IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received April 7, 2018, accepted August 24, 2018, date of publication October 22, 2018, date of current version December 3, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2875862

Computer Vision and Machine Learning for Viticulture Technology

KAH PHOOI SENG[1,2], (Member, IEEE), LI-MINN ANG[1,2], (Senior Member, IEEE), LEIGH M. SCHMIDTKE[2], AND SUZY Y. ROGIERS[2,3]

[1]School of Computing & Mathematics, Wagga Wagga Campus Ringgold Standard Institution, Charles Sturt University, Wagga Wagga, NSW 2650, Australia
[2]National Wine and Grape Industry Centre Ringgold Standard Institution, Wagga Wagga, NSW 2678, Australia
[3]NSW Department of Primary Industries, Wagga Wagga, NSW 2678, Australia

Corresponding author: Kah Phooi Seng (jasmine.seng@gmail.com)

This work was supported by the Australian Wine Industry through their investment body Wine Australia with matching funds from the Commonwealth Government. The National Wine and Grape Industry Centre is an alliance between Charles Sturt University, New South Wales Department of Primary Industry and the New South Wales Wine Industry Association.

ABSTRACT This paper gives two contributions to the state-of-the-art for viticulture technology research. First, we present a comprehensive review of computer vision, image processing, and machine learning techniques in viticulture. We summarize the latest developments in vision systems and techniques with examples from various representative studies, including, harvest yield estimation, vineyard management and monitoring, grape disease detection, quality evaluation, and grape phenology. We focus on how computer vision and machine learning techniques can be integrated into current vineyard management and vinification processes to achieve industry relevant outcomes. The second component of the paper presents the new GrapeCS-ML database which consists of images of grape varieties at different stages of development together with the corresponding ground truth data (e.g., pH and Brix) obtained from chemical analysis. One of the objectives of this database is to motivate computer vision and machine learning researchers to develop practical solutions for deployment in smart vineyards. We illustrate the usefulness of the database for a color-based berry detection application for white and red cultivars and give baseline comparisons using various machine learning approaches and color spaces. This paper concludes by highlighting future challenges that need to be addressed prior to successful implementation of this technology in the viticulture industry.

INDEX TERMS Viticulture, computer vision, machine vision, visual computing, image processing, machine learning.

I. INTRODUCTION

The domesticated grape is an important fruit crop from an economic perspective and is also one of the oldest with a long history of cultural significance. It is believed that *Vitis vinifera* has its beginnings in an area between the Black Sea and Caspian Sea but today there are over ten thousand varieties grown across the globe. In terms of land area designated for wine production, Spain is first, followed by other countries like France and Italy [1]. The viticulture industry is also important in countries like the United States, Australia and Chile. Suitable environmental conditions and appropriate cultural practices throughout the season are required to ensure optimal grapevine performance and grapes that will match the desired wine style [2]. The harvest can vary substantially from year to year and also within the vineyard due to soil conditions, climate, disease, pests, and vineyard management practices. In vineyards using traditional practices, tasks are human performed; they can be time consuming and lead to physical stress and fatigue. In recent decades and especially over the last few years, new technologies have been implemented to allow the automation of many tasks.

Such technologies include robotics, remote sensing, and wireless sensor network (WSN) technologies. Modern agricultural machines utilize automation technologies to control the movement within the vineyard (in terms of speed and direction of travel and steering angle) and to manage the agronomic operations. Advanced location technology makes it possible to have an automatic guidance system based on the use of GPS and sensors [3]. For example, tractors have been engineered to perform site-specific operations autonomously without human intervention through the interpretation of prescription maps made with monitoring sensors mounted on board. There are many commercial solutions for Variable Rate Technology (VRT) deployment in vineyards.

The practical deployment of robotics in precision viticulture is still in the emerging phase, but many projects are already in the final stages of development, and some have already been put on the market. Examples of robot prototypes and commercial solutions for viticulture are VineRobot [4], VINBOT [5], VineGuard [6], Wall-Ye [7], VRC Robot [8], Vitirover [9], and Forge Robotic Platform [10].

The application of remote sensing technologies to precision viticulture has allowed the description of vineyard spatial variability with high resolution. The use of image acquisition performed at a distance with different scales of resolution is able to describe the vineyard by detecting and recording sunlight reflected from the surface of objects on the ground. Platforms used in remote sensing are satellites, aircraft, helicopter and unmanned aerial vehicles (UAVs). However, they either produce single or few synoptic views over the entire vineyard because data capture is expensive, and therefore unlikely to be adopted by vineyard managers for continuous measurements or monitoring. Wireless sensor network (WSN) technologies are useful and efficient for remote and real-time monitoring of important variables involved in grape production. A WSN is a network of peripheral nodes consisting of a sensor board equipped with sensors and a wireless module for data transmission from nodes to a base station. The data can be processed or stored and is accessible to the user. A comprehensive review on the state of the art of WSNs in agriculture can be found in Ruiz-Garcia *et al.* [11]. The use of remote image sensing has been the focus of much of the research in viticulture but it falls outside the scope of this review. Similarly, WSNs, automation technologies and robots without image sensing or computer vision and machine learning also fall outside of the scope of this paper. The reader can refer to the available reviews on automation and robotics [12], [13], remote sensing [14], [15], and WSNs [11], [16] in viticulture and agriculture.

Potential emerging viticulture technologies are not fully mature and there are several challenges to be addressed. While much of the work to date is promising, we have not yet achieved the ''vineyard of the future'', where these technologies can provide powerful tools that can be adopted by viticulturists to inform the management of their vineyards. These involve automatic leaf area estimation, fruit harvesting, yield estimation, grape quality evaluation and grapevine variety identification. Further challenges include accurate yield estimation and quality control, because such factors are affected by environmental and biotic variables (soil factors, climate, plant diseases), farming factors such as irrigation and the application of agrichemicals (pesticides, fertilizers, herbicides) [18], [19], and other agricultural tasks [20] (shoot thinning, bunch thinning, etc.).

This paper gives two contributions to the state-of-the-art for viticulture technology research. The first component presents a comprehensive review of the use of computer/machine vision, image/visual processing, and machine learning techniques in viticulture. To the best of our knowledge, such a comprehensive review of these fields for viticulture has not yet been reported. We review the latest developments in these areas for both laboratory-based and in-field techniques. We will demonstrate that these vineyard monitoring techniques are targeted at harvest yield estimation, grape disease detection, grape phenology assessment and crop quality evaluation, with the overall aim to aid vineyard management decisions. The second part of the paper presents a new database called GrapeCS-ML which consists of images of grape varieties at different stages of development together with the corresponding ground truth data (e.g. sugar content, acid levels, etc.) obtained from chemical analysis. Again, to the best of our knowledge, no such database is currently available for the research community in computer vision and machine learning. The availability of such a database is important to computer vision and machine learning researchers so that they are able to compare between techniques using common datasets. It is expected that the information contained in the database will spur new computer vision and machine learning research by providing training data for new algorithms and image processing techniques.

The remainder of the paper is organized as follows. Section II provides a comprehensive review of computer vision and machine learning for viticulture technology research focusing on representative studies. Section III presents the GrapeCS-ML database and gives details on the datasets. Section IV presents an illustration of the usefulness of the database to estimate the optimal harvest time for white grape cultivars using changes in hue color information. Future challenges for viticulture technology research are presented in Section V. Finally, Section VI concludes the paper.

II. REVIEW OF TECHNOLOGIES AND RESEARCH WITH A FOCUS ON THE FIELDS OF COMPUTER VISION AND MACHINE LEARNING FOR VITICULTURE

This section presents a review of recent research relevant to the application of computer vision, machine vision, image processing and machine learning research for viticulture technology focusing on five topics relevant to viticulture including harvest yield estimation, vineyard management and monitoring, grape disease detection, quality evaluation, and grape phenology. Tables 1 to 5 list the individual studies relevant to each of these topics – the imaging method used, the computer vision/machine learning techniques applied, and a value assessment of the study.

The methods can be broadly divided into two main approaches: (i) laboratory-based techniques; and (ii) in-field techniques. Laboratory-based techniques have the advantage of controlled lighting conditions and in the case for accurate berry detection the problem of obstruction by leaves and other bunches is avoided. The drawback, however, is that these methods are destructive. The more challenging approach is to perform berry detection in-field in a non-destructive manner. In this case, the illumination conditions cannot be controlled, and there is the additional obstruction problem. For each representative viticulture topic, we will first discuss the laboratory-based approaches which have been proposed

TABLE 1. Representative studies using computer vision and machine learning to estimate yield in viticulture.

Authors	Year	Grape variety	Imaging method	Computer vision and machine learning techniques	Value
			Laboratory-based techniques		
Battany et al. [26]	2008	Pinot Noir	Grayscale images	Conversion to binary images and watershed segmentation used to separate the joined berries.	More accurate and faster than manual berry counting, but involves destructive harvesting.
Tardaguila et al. [31]	2012			Determine the size and weight of grapes by extracting the morphology of a grape using Freeman chain code algorithm.	Approach is impractical for accurate and rapid measurement of grape size and weight in the field.
			In-field techniques		
Dunn & Martin [23]	2004	Cabernet Sauvignon	16 color RGB canopy images	RGB color features and threshold and tolerance values manually set to select "fruit" pixels.	85% accuracy of the variation for in yield combinations.
Chamelat et al. [24]	2006	Red grape clusters	Color outdoor images	Shape detection using Zernike moments and color information using semi-supervised SVM.	Detection of grape clusters in any orientation and size with 99% accuracy.
Rabatel & Guizard [25]	2007		Luminance images	Watershed algorithm and ellipse model fitting to contour arcs using least square algorithm.	Detection of two-thirds of visible berries on vine.
Reis et al. [27], [28]	2011, 2012	White and red grape cultivars	Night captured images	Color segmentation and mapping and morphological operations to fill in holes and remove falsely detected small regions. Extension work to differentiate between white and red grapes	False detection rate of 9%. Classification rates of 97% and 91% for red and white grapes respectively.
Nuske et al. [29], [30]	2011, 2012	Green grape cultivars	Visible light camera mounted on vehicle	Radial symmetry transform, color, texture and k-Nearest Neighbor classifier to classify the detected points. Extension work by utilizing calibration data obtained from previous harvests and handpicked samples.	Prediction of yield to within 9.8% of actual crop weight. Achieved a 4% and 3% improvement in yield estimation accuracy using harvest calibration and handpicked samples.
Murillo-Bracamontes et al. [32]	2012			Segment individual grapes from the image of a cluster using the circular Hough transform. Reduce false detections using color.	Method detected berries including those partially occluded.
Diago et al. [33]	2012		70 grapevine RGB images acquired from vineyard	Supervised classification from RGB images based on Mahalanobis distance to characterize grapevine canopy and assess leaf area and yield.	Methodology is able to discriminate among seven different classes. Performance of 92% accuracy for leaves and 98% for grape classes.
Farias et al. [34]	2012		RGB images	FCM-GK and SVM for cluster identification, SIFT for mosaic image to avoid overlapping regions among images.	Performance more successful than [33], accounts for effects of illumination and automatic clusters.
Liu et al. [35]	2013	Shiraz	RGB, HSV, and YCrCb images	Several approaches for classification (color histogram, RBF thresholding, and fuzzy clustering and SVM).	RGB thresholding gave a true positive rate of 87% with false positive rate of 5%, fuzzy clustering and SVM gave true positive rate of 97% with false positive rate of 16%.
Nuske et al. [36], [37]	2014	Wine and table grape cultivars	Vehicle-mounted vision system	Algorithms exploited three prominent visual cues (shape, color and texture) using a classifier which detects berries which has similar color to the background of vine leaves.	75% of spatial yield variance and with an average error between 3% and 11% of total yield.
Davinia et al. [38]	2014	Red table grape cultivars	High-resolution images (night) with artificial illumination	Threshold-based, Bayesian classifier, Mahalanobis distance, histogram segmentation and linear color model segmentation for RGB and HSV color spaces.	Best segmentation method was threshold segmentation in HSV color space (10.01% estimation error). Yield errors obtained were 16% and 17% for two yield estimation methods.
Liu et al. [39], [40]	2015	Red grape cultivars	Standard compact camera	Combination of texture and color information followed by SVM classification. Estimate the 3D structure of grape bunches from a single image.	Average accuracy of 87.3% relative to the actual number of berries on a bunch.
Luo et al. [41]	2015	Black grape images		Improved artificial swarm optimization fuzzy clustering.	Accuracy of 90.33% was achieved.
Luo et al. [42]	2016		Digital camera	Artificial bee colony and fuzzy clustering with AdaBoost framework.	Accuracy rate up to 96.56% was achieved. Under three various illuminations in the vineyard, average detection rate was 93.74%.
Vincent et al. [43]	2016		Color-based grape images	Feedforward neural networks (FFNN) with four classes (night time red berries, night time white berries, day time red berries and day time white berries).	Average classification rate of 93% could be achieved. FFNN could slightly outperform SVM in computation time.
Aquino et al. [44]	2017		Color-based images	Smartphone application using mathematical morphology and pixel classification (three-layer neural network, SVM) for grapevine berry counting.	Three-layer neural network performed better than the SVM.

TABLE 2. Representative studies focusing on pruning and shoot characteristics using computer vision and machine learning.

Authors	Year	Application	Imaging method	Computer vision & machine learning techniques	Value
McFarlane et al. [45]	1997	Grapevine pruning			Success rate of 80% to the problem of vine pruning.
Svensson et al. [46]	2002	Shoot count and canopy density			Shoot counting and assessment of the canopy to estimate density.
Gao & Fu [47]	2006	Grapevine pruning			
Gao [48]	2011	Grapevine pruning	Stereo cameras		Success rate of 85% for locating pruning and cutting positions.
Jaime et al. [49]	2011	Multipurpose stress detection in vine leaves	WSNs with image sensing nodes	Thresholding of leaf size to discriminate between stressed leaf and ground.	Sensor node sends message to WSN sink to notify grower when unusual leaves detected.
Xu et al. [50]	2014	Grapevine bud detection	Color RGB images	Preprocessing, Rosenfeld thinning algorithm, Harris corner detector	Detection rate of 70.2%.
Luo et al. [51]	2016	Locate cutting points on bunchstem	Binocular stereo cameras	Image calibration,	Success rate of approximately 87%. Elapsed time was less than 0.7s, feasible for deployment on harvesting robots.
Perez et al. [52]	2017	Grapevine bud detection		Scale-Invariant Feature Transform (SIFT) for low-level features, Bag-of-Features for image descriptors, SVM for classification.	Classification recall greater than 0.89 in patches containing at least 60% of the original bud pixels.

followed by the in-field approaches. We also attempt to present a chronological sequence based on the publication year. Details on the grape variety are also included.

A. COMPUTER VISION AND MACHINE LEARNING STUDIES FOR HARVEST YIELD ESTIMATION IN VITICULTURE

Yield estimation or forecasting is of critical importance in the wine industry. Traditionally, yield forecasts have been generated by counting vine number, bunch number per vine and includes the manual and destructive sampling of bunches to determine their weights, berry size, and berry numbers. Details of yield estimations involving traditional methods such as the lag phase method and others can be found in [21] and [22]. The manual process is labor intensive, expensive, and inaccurate. For each selected vine, the hand-harvested bunches are weighed and counted. From this data, the average number of bunches per vine and the average weight per bunch can be calculated and this information is then extrapolated to the vineyard on the basis of the number of vines per acre. The method can be inaccurate if the yield is unevenly distributed across the vineyard. Traditional manual sampling methods are destructive because a subsample of the bunches or berries are removed from the vine.

Laboratory-based techniques for harvest yield estimation can be found in the works by [26] and [31]. Battany [26] used a flatbed scanner to take images of detached Pinot Noir berries. The grayscale images were converted to binary and watershed segmentation was used to separate the joined berries and counted. Their approach was more accurate and faster than manual berry counting, but also involves destructive harvesting. In practice, this would also require subjective sampling which may cause inaccuracies for yield estimation. Tardaguila *et al.* [31] proposed a methodology to determine the size and weight of grapes by extracting the morphology of a grape using the Freeman chain code algorithm. Their method was not developed for grape bunches but for individual berries under laboratory conditions. Although significant progress has been made, the approach is still impractical for the accurate and rapid measurement of berry size and weight in the field.

Field-based techniques for harvest yield estimation can be found in the works by [23]–[25], [27]–[30], and [32]–[44]. An early approach was proposed by Dunn and Martin [23] 2004. The authors studied the relationship between fruit weight and the ratio of fruit pixels to total pixels from 16 color RGB images of the canopy of Cabernet Sauvignon grapevines as the vine was progressively harvested. Threshold and tolerance values were then set manually to select the "fruit" pixels from a single image. These values were then used for the subsequent analysis of the remaining images, and the segmented "fruit" pixels were counted. Using this approach, their experiments accounted for 85% of the variation in yield for the various levels of fruit removal. Chamelat *et al.* [24] developed an approach that combined shape detection with color information using a semi-supervised Support Vector Machine (SVM) classifier to detect red grape bunches. Their technique allowed the detection of the grape bunches in different orientations and sizes with a 99% success rate. The method by Rabatel and Guizard [25] used a watershed algorithm to detect the separation of berry contours from luminance discontinuities with ellipse model fitting of the contour arcs using the least square algorithm. Their method could detect two thirds of the visible berries on the vine. The authors

TABLE 3. Representative studies focusing on disease detection in viticulture using computer vision and machine learning.

Authors	Year	Vine Disease	Imaging method	Computer vision and machine learning techniques	Value
Boso et al. [60]	2004	Downy mildew	Mature leaves with oily spots photographed on the vine	Analyzed using the anaySIS 3.0 software tool, spot count to determine disease severity and intensity.	
Meunkaewjinda et al. [61]	2008	Scab, rust disease		Hybrid approach using self-organizing feature map (SFOM) together with backpropagation (BP) network for color recognition, SVM for disease classification.	
Peresotti et al. [62]	2011	Downy mildew	Inoculated and photographed small discs of grapevine leaf	Quantification of grapevine downy mildew sporulation using compact digital camera and ImageJ.	
Li et al. [63]	2012	Downy and powdery mildew		Pre-processing using nearest neighbor interpolation, *k*-means clustering, and SVM to perform disease classification.	Recognition rates of downy mildew (90%), powdery mildew (93.33%).
Sanjeev et al. [64]	2013			Thresholding, *k*-means clustering, feedforward BP network for classification.	
Pradnya et al. [65]	2014	Black rot, downy and powdery mildew	RGB leaf images	Thresholding with color co-occurrence method.	Accurate leaf diseases detection with lower computational cost.
Neeraj et al. [66]	2015	Downy and powdery mildew, anthracnose		HSV color extraction algorithm.	
Rajendra et al. [67]	2015		Image processing on Android	Color transformation, masking of green pixels, segmentation, and texture feature analysis.	
Harshal et al. [68]	2016	Downy mildew, black rot		Leaf texture was retrieved using unique fractal based texture feature and multiclass SVM used to classify extracted texture pattern.	Experimental results gave an accuracy of 96.6%.
Shilpa et al. [69]	2016	Black rot, downy and powdery mildew, anthracnose gray mold, crown gall		Haar wavelet transfom for feature extraction and feedforward network with backpropagation for classification.	Experimental results gave an accuracy of 93%.
Perez-Exposito et al. [70]	2017	Downy mildew		VineSens predictive decision-support viticulture system with WSNs.	Alert sent to grower if the accumulated index exceeds 80%.

TABLE 4. Representative studies focusing on bunch compactness using computer vision and machine learning.

Authors	Year	Imaging method	Computer vision and machine learning techniques	Value
Cubero et al. [74]	2015	Color images of 90 bunches from nine red varieties	Supervised segmentation, morphological features extraction, and predictive least squares model.	Experimental results gave 85.3% correct prediction rate.
Universitat Politècnica [75]	2015	Camera and lighting subsystem		Provide information on grape bunches characteristics based on morphological properties, color impractical for accurate and rapid measurement of grape size and weight in the field.

concluded that the size estimation would be more accurate by introducing adaptive thresholding in the watershed algorithm and the model fitting using a multivariate semi-supervised classification.

A different approach was proposed by Reis *et al.* [27] to detect bunches from white and red grape cultivars using night captured images. Color segmentation and mapping was implemented to generate a binary image. Morphological dilation was applied to fill in holes between pixels and small regions were removed. The orientation of each bunch and the stem location was determined from the pixel distribution and density around the bunch centre. Reis *et al.* [28] reported a

TABLE 5. Representative studies focusing on grape seed maturity using computer vision and machine learning.

Authors	Year	Application	Imaging method	Computer vision & machine learning techniques	Value
Rodriquez et al. [76]	2012	Grape seed phenology	RGB images of *Vitis vinifera* L.	DigiEye system and DigiFood software to obtain morphological and appearance parameters (CIELab coordinates).	Identified 21 phenolic compounds with seed descriptors along grape ripening stages.
Rodriquez et al. [77]	2012	Grape seed phenology		Discriminant analysis models for morphological differences of different varieties.	Classification of grape seeds with high accuracy.
Avila et al. [78]	2014	Grape seed maturity	120 seed images	Two-class (mature, immature) hybrid segmentation technique. 379 different descriptors.	Two descriptors (Haralick and Gabor) could be used to separate classes. 100% rate for immature class, 93% rate for mature class.
Zuniga et al. [79]	2014	Grape seed maturity	277 seed images	Invariant color model to avoid shadows, classification architecture of three MLP networks trained using Bayesian Regularization.	Recognition rate of 90% and 86% for training and test set respectively.

false detection rate of 9% for all images used in their experiment. The authors extended the work in 2012 to differentiate between white and red grapes and achieved classification rates of 97% and 91% for red and white grapes respectively. Nuske *et al.* [29] proposed an automated computer vision method based on shape and visual texture to identify and count green grape berries against a green leaf background. Their approach used a visible light camera mounted on a small vehicle driven along the rows in a vineyard. Their algorithm was comprised of several components to enable berry detection. They first used the radial symmetry transform to identify berry locations. Then, a combination of color and texture features followed by the k-Nearest Neighbor classifier was used to classify the detected points. The final stage removes false positive detections for berries which do not have at least five berries in close proximity. Their approach can predict yield to within 9.8% of the actual crop weight. Nuske *et al.* [30] performed an extension of the work in 2012 by utilizing calibration data obtained from previous harvests and a small set of handpicked samples. This approach achieved a 4% and 3% improvement in yield estimation accuracy above the previous harvest calibration and the handpicked samples respectively. Murillo-Bracamontes *et al.* [32] proposed an advanced approach to segment and identify individual grapes from the image of a cluster using the circular Hough transform. Their method was robust enough to detect partially occluded berries. False detections were reduced using color information. A group of researchers in Spain [33] proposed a grapevine yield and leaf area estimation technique using supervised classification in RGB images based on the Mahalanobis distance parameter to characterize the grapevine canopy and assess the leaf area and yield. Their classification methodology is able to discriminate among seven different classes (grape, wood, background and leaf (with four classes based on increasing leaf age). Their results revealed a high performance of 92% accuracy for leaves and 98% for clusters. Their method is more successful than other approaches due to its capability to identify various classes of tissue.

Farias *et al.* [34] proposed an image acquisition and processing framework for in-field grape and leaf detection and quantification. Their framework has six steps: (1) image segmentation based on Fuzzy C-Means with Gustafson Kessel (FCM-GK) clustering; (2) obtaining the centroids which are the FCM-GK outputs as seeding for k-Means clustering; (3) Cluster identification generated by k-Means using SVM; (4) Morphological operations over grape and leaf clusters to fill holes and eliminate small clusters; (5) a Scale-Invariant Feature Transform (SIFT) to create a mosaic image to avoid overlapping regions among images; and (6) Finding centroids in the grape bunches by calculating the areas of leaves and grapes. The performance of their method is more successful than that of [33] since the method accounts for illumination artifacts and automatically clusters the training data. The work by Liu *et al.* [35] aimed to accurately estimate the weight of fruit on the vine. They first photographed manually harvested bunches in a laboratory environment to provide a baseline for the accuracy of the weight calculation. The authors investigated several approaches for classification (color histogram, RBF thresholding, and fuzzy clustering and SVM). The authors concluded that two important parameters affect the performance of the histograms: (i) the color space used, and (ii) the number of bins in the histogram. Their results showed that RGB thresholding gave a true positive rate of 87%, with a false positive rate of 5%, whilst fuzzy clustering and SVM results in a true positive rate of 97%, with a false positive rate of 16%.

In 2014, Nuske *et al.* extended work [36], [37] that was centered on a vehicle-mounted vision system. Their algorithms processed images by exploiting three prominent visual cues (shape, color and texture) using a classifier which detects berries which has similar color to the background of vine leaves. Methods were also introduced to maximize the spatial variance and the accuracy of the yield estimates by optimizing the relationship between image measurements and yield. The experimental results conducted over four growing seasons for wine and table grapes demonstrated yield estimates that capture up to 75% of spatial yield variance and with an average error between 3% and 11% of total yield. Another approach was proposed by Font *et al.* [38] for yield estimation using the analysis of high-resolution images obtained with artificial illumination at night. Their work first assessed different pixel-based segmentation approaches to detect red grapes to obtain the best estimation of the cluster areas in these illumination conditions. They used various methods including threshold-based, Bayesian classifier, Mahalanobis distance, histogram segmentation and linear color model segmentation, and investigated the RGB and HSV color spaces. Their results showed that the best segmentation method for non-occluded red table grapes was threshold segmentation in HSV color space, resulting in 10% estimation error after morphological filtering. The authors proposed two procedures for yield estimation: (1) The number of pixels corresponding to a cluster of grapes is computed and converted directly into a yield estimate; and (2) The area of a cluster of grapes is converted into a volume. The results with these proposed methods gave yield errors of 16% and 17% respectively.

Liu *et al.* [39] presented a work in 2015 using a combination of texture and color information with SVM classification. The bunch segmentation method has three stages (image pre-processing, training using a training dataset and testing segmentation on the test dataset). Morphological operations are performed in HSV color space on both training and testing images to extract the initial bunch hypotheses. A shape filter is then applied to exclude incorrectly identified bunches. A new approach for yield estimation was proposed by Liu *et al.* [40] to estimate the 3D structure of grape bunches from a single image. The proposed 3D model based on a single image is appropriate for a bunch with distinguishing shoulders but it cannot achieve a good estimation of berry numbers on a bunch with overlapping shoulders. Their experiments on two varieties revealed an average accuracy of 87.3% relative to the actual number of berries on a bunch. Researchers in China aimed to detect the grape clusters in a vineyard using image processing and machine learning [41]. They proposed an image segmentation method based on an improved artificial swarm optimization fuzzy clustering. The fitness function of the artificial colony was improved based on the objective function of the fuzzy C-average clustering (FCM) algorithm. Image segmentation was then performed based on the maximum membership principle. They conducted their experiment on black grape images taken under normal light illumination and an accuracy of 90.33% was achieved. Luo *et al.* continued their research by proposing grape image segmentation based onartificial bee colony and fuzzy clustering and the AdaBoost framework [42]. In the initial step, the effective color components of grape clusters were extracted to construct the linear classification models based on a threshold. In the second component, an advance classifier was constructed by using the AdaBoost framework. The authors used 900 testing samples to verify the performance and an accuracy rate of up to 96.56% was achieved. They also tested the performance of their work using 200 images captured under three various illuminations in the vineyard and the average detection rate was 93.74%.

Vincent Casser *et al.* [43] applied feedforward neural networks (FFNN) to address the problem of color-based grape detection for in-field images. The authors considered four classes (night time red berries, night time white berries, day time red berries and day time white berries). Different light conditions on grape varieties were investigated and the influence of different color models was also examined. Their simulation results showed that an average classification rate of 93% could be achieved. The comparison with SVM revealed that FFNN could slightly outperform SVM in computation time. A recent approach for a smartphone application was proposed by Aquino *et al.* [44] in 2017. The grape cluster is placed in front of a dark cardboard for analysis. The authors proposed a new image analysis algorithm based on mathematical morphology and pixel classification for grapevine berry counting. The methodology has two main stages. Initially, images were down-sized and converted to the CIELab color space. In the first stage, a set of berry candidates was extracted from the image using morphological filtering. The bright spots produced by light reflection from the berry surface were detected by finding the regional maxima of illumination. In the second stage, false positives (FP) were eliminated. This elimination process was performed by means of pixel classification using a classifier input with a set of key descriptors, and trained by supervised learning. This process involved a set of six morphological and statistical descriptors (grouped into shape (one descriptor), normality (one descriptor) and color descriptors (four descriptors)) to form a feature space used to train a classifier for FP discrimination. Two classifiers, a three-layer neural network and an optimized SVM were considered in their work. Their experimental results showed that the three-layer neural network performed better than the SVM. The authors informed that the method would be implemented in smartphone devices in the near future.

B. COMPUTER VISION AND MACHINE LEARNING FOR PRUNING AND ASSESSMENTS OF SHOOT CHARACTERISTICS FOR VINEYARD MANAGEMENT AND MONITORING IN VITICULTURE

Wireless Sensor Networks (WSNs) are popular in vineyard management and monitoring. WSN technologies can provide an efficient and useful tool for remote and real-time monitoring of essential parameters involved in grape production, processing the data and transmitting the required information to the grape growers. Works for viticulture on WSNs without image processing technologies can be found in [45]–[49]. There are commercial companies currently offering such monitoring solutions for vineyards. For example, VintiOS [53] is a precision agriculture software that supports vine growers. Another tool named Monet [54] monitors the health of a vineyard including the risk of developing certain diseases, weather information, and other relevant events. Other solutions have been developed by Ranchsystems [55], SmartVineyard [56] and Save [57]. For this paper, we do not review WSNs or commercial technologies if they do not contain an image sensing, computer vision or machine learning component.

Computer vision and machine learning techniques for vineyard management and monitoring can be found in the works by [45]–[52]. An early work by McFarlane *et al.* [45] applied image analysis to vine pruning. The authors suggested that the bottom position of the branches could not be determined accurately enough because the visualization system had very little understanding of the vine structure but they reported a success rate of 80% with their techniques. The work by Svensson *et al.* [46] applied image processing to determine shoot count and canopy density. In 2006, a research team from the University of Adelaide (Gao and Lu) [47] proposed a new technique based on computer vision to tackle pruning of those grapevine varieties that are fruitful in the basal bud area and thus suitable for the 2-bud spur pruning method. This group later extended the work to include stereo vision [48]. The authors developed a new algorithm using image processing, image analysis and stereo vision to locate the pruning positions and demonstrated the feasibility of automatic grapevine pruning. The images captured from the stereo cameras were first pre-processed to obtain binary images. Image analysis was then used to identify different parts of the grapevine and obtain the 2D positions of the cutting points. The authors designed algorithms to locate the cordon, the branch and the nodes. Their experimental results gave a success rate of 85%. A vineyard health assessment protocol combining WSNs with image sensing techniques was proposed by Lloret *et al.* [49]. The researchers introduced a WSN where each sensor node captured images from the field and used image analysis to detect leaf color changes induced by physiological deficiencies, pests and diseases or other harmful agents. The first step estimates an average leaf size for use in later steps. A threshold is then applied to the remaining pixels to eliminate those that do not meet a color condition corresponding with the bad (stressed) leaves. Further processing makes sure that the ground is not mistakenly identified as stressed leaves because of their similar color. When the symptom is detected, the sensor node sends a message to the WSN sink to notify the grower.

There are several applications where bud detection in vineyard images is critical for providing potential solutions to grapevine pruning, grapevine plant phenotyping and 3D reconstruction of the plant structure and components. The work by Xu *et al.* [50] proposed a machine vision algorithm to detect the buds of grape vines in winter. Color RGB images were captured indoors. The blue component was used for image preprocessing such as filtering, threshold segmentation and noise removal to obtain the binary image. The Rosenfeld algorithm for thinning was then applied to the binary image to extract the skeleton of the grape branches, and the Harris corner detection algorithm was applied to detect the point of buds from the skeleton image. Their experimental results gave a detection rate of 70.2%. A recent approach combining machine vision with robotics to locate the spatial coordinates of the cutting points on a peduncle of grape bunches can be found in the work by Luo *et al.* [51]. The authors proposed a technique to acquire spatial information of grape bunches based on binocular stereo vision. Their technique consisted of four stages. The first stage performed a calibration of the binocular cameras and then applies a correction. The second stage detects the cutting points on the peduncle and the centers of the grape berries. This is followed by extraction of the three-dimensional spatial coordinates of the points, and the final stage calculates the bounding volume of the grape clusters. In their experiments, 300 images from the vineyard were captured and tested to verify the performance of their technique. Their results gave a success rate of approximately 87%. The authors also found that the elapsed time of the overall technique was less than 0.7s, indicating that their algorithms could be deployed on harvesting robots.

Recently, a comprehensive approach for grapevine bud detection under natural field conditions to aid in winter pruning was proposed by Diego *et al.* [52]. Their proposed approach used the Scale-Invariant Feature Transform (SIFT) for obtaining the low-level image features, Bag-of-Features for building the image descriptors and the SVM for classification. The classification algorithm was intended to be used on patches produced by scanning-window detection algorithms. Their experiment evaluated images containing buds of at least 100 pixels in diameter. Their results showed that the approach could achieve a classification recall greater than 0.89 in patches containing at least 60% of the original bud pixels, where the proportion of bud pixels in the patch is greater than 20%, and the bud is at least 100 pixels in diameter. Better results were obtained for patches that hold between 90% and 100% of the bud pixels and these pixels represent between 20% and 30% of the patch, i.e. patches from three to five times larger than buds

C. COMPUTER VISION AND MACHINE LEARNING STUDIES FOR DISEASE DETECTION IN VITICULTURE

Disease detection is an intensive research area in viticulture. Diseases can be caused by fungi or bacteria. Common grape diseases caused by fungi are downy mildew, powdery mildew, anthracnose, grey mold and black rot. The grown call disease is an example of a disease caused by bacteria. Fungal diseases such as *powdery mildew*, *downy mildew* and *botrytis* can cause severe problems economic losses. For example, botrytis can decrease yield and wine quality [58] and downy mildew can taint the flavor of wine [59]. Given the significant impact and economic costs of diseases, it is important to automate the early detection of these diseases in vineyards. The use of imaging techniques for disease detection is challenging for several reasons: (1) The grapes may be covered by a natural bloom and this has similar visual characteristics to that of diseased berries, thus decreasing the detection accuracy; (2) The signs and symptoms exhibited by a disease may be different depending on the development stage of the disease and the variety of the grape; (3) More than one disease can be present at the same time; and (4) Factors such as nutrient deficiencies, pesticides, and weather can also produce similar symptoms to those of diseases. This section reviews current research using image processing, computer vision and machine learning for the detection of diseases in viticulture.

An image technique for downy mildew detection was proposed by Boso *et al.* [60] in 2004. In this early study, mature leaves with oily spots exhibiting symptoms of downy mildew were digitally photographed on the vine and analyzed using the anaySIS 3.0 software tool. The number of spots to determine the severity and intensity of the infection of eight different clones of the grape cultivar Albariño were counted. This work showed that image processing techniques could deliver a means of rapid, reliable and quantitative early detection of the disease. Meunkaewjinda *et al.* [61] proposed an automatic plant disease diagnosis for grape leaf disease. Their system has three main stages (color segmentation of the grape leaf, grape leaf disease segmentation, and analysis & classification of the disease). Grape leaf color segmentation was first performed to filter out irrelevant background information. The authors applied a hybrid approach using a self-organizing feature map (SFOM) together with a backpropagation (BP) neural network to recognize colors of the grape leaf. A modified DOM model with a genetic algorithm (GA) for optimization was used to perform the grape leaf disease segmentation. The segmented image was then passed through a Gabor wavelet filter to allow more efficient analysis of leaf disease color features. The SVM was applied to classify the grape leaf disease. Their approach could categorize the leaf images into three classes (scab disease, rust disease and no disease) and demonstrated the potential for automatic diagnosis of grapevine diseases. Peresotti *et al.* [62] reported the development of a simple image analysis-based semi-automatic method for the quantification of grapevine downy mildew sporulation using a compact digital camera and the open source software ImageJ. They first artificially inoculated small discs of a grapevine leaf and then took photographs over several days. The color of the capture images was then balanced using ImageJ. Rolling Ball background subtraction and median-cut color quantization were then used to quantify the sporulation of the image to 8-bits, and the ImageJ auto-thresholding feature was used to select the area to be measured.

Li *et al.* [63] proposed an image recognition technique to conduct the identification and diagnosis of grape downy mildew and grape powdery mildew. In their approach, images were pre-processed using nearest neighbor interpolation to compress the image prior to removal by a median filter. The k-means clustering algorithm was used to perform unsupervised segmentation of the disease images. Fifty shape, color and texture features were extracted from the images of the diseases, and the SVM classifier was used to perform the disease recognition. Their experimental results (testing phase) gave recognition rates of grape downy mildew and grape powdery mildew of 90% and 93.33%, respectively. The authors work provided an effective approach for rapid and accurate identification and diagnosis of plant diseases. It also provided a basis and reference for further development of automatic diagnostic systems for plant diseases.

In 2013, grape farming in India faced a threat from leaf diseases. Sannakki *et al.* [64] proposed a diagnosis and classification approach for grape leaf diseases using neural networks. In their approach, the grape leaf image with a complex background is input to the system. Thresholding was then applied to mask green pixels. This was followed by noise removal using anisotropic diffusion, followed by grape leaf disease segmentation using k-means clustering. The authors used the feedforward BP network to perform the classification.

Narvekar *et al.* [65] developed a system for grape disease detection by inspection of leaf features. The authors used five steps in their approach (color transformation, masking green pixels, segmentation, color co-occurrence, and texture feature analysis). The RGB leaf images were first captured and converted into the Hue Saturation Intensity (HSI) color space. Green colored pixels were identified based on a specified and varying threshold value obtained using Otsu's method. The infected portion of the leaf was extracted, and this infected region was segmented into patches of equal size (32×32). In the color co-occurrence method (CCM), both the color and texture of the image were considered to represent the image. The CCM was developed based on spatial gray-level dependence matrices (SGDM). The proposed method was tested on black rot, downy mildew and powdery mildew. Their experimental results showed that their method could support an accurate leaf disease detection with lower computational cost.

Wadekar *et al.* [66] developed an automatic system for diagnosis of grape leaf diseases using image processing and an automatic pesticide spraying mechanism to detect and monitor three types of diseases (downy mildew, powdery mildew and anthracnose). Using the HSV color extraction algorithm, it can perform the diagnosis on grape leaf images. Depending on the image processing result the disease severity is determined and the pesticides are sprayed accordingly. No detail of the technical work associated with the image processing can be found in their article. The work by Kajale *et al.* [67] proposed detection and recognition of plant leaf diseases using image processing on Android. The authors applied techniques like color transformation, masking of green pixels, segmentation, and texture feature analysis. Waghmare *et al.* [68] focused on detecting downy mildew and black rot through background removal segmentation, leaf texture analysis and pattern recognition. The segmented leaf texture was retrieved using a unique fractal based texture feature and the multiclass SVM was used to classify the extracted texture pattern. Their experimental results gave an accuracy of 96.6%. Gujjar and Angadi [69] proposed techniques to detect the diseases black rot, downy mildew, powdery mildew, anthracnose, gray mold, and crown gall. The authors used the Haar wavelet transfom for feature extraction and the feedforward network with backpropagation was used for classification. Their experimental results gave an accuracy of 93%. Recently in 2017, Pérez-Expósito *et al.* [70] proposed a predictive decision-support viticulture system with WSNs termed VineSens to automate the detection of both primary and secondary downy mildew infections. The central server checks the infection status daily using environmental parameters, and if the accumulated index exceeds a pre-set threshold (e.g., 80%), an alert is sent to the grower.

D. COMPUTER VISION AND MACHINE LEARNING STUDIES FOR THE EVALUATION OF BUNCH COMPACTNESS IN VITICULTURE

Bunch compaction is an emerging focus of computer vision and machine learning in viticulture because this bunch characteristic has consequences on berry size, yield, fruit split and disease incidence [71]–[73]. Traditionally, assessment of bunch compactness requires visual inspection by trained evaluators and is comprised of subjective and qualitative values. Computer vision research for the assessment of quality has been frequently performed in the laboratory while research involving the assessment of these properties in the field is still in its infancy. Works to determine bunch compactness using vision systems can be found in [74] and [75].

The study by Cubero *et al.* [74] in 2015 proposed an approach to assess grape bunch compactness in a non-invasive, objective and quantitative manner using automated image analysis. In their approach, color images were taken of 90 bunches from nine different red varieties. Supervised segmentation was performed followed by morphological features extraction, and a predictive partial least squares (PLS) model was used to assess bunch compactness. Their experimental results gave an 85.3% correct prediction rate for bunch compactness. The authors also found that the most discriminant parameter of the model was highly correlated with the tightness of the berries in the bunch and the shape of the bunch. Tightness was proportional to the visibility of berries and rachis and the number of holes within the bunch, whereas bunch shape was proportional to the roundness, the compactness, shape factor and aspect ratio. Computer vision methods to assess bunch compactness were also studied by researchers from the Universitat Politècnica de València, the Valencian Institute of Agrarian Research (IVIA) and the Instituto de Ciencias de la Vid y del Vino (Research Centre of Vine-and-Wine-related Science) (ICVV) [75]. As in the previous study, their system could provide information on the characteristics of grape bunches based on their morphological properties and color. They used a system with a camera and incorporated four light sources. Their approach also gave information on the visibility of the pedicels, the presence of berries deformed by pressure and the spatial relationships between geometric characteristics.

E. COMPUTER VISION AND MACHINE LEARNING STUDIES FOR ASSESSMENT OF GRAPE SEED MATURITY

Seed maturity is sometimes used as an indicator for the optimal time for harvest. Traditional methods for identifying maturity is time consuming and subjective because it is often performed by a visual and sensory analysis. This can potentially be improved, however, with the application of emerging image processing and machine learning techniques specifically targeted for this purpose.

Rodríguez-Pulido *et al.* [76] presented a study to evaluate the potential of computer vision to determine the phenolic maturity of grape seeds. The aim of their study was to find relationships between the chemical (phenolic composition) and the appearance (color and morphological) of the seeds. Their study included descriptors such as lightness, chroma, seed length, roundness and aspect ratio. The authors identified 21 phenolic compounds in the seeds and assessed them in relation to the morphological seed descriptors. The DigiEye system was used to acquire images of the seeds from 100 berry samples, and the DigiFood software was used to obtain morphological and appearance parameters including the CIELab coordinates from RGB. The authors concluded that in some cases there were good relationships between the chemical and appearance data, and that it is possible to estimate the stage of seed maturity by applying forward stepwise multiple regression models to this data. A similar work by Rodríguez-Pulido *et al.* [77] not only characterized the seeds but also included an analysis of the berries themselves. Berry size and developmental stage was determined by image analysis and the authors established an objective Browning Index for the seeds. The authors studied the morphological differences among different varieties by applying discriminant analysis models to allow the classification of the grape seeds with high accuracy.

Avia *et al.* [78] presented a hybrid segmentation technique to classify seeds according to their degree of maturity. The authors used a two-class (mature and immature) classification strategy. Their hybrid segmentation technique involved a combination of supervised and unsupervised segmentation with invariant color models. The supervised segmentation used the multilayer perceptron (MLP). For feature extraction, 379 different descriptors such as Haralick descriptors, intensity descriptors, local binary patterns, Gabor features, crossing line profiles, Fourier descriptors, and contrast descriptors were computed. The Sequential Forward Selection algorithm (SFS) was used to determine the most significant descriptors. The study revealed that two descriptors (Haralick and Gabor descriptors) could be used to separate the two classes. Their experiments used a database comprising a total of 120 seed images (80 for training and 40 for testing). The classification results showed 100% effectiveness for both mature and immature classes during training. For the test set, a 100% effectiveness was obtained for the immature class and a 93% effectiveness for the mature class.

Zuñiga *et al.* [79] proposed another grape maturity estimation method based on seed images. Their approach allowed the classification of three seed classes (immature, mature, and over-mature). Their method included image acquisition, segmentation, descriptor computation and classification. For seed segmentation, the invariant color model [81] was applied to avoid shadows and highlights. The c3 channel was chosen based on the favorable results obtained by Avila *et al.* [80]. The automatic segmentation of this channel was performed by the Otsu method [83]. The classification architecture comprised of three MLPs (one for each class to be identified).

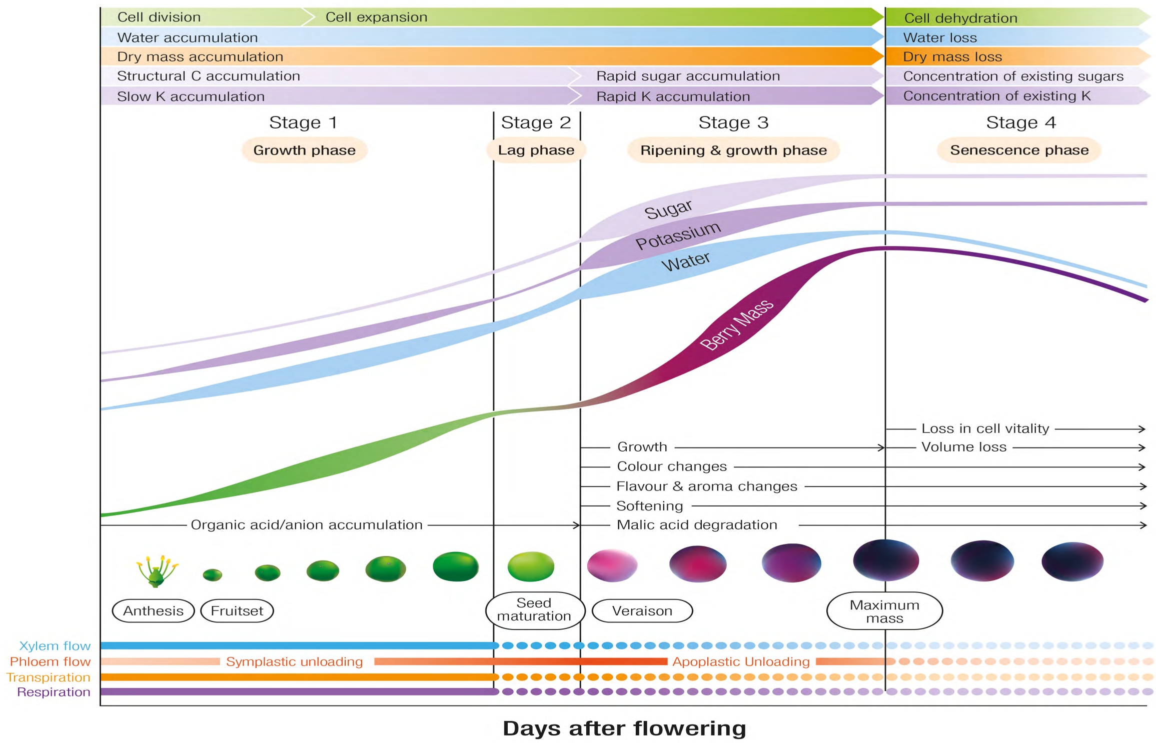

FIGURE 1. Shiraz berry growth and ripening curves. Image first published in [88].

The MLP training was carried out by the Bayesian Regularization algorithm [82] which provides an objective criterion to find the number of neurons in the hidden layer of the network and avoids model overfitting. Their results gave a recognition rate of 90% for the training and 86% for the test set.

III. GrapeCS-ML DATABASE

Datasets in an accessible form are required by researchers to make progress and advancements in computer vision, image processing and machine learning. A dataset is a collection of data, images or videos that can be used to evaluate techniques for specific applications. Examples of datasets appropriate for general applications in computer vision can be found in [84]. An evaluation of a suitable and unbiased dataset can validate a proposed technique or algorithm. Interestingly, the evolution of datasets can also reflect the progress of research in these fields. Researchers in computer vision gather datasets that are groomed to be within an attainable level of difficulty. Once the researchers have saturated performance on those datasets, they go in search of another more complicated dataset in order to design even better techniques. It is also important to leverage multiple datasets because of the bias inherent in any single dataset. Viticultural databases include the European Vitis Database [85] and the Vitis International Variety Catalogue VIVC [86]. However, these databases were not designed for computer vision or machine learning research. For example, the VIVC currently has data for 23000 cultivars. However, only one or few samples are available for each cultivar. This is in contrast to the requirements for developing machine learning algorithms which require many samples from the same cultivar for training and evaluation.

Here we present a new database called GrapeCS-ML Database which has been specifically designed to progress computer vision and machine learning research for viticulture. A detailed explanation of the considerations and procedures in the database construction are also presented. The database consists of images of bunches from different grape varieties captured in three Australian vineyards and contains different datasets for evaluation. To the best of our knowledge, no such database is currently available for the research community in computer vision and machine learning for viticulture technology. The availability of such a database is important to researchers because data is required for machine training or learning and testing. We hope that the information contained in the database will help to spur extensive computer vision and machine learning research by providing significant training data for learning algorithms and image processing techniques. The database consists of five datasets for 15 grape varieties taken at several stages of development and includes size and/or Macbeth color references. Altogether, the database contains a total of 2078 images. Some datasets also include the corresponding ground truth data (e.g. TSS, pH, etc.) obtained from chemical laboratory analysis.

Dataset 1: Dataset 1 contains images of Merlot bunches taken in seven rounds from the period Jan. to Apr. 2017. Fig. 1 shows a typical growth curve. Initially after flowering, the grape berries increase in size rapidly but remains hard and green. This is followed by a lag phase, and then with onset of *veraison*, a second growth period occurs along with softening and colour development. This phase of grape berry growth is followed by a period of *engustment* when the aromas and flavors of the grape intensify [87]. The images in Dataset 1 allow for the construction of about 250 growth curves. These data can be used to perform the dynamic analysis to inform on the optimal berry harvest time based on berry size and color. Fig. 2 shows some sample images from the dataset.

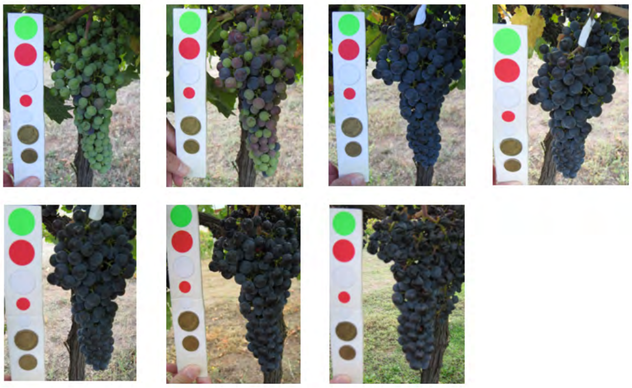

FIGURE 2. **Dataset 1 – Sample images from dataset 1 at various stages of development.**

Dataset 2: Dataset 2 contains the subsets for 13 different varieties: Merlot, Cabernet Sauvignon (CS), Saint Macaire, Flame Seedless, Viognier, Ruby Seedless, Riesling, Muscat Hamburg, Purple Cornichon, Sultana, Sauvignon Blanc and Chardonnay. Each folder consists of images of bunches at several stages of development of the different varieties. Fig. 3-6 shows some samples from the dataset. This dataset is

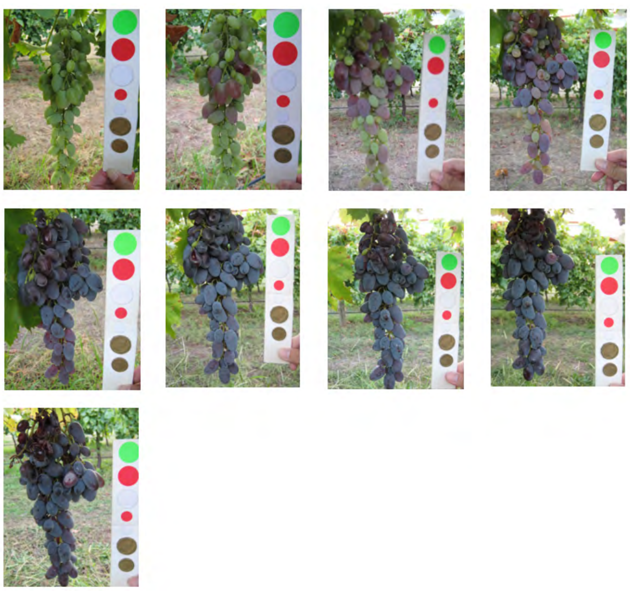

FIGURE 3. **Dataset 2 – Sample images from dataset 2 including a volume reference.**

FIGURE 4. **Dataset 2 – Sample images from dataset 2 showing development following veraison and includes a color reference.**

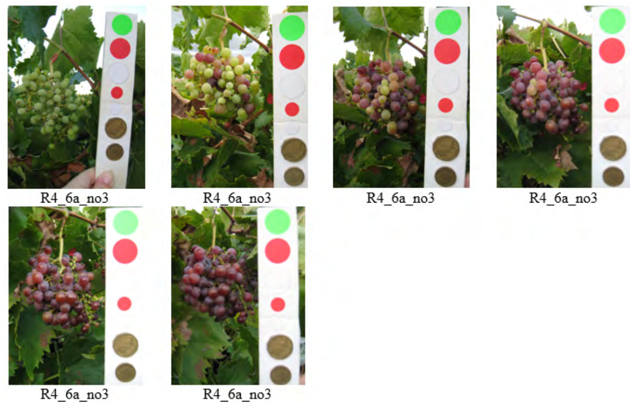

FIGURE 5. **Dataset 2 – Sample images from dataset 2 including a volume reference.**

FIGURE 6. **Dataset 2 – Sample images from dataset 2 at various stages of bunch development with a color reference included.**

designed for research on berry and bunch volume and color as the grapes mature.

Dataset 3: Dataset 3 contains the subsets for two varieties (Cabernet Sauvignon and Shiraz) taken at dates close to maturity. Each image has been taken twice at the same time, once with the size reference and a second time with the color reference. Thus, this dataset allows the relationship between size and color transitions to be modelled at different stages of growth. Fig. 7-8 depicts sample images from the dataset.

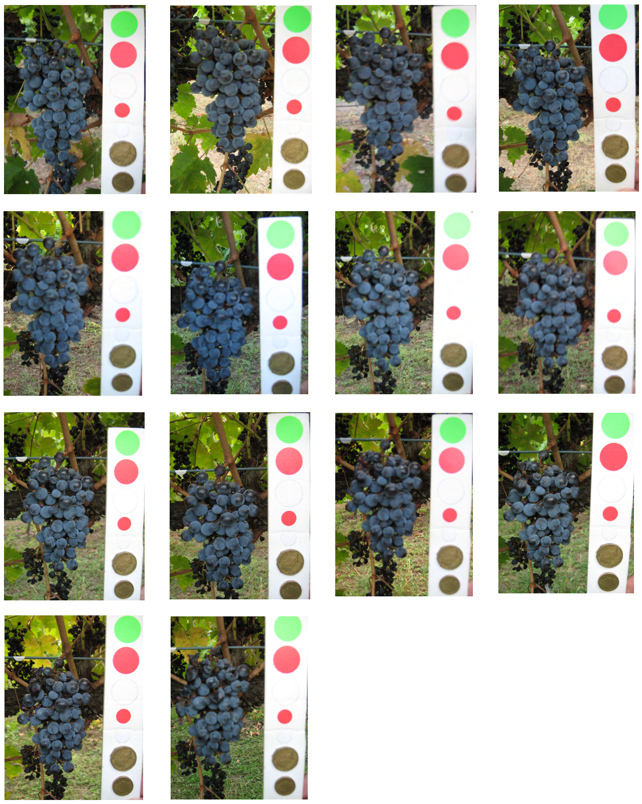

FIGURE 7. **Dataset 3 – Sample images from dataset 3 at various stages of bunch development.**

Dataset 4: Dataset 4 contains subsets of images for two varieties (Pinot Noir and Merlot) taken at dates close to maturity, with the focus on the color changes with the onset of ripening. These images were taken almost daily and includes the color reference. Thus, this dataset allows color transitions to be modelled at different stages of development (Fig. 9).

Dataset 5: Dataset 5 contains the images of Sauvignon Blanc bunches taken on three different dates. Each image also contains a hand-segmented region defining the boundaries of the grape bunch to serve as the ground truth for evaluating computer vision techniques such as image segmentation. The grape bunches were also analyzed in the laboratory for their basic composition including total soluble solids (TSS) and pH. Bunch weight, average berry fresh weight, number of berries per bunch, berry volume, dominant hue, etc. are also presented. This dataset can be used to relate the image data with the chemical composition of the bunches. Fig. 10 provides an example of samples from the dataset.

FIGURE 8. **Dataset 3 – Sample images from dataset 3 at various stages of bunch development.**

FIGURE 9. **Dataset 4 – Sample images from dataset 4 at various stages of bunch development.**

IV. COLOR-BASED BERRY DETECTION APPLICATION USING DATABASE

This section presents an illustration of the usefulness of the database and gives baseline comparisons for a color-based berry detection application to detect berry pixels from the background using various machine learning approaches and color spaces. The comparisons were performed for white and red berry cultivars from the images collected in the field. We performed a segmentation by hand to locate the grape

Dataset 1	Variety	Detail (optimization)
	Merlot (large scale)	- 7 subfolders contain the grape images taken in different rounds: Round 1 (16-19/1/17), Round 2 (22-19/1/17), Round 3 (6-9/2/17), Round 4 (16-19/2/17), Round 5 (27/2-4/3/17), Round 6 (20-22/3/17) and Round 7 (13/4/17) - Initial number of bunches: 242 - volume reference - dates
Dataset 2	**Variety**	**Detail**
	13 varieties	- Varieties: Purple Cornichon, Merlot, Flame Seedless, Chardonnay, Cabernet Sauvignon, Saint Macaire, Viognier, Ruby Seedless, Riesling, Muscat Hamburg, Sultana and Sauvignon Blanc. - 13 subfolders. - Initial number of bunches: 1-5 bunches depending on variety. - volume reference - color reference - dates
Dataset 3	**Variety**	**Detail**
A	Cabernet Sauvignon	- 14 subfolders contain the grape images taken on different dates. - Initial number of bunches: 4 - volume reference - color reference - dates
B	Shiraz	- 4 subfolders contain the grape images taken on different dates. - Initial number of bunches: 15 - volume reference - color reference - dates
Dataset 4	**Variety**	**Detail**
A	Pinot Noir	- 11 subfolders contain the grape images taken on different dates. - Initial number of bunches: 12 - color reference - dates
B	Merlot	- 7 subfolders contain the grape images taken on different dates. - Initial number of bunches: 12 - color reference - dates
Dataset 5	**Variety**	**Detail**
	Sauvignon Blanc	- 3 subfolders contain the grape images taken on different dates. - Initial number of bunches: 10-12 bunches for each subfolder. - Segmented images - Corresponding laboratory data: TSS, berry weight, number of berries, volume, pH, dominant hue, etc. - dates

bunch region from the background as shown in Fig. 10. These served as the ground truth images and are included in the GrapeCS-ML database for use by other researchers. We then transformed each bunch region into four color spaces (RGB, YCbCr, HSV, and Lab) and applied seven machine learning classifiers (SVM, k-NN, logistic regression, classification tree, boosted tree, SAE) towards the berry detection

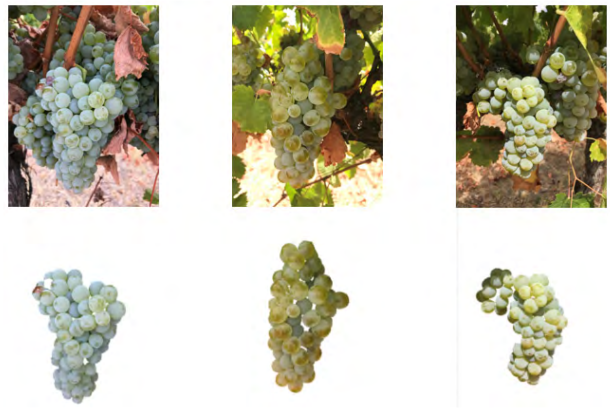

FIGURE 10. Dataset 5 – Images and corresponding segmented bunch regions.

application. The SAE is a learning neural network algorithm constructed from multiple layers of autoencoders where the output of each layer is connected to the input of the next layer [91]. Readers can refer to [90] for more details on general machine learning algorithms and to [91] for details on the SAE. For our experiments, the SVM classifier used the Gaussian kernel, the value of $k = 10$ was used for the k-NN, whereas the Boosted tree used the Adaboost [89] method. Each autoencoder in the SAE was trained separately using a greedy-based training approach and then stacked onto those already trained. Table 6 and Table 7 show the classification rates which were obtained for white berry cultivars and red berry cultivars respectively. Among the machine learning approaches, the SVM gave the highest performance among the classifiers followed by the SAE and k-NN. This showed

TABLE 6. Classification rate (%) for white berry cultivars using various machine learning approaches and color spaces.

	Color space			
Classifier	RGB	YCbCr	HSV	Lab
SVM	82.8	**84.3**	**84.4**	**84.4**
k-NN	83.1	83.5	83.7	83.7
Logistic regression	78.1	78.1	78.9	77.9
Classification tree	78.1	80.1	80.4	79.9
Boosted tree	78.7	80.9	81.8	81.8
SAE	**83.2**	83.6	84.0	83.6

TABLE 7. Classification rate (%) for red berry cultivars using various machine learning approaches and color spaces.

	Color space			
Classifier	RGB	YCbCr	HSV	Lab
SVM	**88.8**	**89.0**	**89.0**	**89.1**
k-NN	88.5	88.8	88.6	88.7
Logistic regression	86.5	86.6	86.4	86.6
Classification tree	85.4	88.3	87.8	87.9
Boosted tree	87.6	88.7	88.4	88.4
SAE	**88.8**	88.6	86.7	88.6

that the k-NN with its advantages of lower computational requirements can be used at a slight decrease in classification performance. For this application of berry detection using the GrapeCS-ML Database, a simpler machine learning model like the k-NN could give as good or even better performance as a more complex model such as the SAE. Oliveira *et al.* [92] gave a similar remark for their application to predict Internet traffic using the multilayer perceptron and SAE. The logistic regression classifier gave the lowest performance. For the different color spaces, the HSV gave the highest performance for white cultivars while the YCbCr gave the highest performance for red cultivars. The highest classification rate obtained for white cultivars was 84.4% and the highest classification rate obtained for red cultivars was 89.1%.

V. CONCLUSION

This paper has provided a comprehensive review on computer vision and machine learning technology for viticulture applications. We have presented the latest developments in vision systems and techniques using various representative studies. These computer vision and machine learning techniques may be applied in smart vineyards, vineyard management and winemaking processes. The paper has presented the GrapeCS-ML Database which has been designed to motivate researchers to develop practical solutions for deployment in smart vineyards. We have illustrated the usefulness of the database for a color-based berry detection application. The paper has also given baseline comparisons using various machine learning approaches and color spaces for future work by researchers for use in viticulture technology applications for smart vineyards. An interesting work in the future when more data have been collected and are available from several harvest seasons, is to extend the comparisons towards more complex deep learning techniques such as convolutional neural networks (CNNs) and deep belief networks (DBNs).

ACKNOWLEDGMENT

The authors gratefully acknowledge Prof. Bernard Pailthorpe and Dr. Nicole Bordes for useful discussions and consultations, and Campbell Meeks who performed the laboratory and chemical analysis of the berry composition for the GrapeCS-ML Database.

REFERENCES

[1] International Organization of Vine and Wine. *Balance de la OIV Sobre la Situacin VitivinCola Mundial En 2009*. Accessed: Jul. 31, 2017. [Online]. Available: http://www.infowine.com/docs/Communique_Stats_Tbilissi_ES.pdf

[2] A. Carbonneau, "A Éléments de la conduite du vignoble favorisant la protection du terroir et l'expression de ses vins," in *Proc. 25th Congrès Mondial de la Vigne et du Vin de l'OIV*, Paris, France, Jun. 2000, pp. 19–23.

[3] M. Vieri, D. Sarri, M. Rimediotti, R. Perria, and P. Storchi, "The new architecture in the vineyard system management for variable rate technologies and traceability," *Acta Horticulture*, vol. 978, pp. 47–53, Jun. 2012.

[4] WineRobot. University of La Rioja. *The VineRobot Project Coordinated by Televitis Group*. Accessed: Aug. 1, 2017. [Online]. Available: http://http://www.vinerobot.eu/

[5] Robotnik. *Valencia: Robotnik Automation SLL*. Accessed: Aug. 2, 2017. [Online]. Available: http://www.robotnik.eu/

[6] Robotics.bgu.ac.il. *The VineGuard Project*. Accessed: Aug. 1, 2017. [Online]. Available: http://robotics.bgu.ac.il/index.php/Development_of_an_Autonomous_vineyard_sprayer

[7] *Wall-ye Softwares and Robots*. Accessed: Aug. 2, 2017. [Online]. Available: http://www.wall-ye.com/

[8] Vision Robotics Corporation. San Diego, CA, USA. *Vision Robotics Solution*. Accessed: Aug. 2, 2017. [Online]. Available: http://www.visionrobotics.com/

[9] *Vitirover Micro Winery Robotics. Saint-Émilion: Vitirover*. Accessed: Aug. 3, 2017. [Online]. Available: http://www.vitirover.com/fr/

[10] ASI, Mendon, UT, USA. *Autonomous Solutions*. Accessed: Aug. 2, 2017. [Online]. Available: http://www.asirobots.com/

[11] L. Ruiz-Garcia, L. Lunadei, P. Barreiro, and I. Robla, "A review of wireless sensor technologies and applications in agriculture and food industry: State of the art and current trends," *Sensors*, vol. 9, no. 6, pp. 4728–4750, 2009.

[12] L. Emmi, M. Gonzalez-de-Soto, G. Pajares, and P. Gonzalez-de-Santos, "New trends in robotics for agriculture: Integration and assessment of a real fleet of robots," *Sci. World J.*, vol. 2014, Mar. 2014, Art. no. 404059, doi: 10.1155/2014/404059.

[13] A. Matese and S. F. D. Gennaro, "Technology in precision viticulture: A state of the art review," *Int. J. Wine Res.*, vol. 7, pp. 69–81, May 2015.

[14] A. Hall, D. W. Lamb, B. Holzapfel, and J. Louis, "Optical remote sensing applications in viticulture—A review," *Austral. J. Grape Wine Res.*, vol. 8, no. 1, pp. 36–47, 2002.

[15] I. Colomina and P. Molina, "Unmanned aerial systems for photogrammetry and remote sensing: A review," *ISPRS J. Photogram. Remote Sens.*, vol. 92, pp. 79–97, Jun. 2014.

[16] J. Burrell, T. Brooke, and R. Beckwith, "Vineyard computing: Sensor networks in agricultural production," *IEEE Pervasive Comput.*, vol. 3, no. 1, pp. 38–45, Jan./Mar. 2004.

[17] C. S. Steel, J. W. Blackman, and L. M. Schmidtke, "Grapevine bunch rots: Impacts on wine composition, quality, and potential procedures for the removal of wine faults," *J. Agricult. Food Chem.*, vol. 61, no. 22, pp. 5189–5206, 2013.

[18] E. Gil, A. Landers, M. Gallart, and J. Llorens, "Development of two portable patternators to improve drift control and operator training in the operation of vineyard sprayers," *Spanish J. Agricult. Res.*, vol. 11, no. 3, pp. 615–625, 2013.

[19] P. J. Herrera, J. Dorado, and A. Ribeiro, "A novel approach for weed type classification based on shape descriptors and a fuzzy decision-making method," *Sensors*, vol. 14, no. 8, pp. 15304–15324, 2014.

[20] J. A. Martínez-Casasnovas and X. Bordes, "Viticultura de precisión: Predicción de cosecha a partir de variables del cultivo e índices de vegetación," *Revista Teledetección*, vol. 24, pp. 67–71, 2005.

[21] K. Brittany and M. Michelle. Vineyard yield estimation. Washington State University. Accessed: Aug. 3, 2017. [Online]. Available: http://cru.cahe.wsu.edu/CEPublications/EM086E/EM086E.pdf

[22] P. Sabbatini, I. Dami, and G. S. Howell. *Predicting Harvest Yield in Juice and Wine Grape Vineyards (E3186)*. Accessed: Aug. 3, 2017. [Online]. Available: http://msue.anr.msu.edu/uploads/resources/pdfs/Predicting_Harvest_Yield_in_Juice_and_Wine_Grape_Vineyards_%28E3186%29.pdf

[23] G. M. Dunn and S. R. Martin, "Yield prediction from digital image analysis: A technique with potential for vineyard assessments prior to harvest," *Austral. J. Grape Wine Res.*, vol. 10, no. 3, pp. 196–198, 2004.

[24] R. Chamelat, E. Rosso, A. Choksuriwong, C. Rosenberger, H. Laurent, and P. Bro, "Grape detection by image processing," in *Proc. IEEE 32nd Annu. Conf. Ind. Electron. (IECON)*, Paris, France, Nov. 2006, pp. 3697–3702.

[25] G. Rabatel and C. Guizard, "Grape berry calibration by computer vision using elliptical model fitting," in *Proc. 6th Eur. Conf. Precis. Agricult. (ECPA)*, Skiathos, Greece, 2007, pp. 581–587.

[26] M. Battany, "A practical method for counting berries based on image analysis," in *Proc. 2nd Annu. Nat. Viticulture Res. Conf.* Davis, CA, USA: University of California, Jul. 2008, pp. 4–5.

[27] M. C. Ries *et al.*, "Automatic detection of white grapes in natural environment using image processing," in *Soft Computing Models in Industrial and Environmental Applications, 6th International Conference SOCO* (Advances in Intelligent and Soft Computing), vol. 87, E. Corchado, V. Snášel, J. Sedano, A. E. Hassanien, J. L. Calvo, and D. Ślęzak, Eds. Berlin, Germany: Springer, 2011.

[28] M. J. C. S. Reis *et al.*, "Automatic detection of bunches of grapes in natural environment from color images," *J. Appl. Logic*, vol. 10, no. 4, pp. 285–290, 2012.

[29] S. Nuske, S. Achar, T. Bates, S. Narasimhan, and S. Singh, "Yield estimation in vineyards by visual grape detection," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, San Francisco, CA, USA, Sep. 2011, pp. 2352–2358.

[30] S. Nuske, K. Gupta, S. Narasimhan, and S. Singh, "Modeling and calibrating visual yield estimates in vineyards," in *Proc. 8th Int. Conf. Field Service Robot.*, Miyagi, Japan, Jul. 2012, pp. 343–356.

[31] J. Tardaguila *et al.*, "Automatic estimation of the size and weight of grapevine berries by image analysis," in *Proc. CIGR AgEng*, 2012. [Online]. Available: http://wcigr.ageng2012.org/images/fotosg/tabla_137_C1735.pdf

[32] E. A. Murillo-Bracamontes *et al.*, "Implementation of hough transform for fruit image segmentation," *Procedia Eng.*, vol. 35, pp. 230–239, 2012.

[33] M.-P. Diiago, C. Correa, B. Millán, P. Barreiro, C. Valero, and T. Javier, "Grapevine yield and leaf area estimation using supervised classification methodology on RGB images taken under field conditions," *Sensors*, vol. 12, no. 12, pp. 16988–17006, 2012.

[34] C. C. Farias, C. V. Ubierna, and P. B. Elorza, "Characterization of vineyard's canopy through fuzzy clustering and SVM over color images," in *Proc. 3rd CIGR Int. Conf. Agricult. Eng. (CIGR-AgEng)*, Jul. 2012, pp. 8–12.

[35] S. Liu, S. Marden, and M. Whitty, "Towards automated yield estimation in viticulture," in *Proc. Australas. Conf. Robot. Autom.*, Sydney, NSW, Australia, vol. 24, Dec. 2013, pp. 213–221.

[36] S. Nuske, K. Gupta, S. Narasimhan, and S. Singh, "Modeling and calibrating visual yield estimates in vineyards," *Field Service Robot.*, vol. 92, pp. 343–356, Dec. 2013.

[37] S. Nuske, K. Wilshusen, S. Achar, L. Yoder, S. Narasimhan, and S. Singh, "Automated visual yield estimation in vineyards," *J. Field Robot.*, vol. 31, no. 5, pp. 837–860, 2014.

[38] D. Font, M. Tresanchez, D. Martínez, J. Moreno, E. Clotet, and J. Palacín, "Vineyard yield estimation based on the analysis of high resolution images obtained with artificial illumination at night," *Sensors*, vol. 15, no. 4, pp. 8284–8301, 2015.

[39] S. Liu, M. Whitty, and S. Cossell, "A lightweight method for grape berry counting based on automated 3D bunch reconstruction from a single image," in *Proc. Workshop Robot. Agricult.*, Seattle, WA, USA, May 2015.

[40] S. Liu, M. Whitty, and S. Cossell, "Automatic grape bunch detection in vineyards for precise yield estimation," in *Proc. 14th IAPR Int. Conf. Mach. Vis. Appl. (MVA)*, vol. 18, May 2015, pp. 238–241.

[41] L. Luo, X. Zou, Z. Yang, G. Li, X. Song, and C. Zhang, "Grape image fast segmentation based on improved artificial bee colony and fuzzy clustering," *Trans. CSAM*, vol. 46, pp. 23–28, 2015.

[42] L. Luo, Y. Tang, X. Zou, C. Wang, P. Zhang, and W. Feng, "Robust grape cluster detection in a vineyard by combining the AdaBoost framework and multiple color components," *Sensors*, vol. 16, no. 12, p. 2098, 2016.

[43] Vincent Casser. *Using Feedforward Neural Networks for Color Based Grape Detection in Field Images*. Accessed: Aug. 3, 2017. [Online]. Available: http://cscubs.cs.uni-bonn.de/2016/proceedings/paper-02.pdf

[44] A. Aquino, M. P. Diago, B. Millán, and J. Tardáguila, "A new methodology for estimating the grapevine-berry number per cluster using image analysis," *Biosyst. Eng.*, vol. 156, pp. 80–95, Apr. 2017.

[45] N. J. B. McFarlane, B. Tisseyre, C. Sinfort, R. D. Tillett, and F. Sevila, "Image analysis for pruning of long wood grape vines," *J. Agricult. Eng. Res.*, vol. 66, no. 2, pp. 111–119, 1997.

[46] J. Svensson. (2002). *Assessment of Grapevine Vigor Using Image Processing*. Accessed: Aug. 3, 2017. [Online]. Available: http://www.diva-portal.org/smash/get/diva2%3A18665/FULLTEXT01.pdf

[47] M. Gao and T.-F. Lu, "Image processing and analysis for autonomous grapevine pruning," in *Proc. IEEE Int. Conf. Mechatronics Automat.*, vol. 28, Jun. 2006, pp. 922–927.

[48] M. Gao, "Image processing and analysis for autonomours grapevine pruning," M.S. thesis, School Mech. Eng., Univ. Adelaide, Adelaide, SA, Australia, 2011.

[49] J. Lloret, I. Bosch, S. Sendra, and A. Serrano, "A wireless sensor network for vineyard monitoring that uses image processing," *Sensors*, vol. 11, no. 6, pp. 6165–6196, 2011.

[50] S. Xu, Y. Xun, T. Jia, and Q. Yang, "Detection method for the buds on winter vines based on computer vision," in *Proc. 7th Int. Symp. Comput. Intell. Design (ISCID)*, vol. 2, Dec. 2014, pp. 44–48.

[51] L. Luo, Y. Tang, X. Zou, M. Ye, W. Feng, and G. Li, "Vision-based extraction of spatial information in grape clusters for harvesting robots," *Biosyst. Eng.*, vol. 151, pp. 90–104, Nov. 2016.

[52] S. P. Diego, F. Bromberg, and A. D. Carlos, "Image classification for detection of winter grapevine buds in natural conditions using scale-invariant features transform, bag of features and support vector machines," *Comput. Electron. Agricult.*, vol. 135, pp. 81–95, Apr. 2017.

[53] *VintiOS*. Accessed: Aug. 4, 2017. [Online]. Available: http://www.vintios.com

[54] *Monet*. Accessed: Aug. 4, 2017. [Online]. Available: http://monet-ti.com

[55] *Ranch Systems*. Accessed: Aug. 4, 2017. [Online]. Available: http://marius.ranchsystems.com/wp/vineyards

[56] *Smart Vineyard*. Accessed: Aug. 4, 2017. [Online]. Available: http://smartvineyard.com

[57] *SAVE GRAPE*. Accessed: Aug. 4, 2017. [Online]. Available: http://www.auroras.eu/save-the-proactive-monitoring-system-for-the-vineyard

[58] N. G. Nair and G. K. Hill, "Bunch rot of grapes caused by Botrytis cinerea," *Plant Diseases of International Importance: Diseases of Fruit Crops*. Upper Saddle River, NJ, USA: Prentice-Hall, 1997, pp. 147–169.

[59] B. E. Stummer, I. L. Francis, T. Zanker, K. A. Lattey, and E. S. Scott, "Effects of powdery mildew on the sensory properties and composition of Chardonnay juice and wine when grape sugar ripeness is standardised," *Austral. J. Grape Wine Res.*, vol. 11, no. 1, pp. 66–76, 2005.

[60] S. Boso, J. L. Santiago, and M. C. Martínez, "Resistance of eight different clones of the grape cultivar Albariño to Plasmopara viticola," *Plant Disease*, vol. 88, no. 7, pp. 741–744, 2004.

[61] A. Meunkaewjinda, P. Kumsawat, K. Attakitmongcol, and A. Srikaew, "Grape leaf disease detection from color imagery using hybrid intelligent system," in *Proc. 5th Int. Conf. Elect. Eng./Electron., Comput., Telecommun. IT (ECTI-CON)*, vol. 1, May 2008, pp. 513–516.

[62] E. Peressotti, E. Duchêne, D. Merdinoglu, and P. Mestre, "A semi-automatic non-destructive method to quantify grapevine downy mildew sporulation," *J. Microbiol. Methods*, vol. 84, pp. 265–271, Feb. 2011.

[63] G. Li, Z. Ma, and H. Wang, "Image recognition of grape downy mildew and grape powdery mildew based on support vector machine," in *Computer and Computing Technologies in Agriculture V*, vol. 370, V. D. Li and Y. Chen, Eds. Berlin, Germany: Springer, 2012, pp. 151–162.

[64] S. S. Sannakki, V. S. Rajpurohit, V. B. Nargund, and P. Kulkarni, "Diagnosis and classification of grape leaf diseases using neural networks," in *Proc. 4th Int. Conf. Comput., Commun. Netw. Technol. (ICCCNT)*, vol. 4, Jul. 2013, pp. 1–5.

[65] P. R. Narvekar, M. M. Kumbhar, and S. N. Patil, "Grape leaf diseases detection & analysis using SGDM matrix method," *Int. J. Innov. Res. Comput. Commun. Eng.*, vol. 2, no. 3, pp. 3365–3372, 2014.

[66] N. B. Wadekar, P. K. Sharma, and N. S. Sapkale, "Detection and controlling of grape leaf diseases using image processing and embedded system," *SSRG Int. J. Elect. Electron. Eng.*, vol. 2, no. 10, pp. 13–15, Oct. 2015.

[67] R. R. Kajale, "Detection & reorganization of plant leaf diseases using image processing and Android OS," *Int. J. Eng. Res. Gen. Sci.*, vol. 3, no. 2, Part 2, Mar./Apr. 2015.

[68] H. Waghmare, R. Kokare, and Y. Dandawate, "Detection and classification of diseases of grape plant using opposite colour local binary pattern feature and machine learning for automated decision support system," in *Proc. 3rd Int. Conf. Signal Process. Integr. Netw. (SPIN)*, Feb. 2016, pp. 513–518.

[69] S. G. Gujjar and S. A. Angadi, "Plant clinic—A mobile app for grape plant disease detection and remedies," *Int. J. Sci. Res. Develop.*, vol. 3, no. 11, pp. 723–726, 2016.

[70] J. Pérez-Expósito, T. Fernández-Caramés, P. Fraga-Lamas, and L. Castedo, "VineSens: An eco-smart decision-support viticulture system," *Sensors*, vol. 17, no. 3, p. 465, Feb. 2017.

[71] B. Hed, H. K. Ngugi, and J. W. Travis, "Relationship between cluster compactness and bunch rot in Vignoles grapes," *Plant Disease*, vol. 93, no. 11, pp. 1195–1201, 2009.

[72] D. Molitor, M. Behr, L. Hoffmann, and D. Evers, "Impact of grape cluster division on cluster morphology and bunch rot epidemic," *Amer. J. Enology Viticulture*, vol. 63, no. 4, pp. 508–514, 2012.

[73] J. Tello and J. Ibáñez, "Evaluation of indexes for the quantitative and objective estimation of grapevine bunch compactness," *Vitis*, vol. 53, no. 1, pp. 9–16, 2014.

[74] S. Cubero *et al.*, "A new method for assessment of bunch compactness using automated image analysis," *Austral. J. Grape Wine Res.*, vol. 21, pp. 101–109, Feb. 2015.

[75] *New Computer Vision System Helps Estimate Compactness of Bunches of Grapes in Vineyards Objectively and Non-Invasively*. Accessed: Aug. 4, 2017. [Online]. Available: https://www.sciencedaily.com/releases/2015/03/150311140852.htm

[76] F. J. Rodríguez-Pulido, R. Ferrer-Gallego, M. L. González-Miret, J. C. Rivas-Gonzalo, M. T. Escribano-Bailón, and F. J. Heredia, "Preliminary study to determine the phenolic maturity stage of grape seeds by computer vision," *Anal. Chim. Acta*, vol. 732, pp. 78–82, Jun. 2012.
[77] F. J. Rodríguez-Pulido, L. Gómez-Robledo, M. Melgosa, B. Gordillo, M. L. González-Miret, and F. J. Heredia, "Ripeness estimation of grape berries and seeds by image analysis," *Comput. Electron. Agricult.*, vol. 82, pp. 128–133, Mar. 2012.
[78] F. Avila, M. Mora, and C. Fredes, "A method to estimate grape phenolic maturity based on seed images," *Comput. Electron. Agricult.*, vol. 101, pp. 76–83, Feb. 2014.
[79] A. Zuñiga, M. Mora, M. Oyarce, and C. Fredes, "Grape maturity estimation based on seed images and neural networks," *Eng. Appl. Artif. Intell.*, vol. 35, pp. 95–104, Oct. 2014.
[80] F. Avila, M. Mora, C. Fredes, and P. Gonzalez, "Shadow detection in complex images using neural networks: application to wine grape seed segmentation," in *Proc. Int. Conf. Adapt. Natural Comput. Algorithms*. Berlin, Germany: Springer, 2013, pp. 495–503.
[81] T. Gevers and A. W. M. Smeulders, "Color-based object recognition," *Pattern Recognit.*, vol. 32, pp. 453–464, Mar. 1999.
[82] F. Dan Foresee and M. T. Hagan, "Gauss-Newton approximation to Bayesian learning," in *Proc. Int. Conf. Neural Netw.*, vol. 3, Jun. 1997, pp. 1930–1935.
[83] N. Otsu, "A threshold selection method from gray-level histograms," *Automatica*, vol. 11, nos. 285–296, pp. 23–27, 1975.
[84] *Databases or Datasets for Computer Vision Applications and Testing*. Accessed: Aug. 5, 2017. [Online]. Available: http://datasets.visionbib.com/
[85] *The European Vitis Database*. Accessed: Aug. 5, 2017. [Online]. Available: http://www.eu-vitis.de/index.php
[86] *Vitis International Variety Catalogue VIVC*. Accessed: Aug. 5, 2017. [Online]. Available: http://www.vivc.de
[87] B. G. Coombe and M. G. McCarthy, "Dynamics of grape berry growth and physiology of ripening," *Austral. J. Grape Wine Res.*, vol. 6, no. 2, pp. 131–135, 2000.
[88] S. Y. Rogiers, Z. A. Coetzee, R. R. Walker, A. Deloire, and S. D. Tyerman, "Potassium in the grape (Vitis vinifera L.) Berry: Transport and function," in *Proc. Front. Plant Sci.*, vol. 8, p. 1629, Sep. 2017.
[89] B. P. Roe, H.-J. Yang, and J. Zhu, "Boosted decision trees, a powerful event classifier," in *Proc. Stat. Problems Part. Phys., Astrophys. Cosmology*, 2005, pp. 139–142.
[90] I. H. Witten, E. Frank, and M. A. Hall, *Data Mining: Practical Machine Learning Tools and Techniques*. San Mateo, CA, USA: Morgan Kaufmann, 2017.
[91] I. Goodfellow, Y. Bengio, A. Courville, and F. Bach, *Deep Learning*. Cambridge, MA, USA: MIT Press, 2016.
[92] T. P. Oliveira, J. S. Barbar, and A. S. Soares, "Multilayer perceptron and stacked autoencoder for Internet traffic prediction," in *Network and Parallel Computing* (Lecture Notes in Computer Science), vol. 8707. Berlin, Germany: Springer, 2014, pp. 61–71.

KAH PHOOI SENG received the B.Eng. and Ph.D. degrees from the University of Tasmania, Australia. She is currently an Adjunct Professor with the School of Computing and Mathematics, Charles Sturt University. She is also a Machine Learning Analytics Specialist with the National Wine and Grape Industry Centre. Before returning to Australia, she was a Professor and the Department Head of Computer Science & Networked System at Sunway University. Before joining Sunway University, she was an Associate Professor with the School of Electrical and Electronic Engineering, Nottingham University. She has published over 230 papers in journals and international refereed conferences. Her research interests are in intelligent visual processing, multimodal signal processing, artificial intelligence, multimedia wireless sensor network, affective computing, the development of intelligent system, and multimodal big data analytics.

LI-MINN ANG (SM'01) received the B.Eng. and Ph.D. degrees from Edith Cowan University, Australia. He is currently a Senior Academic Staff with the School of Computing & Mathematics, Charles Sturt University, Australia, and also the Leader with the Intelligent Analytics and Sensing Research Group, CSU. He was previously an Associate Professor at Nottingham Malaysia. He has published over 100 papers in journals and international refereed conferences, and is the author of the book *Wireless Multimedia Sensor Networks on Reconfigurable Hardware*. His research interests are in visual information processing, embedded systems and wireless sensor networks, reconfigurable computing, the development of real-world computer systems, large-scale data gathering in wireless multimedia sensor systems, big data analytics for sensor networks, and multimedia Internet-of-Things. He is a fellow of the Higher Education Academy, U.K.

LEIGH M. SCHMIDTKE received the Ph.D. degree in wine chemistry and micro-oxygenation of red wine from Charles Sturt University in 2011. He is currently with the National Wine and Grape Industry Centre. He has contributed to the development of several chemometric algorithms which are routinely used for metabolomics-based experiments employing a design of experiment concept. He has been involved in investigations of the impact of abiotic factors on grape and wine composition, wine oxidation, and wine sensory features for the past 15 years using a range of targeted and untargeted workflows. He has developed methods for rapid assessment of plant and wine composition based upon measures of infrared spectra and chemometric modeling of data.

SUZY Y. ROGIERS is currently a Principal Research Scientist with the NSW Department of Primary Industries. She is also with the National Wine and Grape Industry Centre, where she undertakes research on abiotic stress responses in grapevines. She has published on topics, such as cell senescence, Shiraz berry shrivel, fruit split, source-sink relations on fruit-set, water-use efficiency, night-time transpiration, and root-zone temperature effects on grapevine physiology and berry development. She is also interested in the underlying mechanisms driving water and sugar flow into berries. From a vineyard perspective, she is interested in developing simple tools for rapid, real-time assessments of vine stress, and berry quality parameters.