Grapevine bunch Digital Twin analysis to detect alternative traits for bunch morphology classification

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Abstract*—The classification of Vitis vinifera bunches occurs by describing many morphological traits. The grapevine bunch's morphology affects the microclimate condition of the grape. Consequently, the grape shape plays a crucial role in degerming the berries juice's composition, and both the pests and diseases spreading. In more detail, the Organisation Internationale de la Vigne et du Vin standard lists among the descriptors 202 to 209 the bunch's features almost evaluated by visual approach. However, many researchers stated the need to propose an objective evaluation method based on rational evidence avoiding personal judgment. The presented study explores the three-dimension analysis of bunch digital twins to identify those crucial differences in the bunch morphology among various Vitis vinifera varieties. The method followed the photogrammetry technique to obtain digital twin of bunches. In addition, five horizontal sections and two vertical ones were extracted. Perimeter, area, axis length and the circumscribed circle were measured in all the sections. Finally, 28 measures and 36 indices were appraised per bunch. A hierarchical clustering and the analysis of variance was performed to isolate the most divergent descriptors between varieties. The estimated volume, the vertical section's size and the sizes of the top and the bottom horizontal sections result as the most prominent features for describing the bunch morphology according to the proposed methodology. The resulting traits could also be tools for future studies focused on the grape compactness assessment.

***Keywords*— Bunch compactness, Bunch morphology, Photogrammetry, Precision phenotyping.**

I. INTRODUCTION

The digital revolution evolved during the past year in proposing digital reflection of common objects of real life into virtual models. Generally, the virtual model of a real object is defined as Digital Twins (DT). DT applications include several sectors, including the agricultural sector [1]. Agriculture could benefit from DT thanks to their introduction in many branches, from the cultivation stages to fruit quality monitoring [2]. A fine example was proposed by [3] where authors rebuild three-dimensional models of grapevine bunches to predict the vineyard yield. In other cases, the three-dimensions analysis were exploited three-dimensional environment analysis to detect apples' number and location in apple trees at field conditions [4]. DT are also useful for monitoring and classifying fruits during the post-harvest chain. Many researchers explored the techniques for various fruits such as bananas, berries, and palm oil fruits [5]–[7]. DT can also be used for deep investigation of fruit morphology. A wide range of articles was based on phenotyping and classifying whole fruits thanks to the three-dimensional analysis [8]. Most of the articles found in the literature review were focused on a deep investigation of grapevine bunches morphology [9]–[11]. Several authors stated the affordability of the DT analysis of bunches due to increasing information compared to a standard visual or two-dimensional analysis. Specifically, volume, surface, and the berries' spatial distribution represent robust data retrieved from the three-dimensional techniques.

Consequently, three-dimensional properties could improve the *Vitis* species classification and variety cataloguing. Nowadays, most grapevine assessments happen by visual evaluation made by human operators. Introducing robust and objective indices could reduce human error due to subjective judgment favouring a more rational assessment [12]–[15]. Moreover, a deep analysis could discriminate clones among the same variety [16]. Finally, other authors succeed even in identifying specific three-dimension features to better describe the grapevine compactness, which is one of the most important bunch properties [17].

Nowadays, several sensors have been tested to rebuild DT of natural objects. The sensor is a crucial factor for detecting the spatial distribution of all the points that made the target object. Finally, the rebuilding techniques compute each point's estimated distance and position, retrieving a digital duplicate of the real object. The most common sensors used for rebuild digital duplicate are infrared structured light camera, laser scanning, standard RGB camera, and other kind of depth RGB cameras [18]–[20]. Several reconstruction techniques are based on artificial neural networks, consisting of algorithms for projecting the objects in virtual coordinates into the digital environment [21]. RGB and depth-RGB cameras are also handy for catching the object's actual colour. Usually, RGB sensors are cheaper compared to the laser scanners. Moreover, high-definition cameras can retrieve subtle details of objects. The most common technique for rebuilding three-dimensional models of real objects is photogrammetry. Photogrammetry is based on the structure for motion computing technique. Photogrammetry aims to join all the photos taken from a target computing the actual distance and position of the camera and items. Then, the digital target is projected into a virtual environment. The most common outputs consist of point cloud or mesh. The point cloud consists of all the points that made the virtual model. The number of points depends on the sensor's resolution and the computing power of the processors used for data processing [22]. The mesh represents the joining of all the external vertexes of the surface in a unique polygon mesh.

Most of the related research works found among literature were based on visual or two-dimensional (2D) analysis. To add another spatial dimension means to multiplicate the number of information achievable from the bunch's morphology. In this context, to sift the no meaningful features. In addition, commercial cameras and the photogrammetry have never been implemented for this scope.

The present study proposes a different approach for classifying grapevine bunches between seven *Vitis vinifera* varieties. A standard RGB camera was used for taking many photos of bunches sampled at harvest time. Then, a DT for each grapevine bunch was rebuilt and analysed thanks to photogrammetry. Many measurements were founded in the literature review, while the authors proposed other measurements and indices to enrich the approach with more three-dimension data.

II. MATERIAL AND METHODS

The research study was carried out in 2022. The bunches were gathered at harvest time between August and September in the northeast of Italy, Veneto region. A total of 45 bunches were considered from seven grapevine cultivars, Cabernet Sauvignon, Carménère, Merlot, Pinot Gris, Pinot Noir, Raboso Piave, and Raboso Veronese. The varieties were chosen based on which are the most cultivated in that area. Also, the approach's feasibility was tested by studying very similar varieties. In particular, the bunch's morphology of Pinot Noir could be confused with Cabernet Sauvignon. In the same way, other varieties might be confused, such as Raboso Piave with Raboso Veronese and Merlot with Carménère. The bunches were sampled following the typical morphological traits of the cultivar and clone. Bunches were classified according to the Organization Internationale de la Vigne et du Vin standard (OIV) [23]. The Bunches' features are listed in Table 1. The methodology steps are explained in more detail in the following paragraphs.

A. *Digital twins reconstruction*

Nikon Coolpix W300 digital camera (Nikon Corporation, Tokyo, Japan) was used to take several photos of each bunch. The camera saved the images at 24-bit, 1628x1078 pixels at 96 dpi resolution. The camera was mounted in a special device which turned around the target at a constant rotation speed. The rotation speed was set to take 33 images per revolution. The camera was mounted at three different positions: I) perpendicular to the bunch's vertical axis; II) at +45°from the perpendicular position; II) at +45°from the perpendicular position; III) at -45° from the perpendicular position. The acquisition from a different point of view allowed the complete representation of the clusters. As a result, 99 images were captured per bunch. All the photos were processed on Metashape 1.7.2 (Agisoft LLC) to build the DT of each bunch. Metashape can generate object and spatial 3D models performing the structure from motion photogrammetry of digital images.

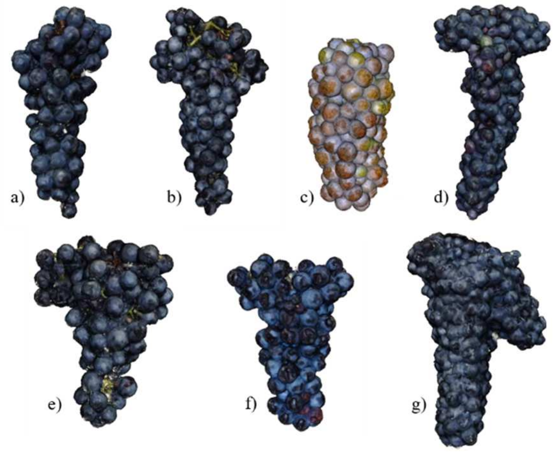

Fig. 1. DT of the studied bunches are showed as the following order: a) Cabernet Sauvignon, b) Merlot, c) Pinot Gris, d) Raboso Veronese, e) Carménère, f) Pinot Noir, g) Raboso Piave. The bunches are not scaled.

TABLE I. LIST OF THE MAIN PROPERTIES OF THE BUNCHES CONSIDERED FOR THIS REASEARCH WORK FOLOWING THE OIV STANDARD [23]. SAMPLES DATA ARE AVERAGED PER GRAPEVINE VARIETY. COMPACTNESS IS RANGED FROM ONE TO NINE, WHERE ONE MEAN "LOOSE BUNCHES", AND NINE MEANS VERY COMPACT BUNCHES. THE SHAPE DESCRIPTION FOLLOWED THE CLASSIFICATION: 1 CYLINDRICAL, 2 CONICAL, 3 FUNNEL SHAPED. THE VOLUME WAS MEASURED FOLLOWING THE WATER DISPLACEMENT METHOD.

Variety	N° Samples	Compactness OIV 204	Wings OIV 209	Shape OIV 208	Weight (g)	Volume (mm^3)	Height OIV 202 (mm)	Width OIV 203 (mm)	N° of Berries
Caberne Sauvignon	6	3.0	1.0	1.8	152.72	$156.68 \cdot 10^{-3}$	14814.3	8422.2	85.2
Carménère	6	3.0	4.3	2.5	215.80	$188.33 \cdot 10^{-3}$	14478.7	8863.5	79.5
Merlot	7	5.0	3.3	2.3	236.03	$208.57 \cdot 10^{-3}$	18795.2	10178.4	110.3
Pinot Gris	7	9.0	1.0	1.0	178.89	$174.28 \cdot 10^{-3}$	12089.4	7097.3	113.0
Pinot Noir	6	7.0	3.0	1.3	146.10	$123.33 \cdot 10^{-3}$	12735.7	7820.1	95.6
Raboso Piave	7	9.0	3.1	1.3	311.36	$290.00 \cdot 10^{-3}$	17808.3	11329.7	141.1
RabosoVeronese	6	7.0	2.0	2.5	250.57	$253.33 \cdot 10^{-3}$	20678.3	9888.2	127.5

The specific functions used for this purpose were: align photos, optimize camera alignment, build a dense cloud, and build mesh. A calibration cube was captured and rebuilt with the bunch. The cube was used to provide a calibrated dimension to the bunches. Finally, the digital models were manually cleaned, deleting the noise and artefacts from the background and the cube. Figure 1 shows a bunch's DT per variety.

B. 3D model analysis

Each DT was deeply investigated thanks to the software CloudCompare (www.cloudcompare.org). Five horizontal sections perpendicular to the bunch's vertical axis and two vertical sections perpendicular to each other were extracted from the digital models. Also, the bunch's surface and the whole mesh's volume were measured. A detail of the horizontal section and vertical ones is shown in Figure 2a and Figure 2b, respectively. The convolutional solid (Figure 2c) was designed considering the horizontal sections' major axis and the bunch's height. The perimeter, area, and axes length of all the sections were measured thanks to AutoCAD 2022.1 (Autodesk^{tm}).

C. Statistical analysis

First, a hierarchical clustering was carried out on all the features in RStudio 2022.12.0 (2009-2022 RStudio) thanks to the 3D analysis. The clustering is a preliminary analysis to verify if a trend exists among the bunches' features according to their variety.

Then, the analysis of variance (ANOVA) was carried out to identify the most divergent features between grapevine variety, shape, and compactness. All the features were considered in the ANOVA, manual, two-dimensional, and three-dimensional measures. Also, Tukey's multiple comparisons test was carried out to detect how many items each feature could distinguish. Then, a correlation matrix was computed to detect the most auto-correlated variable. Finally, the most representative features among autocorrelated ones were selected to reduce the number of items.

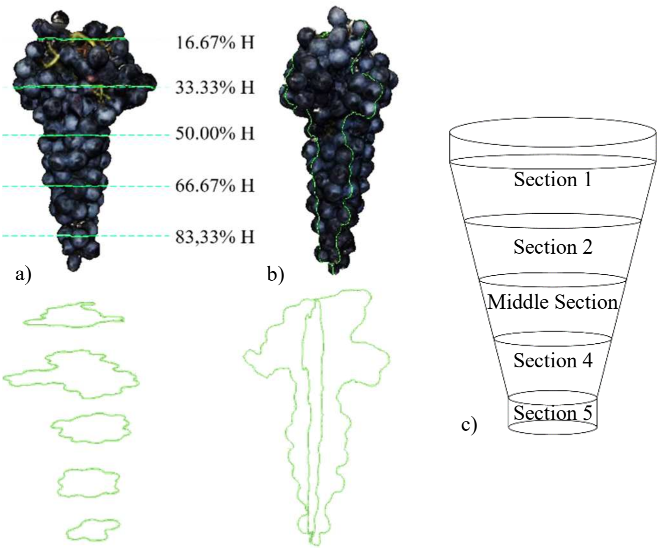

Fig. 2. a) Horizontal sections, in which H means bunch's height; b) vertical sections; c) diagram of the coevolutional solid volume. Each circle is refeared to the horizontal section position. The circle's diameter correspond to the maximum axis of each section.

III. RESULTS

The hierarchical clustering in shown in Figure 3. First, most of the Pinot Gris and Pinot Noir bunches are clustered in the same sub-branch. On the right side of the dendrogram, close to the Pinot clustering, there are mostly Cabernet Sauvignon bunches and three Carménère ones. On the other hand, in the left side there are mostly the Raboso and Merlot bunches. Finally, in the middle of the scheme, there is a mixture of variety exception for the Pinot bunches.

All the features have been analysed, but only the most prominent ones were presented in this paper. Thanks to the Tukey test, the feature selection was based on the variability

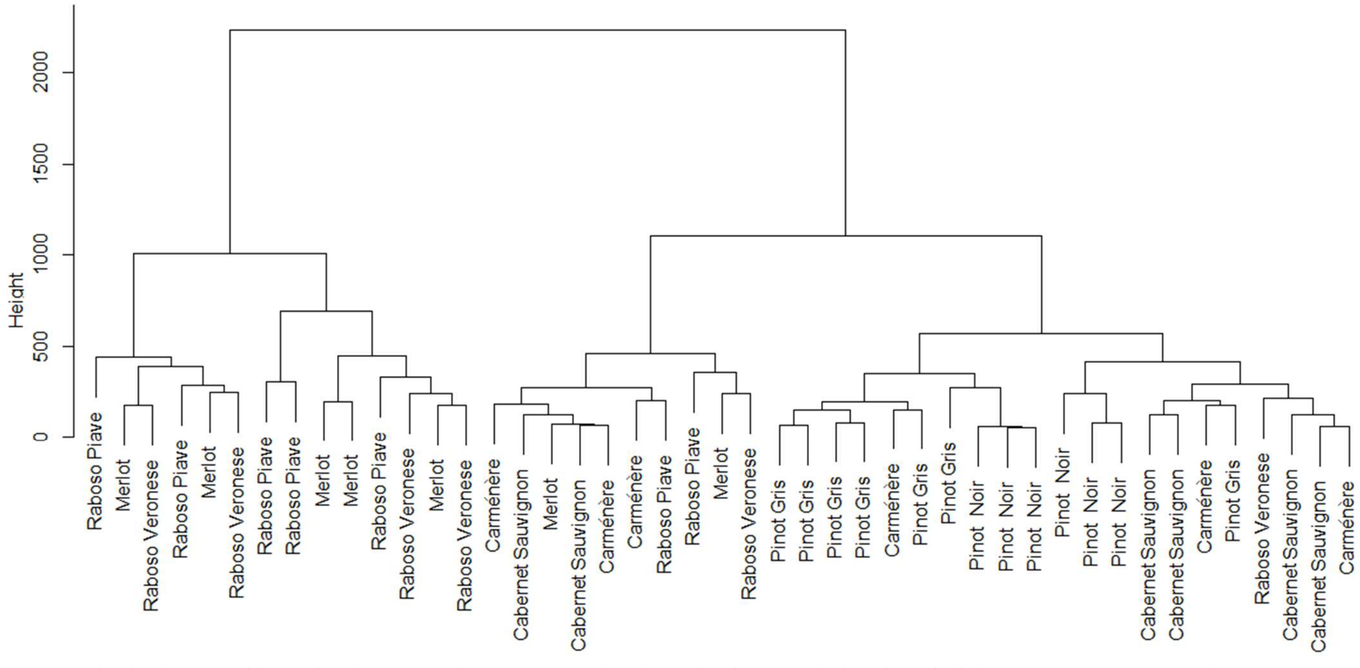

Fig. 3. The dendrogram of hierarchical cluster analysis represents the relationship between the bunches of all the grapevine varieties. Each item (45) means a repetition of the bunches sampled per variety. The dendrogram was build considering the features extracted thanks to the 3D analysis.

and the number of items discerned. Because seven varieties, four compactness scores, and three shape types were compared, the multiple comparisons test were carried out on 21 combinations of varieties, six combination of compactness, and three shapes. Table 2 shows the results of the ANOVA and Tukey's multiple comparisons tests. The features are defined in Table 3. The total number of berries, the bunch's height, and the maximum bunch's width are the manual measures that showed the highest variability across variety, shape, and compactness.

TABLE II. OUTPUTS OF THE STATISTICAL ANALYSIS. THE SYMBOL IN THE ANOVA'S COLUMN ARE REFERENCED TO THE MULTIFACTORIAL ANOVA BETWEEN THE MORPHOLOGY TRAITS AND THE THREE INVESTIGATED VARIABLES: "***" A *P*-VALUE< 0.001, "**" A *P*-VALUE <0.01, "*" A *P*-VALUE <0.05, WHILE "NS" NON-SIGNIFICANT. THE TUKEY COLUMN REASUME THE NUMBER OF ITEMS WHICH PROVED RELEVANT DIFFERENCES ACCORDING THE TUKEY'S TEST.

Features	**Variety**		**Compactness**		**Shape**	
	ANOVA	**Tukey**	**ANOVA**	**Tukey**	**ANOVA**	**Tukey**
Tot. Berries	***	12/21	***	4/6	***	1/3
Height	***	15/21	***	2/6	***	2/3
Max Width	***	10/21	ns		***	1/3
Surface	***	9/21	ns		*	1/3
Mesh_V	***	10/21	ns		*	1/3
N°Berries	***	9/21	ns		***	2/3
C_Vol-Mesh	***	6/21	***	3/6	***	3/3
S/H	***	10/21	*	1/6	*	1/3
P_VX	***	12/21	***	3/6	***	2/3
Rar_VX	***	9/21	***	1/6	***	2/3
A_H2	***	9/21	ns		ns	
A_H5	***	7/21	***	4/6	***	2/3
AP_H1	***	7/21	*	1/6	ns	
AP_H5	***	8/21	***	4/6	***	2/3

TABLE III. ABBREVIATION AND RELATED DEFINITION FOR THE FEATURES INTRODUCED INT THIS PAPER. REFERENCE INDICATES THE CITATION, "***" MEANS WHICH MEASURES WERE PROPOSED IN THIS STUDY, AND EMPTY CELLS MEAN GENERAL GEOMETRY RULES.

Abbreviation	**Definition**	**Reference**
Tot Berries	Total number of berries per bunch	[28]
Height	Bunch's height	[23]
Max Width	Bunch's maximum width	[23]
Surface	Surface of the DT's mesh	***
Mesh_V	Volume of the DT's mesh	***
N°Berries	Number of berries across the middle horizontal section	***
C_Vol-Mesh	Difference between the convolutional solid volume and the mesh's volume	***
S/H	Ratio between the DT mesh Surface and the bunch height	***
P_VX	Perimeter of the vertical section according the narrowest side	
Rar_VX	Ratio between the area of the vertical section and the area of the smallest rectangular containing the section	[11]
A_H2	Area of the horizontal section placed at 33.66% of the height	
A_H5	Area of the horizontal section placed at 83.33% of the height	
AP_H1	Ratio between area and perimeter of the horizontal section placed at 33.33% of the height	[26]
AP_H5	Ratio between area and perimeter of the horizontal section placed at 83.33% of the height	[26]

Among the three-dimensional measures, the size of the vertical section according to the narrowest side of the bunch was stated as the most variable feature across variety, shape, and compactness. The perimeter, the area, the compactness, and the axis ratio of the vertical section were relevant, but just the perimeter was selected as the most representative. Also, the ratio between the area of the vertical section and the area of the smallest rectangular containing the section resulted as relevant. The whole bunch's surface was relevant for discerning between varieties and shapes. The mesh volume means the volume of the whole DT, which means the sum of the berries' volume and the volume of the blank inside the bunch. The mesh volume was more accurate than the bunch's actual volume for the assessment. Finally, the number of berries counted in the middle was relevant for discriminating the varieties and the shapes. The second and last horizontal sections' sizes seem useful for classifying varieties. In contrast, the size of the last section is helpful for compactness and shape classification. Table 2 reported just the area of the last section. Regarding the three-dimensional indices, the difference between the convolutional solid volume and the mesh's volume was relevant for all the variables investigated. The convolutional solid volume (CVol) could be the volume of the ideal polygon containing the bunch. CVol means the volume of the solid illustrated in Figure 2c. More in detail, the convolutional solid volume could discern 3 out of 3 combinations of shape classes.

The ratio between the bunch's surface and the whole mesh volume was the more accurate index than the single native measures. Finally, the ratio between the area and the perimeter of the first and the last horizontal section seem useful for classifying varieties. As mentioned above, only the ratio of the last section is helpful for compactness and shape classification.

IV. DISCUSSION

The hierarchical clustering retrieves an acceptable classification of the samples based almost on the bunch size and shape, underling the prospect of using objective measures and index for the varieties classification. According to the classification made by the hierarchical clustering, the two main branches split the bunches according to their size. The heaviest bunches, such as Raboso Piave and Merlot, are clustered on the left brunch. In the left branch, the average and the lowest bunches' weights are 283.90 g and 178.4 g, respectively. Also, the average and the lowest computed volume are $388.91\cdot10^{-3}$ mm^3 and $238.59\cdot10^{-3}$ mm^3. Also, both Raboso Piave and Merlot have a typical conic shape. The conical Raboso Veronese bunches are among the left-branching, however. The "big bunches" are also proven by the highest computed volume, number of total berries, width, and the sections' sizes.

Then, the right branch is made of "small bunches", almost cylindric or funnel shape. The Pinot Gris and Pinot Noir bunches are grouped in the same cluster. The Pinot bunches are among the lightest analysed varieties. Also, the Pinot bunches have a cylinder shape. The most petite and cylindric bunches of Cabernet Sauvignon are clustered together with the Pinot samples. Following the Pinot, on the right side of the chart, there are Cabernet Sauvignon and other funnel-shaped bunches. While the Cabernet Sauvignon bunches are very light, the Raboso Veronese and Carménère bunches have a typical funnel shape (Fig. 2). The average and the highest bunches' weights are 176.98 g and 236.41 g, respectively. Also, the average and the lowest computed volumes are $200.23\cdot10^{-3}$ mm^3 and $280.99\cdot10^{-3}$ mm^3. Moreover, the right branch includes compact bunches, as shown by the average values of the indices AP_H1, AP_H5, and Rar_VX. More in detail, the compactness of the bottom section expressed as AP_H5 was found divergent across the dendrogram. The average AP_H5 measured 0.74 mm and 0.59 mm in the left and right branches, respectively.

The selected features from the ANOVA take into account the most essential traits of the bunches. The number of berries and the height are related to the bunch size. The remaining features could be more related to the bunch's shape and compactness. For example, the surface depends on the total area made by the surfaces of the berries, but also, loose bunches showed a higher surface value than compact ones. Hence, the berry's arrangement is essential to the 3D features. Moreover, Cvol showed good performance for the bunches classification, as verified by [17]. In particular, Cvol retrieves helpful information about the presence of wings, hence the bunch's shape. Moreover, Cvol might be related to the bunch's compactness, so its indices could be considered a crucial trait for the grapevine bunchs' evaluation.

Finally, general information about grapevine morphology seems helpful for the variety cataloguing [26]. In addition, the size and compactness of the bottom part of the bunch are essential information for compactness and shape classification [11], [17], [29]. For example, the features A_H5 and AP_H5 can discern between the cylindric and funnel shapes with the conical one. Because the typical bunch's morphology traits inspire all the proposed variables, the analysis could be conducted on any *Vitis vinifera* variety from different cultivation areas.

Deep analysis of the bunch's morphology based on 3D techniques allows extracting several numeric descriptors and indices. Measures and indices could be executed in a mathematical model to retrieve the objective threshold for the bunch morphology evaluation and classification [26]. Implementing objective indices and temporary stable thresholds should avoid misclassification or human error due to personal judgment.

V. CONCLUSION

The research study aims to propose more detailed measures and indices for improving the grapevine bunches morphology description thanks to three-dimensional analysis. Including the three-dimensional analysis in the standard visual could help to achieve a more accurate description of each grapevine variety, bunch's shape, and compactness. Especially, future studies could define specific traits between clones of the same variety or to recognize thin difference among the compactness evaluation. Finally, an artificial intelligence architecture could be implemented for the automatization of the bunch classification.

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