Matteo Francioni¹, Chiara Rivosecchi^{1,2}, Roberto Orsini¹, Paride D'Ottavio¹, Paola A. Deligios¹ and Luigi Ledda¹

¹Università Politecnica delle Marche, Dipartimento di Scienze Agrarie, Alimentari ed Ambientali, Via Brecce Bianche, 10, 60131 Ancona.

²Università della Sapienza, Department of Civil, Building, and Environmental Engineering (DICEA), Via Eudossiana 18, 00184 Rome, RM

*E-mail: f.mammarella@pm.univpm.it

Abstract. Climate change and extreme weather events, such as hailstorms, increasingly threaten high-value crops like grapes, causing substantial yield losses and economic risks for farmers. Traditional damage assessment methods, typically based on manual field inspections, are time-consuming, subjective, and error-prone, leading to delays in compensation and inefficient risk management. To address these limitations, innovative approaches combining artificial intelligence (AI) and edge computing are required to ensure objective and timely evaluations of vineyard damage. This study developed and tested a low-cost hardware–software system that integrates edge computing and deep learning to automate grape detection and spatial variability mapping. Two state-of-the-art models (RT-DETR and YOLOv8) were trained on 8,931 labeled images compiled from three open-source datasets and a dedicated acquisition campaign. The best-performing model, YOLOv8, was deployed on a Raspberry Pi 5 equipped with dual cameras and GPS to acquire geo-referenced data in a commercial vineyard in central Italy. The resulting grape counts were analyzed using univariate geostatistics and ordinary kriging to generate prediction and standard deviation maps. YOLOv8 achieved the best performance, with precision = 0.89, recall = 0.78, and mAP50 = 0.87. During field testing, 671 data points were collected every four seconds, each containing an image, GPS coordinates, and AI-based grape inferences. The geostatistical analysis confirmed data symmetry (skewness = 0.78) and identified the spherical model as optimal (RMSE = 0.24). The resulting variability maps showed grape counts ranging from 1 to 12 and standard deviation values between 1 and 3. The proposed system demonstrates that low-cost edge devices can effectively support objective, rapid and reproducible vineyard damage assessments, offering valuable tools for climate insurance applications. In addition to damage evaluation, the system can also provide detailed spatial information on total grape distribution, supporting precision viticulture practices such as differential fertilization and optimized harvest planning. Future developments will focus on integrating multispectral and thermal imaging and incorporating distance sensors to estimate grape weight, further enhancing both agronomic and insurance-related decision-making.



1. Introduction

Climate change and increasing weather variability are intensifying the occurrence of extreme weather events, such as hailstorms, which represent a persistent threat to agricultural production, particularly for high-value crops including vineyards, orchards, and horticultural systems. European farmers, increasingly exposed to extreme weather risks, have experienced substantial crop yield losses in recent years and are expected to face even higher yield volatility in the future (Bucheli et al., 2023; Trnka et al., 2014; Webber et al., 2020). Extreme climate events may increase in the future if global warming leads to further temperature increases. In addition, these weather events can lead to significant economic losses for farmers, potentially causing the closure of farms (Hristov et al., 2024; McMaster, 2001; Vinet, 2001).

This situation poses risks to economic development and requires additional expenditure to prevent extreme events or to compensate for damage already caused. The World Economic Forum (WEF) Global Risk Report 2022 recognizes climate change and its disruptive consequences as the greatest risk to economic activity (Woodworth, 2023).

Due to the increasing number of climate-related extreme weather events and the associated agricultural production losses, climate insurance has garnered considerable attention, becoming an important issue for the economy in general and for the insurance industry in particular. However, quantifying the contribution of climate change to historical agricultural losses remains challenging due to the rarity of extreme events, inconsistencies in data recording, and the lack of open-source datasets for such evaluations.

Furthermore, the inherent uncertainty and limited predictability of extreme weather events currently hinder the development of effective insurance schemes, as companies remain reluctant to provide coverage for such unpredictable risks. The European Union has recognized this issue and currently promotes and subsidizes agricultural insurance schemes through the European agricultural risk management framework to protect producers from risks associated with extreme weather events (Meuwissen et al., 2018).

Among the crops most affected by extreme weather events, grapevine (*Vitis vinifera* L.) represents one of the most economically and culturally significant species in Europe. According to the (OIV, 2019), grapevine covers approximately 3.2 Mha across the European Union, generating substantial economic value through wine production and related industries. However, grapevine is highly sensitive to climatic variability (particularly to hail, frost and heat stress) which can severely damage grapes and leaves, directly affecting yield and fruit quality (Di Lena et al., 2019). Monitoring grape development is therefore a key agronomic practice, as it provides early insights into potential yield, informs canopy and irrigation management, and supports harvest planning and quality control (Lanari et al., 2014). Accurate and spatially detailed information on grape distribution is also essential for assessing damage after adverse weather events and for improving the reliability of insurance evaluations (N. Zhou & Vilar-Zanón, 2025). If a loss occurs in an insurance business, the insurance company sends technicians/agronomist to take manual measurements to estimate the damage generated and the way to determine the amount of damage is reported within the insurance policy signed by both the farmer and insurance company. However, accurate damage assessment in agriculture is a complex and error-prone process (Chauhan et al., 2019) with significant economic implications for both farms and insurance companies (Kapsambelis et al., 2019).

Currently, most compensation assessments for damage caused by extreme weather events such as hail are still based on manual or visual inspections and rough estimates, which may lack accuracy and objectivity (Barbedo, 2013). Moreover, the related documentation process often

delays the disbursement of compensation payments, potentially causing cash flow issues for farms and forcing them to seek loans or, in severe cases, cease operations. Another major limitation of manual inspections is that they cannot be carried out quickly by technicians or agronomists, given the need to sample wide affected areas. In addition, potential conflicts of interest may arise, which can ultimately lead to legal disputes (Maria et al., 2017).

More in detail, in the context of the vineyards, there is an urgent need for tools that can ensure a more detailed, reproducible and accurate estimation of grapes amount, minimizing uncertainty, subjectivity, and potential conflicts of interest in damage assessment processes (Botzen et al., 2010). Moreover, knowing the grape number spatial variability is critical also for monitoring and managing productivity.

The efficient management of agronomic inputs, such as seeds, soil and nutrient management (Fiorentini et al., 2024; Francioni et al., 2025) is essential to improve the sustainability of agricultural systems. Precision agriculture technologies further enhance this efficiency by enabling data-driven optimization of fertilizers and phytopharmaceutical applications (Cossu et al., 2025; Lindoet al., 2024). Precision Agriculture is a management strategy that gathers, processes and analyses temporal, spatial and individual plant and animal data and combines it with other information to support management decisions according to estimated variability for improved resource use efficiency, productivity, quality, profitability and sustainability of agricultural production (Orsini et al., 2019).

Many authors show up how the precision agriculture enables precision fertilization based on crop need (Charvát et al., 2021; Fiorentini et al., 2024; Fontanet et al., 2020; Khosla et al., 2005; Orsini et al., 2023), seeding with different varieties based on soil type (Jibon et al., 2023; Munna et al., 2021; Naik et al., 2016), distributing a differentiated dose of phytopharmaceuticals (Vasileiou et al., 2024).

The new frontier of precision agriculture is the integration with artificial intelligence (Kamilaris & Prenafeta-Boldú, 2018) which through sophisticated procedures and algorithms (Chollet, 2021) can generate specific recommendations as the power and amount of technology and data in agriculture is growing (Vasileiou et al., 2024). A branch of artificial intelligence is the vision-based intelligent systems, which combine computer vision and artificial intelligence that allow machines to mimic human visual and cognitive abilities to make informed decisions (Chlingaryan et al., 2018).

Attri et al., (2023) reviews 129 papers to discuss the application of deep learning in precision agriculture, categorizing them into seven areas: crop yield prediction (Fiorentini et al., 2022; Rivosecchi et al., 2024), and pest detection (Subeesh et al., 2022), disease detection (Grijalva et al., 2023), water management (Abdallah et al., 2021), seed analysis (Qiu et al., 2018), and soil analysis (Li et al., 2020). However few authors explore how to use artificial intelligence in the agricultural insurance domain. Biagini, (2022) uses machine learning in establishing ratemaking for new insurance schemes, while Ghahari et al., (2019) uses deep learning and weather data to predict the extreme weather events. However, none of them combine the use of edge computing, deep learning and cloud computing to determine the spatial variability of the grape's numbers in the field.

The adoption of edge computing systems and machine vision techniques promises to revolutionize risk management, significantly improving the accuracy of damage assessment and reducing the time and costs associated with manual inspections. An automated system that can detect and count of grapes and geo-reference images accurately could represent a major shift in how pre-harvest and post-damage assessments are performed. To address this urgent need, this

study aims to develop low-cost and effective hardware–software systems based on edge computing capable of generating grape variability maps. These systems are intended to improve the field measurement phase and enable an objective, reproducible, and transparent assessment of damage caused by adverse weather events in vineyards.

2. Materials and Methods

2.1 Experimental site

The trial was carried out during the 2024 growing season (beginning of May until last decade of September) in a non-irrigated commercial vineyard located in central Italy (Marche region), near Falconara Marittima (Ancona, 43°35' lat. N and 13°24' long. E, elevation 76 m a.s. l.), characterized by a clay-loam soil, at the “Davide Luconi” farm. The vineyard, established in 2001, consists of *Vitis vinifera* L. cv. Sangiovese (Figure 1) grafted onto 420A rootstock, planted at 2.5 m × 0.8 m inter-row and intra-row, and trained to a vertically shoot-positioned, spur-pruned cordon trellis with a bud-load of 2–3 nodes per metre of row length. Pest management practices followed local standards and shoots were mechanically trimmed when most had grown above the top wire.



Figure 1. Experimental site location.

2.2 Workflow

The workflow adopted to create the system was composed of four steps: i) dataset creation; ii) model building and evaluation; iii) hardware, software and design development; iv) geostatistical approach.

2.2.1 Dataset creation

To train the deep learning models was used three open-source datasets for a total of 2.020 labelled images, and an image acquisition campaign was also conducted to increase the data source.

A total of 6,911 labelled images were collected at the Davide Luconi Farm. For training and evaluating the deep learning models 8,931 labelled images were utilized. The images comprised both red and white grape, representing multiple varieties, and were captured since veraison to harvest. . The characteristics of the datasets used in this work is report at the Table 1.

Table 1. Datasets names, references and details used to train deep learning models.

Dataset Name	References	Country	N. total of images	Red/white grape	Multi variety	Multiple Growth Stages
wGrapeUNIP D-DL	Sozzi et al., (2022)	Italy	373	Red grape	Yes	Yes
AI4Agriculture Grape Dataset	10.5281/zenodo.5660080	Spain	250	White grape	No	No
DataSet_Real one	https://universe.roboflow.com/arab-academy-for-science-technology-maritime-transport-smart-village-campus-he7gz/dataset_realone	Multiple	1397	Red and white grape	Yes	Yes
Acquisition Campaign	None	Italy	6,911	Red and white grape	Yes	Yes

2.2.2 Deep Learning model building and evaluation

In this study, we tested two models: YOLO(You Only Look Once) version 8.2 (Redmon et al., 2015) and the RT-DETR model (Zhao et al., 2023). To prevent possible overfitting, transformations such as flip, rotate, shear, noise, brightness modification, and saturation modification were applied to the original dataset images. This increased the total number of images to approximately 8931, with 6252 used for training, 1786 for validation, and the remaining 893 for testing.

The classes analysed were "red grape" and "white grape," with a similar number of instances for each class. During training and validation, metrics were constantly monitored to prevent overfitting or underfitting. This evaluation allowed us to identify the best configuration and adjust hyperparameters to ensure optimal performance. For YOLO, we used the pretrained model "yolov8m" (medium size, 25M parameters) and for RT-DETR, we used the pretrained "rtdetr-x", as other models resulted in overfitting or underfitting situations.

2.2.3 Hardware and software development and design

The primary objective of the hardware and software system developed is to deploy the best-performing model, selected during the model building and evaluation phase, for real-world applications. The best model was integrated into the system using the YOLOv8 API (Reis et al., 2023), facilitating efficient real-time inference.

To achieve this, a Raspberry Pi 5 with 8 GB of random-access memory (RAM) was selected for its high processing speed and Graphics Processing Unit (GPU) capabilities, which are critical for rapid model inference. The choice of 8 GB of RAM was made to enhance computation speed, ensure smooth operation of the deep learning model and low-cost.

The system employs dual Raspberry Pi Camera V3 modules (Rolling Shutter) with a 12 MP resolution and a 120° wide-angle lens. These cameras are synchronized to enable simultaneous image acquisition from both rows of the vineyard, ensuring comprehensive

coverage. The cameras are directly mounted to the Raspberry Pi 5 and capture high-resolution images necessary for accurate analysis.

For spatial positioning, the system utilizes the SIM7600G-H module to acquire Global Positioning System (GPS) coordinates. Although specific details of the GPS data integration are not provided, the system records and logs GPS data in conjunction with each inference, allowing for precise geolocation of captured images.

2.2.4 Univariate geostatistical approach

Univariate geostatistics was used to identify the spatial variability of grape counting of the experimental site. The creation of the grape counting variability maps involved six steps: i) checking for symmetric data distribution; ii) creating the experimental variograms; iii) developing and fitting different spatial models to the experimental variograms; iv) evaluation of the best spatial model based through cross-validation for each point; v) executing ordinary kriging (Wackernagel, 1995); and vi) producing prediction and variance maps.

The assessment of symmetric data distribution relied on skewness. Data were deemed to exhibit a symmetric distribution when the skewness fell within the range of -1 to +1. The skewness test was performed using the 'skewness R function' from the 'e1071' R package (Meyer et al., 2021).

All remaining four steps were performed using several functions of the 'gstat' R package (Gräler et al., 2016) which allows to create the experimental variograms, fitting several spatial models, evaluate the best spatial model based on cross validation and produce the prediction and variance maps. The experimental variograms were created by using the 'variogram' function which calculates the sample variogram from data, or in case of a linear model is given, for the residuals, with options for directional, robust, and pooled variograms, and for irregular distance intervals. To fit several spatial models to the experimental variograms, the 'fit.variogram' function was used where model argument was assigned to the 'vgm' function which allow to define the different spatial models. The spatial models that were tested are Matérn, spherical and exponential models.

To select the best spatial model, a 10 k-fold cross validation by using the 'krige.cv' function of the 'gstat' R package was performed (Gräler et al., 2016) and the model with lower root mean square error was selected. Subsequently, the ordinary kriging algorithm (Wackernagel, 1995) was used by the 'krige' function which allows to produce the prediction and variance of the grape counting variability map. All the geostatistical and machine learning computations were made with R statistical programming language (Core Team, 2014).

3. Results

3.1 Deep Learning model building & evaluation

From the preliminary tests conducted, it is evident that the model's training, validation, and testing operations yielded good results, as shown in Figure 2.

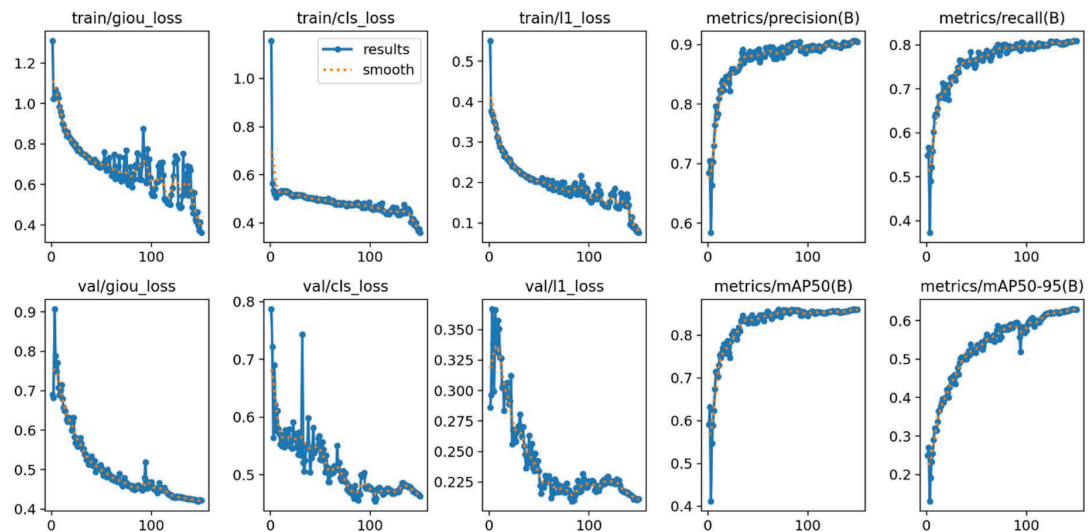


Figure 2. Precision, recall, loss and mAP error metrics trend over the training epochs related to Yolov8.

From the results obtained, the RT-DETR model (XL size) showed the following performance on a validation dataset composed of images with a size of 1000 px: Overall Precision = 0.91, Recall = 0.80, mAP50 = 0.86. The Yolov8.2 model (medium size) achieved the best performance on the same dataset, with Overall Precision = 0.89, Recall = 0.78, mAP50 = 0.87.

Regarding inference times, using the YOLO model on AMD Ryzen 5 CPU, inference took approximately 2035.4 ms per image, while on an Nvidia GTX1080 GPU, it required only 28.2 ms per image. The RT-DETR model exhibited inference times roughly three times longer; therefore, the YOLO model was selected for implementation in our system.

These inference times make the proposed solution suitable for both edge computing (with SBC devices like Raspberry Pi or NVIDIA Jetson) and remote processing, where images are collected on a server and inference is performed via GPU. The ability to process data through a server or cloud system equipped with a mid-range GPU enables remote data analysis, allowing centralized management of data from multiple, geographically dispersed fields. This approach reduces on-field operations to the simple task of image acquisition, which can be performed using low-cost hardware such as smartphones, drones, or SBC devices like Nvidia Jetson or Raspberry Pi (enabling on-field image inference).

3.2 Grape variability map

A total of 671 data points was generated by Raspberry Pi 5 during the system test day on 2 August 2024. Every 4 seconds, the device captured an image, recorded the GPS location, and performed inference to determine the number of grapes.

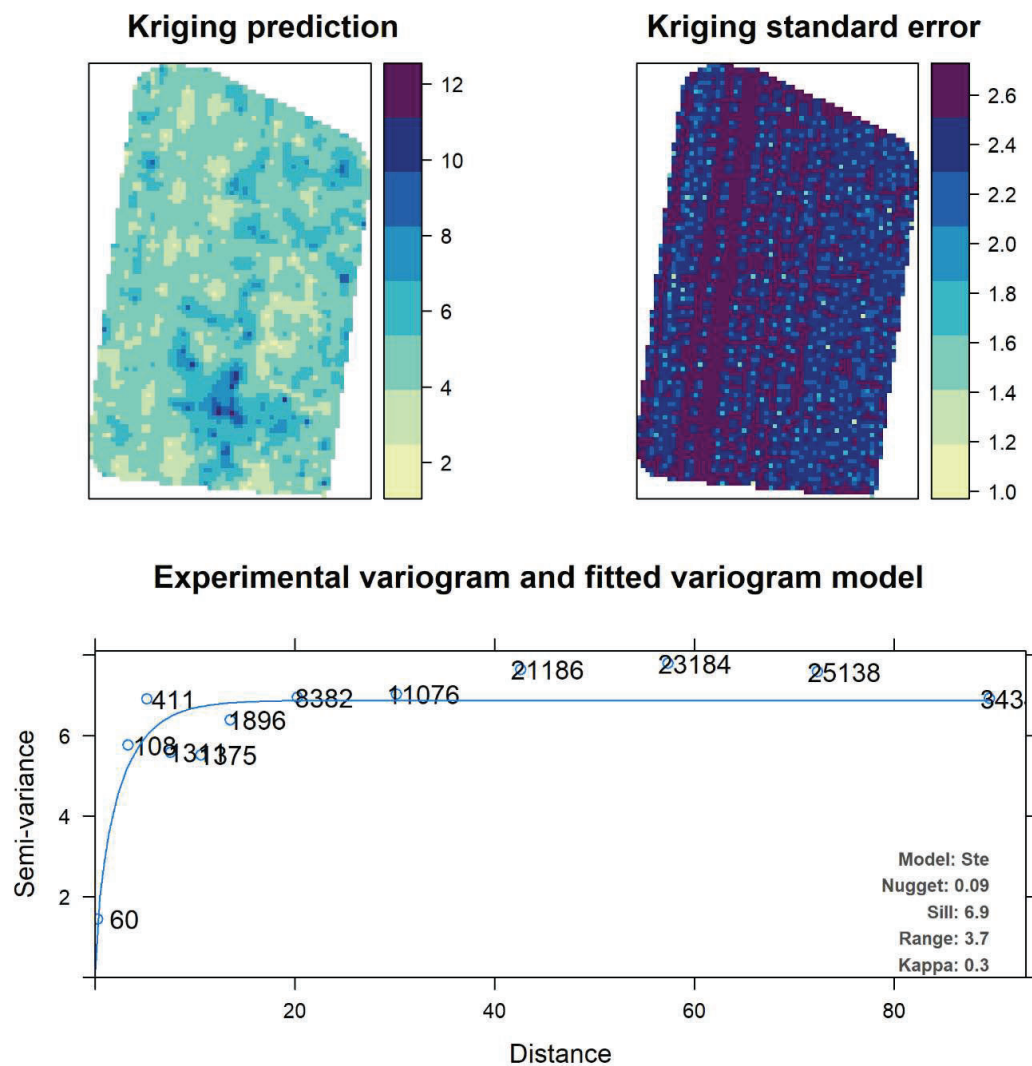


Figure 3. Fitted experimental variogram with the Matérn spatial model and kriging prediction and standard error.

Based on the geolocated data, the skewness of the grape counts estimated by the AI model inference was calculated and found to be within the range of -1 to +1 (0.78), indicating that the univariate geostatistical assumption of a 'symmetric distribution of data' was met. Consequently, semi-variogram analysis were performed using Matérn, spherical and exponential spatial models without the need for any data transformation. The spatial model that reported the lowest RMSE value was the Matérn one (Figure 3).

According with (Wackernagel, 1995) approach, the ordinary kriging algorithm, fitted using the best spatial models (Figure 3), was employed to generate the grape variability

prediction map (Wackernagel, 1995). The experimental site showed a variation in grape counts ranging from 1 to 12 (Figure 4).

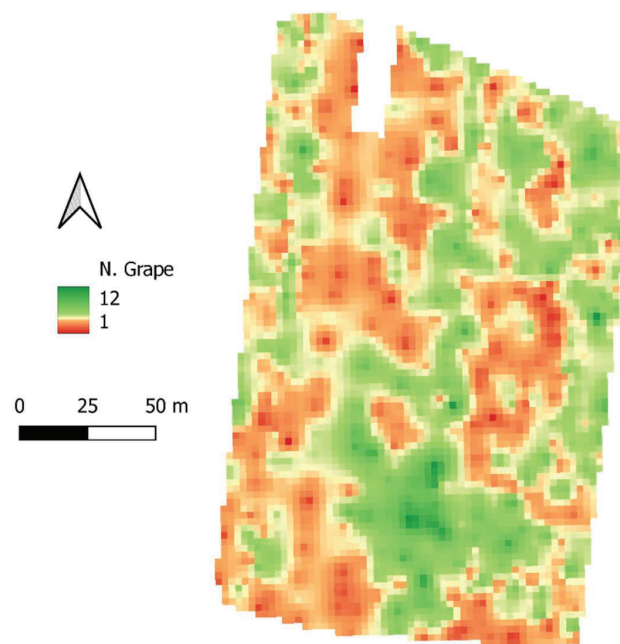


Figure 4. Prediction and standard deviation maps of grape counts estimated by the AI model inference.

4. Discussions

The previously described system automates the grape counting process, one of the crop development monitoring activities typically carried out annually in many vineyards. It eliminates potential human errors associated with sampling, recording and transferring data into digital formats that can be analyzed and processed (Barbedo, 2013).

Several authors have trained object detection models for grape counting, reporting accuracy levels comparable to those obtained in this study (Shen et al., 2023; Sozzi et al., 2022a; Zhang et al., 2022) but none of those studies reported a grape variability map based on AI edge inferences. The production variability map is fundamental from various points of view, both agronomic, to identify areas of higher and lower production, and to produce prescription maps for applying precision farming techniques (Sams et al., 2017).

Moreover, grape variability maps are fundamental to verify whether the pruning carried out and the production targets for each spur have borne one or two grapes. In fact, considering the planting density of the experimental site, the number of target spurs per linear meter and Figure 4, the system had to measure approximately 8-10 clusters for each point, while the grape variability map reported few points with those characteristics. This information is quite

important to understand the future pruning and agronomic management that should be applied at that field (Di Lena et al., 2019; Lanari et al., 2014).

However, object detection methods (e.g., YOLO and similar architectures) generate bounding boxes that encompass the entire grape but also include non-grape pixels, which limit the precision in estimating the actual area and, consequently, the weight. For this reason, it is often preferable to adopt instance segmentation approaches.

To overcome this limitation and enable more reliable yield estimation, it is advantageous to train instance segmentation models (e.g., Mask R-CNN and its variants) that can accurately identify the shape and the exact number of pixels belonging exclusively to the grape. This makes it possible to establish correlations between pixel area and measured grape weight, thus allowing yield estimation directly from images (Du & Liu, 2023; Font et al., 2015; Huang et al., 2024; Victorino et al., 2022).

However, segmentation models require electronic boards with higher computational capacity, particularly in terms of graphical processing power, compared to the hardware currently employed in the described system. This requirement may increase the overall cost and energy consumption of the solution. Moreover, deploying such models under real-time field conditions may necessitate optimized or lightweight architectures capable of maintaining satisfactory accuracy while reducing inference time and memory usage (e.g., MobileNet, EfficientNet, or lightweight versions of Mask R-CNN). Future research should aim to achieve an optimal trade-off between model complexity, computational efficiency, and cost, ensuring suitability for on-board vineyard applications without compromising performance.

Obtaining information on the total number of grapes and their spatial variability provides several key management benefits for a vineyard, including: i) enabling differentiated vineyard management according to production levels (Sams et al., 2017); ii) generating prescription maps for variable-rate technology (Garcia-Ruiz et al., 2023); iii) assessing the workforce required to ensure timely harvesting (Strub et al., 2021); iv) planning and organizing all necessary inputs for the winemaking phase in the winery (Laurent et al., 2021); v) supplying data for compensation assessments in the event of hailstorms when an insurance policy is in place (Mare et al., 2022).

Moreover, the tested system reduces the time and cost that farms need to allocate for grape counting (Shen et al., 2023) and for assessing spatial variability within fields (Ferro et al., 2023a), as it can be easily integrated with tractors and employed during routine vineyard operations throughout the grape growth period, such as crop protection treatments, green pruning and topping.

Several limitations currently affect the accuracy of the system: i) when grape are partially covered by leaves, accuracy is compromised. This issue could be addressed by training a GAN-based algorithm to remove leaf occlusion and reconstruct the grape structure, by employing an ultrasonic phased array technique (Parr et al., 2021), or by conducting the survey after defoliation (although this practice may increase the risk of grape sunburn or mechanical damage); ii) pits or uneven terrain may generate vibrations or alter camera orientation, thereby reducing measurement accuracy. This limitation can be mitigated by using a fast global-shutter camera with a high frame rate and low focal length, which allows more light to reach the sensor, though it would consequently increase material costs; iii) excessive forward speed of the tractor can negatively affect the system's performance. Limiting the speed represents a straightforward solution, allowing image acquisition to be performed during field operations that are typically carried out at low speed; iv) the current system does not estimate grape weight. This limitation could be overcome by incorporating a sensor to measure the distance between the lens and the

canopy. These data would enable the conversion of pixel area into surface area (cm^2), which can then be correlated with measured weight.

Future developments will aim to address these limitations and to integrate multispectral and thermal cameras. Such enhancements are expected to improve not only object counting but also enable additional applications, including pathology detection (Kerkech et al., 2020; Vélez et al., 2023b, 2023a), water stress assessment (Atencia Payares et al., 2024; Z. Zhou et al., 2021), leaf area index estimations (Ferro et al., 2023b; Ilniyaz et al., 2022; Johnson et al., 2003), detection of nutritional deficiencies (Jeong et al., 2025) and failure detection (Cándido-Mireles et al., 2023; Di Gennaro et al., 2023).

5. Conclusions

This study presents a novel, low-cost hardware–software system that leverages edge computing and deep learning techniques to automate grape detection and spatial variability mapping in vineyards. The integration of state-of-the-art models (most notably YOLOv8) into a portable platform such as the Raspberry Pi 5 enhances the accuracy and timeliness of damage assessments compared with traditional manual inspections. In the context of climate change and the increasing frequency of extreme weather events, the ability to rapidly and objectively assess vineyard damage represents the system’s main contribution, offering a valuable tool for timely insurance claims and financial risk mitigation.

Beyond damage evaluation, the system also enables accurate estimation of total grape counts and their spatial distribution, supporting additional applications in precision viticulture. The generation of detailed grape variability maps provides growers with actionable information for targeted agronomic interventions, such as differential fertilization, optimized harvesting logistics, and timely pest or disease management. This dual capability strengthens the integration between precision agriculture practices and climate insurance frameworks, ultimately contributing to more sustainable and resilient vineyard management.

While the current system exhibits several limitations (such as leaf covering, terrain-induced measurement errors, and the absence of weight estimation) it also highlights opportunities for further research. Future developments will focus on addressing these challenges through enhanced imaging approaches, including the integration of multispectral and thermal cameras, and the development of advanced algorithms to mitigate covering issues. Additionally, incorporating sensors for real-time distance measurement could extend the system’s capabilities to include weight estimation, enriching the dataset for both agronomic decision-making and insurance assessments. Collectively, these advancements are expected to drive the next generation of precision agriculture and risk management tools, ensuring a more effective response to the growing challenges posed by climate variability.

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