Image Processing to Evaluate Post-harvest Damages on Grapes and Their Impact on Fruit Aspect

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Abstract— **The interaction between grapes and fungi is a topic that recently has increased its interest since it can benefit or reduce fruit quality. Multiple factors determine the quality of grapes, which is directly affected by their ripeness, flavour, colour and overall health. In the post-harvest process, decay due to water loss and fungal decay are major challenges in grape quality and preservation. In this paper, we aim to develop an image tool capable of spotting anomalies in the skin of grapes using image processing and machine learning. A series of cameras connected to nodes identify irregularities on grape skin. Pictures are processed, and the results are sent to a database where the feature extraction happens. Data is sent to the cloud, where machine learning classifies the state of the fruit. In order to perform our tests, 2 bunches of grapes were studied for 14 days. One bunch had their skin punctured, while the other was left untouched. The metrics selected to evaluate quality detection were accuracy and recall. According to the results, the modules that represent the most accuracy and recall are K-Nearest-Neighbor (KNN), followed by Artificial Neural Network (ANN). In the case of KNN, when 4 parameters are included, the accuracy reaches 100 %. Following this same pattern, the ANN module rose an accuracy of 95 % when 4 parameters were added. In addition, in the recall metric, KNN spiked at 95 % with the incorporation of 3 parameters, while ANN escalated to 90 % by adding 4 parameters.**

Keywords— Fungal disease; quality; image analysis techniques; Machine Learning; disease detection.

I. INTRODUCTION

Grapes are known to be the primary source of many of the world's most popular wines, so understanding how to grow and cultivate high-quality grapes is essential for the wine industry and daily consumption [1]. Since it is such an important crop, the number of studies on this topic has increased in the last decades. Therefore, a vast number of studies have been focused on vineyard yields, specifically on the surrounding environment, climate, soil, and human interaction [2]. The quality is a property of the grapes, which might be strongly affected by time and is closely related to the presence of fungi. There are several aspects that can determine the quality of grapes, including their ripeness, flavour, colour, and overall health. During post-harvest, grapes are prone to rapid deterioration following harvest due to significant water loss from the drying of the rachis and pedicel. This dehydration leads to berry softening, weight loss, and browning [3]. In addition, significant losses are incurred due to fungal decay, primarily caused by necrotrophic pathogens. It has been studied that fungi have a rapid growth rate and can easily spread through berries, making their preservation challenging [4].

On the one hand, many reviews have described technological factors used to enhance the quality of grapes during the post-harvest stage [5]. Nevertheless, despite the need to improve methods for preserving the quality of table grapes during post-harvest, consumers are reluctant to use existing chemical treatments. Therefore, exploring and enhancing the physical processes during the post-harvest is important. The objective is to keep the grapes in environmental conditions that prevent the proliferation of fungi and water loss to keep the quality of the grapes [6].

On the other hand, monitoring systems based on sensors and image processing are being used in agriculture to identify fungal diseases and fruit quality. Nowadays, hyper- and multispectral imaging can be used to detect foliar symptoms of grapevine trunk diseases [7]. Additionally, image processing and Machine Learning (ML) techniques can be used to develop an automatic system for detecting grapevine diseases [8]. By doing this, it was detected that reflectance data could potentially serve as a means for evaluating crop damage [9]. Though, most research has been carried out on leaves rather than on the fruit itself. Nevertheless, as far as we are concerned, no papers focusing on the use of images for detecting loss of grape quality during the post-harvest due to the proliferation of fungi have been found.

The aim of the paper is to develop a tool capable of detecting anomalies in grapes by using image analysis techniques. To achieve this goal, 2 bunches of grapes were used. The first one was punctured, and the second one was left untreated. The process took 14 days before fungi appeared. During the study, 3 sets of photos were taken each day to observe grape and fungi development. The main novelty of this study was to cast aside molecular and chemical techniques to use a more visual and technological approach and apply it to the fruit instead of leaves. The process would be based on a camera connected to a node. This camera will take pictures to every grape bunch. Then, these images will be processed and detect the presence or absence of anomalies and an evaluation of their quality, informing the operator. Furthermore, this study will provide easier identification and presence of fungi in grapes.

The rest of the paper is structured as follows: Section 2 outlines the related work. The proposed system is fully described in Section 3. Following Section 4 details the test bench. The results are discussed in Section 5. Finally, Section 6 summarises the conclusion and future work.

II. RELATED WORK

In this section, we will summarise the current image analysis, the processing techniques used on leaves and the traditional methods for fungi detection and techniques to determine the quality of grapes.

A. *Use of image analysis on leaves.*

In [10], Meena et al. proposed the use of a Convolutional Neural Net (CNN) to classify picture pre-processing, image segmentation, and feature extraction in 5 different types of plants. By doing this, they analysed the colour, shape, and texture of the leaf and allowed them to locate the disease in the leaves. Similar to this study, Jaisakthi et al. [8] proposed an automatic system capable of identifying diseases in grape vines by analysing the leaves with image processing and machine learning. By doing this, they observed a difference between the possible diseases affecting the leaves.

The aforementioned examples show the use of image processing to analyse the presence of diseases in leaves and cannot be applied directly in post-harvest monitoring of grapes. These techniques can be applied in our case, but specific indexes or feature extraction settings must be adapted or developed.

B. *Traditional methods for fungi and quality detection.*

Among the methods to detect the fungi's presence, most of them are based on chemical and molecular techniques. In [11], Diguta et al. used a restriction digestion analysis of the Internal Transcriber Spacer (ITS) products. This is a relatively easy method that involves using biological procedures to digest the ITS products of the fungal isolation from grapes. Then, the resulting fragments can be analysed to determine and identify the type of fungi. This method is known to be rapid and reliable. However, it can only be used to study only filamentous fungi. On another note, additional widely used techniques are the DNA-based molecular methods. This involves studying the DNA of the fungi to identify them. For example, in [12], Zhang et al. isolated colonies from grapes by HPLC-FLD tests. They detected the production of certain toxins. Meanwhile, amplification products were analysed and compared with other sequences with PCR. In another study, Han et al. [13] tested microRNAs by extracting and sequencing RNA with a subsequent PCR to find resistance to a certain type of fungal disease. A similar study was developed by Zhu et al. in [14], where they studied fungal communities in the maturation process by using DNA extraction and amplification with PCR, purification, and analysis.

Regarding the methods for determining fruit quality, there are many sample-based laboratory analyses, such as PCR or DNA-based molecular methods. However, in 2017, Doerflinger et al. [15] proposed a digital image analysis that involves assessing berry quality using MATLAB programming language, providing an accurate description of berry quality. Kasimati et al. [16] used a machine learning-based data analysis technique. The use of ML algorithms to predict yield and quality has become increasingly popular in recent years.

Although these biological procedures are easy to repeat and conduct in the laboratory, it is essential to remark that technological tools are much faster and more efficient options. For example, direct observation and identification with sensors and cameras [17], [18] can provide a faster response than the aforementioned biological methods. Moreover, the biological procedures require specific equipment, reagents, trained personnel, damage the samples, and are time-consuming.

III. PROPOSAL

In this section, we detail the proposed system to analyse the grape skin in order to find the presence of anomalies. First, we present the system description, with details of all the different included devices. Subsequently, the used sensor and nodes are identified. Following, the architecture of the proposed system is depicted. Finally, all the image processing techniques are explained.

A. *System description*

The system consists of a series of cameras connected to nodes along the warehouse. The system aims to identify the quality of fruit and possible damages along the different parts of the treatment and packaging chain.

Sensor nodes will be programmed to capture pictures at specific time periods. Subsequently, these photos will be first processed in the edge, applying a vegetation index, and then sent to the database (DB). Then, in the DB, fog computing is performed to classify and segment the images. Moreover, in the DB, the feature extraction process is conducted. The obtained data is sent to the cloud, where ML is applied to classify the state of the fruit.

Regarding image processing, our system will be based on a mathematical combination of different bands. By doing so, we are able to identify between a healthy grape and an infected grape. Therefore, we will explore the differences in the values of healthy and infected grapes, emphasising on the fungi, and find mathematical functions that enhance these distinctions in the resulting bitmap image. This will be carried out by the node. Then, with the index, we are going to apply a reclassification. This will allow us to convert the original pixel value to a new value which represents a class. Following, image segmentation and feature extraction will be conducted. These steps will be done in the DB.

Tagged images are used for the classification of data with ML. The tagged data is based on the fruit colour and the existence of visible damage in the grapes.

B. *Camera description*

A camera that accomplishes the following requirements is needed for the proposed system. First of all, the minimum size for this application is 9024 x 12032 pixels with a vertical and horizontal resolution of 72 ppi. The RGB camera should offer a bit resolution of 24 bits.

The cameras should be placed at a maximum distance of 30 cm from the fruit. Flash will be used to ensure a homogeneous illumination in all the pictures.

C. *Node selection*

A Raspberry Pi 4 model B node is selected for this application. This node is used because of its high computational capacity compared with other nodes, such as Arduino Mega or EPS32. The selected node can perform some simple image-processing steps. Thus, edge computing can be included, reducing the required bandwidth to forward the data.

D. *Architecture*

The architecture of the proposed system can be seen in Figure 1. The network system is based on a series of cameras connected to the nodes, an Access Point (AP), a DB, and a cloud server. Cameras are connected to Raspberry Pi 4 model B microcontrollers that are able to identify and take photos of the grapes and apply the initial index. Then, the nodes forward the result of the index to the DB using a WiFi AP. The DB stores the data and performs some additional image-processing steps. The extracted features are sent to the cloud server, where the ML tools are applied to classify the grapes.

E. Image processing and ML classification

This subsection explains the different conducted processes for feature extraction of the captured images. The different steps include index calculation, reclassification, segmentation and feature extraction.

Concerning the index calculation, also known as band combination, we have used an existing index. The index was initially designed to estimate the chlorophyll content in leaves; nonetheless, it can be applied in this case to evaluate the greenness versus ripeness of the grapes. The index is named Green Leaf Index (GLI) [19] and is described in (1)

$$GLI = \frac{(2G - R - B)}{(2G + R + B)} \qquad (1)$$

For image reclassification, a series of thresholds have been defined. The thresholds, based on the quartiles of the first processed image, can be seen in Table 1. After the reclassification, the new values range from 1 to 5 - the lower the values, the better the quality. The pixels from class 5 include areas of the grape with damages.

TABLE I. SUMMARY OF CAMERA FEATURES

Class	Original GLI	
	Minimum value	*Maximum Value*
1	-100	-1
2	-1	0
3	0	6
4	6	13
5	13	100

With regard to the segmentations, the centre of each grape is identified and a radial buffer of 125 pixels is generated. The included pixels in the circle are the analysed area of the grape, which are the included segments of the reclassified image.

Feature extraction consists of obtaining histograms of the different segments. The histograms will contain the number of pixels for each one of the pixel values, which can be 1 to 5. Thus, the generated histograms will include 5 classes.

The obtained data from the histograms are used for the classification with the ML module. For the classification, the segments must be tagged. An expert has classified the portions according to their colour and the presence of damages by providing two scores. The scores range from 1 to 5, the latter of which represents the lower quality. Then, an overall score is calculated by averaging both scores, which is an integer number. If the result of the mathematical operation is not an integer number, the next integer number is considered the result.

Finally, for the ML module, 5 alternatives are considered: Support Vector Machine (SMV), Discriminant Analysis (DA), ANN, Bayesian Network (BN) and K-Nearest-Neighbor (KNN). The selection of the most appropriate number of parameters for the classification is studied. The parameters are the values of the histograms obtained from the segments of the reclassified index, which are the 5 classes. A larger number of parameters will increase the accuracy of the system. Nevertheless, a greater energy consumption will be linked to the obtention of these parameters. Selecting the number of parameters, we balance the accuracy and energy consumption. Concerning the dataset, 6 pictures are used, and features were extracted from 12 and 13 areas of each picture. Thus, 75 areas are used in our proposal.

All the steps for the grape's classification are summarised in Figure 2.

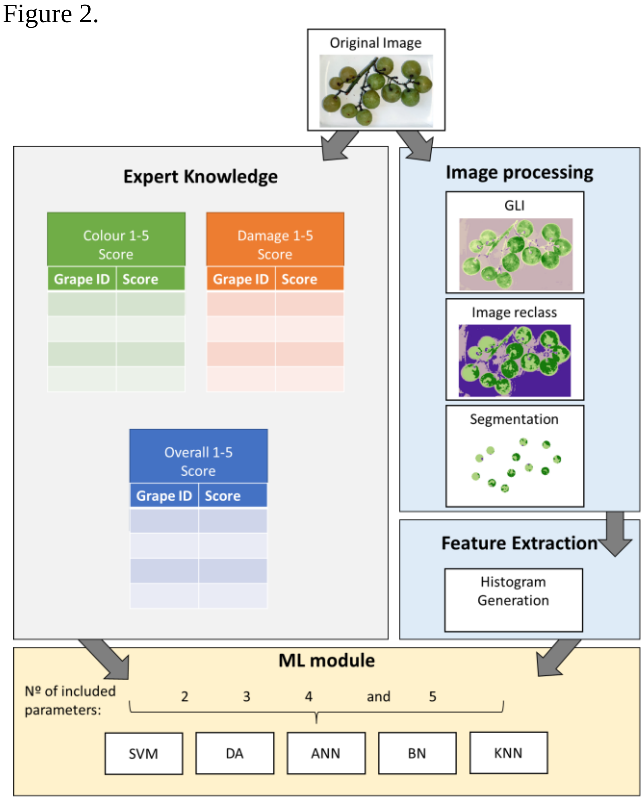

Figure 2. Summary of image processing and ML tools for the multimedia monitoring system for grape quality detection.

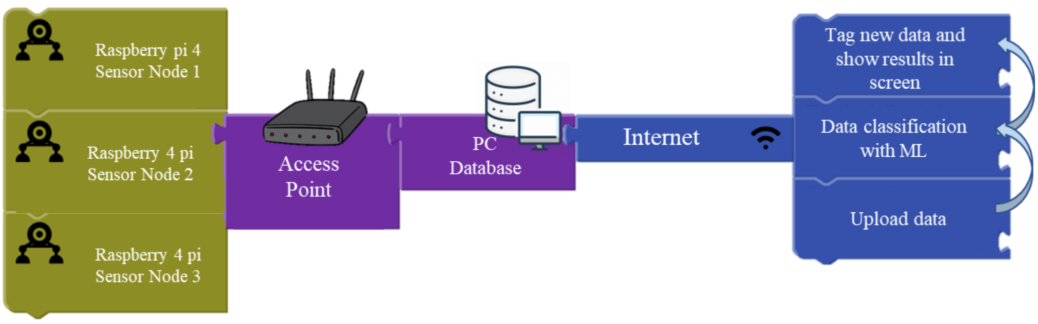

Figure 1. Architecture of proposed multimedia monitoring system.

IV. Test Bench

In this section, the complete test bench is detailed. First of all, the equipment and the image-capturing process is described. Then, the sample preparation is presented. Finally, the metrics employed to assess the results are shown.

A. Equipment and image-capturing process

In order to capture the images, a regular camera has been used. The camera lens corresponds to a sensor model with 108 Mpx, 1/1,33 inches in size and 1,66 µm pixels. Pictures were taken from a distance of 20 cm, and the flash was active in each case. Photos were taken 3 times a day, at 8 am, 4 pm and 12 pm, for 14 days. They were placed in two transparent plastic containers to prevent the grapes from being lost and to obtain a better study of their quality. A white filter paper was placed at the bottom of the compartment to simplify the process in the following image analysis. The dimensions of each receptacle were about 22x15x5 cm. These containers were selected with the objective of representing a similar situation as in real post-harvest. The grapes are carefully placed to avoid overlapping effects in this preliminary step.

B. Sample preparation

In order to perform our tests, 2 bunches of grapes were studied. All grapes were white seedless grapes, the variety Autumn Crisp. Each group had about 12-13 grapes, and all of them were attached to the stem. Both bunches of grapes were displayed in two compartments exposed to the air. The diameter of the studied grapes was around 2 and 3 cm.

To test the environmental influence and post-harvest quality, one bunch of grapes was left untouched, while the other had small punctures since day 1.

C. Selected Metrics

Two metrics are used to evaluate the performance of the different available ML modules. The selected metrics are accuracy (1) and recall (2), which can be seen below:

$$Accuracy = \frac{TP}{TP + FP} \quad (1)$$

$$Recall = \frac{TP}{TP + FN} \quad (2)$$

where TP is the number of True Positive classified cases, FP is the number of False Positive classified cases, and FN is the number of False Negative classified cases.

Considering this is a multiclass problem, each class's metrics are calculated individually. Then, macro-averaged accuracy and recall are calculated as the average of all classes for each ML module. Since we have tested the inclusion of different numbers of parameters, macro-averaged metrics are calculated for each number of parameters.

V. Results

In this section, the results of image processing and data classification are conducted. First, the results obtained after applying the GLI and the reclassification are described. Then, each grape's estimated quality is described. Finally, the classification results based on ML algorithms are discussed.

A. Image processing

The application of GLI allows, on the one hand, to reduce the image size by having a single band instead of three bands. On the other hand, the new band maximises the differences between the greener areas, the healthy grapes, and areas with other colours, such as bumps, damages or fungic infections.

The RGB and the index have been calculated for the RGB images captured during the experiments. Results can be seen in Figure 3. Next, the reclassified image according to the established thresholds in Table I is displayed with the circles indicating the segments to be analysed.

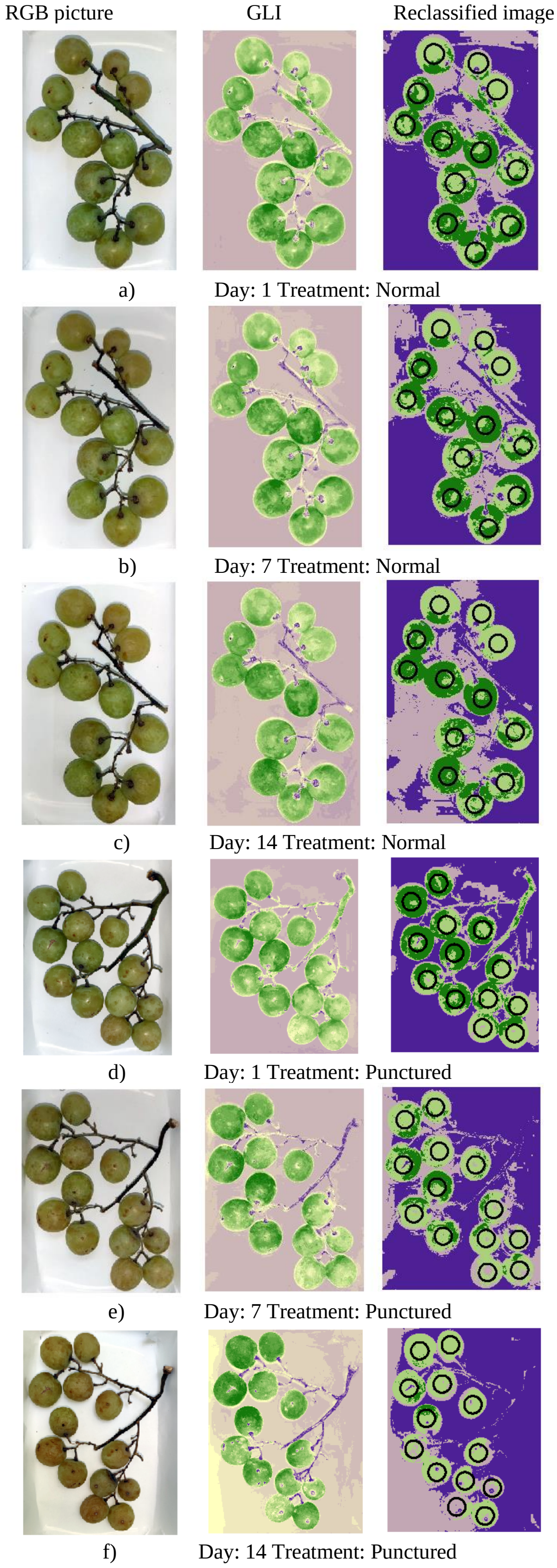

Figure 3. Process followed for image classification.

In Figure 3 a) and d), we can see the image of the first day with the standard treatment and punctured grapes. Figure 3 b) and e) correspond to the pictures after 7 days for the normal and the punctured treatment. Finally, Figure 3 c) and e) correspond to the images after 14 collections with the different treatments. It is possible to see that there are differences among the treatments and over time in the RGB image. Nonetheless, the differences are much more evident when the GLI is applied and when the image is reclassified.

Concerning the feature extraction results, an example of data of obtained histograms from a random grape of normal treatment and a random grape of standard treatment can be seen in Table 2. In the Table, it is possible to see the number of pixels contained in the studied segments for each one of the 4 classes.

TABLE II. EXAMPLE OF OBTAINED HISTOGRAMS

Class	Example of Grape of Normal Treatment			Example of Grape of Punctured Treatment		
	Day 1	*Day 7*	*Day 14*	*Day 1*	*Day 7*	*Day 14*
1	0	0	1092	0	6	889
2	0	0	203	0	136	314
3	355	27	1339	1020	6312	6441
4	27292	33739	43166	42276	42520	41382
5	21394	15280	3243	5727	63	13

B. *Classification results*

This subsection presents the results of different ML modules for solving the multiclass problem based on data obtained in the previous subsection. In Figure 4, the macro-accuracy results can be seen. Regardless of the number of included parameters, the KNN is the algorithm that offers a better performance in terms of accuracy, followed by ANN. When the KNN algorithm is used with 4 or more parameters, 100 % of accuracy is reached. No other algorithms achieve similar results. In the case of results with the ANN, the maximum accuracy is 95.2 % with both 4 and 5 parameters. The worst accuracies are obtained with BN with maximum accuracy of 78 %, SVM, and DA, the last two of which have similar performances.

Concerning the macro-averaged recall, the results can be seen in Figure 5. Again, the KNN algorithm's performance is the best among the tested ML methods. As for accuracy, 100 % of recall is achieved when 4 and 5 parameters are used. In the case of the ANN, the recall reaches 92 % when 4 or more parameters are used.

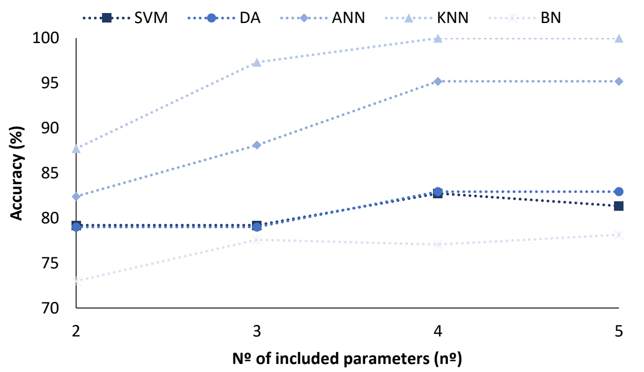

Figure 4. Macro-averaged accuracy results for the different tested algorithms and with different numbers of included parameters.

Contrary to what happened in the case of accuracy, the worst results are linked with SVM, with recall values below 40 % in all the cases. The performance of DA is slightly better than that of SVM, with a maximum recall of 46 %. Finally, BN is in the third position among the tested algorithms. It is the only one that has an increase in its performance when the last parameters are included, rising from 55 % with 4 parameters to 67 % with 5 parameters.

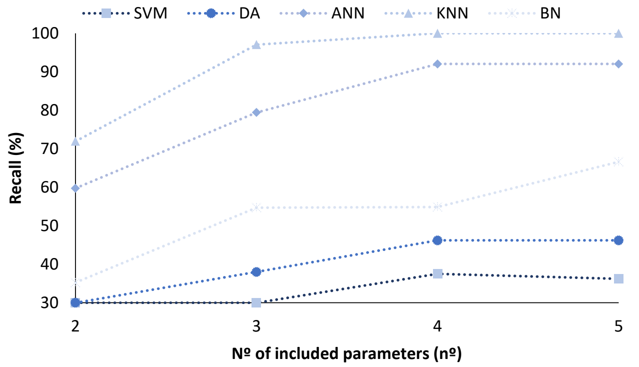

Figure 5. Macro-recall accuracy results for the different tested algorithms and with different numbers of included parameters.

After analysing the results, it is possible to affirm that in order to maximise the performance of the system, it is required to use the KNN algorithms as an ML tool to classify the data. It is recommended to use 4 parameters since the results when an additional parameter is included do not increase, and a lower number of parameters will have less space in the DB and less information to be exchanged with the cloud server, thus decreasing the network requirements and energy use.

We can affirm that the proposed methodology for fruit quality determination using image processing and ML tools offered promising results. Accuracy and recall equal to 100 % have been achieved. For the application of this system in real conditions, it will be recommended to include additional cameras to gather more images from the same bunch to avoid the overlapping effect.

C. *Limitations*

There is a series of constraints to be considered in this study before its implementation in real conditions. As mentioned in Section IV A, to avoid overlapping two or more grapes, they were carefully distributed to make it easier for the program to detect the area of the grapes. It remains to be determined in which sense this overlap affects the image generated. The program may detect one grape instead of two. Further studies should be carried out to study how to avoid this overlapping and how to solve it.

In this study, the camera used to obtain the images of the bunch of grapes was a conventional camera. For future studies, it would be advisable to use a higher resolution camera to better delimit the area of each grape.

VI. CONCLUSIONS AND FUTURE WORK

Rapid fruit quality evaluation is extremely important in warehouses along the value chain. While there are several proposals to control and reduce fruit quality decay, few

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methods are found to evaluate the fruit quality remotely during the storing and processing periods.

In this paper, we have proposed, analysed and verified a methodology to determine the fruit's quality and the fungi's presence based on image processing. The proposed method is based on applying GLI, image segmentation and using ML to classify extracted features. With KNN, accuracy and recall of 100 % are achieved even if not all the extracted features are included in the classification.

The future work will include adding additional sensors, such as gas sensors [20] with the aim of predicting the fruit's quality decay. In addition, the study of other grape varieties and other berries is foreseen to evaluate the suitability of this method with fruits characterised by other colours.

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